The impact and performance of new equity derivatives : evidence from universal stock futures

Chau, Frankie Ho-Chi

The Impact and Performance of New Equity Derivatives:

Evidence from Universal Stock Futures

By

Frankie Ho-Chi Chau

A thesis submitted in partial fulfilment of the requirements

for the degree of Doctor of Philosophy in Economics

Department of Economics and Finance

Durham Business School

University of Durham

May 2007

Abstract

Over the last few decades, a large number of new equity derivatives have emerged in the international financial system. Examples of these innovations include equity options, stock index futures, and more recently, futures on individual stocks. Whether the creation of these new derivative instruments has social or economic value is of central concern for both policy-makers and scholars. Advocates argue that the new derivative instruments make markets more complete, enhance information dissemination, and allow a more optimal allocation of risk in the economy. However, there are many who argue that derivatives have a negative impact on financial markets, by allowing more investors to take highly leveraged speculative positions.

A considerable amount of research has been directed towards examining the impact and performance of different commodity and financial derivatives markets. However, as a recent entrant to the global derivatives market, the evidence on Universal Stock Futures (USFs) market is very limited. This thesis, therefore, aims to provide new evidence in the literature by examining the role and functioning of USF contracts. Given their unique characteristics, the investigation of USFs provides more reliable and wider ranging insights into the economic benefits and costs of futures market. The empirical results can be summarised as follows. First, the introduction of USFs has not had a detrimental effect on the underlying markets. On the contrary, the influence appears to have been positive leading to a small reduction in noise trading and improved efficiency. Second, USFs perform the price discovery function efficiently since futures prices contribute to the discovery of new information. Furthermore, many USF contracts influence the volatility of the relevant stock, and therefore, further support the notion of price discovery. Third, the market also seems to perform its risk management function satisfactorily, although some contracts fail to reduce the price risk to the extent evidenced in other markets in the literature. Finally, sub-period/sub-sample analysis indicates that the effectiveness of USF contract as a centre for price discovery and risk management has strengthened over the years; and are influenced by market-specific factors (liquidity and trading costs), futures characteristics like contract size, and geographical origin of underlying stock. The overall finding of this thesis is that USF markets are well-functioning and do not undermine the existing markets. These results should provide useful reference for other emerging markets which have introduced and/or been considering to launch single stock futures to their markets.

Declaration

The material contained in this thesis has not been submitted in support of an application for another degree or qualification in this or any other University.

Acknowledgements

It is impossible to name everybody who has helped me during the preparation of this thesis. First, I would like to thank my supervisors, Professor Phil Holmes and Professor Krishna Paudyal, for their invaluable advice, guidance and encouragement. They have been extremely supportive and patient throughout the supervision process, and during the time when I was distracted and lost focus. This thesis would not have come into existence without their simulating comments and suggestions.

Second, I would like to express my gratitude to all my colleagues and friends for their constructive discussions on my work; and for providing such a pleasant academic environment. My sincere appreciation also goes to Rataporn Deesomsak for her endless care and understanding during those crucial years of my life.

Third, I gratefully acknowledge the financial support from the University of Durham in the form of Departmental Bursary for the first two years of my doctorate program. I am particularly grateful to my viva examiners, Professor Robert Watson at Durham University and Professor Gregory Koutmos at Fairfield University, for sharing their views on the improvement of this thesis. My research has clearly benefited from their valuable comments and suggestions. I am also indebted to an anonymous referee at the Journal of Futures Markets for helpful comments on a paper based on chapter 2.

Finally, my greatest thanks go to my family for their unconditional love, financial and moral support. I would not have come this far without their unwavering support and motivation over the years.

Thank you all.

Frankie Chau
May 2007

Publications

(i) Paper Under Review:

Authors: Frankie Chau, Phil Holmes and Krishna Paudyal

Title: The Impact of Single Stock Futures on Feedback Trading and Volatility Dynamics

Journal: Journal of Business Finance and Accounting

Date: March 2007

(ii) Conference Paper:

Authors: Frankie Chau, Phil Holmes and Krishna Paudyal

Title: The Impact of Single Stock Futures on Feedback Trading and the Market Dynamics of the Cash Market: The Case of Domestic and Cross-Border Universal Stock Futures

Conference: European Financial Management Association 15th Annual Meeting

Venue: Universidad Complutense, Madrid, Spain.

Date: June 28 – July 1, 2006

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1
Introduction

1.1 Introduction

Over the last few decades, a proliferation of new financial instruments has emerged and changed the financial landscape dramatically. Nobel economist, Merton Miller characterized the surge of new financial instruments from mid-1960s to mid-1980s as a twenty-year "revolution" in the history of financial innovation (see Miller, 1986). In the years since Miller's (1986) view, financial markets have continued to produce a multitude of new products. Alan Greenspan, Chairman of US Federal Reserve Board, stated that "By far the most significant event in finance during the past decade has been the extraordinary development and expansion of financial derivatives."[1]

Derivatives trading is now the world's biggest business, with an estimated daily turnover of over US$ 5.6 trillion and an annual growth rate of around 22%.[2] Yet, despite the large and important role that derivatives play in the financial markets, there is considerable controversy about their benefits and risks on the economy. According to Alan Greenspan, "Although the benefits and costs of derivatives remain the subject of spirited debate, the performance of the economy and the financial system in recent years suggests that those benefits have materially exceeded the costs." However, Buffett's view is that "Derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal."[3]

---

[1] This quote is from an address by Alan Greenspan to the Futures Industry Association (FIA) in Boca Raton, Florida on March 19, 1999. In chemistry, the term "derivative" is defined by *Merriam-Webster's Collegiate Dictionary* as "substance related structurally to another substance and theoretically derivable from it". Economists use the word "derivative" in a similar fashion to describe a financial contract whose value is derived from an underlying asset such as a commodity, security, index or event. The main types of financial derivatives include forwards, futures, options and swaps. See Swain (2000) for a comprehensive account of the history of derivatives.

[2] From the Bank for International Settlements (BIS) Quarterly Review, March 2006.

[3] These two quotes are from Alan Greenspan's Speech on May 8 to the 2003 Conference on Bank Structure and Competition. Warren Buffett's (Forbes-listed as the second richest person in the world) Annual Letter to shareholders of Berkshire Hathaway, March 8, 2003.

In spite of the debate, derivatives trading has proven to be highly popular and the number and scope of derivative markets have grown considerably in recent years. One of the most interesting developments on the derivatives scene is the coming of age of Single Stock Futures (SSFs). These instruments, which allow investors to buy exposure to individual stocks very economically, have been traded for some years on small regional markets such as Australia, Sweden, South Africa and Hong Kong. However, many big exchanges shunned them, and they were even banned in the US because of the regulatory concern for their potential negative impact on the economy. All that changed in 2001. During the year 2001, the London International Financial Futures and Options Exchange (LIFFE) launched a major programme of nearly 100 Universal Stock Futures (USFs) - its brand name corresponding to SSFs - on a wide rang of blue-chip stocks from 10 countries.[4] Later that year, the US Congress passed legislation that reversed its ban on SSFs, opening the way for the large US derivative exchanges to enter the field. By the end of 2001, there were 15 exchanges around the world trading over 300 SSF contracts.[5] These numbers have continued to grow in recent years as more exchanges have come on board and started trading SSFs.

The success of the SSFs has been remarkable as witnessed by the phenomenal growth of the volume of contracts traded which has significantly surpassed the volume of contracts traded in stock options markets. For example, volume in USFs now exceeds volume in single sock options traded in the LIFFE (see Table 1.2). Furthermore, the rapid growth of single stock futures is not a phenomenon experienced only in the London market. Several smaller exchanges, such as the Spanish Exchange for Financial Futures and Options (MEFF) and National Stock

[4] Following the purchase of LIFFE by Euronext in January 2002, LIFFE became part of Euronext.liffe, comprising of Amsterdam, Brussels, LIFFE, Lisbon and Paris derivatives markets. For convenience, the term "LIFFE" is used throughout this thesis for either LIFFE or Euronext.liffe.
[5] See Lascelles (2002) for a survey of exchanges trading SSF contracts in 2001.

Exchange of India (NSE), have actively traded futures contracts on individual stocks. Thus, the impressive success of these new instruments is indeed a global innovation.[6]

Although SSF is arguably the most exciting new product launch within the equity derivatives arena in the 21st century, whether the creation of these derivatives has economic or social value is of central concern for both policy-makers and scholars. While most authors acknowledge that SSF revolution (as any other types of derivatives innovation) has both positive and negative impacts on society, their conclusion regarding the net impact of these new financial derivatives in general reflects a diversity of opinions.[7] On one hand, proponents of SSF trading believe that it enhances the efficiency and price discovery of financial markets, allows for low cost trading and provides an avenue for investors to hedge risk. On the other hand, there are many who argue that SSF trading is destabilising in that it attracts speculative traders who induce excess volatility in the market (see USGAO, 2000).

Unfortunately, despite increasing usage and growing interest, little is known about the economic benefits and costs of the new SSF contracts.[8] In particular, while a body of evidence exists for the role and functioning of derivative markets, academic studies on derivative instruments have typically focused on the stock options and stock index derivatives (see, e.g., Mayhew, 2000). As a result of their lack of history, SSFs have been subject to very little attention in the academic research.[9] Therefore,

---

[6] In a survey conducted in 2002 by the Centre of the Study of Financial Innovation (CSFI), the SSF contract is described as "ultimate" derivatives, representing another "revolution" in derivative trading. The popular press also espouses a similar view (see, for instance, Young and Sidey, 2003).

[7] For example, new derivative products in Australia created much disagreement between Sydney Futures Exchange (SFE) and the Australian Stock Exchange (ASX) engaging in legal battles over the introduction of the Individual Share Futures (ISF) contracts (see McKenzie et al., 2001).

[8] See, e.g., Zwick and Collins, "One year in and the jury is still out", *Futures*, January 2004.

[9] Exceptions include Dutt and Wein (2003) who suggest appropriate margin requirements for the US SSF market, and McKenzie et al. (2001) who investigate the impact of ISF listing on the underlying stock market in Australia. See also Brailsford and Cusack (1997), Lee and Tong (1998), Hung et al. (2003), Ang and Cheng (2005a, 2005b).

the main objective of this thesis is to fill this gap in the literature by providing a detailed investigation into the role and functioning of Universal Stock Futures (USF) contracts, the only SSF contracts written on both domestic and foreign stocks.[10] More specifically, this thesis investigates three different, but interrelated, issues regarding the impact and functioning of USF markets. First, it analyses the impact of USF trading on the underlying stock market. Second, it investigates the price discovery function of USF market. Third, it examines the risk management function of USF contract by measuring its hedging effectiveness.

The analysis of these three issues should be of interest and direct benefit to both the academic and financial communities. For instance, an understanding of the impact of USF trading on the underlying stock market should provide important insights to policy-makers and exchange regulators in formulating appropriate policies on these innovative instruments. Moreover, if the findings show that the USF market contributes significantly to price discovery, this indicates that some information is first reflected in that market, and movements in these markets will be relevant to investors trading the underlying shares. In addition, an analysis of the hedging effectiveness of USF contracts should be of particular interest to those investors who have concentrated holdings on an individual stock, and enable them to design more efficient hedging strategies to minimise their risk to individual stock exposure.

The purpose of this chapter is to provide an introduction to the thesis. It is divided into three main sections where each section considers the following issues. The first section discusses the economics of futures trading. It begins with an overview of the

[10] Although SSF contracts based on overseas stocks was briefly trialled before in some smaller exchanges such as Hong Kong Exchanges and Clearing (HKEx) in 2001, the trading of these initial contracts was suspended after a short life due to the slim market turnover. The HKEx has argued that the lack of volume in international stock futures was due to the large contract size (e.g. 10,000 shares for Taiwanese stocks) and the immaturity of the market.

importance of derivative markets in the complete financial system, and presents an appropriate framework that the presence of new financial derivatives should be analysed. Subsequently, the role and functions of futures markets are discussed. It describes the social benefits that futures markets provide to the market participants. The second section presents an overview of USF market. It provides the contract specifications and a historical background of the evolution in this market, illustrates the potential uses of the contract, and assesses the unique characteristics of this market that set it apart from other futures markets investigated so far in the literature. Finally, this chapter concludes by presenting the three research topics that are investigated in this thesis as well as their contributions to the literature.

1.2 The Economics of Futures Trading

1.2.1 The Importance of Derivative Instruments

Derivatives are now an integral component of a complete financial market system. This is despite derivatives being the subject of much recent controversy, arising from their much-publicised use as speculative trading instruments. For example, the magnitude of derivatives-related losses such as Barings plc through Nikkei index futures, Metallgesellschaft AG through oil futures hedging, Procter & Gamble through interest rate swaps, and, more recently, Enron's active participation in derivative markets, have exaggerated popular fears of these products. These (and other) losses and a growing cautiousness in the market have led to an increased focus on the role and use of derivative instruments. As the academic society has struggled, in the early days, to reach a common verdict on the economic benefits and risks of derivatives, there have been strong calls for increased regulation of these instruments from both within and outside the financial markets.[11] However, any further restrictions imposed on derivatives trading, if not fully documented, may result in the trading anomalies causing a disruption in the efficient wealth allocation.[12]

As Merton (1990, p.263) points out "The core function of the financial system is to facilitate the allocation and development of economic resources, both spatially and across time, in an uncertain environment." To fully appreciate and assess the role of derivative markets, perhaps it would be very useful to put the above into perspective. In the absence of capital markets, members of the society have to balance earnings and spending over every period. The presence of a financial institution will enable individuals to reach this equilibrium across time.[13] However, the intertemporal nature of financial decisions implies uncertainty and market participants start to face the risk of deferring spending into less favourable future and having to assess the available information. Nonetheless, the capital markets should provide a wide range of instruments to either eliminate or re-allocate the uncertainty among market participants, from those who want to avoid risk to those who are willing to accept it. As Gibson and Zimmermann (1994) states "In order to achieve an unconstrained Pareto-efficient allocation of these risks within a market system, capital markets must provide sufficient opportunities to trade and price the various kinds of risk." Hence, it is obvious that the socially required role of financial markets is to expand the opportunity sets for investors and to facilitate the flow of relevant information.

---

[11] There are more than 200 proposals to prohibit, limit, tax or regulate derivatives trading in the US in the last century. For example, see the Presidential Task Force Report (1988), the Group of Thirty report on OTC derivatives (1993), and the US Government Accounting Office Report (1994).

[12] For instance, there are a substantial number of studies showing that short-sales restrictions increase the level of mispricing and impose a serious limitation to the allocative efficiency of a market system (see. e.g., Kempf, 1998; Fung and Draper, 1999).

[13] According to Gibson and Zimmermann (1994), the economic function of financial markets can be seen in three dimensions: time, risk, and information. Borrowing and saving are the major functions of the financial systems in order to achieve an efficient intertemporal allocation of funds. Capital markets allow households and firms to match earnings and expenses in each period by issuing or acquiring claims against their future income. To achieve this purpose, they would write financial contracts.

It is within this framework that the presence of financial derivatives should be considered. In particular, there are two pertinent questions to be answered with regard to the existence of new derivative markets; (i) whether they have detrimental effects on the underlying market and (ii) whether they really serve the socially justified requirements of a financial system (price discovery and risk management). An assessment of these issues in relation to the new USF contracts forms the main part of this thesis. However, before going on to undertake analysis of these issues, it would be appropriate to begin with a brief summary of the role and functions of futures markets in general, and then proceed to present an overview of USF markets. An understanding of the environment in which USF markets operate and the way in which they operate is a prerequisite to a proper appreciation of the subject matter of this thesis.

1.2.2 The Role and Functions of Futures Markets

A futures contract is an obligation (i.e. a legally binding agreement between a buyer and a seller) to receive or deliver a standard quantity of a particular commodity or financial instrument at a future date for a price which is agreed at the time the contract is drawn up.[14] Organised trading in futures contracts dates back to the mid-nineteenth century with the opening of Chicago Board of Trade (CBOT) in the US. Since then, there has been an explosion in both the range and trading volume in futures contracts. Currently, there are 65 exchanges throughout the world, trading more than 1,000 futures contracts written on different underlying instruments such as commodity, currency, financial securities or index.[15] This growth in futures trading

[14] Futures contracts have a number of characteristics in common with equities, forward contracts and over-the-counter (OTC) derivatives, as well as a number of dissimilarities. The distinguishing characteristics of these instruments are discussed in many good texts. See, for example, Kolb (2000).
[15] From *Futures and Options Fact Book* published by The Institute for Financial Markets (IFM), which is available at: http://www.theifm.org/

activity and the variety of contracts reflects the increased economic benefits that futures markets provide to market participants. As Kolb (2000, p.25) points out "Any industry as old and as large as the futures market must serve some social purpose. If it did not, it would most likely have passed from existence some time ago."

In general, the two main social functions of futures markets are price discovery and risk management through hedging. Price discovery is the process of revealing information about current and future cash prices through the futures markets. Risk management refers to investors using futures contracts to control their spot price risk. These dual roles of price discovery and hedging provide benefits that cannot be offered in the spot market alone and are often presented as the justification for futures trading (see, e.g., Garbade and Silber, 1983). For example, in determining approval for trading in a new futures contract, the US Commodity Futures Trading Commission (CFTC) requires the contract to pass the "economic purpose test", which provides that a proposed futures contract should meet the following criteria; (i) must contribute to price discovery in the market, (ii) must be useful for hedging, and (iii) must not be detrimental to the existing cash market (see, e.g., Figlewski, 1987; Hahn and Tetlock, 2006).[16] Undoubtedly, the performance (success or failure) of a new futures contract is dependent upon the contract providing benefits to economic agents, over and above the benefits they can get in the spot market alone. These benefits are price discovery and hedging. However, while this thesis intends to examine the role and functioning of new USF contracts in detail, it is important to have some understanding of the social functions of futures markets in general, and single stock futures in particular, before proceeding.

[16] Also see the CFTC's publication on "Economic and Public Requirements for Contract Market Designation", in 1998 (which is available at: http://www.cftc.gov/foia/fedreg98/foi980717b.htm). According to these requirements, an exchange must demonstrate "economic justification" of a proposed contract prior to approval. In other words, there must be proof of economic purpose/benefit before any new futures contract can come into being.

1.2.2.1 Price Discovery Function

Physical and financial asset prices are determined through the interaction of supply and demand forces in the economy. The existence of futures markets provides a mechanism in which the supply and demand for an asset are brought into alignment. For example, if new information becomes available which suggests that the future supply of an asset will be tighter than previously expected, the futures price for a later delivery period would be expected to increase. Also, the spot price which is finally observed in the later period should be higher than it would have been without the new supply information. By allowing investors to send a collective message about how new information is expected to impact the spot market, futures markets play a crucial role in gathering the information about current and future spot prices.[17]

The existence of a strong relationship between futures and spot prices also has implications for the risk management function of the market. The greater the degree of interdependence between spot and futures prices, the greater the effectiveness of the futures market in terms of hedging. Specifically, if spot and futures prices respond in a similar fashion to the arrival of new information, then they will tend to move closely together over time. As a result, market participants can use futures contracts to effectively control their future spot price risk since any loss in one market (spot or futures) will be largely/entirely offset by gains in the other market (see Table 1.1 for an example).

[17] According to Edwards and Ma (1992), the process of revealing spot price information through the futures markets has two main parts. The first part relates to the ability of futures price to form unbiased estimator of the spot prices that will prevail at the contract expiration date, which has manifested itself in what has come to be known as the "unbiased hypothesis" in the literature. The second part examines whether futures markets help to discover information regarding current spot prices, which has been regarded as the analysis of the "lead-lag" relationship between two markets. Following the more recent literature, see Mayhew (2000), this thesis deals mainly with the latter.

1.2.2.2 Risk Management Purpose

Market participants are confronted with various risks that arise from the ordinary conduct of their business. The existence of futures markets provides a way in which these risks may be transferred to other individuals who are willing to bear them. Hedging (i.e., the trading of futures contracts with the objective of reducing or controlling future spot price risk) is seen to be the major function of futures markets. According to Kolb (2000), the opportunity to control price risk through futures hedging is "...perhaps the greatest contribution of futures markets to society" (p.85). If price risk can be controlled efficiently through futures hedging, then profitable investment opportunities involving a high level of risk can be pursued and, as a result, society as a whole benefits economically.

Hedging involves taking a position in the futures market that is opposite to the position that one already has in the spot market. For a futures contract to be an effective hedging vehicle, any gains or losses in the value of the spot position, due to changes in the spot prices, will have to be countered by offsetting changes in the value of the futures position. Generally speaking, hedges are either "short" or "long". A short hedge involves selling futures contracts as a protection against a perceived decline in spot prices, whereas a long hedge involves buying futures as a protection against a price increase.

The above discussion clearly shows that futures markets play an essential role in economy and provide economic benefits to the market agents through their price discovery and risk management functions. The extent to which different commodity and financial futures markets have served as efficient centres for risk-sharing and information gathering has been the focus of considerable research in the literature.

The full list is too long to provide a census, but notable examples using currency futures markets data include studies by Kroner and Sultan (1993), and Chatrath and Song (1998). Examples of studies examining stock index futures markets include Figlewski (1984), Butterworth and Holmes (2000, 2001), and So and Tse (2004). More recently, the E-mini index futures has also attracted the attention of academics. Examples using U.S. data include Hasbrouck (2003), and Kurov and Lasser (2004).

Despite this plethora of studies in various commodities and financial futures markets, the evidence on the Single Stock Futures (SSF) contracts is very limited, primarily due to their lack of history and the unavailability of data. Although these contracts have been the focus of some recent research, the issue of whether the market serves the price discovery and risk management functions has been subject to very little attention in published research. This is particularly true for USF market. Such a lack of understanding also exists regarding to their impact on the underlying stock market. It is the objective of this thesis, therefore, to investigate these issues and provide new evidence in the literature regarding a futures market which has unique characteristics. These characteristics are described in more detail in the following section.

1.2.2.3 Speculation Role

While futures markets can be seen to be enhancing economic welfare by allowing for new positions and expanding the investment sets or enabling existing positions to be taken at lower costs, they have been criticised for destabilising underlying markets. This criticism has its origin in the debate over the impact of speculators and the fact that it can be argued that futures encourages speculation. This "encouragement" of speculation emerges through the nature of the futures contract itself. As discussed earlier, futures is a highly standardised contract in which the buyer of the contract is purchasing a claim on the spot asset at some time in the future. Furthermore, engaging in a futures market transaction only requires the posting of a margin which is a fraction of the price. Thus, as Goss and Yamey (1978) point out, futures markets make a distinctive contribution to speculation since they allow individuals to undertake speculative activity without them having to become involved in the production or processing of the commodity or asset. In addition, because they are standardised contracts, futures facilitate the specialisation in speculation without a large amount of funds being committed. Therefore, there has been considerable concern regarding the impact that futures markets might have on the underlying spot market. Indeed, this concern dates back almost to the inception of futures trading.

In general there are two main beliefs among market participants. The classical view is that the speculators in futures markets have a destabilising impact on spot markets. In contrast there have been a number of market agents/economists who have argued that the activities of speculators will have a stabilising impact on spot market prices. It can also be argued that futures markets require speculators providing its liquidity and enable hedgers to transfer risk. This controversial issue has been the subject of considerable theoretical and empirical analysis and has received the repeated attention of policymakers. Despite the volume of research, futures trading is still viewed with considerable suspicion by market participants and policymakers alike. Such suspicion has led to suggestions that futures trading should be further regulated, including, for example, higher margins (the Presidential Task Force Report, 1988). However, further regulation may have a negative impact on the working of financial markets and hence on economic welfare and it is therefore important to carefully consider whether such action is justified / beneficial. This thesis aims to investigate this critical issue and to provide new additional evidence in the literature.

1.3 Universal Stock Futures (USF) Markets

While the history of futures trading is replete with examples of significant innovations, the onset of Single Stock Futures (SSF) trading in the world's financial markets is arguably the most important of such milestones (see Lascelles, 2002). As the name suggests, SSFs are futures contracts on individual stocks and, as with any futures contract, they represent an obligation, in this case the obligation to buy/sell shares of an individual company, some time in the future at a price agreed today.[18] Futures contracts on individual stocks are not an entirely new phenomenon in the international marketplace. During the 1990s some small European, Australian and Asian exchanges introduced SSF contracts on a limited number of domestic stocks, but for the most part these contracts registered modest trading activity. However, all this has changed dramatically in the early 2000s. In January 2001, LIFFE launched Universal Stock Futures (USFs) – a range of SSFs based on several dozen world-class stocks.[19] This move by one of the world's leading derivative exchange lifted SSFs out of obscurity and placed them firmly on the international investment menu.

The importance of USFs to market participants is clearly shown by the rapid growth in the number of stocks on which USFs are written. At the first listing date (29 January 2001) 25 USFs were listed on stocks traded in 8 countries. Subsequently, the number traded had increased to 97 by the end of 2001 (11 countries) and to 433 by June 2005 (13 countries). In 2005 trading volume exceeded 11.7 million contracts, making it the world's largest SSF exchange in terms of trading volume.

[18] For instance, someone who buys a June 2007 Vodafone futures today has made a contract to take delivery of Vodafone stock in June 2007 at the price transacted in the futures market today.

[19] USFs – the term LIFFE uses for single stock futures - first started trading on the exchange's electronic trading system, LIFFE Connect, on January 29, 2001, with the launch of 25 contracts linked to stocks from eight countries and five sectors, denominated in three currencies. An up-to-date list of the contracts can be found on the USF's website at http://www.universal-stockfutures.com/

Since the subject matter of the investigations undertaken in this thesis is USFs, this section provides a brief summary of these revolutionary new products. First, it summarise the contract specifications by highlighting their unique characteristics. Second, it discusses their potential uses and the major regulatory concern. Finally, the growth of this market is assessed by examining the behaviour of trading volume.

1.3.1 Contract Specifications

The USF contracts are global products with contracts available on an international list of stocks. With futures traded on the shares of 433 companies, in 13 countries, they enable investors to gain broad exposure to equity prices, using a single exchange, under a single regulatory regime, on a single electronic platform, on a range of possible currencies. Also, trading with UK USF has an added benefit of not having to pay "stamp duty" because futures contracts are not counted as securities for tax purposes.[20] The salient features of USF contract specifications are as follows:[21]

1) Each futures contract represents a certain number of underlying shares. This number is known as the lot size. The standard lot size for USFs is 100 shares, except for Italian and UK futures, where one USF represents 1,000 shares.
2) The currency of trading for USF contracts reflects the currency of trading of the underlying share. LIFFE lists futures contracts based in seven currencies.
3) LIFFE's USFs are cash settled contracts, except for Danish and Norwegian futures where contracts are physically delivered. At the end of the life of the contract, no shares change hands. Instead, throughout the life of the contract, the buyer and seller exchange the daily profit/loss on the futures trade.

[20] In the UK, purchasers of cash equities will have to pay one of the world's more regressive taxes - "stamp duty" - on every transaction. This does not apply to USFs, thus making them a much more cash-efficient trading tool, compared to trading in the stock market.

[21] Many of the contract features vary across different contracts, depending on the underlying stock on which the futures is written on. Detailed contract specifications can be found on LIFFE's website.

4) USF contracts are listed with up to six months' life. An investor can trade the nearest two of March, June, September and December. In addition, he can trade the nearest two contract months closest to the current calendar month.

1.3.2 Potential Uses and Major Concern

As stated earlier, futures trading provides an important tool that assists everyone in the marketplace determine value. Through the futures markets, information about the expectation of all market participants regarding future development in the spot market can be assimilated to produce a single forecast of the expected spot price. This availability of information reduces "search" costs and provides signals that guide investors to make the efficient and informed decisions. Similarly, since USF contracts are traded for delivery at various points in the future, they reflect the current expectation of the market about the level of the underlying stock some time in the future. For instance, if the USF price 2 months from maturity is trading above the current stock price, this reflects the current market expectation that this stock, two months from now will be above its current level.

The following is an example: On 1 January 2001, the Vodafone shares are priced 241p, and with its USF contract for delivery in March 2001 currently trading at 253p. This suggests that the market expects the value of Vodafone shares to strengthen, over the period January to March 2001, and will rise above its current value of 241p. Therefore, through the USF markets the market participants can get an indication of the expected level of underlying stock prices in the future. This ability to achieve and disseminate price information (i.e. price discovery) benefits not only the futures markets participants, but also those who are active in both stock and futures markets. Empirical tests for this benefit of USF market are presented in chapter 3 of the thesis.

The second benefit that USF contract provides to market participants is the possibility to control their risk exposure through hedging. Hedging is the process of eliminating or reducing price risk through the futures trading which involves setting up an opposite position on the futures markets as to that held on the stock market. For instance, when a short term fall in a stock price is anticipated, the shareholder of the stock can sell a future to avoid making a loss without having to sell the share. Any loss caused by a fall in stock price may be offset by gains on futures position.

Table 1.1 presents an example, adapted from LIFFE's website, illustrating the use of USF for hedging the "event risk" of a particular stock. Consider an investor who holds 10,000 shares of a UK biomedical stock ABC that has a significant new product pending approval from the authority. ABC shares are currently priced at 500p, but this investor fears that the new drug disapproval could lead to a large drop in the price of the stock within the next month. In an effort to protect his income against this price fall, this investor initiates a futures hedge by selling USF contracts on ABC for delivery in one month at a price of 508p. As one USF contract for UK contracts is based on 1,000 shares, the investor sells 10 ABC futures.

A month later, the proposed new drug is indeed disapproved by the authority and ABC share price falls to 480p. However, the drop in ABC stock price is also accompanied by a drop in the price of its USF contract which now stands at 486p. The investor closes out the futures position by buying back the 10 ABC futures at 486p (i.e. unwinds the hedge). Since the shares have fallen 20p each and the futures have fallen 22p (assuming it has sold), this investor gains from the fall in the futures price. Table 1.1 illustrates how the investor has protected his shareholdings.[22]

[22] In order to establish this futures position, the investor contracts a broker at LIFFE who executes the transaction on behalf of the investor. In return of this service, however, the broker charges some fees. For simplicity, brokerage fees and other costs are not incorporated in the calculation of this example.

However, despite the profits from the hedged portfolio, it should be noted that the performance of this hedge is far from perfect. For a perfect hedge, the variability of the net cash flows from the hedged position should have been zero in this example. The fact that this is not the case can be partly attributed to the use of "naïve" (i.e., one-to-one) hedging strategy. A one-to-one hedge is effective as long as stock and futures prices change by the same amount. In practice, however, there is unlikely to be perfect correlation between the stock and futures prices and hence two prices do not always move together. Therefore, an alternative strategy must be used to determine the hedge ratio that minimises the difference between losses in the stock market and gains in the futures market or vice versa. The effectiveness of such a strategy is investigated empirically in chapter 4 of this thesis.

As with other types of derivatives, the central regulatory concern involving USFs is the potential negative impacts of the onset of their trading on the underlying markets. There is a fear that they encourage speculation which destabilise the market for the underlying by driving the underlying equity prices away from fundamental values. Consequently, the price discovery function of futures markets would be damaged. Nevertheless, for the most part, the potential negative impacts associated with stock futures have neither been supported by previous related literature nor by the experiences of foreign countries which permit trading futures on individual stocks. For example, the evidence reported by Lee and Tong (1998), Dennis and Sim (1999) and McKenzie et al. (2001) suggest that the onset of SSF trading has little or no effect on cash market volatility.[23] All these three studies focus on the Individual Share Futures (ISF) market in Australia. However, no one has yet conducted any study of the impact of USFs on the underlying stock. The detailed investigations on this public concern for the USF contracts are carried out in chapter 2 of this thesis.

---

[23] The findings of the previous related research are discussed more thoroughly in chapter 2.

1.3.3 Market Performance

Trading volume is often used to measure the performance of a futures contract (see, e.g., Silber, 1981; Carlton, 1984; Black, 1986). Successful contracts often have manifest active trading volume while less successful contracts tend to exhibit thin trading volume. Volume of trading is also generally used as a measure of liquidity.[24] The concept of a liquid market is closely tied to the issue of fair pricing. It is a common belief that the more liquid the market, the greater the number of traders and hence the more competitive is the market, which ultimately results in fair pricing. Therefore, the USF trading activity or liquidity is an important factor in ensuring a fair futures market.[25] Open interest (i.e. the total number of outstanding contracts) provides a different measure of contract activity, as it excludes by definition all short-term trading by the day traders, many of whom are inspired by speculative motives. From this perspective, one could argue that open interest primarily reflects hedging demand (see Bessembinder and Seguin, 1993). Extant literature points out the prerequisite for a successful futures contract is the presence of hedging demand in addition to an environment that is conductive to futures trading (see Cuny, 1993).

In the light of the above discussion, this section assesses the success (or failure) of USF contracts based on the volume and open interest measures in terms of the numbers of contracts traded. Figure 1.1 shows the monthly total volume and open interest on all USF contract traded on LIFFE from its launch date to December 2005. For comparison purposes, the daily average volume of LIFFE's stock options and USFs are also computed and presented in Table 1.2. View collectively, Figure 1.1 and Table 1.2 should provide useful information about USF market performance.

---

[24] Previous literature has also adopted other measures to proxy for market liquidity, including the bid-ask spread, depth of orders, frequency of trading and number of traders (see, e.g., Aitken and Comerton-Forde, 2003).

[25] While it is argued here that an active and liquid market ensures fair pricing, some believe that this is probably necessary but not sufficient condition as liquid markets can exist because of price markers.

As illustrated by Figure 1.1, the level of trading volume and open interest on all USFs has increased gradually from the early months of trading. Moreover, USF contracts appear to be mostly heavily traded in the second quarter of each year (i.e., April, May, and June). This is understandable given the fact that many companies make announcements such as earnings or other corporate news around those few months. In today's marketplace, any publicly traded company that is announcing earnings is typically a candidate for high volatility, which may result in increased demand for futures hedging to protect against the possible adverse price movement.

This conjecture is also supported by inspecting the patterns in the monthly total open interest. It is evident from Figure 1.1 that the total open interest shows the same heterogeneity as the total trading volume, characterised by frequent heavy trading during the second quarters. This in turn implies that the hedging demand for USFs is at the highest during the period when many companies make their corporate announcements.

The growth of the USF trading can be put into perspective by considering the trading volume of other existing (or competing) equity derivatives such as stock options. With reference to Table 1.2, the USF's trading records are very successful, especially in contrast to comparable options contracts.[26] Although the average daily volume levels remained modest during the first year of its existence, they have taken off thereafter and reached the highest record of 49,920 contracts traded per day in their fourth year of trading. On the contrary, it took over 10 years (i.e. from 1992 to 2002) to build that daily average volume in single stock options at LIFFE.

[26] However, it should be noted that the figures in Table 1.2 should be interpreted with some caution because of two reasons. First, the figures only give the number of contracts traded and not the number of individual transactions. Second, since the figures are averages they can be distorted by infrequent heavy periods of trading.

One reason for this rapid growth in USF trading is the emergence of new players in the market. Max Butti, LIFEE product manager for USF, explained that "As well as participants in the German, French and Dutch markets, hedge funds are seizing the opportunity to trade global blue-chip stocks in a cheap, easy and efficient manner using Universal Stock Futures."[27] Despite the fact that USF were only launched by LIFFE in January 2001 and are still relatively young product, they are now trading at a level only achieved by equity options after more than ten years of trading. In fact, since 2004, volume in USFs has exceeded volume on stock options traded in LIFFE.

Overall, LIFEE's USF contracts seem to have attracted a fair amount of trading volume in their early years of trading. This, however, represents neither a necessary nor a sufficient condition for long-term success of the products. That is, the success (or failure) of the contract cannot simply be judged in terms of trading volume alone. As discussed in section 1.2.2, the success of a futures contract is highly dependent upon the contract providing benefits to economic agents, over and above the benefits they can get in the spot market alone. If no such benefits exist, then market participants have no reason to trade in futures market instead of the stock market. Therefore, if the success of the new USF contract is to be assessed, it is essential that detailed investigation be carried out as regard to the nature and economic roles of USF market. First, it is necessary to assess the impact, if any, of the introduction of these futures contracts on the underlying stock markets. Second, it is necessary to examine whether the futures contract has succeeded in fulfilling the economic roles expected of such a contract (i.e., the price discovery and risk management functions). This thesis aims to address these important issues in detail.

[27] This quote is from the presentation given by Max Butti to the Futures and Options World (FOW) Derivatives and Securities forum held in Madrid on October 14, 2003.

1.4 Structure of the Thesis and its Contribution to the Literature

This section presents the research issues that are addressed in this thesis, along with its contributions to the current literature. This thesis consists of five chapters, including the present one. Three research issues identified in the preceding discussion are investigated in chapter 2 to 4 accordingly. The common theme of these three chapters relates to the economic roles of Universal Stock Futures (USF), and how the introduction of these contracts has affected the underlying stock market. The general structure of these empirical chapters is similar: each chapter begins with an introduction on the background of the research area in question; discusses the relevant theory and related issues; describes the methodology and testing procedure to be used; reports and discusses the empirical findings; and draws conclusions.

As stated earlier, while futures markets can be seen to be enhancing economic welfare by facilitating the risk-sharing and information dissemination, they have been criticised for destabilising the underlying markets. Despite the plethora of studies, there exists no study on the effect of USF trading on the stock market upon which the futures contract is based. For this reason, chapter 2 investigates the impacts on the stock market due to the introduction of a corresponding USF contract. Unlike previous studies, the heterogeneous trader model of Sentana and Wadhwani (1992) is used to examine this issue. This theoretical model captures the behaviour of both rational traders and irrational trend-chasers (i.e., traders adhering to positive feedback trading strategies), and thus enables the deeper insights into the changes of return characteristics caused by the onset of futures trading to be assessed. Combined with a GARCH specification for conditional volatility, this model allows examining the consequences of USF trading not only on underlying volatility, but also on the extent to which futures inhibit / promote the level of noise trading in stock market.

The investigation begins by examining the futures listing choices of LIFFE in order to identify the control stocks that explicitly account for the endogenous bias inherent in many previous studies. The main analysis of the investigation remains, however, with the use of the heterogeneous trader model to exploit the changes in return autocorrelation and volatility induced by USF trading, a practice which constitutes the main contribution of the investigation. In addition, given the significance and unique characteristics of USF contracts, this chapter also able to investigate a wide range of important issues that have not been addressed previously in the literature. For example, the large number of USFs listed on stocks from various industries across different countries provides a key opportunity to examine the potential country and/or industry effects in the impact of futures trading.

The main findings are that there is a limited feedback trading in the underlying stock markets, but the degree of feedback trading has fallen further since the onset of USF trading. While there are some changes in the underlying volatility level and nature, similar changes are also observed in the control stocks, suggesting that these changes are not futures induced. Taken together, the results from this analysis show that the introduction of USFs has not impacted negatively on the underlying markets, and to the extent that USFs have impacted on market dynamics, the influence appears to have been positive, leading to a small reduction in feedback trading and improved efficiency. This implies that the public concern over the adverse impact of futures trading is not entirely justified and calls for further regulation on these markets (such as higher margins and restrictions on the issue of new contracts) is unwarranted.

The provision of hedging opportunities is arguably the most important benefit of futures markets, but for USFs to perform this economic function efficiently, the informational role of futures must be satisfied. The ability to achieve and disseminate price information (i.e. price discovery) available to market participants is an essential role of futures market in ensuring an efficient and complete financial market system. A considerable amount of empirical research has been directed towards examining the lead-lag relationship and the price discovery function in a variety of derivatives markets. However, studies that explicitly investigate the relationships between single stock futures (SSFs) and the underlying stock are virtually nonexistent, primarily due to their lack of history and the unavailability of data.

Investigation in chapter 3 not only provides, for the first time, evidence on the price discovery function of USF contract but also contributes to the current understanding of linkages between derivatives and underlying markets in following aspects. First, unlike the market-wide instruments, the USF contracts are based on individual stocks which by definition can be directly traded. This tradable nature of the underlying market implies that stock and futures prices are more closely linked by the "cost-of-carry" relationship, and hence USF prices may not contribute to the discovery of new information to the same extent as the markets for non-tradable underlying assets such as index futures contracts. Investigation of the price discovery role of USF market can thus provide a direct answer to this important issue.

Second, the examination of the USF price discovery role over different time periods, and across several markets, could provide insights on the relative price discovery of derivatives markets at the different stages of their developments. In addition, the cross-border USF contracts on non-U.K. stocks allow us to cater a further dimension in the current literature: pricing dynamics and information transmission mechanisms between foreign-listed SSFs and the domestic underlying stock markets. Moreover, they also permit us to examine whether there is a "country effect" in the SSFs' contribution to price discovery. A number of studies argue, in the context of cross-listed stock index futures, that the price discovery ability of futures markets will largely depend on the market structures and institutional differences of the markets at which the underlying indices are being traded (see, e.g., Board and Sutcliffe, 1996). The conclusion from these studies is that the markets with lower transaction costs are more conductive to information incorporation, and that price discovery primarily originates from the home market (i.e. home-bias hypothesis). Accordingly, it would be interesting to see whether these results are applicable to the cross-listed USF contracts that are based on foreign underlying stocks, and if USFs price discovery function can be attributed to the differences in the underlying stock market conditions and/or locations.

Third, the relatively large sample also permits us to examine the dominant characteristics that determine the relative price discovery contributions of futures markets by using a cross-sectional analysis. Finally, whether there are interactions in second moments of the stock and USFs markets is another important issue that investigated in this chapter. This particular issue has vital implications for the relative price discovery and informational efficiency of these two markets.

Another distinguishing characteristic of this chapter is the comparison of stock and futures markets ability in reflecting the firm-specific and market-wide information. Previous research which has examined the lead-lag patterns between stock index and index futures markets documented considerable variation in price discovery contributions of each market depending on the information types (see, e.g., Chan, 1992; Crain and Lee, 1995; Frino et al., 2000). In particular, these studies suggest that the lead of futures market will become greater around the "market-wide" information releases periods, while transmission of information will run from the stock to the futures market in the case of the "firm-specific" information. It would therefore be interesting to analyse whether the kind of information (market-wide versus firm-specific) may affect the USFs contracts' contributions to the price discovery process. It would also be interesting to test whether the price discovery role can vary depending on the information content is "positive" or "negative". Chapter 3 directly addresses these two issues using USFs data. The use of USFs is particularly useful in studying the transmission of firm-specific information because the USFs' tradings are mainly based on the news relating to the individual stocks.

To examine the part that USFs play in discovery the information about their underlying stock prices, and the factors that influence this role. The empirical analysis of chapter 3 consists of four main components. Firstly, we determine whether price discovery occurs on the futures markets by applying the approach developed by Gonzalo and Granger (1995) to quantify the contribution of USF to determination of stock price. Secondly, both the market-wide and firm-specific information flows are documented for the whole sample period, as well as the introduction and maturity periods of USFs. An investigation into the impact of several variables which may influence the proportion of new information that is incorporated via the futures markets forms the third focus of this chapter. Finally, this chapter also characterises the dynamic interdependence of the stock and futures markets by explicitly modelling the ways in which these two markets interact through their second moments (i.e., the "volatility-spillovers" effect).

In summary, the results of this chapter suggest that price discovery take places in both stock and futures markets, but USF markets on average play a relatively smaller role in the price discovery than their underlying stocks. The price contributions of USFs vary considerably over time and across firms depending on the geographical origin of underlying stocks, the development stage of a futures contract, the relative trading characteristics such as the market liquidity and trading costs, the contract design and specifications, as well as the information types and content. For instance, the results from volatility-spillovers analysis show that futures market seems to play a more pronounced role in discovery of negative information, perhaps due to the limitations of short-selling in the stock markets pushing the investors who have negative information to trade in the futures rather than in the stock market.

The findings of this chapter should be of great interest to the investors, fund managers and regulators. For the investors and fund managers who trade in both stocks and derivatives (as well as those who are active in only one market), the results that stock markets contribute more to the price discovery indicate that some information is first reflected in that market, and movements in these markets has important implications for investors trading the futures contracts based on these underling shares in forecasting price behaviours, speculating the price movements. Additionally, the cash-futures price relationship is also an important factor for hedgers in developing effective hedging strategies. The traditional theory of hedging asserts that the effectiveness of a hedge largely depends on the parallelism of movements in spot and futures prices. Moreover, our results from the analysis of price discovery determinants should also provide policymakers important insights on the designs of securities, trading mechanisms, and the market structures that are more conductive to the timely dissemination of the new information.

Further, as the understanding of the price discovery dynamics between stock and futures markets could shed light on the market preference of informed traders, our finding that stock prices tend to lead the futures markets implies that informed traders are more likely to choose this particular market to reveal their private information. This is particularly important as the knowledge of where informed traders choose to trade and the factors influencing their choices are highly relevant to market makers and regulators (aid the regulators to prevent illegal insider trades). Finally, the price discovery role of LIFFE's USF contracts we documented in this chapter also provides justification for other exchanges to launch the single-stock futures as a means of enhancing information dissemination process in their markets.

The main reason for the existence of futures markets is to provide instruments for market participants to reduce or control the unwanted risk of price change by transferring it to others more willing to bear the risk. This function of futures markets is performed through hedging. Despite its popularity and the additional benefits provided by the new SSF contracts (such as USFs), we could identify no study of the hedging strategies and hedging effectiveness for these important new markets. Therefore, chapter 4 is devoted to fill in this literature gap by assessing the degree of success that has been achieved by USFs in fulfilling this economic role.

The constant minimum-variance hedge ratio methodology is extended to a time-varying framework, and a more general BEKK-GARCH model is proposed and used to evaluate the hedging effectiveness of USFs by applying the variance-reduction and utility-based performance evaluation criterion for within- and out-of-sample periods. The empirical findings suggest that the majority of USF contracts have served as efficient risk management tools in hedging against the individual stock exposures.

Moreover, we also find that the basis (i.e., the difference between spot and futures prices) and asymmetry effects in the time-varying variance-covariance structure have important implications in the estimation of hedge ratio, and the proposed dynamic hedging strategy that incorporates both of these effects can produce additional hedging benefits for investors who want to hedge their exposure to a stock position.

Given the considerable variations in the USFs hedging effectiveness across different contracts, this chapter proceeds to undertake a rigorous analysis on the determinants of the hedging efficiency with USF contracts. To this end, a cross-sectional analysis is performed to identify the factors affecting the hedging effectiveness of each USF. The results indicate that the variables measuring relative market quality such as the ratios of trading volume and bid-ask spread are major determinants of the degree of hedging effectiveness across USFs. In addition, we also uncover clear evidence that the hedging role of futures is more pronounced for the smaller sized USF contracts.

Since all the stocks on which USFs are written are also component stocks of the stock indices on which futures already exist, it may be possible to use stock index futures (SIF) to hedge. Also, for those hedgers who hold more than one component stocks in their portfolio, multiple hedging by USFs may not be as effective as SIF since there are some correlations between the returns of the stocks with stock indices. Therefore, the final stage of this chapter is to investigate the relative hedging effectiveness of USF versus stock index futures, and assess the efficiency of creating a USF portfolio in hedging the cash portfolio containing a small number of stocks. While these questions have been recognised as important issues, this thesis is the first study to compare the *direct* hedging effectiveness of USF with the *cross*-hedging effectiveness of stock index futures contracts. As expected, by comparing the hedging effectiveness of USFs and several stock indices futures, clear evidence emerges that hedging with USF has a better performance than hedging with index futures for individual stock positions. In addition, hedging simultaneously with USF and index futures further improves hedging efficiency compared to hedging with USF contracts alone. Further, the result suggests that creating an equally-weighted USF portfolio to hedge multiple stock portfolios is more effective than that of using index futures in hedging the small-sized portfolio consisting of only 5 to10 stocks.

View collectively, this chapter not only provides, for the first time, empirical evidence on the hedging performance of USFs but also contributes to the current understanding on the risk management role of futures markets in following aspects. First, unlike the stock index futures, the USF contracts are based on individual stocks which by definition can be directly traded and thus provide a unique opportunity to examine the hedging effectiveness of futures in which the underlying stock of the futures contract is exactly the same as the spot asset. This matching nature implies that USF may be a better hedging instrument in hedging the individual stock exposure than the market-wide instrument such as stock index futures. Findings from the investigation of the relative hedging efficiency support this general anticipation. Second, empirical results from the examination of the dominant characteristics that determine hedging efficiency of futures markets could provide policymakers insights on the importance of several factors in security designs and market structures. Finally, another important contribution of this chapter is the proposed use of a new general multivariate GARCH model to estimate the dynamic hedge ratios, which incorporates the time-varying volatility, the volatility spillovers, the basis and asymmetric effects associated with the spot-futures covariance structure while still allowing correlations between security returns to vary over time.

Chapter 5 concludes the thesis by summarising the main findings in this thesis and by discussing the practical implications of those results. In addition, the chapter identifies a number of research issues, which are not undertaken in this thesis due to time and space constraints, but merit further investigation.

Table 1.1: Hedging with USF contract - An Example

		Per Share	Position Value
ABC Shares	Opening price	500p	£50,000
	Closing price	480p	£48,000
	Loss on shares	20p	£2,000
ABC Futures	Opening price	508p	£50,800
	Closing price	486p	£48,600
	Gain on futures	22p	£2,200

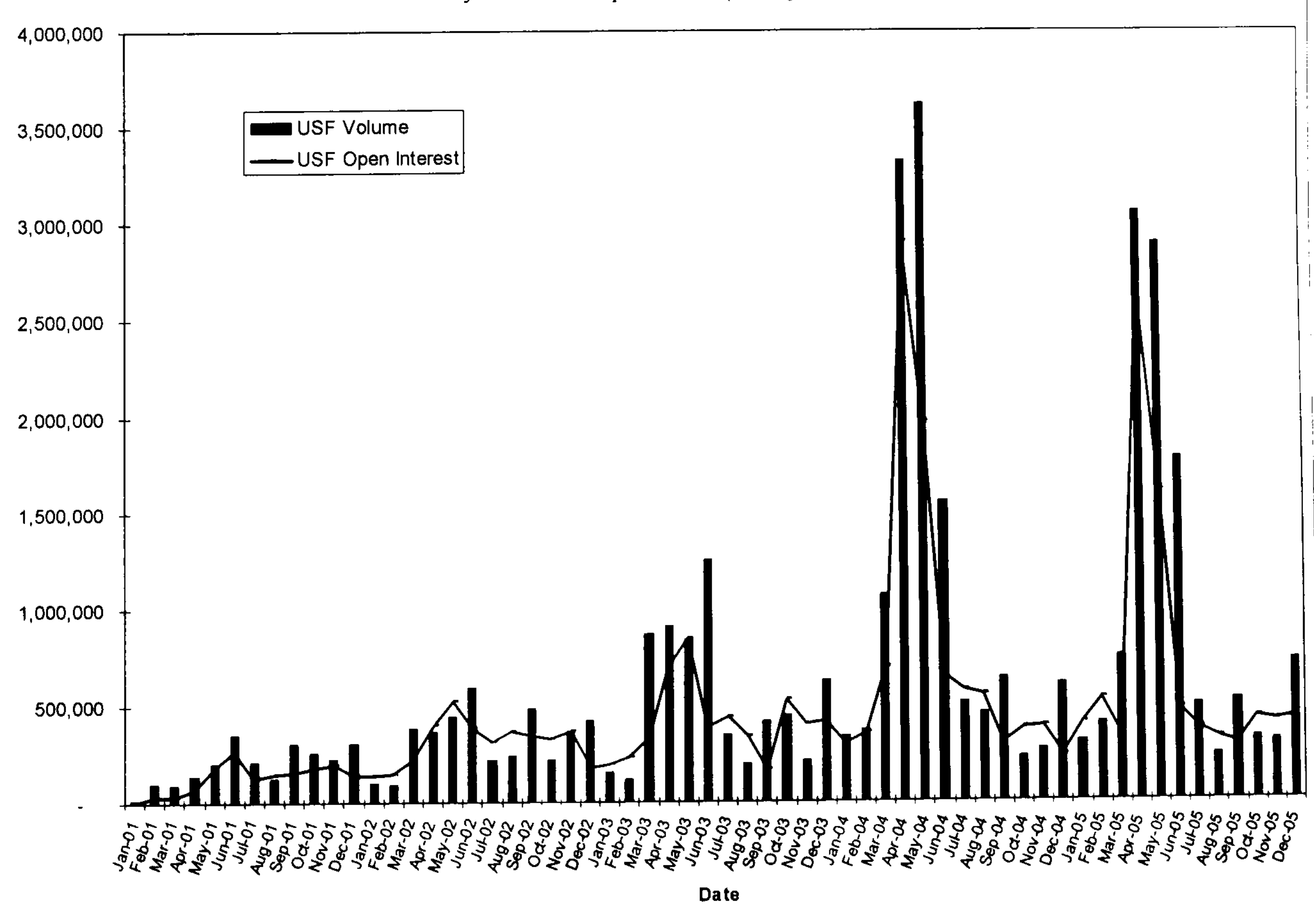
* The gain on the futures position has offset the short term loss on the shares.

Table 1.2: Average Daily Volume of the LIFFE's Stock Options and USF contracts (January 2001 - December 2005)

Year	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Stock Options	**17934**	**18842**	17095	15777	16921	16980	13075	14123	**21594**	**41895**	**50349**	39485	44706	36824
USFs	-	-	-	-	-	-	-	-	-	**9813**	**15372**	**24802**	**49920**	45700

Notes: Figures highlighted in **bold** denotes High records achieved

Figure 1.1
USF Monthly Volume and Open Interest (January 2001 - December 2005)



* Source for Tables 1.1 and 1.2 and Figure 1.1: LIFFE

Chapter 2*

The Impact of Universal Stock Futures on the Underlying Market

2.1 Introduction

It was shown in chapter 1 that the impact of futures trading on the underlying market has been an area of concern since the introduction of futures contracts on the world's financial markets. Proponents of futures trading argue that it enhances the efficiency and price discovery of financial markets, and provides an additional avenue for investors to hedge risk (to what extent USF contracts have succeeded in fulfilling these economic functions will be examined in chapters 3 and 4). However, there are many who argue that futures trading is destabilising in that it attracts speculative traders who induce excess volatility in the market. For example, in the United States futures on individual stocks were banned for 20 years largely because of the regulatory concern about the possible destabilising effects of such contracts on the underlying stock prices.

It is therefore important, in examining the economic role and performance of USF, to analyse the impact on the underlying market of the introduction of USF trading. However, in contrast to earlier studies in the literature, the central theme of this chapter is not whether futures trading has increased or decreased the volatility of prices in the underlying stock market. Rather, the concern here is to investigate the extent to which the introduction of USF contracts affected the degree of feedback trading in the stock markets. The rationale for this empirical focus is provided by Antoniou et al. (2005) who argue that "If derivative markets were to attract noise traders in general and positive feedback traders in particular, then the potential for destabilization would be real and the claim for further regulation warranted." (Antoniou et al., 2005, p.221).

* The main elements of this chapter have appeared in Chau et al. (2005).

Therefore, to clearly understand the impact of futures on the underlying market, it is necessary not only to consider whether the underlying volatility has changed post-futures, but also to give consideration to the effect of futures on wider market dynamics. By investigating both the extent of feedback trading and the nature of volatility pre- and post-futures, more reliable conclusions can be drawn about whether further regulation of derivative markets (via measures such as higher margins, narrow price fluctuation limits and restrictions on the issue of new contracts) is justified.

To this end, rather than simply looking at the volatility of the underlying market, this chapter examines the impact of USF trading on the underlying stock market by investigating the first and second moments of returns behaviour using Sentana and Wadhwani's (1992) heterogeneous trader model.[28] This model explicitly recognises the existence of both market participants who are rational expected utility maximisers and also those who are feedback investors, and thus allows consideration of the consequences of futures not only on underlying volatility, but also on the extent to which futures inhibit or promote feedback trading in the stock market. Antoniou et al. (2005) use this model to examine the effect of index futures trading on a range of indexes and find that futures trading stabilises the market by reducing the impact of feedback traders.

While Antoniou et al. (2005) has moved the debate forward and provided an important framework for the investigation of whether futures trading has any positive or adverse effects on the underlying market, their empirical analysis is limited to the effects of trading stock index futures in six countries, with only one 'event date' in each country.

[28] Sentana and Wadhwani (1992) originally investigated stock returns for the US using this model. Since then, it has also been used to examine the behaviour of stock returns in a range of other markets. See, for example, Koutmos (1997), Koutmos and Saidi (2001) and Bohl and Reitz (2006).

As McKenzie et al. (2001) point out, studies of stock index futures are useful in assessing the market-wide impact, but any effect on the underlying market can be dissipated across many constituent stocks in the index, making the true effect difficult to detect. In addition, the stock index itself is not a tradeable asset, whereas stocks are. Hence, the influence of futures on feedback trading and volatility might be more noticeable at the level of individual stocks. Indeed, the concern that single stock futures (SSFs) might have an adverse impact on the underlying has led to tighter restrictions on such instruments than on the index futures.[29]

SSFs were introduced on the LIFFE in January 2001 with the introduction of Universal Stock Futures (USFs).[30] These contracts contain some special features that do not appear in other futures markets. In particular, USFs are listed on stocks traded in a range of different markets and LIFFE was the first exchange to launch the 'cross-border' SSFs. Due to these unique characteristics, USFs represent an important additional instrument for investors, which allows a better match for investment and risk management purposes than do broad based index futures or domestic SSFs.[31] The importance of USFs to market participants is shown by the rapid growth in their trading volume and the number of stocks on which USFs are written (see section 1.3). In spite of their popularity, concerns about their impact on the underlying market still remain. It is, therefore, important and informative to investigate the extent to which USF trading has changed the characteristics of the first and second moment of returns in the stock market.

[29] For example, futures on individual stocks were banned in the U.S for 20 years under the Shad-Johnson Accord largely because of the belief that SSF trading could destabilise the stock market.
[30] As mentioned in the introduction to this thesis, the LIFFE was purchased by Euronext in January 2002, and became part of Euronext.liffe. For convenience we use the term LIFFE throughout this thesis to refer to either LIFFE or Euronext.liffe.
[31] For example, USFs allow individual components of a portfolio to be hedged without having to change the make-up of the portfolio and they also offer tax benefits (e.g. they are exempt from stamp duty for UK stocks due to them being cash settled).

By examining how trading in USFs affected the underlying market dynamics (i.e., volatility and the level of feedback trading), this chapter extends the empirical literature on the relationship between futures trading and stock market in the following ways. First, unlike previous studies, we employ the heterogeneous trader model of Sentana and Wadhwani (1992) as the theoretical framework, together with an asymmetric GARCH-type model, in order to gain deeper insights into the impact of futures trading. Consideration is given to both feedback trading and volatility, including the asymmetric response of volatility to positive and negative news on a stock by stock basis. Antoniou et al. (1998, 2005) argue that futures markets may improve the underlying market dynamics, as reflected by a reduction in the asymmetric volatility response and the role of feedback traders. The prior literature has generally restricted itself to testing changes in stock price volatility and has not considered whether the influence of feedback trading for example, has reduced from futures introduction. Such a restricted testing framework is overly limited and may even lead to inappropriate policy conclusions.

Second, in spite of extensive research, futures on single stocks (such as USFs) have been subject to very little attention in the academic literature to date. One notable exception is McKenzie et al. (2001) which investigates the effects of the introduction of individual share futures (ISFs) on stock market volatility in Australia. However, at the time of McKenzie et al's (2001) work there were only 10 stocks on which ISFs were traded and all of these were shares listed on the domestic market. Also, the level of trading in ISFs during the period analysed was low compared to USFs.[32] Furthermore, McKenzie et al.

[32] During their period analysed the annual volume of ISFs contracts traded declined from 111,696 in 1995 to 8,646 in 1998. From 1995 to 1998 the volume of trade fell. For USFs the number of contracts traded annually increased from 2.326 million in 2001 to 6.349 million in 2003 and in excess of 11.7 million in 2005.

(2001) examine the impact on the systematic risk and volatility of the underlying shares, rather than using an approach which recognizes the existence of non-rational traders.

Third, given the significance and unique characteristics of USFs, this market allows us to overcome many of the methodological difficulties inherent in the previous studies, and provides a key opportunity to investigate a range of issues not previously addressed. For example, because USFs are stock-specific contracts, any futures-induced effects on the volatility and/or market dynamics should be easier to identify. Furthermore, studies that have examined the introduction of index futures have by definition only examined one event date, within a given market setting.[33] In the case of USFs, there have been multiple introduction dates and contracts are listed on stocks traded in different markets. Since each market has different characteristics, it will be possible to determine if these characteristics influence the impact on the underlying.[34] Moreover, given the large number of USFs listed on stocks trading in different sectors, it is also possible to examine whether the impact of futures differs across industries. In addition, the cross-border nature of USFs allows us to investigate the impact of foreign-listed futures on their domestic underlying stock markets. While much work has been done on the effects of foreign-listed stocks on their domestic stock markets, there has been little attention given to the impact of foreign-listed derivatives on their domestic underlying markets.[35] Therefore, examining the impact of cross-border USFs would allow us to cater a new

[33] With only one event date it is possible that other market-wide factors which occurred at about the same time as the introduction of futures trading may affect the results (i.e. spurious effects may be documented).

[34] According to Harris (1989), stock option/futures listing do not have a uniform impact on the volatility of the underlying stocks. He argues that the effect of option listing will depend on: i) the sophistication of the market participants; ii) the existence of constraining regulations such as a prohibition of short selling; and iii) the liquidity of the markets. It is possible that for these reasons, authors, such as Damodaran and Lim (1991) and Bollen (1998) have suspected that options may have a differential impact in different trading locations. Indeed, their empirical evidence supports this.

[35] See, for example, Foerster and Karolyi (1998, 1999) and Grammig et al. (2005).

dimension in the literature. Also, with USFs it is possible to consider how market dynamics have changed over the sample period for a control sample of individual stocks, in a way which is not feasible for index futures. By first modelling the LIFFE's listing decision for USFs and basing the choice of the control sample on this model, it is possible to overcome potential endogeniety problems inherent in previous studies. Overall, investigation of the introduction of USFs should provide additional and more reliable insights about the extent to which futures trading affects the market dynamics of underlying stock.

Finally, we conducted a number of empirical exercises that strengthen confidence in our findings. Our results survive a number of robustness experiments, including controlling for the possibility of asymmetries in the feedback trading mechanism where feedback trading is allowed to be more pronounced during market declines, and extending the individual stock approach to the portfolio approach. In addition, the results are also robust to alternative measurement windows of the futures listing effect.

The findings of this chapter should be of interest to the investors and market regulators, and could provide a useful reference for other derivatives markets which have introduced and/or been considering to launch single stock futures (SSF) to their markets. It may help the exchange executives make decisions on whether these new products should be listed in their markets. More importantly, it can also provide market regulators with important insights into the question of derivatives regulation. If futures markets cause a change in the level of volatility in the stock market (as in the arguments that futures attract mainly irrational speculators increase volatility in destabilising fashion) and this, in turn, is associated with greater uncertainty and unduly higher required rates of return, then there may well be a case for increasing the regulation on these markets. However, if futures contracts lead to new channels of information being provided. more information due to more transaction and a significant reduction in uninformed investors, then these contracts provide useful services to the economy and calls for their regulation are unwarranted and could even be counter-productive.

The rest of the chapter is organised as follows. The next section briefly discusses the literature on the impact of futures trading, sets out the main features of the feedback trading model and identifies the hypotheses to be tested. Section 2.3 discusses the data to be used in the empirical analysis and the methodology for selecting a control sample. The empirical results are then presented in section 2.4. Results of several robustness tests are also given in this section. Finally, section 2.5 concludes the chapter.

2.2 The Futures Trading Effect on Underlying Market and Feedback Trading

This section briefly reviews the literature on the effects of futures trading, outlines the main features of the feedback trading model and identifies the hypotheses to be tested. Due to the newness of single-stock futures, there are very few theoretical and empirical studies that directly examine the effect of such products on the underlying stock. Therefore, the research undertaken on the impact of other derivatives, such as options and index futures, can be considered as a relevant method for us to understand the key issues in the literature and their implications on the examination of USF trading.[36]

---

[36] The literature on whether derivatives (futures and options) trading stabilises and destabilises the spot market is voluminous and the review in this section is not exhaustive. Rather it seeks to identify the most important issues in this area. For a more comprehensive review of the literature, see Damodaran and Subrahmanyam (1992), Sutcliffe (1997), and Mayhew (2000).

2.2.1 A Brief Review of Related Issues

From a theoretical standpoint, the question of whether the introduction of derivatives (futures or options) trading has positive or adverse effects on the underlying market is a topic related to the more fundamental question of what kinds of additional market participants and traders are attracted into the underlying market by the existence of these derivatives contracts. The main argument levelled against derivatives trading is that their existence primarily attracts destabilising speculators, which may in turn lead to higher stock market volatility (a perception of higher risk), thus, potentially raising the cost of capital and impacting on the wider economy (see, e.g., Stein 1987; Edwards 1988a,b).[37]

Another view posits that the introduction of derivatives market will attract additional group of rational traders into the market, who expand the routes over which information can reach the stock market, and thus reduce the impact of noise trading in the price formation process. This view is based on the belief that financial leverage provided by derivatives can lower the transaction costs, thereby attracting otherwise unprofitable informed traders (see, e.g., Cox, 1976). If this were the case, volatility necessarily increases in an efficient market (see Ross, 1989; Antoniou and Holmes, 1995).[38] Hence, in the light of the above discussion, it has been argued that derivatives contracts can be either stabilising or destabilising depending on which type of investors (speculators) were brought to the underlying stock markets through the onset of derivatives trading.

---

[37] In fact, there seems to be no objection in the literature to the view that derivatives markets permit, and indeed encourage speculation. For example, as Goss and Yamey (1978) point out, futures markets make a distinctive contribution to speculation because (i) they are highly standardised contracts that have low margin requirements, (ii) relatively low transaction costs and do not subjected to short sales restrictions, and (iii) enable investors to take a certain position on a stock with little or no cost of carry. The contentious issues relate to the effect of this speculation (see Bekaert et al., 1995).

[38] As Ross (1989) point out, according to the Efficient Markets Hypothesis (EMH), asset prices in a market depend upon the information which is currently available in that market. When new information becomes available in an efficient market, prices will adjust rapidly to reflect that new information. Thus price movements, and hence price volatility, are related to information arrival in an efficient market.

Since both arguments have a strong theoretical merit, the issue of whether the existence of derivatives markets is destabilizing or not is ultimately an empirical question.

Due to lack of trading in single stock futures contracts, the evidence on the effects of *equity* derivatives trading comes mainly from tests using options and stock index futures. So far, the results of previous empirical studies have reached no conclusive evidence. With respect to stock index futures, the empirical literature in this field is very extensive and to discuss this work in detail would be cumbersome. As such we provide a tabulated summary of selected studies in Table 2.1 (many of these are reviewed by Sutcliffe, 1997; Ch.14).[39] The papers summarised in this table use one (or a combination) of three basic approaches to test whether index futures trading influence cash price: (i) Before-and-after tests, (ii) Cross-section analysis, and (iii) Time-series Studies. This table reveals that empirical results are largely ambiguous. The majority of the studies listed reported that introduction of stock index futures has had no significant effect on the underlying index volatility. Others, including Gulen and Mayhew (2000) find evidence that volatility decreased with introduction of index futures in many emerging countries. On the other hand, Harris (1989) report a volatility increase in highly developed markets such as the United States. The inconclusiveness of empirical results becomes even more obvious by looking at the studies that examine the same index futures reach different conclusions. For example, in relation to the work on FTSE100 futures, Robinson (1994) find a decreased volatility following the existence of index futures whilst Antoniou and Holmes (1995) observe an increase, but Board and Sutcliffe (1993) report that introduction of FTSE100 futures has had no significant effect on stock market volatility.

[39] This table is in no way exhaustive but highlights the main techniques used in empirical studies and assesses the weight of evidence for both sides of the debate.

As for stock options, most studies examine options on individual stocks and generally report a significant decrease in volatility following options listings. Examples of studies examining the U.S. options markets include Skinner (1989), Conrad (1989), Detemple and Jorion (1990), Wei et al. (1997), St. Pierre (1998), and Mayhew and Mihov (2004), to name but a few. Among the authors who have addressed the issue in other equity options markets are Watt et al. (1992), Chaudhury and Elfakhani (1997), Alkeback and Hagelin (1998), and Hagelin (2000). However, there is a difficulty in drawing inferences from these studies. As Bollen (1998), Sorescu (2000), and Mayhew and Mihov (2004) show, the directions of the options listing effects vary depending on the periods studied.

While the opposite findings in different sub-periods can be explained by the 'market-completing' argument where early-listed options play a bigger role in completing the markets than recently-listed options do, it is also possible that the effects are spurious.[40] The effects will be spurious if the decision to list options depends on the exchange' observation or expectation of the underlying stocks' volatility. As Bollen (1998, p.1183) point out "Exchange officials have indicated that unusually high or rising variance is a criterion for selecting the stocks on which to list options." Therefore, if variances follow a mean-reverting process, then this practice will create a selection bias, as the variance should decline sometime after option introduction even the listing itself has no effect. More recently, Mayhew and Mihov (2004) even argue that exchanges may be 'forward-looking' and list options in anticipation of increasing volatility. In this case, one might incorrectly attribute the observed increase in volatility to option trading when in fact none exists.

[40] Detemple and Jorion (1990) argue that one would observe a difference between early and late option listings, since earliest option listings had more of a 'market-completing' role than the later listings.

In an attempt to address this endogeneity issue, some researchers have excluded the period immediately prior to the option listing from their pre-event window and used earlier data for their pre-listing sample (see, e.g., Skinner, 1989). However, as discussed extensively in Mayhew and Mihov (2004), this procedure will only correct for the selection bias in a special case where the options are listed in response to recent but transitory shocks in the market. However, in many other cases, this procedure might introduce selection bias rather than correcting for it.[41] Mayhew and Mihov (2004) argue that the much existing research has not adequately accounted for this endogeneity / selection bias, which results from the endogenous listing decisions made by exchanges and regulators. In any cases, if the LIFFE use the same criterion for single-stock futures contracts listing decision, then the same selection bias will also occur in our empirical study on the introduction of USF contracts. To this end, we model the futures listing selection process and then using the expected probability of being listed (i.e. propensity score) from the logistic regressions to form our 'one-to-one' control stocks.

Overall, while there is a vast literature examining the impact of equity derivatives trading on the underlying stock market, most of the evidence comes from studies of either stock index futures or single stock options. The results of previous studies are mixed; with some suggesting volatility has increased after the introduction of futures (or options) trading while others have suggested volatility has decreased. Besides the differences in the testing methodologies and samples period, it has been suggested that the mixed evidence are possibly due to the selection bias resulting from the fact that listing decision is endogenous. Nevertheless, the results of these studies need to be

[41] Mayhew and Mihov (2004) present four possible scenarios for this endogeneity problem.

interpreted with caution since the perception inherent in these earlier studies is that; an increased volatility is undesirable (or 'bad') and any reduction in volatility is desirable.

At a theoretical level, however, it has been recognised in recent years that such a restricted view of the potential impact of derivatives on volatility is misguided because it fails to recognise the connecting link between information and price volatility. Following the work of Ross (1989) it has been acknowledged that increased volatility may be the result of greater information flows to the market rather than necessarily being the result of destabilising speculation. Antoniou and Holmes (1995) and Chatrath and Song (1998), among others, found that the introduction of futures trading increased the volatility in spot prices. These authors concluded that the increase in volatility post-futures was due to an increased information flow rather than destabilising speculation. While the increased information flow would increase price volatility (Ross, 1989), the introduction of futures market improves market efficiency by moving prices towards the fundamentals. Hence, in order to fully appreciate and assess the impact of USF markets on underlying market, perhaps it would be useful to put the above into perspective.

More recently, research in this area has taken account of the possible existence of noise and other non-rational traders in the market and of how these might impact on the volatility of the underlying following the introduction of futures trading. For example, the asymmetric response of volatility to news has been examined using an asymmetric GARCH framework (see, for example, Antoniou et al., 1998; McKenzie et al., 2001; Kavussanos et al., 2004). According to Antoniou et al. (1998), whether changes in the underlying volatility post-futures is a desirable or undesirable phenomenon depends on the nature of these changes as well as the impact in the market dynamics. This is turn requires an understanding of the causes of volatility and particularly of the phenomena of volatility clustering and asymmetric response of volatility to news commonly observed in previous research. In particular, if the actions of feedback and noise traders are the casual factors in the stock market, then it is possible that the introduction of futures will affect not only the level of volatility but also its nature and characteristics.[42]

Along the same line of reasoning, Antoniou et al. (2005) further argue that it is not sufficient to examine the impact of futures trading on volatility, rather it is necessary to also investigate how serial correlation of returns changes post-futures. Specifically they argue that "As long as futures trading encourages rational speculators, the introduction of derivative markets should move asset prices towards fundamentals and thus stabilize asset prices." (Antoniou et al., 2005, p.220). Therefore, rather than simply looking at the volatility of the underlying market, Antoniou et al. (2005) investigate the first and second moments of returns behaviour using Sentana and Wadhwani's (1992) heterogeneous trader model in which there are both rational traders and feedback traders. By examining the extent to which the introduction of futures promotes/inhibits feedback trading, it is possible to determine whether changes in market dynamics are due to improved information flows or whether they are the result of destabilising speculation and, hence, whether further regulation is warranted. Overall, their analysis on six major index futures support the view that futures help to stabilise the underlying markets by reducing the impact of feedback traders in the price formation process. Based on these

[42] It has been well documented in the literature that stock price volatility responds asymmetrically to bad and good news. Traditional explanations of this phenomenon relate either to the leverage effect or the time varying market risk premium effect (see Black, 1976b; and Christie, 1982). However, empirical evidence seems to suggest that these explanations of asymmetric nature of volatility are not very satisfactory. Market dynamics in terms of overreaction and trend-chasing by noise traders (whose responses to bad news lead to a greater volatility than do responses to good news) has recently put forwarded as an alternative explanation of asymmetric response of stock prices to news (see, e.g., Antoniou et al., 1999).

findings, the authors argue that any proposal for further regulation directed at stock index futures trading seem unwarranted, and that futures markets can only be blamed if they attract or facilitate, otherwise non-existent, uninformed feedback trading.[43]

To briefly summaries the review thus far, the above discussion suggests that, based on theoretical considerations alone it is not possible to reach unambiguous conclusions about the stabilizing/destabilising impact of futures on underlying market, since changed volatility can be the result of either destabilising speculation or improved information flows brought by the additional informed traders. From this perspective, if reliable conclusions and associated policy implications are to be drawn from empirical analysis, it is necessary to adopt an approach which distinguishes between the different causes of changes in volatility levels. In particular, to clearly understand the impact of futures on the underlying market, it is necessary not only to consider whether the underlying volatility has changed post-futures, but also to give consideration to the effect of futures on wider market dynamics, particularly of the phenomenon of feedback trading.

To this end, this chapter examines, for the first time, the impact of USF trading on the underlying stock market by investigating both the extent of feedback trading and the nature of volatility pre- and post-futures. Following the work of Antoniou et al. (2005), consideration is given to both the first and second moments of stock returns behaviour using Sentana and Wadhwani's (1992) heterogeneous trader model as the theoretical framework, together with an asymmetric GARCH specification. The main features of this model are considered next.

---

[43] In another empirical analysis of the S&P500 index futures contract, Kodres (1994) has examined the frequency of a particular type of speculation (i.e. positive feedback trading) and its relationship with price changes. The evidence suggests that there is a significant level of positive feedback trading which has a positive relationship between the price volatility.

2.2.2 The Heterogeneous Trader Model

Sentana and Wadhwani (1992) model the behaviour of two groups of investors: rational 'smart money' investors who respond rationally to expected returns subject to their wealth limitation; and feedback traders who do not base their investment decisions on fundamental value, but rather react to previous price changes.

The demand for stocks by rational/smart money traders (S_t) is determined by a mean-variance model:

$$S_t = (E_{t-1}R_t - \alpha)/\mu\sigma_t^2 \qquad (2.1)$$

where E_{t-1} denotes the expectation operator, α is the return on a risk free asset and $\mu\sigma^2_t$ is the risk premium, modelled as a positive function of the conditional variance (σ^2_t) of the stock price where μ is the coefficient of risk aversion.

The demand for stocks by feedback traders (F_t) is modelled as:

$$F_t = \gamma R_{t-1} \qquad (2.2)$$

where R_{t-1} denotes the return in the previous period. The value of γ allows discrimination between two types of feedback traders: $\gamma > 0$ refers to the case of positive feedback traders, who buy stocks after a price rise and sell after a price fall; $\gamma < 0$ indicates negative feedback traders, who sell after a price rise and buy after a price fall. Positive feedback trading can result from extrapolating expectations about stock prices or trend chasing. Note that feedback traders of either type have the effect of moving prices away from their fundamental value. If futures trading promotes feedback trading in the cash market, then a case may be made for further regulation since the market's ability to allocate resources efficiently will be undermined.

Equilibrium in the stock market requires that all stocks are held:

$$S_t + F_t = 1 \qquad (2.3)$$

If all investors are smart money/rational investors (i.e. $F_t = 0$), then market equilibrium ($S_t = 1$) yields Merton's (1973) dynamic capital asset pricing model:

$$E_{t-1}R_t - \alpha = \mu(\sigma_t^2) \qquad (2.4)$$

Allowing the existence of both types of traders in the market, substituting (2.1) and (2.2) in (2.3) and assuming rational expectations yields:

$$R_t = \alpha + \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} + \varepsilon_t \qquad (2.5)$$

As can be seen from equation (2.5) in a market with rational investors as well as feedback traders the return equation contains the additional term R_{t-1}, so that stock returns exhibit autocorrelation. The pattern of autocorrelation depends on the type of feedback traders captured by γ. Positive (negative) feedback trading, $\gamma > 0$ ($\gamma < 0$), implies negatively (positively) autocorrelated returns. Furthermore, the extent to which returns exhibit autocorrelation varies with volatility, $\mu(\sigma_t^2)$. Modifications of equation (2.5) are required to account for autocorrelation due to market frictions/inefficiency.

Therefore, the empirical version of the model is given by:

$$R_{it} = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{it-1} + \varepsilon_t \;; \qquad \varepsilon_t \sim GED(0, \sigma_t^2) \qquad (2.6)$$

where R_{it} is the return of the underlying stock i on day t. σ^2_t is the conditional variance of returns at time t, and ε_t is the residual that is assumed to follow a Generalized Error Distribution (GED) with mean zero and time-varying variance σ^2_t. The coefficient φ_0 is used to capture the autocorrelation induced by potential market frictions or thin-trading.[44] The coefficient $\varphi_1 = -\gamma\mu$ and the presence of positive (negative) feedback trading implies that φ_1 is negative (positive) and statistically significant.

It is clear from equation (2.6) that the variance of returns varies over time. Thus, to complete the model it is necessary to specify the conditional variance. It is now well established in the literature that stock returns are characterized by conditional heteroskedasticity. The model is, therefore, completed using a GARCH specification for conditional volatility. In order to determine which GARCH specification to use in the analysis, extensive tests were conducted to see which form of the conditional volatility equation best models the return data.[45] The symmetric model was compared with the two most popular asymmetric models, namely the Glosten et al. (1993), GJR-GARCH, model and the exponential GARCH (EGARCH) model of Nelson (1991). On the basis of the log-likelihood, Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC), the asymmetric models tend to fit the data better than the symmetric GARCH model, with GJR-GARCH performing better than EGARCH.[46]

Therefore, following the above results, the main analysis based on the GJR-GARCH (1,1) model which specifies the conditional variance of returns as the following process:

---

[44] Although the stocks on which USF are traded tend to be the most frequently traded and largest stocks in their domestic markets, they may not be completely free of thin-trading bias because they might not trade every day.

[45] The search and application of an appropriate GARCH model specification is important to ensure that the 'non-convergence' problem is reduced to minimal because most univariate GARCH models should encounter few convergence problems if a model is well specified and fit data reasonably well (see Alexander, 2001).

[46] The results of these specification tests are presented in Appendix 2A, and the best-performing model for each USF stock are further summarised in Appendix 2B. In all models, only the (1,1) specification are considered, based on the observation that in many empirical instances the p=q=1 specification performs well (see, e.g., Bollerslev et al., 1992). The superiority of GJR-GARCH model is consistent with the previous findings of Engle and Ng (1993) for Japanese market and that of Kim and Kon (1994) for US market indices and individual stocks.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta X_{t-1} \varepsilon_{t-1}^2 \qquad (2.7)$$

where σ^2_t is the conditional volatility at time t, ε_{t-1} is the innovation at time t-1 and X_{t-1} is a dummy variable which assumes a value of one in response to bad news ($\varepsilon_{t-1}<0$) and zero in response to good news ($\varepsilon_{t-1}\geq 0$). If the coefficient δ is positive and statistically significant, then it would indicate that a negative shock has a greater impact on future volatility than a positive shock of the same size. α_1 is typically referred to as the news coefficient, since it captures the impact of the most recent innovation and β is a measure of persistence. α_0 represents the unconditional volatility.

2.2.3 Hypotheses Development and Testing Method

In the light of the above discussion and the characteristics of USFs outlined in the introduction, this chapter seeks to examine a number of issues relating to the impact of trading in USFs on the underlying market using Sentana and Wadhwani's (1992) heterogeneous trader model approach. We estimate the model as described in equations (2.6) and (2.7) for both a pre-futures period and a post-futures period. Comparisons can then be made of the estimated coefficients to draw conclusions about whether differences exist between pre- and post-futures periods in terms of the degree of feedback trading and the level and nature of volatility in the underlying market. Specifically, with respect to equations (2.6) and (2.7) we test the null hypotheses that there is no difference between the pre- and post-futures period in relation to the coefficient relating to feedback trading φ_1, that relating to the constant component of autocorrelation, φ_0, and the coefficients which describe the conditional volatility of returns, α_0, α_1, β and δ. The alternative hypotheses are that there are differences in these coefficients between the two time periods.

If the view that the introduction of futures will lead to an improved information flow, an associated improvement of informational efficiency and a reduction in the impact of feedback and other noise traders is correct, then we expect to reject the null hypotheses (see, for example, the arguments put forward by Cox, 1976; Ross, 1989). In particular, we expect a reduction in feedback trading, in the constant component of autocorrelation, in the asymmetric response of volatility to news post futures and in the persistence coefficient and an increase in the news coefficient. On the other hand, if futures trading is destabilising and promotes feedback trading we might expect the opposite. In addition, we will also examine whether there are differences in findings for USFs written on stocks listed in different countries (to examine cross-border and market regulation effects) and in different industries.

It needs, of course to be recognised that, it is possible that factors other than the introduction of futures may affect the variables considered in each of our hypothesis tests. For example, market-wide changes that altered the dynamics of the market may have occurred around the time of the USF introduction dates. Tests may erroneously attribute such a change, if it occurred, to the introduction of USFs. Therefore, to ensure the reliability of any conclusions and policy implications drawn from empirical analysis, it is necessary to implement a control procedure to account for these possible sources of bias. Thus, to test the robustness of results about the effect of futures on the underlying market, equations (2.6) and (2.7) are also estimated for a sample of control stocks on which USFs are not written. However, as McKenzie et al. (2001) point out, one problem associated with a control group is that the distinguishing feature between the SSF stocks and the control stocks, namely that the former sample contains stocks with individual futures written on them, may be endogenous. In other words, USF stocks may have futures written on them *because* of their characteristics in the pre-listing period. in line with Mayhew and Mihov's (2004) argument for option listing decision. Thus, even using a control sample may fail to provide a true test of robustness unless this endogeneity problem is addressed. Therefore, in a similar fashion to Mayhew and Mihov (2004), our control stock is selected using a 'propensity-score matching' approach to take account of the endogeneity issue. In particular, we choose the control sample by identifying the 'nearest-neighbour' stocks that were eligible, but not selected for futures listing. The procedure for the selection of control stocks is outlined in the next section.

By comparing apparent listing effects between the USF stocks and the control stocks, it is possible to distinguish between the changes that may have been caused by futures listing and those caused by other factors, such as the endogenous nature of the USF listing decision and/or changes in market-wide trends. Specifically, if the USF sample behaves differently to the control stocks, then conclusions drawn with respect to the impact of futures introduction are strengthened.

2.3 Data and the Choice of Control Stocks

As mentioned in the introduction to this thesis, LIFFE began trading 25 USFs on January 29, 2001. Each USF contract represents 100 shares of the underlying stocks, except contracts written on UK and Italian based stocks which represent 1000 stocks. The level of volume and open interest has increased rapidly from the early months of trading as illustrated by Figure 1.1 which shows the monthly total volume and open interest on all USFs traded on LIFFE from its launch date to December 2005.[47]

[47] The LIFFE website provides comprehensive information of all the USF stocks and the dates of their listing (see http://www.databyeuronext.com).

2.3.1 The USF Sample

The first step in the sample selection process was to identify all stocks with USFs listed between January 2001 and December 2001. The sample is restricted to such stocks for two reasons. First, being the earliest listed USFs it is believed that these might have a more prominent impact (if any) on the underlying market than USFs listed later.[48] Second, GARCH estimates are less reliable in small samples and by restricting the sample to USFs listed in 2001 a sufficiently long post-futures period is available.[49] In order to focus our analysis on the effect of USF trading, the only stocks included are those with futures first introduced on LIFFE and not listed in any other futures exchange within the sample period. Including stocks which have futures traded in their domestic markets would make it difficult to identify the effect of USF listing.[50] Furthermore, any stocks with futures delisted in the sample period were also omitted from the analysis since there may be other fundamental factors affecting their returns or their USFs may be characterised by very thin trading. Finally, to be selected, a stock must also have daily price data for the whole sample period.[51]

In total, there are 80 USF stocks survive these criteria. Table 2.2 provides a list of the sample of USF stocks used in this chapter, with information on their market capitalisation, industry sector and home country. Daily closing stock prices are obtained from Datastream for a period of three years prior, to three years after the USF listing of

[48] Also, while more USFs have been listed subsequently, the major wave of listings took place in 2001.
[49] Various authors have acknowledged difficulty of obtaining reliable GARCH estimates in small sample. For example, Hwang and Valls (2006) suggest at least 500 daily data for proper GARCH (1,1) estimation.
[50] For example, since LIFFE introduced USFs, the Finland Helsinki Stock Exchange (HEX) has started trading SSF on one of the USF stocks, Nokia. In order to avoid interpretation problems, this particular stock was excluded from the empirical analysis.
[51] This restriction is imposed to mitigate the thin-trading problem. Thin-trading problem may be minimal in the earlier period of futures listing, as exchanges tend to list mostly large and well-known stocks first. However, this problem may be important in more recent periods as there is evidence that exchanges are moving towards listing small stocks and low trading volume stocks (see Mayhew and Mihov, 2004).

each stock, yielding in excess of 750 observations per stock for each of the sub-periods. Returns are calculated as in equation (2.8):

$$R_{i,t} = 100 * (\ln P_{i,t} - \ln P_{i,t-1}) \quad (2.8)$$

where $R_{i,t}$ and $P_{i,t}$ are the return and the closing price of stock i on day t.

2.3.2 Selection of Control Stocks

The next stage involves selecting the control stocks. To this end, analysis is undertaken of the futures listing choices by LIFFE, to allow determination of control stocks that explicitly account for any endogeneity issues in the futures listing decision. The basic approach of our analysis is as follows. First, the relative importance of various firm-specific trading characteristics influencing the exchange's listing choice is examined using a logit model similar to that of Mayhew and Mihov (2004) and Ang and Cheng (2005) who successfully modelled the selection for derivatives listing in the U.S.

Specifically, the following versions of the logistic regression (equations 2.9 to 2.12) are used to study the futures listing choices by LIFFE:

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SIZE + \varepsilon \quad (2.9)$$

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SVOL + \alpha_4 SSTD + \alpha_5 SIZE + \varepsilon \quad (2.10)$$

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SIZE + \alpha_4 MKT + \alpha_5 IND + \varepsilon \quad (2.11)$$

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SVOL + \alpha_4 SSTD + \alpha_5 SIZE + \alpha_6 MKT + \alpha_7 IND + \varepsilon \quad (2.12)$$

The dependent variable is the log-odds ratio of being selected for USF listing. P is the probability of being selected. If a stock is picked up for futures listing by LIFFE, the listing dummy is 1, otherwise it is 0. VOL is the daily average trading volume over the 250 trading days prior to the listing month. STD is the standard deviation of daily stock return over the same period. SIZE is the market capitalisation of the firm at the month end prior to the listing month. The variables SVOL and SSTD are ratios of 30-day to 250-day average daily trading volume and standard deviation, which are used as proxies for the short-term volume and volatility relative to the volume and volatility within the year prior to the listing months. MKT and IND are market and industry indicators used to test whether trading location and the industry group affect the probability of a stock being selected for futures listing. Equations (2.9) - (2.12) are estimated for a pooled dataset containing daily observations for all stocks that were classified as eligible for futures listing, but had not yet had futures listed.[52]

Next, following the estimation of the logistic regressions, the predicted probability of being listed for each eligible stock at each listing date is generated (i.e. the propensity-score). Finally, control stocks are selected by choosing those that trade in the same market and industry as their USF counterpart and which match the USF sample as closely as possible in terms of the propensity-score, as estimated by the logit model (i.e.

[52] Contrary to the U.S. derivatives markets, it is very difficult to know exactly how to define eligibility for the USF listing as there seems to be no explicit quantitative listing requirements, and the listing eligibility was restricted only by qualitative statements such as 'widely held' and 'actively traded'. In a telephone conversation and emails with the product manager for USF, Max Butti, it is confirmed that there is no hard set of rules that the exchange officials adopt to list USF. They tend to concentrate on coverage of the main components of the main local stock indices. Therefore, we initially treat all the stocks that are traded in the local benchmark indices at the time of each listing months as eligible stocks for that particular listing date. And from the USF listing/delisting information obtained from the LIFFE website, we determine the first trading date of each USF and exclude those stocks already have USF listed from our eligible stocks universe at the time of new listing date. This is to ensure that all our sample stocks are those classified as eligible for futures listing but not yet have futures listed.

the 'nearest-neighbour'). To be selected, control stocks must not have any futures listed at any time within the subsequent three year period.[53] In addition, stocks that have been already included in the control sample are excluded from subsequent consideration.

Table 2.3 reports the results of logistic regressions for Equations (2.9) - (2.12) in examining the relative importance of various factors influencing the exchange's decision of which futures to list.[54] As expected, the results presented in Table 2.3 shows that the market capitalization (SIZE), 250-day volume (VOL) and volatility (STD) are all significant predictors for USF listing in all cases. Looking at the sign of the coefficients on VOL, we find that the higher is the long-term volume, the greater is the probability of being listed. Similarly, the larger firms have a higher chance to be listed after the volatility and volume are controlled.[55] However, we find evidence of a tendency for exchange to list futures in periods when stocks in general have experienced declining volatility. The 250-day volatility (STD) is significantly negative in all of the estimations.

The ratios of 30-day to 250-day volume (SVOL) do not have significant impact. With respect to the short-term volatility in the thirty days prior to future listing (SSTD), we find that the coefficients are positive and significant in both models 2.10 and 2.12. This

[53] The reason for this exclusion is to ensure that the control sample is composed entirely of non-USF stocks over the entire period over which the impact of futures listing is measured.

[54] We estimate the logit models only for the sample of stocks that have USF listed in 2001. The listing dates in year 2001 (i.e. 29 Jan 2001, 19 Mar 2001, 02 Apr 2001, 14 May 2001 and 31 Oct 2001) seem to be natural choice for our futures selection analysis because (i) these dates represent the largest waves of USF listing, and (ii) our main analysis of listing effect is based on those stocks that have futures contracts listed in 2001.

[55] These suggest that trading volume and size are important variables to consider in determining which stocks may be allowed to trade in the futures markets. Because of the possibility of market manipulation, it is likely that LIFFE list futures only on stocks with large market capitalization and stocks that are actively traded. This is consistent with the findings of Mayhew and Mihov (2004) and Ang and Cheng (2005) for the selection for derivatives listing in the U.S.

seems to suggest that the exchange selected futures on stocks going through periods of unusually high short-term volatility during this period. In the context of option listing, it has been suggested that option exchanges are more likely to list options on stocks undergoing periods of unusually high volatility, and this might explain why volatility of underlying stock *appears* to decline after options are listed (see, e.g., Skinner, 1989). If exchanges use the same criterion for futures and options listing, then our results here are in support of this claim. Finally, examining the coefficients on MKT and IND, we also see significant, positive coefficients, suggesting that the likelihood of futures listing is also a function of where the underlying stocks trade and in which industry group.

Overall, the results in Table 2.3 suggest that the logistic regression models capture the USFs selection process well, with 82%-86% of stocks being correctly classified. Since the base model (equation (2.9)) performs best, control stocks are selected using the propensity-score estimated with this model.[56]

2.3.3 Summary Statistics

Table 2.4 provides summary statistics for portfolios of USF stocks and the control stocks, based on country (panel A) and industry (panel B). The estimates for stocks based in the UK, US, France Germany and other countries are reported.[57] The table shows the mean (μ), standard deviation (σ), measures of skewness (S) and excess

[56] Compared to the conventional 'characteristics matching' method, it is believed that choosing the control stocks by this 'propensity-score matching' approach is more likely to correct for the possible bias due to both the endogeneity of futures listing and changes in market-wide trends when examining the effect of futures listing on the underlying market. See, for example, Mayhew and Mihov (2004). In addition, Cheng (2003) also presents a detailed comparison of these two types of matching approaches.

[57] To avoid reporting statistics and results for portfolios containing only a small number of stocks, a composite portfolio (referred to as 'Others') is created for USF stocks traded in Italy, the Netherlands, Spain, Sweden and Switzerland. As well as having the smallest number of USFs written on their stocks, these markets represent the smallest markets in the sample in terms of market capitalization.

Kurtosis (K), the Jarque-Bera test of normality (JB), the ARCH test and the Ljung-Box statistic (LB) for 5 lags. There is clear evidence of significant departures from normality (see JB) across all portfolios (USF and control) and clear evidence of ARCH effects. The LB statistics show evidence of temporal dependencies in the first moment of the distribution of returns in more than half of all portfolios, while for squared returns, LB statistic is significant in all cases. However, to examine the extent of interrelationships between autocorrelation and volatility, further investigation is required.

2.4 Empirical Results

To address the main research question of this chapter relating to the impact of trading in USFs on the underlying market dynamics, equations (2.6) and (2.7) are estimated for 80 USF stocks in the sample for pre- and post-futures periods separately.[58] The same 160 estimations are undertaken for the control stocks. Given the voluminous results, the results of these estimations are summarized in a number of tables, rather than presenting the results of all 320 estimations separately.[59]

Tables 2.5, 2.6 and 2.7 summarise the results of the maximum likelihood estimates of the empirical version of the feedback model, allowing for asymmetric responses of volatility to news (i.e. equations (2.6) and (2.7)) for both USF and control stocks. Summary results relating to the six key coefficients (φ_0, φ_1, α_0, α_1, β and δ) are reported. The mean values of each of the coefficients in the pre- and post-futures

[58] The method of estimation used in this chapter is based on the Berndt et al. (1974) algorithm.

[59] Detailed results of the individual estimations are presented in Appendices 2C – 2J. The results for 80 USF stocks (sorted by country) for pre- and post-futures periods are reported in Appendices 2C and 2D, respectively. Appendices 2E and 2F presented the *same* 160 estimations results for 80 USF stocks (sorted by industry). Estimation results for 80 control stocks are reported in Appendices 2G – 2J. They are organised in the same way as Appendices 2C – 2F.

periods are reported in Table 2.5. Panel A relates to USF stocks and panel B to control stocks. Within each panel results are reported firstly for the whole sample (sub-panels A1 and B1) and then for stocks sorted by country (A2 and B2) and by industry (A3 and B3).[60] To allow a distinction to be drawn between negative and positive feedback trading, results are reported separately for positive values of φ_1 (negative feedback trading) and negative values of φ_1 (positive feedback trading). For the whole sample the table also reports the results of the non-parametric Kruskal-Wallis test examining whether the coefficients in the post-futures period are significantly different from the pre-futures period.[61]

As Table 2.5 shows, with the exception of φ_1 (positive), the post-futures mean is significantly different from the pre-futures mean value in all cases for USF stocks, providing prima facie evidence that USF trading may have impacted on market dynamics. If futures trading has led to improvements in information flows and a reduction in feedback trading, then we would expect that in the post-futures period there would be an increase in α_1, a reduction in β and δ and a decrease (increase) in the value of φ_1 when it is positive (negative). While the mean values of φ_1 are consistent with this, the results in Table 2.5 suggest that α_1 has fallen and β and δ have risen. The latter are consistent with there being destabilising speculation. However, it should be noted that a similar pattern of results is evident for control stocks; although the magnitude of changes is lower than for USF stocks and the mean value of δ is not significantly

---

[60] The stocks are assigned to one of five industry groups, namely services, consumer goods, technology, financial and general and resources based on the Datastream industry classification definitions.
[61] Tests for differences between pre- and post-futures values of the coefficients were also undertaken based on the t-statistic and Mood's median test. The results (not reported here) are qualitatively similar. Tests are not done for country and industry-based sub-samples due to the relatively small sample sizes.

different between the two sample periods for control stocks. Nonetheless, initial findings suggest further investigations are warranted.

Table 2.6 shows the percentage of stocks for which each coefficient was statistically significantly different from zero for the pre-futures and post-futures periods. The structure of this table (and of Table 2.7) follows that of Table 2.5. Table 2.7 shows the percentage of USF stocks for which the relevant coefficient post-futures was either significantly increased or significantly decreased compared to the pre-futures value, based on the Wald statistic at the 10% level.[62] In Tables 2.6 and 2.7 results are again reported separately for positive and negative values of φ_1.

Overall, as shown in Table 2.6, there is clear evidence of GARCH effects with α_1 (the impact of news on volatility) being significant in more than a third of cases pre-futures and β (the persistence of innovations) being significant in all cases pre- and post-futures for both USF and control stocks. In addition, the GJR-GARCH model appears generally appropriate given that in both time sub-samples and for both USF and control stocks the asymmetry coefficient (δ) is significant in considerably more than half of the estimations.

2.4.1 Feedback Trading

A striking feature of the results is the overall low level of feedback trading (φ_1) either pre- or post-futures. In the pre-futures period, as shown in Table 2.6, panel A1, only

[62] The Z statistic has also been calculated to test whether a significant difference exists in the percentage of significantly changed coefficients between the USF sample and the control sample for each sub-period. These results are referred to in the text, where appropriate, but not reported here.

13.75% of USF stocks exhibit feedback trading (2.5% is negative feedback trading and 11.25% positive feedback trading). This falls to 5% for the post-futures period (of which 3.75% is negative feedback trading). This is in contrast to the evidence presented in Antoniou et al. (2005) where five out of six markets exhibit statistically significant feedback trading pre-futures. However, Antoniou et al. (2005) also find that in the post-futures period only one market has statistically significant feedback trading. The fall in the number of stocks for which φ_1 is statistically significant post-futures suggests that, to the extent that futures trading has an impact, USFs have had a positive effect by reducing the level of feedback trading. This is confirmed by the results presented in Table 2.7, panel A1. When φ_1 is positive (negative) a significant decrease (increase) represents a reduction in the impact of feedback trading and hence, a move towards fundamental value. Table 2.7, panel A1, shows that in 12.5% of cases there is a significant reduction in feedback trading, while it increases in only 1.25% of cases. While a similar pattern is evident for the control stocks (Table 2.7, panel B1), the changes post-futures are less clear, with 7.5% of stocks exhibiting a significant increase in feedback trading (for 3.75% there is a significant increase in positive values of φ_1 and for 3.75% there is a significant decrease in negative values of φ_1) and 12.5% a decrease. Thus the changes for the USF stocks appear more marked, suggesting the change post-futures, while limited, is at least in part due to the onset of futures trading.

The results in relation to φ_1 in panel A2 of Table 2.6 show that there are differences in the level of feedback trading between countries. Negative feedback trading is only evident in the US stocks pre-futures, while there is evidence of such trading in the UK, the US and, to a very limited extent, in the small ('Other') markets post-futures. Positive feedback trading is reduced in all markets post-futures, with the exception of Germany where there is no evidence of such trading in either period. The pattern for the control stocks (Table 2.6, panel B2) is broadly similar, although again the reduction in feedback trading is less marked, except in the case of the US and France. Finally, panels A3 and B3 in Tables 2.6 and 2.7 suggest that there are some differences across industries, but there is no evidence that these are related to the onset of trading USFs.

In relation to the constant component of autocorrelation, φ_0, the findings for USF stocks (Table 2.6, panel A1) are broadly similar to those for φ_1. Specifically, while the coefficient is significant for less than 30% of stocks pre-futures, this falls by more than ten percentage points post-futures. Antoniou et al. (2005) state that "improvements in efficiency will most likely show up as reductions in φ_0 rather than changes in φ_1." (p.231). From this perspective, the introduction of USF trading appears to have improved the efficiency of underlying market. Examination of the results for the control sample in Table 2.6, panel B1, reveals that the percentage of stocks which exhibit a significant φ_0 pre-futures is the same as for the USF stocks. However, the percentage rises for the control sample by over 6 percentage points in the post-futures period. The Z statistic demonstrates that there is a significant difference between the USF and control samples in the percentage of stocks for which there is a significant increase in φ_0 in the post-futures period. Thus, view collectively, this provides some evidence to suggest that trading in USFs has had a positive effect on the efficiency of the underlying market. Again, the results for USF stocks by country (Table 2.6, panel A2) show differences, with big improvements in efficiency for the UK and the smaller ('Other') markets, while for the control stocks the movements are opposite. Panels A3 and B3 of Tables 2.6 and

2.7 again demonstrate industry effects, but with the exception of the consumer goods and financial industries, the findings for the USF and control stocks are broadly similar.

2.4.2 Volatility Level and Dynamics

The impact of USF trading on stock market volatility can be assessed first through a comparison of the α_0 coefficient in the pre- and post-USF periods. An increase in α_0 would be an indication of increased unconditional volatility in the post-USF period. From Table 2.6, panel A1, it is evident that the percentage of stocks with a significant α_0 has increased marginally post futures (from 66.25% to 71.25%). In contrast, for the control sample, there has been a decrease (from 77.5% to 63.75%, Table 2.6, panel B1). However, examination of panels A1 and B1 of Table 2.7 reveals that the two samples (USF and control) have very similar patterns in terms of statistically significant changes. α_0 has shown a significant increase for 23.75% of USF stocks and 18.75% of control stocks, while the percentages exhibiting a decrease are 57.5% and 60.0% respectively. From panel A2 and B2 of Tables 2.6 and 2.7 there is no clear pattern of country differences, while panels A3 and B3 of these tables suggest that again there are differences across industries, but that these are not related to the onset of futures trading.

Consideration of changes in α_1 and β from pre- to post-futures provides some initially surprising results. The number of stocks for which α_1 is statistically significant falls post-futures (Table 2.6, panel A1), while the percentage of stocks exhibiting a statistically significant increase in α_1 post-futures (16.25%) is less than that exhibiting a decrease (18.75%) (Table 2.7, panel A1). Similarly, the percentage of USF stocks for which there is a statistically significant increase in β (56.25%, see Table 2.7, panel A1) is much greater than that for which there is a decrease (15%). This suggests that news is having less impact and old innovations more persistence post-futures. However, when control stocks are examined (Table 2.7, panel B1), a very similar pattern of results emerges (α_1 increases for 20% and falls for 31.25% of stocks, while β is significantly higher for 55% and lower for 21.25% post-futures). Thus, to the extent that there is a change from the pre-futures to the post-futures period, this does not appear to be futures induced. These results clearly highlight the need for a control sample to be analysed to ensure that inappropriate inferences and policy recommendations are not reached concerning the impact of futures. If consideration had only been given to USF stocks a conclusion may have been incorrectly drawn that futures trading had impacted negatively on the underlying market dynamics and, hence, further regulation was warranted. Analysis of panels A2, B2, A3 and B3 of Tables 2.6 and 2.7 provide no clear evidence of country effects, although again there are some differences by industry.[63] However, there is no evidence that these differences are futures induced. Again, this provides important insights about the control sample. Not only is there a need to undertake analysis for a control sample, but it is important that the make up of the control sample is determined by a number of factors including industry.

The asymmetry coefficient (δ) shows marked changes from the pre- to the post-futures period for USF stocks. The percentage of stocks with a value of δ significantly different from zero increases from 57.5% pre-futures to 88.75% post-futures (Table 2.6, panel A1), while Table 2.7, panel A1, demonstrates that there is a significant increase in δ in

[63] For example, for technology stocks β increases significantly post-futures for 11 of the 12 USF stocks and 10 control stocks. In contrast, for general & resources stocks only 7 out of 14 exhibit a significant increase for USF stocks and 5 out of 14 for the control sample.

50% of all USF stocks. One explanation which has been put forward in relation to δ is that asymmetries are related to noise trading (see Antoniou et al. 1998, 1999). Thus, the increase in δ could be indicative of more movements away from fundamental value post-futures, although the evidence in relation to φ_1 discussed above suggests that it is not feedback trading which has increased. However, it is again informative to examine the results for the control stocks. The pattern for these stocks as shown in panel B of Tables 2.6 and 2.7 is very similar to that for the USF stocks (40% exhibit a statistically significant increase in the value of δ post-futures), again suggesting that any changes are unrelated to the introduction of USFs. Country differences are evident from panel A2 of the tables, with the US showing a reduction in the percentage of USF stocks for which δ is significant (similar to Antoniou et al., 2005, which finds that δ decreases post-futures for the US), while other markets are subject to an increase. For control stocks even the US exhibits an increase in the number of stocks for which δ is significant. Once again, there are differences across industries, but no clear pattern of differences between the USF and control stocks.

2.4.3 Robustness Tests

To check the robustness of the results further estimations were undertaken. Specifically, two types of equally-weighted portfolios of stocks were created, namely portfolios based on the country in which the underlying is traded (5 portfolios each for USF stocks and control stocks) and portfolios based on the industry of the stock (5 portfolios for USF and 5 for control). Equations (2.6) and (2.7) were then estimated for these 20 portfolios. Table 2.8 presents the p values from the Wald test of the hypothesis that the post-futures value of the coefficient is not significantly different from the pre-futures value. Overall, the findings are qualitatively similar to the results presented in Tables 2.5 to 2.7. This finding, together with the results presented earlier, is interesting given that the markets on which the stocks underlying USFs are traded vary significantly. For example, there are major differences in the characteristics of market participants and the regulation and size of the markets between the UK, the US, larger continental markets, such as France and Germany, and the smaller markets, like Sweden and Switzerland. Concerns about the impact of derivative trading on the underlying market are arguably stronger for smaller, less liquid markets.[64] This is particularly true in relation to cross-border futures on underlyings traded in small markets, where the futures contracts are traded in a major derivatives market such as LIFFE. However, the results presented here suggest that such concerns are unfounded, since they indicate that there is little systematic difference between the way small and large markets are affected by the introduction of USFs. For example, the country portfolio results show that as far as significant changes in coefficients are concerned, the movements in relation to the US market and the smaller ('Other') markets are the same for all coefficients except φ_1. For the smaller markets φ_1 increased post-futures, but it did not for the markets in France, Germany, UK and US. However, the same result is found for control stocks.

The results in relation to the industry-based portfolios, again suggest that there are differences across industries in terms of feedback trading and autocorrelation. For example, for the USF stock portfolios φ_0 is significantly lower post-futures for the general and resources, consumer goods and services industries, but not for the other industries. However, while industry differences in feedback trading are interesting and

[64] Gulen and Mayhew (2000) empirically investigated the impact of stock index futures trading on 25 markets. They found very different results for highly developed and less developed countries.

possibly worthy of further investigation, the overall pattern of results from Tables 2.5-2.8 suggests that these industry-based differences are unrelated to futures trading.[65]

Consideration is also given to the possibility of there being asymmetries in the feedback mechanism to investigate whether feedback trading is more intense during market declines. Hence, an additional term, $\varphi_2 \mid R_{t-1} \mid$, is added to equation (2.6) to capture any such possible effects (see Antoniou et al. 2005, equation (9)). In all cases the additional term is insignificantly different from zero and the general results in relation to other coefficients are very similar. Finally, the feedback model was also estimated for windows of two years either side of the introduction of futures for country and industry portfolios.[66] Generally, the qualitative findings in relation to feedback trading for the two-year and three-year windows are consistent, although there are some differences in relation to the findings for α_0. Specifically, the post-futures α_0 is generally insignificantly different from its pre-futures value when a two-year window is used. However, the findings are similar for both USF and control portfolios suggesting that the conclusion that changes in α_0 are not futures induced remains valid. Thus, the general conclusions discussed earlier appear to be robust, given the range of additional tests undertaken.

---

[65] These industry based differences may be due to other factors unrelated to futures, the identification of which is beyond the scope of this chapter.

[66] The method of trading changed for USFs written on UK based stocks at the end of November 2003, with the introduction of the MATCH facility. See the LIFFE web site for details. By estimating the model for 2 years either side of the introduction of USFs the sample period excludes the change to the MATCH system and allows determination of the extent to which the change impacted on the findings.

2.5 Conclusions

While many derivatives markets (futures or options) can be seen to be enhancing economic welfare by allowing for new positions, expanding investment sets, providing instruments for reducing risks or enabling existing positions to be taken at lower costs, they have been criticized for destabilizing the underlying market. This controversial issue has been the subject of considerable empirical analysis and has received the attention of policy-markets. Despite the vast literature examining the impact of derivatives trading on the underlying market, the prior literature has generally restricted itself to testing changes in stock price volatility and has not considered the impact of derivatives on the wider market dynamics, as reflected by the changes in the extent of feedback trading and the asymmetric nature of volatility. In particular, most of the previous studies view an increased volatility is an undesirable phenomenon and any reduction in volatility is desirable. At a theoretical level, it has been recognized in recent years that such a restricted testing framework of the potential impact of derivatives is overly limited and may lead to inappropriate policy conclusions.

This chapter extends the literature and examines the impact of recently established USF trading on underlying market dynamics using a model which takes account not only of volatility, but also the extent to which derivatives promote or inhibit feedback trading. By examining the behaviour of the underlying markets for stocks on which USFs are traded, it is possible to gain insights not previously possible. Specifically, since USFs are listed on a range of stocks traded on a number of different markets with different characteristics and across a range of industries, it is possible to identify the extent to which there are country/market or industry specific effects. This is particularly important given the cross-border nature of USFs and that concerns about futures listing might be greater for stocks listed in less liquid, smaller markets. Furthermore, if derivatives do have an impact on the cash market, such effects are more likely to be evident in the behaviour of individual stocks which are tradable, rather than in the market dynamics of a non-tradable index. In addition, given the nature of USFs it is possible to address endogeniety issues inherent in previous studies, by constructing a control sample based on the factors affecting the listing decision, and to examine more than one event date within a given market. Taking these factors into account means that results from this chapter should provide more reliable and wider ranging insights into the impact of derivative trading on the underlying market.

There is clear evidence that the level of feedback trading is low in both the pre-futures and post-futures period for the USF and control stocks, with the pre-futures period exhibiting marginally more feedback trading. To the extent that there is a change post-futures, there is a greater reduction in feedback trading for USF stocks than for control stocks. Thus, any effect of futures on feedback trading appears to be small, but beneficial. For USF stocks changes in relation to the impact of news on volatility (α_1) and the persistence of innovations (β) and the extent to which volatility is affected asymmetrically by good and bad news (δ) look initially surprising. α_1 tends to fall post futures, and β and δ rise. This appears to suggest that futures are having a destabilising impact. However, when these coefficients are examined for control stocks, the same picture is evident, suggesting that any changes in these parameters from the pre- to the post-futures period are not futures related. Equally, unconditional volatility (α_0) behaves in a similar manner for both the USF and control stocks.

These findings demonstrate the importance of undertaking estimations not only for stocks on which USFs are written, but also for control stocks. In the absence of the results for control stocks, inappropriate policy conclusions may have been reached. Specifically, the evidence in relation to α_1, β and δ suggests that post-futures there has been a negative effect on market dynamics and, hence, further regulation of USFs may have been called for. However, by also examining control stocks selected on the basis of modelling the listing decision, it is clear that such calls are unwarranted.

Examination of any possible differential impact by country suggests that systematic differences between the way small and large markets are affected by the introduction of USFs do not exist. Thus, concerns that USFs might impact (more) negatively on smaller, less liquid markets appear unfounded. The results also suggest that there are clear differences in the pattern of market dynamics between industries, but that such differences are not futures induced. Examination of why such differences exist is worthy of further study, but is beyond the scope of this chapter. However, the results in relation to industry differences clearly demonstrate the need to construct a control sample in a way which directly takes account of the industry in which the stock is based.

Overall, the findings provide useful insights and suggest that the listing of USFs has not impacted negatively on the underlying markets. It should, of course, be recognised that in all of the markets considered here index futures already existed prior to the introduction of USFs. Thus, it might be expected that these stocks would be less affected by the introduction of single stock futures. Nonetheless, to the extent that USFs have impacted on feedback trading and wider market dynamics, the influence appears to have been positive, leading to a small reduction in feedback trading and improved efficiency.

Table 2.1: Results of Various Studies on the Volatility Effect of Stock Index Futures

Panel A: Before and After Studies

Study	Index	Period	Volatility Increase	Volatility No Change	Volatility Decrease	Mixed Results
Santoni (1987)	S&P 500	1975-1986	--	√	--	--
Edwards (1988a, 1988b)	S&P 500	1973-1987	--	--	√	--
	Value Line	1973-1987	--	√	--	--
Becketti and Roberts (1990)	S&P 500	1962-1990	--	√	--	--
Lockwood and Linn (1990)	DJIA	1964-1989	--	--	--	√
Freris (1990)	Hang Seng	1984-1987	--	√	--	--
Chan and Karolyi (1991)	Nikkei 225	1985-1987	--	√	--	--
Hodgson and Nicholls (1991)	Australian AOI	1981-1987	--	√	--	--
Brorsen (1991)	S&P 500	1962-1986	--	--	--	√
Maberly et al. (1989)	S&P 500	1963-1988	--	--	--	√
Harris (1989)	S&P 500	1975-1987	√	--	--	--
Lee and Ohk (1992)	Various	Various	--	--	--	√
Kamara et al. (1992)	S&P 500	1976-1988	--	√	--	--

Panel B: Cross-Section Studies

Study	Index	Period	Volatility Increase	Volatility No Change	Volatility Decrease	Mixed Results
Aggarwal (1988)	S&P 500, DJIA	1981-1987	--	√	--	--
Harris (1989)	S&P 500	1975-1987	√	--	--	--
Damodaran (1990)	S&P 500	1977-1987	√	--	--	--
Laatsch (1991)	MMI	1982-1986	--	√	--	--
Gerety and Mulherin (1991)	DJIA	1974-1989	--	√	--	--
Lee and Ohk (1992)	Various	Various	--	--	--	√
Kamara et al. (1992)	S&P 500	1976-1988	--	√	--	--
Koch and Koch (1993)	S&P 500, MMI	1987-1988	--	√	--	--

Panel C: Time Series Studies

Study	Index	Period	Volatility Increase	Volatility No Change	Volatility Decrease	Mixed Results
Lee and Ohk (1992)	Various	Various	--	--	--	√
Bessembinder and Seguin (1992)	S&P 500	1978-1989	--	--	√	--
Board and Sutcliffe (1993)	**FTSE 100**	**1977-1991**	--	**√**	--	--
Robinson (1994)	**FTSE 100**	**1980-1993**	--	--	**√**	--
Antoniou and Holmes (1995)	**FTSE 100**	**1980-1991**	**√**	--	--	--
Pericli and Koutmos (1997)	S&P 500	1953-1994	--	√	--	--
Antoniou et al. (1998)	Various	Various	--	--	--	√
Butterworth (2000)	FTSE Mid 250	1992-1995	√	--	--	--
Gulen and Mayhew (2000)	Various	Various	--	--	--	√
Yu (2001)	Various	Various	--	--	--	√
Pilar and Rafael (2002)	Ibex-35	1990-1994	--	--	√	--
Bologna and Cavallo (2002)	MIB-30	1990-1997	--	--	√	--

Table 2.2: The Sample of Stocks Used on which Universal Stock Futures are Listed

I.D Code	Stock Name	Country	Sector	Market Cap (£m) 25 Oct 2001	Introduction Date
FR1	Total Fina Elf SA	France	General & Resources	114,402	01/29/01
FR2	France Telecom SA	France	Services	48,138	01/29/01
FR3	Alcatel SA	France	Technology	20,209	01/29/01
FR4	Axa SA	France	Financial	42,590	04/02/01
FR5	Vivendi Universal SA	France	Services	55,095	05/14/01
FR6	BNP Paribas SA	France	Financial	41,021	05/14/01
FR7	Carrefour SA	France	Services	40,749	05/14/01
FR8	Sanofi-Synthelabo SA	France	Consumer Goods	55,660	31/10/01
FR9	Suez SA	France	General & Resources	34,681	31/10/01
GER1	Deutsche Telekom AG	Germany	Services	78,414	01/29/01
GER2	Deutsche Bank AG	Germany	Financial	38,532	01/29/01
GER3	Siemens AG	Germany	General & Resources	48,399	01/29/01
GER4	Allianz AG	Germany	Financial	72,356	04/02/01
GER5	Münchener Rücksversicherungs Gesellschaft AG	Germany	Financial	55,720	04/02/01
GER6	DaimlerChrysler AG	Germany	Consumer Goods	40,582	05/14/01
GER7	E.ON AG	Germany	General & Resources	44,577	05/14/01
GER8	Bayerische Hypo-und Vereinsbank AG	Germany	Financial	18,574	05/14/01
GER9	Volkswagen AG	Germany	Consumer Goods	11,592	05/14/01
GER10	BASF AG	Germany	General & Resources	23,630	31/10/01
GER11	Bayer AG	Germany	General & Resources	24,518	31/10/01
GER12	SAP AG	Germany	Technology	36,302	31/10/01
UK1	Vodafone Group plc	UK	Services	174,397	01/29/01
UK2	BP plc	UK	General & Resources	198,232	01/29/01
UK3	HSBC Holdings plc	UK	Financial	116,313	01/29/01
UK4	GlaxoSmithKline plc	UK	Consumer Goods	185,898	01/29/01
UK5	AstraZeneca plc	UK	Consumer Goods	88,156	01/29/01
UK6	BT Group plc	UK	Services	48,100	04/02/01
UK7	Lloyds TSB Group plc	UK	Financial	62,597	04/02/01
UK8	Shell Transport & Trading Company plc	UK	General & Resources	80,652	05/14/01
UK9	Barclays plc	UK	Financial	55,576	05/14/01
UK10	Royal Bank of Scotland Group plc	UK	Financial	75,901	05/14/01
UK11	Tesco Plc	UK	Services	26,585	31/10/01
UK12	Diageo Plc	UK	Consumer Goods	36,958	31/10/01
UK13	Legal & General Group Plc	UK	Financial	12,334	31/10/01
UK14	Unilever Plc	UK	Consumer Goods	22,723	31/10/01
UK15	HBOS Plc	UK	Financial	44,783	31/10/01
UK16	Sainsbury (J) Plc	UK	Services	11,425	31/10/01
UK17	Abbey National Plc	UK	Financial	24,039	31/10/01
US1	Microsoft Corporation	USA	Technology	369,701	01/29/01
US2	Cisco Systems Inc	USA	Technology	141,138	01/29/01
US3	Intel Corporation	USA	Technology	191,186	01/29/01
US4	Exxon Mobil Corporation	USA	General & Resources	305,899	01/29/01
US5	Citigroup Inc	USA	Financial	273,381	01/29/01
US6	Merck & Co. Inc	USA	Consumer Goods	170,835	01/29/01
US7	Oracle Corporation	USA	Technology	91,066	04/02/01
US8	Sun Microsystems Inc	USA	Technology	33,250	04/02/01
US9	General Electric Company	USA	General & Resources	411,450	04/02/01
US10	Qualcomm Inc	USA	Technology	45,218	05/14/01
US11	JDS Uniphase Corporation	USA	Technology	13,415	05/14/01
US12	Amgen Inc	USA	Consumer Goods	66,756	05/14/01
US13	Juniper Networks Inc	USA	Technology	9,659	05/14/01
US14	Pfizer Inc	USA	Consumer Goods	302,898	05/14/01
US15	Wal-Mart Stores Inc	USA	Services	261,832	05/14/01
US16	International Business Machines Corporation	USA	Technology	210,002	05/14/01
IT1	Eni SpA	Italy	General & Resources	55,968	01/29/01
IT2	Assicurazioni Generali SpA	Italy	Services	38,467	03/19/01
IT3	Enel SpA	Italy	General & Resources	40,144	03/19/01
IT4	Telecom Italia SpA	Italy	Services	49,137	01/29/01
IT5	UniCredito Italiano SpA	Italy	Financial	20,209	03/19/01
IT6	San Paolo-IMI SpA	Italy	Financial	16,230	31/10/01
IT7	Mediaset SpA	Italy	Services	8,412	31/10/01
NET1	Royal Dutch Petroleum Company	Netherlands	General & Resources	118,521	01/29/01
NET2	ING Groep NV	Netherlands	Financial	55,253	01/29/01
NET3	Koninklijke Philips Electronics NV	Netherlands	General & Resources	31,809	04/02/01
NET4	ABN AMRO Holdings NV	Netherlands	Financial	26,036	05/14/01
NET5	Aegon NV	Netherlands	Financial	40,463	05/14/01
NET6	Koninklijke Ahold NV	Netherlands	Services	27,844	05/14/01
SP1	Telefonica SA	Spain	Services	63,538	01/29/01
SP2	Santander Central Hispano SA	Spain	Financial	42,153	01/29/01
SP3	Banco Bilbao Vizcaya Argentaria SA	Spain	Financial	41,930	05/14/01
SWD1	Telefonaktiebolaget LM Ericsson AB	Sweden	Technology	34,833	31/10/01
SWD2	Nordea AB	Sweden	Financial	16,068	31/10/01
SWD3	Telia AB	Sweden	Services	15,029	31/10/01
SWD4	Hennes & Mauritz AB	Sweden	Services	15,007	31/10/01
SWD5	Svenska Handelsbanken AB	Sweden	Financial	9,373	31/10/01
SWT1	Novartis AG	Switzerland	Consumer Goods	111,729	31/10/01
SWT2	Nestle SA	Switzerland	Consumer Goods	89,023	31/10/01
SWT3	UBS AG	Switzerland	Financial	66,815	31/10/01
SWT4	Roche Holding AG	Switzerland	Consumer Goods	54,455	31/10/01
SWT5	Credit Suisse Group	Switzerland	Financial	47,309	31/10/01

Table 2.3: Logit Models of USF Listing Choice

Variable	Model (2.9)		Model (2.10)		Model (2.11)		Model (2.12)	
Intercept	-3.7343	***	-6.0529	***	-6.6091	***	-8.4017	***
	(-10.800)		(-11.400)		(-10.400)		(-11.200)	
VOL	0.0092	***	0.0092	***	0.0128	***	0.0124	***
	(7.440)		(7.080)		(8.810)		(8.280)	
STD	-0.4793	***	-0.5000	***	-0.5498	***	-0.5685	***
	(-3.520)		(-3.460)		(-3.790)		(-3.790)	
SVOL			0.4040				0.3733	
			(1.160)				(1.010)	
SSTD			1.6833	***			1.4740	***
			(5.790)				(4.780)	
SIZE	0.0016	***	0.0017	***	0.0015	***	0.0016	***
	(8.460)		(8.590)		(7.870)		(7.850)	
MKT					0.2764	***	0.2192	***
					(5.770)		(4.540)	
IND					0.0149	***	0.0157	***
					(3.510)		(3.610)	
Number of Observations	3872		3872		3872		3872	
Percent Classified Correctly	85.77%		85.56%		82.49%		85.18%	
Percent Classified Incorrectly	14.23%		14.44%		17.51%		14.82%	

Notes:
The table presents the results from logistic estimation of USF listing as a function of characteristics of the underlying stocks (t-value in parentheses). *,** and *** denote significant at 10%, 5% and 1% respectively. The sample includes all the firms that meet the eligibility criteria by the time of listing (e.g Jan, 2001). If a firm is listed by LIFFE, the dependent variable is 1, otherwise 0. The variable VOL and STD are measured as the average daily trading volume and standard deviation of daily returns on the underlying stock over the prior 250 trading days. The variables SVOL and SSTD are ratios of 30-day to 250-day prior trading volume and standard deviation. The variable SIZE is the market capitalization of the firm. MKT and IND are market and industry indicators

$$\log\left(\frac{p}{1-p}\right) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SIZE + \varepsilon \qquad (2.9)$$

$$\log\left(\frac{p}{1-p}\right) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SVOL + \alpha_4 SSTD + \alpha_5 SIZE + \varepsilon \qquad (2.10)$$

$$\log\left(\frac{p}{1-p}\right) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SIZE + \alpha_4 MKT + \alpha_5 IND + \varepsilon \qquad (2.11)$$

$$\log\left(\frac{p}{1-p}\right) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SVOL + \alpha_4 SSTD + \alpha_5 SIZE + \alpha_6 MKT + \alpha_7 IND + \varepsilon \qquad (2.12)$$

Table 2.4: Summary Statistics of Portfolios Returns

	USF Stocks							
	μ	σ	S	K	JB	LB(5)	$LB^2(5)$	ARCH
Panel A: Country								
France (9)	-0.013	1.238	-0.117 *	2.005 ***	265.580 ***	26.473 ***	138.316 ***	16.625 ***
Germany (12)	-0.022	1.113	-0.065	0.700 ***	33.068 ***	11.113 **	141.092 ***	15.955 ***
UK (17)	-0.007	0.854	-0.014	1.080 ***	76.129 ***	31.150 ***	112.697 ***	25.588 ***
US (16)	0.032	1.357	0.124 **	0.882 ***	54.788 ***	0.786	113.163 ***	37.962 ***
Others (26)	-0.003	0.902	0.006	1.359 ***	120.420 ***	15.381 ***	219.115 ***	41.580 ***
Panel B: Industry								
Services (16)	-0.005	1.016	-0.143 **	2.638 ***	459.180 ***	21.938 ***	66.573 ***	2.842 *
Consumer Goods (13)	-0.001	0.845	-0.127 **	0.690 ***	35.197 ***	20.272 ***	112.953 ***	29.568 ***
Technology (12)	0.023	1.663	0.136 **	1.098 ***	83.397 ***	2.346	129.339 ***	54.250 ***
Financial (25)	-0.011	0.927	-0.014	1.593 ***	165.500 ***	38.192 ***	230.591 ***	39.055 ***
General & Resources (14)	0.003	0.867	-0.156 **	0.546 ***	25.773 ***	16.082 ***	103.473 ***	18.932 ***

	Control Stocks							
	μ	σ	S	K	JB	LB(5)	$LB^2(5)$	ARCH
Panel A: Country								
France (9)	0.016	1.004	0.005	1.172 ***	89.628 ***	5.982	104.372 ***	15.151 ***
Germany (12)	-0.033	1.021	-0.029	1.029 ***	69.243 ***	9.134	44.196 ***	5.853 **
UK (17)	-0.015	0.797	-0.118 *	1.233 ***	102.770 ***	19.539 ***	28.615 ***	5.535 **
US (16)	0.031	1.358	-0.030	0.930 ***	56.658 ***	6.016	42.958 ***	13.152 ***
Others (26)	-0.001	0.883	0.080	1.471 ***	142.800 ***	25.197 ***	260.849 ***	39.243 ***
Panel B: Industry								
Services (16)	0.002	0.772	-0.033	1.155 ***	87.305 ***	14.231 **	42.695 ***	13.893 ***
Consumer Goods (13)	0.024	0.756	-0.027	0.653 ***	28.032 ***	14.568 **	135.889 ***	13.756 ***
Technology (12)	0.016	1.730	-0.038	0.446 ***	13.322 ***	4.541	44.833 ***	15.379 ***
Financial (25)	-0.029	0.865	-0.056	1.798 ***	211.560 ***	33.187 ***	171.087 ***	29.162 ***
General & Resources (14)	0.009	0.921	0.021	0.455 ***	13.598 ***	5.907	38.099 ***	5.571 **

Notes:

*,**,*** Significant at 10%, 5% and 1% level, respectively.

( ) Number of stocks in each portfolios.

μ = mean; σ = standard deviation; S = skewness; K = excess Kurtosis; JB = Jarque-Bera test for normality and distributed as chi-squared with 2 degree of freedom.

ARCH Test is the Lagrange Multiplier [LM(1)] test for ARCH effects and distributed as chi-squared with 1 degree of freedom.

LB(N) and $LB^2(N)$ are the Ljung-Box statistics for Rt and R^2t respectively distributed as chi-squared with N degree of freedom where N is the number of lags.

The Ljung-Box statistics for N lags is calculated as $LB(N) = T(T+2)\sum(\rho / T-j)$ where ρ is the sample autocorrelation for j lags and T is the sample size.

Table 2.5: Mean Value of Key Coefficients from Equations (2.6) and (2.7) in the Pre- and Post-Futures Periods: USF and Control stocks

	φ_0		φ_1 (positive)		φ_1 (negative)		α_0		α_1		β		δ	
	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures
Panel A : USF stocks														
A1 : Total														
Total (80)	0.059	-0.037 <0.000> ***	0.009	0.007 <0.265>	-0.015	-0.006 <0.005> ***	0.430	0.079 <0.000> ***	0.041	0.026 <0.000> ***	0.859	0.914 <0.000> ***	0.090	0.105 <0.073> *
A2 : Country														
France (9)	0.085	-0.034	0.008	0.007	-0.018	-0.004	0.390	0.085	0.041	0.023	0.858	0.904	0.053	0.120
Germany (12)	0.046	-0.031	0.006	0.002	-0.005	-0.005	0.345	0.073	0.036	0.022	0.883	0.924	0.072	0.114
UK (17)	0.106	-0.036	0.008	0.009	-0.025	-0.012	0.364	0.098	0.048	0.031	0.859	0.892	0.065	0.114
US (16)	-0.042	-0.079	0.014	0.011	-0.007	-0.003	0.828	0.082	0.043	0.022	0.843	0.939	0.140	0.064
Others (26)	0.088	-0.014	0.008	0.006	-0.015	-0.004	0.283	0.066	0.039	0.028	0.858	0.912	0.098	0.114
A3 : Industry														
Services (16)	0.112	-0.020	0.020	0.008	-0.012	-0.011	0.428	0.058	0.066	0.022	0.848	0.927	0.082	0.101
Consumer Goods (13)	0.095	-0.056	0.012	0.018	-0.025	-0.009	0.581	0.102	0.040	0.033	0.809	0.897	0.095	0.085
Technology (12)	-0.006	-0.032	0.001	0.002	-0.003	-0.004	0.890	0.062	0.048	0.017	0.853	0.968	0.119	0.053
Financial (25)	0.041	-0.020	0.006	0.005	-0.013	-0.003	0.236	0.095	0.031	0.033	0.886	0.890	0.082	0.140
General & Resources (14)	0.053	-0.072	0.013	0.006	-0.022	-0.006	0.246	0.068	0.028	0.020	0.876	0.912	0.085	0.109
Panel B : Control stocks														
B1 : Total														
Total (80)	0.032	-0.015 <0.001> ***	0.006	0.009 <0.169>	-0.014	-0.010 <0.008> ***	0.501	0.221 <0.000> ***	0.054	0.044 <0.001> ***	0.861	0.897 <0.000> ***	0.081	0.085 <0.368>
B2 : Country														
France (9)	0.060	-0.045	0.008	0.004	-0.020	-0.010	0.557	0.054	0.043	0.015	0.850	0.922	0.078	0.106
Germany (12)	0.034	0.014	0.005	0.008	-0.015	-0.004	0.283	0.064	0.046	0.059	0.879	0.897	0.071	0.088
UK (17)	-0.001	-0.042	0.005	0.014	-0.018	-0.015	0.357	0.131	0.051	0.043	0.872	0.895	0.074	0.085
US (16)	0.060	0.021	0.002	0.005	-0.008	-0.022	1.040	0.079	0.034	0.014	0.872	0.948	0.110	0.073
Others (26)	0.027	-0.023	0.008	0.010	-0.016	-0.004	0.344	0.497	0.076	0.066	0.842	0.858	0.073	0.085
B3 : Industry														
Services (16)	-0.007	-0.048	0.007	0.009	-0.019	-0.005	0.347	0.152	0.064	0.045	0.854	0.885	0.079	0.092
Consumer Goods (13)	0.028	-0.039	0.007	0.011	-0.023	-0.029	0.304	0.075	0.067	0.027	0.864	0.910	0.060	0.087
Technology (12)	0.029	0.024	0.001	0.002	-0.003	-0.004	1.303	0.069	0.024	0.018	0.866	0.963	0.130	0.048
Financial (25)	0.043	0.007	0.006	0.013	-0.014	-0.008	0.249	0.118	0.062	0.049	0.868	0.886	0.070	0.106
General & Resources (14)	0.066	-0.029	0.005	0.005	-0.016	-0.011	0.622	0.748	0.045	0.071	0.849	0.861	0.079	0.071

Notes:
This table summarises the results from estimating the feedback trading model (Eq. 2.6 and 2.7) for each USF and control stock in both the pre- and post-futures periods:

$$R_{t} = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim GED(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta X_{t-1}\varepsilon_{t-1}^2$$

The mean value of each key coefficient is reported. Panel A1 shows results for the whole USF sample, panel A2 provides the figures broken down by the country in which the underlying stocks being traded, while panel A3 provides the same information by industry. The number of stocks in each subsamples are shown in parentheses. Panel B presents the same information for control sample.

< > P-values of the non-parametric Kruskal-Wallis test which examines whether the coefficients in the post-futures period is significantly different from the pre-futures period. Test reported for total samples only.

*,**,*** Significant at 10%, 5% and 1% level, respectively.

Table 2.6: Percentage of Statistically Significant Coefficients from Equations (2.6) and (2.7) in the Pre- and Post-Futures Periods: USF and Control stocks

	φ_0		φ_1 (positive)		φ_1 (negative)		α_0		α_1		β		δ	
	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures
Panel A : USF stocks														
A1 : Total														
Total (80)	28.75	17.50	2.50	3.75	11.25	1.25	66.25	71.25	33.75	23.75	100.00	100.00	57.50	88.75
A2 : Country														
France (9)	22.22	33.33	0.00	0.00	11.11	0.00	66.67	77.78	33.33	11.11	100.00	100.00	55.56	88.89
Germany (12)	8.33	16.67	0.00	0.00	0.00	0.00	50.00	66.67	41.67	25.00	100.00	100.00	41.67	91.67
UK (17)	29.41	11.76	0.00	5.88	17.65	5.88	64.71	82.35	41.18	23.53	100.00	100.00	41.18	94.12
US (16)	31.25	25.00	12.50	6.25	12.50	0.00	75.00	56.25	31.25	31.25	100.00	100.00	81.25	75.00
Others (26)	38.46	11.54	0.00	3.85	11.54	0.00	69.23	73.08	26.92	23.08	100.00	100.00	61.54	92.31
A3 : Industry														
Services (16)	50.00	12.50	6.25	0.00	12.50	6.25	50.00	50.00	62.50	6.25	100.00	100.00	31.25	93.75
Consumer Goods (13)	23.08	23.08	7.69	15.38	15.38	0.00	61.54	84.62	23.08	30.77	100.00	100.00	38.46	69.23
Technology (12)	16.67	8.33	0.00	0.00	8.33	0.00	83.33	16.67	41.67	41.67	100.00	100.00	75.00	83.33
Financial (25)	28.00	8.00	0.00	4.00	12.00	0.00	68.00	96.00	36.00	28.00	100.00	100.00	72.00	96.00
General & Resources (14)	21.43	42.86	0.00	0.00	7.14	0.00	71.43	85.71	0.00	14.29	100.00	100.00	71.43	92.86
Panel B : Control stocks														
B1 : Total														
Total (80)	28.75	35.00	5.00	5.00	20.00	10.00	77.50	63.75	51.25	41.25	100.00	100.00	55.00	77.50
B2 : Country														
France (9)	33.33	33.33	0.00	0.00	33.33	0.00	66.67	55.56	22.22	0.00	100.00	100.00	55.56	88.89
Germany (12)	25.00	41.67	0.00	0.00	0.00	0.00	75.00	50.00	66.67	58.33	100.00	100.00	83.33	91.67
UK (17)	29.41	35.29	11.76	11.76	17.65	17.65	82.35	70.59	52.94	47.06	100.00	100.00	52.94	70.59
US (16)	25.00	12.50	0.00	0.00	31.25	12.50	75.00	56.25	31.25	25.00	100.00	100.00	68.75	93.75
Others (26)	30.77	46.15	7.69	7.69	19.23	11.54	80.77	73.08	65.38	53.85	100.00	100.00	34.62	61.54
B3 : Industry														
Services (16)	37.50	25.00	18.75	0.00	18.75	12.50	75.00	43.75	62.50	50.00	100.00	100.00	43.75	62.50
Consumer Goods (13)	38.46	61.54	0.00	7.69	15.38	7.69	69.23	69.23	69.23	38.46	100.00	100.00	30.77	92.31
Technology (12)	8.33	7.69	0.00	0.00	25.00	8.33	75.00	30.77	16.67	30.77	100.00	100.00	91.67	84.62
Financial (25)	24.00	40.00	4.00	8.00	20.00	12.00	88.00	84.00	76.00	40.00	100.00	100.00	60.00	80.00
General & Resources (14)	35.71	35.71	0.00	7.14	21.43	7.14	71.43	71.43	21.43	42.86	100.00	100.00	50.00	71.43

Notes:
This table summarises the results from estimating the feedback trading model (Eq. 2.6 and 2.7) for each USF and control stock in both the pre- and post-futures periods:

$$R_t = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim GED(0,\sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta X_{t-1}\varepsilon_{t-1}^2$$

The percentage of stocks for which each key coefficient is statistically significant at 10% level are reported. Panel A1 shows results for the whole USF sample, panel A2 provides the figures broken down by the country in which the underlying stocks being traded, while panel A3 provides the same information by industry. The number of stocks in each subsamples are shown in parentheses. Panel B presents the same information for control sample.

Table 2.7: Test of Significance of Differences in the Coefficients from the Pre-Futures to the Post-Futures Period by Direction of Change: USF and Control stocks

	φ_0		φ_1 (positive)		φ_1 (negative)		α_0		α_1		β		δ	
	Sign. Increase	Sign. Decrease	Sign. Increase	Sign. Decrease	Sign. Increase	Sign. Decrease	Sign. Increase	Sign. Decrease	Sign. Increase	Sign. Decrease	Sign. Increase	Sign. Decrease	Sign. Increase	Sign. Decrease
Panel A : USF stocks														
A1 : Total														
Total (80)	2.50	30.00	0.00	1.25	11.25	1.25	23.75	57.50	16.25	18.75	56.25	15.00	50.00	21.25
A2 : Country														
France (9)	11.11	44.44	0.00	0.00	11.11	0.00	22.22	66.67	11.11	33.33	55.56	33.33	55.56	0.00
Germany (12)	0.00	16.67	0.00	0.00	0.00	0.00	33.33	41.67	16.67	25.00	50.00	16.67	66.67	8.33
UK (17)	5.88	35.29	0.00	0.00	17.65	5.88	23.53	47.06	11.76	23.53	47.06	29.41	70.59	0.00
US (16)	0.00	18.75	0.00	6.25	12.50	0.00	25.00	68.75	18.75	18.75	75.00	0.00	18.75	68.75
Others (26)	0.00	34.62	0.00	0.00	11.54	0.00	19.23	61.54	19.23	7.69	53.85	7.69	46.15	19.23
A3 : Industry														
Services (16)	6.25	37.50	0.00	6.25	12.50	6.25	25.00	50.00	0.00	50.00	62.50	12.50	62.50	18.75
Consumer Goods (13)	0.00	30.77	0.00	0.00	23.08	0.00	23.08	46.15	23.08	15.38	69.23	15.38	46.15	30.77
Technology (12)	0.00	8.33	0.00	0.00	0.00	0.00	8.33	83.33	33.33	33.33	91.67	0.00	25.00	66.67
Financial (25)	4.00	24.00	0.00	0.00	12.00	0.00	32.00	56.00	16.00	4.00	32.00	24.00	60.00	4.00
General & Resources (14)	0.00	50.00	0.00	0.00	7.14	0.00	21.43	57.14	14.29	0.00	50.00	14.29	42.86	7.14
Panel B : Control stocks														
B1 : Total														
Total (80)	13.75	30.00	3.75	3.75	8.75	3.75	18.75	60.00	20.00	31.25	55.00	21.25	40.00	15.00
B2 : Country														
France (9)	22.22	22.22	0.00	0.00	33.33	0.00	11.11	66.67	0.00	22.22	77.78	11.11	55.56	0.00
Germany (12)	8.33	16.67	0.00	0.00	0.00	0.00	16.67	50.00	33.33	16.67	33.33	41.67	25.00	8.33
UK (17)	11.76	35.29	5.88	5.88	5.88	5.88	17.65	58.82	23.53	29.41	41.18	23.53	41.18	5.88
US (16)	6.25	18.75	0.00	0.00	6.25	12.50	18.75	75.00	12.50	31.25	68.75	6.25	31.25	37.50
Others (26)	19.23	42.31	7.69	7.69	7.69	0.00	23.08	53.85	23.08	42.31	57.69	23.08	46.15	15.38
B3 : Industry														
Services (16)	12.50	31.25	0.00	18.75	12.50	0.00	12.50	56.25	25.00	37.50	56.25	18.75	37.50	18.75
Consumer Goods (13)	7.69	69.23	7.69	0.00	7.69	7.69	23.08	61.54	7.69	46.15	53.85	23.08	69.23	7.69
Technology (12)	8.33	0.00	0.00	0.00	0.00	8.33	8.33	75.00	25.00	16.67	83.33	0.00	8.33	50.00
Financial (25)	20.00	16.00	4.00	0.00	8.00	0.00	16.00	52.00	12.00	40.00	52.00	36.00	44.00	4.00
General & Resources (14)	14.29	42.86	7.14	0.00	14.29	7.14	35.71	64.29	35.71	7.14	35.71	14.29	35.71	7.14

Notes:
This table summarises the results from Wald tests on the equality of the feedback trading model coefficients (Eq. 2.6 and 2.7) for pre- and post-futures periods for USF and control stocks:

$$R_{t} = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim GED(0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta X_{t-1}\varepsilon_{t-1}^2$$

The percentage of stocks for which each key coefficient is significantly changed (increase or decrease) at 10% level are reported. Panel A1 shows results for the whole USF sample, panel A2 provides the figures broken down by the country in which the underlying stocks being traded, while panel A3 provides the same information by industry. The number of stocks in each subsamples are shown in parentheses. Panel B presents the same information for control sample.

Table 2.8: Country and Industry Portfolio Results: Tests of Differences in the Pre- and Post-Futures Coefficients

	Null Hypothesis					
	$\varphi_{0\_pre} = \varphi_{0\_post}$	$\varphi_{1\_pre} = \varphi_{1\_post}$	$\alpha_{0\_pre} = \alpha_{0\_post}$	$\alpha_{1\_pre} = \alpha_{1\_post}$	$\beta_{\_pre} = \beta_{\_post}$	$\delta_{\_pre} = \delta_{\_post}$
Panel A : USF Portfolios						
A1 : Country						
France (9)	0.3434	0.2970	0.9026	0.0441 ↑ **	0.0000 ↑ ***	0.0000 ↑ ***
Germany (12)	0.1945	0.6722	0.4654	0.0300 ↑ **	0.0000 ↑ ***	0.4800
UK (17)	0.1547	0.8941	0.0000 ⇓ ***	0.0000 ↑ ***	0.0000 ↑ ***	0.0000 ↑ ***
US (16)	0.0402 ⇓ **	0.2243	0.0000 ⇓ ***	0.0000 ⇓ ***	0.0000 ↑ ***	0.0000 ⇓ ***
Others (26)	0.0000 ⇓ ***	0.0000 ↑ ***	0.0000 ⇓ ***	0.0000 ⇓ ***	0.0000 ↑ ***	0.0000 ⇓ ***
A2 : Industry						
Services (16)	0.0000 ⇓ ***	0.8868	0.0000 ⇓ ***	0.4501	0.0000 ↑ ***	0.6045
Consumer Goods (13)	0.0000 ⇓ ***	0.0000 ⇓ ***	0.0000 ⇓ ***	0.0131 ⇓ **	0.0000 ↑ ***	0.0946 ⇓ *
Technology (12)	0.3932	0.5583	0.0000 ⇓ ***	0.0000 ⇓ ***	0.0000 ↑ ***	0.6042
Financial (25)	0.3414	0.2789	0.0000 ⇓ ***	0.1652	0.2004	0.0604 ↑ *
General & Resources (14)	0.0000 ⇓ ***	0.0000 ↑ ***	0.0000 ⇓ ***	0.0000 ⇓ ***	0.0000 ↑ ***	0.0000 ↑ ***
Panel B : Control Portfolios						
B1 : Country						
France (9)	0.9426	0.8168	0.0000 ⇓ ***	0.0020 ↑ ***	0.0000 ↑ ***	0.3578
Germany (12)	0.7118	0.4783	0.0001 ⇓ ***	0.2453	0.0041 ↑ ***	0.1849
UK (17)	0.6747	0.8516	0.9455	0.0000 ↑ ***	0.0000 ↑ ***	0.0000 ⇓ ***
US (16)	0.2188	0.6417	0.0000 ⇓ ***	0.0283 ↑ **	0.0000 ↑ ***	0.0000 ⇓ ***
Others (26)	0.2739	0.0752 ↑ **	0.0000 ⇓ ***	0.1908	0.0022 ↑ ***	0.1990
B2 : Industry						
Services (16)	0.3715	0.2603	0.0000 ⇓ ***	0.1114	0.0000 ↑ ***	0.8080
Consumer Goods (13)	0.0175 ↑ **	0.1246	0.0000 ⇓ ***	0.4971	0.0000 ↑ ***	0.5643
Technology (12)	0.4369	0.2246	0.0398 ↑ **	0.0001 ↑ ***	0.8700	0.6229
Financial (25)	0.2993	0.1182	0.0000 ⇓ ***	0.0330 ↑ **	0.0000 ↑ ***	0.4150
General & Resources (14)	0.7462	0.9960	0.0060 ⇓ ***	0.0030 ⇓ ***	0.1711	0.0115 ↑ **

Notes:

This table reports p-values associated with Wald tests of the null hypotheses in the model :

$$R_t = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim \text{GED}\ (0, \sigma_t^2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta X_{t-1}\varepsilon_{t-1}^2$$

The model is estimated for a number of equally-weighted USF & Control portfolios. ↑(⇓) represents the coefficient significantly increased (decreased) in the post-futures period.

*,** and *** denote significant at 10%, 5% and 1% respectively.

Appendix 2A: Results of Specification Tests for Various GARCH Models

	GARCH (1,1)			EGARCH (1,1)			GJR-GARCH (1,1)		
	Log L	AIC	SBC	Log L	AIC	SBC	Log L	AIC	SBC
FR1	-3286.34	4.22109	4.23483	-3294.34	4.23392	4.25452	-3285.96	4.22189	[illegible]
FR2	-4028.48	5.17316	5.18689	-4024.39	5.17048	5.19108	-4024.31	5.16909	5.18626
FR3	-4290.68	5.50954	5.52327	-4285.05	5.50488	5.52547	-4286.75	5.50577	5.52294
FR4	-3608.44	4.63431	4.64804	-3591.05	4.61455	4.63515	-3593.53	4.61646	4.63362
FR5	-3662.66	4.70386	4.71759	-3653.30	4.69442	4.71502	-3650.27	4.68926	4.70642
FR6	-3429.51	4.40476	4.41849	-3439.42	4.42004	4.44064	-3422.41	4.39694	4.41410
FR7	-3373.84	4.33334	4.34707	-3392.71	4.36012	4.38071	-3363.27	4.32106	4.33823
FR8	-3486.30	4.47761	4.49134	-3482.03	4.47470	4.49530	-3480.72	4.47174	4.48890
FR9	-3344.42	4.29560	4.30933	-3365.38	4.32505	4.34565	-3334.57	4.28424	4.30141
GER1	-3877.10	4.97896	4.99269	-3876.12	4.98027	5.00087	-3875.65	4.97839	4.99555
GER2	-3581.95	4.60032	4.61405	-3581.14	4.60185	4.62245	-3570.47	4.58687	4.60404
GER3	-3743.91	4.80810	4.82183	-3734.01	4.79796	4.81855	-3728.65	4.78980	4.80696
GER4	-3635.39	4.66887	4.68260	-3634.45	4.67024	4.69084	-3624.27	4.65590	4.67306
GER5	-3710.40	4.76511	4.77884	-3705.11	4.76089	4.78149	-3702.28	4.75597	4.77313
GER6	-2967.46	4.41524	4.43071	-2973.16	4.42669	4.44989	-2960.42	4.40627	4.42560
GER7	-3298.86	4.23715	4.25088	-3279.76	4.21522	4.23581	-3283.42	4.21862	4.23579
GER8	-3789.25	4.86626	4.87999	-3794.98	4.87617	4.89677	-3786.17	4.86359	4.88075
GER9	-3540.78	4.54750	4.56123	-3551.94	4.56439	4.58499	-3536.82	4.54370	4.56087
GER10	-3271.95	4.20263	4.21636	-3256.59	4.18549	4.20609	-3251.78	4.17804	4.19521
GER11	-3497.22	4.49162	4.50535	-3473.42	4.46365	4.48425	-3466.17	4.45307	4.47023
GER12	-4165.46	5.34889	5.36262	-4155.23	5.33833	5.35893	-4151.84	5.33270	5.34986
IT1	-3143.98	4.03846	4.05219	-3139.09	4.03475	4.05535	-3140.32	4.03505	4.05222
IT2	-3765.81	4.83619	4.84992	-3799.12	4.88149	4.90208	-3762.25	4.83290	4.85006
IT3	-2020.73	3.74257	3.76101	-2014.31	3.73439	3.76205	-2017.89	3.73917	3.76222
IT4	-3480.63	4.47033	4.48407	-3478.85	4.47062	4.49122	-3477.25	4.46729	4.48445
IT5	-3247.80	4.17165	4.18538	-3257.56	4.18674	4.20734	-3243.99	4.16805	4.18521
IT6	-3632.10	4.66466	4.67839	-3661.77	4.70528	4.72588	-3626.21	4.65838	4.67555
IT7	-3592.69	4.61410	4.62783	-3606.45	4.63432	4.65491	-3592.25	4.61481	4.63198
NET1	-3102.73	3.98554	3.99927	-3094.19	3.97715	3.99775	-3096.06	3.97827	3.99544
NET2	-3473.35	4.46101	4.47474	-3448.32	4.43146	4.45206	-3452.30	4.43528	4.45245
NET3	-4021.00	5.16357	5.17730	-4024.98	5.17123	5.19183	-4008.35	5.14863	5.16579
NET4	-3357.37	4.31222	4.32595	-3345.20	4.29917	4.31977	-3337.70	4.28827	4.30543
NET5	-3661.59	4.70248	4.71622	-3648.65	4.68845	4.70905	-3643.90	4.68108	4.69825
NET6	-3852.73	4.94770	4.96143	-3734.87	4.79906	4.81966	-3774.24	4.84828	4.86545
SP1	-3520.52	4.52152	4.53525	-3517.89	4.52070	4.54130	-3510.47	4.50990	4.52706

Appendix 2A: Results of Specification Tests for Various GARCH Models (Continued)

	GARCH (1,1)			EGARCH (1,1)			GJR-GARCH (1,1)		
	Log L	AIC	SBC	Log L	AIC	SBC	Log L	AIC	SBC
SP2	-3427.85	4.40263	4.41636	-3417.96	4.39251	4.41311	-3416.62	4.38951	4.40667
SP3	-3343.83	4.29485	4.30858	-3334.55	4.28550	4.30610	-3329.74	4.27805	4.29522
UK1	-3798.98	4.87875	4.89248	-3812.11	4.89815	4.91875	-3789.57	4.86795	4.88512
UK2	-3182.70	4.08813	4.10186	-3191.07	4.10143	4.12203	-3177.40	4.08262	4.09978
UK3	-3258.83	4.18580	4.19953	-3248.82	4.17552	4.19612	-3243.78	4.16778	4.18494
UK4	-3318.39	4.26221	4.27594	-3352.92	4.30908	4.32967	-3318.17	4.26321	4.28037
UK5	-3291.49	4.22770	4.24143	-3287.85	4.22559	4.24619	-3280.04	4.21429	4.23146
UK6	-3733.38	4.79459	4.80832	-3730.50	4.79346	4.81406	-3725.80	4.78614	4.80331
UK7	-3521.52	4.52279	4.53652	-3519.14	4.52231	4.54290	-3511.11	4.51073	4.52789
UK8	-3199.21	4.10932	4.12305	-3196.55	4.10847	4.12907	-3189.70	4.09840	4.11556
UK9	-3489.71	4.48199	4.49572	-3484.96	4.47846	4.49906	-3473.63	4.46265	4.47981
UK10	-3525.92	4.52844	4.54217	-3512.35	4.51360	4.53420	-3510.91	4.51047	4.52763
UK11	-3214.33	4.12871	4.14244	-3215.82	4.13319	4.15378	-3213.68	4.12916	4.14632
UK12	-3237.38	4.15828	4.17202	-3230.82	4.15243	4.17302	-3230.49	4.15073	4.16789
UK13	-3569.52	4.58438	4.59811	-3578.60	4.59858	4.61918	-3564.21	4.57885	4.59602
UK14	-3243.30	4.16588	4.17961	-3237.17	4.16057	4.18117	-3239.16	4.16185	4.17901
UK15	-3457.81	4.44106	4.45479	-3464.03	4.45161	4.47221	-3445.06	4.42599	4.44315
UK16	-3339.82	4.28970	4.30343	-3338.99	4.29120	4.31180	-3327.98	4.27579	4.29296
UK17	-3568.22	4.58271	4.59644	-3571.82	4.58989	4.61049	-3565.30	4.58024	4.59740
US1	-3632.41	4.66506	4.67879	-3642.36	4.68038	4.70098	-3623.68	4.65513	4.67230
US2	-4047.85	5.19801	5.21175	-4017.36	5.16146	5.18206	-4014.97	5.15712	5.17428
US3	-4030.48	5.17572	5.18945	-4015.79	5.15945	5.18004	-4017.72	5.16064	5.17780
US4	-2899.03	3.72422	3.73796	-2897.67	3.72504	3.74564	-2893.16	3.71797	3.73514
US5	-3538.65	4.54478	4.55851	-3533.97	4.54133	4.56193	-3524.58	4.52801	4.54517
US6	-3214.47	4.12888	4.14262	-3214.63	4.13166	4.15226	-3209.14	4.12333	4.14049
US7	-4308.77	5.53273	5.54647	-4343.52	5.57988	5.60048	-4301.44	5.52462	5.54179
US8	-4391.81	5.63927	5.65300	-4410.09	5.66529	5.68589	-4388.15	5.63586	5.65302
US9	-3311.51	4.25338	4.26711	-3271.83	4.20504	4.22563	-3281.15	4.21571	4.23288
US10	-4378.38	5.62205	5.63578	-4414.44	5.67086	5.69146	-4375.47	5.61959	5.63676
US11	-4731.92	6.07559	6.08932	-4765.75	6.12155	6.14215	-4728.62	6.07264	6.08980
US12	-3778.64	4.85265	4.86638	-3784.08	4.86220	4.88279	-3771.65	4.84497	4.86214
US13	-3637.96	6.20965	6.22693	-3651.82	6.23670	6.26261	-3633.62	6.20395	6.22555
US14	-3330.69	4.27799	4.29172	-3334.93	4.28600	4.30659	-3330.12	4.27854	4.29571
US15	-3369.11	4.32727	4.34101	-3375.10	4.33753	4.35813	-3366.54	4.32526	4.34243

Appendix 2A: **Results of Specification Tests for Various GARCH Models (Continued)**

	GARCH (1,1)			EGARCH (1,1)			GJR-GARCH (1,1)		
	Log L	AIC	SBC	**Log L**	AIC	SBC	**Log L**	AIC	SBC
US16	-3477.54	4.46637	4.48011	-3453.15	4.43766	4.45825	-3454.14	4.43764	4.45481
SWT1	-2818.92	3.62145	3.63518	-2812.56	3.61586	3.63646	-2805.47	3.60548	3.62265
SWT2	-2758.06	3.54337	3.55710	-2749.86	3.53543	3.55602	-2745.10	3.52803	3.54520
SWT3	-3213.32	4.12742	4.14115	-3186.57	4.09567	4.11627	-3189.25	4.09781	4.11498
SWT4	-2808.19	3.60768	3.62141	-2799.14	3.59864	3.61923	-2793.49	3.59011	3.60727
SWT5	-3518.90	4.51944	4.53317	-3501.76	4.50001	4.52061	-3498.15	4.49409	4.51126
SWD1	-4321.27	5.54878	5.56251	-4322.52	5.55294	5.57354	-4317.31	5.54498	5.56214
SWD2	-3471.06	4.45807	4.47180	-3493.06	4.48885	4.50945	-3467.41	4.45467	4.47183
SWD3	-2261.21	4.91901	4.93997	-2255.53	4.91103	4.94247	-2254.85	4.90739	4.93359
SWD4	-3618.64	4.64739	4.66112	-3605.15	4.63265	4.65325	-3617.56	4.64728	4.66445
SWD5	-3142.51	4.03658	4.05031	-3143.16	4.03997	4.06057	-3133.09	4.02577	4.04294

Notes: Log L is Log-likelihood function
AIC and SBC are the Akaike Information Creiterion and the Schwarz Bayesian Cnterion respectively
For the stock identification, refer to Table 2.2

Appendix 2B Best Performance GARCH Specifications, based on Log L, AIC and SBC

	Log L	AIC	SBC
FR1	GJR GARCH (1,1)	GARCH (1,1)	GARCH (1,1)
FR2	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
FR3	EGARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
FR4	EGARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
FR5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
FR6	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
FR7	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
FR8	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
FR9	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER1	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
GER2	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER3	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER4	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER6	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER7	EGARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
GER8	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
GER9	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER10	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER11	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
GER12	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
IT1	EGARCH (1,1)	EGARCH (1,1)	GARCH (1,1)
IT2	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
IT3	EGARCH (1,1)	EGARCH (1,1)	GARCH (1,1)
IT4	EGARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
IT5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
IT6	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
IT7	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
NET1	GJR GARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
NET2	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)
NET3	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
NET4	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
NET5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
NET6	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)
SP1	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SP2	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SP3	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK1	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK2	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK3	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK4	GJR GARCH (1,1)	GARCH (1,1)	GARCH (1,1)
UK5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK6	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK7	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK8	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK9	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK10	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK11	GJR GARCH (1,1)	GARCH (1,1)	GARCH (1,1)
UK12	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK13	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK14	EGARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
UK15	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK16	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
UK17	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
US1	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US2	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US3	EGARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
US4	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US6	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US7	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US8	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
US9	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)
US10	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
US11	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
US12	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US13	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
US14	GJR GARCH (1,1)	GARCH (1,1)	GARCH (1,1)
US15	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
US16	EGARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWT1	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWT2	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWT3	EGARCH (1,1)	EGARCH (1,1)	GJR GARCH (1,1)
SWT4	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWT5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWD1	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWD2	GJR GARCH (1,1)	GJR GARCH (1,1)	GARCH (1,1)
SWD3	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)
SWD4	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)
SWD5	GJR GARCH (1,1)	GJR GARCH (1,1)	GJR GARCH (1,1)

Notes: Log L is Log-Likehood function
AIC and SBC are the Akaike Information Creitenon and the Schwarz Bayesian Criterion respectively
For the stock identification, refer to Table 2 2

Appendix 2C: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period

This table reports the estimated coefficients (t-statistics in parentheses) for the model:

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the underlying equity of stock *i* (on which an USF has been introduced) at time period *t*.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : France									
FR1	0.3155	-0.7214 **	-0.1250	0.0245	0.2810 ***	0.0087	0.9499 ***	-0.0504 **	1.4675 ***
t-statistics	(0.233)	(-2.452)	(-0.355)	(0.288)	(8.532)	(1.191)	(84.379)	(-2.249)	(8.955)
FR2	0.3425	-0.0347	0.0755	0.0009	0.1068	0.0577 ***	0.9414 ***	-0.0182	1.5024 ***
t-statistics	(1.471)	(-1.373)	(0.910)	(0.140)	(1.275)	(2.913)	(45.181)	(-0.583)	(18.328)
FR3	0.0449	0.0053	0.1406	-0.0068	0.3989 *	0.0570 **	0.8856 ***	0.0476	1.5352 ***
t-statistics	(0.170)	(0.204)	(1.530)	(-0.978)	(1.941)	(2.033)	(23.112)	(1.148)	(13.079)
FR4	-0.4053 **	0.0957 **	0.1016	0.0041	0.2923 **	0.0252	0.8710 ***	0.0855 **	1.4722 ***
t-statistics	(-2.087)	(2.244)	(1.508)	(0.405)	(2.084)	(1.310)	(19.169)	(2.280)	(15.999)
FR5	-0.2247	0.0540	0.1453 *	0.0035	0.1173	0.0481 *	0.9226 ***	0.0068	1.2722 ***
t-statistics	(-1.189)	(1.218)	(1.767)	(0.238)	(1.543)	(1.914)	(30.999)	(0.221)	(13.361)
FR6	-0.0607	0.0131	-0.0266	0.0046	0.0340	0.0054	0.9612 ***	0.0555 ***	1.3593 ***
t-statistics	(-0.508)	(0.571)	(-0.516)	(0.807)	(1.253)	(0.353)	(69.084)	(2.631)	(13.911)
FR7	0.1429	-0.0229	0.1565 **	-0.0128	0.3941 **	0.0548	0.8180 ***	0.1127 **	1.2871 ***
t-statistics	(0.866)	(-0.673)	(2.298)	(-1.438)	(2.329)	(1.439)	(15.096)	(2.054)	(15.923)
FR8	-0.0627	0.0176	0.2509	-0.0396 *	1.2500 *	0.0521	0.7025 ***	0.1022	1.6930 ***
t-statistics	(-0.153)	(0.259)	(1.508)	(-1.677)	(1.878)	(1.383)	(05.437)	(1.550)	(12.144)
FR9	-0.3616 **	0.1319 **	0.0422	-0.0131	0.6401 **	0.0565	0.6701 ***	0.1359 *	1.2498 ***
t-statistics	(-2.114)	(2.241)	(0.631)	(-0.929)	(2.445)	(1.564)	(05.972)	(1.957)	(16.810)
Panel B : Germany									
GER1	0.0261	-0.0017	0.1142	-0.0036	0.1857	0.0529 **	0.9200 ***	0.0287	1.2492 ***
t-statistics	(0.115)	(-0.071)	(1.258)	(-0.497)	(1.330)	(2.334)	(30.966)	(0.700)	(15.063)
GER2	0.1009	-0.0088	-0.0489	0.0108	0.4604 **	0.0523 **	0.8207 ***	0.1080	1.2530 ***
t-statistics	(0.562)	(-0.266)	(-0.723)	(1.298)	(2.162)	(2.225)	(13.492)	(1.625)	(19.301)
GER3	0.0202	0.0119	0.1358 **	-0.0084	0.2008 **	0.0154	0.9139 ***	0.0878 **	1.3035 ***
t-statistics	(0.119)	(0.461)	(2.001)	(-1.116)	(2.204)	(0.928)	(36.245)	(2.494)	(21.518)
GER4	-0.2260	0.0425	-0.0066	0.0024	0.1760 **	0.0190	0.9123 ***	0.0764 **	1.1110 ***
t-statistics	(-1.600)	(1.456)	(-0.120)	(0.336)	(2.168)	(1.505)	(32.813)	(2.147)	(20.444)
GER5	-0.0745	0.0122	0.1177	-0.0104	0.1947	0.0276 *	0.9246 ***	0.0399	1.3972 ***
t-statistics	(-0.287)	(0.299)	(1.125)	(-0.766)	(1.388)	(1.676)	(25.258)	(1.136)	(19.667)
GER6	-0.8768 **	0.2180 *	0.0520	-0.0024	0.1424	0.0128	0.9276 ***	0.0410	1.4815 ***
t-statistics	(-1.964)	(1.671)	(0.306)	(-0.055)	(1.467)	(0.805)	(24.959)	(1.359)	(12.794)
GER7	-0.1394	0.0259	-0.0123	0.0102	0.1657	0.0362	0.8963 ***	0.0749 *	1.4443 ***
t-statistics	(-0.710)	(0.627)	(-0.119)	(0.590)	(1.488)	(1.290)	(22.666)	(1.787)	(16.102)
GER8	0.0145	-0.0025	-0.0506	0.0030	0.0688	0.0390 **	0.9406 ***	0.0211	1.3260 ***
t-statistics	(0.094)	(-0.105)	(-0.763)	(0.441)	(1.244)	(2.003)	(49.323)	(0.782)	(13.684)
GER9	-0.1082	0.0158	0.0797	-0.0019	0.2667 **	0.1023 **	0.8547 ***	0.0009	1.2598 ***
t-statistics	(-0.769)	(0.625)	(1.325)	(-0.286)	(2.236)	(2.453)	(21.945)	(0.017)	(14.393)
GER10	-0.1474	0.0361	0.0362	-0.0069	0.5246 **	0.0123	0.7749 ***	0.1639 ***	1.4023 ***
t-statistics	(-0.754)	(0.665)	(0.538)	(-0.506)	(2.029)	(0.512)	(8.763)	(2.590)	(13.539)
GER11	-0.0973	0.0242	0.0233	0.0027	0.1041	0.0090	0.9520 ***	0.0275	1.0855 ***
t-statistics	(-0.562)	(0.550)	(0.340)	(0.193)	(1.185)	(0.440)	(27.787)	(1.004)	(23.038)
GER12	-0.4792 *	0.0305 *	0.1056	-0.0022	1.6550 ***	0.0486	0.7601 ***	0.1916 ***	1.3197 ***
t-statistics	(-1.818)	(1.696)	(1.493)	(-0.713)	(2.911)	(1.404)	(14.082)	(3.143)	(15.166)
Panel C : UK									
UK1	0.0332	0.0052	0.3607 ***	-0.0229 ***	0.5273 **	0.0847 **	0.8279 ***	0.0736	1.4844 ***
t-statistics	(0.151)	(0.198)	(4.278)	(-2.922)	(2.212)	(2.456)	(18.304)	(1.547)	(15.710)
UK2	-0.9650 **	0.2517 **	0.1763	-0.0417	0.1513 *	0.0004	0.9390 ***	0.0477 **	1.3958 ***
t-statistics	(-1.992)	(1.964)	(1.206)	(-1.170)	(1.758)	(0.044)	(36.665)	(2.261)	(13.562)
UK3	0.0484	0.0036	-0.0130	0.0055	0.0911	0.0175	0.9327 ***	0.0716 **	1.3171 ***
t-statistics	(0.296)	(0.113)	(-0.166)	(0.483)	(1.634)	(0.945)	(39.331)	(2.306)	(13.030)
UK4	0.0257	-0.0025	0.2438	-0.0434	1.0578	0.0122	0.7647 ***	0.0252	1.1815 ***
t-statistics	(0.034)	(-0.017)	(0.902)	(-0.821)	(0.772)	(0.411)	(2.679)	(0.524)	(22.789)
UK5	-0.3506	0.0935	0.5164 ***	-0.0902 ***	0.4326 **	0.0701 **	0.8131 ***	0.0174	1.4605 ***
t-statistics	(-1.348)	(1.374)	(3.822)	(-2.847)	(2.234)	(2.309)	(14.182)	(0.564)	(16.913)
UK6	-0.0642	0.0004	0.1361 *	-0.0025	0.2094	0.0306	0.9163 ***	0.0706	1.3133 ***
t-statistics	(-0.307)	(0.016)	(1.736)	(-0.340)	(1.476)	(1.163)	(28.381)	(1.613)	(15.601)
UK7	-0.4133 *	0.0575	0.2002 ***	-0.0183 *	0.0633	0.0034	0.9865 ***	0.0787 ***	1.5530 ***
t-statistics	(-1.828)	(1.518)	(2.606)	(-1.678)	(1.346)	(1.484)	(49.170)	(5.787)	(13.277)
UK8	-0.3565 *	0.0820	0.1379	-0.0182	0.1399 *	0.0215	0.9099 ***	0.0792 ***	1.6443 ***
t-statistics	(-1.797)	(1.626)	(1.416)	(-0.968)	(1.825)	(1.189)	(33.424)	(2.623)	(14.606)

Appendix 2C: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : UK									
UK9	-0.1689	0.0309	0.1015	0.0011	0.1639 *	0.0337	0.9026 ***	0.0819 **	1.7223 ***
t-statistics	(-0.923)	(1.003)	(1.321)	(0.117)	(1.911)	(1.563)	(35.486)	(2.181)	(10.806)
UK10	-0.2988 *	0.0542 **	-0.0058	0.0075	0.5777 **	0.0452 *	0.8092 ***	0.1397 **	1.2676 ***
t-statistics	(-1.702)	(2.046)	(-0.080)	(1.040)	(2.244)	(1.670)	(13.601)	(2.075)	(16.331)
UK11	-0.1624	0.0435	0.0785	-0.0278	0.4945 **	0.0753 **	0.7967 ***	0.0332	1.3528 ***
t-statistics	(-0.705)	(0.789)	(0.676)	(-1.284)	(1.971)	(2.064)	(10.244)	(0.663)	(14.510)
UK12	-0.0364	0.0132	-0.0255	0.0078	0.0984	0.0321	0.9280 ***	0.0362	1.2915 ***
t-statistics	(-0.210)	(0.327)	(-0.284)	(0.483)	(1.637)	(1.557)	(38.382)	(1.004)	(15.493)
UK13	-0.1932	0.0279	-0.2397 ***	0.0201	0.0884	0.0307 *	0.9382 ***	0.0360	1.3552 ***
t-statistics	(-0.952)	(0.755)	(-2.616)	(1.488)	(1.325)	(1.873)	(44.764)	(1.439)	(15.794)
UK14	0.0274	-0.0049	0.0174	-0.0012	0.0842 *	0.0279	0.9401 ***	0.0274	1.1354 ***
t-statistics	(0.187)	(-0.147)	(0.255)	(-0.114)	(1.769)	(1.182)	(47.324)	(0.857)	(18.801)
UK15	-0.2598	0.0449	-0.0418	0.0070	0.3568 ***	0.0407	0.8480 ***	0.1044 **	1.3996 ***
t-statistics	(-1.600)	(1.527)	(-0.738)	(1.192)	(2.611)	(1.490)	(21.729)	(2.305)	(14.993)
UK16	-0.1409	0.0309	0.0562	-0.0030	1.3084 ***	0.2364 **	0.4714 ***	0.1573	1.1353 ***
t-statistics	(-1.249)	(1.334)	(1.010)	(-0.644)	(3.818)	(2.480)	(4.569)	(1.182)	(15.598)
UK17	-0.1372	0.0212	0.1007	-0.0038	0.3380 *	0.0614 *	0.8748 ***	0.0221	1.2911 ***
t-statistics	(-0.629)	(0.583)	(1.174)	(-0.357)	(1.781)	(1.685)	(16.896)	(0.576)	(15.595)
Panel D : US									
US1	0.1256	-0.0107	-0.0353	0.0025	0.5048 **	0.0424	0.8582 ***	0.0796 *	1.2665 ***
t-statistics	(0.574)	(-0.366)	(-0.573)	(0.482)	(2.520)	(1.343)	(20.201)	(1.781)	(16.681)
US2	0.1846	0.0018	-0.0739	-0.0015	0.7402 ***	0.0092	0.7919 ***	0.2737 ***	1.7002 ***
t-statistics	(1.091)	(0.098)	(-1.381)	(-0.526)	(3.757)	(0.316)	(21.634)	(4.805)	(13.533)
US3	0.0762	0.0060	-0.1078 *	0.0019	0.9001 ***	0.0241	0.8531 ***	0.1749 ***	1.4232 ***
t-statistics	(0.313)	(0.256)	(-1.909)	(0.569)	(2.831)	(0.859)	(19.151)	(3.016)	(20.186)
US4	-0.3048	0.1167	-0.0804	0.0150	0.1433	0.0216	0.9086 ***	0.0439	1.6272 ***
t-statistics	(-1.091)	(1.216)	(-0.526)	(0.327)	(1.299)	(1.113)	(18.063)	(1.151)	(11.889)
US5	-0.2771	0.0518	-0.0734	0.0095	0.2261 **	0.0065	0.9430 ***	0.0652 ***	1.4008 ***
t-statistics	(-1.115)	(1.419)	(-1.065)	(1.178)	(2.255)	(1.031)	(44.629)	(3.003)	(19.596)
US6	-0.1989	0.0570	0.1031	-0.0102	0.2383 *	0.0029	0.8931 ***	0.0964 **	1.5263 ***
t-statistics	(-0.937)	(1.082)	(1.139)	(-0.590)	(1.877)	(0.139)	(18.112)	(2.439)	(16.492)
US7	0.5160 *	-0.0249 *	0.1619 ***	-0.0044 **	0.6443 **	0.0236 ***	0.9206 ***	0.1667 ***	1.2434 ***
t-statistics	(1.884)	(-1.701)	(4.519)	(-2.357)	(2.118)	(5.305)	(33.853)	(3.890)	(19.189)
US8	0.5524 **	-0.0229	-0.1076	0.0009	0.7128 ***	0.0228	0.8557 ***	0.1629 ***	1.6618 ***
t-statistics	(2.200)	(-1.284)	(-1.485)	(0.261)	(2.593)	(0.846)	(23.765)	(3.257)	(13.331)
US9	-0.1050	0.0269	0.1411 *	-0.0266 *	0.1568 **	0.0147	0.9182 ***	0.1268 ***	1.6185 ***
t-statistics	(-0.611)	(0.629)	(1.833)	(-1.852)	(2.317)	(0.957)	(33.349)	(4.078)	(13.669)
US10	0.0788	0.0023	-0.0260	-0.0006	2.1967 ***	0.1092 ***	0.7450 ***	0.1647 **	1.3154 ***
t-statistics	(0.271)	(0.187)	(-0.392)	(-0.387)	(2.796)	(2.754)	(12.179)	(1.977)	(16.575)
US11	0.2080	-0.0036	0.0068	-0.0011	1.2390 **	0.0393	0.8663 ***	0.1295 **	1.4071 ***
t-statistics	(0.661)	(-0.338)	(0.099)	(-0.791)	(2.343)	(1.481)	(23.993)	(2.355)	(17.270)
US12	-0.4209	0.0604 *	-0.1398 *	0.0082 *	2.9915 ***	0.0414	0.5876 ***	0.2333 **	1.5038 ***
t-statistics	(-1.131)	(1.764)	(-1.748)	(1.667)	(2.881)	(1.054)	(5.140)	(2.476)	(15.503)
US13	-0.3495	0.0092	-0.0690	0.0012	1.0453 ***	0.0481 ***	0.8241 ***	0.1078 ***	1.4002 ***
t-statistics	(-0.560)	(0.660)	(-1.348)	(1.006)	(2.858)	(5.832)	(18.934)	(3.077)	(11.467)
US14	-0.5107	0.1048	0.0195	0.0038	0.3853	0.1211 **	0.7132 ***	0.1372	1.5825 ***
t-statistics	(-1.266)	(1.400)	(0.215)	(0.302)	(0.433)	(2.000)	(2.831)	(1.509)	(14.211)
US15	-0.3976 ***	0.6435 ***	-0.3301 **	0.0856 ***	0.5227	0.0340 ***	0.9122 ***	0.3478 ***	1.3517 ***
t-statistics	(-3.016)	(3.117)	(-2.063)	(3.311)	(0.367)	(3.259)	(2.735)	(3.430)	(14.405)
US16	-0.2073	0.0394	-0.0601	-0.0040	0.5962	0.1339	0.9015 ***	-0.0688	1.0877 ***
t-statistics	(-0.397)	(0.493)	(-0.821)	(-0.469)	(0.302)	(1.504)	(14.050)	(-0.671)	(20.042)
Panel E : Italy									
IT1	-0.1383	0.0373	0.0781	-0.0320	0.2301 *	0.0197	0.8835 ***	0.0789 *	1.5911 ***
t-statistics	(-0.606)	(0.605)	(0.754)	(-1.416)	(1.697)	(0.903)	(17.287)	(1.868)	(14.723)
IT2	-0.2886	0.0404	0.1998 **	-0.0097	1.0335 **	0.0543	0.7844 ***	0.1313 **	1.3156 ***
t-statistics	(-1.059)	(1.400)	(2.450)	(-1.532)	(2.121)	(1.446)	(10.916)	(2.178)	(15.604)
IT3	-0.0227	-0.0233	-0.0319	-0.0206	0.1323 *	0.1506	0.7427 ***	0.2087	1.1637 ***
t-statistics	(-0.250)	(-0.623)	(-0.351)	(-1.163)	(1.759)	(1.589)	(10.108)	(1.398)	(8.086)
IT4	-0.0046	0.0031	0.2934 ***	-0.0307 ***	0.2111 *	0.0717 ***	0.8934 ***	0.0167	1.6683 ***
t-statistics	(-0.021)	(0.102)	(3.201)	(-2.969)	(1.851)	(3.018)	(29.474)	(0.518)	(12.022)
IT5	-0.0340	0.0079	0.1075 **	-0.0073 *	0.0748 *	0.0674 ***	0.8960 ***	0.0515	1.3991 ***
t-statistics	(-0.374)	(0.425)	(2.186)	(-1.699)	(1.938)	(2.684)	(48.205)	(1.223)	(15.789)
IT6	-0.2235	0.0326	0.0523	-0.0066	0.3986 **	0.0454	0.8444 ***	0.0904 *	1.4491 ***
t-statistics	(-1.143)	(0.922)	(0.743)	(-0.784)	(1.996)	(1.624)	(14.603)	(1.924)	(14.605)
IT7	-0.0948	0.0154	0.0850	-0.0045	0.1712 *	0.0791 ***	0.8990 ***	0.0063	1.5991 ***
t-statistics	(-0.518)	(0.639)	(1.208)	(-0.777)	(1.745)	(3.012)	(34.187)	(0.220)	(14.095)

Appendix 2C: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel F : Netherland									
NET1	-0.3787	0.1352	0.1170	-0.0442	0.1112	0.0007	0.9324 ***	0.0600	1.6768 ***
t-statistics	(-1.048)	(1.094)	(0.601)	(-0.761)	(1.023)	(0.024)	(16.816)	(1.320)	(7.791)
NET2	0.0454	0.0090	0.1143 **	-0.0004	0.0766 **	0.0279	0.9079 ***	0.0974 ***	1.2152 ***
t-statistics	(0.561)	(0.431)	(2.532)	(-0.065)	(1.978)	(1.277)	(38.848)	(2.601)	(13.405)
NET3	-0.2469	0.0331	0.1101 *	-0.0041	0.4576 **	0.0286	0.8730 ***	0.1103 ***	1.5522 ***
t-statistics	(-1.078)	(1.414)	(1.700)	(-0.916)	(2.274)	(1.108)	(23.719)	(2.854)	(13.698)
NET4	-0.0639	0.0189	0.1078 **	-0.0067	0.1277 ***	0.0005	0.9066 ***	0.1223 ***	1.3320 ***
t-statistics	(-0.622)	(0.718)	(2.025)	(-0.825)	(2.667)	(0.024)	(35.626)	(3.302)	(13.848)
NET5	-0.1918	0.0409	0.1762 **	-0.0091	0.1092 **	0.0127	0.9313 ***	0.0713 ***	1.6263 ***
t-statistics	(-1.071)	(1.057)	(2.289)	(-0.706)	(2.119)	(0.799)	(45.765)	(2.967)	(13.820)
NET6	0.0402	-0.0001	0.0398	0.0098	0.0812	0.0680 ***	0.8834 ***	0.0590	1.4915 ***
t-statistics	(0.350)	(-0.004)	(0.565)	(0.684)	(1.612)	(2.659)	(32.301)	(1.338)	(13.462)
Panel G : Spain									
SP1	0.0714	-0.0046	0.1052	-0.0030	0.1898	0.0298	0.9067 ***	0.0783 **	1.5614 ***
t-statistics	(0.331)	(-0.132)	(1.270)	(-0.291)	(1.611)	(1.577)	(28.986)	(2.064)	(12.727)
SP2	0.0255	0.0142	-0.0805	0.0059	0.1159 **	0.0069	0.9174 ***	0.0973 ***	1.3563 ***
t-statistics	(0.253)	(0.645)	(-1.600)	(1.036)	(2.488)	(0.329)	(45.270)	(3.916)	(16.799)
SP3	-0.0508	0.0134	0.0538	0.0015	0.1073 ***	0.0340 *	0.8560 ***	0.1852 ***	1.5108 ***
t-statistics	(-0.706)	(0.774)	(1.186)	(0.412)	(2.593)	(1.915)	(33.976)	(4.144)	(14.709)
Panel H : Switzerland									
SWT1	0.1313	-0.0675	0.0320	0.0136	0.0080	0.0088	0.9681 ***	0.0415 *	1.1377 ***
t-statistics	(1.539)	(-1.541)	(0.449)	(0.505)	(1.028)	(0.624)	(87.657)	(1.726)	(15.960)
SWT2	-0.1312	0.0914	-0.0193	0.0250	0.3110 ***	0.0005	0.7239 ***	0.2506 ***	1.1949 ***
t-statistics	(-1.303)	(1.642)	(-0.343)	(1.269)	(2.977)	(0.013)	(9.168)	(2.976)	(15.075)
SWT3	-0.2699 *	0.0947 **	0.1270 **	-0.0133	0.3884 **	0.0164	0.7993 ***	0.1461 ***	1.2074 ***
t-statistics	(-1.875)	(2.148)	(2.163)	(-1.140)	(2.456)	(0.533)	(12.780)	(2.669)	(15.350)
SWT4	-0.1752 **	0.1087 **	0.1026 **	-0.0111	0.2926 ***	0.0374	0.6971 ***	0.2209 **	1.0286 ***
t-statistics	(-2.234)	(2.212)	(2.361)	(-0.865)	(2.752)	(0.884)	(8.721)	(2.407)	(14.094)
SWT5	-0.0452	0.0236	0.0241	-0.0085 *	0.1536 ***	0.0477 *	0.8566 ***	0.1343 ***	1.1948 ***
t-statistics	(-0.515)	(1.139)	(0.525)	(-1.712)	(2.639)	(1.738)	(26.712)	(2.730)	(14.982)
Panel I : Sweden									
SWD1	0.5985 **	-0.0346	-0.0018	0.0008	0.0515	0.0238 **	0.9736 ***	0.0007	1.2981 ***
t-statistics	(2.026)	(-1.632)	(-0.020)	(0.165)	(0.886)	(2.213)	(90.702)	(0.044)	(18.221)
SWD2	0.0126	-0.0108	-0.0136	-0.0098	0.3722	0.0504	0.8541 ***	0.0477	1.2261 ***
t-statistics	(0.055)	(-0.220)	(-0.151)	(-0.670)	(1.518)	(1.644)	(12.054)	(0.932)	(14.246)
SWD3	-0.8070 **	0.0625	0.2025	-0.0105	0.2539	0.0230	0.9005 ***	0.1223 *	1.5777 ***
t-statistics	(-2.029)	(1.321)	(1.427)	(-0.784)	(0.989)	(0.649)	(19.548)	(1.907)	(7.927)
SWD4	0.0238	0.0005	0.0713 *	0.0003	1.0481 ***	0.0523	0.7687 ***	0.0903	1.0297 ***
t-statistics	(0.144)	(0.022)	(1.902)	(0.160)	(2.584)	(1.255)	(10.798)	(1.227)	(25.866)
SWD5	0.1763	-0.0628	0.2400	-0.0587	0.8385	0.0488	0.7120 ***	0.0258	1.3049 ***
t-statistics	(0.373)	(-0.477)	(1.078)	(-1.044)	(1.176)	(1.219)	(03.187)	(0.415)	(14.487)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively
For the stock identification, refer to Table 2.2
v is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for v=2) and the Laplace/double exponential (for v=1).

Appendix 2D: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period

This table reports the estimated coefficients (t-statistics in parentheses) for the model:

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the underlying equity of stock i (on which an USF has been introduced) at time period t.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : France									
FR1	-0.0985	0.0343	-0.1435 **	0.0154	0.1229 ***	0.0166	0.8588 ***	0.1689 ***	1.9535 ***
t-statistics	(-1.030)	(1.049)	(-2.217)	(1.214)	(2.808)	(0.626)	(26.496)	(3.699)	(12.050)
FR2	-0.1282	0.0002	0.0984 *	-0.0016	0.0463	0.0178	0.9305 ***	0.0998 ***	2.1870 ***
t-statistics	(-1.074)	(0.019)	(1.742)	(-0.691)	(1.441)	(1.173)	(61.882)	(4.560)	(10.344)
FR3	-0.1632	-0.0017	0.0643	-0.0024	0.0403	0.0028	0.9632 ***	0.0618 ***	1.5277 ***
t-statistics	(-0.781)	(-0.136)	(1.048)	(-0.985)	(0.733)	(0.242)	(81.995)	(4.026)	(15.766)
FR4	-0.1088	0.0096	0.0089	0.0025	0.0949 ***	0.0002	0.9224 ***	0.1337 ***	1.6784 ***
t-statistics	(-1.015)	(0.736)	(0.151)	(0.738)	(2.585)	(0.012)	(52.160)	(4.319)	(13.321)
FR5	-0.1183	0.0032	-0.0039	0.0014	0.1720 ***	0.0020	0.8868 ***	0.2059 ***	1.3562 ***
t-statistics	(-1.198)	(0.334)	(-0.099)	(1.456)	(2.793)	(0.080)	(43.311)	(4.310)	(14.307)
FR6	0.0277	0.0065	-0.0684	0.0078	0.0688 **	0.0281	0.8823 ***	0.1588 ***	1.4332 ***
t-statistics	(0.368)	(0.344)	(-1.357)	(1.419)	(2.156)	(0.978)	(36.502)	(3.167)	(18.020)
FR7	-0.2126 **	0.0286	-0.0629	-0.0068	0.0774 **	0.0264	0.9130 ***	0.0883 ***	1.4242 ***
t-statistics	(-2.189)	(1.197)	(-1.197)	(-0.953)	(1.989)	(1.204)	(40.307)	(2.617)	(14.037)
FR8	-0.0131	0.0044	-0.0812	0.0131	0.0972 *	0.0803 **	0.8845 ***	0.0282	1.3045 ***
t-statistics	(-0.129)	(0.163)	(-1.286)	(1.294)	(1.887)	(2.554)	(28.795)	(0.623)	(15.139)
FR9	-0.0002	-0.0006	-0.1151 ***	0.0006	0.0493 **	0.0285	0.8953 ***	0.1376 ***	1.4343 ***
t-statistics	(-0.003)	(-0.046)	(-2.607)	(0.249)	(2.315)	(1.368)	(50.602)	(3.508)	(13.670)
Panel B : Germany									
GER1	0.0386	-0.0146	-0.0620	-0.0025	0.0353 *	0.0237	0.9238 ***	0.1021 ***	1.7230 ***
t-statistics	(0.349)	(-1.008)	(-0.975)	(-0.604)	(1.767)	(1.483)	(53.460)	(3.241)	(13.417)
GER2	-0.0830	0.0052	-0.0443	0.0005	0.1085 **	0.0071	0.9110 ***	0.1561 ***	1.7514 ***
t-statistics	(-0.769)	(0.275)	(-0.776)	(0.096)	(2.539)	(0.466)	(47.098)	(5.448)	(12.989)
GER3	-0.0165	-0.0024	0.0183	0.0000	0.0451	0.0104	0.9576 ***	0.0962 ***	1.9292 ***
t-statistics	(-0.111)	(-0.123)	(0.212)	(0.002)	(1.532)	(0.856)	(66.581)	(4.122)	(11.364)
GER4	-0.1088	-0.0007	0.0042	-0.0004	0.1096 **	0.0275	0.8936 ***	0.1368 ***	1.8432 ***
t-statistics	(-0.960)	(-0.049)	(0.074)	(-0.092)	(2.399)	(1.079)	(39.439)	(4.276)	(13.273)
GER5	-0.1736 *	0.0090	-0.0274	0.0027	0.1126 **	0.0405	0.8630 ***	0.1776 ***	1.6300 ***
t-statistics	(-1.870)	(0.647)	(-0.519)	(0.911)	(2.280)	(1.395)	(32.053)	(4.771)	(15.043)
GER6	0.1306	-0.0265	0.0340	-0.0059	0.0483	0.0169	0.9254 ***	0.1069 ***	1.9603 ***
t-statistics	(0.858)	(-1.048)	(0.471)	(-0.776)	(1.103)	(0.737)	(42.453)	(4.004)	(10.440)
GER7	-0.0064	0.0129	-0.2080 ***	0.0046	0.0523 **	0.0118	0.9248 ***	0.1394 ***	1.5296 ***
t-statistics	(-0.076)	(0.505)	(-3.396)	(0.405)	(2.165)	(0.509)	(40.933)	(4.222)	(13.649)
GER8	-0.3421 **	0.0159	-0.0255	0.0016	0.2130 **	0.0824 **	0.8736 ***	0.0631	1.3679 ***
t-statistics	(-2.369)	(1.101)	(-0.399)	(0.465)	(2.144)	(2.385)	(28.157)	(1.462)	(14.159)
GER9	-0.1957	0.0227	0.0720	-0.0073	0.0795 **	0.0099	0.9296 ***	0.0944 ***	1.6525 ***
t-statistics	(-1.559)	(0.963)	(1.080)	(-0.962)	(2.076)	(0.506)	(48.169)	(3.445)	(12.501)
GER10	-0.0087	0.0162	-0.1056 *	0.0003	0.0426 **	0.0009	0.9191 ***	0.1382 ***	1.4761 ***
t-statistics	(-0.112)	(0.638)	(-1.804)	(0.028)	(2.093)	(0.067)	(45.965)	(3.992)	(12.821)
GER11	-0.0351	-0.0044	-0.0009	-0.0065	0.0112	0.0176 **	0.9714 ***	0.0920 ***	1.3928 ***
t-statistics	(-0.403)	(-0.264)	(-0.018)	(-1.579)	(0.675)	(2.493)	(93.485)	(6.272)	(15.778)
GER12	0.0385	-0.0122	-0.0264	0.0022	0.0120	0.0154 ***	0.9910 ***	0.0595 ***	1.4141 ***
t-statistics	(0.377)	(-0.793)	(-0.560)	(0.475)	(0.944)	(4.074)	(201.657)	(6.310)	(18.291)
Panel C : UK									
UK1	-0.1384	0.0118	0.0162	-0.0064	0.0699 **	0.0108	0.9367 ***	0.1340 ***	1.9115 ***
t-statistics	(-1.135)	(0.632)	(0.249)	(-0.944)	(2.349)	(1.037)	(54.425)	(3.649)	(15.275)
UK2	-0.1023	0.0279	-0.0919	0.0051	0.0985 **	0.0315	0.8741 ***	0.1262 ***	1.6887 ***
t-statistics	(-1.019)	(0.832)	(-1.423)	(0.420)	(2.462)	(1.051)	(33.410)	(2.818)	(12.525)
UK3	-0.1000	0.0307	-0.0257	-0.0057	0.0977 ***	0.0054	0.8972 ***	0.1493 ***	1.2572 ***
t-statistics	(-1.258)	(1.044)	(-0.549)	(-0.563)	(2.685)	(0.254)	(42.579)	(3.862)	(18.279)
UK4	-0.3747 ***	0.0987 ***	-0.1115 *	0.0169	0.2167 ***	0.0060	0.8438 ***	0.1978 ***	1.5224 ***
t-statistics	(-3.370)	(2.785)	(-1.797)	(1.408)	(3.189)	(0.246)	(23.051)	(3.678)	(18.273)
UK5	-0.2298 **	0.0522 *	-0.0799	0.0158 *	0.1569 ***	0.0016	0.8822 ***	0.1741 ***	1.4203 ***
t-statistics	(-2.138)	(1.832)	(-1.406)	(1.802)	(2.639)	(0.095)	(29.036)	(3.429)	(15.829)
UK6	-0.1117	0.0019	-0.1005	0.0044	0.0199	0.0018	0.9457 ***	0.1008 ***	1.6874 ***
t-statistics	(-1.046)	(0.097)	(-1.520)	(0.595)	(0.965)	(0.116)	(61.025)	(3.359)	(13.692)
UK7	-0.0640	0.0035	-0.0083	-0.0018	0.0739 *	0.0685 **	0.8748 ***	0.0922 **	1.5512 ***
t-statistics	(-0.670)	(0.160)	(-0.129)	(-0.252)	(1.710)	(2.134)	(28.546)	(2.258)	(12.733)
UK8	-0.0487	0.0213	-0.0082	-0.0052	0.1138 ***	0.0208	0.8804 ***	0.1178 **	1.4157 ***
t-statistics	(-0.514)	(0.697)	(-0.138)	(-0.505)	(2.893)	(0.592)	(29.322)	(2.456)	(15.205)

Appendix 2D: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : UK									
UK9	-0.0624	0.0149	-0.0286	0.0065	0.0883 **	0.0126	0.8944 ***	0.1561 ***	1.4914 ***
t-statistics	(-0.681)	(0.694)	(-0.523)	(0.965)	(2.375)	(0.586)	(41.345)	(3.904)	(15.804)
UK10	-0.1110	0.0361 *	-0.1020 **	0.0034	0.1878 ***	0.0273	0.8256 ***	0.2152 ***	1.3498 ***
t-statistics	(-1.409)	(1.801)	(-2.070)	(0.628)	(3.309)	(0.944)	(22.234)	(3.413)	(15.305)
UK11	0.0436	-0.0034	-0.0817	-0.0190	0.0283	0.0270	0.9397 ***	0.0450 *	1.3043 ***
t-statistics	(0.540)	(-0.101)	(-1.515)	(-1.426)	(1.591)	(1.339)	(53.335)	(1.703)	(16.017)
UK12	-0.0219	0.0179	0.0102	-0.0147	0.0170	0.0056	0.9622 ***	0.0479 **	1.0942 ***
t-statistics	(-0.332)	(0.551)	(0.206)	(-0.950)	(1.551)	(0.384)	(77.463)	(2.170)	(14.876)
UK13	-0.1042	0.0137	-0.0744	-0.0061	0.0434 *	0.0366 *	0.9328 ***	0.0419 *	1.6397 ***
t-statistics	(-0.976)	(0.579)	(-1.235)	(-0.839)	(1.883)	(1.691)	(51.559)	(1.671)	(14.132)
UK14	-0.0293	0.0234	-0.0034	-0.0137	0.1568 **	0.1038 *	0.8222 ***	0.0229	1.0885 ***
t-statistics	(-0.381)	(0.662)	(-0.069)	(-1.226)	(2.216)	(1.955)	(13.962)	(0.387)	(20.537)
UK15	-0.1504	0.0404	0.0104	-0.0092	0.0536 **	0.0204	0.9222 ***	0.0850 **	1.6280 ***
t-statistics	(-1.618)	(1.501)	(0.184)	(-1.010)	(2.017)	(0.900)	(42.465)	(2.536)	(15.664)
UK16	-0.0409	-0.0011	0.0638	-0.0477 ***	0.0412 *	0.0067	0.9482 ***	0.0634 ***	1.3361 ***
t-statistics	(-0.384)	(-0.033)	(0.991)	(-3.141)	(1.714)	(0.404)	(57.762)	(2.727)	(15.852)
UK17	0.1305 *	-0.0287 *	-0.0022	-0.0020	0.1975 ***	0.1338 ***	0.7812 ***	0.1686 **	1.0973 ***
t-statistics	(1.682)	(-1.716)	(-0.043)	(-0.445)	(2.609)	(2.820)	(18.971)	(2.113)	(21.434)
Panel D : US									
US1	-0.1217	0.0264	-0.0257	-0.0093	0.1016	0.0211	0.9179 ***	0.0824 **	1.3638 ***
t-statistics	(-0.846)	(0.890)	(-0.355)	(-0.931)	(1.597)	(0.902)	(32.234)	(2.385)	(15.499)
US2	0.0347	0.0004	-0.0716	0.0013	0.1218 **	0.0150	0.9542 ***	0.0977 ***	1.5667 ***
t-statistics	(0.216)	(0.029)	(-1.169)	(0.375)	(2.080)	(1.469)	(56.910)	(3.663)	(16.600)
US3	0.1808	-0.0219	-0.0508	0.0013	0.0418	0.0246 **	0.9744 ***	0.0957 ***	1.4026 ***
t-statistics	(1.170)	(-1.368)	(-0.828)	(0.336)	(1.136)	(2.004)	(110.112)	(4.219)	(21.060)
US4	-0.0165	0.0260	-0.1406 **	0.0062	0.0703 **	0.0153	0.8868 ***	0.1170 ***	1.5777 ***
t-statistics	(-0.207)	(0.660)	(-2.436)	(0.391)	(2.545)	(0.614)	(32.252)	(3.419)	(13.317)
US5	-0.0514	0.0155	-0.0328	-0.0006	0.0572 **	0.0024	0.9226 ***	0.1213 ***	1.4103 ***
t-statistics	(-0.601)	(0.743)	(-0.718)	(-0.140)	(2.002)	(0.127)	(50.848)	(3.883)	(15.255)
US6	-0.3123	0.1032	-0.1666	0.0550 *	0.2864 *	0.0588	0.8482 ***	0.0030	1.2003 ***
t-statistics	(-1.365)	(1.335)	(-1.611)	(1.924)	(1.750)	(1.243)	(11.574)	(0.071)	(18.170)
US7	-0.1243	0.0080	-0.1451 *	0.0040	0.0108	0.0074	0.9839 ***	0.0430 ***	1.4897 ***
t-statistics	(-0.797)	(0.469)	(-1.924)	(0.689)	(0.638)	(0.802)	(158.592)	(2.810)	(17.588)
US8	0.1315	-0.0112	-0.0161	0.0007	0.0874	0.0215	0.9755 ***	-0.0042	1.1248 ***
t-statistics	(0.353)	(-0.548)	(-0.172)	(0.162)	(0.767)	(1.588)	(74.361)	(-0.262)	(19.114)
US9	-0.0626	0.0001	-0.0668	0.0110	0.0404 *	0.0028	0.9557 ***	0.0783 ***	1.3333 ***
t-statistics	(-0.575)	(0.003)	(-1.036)	(0.943)	(1.736)	(0.238)	(66.297)	(2.891)	(17.476)
US10	0.0097	-0.0011	-0.0699	0.0006	0.0533	0.0067	0.9748 ***	0.0534 ***	1.5448 ***
t-statistics	(0.055)	(-0.056)	(-0.928)	(0.098)	(1.583)	(0.762)	(100.395)	(2.902)	(14.018)
US11	-0.0022	-0.0071	-0.0308	-0.0006	0.1197	0.0376 **	0.9524 ***	0.0118	1.2987 ***
t-statistics	(-0.008)	(-0.589)	(-0.434)	(-0.283)	(1.110)	(2.444)	(58.715)	(0.566)	(14.627)
US12	-0.1029	0.0176	-0.1195 **	0.0035	0.0815 **	0.0016	0.9233 ***	0.1251 ***	1.5468 ***
t-statistics	(-0.976)	(0.748)	(-2.299)	(0.603)	(2.397)	(0.095)	(51.838)	(3.651)	(13.781)
US13	0.0495	-0.0069	0.0231	0.0008	0.0275	0.0208 ***	0.9710 ***	0.0400 ***	1.4130 ***
t-statistics	(0.222)	(-0.607)	(0.301)	(0.295)	(0.769)	(3.514)	(181.842)	(4.466)	(13.780)
US14	-0.0444	0.0066	-0.1024	0.0110	0.0905 *	0.0666 *	0.8835 ***	0.0437	1.3705 ***
t-statistics	(-0.414)	(0.185)	(-1.599)	(0.803)	(1.818)	(1.861)	(23.677)	(0.906)	(12.779)
US15	-0.3100 **	0.1145 **	-0.2293 **	0.0376	0.1068 **	0.0280	0.8958 ***	0.0756 *	1.5235 ***
t-statistics	(-2.165)	(2.047)	(-2.506)	(1.478)	(2.037)	(1.368)	(24.288)	(1.880)	(12.779)
US16	0.0007	-0.0062	-0.0181	-0.0027	0.0134 *	0.0212 ***	0.9997 ***	0.0479 ***	1.2963 ***
t-statistics	(0.007)	(-0.227)	(-0.247)	(-0.185)	(1.817)	(4.999)	(272.031)	(4.773)	(14.657)
Panel E : Italy									
IT1	-0.1037	0.0584 *	-0.1012	0.0103	0.0814 **	0.0289	0.9021 ***	0.0786 **	1.3424 ***
t-statistics	(-1.052)	(1.743)	(-1.537)	(0.737)	(2.199)	(1.107)	(33.878)	(2.030)	(15.266)
IT2	0.0505	-0.0080	0.0445	-0.0043	0.0192	0.0052	0.9588 ***	0.0588 **	1.2298 ***
t-statistics	(0.568)	(-0.458)	(0.947)	(-0.960)	(1.168)	(0.313)	(89.865)	(2.568)	(19.832)
IT3	-0.0175	0.0155	-0.1017 **	0.0021	0.0686 *	0.0662 *	0.8908 ***	0.0356	1.2178 ***
t-statistics	(-0.246)	(0.522)	(-2.043)	(0.212)	(1.870)	(1.663)	(22.655)	(0.755)	(23.794)
IT4	-0.1817 **	0.0378	-0.0033	-0.0072	0.0487 **	0.0074	0.9184 ***	0.1213 ***	1.4365 ***
t-statistics	(-2.187)	(1.562)	(-0.057)	(-0.704)	(2.486)	(0.397)	(49.557)	(3.786)	(14.773)
IT5	-0.0700	0.0228	-0.0007	0.0031	0.0437 **	0.0322	0.9008 ***	0.1094 ***	1.3366 ***
t-statistics	(-1.160)	(1.122)	(-0.016)	(0.474)	(2.496)	(1.211)	(41.854)	(2.830)	(17.614)
IT6	0.0401	-0.0082	-0.0702	-0.0028	0.0198	0.0151	0.9553 ***	0.0493 **	1.6050 ***
t-statistics	(0.363)	(-0.341)	(-1.118)	(-0.338)	(1.023)	(0.900)	(70.792)	(2.379)	(12.723)
IT7	-0.0224	0.0063	-0.0554	0.0053	0.0020	0.0200	0.9683 ***	0.0216	1.5639 ***
t-statistics	(-0.204)	(0.201)	(-0.763)	(0.354)	(0.175)	(1.624)	(98.551)	(1.156)	(12.670)

Appendix 2D: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel F : Netherland									
NET1	-0.0492	0.0091	0.0055	-0.0052	0.0425 *	0.0197	0.9106 ***	0.1083 ***	1.6518 ***
t-statistics	(-0.568)	(0.313)	(0.096)	(-0.550)	(1.806)	(0.943)	(49.386)	(3.252)	(13.356)
NET2	-0.1374	0.0101	0.0974 *	-0.0040	0.1082 ***	0.0030	0.8936 ***	0.1942 ***	1.5763 ***
t-statistics	(-1.520)	(0.868)	(1.872)	(-1.526)	(3.055)	(0.137)	(51.688)	(5.107)	(14.826)
NET3	-0.1081	0.0084	0.0567	-0.0054	0.1089 *	0.0023	0.9394 ***	0.0939 ***	1.7890 ***
t-statistics	(-0.634)	(0.509)	(0.841)	(-1.297)	(1.804)	(0.197)	(60.671)	(3.885)	(13.682)
NET4	-0.0663	0.0098	-0.0211	-0.0024	0.0682 **	0.0202	0.8852 ***	0.1673 ***	1.6079 ***
t-statistics	(-0.919)	(0.676)	(-0.411)	(-0.611)	(2.568)	(0.754)	(41.184)	(4.515)	(14.845)
NET5	-0.1719	0.0026	-0.0174	0.0006	0.0985 *	0.0039	0.9028 ***	0.1819 ***	1.6813 ***
t-statistics	(-1.619)	(0.217)	(-0.354)	(0.290)	(1.938)	(0.165)	(40.777)	(5.228)	(13.566)
NET6	-0.0961	-0.0001	0.0280	0.0000	0.1779	0.1692 **	0.7790 ***	0.3037 ***	0.9236 ***
t-statistics	(-1.591)	(-0.028)	(0.899)	(0.223)	(1.489)	(2.564)	(17.827)	(3.056)	(29.827)
Panel G : Spain									
SP1	-0.0084	-0.0005	0.0014	0.0015	0.0340 *	0.0066	0.9413 ***	0.0902 ***	1.7425 ***
t-statistics	(-0.073)	(-0.022)	(0.018)	(0.133)	(1.788)	(0.509)	(60.282)	(3.395)	(14.280)
SP2	-0.0158	0.0037	0.0211	-0.0053	0.0373 **	0.0114	0.9292 ***	0.1506 ***	1.7037 ***
t-statistics	(-0.184)	(0.224)	(0.369)	(-0.942)	(2.037)	(0.642)	(57.905)	(4.965)	(13.025)
SP3	-0.1498 *	0.0258 *	0.0158	-0.0027	0.0454 ***	0.0450 ***	0.9589 ***	0.1551 ***	1.7416 ***
t-statistics	(-1.913)	(1.695)	(0.256)	(-0.366)	(3.046)	(2.769)	(86.380)	(6.716)	(13.549)
Panel H : Switzerland									
SWT1	-0.0301	0.0115	-0.0646	0.0255	0.0278 *	0.0010	0.9277 ***	0.1228 ***	1.2389 ***
t-statistics	(-0.480)	(0.318)	(-1.178)	(1.330)	(1.933)	(0.069)	(41.582)	(3.534)	(15.133)
SWT2	0.0158	-0.0064	-0.1069 **	0.0040	0.0338 **	0.0603 **	0.8887 ***	0.0619 *	1.3742 ***
t-statistics	(0.293)	(-0.186)	(-2.051)	(0.253)	(2.082)	(2.056)	(29.359)	(1.816)	(15.880)
SWT3	-0.0810	0.0516 **	-0.0803	0.0201 **	0.0701 ***	0.0076	0.8784 ***	0.2015 ***	1.4813 ***
t-statistics	(-1.312)	(2.197)	(-1.593)	(2.017)	(2.733)	(0.364)	(35.096)	(4.377)	(12.411)
SWT4	-0.0426	0.0200	-0.0057	-0.0013	0.0390 *	0.0128	0.9352 ***	0.0734 ***	1.4641 ***
t-statistics	(-0.503)	(0.557)	(-0.103)	(-0.091)	(1.947)	(0.723)	(45.002)	(2.731)	(13.452)
SWT5	-0.0407	0.0095	0.0451	-0.0008	0.0804 **	0.0355	0.8985 ***	0.1024 ***	1.3579 ***
t-statistics	(-0.487)	(0.635)	(0.974)	(-0.253)	(2.100)	(1.368)	(46.010)	(2.691)	(13.696)
Panel I : Sweden									
SWD1	0.0381	-0.0052	-0.0130	0.0021	0.1117	0.0109	0.9600 ***	0.0469 **	1.2413 ***
t-statistics	(0.205)	(-0.460)	(-0.256)	(1.173)	(1.483)	(0.926)	(72.318)	(2.507)	(18.416)
SWD2	0.0000	0.0000	0.0000	0.0000	0.2151 **	0.0937 *	0.7822 ***	0.2245 **	1.0338 ***
t-statistics	(0.000)	(0.001)	(0.000)	(0.001)	(2.547)	(1.709)	(15.679)	(2.145)	(17.944)
SWD3	-0.0001	0.0000	0.0003	-0.0001	0.0257	0.0041	0.9701 ***	0.0604 **	1.0370 ***
t-statistics	(-0.001)	(0.001)	(0.007)	(-0.022)	(1.403)	(0.328)	(83.088)	(2.553)	(17.156)
SWD4	-0.0017	0.0005	0.0245	-0.0133	0.0214	0.0007	0.9696 ***	0.0449 **	1.1403 ***
t-statistics	(-0.017)	(0.016)	(0.403)	(-0.969)	(1.356)	(0.068)	(88.954)	(2.379)	(18.936)
SWD5	-0.0180	0.0098	-0.0724	0.0093	0.0742 **	0.0554 **	0.8698 ***	0.0982 **	1.1711 ***
t-statistics	(-0.264)	(0.315)	(-1.440)	(0.788)	(1.981)	(2.010)	(24.909)	(2.014)	(15.226)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively

For the stock identification, refer to Table 2.2

ν is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for ν=2) and the Laplace/double exponential (for ν=1).

Appendix 2E: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period (sorted by industry)

This table reports the estimated coefficients (t-statistics in parentheses) for the model :

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the underlying equity of stock i (on which an USF has been introduced) at time period t.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : Services									
FR2	0.3425	-0.0347	0.0755	0.0009	0.1068	0.0577 ***	0.9414 ***	-0.0182	1.5024 ***
t-statistics	(1.471)	(-1.373)	(0.910)	(0.140)	(1.275)	(2.913)	(45.181)	(-0.583)	(18.328)
FR5	-0.2247	0.0540	0.1453 *	0.0035	0.1173	0.0481 *	0.9226 ***	0.0068	1.2722 ***
t-statistics	(-1.189)	(1.218)	(1.767)	(0.238)	(1.543)	(1.914)	(30.999)	(0.221)	(13.361)
FR7	0.1429	-0.0229	0.1565 **	-0.0128	0.3941 **	0.0548	0.8180 ***	0.1127 **	1.2871 ***
t-statistics	(0.866)	(-0.673)	(2.298)	(-1.438)	(2.329)	(1.439)	(15.096)	(2.054)	(15.923)
GER1	0.0261	-0.0017	0.1142	-0.0036	0.1857	0.0529 **	0.9200 ***	0.0287	1.2492 ***
t-statistics	(0.115)	(-0.071)	(1.258)	(-0.497)	(1.330)	(2.334)	(30.966)	(0.700)	(15.063)
IT2	-0.2886	0.0404	0.1998 **	-0.0097	1.0335 **	0.0543	0.7844 ***	0.1313 **	1.3156 ***
t-statistics	(-1.059)	(1.400)	(2.450)	(-1.532)	(2.121)	(1.446)	(10.916)	(2.178)	(15.604)
IT4	-0.0046	0.0031	0.2934 ***	-0.0307 ***	0.2111 *	0.0717 ***	0.8934 ***	0.0167	1.6683 ***
t-statistics	(-0.021)	(0.102)	(3.201)	(-2.969)	(1.851)	(3.018)	(29.474)	(0.518)	(12.022)
IT7	-0.0948	0.0154	0.0850	-0.0045	0.1712 *	0.0791 ***	0.8990 ***	0.0063	1.5991 ***
t-statistics	(-0.518)	(0.639)	(1.208)	(-0.777)	(1.745)	(3.012)	(34.187)	(0.220)	(14.095)
NET6	0.0402	-0.0001	0.0398	0.0098	0.0812	0.0680 ***	0.8834 ***	0.0590	1.4915 ***
t-statistics	(0.350)	(-0.004)	(0.565)	(0.684)	(1.612)	(2.659)	(32.301)	(1.338)	(13.462)
SP1	0.0714	-0.0046	0.1052	-0.0030	0.1898	0.0298	0.9067 ***	0.0783 **	1.5614 ***
t-statistics	(0.331)	(-0.132)	(1.270)	(-0.291)	(1.611)	(1.577)	(28.986)	(2.064)	(12.727)
UK1	0.0332	0.0052	0.3607 ***	-0.0229 ***	0.5273 **	0.0847 **	0.8279 ***	0.0736	1.4844 ***
t-statistics	(0.151)	(0.198)	(4.278)	(-2.922)	(2.212)	(2.456)	(18.304)	(1.547)	(15.710)
UK6	-0.0642	0.0004	0.1361 *	-0.0025	0.2094	0.0306	0.9163 ***	0.0706	1.3133 ***
t-statistics	(-0.307)	(0.016)	(1.736)	(-0.340)	(1.476)	(1.163)	(28.381)	(1.613)	(15.601)
UK11	-0.1624	0.0435	0.0785	-0.0278	0.4945 **	0.0753 **	0.7967 ***	0.0332	1.3528 ***
t-statistics	(-0.705)	(0.789)	(0.676)	(-1.284)	(1.971)	(2.064)	(10.244)	(0.663)	(14.510)
UK16	-0.1409	0.0309	0.0562	-0.0030	1.3084 ***	0.2364 **	0.4714 ***	0.1573	1.1353 ***
t-statistics	(-1.249)	(1.334)	(1.010)	(-0.644)	(3.818)	(2.480)	(4.569)	(1.182)	(15.598)
US15	-0.3976 ***	0.6435 ***	-0.3301 **	0.0856 ***	0.5227	0.0340 ***	0.9122 ***	0.3478 ***	1.3517 ***
t-statistics	(-3.016)	(3.117)	(-2.063)	(3.311)	(0.367)	(3.259)	(2.735)	(3.430)	(14.405)
SWD3	-0.8070 **	0.0625	0.2025	-0.0105	0.2539	0.0230	0.9005 ***	0.1223 *	1.5777 ***
t-statistics	(-2.029)	(1.321)	(1.427)	(-0.784)	(0.989)	(0.649)	(19.548)	(1.907)	(7.927)
SWD4	0.0238	0.0005	0.0713 *	0.0003	1.0481 ***	0.0523	0.7687 ***	0.0903	1.0297 ***
t-statistics	(0.144)	(0.022)	(1.902)	(0.160)	(2.584)	(1.255)	(10.798)	(1.227)	(25.866)
Panel B : Consumer Goods									
FR8	-0.0627	0.0176	0.2509	-0.0396 *	1.2500 *	0.0521	0.7025 ***	0.1022	1.6930 ***
t-statistics	(-0.153)	(0.259)	(1.508)	(-1.677)	(1.878)	(1.383)	(05.437)	(1.550)	(12.144)
GER6	-0.8768 **	0.2180 *	0.0520	-0.0024	0.1424	0.0128	0.9276 ***	0.0410	1.4815 ***
t-statistics	(-1.964)	(1.671)	(0.306)	(-0.055)	(1.467)	(0.805)	(24.959)	(1.359)	(12.794)
GER9	-0.1082	0.0158	0.0797	-0.0019	0.2667 **	0.1023 **	0.8547 ***	0.0009	1.2598 ***
t-statistics	(-0.769)	(0.625)	(1.325)	(-0.286)	(2.236)	(2.453)	(21.945)	(0.017)	(14.393)
UK4	0.0257	-0.0025	0.2438	-0.0434	1.0578	0.0122	0.7647 ***	0.0252	1.1815 ***
t-statistics	(0.034)	(-0.017)	(0.902)	(-0.821)	(0.772)	(0.411)	(2.679)	(0.524)	(22.789)
UK5	-0.3506	0.0935	0.5164 ***	-0.0902 ***	0.4326 **	0.0701 **	0.8131 ***	0.0174	1.4605 ***
t-statistics	(-1.348)	(1.374)	(3.822)	(-2.847)	(2.234)	(2.309)	(14.182)	(0.564)	(16.913)
UK12	-0.0364	0.0132	-0.0255	0.0078	0.0984	0.0321	0.9280 ***	0.0362	1.2915 ***
t-statistics	(-0.210)	(0.327)	(-0.284)	(0.483)	(1.637)	(1.557)	(38.382)	(1.004)	(15.493)
UK14	0.0274	-0.0049	0.0174	-0.0012	0.0842 *	0.0279	0.9401 ***	0.0274	1.1354 ***
t-statistics	(0.187)	(-0.147)	(0.255)	(-0.114)	(1.769)	(1.182)	(47.324)	(0.857)	(18.801)
US6	-0.1989	0.0570	0.1031	-0.0102	0.2383 *	0.0029	0.8931 ***	0.0964 **	1.5263 ***
t-statistics	(-0.937)	(1.082)	(1.139)	(-0.590)	(1.877)	(0.139)	(18.112)	(2.439)	(16.492)
US12	-0.4209	0.0604 *	-0.1398 *	0.0082 *	2.9915 ***	0.0414	0.5876 ***	0.2333 **	1.5038 ***
t-statistics	(-1.131)	(1.764)	(-1.748)	(1.667)	(2.881)	(1.054)	(5.140)	(2.476)	(15.503)
US14	-0.5107	0.1048	0.0195	0.0038	0.3853	0.1211 **	0.7132 ***	0.1372	1.5825 ***
t-statistics	(-1.266)	(1.400)	(0.215)	(0.302)	(0.433)	(2.000)	(2.831)	(1.509)	(14.211)
SWT1	0.1313	-0.0675	0.0320	0.0136	0.0080	0.0088	0.9681 ***	0.0415 *	1.1377 ***
t-statistics	(1.539)	(-1.541)	(0.449)	(0.505)	(1.028)	(0.624)	(87.657)	(1.726)	(15.960)
SWT2	-0.1312	0.0914	-0.0193	0.0250	0.3110 ***	0.0005	0.7239 ***	0.2506 ***	1.1949 ***
t-statistics	(-1.303)	(1.642)	(-0.343)	(1.269)	(2.977)	(0.013)	(9.168)	(2.976)	(15.075)
SWT4	-0.1752 **	0.1087 **	0.1026 **	-0.0111	0.2926 ***	0.0374	0.6971 ***	0.2209 **	1.0286 ***
t-statistics	(-2.234)	(2.212)	(2.361)	(-0.865)	(2.752)	(0.884)	(8.721)	(2.407)	(14.094)

Appendix 2E: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : Technology									
FR3	0.0449	0.0053	0.1406	-0.0068	0.3989 *	0.0570 **	0.8856 ***	0.0476	1.5352 ***
t-statistics	(0.170)	(0.204)	(1.530)	(-0.978)	(1.941)	(2.033)	(23.112)	(1.148)	(13.079)
GER12	-0.4792 *	0.0305 *	0.1056	-0.0022	1.6550 ***	0.0486	0.7601 ***	0.1916 ***	1.3197 ***
t-statistics	(-1.818)	(1.696)	(1.493)	(-0.713)	(2.911)	(1.404)	(14.082)	(3.143)	(15.166)
US1	0.1256	-0.0107	-0.0353	0.0025	0.5048 **	0.0424	0.8582 ***	0.0796 *	1.2665 ***
t-statistics	(0.574)	(-0.366)	(-0.573)	(0.482)	(2.520)	(1.343)	(20.201)	(1.781)	(16.681)
US2	0.1846	0.0018	-0.0739	-0.0015	0.7402 ***	0.0092	0.7919 ***	0.2737 ***	1.7002 ***
t-statistics	(1.091)	(0.098)	(-1.381)	(-0.526)	(3.757)	(0.316)	(21.634)	(4.805)	(13.533)
US3	0.0762	0.0060	-0.1078 *	0.0019	0.9001 ***	0.0241	0.8531 ***	0.1749 ***	1.4232 ***
t-statistics	(0.313)	(0.256)	(-1.909)	(0.569)	(2.831)	(0.859)	(19.151)	(3.016)	(20.186)
US7	0.5160 *	-0.0249 *	0.1619 ***	-0.0044 **	0.6443 **	0.0236 ***	0.9206 ***	0.1667 ***	1.2434 ***
t-statistics	(1.884)	(-1.701)	(4.519)	(-2.357)	(2.118)	(5.305)	(33.853)	(3.890)	(19.189)
US8	0.5524 **	-0.0229	-0.1076	0.0009	0.7128 ***	0.0228	0.8557 ***	0.1629 ***	1.6618 ***
t-statistics	(2.200)	(-1.284)	(-1.485)	(0.261)	(2.593)	(0.846)	(23.765)	(3.257)	(13.331)
US10	0.0788	0.0023	-0.0260	-0.0006	2.1967 ***	0.1092 ***	0.7450 ***	0.1647 **	1.3154 ***
t-statistics	(0.271)	(0.187)	(-0.392)	(-0.387)	(2.796)	(2.754)	(12.179)	(1.977)	(16.575)
US11	0.2080	-0.0036	0.0068	-0.0011	1.2390 **	0.0393	0.8663 ***	0.1295 **	1.4071 ***
t-statistics	(0.661)	(-0.338)	(0.099)	(-0.791)	(2.343)	(1.481)	(23.993)	(2.355)	(17.270)
US13	-0.3495	0.0092	-0.0690	0.0012	1.0453 ***	0.0481 ***	0.8241 ***	0.1078 ***	1.4002 ***
t-statistics	(-0.560)	(0.660)	(-1.348)	(1.006)	(2.858)	(5.832)	(18.934)	(3.077)	(11.467)
US16	-0.2073	0.0394	-0.0601	-0.0040	0.5962	0.1339	0.9015 ***	-0.0688	1.0877 ***
t-statistics	(-0.397)	(0.493)	(-0.821)	(-0.469)	(0.302)	(1.504)	(14.050)	(-0.671)	(20.042)
SWD1	0.5985 **	-0.0346	-0.0018	0.0008	0.0515	0.0238 **	0.9736 ***	0.0007	1.2981 ***
t-statistics	(2.026)	(-1.632)	(-0.020)	(0.165)	(0.886)	(2.213)	(90.702)	(0.044)	(18.221)
Panel D : Financial									
FR4	-0.4053 **	0.0957 **	0.1016	0.0041	0.2923 **	0.0252	0.8710 ***	0.0855 **	1.4722 ***
t-statistics	(-2.087)	(2.244)	(1.508)	(0.405)	(2.084)	(1.310)	(19.169)	(2.280)	(15.999)
FR6	-0.0607	0.0131	-0.0266	0.0046	0.0340	0.0054	0.9612 ***	0.0555 ***	1.3593 ***
t-statistics	(-0.508)	(0.571)	(-0.516)	(0.807)	(1.253)	(0.353)	(69.084)	(2.631)	(13.911)
GER2	0.1009	-0.0088	-0.0489	0.0108	0.4604 **	0.0523 **	0.8207 ***	0.1080	1.2530 ***
t-statistics	(0.562)	(-0.266)	(-0.723)	(1.298)	(2.162)	(2.225)	(13.492)	(1.625)	(19.301)
GER4	-0.2260	0.0425	-0.0066	0.0024	0.1760 **	0.0190	0.9123 ***	0.0764 **	1.1110 ***
t-statistics	(-1.600)	(1.456)	(-0.120)	(0.336)	(2.168)	(1.505)	(32.813)	(2.147)	(20.444)
GER5	-0.0745	0.0122	0.1177	-0.0104	0.1947	0.0276 *	0.9246 ***	0.0399	1.3972 ***
t-statistics	(-0.287)	(0.299)	(1.125)	(-0.766)	(1.388)	(1.676)	(25.258)	(1.136)	(19.667)
GER8	0.0145	-0.0025	-0.0506	0.0030	0.0688	0.0390 **	0.9406 ***	0.0211	1.3260 ***
t-statistics	(0.094)	(-0.105)	(-0.763)	(0.441)	(1.244)	(2.003)	(49.323)	(0.782)	(13.684)
IT5	-0.0340	0.0079	0.1075 **	-0.0073 *	0.0748 *	0.0674 ***	0.8960 ***	0.0515	1.3991 ***
t-statistics	(-0.374)	(0.425)	(2.186)	(-1.699)	(1.938)	(2.684)	(48.205)	(1.223)	(15.789)
IT6	-0.2235	0.0326	0.0523	-0.0066	0.3986 **	0.0454	0.8444 ***	0.0904 *	1.4491 ***
t-statistics	(-1.143)	(0.922)	(0.743)	(-0.784)	(1.996)	(1.624)	(14.603)	(1.924)	(14.605)
NET2	0.0454	0.0090	0.1143 **	-0.0004	0.0766 **	0.0279	0.9079 ***	0.0974 ***	1.2152 ***
t-statistics	(0.561)	(0.431)	(2.532)	(-0.065)	(1.978)	(1.277)	(38.848)	(2.601)	(13.405)
NET4	-0.0639	0.0189	0.1078 **	-0.0067	0.1277 ***	0.0005	0.9066 ***	0.1223 ***	1.3320 ***
t-statistics	(-0.622)	(0.718)	(2.025)	(-0.825)	(2.667)	(0.024)	(35.626)	(3.302)	(13.848)
NET5	-0.1918	0.0409	0.1762 **	-0.0091	0.1092 **	0.0127	0.9313 ***	0.0713 ***	1.6263 ***
t-statistics	(-1.071)	(1.057)	(2.289)	(-0.706)	(2.119)	(0.799)	(45.765)	(2.967)	(13.820)
SP2	0.0255	0.0142	-0.0805	0.0059	0.1159 **	0.0069	0.9174 ***	0.0973 ***	1.3563 ***
t-statistics	(0.253)	(0.645)	(-1.600)	(1.036)	(2.488)	(0.329)	(45.270)	(3.916)	(16.799)
SP3	-0.0508	0.0134	0.0538	0.0015	0.1073 ***	0.0340 *	0.8560 ***	0.1852 ***	1.5108 ***
t-statistics	(-0.706)	(0.774)	(1.186)	(0.412)	(2.593)	(1.915)	(33.976)	(4.144)	(14.709)
UK3	0.0484	0.0036	-0.0130	0.0055	0.0911	0.0175	0.9327 ***	0.0716 **	1.3171 ***
t-statistics	(0.296)	(0.113)	(-0.166)	(0.483)	(1.634)	(0.945)	(39.331)	(2.306)	(13.030)
UK7	-0.4133 *	0.0575	0.2002 ***	-0.0183 *	0.0633	0.0034	0.9865 ***	0.0787 ***	1.5530 ***
t-statistics	(-1.828)	(1.518)	(2.606)	(-1.678)	(1.346)	(1.484)	(49.170)	(5.787)	(13.277)
UK9	-0.1689	0.0309	0.1015	0.0011	0.1639 *	0.0337	0.9026 ***	0.0819 **	1.7223 ***
t-statistics	(-0.923)	(1.003)	(1.321)	(0.117)	(1.911)	(1.563)	(35.486)	(2.181)	(10.806)
UK10	-0.2988 *	0.0542 **	-0.0058	0.0075	0.5777 **	0.0452 *	0.8092 ***	0.1397 **	1.2676 ***
t-statistics	(-1.702)	(2.046)	(-0.080)	(1.040)	(2.244)	(1.670)	(13.601)	(2.075)	(16.331)
UK13	-0.1932	0.0279	-0.2397 ***	0.0201	0.0884	0.0307 *	0.9382 ***	0.0360	1.3552 ***
t-statistics	(-0.952)	(0.755)	(-2.616)	(1.488)	(1.325)	(1.873)	(44.764)	(1.439)	(15.794)
UK15	-0.2598	0.0449	-0.0418	0.0070	0.3568 ***	0.0407	0.8480 ***	0.1044 **	1.3996 ***
t-statistics	(-1.600)	(1.527)	(-0.738)	(1.192)	(2.611)	(1.490)	(21.729)	(2.305)	(14.993)
UK17	-0.1372	0.0212	0.1007	-0.0038	0.3380 *	0.0614 *	0.8748 ***	0.0221	1.2911 ***
t-statistics	(-0.629)	(0.583)	(1.174)	(-0.357)	(1.781)	(1.685)	(16.896)	(0.576)	(15.595)
US5	-0.2771	0.0518	-0.0734	0.0095	0.2261 **	0.0065	0.9430 ***	0.0652 ***	1.4008 ***
t-statistics	(-1.115)	(1.419)	(-1.065)	(1.178)	(2.255)	(1.031)	(44.629)	(3.003)	(19.596)

Appendix 2E: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel D : Financial									
SWT3	-0.2699 *	0.0947 **	0.1270 **	-0.0133	0.3884 **	0.0164	0.7993 ***	0.1461 ***	1.2074 ***
t-statistics	(-1.875)	(2.148)	(2.163)	(-1.140)	(2.456)	(0.533)	(12.780)	(2.669)	(15.350)
SWT5	-0.0452	0.0236	0.0241	-0.0085 *	0.1536 ***	0.0477 *	0.8566 ***	0.1343 ***	1.1948 ***
t-statistics	(-0.515)	(1.139)	(0.525)	(-1.712)	(2.639)	(1.738)	(26.712)	(2.730)	(14.982)
SWD2	0.0126	-0.0108	-0.0136	-0.0098	0.3722	0.0504	0.8541 ***	0.0477	1.2261 ***
t-statistics	(0.055)	(-0.220)	(-0.151)	(-0.670)	(1.518)	(1.644)	(12.054)	(0.932)	(14.246)
SWD5	0.1763	-0.0628	0.2400	-0.0587	0.8385	0.0488	0.7120 ***	0.0258	1.3049 ***
t-statistics	(0.373)	(-0.477)	(1.078)	(-1.044)	(1.176)	(1.219)	(03.187)	(0.415)	(14.487)
Panel E : General and Resources									
GER3	0.0202	0.0119	0.1358 **	-0.0084	0.2008 **	0.0154	0.9139 ***	0.0878 **	1.3035 ***
t-statistics	(0.119)	(0.461)	(2.001)	(-1.116)	(2.204)	(0.928)	(36.245)	(2.494)	(21.518)
NET3	-0.2469	0.0331	0.1101 *	-0.0041	0.4576 **	0.0286	0.8730 ***	0.1103 ***	1.5522 ***
t-statistics	(-1.078)	(1.414)	(1.700)	(-0.916)	(2.274)	(1.108)	(23.719)	(2.854)	(13.698)
US9	-0.1050	0.0269	0.1411 *	-0.0266 *	0.1568 **	0.0147	0.9182 ***	0.1268 ***	1.6185 ***
t-statistics	(-0.611)	(0.629)	(1.833)	(-1.852)	(2.317)	(0.957)	(33.349)	(4.078)	(13.669)
GER10	-0.1474	0.0361	0.0362	-0.0069	0.5246 **	0.0123	0.7749 ***	0.1639 ***	1.4023 ***
t-statistics	(-0.754)	(0.665)	(0.538)	(-0.506)	(2.029)	(0.512)	(8.763)	(2.590)	(13.539)
GER11	-0.0973	0.0242	0.0233	0.0027	0.1041	0.0090	0.9520 ***	0.0275	1.0855 ***
t-statistics	(-0.562)	(0.550)	(0.340)	(0.193)	(1.185)	(0.440)	2(7.787)	(1.004)	(23.038)
FR1	0.3155	-0.7214 **	-0.1250	0.0245	0.2810 ***	0.0087	0.9499 ***	-0.0504 **	1.4675 ***
t-statistics	(0.233)	(-2.452)	(-0.355)	(0.288)	(8.532)	(1.191)	(84.379)	(-2.249)	(8.955)
FR9	-0.3616 **	0.1319 **	0.0422	-0.0131	0.6401 **	0.0565	0.6701 ***	0.1359 *	1.2498 ***
t-statistics	(-2.114)	(2.241)	(0.631)	(-0.929)	(2.445)	(1.564)	(5.972)	(1.957)	1(6.810)
GER7	-0.1394	0.0259	-0.0123	0.0102	0.1657	0.0362	0.8963 ***	0.0749 *	1.4443 ***
t-statistics	(-0.710)	(0.627)	(-0.119)	(0.590)	(1.488)	(1.290)	(22.666)	(1.787)	(16.102)
IT1	-0.1383	0.0373	0.0781	-0.0320	0.2301 *	0.0197	0.8835 ***	0.0789 *	1.5911 ***
t-statistics	(-0.606)	(0.605)	(0.754)	(-1.416)	(1.697)	(0.903)	(17.287)	(1.868)	(14.723)
IT3	-0.0227	-0.0233	-0.0319	-0.0206	0.1323 *	0.1506	0.7427 ***	0.2087	1.1637 ***
t-statistics	(-0.250)	(-0.623)	(-0.351)	(-1.163)	(1.759)	(1.589)	(10.108)	(1.398)	(8.086)
NET1	-0.3787	0.1352	0.1170	-0.0442	0.1112	0.0007	0.9324 ***	0.0600	1.6768 ***
t-statistics	(-1.048)	(1.094)	(0.601)	(-0.761)	(1.023)	(0.024)	(16.816)	(1.320)	(7.791)
UK2	-0.9650 **	0.2517 **	0.1763	-0.0417	0.1513 *	0.0004	0.9390 ***	0.0477 **	1.3958 ***
t-statistics	(-1.992)	(1.964)	(1.206)	(-1.170)	(1.758)	(0.044)	(36.665)	(2.261)	(13.562)
UK8	-0.3565 *	0.0820	0.1379	-0.0182	0.1399 *	0.0215	0.9099 ***	0.0792 ***	1.6443 ***
t-statistics	(-1.797)	(1.626)	(1.416)	(-0.968)	(1.825)	(1.189)	(33.424)	(2.623)	(14.606)
US4	-0.3048	0.1167	-0.0804	0.0150	0.1433	0.0216	0.9086 ***	0.0439	1.6272 ***
t-statistics	(-1.091)	(1.216)	(-0.526)	(0.327)	(1.299)	(1.113)	(18.063)	(1.151)	(11.889)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively

For the stock identification, refer to Table 2.2

ν is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for ν=2) and the Laplace/double exponential (for ν=1).

Appendix 2F: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period (sorted by industry)

This table reports the estimated coefficients (t-statistics in parentheses) for the model:

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$
$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the underlying equity of stock *i* (on which an USF has been introduced) at time period *t*.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : Services									
FR2	-0.1282	0.0002	0.0984 *	-0.0016	0.0463	0.0178	0.9305 ***	0.0998 ***	2.1870 ***
t-statistics	(-1.074)	(0.019)	(1.742)	(-0.691)	(1.441)	(1.173)	(61.882)	(4.560)	(10.344)
FR5	-0.1183	0.0032	-0.0039	0.0014	0.1720 ***	0.0020	0.8868 ***	0.2059 ***	1.3562 ***
t-statistics	(-1.198)	(0.334)	(-0.099)	(1.456)	(2.793)	(0.080)	(43.311)	(4.310)	(14.307)
FR7	-0.2126 **	0.0286	-0.0629	-0.0068	0.0774 **	0.0264	0.9130 ***	0.0883 ***	1.4242 ***
t-statistics	(-2.189)	(1.197)	(-1.197)	(-0.953)	(1.989)	(1.204)	(40.307)	(2.617)	(14.037)
GER1	0.0386	-0.0146	-0.0620	-0.0025	0.0353 *	0.0237	0.9238 ***	0.1021 ***	1.7230 ***
t-statistics	(0.349)	(-1.008)	(-0.975)	(-0.604)	(1.767)	(1.483)	(53.460)	(3.241)	(13.417)
IT2	0.0505	-0.0080	0.0445	-0.0043	0.0192	0.0052	0.9588 ***	0.0588 **	1.2298 ***
t-statistics	(0.568)	(-0.458)	(0.947)	(-0.960)	(1.168)	(0.313)	(89.865)	(2.568)	(19.832)
IT4	-0.1817 **	0.0378	-0.0033	-0.0072	0.0487 **	0.0074	0.9184 ***	0.1213 ***	1.4365 ***
t-statistics	(-2.187)	(1.562)	(-0.057)	(-0.704)	(2.486)	(0.397)	(49.557)	(3.786)	(14.773)
IT7	-0.0224	0.0063	-0.0554	0.0053	0.0020	0.0200	0.9683 ***	0.0216	1.5639 ***
t-statistics	(-0.204)	(0.201)	(-0.763)	(0.354)	(0.175)	(1.624)	(98.551)	(1.156)	(12.670)
NET6	-0.0961	-0.0001	0.0280	0.0000	0.1779	0.1692 **	0.7790 ***	0.3037 ***	0.9236 ***
t-statistics	(-1.591)	(-0.028)	(0.899)	(0.223)	(1.489)	(2.564)	(17.827)	(3.056)	(29.827)
SP1	-0.0084	-0.0005	0.0014	0.0015	0.0340 *	0.0066	0.9413 ***	0.0902 ***	1.7425 ***
t-statistics	(-0.073)	(-0.022)	(0.018)	(0.133)	(1.788)	(0.509)	(60.282)	(3.395)	(14.280)
UK1	-0.1384	0.0118	0.0162	-0.0064	0.0699 **	0.0108	0.9367 ***	0.1340 ***	1.9115 ***
t-statistics	(-1.135)	(0.632)	(0.249)	(-0.944)	(2.349)	(1.037)	(54.425)	(3.649)	(15.275)
UK6	-0.1117	0.0019	-0.1005	0.0044	0.0199	0.0018	0.9457 ***	0.1008 ***	1.6874 ***
t-statistics	(-1.046)	(0.097)	(-1.520)	(0.595)	(0.965)	(0.116)	(61.025)	(3.359)	(13.692)
UK11	0.0436	-0.0034	-0.0817	-0.0190	0.0283	0.0270	0.9397 ***	0.0450 *	1.3043 ***
t-statistics	(0.540)	(-0.101)	(-1.515)	(-1.426)	(1.591)	(1.339)	(53.335)	(1.703)	(16.017)
UK16	-0.0409	-0.0011	0.0638	-0.0477 ***	0.0412 *	0.0067	0.9482 ***	0.0634 ***	1.3361 ***
t-statistics	(-0.384)	(-0.033)	(0.991)	(-3.141)	(1.714)	(0.404)	(57.762)	(2.727)	(15.852)
US15	-0.3100 **	0.1145 **	-0.2293 **	0.0376	0.1068 **	0.0280	0.8958 ***	0.0756 *	1.5235 ***
t-statistics	(-2.165)	(2.047)	(-2.506)	(1.478)	(2.037)	(1.368)	(24.288)	(1.880)	(12.779)
SWD3	-0.0001	0.0000	0.0003	-0.0001	0.0257	0.0041	0.9701 ***	0.0604 **	1.0370 ***
t-statistics	(-0.001)	(0.001)	(0.007)	(-0.022)	(1.403)	(0.328)	(83.088)	(2.553)	(17.156)
SWD4	-0.0017	0.0005	0.0245	-0.0133	0.0214	0.0007	0.9696 ***	0.0449 **	1.1403 ***
t-statistics	(-0.017)	(0.016)	(0.403)	(-0.969)	(1.356)	(0.068)	(88.954)	(2.379)	(18.936)
Panel B : Consumer Goods									
FR8	-0.0131	0.0044	-0.0812	0.0131	0.0972 *	0.0803 **	0.8845 ***	0.0282	1.3045 ***
t-statistics	(-0.129)	(0.163)	(-1.286)	(1.294)	(1.887)	(2.554)	(28.795)	(0.623)	(15.139)
GER6	0.1306	-0.0265	0.0340	-0.0059	0.0483	0.0169	0.9254 ***	0.1069 ***	1.9603 ***
t-statistics	(0.858)	(-1.048)	(0.471)	(-0.776)	(1.103)	(0.737)	(42.453)	(4.004)	(10.440)
GER9	-0.1957	0.0227	0.0720	-0.0073	0.0795 **	0.0099	0.9296 ***	0.0944 ***	1.6525 ***
t-statistics	(-1.559)	(0.963)	(1.080)	(-0.962)	(2.076)	(0.506)	(48.169)	(3.445)	(12.501)
UK4	-0.3747 ***	0.0987 ***	-0.1115 *	0.0169	0.2167 ***	0.0060	0.8438 ***	0.1978 ***	1.5224 ***
t-statistics	(-3.370)	(2.785)	(-1.797)	(1.408)	(3.189)	(0.246)	(23.051)	(3.678)	(18.273)
UK5	-0.2298 **	0.0522 *	-0.0799	0.0158 *	0.1569 ***	0.0016	0.8822 ***	0.1741 ***	1.4203 ***
t-statistics	(-2.138)	(1.832)	(-1.406)	(1.802)	(2.639)	(0.095)	(29.036)	(3.429)	(15.829)
UK12	-0.0219	0.0179	0.0102	-0.0147	0.0170	0.0056	0.9622 ***	0.0479 **	1.0942 ***
t-statistics	(-0.332)	(0.551)	(0.206)	(-0.950)	(1.551)	(0.384)	(77.463)	(2.170)	(14.876)
UK14	-0.0293	0.0234	-0.0034	-0.0137	0.1568 **	0.1038 *	0.8222 ***	0.0229	1.0885 ***
t-statistics	(-0.381)	(0.662)	(-0.069)	(-1.226)	(2.216)	(1.955)	(13.962)	(0.387)	(20.537)
US6	-0.3123	0.1032	-0.1666	0.0550 *	0.2864 *	0.0588	0.8482 ***	0.0030	1.2003 ***
t-statistics	(-1.365)	(1.335)	(-1.611)	(1.924)	(1.750)	(1.243)	(11.574)	(0.071)	(18.170)
US12	-0.1029	0.0176	-0.1195 **	0.0035	0.0815 **	0.0016	0.9233 ***	0.1251 ***	1.5468 ***
t-statistics	(-0.976)	(0.748)	(-2.299)	(0.603)	(2.397)	(0.095)	(51.838)	(3.651)	(13.781)
US14	-0.0444	0.0066	-0.1024	0.0110	0.0905 *	0.0666 *	0.8835 ***	0.0437	1.3705 ***
t-statistics	(-0.414)	(0.185)	(-1.599)	(0.803)	(1.818)	(1.861)	(23.677)	(0.906)	(12.779)
SWT1	-0.0301	0.0115	-0.0646	0.0255	0.0278 *	0.0010	0.9277 ***	0.1228 ***	1.2389 ***
t-statistics	(-0.480)	(0.318)	(-1.178)	(1.330)	(1.933)	(0.069)	(41.582)	(3.534)	(15.133)
SWT2	0.0158	-0.0064	-0.1069 **	0.0040	0.0338 **	0.0603 **	0.8887 ***	0.0619 *	1.3742 ***
t-statistics	(0.293)	(-0.186)	(-2.051)	(0.253)	(2.082)	(2.056)	(29.359)	(1.816)	(15.880)
SWT4	-0.0426	0.0200	-0.0057	-0.0013	0.0390 *	0.0128	0.9352 ***	0.0734 ***	1.4641 ***
t-statistics	(-0.503)	(0.557)	(-0.103)	(-0.091)	(1.947)	(0.723)	(45.002)	(2.731)	(13.452)

Appendix 2F: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : Technology									
FR3	-0.1632	-0.0017	0.0643	-0.0024	0.0403	0.0028	0.9632 ***	0.0618 ***	1.5277 ***
t-statistics	(-0.781)	(-0.136)	(1.048)	(-0.985)	(0.733)	(0.242)	(81.995)	(4.026)	(15.766)
GER12	0.0385	-0.0122	-0.0264	0.0022	0.0120	0.0154 ***	0.9910 ***	0.0595 ***	1.4141 ***
t-statistics	(0.377)	(-0.793)	(-0.560)	(0.475)	(0.944)	(4.074)	(201.657)	(6.310)	(18.291)
US1	-0.1217	0.0264	-0.0257	-0.0093	0.1016	0.0211	0.9179 ***	0.0824 **	1.3638 ***
t-statistics	(-0.846)	(0.890)	(-0.355)	(-0.931)	(1.597)	(0.902)	(32.234)	(2.385)	(15.499)
US2	0.0347	0.0004	-0.0716	0.0013	0.1218 **	0.0150	0.9542 ***	0.0977 ***	1.5667 ***
t-statistics	(0.216)	(0.029)	(-1.169)	(0.375)	(2.080)	(1.469)	(56.910)	(3.663)	(16.600)
US3	0.1808	-0.0219	-0.0508	0.0013	0.0418	0.0246 **	0.9744 ***	0.0957 ***	1.4026 ***
t-statistics	(1.170)	(-1.368)	(-0.828)	(0.336)	(1.136)	(2.004)	(110.112)	(4.219)	(21.060)
US7	-0.1243	0.0080	-0.1451 *	0.0040	0.0108	0.0074	0.9839 ***	0.0430 ***	1.4897 ***
t-statistics	(-0.797)	(0.469)	(-1.924)	(0.689)	(0.638)	(0.802)	(158.592)	(2.810)	(17.588)
US8	0.1315	-0.0112	-0.0161	0.0007	0.0874	0.0215	0.9755 ***	-0.0042	1.1248 ***
t-statistics	(0.353)	(-0.548)	(-0.172)	(0.162)	(0.767)	(1.588)	(74.361)	(-0.262)	(19.114)
US10	0.0097	-0.0011	-0.0699	0.0006	0.0533	0.0067	0.9748 ***	0.0534 ***	1.5448 ***
t-statistics	(0.055)	(-0.056)	(-0.928)	(0.098)	(1.583)	(0.762)	(100.395)	(2.902)	(14.018)
US11	-0.0022	-0.0071	-0.0308	-0.0006	0.1197	0.0376 **	0.9524 ***	0.0118	1.2987 ***
t-statistics	(-0.008)	(-0.589)	(-0.434)	(-0.283)	(1.110)	(2.444)	(58.715)	(0.566)	(14.627)
US13	0.0495	-0.0069	0.0231	0.0008	0.0275	0.0208 ***	0.9710 ***	0.0400 ***	1.4130 ***
t-statistics	(0.222)	(-0.607)	(0.301)	(0.295)	(0.769)	(3.514)	(181.842)	(4.466)	(13.780)
US16	0.0007	-0.0062	-0.0181	-0.0027	0.0134 *	0.0212 ***	0.9997 ***	0.0479 ***	1.2963 ***
t-statistics	(0.007)	(-0.227)	(-0.247)	(-0.185)	(1.817)	(4.999)	(272.031)	(4.773)	(14.657)
SWD1	0.0381	-0.0052	-0.0130	0.0021	0.1117	0.0109	0.9600 ***	0.0469 **	1.2413 ***
t-statistics	(0.205)	(-0.460)	(-0.256)	(1.173)	(1.483)	(0.926)	(72.318)	(2.507)	(18.416)
Panel D : Financial									
FR4	-0.1088	0.0096	0.0089	0.0025	0.0949 ***	0.0002	0.9224 ***	0.1337 ***	1.6784 ***
t-statistics	(-1.015)	(0.736)	(0.151)	(0.738)	(2.585)	(0.012)	(52.160)	(4.319)	(13.321)
FR6	0.0277	0.0065	-0.0684	0.0078	0.0688 **	0.0281	0.8823 ***	0.1588 ***	1.4332 ***
t-statistics	(0.368)	(0.344)	(-1.357)	(1.419)	(2.156)	(0.978)	(36.502)	(3.167)	(18.020)
GER2	-0.0830	0.0052	-0.0443	0.0005	0.1085 **	0.0071	0.9110 ***	0.1561 ***	1.7514 ***
t-statistics	(-0.769)	(0.275)	(-0.776)	(0.096)	(2.539)	(0.466)	(47.098)	(5.448)	(12.989)
GER4	-0.1088	-0.0007	0.0042	-0.0004	0.1096 **	0.0275	0.8936 ***	0.1368 ***	1.8432 ***
t-statistics	(-0.960)	(-0.049)	(0.074)	(-0.092)	(2.399)	(1.079)	(39.439)	(4.276)	(13.273)
GER5	-0.1736 *	0.0090	-0.0274	0.0027	0.1126 **	0.0405	0.8630 ***	0.1776 ***	1.6300 ***
t-statistics	(-1.870)	(0.647)	(-0.519)	(0.911)	(2.280)	(1.395)	(32.053)	(4.771)	(15.043)
GER8	-0.3421 **	0.0159	-0.0255	0.0016	0.2130 **	0.0824 **	0.8736 ***	0.0631	1.3679 ***
t-statistics	(-2.369)	(1.101)	(-0.399)	(0.465)	(2.144)	(2.385)	(28.157)	(1.462)	(14.159)
IT5	-0.0700	0.0228	-0.0007	0.0031	0.0437 **	0.0322	0.9008 ***	0.1094 ***	1.3366 ***
t-statistics	(-1.160)	(1.122)	(-0.016)	(0.474)	(2.496)	(1.211)	(41.854)	(2.830)	(17.614)
IT6	0.0401	-0.0082	-0.0702	-0.0028	0.0198	0.0151	0.9553 ***	0.0493 **	1.6050 ***
t-statistics	(0.363)	(-0.341)	(-1.118)	(-0.338)	(1.023)	(0.900)	(70.792)	(2.379)	(12.723)
NET2	-0.1374	0.0101	0.0974 *	-0.0040	0.1082 ***	0.0030	0.8936 ***	0.1942 ***	1.5763 ***
t-statistics	(-1.520)	(0.868)	(1.872)	(-1.526)	(3.055)	(0.137)	(51.688)	(5.107)	(14.826)
NET4	-0.0663	0.0098	-0.0211	-0.0024	0.0682 **	0.0202	0.8852 ***	0.1673 ***	1.6079 ***
t-statistics	(-0.919)	(0.676)	(-0.411)	(-0.611)	(2.568)	(0.754)	(41.184)	(4.515)	(14.845)
NET5	-0.1719	0.0026	-0.0174	0.0006	0.0985 *	0.0039	0.9028 ***	0.1819 ***	1.6813 ***
t-statistics	(-1.619)	(0.217)	(-0.354)	(0.290)	(1.938)	(0.165)	(40.777)	(5.228)	(13.566)
SP2	-0.0158	0.0037	0.0211	-0.0053	0.0373 **	0.0114	0.9292 ***	0.1506 ***	1.7037 ***
t-statistics	(-0.184)	(0.224)	(0.369)	(-0.942)	(2.037)	(0.642)	(57.905)	(4.965)	(13.025)
SP3	-0.1498 *	0.0258 *	0.0158	-0.0027	0.0454 ***	0.0450 ***	0.9589 ***	0.1551 ***	1.7416 ***
t-statistics	(-1.913)	(1.695)	(0.256)	(-0.366)	(3.046)	(2.769)	(86.380)	(6.716)	(13.549)
UK3	-0.1000	0.0307	-0.0257	-0.0057	0.0977 ***	0.0054	0.8972 ***	0.1493 ***	1.2572 ***
t-statistics	(-1.258)	(1.044)	(-0.549)	(-0.563)	(2.685)	(0.254)	(42.579)	(3.862)	(18.279)
UK7	-0.0640	0.0035	-0.0083	-0.0018	0.0739 *	0.0685 **	0.8748 ***	0.0922 **	1.5512 ***
t-statistics	(-0.670)	(0.160)	(-0.129)	(-0.252)	(1.710)	(2.134)	(28.546)	(2.258)	(12.733)
UK9	-0.0624	0.0149	-0.0286	0.0065	0.0883 **	0.0126	0.8944 ***	0.1561 ***	1.4914 ***
t-statistics	(-0.681)	(0.694)	(-0.523)	(0.965)	(2.375)	(0.586)	(41.345)	(3.904)	(15.804)
UK10	-0.1110	0.0361 *	-0.1020 **	0.0034	0.1878 ***	0.0273	0.8256 ***	0.2152 ***	1.3498 ***
t-statistics	(-1.409)	(1.801)	(-2.070)	(0.628)	(3.309)	(0.944)	(22.234)	(3.413)	(15.305)
UK13	-0.1042	0.0137	-0.0744	-0.0061	0.0434 *	0.0366 *	0.9328 ***	0.0419 *	1.6397 ***
t-statistics	(-0.976)	(0.579)	(-1.235)	(-0.839)	(1.883)	(1.691)	(51.559)	(1.671)	(14.132)
UK15	-0.1504	0.0404	0.0104	-0.0092	0.0536 **	0.0204	0.9222 ***	0.0850 **	1.6280 ***
t-statistics	(-1.618)	(1.501)	(0.184)	(-1.010)	(2.017)	(0.900)	(42.465)	(2.536)	(15.664)
UK17	0.1305 *	-0.0287 *	-0.0022	-0.0020	0.1975 ***	0.1338 ***	0.7812 ***	0.1686 **	1.0973 ***
t-statistics	(1.682)	(-1.716)	(-0.043)	(-0.445)	(2.609)	(2.820)	(18.971)	(2.113)	(21.434)
US5	-0.0514	0.0155	-0.0328	-0.0006	0.0572 **	0.0024	0.9226 ***	0.1213 ***	1.4103 ***
t-statistics	(-0.601)	(0.743)	(-0.718)	(-0.140)	(2.002)	(0.127)	(50.848)	(3.883)	(15.255)

Appendix 2F: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel D : Financial									
SWT3	-0.0810	0.0516 **	-0.0803	0.0201 **	0.0701 ***	0.0076	0.8784 ***	0.2015 ***	1.4813 ***
t-statistics	(-1.312)	(2.197)	(-1.593)	(2.017)	(2.733)	(0.364)	(35.096)	(4.377)	(12.411)
SWT5	-0.0407	0.0095	0.0451	-0.0008	0.0804 **	0.0355	0.8985 ***	0.1024 ***	1.3579 ***
t-statistics	(-0.487)	(0.635)	(0.974)	(-0.253)	(2.100)	(1.368)	(46.010)	(2.691)	(13.696)
SWD2	0.0000	0.0000	0.0000	0.0000	0.2151 **	0.0937 *	0.7822 ***	0.2245 **	1.0338 ***
t-statistics	(0.000)	(0.001)	(0.000)	(0.001)	(2.547)	(1.709)	(15.679)	(2.145)	(17.9[illegible])
SWD5	-0.0180	0.0098	-0.0724	0.0093	0.0742 **	0.0554 **	0.8698 ***	0.0982 **	1.1711 ***
t-statistics	(-0.264)	(0.315)	(-1.440)	(0.788)	(1.981)	(2.010)	(24.909)	(2.014)	(15.226)
Panel E : General and Resources									
GER3	-0.0165	-0.0024	0.0183	0.0000	0.0451	0.0104	0.9576 ***	0.0962 ***	1.9292 ***
t-statistics	(-0.111)	(-0.123)	(0.212)	(0.002)	(1.532)	(0.856)	(66.581)	(4.122)	(11.364)
NET3	-0.1081	0.0084	0.0567	-0.0054	0.1089 *	0.0023	0.9394 ***	0.0939 ***	1.7890 ***
t-statistics	(-0.634)	(0.509)	(0.841)	(-1.297)	(1.804)	(0.197)	(60.671)	(3.885)	(13.682)
US9	-0.0626	0.0001	-0.0668	0.0110	0.0404 *	0.0028	0.9557 ***	0.0783 ***	1.3333 ***
t-statistics	(-0.575)	(0.003)	(-1.036)	(0.943)	(1.736)	(0.238)	(66.297)	(2.891)	(17.476)
GER10	-0.0087	0.0162	-0.1056 *	0.0003	0.0426 **	0.0009	0.9191 ***	0.1382 ***	1.4761 ***
t-statistics	(-0.112)	(0.638)	(-1.804)	(0.028)	(2.093)	(0.067)	(45.965)	(3.992)	(12.821)
GER11	-0.0351	-0.0044	-0.0009	-0.0065	0.0112	0.0176 **	0.9714 ***	0.0920 ***	1.3928 ***
t-statistics	(-0.403)	(-0.264)	(-0.018)	(-1.579)	(0.675)	(2.493)	(93.485)	(6.272)	(15.778)
FR1	-0.0985	0.0343	-0.1435 **	0.0154	0.1229 ***	0.0166	0.8588 ***	0.1689 ***	1.9535 ***
t-statistics	(-1.030)	(1.049)	(-2.217)	(1.214)	(2.808)	(0.626)	(26.496)	(3.699)	(12.050)
FR9	-0.0002	-0.0006	-0.1151 ***	0.0006	0.0493 **	0.0285	0.8953 ***	0.1376 ***	1.4343 ***
t-statistics	(-0.003)	(-0.046)	(-2.607)	(0.249)	(2.315)	(1.368)	(50.602)	(3.508)	(13.670)
GER7	-0.0064	0.0129	-0.2080 ***	0.0046	0.0523 **	0.0118	0.9248 ***	0.1394 ***	1.5296 ***
t-statistics	(-0.076)	(0.505)	(-3.396)	(0.405)	(2.165)	(0.509)	(40.933)	(4.222)	(13.649)
IT1	-0.1037	0.0584 *	-0.1012	0.0103	0.0814 **	0.0289	0.9021 ***	0.0786 **	1.3424 ***
t-statistics	(-1.052)	(1.743)	(-1.537)	(0.737)	(2.199)	(1.107)	(33.878)	(2.030)	(15.266)
IT3	-0.0175	0.0155	-0.1017 **	0.0021	0.0686 *	0.0662 *	0.8908 ***	0.0356	1.2178 ***
t-statistics	(-0.246)	(0.522)	(-2.043)	(0.212)	(1.870)	(1.663)	(22.655)	(0.755)	(23.794)
NET1	-0.0492	0.0091	0.0055	-0.0052	0.0425 *	0.0197	0.9106 ***	0.1083 ***	1.6518 ***
t-statistics	(-0.568)	(0.313)	(0.096)	(-0.550)	(1.806)	(0.943)	(49.386)	(3.252)	(13.356)
UK2	-0.1023	0.0279	-0.0919	0.0051	0.0985 **	0.0315	0.8741 ***	0.1262 ***	1.6887 ***
t-statistics	(-1.019)	(0.832)	(-1.423)	(0.420)	(2.462)	(1.051)	(33.410)	(2.818)	(12.525)
UK8	-0.0487	0.0213	-0.0082	-0.0052	0.1138 ***	0.0208	0.8804 ***	0.1178 **	1.4157 ***
t-statistics	(-0.514)	(0.697)	(-0.138)	(-0.505)	(2.893)	(0.592)	(29.322)	(2.456)	(15.205)
US4	-0.0165	0.0260	-0.1406 **	0.0062	0.0703 **	0.0153	0.8868 ***	0.1170 ***	1.5777 ***
t-statistics	(-0.207)	(0.660)	(-2.436)	(0.391)	(2.545)	(0.614)	(32.252)	(3.419)	(13.317)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively

For the stock identification, refer to Table 2.2

v is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for v=2) and the Laplace/double exponential (for v=1).

Appendix 2G: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period_Control

This table reports the estimated coefficients (t-statistics in parentheses) for the model:

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the control stock i at time period t.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : France									
FR1C	-0.5349 *	0.1001 *	0.1627 **	-0.0216 **	1.6015 ***	0.0380	0.6551 ***	0.2118 ***	1.5679 ***
t-statistics	(-1.687)	(1.769)	(2.345)	(-2.352)	(3.086)	(1.259)	(6.262)	(2.935)	(13.661)
FR2C	0.1703	-0.0337	0.1561 *	-0.0465 **	0.0902	0.0748 ***	0.9092 ***	-0.0134	1.2866 ***
t-statistics	(1.178)	(-0.808)	(1.742)	(-2.268)	(1.622)	(2.692)	(30.359)	(-0.365)	(14.067)
FR3C	-1.1962 **	0.0965 **	0.1279	-0.0052	1.9134 ***	0.0028	0.8052 ***	0.1221 **	1.5995 ***
t-statistics	(-2.104)	(2.276)	(1.167)	(-0.766)	(2.817)	(0.120)	(12.913)	(2.421)	(11.837)
FR4C	-0.0533	0.0078	0.0377	-0.0038	0.1131 **	0.0126	0.9530 ***	0.0830 ***	1.5308 ***
t-statistics	(-0.285)	(0.212)	(0.523)	(-0.343)	(2.031)	(0.834)	(53.638)	(3.412)	(13.818)
FR5C	-0.2053	0.0313	-0.0206	-0.0011	0.2406 **	0.0114	0.9004 ***	0.1447 ***	1.6316 ***
t-statistics	(-1.225)	(1.036)	(-0.354)	(-0.157)	(2.276)	(0.653)	(28.478)	(3.547)	(13.501)
FR6C	-0.2947	0.0847 *	0.1109	-0.0202	0.3661 **	0.0455	0.8324 ***	0.0704 *	1.3533 ***
t-statistics	(-1.484)	(1.682)	(1.349)	(-1.284)	(2.362)	(1.538)	(15.130)	(1.668)	(16.765)
FR7C	0.1016	-0.0191	0.1291	-0.0447 *	0.1379	0.0664 **	0.9000 ***	-0.0015	1.3209 ***
t-statistics	(0.558)	(-0.382)	(1.230)	(-1.906)	(1.605)	(2.308)	(23.624)	(-0.040)	(13.994)
FR8C	-0.2275	0.0624	0.0658	-0.0176	0.5133 **	0.0703	0.7706 ***	0.0799	1.2100 ***
t-statistics	(-1.303)	(1.404)	(0.866)	(-1.312)	(2.429)	(1.623)	(10.324)	(1.359)	(16.937)
FR9C	-0.1760	0.0627	-0.2282 **	0.0083	0.0383	0.0679	0.9220 ***	0.0060	1.2228 ***
t-statistics	(-1.188)	(1.523)	(-2.042)	(0.413)	(1.152)	(1.341)	(26.093)	(0.104)	(09.757)
Panel B : Germany									
GER1C	0.0526	-0.0080	0.0132	-0.0062	0.4335 *	0.0844 **	0.8258 ***	0.0349	1.3525 ***
t-statistics	(0.280)	(-0.236)	(0.187)	(-0.756)	(1.874)	(2.060)	(12.200)	(0.657)	(12.949)
GER2C	-0.1874	0.0393	0.0594	-0.0130	0.0937 *	0.0335 **	0.9078 ***	0.0795 **	1.5380 ***
t-statistics	(-1.361)	(1.090)	(0.835)	(-1.011)	(1.806)	(1.972)	(34.151)	(2.449)	(15.444)
GER3C	-0.3354	0.0433	0.0557	-0.0108	0.2047 *	0.0421 *	0.8987 ***	0.0678 *	1.3667 ***
t-statistics	(-1.501)	(1.160)	(0.565)	(-0.820)	(1.699)	(1.907)	(25.806)	(1.694)	(13.446)
GER4C	-0.1954	0.0388	0.1322 *	-0.0200	0.0827 *	0.0367 **	0.9125 ***	0.0670 **	1.5208 ***
t-statistics	(-1.452)	(1.095)	(1.890)	(-1.569)	(1.734)	(2.096)	(36.006)	(2.212)	(15.489)
GER5C	-0.1954	0.0388	0.1322 *	-0.0200	0.0827 *	0.0367 **	0.9125 ***	0.0670 **	1.5208 ***
t-statistics	(-1.452)	(1.095)	(1.890)	(-1.569)	(1.734)	(2.096)	(36.006)	(2.212)	(15.489)
GER6C	-0.0938	0.0169	-0.1087	0.0154	0.0473	0.0122	0.9569 ***	0.0443 *	1.2426 ***
t-statistics	(-0.608)	(0.582)	(-1.481)	(1.428)	(1.142)	(0.700)	(60.634)	(1.672)	(13.364)
GER7C	0.0069	-0.0018	0.0690	-0.0156	0.1526 *	0.0398 *	0.8942 ***	0.0801 *	1.1865 ***
t-statistics	(0.048)	(-0.059)	(0.925)	(-1.462)	(1.925)	(1.760)	(29.479)	(1.852)	(15.284)
GER8C	-0.0680	0.0098	0.1320 **	-0.0177	0.0246	0.0447 **	0.9133 ***	0.0846 **	1.4533 ***
t-statistics	(-0.659)	(0.341)	(2.146)	(-1.635)	(0.777)	(2.299)	(40.675)	(2.439)	(14.795)
GER9C	-0.1686	0.0255	0.0060	0.0041	1.4587 **	0.1470 **	0.6010 ***	0.0569	1.1834 ***
t-statistics	(-0.796)	(0.711)	(0.084)	(0.564)	(2.376)	(2.037)	(4.383)	(0.627)	(17.092)
GER10C	-0.0903	0.0149	-0.0898	0.0032	0.0826 *	0.0346	0.9108 ***	0.0807 **	1.1544 ***
t-statistics	(-0.892)	(0.572)	(-1.542)	(0.344)	(1.769)	(1.210)	(30.559)	(2.113)	(16.713)
GER11C	-0.0903	0.0149	-0.0898	0.0032	0.0826 *	0.0346	0.9108 ***	0.0807 **	1.1544 ***
t-statistics	(-0.892)	(0.572)	(-1.542)	(0.344)	(1.769)	(1.210)	(30.559)	(2.113)	(16.713)
GER12C	-0.8131	0.0305	0.0936	0.0006	0.6483	0.0012	0.9028 ***	0.1111 **	2.0257 ***
t-statistics	(-1.637)	(0.914)	(000.748)	(0.088)	(1.251)	(0.040)	(15.522)	(2.359)	(10.416)
Panel C : UK									
UK1C	0.0600	-0.0069	-0.0194	0.0051	0.4967 **	0.0505	0.7940 ***	0.1818 ***	1.4366 ***
t-statistics	(0.335)	(-0.234)	(-0.278)	(0.693)	(2.542)	(1.339)	(15.484)	(2.696)	(12.241)
UK2C	0.0702	-0.0196	-0.0415	-0.0046	0.1452 *	0.0523	0.8998 ***	0.0463	1.2956 ***
t-statistics	(0.445)	(-0.603)	(-0.556)	(-0.432)	(1.653)	(1.632)	(26.284)	(1.058)	(14.433)
UK3C	0.0005	-0.0001	-0.1221 ***	0.0065 **	0.3545 *	0.0819 **	0.8624 ***	0.0445	0.9195 ***
t-statistics	(0.005)	(-0.005)	(-3.200)	(2.121)	(1.960)	(2.037)	(20.003)	(0.851)	(20.367)
UK4C	0.0511	-0.0122	-0.0404	-0.0053	0.1327	0.0441	0.9092 ***	0.0466	1.2970 ***
t-statistics	(0.316)	(-0.365)	(-0.538)	(-0.487)	(1.603)	(1.530)	(28.132)	(1.188)	(14.576)
UK5C	-0.3180	0.0807 *	-0.0882	0.0016	0.3545 **	0.0573 *	0.8580 ***	0.0372	1.1854 ***
t-statistics	(-1.569)	(1.953)	(-1.282)	(0.171)	(2.036)	(1.844)	(17.741)	(0.851)	(18.727)
UK6C	-0.0396	0.0038	-0.1940 ***	0.0087 **	0.2313 *	0.0973 **	0.8788 ***	0.0149	0.9131 ***
t-statistics	(-0.384)	(0.268)	(-4.560)	(2.413)	(1.892)	(2.499)	(26.058)	(0.339)	(20.637)
UK7C	-0.2469	0.0242	0.0033	0.0003	0.0997 *	0.0043	0.9508 ***	0.0667 **	1.4165 ***
t-statistics	(-1.164)	(0.761)	(0.042)	(0.031)	(1.646)	(0.310)	(57.617)	(2.571)	(14.301)
UK8C	0.2071	-0.0248	0.1266	-0.0085	0.3866	0.0230	0.9105 ***	0.0573	1.2331 ***
t-statistics	(0.681)	(-0.726)	(1.361)	(-0.974)	(1.421)	(1.134)	(19.358)	(1.501)	(15.500)

Appendix 2G: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period_Control (continued)

	Mean Equation				Variance Equation				
	α	θ	φ0	φ1	α0	α1	β	δ	ν
Panel C : UK									
UK9C	-0.2412	0.0263	-0.0459	0.0055	0.0603 *	0.0173 *	0.9763 ***	0.0670 ***	1.4641 ***
t-statistics	(-1.160)	(0.836)	(-0.571)	(0.517)	(1.772)	(1.780)	(104.647)	(4.080)	(14.059)
UK10C	-0.3141	0.0336	-0.0145	0.0076	0.4734 **	0.0372 *	0.8783 ***	0.0758 *	1.3189 ***
t-statistics	(-1.165)	(1.108)	(-0.170)	(1.086)	(2.065)	(1.669)	(21.534)	(1.817)	(16.030)
UK11C	-0.4581 **	0.0314	-0.0451	0.0053	1.2057 ***	0.1007 **	0.7389 ***	0.1559 *	1.2637 ***
t-statistics	(-2.061)	(1.543)	(-0.676)	(1.470)	(2.797)	(2.115)	(11.281)	(1.875)	(16.372)
UK12C	0.0546	-0.0077	0.1057 **	-0.0045	0.1378 *	0.0641 ***	0.9214 ***	0.0097	1.0835 ***
t-statistics	(0.427)	(-0.552)	(2.321)	(-1.520)	(1.717)	(2.589)	(42.310)	(0.319)	(19.247)
UK13C	-0.1273	0.0096	0.1113	-0.0223 *	0.2999 **	0.0420	0.8430 ***	0.1185 **	1.1672 ***
t-statistics	(-0.841)	(0.289)	(1.446)	(-1.834)	(2.113)	(1.381)	(17.213)	(2.028)	(12.309)
UK14C	0.0317	-0.0105	-0.1456 **	0.0071	0.1096	0.0457 *	0.9179 ***	0.0528	1.3166 ***
t-statistics	(0.188)	(-0.438)	(-2.102)	(1.081)	(1.414)	(1.914)	(35.250)	(1.435)	(15.818)
UK15C	-0.1698	0.0186	0.1091	-0.0056	1.2730 **	0.0796 *	0.7136 ***	0.1350 *	1.2405 ***
t-statistics	(-0.750)	(0.665)	(1.499)	(-0.940)	(2.460)	(1.669)	(07.688)	(1.772)	(17.354)
UK16C	-0.2532	0.0362	0.1127 *	-0.0118 *	0.1801 *	0.0327	0.9120 ***	0.0580 *	1.2214 ***
t-statistics	(-1.510)	(1.376)	(1.707)	(-1.659)	(1.788)	(1.160)	(29.664)	(1.688)	(15.914)
UK17C	-0.0728	0.0279	0.1698	-0.0793 *	0.1248 *	0.0375	0.8577 ***	0.0954 **	1.2201 ***
t-statistics	(-0.581)	(0.420)	(1.608)	(-1.730)	(1.769)	(1.636)	(16.467)	(1.978)	(14.381)
Panel D : US									
US1C	0.6265 *	-0.0393	0.0779	-0.0043	1.9979 ***	0.0299	0.7464 ***	0.1839 ***	1.5821 ***
t-statistics	(1.735)	(-1.488)	(0.958)	(-0.988)	(2.966)	(0.725)	(12.422)	(2.753)	(14.592)
US2C	0.1976	-0.0040	0.0562	-0.0064 *	0.4567	0.0286	0.9163 ***	0.0661 **	1.8363 ***
t-statistics	(0.526)	(-0.183)	(0.649)	(-1.682)	(1.583)	(1.475)	(37.420)	(2.145)	(13.261)
US3C	0.5515	-0.0174	0.0104	-0.0013	1.6025 **	0.0703 **	0.8469 ***	0.0756	1.3863 ***
t-statistics	(1.299)	(-1.111)	(0.125)	(-0.639)	(2.001)	(2.388)	(18.058)	(1.600)	(15.296)
US4C	-1.2248 **	0.0517 **	0.2431 **	-0.0071 *	2.5234 **	0.0760 **	0.7906 ***	0.0712	1.4760 ***
t-statistics	(-2.169)	(2.122)	(2.224)	(-1.919)	(2.440)	(2.259)	(12.865)	(1.540)	(14.895)
US5C	0.0644	-0.0009	0.0428	-0.0038	0.2294 *	0.0250	0.9047 ***	0.0815 **	1.7618 ***
t-statistics	(0.281)	(-0.025)	(0.623)	(-0.498)	(1.949)	(0.935)	(29.041)	(2.313)	(11.695)
US6C	-0.2432	0.0775	0.1222 **	-0.0047	0.2003 ***	0.0294 **	0.8946 ***	0.1573 ***	1.5730 ***
t-statistics	(-1.613)	(1.573)	(1.986)	(-0.324)	(2.797)	(1.984)	(28.717)	(3.702)	(16.160)
US7C	0.6163	-0.0232	0.0208	-0.0017	1.0457 **	0.0581 **	0.8827 ***	0.0611 *	1.4029 ***
t-statistics	(1.561)	(-1.588)	(0.255)	(-0.808)	(1.966)	(2.473)	(25.141)	(1.651)	(15.972)
US8C	0.1415	0.0034	-0.1529 *	0.0018	0.6188 *	0.0102	0.9255 ***	0.0755 **	1.5925 ***
t-statistics	(0.352)	(0.181)	(-1.851)	(0.572)	(1.768)	(0.455)	(32.226)	(2.205)	(15.986)
US9C	-0.0485	0.0046	0.3119 **	-0.0663 *	0.1149	0.0304	0.9316 ***	0.0219	1.3170 ***
t-statistics	(-0.199)	(0.072)	(2.161)	(-1.959)	(1.408)	(1.641)	(28.360)	(0.875)	(14.284)
US10C	0.1352	-0.0017	0.0768	-0.0020 **	2.7239 ***	0.0208	0.8071 ***	0.2953 ***	1.5801 ***
t-statistics	(0.427)	(-0.165)	(1.506)	(-2.010)	(3.567)	(0.958)	(19.537)	(4.708)	(14.178)
US11C	0.1633	-0.0026	0.0670	-0.0019 **	2.5631 ***	0.0113	0.8016 ***	0.2822 ***	1.5164 ***
t-statistics	(0.581)	(-0.263)	(1.374)	(-2.018)	(3.744)	(0.483)	(19.370)	(4.591)	(15.115)
US12C	0.0842	-0.0011	0.0918	-0.0053	0.1131 *	0.0862 ***	0.8930 ***	0.0201	1.3165 ***
t-statistics	(0.686)	(-0.054)	(1.603)	(-1.031)	(1.692)	(2.732)	(33.247)	(0.493)	(14.280)
US13C	-0.2479	0.0131	-0.0940	-0.0003	1.3849 **	0.0195	0.9064 ***	0.1298 ***	1.6597 ***
t-statistics	(-0.540)	(0.742)	(-1.241)	(-0.110)	(2.435)	(1.175)	(30.287)	(3.687)	(16.051)
US14C	-0.0596	0.0135	0.0303	-0.0066	0.2050	0.0287	0.9303 ***	0.0175	1.1529 ***
t-statistics	(-0.249)	(0.351)	(0.383)	(-0.703)	(1.521)	(1.457)	(30.254)	(0.790)	(16.632)
US15C	0.0120	0.0073	0.0549	-0.0005	0.7234 ***	0.0187	0.8132 ***	0.1787 ***	1.2032 ***
t-statistics	(0.073)	(0.344)	(1.179)	(-0.142)	(2.714)	(0.571)	(15.694)	(3.165)	(24.072)
US16C	0.1653	-0.0147	0.0011	-0.0022	0.1372	0.0087	0.9628 ***	0.0351 *	1.3444 ***
t-statistics	(0.473)	(-0.470)	(0.012)	(-0.294)	(1.082)	(0.512)	(42.991)	(1.727)	(14.375)
Panel E : Italy									
IT1C	-0.3375	0.0416	0.0789	-0.0103	0.5783 *	0.0626	0.8264 ***	0.0672	1.3207 ***
t-statistics	(-1.298)	(1.041)	(0.815)	(-0.954)	(1.870)	(1.635)	(11.763)	(1.209)	(14.749)
IT2C	-0.0486	0.0071	-0.1185 *	0.0114	0.0976	0.0806 ***	0.8981 ***	0.0030	1.2331 ***
t-statistics	(-0.362)	(0.210)	(-1.777)	(1.101)	(1.437)	(2.814)	(27.727)	(0.067)	(12.382)
IT3C	-0.4287 **	0.0576	-0.0017	0.0024	0.2200 *	0.0035	0.9284 ***	0.0792 *	1.1492 ***
t-statistics	(-1.983)	(1.474)	(-0.025)	(0.251)	(1.711)	(0.312)	(27.754)	(1.960)	(16.844)
IT4C	-0.0882	0.0143	-0.0935	0.0076	0.0691	0.0749 ***	0.9024 ***	0.0207	1.2339 ***
t-statistics	(-0.781)	(0.470)	(-1.493)	(0.781)	(1.328)	(2.971)	(32.354)	(0.486)	(12.961)
IT5C	0.0601	-0.0321	0.0192	-0.0083	0.1023	0.0748 **	0.8928 ***	0.0108	1.1415 ***
t-statistics	(0.415)	(-0.670)	(0.212)	(-0.412)	(1.298)	(2.055)	(18.552)	(0.197)	(11.593)
IT6C	-0.1478	0.0256	-0.0062	-0.0056	0.5114 ***	0.1193 **	0.7574 ***	0.0771	1.2939 ***
t-statistics	(-1.026)	(0.887)	(-0.109)	(-0.933)	(2.648)	(2.456)	(12.874)	(1.188)	(17.286)
IT7C	-0.1288	0.0313	-0.1296 **	0.0130 *	0.1910 **	0.1279 ***	0.7913 ***	0.1030	1.2207 ***
t-statistics	(-1.457)	(1.198)	(-2.364)	(1.685)	(2.472)	(3.550)	(19.651)	(1.563)	(16.698)

Appendix 2G: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period_Control (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel F : Netherland									
NET1C	-0.4483 *	0.1263 *	0.0293	0.0085	1.4733 **	0.0579	0.5209 ***	0.1749 *	1.1131 ***
t-statistics	(-1.672)	(1.882)	(0.401)	(0.665)	(2.390)	(1.376)	(3.068)	(1.747)	(17.374)
NET2C	-0.0406	0.0020	0.0817 **	-0.0065 ***	0.3591 **	0.1569 ***	0.8420 ***	-0.0604	0.8967 ***
t-statistics	(-0.452)	(0.187)	(2.050)	(-2.880)	(2.460)	(3.328)	(23.371)	(-1.208)	(14.930)
NET3C	-0.4979	0.0067	0.2923 ***	-0.0037	1.1098	0.0603	0.8838 ***	0.0671	1.0305 ***
t-statistics	(-1.074)	(0.468)	(2.789)	(-1.450)	(1.223)	(1.594)	(17.496)	(1.198)	(9.811)
NET4C	-0.1558	0.0456	0.0912 *	-0.0056	0.3463 **	0.0845 **	0.7874 ***	0.0980	1.3818 ***
t-statistics	(-1.292)	(1.503)	(1.751)	(-0.946)	(2.366)	(2.454)	(14.143)	(1.637)	(18.942)
NET5C	0.0104	-0.0065	0.0635	-0.0048 *	0.2718 **	0.1388 ***	0.8684 ***	-0.0687	0.9062 ***
t-statistics	(0.113)	(-0.557)	(1.600)	(-1.905)	(2.252)	(3.139)	(25.898)	(-1.397)	(14.848)
NET6C	-0.1597 ***	0.0164 ***	0.0579 ***	0.0031 ***	0.1958 **	0.0447	0.8807 ***	0.0997 ***	1.0415 ***
t-statistics	(-11.262)	(4.071)	(136.495)	(5.817)	(2.060)	(1.519)	(23.823)	(2.869)	(19.355)
Panel G : Spain									
SP1C	-0.1395	0.0406	-0.0006	-0.0192	0.1549 *	0.0547 *	0.8810 ***	0.0395	1.3013 ***
t-statistics	(-0.935)	(0.884)	(-0.007)	(-1.029)	(1.705)	(1.946)	(18.927)	(0.768)	(14.874)
SP2C	-0.1359	0.0386	-0.0140	-0.0161	0.1695 *	0.0603 **	0.8751 ***	0.0341	1.3089 ***
t-statistics	(-0.899)	(0.837)	(-0.166)	(-0.874)	(1.739)	(2.056)	(17.957)	(0.654)	(15.232)
SP3C	0.0194	-0.0058	0.0120	0.0027	0.1897 *	0.1013 ***	0.8818 ***	-0.0201	1.0715 ***
t-statistics	(0.168)	(-0.278)	(0.240)	(0.557)	(1.752)	(2.615)	(22.615)	(-0.440)	(16.993)
Panel H : Switzerland									
SWT1C	-0.0121	0.0132	0.1472 ***	-0.0134 *	0.4507 **	0.1334 ***	0.7738 ***	0.0071	1.1151 ***
t-statistics	(-0.099)	(0.471)	(2.705)	(-1.795)	(2.214)	(2.599)	(11.919)	(0.121)	(15.767)
SWT2C	0.0503	-0.0901	0.0776	-0.1400	0.0340 ***	0.0747 ***	0.9704 ***	0.1284 ***	1.1828 ***
t-statistics	(0.573)	(-0.792)	(0.889)	(-1.324)	(2.667)	(3.253)	(54.273)	(3.640)	(8.247)
SWT3C	-0.0295	0.0265	0.0053	-0.0068	0.1008 ***	0.0237	0.8095 ***	0.2856 ***	0.9393 ***
t-statistics	(-0.853)	(1.547)	(0.165)	(-1.500)	(2.977)	(0.784)	(23.659)	(3.692)	(17.174)
SWT4C	0.0299	-0.0017	0.1007 *	-0.0121 *	0.1900 **	0.0733 **	0.8305 ***	0.1194 **	1.2895 ***
t-statistics	(0.309)	(-0.069)	(1.956)	(-1.857)	(2.482)	(1.980)	(20.590)	(2.382)	(13.461)
SWT5C	-0.0008	0.0012	0.0031	-0.0038 **	0.0797 ***	0.1789 ***	0.7759 ***	0.0983	0.8848 ***
t-statistics	(-0.033)	(0.112)	(0.110)	(-2.284)	(3.043)	(4.473)	(21.771)	(1.351)	(18.511)
Panel I : Sweden									
SWD1C	0.3065	-0.0148	0.0671	-0.0029	0.5430 **	0.0221	0.8857 ***	0.1233 ***	1.2461 ***
t-statistics	(1.330)	(-0.873)	(0.984)	(-0.826)	(2.110)	(0.882)	(28.511)	(2.599)	(21.833)
SWD2C	-0.0297	0.0018	0.0596	-0.0020	0.1054	0.0453 **	0.9316 ***	0.0374	1.4495 ***
t-statistics	(-0.159)	(0.100)	(0.898)	(-0.509)	(1.304)	(2.221)	(52.138)	(1.357)	(18.239)
SWD3C	-0.3090	0.0425 *	0.0189	0.0072	0.3197 *	0.0696 **	0.8711 ***	0.0540	1.2271 ***
t-statistics	(-1.616)	(1.724)	(0.256)	(1.116)	(1.860)	(2.363)	(22.005)	(1.331)	(13.817)
SWD4C	-0.2417	0.0408	-0.0363	0.0052	0.7788 ***	0.0362	0.7751 ***	0.1949 ***	1.0779 ***
t-statistics	(-1.456)	(1.563)	(-0.613)	(0.840)	(2.652)	(1.382)	(13.651)	(2.916)	(19.117)
SWD5C	-0.2547	0.0510	-0.1013	0.0162	0.3024 **	0.0194	0.8518 ***	0.1180 **	1.3483 ***
t-statistics	(-1.368)	(1.079)	(-1.246)	(1.019)	(2.122)	(0.730)	(16.429)	(2.407)	(12.826)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively

For the stock identification, refer to Table 2.2

v is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for v=2) and the Laplace/double exponential (for v=1).

Appendix 2H: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period_Control

This table reports the estimated coefficients (t-statistics in parentheses) for the model:

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the control stock i at time period t.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : France									
FR1C	-0.1917 *	0.0428	-0.1635 ***	-0.0029	0.1454 **	0.0093	0.8746 ***	0.1560 ***	1.6329 ***
t-statistics	(-1.729)	(1.455)	(-2.625)	(-0.306)	(2.373)	(0.324)	(23.740)	(3.099)	(18.585)
FR2C	0.0226	-0.0399	-0.1795 **	0.0096	0.0155	0.0040	0.9628 ***	0.0597 ***	1.3531 ***
t-statistics	(0.215)	(-0.984)	(-2.393)	(0.456)	(1.030)	(0.346)	(68.504)	(3.329)	(14.314)
FR3C	-0.3281 *	0.0215	0.1488 **	-0.0050	0.1122 *	0.0034	0.9420 ***	0.0900 ***	1.7175 ***
t-statistics	(-1.820)	(1.235)	(2.021)	(-1.008)	(1.815)	(0.188)	(51.195)	(3.139)	(13.615)
FR4C	-0.0088	0.0096	-0.0287	0.0006	0.0474	0.0444	0.8586 ***	0.2142 ***	1.2047 ***
t-statistics	(-0.135)	(0.737)	(-0.694)	(0.233)	(1.481)	(1.159)	(29.543)	(3.791)	(19.524)
FR5C	-0.0694	0.0028	-0.0596	-0.0007	0.0542	0.0062	0.9342 ***	0.1028 ***	1.5223 ***
t-statistics	(-0.616)	(0.124)	(-1.127)	(-0.117)	(1.585)	(0.319)	(59.338)	(3.463)	(14.909)
FR6C	-0.0335	0.0088	-0.0012	-0.0238	0.0321 *	0.0389	0.9166 ***	0.0594	1.0932 ***
t-statistics	(-0.493)	(0.229)	(-0.023)	(-1.282)	(1.664)	(1.523)	(37.410)	(1.475)	(15.841)
FR7C	0.0492	-0.0502	-0.1226	0.0037	0.0212	0.0054	0.9615 ***	0.0550 ***	1.3768 ***
t-statistics	(0.448)	(-1.159)	(-1.629)	(0.170)	(1.331)	(0.433)	(62.830)	(2.922)	(14.245)
FR8C	-0.0250	0.0050	-0.0213	-0.0152	0.0295 *	0.0188	0.9223 ***	0.0823 **	1.2681 ***
t-statistics	(-0.349)	(0.088)	(-0.363)	(-0.503)	(1.785)	(0.971)	(34.838)	(2.235)	(14.611)
FR9C	-0.0293	-0.0053	0.0187	0.0005	0.0270 *	0.0075	0.9240 ***	0.1363 ***	1.2377 ***
t-statistics	(-0.521)	(-0.334)	(0.434)	(0.107)	(1.658)	(0.484)	(52.489)	(3.812)	(16.208)
Panel B : Germany									
GER1C	-0.0258	-0.0040	0.0817	-0.0036	0.0896	0.0386	0.9180 ***	0.0714 **	1.2113 ***
t-statistics	(-0.212)	(-0.217)	(1.565)	(-0.827)	(1.597)	(1.611)	(38.927)	(2.470)	(16.759)
GER2C	-0.0477	-0.0058	0.1215 **	-0.0029	0.0597 *	0.1100 ***	0.8529 ***	0.1011 **	1.1979 ***
t-statistics	(-0.658)	(-0.489)	(2.531)	(-1.002)	(1.876)	(2.943)	(30.944)	(1.981)	(13.652)
GER3C	-0.1503	0.0158	0.0387	-0.0048	0.0499	0.0389 *	0.9304 ***	0.0506 **	1.5875 ***
t-statistics	(-1.116)	(0.745)	(0.590)	(-0.701)	(1.245)	(1.841)	(48.005)	(2.227)	(14.165)
GER4C	-0.0600	-0.0033	0.0861 *	-0.0018	0.0839 **	0.1275 ***	0.8266 ***	0.1307 **	1.2152 ***
t-statistics	(-0.807)	(-0.279)	(1.749)	(-0.624)	(2.152)	(3.081)	(26.928)	(2.221)	(13.529)
GER5C	-0.0600	-0.0033	0.0861 *	-0.0018	0.0839 **	0.1275 ***	0.8266 ***	0.1307 **	1.2152 ***
t-statistics	(-0.807)	(-0.279)	(1.749)	(-0.624)	(2.152)	(3.081)	(26.928)	(2.221)	(13.529)
GER6C	0.0679	-0.0188	-0.1869 ***	0.0138	0.0819 **	0.0034	0.8927 ***	0.1649 ***	1.2070 ***
t-statistics	(0.845)	(-0.542)	(-3.150)	(0.801)	(2.265)	(0.108)	(27.279)	(3.400)	(14.855)
GER7C	-0.0154	-0.0002	-0.0690	-0.0078	0.0558 **	0.0324	0.9066 ***	0.0936 ***	1.7335 ***
t-statistics	(-0.167)	(-0.009)	(-1.178)	(-0.813)	(1.961)	(1.546)	(42.370)	(3.022)	(14.309)
GER8C	-0.1238	0.0018	0.0726	-0.0016	0.1154 **	0.0967 ***	0.8539 ***	0.1007 **	1.2850 ***
t-statistics	(-1.327)	(0.127)	(1.400)	(-0.476)	(2.161)	(2.890)	(30.088)	(2.172)	(13.612)
GER9C	0.0544	-0.0190	-0.0775 *	0.0027	0.0507	0.0437 *	0.9222 ***	0.0666 *	1.1925 ***
t-statistics	(0.586)	(-1.104)	(-1.649)	(0.681)	(1.345)	(1.751)	(48.985)	(1.899)	(17.486)
GER10C	-0.0018	0.0017	-0.0212	-0.0094	0.0178	0.0093	0.9541 ***	0.0658 ***	1.3337 ***
t-statistics	(-0.023)	(0.064)	(-0.371)	(-0.825)	(1.215)	(0.657)	(61.200)	(2.847)	(14.165)
GER11C	-0.0018	0.0017	-0.0212	-0.0094	0.0178	0.0093	0.9541 ***	0.0658 ***	1.3337 ***
t-statistics	(-0.023)	(0.064)	(-0.371)	(-0.825)	(1.215)	(0.657)	(61.200)	(2.847)	(14.165)
GER12C	-0.1256	0.0031	0.0609	-0.0013	0.0613	0.0672 ***	0.9222 ***	0.0123	1.8145 ***
t-statistics	(-0.809)	(0.225)	(0.995)	(-0.458)	(0.989)	(3.284)	(48.493)	(0.438)	(14.310)
Panel C : UK									
UK1C	0.0185	-0.0043	0.0314	-0.0037	0.0511	0.0192 ***	0.9836 ***	0.0609 ***	1.6008 ***
t-statistics	(0.075)	(-0.185)	(0.366)	(-0.525)	(1.244)	(2.906)	(109.890)	(3.741)	(12.804)
UK2C	-0.0220	0.0121	-0.1600 **	-0.0068	0.0344 *	0.0265	0.9244 ***	0.0766 **	1.7020 ***
t-statistics	(-0.225)	(0.383)	(-2.543)	(-0.569)	(1.936)	(1.035)	(50.647)	(2.010)	(11.773)
UK3C	-0.1307	0.0535 **	-0.0472	-0.0004	0.3653 ***	0.1335 **	0.7252 ***	0.1014	1.0391 ***
t-statistics	(-1.571)	(2.027)	(-0.968)	(-0.066)	(2.917)	(2.060)	(09.993)	(1.084)	(20.167)
UK4C	0.0137	0.0017	-0.1670 ***	-0.0059	0.0240	0.0316	0.9235 ***	0.0762 **	1.7606 ***
t-statistics	(0.139)	(0.054)	(-2.669)	(-0.501)	(1.093)	(1.217)	(50.826)	(2.019)	(11.350)
UK5C	-0.1257	0.0313	-0.1660 ***	0.0049	0.1718 ***	0.0233	0.8541 ***	0.1569 ***	1.6005 ***
t-statistics	(-1.131)	(0.986)	(-2.725)	(0.493)	(2.646)	(0.829)	(25.215)	(3.241)	(16.742)
UK6C	-0.1076	0.0488 *	-0.0293	-0.0020	0.3703 ***	0.1408 **	0.7178 ***	0.0998	1.0305 ***
t-statistics	(-1.370)	(1.924)	(-0.622)	(-0.321)	(2.953)	(2.107)	(9.734)	(1.039)	(20.574)
UK7C	-0.1389	-0.0038	-0.0652	0.0014	0.2860 **	0.0434	0.8730 ***	0.1381 ***	1.2476 ***
t-statistics	(-1.061)	(-0.310)	(-1.273)	(0.676)	(2.319)	(1.233)	(23.264)	(3.003)	(19.208)
UK8C	-0.1230	0.0488	0.2681 **	-0.0497 *	0.1341 *	0.0617 **	0.9100 ***	-0.0136	1.6021 ***
t-statistics	(-0.568)	(0.819)	(2.308)	(-1.883)	(1.808)	(2.277)	(29.953)	(-0.448)	(13.811)

Appendix 2H: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period_Control (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : UK									
UK9C	-0.1370	-0.0031	-0.0741	0.0014	0.3474 **	0.0604	0.8440 ***	0.1621 ***	1.2022 ***
t-statistics	(-1.106)	(-0.266)	(-1.484)	(0.707)	(2.434)	(1.585)	(21.099)	(2.854)	(19.170)
UK10C	-0.1426	0.0235	-0.0273	-0.0029	0.0592 *	0.0040	0.9198 ***	0.1384 ***	1.4427 ***
t-statistics	(-1.543)	(0.929)	(-0.557)	(-0.402)	(1.855)	(0.215)	(44.250)	(3.842)	(17.059)
UK11C	-0.0073	0.0001	-0.0098	0.0006	0.1739 **	0.0385 *	0.8989 ***	0.1001 **	1.0207 ***
t-statistics	(-0.084)	(0.007)	(-0.303)	(0.688)	(2.191)	(1.745)	(49.270)	(2.105)	(22.033)
UK12C	0.0402	-0.0142	-0.0271	-0.0014	0.0346	0.0086	0.9786 ***	0.0480 ***	1.2334 ***
t-statistics	(0.226)	(-0.501)	(-0.376)	(-0.147)	(1.066)	(1.025)	(120.260)	(3.626)	(18.030)
UK13C	-0.0238	0.0106	0.0156	-0.0142 *	0.0503 *	0.0082	0.9368 ***	0.0866 ***	1.3216 ***
t-statistics	(-0.250)	(0.479)	(0.287)	(-1.903)	(1.896)	(0.393)	(49.455)	(2.646)	(13.869)
UK14C	0.0600	-0.0180	-0.1426 ***	0.0456 **	0.0178 **	0.0078 ***	0.9769 ***	0.0473 ***	1.1077 ***
t-statistics	(0.882)	(-0.491)	(-3.075)	(2.399)	(2.370)	(3.102)	(135.767)	(4.031)	(21.537)
UK15C	-0.0464	0.0223	-0.1585 **	0.0295 *	0.0164	0.0224 *	0.9282 ***	0.0964 ***	1.6246 ***
t-statistics	(-0.556)	(0.659)	(-2.241)	(1.650)	(0.949)	(1.904)	(48.120)	(2.896)	(12.937)
UK16C	-0.0850	0.0370	0.0026	-0.0177 **	0.0277	0.0419 *	0.9336 ***	0.0306	1.3914 ***
t-statistics	(-1.019)	(1.438)	(0.048)	(-2.025)	(1.396)	(1.669)	(45.242)	(1.147)	(12.903)
UK17C	0.1183	-0.0485	0.0457	-0.0567	0.0611 *	0.0537	0.8819 ***	0.0470	1.3400 ***
t-statistics	(1.294)	(-0.750)	(0.591)	(-1.442)	(1.709)	(1.560)	(20.754)	(1.194)	(12.561)
Panel D : US									
US1C	-0.0894	0.0124	-0.0558	0.0030	0.0622 *	0.0147	0.9383 ***	0.1431 ***	1.4991 ***
t-statistics	(-0.866)	(0.744)	(-1.026)	(0.623)	(1.736)	(1.074)	(64.475)	(4.467)	(13.978)
US2C	-0.2717	0.0149	0.1201	-0.0090	0.2020 *	0.0106	0.9524 ***	0.0915 ***	1.7195 ***
t-statistics	(-0.987)	(0.717)	(1.178)	(-1.494)	(1.772)	(0.863)	(59.939)	(3.414)	(13.195)
US3C	0.0321	-0.0008	0.0653	-0.0052	0.0322	0.0094	0.9877 ***	0.0365 ***	1.1956 ***
t-statistics	(0.140)	(-0.038)	(0.818)	(-1.026)	(0.810)	(1.136)	(117.893)	(2.683)	(13.786)
US4C	-0.0009	-0.0009	0.0279	0.0005	0.0714	0.0206	0.9469 ***	0.0505 **	1.7152 ***
t-statistics	(-0.005)	(-0.037)	(0.388)	(0.087)	(1.429)	(1.322)	(61.667)	(2.060)	(12.751)
US5C	-0.0086	0.0030	-0.0842	0.0098	0.0689 **	0.0117	0.9307 ***	0.1411 ***	1.5119 ***
t-statistics	(-0.082)	(0.131)	(-1.566)	(1.525)	(1.968)	(0.783)	(50.037)	(4.135)	(18.337)
US6C	-0.1169	0.0706 *	-0.0277	0.0008	0.0962 **	0.0201	0.8820 ***	0.1048 **	1.2589 ***
t-statistics	(-1.392)	(1.731)	(-0.662)	(0.085)	(2.204)	(0.738)	(25.097)	(2.438)	(17.484)
US7C	-0.0436	0.0020	0.0943	-0.0063 **	0.0963 *	0.0204 **	0.9787 ***	0.0749 ***	1.2282 ***
t-statistics	(-0.210)	(0.148)	(1.396)	(-2.000)	(1.736)	(2.116)	(106.531)	(3.708)	(14.871)
US8C	-0.0189	0.0018	-0.1082	0.0017	0.0556	0.0058	0.9643 ***	0.0521 ***	1.5192 ***
t-statistics	(-0.094)	(0.120)	(-1.326)	(0.423)	(1.157)	(0.564)	(79.040)	(2.606)	(13.506)
US9C	-0.1839 *	0.0962 *	-0.1511 **	0.0240	0.1144 ***	0.0041	0.8849 ***	0.1291 ***	1.2216 ***
t-statistics	(-1.710)	(1.800)	(-2.328)	(1.059)	(2.577)	(0.281)	(26.174)	(3.096)	(17.420)
US10C	-0.0417	-0.0029	0.0303	-0.0015	0.0518	0.0067	0.9733 ***	0.0299 *	1.5326 ***
t-statistics	(-0.192)	(-0.224)	(0.418)	(-0.535)	(1.266)	(0.551)	(105.575)	(1.895)	(14.528)
US11C	0.2064	-0.0129	0.0153	-0.0011	0.0304	0.0072	0.9726 ***	0.0323 *	1.6155 ***
t-statistics	(0.808)	(-0.923)	(0.178)	(-0.347)	(0.587)	(0.557)	(96.246)	(1.840)	(12.800)
US12C	0.3788	-0.0968	0.5192 ***	-0.1417 **	0.0373 *	0.0153 **	0.9856 ***	-0.0279 ***	1.2900 ***
t-statistics	(1.234)	(-0.952)	(2.656)	(-2.209)	(1.777)	(2.108)	(114.081)	(-2.629)	(15.047)
US13C	-0.0894	0.0024	-0.0893	0.0007	0.0679	0.0097	0.9775 ***	0.0565 ***	1.5582 ***
t-statistics	(-0.356)	(0.134)	(-1.075)	(0.151)	(1.325)	(0.894)	(109.150)	(2.963)	(14.015)
US14C	-0.0088	0.0056	0.0165	-0.0057	0.1481 ***	0.0107	0.8732 ***	0.1500 ***	0.9562 ***
t-statistics	(-0.147)	(0.288)	(0.487)	(-1.309)	(3.556)	(0.815)	(36.685)	(3.333)	(19.907)
US15C	-0.0522	0.0102	-0.0074	-0.0040	0.0748 **	0.0251 **	0.9567 ***	0.1058 ***	1.1931 ***
t-statistics	(-0.482)	(0.500)	(-0.129)	(-0.585)	(2.328)	(2.458)	(81.372)	(4.560)	(15.738)
US16C	-0.0382	0.0027	-0.0341	0.0010	0.0478	0.0293 *	0.9683 ***	-0.0096	1.0838 ***
t-statistics	(-0.217)	(0.115)	(-0.454)	(0.137)	(0.960)	(1.864)	(76.589)	(-0.548)	(20.138)
Panel E : Italy									
IT1C	-0.0173	0.0078	-0.0879	0.0029	0.1709 **	0.0453 *	0.8631 ***	0.1305 ***	1.3268 ***
t-statistics	(-0.152)	(0.339)	(-1.483)	(0.432)	(2.190)	(1.666)	(28.860)	(2.585)	(18.470)
IT2C	-0.0685	0.0653 **	-0.0917 ***	0.0034	0.2439 ***	0.0539 *	0.7043 ***	0.2777 **	0.9318 ***
t-statistics	(-1.501)	(2.478)	(-2.739)	(0.550)	(3.377)	(1.743)	(9.991)	(2.543)	(19.730)
IT3C	0.0000	0.0000	0.0000	0.0000	0.5285 ***	0.4015 ***	0.6214 ***	-0.0022	0.7990 ***
t-statistics	(0.000)	(0.000)	(0.001)	(0.003)	(3.342)	(2.780)	(8.826)	(-0.013)	(18.847)
IT4C	-0.0712	0.0657 **	-0.0746 **	0.0031	0.2615 ***	0.0412	0.7031 ***	0.2953 **	0.8935 ***
t-statistics	(-1.589)	(2.514)	(-2.465)	(0.530)	(3.346)	(1.517)	(9.690)	(2.522)	(19.370)
IT5C	-0.0588	0.0135	0.0042	-0.0028	0.0724 *	0.0025	0.9405 ***	0.0769 ***	1.2329 ***
t-statistics	(-0.469)	(0.455)	(0.063)	(-0.256)	(1.740)	(0.165)	(43.665)	(2.972)	(14.358)
IT6C	-0.0351	0.0065	0.0419	-0.0059	0.0612	0.0635 **	0.9160 ***	0.0249	1.2096 ***
t-statistics	(-0.340)	(0.336)	(0.826)	(-1.126)	(1.304)	(2.508)	(40.713)	(0.812)	(14.451)
IT7C	-0.0013	0.0016	0.0080	-0.0091 **	0.0784 **	0.0218	0.8661 ***	0.1465 **	0.8584 ***
t-statistics	(-0.043)	(0.074)	(0.326)	(-2.029)	(2.121)	(1.406)	(17.757)	(2.044)	(20.154)

Appendix 2H: Maximum Likelihood Estimates of the Feedback Model. Post-Futures Period_Control (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	v
Panel F : Netherland									
NET1C	-0.0581	0.0117	-0.0901 ***	0.0022 **	0.2700 ***	0.0910 ***	0.8649 ***	0.0483	0.8862 ***
t-statistics	(-0.744)	(1.259)	(-2.836)	(2.350)	(2.641)	(2.628)	(30.391)	(0.982)	(18.884)
NET2C	-0.2659 **	0.0247 *	0.2045 ***	-0.0094 ***	0.1342 **	0.0058	0.9534 ***	0.0463 **	0.8921 ***
t-statistics	(-2.136)	(1.916)	(4.772)	(-3.395)	(2.019)	(0.284)	(65.285)	(2.160)	(18.09[illegible])
NET3C	0.0000	0.0000	0.0059	-0.0002	8.8357 **	0.2427 **	0.4982 ***	0.0038	0.6883 ***
t-statistics	(0.000)	(0.000)	(0.563)	(-1.178)	(2.046)	(2.021)	(2.783)	(0.023)	(14.226)
NET4C	-0.0451	0.0114	-0.0176	0.0023	0.1103 ***	0.0324	0.8633 ***	0.1741 ***	1.4030 ***
t-statistics	(-0.580)	(0.824)	(-0.361)	(0.727)	(3.000)	(0.840)	(34.551)	(3.446)	(15.054)
NET5C	-0.2374 *	0.0206	0.1834 ***	-0.0076 ***	0.1666 **	0.0148	0.9420 ***	0.0467 *	0.9031 ***
t-statistics	(-1.937)	(1.636)	(4.325)	(-2.895)	(1.989)	(0.574)	(48.947)	(1.849)	(18.310)
NET6C	-0.0154	-0.0101	-0.0151	-0.0003	0.5130 *	0.1612 ***	0.8437 ***	-0.0206	0.9674 ***
t-statistics	(-0.108)	(-1.130)	(-0.413)	(-0.317)	(1.822)	(2.768)	(22.078)	(-0.351)	(19.813)
Panel G : Spain									
SP1C	0.0725	-0.0426	-0.2176 ***	0.0395	0.0127	0.0722 ***	0.9337 ***	-0.0268	1.1514 ***
t-statistics	(1.111)	(-0.908)	(-2.934)	(1.092)	(1.195)	(2.936)	(44.609)	(-0.866)	(17.535)
SP2C	0.0577	-0.0345	-0.1841 **	0.0259	0.0262	0.0837 ***	0.9186 ***	-0.0373	1.1785 ***
t-statistics	(0.749)	(-0.652)	(-2.356)	(0.699)	(1.606)	(2.878)	(35.059)	(-1.080)	(16.422)
SP3C	-0.0071	0.0066	-0.1817 ***	0.0307 **	0.0599 **	0.0461 *	0.8718 ***	0.1272 ***	1.2778 ***
t-statistics	(-0.096)	(0.200)	(-3.326)	(2.308)	(2.438)	(1.663)	(29.677)	(2.940)	(14.581)
Panel H : Switzerland									
SWT1C	0.0118	-0.0039	-0.0274	-0.0015	0.0430	0.0099	0.9430 ***	0.0827 ***	1.4096 ***
t-statistics	(0.103)	(-0.163)	(-0.450)	(-0.179)	(1.549)	(0.560)	(56.100)	(2.626)	(13.453)
SWT2C	0.0495	-0.0273	-0.0876 *	0.0012	0.1556 **	0.1124 *	0.7818 ***	0.0983	1.0117 ***
t-statistics	(0.693)	(-0.737)	(-1.868)	(0.118)	(2.083)	(1.702)	(11.315)	(1.315)	(15.888)
SWT3C	-0.0770	-0.0064	0.1074 **	-0.0039	0.0674 *	0.0289	0.9025 ***	0.1265 ***	1.1969 ***
t-statistics	(-1.061)	(-0.475)	(2.474)	(-1.280)	(1.900)	(1.219)	(38.382)	(3.233)	(13.311)
SWT4C	-0.0810	0.0301	-0.1105 *	0.0058	0.0862 **	0.0410 *	0.8994 ***	0.0794 **	1.4534 ***
t-statistics	(-0.768)	(1.154)	(-1.799)	(0.671)	(2.010)	(1.655)	(33.315)	(2.271)	(13.232)
SWT5C	-0.1085	0.0015	0.1156 **	-0.0003	0.1429 **	0.0475 *	0.8812 ***	0.1293 ***	1.2238 ***
t-statistics	(-1.080)	(0.134)	(2.468)	(-0.132)	(1.968)	(1.909)	(36.372)	(3.203)	(14.394)
Panel I : Sweden									
SWD1C	0.0692	-0.0079	0.0389	-0.0011	0.0092	0.0343 **	0.9799 ***	-0.0286 *	1.0681 ***
t-statistics	(0.446)	(-0.409)	(0.579)	(-0.159)	(0.298)	(2.404)	(113.744)	(-1.945)	(18.511)
SWD2C	-0.0563	0.0015	-0.0067	-0.0004	0.3798 **	0.0078	0.8675 ***	0.1968 ***	1.2583 ***
t-statistics	(-0.435)	(0.135)	(-0.158)	(-0.272)	(2.496)	(0.350)	(25.657)	(3.741)	(15.448)
SWD3C	0.0153	-0.0063	-0.0799	0.0094	0.0203	0.0084	0.9739 ***	0.0278	1.1085 ***
t-statistics	(0.109)	(-0.201)	(-1.104)	(0.843)	(0.806)	(0.647)	(62.487)	(1.490)	(16.138)
SWD4C	0.0000	0.0000	0.0000	0.0000	0.4279	0.0381	0.8646 ***	0.0898	0.9422 ***
t-statistics	(0.000)	(0.000)	(0.000)	(0.000)	(1.584)	(0.787)	(14.724)	(1.319)	(14.225)
SWD5C	-0.0383	0.0405	-0.0404	-0.0035	0.0494 **	0.0127	0.9139 ***	0.0988 ***	1.3494 ***
t-statistics	(-0.512)	(1.082)	(-0.722)	(-0.213)	(2.109)	(0.557)	(35.757)	(2.948)	(14.542)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively

For the stock identification, refer to Table 2.2

v is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for v=2) and the Laplace/double exponential (for v=1)

Appendix 2I: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period_Control (sorted by industry)

This table reports the estimated coefficients (t-statistics in parentheses) for the model :

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the control stock i at time period t.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : Services									
FR2C	0.1703	-0.0337	0.1561 *	-0.0465 **	0.0902	0.0748 ***	0.9092 ***	-0.0134	1.2866 ***
t-statistics	(1.178)	(-0.808)	(1.742)	(-2.268)	(1.622)	(2.692)	(30.359)	(-0.365)	(14.067)
FR5C	-0.2053	0.0313	-0.0206	-0.0011	0.2406 **	0.0114	0.9004 ***	0.1447 ***	1.6316 ***
t-statistics	(-1.225)	(1.036)	(-0.354)	(-0.157)	(2.276)	(0.653)	(28.478)	(3.547)	(13.501)
FR7C	0.1016	-0.0191	0.1291	-0.0447 *	0.1379	0.0664 **	0.9000 ***	-0.0015	1.3209 ***
t-statistics	(0.558)	(-0.382)	(1.230)	(-1.906)	(1.605)	(2.308)	(23.624)	(-0.040)	(13.994)
GER1C	0.0526	-0.0080	0.0132	-0.0062	0.4335 *	0.0844 **	0.8258 ***	0.0349	1.3525 ***
t-statistics	(0.280)	(-0.236)	(0.187)	(-0.756)	(1.874)	(2.060)	(12.200)	(0.657)	(12.949)
IT2C	-0.0486	0.0071	-0.1185 *	0.0114	0.0976	0.0806 ***	0.8981 ***	0.0030	1.2331 ***
t-statistics	(-0.362)	(0.210)	(-1.777)	(1.101)	(1.437)	(2.814)	(27.727)	(0.067)	(12.382)
IT4C	-0.0882	0.0143	-0.0935	0.0076	0.0691	0.0749 ***	0.9024 ***	0.0207	1.2339 ***
t-statistics	(-0.781)	(0.470)	(-1.493)	(0.781)	(1.328)	(2.971)	(32.354)	(0.486)	(12.961)
IT7C	-0.1288	0.0313	-0.1296 **	0.0130 *	0.1910 **	0.1279 ***	0.7913 ***	0.1030	1.2207 ***
t-statistics	(-1.457)	(1.198)	(-2.364)	(1.685)	(2.472)	(3.550)	(19.651)	(1.563)	(16.698)
NET6C	-0.1597 ***	0.0164 ***	0.0579 ***	0.0031 ***	0.1958 **	0.0447	0.8807 ***	0.0997 ***	1.0415 ***
t-statistics	(-11.262)	(4.071)	(136.495)	(5.817)	(2.060)	(1.519)	(23.823)	(2.869)	(19.355)
SP1C	-0.1395	0.0406	-0.0006	-0.0192	0.1549 *	0.0547 *	0.8810 ***	0.0395	1.3013 ***
t-statistics	(-0.935)	(0.884)	(-0.007)	(-1.029)	(1.705)	(1.946)	(18.927)	(0.768)	(14.874)
UK1C	0.0600	-0.0069	-0.0194	0.0051	0.4967 **	0.0505	0.7940 ***	0.1818 ***	1.4366 ***
t-statistics	(0.335)	(-0.234)	(-0.278)	(0.693)	(2.542)	(1.339)	(15.484)	(2.696)	(12.241)
UK6C	-0.0396	0.0038	-0.1940 ***	0.0087 **	0.2313 *	0.0973 **	0.8788 ***	0.0149	0.9131 ***
t-statistics	(-0.384)	(0.268)	(-4.560)	(2.413)	(1.892)	(2.499)	(26.058)	(0.339)	(20.637)
UK11C	-0.4581 **	0.0314	-0.0451	0.0053	1.2057 ***	0.1007 **	0.7389 ***	0.1559 *	1.2637 ***
t-statistics	(-2.061)	(1.543)	(-0.676)	(1.470)	(2.797)	(2.115)	(11.281)	(1.875)	(16.372)
UK16C	-0.2532	0.0362	0.1127 *	-0.0118 *	0.1801 *	0.0327	0.9120 ***	0.0580 *	1.2214 ***
t-statistics	(-1.510)	(1.376)	(1.707)	(-1.659)	(1.788)	(1.160)	(29.664)	(1.688)	(15.914)
US15C	0.0120	0.0073	0.0549	-0.0005	0.7234 ***	0.0187	0.8132 ***	0.1787 ***	1.2032 ***
t-statistics	(0.073)	(0.344)	(1.179)	(-0.142)	(2.714)	(0.571)	(15.694)	(3.165)	(24.072)
SWD3C	-0.3090	0.0425 *	0.0189	0.0072	0.3197 *	0.0696 **	0.8711 ***	0.0540	1.2271 ***
t-statistics	(-1.616)	(1.724)	(0.256)	(1.116)	(1.860)	(2.363)	(22.005)	(1.331)	(13.817)
SWD4C	-0.2417	0.0408	-0.0363	0.0052	0.7788 ***	0.0362	0.7751 ***	0.1949 ***	1.0779 ***
t-statistics	(-1.456)	(1.563)	(-0.613)	(0.840)	(2.652)	(1.382)	(13.651)	(2.916)	(19.117)
Panel B : Consumer Goods									
FR8C	-0.2275	0.0624	0.0658	-0.0176	0.5133 **	0.0703	0.7706 ***	0.0799	1.2100 ***
t-statistics	(-1.303)	(1.404)	(0.866)	(-1.312)	(2.429)	(1.623)	(10.324)	(1.359)	(16.937)
GER6C	-0.0938	0.0169	-0.1087	0.0154	0.0473	0.0122	0.9569 ***	0.0443 *	1.2426 ***
t-statistics	(-0.608)	(0.582)	(-1.481)	(1.428)	(1.142)	(0.700)	(60.634)	(1.672)	(13.364)
GER9C	-0.1686	0.0255	0.0060	0.0041	1.4587 **	0.1470 **	0.6010 ***	0.0569	1.1834 ***
t-statistics	(-0.796)	(0.711)	(0.084)	(0.564)	(2.376)	(2.037)	(4.383)	(0.627)	(17.092)
UK4C	0.0511	-0.0122	-0.0404	-0.0053	0.1327	0.0441	0.9092 ***	0.0466	1.2970 ***
t-statistics	(0.316)	(-0.365)	(-0.538)	(-0.487)	(1.603)	(1.530)	(28.132)	(1.188)	(14.576)
UK5C	-0.3180	0.0807 *	-0.0882	0.0016	0.3545 **	0.0573 *	0.8580 ***	0.0372	1.1854 ***
t-statistics	(-1.569)	(1.953)	(-1.282)	(0.171)	(2.036)	(1.844)	(17.741)	(0.851)	(18.727)
UK12C	0.0546	-0.0077	0.1057 **	-0.0045	0.1378 *	0.0641 ***	0.9214 ***	0.0097	1.0835 ***
t-statistics	(0.427)	(-0.552)	(2.321)	(-1.520)	(1.717)	(2.589)	(42.310)	(0.319)	(19.247)
UK14C	0.0317	-0.0105	-0.1456 **	0.0071	0.1096	0.0457 *	0.9179 ***	0.0528	1.3166 ***
t-statistics	(0.188)	(-0.438)	(-2.102)	(1.081)	(1.414)	(1.914)	(35.250)	(1.435)	(15.818)
US6C	-0.2432	0.0775	0.1222 **	-0.0047	0.2003 ***	0.0294 **	0.8946 ***	0.1573 ***	1.5730 ***
t-statistics	(-1.613)	(1.573)	(1.986)	(-0.324)	(2.797)	(1.984)	(28.717)	(3.702)	(16.160)
US12C	0.0842	-0.0011	0.0918	-0.0053	0.1131 *	0.0862 ***	0.8930 ***	0.0201	1.3165 ***
t-statistics	(0.686)	(-0.054)	(1.603)	(-1.031)	(1.692)	(2.732)	(33.247)	(0.493)	(14.280)
US14C	-0.0596	0.0135	0.0303	-0.0066	0.2050	0.0287	0.9303 ***	0.0175	1.1529 ***
t-statistics	(-0.249)	(0.351)	(0.383)	(-0.703)	(1.521)	(1.457)	(30.254)	(0.790)	(16.632)
SWT1C	-0.0121	0.0132	0.1472 ***	-0.0134 *	0.4507 **	0.1334 ***	0.7738 ***	0.0071	1.1151 ***
t-statistics	(-0.099)	(0.471)	(2.705)	(-1.795)	(2.214)	(2.599)	(11.919)	(0.121)	(15.767)
SWT2C	0.0503	-0.0901	0.0776	-0.1400	0.0340 ***	0.0747 ***	0.9704 ***	0.1284 ***	1.1828 ***
t-statistics	(0.573)	(-0.792)	(0.889)	(-1.324)	(2.667)	(3.253)	(54.273)	(3.640)	(8.247)
SWT4C	0.0299	-0.0017	0.1007 *	-0.0121 *	0.1900 **	0.0733 **	0.8305 ***	0.1194 **	1.2895 ***
t-statistics	(0.309)	(-0.069)	(1.956)	(-1.857)	(2.482)	(1.980)	(20.590)	(2.382)	(13.461)

Appendix 2I: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period_Control (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : Technology									
FR3C	-1.1962 **	0.0965 **	0.1279	-0.0052	1.9134 ***	0.0028	0.8052 ***	0.1221 **	1.5995 ***
t-statistics	(-2.104)	(2.276)	(1.167)	(-0.766)	(2.817)	(0.120)	(12.913)	(2.421)	(11.837)
GER12C	-0.8131	0.0305	0.0936	0.0006	0.6483	0.0012	0.9028 ***	0.1111 **	2.0257 ***
t-statistics	(-1.637)	(0.914)	(000.748)	(0.088)	(1.251)	(0.040)	(15.522)	(2.359)	(10.416)
US1C	0.6265 *	-0.0393	0.0779	-0.0043	1.9979 ***	0.0299	0.7464 ***	0.1839 ***	1.5821 ***
t-statistics	(1.735)	(-1.488)	(0.958)	(-0.988)	(2.966)	(0.725)	(12.422)	(2.753)	(14.592)
US2C	0.1976	-0.0040	0.0562	-0.0064 *	0.4567	0.0286	0.9163 ***	0.0661 **	1.8363 ***
t-statistics	(0.526)	(-0.183)	(0.649)	(-1.682)	(1.583)	(1.475)	(37.420)	(2.145)	(13.261)
US3C	0.5515	-0.0174	0.0104	-0.0013	1.6025 **	0.0703 **	0.8469 ***	0.0756	1.3863 ***
t-statistics	(1.299)	(-1.111)	(0.125)	(-0.639)	(2.001)	(2.388)	(18.058)	(1.600)	(15.296)
US7C	0.6163	-0.0232	0.0208	-0.0017	1.0457 **	0.0581 **	0.8827 ***	0.0611 *	1.4029 ***
t-statistics	(1.561)	(-1.588)	(0.255)	(-0.808)	(1.966)	(2.473)	(25.141)	(1.651)	(15.972)
US8C	0.1415	0.0034	-0.1529 *	0.0018	0.6188 *	0.0102	0.9255 ***	0.0755 **	1.5925 ***
t-statistics	(0.352)	(0.181)	(-1.851)	(0.572)	(1.768)	(0.455)	(32.226)	(2.205)	(15.986)
US10C	0.1352	-0.0017	0.0768	-0.0020 **	2.7239 ***	0.0208	0.8071 ***	0.2953 ***	1.5801 ***
t-statistics	(0.427)	(-0.165)	(1.506)	(-2.010)	(3.567)	(0.958)	(19.537)	(4.708)	(14.178)
US11C	0.1633	-0.0026	0.0670	-0.0019 **	2.5631 ***	0.0113	0.8016 ***	0.2822 ***	1.5164 ***
t-statistics	(0.581)	(-0.263)	(1.374)	(-2.018)	(3.744)	(0.483)	(19.370)	(4.591)	(15.115)
US13C	-0.2479	0.0131	-0.0940	-0.0003	1.3849 **	0.0195	0.9064 ***	0.1298 ***	1.6597 ***
t-statistics	(-0.540)	(0.742)	(-1.241)	(-0.110)	(2.435)	(1.175)	(30.287)	(3.687)	(16.051)
US16C	0.1653	-0.0147	0.0011	-0.0022	0.1372	0.0087	0.9628 ***	0.0351 *	1.3444 ***
t-statistics	(0.473)	(-0.470)	(0.012)	(-0.294)	(1.082)	(0.512)	(42.991)	(1.727)	(14.375)
SWD1C	0.3065	-0.0148	0.0671	-0.0029	0.5430 **	0.0221	0.8857 ***	0.1233 ***	1.2461 ***
t-statistics	(1.330)	(-0.873)	(0.984)	(-0.826)	(2.110)	(0.882)	(28.511)	(2.599)	(21.833)
Panel D : Financial									
FR4C	-0.0533	0.0078	0.0377	-0.0038	0.1131 **	0.0126	0.9530 ***	0.0830 ***	1.5308 ***
t-statistics	(-0.285)	(0.212)	(0.523)	(-0.343)	(2.031)	(0.834)	(53.638)	(3.412)	(13.818)
FR6C	-0.2947	0.0847 *	0.1109	-0.0202	0.3661 **	0.0455	0.8324 ***	0.0704 *	1.3533 ***
t-statistics	(-1.484)	(1.682)	(1.349)	(-1.284)	(2.362)	(1.538)	(15.130)	(1.668)	(16.765)
GER2C	-0.1874	0.0393	0.0594	-0.0130	0.0937 *	0.0335 **	0.9078 ***	0.0795 **	1.5380 ***
t-statistics	(-1.361)	(1.090)	(0.835)	(-1.011)	(1.806)	(1.972)	(34.151)	(2.449)	(15.444)
GER4C	-0.1954	0.0388	0.1322 *	-0.0200	0.0827 *	0.0367 **	0.9125 ***	0.0670 **	1.5208 ***
t-statistics	(-1.452)	(1.095)	(1.890)	(-1.569)	(1.734)	(2.096)	(36.006)	(2.212)	(15.489)
GER5C	-0.1954	0.0388	0.1322 *	-0.0200	0.0827 *	0.0367 **	0.9125 ***	0.0670 **	1.5208 ***
t-statistics	(-1.452)	(1.095)	(1.890)	(-1.569)	(1.734)	(2.096)	(36.006)	(2.212)	(15.489)
GER8C	-0.0680	0.0098	0.1320 **	-0.0177	0.0246	0.0447 **	0.9133 ***	0.0846 **	1.4533 ***
t-statistics	(-0.659)	(0.341)	(2.146)	(-1.635)	(0.777)	(2.299)	(40.675)	(2.439)	(14.795)
IT5C	0.0601	-0.0321	0.0192	-0.0083	0.1023	0.0748 **	0.8928 ***	0.0108	1.1415 ***
t-statistics	(0.415)	(-0.670)	(0.212)	(-0.412)	(1.298)	(2.055)	(18.552)	(0.197)	(11.593)
IT6C	-0.1478	0.0256	-0.0062	-0.0056	0.5114 ***	0.1193 **	0.7574 ***	0.0771	1.2939 ***
t-statistics	(-1.026)	(0.887)	(-0.109)	(-0.933)	(2.648)	(2.456)	(12.874)	(1.188)	(17.286)
NET2C	-0.0406	0.0020	0.0817 **	-0.0065 ***	0.3591 **	0.1569 ***	0.8420 ***	-0.0604	0.8967 ***
t-statistics	(-0.452)	(0.187)	(2.050)	(-2.880)	(2.460)	(3.328)	(23.371)	(-1.208)	(14.930)
NET4C	-0.1558	0.0456	0.0912 *	-0.0056	0.3463 **	0.0845 **	0.7874 ***	0.0980	1.3818 ***
t-statistics	(-1.292)	(1.503)	(1.751)	(-0.946)	(2.366)	(2.454)	(14.143)	(1.637)	(18.942)
NET5C	0.0104	-0.0065	0.0635	-0.0048 *	0.2718 **	0.1388 ***	0.8684 ***	-0.0687	0.9062 ***
t-statistics	(0.113)	(-0.557)	(1.600)	(-1.905)	(2.252)	(3.139)	(25.898)	(-1.397)	(14.848)
SP2C	-0.1359	0.0386	-0.0140	-0.0161	0.1695 *	0.0603 **	0.8751 ***	0.0341	1.3089 ***
t-statistics	(-0.899)	(0.837)	(-0.166)	(-0.874)	(1.739)	(2.056)	(17.957)	(0.654)	(15.232)
SP3C	0.0194	-0.0058	0.0120	0.0027	0.1897 *	0.1013 ***	0.8818 ***	-0.0201	1.0715 ***
t-statistics	(0.168)	(-0.278)	(0.240)	(0.557)	(1.752)	(2.615)	(22.615)	(-0.440)	(16.993)
UK3C	0.0005	-0.0001	-0.1221 ***	0.0065 **	0.3545 *	0.0819 **	0.8624 ***	0.0445	0.9195 ***
t-statistics	(0.005)	(-0.005)	(-3.200)	(2.121)	(1.960)	(2.037)	(20.003)	(0.851)	(20.367)
UK7C	-0.2469	0.0242	0.0033	0.0003	0.0997 *	0.0043	0.9508 ***	0.0667 **	1.4165 ***
t-statistics	(-1.164)	(0.761)	(0.042)	(0.031)	(1.646)	(0.310)	(57.617)	(2.571)	(14.301)
UK9C	-0.2412	0.0263	-0.0459	0.0055	0.0603 *	0.0173 *	0.9763 ***	0.0670 ***	1.4641 ***
t-statistics	(-1.160)	(0.836)	(-0.571)	(0.517)	(1.772)	(1.780)	(104.647)	(4.080)	(14.059)
UK10C	-0.3141	0.0336	-0.0145	0.0076	0.4734 **	0.0372 *	0.8783 ***	0.0758 *	1.3189 ***
t-statistics	(-1.165)	(1.108)	(-0.170)	(1.086)	(2.065)	(1.669)	(21.534)	(1.817)	(16.030)
UK13C	-0.1273	0.0096	0.1113	-0.0223 *	0.2999 **	0.0420	0.8430 ***	0.1185 **	1.1672 ***
t-statistics	(-0.841)	(0.289)	(1.446)	(-1.834)	(2.113)	(1.381)	(17.213)	(2.028)	(12.309)
UK15C	-0.1698	0.0186	0.1091	-0.0056	1.2730 **	0.0796 *	0.7136 ***	0.1350 *	1.2405 ***
t-statistics	(-0.750)	(0.665)	(1.499)	(-0.940)	(2.460)	(1.669)	(07.688)	(1.772)	(17.354)
UK17C	-0.0728	0.0279	0.1698	-0.0793 *	0.1248 *	0.0375	0.8577 ***	0.0954 **	1.2201 ***
t-statistics	(-0.581)	(0.420)	(1.608)	(-1.730)	(1.769)	(1.636)	(16.467)	(1.978)	(14.381)
US5C	0.0644	-0.0009	0.0428	-0.0038	0.2294 *	0.0250	0.9047 ***	0.0815 **	1.7618 ***
t-statistics	(0.281)	(-0.025)	(0.623)	(-0.498)	(1.949)	(0.935)	(29.041)	(2.313)	(11.695)

Appendix 2I: Maximum Likelihood Estimates of the Feedback Model, Pre-Futures Period_Control (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel D : Financial									
SWT3C	-0.0295	0.0265	0.0053	-0.0068	0.1008 ***	0.0237	0.8095 ***	0.2856 ***	0.9393 ***
t-statistics	(-0.853)	(1.547)	(0.165)	(-1.500)	(2.977)	(0.784)	(23.659)	(3.692)	(17.174)
SWT5C	-0.0008	0.0012	0.0031	-0.0038 **	0.0797 ***	0.1789 ***	0.7759 ***	0.0983	0.8848 ***
t-statistics	(-0.033)	(0.112)	(0.110)	(-2.284)	(3.043)	(4.473)	(21.771)	(1.351)	(18.511)
SWD2C	-0.0297	0.0018	0.0596	-0.0020	0.1054	0.0453 **	0.9316 ***	0.0374	1.4495 ***
t-statistics	(-0.159)	(0.100)	(0.898)	(-0.509)	(1.304)	(2.221)	(52.138)	(1.357)	(18.239)
SWD5C	-0.2547	0.0510	-0.1013	0.0162	0.3024 **	0.0194	0.8518 ***	0.1180 **	1.3483 ***
t-statistics	(-1.368)	(1.079)	(-1.246)	(1.019)	(2.122)	(0.730)	(16.429)	(2.407)	(12.826)
Panel E : General and Resources									
GER3C	-0.3354	0.0433	0.0557	-0.0108	0.2047 *	0.0421 *	0.8987 ***	0.0678 *	1.3667 ***
t-statistics	(-1.501)	(1.160)	(0.565)	(-0.820)	(1.699)	(1.907)	(25.806)	(1.694)	(13.446)
NET3C	-0.4979	0.0067	0.2923 ***	-0.0037	1.1098	0.0603	0.8838 ***	0.0671	1.0305 ***
t-statistics	(-1.074)	(0.468)	(2.789)	(-1.450)	(1.223)	(1.594)	(17.496)	(1.198)	(9.811)
US9C	-0.0485	0.0046	0.3119 **	-0.0663 *	0.1149	0.0304	0.9316 ***	0.0219	1.3170 ***
t-statistics	(-0.199)	(0.072)	(2.161)	(-1.959)	(1.408)	(1.641)	(28.360)	(0.875)	(14.284)
GER10C	-0.0903	0.0149	-0.0898	0.0032	0.0826 *	0.0346	0.9108 ***	0.0807 **	1.1544 ***
t-statistics	(-0.892)	(0.572)	(-1.542)	(0.344)	(1.769)	(1.210)	(30.559)	(2.113)	(16.713)
GER11C	-0.0903	0.0149	-0.0898	0.0032	0.0826 *	0.0346	0.9108 ***	0.0807 **	1.1544 ***
t-statistics	(-0.892)	(0.572)	(-1.542)	(0.344)	(1.769)	(1.210)	(30.559)	(2.113)	(16.713)
FR1C	-0.5349 *	0.1001 *	0.1627 **	-0.0216 **	1.6015 ***	0.0380	0.6551 ***	0.2118 ***	1.5679 ***
t-statistics	(-1.687)	(1.769)	(2.345)	(-2.352)	(3.086)	(1.259)	(6.262)	(2.935)	(13.661)
FR9C	-0.1760	0.0627	-0.2282 **	0.0083	0.0383	0.0679	0.9220 ***	0.0060	1.2228 ***
t-statistics	(-1.188)	(1.523)	(-2.042)	(0.413)	(1.152)	(1.341)	(26.093)	(0.104)	(09.757)
GER7C	0.0069	-0.0018	0.0690	-0.0156	0.1526 *	0.0398 *	0.8942 ***	0.0801 *	1.1865 ***
t-statistics	(0.048)	(-0.059)	(0.925)	(-1.462)	(1.925)	(1.760)	(29.479)	(1.852)	(15.284)
IT1C	-0.3375	0.0416	0.0789	-0.0103	0.5783 *	0.0626	0.8264 ***	0.0672	1.3207 ***
t-statistics	(-1.298)	(1.041)	(0.815)	(-0.954)	(1.870)	(1.635)	(11.763)	(1.209)	(14.749)
IT3C	-0.4287 **	0.0576	-0.0017	0.0024	0.2200 *	0.0035	0.9284 ***	0.0792 *	1.1492 ***
t-statistics	(-1.983)	(1.474)	(-0.025)	(0.251)	(1.711)	(0.312)	(27.754)	(1.960)	(16.844)
NET1C	-0.4483 *	0.1263 *	0.0293	0.0085	1.4733 **	0.0579	0.5209 ***	0.1749 *	1.1131 ***
t-statistics	(-1.672)	(1.882)	(0.401)	(0.665)	(2.390)	(1.376)	(3.068)	(1.747)	(17.374)
UK2C	0.0702	-0.0196	-0.0415	-0.0046	0.1452 *	0.0523	0.8998 ***	0.0463	1.2956 ***
t-statistics	(0.445)	(-0.603)	(-0.556)	(-0.432)	(1.653)	(1.632)	(26.284)	(1.058)	(14.433)
UK8C	0.2071	-0.0248	0.1266	-0.0085	0.3866	0.0230	0.9105 ***	0.0573	1.2331 ***
t-statistics	(0.681)	(-0.726)	(1.361)	(-0.974)	(1.421)	(1.134)	(19.358)	(1.501)	(15.500)
US4C	-1.2248 **	0.0517 **	0.2431 **	-0.0071 *	2.5234 **	0.0760 **	0.7906 ***	0.0712	1.4760 ***
t-statistics	(-2.169)	(2.122)	(2.224)	(-1.919)	(2.440)	(2.259)	(12.865)	(1.540)	(14.895)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively

For the stock identification, refer to Table 2.2

v is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for v=2) and the Laplace/double exponential (for v=1).

Appendix 2J: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period_Control (sorted by industry)

This table reports the estimated coefficients (t-statistics in parentheses) for the model :

$$R_{it} = \alpha + \theta\sigma^2_t + (\varphi_0 + \varphi_1\sigma^2_t)R_{t-1} + \varepsilon_t$$

$$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \delta X_{t-1}\varepsilon^2_{t-1}$$

where R_{it} is the log price relative of the control stock i at time period t.

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel A : Services									
FR2C	0.0226	-0.0399	-0.1795 **	0.0096	0.0155	0.0040	0.9628 ***	0.0597 ***	1.3531 ***
t-statistics	(0.215)	(-0.984)	(-2.393)	(0.456)	(1.030)	(0.346)	(68.504)	(3.329)	(14.314)
FR5C	-0.0694	0.0028	-0.0596	-0.0007	0.0542	0.0062	0.9342 ***	0.1028 ***	1.5223 ***
t-statistics	(-0.616)	(0.124)	(-1.127)	(-0.117)	(1.585)	(0.319)	(59.338)	(3.463)	(14.909)
FR7C	0.0492	-0.0502	-0.1226	0.0037	0.0212	0.0054	0.9615 ***	0.0550 ***	1.3768 ***
t-statistics	(0.448)	(-1.159)	(-1.629)	(0.170)	(1.331)	(0.433)	(62.830)	(2.922)	(14.245)
GER1C	-0.0258	-0.0040	0.0817	-0.0036	0.0896	0.0386	0.9180 ***	0.0714 **	1.2113 ***
t-statistics	(-0.212)	(-0.217)	(1.565)	(-0.827)	(1.597)	(1.611)	(38.927)	(2.470)	(16.759)
IT2C	-0.0685	0.0653 **	-0.0917 ***	0.0034	0.2439 ***	0.0539 *	0.7043 ***	0.2777 **	0.9318 ***
t-statistics	(-1.501)	(2.478)	(-2.739)	(0.550)	(3.377)	(1.743)	(9.991)	(2.543)	(19.730)
IT4C	-0.0712	0.0657 **	-0.0746 **	0.0031	0.2615 ***	0.0412	0.7031 ***	0.2953 **	0.8935 ***
t-statistics	(-1.589)	(2.514)	(-2.465)	(0.530)	(3.346)	(1.517)	(9.690)	(2.522)	(19.370)
IT7C	-0.0013	0.0016	0.0080	-0.0091 **	0.0784 **	0.0218	0.8661 ***	0.1465 **	0.8584 ***
t-statistics	(-0.043)	(0.074)	(0.326)	(-2.029)	(2.121)	(1.406)	(17.757)	(2.044)	(20.154)
NET6C	-0.0154	-0.0101	-0.0151	-0.0003	0.5130 *	0.1612 ***	0.8437 ***	-0.0206	0.9674 ***
t-statistics	(-0.108)	(-1.130)	(-0.413)	(-0.317)	(1.822)	(2.768)	(22.078)	(-0.351)	(19.813)
SP1C	0.0725	-0.0426	-0.2176 ***	0.0395	0.0127	0.0722 ***	0.9337 ***	-0.0268	1.1514 ***
t-statistics	(1.111)	(-0.908)	(-2.934)	(1.092)	(1.195)	(2.936)	(44.609)	(-0.866)	(17.535)
UK1C	0.0185	-0.0043	0.0314	-0.0037	0.0511	0.0192 ***	0.9836 ***	0.0609 ***	1.6008 ***
t-statistics	(0.075)	(-0.185)	(0.366)	(-0.525)	(1.244)	(2.906)	(109.890)	(3.741)	(12.804)
UK6C	-0.1076	0.0488 *	-0.0293	-0.0020	0.3703 ***	0.1408 **	0.7178 ***	0.0998	1.0305 ***
t-statistics	(-1.370)	(1.924)	(-0.622)	(-0.321)	(2.953)	(2.107)	(9.734)	(1.039)	(20.574)
UK11C	-0.0073	0.0001	-0.0098	0.0006	0.1739 **	0.0385 *	0.8989 ***	0.1001 **	1.0207 ***
t-statistics	(-0.084)	(0.007)	(-0.303)	(0.688)	(2.191)	(1.745)	(49.270)	(2.105)	(22.033)
UK16C	-0.0850	0.0370	0.0026	-0.0177 **	0.0277	0.0419 *	0.9336 ***	0.0306	1.3914 ***
t-statistics	(-1.019)	(1.438)	(0.048)	(-2.025)	(1.396)	(1.669)	(45.242)	(1.147)	(12.903)
US15C	-0.0522	0.0102	-0.0074	-0.0040	0.0748 **	0.0251 **	0.9567 ***	0.1058 ***	1.1931 ***
t-statistics	(-0.482)	(0.500)	(-0.129)	(-0.585)	(2.328)	(2.458)	(81.372)	(4.560)	(15.738)
SWD3C	0.0153	-0.0063	-0.0799	0.0094	0.0203	0.0084	0.9739 ***	0.0278	1.1085 ***
t-statistics	(0.109)	(-0.201)	(-1.104)	(0.843)	(0.806)	(0.647)	(62.487)	(1.490)	(16.138)
SWD4C	0.0000	0.0000	0.0000	0.0000	0.4279	0.0381	0.8646 ***	0.0898	0.9422 ***
t-statistics	(0.000)	(0.000)	(0.000)	(0.000)	(1.584)	(0.787)	(14.724)	(1.319)	(14.225)
Panel B : Consumer Goods									
FR8C	-0.0250	0.0050	-0.0213	-0.0152	0.0295 *	0.0188	0.9223 ***	0.0823 **	1.2681 ***
t-statistics	(-0.349)	(0.088)	(-0.363)	(-0.503)	(1.785)	(0.971)	(34.838)	(2.235)	(14.611)
GER6C	0.0679	-0.0188	-0.1869 ***	0.0138	0.0819 **	0.0034	0.8927 ***	0.1649 ***	1.2070 ***
t-statistics	(0.845)	(-0.542)	(-3.150)	(0.801)	(2.265)	(0.108)	(27.279)	(3.400)	(14.855)
GER9C	0.0544	-0.0190	-0.0775 *	0.0027	0.0507	0.0437 *	0.9222 ***	0.0666 *	1.1925 ***
t-statistics	(0.586)	(-1.104)	(-1.649)	(0.681)	(1.345)	(1.751)	(48.985)	(1.899)	(17.486)
UK4C	0.0137	0.0017	-0.1670 ***	-0.0059	0.0240	0.0316	0.9235 ***	0.0762 **	1.7606 ***
t-statistics	(0.139)	(0.054)	(-2.669)	(-0.501)	(1.093)	(1.217)	(50.826)	(2.019)	(11.350)
UK5C	-0.1257	0.0313	-0.1660 ***	0.0049	0.1718 ***	0.0233	0.8541 ***	0.1569 ***	1.6005 ***
t-statistics	(-1.131)	(0.986)	(-2.725)	(0.493)	(2.646)	(0.829)	(25.215)	(3.241)	(16.742)
UK12C	0.0402	-0.0142	-0.0271	-0.0014	0.0346	0.0086	0.9786 ***	0.0480 ***	1.2334 ***
t-statistics	(0.226)	(-0.501)	(-0.376)	(-0.147)	(1.066)	(1.025)	(120.260)	(3.626)	(18.030)
UK14C	0.0600	-0.0180	-0.1426 ***	0.0456 **	0.0178 **	0.0078 ***	0.9769 ***	0.0473 ***	1.1077 ***
t-statistics	(0.882)	(-0.491)	(-3.075)	(2.399)	(2.370)	(3.102)	(135.767)	(4.031)	(21.537)
US6C	-0.1169	0.0706 *	-0.0277	0.0008	0.0962 **	0.0201	0.8820 ***	0.1048 **	1.2589 ***
t-statistics	(-1.392)	(1.731)	(-0.662)	(0.085)	(2.204)	(0.738)	(25.097)	(2.438)	(17.484)
US12C	0.3788	-0.0968	0.5192 ***	-0.1417 **	0.0373 *	0.0153 **	0.9856 ***	-0.0279 ***	1.2900 ***
t-statistics	(1.234)	(-0.952)	(2.656)	(-2.209)	(1.777)	(2.108)	(114.081)	(-2.629)	(15.047)
US14C	-0.0088	0.0056	0.0165	-0.0057	0.1481 ***	0.0107	0.8732 ***	0.1500 ***	0.9562 ***
t-statistics	(-0.147)	(0.288)	(0.487)	(-1.309)	(3.556)	(0.815)	(36.685)	(3.333)	(19.907)
SWT1C	0.0118	-0.0039	-0.0274	-0.0015	0.0430	0.0099	0.9430 ***	0.0827 ***	1.4096 ***
t-statistics	(0.103)	(-0.163)	(-0.450)	(-0.179)	(1.549)	(0.560)	(56.100)	(2.626)	(13.453)
SWT2C	0.0495	-0.0273	-0.0876 *	0.0012	0.1556 **	0.1124 *	0.7818 ***	0.0983	1.0117 ***
t-statistics	(0.693)	(-0.737)	(-1.868)	(0.118)	(2.083)	(1.702)	(11.315)	(1.315)	(15.888)
SWT4C	-0.0810	0.0301	-0.1105 *	0.0058	0.0862 **	0.0410 *	0.8994 ***	0.0794 **	1.4534 ***
t-statistics	(-0.768)	(1.154)	(-1.799)	(0.671)	(2.010)	(1.655)	(33.315)	(2.271)	(13.232)

Appendix 2J: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period_Control (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel C : Technology									
FR3C	-0.3281 *	0.0215	0.1488 **	-0.0050	0.1122 *	0.0034	0.9420 ***	0.0900 ***	1.7175 ***
t-statistics	(-1.820)	(1.235)	(2.021)	(-1.008)	(1.815)	(0.188)	(51.195)	(3.139)	(13.615)
GER12C	-0.1256	0.0031	0.0609	-0.0013	0.0613	0.0672 ***	0.9222 ***	0.0123	1.8145 ***
t-statistics	(-0.809)	(0.225)	(0.995)	(-0.458)	(0.989)	(3.284)	(48.493)	(0.438)	(14.310)
US1C	-0.0894	0.0124	-0.0558	0.0030	0.0622 *	0.0147	0.9383 ***	0.1431 ***	1.4991 ***
t-statistics	(-0.866)	(0.744)	(-1.026)	(0.623)	(1.736)	(1.074)	(64.475)	(4.467)	(13.978)
US2C	-0.2717	0.0149	0.1201	-0.0090	0.2020 *	0.0106	0.9524 ***	0.0915 ***	1.7195 ***
t-statistics	(-0.987)	(0.717)	(1.178)	(-1.494)	(1.772)	(0.863)	(59.939)	(3.414)	(13.195)
US3C	0.0321	-0.0008	0.0653	-0.0052	0.0322	0.0094	0.9877 ***	0.0365 ***	1.1956 ***
t-statistics	(0.140)	(-0.038)	(0.818)	(-1.026)	(0.810)	(1.136)	(117.893)	(2.683)	(13.786)
US7C	-0.0436	0.0020	0.0943	-0.0063 **	0.0963 *	0.0204 **	0.9787 ***	0.0749 ***	1.2282 ***
t-statistics	(-0.210)	(0.148)	(1.396)	(-2.000)	(1.736)	(2.116)	(106.531)	(3.708)	(14.871)
US8C	-0.0189	0.0018	-0.1082	0.0017	0.0556	0.0058	0.9643 ***	0.0521 ***	1.5192 ***
t-statistics	(-0.094)	(0.120)	(-1.326)	(0.423)	(1.157)	(0.564)	(79.040)	(2.606)	(13.506)
US10C	-0.0417	-0.0029	0.0303	-0.0015	0.0518	0.0067	0.9733 ***	0.0299 *	1.5326 ***
t-statistics	(-0.192)	(-0.224)	(0.418)	(-0.535)	(1.266)	(0.551)	(105.575)	(1.895)	(14.528)
US11C	0.2064	-0.0129	0.0153	-0.0011	0.0304	0.0072	0.9726 ***	0.0323 *	1.6155 ***
t-statistics	(0.808)	(-0.923)	(0.178)	(-0.347)	(0.587)	(0.557)	(96.246)	(1.840)	(12.800)
US13C	-0.0894	0.0024	-0.0893	0.0007	0.0679	0.0097	0.9775 ***	0.0565 ***	1.5582 ***
t-statistics	(-0.356)	(0.134)	(-1.075)	(0.151)	(1.325)	(0.894)	(109.150)	(2.963)	(14.015)
US16C	-0.0382	0.0027	-0.0341	0.0010	0.0478	0.0293 *	0.9683 ***	-0.0096	1.0838 ***
t-statistics	(-0.217)	(0.115)	(-0.454)	(0.137)	(0.960)	(1.864)	(76.589)	(-0.548)	(20.138)
SWD1C	0.0692	-0.0079	0.0389	-0.0011	0.0092	0.0343 **	0.9799 ***	-0.0286 *	1.0681 ***
t-statistics	(0.446)	(-0.409)	(0.579)	(-0.159)	(0.298)	(2.404)	(113.744)	(-1.945)	(18.511)
Panel D : Financial									
FR4C	-0.0088	0.0096	-0.0287	0.0006	0.0474	0.0444	0.8586 ***	0.2142 ***	1.2047 ***
t-statistics	(-0.135)	(0.737)	(-0.694)	(0.233)	(1.481)	(1.159)	(29.543)	(3.791)	(19.524)
FR6C	-0.0335	0.0088	-0.0012	-0.0238	0.0321 *	0.0389	0.9166 ***	0.0594	1.0932 ***
t-statistics	(-0.493)	(0.229)	(-0.023)	(-1.282)	(1.664)	(1.523)	(37.410)	(1.475)	(15.841)
GER2C	-0.0477	-0.0058	0.1215 **	-0.0029	0.0597 *	0.1100 ***	0.8529 ***	0.1011 **	1.1979 ***
t-statistics	(-0.658)	(-0.489)	(2.531)	(-1.002)	(1.876)	(2.943)	(30.944)	(1.981)	(13.652)
GER4C	-0.0600	-0.0033	0.0861 *	-0.0018	0.0839 **	0.1275 ***	0.8266 ***	0.1307 **	1.2152 ***
t-statistics	(-0.807)	(-0.279)	(1.749)	(-0.624)	(2.152)	(3.081)	(26.928)	(2.221)	(13.529)
GER5C	-0.0600	-0.0033	0.0861 *	-0.0018	0.0839 **	0.1275 ***	0.8266 ***	0.1307 **	1.2152 ***
t-statistics	(-0.807)	(-0.279)	(1.749)	(-0.624)	(2.152)	(3.081)	(26.928)	(2.221)	(13.529)
GER8C	-0.1238	0.0018	0.0726	-0.0016	0.1154 **	0.0967 ***	0.8539 ***	0.1007 **	1.2850 ***
t-statistics	(-1.327)	(0.127)	(1.400)	(-0.476)	(2.161)	(2.890)	(30.088)	(2.172)	(13.612)
IT5C	-0.0588	0.0135	0.0042	-0.0028	0.0724 *	0.0025	0.9405 ***	0.0769 ***	1.2329 ***
t-statistics	(-0.469)	(0.455)	(0.063)	(-0.256)	(1.740)	(0.165)	(43.665)	(2.972)	(14.358)
IT6C	-0.0351	0.0065	0.0419	-0.0059	0.0612	0.0635 **	0.9160 ***	0.0249	1.2096 ***
t-statistics	(-0.340)	(0.336)	(0.826)	(-1.126)	(1.304)	(2.508)	(40.713)	(0.812)	(14.451)
NET2C	-0.2659 **	0.0247 *	0.2045 ***	-0.0094 ***	0.1342 **	0.0058	0.9534 ***	0.0463 **	0.8921 ***
t-statistics	(-2.136)	(1.916)	(4.772)	(-3.395)	(2.019)	(0.284)	(65.285)	(2.160)	(18.095)
NET4C	-0.0451	0.0114	-0.0176	0.0023	0.1103 ***	0.0324	0.8633 ***	0.1741 ***	1.4030 ***
t-statistics	(-0.580)	(0.824)	(-0.361)	(0.727)	(3.000)	(0.840)	(34.551)	(3.446)	(15.054)
NET5C	-0.2374 *	0.0206	0.1834 ***	-0.0076 ***	0.1666 **	0.0148	0.9420 ***	0.0467 *	0.9031 ***
t-statistics	(-1.937)	(1.636)	(4.325)	(-2.895)	(1.989)	(0.574)	(48.947)	(1.849)	(18.310)
SP2C	0.0577	-0.0345	-0.1841 **	0.0259	0.0262	0.0837 ***	0.9186 ***	-0.0373	1.1785 ***
t-statistics	(0.749)	(-0.652)	(-2.356)	(0.699)	(1.606)	(2.878)	(35.059)	(-1.080)	(16.422)
SP3C	-0.0071	0.0066	-0.1817 ***	0.0307 **	0.0599 **	0.0461 *	0.8718 ***	0.1272 ***	1.2778 ***
t-statistics	(-0.096)	(0.200)	(-3.326)	(2.308)	(2.438)	(1.663)	(29.677)	(2.940)	(14.581)
UK3C	-0.1307	0.0535 **	-0.0472	-0.0004	0.3653 ***	0.1335 **	0.7252 ***	0.1014	1.0391 ***
t-statistics	(-1.571)	(2.027)	(-0.968)	(-0.066)	(2.917)	(2.060)	(09.993)	(1.084)	(20.167)
UK7C	-0.1389	-0.0038	-0.0652	0.0014	0.2860 **	0.0434	0.8730 ***	0.1381 ***	1.2476 ***
t-statistics	(-1.061)	(-0.310)	(-1.273)	(0.676)	(2.319)	(1.233)	(23.264)	(3.003)	(19.208)
UK9C	-0.1370	-0.0031	-0.0741	0.0014	0.3474 **	0.0604	0.8440 ***	0.1621 ***	1.2022 ***
t-statistics	(-1.106)	(-0.266)	(-1.484)	(0.707)	(2.434)	(1.585)	(21.099)	(2.854)	(19.170)
UK10C	-0.1426	0.0235	-0.0273	-0.0029	0.0592 *	0.0040	0.9198 ***	0.1384 ***	1.4427 ***
t-statistics	(-1.543)	(0.929)	(-0.557)	(-0.402)	(1.855)	(0.215)	(44.250)	(3.842)	(17.059)
UK13C	-0.0238	0.0106	0.0156	-0.0142 *	0.0503 *	0.0082	0.9368 ***	0.0866 ***	1.3216 ***
t-statistics	(-0.250)	(0.479)	(0.287)	(-1.903)	(1.896)	(0.393)	(49.455)	(2.646)	(13.869)
UK15C	-0.0464	0.0223	-0.1585 **	0.0295 *	0.0164	0.0224 *	0.9282 ***	0.0964 ***	1.6246 ***
t-statistics	(-0.556)	(0.659)	(-2.241)	(1.650)	(0.949)	(1.904)	(48.120)	(2.896)	(12.937)
UK17C	0.1183	-0.0485	0.0457	-0.0567	0.0611 *	0.0537	0.8819 ***	0.0470	1.3400 ***
t-statistics	(1.294)	(-0.750)	(0.591)	(-1.442)	(1.709)	(1.560)	(20.754)	(1.194)	(12.561)
US5C	-0.0086	0.0030	-0.0842	0.0098	0.0689 **	0.0117	0.9307 ***	0.1411 ***	1.5119 ***
t-statistics	(-0.082)	(0.131)	(-1.566)	(1.525)	(1.968)	(0.783)	(50.037)	(4.135)	(18.337)

Appendix 2J: Maximum Likelihood Estimates of the Feedback Model, Post-Futures Period_Control (sorted by industry) (continued)

	Mean Equation				Variance Equation				
	α	θ	φ_0	φ_1	α_0	α_1	β	δ	ν
Panel D : Financial									
SWT3C	-0.0770	-0.0064	0.1074 **	-0.0039	0.0674 *	0.0289	0.9025 ***	0.1265 ***	1.1969 ***
t-statistics	(-1.061)	(-0.475)	(2.474)	(-1.280)	(1.900)	(1.219)	(38.382)	(3.233)	(13.311)
SWT5C	-0.1085	0.0015	0.1156 **	-0.0003	0.1429 **	0.0475 *	0.8812 ***	0.1293 ***	1.2238 ***
t-statistics	(-1.080)	(0.134)	(2.468)	(-0.132)	(1.968)	(1.909)	(36.372)	(3.203)	(14.394)
SWD2C	-0.0563	0.0015	-0.0067	-0.0004	0.3798 **	0.0078	0.8675 ***	0.1968 ***	1.2583 ***
t-statistics	(-0.435)	(0.135)	(-0.158)	(-0.272)	(2.496)	(0.350)	(25.657)	(3.741)	(15.448)
SWD5C	-0.0383	0.0405	-0.0404	-0.0035	0.0494 **	0.0127	0.9139 ***	0.0988 ***	1.3494 ***
t-statistics	(-0.512)	(1.082)	(-0.722)	(-0.213)	(2.109)	(0.557)	(35.757)	(2.948)	(14.542)
Panel E : General and Resources									
GER3C	-0.1503	0.0158	0.0387	-0.0048	0.0499	0.0389 *	0.9304 ***	0.0506 **	1.5875 ***
t-statistics	(-1.116)	(0.745)	(0.590)	(-0.701)	(1.245)	(1.841)	(48.005)	(2.227)	(14.165)
NET3C	0.0000	0.0000	0.0059	-0.0002	8.8357 **	0.2427 **	0.4982 ***	0.0038	0.6883 ***
t-statistics	(0.000)	(0.000)	(0.563)	(-1.178)	(2.046)	(2.021)	(2.783)	(0.023)	(14.226)
US9C	-0.1839 *	0.0962 *	-0.1511 **	0.0240	0.1144 ***	0.0041	0.8849 ***	0.1291 ***	1.2216 ***
t-statistics	(-1.710)	(1.800)	(-2.328)	(1.059)	(2.577)	(0.281)	(26.174)	(3.096)	(17.420)
GER10C	-0.0018	0.0017	-0.0212	-0.0094	0.0178	0.0093	0.9541 ***	0.0658 ***	1.3337 ***
t-statistics	(-0.023)	(0.064)	(-0.371)	(-0.825)	(1.215)	(0.657)	(61.200)	(2.847)	(14.165)
GER11C	-0.0018	0.0017	-0.0212	-0.0094	0.0178	0.0093	0.9541 ***	0.0658 ***	1.3337 ***
t-statistics	(-0.023)	(0.064)	(-0.371)	(-0.825)	(1.215)	(0.657)	(61.200)	(2.847)	(14.165)
FR1C	-0.1917 *	0.0428	-0.1635 ***	-0.0029	0.1454 **	0.0093	0.8746 ***	0.1560 ***	1.6329 ***
t-statistics	(-1.729)	(1.455)	(-2.625)	(-0.306)	(2.373)	(0.324)	(23.740)	(3.099)	(18.585)
FR9C	-0.0293	-0.0053	0.0187	0.0005	0.0270 *	0.0075	0.9240 ***	0.1363 ***	1.2377 ***
t-statistics	(-0.521)	(-0.334)	(0.434)	(0.107)	(1.658)	(0.484)	(52.489)	(3.812)	(16.208)
GER7C	-0.0154	-0.0002	-0.0690	-0.0078	0.0558 **	0.0324	0.9066 ***	0.0936 ***	1.7335 ***
t-statistics	(-0.167)	(-0.009)	(-1.178)	(-0.813)	(1.961)	(1.546)	(42.370)	(3.022)	(14.309)
IT1C	-0.0173	0.0078	-0.0879	0.0029	0.1709 **	0.0453 *	0.8631 ***	0.1305 ***	1.3268 ***
t-statistics	(-0.152)	(0.339)	(-1.483)	(0.432)	(2.190)	(1.666)	(28.860)	(2.585)	(18.470)
IT3C	0.0000	0.0000	0.0000	0.0000	0.5285 ***	0.4015 ***	0.6214 ***	-0.0022	0.7990 ***
t-statistics	(0.000)	(0.000)	(0.001)	(0.003)	(3.342)	(2.780)	(8.826)	(-0.013)	(18.847)
NET1C	-0.0581	0.0117	-0.0901 ***	0.0022 **	0.2700 ***	0.0910 ***	0.8649 ***	0.0483	0.8862 ***
t-statistics	(-0.744)	(1.259)	(-2.836)	(2.350)	(2.641)	(2.628)	(30.391)	(0.982)	(18.884)
UK2C	-0.0220	0.0121	-0.1600 **	-0.0068	0.0344 *	0.0265	0.9244 ***	0.0766 **	1.7020 ***
t-statistics	(-0.225)	(0.383)	(-2.543)	(-0.569)	(1.936)	(1.035)	(50.647)	(2.010)	(11.773)
UK8C	-0.1230	0.0488	0.2681 **	-0.0497 *	0.1341 *	0.0617 **	0.9100 ***	-0.0136	1.6021 ***
t-statistics	(-0.568)	(0.819)	(2.308)	(-1.883)	(1.808)	(2.277)	(29.953)	(-0.448)	(13.811)
US4C	-0.0009	-0.0009	0.0279	0.0005	0.0714	0.0206	0.9469 ***	0.0505 **	1.7152 ***
t-statistics	(-0.005)	(-0.037)	(0.388)	(0.087)	(1.429)	(1.322)	(61.667)	(2.060)	(12.751)

Notes: *, **, *** Significant at 10%, 5% and 1% respectively
For the stock identification, refer to Table 2.2
v is a scale parameter or degrees of freedom estimated endogenously. The GED nests the normal (for v=2) and the Laplace/double exponential (for v=1).

Chapter 3

The Price Discovery Role of Universal Stock Futures

"The big benefit from futures markets is...the fact that participants in the futures markets can make production, storage, and processing decisions by looking at the pattern of futures prices, even if they don't take positions in that market."

Black (1976a, p.176)

3.1 Introduction

In chapter 1 it was shown that price discovery is an important function of futures markets and is one of the main reasons underlying their evolution. In this chapter we examine whether the USF contracts have succeeded in fulfilling this economic role. In discussing the economic functions of financial markets, Merton (1990, p.263) points out "The core function of the financial system is to facilitate the allocation and development of economic resources, both spatially and across time, in an uncertain environment." However, the capital-allocation role of financial markets rests on the informational efficiency of security prices. For the capital-allocation determined by markets to be efficient, it is essential that security prices reflect all relevant information fully and accurately to market participants (Fama, 1970). It is obvious that an integral role of financial markets is the efficient dissipation of information. Therefore, price discovery (i.e., process by which a security market impounds new information and finds equilibrium price) is arguably the most important product of a security market (Schreiber and Schwartz, 1986; Hasbrouck, 1995; O'Hara, 2003).

Recent advances in information technology and telecommunications technique have led to some dramatic changes in the structure of global financial markets over time. One of the main developments is the growing number of individual assets or multiple highly related assets are traded on more than one market. When an asset or several related assets are traded on multiple markets, a crucial question naturally arises: which market contributes most to the price discovery and information incorporation?

A prominent example of highly related financial assets trading in different markets is a stock and its derivatives. In a rational, efficiently functioning and frictionless market, prices of stock and derivatives must simultaneously reflect new information. As a result, returns of these two markets should be perfectly contemporaneously correlated. If this were not the case, arbitrage profits would be possible (Kolb, 2000). However, due to market frictions such as transaction costs and market microstructure effects, one market may play a larger role in price discovery and reflect information faster than the other thus causing a lead-lag relation in returns. Intuitively, the market that provides a combination of greater liquidity, lower execution costs and greater leverage opportunities should dominate price discovery process (Booth et al., 1999).

Due to the nature of derivative contracts (such as lower transaction costs, less capital outlays, higher leverage, and lesser trading restrictions), they constitute an additional and attractive venue for informed traders to trade on their private information and others to discover that information. Accordingly, derivatives are expected to lead the underlying assets in impounding information and may provide information that simply cannot be inferred from the stock markets.[67] This argument is reinforced when one considers that any restrictions on stock trading (e.g., uptick rule on shorting) mean that stock prices are slower in adjusting to information, especially bad news.

A considerable amount of empirical research has been directed towards examining the lead-lag relationship and the price discovery function in a variety of derivatives markets such as commodities derivatives markets, currency futures markets, stock

[67] As the quote at the beginning of this chapter suggests, price discovery is an essential function performed by futures markets. Their ability to incorporate new information to 'derive' the underlying assets' value is often presented as the key justification for these markets (Garbade and Silber, 1983). For the reasons why futures can alter amount and/or speed of information flow, see Cox (1976).

index futures and/or index options markets, and individual equity options markets. The full list is too long to provide a census, but notable examples using currency futures markets data include studies by Chatrath and Song (1998) and Wang and Wang (2001). Examples of studies examining stock index futures and/or options markets include Chan et al. (1991), Koutmos and Tucker (1996), Fleming et al. (1996), Booth et al. (1999), Chiang and Fong (2001), and So and Tse (2004), to name but a few. Among the authors who have addressed the issue in individual equity options are Stephan and Whaley (1990), O'Connor (1999), Hatch (2003) and Chakravarty et al. (2004). More recently, the nature of relationships among the stock index, regular index futures and E-mini index futures has also attracted the attention of practitioners and academics. Examples using U.S. data include studies by Hasbrouck (2003), Kurov and Lasser (2004), Ates and Wang (2005), and Tse and Xiang (2006). Overall, findings of these and similar studies generally support the notion that movement in derivative prices leads the underlying assets prices and hence contributes to the discovery of new information regarding the future level of spot prices.

Despite this plethora of studies in various commodities and financial derivatives markets, studies that explicitly investigate the relationships between single stock futures (SSFs) and the underlying stock, to the best of our knowledge, are virtually nonexistent, primarily due to their lack of history and the unavailability of data.[68] Although these new derivative contracts have been the focus of some recent research, the issue of whether the SSFs market plays an important role in price discovery and

[68] For instance, futures on individual stocks have been banned in the U.S. for the last two decades under the Shad-Johnson Accord, an agreement between the SEC and CFTC on sharing the regulatory authority over futures on securities, and only recently become legal in mid-2001 (see USGAO, 2000).

thus carries predictive information about the future movements in the underlying stock prices has been subject to very little (if any) attention in published research.[69]

Therefore, the primary objective of this chapter is to fill this gap in the literature and investigate the dynamics of interaction between single stock futures markets and underlying stock markets by using a set of Universal Stock Futures (USFs), the newly established SSFs contracts in U.K. LIFFE.[70] The USFs data is analysed because of the following special features of this market. First, although there are a few countries (such as in Sweden, Australia, South Africa and Hong Kong, etc.) which have stock futures trading in a small number of domestic stocks, such trading has so far been inconsequential and not much evidence can be drawn from their illiquid trading. The situation in LIFFE is different in as much as the volume of Universal Stock Futures (USFs) trading promises to be substantial in relation to their stock markets.[71] And as the market continues to grow, perhaps the data quality will be better than that of other small exchanges for drawing meaningful conclusions about the nature of inter-relationships between the futures and stock markets.

Another significance of USFs is that LIFFE is the first exchange in the world to offer stock futures contracts on foreign underlying stocks.[72] Hence, in this sense, USF contract is being seen by the rest of the world as an experiment. If such futures

[69] McKenzie et al. (2001) examine the impact of SSF listing on the volatility of the stock market in Australia, Dutt and Wein (2003) analyse the suitable margin requirements for the U.S. SSF market, and Lien and Yang (2004) examine the effects of change in Australian SSF contracts specifications.

[70] The single stock futures (SSFs) has been traded in some smaller exchanges such as the Hong Kong Futures Exchange (HKFE) and the Sydney Futures Exchange (SFE); however, these contracts have not proven particular attractive to the investors. The LIFFE has argued that the lack of volume on these local contracts was due to the limited range of domestic stocks and the immaturity of these markets. Indeed LIFFE is the first major exchange to launch 'cross-border' SSFs and, with recent lifting of the ban on these contracts in the U.S., there are about 15 exchanges trade SSFs covering over 300 stocks (see Lascelles, 2002 for a survey of exchanges trading SSF contracts).

[71] During August 2004, USFs trading volume was 473,192 contracts, average daily volume was 21,509 contracts, and end-of month open interest was 565,727 contracts. The year-to-date volume of over 11 million (124% year-on-year growth) makes it the world's largest SSF exchange in terms of trading volume (see http://www.databyeuronext.com/nexthistory).

[72] LIFFE listed a total of 433 USF contracts from 13 different countries in June 2005.

trading is successful it is likely that other exchanges will follow. More importantly, while insights can be gained by examining the inter-dependence between domestic listed SSFs and the underlying stock markets, the cross-border stock futures such as the USF contracts offered by LIFFE in non-UK stocks allows us to cater for a further dimension in the literature: pricing dynamics and information transmission mechanisms between foreign-listed SSFs and the domestic underlying stock markets. Moreover, they also permit us to examine whether there is a 'country effect' in the SSFs' contribution to price discovery. A number of studies argue, in the context of cross-listed stock index futures, that the price discovery ability of futures markets will largely depend on the market structures and institutional differences of the markets at which the underlying indices are being traded (see, e.g., Board and Sutcliffe, 1996; Roope and Zurbruegg, 2002; Frino and West, 2003; and Covrig et al., 2004). The conclusion from these studies is that the markets with lower transaction costs are more conductive to information incorporation, and that price discovery primarily originates from the home market (i.e. home-bias hypothesis). Therefore, it would be interesting to see whether these results are applicable to the cross-listed USF contracts that are based on foreign stocks, and if USFs price discovery function can be attributed to the differences in the underlying stock market conditions or locations.

To this end, this chapter investigates, for the first time, the nature and extent to which USFs contribute to the price discovery process. In particular, we consider the part that USFs play in discovering the information about their underlying stock prices, and the factors that influence this role. Firstly, we determine whether price discovery occurs on the futures markets by applying the approach developed by Gonzalo and Granger (1995) to quantify the contribution of USF to determination of stock price.

Secondly, both the market-wide and firm-specific information flows are documented for the whole sample period, as well as the introduction and maturity periods of USF. An investigation into the impact of several variables which may influence the proportion of new information that is incorporated via the futures markets forms the third focus of this chapter. These include the trading characteristics (relative liquidity and trading costs), futures specifications like 'contract size', and information types. Additionally, we also consider the impact of geographical origin of underlying stock market (trading location) on proportional of USFs price discovery. All these analyses into the influences on the USFs price discovery process are done by considering certain periods and/or groups, and by means of the cross-sectional regression models. Most importantly, the current study also characterises the dynamic interdependence of the stock and futures markets by explicitly modelling the ways in which these two markets interact through their second moments (i.e., the 'volatility-spillovers' effect). To our knowledge, while this has been recognised as an important issue (see, e.g., Chan et al., 1991; Abhyankar, 1995; and Chatrath et al., 2000), this is the first study to directly examine the higher moment dependence between futures and stock markets at the individual stock level.

Volatility-spillover is an important issue in the study of information transmission process for a variety of reasons. First, volatility is often regarded as a useful measure for information flow. Two seminal papers (French and Roll, 1986; Ross, 1989) show that the variance of an asset's price, and not the asset's simple price change, is directly related to the rate of information flow under the competitive markets. In addition, Cheung and Ng (1996) also point out that volatility change is a process of reflecting the arrivals of new information and of how the market evaluates and assimilates the information. These suggest that the interaction between conditional variances has significant implications concerning the information transmission mechanism between the assets or markets. Therefore, in order to gain a more thorough understanding of the information flows between stock and futures markets, it is important to investigate how volatility is transmitted between these two markets. If information arrives first in the futures market, one should expect to see volatility spillover from derivatives to stock market. Second, the examination of volatility-spillover dynamics between stock and futures markets pertains to the perceived destabilising effects of futures trading. Specifically, these markets have long been suspected of exerting a destabilising influence on the underlying stock market. Although this debate is still largely unsettled at both the theoretical and empirical levels, there is growing evidence that trade in futures does not destabilise the underlying markets. To the extent that volatility is induced by trading in response to new information, the volatility-spillover from futures to stock markets should be treated as the beneficial effect because it is purely a reflection of futures markets expanding the channels of information flow in the stock markets and performing its role as a source of information transmission (see Cox, 1976; Ross, 1989; and Antoniou and Holmes, 1995).

Third, intuitively, the futures and their underlying stock markets are both affected by the same information set. Therefore, differences in their information transmission abilities (as measured by strength of volatility transmission) reflect the relative efficiencies in their information processing. Fourth, it is well documented that the variance of error terms in Ordinary Least Squares (OLS) equations are both time-varying and highly persistent, and there is a reason to suspect that the variances are correlated across stock and futures. Failure to incorporate such effects can invalidate the statistical inferences relating to the intermarket relationships. Consequently, to study the price dynamics in the stock and futures contracts, it is important to take into account the intermarket volatility spillover. Therefore, an appropriate extension to our price discovery analysis is to simultaneously model return and volatility interactions between USF and stock markets.

Taken together, this chapter not only provides, for the first time, empirical evidence on the price discovery function of USF contracts but also contributes to the current understanding of linkages between derivatives and underlying markets in the following aspects.[73] First, unlike the market-wide instruments, the USF contracts are based on individual stocks which by definition can be directly traded. This tradable nature of the underlying market implies that stock and futures prices are more closely linked by a cost-of-carry relationship, and hence USF prices may not contribute to the discovery of new information to the same extent as the markets for non-tradable underlying assets such as index futures contracts. Investigation of the price discovery role of the USFs market can thus provide a direct answer to this important issue. Second, our examination of the USF price discovery role over different time periods, and across several markets, could provide insights on the relative price discovery of derivatives markets at the different stages of their developments.[74] In addition, the cross-border USF contracts on non-U.K. stocks allow us to shed more light on the possible 'home-bias' effect in the information transmission mechanisms between foreign-listed futures and their domestic underlying stock markets.

Third, the relatively large sample (i.e., 50 USFs) also permits us to examine the dominant characteristics that determine relative price discovery contributions of the futures markets by using a cross-sectional analysis. Empirical results would provide

[73] See Appendix 3A for an overview of the main contributions of this chapter to the current literature.
[74] This sub-period analysis is motivated by the findings that mature markets process information faster than less mature markets (see, for instance, Chiang and Fong, 2001; and Frino and West, 2003).

policy-makers important insights on the importance of several factors in security designs and market structures. Finally, whether there are interactions in second moments of the stock and USFs markets is another important issue that is investigated in this chapter. As discussed before, this has vital implication for the issues regarding the relative price discovery and informational efficiency of these two markets.

Another distinguishing characteristic of this study is the comparison of stock and futures markets ability in reflecting the firm-specific and market-wide information. Previous research which has examined the lead-lag patterns between stock index and stock index futures markets documented considerable variation in price discovery contributions of each market depending on the information types.[75] In particular, these studies suggest that the lead of futures markets will become greater around the 'market-wide' information release periods, while transmission of information will run from the stock to the futures market in the case of the 'firm-specific' information. It would therefore be interesting to analyse whether the kind of information may affect the USFs contracts' contributions to the price discovery process. It would also be interesting to test whether the price discovery role can vary depending on the information content. This study directly addresses these two issues using USFs data. Although our focus is on the reflection of firm-specific information in the stock and USF markets, we also consider the market-wide information as well as whether the information content is 'positive' or 'negative'.[76]

Findings of this chapter should benefit both the academic and financial communities. The latter include investors who trade in both stocks and derivatives, as well as those

[75] See, for example, Chan (1992), Crain and Lee (1995), Frino et al. (2000), amongst others.
[76] The use of USFs is particularly useful in studying the transmission of firm-specific information because the USFs' tradings are mainly based on the news relating to the individual stocks.

who are active in only one market. For instance, if the results show that futures market contribute significantly to the price discovery, this indicates that some information is first reflected in that market, and movements in these markets will be of interest to investors trading the underling shares.[77] Additionally, the cash-futures price relationship is also an important factor for hedgers in developing effective hedging strategies. According to the traditional theory of hedging, the effectiveness of hedge largely depends on the parallelism of movements in spot and futures prices. Further, an investigation of the price discovery dynamics between stock and futures markets could shed light on the market preference of informed traders. Intuitively, if informed traders are more likely to choose one particular market to reveal their private information, prices on this market tend to lead on the other markets. This is particularly important as a greater understanding of where informed traders choose to trade and the factors influencing this choice are highly relevant to market makers and regulators. For example, knowledge of the informed traders' market preferences will aid the regulators in preventing illegal insider trades. In addition, an analysis of the price discovery role of LIFFE USFs contracts could also provide useful references for other derivatives markets which have introduced and/or been considering to launch the single stock futures. For instance, it may help exchange executives make decisions on whether such derivatives products should be listed in their markets as a means of enhancing information dissemination.

The structure of this chapter is as follows. The next section provides a brief review on the literature in the price discovery function of derivatives markets. The theoretical pricing relationship between the futures and stock markets, together with the results of some previous empirical research are reviewed. Section 3.3 describes

[77] According to a recent survey conducted by Greenwich Associates, over 60% of investors identified 'price discovery' as one of their primary concerns about the current security markets (G.A. 2005).

the data and sample selection criteria. Section 3.4 outlines the empirical procedures we use to investigate the contributions of USFs to the price discovery process, their variations across stocks and through time, the factors that cause the variations, and the volatility interactions between these two markets. The empirical results and robustness checks are also presented in this section. Finally, section 3.5 concludes this chapter, outlines the limitations and discusses the potential extensions for further research.

3.2 Literature Review

The price discovery process in fragmented markets has attracted much attention from the academic and financial communities in recent years as more and more assets are traded in different markets in different forms. Intuitively, as the prices of the identical or multiple highly related assets are driven by the same underlying information, all markets should impound the common information instantaneously and simultaneously in a perfectly efficient and integrated financial system, so that their prices adjust to a new equilibrium level with no lag. As mentioned earlier, however, there are significant differences in their market frictions, market structures, and security designs that affect the speed at which each market reflects and digests the incoming new information. Consequently, it is possible that some securities are more capable of incorporating the new information than others, even though they are based on the same underlying asset.

Numerous studies have been devoted to examine the price dynamics among the informationally-linked security markets such as the derivatives and spot markets, international derivatives written on same cash index, internationally cross-listed stocks and domestic stock markets, international currency markets, and domestic stock exchanges trading the same securities.[78] Two crucial questions these studies attempt to address are: (1) which market contributes most to the information incorporation? and (2) what are the dominant characteristics that determine the price discovery function of a security or market? Different approaches have been put forward to study these issues. Nevertheless, the outcomes of the empirical investigations in the current literature are still inconclusive and making these issues open questions.

A prominent example of informationally-linked financial assets trading in different markets is a stock and its futures. Since futures prices and spot prices are driven by the same underlying information, they should be closely related. Specifically, if futures and spot market are perfectly efficient, the futures and spot prices are expected to satisfy three conditions: (i) changes in spot prices and changes in futures prices are expected to occur at the same, but (ii) current futures price change is expected not to be related to previous spot price change, and (iii) current spot price change is also expected not to be related to previous futures price change. That is, these two markets should reflect the same information simultaneously; and there should be no lead-lag relationship between futures and spot price changes (i.e. returns).

3.2.1 Linkage between the Futures and Spot Prices

According to the cost-and-carry theory (see, e.g., MacKinly and Ramaswamy, 1988), the prices of futures and spot can be expressed in the following relationship:

$$P_{F,t} = P_{S,t}e^{(r-d)(T-t)}$$

[78] For derivatives and spot markets, see Stoll and Whaley (1990), Chan (1992), Fleming et al. (1996). For international derivatives trading same index, see Frino and West (2003) and Covrig et al. (2004). For the internationally listed companies, see Eun and Sabherwal (2003), and Grammig et al. (2005). For international currency markets, see Arshanapalli and Doukas (1993), Chatrath and Song (1998). For different domestic stock exchanges, see DeB Harris et al. (1995), Hasbrouck (1995), and Tse (1999).

where $P_{F,t}$ is the fair futures price, $P_{S,t}$ is the spot price, r is a continuously compounded risk-free rate of interest, d is the continuously compounded yield in terms of dividends derived from the stock until futures contract matures, and $T-t$ is time to maturity of the futures contract. Taking logarithms of both sides gives:

$$F_t = S_t + (r_t - d_t)(T - t)$$

This suggests that the long-term relationship between the log of the fair futures price (F_t) and spot price (S_t) should be 'one-to-one'. Thus the basis (difference between the futures and spot prices after adjusting for the carrying cost) should be stationary. When this wanders without bound, arbitrage opportunities would arise, which would be assumed to be quickly exploited by arbitrageurs such that the relationship between spot and futures prices will be brought back to the long-run equilibrium.

In other words, if the markets are frictionless and functioning efficiently, the price change in the spot price and its corresponding changes in the futures price would be expected to be perfectly and contemporaneously correlated and not cross-autocorrelated. Mathematically, these notions can be represented as:

$$corr(\Delta F_t, \Delta S_t) \approx 1 \qquad \text{condition (i)}$$

$$corr(\Delta F_t, \Delta S_{t-p}) \approx 0 \;;\; \forall p > 0 \qquad \text{condition (ii)}$$

$$corr(\Delta F_{t-q}, \Delta S_t) \approx 0 \;;\; \forall q > 0 \qquad \text{condition (iii)}$$

However, because of market frictions (such as transaction costs, infrequent trading, short sales restriction, etc), market structure and security designs effects, one market may play a larger role in price discovery and reflect information faster than the other and causing a lead-lag relation of returns in the short-run. From an empirical point of view, departures from the above perfect market assumptions/conditions in the real world raise two important questions: (a) is the cost-of-carry model tenable as a long-term relationship linking spot and futures markets?, and (b) if this is case, how does each market react / adjust to the short-run price deviation from their equilibrium level?[79] Sutcliffe (1997), Mayhew (2000), and Whaley (2003) provide excellent reviews on the first issue. Since the focus of this chapter is the price discovery function of futures, we deal mainly with the second issue. As Garbade and Silber (1983) argue, whether corrections to disequilibrium are driven by the movements of the futures or spot prices has important implications for the price discovery role of each market. They propose the terminology of "dominant" and 'satellite' to categorize the price "discovery" and the price 'adjustment' markets. In general, the dominant markets lead the satellite markets and are more influential in the price discovery process. A satellite market relies on dominant market as a primary source of information as its price movements are just a reflection to the news that takes place on other markets.

From a theoretical point of view, the issue of whether stock or futures markets reflect the new information first (and ultimately where the price discovery take place) is a topic closely related to the more fundamental question of where informed traders choose to trade. If informed traders prefer one particular market to exploit their information, we would expect to see price discovery in this market and its price will lead the other market price. Put it another way, if a systematic price discovery or lead-lag relationship is found, we might interpret this as evidence of where informed traders might choose to transact. This in turn allows us to consider possible reasons why informed traders choose one market rather than the others to trade.[80]

[79] However, it should be noted that observed lead-lag relationships may be a result of market imperfections; the evidence of small adjustment time to news need not imply market inefficiency.
[80] Indeed, the informational-based models demonstrate that new information becomes impounded in prices as a result of trading by informed traders (see, for example, Kyle, 1985; Glosten and Milgrom, 1985; and Easley et al., 1998). O'Hara (1995) provides a comprehensive review on this literature.

3.2.2 Price Discovery Hypotheses

Several hypotheses have been proposed to explain the market preference of informed traders (and, by extension, the lead-lag relationship or price discovery process) according to different market structures and security designs. Generally speaking, the following intuitive hypotheses have been identified in the literature:

1) Leverage Hypothesis: Derivatives (such as futures/options) provide investors with higher leverage than the stock, and with the same amount of capital available; high-leverage contracts provide more return on investment than low-leverage instruments. Therefore, traders with superior information prefer to trade high-leverage instruments, holding other factors equal. As a result, it is expected that the high-leverage securities provide better price discovery. Indeed, the view that informed investors choose to trade derivatives because of the higher leverage offered by such instruments has long been recognised and can often be found in the popular press.[81]

2) Trading Cost Hypothesis: As profit is reduced by trading costs, informed traders have an incentive to trade in the market with the lower costs to maximise the value of their information. All else equal, lower cost markets will lead higher cost markets. Therefore, the price discovery is expected to occur mainly in the lowest cost market. Since trading costs of futures, on balance, appear to be the lower than stock, futures price has been found to lead its underlying stock price (see, Fleming et al., 1996). Kim et al. (1999) test the trading cost hypothesis by examining lead-lag relationship among index futures and among cash indexes, while Frino and West (2003) take a

[81] Black (1975) shows that options provide the investors with higher leverage for the underlying asset. For example, a recent study on the 'unusual option market activity' and 'the terrorist attacks of September 11, 2001' indicate that long put volume appears to be unusually high which is consistent with informed investors having traded in the option market in advance of the attacks (see Poteshman, 2006). In addition, on July 25, 2002, the Wall Street Journal reported that the Chicago Board Options Exchange (CBOE) was investigating "unusual trading activity" in options on shares of Wyeth (the U.S. pharmaceuticals giant) which experienced a sharp increase in trading volume earlier that month.

slightly different approach and test this hypothesis by analysing the leadership between cross-listed index futures and their underlying index. The results of these studies (and many others) provide clear evidence to support this explanation.[82]

3) Liquidity Hypothesis: The ability of informed traders to hide their trades is important to them. Since markets have greater liquidity expected to aid the anonymity of traders, market preference of informed traders is likely to be a function of the relative market liquidity/depth. This idea is supported by Garbade and Silber (1983), who provide a formal treatment of this issue and present a model which suggests that price discovery is a function of the relative size of the market (as measured by the number of market participants). Along this line, Stephan and Whaley (1990) also suggest that there is a causal relationship between trading activity (as proxied by the number of transactions or volume) and the lead-lag relationship. Accordingly, price discovery will occur in the more liquid market (stock market in our case).[83]

4) Uptick Rule Hypothesis: In many stock exchanges, a short sale of a stock can take place only when the last recorded stock price change is non-negative (uptick rule). However, as derivatives contract trades are not subject to the uptick rule, their prices should more efficiently incorporate information, especially during market downturn. According, futures are expected to have a larger price discovery role than the stock, especially for the falling markets (bad news). This prediction is broadly consistent with the proposition of Miller's (1977) overvaluation model. Chan (1992) confirms

[82] It should, however, be pointed out that transaction cost has three main components (bid-ask spread, brokerage fees, and 'market impact' cost). If informed traders chose to trade in derivatives, then the adverse selection component of bid-ask spread would become very large. Thus benefits of increased leverage in the derivatives may be offset by additional costs of trading (John et al., 2003).

[83] Again, it should be noted that because the adverse selection component of the bid-ask spread (a major component of trading cost) will be widened if informed traders are attracted by high trading activity/liquidity (or low leverage), transaction costs and market liquidity are likely to have offsetting impact on lead-lag or price discovery relation between futures and stocks (John et al., 2003).

this hypothesis and finds strong evidence that the lead-lag relation between MMI/S&P 500 indexes and their index futures is fundamentally different for good and bad news. Chan's (1992) result is consistent with the implications of the uptick rule hypothesis. Additionally, Hodgson et al. (2003) uncover more direct evidence and show that the futures informational domination stands out clearer in the falling markets.

5) Market Maturation Hypothesis: Rate of price discovery also depends on the market maturity of each market. In mature markets, market participants are well acquainted with these securities, which tend to be common investment and financial management tools. On the other hand, the less mature markets may encounter low liquidity because they are unfamiliar to investors. Therefore, relative informational efficiency depends on the different stage of development across markets and/or over time (see, for instance, Stoll and Whaley, 1990). As stocks are more well-developed and matured than the futures, we expect them to contribute more to price discovery. This conjecture is supported by Chiang and Fong (2001), who study the lead-lag relationship among index derivatives and spot index in the Hang Seng Index (HSI) and find that option returns lag both index and futures returns. They attribute this finding to the fact that HSI option market is less mature than the spot index and futures markets. The results of Frino and West (2003) also support this explanation.

6) Market-wide Information Hypothesis: With special reference to the stock index futures contracts, Chan (1992) argues and provides evidence that index futures markets can process market-wide information better than cash markets. Moreover, Frino et al. (2000) also find that the lead of index futures markets is greater around the macroeconomic information releases. These results are consistent with the

hypothesis that investors with better market-wide information prefer to trade in stock index derivatives markets. A formal treatment of this issue is given by Subrahmanyam (1991) who provides a theoretical model to demonstrate that index derivatives allow traders to trade more efficiently because the security-specific component of adverse selection is diversified away in such markets. His model also implies that basket of securities with similar reactions to certain kinds of information facilitates trading on that information, thus enhancing price discovery. However, as the objective of this chapter is to analyse the price discovery function of single-stock futures market such as USFs, this hypothesis is not directly applicable in our case. Rather we speculate that because of the stock-specific nature of USFs contracts, coupled with their favourable trading conditions such as high leverage, they present an attractive venue for investors with insider news to exploit their private information. It is believed that USF facilitates the firm-specific information flow and serve as a primary market for the discovery of information that is expected to move a particular stock (we term our conjecture as "Firm-specific Information Hypothesis").

7) Market Trading Mechanism Hypothesis: The literature also suggests that the market trading mechanism is another important factor (see, for instance, Harris, 1990). For example, screen trading speeds up the process of information collection and dissemination, and the order execution. Electronic trading markets are thus expected to have greater price discovery role than floor trading markets (see, e.g., Martens, 1998; Theissen, 2002; Ates and Wang, 2005; for the empirical evidence). Nevertheless, it is expected that this hypothesis should not carry much explanatory power in explaining the price discovery of USFs because both USFs and their underlying stocks are being traded under an electronic platform, LIFFE CONNECT.

8) Other factors: Apart from the intuitive hypotheses identified above, there are of course some other technical reasons which can possibly explain why returns on a particular market tend to lead returns on other markets. Potential factors include the following: i) infrequent trading in market index component stocks (see, e.g., Stoll and Whaley, 1990), ii) nonsynchronous trading (see, e.g., DeB Harris et al., 1995), and iii) other methodological bias.

Table 3.1 provides some predictions on the relative price discovery contributions of the USF and its underlying stock market, according to the implications of the above hypotheses. Overall, the hypotheses in this table predict that both stock and futures markets will contribute to the price discovery process with no clear distinction between these two markets. Perhaps futures play a more important role during the periods of stock-specific information releases, while stocks may have more significant contributions to the assimilation of market-wide information due to its favourable market liquidity and maturation. The futures market enjoys the advantages of high leverage, low trading costs, and the absence of uptick rule for short-selling, but low liquidity due to market immaturity tends to weaken its price discovery role. It is important to note that these hypotheses are not mutually exclusive, and the price discovery role of a market could be a result of a joint effect of several factors. It is therefore inappropriate to simply do a 'horse-race' for these complementary hypotheses and attribute the lead-lag or price discovery pattern to only one of the hypotheses discussed above. Rather a more appropriate approach is to identify the most influential market structure and security design factors in determining the price discovery function in each market. Informed traders may assess trade-off of USFs market benefits with benefits of market maturity and high liquidity in stock markets. The result of this trade-off faced by informed traders (and thus the price discovery of each market) is an empirical question that we attempt to address in this chapter.

3.2.3 Previous Empirical Research

A considerable amount of empirical research have examined the lead-lag relationship and price discovery function in a variety of equity derivatives markets such as the index futures and/or index option markets, and the individual stock option markets. Both weekly and daily data have been used, although the recent studies have turned to the high-frequency transactional level data. According to So and Tse (2004), three major approaches have been commonly used in the literature to study the information transmission among different markets. The first approach focuses on the lead-lag relationship between the prices of related markets or assets. The second approach involves examination of the role of volatility in the information transmission process. The third approach measures directly the proportion of price discovery across markets by using the Hasbrouck (1995) and/or Gonzalo and Granger (1995) models. For a list of research publications categorised as above, one can refer to Sutcliffe (1997) and So and Tse (2004). This chapter will apply all these three approaches to investigate how information is transmitted between USF and stock markets.

In general, the results of previous studies show that both the stock index futures and index option markets tend to lead the stock market index, while the results for individual equity options appear to be less conclusive and mixed (see the review by Sutcliffe, 1997; Ch.7). Nonetheless, the existing literature has several shortcomings. First, while many authors have reported that stock index futures and/or index options lead the underlying cash index, the underlying index is not a traded asset, and may be composed of stale prices. This is because the constituent stocks of the index trade infrequently, introducing distinct serial correlation patterns into time series of index returns which may induce a spurious lead of the futures markets (see. Stoll and Whaley, 1990). Therefore, the results from these studies are questionable and do not shed much light on the question of information transmission or informed trading. Unlike the market-wide instruments, single stock futures (SSF) contracts are based on individual stocks which by definition can be directly traded. This implies that the non-synchronous trading problem may be less pronounced in examining stock futures.

However, being the more recent entrants to the global derivatives markets, there is very little direct evidence on the price discovery role of stock futures markets to date. One notable exception is Lien and Yang (2004) who test the Geweke's (1982) measures of information flow between stock and futures markets to examine the price discovery function of 10 Australian Individual Share Futures (ISF) contracts. Their findings indicate that the stock market dominates the futures market, and the stock market rather than the futures market provides a price discovery function. This result is inconsistent with the relation between spot and futures of the stock index and commodity markets documented in the current literature. They attribute the inconsistency to the relative intensity of trading activity in these two markets. However, any inference drawn on only 10 thinly traded contracts is questionable.

More importantly, most studies explain the lead-lag or price discovery relation they uncover in terms of the *one* of several hypotheses we discuss before. However, as mentioned earlier, the informed investors face a trade-off between trading costs and market liquidity and their market preferences are likely to be affected by both market structure and security design factors; therefore, it is possible that the observed lead-lag relationships are the joint effect of multiple factors. Due to the large number of theoretical hypotheses with overlapping and ambiguous predictions / implications, we are reluctant to interpret our results (shown in the later sections) as favouring any particular hypothesis. Perhaps the new information is transmitted through multiple, off-setting channels into the stock and futures markets. Indeed, the empirical results of Chakravarty et al. (2004) and Ates and Wang (2005) provide clear evidence to support the notion that operational efficiency and relative liquidity jointly determine the rate of price discovery in derivatives and spot markets. Therefore, because of the complexity of the price discovery process between the futures and its underlying stock markets, focusing exclusively on one or two views is overly simplistic and potentially sub-optimal from a policy perspective.

Whatever the case may be (which hypothesis or factors), it is apparent that there is a gap in price adjustments processes for securities when they are traded in different markets in different forms, and all available information (especially private components) are not reflected in the equilibrium prices on the same securities in different markets simultaneously. This chapter applies both Vector Error Correction Model (VECM) and Generalized Autoregressive Conditional Heteroscedastic (GARCH) modelling frameworks to identify the lead-lag relationship, the price discovery process and the volatility-spillovers between the stock and USF markets. To our knowledge, this is the first paper to measure directly the proportion of price discovery across SSF and stock markets, and represent first evidence on the price discovery role of USFs market.

3.3 Sample Selection and Data Sources

3.3.1 Sample Selection

LIFFE began trading 25 USFs on January 29, 2001. Each USF contract represents 100 shares of the underlying stocks, except contracts written on UK and Italian based stocks which represent 1000 stocks. During August 2004, USFs trading volume was 473,192 contracts, average daily volume was 21,509 contracts, and end-of month open interest was 565,727 contracts. The year-to-date volume of over 11 million (124% year-on-year growth) makes it the world's largest SSF exchange in terms of trading volume (see http://www.databyeuronext.com/nexthistory). As of June 2005, LIFFE listed a total of 433 USFs on the stocks from 13 different countries.

Similar to chapter 2, the first step in the sample selection process is to identify all the USFs that were introduced between January 2001 and December 2001. The sample is restricted to such contracts for the following two reasons. First, being the earliest listed futures it is believed that they might have a more significant price discovery role than the recently introduced contracts as the latter are less well-established and matured than the former. Second, the estimates of the time-series techniques that are employed in this chapter (i.e., both VECM and GARCH models) are less reliable in small samples, and by restricting the sample to the stock futures listed in 2001 a sufficiently long time-series data is obtained for the economically 'meaningful' statistical results.[84] Next, a total of 97 USFs contracts that were listed in 2001 were screened using several criteria, to remove any observation that may have introduced the potential bias to the empirical results.[85]

[84] For example, Hwang and Valls (2006) suggest using at least 500 daily observations if reliable estimates are to be achieved using a GARCH-type of model.

[85] An additional issue related to internationally cross-listed stocks / futures is the incorporation of an exchange rate factor. However, as all USFs and their underlying stocks are quoted traded in the common local currency, any effect from exchange rate movement (if any) is expected to be minimal.

In order to mitigate the non-synchronous error, we exclude all contracts written on the U.S. stocks and focus our empirical analysis on the U.K. and European USFs. Due to the fact that the U.S. stock markets are operated on totally different trading hours from the U.K and/or European markets, including the futures contracts based on stocks trading in the U.S. markets would make it difficult to mitigate the potential non-synchronous error in the daily closing prices of the stock and futures markets (See Figure 3.1 for a summary of the opening/closing trading times in the USFs and their underlying stocks markets). Moreover, since our focus is to examine the price discovery contributions of USFs, the only samples included are those with futures first introduced on Euronext.LIFFE and listed nowhere else within the study period. Including stocks which have futures traded in their domestic markets would make it impossible to identify the channels by which the new information is transmitted. Additionally, any stocks with futures delisted in the sample period were also omitted. In total, there are 65 USFs contracts that fulfil the above selection requirements.

However, out of the existing 65 USFs samples, many are not sufficiently liquid. Since price efficiency (and price discovery) of less liquid stock futures is not trustworthy, only the most liquid contracts (across the study period) are selected. The criterion for selection is the average daily trading volume (no. of contracts) of USF futures relative to its underlying stocks from the first day of each USF contract listed to December 30, 2005. Specifically, only those USFs that have the relative trading volume (i.e., USF/Stock) of a minimum 0.5% or higher are selected. This restriction is imposed in order to mitigate the different trading intensity/liquidity between the futures markets and its matured stock markets. Finally, this leaves us with a total of 50 USFs contracts to be included in our final sample. The list of 50 USFs, along with their underlying stocks trading location and the sample period, is given in Table 3.2.

3.3.2 Sources of Data

For this chapter, daily data is used in the absence of higher frequency data.[86] Daily closing prices of 50 individual stocks and the corresponding USF contracts are used. Given the paired two price series, daily basis calculated as the difference between the natural logarithms of two series. Returns of each price series are computed as the natural logarithms of price relative. The data are taken from various sources. Specifically, the daily closing prices of stocks are taken from Datastream, while the USFs price series are collected from the NextHistory database of the LIFFE and then matched with that provided by Datastream. These databases also provided us with the daily trading volume data for stock and futures markets. Data on the daily closing prices of several stock index futures contracts come from the EcoWin.

The sample period spans almost five years from the first day of each USF contract listed to December 30, 2005. All the days that either stock or futures markets were closed are removed. The number of observations on 50 matched price series data vary from 1060 to 1267. Although the stock price can be used directly, futures prices cannot be. This is because each futures is characterized by more than one contract with each contract having a different expiration date. This problem is solved in conventional manner by constructing the pseudo-price series. In this study, the pseudo-price series is constructed by splicing together the prices of sequential nearby futures contracts. In particular, a single continuous futures price series for each USF contract is constructed using closing prices from the nearest contract with rolling over at the beginning of the delivery month to the next nearby contract in order to prevent the thin markets and contract expiration effects.

---

[86] Ideally, the analysis of price discovery would better be undertaken using intraday transaction data. However, due to the data availability, the daily data is used in this chapter. Provided that sufficient and reliable data are available, an examination of intra-daily price discovery process between the stock and USF markets is worthy of further study.

3.4 Methodology and Empirical Results

This section outlines the empirical procedures and the results of our investigation on the price discovery function of USF contracts. The time-series techniques we employ are sequentially interrelated. First, we provide the unit root tests for each pair of stock and futures price series in order to establish that they are non-stationary and integrated of order one, I(1). Next, we use Johansen (1988) method to confirm the cointegration of two price series and thus justifying the error correction specifications. Then, we describe a bivariate error-correction model that is intended to assess the lead-lag relationships between stock and futures returns. Subsequently, we 'quantify' the relative contribution of each market to the price discovery process by applying Gonzalo and Granger (1995) extension of 'common factor' approach developed by Schwarz and Szakmary (1994). The time-series and cross-sectional variations in price discovery levels are then considered for certain periods/groups by means of the sub-period/sub-sample analyses. Following that, we examine the cross-sectional determinants of the USFs' contributions to the price discovery process. Finally, in the last subsection we further investigate the higher moment dependencies among these two markets (i.e., volatility-spillovers) and assess the role of volatility in the information transmission process.

3.4.1 Preliminary Data Analysis

Stock and derivatives markets are strongly linked to each other by complex arbitrage relationship which ensure long-run price tendency towards an equilibrium constraint. Their price series cannot diverge and follow paths that cannot drift too far apart. For example, according to the cost-of-carry theory, futures and stock prices should move up and down together in the long run whereas short-run deviations from the long-run equilibrium take place because of the mispricing of either futures or stock prices.

Therefore, before discussing the models we use to analyse inter-relationships between stocks and futures, it is necessary to perform unit root and cointegration tests on their price and return series to check if this is really the case. If the price series of stock and futures are non-stationary but the changes of prices are stationary, the cointegration concept becomes relevant in the subsequent empirical analysis.

3.4.1.1 Unit Root Tests

We first perform augmented Dickey-Fuller (ADF) unit root tests on each stock and futures price series and their first differences to investigate the stationarity of the price and price change series. Let P_{st} and P_{ft} denote the natural logarithm of stock and its futures prices at time t, respectively. The changes of stock and its futures prices at time t are calculated as $\Delta P_{st} = P_{st} - P_{s,t-1}$ and $\Delta P_{ft} = P_{ft} - P_{f,t-1}$, respectively. For each price series, we consider the following three regression equations:

$$\Delta P_t = \gamma P_{t-1} + \sum_{i=1}^{k-1} \psi_i \; \Delta P_{t-i} + \mu_t \qquad \text{(3.1) Random walk}$$

$$\Delta P_t = \alpha + \gamma P_{t-1} + \sum_{i=1}^{k-1} \psi_i \; \Delta P_{t-i} + \mu_t \qquad \text{(3.2) Random walk with drift}$$

$$\Delta P_t = \alpha + \beta t + \gamma P_{t-1} + \sum_{i=1}^{k-1} \psi_i \; \Delta P_{t-i} + \mu_t \qquad \text{(3.3) Random walk with drift \& time trend}$$

The differences among the three regression equations are concerned with the presence of a drift term and/or a linear time trend. The null hypothesis in all three cases is that $\gamma = 0$; if the null cannot be rejected, the prices series $\{P_{st}\}$or $\{P_{ft}\}$ contains a unit root, and hence it is non-stationary. We use the Schwarz Bayesian criterion (Schwarz, 1978) to determine k, the optimal number of lags in the models. The critical values of the t-statistics depend on the equation being estimated. The critical values of MacKinnon (1996) are used in this chapter.

The empirical results of testing unit roots for the price and return series are reported in Table 3.3. ADF test statistics from equation (3.3) for the price series are shown in the first two columns of the table. As expected, the null hypotheses of a unit root for these series are not rejected at the 5% level in most cases. Although we obtain rejections at the 5% significance level for 6 price series (and for 3 series at 1% level), the results indicates that almost all the stock and futures prices are non-stationary. The ADF unit root test is also applied to the changes of stock and futures prices (i.e., returns). The test statistics from equation (3.2) on the return series are reported in columns 3 and 4 of Table 3.3. The null hypotheses of a unit root for the return series for all 50 pairs are rejected at the 1% level suggesting that both stock and futures return series are stationary. Overall, we conclude that most price series can be characterised as I(1) processes and the return series are all I(0).[87]

3.4.1.2 Cointegration Tests

Having confirmed the presence of I(1) price series, we proceed to test for the presence of equilibrium relationship in the non-stationary stock and futures price series, by applying the Engle and Granger (1987) and Johansen (1988) cointegration testing methods. The Engle and Granger (1987) cointegration test is based on assessing whether single-equation estimates of the equilibrium errors appear to be stationary. As reported in the last column of Table 3.3, the null hypothesis of no cointegration between futures and stock prices is rejected for each pair of price series at the 5% significance level (except for 6 cases cannot reject the null hypothesis).[88] The results suggest that most pairs of stocks and its futures prices are cointegrated. This finding is consistent with the prediction of the cost-of-carry theory.

---

[87] I(d) stands for a time-series variable which is integrated of order d ; that it is need to be differenced d times in order to become stationary.

[88] In order to test the robustness of the results, the ADF test is also applied to the basis series. Results reported in the fifth column of Table 3.3 are broadly consistent with the EG cointegration test results.

While the Engle and Granger (1987) cointegration test is very easily implemented, it has relatively low power and contains several limitations (see Harris and Sollis, 2003). Therefore, we use Johansen (1988) reduced rank regression procedure to further test for cointegration of the stock and futures price series and to identify the long-run equilibrium relationship between these two series.[89] The Johansen (1988) procedure has several advantages. First, this procedure provides more efficient estimates of the cointegrating vector compared to the EG two-step approach (Gonzalo, 1994). Second, in contrast to the EG approach, inferences on the model (and hence tests of Granger causality) do not depend on the ordering of the variables in the cointegrating regression. Moreover, Johansen's (1988) tests are shown to be fairly robust to the presence of non-normal innovations (Cheung and Lai, 1993) and heteroscedastic disturbances (Lee and Tse, 1996). This is particularly important since the stock and futures prices in this study share these characteristics (see next section for a discussion on this).

---

[89] The Johansen (1988) cointegration test is based on a vector error correction model (VECM): $\Delta X = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t$ where Δ denotes the first-difference lag operator; X_t is a (n × 1) vector of I(1) time-series variables; ε_t is zero mean n-dimensional white noise vector; Γ_i are (n × n) matrices of parameters, and Π is (n x n) matrix of parameters whose rank is equal to the number of independent cointegrating vectors; and n is the number of series (n = 2 in this chapter). The hypothesis, that the number of cointegrating vectors is at most r, is tested using either $\lambda_{trace}(r)$ or $\lambda_{\max}(r, r+1)$:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$$

where r is the number of cointegrating vectors in the system; T is the number of sample size actually used for estimation; $\hat{\lambda}_i$ is the estimated value of the characteristic root (i.e., eigen-value) obtained from the estimated cointegrating matrix. The statistic $\lambda_{trace}(r)$ tests the null hypothesis that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r. The statistic $\lambda_{\max}(r, r+1)$ tests the null that the number of cointegrating vectors is r, against the alternative of r+1. Critical values for both statistics are given in Osterwald-Lenum (1992). We carry out the tests using Johansen methodology implemented in Eviews statistical software.

The results of the Johansen cointegration rank tests are presented in Table 3.4. The multivariate version of the Schwarz Bayesian criterion, used to determine the optimal lag length, indicates four lags for all but a few pairs of stock and futures prices. Therefore, in the interest of consistency, we estimate all models with four lags. According to the cost-of-carry theory, futures and stock prices should move up and down together in the long run and form a cointegrating system which has one long-run cointegrating relationship corresponding to their lagged basis (i.e., the difference between stock and futures prices). Hence, if the theory of cost-of-carry is a valid characterisation of the stock and futures prices, we should expect to find exactly one cointegrating vector with $\beta' = (1, 0, -1)$ form.[90]

On the basis of the 5% significance level and the estimated λ_{trace} statistics, we can reject the null hypothesis of no cointegration (H_0: r = 0) for all pairs of prices, apart from five cases where the tests reject the null of one cointegrating vector in favour of two vectors. However, we do not include two vectors in subsequent VECM specifications of these five stocks as we cannot find any economic justification for such relationships. To examine whether the equilibrium relationship is equal to the lagged basis, we further examine the cointegrating vector, $B_t = \beta' X_t = (S_t \quad \beta_1 \quad F_t)'$. We normalise the estimates by setting the coefficient of the stock price, S_t, equals to one. If the results show that $\beta' = (1, 0, -1)$, then the cointegrating vector reflects the lagged spread/basis (i.e., $B_{t-1} = S_{t-1} - F_{t-1}$) as indicated by the cost-of-carry theory.

[90] In fact, this is exactly the implication of the 'Forward Unbiaseness Hypothesis (FUH)' on the stock-future pricing relationship (Kolb, 2000).

The normalised coefficient estimates of the cointegrating vector $\beta' = (1, \beta_1, \beta_2)$ in Table 3.4 show that all the elements of the cointegrating vectors are close to the form of $\beta' = (1, 0, -1)$ with only a few exceptions (i.e., 11 cases). This finding is generally confirmed by the Wald tests of restrictions on $\beta_1 = 0$ and $\beta_2 = -1$. We also find that the median value of β_1 equals to -0.01331, and the median value of β_2 equals to -0.99716. The small divergence from the theoretical cost-and-carry value is possibly caused by transaction cost bounds which imply that small 'mispricing' cannot be arbitraged away.[91] Nevertheless, in the following section, we estimate our error correction model with $\beta' = (1, 0, -1)$ restriction in the stock-future long-run relationship and include the exact lagged basis as an error-correction term (ECT) in the VECM specification.

Overall, the Johansen tests results reported in Table 3.4 are generally consistent with our previous Engle and Granger (1987) cointegration test results, suggesting that each set of two prices in stock and futures markets share a stable long-run relationship.[92] Taken together, these two cointegration test results (commonly found in the academic literature) validate the VECM specification in our subsequent price discovery analysis.[93]

[91] However, many studies show that the basis spread is not a good proxy for the long-run relation between spot and futures prices because it ignores the carrying charges (e.g., see Zhong et al., 2004). As a result, a number of general equilibrium models have been proposed in the literature. (see, for instance, Hemler and Longstaff, 1991).

[92] Note that, in contrast to the EG tests, results from the Johansen test indicate that 3 pairs price series (FTE, RD, and TEF) are cointegrated. This discrepancy in two cointegration tests results may be attributed to the low power of residual-based EG cointegration tests compared to the Johansen tests.

[93] 'Granger Representation Theorem' suggests that if two time-series are cointegrated then ECM exists.

3.4.1.3 Summary Statistics

Apart from the ADF unit root test, and EG and Johansen cointegration tests, we also provide some descriptive statistics for the stock, futures return series and basis series. Table 3.5 reports the summary statistics of mean (μ), standard deviation (σ), measures of skewness (S) and excess kurtosis (K), the Jarque-Bera test of normality (JB), the ARCH test and the Ljung-Box Q statistic (Q) for 12 lags.

The results indicate excess skewness and kurtosis in all time-series. Data sets with excess kurtosis are likely to have a distinct peak near their mean values, decline rather rapidly, and have heavy tails (i.e., leptokurtic). The statistics presented in Table 3.5 show that, in general, the futures price series exhibit higher excess kurtosis than the stock prices (average excess kurtosis is 79.14 for futures and 9.30 for stock). This seems to suggest that stock prices tend to fluctuate around their equilibrium prices in much smaller intervals compared to futures price series, which may be the result of more mature and better functioning stock markets requiring less fluctuation in prices before reaching the equilibrium. However, to examine the dynamic of price discovery process between stock and USF markets, further investigation is required.

There is also clear evidence of significant departures from normality (see JB) across all the stocks, futures and basis series. The Ljung-Box Q statistics show evidence of temporal dependencies in 80 percent (i.e., 120 out of 150) in the first moment of the time-series distributions, while for the squared returns / basis series, the LB statistic is significant in almost all cases. Likewise, the ARCH effects are also clearly evident. The presence of non-normality and heteroscedasticity in stock and futures prices justify our use of Johansen's method in previous cointegration tests.

3.4.2 Error Correction Model and Price Discovery Process

In the previous section, we confirm that the USFs and its underlying stock prices are cointegrated, sharing a stochastic common trend with one cointegrating vector near $\beta' = (1, 0, -1)$ form. In this section, we proceed to explore how the series react to deviations from their long-run equilibrium and to measure the relative contributions of each market to price discovery process. A market's proportion of price discovery is related to its relative contribution to the variance of innovation in the common trend, which can be identified indirectly by examining the Granger causality (i.e., lead-lag relationship) or directly by carrying out the common-factor analysis (i.e., price discovery), within a Vector Error Correction Model (VECM) framework.

3.4.2.1 Error Correction Model

According to the 'Granger Representation Theorem' (Engle and Granger, 1987), if two I(1) time-series are cointegrated, then the short-term disequilibrium relationship between them can always be expressed in the error correction form (ECM exists).[94] Given the above evidence of cointegration between the futures and underlying stock price series, both the lead-lag relationship and price discovery analyses need to be examined under the Vector Error Correction Model (VECM) modelling framework. However, as mentioned earlier, the focus of this study is on the reflection of the 'firm-specific' information in stock and futures markets, hence we control for the discovery of systematic market-wide information by including several stock index futures returns in our VECM model specifications.[95]

[94] Conversely, if two I(1) variables can be modeled as an ECM, then these variables are cointegrated.
[95] As discussed before, the USFs are particularly useful in studying the transmission of firm-specific information because, unlike the market-wide instrument, the USFs' tradings are mainly based on the news relating to the individual stocks. Indeed, Hatch (2003) has also applied a similar technique in his price discovery analysis across NYSE stocks and CBOE options markets.

In particular, the following bivariate VECM is used to represent the cointegrated system of stock and futures prices:

$$\Delta X = \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \Psi SIF_{t-1} + \varepsilon_t \, ; \;\; \varepsilon_t = \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{F,t} \end{pmatrix} \sim N(0, \Omega) \quad (3.4)$$

where SIF_{t-1} is the lagged stock index futures return at time t – 1, which is included in the stock-futures system as an exogenous variable; Γ_i matrix contains information on short-term interactions between $\{\Delta S_t\}$ and $\{\Delta F_t\}$, and Π matrix contains information on the long-run equilibrium relation between $\{S_t\}$ and $\{F_t\}$. Hence, both Γ_i and Π matrices contain important information regarding the inter-dependence between stock and futures returns.[96]

Denoting stock (futures) return as $R_{s,t} = \Delta S_t = S_t - S_{t-1}$ ($R_{F,t} = \Delta F_t = F_t - F_{t-1}$), we can rewrite (expand) the VECM model (3.4) into a linear structure and show more clearly of each stock and futures return equations as the following form:

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t} \quad (3.5a)$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t} \quad (3.5b)$$

where $R_{SIF,t-1}$ denotes the lagged returns of stock index futures, which is included in the model to isolate the flow of firm-specific information;[97] $B_{t-1} = \beta' X_{t-1}$ serves as the error-correction term (ECT) to make sure that stock and futures prices never wander far from each other. Given the cointegrating vector test result from Table 3.4,

[96] The short-term relationship between stock returns and futures returns may also include intercepts. However, for simplicity, the intercept terms are not included in our VECM specifications.

[97] Specifically, we include the returns of following stock index futures in our VECM specifications for underlying stocks trading in different stock markets: (i) CAC40 for France, (ii) DAX for Germany, (iii) MIB for Italy, (iv) AEX for Netherlands, (v) IBEX35 for Spain, (vi) OMX for Sweden, (vii) SMI for Switzerland, and (viii) FTSE100 for U.K. stocks.

we apply the restrictions $\beta' = (1, 0, -1)$ on the cointegrating vector and set the error-correction term (ECT) to be the lagged basis (i.e., $B_{t-1} = S_{t-1} - F_{t-1}$).[98]

As discussed earlier, the above VECM specification incorporates both short- and long-run reaction of $R_{s,t}$ and $R_{F,t}$ to changes in their equilibrium relationship. The short-run adjustment is captured by current and past values of $R_{s,t}$ as well as lagged values of $R_{F,t}$. The long-run effects are incorporated into the model through ECT, $B_{t-1} = S_{t-1} - F_{t-1}$, which measures the distance the system is away from equilibrium. If equilibrium holds, then $B_{t-1} = 0$. On the other hand, during the periods of disequilibrium, this term is different from zero. Therefore, the error-correction coefficients, γ_s and γ_F, serve two purposes: (i) to measure the *speed* of adjustment to the long-run equilibrium and (ii) to identify the *direction* of causality between two variables. For instance, when the stock return exceeds the futures return at time t – 1 (i.e., $B_{t-1} > 0$), the stock price tends to decrease whereas the futures price tends to increase in the next period in order to maintain the long-run equilibrium relationship. Similarly, suppose the stock price falls below the futures price at time t – 1 (i.e., $B_{t-1} < 0$), the stock tends to increase and futures price tends to decrease at time t. This would lead one to predict that $\gamma_s < 0$ and $\gamma_F > 0$. Indeed, this represents a principal feature of cointegrated variables (i.e., their time paths must be influenced by the extent of any deviation from their long-run equilibrium).

---

98 As the robustness tests, several other specifications are also considered. For instance, we also estimate (i) the VECM model with an *unrestricted and a fully identified* long-run matrix $\beta' = (1, \beta_1, \beta_2)$, and (ii) the VECM model *without* the lagged stock index futures return SIF_{t-1}. The results are very similar to those from equations (3.5a and 3.5b). Detailed estimation results of these specifications are presented in the later 'robustness tests' section 3.4.2.5.

3.4.2.2 Evaluating Lead-Lag Relationships

Granger (1988) shows that if two variables are cointegrated, then causality must exist in at least one direction. Given the above evidence of cointegration between the stock and its futures prices, the Granger causality (i.e., lead-lag relationship) between these two markets is examined in this section by using a set of formal causality tests within the above VECM framework.[99]

The study of the lead-lag relationship between USFs and underlying stock markets is important and provides initial insights into price discovery role of these two markets. Intuitively, if price discovery is faster in one market (reflect new information first), returns on this market should be expected to lead the returns on the other market. In particular, in terms of the equations (3.5a) and (3.5b), the leading market should exhibit the smaller (in magnitude) adjustment coefficient (i.e., γ_i; where $i = S, F$).[100] An γ_i equals to zero indicates a market that has no response to shocks. For example, if $\gamma_s = 0$ then all adjustments to shocks occur in the futures market, which is a strong indication of stock market leading behaviour. Additionally, the lagged 'cross-coefficients' (i.e., α_{Fi} and β_{Si}; where $i = 1, 2, \ldots p-1$) are also important to assess the lead-lag relationship. Significant values for the α_{Fi} coefficients suggest that lagged $R_{s,t-i}$ observations affect current $R_{F,t}$ values. Likewise, significant β_{Si} parameters indicate that lagged $R_{F,t-i}$ observation influence current $R_{S,t}$ values.

---

99 Since cointegration exists between two markets, an error-correction term is needed in testing Granger causality between these variables because the cointegrated variables share a long-run equilibrium relationship, which may directly affect the causality test results.

100 As explained earlier, these error-correction coefficients show how the prices arrive at a new equilibrium after being perturbed, and hence provide some insights into the adjustment process of two prices towards equilibrium and give us an indication on how vigorously each market responds to shocks to the equilibrium process (i.e., the burden of convergence among the two markets).

To evaluate empirically the lead-lag behaviour in the stock and USFs market, we conduct the following Granger causality tests in the VECM (3.5a) and (3.5b):[101]

$$H_{01} : \beta_{S1} = \beta_{S2} = \cdots = \beta_{S,p-1} = 0 \tag{3.6a}$$

$$H_{02} : \alpha_{F1} = \alpha_{F2} = \cdots = \alpha_{F,p-1} = 0 \tag{3.6b}$$

Therefore, H_{01} (H_{02}) hypothesizes that the lagged $R_{F,t-i}$ ($R_{s,t-i}$) cross-coefficients are jointly zero. Rejection of H_{01} implies that futures returns Granger-cause (i.e., lead) returns in stock market. Similarly, rejecting H_{02} implies that stock returns Granger-cause (i.e., lead) futures return. If both hypotheses of no Granger causality are rejected then two-way feedback relationship exists (i.e., bi-directional causality).

$H_{03} : \gamma_S = 0$ (3.7a) ; and $H_{04} : \gamma_F = 0$ (3.7b)

Likewise, failing to reject H_{03} (H_{04}) implies that all adjustments/corrections to shocks occur in the futures (stock) market, which is another indication of stock (futures) market leading behaviour. If both hypotheses cannot be rejected then each price responds to shocks to the equilibrium and make adjustments accordingly towards new equilibrium (i.e., both markets contribute to price discovery process). These hypotheses may be tested using traditional t-tests for the significance of the error-correction coefficients (H_{03} and H_{04}) and F-tests on the joint significance of the lagged cross-coefficients (H_{01} and H_{02}). However, since F-tests rely on the assumption of homoskedasticity, the χ^2 distributed Wald-test statistics are employed in this study to test for Granger causality (see Greene, 1997, p.548). To correct for heteroskedasticity, the t-statistics are also adjusted by White's (1980) method.[102]

[101] Since cointegration exists between our variables, an error-correction term is needed in testing Granger causality between variables because the cointegrated variables share a long-run equilibrium relationship, which may directly influence the causality test results.
[102] In fact, our residual diagnostic tests indicate the existence of heteroskedasticity in most cases. Also note that if stock and USF prices are indeed cointegrated then at least one of H_{03} / H_{04} can be rejected.

The VECM estimation results and the χ^2 distributed Wald-test statistics are presented in Table 3.6. The lag length in the equations (3.5a) and (3.5b) is chosen on the basis of the multivariate version of the Schwarz Bayesian criterion (Schwarz, 1978).[103] Since the model contains a common set of regressors, without the loss of efficiency, each equation is separately estimated using Ordinary Least Squares (OLS) technique.[104] Both t-statistics and Wald-test statistics are calculated using White's (1980) heteroscedasticity consistent variance-covariance matrix in order to correct for heteroskedasticity.[105]

The most evident result from Table 3.6 is that, the coefficient estimates on $R_{SIF,t-i}$ (δ_S and δ_F) are positive and significant at 1% level in all cases. To the extent that index futures markets trading reflect the market-wide information, this provides clear evidence that the trading in both individual stock and USFs markets responses to the macroeconomic information.[106] This finding is consistent with the recent empirical work of McKenzie and Brooks (2003) who show that stocks and single-stock futures (SSF) trading in Hong Kong are motivated by both firm-specific and market-wide information. Overall, the results lend further support to the use of the lagged index futures returns in our VECM model to control for the influences of systematic market-wide information in order to obtain valid inference on the relative price discovery contributions of the 'firm-specific' information in the stock and futures markets.

[103] Similar to our previous Johansen test results, the Schwarz Bayesian criterion indicates four lags in the VECM equations (3.5a and 3.5b) for all but a few pairs of stock and futures returns. Therefore, for consistency, we again estimate all models with four lags.
[104] It is well known in the literature on cointegration between conventional I(1) process that the OLS estimator of the cointegrating vector is super-consistent (see, for instance, Stock, 1987; Tse, 1999).
[105] Indeed, the residual diagnostic tests indicate the existence of heteroskedasticity in most cases.
[106] A number of studies provide evidence on the stock index futures markets' advantages in processing and trading the market-wide macroeconomic information (see, Chan, 1992; and Frino et al., 2000). These studies also show that the lead-lag patterns may depend on whether the information is market-wide or firm-specific.

The bivariate VECM equations (3.5a) and (3.5b) produce a large number of coefficient estimates. However, as explained earlier, the speed of adjustment coefficients (γ_S and γ_F) and the lagged cross-coefficients (i.e., α_{Fi} and β_{Si} ; where $i = 1, 2, \ldots 4$) are most important to assess the lead-lag relationships. Therefore, rather than analysing each individual coefficient estimate separately, we summarise the results of four hypotheses identified in previous section in Table 3.7. The first two columns of this table show, respectively, the Wald-tests results for $H_{02}: \alpha_{F1} = \alpha_{F2} = \cdots = \alpha_{F,p-1} = 0$ and $H_{01}: \beta_{S1} = \beta_{S2} = \cdots = \beta_{S,p-1} = 0$ on the lagged cross-coefficients in equations (3.5b) and (3.5a). Some qualitative results are observed. Specifically, the effects of the lagged stock returns on the current futures returns are significant (rejection of H_{02}) for 44 of 50 stocks, whereas the effects of the lagged futures returns on the current stock returns are significant (rejection of H_{01}) for 15 of 50 stocks. The above observations suggest that the information in the stock market is more relevant in predicting the price movement in the futures market when compared with the prediction of stock price movement using the information in the futures market. Although there is a bi-directional causality (rejecting both H_{02} and H_{01}) in 14 cases, stock market seems to be the "dominant" market in lead-lag relationship between stock and USF markets.[107]

Secondly, the t-test results for $H_{04}: \gamma_F = 0$ and $H_{03}: \gamma_S = 0$ in the third and fourth columns of Table 3.7 show that the lagged basis (serves as an error-correction term to capture the deviation from the long-run equilibrium) has significant positive

[107] Garbade and Silber (1983) suggest the terminology of "dominant" and "satellite" markets. Dominant markets lead satellite markets; that is, they are more influential in the price discovery process. Satellite markets rely on dominant markets as the primary source of information. Using these terminologies, the stock market is the "dominant" market whereas the USFs market is the "satellite" market.

effect on the current futures returns (rejection of H_{04}) for 20 of 50 USFs markets, suggesting that the futures price tends to move closer to the stock price. In contrast, the effects of the lagged basis on the current stock return are significant for only 8 of 50 stock markets (rejection of H_{03}). This implies that the futures markets tend to follow the movement of stock markets in order to maintain the long-run equilibrium relationship, which is another indication of stock market leading behaviour.

Overall, the above results suggest that the individual stock market tends to lead the corresponding USF market. This lead-lag pattern differs from what has been documented in other financial markets. For example, Stoll and Whaley (1990) show that S&P500 and MMI indices futures market lead their cash markets. Chan (1992) also document that the stock index futures markets dominate stock index markets.

Possible explanations for the different findings for the informational role of USFs market are the followings. First, the most likely explanation is the error-correction models in this study specifically capture the flow of firm-specific information between stock and futures markets. For example, Grunbichler et al. (1994) argue that the lead-lag patterns between stock and futures markets vary considerably depending on whether the kind of information is market-wide or firm-specific information. They show that the transmission of information will generally run from the stock to the futures market in the case of the 'firm-specific' information. In addition, focusing on the flow of firm-specific information, Hatch (2003) finds that individual stock returns tend to lead option market returns by at least thirty minutes throughout his sample period. A second differentiating factor may be that the informational dynamics in intraday (commonly analysed in the literature) are very different from the daily time-series observations we analyse in this study. For instance, Schwarz and Laatsch (1991) measure the price changes in MMI index markets using both daily and intraday data, and conclude that the relationship between spot and futures prices varies considerably.

Different findings of the lead-lag behaviour and informational role of a futures market may arise from different intensities of trading activity in stock and futures markets. Chan (1992) argues that lower trading activity means that the security is less frequently traded and thus the observed price tends to lag the 'true' value more. In LIFFE market, the USFs contracts are traded far less frequently than their underlying stocks. To illustrate this, consider the 50 USFs contracts being analysed: the daily average trading volume of USF represents only about 0.5% to 8.32% of its corresponding stock's trading volume during our sample period. This could cause the lead-lag relation between stock and futures markets to favour the individual stocks. In addition, Admati and Pfleiderer (1988) show that both liquidity and informed traders prefer to trade with each other when the market is thick. This induces more information to be released. Therefore, in comparison with their USFs counterparts, the stock markets are more likely to play the leading role in disseminating the information because of their high level of trading activities.

Finally, the special nature of USFs contracts such as market immaturity may also contribute to the stock market leading behaviour.[108] Stoll and Whaley (1990) argue that the rate of price discovery depends on the stage of developments across markets. Mature markets tend to lead the less mature markets because market participants are familiar with these securities and use them as common investment and financial management tools (see, e.g., Chiang and Fong, 2001; and Frino and West, 2003).

[108] Merton (1995) argues that there is a "learning curve" associated with financial innovations.

3.4.2.3 Price Discovery Contributions

In the previous section, we use the conventional Granger causality tests to provide evidence about the lead-lag relationship between stock and futures returns. However, a more satisfactory approach which attracts great attention from academia in recent studies of information transmission among different markets is the so-called "price discovery" techniques.[109] An important aspect of such analysis is that it directly 'quantifies' the contributions of each market to the information discovering process. Therefore, this section further investigates the information role and price discovery function of USFs markets by applying these new "price discovery" techniques.

Building on the common factor (or implicit efficient price) among cointegrated prices, two different methods have been proposed to measure/quantify the contribution of information from different markets for the same asset. Hasbrouck (1995) introduces the information share (IS) measure. In a cointegrated system such as in equation (3.4), Hasbrouck (1995) estimates a market's contribution to the price discovery process on the basis of the contribution of its innovations to the total innovations in the common efficient price, represented by the common stochastic trend of the cointegrated system (Stock and Watson, 1988).[110] However, the Hasbrouck's (1995) modelling framework is problematic because, whenever the contemporaneous correlation of shocks across markets is substantive (i.e., error terms in two equations are correlated), only the upper and lower bounds of each market's information share can be obtained and leads to non-unique IS results.[111]

---

[109] A special issue of the *Journal of Financial Markets* (JFM) (Issue 3, 2002) has been devoted to discuss the issues and measuring techniques in this growing 'price discovery analysis' literature.

[110] See Hasbrouck (1995, p.1178-1183) for the formal derivations of information share (IS) measure.

[111] In practice, the innovations of the cointegrated markets are usually correlated unless the ultra-high frequency dataset are used (e.g., 1-minute or 5-minute sampling frequency). Therefore, IS approach is not conductive to our analysis as only the daily data are used in this study.

An alternative approach to study the price discovery process is the common factor weight (CFW) measure. This has first been proposed by Schwarz and Szakmary (1994) on intuitive ground. A formal justification, based on the work of Gonzalo and Granger (1995), has been given by Booth et al. (2002) and DeB Harris et al. (2002). Recently, an overwhelming number of studies have employed this technique to examine price discovery process among the informationally-linked financial markets. For example, among the authors who have employed the common factor weight approach to address the price discovery issue, Theissen (2002) applies this measure to assess the relative price discovery contributions of same stock trading in electronic trading versus floor trading in German equity markets.[112]

Given that the CFW price discovery measure is both theoretically well-founded and easy to calculate, we therefore employ the CFW measure to explore the relative price discovery contributions of USF and its underlying stock market in this study.[113] This simple measure is also more conductive to our analysis because it overcomes the 'non-uniqueness' problem of the alternative Hasbrouck's IS measure, and thus enables us to proceed with a cross-sectional analysis on the determinants of USFs price discovery ability in the next section.[114] This is particularly important since performing the cross-sectional regressions require us to use the measure of price discovery contribution as the dependent variable; therefore, we need a unique value of the USF market's contribution instead of their upper and lower bounds.

---

[112] Booth et al. (1999) also employed CFW to study price discovery in the German equity derivatives markets. DeB Harris et al. (2002) applied this techniques to study price discovery of Dow stocks trading in informationally-linked exchanges.

[113] For a formal comparison of the two methods see Baillie et al. (2002), Lehman (2002), Theissen (2002) and de Jong (2002). Both methods are primarily derived from the error-correction vector in the VECM and they tend to provide similar results if the VECM residuals are uncorrelated.

[114] For example, Martens (1998), Huang (2002), and Booth et al. (2002) find that the range between upper and lower bounds of IS measure may be quite substantial.

The CFW measure defines the contribution of an individual market in terms of the other market's adjustments to the deviation from the equilibrium of a cointegrated system, which can be easily obtained from the error-correction terms (ECTs) in a VECM. To illustrate this, consider a VECM such as in equations (3.5a) and (3.5b):

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t} \qquad (3.5a)$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t} \qquad (3.5b)$$

As explained earlier, the error-correction coefficients γ_S and γ_F provide information on the adjustment of each series to the deviation from the equilibrium in the previous period. Either or both stock and USF prices must respond to departures from equilibrium to prevent the riskless arbitrage opportunities. For example, if the stock return exceeds the futures return at time t – 1 (i.e., $B_{t-1} > 0$), the stock price will decrease whereas the futures price will increase in the next period in order to restore the long-run equilibrium. Similarly, if the stock price falls below the futures price at time t – 1 (i.e., $B_{t-1} < 0$), the stock will increase and futures price will decrease at time t. Therefore, this would lead one to predict that $\gamma_s < 0$ and $\gamma_F > 0$. The absolute values of γ_S and γ_F show the *magnitude* of response of the stock and futures markets, and thus can be used to infer each market's share to the price discovery process. Intuitively, a market contributes to price discovery if feedback from that market drives prices in the other market. Given that the total adjustment to restore the equilibrium level is reflected by the sum of the *absolute values* γ_S of γ_F, the price discovery contribution of a market can be measured by the proportion of total adjustment that occurs in the *other* market (Schwarz and Szakmary, 1994).[115]

[115] In particular, the "price-discovering" market should exhibit the smaller (in magnitude) γ coefficient.

Accordingly, for every sample stock-futures paired prices, we define the stock and USF market contributions to price discovery process as Θ_S and Θ_F, respectively; where:

$$\Theta_S = \frac{\gamma_F}{\gamma_F + |\gamma_S|} \quad ; \text{and} \quad \Theta_F = 1 - \Theta_S = \frac{|\gamma_S|}{|\gamma_S| + \gamma_F} \tag{3.8}$$

If the price discovery takes place exclusively in the stock market (i.e., there is no feedback provided by the USF market and the stock price does not adjust to prior deviations from equilibrium), then $\gamma_S = 0$ and $\Theta_S = 1$ ($\Theta_F = 0$). In the other extreme, if the price discovery occurs in the futures market only (all the adjustment to the departure takes place in stock market), then $\gamma_F = 0$ and $\Theta_F = 1$ ($\Theta_S = 0$). If both markets contribute equally to price discovery process, $\Theta_S = \Theta_F = 0.5$.[116] As shown above, the common factor weights (CFW), Θ_S and Θ_F, are summed to one. The *larger* the factor weight of a market price suggests that this market price has *greater* contribution to the price discovery process. On the basis of the estimated VECM adjustment coefficients in equations (3.5a) and (3.5b), we calculate the stock and USF share in the price discovery process for each of the stocks in our sample as given by formula (3.8).

[116] It should be noted that the contributions to the price discovery as proposed by Schwarz and Szakmary (1994) are *equal to* the weights with which the time-series enters the common long memory component identified by Gonzalo and Granger (1995) (see Theissen (2002) for the formal comparison). In addition, Theissen (2002) shows that both the common factor weights (CFW) and information shares (IS) of Hasbrouck (1995) are very likely to lead to qualitatively similar conclusions on price discovery issue as the Schwarz and Szakmary's (1994) measure.

The results are reported in the last two columns of Table 3.7.[117] Similar to previous lead-lag relationship analysis results, we find a dominant role of the stock market in price discovery. The stocks' common factor weight (Θ_S) averages 0.605 with a minimum of 0.001 and a maximum of 0.993. In USF markets, the mean value of Θ_F is 0.395 and ranges from 0.007 to 0.999. Inspection of each individual CFW estimate (i.e., the price discovery contributions) indicates that there are 31 cases where Θ_F falls below 0.5 while only 18 where Θ_S is lower than 0.5. On balance, these results indicate that although the two markets contribute to the price discovery process, the major part of price discovery is in fact achieved in the stock market, which is consistent with our previous results of the lead-lag analysis.

An alternative way to assess the proportion of the total adjustment that occurs in a individual market (and to infer the price discovery contribution of the *other* market) is to look at a scatter plot of the adjustment coefficients (Eun and Sabherwal, 2003). Figure 3.2 shows the results of this analysis and depicts the adjustment coefficients for two markets. It reports, on the horizontal axis, the responses of stock markets to the departures from equilibrium and, on the vertical axis, the responses of USFs markets. Points above (below) the 45^0 line represents firms with a larger (smaller) adjustment in the futures market compared to the adjustment in the stock market, and hence larger (smaller) contribution of the stock market to the price discovery process. As can be seen from the figure, most observations lie above the 45^0 line, implying that stock markets contribute more to the price discovery process in most cases.

[117] Since the formula assumes the adjustment in both markets in the direction predicted by the theory of error-correction modelling (i.e., a negative sign of the adjustment coefficient in the stock market ($\gamma_s < 0$) and a positive one for the USF ($\gamma_F > 0$), we have to modify it for the stocks in which we find adjustment coefficients with a sign opposite to the one expected (e.g., both to be negative). In those cases we arbitrarily assign 99% share in the price discovery for the "non-adjusting" market. Inspection of the estimates of the adjustment coefficients (the error-correction terms) indicates that most of them are of the expected sign except in one case (LLO) where γ_F is negative.

Taken as a whole, the empirical evidence presented in this and previous sections suggests that the arrival and the aggregation of new information into prices is achieved (i.e. price discovering) primarily through stocks trading, and that the futures markets have to do most adjustments towards the new equilibrium price level.

3.4.2.4 Cross-sectional and Time-series Variations

In the previous two sections, the results of our Granger causality tests and price discovery analysis for the entire sample (full period) indicate that the USFs markets make significant contributions to the price discovery process, although in majority of cases new information is disseminated first through their underlying stocks trading. However, prior research has documented a considerable variation in the price discovery functions of derivatives markets both through time (Abhyankar, 1995; Ates and Wang, 2005) and across the firms or markets (Chakravarty et al., 2004). A number of possible explanations for this variation have been examined by prior literature including: (i) trading systems and institutional differences of the markets at which underlying assets being traded (Grunbichler et al., 1994), (ii) the geographical origin of the underlying stock markets (Fung et al., 2001), (iii) market maturation (Stoll and Whaley, 1990), (iv) trading characteristics such as relative liquidity and trading costs (Fleming et al., 1996), (v) contract features/designs (Hasbrouck, 2003), and (vi) information types and contents (Frino et al., 2000; Chatrath et al., 2002).

As mentioned before, the special features of USF contracts provide us a unique opportunity to further examine whether these factors could significantly affect the price discovery role of a derivatives market. For example, with underlying stocks trading in several different markets and countries, our USFs samples enable us to extend the analysis by investigating whether the USF markets' information contributions could be influenced by the geographical origin of their underlying stock markets and/or the underlying stock trading locations and systems. It could also be interesting to investigate the extent to which the price discovery contributions of futures markets vary across their 'introduction/learning' and 'maturation' periods. These are the issues we wish to address in the next three sections.

Country Effects

The first issue we wish to address is whether there is any significant variation in the price discovery contributions of USFs whose underlying stocks are being traded in the geographically-separated stock markets. That is, does the 'country effect' exist? As discussed before, a number of studies show, in the context of cross-listed stock index futures, that the price discovery ability of futures markets depends on the market structures and institutional differences of the markets at which the underlying indices are being traded (see, e.g., Frino and West, 2003; Covrig et al., 2004). Therefore, it would be interesting to see whether this result is applicable to USF contracts that are based on stocks from different markets, and if USFs price discovery role can be attributed to different underlying market conditions / locations.

We can address this question by partitioning our previous VECM and price discovery results in Table 3.7 into several USFs groups according to their underlying stock market location. Altogether, our sample consists of a total of 50 USF contracts including (i) 10 USFs based on stocks traded in the U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland.

Table 3.8 presents the cross-sectional descriptive statistics on the estimated price discovery contributions (i.e., the CFW Θ_F in Table 3.7) for our entire USF sample and for each of the USF group. The results reported in this table indicate that, while our whole USF sample (on average) contributes almost 40% (mean Θ_F value is 0.3951) of the price discovery process, there is a considerable variation in the amount of price discovery across different USF groups. Specifically, of the eight groups examined, the USF trading in Italian and U.K. stocks both share more than 50% of the information discovery role. The mean Θ_F value is 0.6027 for the Italian USFs and the Θ_F averages 0.5202 for U.K. USFs. As discussed before, the larger the factor weight of a market price suggests that this market price has greater contribution to the price discovery process. Therefore, the result implies that UK and Italian USFs exhibit a dominant role in price discovery process in comparison to their underlying stock markets, contradicting the evidence obtained from entire sample analysis.

On the other hand, for those USFs whose underlying stocks are being traded in France and the Netherlands, only less than 25% of total price discovery contributions come from futures markets. The average common factor weights (CFW) of these two markets groups are 0.2459 and 0.2363, respectively, which are only less than half of contributions from U.K. and Italian USF contracts. Since the eight markets considered in this study have considerable differences in their trading systems and market structures, the finding of significant variations in the USF price discovery role across these markets is, perhaps, not very surprising. Overall, the results indicate that there is a 'country-effect' in the contributions of different USF contracts, and that the geographical origin of its underlying stock may influence the ability of a futures market to incorporate the new information. This finding is consistent with the prior research which has examined the same issue in other derivatives markets.

Home-Bias Hypothesis

The issue of whether the trading location of the underlying stocks could affect the price discovery contributions of the USFs contracts is further analysed in this section. In particular, we compare the relative price discovery contributions of domestic-listed and cross-listed USFs and intend to provide an answer to the following question: whether, and to what extent, the price discovery function of a future market is influenced by the trading location of the underlying stock.

The price discovery dynamics of internationally listed securities has been the subject of intensive empirical research in recent years. The literature, dominated by the studies on the importance of location of trade for the pricing of securities, focused on the cross-listed of non-US stocks on the US exchanges. Among the authors who have addressed this issue are Kim et al. (2000), Eun and Sabherwal (2003), and Grammig et al. (2004; 2005). The general conclusion from these studies is that the price discovery primarily originates from the home market (i.e. home-bias).

Several studies have also examined the issue using stock index futures that are cross-listed / dual-listed in different countries and further confirmed the home market's dominance in the international price discovery process (see e.g., Covrig et al. 2004). However, while much work has been done on the price dynamics of internationally listed stocks and/or cross-listed index derivatives, there has been little (if any) attention given to the price discovery process of cross-listed single stock futures (SSFs). To this end, the purpose of this section is to fill this gap in the current literature and to investigate the relative price discovery role of domestic-listed and cross-listed SSFs by comparing the price discovery contributions of the USFs contracts listed on U.K. (domestic) and European (foreign) stocks.

The home-bias hypothesis argues that as firm-specific information such as earnings, dividends, and financing announcements is likely to be dominated by home factors, home bias arises because investors are on average better informed about domestic firms (see Tesar and Werber, 1995). Since the single stock futures (SSFs) contracts such as USFs were designed for investors to manage the firm-specific risk, the underlying stock markets could be more sensitive to stock futures movement. Hence, by comparing the price discovery functions of the U.K. USFs and European USFs contracts, a more reliable conclusion could be made in relation to the "international" price discovery dynamics of the cross-listed stock / derivatives. In addition, the findings of this section could provide insights to global investors on the importance of U.K. futures trading in the foreign underlying stock market price movements.

To achieve the above objective, we employ a similar technique as in the previous section and partition our entire USFs sample into two groups; one includes the 10 USFs that are trading on U.K. stocks and the other one includes all the remaining USFs that are based on 40 European stocks. Cross-sectional descriptive statistics of the estimated adjustment coefficients from the VECM equations (3.5a) and (3.5b) are presented in Panel A of Table 3.9. Generally, among the U.K. USF markets, the average adjustment of stock market prices, γ_S , is smaller than average correction originating in the futures market, γ_F , implying larger contribution of the stock exchange to the price discovery process. The dominant role of the stock markets in price discovery is also prevalent in the European USF markets. However, inspecting the *magnitude* of mean γ_F value in each group of USFs suggests that the cross-listed foreign USFs take up more adjustment burden and less price discovery role compared to the domestic-listed U.K. USFs.

Comparing the relative price discovery contributions (θ_F) of these two different USF groups in Panel B of Table 3.9 lends further support to the dominance of the domestic-listed USFs in their stock-futures pricing process. More specifically, the USF trading in U.K. stocks share more than 50% of the price discovery role (i.e., mean Θ_F value is 0.5202); whereas for the cross-listed USFs whose underlying stocks are being traded in the European stocks markets, only 36% of total price discovery contributions come from the futures markets (mean Θ_F value is 0.3639). In order to analyse whether the cross-listed European USFs in fact contribute less to the process of price discovery, we test whether the average CFW (Θ_F) in European USFs is significantly lower than that of domestic-listed U.K USFs by performing a non-parametric Wilcoxon signed rank test. As can be seen from the test result, the null hypothesis that the average price discovery contributions of the two USF groups are equal is clearly rejected at the 10% significance level.

Overall, we find that the level of price discovery in a futures market is largely affected by the trading location of the underlying stock. On average, we find that the domestic-listed USFs whose underlying stocks are trading in domestic markets contribute more to the price discovery process compared to the cross-listed USFs who make only a small contribution to the information aggregation process. That is, to the extent that some new information in fact comes from the foreign-listed USFs markets, their contributions to price discovery process are, at best, marginal (i.e., the "international" price discovery is not pronounced). This result is consistent with the previous evidence presented in the cross-listed stock / index futures literature which show that home markets are still more conductive to information incorporation, despite the recent globalisation of the international financial markets.

Market Maturity Effects

Our price discovery analysis over the entire sample period indicates that the USF market makes a contribution to the price discovery process, though the major part of the price discovery is in fact achieved in the underlying stocks. However, many studies which have examined the price discovery functions of derivatives markets show that the information role of a new derivative contract may be dependent on its stage of development. As Merton (1995) argues, there is a "learning curve" associated with any financial innovations and their initial introduction period will only serve as a learning period for traders to become familiar with the contracts and to construct the new trading strategies.[118]

As an example, Ates and Wang (2005) have recently addressed this 'market maturity' issue and examined whether the development stages of the U.S. E-mini index futures have influenced the price discovery roles of these new futures markets. Applying both common factor weights (CFW) and information shares (IS) price discovery measures, they find that, in their introduction period, E-mini index futures' price discovery contributions are relatively low but they gradually become the "dominant" markets in the price discovery process during their maturity period.

Therefore, in this section, we extend our empirical analysis and further investigate the price discovery functions of USF markets over the different development stages. The following steps are involved in our analysis. First, the whole sample period of daily stock and USF prices is divided into two sub-periods, which are dictated by the

[118] As for the USF contracts, they provide many new trading strategies (e.g., the so-called "Relative-Strength and Pairs investing"). However, Johnson (2005) points out that even experienced traders such as mutual funds, insurance companies, and banks may find it difficult to follow such new trading strategies and might prefer to learn more about the products before investing in these new derivatives instruments.

different development stages of the market. The first period is the initial introduction period and corresponds to around the first two years of trading in 50 USF samples. The second period covers the next two years of trading (i.e., the maturity period). Second, the causality tests and price discovery analysis, along the lines set out in previous sections, are repeated and performed over the two sub-periods so as to investigate the temporal variability of the futures markets' price discovery role.[119]

Tables 3.10 and 3.11 present VECM estimates and the Granger causality Wald test statistics for the introduction (i.e. P1) and maturity (i.e. P2) periods, respectively. Tables 3.12 and 3.13 summarise the results of the four causality hypotheses and report each stock and USF common factor weights for the P1 and P2 periods. Figures 3.3 and 3.4 depict the adjustment coefficients of stock and USF for the two sub-periods. Finally, cross-sectional descriptive statistics of USF share in price discovery process (i.e., CFW Θ_F as given in formula (3.8)) are presented in Table 3.14.

Based on these empirical results, we summarise our interesting findings as follows:

(i) Same as the results from the full period analysis, the coefficient estimates on $R_{SIF,t-i}$ are positive and significant at 1% level in all cases for both sub-periods (see Tables 3.10 and 3.11). Again, the results support the use of the lagged stock index returns in our VECM models to control for the influences of systematic market-wide information in order to obtain valid inference on the relative price discovery contributions of the 'firm-specific' information in the stock and futures markets.

[119] View alternatively, we can treat the investigation of the price discovery functions of USF markets over different periods as additional supporting evidence to our results from the analysis of entire sample which enables us to rule out the possibility that the results are sensitive to the period of time examined.

(ii) Based on Table 3.12 and 3.13, we confirm the dominant role of the stock market in price discovery. As a whole, the stock markets prices contribute to 62.1% and 51.5% of price discovery in the introduction (P1) and maturity (P2) sub-periods, comparable to the 60.5% contributions in the full sample period. More importantly, as predicted by the 'market maturity' hypothesis, the information share attributable to the USF futures market appears to have increased slightly over our sample period; the average CFW of USFs has risen from 0.379 in P1 to 0.485 in P2 period. The Wilcoxon Z-test shows that this increase is statistically and economically significant. The increase in USFs' CFW becomes clearer when we compare the scatter plots of the adjustment coefficients during the two sub-periods (refer to Figures 3.3 and 3.4). As can be seen from the figures, more observations are now below the 45^0 line in P2 period than in P1, implying that stock markets have taken up more adjustments burden and futures markets contribute more to price discovery process in P2 period.

(iii) Based on Table 3.14, we observe that, when the CFW figures from Table 3.12 and 3.13 are broken down by country groups, most of the European USFs have experienced an increase in their price discovery role although the majority of these increases are not statistically significant as indicated by the results of Z-tests (with an exception of USFs trading on German underlying stocks). The inspection on the magnitude of mean CFW values for each USF group does not support the hypothesis that overall increase is only driven by the large increases of German USFs' shares.[120] While most USFs have enjoyed an increase in their information role, the average price discovery contributions of the 10 domestic U.K. USFs decreased slightly, although this decrease is not statistically significant.

[120] In particular, the average CFW of Germany USFs has increased over 100% across two sub-periods and risen from 0.3115 in P1 period to 0.6392 in P2 period.

View collectively, the results of sub-sample and sub-period analyses are consistent with most of the previous studies and indicate that there is a large cross-sectional and time-series variation in the futures markets' price discovery contributions. Differences in the underlying stocks trading location, market structure, and market maturity are possible reasons causing these variations. However, as these results may also be driven by a set of different trading and contract design factors, any far reaching conclusions cannot be drawn at this stage. As discussed earlier, the relatively large size of our USFs sample (i.e., 50) allows us to control for these factors and explore the cross-sectional determinants of USF markets price discovery contributions in a later section.

Other possible explanations for the variation in USF price discovery contributions include the trading characteristics such as relative liquidity and trading costs, futures contract designs, and information types and contents. For example, our findings that information role of USF futures markets has increased over time may be related to the fact that between the two sub-periods we examined, the trading volume of USFs markets has increased substantially. To examine the influences on the proportion of information that is incorporated via futures markets, further investigation is required.

3.4.2.5 Robustness Tests

In order to investigate the sensitivity of our results to empirical design choices, we conduct several robustness checks in this section. Specifically, we consider the implications of the following specifications: (i) allowing an unrestricted and a fully identified long-run matrix, $\beta' = (1, \beta_1, \beta_2)$, in our vector error-correction model (VECM), and (ii) including the effect of the market-wide information in the price discovery analysis.

Unrestricted VECM

In our main analysis, the price discovery measures of USFs (i.e., $CFW\Theta_F$) are computed from the estimated adjustment coefficients of an restricted VECM (3.5a) and (3.5b) where we restricted the cointegrating vector to be of $\beta' = (1, 0, -1)$ form implying that the lagged basis ($B_{t-1} = S_{t-1} - F_{t-1}$; i.e., the difference between stock and futures prices) reflects the error correction term (ECT) in the cointegrated stock-futures prices system. Although we have formally tested and verified this restriction using the testing procedure developed by Johansen and Juselius (1990), a number of recent studies show that the basis spread ($S_{t-1} - F_{t-1}$) may not be a good proxy for the long-run relationship between stock and futures prices because it ignores most of the carrying charges (see the appendix A of Zhong et al. (2004) for a formal proof). Therefore, it is important to test the sensitivity of our prices discovery measures to the different specifications of the stock-futures cointegrating relationship. To accomplish this objective, we re-run the VECM (3.5a) and (3.5b) allowing the ECT to be an unrestricted and a fully identified long-run matrix, $\beta' = (1, \beta_1, \beta_2)$ (i.e., to let the data to estimate the 'true' values of β_1 and β_2 so as to identify the exact long-run relationship between stock and futures).

Tables 3.15 presents the full VECM estimates, the β_1 and β_2 estimates, as well as the Granger causality test statistics for our entire sample over the full period. The results of the four causality hypotheses and the computed CFW measures are summarised in Table 3.16. Figure 3.5 depicts the adjustment coefficients estimated from the unrestricted version of VECM. Finally, cross-sectional descriptive statistics of USF share in price discovery are presented in Table 3.17.

Inspections of these tables and figure do not indicate any qualitative change in the results. Specifically, although there appears to have been a small increase in the USF price discovery level compared to the restricted model, as a whole, the stock (USF) markets prices contribute to 56.7% (43.3%) of price discovery, which is directly comparable to the 60.5% (39.5%) contributions computed in the restricted model. Cross-sectional descriptive statistics on the estimated cointegrating vectors in Table 3.17 show that the average estimates of the elements of the cointegrating vector are close to the form $\beta' = (1, 0, -1)$. We find that the median values of β_1 and β_2 are equal to -0.0185 and -0.9952 respectively.[121] This finding lends further support to our application of the restrictions $\beta_1 = 0$ and $\beta_2 = -1$ in the equations (3.5a) and (3.5b) in the main analysis. Overall, these suggest that the results from our main analysis are robust to the model specification.

Market-wide Information Effects

As the focus of this study is on the reflection of the 'firm-specific' information in stock and futures markets, we include the lagged stock index futures returns in our VECM model (3.5a) and (3.5b) so as to 'filter out' the effect of the systematic market-wide information flow. However, many previous studies argue that the price discovery ability of a futures market may depend on information types; that is, a futures market tends to contribute more in price discovery process in relation to the 'market-wide' information (see, for example, Chan, 1992; Crain and Lee, 1995; and Frino et al., 2000).

---

[121] Note that, in our previous cointegration tests, we conduct restriction tests on the Johansen's estimates of these two coefficients and find slightly different median values. In particular, we find that the median value of β_1 equals to -0.01331, and median β_2 equal -0.99716. This small discrepancy is not surprising as the Johansen cointegration method uses ML technique to simultaneously estimate all the VECM coefficients whereas in this study we adopt the OLS approach to estimate each VECM equation separately. A second differentiating factor may be the inclusion of lagged stock index returns in our bivariate vector error-correction model.

To allow for this possible variation, and to further assess the issue of whether (and to what extent) the USF markets contribute in aggregating the market-wide information, we re-estimate the VECM equations (3.5a) and (3.5b) *excluding* the lagged stock index futures returns, SIF_{t-1}. In general, results are very similar to those with SIF_{t-1}. Detailed estimation results of this new model specification are presented in Table 3.18. The results of the four causality hypotheses and the computed CFW measures are both summarised in Table 3.19. Figure 3.6 depicts the adjustment coefficients estimated from this new version of VECM. Finally, cross-sectional descriptive statistics of USF share in price discovery are presented in Table 3.20.

Various points can be made. First, opposite to the findings of the current literature which examine the stock index futures price discovery role, we find that the single stock futures markets such as USFs are less able to incorporate the systematic market-wide information when compared to their stocks counterpart. In our previous main analysis, the results show that the USF prices account for 39.5% of price discovery in firm-specific information. However, regarding the market-wide information type, they can only share 28.4% of total price discovery. This is confirmed by the results presented in Wilcoxon Z-test which show that the difference we find in USFs price discovery ability is highly significant. Second, the difference in USFs price discovery role becomes even clearer if we look at Figure 3.6 and compare it with the scatter plot in Figure 3.2. As can be seen clearly from the Figure 3.6, more observations are now above the 45^0 line, implying that USF have taken up more adjustments burden and stock markets contribute more to price discovery in respect to the market-wide information. These results imply that the information role of USF contracts vary considerably depending on whether the information is market-wide or firm-specific.

3.4.3 Cross-sectional Determinants of Price Discovery Process

The results from previous sections clearly reject the null hypothesis that the price discovery contribution attributable to futures markets is equal across all the firms in our sample. They vary considerably through time and across firm or market. Consequently, in this section, we perform a set of OLS cross-sectional regressions in order to identify the factors affecting the level of USFs price discovery contributions. In the current literature, there is scare direct evidence on the factors influencing the price discovery ability of the derivatives contracts, and only a limited number of studies have examined whether the informativeness of the derivative markets is related to contemporaneous market conditions such as liquidity, trading costs and volatility.

A notable example is the recent empirical work of Chakravarty et al. (2004) who used a sample of 60 stocks with traded options to investigate the determinants of the information shares of U.S. equity options market. They find that option market price discovery is cross-sectionally related to trading volume and spreads in both markets, and stock volatility. However, to our knowledge, studies that explicitly examine this relationship for the Single Stock Futures (SSF) markets are virtually nonexistent, perhaps due to their lack of trading history and the unavailability of data.

What determines the contributions of the USF market to the price discovery process? This is the principal question we wish to address in this section. Our empirical results are particularly important as they could provide policy makers important insights on the importance of several factors in new contract designs and market structure revisions which can enhance information dissemination process in the market.

Most previous studies were unable to address this important issue because in order to do so with any degree of confidence requires a fairly large sample. The relatively large size of our sample, 50 USFs in total, enables us to explore the cross-sectional determinants of futures market price discovery contributions.

3.4.3.1 Graphical Illustration

Before performing the formal cross-sectional regression analysis, it would be useful to see visually whether the informativeness of USFs markets is related to the observable market variables, such as the trading volume and spread. Therefore, we sorted the estimated price discovery contributions (i.e., the CFW Θ_F in Table 3.7) for 50 USFs by (i) trading volume, and (ii) effective spread, in an ascending order. Figure 3.7 and Figure 3.8 illustrate the results for USFs sorted by trading volume and spread, respectively. Inspecting these two figures, it appears that the common factor weights of USFs (CFW) are positively related to the trading volume, but negatively related to the trading costs in futures markets (as proxied by the effective spread).[122] This is corroborated by a correlation analysis. In particular, the correlation between the CFW (Θ_F) and the average daily trading volume is 0.396, and is -0.304 for the effective spread. Both coefficients are significantly different from zero at 5% level. On the basis of these, it seems to suggest that the level of price discovery in USF market may be affected by both the liquidity and transaction cost of the markets.

3.4.3.2 Cross-sectional Analysis

In order to obtain more detailed insights into the cross-sectional determinants of USF price discovery contributions, we perform a set of OLS cross-sectional regressions.

[122] Figure 3.9 and Figure 3.10 visualize the relationships between CFW and the relative trading volume and spread ratio in both stock and USF markets. Patterns are similar to the one observed in Figure 3.7 and Figure 3.8.

Our testing framework is similar to that of Chakravarty et al. (2004). However, their results for U.S. option markets may not hold for the futures markets such as USFs because of the fundamental differences of these two types of derivatives products. Hence, one by-product of the results from this section is to shed light on this issue. First, we define the dependent variable that is used in the cross-sectional regressions. We then discuss our explanatory variables and the associated hypotheses, followed by the summary statistics of explanatory variables and regression results. Finally, to investigate the sensitivity of our results, we also conduct several robustness checks.

A. Dependent Variable

Our dependent variable is the logistic transformation of the USF market contribution to price discovery, $\ln[\Theta_F/(1-\Theta_F)]$, where Θ_F is directly extracted from Table 3.7. The logistic transformation ensures that the predicted regression values lie between zero and one, which by definition are the bounds of the price discovery contribution. Chakravarty et al. (2004) apply this transformation technique to their dependent variable when analysing the determinants of price discovery in U.S. option markets. Eun and Sabherwal (2003) also employ this method to examine the factors influencing the contribution of NYSE stock price to the cross-listed Canadian stocks.

B. Explanatory Variables

There are many variables that may have explanatory power for USFs' factor weights. Our main explanatory variables are identified by the previous literature and reflect the most influential market characteristic/contract design factors in the price discovery function of these markets. In this study we test not only the relative trading characteristics used by Chakravarty et al. (2004) to explain the information shares of U.S. equity options, but also for the factors relating to the USF contracts design features, such as the contract size, which have been identified by earlier work. Additionally, we also include a list of control variables (market maturity and trading location) which may have an impact on the price discovery process, as suggested by the results of our previous analysis. These explanatory variables are discussed below.

B.1. Relative Trading Characteristics:

I. USF Share of Trading Volume

To the extent that information is incorporated into prices through trading, we would expect to see a positive relation between the amount of price discovery in futures markets and the relative trading volume in both futures and its stock markets.[123] Many previous studies show that, when an asset or several related assets are traded on multiple markets, the market with the larger market share contributed more to the price discovery process. For example, Stephan and Whaley (1990) examine the relations between intraday price change and trading volume in the stock and options market. Their findings suggest that price discovery and trading activity are positively related. More recently, Chakravarty et al. (2004) also confirm this positive relationship in the U.S. stock and options markets. In another study of the NYSE contribution to price discovery relative to the regional exchanges for 30 Dow Jones stocks, Hasbrouck (1995) finds a positive and significant correlation between the NYSE contribution to price discovery and its market share by trading volume. Therefore, we use the ratio of USF trading volume to stock volume *(VolumeRatio)* as an explanatory variable. Given the results of these and other similar studies, we expect that the coefficient of our variable *VolumeRatio* will be positive and statistically significant.

[123] Indeed, trading volume has been widely used as a measure of the rate of information arrival. This relationship is consistent with earlier work of Clark (1973), Copeland (1976), and Karpoff (1987).

II. Relative Trading Costs in USF and Stock Markets

According to the market microstructure models, new information becomes impounded in prices largely because of trading of informed traders (Easley and O'Hara, 1987). As profit is reduced by the trading costs, informed traders have an incentive to trade in the market with the lowest costs to maximise the value of their information. Therefore, all else equal, lower cost markets are expected to be more informative than higher cost markets (Stephan and Whaley, 1990; and Chan, 1992). This is also consistent with earlier studies relating price discovery to trading costs. For example, Fleming et al. (1996) suggest that trading cost is the major factor explaining relative rates of price discovery in stocks, futures and option markets, and price discovery will occur in the market with lowest cost since the informed traders choose to trade in that market. DeB Harris et al. (2002) arrive at the same conclusion on the basis of their analysis of 30 Dow Jones stocks. Bid-ask spread is one of the common measures of trading cost, and narrower spread implies lower trading costs. We therefore include the ratio of effective USF spread to effective stock spread *(SpreadRatio)* as another right-hand-side (RHS) variable.[124] Since traders prefer to trade in lower cost markets, it is expected that the coefficient of *SpreadRatio* will be negatively related to USF price discovery.[125]

III. Relative Trading Frequency of USF and Stock Markets

As discussed before, we expect the contribution of USF market to price discovery to be positively related to its share in total trading volume. Another reason to expect the above relationship is that the markets have more trading activity, and therefore greater liquidity may aid the anonymity of traders. Since the ability of informed

[124] Roll's (1984) measure is used to calculate the effective bid-ask spread of each market. The formula is equal to $S_i = 2\sqrt{-\operatorname{cov}(r_i, r_{i-1})}$, where r_i is the daily return of market i. Anand and Karagozoglu (2006) provide for a performance comparison of various bid-ask spread estimators in futures market.

[125] However, it should be noted that if market makers set wider spreads in fear of informed trading, this might induce a positive relationship between our variable *SpreadRatio* and USF price discovery.

traders to hide their trades is important to them, the market preference of informed traders is likely to be a function of the relative market depths in both markets.[126] Therefore, as an alternative measure to market liquidity, we add the ratio of USF trading frequency to stock trading frequency *(TradeFrequency)* as an additional explanatory variable.[127]As price discovery occurs in more liquid and frequently traded market, we expect the coefficient of *TradeFrequency* to be positive and significant.

IV. Volatility of Underlying Stock Markets

The price discovery role of a futures market may also be influenced by the volatility in the underlying stock market. Intuitively, higher stock volatility indicates higher level of uncertainty in the underlying market, and hence increases their demand for hedging, which would suggest that more trading activity, and therefore price discovery, will occur in the USF market whose underlying stocks are more volatile.[128] However, Chakravarty et al. (2004) provide evidence inconsistent with the above argument and show that less price discovery occurs in the option market when the level of uncertainty is high. In the distinct but related research, it has also been suggested that E-mini index futures contribute relatively lower information share in high volatility periods (see, e.g., Martens, 1998; Ates and Wang, 2005). Thus, we expect the price discovery in USF market relative to stock market to be affected by the underlying stock volatility level. We capture this effect by including a

[126] Harris (2003, p.243) states "How informative prices are depends on the costs of acquiring information and on how much liquidity is available to informed traders. If information is expensive, or the market is not liquid, prices will not be very informative." The positive relation between price informativeness and liquidity is supported by Admati and Pfleiderer (1988) or Hong and Rady (2002).
[127] Aitken and Comerton-Forde (2003) provide a detailed comparison on a range of measures for market liquidity. They compared the trade-based and order-based measures and concluded that order-based measures provide a better proxy for liquidity. However, there is no direct order data available for our study. Therefore, we used trade frequency as an alternative proxy for market liquidity.
[128] For example, the empirical results of Chang et al. (2000) suggest that increases in stock market volatility increase the demand for hedging in S&P 500 index futures market.

variable, *Volatility*, which is the standard deviation of daily stock return. It is expect that the coefficient of *Volatility* could be either positive or negative.

B.2. Contract Design/Features: Contract Size

In addition to the relative trading characteristics of stocks and USF markets, we also include a variable which reflects the contract feature of USF. In designing a new derivative security, exchanges carefully consider how its attributes (such as method of settlement, contract size, and minimum price increment (i.e., tick size)) affect different investors' accessibility, and hence the success/failure of the new contract. From a practical standpoint, the primary objective of an exchange is to identify the optimal combination of contract attributes that will maximize the operational and informational efficiency of these new markets, and thus provide more conductive conditions for the price discovery process (see, for example, Bollen et al., 2003).[129]

Since the launch of trading in January 2001, LIFFE has defined each USF contract as representing 100 shares of the underlying stocks, except contracts written on UK and Italian based stocks which represent 1000 stocks. The primary argument supporting a smaller contract size is investor accessibility. Specifically, it is believed that the smaller contract can reach out to more traders, especially the small investors. However, since trading costs such as brokerage commissions and exchange fees are usually quoted on 'per contract' basis, small contract size means higher trading costs. Consequently, these higher trading costs have potential of curtailing trading demand. Hence, we expect larger-sized USF contracts to play a larger role in price discovery. To capture this possible effect, we include a dummy variable, *ContractSize*, which take a value of one for the U.K. and Italian USFs and zero for the other contracts.

[129] Ates and Wang (2005) provide evidence consistent with the argument that the operational efficiency and liquidity will both affect the rate of price discovery in the futures markets.

Our null hypothesis is that the coefficient of *ContractSize* is positive and statistically significant.[130]

B.3. Control Variables

Apart from the factors identified above relating to the trading characteristics of USF markets relative to stock markets and futures contracts features, we additionally include a list of control variables which may have an impact on the relative contribution of each USF to the price discovery process.

I. Market Maturity

Since our 50 sample USFs have been listed over a range of introduction dates, each regression controls for the development stages of the USF trading by a variable, *MonthsListed,* which is measured as the number of months for which a USF has been listed in the LIFFE through December 30, 2005. We expected a positive relation between *MonthsListed* and the level of price discovery in futures markets, because as founded by the results of previous sections, more mature market tends to contributes more to the price discovery process. One of the possible reasons is increased investors' familiarity and accessibility to such futures contracts over time.

II. Country of Origin

In addition, we controls for the trading location of the underlying stocks by including a dummy variable, *HomeMarket*, which equals 1 for British USFs and 0 for the 'cross-border' European USFs. There may be, on average, higher contribution from the domestic-listed U.K. USFs to pricing of British stocks, because of higher cultural, language and regulatory proximity, which are found to be important

[130] This prediction is also consistent with our earlier results relating the variations of USF price discovery functions to the countries in which their underlying stocks are traded (see Table 3.8).

determinants in explaining the different price discovery ability of the cross-listed versus domestic-listed financial securities (see Table 3.9).

C. Summary Statistics of the Explanatory Variables

Table 3.21 presents descriptive statistics and correlation coefficients between independent variables of our cross-sectional regressions. They provide further insight into our sample and the relative trading characteristics in the stock and USF markets. The findings suggest that, on average, futures markets are associated with lower trading activity and are less frequently traded as compared to its underlying stocks. Specifically, the median values of the *VolumeRatio* and *TradeFrequency* are 0.4350 and 0.4615 respectively, implying that USFs are far less actively traded than stocks. One reason for this might be the associated higher transaction costs on futures markets. In general, USFs markets suffer from wider spreads, as the mean *SpreadRatio* is greater than one and equal to 1.1351. Also, Table 3.21 shows that USF stocks are not particularly volatile with an average standard deviation of 0.0225.

We find a strong positive correlation between the *VolumeRatio* and *TradeFrequency*, which is not surprising, as one can expect that the market with higher trading activity tends to be the more frequently traded market. However, inconsistent with previous studies examining volume and volatility relationship, we document an inverse relationship between these two variables, presumably because our variable *VolumeRatio* measures the relative trading volume in both markets.[131]

From a technical point of view, high correlation between explanatory variables may lead to multicollinearity when correlated variables are jointly included in regressions.

[131] The relationship between volume and volatility has received much attention in the literature. Studies from a number of different market settings suggest that there is a positive relationship volatility and volume (see, for instance, Karpoff, 1987).

In our sample, we find *VolumeRatio* is correlated with both *TradeFrequency* and *Volatility* with the correlation coefficients of 0.3219 and -0.2147, respectively. Consequently, we run a set of regressions including these main variables separately.

D. Regression Models and Results

As explained earlier, in order to avoid multicollinearity we do not include our main explanatory variables at the same time but rather estimate five separate models. Specifically, the following cross-sectional regressions are estimated one by one:[132]

$$\ln[\Theta_{F,i}/(1-\Theta_{F,i})] = \alpha_0 + \alpha_1 MonthListed_i + \alpha_2 HomeMarket_i + \alpha_3 VolumeRatio_i + \varepsilon_i \quad (1)$$

$$\ln[\Theta_{F,i}/(1-\Theta_{F,i})] = \beta_0 + \beta_1 MonthListed_i + \beta_2 HomeMarket_i + \beta_3 TradeFrequency_i + \nu_i \quad (2)$$

$$\ln[\Theta_{F,i}/(1-\Theta_{F,i})] = \phi_0 + \phi_1 MonthListed_i + \phi_2 HomeMarket_i + \phi_3 SpreadRatio_i + \eta_i \quad (3)$$

$$\ln[\Theta_{F,i}/(1-\Theta_{F,i})] = \gamma_0 + \gamma_1 MonthListed_i + \gamma_2 HomeMarket_i + \gamma_3 Volatility_i + \xi_i \quad (4)$$

$$\ln[\Theta_{F,i}/(1-\Theta_{F,i})] = \lambda_0 + \lambda_1 MonthListed_i + \lambda_2 HomeMarket_i + \lambda_3 ContractSize_i + \omega_i \quad (5)$$

where: $\ln[\Theta_{F,i}/(1-\Theta_{F,i})]$ is logistic transformation of USF_i price discovery contribution; $MonthListed_i$ is a control variable measured as the number of months for which a USF has been listed; $HomeMarket_i$ is a dummy variable equal 1 for U.K. USFs, and 0 for the "cross-border" European USFs; $VolumeRatio_i$ is the ratio of each paired markets trading volume; $TradeFrequency_i$ is the ratio of each paired markets trading days; $SpreadRatio_i$ is the ratio of effective spread of each pair markets; $Volatility_i$ is measured as the standard deviation daily stock returns; $ContractSize_i$ is a dummy variable equal 1 for U.K and Italian USFs, and 0 for other smaller-sized contracts which only represent 100 underlying stocks.

[132] Ates and Wang (2005) used similar regressions to examine the time-series determinants of E-mini index futures contribution to price discovery process. Chakravarty et al. (2004) also used a similar approach to examine the determinants of the information shares in the U.S. options market.

Ordinary Lest Squares (OLS) is used to estimate the parameters of models (1) to (5). In addition, we use the Newey and West's (1987) procedure to calculate the consistent standard errors (and the associated t-statistics) of the regression parameter estimates in order to adjust for the serially correlated and/or heteroskedastic error process.

The estimated coefficients of a set of OLS cross-sectional regressions are reported in columns 3 through 7 of Table 3.22. In all five specifications, we control for both market maturity effect and country effect, as indicated by our findings from the previous sub-periods and sub-samples analysis. In general, we find evidence that price discovery in the USF market is related to the relative trading volume and bid-ask spreads in the stock and futures markets, which is consistent with findings in Chakravarty et al. (2004) for the option markets.

In model (1), the coefficient of $VolumeRatio_i$ is positive and statistically significant at the 1% level, implying that the higher the volume of trading in the USF in relation to stock, the greater proportion of total price discovery that occurs in the futures market. In model (2), we included only the $TradeFrequency_i$ but found it to be statistically insignificant indicating that the ratio of each market trading days does not provide explanatory power on the variation in USF price discovery contributions. The coefficient of $SpreadRatio_i$ in model (3) is highly significant and has a priori expected negative sign, which is consistent with the argument that the USF market with relatively lower transaction costs induce a greater competitive threat to its underlying stock, attracting more informed trading in futures market, and consequently more price discovery. This result supports the trading cost hypothesis of Fleming et al. (1996) which suggests that the lower trading costs are more conductive to price discovery. We then explored the effect of stock volatility on price discovery process by estimating model (4). We find that the coefficient of variable $Volatility_i$ as measured by the standard deviation of daily stock return during the sample period, is negative but statistically insignificant, implying that USFs price discovery contributions are not directly related to their underlying stocks volatility.

Finally, we find support to our conjecture that price discovery of a USF contract is affected by not only the relative trading characteristics of stocks and futures markets, but also the contract feature of USFs. The coefficient of $ContractSize_i$ in model (5) is positive and statistically significant, indicating that the larger size of USF contract, the greater the price discovery in the futures markets.[133] This is consistent with the results of Bollen et al. (2003) who analyse the impact of futures contract splits on the market liquidity, transaction costs, and other market dynamics. They find the reduction in the size of S&P 500 futures contract results in lower trading volume and wider bid-ask spread, implying that smaller future contracts are less favourable for informed trading and consequently futures trading become less informative.

Across all five regression models, the estimated coefficients of our control variables, $HomeMarket_i$ and $MonthListed_i$, have priori expected positive signs. However, the coefficient of $HomeMarket_i$ dummies are marginally significant in only two models, and $MonthListed_i$ are insignificant across all models which indicates that, after controlling for the relative trading characteristics in both markets, the underlying stocks trading location and market maturity tend not to impact USF price discovery contribution, contrasting to our earlier sub-sample/sub-period results.

[133] However, it is noted that the direct interpretation on the magnitude of estimated coefficients is difficult because we use the logistic transformation of the USF share in price discovery as the dependent variable (see Eun and Sabherwal, 2003).

Taken together, our analysis of the cross-sectional determinants of USF contributions to price discovery reveals that, first, the variables measuring relative market quality such as the ratios of trading volume and bid-ask spread are major determinants of the degree of USF price contribution across firms, and that, second, the price discovery role of futures are more pronounced for larger-sized U.K. and Italian USF contracts.

E. Robustness Tests

To investigate the sensitivity of our cross-sectional regressions results, we conduct several robustness checks. We first see if any outlier extremes are driving the results. Using the Cook's distance diagnostic, we identify two outliers in our dependent variable $\ln[\Theta_F/(1-\Theta_F)]$ and re-run the regressions (1) to (5) without these outliers.[134] The results of these regressions are presented in Table 3.23. As can be seen from this table, there are hardly any changes to either the sign or the statistical significance of the coefficients. For example, $VolumeRatio_i$ and $ContractSize_i$ coefficients both remain positive and significant at the 1% level, and the coefficient on the ratio of effective spreads, $SpreadRatio_i$, is still negative and statistically significant.

We also do not find any change in results when we exclude the USF contract written on ENI which has a very high relative trading volume relative to its underlying stock. We confirm that USF market contribution to price discovery is positively related to its contract size and the ratio of trading in USF relative to stock markets, and inversely related to the ratio of spreads in futures and stock markets (see Table 3.24).

[134] Cook's distance is a metric for deciding whether a particular point alone affects regression estimates much. After a regression is run one can consider for each data point how far it is from the means of the independent variables and the dependent variable. If it is far from the means of the independent variables it may be very influential and one can consider whether the regression results are similar without it (see, http://economics.about.com/od/economicsglossary/index.htm).

To ensure that our results are not driven by any possible industry effects, we also estimate the models with industry dummies.[135] The estimated coefficients on industry dummies are reported in Table 3.25 and found to be statistically insignificant, except *Services* and *Financial*, possibly caused by the predominance of our USF samples written on stocks in these two industries. The main results remain unaffected.

In our main regressions, we used the logistic transformation of the measures on the contribution to price discovery (i.e., $\ln[\Theta_{F,i}/(1-\Theta_{F,i})]$) as our dependent variable. To check whether our cross-sectional findings are robust to this empirical choice, we also estimated a separate set of regressions using a Tobit model with the 'nontransformed' $\Theta_{F,i}$ as the dependent variable and applied zero and one as the left and right censoring points, respectively. The results presented in Table 3.26 show that our main findings on the importance of the relative trading volume of USF and stock markets, the ratio of spreads in two markets, and futures contract size in explaining the variation in USF price discovery contributions continue to hold.

To further understand the direct impact of USF volume, stock volume, USF trading frequency, stock trading frequency, USF spread, and stock spread on the futures market price discovery contributions, we follow the approach of Chakravarty et al. (2004) and repeat our cross-sectional analysis using an alternative specification in which the USF volume, stock volume, USF trade frequency, stock trade frequency, USF spread, and stock spread all enter the regression equations as separate variables. Due to multicollinearity, they are included in regression one by one (see Table 3.27). The results for this new specification are reported in Table 3.28. The coefficient on

[135] We classify 50 USFs in six industry groups, according to the industry sectors of their underlying stocks. *Resources, Services, ConsumerGoods, Technology*, and *Financial* are dummies corresponding to five of these groups. The sixth industry group includes 2 USFs based on stocks in General industry.

the USF (stock) volume is positive (negative) and the coefficient on the USF (stock) effective spread is negative (positive), implying that more price discovery occurs in the futures market when USF volume is higher and stock volume is lower. and when USF effective spreads are narrower and stock effective spreads are wider. This is generally consistent with the results of our main regressions that USF contribution to price discovery is positively related to the ratio of trading in USF relative to stock markets, and inversely related to the ratio of spreads in futures and stock markets.

3.4.4 Multivariate GARCH Model and Volatility Spillovers

In previous sections, we have applied the Granger causality tests and the Granger-Gonzalo price discovery technique within the VECM framework to identify the lead-lag relationship and price discovery process between stock and USF markets. Overall, the evidence from these analyses suggests that there is a bi-directional Granger causality between stock and futures markets. However, when the price relationship deviates away from the long-run equilibrium, it depends on futures markets to make most of the adjustments to return it back to equilibrium level. Consequently, stock markets tend to play a more important role in price discovery.

However, as mentioned before, another important aspect of price discovery is the volatility-spillovers. Intuitively, if information in fact arrives first in the stock market, one should expect to see volatility spillover from the stock to futures market. Therefore, in order to gain a more thorough understanding of the information transmission mechanism between stock and futures markets, we extend the above VECM analyses and explicitly model the ways in which these two markets interact through their second moments by using a bivariate asymmetric GARCH-X model.

Understanding the volatility-spillovers process is important as it has significant implications concerning the information transmission mechanism between markets. As shown by Ross (1989), the variance of price changes (not the price change itself) is related directly to the rate of information flow. French and Roll (1986) compare the volatility of NYSE stocks during trading period with those of non-trading period. They find greater return variances during trading than non-trading periods and conclude that the flow of information during trading period causes greater volatility. Cheung and Ng (1996) point out that volatility change is a process of reflecting the arrivals of new information and how the market evaluates and assimilates the information. Booth et al. (1997) find that the causal relationships between price volatilities can provide keen implications of asset price dynamics. The results of these studies imply that another useful way to gauge the informational flow between assets / markets is to look at how volatility in one market is affected by the other. In addition, examination of volatility-spillovers dynamics between stock and futures markets is also pertinent to the perceived destabilising effects of futures trading, and could shed light on the relative informational efficiency across these two markets.

Many studies (see, e.g., Chan et al.,1991; Koutmos and Tucker, 1996; and Tse,1999) have examined volatility spillovers between the stock index and its futures markets. However, while this has been recognised as an important issue, to our knowledge this is the first study to directly examine the higher moment dependences between futures and stock markets at the individual stock level. To this end, the primary objective of this section is to fill this gap in the literature and investigate the information transmission mechanism between the stock and USF markets by examining the volatility-spillover process between the two markets. Specifically, using a bivariate asymmetric GARCH-X model, the following questions are addressed in this section:

1. Are the stock and USF markets linked through their second moments? In other words, is volatility of each market influenced by the developments in the other market?

2. Is this influence asymmetric in the sense that bad news and good news in one market exert an asymmetric impact on the other market's volatility? That is, whether USF price discovery role is asymmetric across the rising and falling markets?

3.4.4.1 Multivariate Asymmetric GARCH Model

It has been well recognised that the variance of asset returns and the covariance among different asset returns are varying over time. To account for this statistical property, multivariate GARCH models are widely adopted to describe the dynamic behaviour of variance of spot and futures return and the covariance between them.[136] Different model specifications and restrictions on the conditional variance-covariance matrix in the multivariate GARCH model have been introduced to overcome the computational difficulty and to ensure a positive definite variance-covariance matrix. For example, there are the VECH model of Bollerslev et al. (1988), the CCORR model of Bollerslev (1990), the BEKK model of Engle and Kroner (1995), the ADC model of Kroner and Ng (1998), and the DCC model of Engle (2002). Each model has advantages and shortcomings, and may fit into one set of data better than others.[137]

---

[136] Chan et al. (1991), Koutmos and Tucker (1996), Tse (1999), So and Tse (2004), and Fung et al. (2005), to name but a few. However, most of these assume that the conditional correlation between spot and futures returns is constant through time. Although this assumption is implied in the cost-of-carry model and can overcome the computational difficulty, it is often rejected by the data (see, for instance, Tse and Tsui, 2002).

[137] See Kroner and Ng (1998) and Bauwens et al. (2006) for the comprehensive reviews of many widely used multivariate GARCH models.

In order to answer the two research questions that we identified above, an *extended* version of the bivariate BEKK GARCH model proposed by Engle and Kroner (1995) is used to describe the joint distribution of the stock and USF returns. The model that governs joint process is presented below. Specifically, assuming $\varepsilon_t = \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix}$ to be conditionally normally distributed, i.e., $\varepsilon_t \backslash \Omega_t \, \square \, N(0, H_t)$, with mean zero and time varying variance-covariance matrix, $H_t = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix}$, the time-series evolution of H_t, is assumed to follow a asymmetric BEKK GARCH (1,1)-X process:

$$H_t = C_0 C_0' + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} + D_{11}' \xi_{t-1} \xi_{t-1}' D_{11} + E_{11} (Z_{t-1})^2 E_{11}' \tag{3.9}$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$;

and, $\xi_t = \begin{bmatrix} \xi_{S,t} \\ \xi_{F,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{S,t}, 0\} \\ \min\{\varepsilon_{F,t}, 0\} \end{bmatrix}$; $Z_t = (P_{S,t} - P_{F,t})$.

The innovations ε_t are the unautocorrelated residuals obtained from our previous VECM in equations (3.5a) and (3.5b); Ω_t is the information set at time t; we specify market 1 to be the stock, market 2 to be the futures. In this specification, it is important to note that there are two variance equations and one covariance equation, with a total of 18 parameters in the conditional variance-covariance system, H_t.[138]

[138] This is perhaps the most general form of the multivariate GARCH class of models and is very popular in the academic literature. For example, Brooks and Henry (2000), Brooks et al. (2002), and Henry and McKenzie (2006) have all used a similar model. The advantage of this specification is that it allows interaction of conditional variances and covariance of two return series, therefore enable us to test the null hypothesis that there is no causality effect in either direction. In addition, the model guarantees by construction that the covariance matrices are positive definite. One more advantage of this specification is that a "leverage" term can be easily introduced in a similar fashion to the univariate asymmetric GARCH model proposed by Glosten et al. (1993).

There are some differences in our *extended* version of BEKK GARCH (1.1) model (3.9) with the original BEKK GARCH specification of the Engle and Kroner (1995). The two main differences are: (i) the asymmetry term, $D_{11}^{'}\xi_{t-1}\xi_{t-1}^{'}D_{11}$ (where $\xi_{i,t} = \min\{\varepsilon_{i,t}, 0\}$, for i = stock and USF); and (ii) the exogenous term, $E_{11}(Z_{t-1})^2 E_{11}^{'}$ where $(Z_{t-1})^2$ is the lagged squared basis, $(P_{S,t-1} - P_{F,t-1})^2$ with the parameter matrix E_{11} restricted to be lower triangular, similar in construction to the constant matrix C_0.[139] By including the asymmetry term, $D_{11}^{'}\xi_{t-1}\xi_{t-1}^{'}D_{11}$, we explicitly allow for potential asymmetries that may exist in the volatility transmission mechanism between markets; that is the possibility that bad news (negative innovations) in one market increase volatility in another market more than the good news (positive innovations). The idea that the covariance matrix may be asymmetric is not new. It is a common finding in finance literature that "bad news" about stock return (negative innovation) raises the conditional variance by more than the equally sized "good news" does.[140]

Directly related to futures markets, Chatrath et al. (2002) and Hodgson et al. (2003) confirm the conclusion of earlier studies that new information is incorporated with greater speed in stock index futures prices. However, they have also documented that the stock index futures leadership is asymmetric across the rising and falling markets. On one hand, Chatrath et al. (2002) demonstrate futures informational domination stands out more clearly in rising markets. On the other hand, Hodgson et al. (2003) uncover evidence of pronounced futures leadership in falling markets. Differences in

---

[139] It should be note that the original symmetric model of Engle and Kroner (1995) is given as a special case of our asymmetric BEKK model (3.9) where all the elements of D_{11} and E_{11} matrices equal zero. Also, the use of the lagged squared basis specification, rather than the lagged level or the lagged absolute value, is justified by the uniformly superior results and is advocated by Lee (1994, p.377).

[140] There is a substantial body of literature which suggested that conditional volatility responds asymmetrically to news, especially at market level (see, for example, Black, 1976b; Christie, 1982; and Koutmos, 1996; among others). More recently, this phenomenon was also found to be pronounced at the individual firm level by Duffee (1995), Wu and Xiao (2002) and Blair et al. (2002).

transaction costs, short-selling restrictions, and other imperfections have been used to explain why the main source of uncertainty in the whole system comes from the futures market, especially with bad news (see Meneu and Torro, 2003). Nonetheless, no matter what cause the asymmetry, and which direction of this asymmetry goes, an allowance should be provided in our model to capture such volatility-spillover asymmetries between these two markets. This allowance also enables us to address our subsidiary research question on whether the USF price discovery contribution will vary depending on whether the information content is 'positive' or 'negative'.[141]

Our second modification to the original BEKK GARCH model is to incorporate the lagged squared basis term, $(Z_{t-1})^2$, into the variance-covariance structure as an ECT. This modification is inspired by several studies. Engle and Yoo (1987) show that the ECT, which is the short-run adjustment from the long-run cointegration relationship, has important predictive power for the conditional variances of cointegrated system. Lee (1994) applied a similar model specification to investigate the predictive power of the basis in forecasting exchange rate volatility. Lee's results suggest that the exchange rates are more volatile and more difficult to predict when the basis becomes larger. Ng and Pirrong (1994) also incorporate the squared basis as an explanatory variable into conditional variance equations to describe the behaviour of metal spot and futures prices, and argued that both the short-run deviation of spot and futures prices (i.e., basis) and shocks to both markets should affect the volatility. Bhar (2001) extends the GARCH model for the conditional variances with an ECT, and demonstrated that it helps in identifying causality in each market's variance. More recently, Zhong et al. (2004) investigate the price discovery role of the Mexico

[141] Of course, an alternative (arguably a more direct) way to address this issue is to examine the subject using disaggregated data (for instance, based on market direction). We leave this for future research.

IPC index futures contracts and found that the departure from the spot-futures prices long-run equilibrium could impact their conditional volatilities.

Based on the results of above studies, it is obvious that addition of the lagged squared basis term could provide better goodness of fits to the data, and ignoring the basis effects may result a misspecified model. Following Lee (1994) and others, we refer to our *extended* model (3.9) as the asymmetric BEKK GARCH (1,1)-X model. This model allows the conditional variance-covariance to be both time-varying and asymmetric, and also incorporate the basis effects in the variance-covariance system. It is a very general model and is perhaps the best multivariate GARCH time-varying correlation model that could be used to assess conditional volatility transmission.

3.4.4.2 Evaluating Volatility-Spillovers

The general setting of our model (3.9) allows for time-variation, asymmetry, and cross-market transmission across the entire variance and covariance matrix of stock (market 1) and futures (market 2) returns.[142] First, the own-market ARCH (GARCH) effects are captured through the main diagonal elements of the A_{11} (B_{11}) matrix, i.e.,

[142] Kroner and Ng (1998) identify three possible forms of asymmetries. Firstly, the covariance matrix displays *own-variance asymmetry* if $h_{S,t}$ ($h_{F,t}$), the conditional variance of S_t (F_t), is affected by the sign of the innovation $\varepsilon_{S,t}$ ($\varepsilon_{F,t}$). Secondly, the covariance matrix displays *cross-variance asymmetry* if the conditional variance $h_{S,t}$ ($h_{F,t}$) is affected by the sign of the innovation $\varepsilon_{F,t}$ ($\varepsilon_{S,t}$). Finally, if the conditional covariance $h_{SF,t}$ is sensitive to the sign of the innovation for either variable then the model is said to display *covariance asymmetry*. It is only through a multivariate approach that the full range of potential asymmetries can be examined (see Brooks et al., 2002).

a_{11} & a_{22} (b_{11} & b_{22}).[143] Second, the off-diagonal elements in A_{11} (B_{11}) matrix, i.e., a_{12} & a_{21} (b_{12} & b_{21}), describe the cross-market innovations (volatility) spillovers between the stock and futures markets. Finally, the main diagonal (off-diagonal) elements of D_{11} matrix, i.e., d_{11} & d_{22} (d_{12} & d_{21}), capture the own-market (cross-market) asymmetric responses to its (another) market's innovations.

Therefore, the econometric model (i.e., bivariate asymmetric BEKK GARCH (1,1)-X model) we proposed here enables us to study the information flow and volatility spillover effects between stock and USFs markets in the following three different dimensions: (i) short-run innovation spillovers, (ii) long-run volatility spillovers, and (iii) asymmetric innovation spillovers.

In our setup, two possible ways for a market to influence another market's volatility would be either through (i) short-run innovation spillovers, or (ii) long-run volatility spillovers. Of course one may individually test the short-run innovation spillovers parameters (a_{12} & a_{21}) and the long-run volatility spillovers parameters (b_{12} & b_{21}). However, in the context of the multivariate GARCH framework it is more appropriate to test the *joint* null hypotheses of no innovation and/or volatility spillover from stock to USF markets ($H_{0,1}: a_{12} = b_{12} = 0$); and the *joint* null hypotheses of no innovation and/or volatility spillover from USF to stock markets ($H_{0,2}: a_{21} = b_{21} = 0$), against the alternative of at least one coefficient being non-

[143] The effects of the error terms $\varepsilon_{S,t-1}$ / $\varepsilon_{F,t-1}$ on the conditional variance $h_{S,t}$ / $h_{F,t}$; and $h_{S,t-1}$ / $h_{F,t-1}$ on the conditional variance $h_{S,t}$ / $h_{F,t}$ are denoted as "ARCH" and "GARCH" effects, respectively.

zero.[144] Significant a_{12} (a_{21}) coupled with the significance of b_{12} (b_{21}) indicates presence innovation/volatility spillover from stock (USF) to USF (stock) markets.[145]

Similarly, to test for (iii) asymmetric innovation spillovers, it is more appropriate to test the *joint* null hypotheses of no asymmetric innovation spillover from stock to USF markets ($H_{0,3}: a_{12} = b_{12} = d_{12} = 0$); and the *joint* null hypotheses of no asymmetric innovation spillover from USF to stock markets ($H_{0,4}: a_{21} = b_{21} = d_{21} = 0$), against the alternative of at least one coefficient being non-zero. For example, significance of the d_{12} (d_{21}) coupled with the significances of a_{12} and b_{12} (a_{21} and b_{21}) implies that the volatility of stock (USF) market is affected by the developments in USF (stock) markets, especially from its bad news (i.e., negative innovations).

3.4.4.3 Estimation Details[146]

A two-step approach of Tse (1999) is used to estimate our model. The first step is to apply VECM in equations (3.5a) and (3.5b) and using the residuals of VECM in the formulation of asymmetric BEKK GARCH (1,1)-X model (3.9) in the second step. Tse mentions that, because the least squares estimator used in VECM is unbiased and consistent even with the presence of heteroscedasticity, this two-step approach is asymptotically equivalent to a joint estimation of the VECM and GARCH models.[147]

---

[144] In the BEKK GARCH parameterisation such as the one in model (3.9), the parameters a_{ij}, b_{ij}, d_{ij} cannot be interpreted on an individual basis. As Kearney and Patton (2000, p.36) argue, "Instead, the functions of the parameters which form the intercept terms and the coefficients of the lagged variance, covariance, and error terms that appear...are of interest".

[145] In these cases, the tests examine both (i) short-run innovation spillovers, and (ii) long-run volatility spillovers effects between the stock and futures markets.

[146] See Brooks et al. (2003) for a discussion on issues in estimating multivariate GARCH models.

[147] Estimating these two models simultaneously in one step is not practical due to the large number of parameters involved (So and Tse, 2004). However, this study also estimated this as a robustness test. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

Assuming the joint distribution of $\varepsilon_t = \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix}$ to be conditionally normally distributed.

i.e., $\varepsilon_t \backslash \Omega_t \sim N(0, H_t)$, the log-likelihood function $L(\theta)$ can be written as:[148]

$$L(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t)$$

where T is the number of observations; N is the number of variables in the system being estimated; and θ is the vector representing the number of estimated parameters. Since the log-likelihood function $L(\theta)$ is highly non-linear, we used numerical maximization techniques to estimate the model. In particular, we used both the simplex and the Broyden et al. (also known as BFGS, see Shanno and Phua, 1980) numerical optimization algorithms in the estimation process, along with the Quasi-maximum likelihood (QML) method of Bollerslev and Wooldridge (1992).[149]

3.4.4.4 Empirical Results

The Quasi-maximum likelihood estimates (QMLE) of our asymmetric BEKK GARCH (1,1)-X model (3.9) and the corresponding robust t-statistics are presented in Table 3.29. As mentioned before, the convention in these estimates is that subscript 1 concerns the stock market and subscript 2 represents the USF market. The coefficients relating to the volatility transfers are indicated in **bold** characters.

[148] As a robustness check, alternative estimations based on the multivariate conditional t-distribution are also carried out for our sample. Results are very similar to those estimated under the assumption of conditional normally distributed error terms. Detailed estimation results of these specifications are presented in a later 'robustness tests' section.

[149] Apart from Quasi-maximum likelihood (QML), volatility models can also be estimated by Maximum likelihood (ML), and GMM methods. For the departures from conditional normality, the QMLE is generally close to the exact MLE. See the excellent review article of Pagan (1996) for further details.

I. Volatility Dynamics

Focusing first on the parameters describing the conditional variance of each market. As discussed before, the own-market ARCH (GARCH) effects are captured through the main diagonal elements of A_{11} (B_{11}) matrix, i.e., a_{11} & a_{22} (b_{11} & b_{22}), while the main diagonal elements of D_{11} matrix, i.e., d_{11} & d_{22}, captures the *own-variance asymmetry* (see Kroner and Ng, 1998).

As can be seen from Table 3.29, the estimates of the main-diagonal elements of A_{11} and B_{11} are significant in most of the cases. The estimates indicate the presence of strong ARCH and GARCH effects in both markets. In particular, the values of a_{11} are significantly different from zero for 21 stocks (ranging from -0.4421 to 0.6450), and 78% (39 out of 50 stocks) of the b_{11} coefficient are significant (ranging from -1.3562 to 1.9844). For the USFs markets, the values of a_{22} are significantly different from zero for 28 USFs (ranging from -0.7904 to 0.8760), and 74% (37 out of 50 USFs) of the b_{22} coefficient are significant (ranging from -2.1228 to 1.2304).

These parameters of the variance equations are consistent with the stylized facts of GARCH models, i.e., the ARCH parameters (a_{11} & a_{22}) are small while the GARCH parameters (b_{11} & b_{22}) are large, suggesting that the GARCH effect dominates the ARCH effect in both stock and futures markets. As a result, both markets exhibit a high degree of persistence in the conditional volatility.

In the *own-variance asymmetry* parameters (i.e., d_{11} & d_{22}), only 32% (16 out of 50) of the estimated d_{11} coefficients are significant, and 40% (20 out of 50) of the d_{22} coefficients are significant, indicating that the volatility in most stock and futures markets do not respond asymmetrically to its own innovations, i.e., not particularly sensitive to the bad news. Our finding of weak volatility asymmetries at the individual stock level is in contrast to Duffee (1995) and Wu and Xiao (2002) who documented significant asymmetry effect in the individual stock volatility. This discrepancy in our results may be partly due to the difference in econometric model, the dataset, and/or the sample period we used. It would be worth focusing on this issue in future research.[150]

The results of the coefficients of the lagged squared basis (e_{11} & e_{22}) in the two variance equations indicate that the basis is significant and affects the volatility of the stock (futures) market in only 21 (8) cases. Most of them are insignificant, implying that the lagged squared basis $(Z_{t-1})^2$ does not assist in explaining the relationship between disequilibrium and volatility. One possible reason for this poor performance may be because the basis is restricted to be the exact spread$\left(P_{S,t} - P_{F,t}\right)$.

II. Volatility Spillovers Hypotheses Tests

From Table 3.29, there is some evidence of presence of strong ARCH and GARCH effects in the conditional variances of stock and futures markets, whereas the asymmetric responses to their own innovations are not as pronounced as some

[150] We are not aware of any published study that explicitly examines the presence of the asymmetric phenomenon on single stock futures markets. However, we feel that the examination of this issue would distract us from our main focus of this section: the cross-market volatility-spillovers effects.

previous studies have documented. However, the focus of this section is on the coefficients that govern the volatility spillovers between these two markets.

The asymmetric BEKK GARCH (1,1)-X model (3.9) produces a large number of coefficient estimates, but only the *off-diagonal* elements in A_{11} (B_{11}) matrix, describing the cross-market innovations (volatility) spillovers; and the *off-diagonal* elements of D_{11} matrix, capturing the cross-market asymmetric responses to another market's innovations, are the most important to assess volatility spillover effects. However, as explained before, they cannot be interpreted on an individual basis. Therefore, Table 3.30 summarises the hypotheses tests results based on the joint significance of these volatility spillovers coefficients.

II.1. Symmetric Volatility Spillovers

The Wald test p-values of the joint null hypothesis of no innovations and/or volatility spillovers from stock to USF markets ($H_{0,1}: a_{12} = b_{12} = 0$) are presented in the first column of Table 3.30. The results show that the null hypothesis of no Stock-to-USF spillovers is rejected for 41 out of 50 pairs at the 5% level. This suggests that the conditional variances for 82% of the USFs are affected by the developments in its underlying stock markets. To the extent that volatility spillover signals information flow in each market, such a strong Stock-to-USF spillover pattern may be explained by the dominant role of stock markets in information transmission process. However, looking further at the USF-to-Stock spillovers results presented in the second column of Table 3.30, it is evident that the news and volatility in the USF markets also have direct influence on the variance of 64% stocks: the null hypothesis of no USF-to-Stock spillovers ($H_{0,2}: a_{21} = b_{21} = 0$) is rejected for 32 out of 50 pairs.

Therefore, the overall results suggest a bi-directional volatility spillover between the stock and futures markets with a stronger effect from the stock to the futures markets. These results are consistent with the results of our previous lead-lag relationship and price discovery analyses; that is, the stock market contributes more in the price discovery process, while the contribution of the futures market is not unimportant. The finding of greater impact of information flows in terms of volatility from stock market to USF market is not surprising because of the fact that USFs contracts are only newly introduced, individual and institutional investors are still in the leaning period to become familiar with these new contracts causing the trading in USF market is much thinner and less intense than the stock market trading.

Notwithstanding the above argument, however, the finding of a significant volatility relationship could have at least two interpretations. First, a casual relationship may in fact exist such that volatility in one market induces volatility in the other market through the spillover effects. Second, common informational factors could also influence volatility in each market, thereby giving rise to an apparent causal relationship between the markets. Given the fact that futures prices and stock prices are driven by the same underlying information, it should not be surprising to find a bi-directional volatility spillover between these two informationally-linked markets.

Nonetheless, the evidence in this section should also add evidence to the perennial discussion about whether the introduction of derivatives contract increases the volatility of the underlying asset. Our empirical findings with USFs and its underlying stocks show that the main source of uncertainty (as proxied by volatility) comes from the stock market. Volatility spillover between both markets, but the spillovers from stock to futures are more pronounced than in the reverse direction.

This finding is in general agreement with the results of Darrat et al. (2002) who study the Value Line and S&P 500 stock indices and its futures contracts using monthly data. They find that futures trading cannot be blamed for the observed volatility in the spot market; rather, they found volatility in the futures markets is itself an outgrowth of the turbulent cash markets.

II. 2. Asymmetric Volatility Spillovers

The analysis can be extended to consider both the impact of shock/volatility of each market and cross-market asymmetric volatility spillovers by testing the (joint) null hypothesis that no cross-market volatility spillovers from either market (i.e., $H_{0,3}: a_{12} = b_{12} = d_{12} = 0$ and $H_{0,4}: a_{21} = b_{21} = d_{21} = 0$). This is particularly important as the differences in transaction costs, short-selling restrictions, and other imperfections could cause new information to incorporate in futures prices first. Many studies have showed that the stock-futures informational relationship, and therefore volatility spillovers, is asymmetric across the rising and falling markets. Bad news and good news in one market exert an asymmetric impact on the other market's volatility. Therefore, to gain a more thorough understanding of the information transmission mechanism between stock and USF markets, it is necessary to extend our symmetric volatility spillover analysis by taking into account of this extra spillover channel.

The outcome of the Wald test for the null hypothesis that no asymmetric cross-market volatility spillovers from stock to USF ($H_{0,3}: a_{12} = b_{12} = d_{12} = 0$) is presented in the third column of Table 3.30. The results indicate that the null hypothesis of no Stock-to-USF asymmetric spillover is rejected for 47 out of 50 pairs at the 5% level. This suggests that the volatility of 94% USFs are affected by the developments in its underlying stock markets, especially the cases of negative news. Similarly, the USF-to-Stock asymmetric spillover results presented in the final column of Table 3.30 suggest that the news from USF markets also influence the variance of 78% stocks, particularly so for the bad news. The null hypothesis of no USF-to-Stock asymmetric spillover ($H_{0,4}: a_{21} = b_{21} = d_{21} = 0$) is clearly rejected for 39 out of 50 pairs.

These results are consistent with the above symmetric volatility spillover analysis, indicating that the volatility spillovers are bi-directional, but the spillovers from stock to futures are slightly stronger than in the other direction. More importantly, the results also suggest that both the innovations of stock and futures returns have asymmetric impact on the variance of each market. Bad news (negative innovation) of either market tends to make another market more volatile than good news (positive innovation), particularly in the case for bad news from the USF markets.[151] On the whole, the finding that futures markets appear to take up more roles in negative information dissemination, provide a support to our conjecture that USF play a relatively more significant role in discovering bad news than the good news. That is, they contribute more to price discovery process in the falling markets, which is generally in agreement with the finding documented by Hodgson et al. (2003) for the stock index futures markets.

Possible explanations for the above finding that USFs, on average, play a relatively more pronounced role in discovering bad news than good news are the followings. First, the most likely explanation is the absence of short sale constraints in futures

[151] The results in Table 3.30 show that, after allowing for both positive and negative news spillovers, there are 22% (i.e., from 32 to 39) more USFs showing significant information/volatility spillover effects to stocks markets. Conversely, there is only a 15% increase for Stock-to-USF spillovers (i.e., from 41 to 47).

market. As Puttonen (1993) argues, whenever bad news is released to the market or during market downturn, it is much easier and cheaper to short sell stock in futures markets than in stock markets. The generally higher transaction costs for short selling stocks increase the price discovery role of futures market for negative information. As Chu et al. (1999) point out, in many stock markets, short sale of a stock can only take place when the last recorded stock price change is non-negative (i.e.uptick rule). As the trading in USFs contracts are not subject to such "uptick rule", it is not surprising for us to find that futures prices are more efficient in incorporating the negative news.

Different informational role of a futures market towards the bad and the good news may also arise from the actions of traders. Building on the earlier work of Shefrin and Statman (1985) and Odean (1998), Chatrath et al. (2002) for instance put forward a "trader-selectivity" hypothesis to explain the asymmetric stock index futures leadership across the rising and falling market. They argue that because most of the investors in the stock market are suffering from the so-called "disposition effect" (i.e., disposed toward realizing their gains but not their losses / reluctance to realise losses), the stock price changes display significant serial correlation when prices are falling. This in turn implies that the stock prices tend to incorporate the negative information with much slower speed than its futures prices.

III. Economic Importance of Volatility Spillovers

The hypotheses tests presented above have established the statistical significance of stock and USF innovation/volatility for explaining the behaviour of another market's volatility, identified which transmission direction is more pronounced, and tested whether the spillovers are asymmetric in the sense that bad and good news in one market exert an asymmetric impact on the other market's volatility. Some hypothesis test results are statistically significant, while others are not. In some cases, however, the volatility spillovers may be statistically significant but not economically meaningful. To help to assess the economic importance of the volatility spillovers effects that are documented in a previous section, we proceed to give an idea of the quantitative value of stock and USF innovations on another market's volatility, i.e., what is the economic significance of the obtained statistical results?

Given the generality of the variance-covariance matrix in our asymmetric BEKK GARCH(1,1)-X model (3.9), the task is not a simple one. Nonetheless, Appendix 3B derives the individual equations of the conditional variance of each markets and their conditional covariance, in order to show the impact of a past shock on the current volatility of each market.[152] More specifically, to evaluate precisely the impact of a shock ($\varepsilon_{i,t-1}$ for i = S,F) at time t-1 on a market to the volatility of another market ($h_{i,t}$ for i = F,S) at time t, we isolate this effect by assuming that all other variables in the system are constant. To determine the impact of a shock on stock to the USF market volatility, we have computed:

[152] The expansion of the variance-covariance matrix in our asymmetric BEKK GARCH(1,1)-X model as given in Appendix 3B is loosely following the approach of Grier et al. (2001).

$$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \setminus \varepsilon_{F,t-1=0} = 2a_{12}^2 \varepsilon_{S,t-1} \text{ for } \varepsilon_{S,t-1} > 0 \text{ (Good news)}$$

and;
$$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \setminus \varepsilon_{F,t-1=0} = 2a_{12}^2 \varepsilon_{S,t-1} + 2d_{12}^2 \xi_{S,t-1} \text{ for } \varepsilon_{S,t-1} < 0 \text{ (Bad news)}$$

Similarly, for the impact of a shock on the USF market to the stock market volatility, we computed:

$$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \setminus \varepsilon_{S,t-1=0} = 2a_{21}^2 \varepsilon_{F,t-1} \text{ for } \varepsilon_{F,t-1} > 0 \text{ (Good news)}$$

and;
$$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \setminus \varepsilon_{S,t-1=0} = 2a_{21}^2 \varepsilon_{F,t-1} + 2d_{21}^2 \xi_{F,t-1} \text{ for } \varepsilon_{F,t-1} < 0 \text{ (Bad news)}$$

Based on the above formula (see Appendix 3B for their derivations), the impact of the last period shock ($\varepsilon_{i,t-1}$ for i = S,F) on a market to the current volatility of another market ($h_{i,t}$ for i = F,S) is now estimated with the coefficients from Table 3.29. Table 3.31 presents the effect of a 5% shock in stock market at the last period ($\varepsilon_{S,t-1} = \pm 0.05$) on the current USF market volatility ($h_{F,t}$), as well as the effect of a 5% shock in the USF market at the last period ($\varepsilon_{F,t-1} = \pm 0.05$) to the current stock market volatility ($h_{S,t}$).

We observe from Table 3.31 that, on average, the positive shocks from the stock market have usually a larger effect on volatility of the USF market than the reverse direction. Good news from stock markets increases the average USFs volatility by 1.53%, whereas the same unit of good news from USF markets increase average stocks volatility by only 0.56%. Consistent to the statistical hypotheses tests results, the quantitative values of these spillover coefficients indicate that there is a volatility spillover, and thus information flow, across both markets for the positive innovations, but the impact from stock market to USF volatility is relatively larger.

In addition, we also notice from Table 3.31 that there are pronounced asymmetric spillovers effects (i.e. *cross-variance asymmetry*) where bad news in one market exerts a much stronger impact on the other market's volatility than the good news does. For example, the average impact of the bad news from stock markets on USF markets (-4.59%) is three times stronger than the effect of good news (1.53%). However, this *cross-variance asymmetry* phenomenon is more obvious from USF markets where their bad news impact on stock volatility (-5.22%) is almost ten times stronger than their good news (0.56%), which implies that bad news from USF markets induces a lot of movement / uncertainty in stock market.

As an initial conclusion of this economic significance analysis, it can be said that the main source of uncertainty / information comes from the stock market, especially from the positive shocks (good news). There is a volatility spillover across both markets for the negative information (bad news), but the dropping effect from futures negative innovations to stock volatility is relatively larger. If volatility is understood as a measure of information flow (see Ross, 1989), then the main source of information comes from the stock market and spreads into the futures markets. On the other hand, USF plays a relatively more pronounced role in transmitting bad news than good news. Overall, these findings are generally consistent with the results we obtained from the previous statistical hypotheses tests.

IV. Specification and Diagnostic Tests

When modelling the conditional variance and covariance, it is important that the specification is a statistically adequate representation of the data in hand. Many different multivariate GARCH models have been used in the literature to describe the dynamic behaviour of variances in stock and futures returns and their covariance. Each model has advantages and shortcomings, and may fit into one set of data better than others. Diagnostic tests for the variance specification therefore become very important to validate the interpretations we made regarding the parameter estimates. Econometric theory does not provide specific guidelines for the appropriate diagnostics for the multivariate GARCH models (see Bauwens et al., 2006). However, at a minimum, the estimated standardized residuals from the asymmetric BEKK GARCH (1,1)-X model (3.9) should (i) have zero mean and unit variance, (ii) obey the assumed distribution with the estimated scale parameter or degrees of freedom, and (iii) exhibit neither linear nor nonlinear dependencies.

As shown in Table 3.32, the means and variances of the standardized residuals fulfil the requirement of zero mean and unit variance, except for the DCY futures residual. As these results satisfy the Bollerslev and Wooldridge (1992) moment conditions, we can be confident that our Quasi-maximum likelihood (QML) estimates are consistent. The skewness and excess kurtosis of standardized residuals are generally lower than the ones for the raw returns series (see Table 3.5). On average, the skewness (0.16) and excess kurtosis (20.78) are much smaller than that of raw returns (-0.80 and 44.22). This implies that a large proportion of excess kurtosis in daily returns is attributable to the conditional heteroskedasticity. The finding of such a reduction in kurtosis, Chan et al. (1991, p. 674) conclude a reasonable fit for the GARCH model they use.

In spite of the improvement from the raw returns, estimated statistics still indicate the presence significant kurtosis and skewness in most series, particularly for the excess kurtosis. This might indicate that a higher order GARCH specification may be appropriate. Several higher order GARCH models have been tried, for example, asymmetric BEKK GARCH (1,2)-X and asymmetric BEKK GARCH (1,3)-X models, but these higher order models do not improve the specification diagnostics, and for some cases there are considerable convergence and optimisation problems perhaps due to the generality of these models. As a result of significant kurtosis and skewness, the normality hypothesis is also rejected by Jarque-Bera tests in all series. Nonetheless, since we use QML estimation, non-normality is not crucial, since standard errors are adjusted to take into account this possible non-normality.

Linear and nonlinear independencies are tested by means of the Ljung-Box Q statistic. The estimated Ljung-Box Q statistics indicate significant autocorrelations in the standardized residuals for more than half of the cases. Likewise, the null hypothesis of no heteroskedasticity (i.e., the Q^2 statistics based on the square standardized residuals) are rejected at the 5% level for 44 out of 100 residual series.[153] However, these residual autocorrelations have improved from the raw returns (see Table 3.5). Moreover, it would be unreasonable to expect an empirical model to completely account for the higher moments, since we use the daily returns that are highly autocorrelated and leptokurtic.

[153] The estimated Ljung-Box Q^2 statistics based on the square standardized residuals is an indirect test of the conditional heteroskedasticity and has been widely adopted in the academic literature (see, for example, Tse, 1999; Koutmos, 1996; and Chatrath et al., 2002) Of course, a more direct test for ARCH effects is the Langrange Multiplier (LM) test proposed by Engle (1982).

The Ljung-Box Q statistic, however, does not provide any indication as to how well the model captures the impact of positive and negative innovations on conditional volatility. For this purpose some diagnostics proposed by Engle and Ng (1993) are used. These tests are conducted jointly in the following OLS regression model:

$$Z_t^2 = a + b_1 S_t^- + b_2 S_t^- \varepsilon_{t-1} + b_3 S_t^+ \varepsilon_{t-1} + v_t$$

where: Z_t = the standardised residuals;

S_t^- = a dummy variable that takes a value of unity if $\varepsilon_{i,t-1} < 0$, zero otherwise;

S_t^+ = a dummy variable that takes a value of unity if $\varepsilon_{i,t-1} > 0$, zero otherwise.

The premise is that if the volatility process is correctly specified, then the square standardized residuals (Z_t) should not be predictable on the basis of observed variables. These tests are composed of three parts: (i) the sign bias test, (ii) the negative size bias test, and (iii) the positive size bias test.[154] The results for these diagnostics have been reported in Table 3.32. For most stocks and futures residuals, the estimated t statistics and F statistics are statistically insignificant, which implies that Z_t cannot be predicted by using observed variables. Put another way, our model captures most of the asymmetric effects in the conditional volatility for both series. On the basis of the various diagnostics performed, it can be said that our asymmetric BEKK GARCH (1,1)-X model (3.9) explains a large (though not all) portion of the volatility dynamic, and that the model provides reasonably adequate descriptions of the daily stock and USF futures returns series.

[154] The sign bias test examines the impact of positive and negative innovation on volatility not predicted by the model. It is based on t statistics for b_1. The negative-size-bias test examines how well the model captures the impact of large and small negative innovations. The calculated t statistics for b_2 is used in this test. The positive-size-bias test examines possible bias associated with large and small positive innovations. Here, the t-statistics for b_3 is used to test for possible bias. A joint F test can also be used, even though the individual tests are more powerful (see Engle and Ng, 1993).

3.4.4.5 Robustness Tests

The results of our asymmetric BEKK GARCH (1,1)-X model (3.9) indicate that innovations in stock and USF markets significantly influence another market's volatility, but the volatility spillovers from the stocks to futures are slightly stronger. Put another way, in general, new information disseminates in the stock markets first. Nevertheless, the current results should be interpreted with caution because the diagnostic checking shows that model (3.9) does not capture all volatility dynamics. To eliminate the possibility that the results obtained might be sensitive to our empirical design choices, it is important to test whether they are robust to alternative model specifications and estimation methods.

I. Asymmetric BEKK GARCH (1,1)-X-student t Model [155]

The model diagnostics on our asymmetric BEKK GARCH (1,1)-X model (3.9) suggest that the assumption of normally distributed standardized innovations, $z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{i,t}}$; for i = S, F, may be tenuous (see Jarque-Bera normality tests on the standardised residuals in Table 3.32). Although we applied the Bollerslev-Wooldridge QML approach to adjust the standard errors (and associated t-statistics) to take into account of this observed non-normality, it would be useful to perform alternative estimations based on a more general multivariate conditional student-t distribution, which allows any excess kurtosis to be modelled explicitly by the distribution shape v. Detailed estimation results of this specification are presented in Table 3.33. Parameter estimates are very similar with negligible difference, but the t-statistics under student-t assumption are in general more significant, and give a small increase in the number of significant volatility-spillover coefficients (see Table 3.29).

[155] See Patton (2006) for a recent empirical application of BEKK GARCH models with multivariate student-t density. Kan and Zhou (2003) compare multivariate t to multivariate normal distribution.

Moreover, as reported in the last column of Table 3.33, the parameter estimates of the student-t distribution (v) are highly significant for all models. Consistent with our earlier model diagnostics in Table 3.32, the estimated values of the shape parameter v are consistently above a value of 4, indicating that the distribution of returns for both stock and USF markets have thicker tails than the standard normal distribution.

The volatility-spillover hypotheses tests based on this asymmetric BEKK GARCH (1,1)-X-student t model were also performed. The results are qualitatively unchanged from those estimated under the assumption of conditional normally distributed error terms, although there is a small increase in the number of significant volatility-spillover coefficients in both markets (and for both symmetric and asymmetric spillovers). The Wald test p-values of the joint null hypothesis of no volatility spillovers between stock and USF markets are summarised in the Table 3.34. Similar to the results reported earlier in Table 3.30, we find that innovations in stock and futures significantly influence another market's volatility, but the volatility spillovers from the stocks to futures are slightly stronger than in the opposite direction.

II. VECM-Asymmetric BEKK GARCH (1,1)-X Model

As discussed before, due to the generality of our Asymmetric BEKK GARCH (1,1)-X Model (3.9), a two-step approach was adopted to estimate the model (the first step for the VECM in equations (3.5a) and (3.5b) and the second step for the asymmetric BEKK GARCH (1,1)-X model (3.9) formulated with the residuals of VECM). Although Tse (1999) has pointed out that this two-step approach is asymptotically equivalent to a joint estimation of the VECM and GARCH models, it is useful to test whether the results are robust to alternative estimation approach by *simultaneously* estimate VECM and asymmetric BEKK GARCH (1,1)-X equations as a system.

Estimating both returns and volatilities interactions together can also provide an additional robustness check to our lead-lag and price discovery results obtained earlier with the VECM equations (3.5a) and (3.5b) alone. In this sense, this section serves the dual purpose of (i) confirming whether the coefficient estimates of model (3.9) are robust to the chosen method of estimation approach, and (ii) verifying the results of the VECM lead-lag / price discovery analysis, and therefore can be regarded as an appropriate extension to the previous sections analysis.[156]

Nevertheless, as mentioned before, there are too many parameters to estimate in the VECM-Asymmetric BEKK GARCH (1,1)-X model (i.e., a total of 38 parameters), and depending on the econometric software used and the nature of the data, there could be considerable convergence and optimization problems. For this study, a number of alternative econometric software packages have been tried to estimate the VECM-Asymmetric BEKK GARCH (1,1)-X model giving very mixed results. Judged by the evaluation of model diagnostics in terms of the Schwartz information criteria (SIC) and the log-likelihood, we decided to perform all the estimations using the latest version of RATS statistical software (i.e., version 6.20). However, despite this software having found to be more flexible in the multivariate GARCH modelling, there are still 7 (out of a total 50) models which do not converge in the estimation / maximization process.[157]

[156] For a recent empirical application of a similar VECM-BEKK-GARCH(1,1)-X model with multivariate normal distribution, see, for example, Kavussanos and Visvikis (2004).
[157] Brooks et al. (2003) compare and contrast four popular econometric software packages available for estimating multivariate GARCH models (GAUSS-FANPAC, RATS, SAS and S-PLUS FINMETRICS) using the FTSE 100 stock index spot and futures returns, and conclude that RATS is the most flexible software among the four packages they examined.

Identical to that outlined for the model (3.9), numerical procedures were used to maximize the log likelihood function using both the simplex and BFGS estimation procedures, and assuming the error terms following a bivariate normal distribution. Table 3.35 show the results of the joint estimation of equations (3.5a), (3.5b) and (3.9). Let us first focus on the results from the variance-covariance equations regarding to the volatility-spillovers parameters. Although we have non-convergence problem in 7 (out of a total 50) models, the estimated parameters describing the volatility-spillovers across two markets are very similar with the ones in Table 3.29, indicating almost the same volatility-spillovers (information flow) patterns between the stocks and futures. In addition, as can be seen from the hypotheses tests results summarised in Table 3.36, our main finding that innovations in stock and futures significantly influence each market's volatility but the volatility spillovers from stocks to futures are slightly stronger than in reverse direction continues to hold.

Focusing next on the parameters describing the conditional mean of VECM-Asymmetric BEKK GARCH (1,1)-X model in Table 3.37, it can be seen that the *nonlinear* estimations of VECM equations (3.5a) and (3.5b) continued to support earlier evidence of bi-directional causality/lead-lag between the stock and USF returns, and the evidence that the stocks generally bear less the burden of convergence between the two markets, contributing more to the price discovery process. This is further confirmed by comparing Figure 3.11 with Figure 3.2; and Table 3.38 with Table 3.7. This result, similar to that obtained from the main VECM analysis, allows us to assert that the stock markets indeed have the dominant role in price discovery process, even there is a small increase in the role of USFs under the *joint* estimations. To sum up, the main conclusion is maintained and, consequently, it seems to be robust to alternative error distributions and estimation methods.

3.5 Conclusions

This chapter investigates whether, and to what extent, the Universal Stock Futures (USFs) contributed to the price discovery process in the markets. Examining the price discovery function of USFs for the first time, not only complements existing studies which typically consider the market-wide instruments, but also enhances the current understanding of information transmission dynamics between futures and spot markets on the directly tradeable underlying asset where the cost-of-carry relationship are more likely to hold.

Moreover, the special features of these futures contracts enable us to cater for further dimensions in the literature by analysing the impact of several factors that may influence the proportion of new information incorporated via futures trading, which includes (i) the trading location of underlying stock, (ii) the development stage of a futures contract, (iii) the contemporaneous market conditions such as the relative liquidity and trading costs, (iv) the futures contract specifications like contract size, (v) the information types (market-wide versus firm-specific information), and (vi) the information content (positive or negative news). Furthermore, we extend the empirical analysis by investigating how stock and futures markets reflect / assimilate the arrivals of new information by means of the cross-market volatility interactions.

Four different, but sequentially interrelated, times-series techniques are employed to measure the USFs contributions to the information transmission process. They are: (1) Johansen cointegration test (2) Vector error correction model; (3) Common factor weights approach of Gonzalo and Granger (1995); and (4) Asymmetric BEKK GARCH-X volatility model. Specification tests, including several robustness checks, confirm the appropriateness of the chosen models and the empirical results.

3.5.1 Summary of Results and Interpretations

In contrast to the previous studies on the relative contribution to price discovery of stock options and index futures/options, the results of this chapter show that single stock futures contracts such as USFs do not dominate the information dissemination, and account for a relatively smaller share of price discovery than the stock markets. Specifically, the major findings of our empirical analysis are summarized as follows:

1. Price Integration: As futures prices and spot prices are driven by the same underlying information, they are expected to be closely related. Indeed, we find that the prices of stock and futures are not independent of one another. Individually, they are nonstationary but they are linked to one another by stationary long-run equilibrium conditions. Put another way, they are found to be cointegrated and share a long-run equilibrium relationship. The number of cointegrating relationship suggests that they are in fact based on common information. This implies that a VECM should be used to investigate the short-run dynamics and the long-run price movements in these two markets.
2. Price Leadership: A bi-directional Granger causality (lead-lag relationship) between stock and futures markets is found from the result of VECM. However, when the price relationship deviates away from the long-run equilibrium, it depends on futures market to make most of the short-run adjustments to return it back to the long-run equilibrium level. In this sense, stock markets can be regarded as the price leaders in the common information dissemination process.
3. Price Discovery: Among the 50 USFs sample, the average price discovery contributions (as measured by Gonzalo-Granger CFW) of stocks is 60.50%, while that of futures is only 39.50%. This suggests that, on average, futures play a relatively less significant price discovery role than stocks, confirming the dominant role of stock market in discovery of new information.

4. Price Discovery Variations and Determinants: By considering certain groups and periods, we uncover evidence that the USF price discovery contributions vary considerably for the information types, through time, and across contracts. First, the price discovery role of futures prices is more pronounced for domestic-listed contracts and has strengthened in the second half of our sample period (maturity period). This is thought to be the result of USF markets becoming more mature and popular over time. Second, the contributions of futures market are more pronounced for the firm-specific information, implying that USF markets react to firm-specific news faster than market-wide news. As a consequence, researchers investigating the market response to firm-specific information, or information linkages between different individual stocks, should consider using futures market data rather than spot market data. Third, by the means of cross-sectional regression models, we find that the level of contribution of futures market to price discovery is influenced not only by the contemporaneous market conditions such as the relative liquidity and trading costs, but also by the futures contract specifications like contract size. Consistent with the trading cost and liquidity hypotheses, futures markets tend to be more informative on average when USF trading volume is high and when stock volume is low, when USF effective spread are narrow and when stock spreads are wide. We also uncover a clear increase of futures price discovery contributions for larger sized USF contracts. Therefore, we can reasonably infer that a degree of price discovery contributions of futures is driven by factors other than difference in trading costs and/or liquidity alone: contract design factor also seem to play an important role. This is particularly important as it implies that the information flow between futures and stock markets is a complex process and influenced by several factors. It is not appropriate to

simply perform a "horse-race" of the different price discovery hypotheses as these hypotheses/factors are not competitive ones, rather they are complementary to each other in explaining the relative contribution of each market to the price discovery process.

5. Volatility Spillovers: In terms of volatility-spillovers, the results from our asymmetric BEKK GARCH-X model suggest a bi-directional volatility spillover between the stock and futures markets with a stronger effect from the stock to the futures markets. These are consistent with the lead-lag relationship and price discovery results; i.e, information disseminates in the stock market first causing the stock market to contribute more in the price discovery process. Moreover, there is evidence that the type of news (as reflected in the innovation of each market) results in an asymmetric impact on the variance of each market. Bad news (negative innovation) of either market tends to make both markets more volatile than good news (positive innovation), particularly the case for the bad news from USF markets. In other words, futures market seems to play a more pronounced role in discovery of negative information, perhaps due to the limitations of short-selling in the stock markets pushing the investors who have negative information to trade futures market rather than in the stock market.

In summary, the results of this chapter suggest that price discovery take places in both stock and futures markets, but USF markets on average play a relatively smaller role in the price discovery than their underlying stocks. The price contributions of USFs vary considerable over time and across firms depending on the geographical origin of underlying stock, the development stage of a futures contract, the relative trading characteristics such as the market liquidity and trading costs, the USF contracts design and specifications, as well as the information types and content.

One explanation for the finding of relatively smaller USF price contributions is the fact that these products are only recently introduced, and therefore investors are still unfamiliar with them causing the trading in USF market to be much thinner and less intense than the stock market trading. Although the advantages of lower transaction costs, higher leverage, and less trading restrictions may make futures markets an attractive venue for informed trading, it would be unreasonable to expect these new contracts to contribute as much as their more matured stocks markets in the price discovery process, especially during the initial introduction period.

Another possibility is that, for all of the underlying stock markets considered here, stock index futures and options contracts already existed prior to the introduction of USFs contracts. Therefore, it is reasonable to believe that the additional price discovery contributions from any new derivatives contracts (e.g. USFs) in such a rich informational environment would be modest as there are already many channels in which new information can be released and/or reflected into these stock markets.

However, it is important to emphasise that price discovery is only a *relative* concept. To say that a market provides more price discovery (or more of an information share) does not necessarily mean that this market is the original source of information. Throughout the entire chapter, we compare only the relative information discovery roles in the stocks and USFs markets. Therefore, our results showing that stocks on average contribute more information than futures trading suggest merely that traders (or the prices from that market) in stocks markets react more quickly than traders in the futures markets to information coming from some sources (see Tse, 1999).

3.5.2 Implications of Findings

Nonetheless, the findings of this chapter should be of great interest to the investors, fund managers and regulators. For the investors and fund managers who trade in both stocks and derivatives (as well as those who are active in only one market), the results that stock markets contribute more to the price discovery indicate that some information is first *reflected* in that market, and movements in these markets, has important implications for investors trading the futures contracts based on these underlying shares in forecasting price behaviours, speculating the price movements. Additionally, the cash-futures price relationship is also an important factor for hedgers in developing effective hedging strategies. The traditional theory of hedging asserts that the effectiveness of hedge is largely dependent on the parallelism of movements in spot and futures prices. Moreover, our results from the analysis of price discovery determinants should also provide policy-makers important insights on the designs and specifications of securities, trading mechanisms, and the market structures that are more conductive to the timely dissemination of new information.

Further, as the understanding of the price discovery dynamics between stock and futures markets could shed light on the market preference of informed traders, our finding that stock prices tend to lead the futures prices implies that informed traders are more likely to choose this particular market to reveal their private information. This is particularly important as the knowledge of where informed traders choose to trade and the factors influencing their choices are highly relevant to market makers and regulators (e.g. aid the regulators to prevent illegal insider trades). Finally, the price discovery role of LIFFE USF contracts we documented in this chapter should also provide justification for other exchanges to launch the single-stock futures as a means of enhancing information dissemination process in their markets.

3.5.3 Limitations

Although we have tried to conduct this research as thoroughly and accurately as possible, there are some important caveats in this chapter. For example, due to the unavailability of high-frequency intraday data for each relevant market, the empirical analysis of the price discovery contributions of Universal Stock Futures (USF) in this chapter have been based on the daily closing prices data from the USFs and the underlying markets. Because of the differences in the trading intensity/frequency and in their opening and closing times (see Figure 3.1), our sample dataset collected from the reported daily closing prices of two markets may be atypical (due to the unusually high trading before the market closes) and may not be perfectly synchronous. Therefore, the empirical results of this chapter should be interpreted with caution.[158]

Nevertheless, one can also argue that the findings of those empirical works using intraday transaction data are not entirely immune from the potential non-synchronicity bias because of the unequally spaced and/or missing observations that are commonly found in the intraday data.[159] This could be a very critical issue in finding the lead-lag/price discovery relationships. For example, De Jong and Nijman (1997) have specifically addressed a number of empirical issues / problems of using intraday data to infer the lead-lag relationships between financial markets. They concluded that analyzing the lead-lag relationships at arbitrarily high frequency, without appropriate adjustments, could induce additional imputation bias.

[158] Ideally, the analysis of price discovery is better to be based on data series observed at the same time. Non-synchronicity of a data series could bias the price discovery ability in favour of a market in which observations are consistently extracted later than other markets.

[159] Cointegration analysis assumes that prices from one observation (a tuple) happen at the same time. However, in reality, there are time discrepancies because observed trades/quotes in one tuple do not occur simultaneously. Trades/quotes reported later tend to incorporate more up-to-date information.

In addition, we also need to point out that adjustments have yet to be made in this chapter to allow for the potential infrequent-trading effects which could induce significant autocorrelation in the returns series, and in turn cause spurious lead-lag relationship and information transmission patterns.[160]

3.5.4 Recommendations for Future Research

Although some interesting results have been uncovered this chapter regarding the information transmission mechanism and price discovery process across the stock and futures markets, further research in this area may help us gain a fuller understanding of the cross-sectional and time-series variations presented here. This will enhance our knowledge of the dynamics of interactions between stock and derivatives markets and shed light on the question of where and how informed traders choose to trade. Firstly, the empirical analysis of this chapter can be extended to the transactions in all of the relevant markets. Using the transactions data might help to overcome the non-synchronicity problem that exists in current study and allow us to identify more precise channels in which the new information transmits between each relevant market.[161] Simultaneous trading of stock futures, stock options and stocks raises an interesting issue related to the velocity of information gathering and price adjustment among these three markets. Considering all three informationally-related markets is expected to contribute to the knowledge in the area of linkages between equity derivatives and underlying markets. As Booth et al. (1999 p.640) argue "All three markets should be considered as a system. Not to do so may mask important price discovery channels."

[160] Although the stocks on which USF are traded tend to be large stocks that are traded quite frequently, they may not be completely free of thin-trading bias as they might not trade every day.

[161] As discussed before, non-synchronicity of a data series could bias the price discovery ability of each relevant market. However, some sort of techniques involve identifying the trading tuples with the closest trading times for the series could be adopted to mitigate the problem of data non-synchronicity (e.g., REPLACE ALL and MINISPAN approaches of DeB Harris et al., 1995 and Booth et al., 1999).

Secondly, it would be an interesting extension of this chapter to implement our time-series techniques to analysis of the information flows within these markets in the periods immediately prior to announcements of the important corporate events, when information asymmetries among the different investors groups are more pronounced. As Chakravarty et al. (2004) points out, the mere existence of price discovery in the derivatives market is not sufficient to show that informed traders trade in these markets. For this reason, Collver (2005) has recently applied similar techniques to examine the price discovery on stock and option markets during the release of earning announcements. However, Collver (2005) focuses only on earning announcements over 6-months in 1995 for the stock and option markets, considerations can also be given to a wider range of corporate announcements (e.g., take-over news) over a longer and more recent period and including the newly introduced single-stock futures markets.

Thirdly, it would be useful to consider the impact of different investors' trading activity (e.g., institutional investors) on proportion of price discovery in each market, and to address the question of from where and whom price discovery is initiated. For example, Kurov and Lasser (2004) and Ates and Wang (2005) examine the price discovery process in the U.S. E-mini index futures markets. Based on the CFTC's reports on different types of traders, they found that price discovery was driven by trades initiated by the exchange locals (floor traders) and the commercials (hedgers).

Additionally, another possible extension of this chapter is to provide an improved methodology to overcome several methodological problems of the existing studies. For instance, cointegrating relation between spot and futures prices implied by the conventional cost-of-carry model is not constant over time but rather changes daily.

This time-variability of the cointegrating relationship can be accounted for by either demeaning the log prices as proposed by Dwyer et al. (1996) or by using discounted futures prices as is done by Martens et al. (1998). Further, the standard error correction model implies that the speed of adjustment in spot and futures prices to deviations from long-run equilibrium is independent of the size of the deviation. However, this is not necessarily the case because many arbitrageurs will only start trading when the deviation is larger than their expected transaction costs. To capture these dynamics, ideally a threshold vector error-correction model (TVECM) should be employed to allow adjustments coefficients to depend on magnitude of deviations (see Yadav et al., 1994; and Theissen, 2005). It would be interesting to test if the results obtained here are robust to these model specifications and adjustments.

Furthermore, another interesting extension of our analysis would be to examine the price discovery process across the stable and volatile periods. Both Martens (1998) and Franke and Hess (2000) suggest that electronic trading systems' contribution to information discovery is relatively larger in quiet periods than in volatile periods. Future research can also put more effort into explaining how the result documented in this chapter can be exploited to formulate the profitable trading strategies.

Finally, the recent transfer of U.K. USF contracts to the MATCH facility (i.e. moving from an organised exchange to the market that does not have market makers or a central order book) on 28 November 2003 offers an unique opportunity to explore the role of market makers in the price discovery process and allows one to examine whether the level of price discovery in U.K. USF markets has changed significantly across these two different trading mechanisms.

Table 3.1: Hypotheses about the Price Discovery Function of USF Markets

Hypothesis	Conditions for Price Discovery	Dominant Market
1) Leverage Hypothesis	High	Futures
2) Trading Cost Hypothesis	Low	Futures
3) Liquidity Hypothesis	High	Stock
4) Uptick Rule Hypothesis	Non-exist	Futures
5) Market Maturation Hypothesis	Matured	Stock
6) Firm-Specific Information Hypothesis	Stock-specific	Futures
7) Market Trading Mechanism Hypothesis	Electronic	Stock and/or Futures

Notes:
The predictions are based on the implications of hypotheses regarding the influence of market structure and security design.
The hypotheses are not mutually exclusive and may exert multiple (or even offsetting) effects on the price discovery function of each market.

Table 3.2 : List of 50 Sample Stock and USF Markets

SAMPLE			STUDY PERIOD		
Exchange	Stock Name	LIFFE Code	Start Date	End Date	No. of Obs.
Euronext Amsterdam	ABN AMRO Holdings NV	AA	31/10/2001	30/12/2005	1,088
Euronext Amsterdam	Aegon NV	AGN	14/05/2001	30/12/2005	1,210
Euronext Amsterdam	Koninklijke Ahold NV	AHL	31/10/2001	30/12/2005	1,088
Deutsche Borse	Allianz AG	ALV	02/04/2001	30/12/2005	1,240
Euronext Paris	Axa SA	AXA	02/04/2001	30/12/2005	1,240
London Stock Exchange	AstraZeneca plc	AZN	31/10/2001	30/12/2005	1,088
London Stock Exchange	Barclays plc	BAR	31/10/2001	30/12/2005	1,088
Euronext Paris	BNP Paribas SA	BNP	14/05/2001	30/12/2005	1,210
London Stock Exchange	BP plc	BPA	29/01/2001	30/12/2005	1,285
London Stock Exchange	BT Group plc	BTL	31/10/2001	30/12/2005	1,088
Bolsa de Madrid	Banco Bilbao Vizcaya Argentaria SA	BVA	31/10/2001	30/12/2005	1,088
Euronext Paris	Carrefour SA	CA	14/05/2001	30/12/2005	1,210
Euronext Paris	Alcatel SA	CGE	31/10/2001	30/12/2005	1,088
Virt-x	Credit Suisse Group	CSG	31/10/2001	30/12/2005	1,088
Deutsche Borse	Deutsche Bank AG	DBK	29/01/2001	30/12/2005	1,285
Deutsche Borse	DaimlerChrysler AG	DCY	14/05/2001	30/12/2005	1,210
Deutsche Borse	Suez SA	DTE	31/10/2001	30/12/2005	1,088
Borsa Italiana	Eni SpA	ENI	29/01/2001	30/12/2005	1,285
Borsa Italiana	Enel SpA	ENL	19/03/2001	30/12/2005	1,250
Deutsche Borse	E.ON AG	EOA	14/05/2001	30/12/2005	1,210
Stockholmsborsen	Telefonaktiebolaget LM Ericsson AB	ERC	31/10/2001	30/12/2005	1,088
Euronext Paris	France Telecom SA	FTE	29/01/2001	30/12/2005	1,285
Borsa Italiana	Assicurazioni Generali SpA	GEN	19/03/2001	30/12/2005	1,250
London Stock Exchange	GlaxoSmithKline plc	GXW	31/10/2001	30/12/2005	1,088
London Stock Exchange	HSBC Holdings plc	HAS	31/10/2001	30/12/2005	1,088
Stockholmsborsen	Hennes & Mauritz AB	HNM	31/10/2001	30/12/2005	1,088
Euronext Amsterdam	ING Groep NV	ING	29/01/2001	30/12/2005	1,285
London Stock Exchange	Lloyds TSB Group plc	LLO	02/04/2001	30/12/2005	1,240
Deutsche Borse	Münch. Rück. Gesellschaft AG	MUV	02/04/2001	30/12/2005	1,240
Stockholmsborsen	Nordea AB	NDA	31/10/2001	30/12/2005	1,088
Virt-x	Nestle SA	NES	31/10/2001	30/12/2005	1,088
Virt-x	Novartis AG	NOV	31/10/2001	30/12/2005	1,088
Euronext Amsterdam	Koninklijke Philips Electronics NV	PHI	02/04/2001	30/12/2005	1,240
London Stock Exchange	Royal Bank of Scotland Group plc	RBO	14/05/2001	30/12/2005	1,210
Euronext Amsterdam	Royal Dutch Petroleum Company	RD	29/01/2001	30/12/2005	1,285
Virt-x	Roche Holding AG	ROG	31/10/2001	30/12/2005	1,088
Bolsa de Madrid	Santander Central Hispano SA	SCH	29/01/2001	30/12/2005	1,285
Stockholmsborsen	Svenska Handelsbanken AB	SHB	31/10/2001	30/12/2005	1,088
London Stock Exchange	Shell Transport	SHE	31/10/2001	30/12/2005	1,088
Deutsche Borse	Siemens AG	SIE	29/01/2001	30/12/2005	1,285
Bolsa de Madrid	Telefonica SA	TEF	29/01/2001	30/12/2005	1,285
Borsa Italiana	Telecom Italia SpA	TI	29/01/2001	30/12/2005	1,285
Borsa Italiana	Telecom Italia Mobile SpA	TIM	19/03/2001	30/12/2005	1,250
Stockholmsborsen	TeliaSonera AB	TLI	31/10/2001	30/12/2005	1,088
Euronext Paris	Total Fina Elf SA	TOT	29/01/2001	30/12/2005	1,285
Virt-x	UBS AG	UBS	31/10/2001	30/12/2005	1,088
Borsa Italiana	UniCredito Italiano SpA	UC	19/03/2001	30/12/2005	1,250
Euronext Paris	Vivendi Universal SA	VIV	14/05/2001	30/12/2005	1,210
London Stock Exchange	Vodafone Group plc	VOF	29/01/2001	30/12/2005	1,285
Deutsche Borse	Volkswagen AG	VOW	14/05/2001	30/12/2005	1,210

Table 3.3: Unit Root and EG Cointergartion Test Results

Code	Stock Name	Stock Price	Futures Price	Stock Return	Futures Return	Basis	Cointegration
AA	ABN AMRO Holdings NV	-3.090	-3.036	-33.511 **	-32.184 **	-6.125 **	[illegible] **
AGN	Aegon NV	-1.812	-2.246	-31.910 **	-26.544 **	-7.042 **	-30.424 **
AHL	Koninklijke Ahold NV	-1.569	-1.732	-19.599 **	-18.936 **	-1.433	-2.215 *
ALV	Allianz AG	-0.846	-0.674	-34.266 **	-32.913 **	-1.631	-1.883
AXA	Axa SA	-1.630	-4.035 **	-32.526 **	-34.440 **	-6.587 **	-4.850 **
AZN	AstraZeneca plc	-1.987	-2.017	-27.073 **	-26.662 **	-4.672 **	-5.203 **
BAR	Barclays plc	-2.725	-1.637	-33.292 **	-33.684 **	-2.265 *	-2.426 *
BNP	BNP Paribas SA	-2.528	-1.805	-32.990 **	-33.656 **	-2.383 *	-1.797
BPA	BP plc	-1.457	-1.864	-23.938 **	-18.223 **	-7.684 **	-8.280 **
BTL	BT Group plc	-2.221	-2.126	-36.203 **	-23.121 **	-3.492 **	-4.050 **
BVA	Banco Bilbao Vizcaya Argentaria SA	-2.231	-2.169	-34.968 **	-33.378 **	-6.058 **	-6.554 **
CA	Carrefour SA	-3.274	-3.193	-37.445 **	-36.329 **	-8.104 **	-8.280 **
CGE	Alcatel SA	-2.591	-2.624	-35.789 **	-37.377 **	-14.081 **	-32.250 **
CSG	Credit Suisse Group	-1.735	-1.713	-16.728 **	-20.609 **	-2.340 *	-2.101 *
DBK	Deutsche Bank AG	-2.331	-2.288	-36.384 **	-33.754 **	-6.403 **	-6.423 **
DCY	DaimlerChrysler AG	-2.179	-2.076	-35.070 **	-32.831 **	-5.268 **	-5.558 **
DTE	Deutsche Telekom AG	-2.983	-3.049	-23.519 **	-23.165 **	-8.724 **	-8.751 **
ENI	Eni SpA	-2.303	-3.209	-36.778 **	-35.312 **	-3.607 **	-2.306 *
ENL	Enel SpA	-2.089	-3.451 *	-37.831 **	-37.003 **	-3.667 **	-2.479 *
EOA	E.ON AG	-1.275	-1.207	-39.677 **	-37.528 **	-8.400 **	-8.417 **
ERC	Telefonaktiebolaget LM Ericsson AB	-2.064	-1.898	-29.584 **	-31.272 **	-2.299 *	-1.777
FTE	France Telecom SA	-2.483	-2.470	-33.568 **	-33.084 **	-1.566	-1.206
GEN	Assicurazioni Generali SpA	-1.494	-1.488	-33.419 **	-32.665 **	-9.667 **	-10.385 **
GXW	GlaxoSmithKline plc	-1.666	-1.624	-27.582 **	-36.054 **	-7.352 **	-7.910 **
HAS	HSBC Holdings plc	-3.902 *	-3.780 *	-27.614 **	-12.729 **	-5.986 **	-6.229 **
HNM	Hennes & Mauritz AB	-2.635	-2.490	-34.578 **	-36.460 **	-8.841 **	-9.226 **
ING	ING Groep NV	-1.710	-2.102	-22.563 **	-34.999 **	-3.469 **	-2.836 **
LLO	Lloyds TSB Group plc	-1.830	-1.863	-35.711 **	-35.604 **	-4.546 **	-4.890 **
MUV	Münchener Rücksversicherungs Gesellschaft AG	-0.933	-1.119	-32.307 **	-32.113 **	-1.546	-2.084 *
NDA	Nordea AB	-2.008	-1.935	-34.458 **	-33.460 **	-6.319 **	-6.333 **
NES	Nestle SA	-1.675	-1.708	-33.878 **	-34.786 **	-6.848 **	-7.134 **
NOV	Novartis AG	-2.327	-2.346	-31.426 **	-31.960 **	-8.005 **	-8.266 **
PHI	Koninklijke Philips Electronics NV	-2.429	-2.386	-33.995 **	-33.608 **	-6.315 **	-9.031 **
RBO	Royal Bank of Scotland Group plc	-4.167 **	-4.059 **	-36.820 **	-35.012 **	-6.095 **	-6.084 **
RD	Royal Dutch Petroleum Company	-1.655	-2.678	-36.292 **	-34.198 **	-1.062	-0.914
ROG	Roche Holding AG	-1.626	-1.671	-32.178 **	-33.037 **	-6.115 **	-6.296 **
SCH	Santander Central Hispano SA	-2.251	-2.143	-36.905 **	-34.883 **	-10.220 **	-10.614 **
SHB	Svenska Handelsbanken AB	-2.350	-2.351	-33.717 **	-34.406 **	-6.432 **	-6.464 **
SHE	Shell Transport & Trading Company plc	-0.945	-0.953	-34.889 **	-35.168 **	-1.178	-2.842 **
SIE	Siemens AG	-2.692	-3.213	-34.611 **	-32.812 **	-4.472 **	-3.596 **
TEF	Telefonica SA	-2.691	-2.646	-35.056 **	-34.305 **	-2.291 *	-0.905
TI	Telecom Italia SpA	-2.959	-2.258	-15.334 **	-35.738 **	-1.186	-2.951 **
TIM	Telecom Italia Mobile SpA	-2.539	-2.460	-34.267 **	-35.601 **	-3.155 **	-4.352 **
TLI	TeliaSonera AB	-3.334	-3.328	-25.401 **	-25.520 **	-1.813	-4.215 **
TOT	Total Fina Elf SA	-2.032	-1.966	-27.975 **	-27.844 **	-6.314 **	-6.314 **
UBS	UBS AG	-2.770	-2.629	-29.491 **	-30.040 **	-4.312 **	-4.350 **
UC	UniCredito Italiano SpA	-2.050	-1.970	-33.496 **	-33.445 **	-8.168 **	-8.162 **
VIV	Vivendi Universal SA	-1.681	-1.681	-19.127 **	-22.920 **	-9.767 **	-10.247 **
VOF	Vodafone Group plc	-2.913	-2.913	-24.547 **	-24.695 **	-6.799 **	-7.380 **
VOW	Volkswagen AG	-2.317	-2.249	-33.350 **	-33.322 **	-8.589 **	-8.607 **

Notes: The following ADF test regressions are run for each series, Schwarz Bayesian criterion (Schwarz, 1978) is used to determine lag length k.

$$\Delta P_t = \alpha + \beta t + \gamma P_{t-1} + \sum_{i=1}^{k-1} \psi_i \, \Delta P_{t-i} + \mu_t$$ Prices series

$$\Delta R_t = \alpha + \gamma R_{t-1} + \sum_{i=1}^{k-1} \psi_i \, \Delta R_{t-i} + \mu_t$$ Returns series

$$\Delta \hat{\varepsilon}_t = \gamma \hat{\varepsilon}_{t-1} + \sum_{i=1}^{k-1} \gamma_i \, \Delta \hat{\varepsilon}_{t-i} + \mu_t;$$ Cointegration Residual and Basis series

For brevity, this table only reports the ADF test statistic of each regression. The critical values of MacKinnon (1996) are used.

*, ** Significant at 5% and 1% level, respectively.

Table 3.4: Johansen Cointegration Tests for Stock and Futures Prices

	Number of Cointegration Vector(s)					*Cointegration Relationship*			
	Null Hypothesis (Trace)	Test Statistic (λ_{Trace})	Critical Values 5%	Critical Values 1%	No. of Cointegration Rank (r)	Estimated Cointegrating Vector $B_t = \beta' = (1, \beta_1, \beta_2)$ β_1	β_2	Joint Hypothesis Test H_0: $B_t = \beta' = (1, 0, -1)$ Chi-Square	P-Value
AA	r = 0	46.22 **	19.96	24.60	1	-0.0083	-0.9979	2.17	0.1403
	r ≤ 1	8.55	9.24	12.97					
AGN	r = 0	153.33 **	19.96	24.60	1	-0.0833	-0.9612	35.06 **	0.0000
	r ≤ 1	5.01	9.24	12.97					
AHL	r = 0	81.19 **	19.96	24.60	1	0.0624	-1.0038	0.55	0.4592
	r ≤ 1	3.77	9.24	12.97					
ALV	r = 0	22.13 *	19.96	24.60	1	-0.2978	-0.9304	2.24	0.1342
	r ≤ 1	4.66	9.24	12.97					
AXA	r = 0	55.39 **	19.96	24.60	1	-0.0213	-0.9897	0.10	0.7548
	r ≤ 1	5.17	9.24	12.97					
AZN	r = 0	45.17 **	19.96	24.60	1	-0.0191	-0.9973	7.55 **	0.0060
	r ≤ 1	3.92	9.24	12.97					
BAR	r = 0	21.09 *	19.96	24.60	1	-6.5481	0.0552	0.00	0.9878
	r ≤ 1	4.71	9.24	12.97					
BNP	r = 0	29.45 **	19.96	24.60	1	9.4751	-3.4128	0.00	0.9875
	r ≤ 1	3.42	9.24	12.97					
BPA	r = 0	52.26 **	19.96	24.60	1	-0.0540	-0.9912	2.15	0.1425
	r ≤ 1	2.44	9.24	12.97					
BTL	r = 0	29.85 **	19.96	24.60	1 or 2	-1.1473	-0.7831	0.01	0.9152
	r ≤ 1	12.25 *	9.24	12.97					
BVA	r = 0	62.71 **	19.96	24.60	1	-0.0093	-0.9969	6.74 **	0.0094
	r ≤ 1	4.61	9.24	12.97					
CA	r = 0	54.19 **	19.96	24.60	1	-0.0229	-0.9937	0.93	0.3336
	r ≤ 1	7.83	9.24	12.97					
CGE	r = 0	192.96 **	19.96	24.60	1 or 2	0.0131	-1.0045	9.04 **	0.0026
	r ≤ 1	11.77 *	9.24	12.97					
CSG	r = 0	22.65 *	19.96	24.60	1	-0.1240	-0.9640	1.35	0.2452
	r ≤ 1	2.78	9.24	12.97					
DBK	r = 0	57.48 **	19.96	24.60	1	-0.0075	-0.9984	0.38	0.5351
	r ≤ 1	5.15	9.24	12.97					
DCY	r = 0	37.60 **	19.96	24.60	1	-0.0727	-0.9804	0.53	0.4672
	r ≤ 1	7.03	9.24	12.97					
DTE	r = 0	88.94 **	19.96	24.60	1 or 2	0.0122	-1.0044	0.16	0.6860
	r ≤ 1	11.96 *	9.24	12.97					
ENI	r = 0	25.68 **	19.96	24.60	1	-0.1161	-0.9492	0.25	0.6148
	r ≤ 1	1.52	9.24	12.97					
ENL	r = 0	28.87 **	19.96	24.60	1	0.5306	-1.2614	1.65	0.1996
	r ≤ 1	2.71	9.24	12.97					
EOA	r = 0	62.39 **	19.96	24.60	1	-0.0202	-0.9950	0.00	0.9496
	r ≤ 1	0.90	9.24	12.97					
ERC	r = 0	25.65 **	19.96	24.60	1	-0.1075	-0.9466	2.48	0.1153
	r ≤ 1	4.69	9.24	12.97					
FTE	r = 0	22.55 *	19.96	24.60	1	2.4994	-1.8025	0.00	0.9450
	r ≤ 1	2.33	9.24	12.97					
GEN	r = 0	89.50 **	19.96	24.60	1	-0.0038	-0.9983	11.12 **	0.0009
	r ≤ 1	3.95	9.24	12.97					
GXW	r = 0	55.34 **	19.96	24.60	1	-0.0366	-0.9948	3.93 *	0.0473
	r ≤ 1	3.46	9.24	12.97					
HAS	r = 0	42.28 **	19.96	24.60	1	-0.1292	-0.9808	0.18	0.6756
	r ≤ 1	8.90	9.24	12.97					
HNM	r = 0	66.88 **	19.96	24.60	1	0.0326	-1.0059	3.42	0.0645
	r ≤ 1	1.43	9.24	12.97					
ING	r = 0	28.23 **	19.96	24.60	1	0.3050	-1.1016	0.01	0.9428
	r ≤ 1	5.82	9.24	12.97					
LLO	r = 0	25.88 **	19.96	24.60	1	-0.0841	-0.9874	2.49	0.1149
	r ≤ 1	3.52	9.24	12.97					
MUV	r = 0	24.50 *	19.96	24.60	1	-0.1349	-0.9672	1.78	0.1825
	r ≤ 1	4.52	9.24	12.97					
NDA	r = 0	35.08 **	19.96	24.60	1	0.0098	-1.0024	0.01	0.9369
	r ≤ 1	1.37	9.24	12.97					
NES	r = 0	46.86 **	19.96	24.60	1	-0.0463	-0.9922	2.58	0.1082
	r ≤ 1	2.12	9.24	12.97					

Table 3.4: Johansen Cointegration Tests for Stock and Futures Prices (continued)

	Number of Cointegration Vector(s)					Cointegration Relationship			
	Null Hypothesis (Trace)	Test Statistic (λ_{Trace})	Critical Values 5%	1%	No. of Cointegration Rank (r)	Estimated Cointegrating Vector $B_t = \beta' = (1, \beta_1, \beta_2)$ β_1	β_2	Joint Hypothesis Test H_0: $B_t = \beta' = (1, 0, -1)$ Chi-Square	P-Value
NOV	r = 0	59.59 **	19.96	24.60	1	-0.0323	-0.9922	1.96	0.1619
	r ≤ 1	4.81	9.24	12.97					
PHI	r = 0	74.78 **	19.96	24.60	1	-0.0071	-0.9973	4.00 *	0.0456
	r ≤ 1	4.61	9.24	12.97					
RBO	r = 0	44.09 **	19.96	24.60	1 or 2	0.0909	-1.0123	0.02	0.8827
	r ≤ 1	11.23 *	9.24	12.97					
RD	r = 0	25.60 **	19.96	24.60	1	-4.7460	0.4398	0.03	0.8670
	r ≤ 1	0.67	9.24	12.97					
ROG	r = 0	41.09 **	19.96	24.60	1	-0.0150	-0.9970	1.21	0.2713
	r ≤ 1	1.40	9.24	12.97					
SCH	r = 0	78.29 **	19.96	24.60	1	-0.0137	-0.9940	2.03	0.1542
	r ≤ 1	4.40	9.24	12.97					
SHB	r = 0	43.07 **	19.96	24.60	1	0.0196	-1.0038	0.22	0.6365
	r ≤ 1	1.61	9.24	12.97					
SHE	r = 0	27.29 **	19.96	24.60	1	-0.9358	-0.8695	0.02	0.8993
	r ≤ 1	0.88	9.24	12.97					
SIE	r = 0	28.86 **	19.96	24.60	1	0.3373	-1.0837	0.00	0.9600
	r ≤ 1	6.51	9.24	12.97					
TEF	r = 0	22.38 *	19.96	24.60	1	0.8374	-1.3263	0.15	0.7019
	r ≤ 1	2.46	9.24	12.97					
TI	r = 0	25.32 **	19.96	24.60	1	-0.9916	0.0491	0.51	0.4749
	r ≤ 1	2.14	9.24	12.97					
TIM	r = 0	23.60 *	19.96	24.60	1	-0.1304	-0.9070	4.44 *	0.0351
	r ≤ 1	5.77	9.24	12.97					
TLI	r = 0	30.31 **	19.96	24.60	1	0.1045	-1.0246	14.72 **	0.0001
	r ≤ 1	5.67	9.24	12.97					
TOT	r = 0	34.28 **	19.96	24.60	1	-0.0129	-0.9974	0.03	0.8684
	r ≤ 1	1.44	9.24	12.97					
UBS	r = 0	27.23 **	19.96	24.60	1	0.0023	-0.9999	0.53	0.4652
	r ≤ 1	1.57	9.24	12.97					
UC	r = 0	61.43 **	19.96	24.60	1	0.0018	-1.0014	0.02	0.8792
	r ≤ 1	5.06	9.24	12.97					
VIV	r = 0	95.89 **	19.96	24.60	1	0.0009	-0.9997	8.64 **	0.0033
	r ≤ 1	7.45	9.24	12.97					
VOF	r = 0	64.05 **	19.96	24.60	1 or 2	-0.0074	-0.9981	7.24 **	0.0071
	r ≤ 1	10.39 *	9.24	12.97					
VOW	r = 0	79.77 **	19.96	24.60	1	-0.0061	-0.9985	0.24	0.6249
	r ≤ 1	7.02	9.24	12.97					

Notes:

The λ_{trace} tests the null hypothesis that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

where $\hat{\lambda}_i$ is the estimated eigenvalues of the Π matrix. Critical values are taken from Osterwald-Lenum (1992), Table 1.

$\beta = (1, \beta_1, \beta_2)$ are the coefficient estiamtes of the cointegrating vector where the coefficient of S_t is normalised to unity, β_1 is the intercept term and β_2 is the coefficient on F_t. The statistic for parameter restrictions $\beta = (1, 0, -1)$ is distributed as χ^2 with 2 degree of freedom.

*, ** Significant at 5% and 1% level, respectively.

Table 3.5: Summary Statistics of Stock Returns, Futures Returns, and Basis

Code	Variables	N	μ	σ	S	K	JB	Q(12)	$Q^2(12)$	ARCH (12)
AA	Stock Returns	1059	-0.0001	0.0238	0.0043	5.2240	1201.90 **	29.49 **	46.50 **	1015.69 **
	Futures Returns	1059	-0.0001	0.0233	-0.0305	5.5973	1380.00 **	27.10 **	806.86 **	24.30 *
	Basis	1060	0.0023	0.0112	0.9210	2.7518	482.94 **	3551.86 **	1947.75 **	61.17 **
AGN	Stock Returns	1059	-0.0011	0.0317	-0.1735	4.5950	935.21 **	56.42 **	917.35 **	29.17 **
	Futures Returns	1059	-0.0011	0.0867	0.1058	396.2100	6913900.00 **	191.07 **	263.86 **	73.27 **
	Basis	1060	-0.0190	0.0617	-26.3760	796.9100	28092000.00 **	220.54 **	0.00	0.00
AHL	Stock Returns	1059	-0.0014	0.0435	-10.8930	254.5900	2875600.00 **	36.05 **	4.01	0.32
	Futures Returns	1059	-0.0016	0.0445	-10.6370	241.5900	2590500.00 **	28.80 **	3.39	0.27
	Basis	1060	-0.1020	0.0814	0.4014	-1.7957	170.41 **	11695.90 **	11219.60 **	2099.20 **
ALV	Stock Returns	1215	-0.0006	0.0268	-0.0766	3.1123	427.63 **	25.32 *	811.35 **	24.70 *
	Futures Returns	1215	-0.0007	0.0257	-0.3043	3.2435	479.65 **	12.86	784.08 **	25.44 *
	Basis	1216	-0.0493	0.0583	-0.0898	-1.8375	150.12 **	11559.50 **	10201.90 **	716.97 **
AXA	Stock Returns	1215	-0.0001	0.0281	0.1146	3.5212	548.38 **	32.25 **	837.42 **	24.28 *
	Futures Returns	1215	-0.0012	0.0492	-17.8460	473.5100	9930600.00 **	5.56	0.02	0.00
	Basis	1216	-0.0410	0.2111	-5.8687	32.5620	52764.00 **	7705.83 **	7683.95 **	1283.20 **
AZN	Stock Returns	1266	-0.0001	0.0188	-0.0821	5.1440	1166.60 **	30.08 **	123.74 **	5.95
	Futures Returns	1266	-0.0001	0.0185	0.0740	5.9612	1566.00 **	32.19 **	120.92 **	5.62
	Basis	1267	-0.0023	0.0062	-0.1294	6.8774	2086.00 **	2113.36 **	128.21 **	8.84
BAR	Stock Returns	1189	0.0001	0.0201	0.0990	2.7912	344.84 **	38.69 **	673.48 **	22.72 *
	Futures Returns	1189	-0.0011	0.0445	-22.9120	661.3400	19355000.00 **	7.89	0.02	0.00
	Basis	1190	-0.2837	0.5605	-1.2833	-0.3514	295.55 **	12064.80 **	12059.70 **	14535.00 **
BNP	Stock Returns	1189	0.0003	0.0200	-0.0750	5.3672	1269.70 **	30.57 **	638.22 **	22.07 *
	Futures Returns	1189	-0.0003	0.0288	-12.2660	285.3200	3611900.00 **	11.85	0.02	0.00
	Basis	1190	-0.1159	0.2590	-1.6056	0.5890	469.44 **	11934.70 **	11957.70 **	12233.00 **
BPA	Stock Returns	1266	0.0000	0.0166	-0.4453	2.4907	308.14 **	45.74 **	402.60 **	15.58
	Futures Returns	1266	0.0000	0.0164	-0.5103	2.5073	322.75 **	41.35 **	355.61 **	14.25
	Basis	1267	-0.0009	0.0051	0.0735	0.6059	17.12 **	103.08 **	2667.95 **	5.59
BTL	Stock Returns	1215	-0.0003	0.0226	0.0871	1.9694	172.15 **	28.46 **	439.53 **	16.98
	Futures Returns	1215	-0.0006	0.0235	-1.1505	12.1960	6783.80 **	34.55 **	20.63	1.33
	Basis	1216	-0.0394	0.0964	-1.9529	2.1547	876.32 **	11297.00 **	10564.30 **	4338.80 **
BVA	Stock Returns	1189	0.0000	0.0204	0.2659	2.6091	312.27 **	20.58	719.02 **	23.01 *
	Futures Returns	1189	-0.0001	0.0196	0.2204	2.1418	210.59 **	12.21	717.98 **	23.12 *
	Basis	1190	0.0017	0.0062	-0.4962	5.2040	1236.10 **	1435.05 **	61.96 **	3.72
CA	Stock Returns	1189	-0.0004	0.0189	-0.0014	3.1984	450.55 **	30.22 **	723.63 **	22.69 *
	Futures Returns	1189	-0.0004	0.0185	-0.1296	3.2021	454.55 **	23.50 *	643.77 **	19.61
	Basis	1190	-0.0010	0.0076	1.6643	9.5169	4476.90 **	2614.11 **	1425.20 **	65.82 **
CGE	Stock Returns	1266	-0.0014	0.0385	0.3362	6.7763	2042.20 **	25.37 *	194.23 **	10.08
	Futures Returns	1266	-0.0014	0.0420	0.7873	18.6620	15447.00 **	20.41	214.83 **	19.30
	Basis	1267	-0.0025	0.0143	-9.6568	270.4400	3237400.00 **	44.10 **	0.92	0.07
CSG	Stock Returns	1057	0.0002	0.0251	-0.2917	5.3674	1283.80 **	42.29 **	936.14 **	38.37 **
	Futures Returns	1057	0.0001	0.0254	-0.0987	5.2765	1227.90 **	36.85 **	955.79 **	33.63 **
	Basis	1058	-0.0183	0.0291	-1.3307	0.4912	322.57 **	11042.10 **	10507.00 **	1101.70 **
DBK	Stock Returns	1266	-0.0002	0.0229	-0.1435	2.9157	378.03 **	12.60	649.36 **	22.28 *
	Futures Returns	1266	-0.0002	0.0223	-0.1337	3.4259	520.06 **	26.76 **	495.42 **	18.24
	Basis	1267	0.0006	0.0102	0.9360	4.4641	1032.00 **	1079.68 **	783.02 **	26.02 *
DCY	Stock Returns	1189	-0.0002	0.0222	-0.0249	2.0325	182.05 **	28.42 **	728.20 **	24.15 *
	Futures Returns	1189	-0.0002	0.0215	-0.0179	1.9810	172.89 **	29.56 **	542.44 **	18.34
	Basis	1190	0.0018	0.0146	2.1033	5.6601	2190.30 **	4232.52 **	5094.35 **	219.83 **
DTE	Stock Returns	1266	-0.0007	0.0262	0.0613	2.8213	351.23 **	35.78 **	673.84 **	22.43 *
	Futures Returns	1266	-0.0007	0.0250	0.0493	2.4183	257.99 **	25.01 *	587.20 **	17.89
	Basis	1267	-0.0006	0.0118	1.2790	9.3324	4124.00 **	272.93 **	259.04 **	11.73
ENI	Stock Returns	1266	0.0004	0.0158	-0.4765	2.0130	218.47 **	21.39 *	386.57 **	15.27
	Futures Returns	1266	0.0010	0.0244	15.5650	398.4600	7035400.00 **	9.62	0.03	0.00
	Basis	1267	0.0342	0.1851	2.8111	5.9447	2948.50 **	11006.90 **	10971.30 **	5467.30 **
ENL	Stock Returns	1217	0.0000	0.0149	-0.9198	6.8661	2225.30 **	34.96 **	216.25 **	9.40
	Futures Returns	1217	0.0005	0.0249	17.5140	466.2500	9628300.00 **	10.60	0.02	0.00
	Basis	1218	-0.0197	0.1632	3.2120	8.5090	5006.30 **	10603.70 **	10658.60 **	4605.90 **

Table 3.5: **Summary Statistics of Stock Returns, Futures Returns, and Basis (continued)**

Code	Variables	N	μ	σ	S	K	JB	Q(12)	$Q^2(12)$	ARCH (12)
EOA	Stock Returns	1189	0.0004	0.0177	0.1321	2.9975	398.78 **	38.55 **	424.45 **	15.39
	Futures Returns	1189	0.0004	0.0167	0.3608	3.3872	528.22 **	33.67 **	340.18 **	12.36
	Basis	1190	0.0006	0.0111	1.4931	4.2985	1206.50 **	2136.90 **	2453.16 **	111.56 **
ERC	Stock Returns	1057	-0.0002	0.0396	-0.1013	6.1009	1641.10 **	47.62 **	345.84 **	15.08
	Futures Returns	1057	-0.0005	0.0414	-0.7603	10.7600	5201.20 **	23.37 *	395.84 **	18.53
	Basis	1058	-0.0632	0.1270	-1.6273	0.6671	486.13 **	11811.20 **	11780.80 **	7162.60 **
FTE	Stock Returns	1266	-0.0011	0.0328	0.3415	3.9404	704.37 **	11.77	958.04 **	29.24 **
	Futures Returns	1266	-0.0012	0.0324	0.2537	4.0058	718.05 **	13.78	739.97 **	24.14 *
	Basis	1267	-0.0669	0.0726	0.0512	-1.9362	165.57 **	12043.70 **	11589.30 **	2450.90 **
GEN	Stock Returns	1217	-0.0001	0.0170	-0.3653	3.4978	562.34 **	34.25 **	1063.81 **	31.40 **
	Futures Returns	1217	-0.0002	0.0167	-0.2440	3.4993	549.77 **	23.27 *	967.77 **	28.74 **
	Basis	1218	-0.0015	0.0054	0.8109	6.1086	1759.20 **	747.93 **	317.78 **	13.09
GXW	Stock Returns	1266	-0.0002	0.0167	0.1016	2.8993	372.04 **	18.33	254.92 **	11.29
	Futures Returns	1266	-0.0002	0.0165	0.1180	3.4904	539.01 **	18.91	267.25 **	12.46
	Basis	1267	-0.0012	0.0049	0.0214	1.5322	103.47 **	2157.97 **	191.94 **	10.20
HAS	Stock Returns	1266	-0.0001	0.0147	-0.6137	8.5458	3282.80 **	55.06 **	143.01 **	7.50
	Futures Returns	1266	-0.0001	0.0143	-0.2025	4.2182	790.85 **	54.21 **	188.12 **	8.65
	Basis	1267	0.0008	0.0087	0.9713	1.9982	342.04 **	5102.36 **	3841.64 **	116.10 **
HNM	Stock Returns	1057	0.0004	0.0176	0.1570	6.3470	1778.50 **	21.02	87.88 **	4.80
	Futures Returns	1057	0.0003	0.0185	-0.0642	9.7072	4150.80 **	33.67 **	215.42 **	17.15
	Basis	1058	-0.0014	0.0078	5.5499	96.6650	416960.00 **	950.06 **	3.89	0.27
ING	Stock Returns	1266	-0.0003	0.0272	0.0660	4.5116	897.20 **	33.43 **	842.91 **	26.20 *
	Futures Returns	1266	-0.0008	0.0330	-5.6587	106.2600	502890.00 **	14.52	0.12	0.01
	Basis	1267	-0.0570	0.1948	-2.6321	4.9576	2303.00 **	11251.30 **	11249.90 **	7215.90 **
LLO	Stock Returns	1215	-0.0003	0.0192	-0.0279	2.7514	333.53 **	22.74 *	741.52 **	22.79 *
	Futures Returns	1215	-0.0003	0.0190	0.1537	2.6079	303.69 **	20.60	588.10 **	20.38
	Basis	1216	0.0047	0.0165	1.5643	1.5322	534.50 **	6498.81 **	6283.11 **	345.67 **
MUV	Stock Returns	1215	-0.0008	0.0265	-0.2905	4.3729	857.05 **	25.47 *	744.85 **	21.47 *
	Futures Returns	1215	-0.0009	0.0268	-0.2778	6.1037	1654.40 **	39.11 **	784.19 **	27.36 **
	Basis	1216	-0.0279	0.0270	0.1870	-1.2973	80.28 **	9351.05 **	5044.89 **	134.36 **
NDA	Stock Returns	1057	0.0005	0.0202	-0.0453	5.3537	1262.70 **	34.30 **	511.40 **	17.07
	Futures Returns	1057	0.0005	0.0196	0.0682	5.7620	1463.00 **	29.80 **	464.05 **	16.02
	Basis	1058	0.0002	0.0115	2.2406	8.0515	3739.50 **	3905.70 **	3219.36 **	142.93 **
NES	Stock Returns	1057	0.0001	0.0130	0.0544	5.6770	1419.90 **	20.25	492.46 **	21.68 *
	Futures Returns	1057	0.0001	0.0131	-0.0453	4.5871	927.07 **	30.59 **	683.85 **	25.11 *
	Basis	1058	0.0014	0.0070	2.3395	7.7833	3632.30 **	2284.17 **	1974.90 **	64.52 **
NOV	Stock Returns	1057	0.0001	0.0132	0.2433	3.4054	521.17 **	24.52 *	371.37 **	14.40
	Futures Returns	1057	0.0001	0.0134	0.4821	3.8651	698.87 **	15.86	324.29 **	12.28
	Basis	1058	0.0007	0.0054	1.5213	7.1561	2663.10 **	1487.26 **	685.45 **	21.87 *
PHI	Stock Returns	1085	-0.0003	0.0308	-0.0094	1.7668	137.50 **	19.14	691.65 **	22.73 *
	Futures Returns	1085	-0.0003	0.0303	0.0846	1.6632	123.08 **	12.10	620.10 **	20.43
	Basis	1086	-0.0013	0.0071	-0.3219	9.3210	3844.60 **	1041.84 **	69.09 **	3.34
RBO	Stock Returns	1189	0.0001	0.0191	-0.1085	3.8822	665.85 **	38.70 **	763.24 **	26.32 **
	Futures Returns	1189	0.0000	0.0184	0.0370	4.0070	707.38 **	37.55 **	691.04 **	23.65 *
	Basis	1190	-0.0005	0.0087	0.8785	3.8954	804.25 **	3559.47 **	774.22 **	31.44 **
RD	Stock Returns	1266	-0.0002	0.0166	-0.6035	4.3048	880.29 **	34.77 **	480.12 **	22.67 *
	Futures Returns	1266	-0.0007	0.0255	-0.5966	4.2807	869.77 **	24.92 *	402.13 **	19.63
	Basis	1267	-0.6286	0.2001	1.2755	1.6318	403.89 **	3715.60 **	3688.10 **	173.07 **
ROG	Stock Returns	1057	0.0005	0.0156	0.0255	2.6770	315.73 **	9.92	442.46 **	19.03
	Futures Returns	1057	0.0005	0.0159	0.2006	2.6275	311.15 **	8.44	401.29 **	15.25
	Basis	1058	0.0008	0.0055	1.4704	4.6049	1314.80 **	1868.53 **	1066.78 **	32.22 **
SCH	Stock Returns	1266	0.0000	0.0213	0.0889	2.5319	283.73 **	26.97 **	827.93 **	27.69 **
	Futures Returns	1266	0.0000	0.0205	0.2521	2.5020	286.90 **	22.16 *	696.45 **	26.31 **
	Basis	1267	0.0008	0.0062	0.0917	1.2071	65.66 **	1238.14 **	288.61 **	10.71
SHB	Stock Returns	1057	0.0004	0.0148	0.0059	3.7828	630.24 **	13.71	446.47 **	19.54
	Futures Returns	1057	0.0004	0.0146	0.1721	3.6645	596.62 **	16.31	461.96 **	22.41 *
	Basis	1058	-0.0003	0.0091	2.8139	9.2811	5188.60 **	3715.05 **	3348.17 **	152.68 **
SHE	Stock Returns	1189	0.0008	0.0351	-0.6836	4.8667	1125.40 **	27.85 **	487.77 **	23.29 *
	Futures Returns	1189	0.0010	0.0399	-0.7729	6.9065	2206.00 **	36.03 **	184.47 **	10.65
	Basis	1190	0.1276	0.0646	0.2376	-0.4806	20.12 **	10448.30 **	10496.60 **	1380.30 **

Table 3.5: Summary Statistics of Stock Returns, Futures Returns, and Basis (continued)

Code	Variables	N	μ	σ	S	K	JB	Q(12)	Q²(12)	ARCH (12)
SIE	Stock Returns	1266	-0.0003	0.0245	0.1397	1.1421	60.89 **	18.93	515.92 **	17.67
	Futures Returns	1266	-0.0006	0.0259	-1.9531	28.3320	36024.00 **	18.58	6.00	0.45
	Basis	1267	-0.0204	0.0887	-3.6917	11.8390	8574.20 **	10144.70 **	10289.10 **	3581.40 **
TEF	Stock Returns	1266	-0.0003	0.0196	0.2632	3.0007	408.75 **	19.73	313.97 **	13.36
	Futures Returns	1266	-0.0004	0.0196	0.3867	3.8068	664.59 **	16.85	361.50 **	18.03
	Basis	1267	-0.0653	0.0439	-0.3888	-1.3315	104.70 **	11896.90 **	11730.90 **	3601.70 **
TI	Stock Returns	1266	-0.0006	0.0215	-0.9834	8.6381	3456.60 **	39.84 **	190.39 **	9.45
	Futures Returns	1266	-0.0013	0.0377	-23.8050	694.0500	21315000.00 **	3.86	0.02	0.00
	Basis	1267	-0.5935	0.5889	0.3706	-1.7697	162.13 **	12278.60 **	12190.00 **	13769.00 **
TIM	Stock Returns	1087	-0.0004	0.0184	0.0191	4.3769	843.78 **	29.27 **	248.06 **	11.34
	Futures Returns	1087	-0.0004	0.0185	-0.2145	3.6191	584.97 **	42.00 **	234.48 **	10.76
	Basis	1088	-0.0151	0.0234	0.1328	0.1267	3.81	8514.98 **	6752.37 **	291.35 **
TLI	Stock Returns	1057	-0.0001	0.0240	0.3845	7.5684	2548.70 **	26.28 **	236.88 **	13.14
	Futures Returns	1057	-0.0001	0.0237	0.3924	7.8888	2768.00 **	26.38 **	250.15 **	13.51
	Basis	1058	-0.0180	0.0096	0.6547	0.5227	87.53 **	5867.69 **	2143.74 **	61.68 **
TOT	Stock Returns	1266	0.0002	0.0162	-0.2827	1.9345	178.91 **	36.87 **	538.90 **	17.67
	Futures Returns	1266	0.0002	0.0156	-0.2077	2.0795	198.05 **	33.85 **	459.68 **	17.00
	Basis	1267	-0.0002	0.0091	1.6872	3.2965	980.08 **	5311.55 **	5212.83 **	237.13 **
UBS	Stock Returns	1057	0.0005	0.0172	0.2496	4.7886	1020.90 **	32.56 **	741.45 **	24.09 *
	Futures Returns	1057	0.0005	0.0178	-0.0172	6.5534	1891.50 **	31.80 **	569.46 **	22.31 *
	Basis	1058	-0.0031	0.0142	-0.3436	1.4936	119.04 **	8205.01 **	5929.59 **	323.33 **
UC	Stock Returns	1217	0.0002	0.0171	0.1678	6.3239	1766.30 **	54.17 **	665.73 **	26.45 **
	Futures Returns	1217	0.0002	0.0167	0.3217	6.4023	1823.50 **	42.63 **	524.66 **	21.30 *
	Basis	1218	0.0001	0.0111	2.6685	9.3028	5065.90 **	2549.31 **	2680.32 **	144.98 **
VIV	Stock Returns	1189	-0.0009	0.0337	-1.3792	15.9300	11511.00 **	72.07 **	470.12 **	23.27 *
	Futures Returns	1189	-0.0009	0.0331	-1.5577	16.6730	12670.00 **	65.62 **	314.28 **	16.50
	Basis	1190	-0.0018	0.0082	-0.0457	9.0622	3617.30 **	715.62 **	227.22 **	8.76
VOF	Stock Returns	1266	-0.0005	0.0235	0.2864	1.7648	151.61 **	41.76 **	415.62 **	13.86
	Futures Returns	1266	-0.0005	0.0229	0.2393	1.7061	138.28 **	46.35 **	389.12 **	14.93
	Basis	1267	-0.0020	0.0067	-3.3445	49.9570	111880.00 **	595.18 **	2.51	0.20
VOW	Stock Returns	1189	-0.0002	0.0219	-0.0155	2.1002	194.31 **	31.37 **	540.34 **	17.05
	Futures Returns	1189	-0.0002	0.0216	-0.2369	2.6484	318.80 **	34.94 **	459.14 **	18.83
	Basis	1190	0.0006	0.0107	0.7181	6.7709	2110.00 **	1015.08 **	532.23 **	16.88

Notes: *, ** Significant at 5% and 1% level, respectively.
N = number of observation; μ = mean; σ = standard deviation; S = skewness; K = excess Kurtosis; JB = Jarque-Bera test for normality.
ARCH (12) test is the Langrange Multiplier [LM(12)] test for ARCH effects and distributed as a χ^2 with 12 degree of freedom.
Q(N) and Q²(N) are the Ljung-Box Q statistics which are distributed as χ^2 with N degree of freedom where N is the number of lags.
The Ljung-Box statistics for N lags is calculated as $LB(N) = T(T+2)\sum(\rho / T - j)$ where rj is the sample autocorrelation for j lags and T is the sample size

Table 3.6: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period

Code	Dep Var	α_{S1} / α_{F1}	α_{S2} / α_{F2}	α_{S3} / α_{F3}	α_{S4} / α_{F4}	β_{S1} / β_{F1}	β_{S2} / β_{F2}	β_{S3} / β_{F3}	β_{S4} / β_{F4}	δ_S / δ_F	γ_S / γ_F	Wald test (H_0: $\beta_S=0$) / Wald test (H_0: $\alpha_F=0$)
AA	R_S	-0.0983	-0.0693	0.0787	0.1531 **	0.0433	0.0055	-0.1262 *	-0.1569 **	1.1074 **	-0.0865 *	11.4322 *
		(-1.620)	(-1.061)	(1.236)	(2.799)	(0.705)	(0.086)	(-1.986)	(-2.898)	(50.640)	(-2.212)	
	R_F	0.4143 **	0.1421 *	0.2177 **	0.1925 **	-0.4314 **	-0.1755 **	-0.2451 **	-0.2040 **	1.0613 **	0.0440	56.3606 **
		(6.544)	(2.086)	(3.275)	(3.374)	(-6.737)	(-2.583)	(-3.697)	(-3.613)	(46.528)	(1.080)	
AGN	R_S	-0.0012	-0.0264	-0.0114	0.0038	0.0054	0.0024	0.0003	-0.0028	1.5144 **	0.0055	0.4779
		(-0.057)	(-1.273)	(-0.575)	(0.209)	(0.413)	(0.191)	(0.027)	(-0.341)	(52.887)	(0.423)	
	R_F	0.4314 **	0.3259 **	0.2622 **	0.0744	-0.4459 **	-0.3372 **	-0.2233 **	-0.1134 **	1.4035 **	0.4408 **	37.5705 **
		(5.304)	(4.110)	(3.447)	(1.065)	(-8.854)	(-7.042)	(-5.282)	(-3.546)	(12.798)	(8.799)	
AHL	R_S	-0.1624	-0.2424 *	-0.3350 **	-0.0986	0.1948 *	0.3167 **	0.2485 *	0.1266	1.2020 **	0.0088	12.7708 *
		(-1.616)	(-2.275)	(-3.148)	(-0.982)	(1.986)	(3.052)	(2.391)	(1.300)	(18.545)	(0.994)	
	R_F	0.2282 *	-0.1300	-0.2653 *	-0.0761	-0.1623	0.2033	0.1900	0.1165	1.0843 **	0.0126	12.8304 *
		(2.147)	(-1.153)	(-2.356)	(-0.716)	(-1.563)	(1.852)	(1.727)	(1.130)	(15.808)	(1.340)	
ALV	R_S	-0.0459	-0.1855 **	-0.0764	-0.0524	0.1032 *	0.1729 **	0.0686	0.0090	1.2799 **	0.0106	13.2153 *
		(-1.187)	(-3.758)	(-1.542)	(-1.296)	(2.433)	(3.409)	(1.372)	(0.232)	(49.746)	(1.793)	
	R_F	0.7082 **	0.2809 **	0.1070 *	-0.0277	-0.5992 **	-0.2567 **	-0.1170 *	-0.0246	1.0410 **	0.0179 **	332.8976 **
		1(7.154)	(5.326)	(2.020)	(-0.640)	(-13.222)	(-4.736)	(-2.189)	(-0.594)	(37.861)	(2.841)	
AXA	R_S	0.1037 **	-0.0358	-0.0263	-0.0368	-0.0013	-0.0073	-0.0012	0.0124	1.2822 **	-0.0009	1.1308
		(4.292)	(-1.480)	(-1.089)	(-1.523)	(-0.097)	(-0.532)	(-0.087)	(0.905)	(35.105)	(-0.331)	
	R_F	0.1760 **	-0.0030	0.0105	-0.0875	-0.0303	-0.0212	-0.0003	0.0150	1.2253 **	0.0403 **	13.3359 **
		(3.207)	(-0.055)	(0.192)	(-1.593)	(-0.970)	(-0.679)	(-0.011)	(0.479)	(14.772)	(6.261)	
AZN	R_S	-0.0975	-0.0350	-0.0017	-0.1285	0.1609	-0.0583	-0.0002	0.1135	0.8312 **	0.0222	7.4805
		(-0.867)	(-0.290)	(-0.015)	(-1.344)	(1.409)	(-0.480)	(-0.002)	(1.196)	(24.028)	(0.277)	
	R_F	0.4829 **	0.3779 **	0.2336 *	-0.0294	-0.4108 **	-0.4520 **	-0.2261	0.0279	0.7565 **	0.1534	22.1036 **
		(4.285)	(3.124)	(2.021)	(-0.306)	(-3.589)	(-3.715)	(-1.953)	(0.293)	(21.814)	(1.914)	
BAR	R_S	0.0532 *	-0.0521 *	0.0152	-0.0300	0.0200 *	-0.0019	-0.0148	-0.0022	1.1709 **	-0.0009	6.5919
		(2.452)	(-2.408)	(0.699)	(-1.381)	(2.051)	(-0.191)	(-1.517)	(-0.225)	(36.849)	(-1.438)	
	R_F	0.1276	-0.0624	-0.1641 *	-0.0408	0.0076	-0.0016	-0.0151	0.0024	1.0944 **	0.0033	11.3332 *
		(1.903)	(-0.932)	(-2.445)	(-0.607)	(0.252)	(-0.055)	(-0.500)	(0.079)	(11.141)	(1.683)	
BNP	R_S	0.1164 **	-0.0614 *	-0.0084	0.0343	-0.0530 **	0.0068	0.0060	-0.0251	0.9231 **	-0.0018	9.8170 *
		(4.250)	(-2.230)	(-0.304)	(1.248)	(-2.770)	(0.357)	(0.313)	(-1.315)	(35.717)	(-1.261)	
	R_F	0.2511 **	-0.0567	0.0113	-0.0144	-0.0881 *	0.0018	0.0175	-0.0184	0.8366 **	0.0035	26.5446 **
		(4.995)	(-1.122)	(0.224)	(-0.285)	(-2.508)	(0.050)	(0.498)	(-0.527)	(17.635)	(1.349)	
BPA	R_S	0.0073	-0.0343	-0.0917	-0.0200	-0.0386	-0.0207	0.0684	0.0373	0.8446 **	-0.1032	0.7811
		(0.063)	(-0.273)	(-0.757)	(-0.194)	(-0.326)	(-0.164)	(0.562)	(0.362)	(29.580)	(-1.277)	
	R_F	0.4823 **	0.2173	-0.0194	0.0551	-0.5095 **	-0.2648 *	-0.0008	-0.0228	0.7947 **	0.0466	20.1866 **
		(4.053)	(1.710)	(-0.158)	(0.529)	(-4.247)	(-2.069)	(-0.007)	(-0.219)	(27.464)	(0.569)	
BTL	R_S	-0.1659 **	-0.0774	0.0619	0.1458 **	0.1844 **	0.0648	-0.1278 *	-0.1262 *	0.9830 **	0.0055	26.2148 **
		(-3.108)	(-1.434)	(1.147)	(2.735)	(3.620)	(1.260)	(-2.481)	(-2.463)	(22.983)	(1.054)	
	R_F	-0.0283	-0.0288	0.0240	0.1325 *	0.0492	0.0104	-0.1155 *	-0.0972	0.8807 **	0.0164 **	5.5370
		(-0.479)	(-0.483)	(0.402)	(2.250)	(0.874)	(0.183)	(-2.030)	(-1.717)	(18.642)	(2.836)	
BVA	R_S	-0.1213	-0.1781 **	-0.0982	-0.0900	0.1423 *	0.1847 **	0.0821	0.0890	1.3214 **	-0.1046 *	9.6271 *
		(-1.905)	(-2.715)	(-1.577)	(-1.770)	(2.168)	(2.763)	(1.294)	(1.740)	(71.382)	(-1.997)	
	R_F	0.3708 **	0.1130	0.0871	0.0550	-0.3216 **	-0.1083	-0.0810	-0.0591	1.2408 **	0.0988	41.5409 **
		(5.799)	(1.717)	(1.394)	(1.077)	(-4.882)	(-1.614)	(-1.274)	(-1.151)	(66.778)	(1.880)	
CA	R_S	-0.1189	-0.0162	0.0121	-0.1628 *	0.0717	-0.0021	-0.0201	0.1437	0.7984 **	-0.0500	6.7820
		(-1.324)	(-0.169)	(0.131)	(-2.111)	(0.785)	(-0.022)	(-0.216)	(1.885)	(29.964)	(-0.770)	
	R_F	0.3915 **	0.2209 *	0.1259	-0.0767	-0.4042 **	-0.2519 **	-0.1089	0.0577	0.7380 **	0.1130	23.7530 **
		(4.351)	(2.305)	(1.357)	(-0.993)	(-4.415)	(-2.619)	(-1.170)	(0.756)	(27.655)	(1.739)	
CGE	R_S	-0.0480	0.0903	0.0820	0.2216 **	0.0563	-0.0497	-0.0645	-0.1924	1.4480 **	0.0390	15.6345 **
		(-0.431)	(0.901)	(0.954)	(3.380)	(0.523)	(-0.515)	(-0.786)	(-0.252)	(25.555)	(0.342)	
	R_F	0.1983	0.2695 *	0.2367 *	0.2810 **	-0.1788	-0.2498 *	-0.2232 *	-3.1127 **	1.3446 **	0.6857 **	16.3500 **
		(1.622)	(2.446)	(2.506)	(3.901)	(-1.512)	(-2.355)	(-2.476)	(-3.703)	(21.595)	(5.475)	
CSG	R_S	-0.1609 *	0.0586	0.0983	0.0914	0.1827 *	0.0088	-0.0919	-0.1174	1.4991 **	0.0110	10.9696 *
		(-2.124)	(0.667)	(1.115)	(1.205)	(2.422)	(0.101)	(-1.056)	(-1.573)	(39.263)	(0.759)	
	R_F	0.4527 **	0.3956 **	0.2530 **	0.0999	-0.4256 **	-0.3262 **	-0.2435 **	-0.1336	1.5010 **	0.0248	38.6167 **
		(5.967)	(4.492)	(2.867)	(1.314)	(-5.635)	(-3.733)	(-2.792)	(-1.788)	(39.248)	(1.711)	
DBK	R_S	-0.0535	-0.0579	-0.0377	-0.0740	0.0465	0.0393	0.0434	0.0520	1.1151 **	-0.0593	1.7809
		(-0.942)	(-0.960)	(-0.659)	(-1.673)	(0.800)	(0.654)	(0.778)	(1.238)	(54.145)	(-1.267)	
	R_F	0.5734 **	0.3823 **	0.1837 **	-0.0355	-0.5097 **	-0.3784 **	-0.1590 **	0.0146	0.9525 **	0.1591 **	100.6916 **
		(9.211)	(5.772)	(2.929)	(-0.731)	(-7.999)	(-5.741)	(-2.594)	(0.318)	(42.157)	(3.098)	
DCY	R_S	-0.0601	-0.0277	0.0541	-0.0067	0.0604	0.0032	-0.0181	0.0363	1.0310 **	-0.0598	3.7742
		(-1.232)	(-0.517)	(1.034)	(-0.152)	(1.196)	(0.060)	(-0.348)	(0.843)	(45.265)	(-1.950)	
	R_F	0.4973 **	0.3214 **	0.2032 **	0.0734	-0.4306 **	-0.3284 **	-0.1603 **	-0.0341	0.8885 **	0.0518	89.8553 **
		(9.471)	(5.566)	(3.610)	(1.552)	(-7.931)	(-5.664)	(-2.864)	(-0.737)	(36.266)	(1.570)	
DTE	R_S	-0.0670	-0.0928	-0.1109	-0.0877	0.0429	0.0608	0.0485	0.0965 *	1.1003 **	-0.1158	4.5076
		(-0.950)	(-1.317)	(-1.712)	(-1.758)	(0.597)	(0.864)	(0.759)	(2.016)	(37.146)	(-1.786)	
	R_F	0.4700 **	0.2552 **	0.1301 *	-0.0074	-0.4172 **	-0.2557 **	-0.1788 **	0.0271	0.9259 **	0.2085 **	53.2779 **
		(6.589)	(3.584)	(1.987)	(-0.146)	(-5.746)	(-3.595)	(-2.768)	(0.561)	(30.925)	(3.181)	
ENI	R_S	-0.0459	-0.0456	-0.0096	-0.0114	0.0244	0.0128	-0.0038	0.0088	0.8063 **	0.0026	3.3222
		(-1.860)	(-1.845)	(-0.391)	(-0.463)	(1.527)	(0.803)	(-0.238)	(0.555)	(29.930)	(1.416)	
	R_F	0.0213	-0.0103	-0.0212	-0.0458	0.0036	-0.0016	0.0051	0.0142	0.7476 **	0.0144 **	[illegible]
		(0.463)	(-0.225)	(-0.461)	(-0.997)	(0.121)	(-0.055)	(0.172)	(0.477)	(14.915)	(4.197)	
ENL	R_S	-0.0630 *	-0.0043	0.0045	-0.0290	-0.0205	-0.0038	0.0000	0.0220	0.7527 **	-0.0002	4.0729
		(-2.484)	(-0.169)	(0.178)	(-1.152)	(-1.359)	(-0.252)	(0.001)	(1.459)	(29.358)	(-0.075)	
	R_F	-0.0043	0.0158	0.0050	-0.0061	-0.0516	0.0154	-0.0123	0.0183	0.6361 **	0.0142 **	0.1231
		(-0.082)	(0.301)	(0.095)	(-0.117)	(-1.648)	(0.490)	(-0.391)	(0.584)	(11.962)	(3.385)	

Table 3.6: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period (continued)

Code	Dep Var	α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_{01}: $\beta_S = 0$)
		α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_{02}: $\alpha_F = 0$)
EOA	R_S	-0.1643 **	-0.0587	-0.0286	0.0882	0.0654	0.0491	0.0182	-0.0879	0.6818 **	-0.0683	6.5878
		(-2.898)	(-0.994)	(-0.506)	(1.841)	(1.122)	(0.822)	(0.317)	(-1.830)	(30.506)	(-1.593)	
	R_F	0.2874 **	0.1712 **	0.0785	0.1059 *	-0.3288 **	-0.1840 **	-0.0662	-0.1050 *	0.5235 **	0.1361 **	26.7391 **
		(4.879)	(2.792)	(1.340)	(2.128)	(-5.434)	(-2.968)	(-1.110)	(-2.105)	(22.558)	(3.056)	
ERC	R_S	0.0438	0.0964	-0.2534 **	-0.2423 **	-0.0071	-0.1449 *	0.1908 **	0.2238 **	1.8163 **	0.0189 **	21.3036 **
		(0.662)	(1.408)	(-3.699)	(-3.653)	(-0.112)	(-2.190)	(2.883)	(3.517)	(29.111)	(2.921)	
	R_F	0.3378 **	0.1162	-0.2217 **	-0.2649 **	-0.3154 **	-0.1564 *	0.1758 *	0.2630 **	1.8067 **	0.0257 **	44.5215 **
		(4.744)	(1.577)	(-3.009)	(-3.713)	(-4.632)	(-2.198)	(2.469)	(3.843)	(26.914)	(3.686)	
FTE	R_S	0.0072	-0.1492	0.1086	0.0585	0.0824	0.1246	-0.0714	-0.0450	1.2130 **	0.0037	3.6189
		(0.079)	(-1.543)	(1.126)	(0.637)	(0.885)	(1.279)	(-0.734)	(-0.488)	(24.910)	(0.476)	
	R_F	0.3597 **	0.0354	0.2413 *	0.1068	-0.2605 **	-0.0479	-0.1950 *	-0.0830	1.1443 **	0.0073	21.4561 **
		(3.897)	(0.364)	(2.488)	(1.158)	(-2.785)	(-0.489)	(-1.997)	(-0.896)	(23.392)	(0.942)	
GEN	R_S	-0.0204	-0.0523	-0.0814	0.0679	0.0952	0.0301	0.0480	-0.0554	1.0191 **	-0.1337	3.4551
		(-0.233)	(-0.590)	(-0.978)	(0.991)	(1.072)	(0.337)	(0.575)	(-0.816)	(40.953)	(-1.757)	
	R_F	0.4203 **	0.1914 *	0.0619	0.1407 *	-0.3314 **	-0.2087 *	-0.0727	-0.1355 *	0.9679 **	0.1447	29.7683 **
		(4.845)	(2.188)	(0.753)	(2.081)	(-3.779)	(-2.365)	(-0.883)	(-2.022)	(39.388)	(1.925)	
GXW	R_S	-0.2282	-0.1849	0.1332	0.0330	0.2192	0.0933	-0.1588	-0.0430	0.8196 **	-0.0928	9.5711 *
		(-1.912)	(-1.474)	(1.117)	(0.332)	(1.821)	(0.740)	(-1.321)	(-0.429)	(28.057)	(-1.039)	
	R_F	0.2915 *	0.1657	0.3194 **	0.0952	-0.3037 *	-0.2530 *	-0.3463 **	-0.0928	0.7648 **	0.0790	11.2558 *
		(2.403)	(1.301)	(2.636)	(0.941)	(-2.482)	(-1.975)	(-2.836)	(-0.910)	(25.769)	(0.870)	
HAS	R_S	-0.1516 *	-0.0526	0.0105	0.0637	0.1558 *	0.0257	0.0193	-0.0100	0.8306 **	-0.0428	5.4240
		(-2.169)	(-0.705)	(0.143)	(0.970)	(2.196)	(0.341)	(0.260)	(-0.151)	(35.938)	(-1.175)	
	R_F	0.2610 **	0.1054	0.0364	0.1018	-0.2394 **	-0.1275	0.0030	-0.0230	0.7970 **	0.0445	17.1849 **
		(3.792)	(1.434)	(0.504)	(1.575)	(-3.423)	(-1.721)	(0.042)	(-0.351)	(34.993)	(1.239)	
HNM	R_S	-0.0202	0.0170	0.0678	0.0301	-0.0824	-0.0716	-0.0935	-0.0657	0.6480 **	-0.1386	1.5628
		(-0.219)	(0.183)	(0.782)	(0.425)	(-0.900)	(-0.778)	(-1.094)	(-0.968)	(20.209)	(-1.709)	
	R_F	0.4784 **	0.3079 **	0.2540 **	0.1292	-0.5702 **	-0.3744 **	-0.2751 **	-0.1389 *	0.6254 **	0.1505	25.9327 **
		(5.017)	(3.200)	(2.836)	(1.768)	(-6.036)	(-3.940)	(-3.120)	(-1.985)	(18.899)	(1.798)	
ING	R_S	0.0103	0.0083	-0.0524 *	0.0116	0.0064	-0.0071	-0.0097	-0.0025	1.4110 **	-0.0014	0.6090
		(0.481)	(0.391)	(-2.456)	(0.544)	(0.362)	(-0.404)	(-0.554)	(-0.141)	(65.490)	(-0.747)	
	R_F	0.0766	-0.0038	-0.0394	0.0286	-0.0404	-0.0073	-0.0067	-0.0103	1.3627 **	0.0089 **	5.2736
		(1.960)	(-0.097)	(-1.008)	(0.733)	(-1.261)	(-0.227)	(-0.209)	(-0.320)	(34.573)	(2.672)	
LLO	R_S	0.0488	-0.0457	0.0823	0.0588	-0.0155	0.0132	-0.0930	-0.0618	1.1040 **	-0.0542 *	3.3609
		(0.829)	(-0.731)	(1.327)	(1.022)	(-0.258)	(0.208)	(-1.481)	(-1.073)	(35.767)	(-2.279)	
	R_F	0.4103 **	0.0228	0.0770	0.0764	-0.3519 **	-0.0824	-0.0749	-0.0979	1.0133 **	0.0000	53.4361 **
		(6.711)	(0.351)	(1.193)	(1.279)	(-5.635)	(-1.254)	(-1.146)	(-1.637)	(31.582)	(0.002)	
MUV	R_S	0.0078	-0.1613 **	-0.1295 *	-0.0887	0.0744	0.1671 **	0.1071	0.0716	1.2180 **	0.0131	7.7825
		(0.163)	(-2.616)	(-2.095)	(-1.787)	(1.479)	(2.723)	(1.773)	(1.536)	(44.574)	(1.062)	
	R_F	0.8367 **	0.4220 **	0.1504 *	0.0596	-0.7020 **	-0.3899 **	-0.1967 **	-0.0692	1.0268 **	0.0269 *	271.1149 **
		(15.715)	(6.175)	(2.196)	(1.082)	(-12.598)	(-5.734)	(-2.937)	(-1.339)	(33.907)	(1.967)	
NDA	R_S	-0.2169 **	-0.1307	-0.1553	-0.0175	0.1296	0.0941	0.1201	-0.0304	0.8732 **	-0.0298	5.0406
		(-2.704)	(-1.547)	(-1.877)	(-0.237)	(1.591)	(1.101)	(1.434)	(-0.405)	(25.805)	(-0.636)	
	R_F	0.1793 *	0.0312	-0.1093	-0.0242	-0.2502 **	-0.0660	0.0555	-0.0238	0.8476 **	0.0846	9.6511 *
		(2.276)	(0.376)	(-1.346)	(-0.334)	(-3.127)	(-0.786)	(0.674)	(-0.324)	(25.513)	(1.842)	
NES	R_S	-0.1769 **	-0.1543 *	-0.1489 *	-0.1396 *	0.1412 *	0.0913	0.0990	0.1311 *	0.7127 **	0.0012	8.7116
		(-2.665)	(-2.198)	(-2.205)	(-2.471)	(2.135)	(1.303)	(1.482)	(2.391)	(32.459)	(0.024)	
	R_F	0.3584 **	0.1579 *	0.0245	-0.0675	-0.3961 **	-0.1970 **	-0.0595	0.0576	0.6472 **	0.1727 **	33.4841 **
		(5.144)	(2.144)	(0.345)	(-1.139)	(-5.707)	(-2.680)	(-0.850)	(1.002)	(28.093)	(3.367)	
NOV	R_S	-0.0212	0.0146	0.0169	0.1108	0.0242	-0.0403	-0.0837	-0.0794	0.7638 **	-0.0737	2.6792
		(-0.265)	(0.176)	(0.215)	(1.726)	(0.301)	(-0.485)	(-1.076)	(-1.276)	(35.846)	(-1.108)	
	R_F	0.4936 **	0.3402 **	0.1865 *	0.1645 **	-0.4815 **	-0.3564 **	-0.2311 **	-0.1164	0.7440 **	0.1633 *	40.7747 **
		(6.219)	(4.145)	(2.403)	(2.590)	(-6.048)	(-4.340)	(-3.006)	(-1.890)	(35.305)	(2.481)	
PHI	R_S	-0.0501	0.0907	0.1126	0.0868	0.0248	-0.1256	-0.0987	-0.0901	1.4321 **	-0.0164	3.5624
		(-0.432)	(0.771)	(1.031)	(1.010)	(0.214)	(-1.064)	(-0.903)	(-1.054)	(48.443)	(-0.161)	
	R_F	0.4472 **	0.3719 **	0.2482 *	0.1215	-0.4689 **	-0.3991 **	-0.2243 *	-0.1214	1.3599 **	0.2755 **	14.2558 **
		(3.737)	(3.062)	(2.202)	(1.370)	(-3.911)	(-3.276)	(-1.990)	(-1.377)	(44.562)	(2.611)	
RBO	R_S	-0.1767 *	-0.0713	0.0264	0.1292	0.1866 *	0.0597	-0.0575	-0.1506 *	1.1201 **	-0.0679	13.1948 *
		(-2.295)	(-0.856)	(0.328)	(1.940)	(2.393)	(0.712)	(-0.707)	(-2.222)	(37.721)	(-1.366)	
	R_F	0.3590 **	0.1997 *	0.1581 *	0.1971 **	-0.3265 **	-0.2345 **	-0.1849 *	-0.2048 **	1.0733 **	0.0510	27.8088 **
		(4.688)	(2.410)	(1.978)	(2.976)	(-4.208)	(-2.814)	(-2.286)	(-3.037)	(36.334)	(1.032)	
RD	R_S	-0.0426	-0.0427	0.0301	0.0260	0.0201	0.0018	-0.0138	0.0009	0.7067 **	-0.0001	2.2200
		(-1.683)	(-1.685)	(1.186)	(1.028)	(1.219)	(0.107)	(-0.838)	(0.053)	(36.425)	(-0.252)	
	R_F	0.0441	-0.0200	0.0774	0.0096	0.0228	-0.0070	-0.0215	0.0070	0.6670 **	0.0008	3.3307
		(0.879)	(-0.399)	(1.538)	(0.191)	(0.697)	(-0.216)	(-0.657)	(0.214)	(17.350)	(0.773)	
ROG	R_S	-0.1145	-0.2239 *	-0.0017	-0.0754	0.1422	0.1844	0.0579	0.1057	0.8960 **	-0.1068	5.5952
		(-1.183)	(-2.249)	(-0.018)	(-0.972)	(1.470)	(1.864)	(0.626)	(1.399)	(34.352)	(-1.358)	
	R_F	0.4387 **	0.2184 *	0.2761 **	0.0756	-0.4077 **	-0.2608 **	-0.2205 *	-0.0432	0.8709 **	0.0910	24.1642 **
		(4.447)	(2.152)	(2.903)	(0.956)	(-4.135)	(-2.586)	(-2.337)	(-0.561)	(32.752)	(1.136)	
SCH	R_S	-0.1492 *	-0.1568 *	-0.0831	-0.0440	0.1608 *	0.1278	0.0797	0.0552	1.3577 **	-0.1609 **	6.0931
		(-2.252)	(-2.310)	(-1.305)	(-0.849)	(2.392)	(1.871)	(1.250)	(1.059)	(72.571)	(-2.912)	
	R_F	0.2970 **	0.1407 *	0.0307	0.0187	-0.2617 **	-0.1618 *	-0.0316	-0.0105	1.2872 **	0.0834	23.5247 **
		(4.490)	(2.076)	(0.483)	(0.361)	(-3.900)	(-2.373)	(-0.496)	(-0.202)	(68.921)	(1.512)	
SHB	R_S	-0.0715	-0.2616 **	-0.1192	0.0651	0.0275	0.2078 **	0.0892	-0.0803	0.6395 **	-0.0074	10.9337 *
		(-0.943)	(-3.317)	(-1.546)	(0.928)	(0.358)	(2.600)	(1.140)	(-1.141)	(25.937)	(-0.168)	
	R_F	0.2640 **	-0.1272	-0.1238	0.0284	-0.3116 **	0.0868	0.0731	-0.0469	0.6135 **	0.1154 **	29.1718 **
		(3.526)	(-1.634)	(-1.625)	(0.410)	(-4.110)	(1.100)	(0.946)	(-0.675)	(25.195)	(2.653)	

Table 3.6: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period (continued)

Code	Dep Var	α_{S1} α_{F1}	α_{S2} α_{F2}	α_{S3} α_{F3}	α_{S4} α_{F4}	β_{S1} β_{F1}	β_{S2} β_{F2}	β_{S3} β_{F3}	β_{S4} β_{F4}	δ_S δ_F	γ_S γ_F	Wald test (H_{01}: β_{S} = 0) Wald test (H_{02}: α_F = 0)	
SHE	R_S	0.2594 *	0.2376	0.2287	0.0408	-0.2441 *	-0.2238	-0.2111	-0.0280	0.9234 **	0.0056	7.0150	
		(1.980)	(1.705)	(1.641)	(0.310)	(-2.102)	(-1.815)	(-1.714)	(-0.242)	(11.978)	(0.530)		
	R_F	0.6973 **	0.4893 **	0.3729 *	0.1206	-0.6303 **	-0.4479 **	-0.3361 *	-0.0871	0.8687 **	0.0075	25.2991	**
		(4.637)	(3.060)	(2.331)	(0.798)	(-4.728)	(-3.166)	(-2.378)	(-0.655)	(09.816)	(0.972)		
SIE	R_S	-0.0262	0.0239	-0.0138	-0.0529	0.0159	-0.0436	-0.0036	0.0306	1.1847 **	0.0050	[illegible]	
		(-0.980)	(0.844)	(-0.485)	(-1.939)	(0.613)	(-1.647)	(-0.136)	(1.231)	(52.450)	(1.139)		
	R_F	0.3341 **	0.0948 *	0.0049	-0.0600	-0.2046 **	-0.1001 **	-0.0160	0.0283	0.9850 **	0.0260 **	88.1485	**
		(9.151)	(2.456)	(0.127)	(-1.612)	(-5.801)	(-2.772)	(-0.442)	(0.834)	(31.980)	(4.356)		
TEF	R_S	-0.1203 *	-0.1816 **	-0.0936	-0.0454	0.1507 **	0.1528 **	0.1138 *	0.0113	1.2250 **	0.0011	13.8126	**
		(-2.496)	(-3.339)	(-1.722)	(-0.930)	(3.085)	(2.833)	(2.119)	(0.239)	(64.085)	(0.334)		
	R_F	0.4322 **	0.1085	0.1488 **	0.0648	-0.3645 **	-0.1257 *	-0.1206 *	-0.1005 *	1.1944 **	0.0052	87.3794	**
		(8.778)	(1.953)	(2.680)	(1.300)	(-7.305)	(-2.283)	(-2.199)	(-2.071)	(61.186)	(1.480)		
TI	R_S	-0.0013	-0.0114	0.0227	0.0477 *	-0.0083	-0.0020	0.0087	0.0067	1.1435 **	0.0000	1.2104	
		(-0.058)	(-0.515)	(1.027)	(2.152)	(-0.656)	(-0.163)	(0.688)	(0.532)	(32.337)	(0.059)		
	R_F	0.0108	-0.0284	0.0047	0.0787	-0.0180	-0.0095	0.0105	0.0194	0.8987 **	0.0016	2.8575	
		(0.214)	(-0.566)	(0.094)	(1.559)	(-0.628)	(-0.333)	(0.366)	(0.677)	(11.173)	(1.335)		
TIM	R_S	-0.1238 **	-0.1433 **	0.0105	0.0548	0.0696	0.1117 *	-0.0189	-0.0431	1.0665 **	-0.0209	8.8085	
		(-2.748)	(-2.971)	(0.218)	(1.227)	(1.541)	(2.307)	(-0.391)	(-0.973)	(39.632)	(-1.607)		
	R_F	0.2872 **	0.0303	0.0825	0.0425	-0.3428 **	-0.0587	-0.0658	-0.0241	0.9902 **	0.0073	39.4496	**
		(5.897)	(0.581)	(1.591)	(0.881)	(-7.014)	(-1.120)	(-1.260)	(-0.504)	(34.031)	(0.519)		
TLI	R_S	-0.0827	-0.2934 *	-0.0801	-0.1575	0.0389	0.1801	0.0314	0.1334	0.9705 **	0.0129	3.4060	
		(-0.730)	(-2.414)	(-0.663)	(-1.410)	(0.338)	(1.466)	(0.256)	(1.184)	(23.467)	(0.434)		
	R_F	0.3743 **	0.0509	0.1503	-0.0375	-0.4097 **	-0.1721	-0.1997	0.0136	0.9417 **	0.0304	14.0137	**
		(3.342)	(0.424)	(1.259)	(-0.340)	(-3.598)	(-1.417)	(-1.651)	(0.122)	(23.036)	(1.031)		
TOT	R_S	-0.2089 **	0.0386	0.1591	0.1463	0.2098 *	-0.1445	-0.1766 *	-0.1449	0.6440 **	0.0072	20.5097	**
		(-2.583)	(0.449)	(1.881)	(1.956)	(2.534)	(-1.660)	(-2.066)	(-1.920)	(28.282)	(0.167)		
	R_F	0.2171 **	0.2074 *	0.2082 *	0.1680 *	-0.1922 *	-0.2956 **	-0.2017 *	-0.1686 *	0.5818 **	0.0959 *	12.4680	*
		(2.686)	(2.411)	(2.464)	(2.248)	(-2.324)	(-3.399)	(-2.361)	(-2.236)	(25.569)	(2.227)		
UBS	R_S	-0.0070	-0.0146	0.0451	-0.0232	0.0707	-0.0331	-0.0574	0.0356	1.1133 **	-0.0241	4.5542	
		(-0.120)	(-0.233)	(0.724)	(-0.402)	(1.234)	(-0.543)	(-0.947)	(0.641)	(48.380)	(-1.135)		
	R_F	0.4087 **	0.1397 *	0.1641 *	0.0405	-0.3314 **	-0.1875 **	-0.1658 **	-0.0327	1.1268 **	0.0191	48.1876	**
		(6.658)	(2.134)	(2.517)	(0.673)	(-5.534)	(-2.940)	(-2.616)	(-0.563)	(46.848)	(0.862)		
UC	R_S	-0.0562	-0.0994	-0.0444	0.0118	0.0850	0.0458	0.0271	-0.0027	0.9478 **	-0.1115 **	2.4609	
		(-1.028)	(-1.767)	(-0.809)	(0.237)	(1.524)	(0.797)	(0.483)	(-0.053)	(34.558)	(-3.099)		
	R_F	0.2774 **	0.0137	-0.0112	-0.0089	-0.2567 **	-0.0494	-0.0016	0.0202	0.9069 **	0.0497	33.6516	**
		(5.102)	(0.246)	(-0.206)	(-0.181)	(-4.629)	(-0.864)	(-0.028)	(0.402)	(33.255)	(1.389)		
VIV	R_S	0.0414	-0.1624	0.2554	0.2018	0.0881	0.0644	-0.2896 *	-0.3065 **	1.1861 **	-0.2774 *	14.9044	**
		(0.274)	(-1.089)	(1.867)	(1.839)	(0.579)	(0.429)	(-2.093)	(-2.780)	(22.925)	(-2.006)		
	R_F	0.4797 **	0.1037	0.4144 **	0.2307 *	-0.3570 *	-0.1954	-0.4493 **	-0.3184 **	1.1582 **	0.0569	28.2482	**
		(3.247)	(0.711)	(3.097)	(2.150)	(-2.397)	(-1.330)	(-3.320)	(-2.953)	(22.886)	(0.421)		
VOF	R_S	-0.1551	-0.1673	-0.0192	0.1149	0.1635	0.1299	-0.0528	-0.1064	1.2548 **	-0.0351	6.2577	
		(-1.402)	(-1.446)	(-0.176)	(1.301)	(1.465)	(1.118)	(-0.481)	(-1.191)	(32.415)	(-0.396)		
	R_F	0.3805 **	0.2006	0.1837	0.2485 **	-0.3645 **	-0.2433 *	-0.2593 *	-0.2357 **	1.1536 **	0.1548	17.7123	**
		(3.374)	(1.700)	(1.656)	(2.758)	(-3.203)	(-2.053)	(-2.318)	(-2.588)	(29.227)	(1.711)		
VOW	R_S	-0.0429	-0.1819 **	-0.1127	-0.0351	0.0933	0.1593 *	0.0970	0.0732	0.9405 **	-0.1426 *	6.7149	
		(-0.675)	(-2.813)	(-1.870)	(-0.724)	(1.459)	(2.455)	(1.615)	(1.563)	(37.787)	(-2.518)		
	R_F	0.4467 **	0.1260	0.0217	0.0691	-0.3744 **	-0.1273	-0.0594	-0.0125	0.7893 **	0.1670 **	62.6056	**
		(6.554)	(1.819)	(0.337)	(1.330)	(-5.463)	(-1.832)	(-0.923)	(-0.249)	(29.600)	(2.752)		

Notes: This table reports the VECM estimates and Granger causality tests results for the model (3.5a) and (3.5b):

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

* and ** denote significant levels of 5% and 1%, respectively.

Figures in the parenthesis (.) are the t statistics.

Granger causality tests are based on the Wald tests of (H_{01}: β_{SI} = 0) and (H_{02}: α_{FI} = 0); the tests statistics are $\chi^2(4)$ distributed.

t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $B_{t-1} = \beta' X_{t-1} = S_{t-1} - F_{t-1}$ is restricted to be the lagged basis in all cases; $R_{SIF,t-1}$ is the lagged stock index returns.

See the equations (3.5a) and (3.5b) in the text for the definitions of the remaining terms.

Table 3.7: Summary Results of VECM_FULL Period

Code	Lead-lag Relationship		Error Correction		Common Factor Weights	
	Stock Leads	Futures Leads	Stock Adjusts	Futures Adjusts	Stock (θ_S)	Futures ($\theta_F = 1-\theta_S$)
AA	√	√	+	−	0.337	0.[illegible]
AGN	√	×	−	+	0.988	0.012
AHL	√	√	−	−	0.588	0.412
ALV	√	√	−	+	0.629	0.371
AXA	√	×	−	+	0.977	0.023
AZN	√	×	−	−	0.874	0.126
BAR	√	×	−	−	0.784	0.216
BNP	√	√	−	−	0.662	0.338
BPA	√	×	−	−	0.311	0.689
BTL	×	√	−	+	0.748	0.252
BVA	√	√	+	−	0.486	0.514
CA	√	×	−	−	0.693	0.307
CGE	√	√	−	+	0.946	0.054
CSG	√	√	−	−	0.693	0.307
DBK	√	×	−	+	0.500	0.501
DCY	√	×	−	−	0.312	0.689
DTE	√	×	−	+	0.643	0.357
ENI	×	×	−	+	0.419	0.581
ENL	×	×	−	+	0.491	0.509
EOA	√	×	−	+	0.666	0.334
ERC	√	√	+	+	0.576	0.424
FTE	√	×	−	−	0.665	0.335
GEN	√	×	−	−	0.520	0.480
GXW	√	√	−	−	0.460	0.540
HAS	√	×	−	−	0.510	0.490
HNM	√	×	−	−	0.520	0.480
ING	×	×	−	+	0.867	0.133
LLO	√	×	+	−	0.001	0.999
MUV	√	×	−	+	0.672	0.328
NDA	√	×	−	−	0.740	0.260
NES	√	×	−	+	0.993	0.007
NOV	√	×	−	+	0.689	0.311
PHI	√	×	−	+	0.944	0.056
RBO	√	√	−	−	0.429	0.571
RD	×	×	−	−	0.858	0.142
ROG	√	×	−	−	0.460	0.540
SCH	√	×	+	−	0.341	0.659
SHB	√	√	−	+	0.940	0.060
SHE	√	×	−	−	0.275	0.726
SIE	√	×	−	+	0.839	0.161
TEF	√	√	−	−	0.819	0.181
TI	×	×	−	−	0.481	0.520
TIM	√	×	−	−	0.166	0.835
TLI	√	×	−	−	0.701	0.299
TOT	√	√	−	+	0.930	0.070
UBS	√	×	−	−	0.442	0.558
UC	√	×	+	−	0.308	0.692
VIV	√	√	+	−	0.405	0.596
VOF	√	×	−	−	0.408	0.593
VOW	√	×	+	+	0.539	0.461
√	44	15	+ 8	20	Mean 0.605	0.395
×	6	35	− 42	30		

Notes: The bivariate Vector Error Correction Model (3.5a) and (3.5b) is run for each 50 pairs of cointegrated stock and futures prices

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

A "√" indicates that the lagged cross-coefficients (β_{Si} or α_{Fi}) in equations are jointly significant at the 5% level (i.e., Recjection of H_{01} or H_{02})
A "+" indicates that the error-correction coefficient (γ_S or γ_{Fi}) in equations is significant at the 5% level (i.e., Recjection of H_{03} or H_{04})
The (θ_S) and (θ_F) is the price discovery contributions (i.e., weight in the common long memory factor) of stock and futures, respectively
The calculations of the price discovery contributions [(θ_S) and (θ_F)] are based on the formula (3.8) in the text

Table 3.8: Descriptive Statistics of USF Share in Price Discovery_FULL Period

	Mean	Std Deviation	25th percentile	Median	75th percentile
USF share in price discovery (θ_F)					
France (7)	0.2459	0.2081	0.0619	0.3067	0.3361
Germany (8)	0.4001	0.1542	0.3326	0.3642	0.4707
Italy (6)	0.6027	0.1362	0.5116	0.5503	0.6640
Netherlands (6)	0.2363	0.2509	0.0754	0.1373	0.3445
Spain (3)	0.4513	0.2451	0.3476	0.5143	0.5865
Sweden (5)	0.3046	0.1632	0.2602	0.2986	0.4242
Switzerland (5)	0.3444	0.2237	0.3070	0.3111	0.5397
UK (10)	0.5202	0.2643	0.3114	0.5555	0.6648
Whole Sample (50)	0.3951	0.2336	0.2252	0.3917	0.5533

Notes: This table presents the cross-sectional descriptive statistics of the USF share in price discoevry estimated on the basis of VECM adjusment coefficients in equations (3.5a) and (3.5b) and as given by formular (3.8). The sample consist of a total of 50 USFs including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland

Table 3.9: VECM Adjustment Coefficients and USF Share in Price Discovery_European vs UK

		Mean	*Z-test*	Std Deviation	25th percentile	Median	75th percentile
A :	**Adjustment coefficients**						
	A.1 : Home Market (10 UK Stocks)						
	γ_s	-0.0364		0.0437	-0.0645	-0.0389	0.0039
	γ_F	0.0556		0.0576	0.0098	0.0455	0.0720
	A.2 : Foreign Market (40 European Stocks)						
	γ_s	-0.0413		0.0665	-0.0769	-0.0046	0.0040
	γ_F	0.0969		0.1306	0.0170	0.0508	0.1382
B :	**USF share in price discovery**						
	B.1 : Home Market (10 UK Stocks)						
	(θ_F)	0.5202		0.2643	0.3114	0.5555	0.6648
	B.2 : Foreign Market (40 European Stocks)						
	(θ_F)	0.3639	$\Downarrow$ <-1.7297> *	0.2179	0.1759	0.3473	0.5156

Notes: This table presents cross-sectional descriptive statistics of adjusments coefficients of VECM and the USF share in price discoevry estimated on the basis of adjusment coefficients as given by formular (3.8). The entire 50 USFs sample were split into two groups, one includes the 10 USFs that trading on U.K. stocks and the other one includes all the remaining USFs that basing on 40 European stocks. Non-parametric Wilcoxon signed rank test (Z-test) examines whether the mean value of (θ_F) in European USFs is significantly lower

< > Wilcoxon Z-test statistics

*, **, *** Significant at 10%, 5% and 1% level, respectively.

$\Uparrow$ = significant hiher share in price discovery ; $\Downarrow$ = significant lower share in price discovery

Table 3.10: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_Period 1

Code	Dep Var	α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_0: $\beta_i=0$)
		α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_0: $\alpha_i=0$)
AA	R_S	-0.0833	-0.0865	0.0780	0.1675 *	0.0228	0.0215	-0.1282	-0.1634 *	1.1545 **	-0.1009	5.7220
		(-0.870)	(-0.854)	(0.802)	(2.081)	(0.236)	(0.212)	(-1.318)	(-2.060)	(37.768)	(-1.388)	
	R_F	0.4595 **	0.1714	0.2645 **	0.2380 **	-0.4814 **	-0.2049 *	-0.2903 **	-0.2370 **	1.1029 **	0.0839	31.6134 **
		(4.683)	(1.652)	(2.652)	(2.884)	(-4.849)	(-1.975)	(-2.911)	(-2.900)	(35.201)	(1.127)	
AGN	R_S	-0.0095	-0.0268	-0.0112	-0.0023	0.0045	0.0019	-0.0005	-0.0033	1.5102 **	0.0043	0.2726
		(-0.326)	(-0.947)	(-0.408)	(-0.090)	(0.268)	(0.117)	(-0.036)	(-0.306)	(37.628)	(0.255)	
	R_F	0.4085 **	0.3295 **	0.2726 *	0.0547	-0.4433 **	-0.3353 **	-0.2231 **	-0.1137 *	1.3932 **	[illegible] **	16.8328 **
		(3.337)	(2.760)	(2.364)	(0.512)	(-6.187)	(-4.930)	(-3.722)	(-2.510)	(8.231)	(6.228)	
AHL	R_S	-0.2336	-0.3441	-0.4708 *	-0.2302	0.2700	0.4328 *	0.3764	0.2764	1.2141 **	0.0083	8.0218
		(-1.251)	(-1.735)	(-2.372)	(-1.236)	(1.450)	(2.194)	(1.901)	(1.498)	(12.883)	(0.631)	
	R_F	0.1599	-0.2695	-0.4188 *	-0.2178	-0.0978	0.3583	0.3372	0.2729	1.0948 **	0.0101	6.5717
		(0.830)	(-1.317)	(-2.046)	(-1.134)	(-0.509)	(1.761)	(1.652)	(1.434)	(11.266)	(0.745)	
ALV	R_S	-0.0605	-0.2048 **	-0.0668	-0.0555	0.1267 *	0.1793 **	0.0617	0.0095	1.3110 **	0.0106	8.5931
		(-1.177)	(-3.090)	(-1.005)	(-1.025)	(2.218)	(2.627)	(0.918)	(0.183)	(36.726)	(1.409)	
	R_F	0.7035 **	0.2665 **	0.1096	-0.0462	-0.5790 **	-0.2503 **	-0.1112	-0.0146	1.0421 **	0.0176 *	183.6478 **
		(12.618)	(3.706)	(1.518)	(-0.787)	(-9.340)	(-3.381)	(-1.525)	(-0.260)	(26.908)	(2.154)	
AXA	R_S	0.1155 **	-0.0435	-0.0215	-0.0531	-0.0018	-0.0067	-0.0017	0.0142	1.3166 **	-0.0009	0.7687
		(3.445)	(-1.296)	(-0.640)	(-1.580)	(-0.099)	(-0.370)	(-0.095)	(0.778)	(25.056)	(-0.230)	
	R_F	0.1862 *	-0.0067	0.0161	-0.1068	-0.0282	-0.0211	-0.0002	0.0165	1.2589 **	0.0403 **	7.3597
		(2.305)	(-0.083)	(0.199)	(-1.321)	(-0.642)	(-0.479)	(-0.005)	(0.375)	(9.946)	(4.459)	
AZN	R_S	-0.0933	0.0048	0.0685	-0.0913	0.1585	-0.1392	-0.0852	0.0743	0.8246 **	0.0135	6.1077
		(-0.544)	(0.028)	(0.424)	(-0.702)	(0.912)	(-0.794)	(-0.527)	(0.577)	(18.929)	(0.091)	
	R_F	0.4489 **	0.4065 *	0.3220 *	0.0120	-0.3735 *	-0.5183 **	-0.3303 *	-0.0078	0.7445 **	0.2447	9.6243 *
		(2.613)	(2.321)	(1.990)	(0.092)	(-2.145)	(-2.952)	(-2.039)	(-0.061)	(17.069)	(1.658)	
BAR	R_S	0.0649 *	-0.0564 *	0.0055	-0.0234	0.0214	-0.0024	-0.0153	-0.0017	1.1828 **	-0.0009	4.8830
		(2.253)	(-1.967)	(0.192)	(-0.812)	(1.787)	(-0.201)	(-1.278)	(-0.138)	(28.465)	(-1.180)	
	R_F	0.1443	-0.0664	-0.2081 *	-0.0348	0.0104	-0.0019	-0.0162	0.0036	1.1011 **	0.0033	7.1587
		(1.417)	(-0.654)	(-2.043)	(-0.341)	(0.244)	(-0.044)	(-0.382)	(0.084)	(07.488)	(1.194)	
BNP	R_S	0.1447 **	-0.0733	-0.0020	0.0278	-0.0583 *	0.0093	0.0043	-0.0222	0.9256 **	-0.0018	6.5295
		(3.865)	(-1.944)	(-0.053)	(0.736)	(-2.336)	(0.371)	(0.170)	(-0.892)	(25.553)	(-0.972)	
	R_F	0.2864 **	-0.0765	0.0253	-0.0293	-0.0884	0.0053	0.0146	-0.0142	0.8325 **	0.0035	16.3718 **
		(3.893)	(-1.033)	(0.342)	(-0.395)	(-1.802)	(0.108)	(0.298)	(-0.290)	(11.695)	(0.967)	
BPA	R_S	-0.0452	-0.0701	-0.1037	-0.0495	0.0054	0.0150	0.0721	0.0657	0.8230 **	-0.1055	0.2577
		(-0.246)	(-0.359)	(-0.558)	(-0.324)	(0.029)	(0.076)	(0.385)	(0.427)	(22.171)	(-0.752)	
	R_F	0.4439 *	0.1879	-0.0401	0.0104	-0.4797 *	-0.2362	0.0122	0.0246	0.7708 **	0.0901	7.5488
		(2.396)	(0.957)	(-0.214)	(0.068)	(-2.568)	(-1.194)	(0.064)	(0.159)	(20.621)	(0.638)	
BTL	R_S	-0.1759 *	-0.0676	0.0591	0.1772 *	0.2070 **	0.0664	-0.1312	-0.1447 *	1.0209 **	0.0053	17.9941 **
		(-2.459)	(-0.936)	(0.818)	(2.484)	(3.056)	(0.971)	(-1.918)	(-2.120)	(17.310)	(0.789)	
	R_F	-0.0477	-0.0246	0.0201	0.1632 *	0.0808	0.0155	-0.1212	-0.1095	0.9066 **	0.0159 *	4.4987
		(-0.592)	(-0.302)	(0.247)	(2.031)	(1.058)	(0.202)	(-1.574)	(-1.426)	(13.648)	(2.097)	
BVA	R_S	-0.1239	-0.1826	-0.0837	-0.1182	0.1445	0.1928	0.0615	0.1227	1.3513 **	-0.1224	6.5261
		(-1.241)	(-1.838)	(-0.908)	(-1.621)	(1.402)	(1.898)	(0.653)	(1.667)	(52.833)	(-1.335)	
	R_F	0.3368 **	0.1073	0.1025	0.0373	-0.2857 **	-0.1012	-0.0974	-0.0364	1.2631 **	0.1578	15.2596 **
		(3.383)	(1.083)	(1.115)	(0.514)	(-2.782)	(-0.999)	(-1.038)	(-0.496)	(49.540)	(1.728)	
CA	R_S	-0.1017	-0.0115	0.0011	-0.2397 *	0.0426	-0.0167	0.0083	0.2007	0.8241 **	-0.0358	5.1127
		(-0.783)	(-0.083)	(0.009)	(-2.184)	(0.321)	(-0.120)	(0.062)	(1.855)	(22.832)	(-0.374)	
	R_F	0.4317 **	0.2458	0.1178	-0.1331	-0.4528 **	-0.2840 *	-0.0775	0.0976	0.7568 **	0.1297	15.4960 **
		(3.328)	(1.771)	(0.878)	(-1.215)	(-3.425)	(-2.039)	(-0.576)	(0.904)	(20.997)	(1.356)	
CGE	R_S	-0.0368	0.1224	0.1018	0.2126 *	0.0386	-0.0728	-0.0729	-0.1979 *	1.4804 **	0.0308	9.4343
		(-0.249)	(0.922)	(0.896)	(2.458)	(0.272)	(-0.574)	(-0.678)	(-2.448)	(18.590)	(0.204)	
	R_F	0.1920	0.2820	0.2459	0.2687 **	-0.1762	-0.2587	-0.2221	-0.2524 **	1.3621 **	0.6994 **	8.7199
		(1.163)	(1.899)	(1.934)	(2.777)	(-1.109)	(-1.822)	(-1.847)	(-2.791)	(15.290)	(4.139)	
CSG	R_S	-0.1936	0.0670	0.1643	0.1284	0.2094	0.0051	-0.1471	-0.1476	1.5660 **	0.0114	7.8669
		(-1.766)	(0.519)	(1.271)	(1.170)	(1.920)	(0.039)	(-1.150)	(-1.362)	(29.406)	(0.605)	
	R_F	0.4492 **	0.4237 **	0.3180 *	0.1206	-0.4272 **	-0.3518 **	-0.2990 *	-0.1497	1.5770 **	0.0236	19.3302 **
		(4.125)	(3.305)	(2.477)	(1.105)	(-3.942)	(-2.768)	(-2.355)	(-1.391)	(29.809)	(1.260)	
DBK	R_S	-0.0950	-0.0816	-0.0492	-0.0914	0.0735	0.0551	0.0560	0.0621	1.1398 **	0.0008	1.5944
		(-1.103)	(-0.939)	(-0.618)	(-1.536)	(0.843)	(0.640)	(0.725)	(1.118)	(41.521)	(0.010)	
	R_F	0.4889 **	0.3584 **	0.1845 *	-0.0503	-0.4453 **	-0.3643 **	-0.1572	0.0215	0.9478 **	0.3197 **	36.2171 **
		(5.159)	(3.748)	(2.105)	(-0.768)	(-4.642)	(-3.848)	(-1.849)	(0.352)	(31.382)	(3.664)	
DCY	R_S	-0.0953	-0.0483	0.0628	-0.0259	0.0856	0.0151	-0.0293	0.0619	1.0471 **	-0.0556	5.0494
		(-1.369)	(-0.638)	(0.863)	(-0.443)	(1.194)	(0.200)	(-0.409)	(1.093)	(35.439)	(-1.099)	
	R_F	0.5178 **	0.3765 **	0.2769 **	0.0887	-0.4514 **	-0.3897 **	-0.2302 **	-0.0441	0.8911 **	0.0917	47.8963 **
		(6.860)	(4.583)	(3.513)	(1.397)	(-5.810)	(-4.757)	(-2.962)	(-0.718)	(27.812)	(1.670)	
DTE	R_S	-0.0202	-0.0586	-0.0870	-0.0769	-0.0065	0.0250	0.0209	0.0855	1.1791 **	-0.1785	2.3676
		(-0.183)	(-0.556)	(-0.924)	(-1.097)	(-0.059)	(0.238)	(0.226)	(1.285)	(27.490)	(-1.647)	
	R_F	0.4516 **	0.2605 *	0.1436	0.0029	-0.4007 **	-0.2605 *	-0.1915 *	0.0177	0.9783 **	0.2703 *	20.2571 **
		(4.040)	(2.437)	(1.505)	(0.041)	(-3.559)	(-2.452)	(-2.044)	(0.262)	(22.489)	(2.461)	
ENI	R_S	-0.0562	-0.0454	-0.0150	-0.0048	0.0220	0.0135	-0.0046	0.0097	0.7834 **	0.0028	1.9221
		(-1.669)	(-1.346)	(-0.445)	(-0.142)	(1.094)	(0.669)	(-0.229)	(0.483)	(21.455)	(1.224)	
	R_F	-0.0025	-0.0021	-0.0243	-0.0467	0.0057	0.0013	0.0027	0.0138	0.7315 **	0.0146 **	0.5544
		(-0.037)	(-0.031)	(-0.351)	(-0.676)	(0.138)	(0.032)	(0.066)	(0.336)	(9.786)	(3.081)	
ENL	R_S	-0.0635	0.0096	0.0093	-0.0399	-0.0234	-0.0055	-0.0023	0.0221	0.7743 **	0.0003	3.1147
		(-1.884)	(0.284)	(0.276)	(-1.194)	(-1.258)	(-0.295)	(-0.123)	(1.186)	(22.866)	(0.114)	
	R_F	-0.0168	0.0352	0.0141	-0.0029	-0.0502	0.0120	-0.0120	0.0198	0.6461 **	0.0152 *	0.2824
		(-0.212)	(0.445)	(0.179)	(-0.037)	(-1.149)	(0.275)	(-0.274)	(0.453)	(8.125)	(2.556)	

Table 3.10: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_Period 1 (continued)

		α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_0: $\beta_S = 0$)
Code	Dep Var	α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_0: $\alpha_F = 0$)
EOA	R_S	-0.1311	-0.0395	-0.0075	0.1046	0.0160	0.0166	0.0036	-0.0898	0.6752 **	-0.0922	2.7691
		(-1.581)	(-0.470)	(-0.096)	(1.609)	(0.190)	(0.197)	(0.046)	(-1.399)	(22.506)	(-1.315)	
	R_F	0.3100 **	0.2003 *	0.1255	0.1410 *	-0.3509 **	-0.2321 **	-0.0952	-0.1190	0.4996 **	0.1903 **	[illegible] **
		(3.610)	(2.301)	(1.537)	(2.092)	(-4.021)	(-2.667)	(-1.154)	(-1.791)	(16.075)	(2.621)	
ERC	R_S	0.0539	0.1027	-0.2853 **	-0.2322 *	-0.0057	-0.1612	0.2155 *	0.2177 *	1.7861 **	0.0192 *	14.6900 **
		(0.576)	(1.073)	(-2.985)	(-2.489)	(-0.065)	(-1.760)	(2.352)	(2.446)	(19.513)	(2.225)	
	R_F	0.3023 **	0.1060	-0.2622 *	-0.2585 *	-0.2812 **	-0.1508	0.2059 *	0.2655 **	1.7930 **	0.0257 **	21.1667 **
		(2.977)	(1.021)	(-2.526)	(-2.552)	(-2.930)	(-1.517)	(2.070)	(2.747)	(18.040)	(2.737)	
FTE	R_S	0.0009	-0.1640	0.1316	0.0501	0.0948	0.1425	-0.0914	-0.0377	1.2610 **	0.0030	2.3937
		(0.007)	(-1.193)	(0.958)	(0.382)	(0.712)	(1.027)	(-0.661)	(-0.286)	(17.586)	(0.286)	
	R_F	0.3405 **	0.0082	0.2652	0.0937	-0.2337	-0.0176	-0.2161	-0.0709	1.1904 **	0.0064	10.9425 *
		(2.589)	(0.060)	(1.928)	(0.713)	(-1.750)	(-0.127)	(-1.557)	(-0.537)	(16.564)	(0.611)	
GEN	R_S	-0.0330	-0.0654	-0.0857	0.0740	0.1092	0.0430	0.0473	-0.0587	1.0656 **	-0.1658	1.7163
		(-0.236)	(-0.480)	(-0.686)	(0.737)	(0.773)	(0.313)	(0.377)	(-0.588)	(30.546)	(-1.259)	
	R_F	0.3574 **	0.1611	0.0661	0.1515	-0.2728 *	-0.1844	-0.0824	-0.1488	1.0045 **	0.2061	9.8972 *
		(2.617)	(1.213)	(0.543)	(1.548)	(-1.981)	(-1.377)	(-0.674)	(-1.530)	(29.533)	(1.605)	
GXW	R_S	-0.1858	-0.1055	0.1833	0.0134	0.1730	0.0062	-0.2133	-0.0374	0.8174 **	-0.1371	5.0864
		(-1.039)	(-0.577)	(1.075)	(0.095)	(0.958)	(0.034)	(-1.239)	(-0.262)	(22.256)	(-0.941)	
	R_F	0.3275	0.2958	0.4231 *	0.0966	-0.3517	-0.3915 *	-0.4568 **	-0.1053	0.7638 **	0.0742	7.4733
		(1.806)	(1.595)	(2.445)	(0.674)	(-1.919)	(-2.095)	(-2.615)	(-0.728)	(20.500)	(0.502)	
HAS	R_S	-0.2088 *	-0.0134	0.0513	0.0574	0.2257 *	-0.0256	-0.0038	-0.0035	0.8299 **	-0.0516	6.4309
		(-2.029)	(-0.121)	(0.473)	(0.595)	(2.149)	(-0.229)	(-0.034)	(-0.036)	(26.684)	(-0.972)	
	R_F	0.2152 *	0.1601	0.0894	0.1035	-0.1774	-0.1930	-0.0303	-0.0222	0.7935 **	0.0315	5.5195
		(2.136)	(1.482)	(0.843)	(1.096)	(-1.724)	(-1.768)	(-0.282)	(-0.231)	(26.055)	(0.607)	
HNM	R_S	0.0182	-0.0186	0.0443	0.0119	-0.1262	-0.0388	-0.0743	-0.0538	0.6665 **	-0.2031	1.4032
		(0.118)	(-0.127)	(0.341)	(0.117)	(-0.825)	(-0.269)	(-0.583)	(-0.554)	(15.426)	(-1.319)	
	R_F	0.4063 *	0.2226	0.2114	0.1080	-0.4978 **	-0.2919	-0.2324	-0.1146	0.6382 **	0.2860	7.0757
		(2.497)	(1.446)	(1.548)	(1.006)	(-3.097)	(-1.926)	(-1.733)	(-1.123)	(14.046)	(1.766)	
ING	R_S	0.0090	0.0140	-0.0584 *	0.0106	0.0040	-0.0091	-0.0100	-0.0030	1.4387 **	-0.0014	0.3811
		(0.314)	(0.490)	(-2.044)	(0.370)	(0.176)	(-0.396)	(-0.434)	(-0.132)	(47.977)	(-0.583)	
	R_F	0.0697	-0.0029	-0.0431	0.0316	-0.0360	-0.0074	-0.0068	-0.0117	1.3883 **	0.0088	2.3914
		(1.245)	(-0.052)	(-0.772)	(0.565)	(-0.800)	(-0.164)	(-0.150)	(-0.260)	(23.692)	(1.900)	
LLO	R_S	0.1509	0.0292	0.1866	0.1580	-0.1188	-0.0755	-0.1970	-0.1700	1.1331 **	-0.1990 **	5.2685
		(1.487)	(0.269)	(1.745)	(1.673)	(-1.129)	(-0.676)	(-1.793)	(-1.769)	(27.216)	(-3.245)	
	R_F	0.5471 **	0.1018	0.1603	0.1756	-0.4967 **	-0.1746	-0.1582	-0.2032 *	1.0388 **	-0.0725	35.4004 **
		(5.291)	(0.919)	(1.472)	(1.824)	(-4.634)	(-1.535)	(-1.413)	(-2.075)	(24.492)	(-1.159)	
MUV	R_S	-0.0088	-0.1924 *	-0.1451	-0.0936	0.0995	0.1946 *	0.1130	0.0726	1.2572 **	0.0149	5.3697
		(-0.134)	(-2.232)	(-1.682)	(-1.366)	(1.432)	(2.273)	(1.342)	(1.134)	(33.325)	(0.912)	
	R_F	0.8852 **	0.4837 **	0.2303 *	0.0988	-0.7386 **	-0.4575 **	-0.2851 **	-0.1115	1.0471 **	0.0249	154.5397 **
		(11.917)	(4.978)	(2.368)	(1.279)	(-9.432)	(-4.743)	(-3.006)	(-1.546)	(24.628)	(1.349)	
NDA	R_S	-0.3119 *	-0.1386	-0.1102	-0.0158	0.2395	0.0858	0.0950	-0.0451	0.9307 **	-0.0188	4.7607
		(-2.480)	(-1.051)	(-0.866)	(-0.145)	(1.885)	(0.645)	(0.740)	(-0.405)	(20.023)	(-0.213)	
	R_F	0.1057	0.0345	-0.0837	-0.0333	-0.1660	-0.0869	0.0402	-0.0314	0.9036 **	0.1576	1.8899
		(0.855)	(0.266)	(-0.669)	(-0.310)	(-1.329)	(-0.665)	(0.319)	(-0.287)	(19.781)	(1.815)	
NES	R_S	-0.2514 *	-0.2392 *	-0.2055 *	-0.1792 *	0.2096 *	0.1600	0.1373	0.1700 *	0.6996 **	0.0409	7.4074
		(-2.477)	(-2.234)	(-2.022)	(-2.183)	(2.086)	(1.501)	(1.373)	(2.152)	(23.757)	(0.518)	
	R_F	0.3667 **	0.1818	0.0552	-0.0523	-0.4174 **	-0.2318 *	-0.0987	0.0549	0.6448 **	0.2196 **	15.1705 **
		(3.471)	(1.631)	(0.521)	(-0.612)	(-3.991)	(-2.089)	(-0.948)	(0.667)	(21.033)	(2.671)	
NOV	R_S	-0.0677	0.0135	0.0654	0.1504	0.0869	-0.0333	-0.1304	-0.1126	0.7357 **	-0.0122	3.6788
		(-0.525)	(0.104)	(0.540)	(1.540)	(0.677)	(-0.258)	(-1.092)	(-1.196)	(26.113)	(-0.107)	
	R_F	0.4223 **	0.3127 *	0.2340 *	0.2038 *	-0.3930 **	-0.3292 **	-0.2811 *	-0.1426	0.7317 **	0.2830 *	12.6227 *
		(3.357)	(2.464)	(1.981)	(2.139)	(-3.136)	(-2.613)	(-2.413)	(-1.554)	(26.616)	(2.548)	
PHI	R_S	-0.0377	0.1516	0.2208	0.1938	0.0069	-0.1922	-0.1972	-0.1858	1.4287 **	-0.0589	3.4104
		(-0.198)	(0.803)	(1.271)	(1.415)	(0.037)	(-1.019)	(-1.137)	(-1.366)	(34.286)	(-0.339)	
	R_F	0.4006 *	0.3762	0.3176	0.2199	-0.4318 *	-0.4096 *	-0.2867	-0.2053	1.3615 **	0.2829	5.4365
		(2.069)	(1.955)	(1.793)	(1.576)	(-2.236)	(-2.130)	(-1.622)	(-1.481)	(32.058)	(1.598)	
RBO	R_S	-0.0895	-0.0103	0.0667	0.1701	0.1188	-0.0032	-0.0962	-0.1935 *	1.1462 **	-0.2131 *	6.3171
		(-0.722)	(-0.081)	(0.558)	(1.801)	(0.950)	(-0.025)	(-0.794)	(-2.003)	(28.880)	(-2.056)	
	R_F	0.4102 **	0.2402	0.1868	0.2292 *	-0.3571 **	-0.2790 *	-0.2136	-0.2375 *	1.1069 **	0.0368	15.1719 **
		(3.340)	(1.892)	(1.574)	(2.446)	(-2.880)	(-2.186)	(-1.778)	(-2.480)	(28.127)	(0.358)	
RD	R_S	-0.3670 **	-0.2241	-0.1375	0.0091	0.3402 **	0.1582	0.1612	0.0027	0.7103 **	0.0000	8.8369
		(-3.080)	(-1.708)	(-1.048)	(0.076)	(2.777)	(1.184)	(1.203)	(0.022)	(28.471)	(-0.045)	
	R_F	0.1343	0.0059	0.0673	0.0765	-0.1492	-0.0763	-0.0341	-0.0609	0.6686 **	0.0001	1.9302
		(1.115)	(0.044)	(0.507)	(0.636)	(-1.204)	(-0.565)	(-0.252)	(-0.496)	(26.505)	(0.139)	
ROG	R_S	-0.1049	-0.3143 *	-0.0115	-0.0229	0.1506	0.2746	0.0792	0.0711	0.8984 **	-0.1847	4.5735
		(-0.704)	(-2.073)	(-0.082)	(-0.202)	(1.009)	(1.814)	(0.567)	(0.644)	(28.137)	(-1.425)	
	R_F	0.4848 **	0.1566	0.3052 *	0.1613	-0.4427 **	-0.2001	-0.2503	-0.1134	0.8791 **	0.0526	17.2953 **
		(3.257)	(1.033)	(2.176)	(1.425)	(-2.969)	(-1.324)	(-1.792)	(-1.028)	(27.562)	(0.406)	
SCH	R_S	-0.1303	-0.1500	-0.0604	-0.0373	0.1451	0.1231	0.0540	0.0484	1.3943 **	-0.2196 *	2.3478
		(-1.278)	(-1.481)	(-0.651)	(-0.509)	(1.409)	(1.211)	(0.581)	(0.657)	(54.140)	(-2.357)	
	R_F	0.2864 **	0.1377	0.0526	0.0169	-0.2522 *	-0.1616	-0.0551	-0.0113	1.3201 **	0.1097	9.4458
		(2.853)	(1.381)	(0.576)	(0.234)	(-2.485)	(-1.613)	(-0.602)	(-0.155)	(52.020)	(1.194)	
SHB	R_S	-0.1412	-0.4819 **	-0.2373	-0.0315	0.0996	0.4188 **	0.2062	-0.0033	0.6565 **	0.0000	12.5350 *
		(-1.147)	(-3.799)	(-1.936)	(-0.290)	(0.797)	(3.255)	(1.655)	(-0.030)	(20.234)	(-0.000)	
	R_F	0.2344 *	-0.2739 *	-0.1489	0.0228	-0.2688 *	0.2216	0.0869	-0.0586	0.6418 **	0.1426	20.2539 **
		(1.985)	(-2.251)	(-1.267)	(0.219)	(-2.243)	(1.796)	(0.728)	(-0.557)	(20.623)	(1.824)	

Table 3.10: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_Period 1 (continued)

		α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_{01}: $\beta_{Si}=0$)
Code	Dep Var	α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_{02}: $\alpha_{Fi}=0$)
SHE	R_S	0.0807	0.1318	0.1890 *	0.0083	-0.1089	-0.1689 *	-0.1954 **	-0.0083	0.9102 **	-0.0009	10.7439 *
		(1.165)	(1.777)	(2.553)	(0.119)	(-1.619)	(-2.341)	(-2.706)	(-0.123)	(24.856)	(-0.237)	
	R_F	0.5064 **	0.3851 **	0.3672 **	0.0912	-0.5383 **	-0.4312 **	-0.3456 **	-0.0439	0.8435 **	-0.0004	56.1042 **
		(6.530)	(4.634)	(4.429)	(1.163)	(-7.145)	(-5.336)	(-4.275)	(-0.581)	(20.570)	(-0.090)	
SIE	R_S	-0.0385	0.0245	-0.0179	-0.0663	0.0153	-0.0440	-0.0041	0.0385	1.2161 **	0.0052	3.7709
		(-1.092)	(0.658)	(-0.477)	(-1.840)	(0.451)	(-1.272)	(-0.119)	(1.188)	(38.453)	(0.920)	
	R_F	0.3273 **	0.0951	-0.0034	-0.0803	-0.1902 **	-0.0993 *	-0.0060	0.0372	0.9880 **	0.0256 **	46.0045 **
		(6.502)	(1.789)	(-0.064)	(-1.561)	(-3.934)	(-2.012)	(-0.122)	(0.803)	(21.881)	(3.199)	
TEF	R_S	-0.1039	-0.2339 **	-0.1673 *	-0.0920	0.1375	0.2022 *	0.1875 *	0.0445	1.2570 **	0.0012	8.0365
		(-1.435)	(-2.765)	(-1.975)	(-1.250)	(1.865)	(2.410)	(2.247)	(0.624)	(47.438)	(0.271)	
	R_F	0.5416 **	0.1515	0.1689 *	0.0930	-0.4728 **	-0.1667 *	-0.1356	-0.1338	1.2227 **	0.0051	62.6400 **
		(7.411)	(1.773)	(1.975)	(1.251)	(-6.354)	(-1.969)	(-1.610)	(-1.859)	(45.712)	(1.106)	
TI	R_S	0.0055	-0.0614	0.0049	0.0442	-0.0317	0.0832	0.0641	0.0229	1.1715 **	-0.0001	3.5658
		(0.128)	(-1.424)	(0.113)	(1.026)	(-0.545)	(1.428)	(1.100)	(0.394)	(23.561)	(-0.095)	
	R_F	0.0526	0.0437	-0.0407	0.0365	-0.1288 **	-0.0758	0.0878 *	0.0012	0.9117 **	0.0000	8.8751
		(1.724)	(1.432)	(-1.334)	(1.198)	(-3.129)	(-1.839)	(2.129)	(0.028)	(25.909)	(-0.096)	
TIM	R_S	-0.1975 **	-0.2146 **	-0.0052	0.0288	0.1277 *	0.1693 *	0.0014	-0.0177	1.1108 **	-0.0119	8.5247
		(-3.066)	(-3.004)	(-0.074)	(0.450)	(1.977)	(2.361)	(0.019)	(-0.280)	(31.763)	(-0.734)	
	R_F	0.3343 **	0.0856	0.1474	0.0585	-0.4067 **	-0.1201	-0.1190	-0.0305	1.0286 **	0.0059	25.1332 **
		(4.712)	(1.088)	(1.885)	(0.829)	(-5.715)	(-1.520)	(-1.511)	(-0.438)	(26.699)	(0.327)	
TLI	R_S	-0.1870	-0.5099 *	-0.2592	-0.1955	0.1367	0.3896	0.2026	0.1732	1.0105 **	0.0302	3.1976
		(-0.964)	(-2.253)	(-1.151)	(-1.028)	(0.694)	(1.713)	(0.896)	(0.911)	(17.647)	(0.623)	
	R_F	0.4999 **	0.0352	0.0581	-0.0287	-0.5352 **	-0.1506	-0.1117	0.0040	0.9881 **	0.0408	9.4776
		(2.611)	(0.158)	(0.261)	(-0.153)	(-2.754)	(-0.671)	(-0.500)	(0.022)	(17.479)	(0.854)	
TOT	R_S	-0.2475 *	0.0033	0.1499	0.2106	0.2570 *	-0.1107	-0.1723	-0.2134	0.6314 **	0.0138	12.5335 *
		(-2.027)	(0.025)	(1.182)	(1.933)	(2.052)	(-0.837)	(-1.340)	(-1.935)	(20.635)	(0.191)	
	R_F	0.2319	0.2362	0.2539 *	0.2789 **	-0.2047	-0.3253 *	-0.2460	-0.2772 *	0.5660 **	0.1146	9.3629
		(1.922)	(1.834)	(2.027)	(2.590)	(-1.654)	(-2.489)	(-1.936)	(-2.544)	(18.722)	(1.602)	
UBS	R_S	-0.0265	-0.0092	0.0047	-0.0974	0.1061	-0.0502	-0.0237	0.1121	1.1257 **	-0.0177	5.5421
		(-0.314)	(-0.102)	(0.052)	(-1.180)	(1.295)	(-0.573)	(-0.272)	(1.406)	(36.424)	(-0.629)	
	R_F	0.4071 **	0.1500	0.1508	-0.0083	-0.3120 **	-0.2100 *	-0.1535	0.0157	1.1490 **	0.0181	24.1555 **
		(4.650)	(1.602)	(1.617)	(-0.097)	(-3.666)	(-2.308)	(-1.696)	(0.189)	(35.789)	(0.618)	
UC	R_S	-0.1045	-0.1780 *	-0.1033	-0.0492	0.1321	0.1126	0.1044	0.0438	1.0006 **	-0.1475 *	3.0139
		(-1.253)	(-2.087)	(-1.259)	(-0.692)	(1.552)	(1.287)	(1.238)	(0.600)	(27.307)	(-2.347)	
	R_F	0.2804 **	-0.0087	-0.0312	-0.0409	-0.2638 **	-0.0433	0.0266	0.0332	0.9532 **	0.0586	19.0836 **
		(3.395)	(-0.103)	(-0.384)	(-0.581)	(-3.128)	(-0.499)	(0.319)	(0.459)	(26.261)	(0.942)	
VIV	R_S	0.1703	-0.0852	0.3706	0.2481	-0.0221	-0.0240	-0.3966	-0.3671 *	1.2235 **	-0.4476	8.6033
		(0.716)	(-0.374)	(1.810)	(1.536)	(-0.092)	(-0.105)	(-1.912)	(-2.258)	(16.009)	(-1.936)	
	R_F	0.5471 *	0.1385	0.5152 **	0.2701	-0.4082	-0.2421	-0.5452 **	-0.3740 *	1.1969 **	-0.0193	17.5227 **
		(2.368)	(0.626)	(2.588)	(1.721)	(-1.753)	(-1.088)	(-2.705)	(-2.367)	(16.113)	(-0.086)	
VOF	R_S	-0.3074	-0.2688	-0.0297	0.1671	0.3158	0.2220	-0.0608	-0.1727	1.2801 **	0.1324	7.7639
		(-1.512)	(-1.391)	(-0.175)	(1.294)	(1.561)	(1.152)	(-0.358)	(-1.327)	(24.492)	(0.649)	
	R_F	0.0750	0.0349	0.1406	0.2957 *	-0.0683	-0.0921	-0.2395	-0.2997 *	1.1659 **	0.5811 **	6.5772
		(0.363)	(0.178)	(0.818)	(2.256)	(-0.332)	(-0.471)	(-1.389)	(-2.268)	(21.974)	(2.804)	
VOW	R_S	-0.0310	-0.1967 *	-0.1340	-0.0505	0.0867	0.1761 *	0.1192	0.0833	0.9425 **	-0.1762 *	4.9624
		(-0.357)	(-2.282)	(-1.694)	(-0.806)	(0.995)	(2.034)	(1.510)	(1.390)	(29.106)	(-2.163)	
	R_F	0.4370 **	0.1160	0.0183	0.0686	-0.3618 **	-0.1168	-0.0564	-0.0132	0.7699 **	0.1994 *	34.7478 **
		(4.675)	(1.251)	(0.215)	(1.019)	(-3.858)	(-1.253)	(-0.664)	(-0.204)	(22.096)	(2.275)	

Notes: This table reports the VECM estimates and Granger causality tests results for the model (3.5a) and (3.5b):

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

* and ** denote significant levels of 5% and 1%, respectively.

Figures in the parenthesis (.) are the t statistics.

Granger causality tests are based on the Wald tests of (H_{01}: $\beta_{Si}=0$) and (H_{02}: $\alpha_{Fi}=0$); the tests statistics are $\chi^2(4)$ distributed.

t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $B_{t-1} = \beta' X_{t-1} = S_{t-1} - F_t$ is restricted to be the lagged basis in all cases; $R_{SIF,t-1}$ is the lagged stock index returns.

See the equations (3.5a) and (3.5b) in the text for the definitions of the remaining terms.

Table 3 11: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_Period 2

Code	Dep Var	α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test ($H_0: \beta_F = 0$)
		α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test ($H_0: \alpha_F = 0$)
AA	R_S	-0.0699	0.0652	0.0753	0.0203	0.0362	-0.0923	-0.1051	-0.0931	0.8501 **	-0.0739 *	5.1149
		(-0.977)	(0.880)	(1.021)	(0.292)	(0.527)	(-1.298)	(-1.487)	(-1.489)	[illegible]	(-2.360)	
	R_F	0.2334 **	0.1540	0.0900	-0.0241	-0.2577 **	-0.1473	-0.1232	-0.0717	0.8437 **	[illegible]	9.9058 *
		(2.878)	(1.834)	(1.076)	(-0.306)	(-3.308)	(-1.827)	(-1.539)	(-0.958)	(22.989)	(0.078)	
AGN	R_S	-0.0575	-0.0875	-0.1681	-0.1022	0.1027	0.0875	0.1705	0.1039	1.5055 **	0.1239 *	[illegible]
		(-0.627)	(-0.896)	(-1.764)	(-1.237)	(1.130)	(0.915)	(1.847)	(1.308)	(34.177)	(2.070)	
	R_F	0.4146 **	0.1585	-0.0460	-0.0604	-0.3312 **	-0.1654	0.0380	0.0678	[illegible] **	[illegible] **	[illegible] **
		(4.174)	(1.500)	(-0.446)	(-0.675)	(-3.365)	(-1.597)	(0.380)	(0.788)	3(0.330)	(3.361)	
AHL	R_S	-0.1025	-0.2184 **	-0.1738 *	-0.1220	0.1316	0.1940 **	0.1524 *	0.0113	1.1113 **	0.0086	10.1551 *
		(-1.287)	(-2.577)	(-2.061)	(-1.531)	(1.919)	(2.660)	(2.096)	(0.165)	(13.453)	(0.856)	
	R_F	0.3248 **	-0.0572	-0.0805	-0.0636	-0.2182 *	0.0402	0.0680	-0.0165	1.0180 **	0.0218	14.5241 **
		(3.285)	(-0.544)	(-0.769)	(-0.643)	(-2.564)	(0.444)	(0.754)	(-0.195)	(09.931)	(1.745)	
ALV	R_S	0.2121 *	0.0825	-0.0979	-0.0075	-0.1845	-0.0433	0.0760	-0.0274	1.1253 **	-0.1497	5.9654
		(2.033)	(0.740)	(-0.911)	(-0.087)	(-1.727)	(-0.382)	(0.703)	(-0.317)	(27.660)	(-1.809)	
	R_F	0.7487 **	0.3279 **	0.0253	0.0882	-0.7123 **	-0.2760 *	-0.0626	-0.1022	1.0576 **	0.0433	59.2818 **
		(07.072)	(2.900)	(0.232)	(1.006)	(-6.570)	(-2.403)	(-0.570)	(-1.167)	(25.612)	(0.575)	
AXA	R_S	-0.0432	-0.0689	-0.0878	0.2411 **	0.0797	0.0620	0.0446	-0.1952 *	1.1194 **	-0.0566	7.7079
		(-0.430)	(-0.651)	(-0.845)	(2.587)	(0.788)	(0.585)	(0.431)	(-2.119)	(23.821)	(-0.991)	
	R_F	0.3676 **	0.0521	0.0151	0.2260 *	-0.3186 **	-0.0554	-0.0353	-0.1926 *	1.0778 **	0.0558	19.1115 **
		(3.555)	(0.478)	(0.141)	(2.354)	(-3.059)	(-0.507)	(-0.331)	(-2.031)	2(2.268)	(0.950)	
AZN	R_S	-0.1303	-0.1669	-0.2087	-0.2461	0.1798	0.1862	0.2552	0.2263	0.8468 **	0.0360	3.1958
		(-0.777)	(-0.907)	(-1.152)	(-1.560)	(1.066)	(1.006)	(1.406)	(1.437)	(10.945)	(0.438)	
	R_F	0.3779 *	0.1511	-0.1108	-0.1810	-0.3293	-0.1235	0.1674	0.1588	0.8032 **	0.0977	8.0301
		(2.250)	(0.820)	(-0.611)	(-1.145)	(-1.950)	(-0.666)	(0.921)	(1.007)	(10.364)	(1.188)	
BAR	R_S	0.1409	-0.0687	-0.0146	-0.0919	-0.1328	0.0516	0.0654	0.0336	1.0835 **	-0.0107	2.[illegible]
		(1.267)	(-0.595)	(-0.127)	(-0.839)	(-1.207)	(0.452)	(0.575)	(0.313)	(16.808)	(-0.252)	
	R_F	0.4289 **	-0.0341	-0.0356	-0.1380	-0.4156 **	0.0094	0.0704	0.0805	1.0285 **	0.0456	18.1426 **
		(3.736)	(-0.286)	(-0.300)	(-1.220)	(-3.658)	(0.080)	(0.599)	(0.726)	(15.447)	(1.046)	
BNP	R_S	-0.2557 **	-0.0888	-0.0943	0.1114	0.2259 *	0.0568	0.0841	-0.0976	0.9048 **	-0.0047	8.8723
		(-2.869)	(-0.957)	(-1.024)	(1.291)	(2.522)	(0.612)	(0.914)	(-1.125)	(23.068)	(-0.123)	
	R_F	0.0527	0.0073	-0.1149	0.0800	-0.0644	-0.0186	0.1213	-0.0735	0.8595 **	0.0651	4.3416
		(0.582)	(0.077)	(-1.227)	(0.913)	(-0.707)	(-0.197)	(1.297)	(-0.834)	(21.562)	(1.673)	
BPA	R_S	0.1453	0.0335	-0.0679	0.0572	-0.1481	-0.0952	0.0550	-0.0374	0.9982 **	-0.1052	2.0177
		(1.000)	(0.218)	(-0.450)	(0.424)	(-1.025)	(-0.622)	(0.368)	(-0.281)	(16.783)	(-1.246)	
	R_F	0.5522 **	0.2554	0.0031	0.1412	-0.5551 **	-0.3079	-0.0160	-0.1186	0.9616 **	0.0010	16.1418 **
		(3.688)	(1.613)	(0.020)	(1.014)	(-3.726)	(-1.953)	(-0.104)	(-0.864)	(15.682)	(0.011)	
BTL	R_S	0.1188	-0.0291	0.0612	-0.2326	-0.1790	-0.0417	-0.0767	0.1850	0.7487 **	-0.0130	4.9944
		(0.947)	(-0.224)	(0.465)	(-1.842)	(-1.419)	(-0.319)	(-0.581)	(1.467)	(10.580)	(-0.261)	
	R_F	0.3645 **	0.0696	0.0085	-0.2331	-0.4219 **	-0.1371	-0.0310	0.1653	0.7233 **	0.0475	12.0736 *
		(2.917)	(0.538)	(0.065)	(-1.852)	(-3.355)	(-1.053)	(-0.236)	(1.316)	(10.255)	(0.952)	
BVA	R_S	-0.0433	-0.1573	-0.1192	0.0338	0.0758	0.1423	0.1354	-0.0600	1.1501 **	-0.0607	7.4898
		(-0.555)	(-1.915)	(-1.483)	(0.472)	(0.983)	(1.754)	(1.707)	(-0.860)	(39.119)	(-1.287)	
	R_F	0.3847 **	0.0443	-0.0175	0.1021	-0.3486 **	-0.0486	0.0292	-0.1240	1.1308 **	0.0514	29.0905 **
		(4.659)	(0.509)	(-0.206)	(1.346)	(-4.273)	(-0.566)	(0.348)	(-1.678)	(36.344)	(1.030)	
CA	R_S	-0.1807	-0.0234	-0.0513	0.0863	0.1981	0.0540	-0.0451	-0.0034	0.6699 **	-0.0833	3.4808
		(-1.461)	(-0.183)	(-0.414)	(0.787)	(1.593)	(0.422)	(-0.363)	(-0.031)	(14.437)	(-1.022)	
	R_F	0.2235	0.1515	0.0651	0.0683	-0.1981	-0.1356	-0.1611	0.0025	0.6418 **	0.0615	3.3338
		(1.781)	(1.169)	(0.518)	(0.613)	(-1.570)	(-1.045)	(-1.280)	(0.023)	(13.635)	(0.743)	
CGE	R_S	-0.4556	-0.6078	-0.1336	0.3135	0.5144	0.6213	0.0836	-0.2211	1.2939 **	0.0758	8.0505
		(-1.349)	(-1.798)	(-0.432)	(1.290)	(1.526)	(1.834)	(0.270)	(-0.917)	(14.975)	(0.253)	
	R_F	0.1281	-0.1566	0.1536	0.4073	-0.0745	0.1764	-0.2021	-0.3191	1.2542 **	0.3501	6.0817
		(0.377)	(-0.461)	(0.494)	(1.666)	(-0.220)	(0.518)	(-0.649)	(-1.315)	(14.429)	(1.160)	
CSG	R_S	0.0222	0.0596	-0.0853	0.0474	0.0245	-0.0461	0.0356	-0.1034	1.1468 **	-0.0378	2.8098
		(0.216)	(0.536)	(-0.773)	(0.478)	(0.239)	(-0.416)	(0.327)	(-1.080)	(20.025)	(-0.763)	
	R_F	0.5067 **	0.3176 **	0.0561	0.1108	-0.4557 **	-0.2874 *	-0.0955	-0.1545	1.0970 **	0.0318	25.2813 **
		(4.800)	(2.772)	(0.493)	(1.085)	(-4.320)	(-2.517)	(-0.851)	(-1.567)	(18.588)	(0.624)	
DBK	R_S	-0.1469	-0.0916	-0.0048	0.0523	0.1870	0.1079	0.0009	-0.0521	0.9668 **	-0.1144 *	4.3124
		(-1.511)	(-0.858)	(-0.046)	(0.583)	(1.946)	(1.029)	(0.008)	(-0.582)	(25.965)	(-2.288)	
	R_F	0.3504 **	0.0701	-0.0322	0.0808	-0.2774 **	-0.0568	0.0375	-0.0783	0.9394 **	-0.0217	15.5685 **
		(3.357)	(0.612)	(-0.285)	(0.839)	(-2.689)	(-0.505)	(0.337)	(-0.814)	(23.501)	(-0.404)	
DCY	R_S	0.1052	0.0380	-0.0457	0.1549	-0.0567	-0.0343	0.0820	-0.1439	0.9421 **	-0.0617	5.9592
		(1.213)	(0.428)	(-0.516)	(1.826)	(-0.652)	(-0.385)	(0.926)	(-1.703)	(21.006)	(-1.801)	
	R_F	0.3319 **	0.1347	-0.0806	0.1753 *	-0.2932 **	-0.1126	0.1143	-0.1338	0.8830 **	-0.0001	21.3699 **
		(3.646)	(1.445)	(-0.869)	(1.968)	(-3.216)	(-1.205)	(1.230)	(-1.509)	(18.758)	(-0.003)	
DTE	R_S	-0.0868	-0.0854	0.0154	-0.0919	0.1164	0.0988	-0.0461	0.0993	0.7032 **	-0.0421	4.7159
		(-0.945)	(-0.898)	(0.165)	(-1.066)	(1.251)	(1.027)	(-0.484)	(1.128)	(20.508)	[illegible]	
	R_F	0.2145 *	0.0008	0.0267	-0.1029	-0.1880	0.0091	-0.0686	0.1314	0.6409 **	0.0607	8.1241
		(2.244)	(0.009)	(0.273)	(-1.148)	(-1.942)	(0.091)	(-0.692)	(1.434)	(17.963)	(1.175)	
ENI	R_S	-0.0333	0.0011	0.0272	-0.0223	0.0641	-0.0593	-0.0186	-0.0204	0.9324 **	[illegible] *	1.9249
		(-0.476)	(0.015)	(0.376)	(-0.318)	(0.893)	(-0.808)	(-0.254)	(-0.291)	(20.043)	(-2.055)	
	R_F	0.2494 **	0.0781	-0.0202	-0.0633	-0.1610 *	-0.1398	0.0283	0.0192	0.8408 **	-0.0111	[illegible] *
		(3.462)	(1.043)	(-0.270)	(-0.878)	(-2.178)	(-1.847)	(0.376)	(0.267)	1(7.534)	(-0.692)	
ENL	R_S	-0.1307 *	-0.1174	-0.0776	0.0012	0.0730	0.0773	0.0813	0.0365	0.6354 **	-0.0067	4.2445
		(-2.093)	(-1.864)	(-1.231)	(0.019)	(1.195)	(1.259)	(1.323)	(0.598)	(13.229)	(-1.142)	
	R_F	0.0679	-0.1177	-0.0492	0.0038	-0.0867	0.1013	-0.0013	-0.0230	0.5792 **	-0.0016	5.1354
		(1.029)	(-1.769)	(-0.738)	(0.058)	(-1.343)	(1.563)	(-0.019)	(-0.356)	1(1.411)	[illegible]	

Table 3.11: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_Period 2 (continued)

Code	Dep Var	α_{S1} / α_{F1}	α_{S2} / α_{F2}	α_{S3} / α_{F3}	α_{S4} / α_{F4}	β_{S1} / β_{F1}	β_{S2} / β_{F2}	β_{S3} / β_{F3}	β_{S4} / β_{F4}	δ_S / δ_F	γ_S / γ_F	Wald test ($H_{01}: \beta_F = 0$) / Wald test ($H_{02}: \alpha_S = 0$)
EOA	R_S	-0.3190 **	-0.0166	0.0119	0.0297	0.2804 **	0.0708	-0.0591	-0.0767	0.7012 **	-0.0347	10.3324 *
		(-3.382)	(-0.170)	(0.124)	(0.332)	(2.917)	(0.713)	(-0.601)	(-0.832)	(17.291)	(-0.742)	
	R_F	-0.0436	0.0261	0.0102	-0.0492	-0.0175	0.0361	-0.0649	-0.0135	0.6334 **	0.0604	0.7743
		(-0.456)	(0.264)	(0.104)	(-0.543)	(-0.180)	(0.358)	(-0.650)	(-0.144)	(15.398)	(1.274)	
ERC	R_S	0.1646	0.2024	0.0598	-0.1486	-0.1843	-0.1982	-0.0884	0.1316	1.9404 **	-0.0592	5.1113
		(0.952)	(1.178)	(0.377)	(-1.208)	(-1.057)	(-1.154)	(-0.562)	(1.099)	(26.000)	(-0.366)	
	R_F	0.6707 **	0.5219 **	0.2957	-0.0594	-0.6637 **	-0.5183 **	-0.2946	0.0454	1.8887 **	0.2822	21.1507 **
		(3.931)	(3.077)	(1.888)	(-0.489)	(-3.856)	(-3.058)	(-1.899)	(0.384)	(25.640)	(1.766)	
FTE	R_S	0.1304	0.0380	-0.0281	0.1371	-0.0976	-0.0802	0.0193	-0.1322	0.9542 **	-0.0149	2.2622
		(0.962)	(0.267)	(-0.201)	(1.080)	(-0.715)	(-0.559)	(0.138)	(-1.051)	(17.669)	(-0.196)	
	R_F	0.5304 **	0.2943 *	0.0893	0.2064	-0.5027 **	-0.3272 *	-0.0921	-0.1927	0.8936 **	0.0750	16.9497 **
		(3.832)	(2.021)	(0.625)	(1.591)	(-3.605)	(-2.231)	(-0.643)	(-1.498)	(16.194)	(0.964)	
GEN	R_S	0.0767	0.0066	-0.0823	-0.0275	0.0044	-0.0077	0.0888	0.0060	0.7680 **	-0.0944	1.5791
		(0.793)	(0.065)	(-0.818)	(-0.315)	(0.046)	(-0.076)	(0.909)	(0.072)	(20.947)	(-1.405)	
	R_F	0.5349 **	0.2127	-0.0442	0.0341	-0.4231 **	-0.1930	0.0530	-0.0327	0.7587 **	0.0801	32.4071 **
		(5.222)	(1.958)	(-0.415)	(0.369)	(-4.195)	(-1.811)	(0.513)	(-0.371)	(19.556)	(1.127)	
GXW	R_S	-0.2770	-0.3566 *	0.0453	0.1274	0.2802	0.2843	-0.0635	-0.0900	0.8555 **	-0.0519	6.1416
		(-1.716)	(-2.023)	(0.263)	(0.876)	(1.734)	(1.622)	(-0.370)	(-0.621)	(13.032)	(-0.506)	
	R_F	0.2412	-0.1484	0.0927	0.1521	-0.2204	0.0775	-0.1128	-0.1121	0.7951 **	0.0761	8.8796
		(1.469)	(-0.828)	(0.529)	(1.028)	(-1.341)	(0.435)	(-0.646)	(-0.760)	(11.913)	(0.730)	
HAS	R_S	-0.0211	-0.1328	-0.1378	0.0964	-0.0051	0.1465	0.0869	-0.0538	0.8249 **	-0.0075	4.5818
		(-0.237)	(-1.417)	(-1.489)	(1.135)	(-0.057)	(1.568)	(0.939)	(-0.645)	(19.277)	(-0.157)	
	R_F	0.3482 **	-0.0125	-0.1418	0.1040	-0.3748 **	0.0243	0.0987	-0.0461	0.8115 **	0.1014 *	26.6600 **
		(3.896)	(-0.133)	(-1.527)	(1.220)	(-4.229)	(0.259)	(1.063)	(-0.551)	(18.908)	(2.104)	
HNM	R_S	-0.0347	0.2158	0.1781	0.0777	-0.0476	-0.2709 *	-0.1883	-0.0863	0.5634 **	-0.1015	6.1665
		(-0.304)	(1.765)	(1.481)	(0.755)	(-0.411)	(-2.194)	(-1.562)	(-0.850)	(10.173)	(-1.317)	
	R_F	0.4462 **	0.4005 **	0.2771 *	0.1333	-0.5316 **	-0.4582 **	-0.2981 *	-0.1479	0.5637 **	0.0472	18.1959 **
		(3.998)	(3.351)	(2.358)	(1.326)	(-4.691)	(-3.796)	(-2.530)	(-1.490)	(10.411)	(0.626)	
ING	R_S	-0.0478	-0.1278	-0.0728	-0.0096	0.1027	0.1120	0.0603	0.0295	1.2259 **	0.0003	3.6102
		(-0.711)	(-1.847)	(-1.063)	(-0.149)	(1.518)	(1.607)	(0.877)	(0.457)	(36.229)	(0.010)	
	R_F	0.2345 **	-0.0097	-0.0433	-0.0319	-0.1806 *	0.0015	0.0283	0.0440	1.1960 **	0.0855 *	14.3644 **
		(3.341)	(-0.134)	(-0.606)	(-0.475)	(-2.558)	(0.020)	(0.394)	(0.654)	(33.870)	(2.485)	
LLO	R_S	0.0257	-0.0025	0.0067	-0.0143	0.0075	0.0352	-0.0335	0.0337	0.9139 **	-0.0078	1.4051
		(0.407)	(-0.038)	(0.104)	(-0.227)	(0.127)	(0.584)	(-0.559)	(0.585)	(16.317)	(-0.444)	
	R_F	-0.0711 **	-0.0731	-0.0727	-0.0709	-0.0664 **	-0.0678	-0.0676	-0.0650	-0.0631 **	-0.0197	16.7169
		(4.033)	(0.722)	(-0.019)	(-0.513)	(-3.169)	(-0.525)	(-0.357)	(0.363)	(13.643)	(1.193)	
MUV	R_S	-0.1064	0.1165	0.1284	0.0749	0.1719	-0.1095	-0.1424	-0.1159	1.0052 **	-0.0413	5.4663
		(-0.906)	(0.871)	(0.961)	(0.641)	(1.437)	(-0.812)	(-1.068)	(-1.006)	(22.646)	(-1.099)	
	R_F	0.4599 **	0.2403	-0.0600	0.0808	-0.3824 **	-0.1861	0.0370	-0.0959	0.9394 **	0.0086	21.7438 **
		(03.977)	(1.826)	(-0.457)	(0.703)	(-3.249)	(-1.404)	(0.282)	(-0.846)	(20.662)	(0.233)	
NDA	R_S	0.0709	-0.1179	-0.3099 **	0.0770	-0.2176 *	0.1463	0.2061 *	-0.0462	0.5923 **	-0.0378	14.9898 **
		(0.738)	(-1.201)	(-3.180)	(0.814)	(-2.246)	(1.464)	(2.074)	(-0.488)	(11.323)	(-0.925)	
	R_F	0.3374 **	-0.0134	-0.2188 *	0.0532	-0.4550 **	0.0498	0.1423	-0.0166	0.5785 **	0.0297	22.4122 **
		(3.543)	(-0.138)	(-2.264)	(0.567)	(-4.736)	(0.503)	(1.444)	(-0.177)	(11.151)	(0.733)	
NES	R_S	-0.0580	0.0062	-0.0634	-0.0487	0.0451	-0.0092	0.0733	0.0221	0.7853 **	-0.0433	1.4373
		(-0.694)	(0.071)	(-0.739)	(-0.628)	(0.534)	(-0.105)	(0.856)	(0.289)	(20.068)	(-0.813)	
	R_F	0.3004 **	0.1213	-0.0317	-0.0791	-0.2948 **	-0.1293	0.0297	0.0240	0.6557 **	0.1075	13.8297 **
		(3.323)	(1.288)	(-0.341)	(-0.941)	(-3.225)	(-1.367)	(0.320)	(0.288)	(15.477)	(1.862)	
NOV	R_S	0.0619	0.0039	-0.0549	0.0422	-0.1116	-0.0561	-0.0224	-0.0383	0.9062 **	-0.1471 *	1.7302
		(0.674)	(0.040)	(-0.586)	(0.539)	(-1.186)	(-0.563)	(-0.238)	(-0.494)	(22.918)	(-2.136)	
	R_F	0.5588 **	0.3447 **	0.0832	0.0760	-0.6068 **	-0.3704 **	-0.1275	-0.0748	0.8000 **	0.0386	39.2718 **
		(5.903)	(3.446)	(0.862)	(0.942)	(-6.266)	(-3.612)	(-1.313)	(-0.937)	(19.649)	(0.544)	
PHI	R_S	-0.0363	0.0092	-0.0812	-0.1140	0.0372	-0.0080	0.0407	0.0612	1.4665 **	0.0280	0.9615
		(-0.317)	(0.077)	(-0.719)	(-1.293)	(0.320)	(-0.066)	(0.358)	(0.695)	(32.574)	(0.289)	
	R_F	0.5653 **	0.3896 **	0.1262	-0.0647	-0.5489 **	-0.3808 **	-0.1520	-0.0048	1.3659 **	0.2370 *	25.9743 **
		(4.555)	(2.990)	(1.031)	(-0.677)	(-4.355)	(-2.887)	(-1.232)	(-0.051)	(28.005)	(2.260)	
RBO	R_S	-0.1272	-0.0488	0.0895	0.0313	0.0389	0.0391	-0.1040	-0.0529	0.9364 **	0.0232	1.7890
		(-1.222)	(-0.446)	(0.827)	(0.309)	(0.371)	(0.356)	(-0.958)	(-0.525)	(16.600)	(0.557)	
	R_F	0.2366 *	0.1561	0.1465	0.0816	-0.3071 **	-0.1668	-0.1515	-0.0958	0.8638 **	0.0681	5.9292
		(2.248)	(1.410)	(1.339)	(0.798)	(-2.896)	(-1.502)	(-1.380)	(-0.940)	(15.141)	(1.612)	
RD	R_S	0.0494	0.0363	0.0212	0.0288	0.0070	0.0021	-0.0191	0.0047	0.6944 **	-0.0001	2.7749
		(1.387)	(1.016)	(0.592)	(0.806)	(0.551)	(0.167)	(-1.516)	(0.378)	(17.291)	(-0.111)	
	R_F	0.3287 **	0.1527	0.1259	-0.0310	0.0152	-0.0116	-0.0255	0.0127	0.6870 **	0.0021	10.5038 *
		(2.743)	(1.270)	(1.045)	(-0.257)	(0.357)	(-0.273)	(-0.601)	(0.301)	(05.083)	(1.148)	
ROG	R_S	-0.1222	-0.0983	-0.0072	-0.1718	0.1111	0.0583	0.0258	0.1571	0.9263 **	-0.0524	3.5600
		(-0.967)	(-0.753)	(-0.058)	(-1.601)	(0.887)	(0.455)	(0.213)	(1.514)	(16.196)	(-0.559)	
	R_F	0.3619 **	0.3132 *	0.2273	-0.0531	-0.3546 **	-0.3557 **	-0.1788	0.0449	0.8541 **	0.1143	11.3033 *
		(2.716)	(2.274)	(1.738)	(-0.469)	(-2.685)	(-2.631)	(-1.396)	(0.410)	(14.164)	(1.157)	
SCH	R_S	-0.0992	-0.0987	-0.1209	0.0192	0.0969	0.0671	0.1445	-0.0046	1.1557 **	-0.0604	4.1049
		(-1.177)	(-1.124)	(-1.413)	(0.249)	(1.143)	(0.767)	(1.705)	(-0.061)	(38.827)	(-1.146)	
	R_F	0.2598 **	0.1322	-0.0803	0.1119	-0.2285 *	-0.1363	0.0808	-0.0861	1.0936 **	0.0758	17.1401 **
		(2.928)	(1.429)	(-0.891)	(1.381)	(-2.559)	(-1.478)	(0.905)	(-1.076)	(34.872)	(1.363)	
SHB	R_S	-0.0029	0.0618	0.0004	0.1975 *	-0.0609	-0.0799	-0.0306	-0.1410	0.5548 **	-0.0171	3.7506
		(-0.033)	(0.669)	(0.005)	(2.286)	(-0.690)	(-0.862)	(-0.333)	(-1.668)	(12.477)	(-0.391)	
	R_F	0.2815 **	0.1246	-0.0925	0.0330	-0.3809 **	-0.1175	0.0751	0.0084	0.4769 **	0.0890	12.1423 *
		(2.998)	(1.281)	(-0.957)	(0.363)	(-4.092)	(-1.203)	(0.778)	(0.095)	(10.181)	(1.929)	

Table 3.11: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_Period 2 (continued)

		α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_{01}: $\beta_{Si}=0$)
Code	**Dep Var**	α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_{02}: $\alpha_{Fi}=0$)
SHE	R_S	0.7114 *	0.5223	0.3509	0.1137	-0.6336 *	-0.4611	-0.3129	-0.0911	0.9215 **	0.0145	5.8925
		(2.186)	(1.499)	(1.008)	(0.346)	(-2.233)	(-1.523)	(-1.035)	(-0.321)	(03.085)	(1.021)	
	R_F	1.2216 **	0.8084 *	0.4432	0.2208	-1.0727 **	-0.7080 *	-0.3953	-0.1797	0.8904 **	0.0176	11.9142 *
		(3.264)	(2.018)	(1.107)	(0.585)	(-3.289)	(-2.034)	(-1.137)	(-0.550)	(02.593)	(1.078)	
SIE	R_S	0.1086	0.0744	0.2206 *	0.3136 **	-0.0560	-0.0859	-0.2117 *	-0.3164 **	1.0287 **	-0.0558	12.4594 *
		(1.030)	(0.665)	(2.026)	(3.439)	(-0.533)	(-0.776)	(-1.963)	(-3.525)	(30.456)	(-0.739)	
	R_F	0.6006 **	0.1966	0.2973 **	0.3930 **	-0.5221 **	-0.2079	-0.3119 **	-0.3740 **	0.9822 **	0.1128	46.2983 **
		(5.403)	(1.666)	(2.589)	(4.087)	(-4.717)	(-1.782)	(-2.744)	(-3.952)	(27.578)	(1.419)	
TEF	R_S	-0.2162 **	-0.1129	0.0050	0.0627	0.2399 **	0.1253 *	0.0206	-0.0318	1.0614 **	-0.0022	19.2178 **
		(-3.757)	(-1.874)	(0.083)	(1.091)	(4.135)	(2.079)	(0.341)	(-0.553)	(35.217)	(-0.327)	
	R_F	0.1254 *	0.0261	0.0913	0.0193	-0.0750	-0.0246	-0.0747	-0.0125	1.0247 **	0.0036	6.1416
		(2.072)	(0.411)	(1.441)	(0.319)	(-1.228)	(-0.388)	(-1.177)	(-0.206)	(32.325)	(0.521)	
TI	R_S	0.0171	0.0125	-0.0490	-0.0018	-0.0058	-0.0089	0.0068	0.0073	1.0066 **	0.0054 *	3.5156
		(0.522)	(0.382)	(-1.491)	(-0.055)	(-0.748)	(-1.150)	(0.884)	(0.943)	(19.172)	(1.965)	
	R_F	0.0560	-0.3400 *	-0.0828	0.3148	-0.0123	0.0049	0.0009	0.0120	0.9880 **	0.1308 **	8.3730
		(0.348)	(-2.114)	(-0.513)	(1.949)	(-0.324)	(0.129)	(0.024)	(0.317)	(03.830)	(9.636)	
TIM	R_S	0.0930	0.0680	-0.0038	0.1070	-0.0755	-0.0288	-0.0635	-0.1287 *	0.8238 **	-0.1235 **	5.1780
		(1.428)	(1.038)	(-0.059)	(1.687)	(-1.143)	(-0.434)	(-0.963)	(-2.023)	(16.350)	(-3.691)	
	R_F	0.2335 **	-0.0008	-0.0423	0.0364	-0.2014 **	0.0170	-0.0101	-0.0574	0.7799 **	-0.0005	12.7615 *
		(3.392)	(-0.012)	(-0.615)	(0.543)	(-2.882)	(0.243)	(-0.146)	(-0.854)	(14.641)	(-0.014)	
TLI	R_S	-0.0227	-0.0744	0.0478	-0.2053	0.0147	-0.0073	-0.0717	0.1544	0.7700 **	-0.0176	2.4764
		(-0.185)	(-0.617)	(0.403)	(-1.702)	(0.118)	(-0.059)	(-0.590)	(1.266)	(11.668)	(-0.557)	
	R_F	0.1586	0.1062	0.2983 *	-0.1424	-0.2022	-0.2332	-0.3118 **	0.1072	0.7454 **	0.0037	11.1243 *
		(1.304)	(0.890)	(2.537)	(-1.193)	(-1.634)	(-1.915)	(-2.594)	(0.888)	(11.414)	(0.117)	
TOT	R_S	-0.1435	0.1289	0.1848	-0.0554	0.1300	-0.2341 *	-0.1859	0.0617	0.7292 **	0.0096	12.0865 *
		(-1.375)	(1.193)	(1.720)	(-0.549)	(1.243)	(-2.186)	(-1.746)	(0.619)	(17.783)	(0.216)	
	R_F	0.1662	0.1694	0.1347	-0.1364	-0.1460	-0.2626 *	-0.1324	0.1199	0.6767 **	0.0825	7.3795
		(1.549)	(1.524)	(1.219)	(-1.314)	(-1.357)	(-2.384)	(-1.209)	(1.169)	(16.042)	(1.806)	
UBS	R_S	0.0624	0.0282	0.1659	0.1700 *	-0.0736	-0.0335	-0.1447	-0.1596 *	1.0385 **	-0.0719	5.9158
		(0.767)	(0.328)	(1.953)	(2.143)	(-0.908)	(-0.391)	(-1.719)	(-2.074)	(25.601)	(-1.828)	
	R_F	0.4202 **	0.1709	0.2084 *	0.1671 *	-0.4302 **	-0.1753	-0.1955 *	-0.1441	1.0017 **	0.0090	26.7577 **
		(4.838)	(1.861)	(2.296)	(1.972)	(-4.962)	(-1.919)	(-2.173)	(-1.752)	(23.106)	(0.215)	
UC	R_S	0.1144	0.0970	-0.0125	0.1434 *	-0.0749	-0.0933	-0.0917	-0.0620	0.6662 **	-0.0699 *	3.4818
		(1.599)	(1.348)	(-0.174)	(2.054)	(-1.075)	(-1.326)	(-1.313)	(-0.921)	(14.134)	(-2.024)	
	R_F	0.2755 **	0.1081	-0.0042	0.0701	-0.2411 **	-0.0701	-0.0467	0.0208	0.6795 **	0.0432	14.8594 **
		(3.710)	(1.446)	(-0.057)	(0.967)	(-3.334)	(-0.961)	(-0.645)	(0.298)	(13.889)	(1.205)	
VIV	R_S	-0.2113	-0.1220	-0.1703	0.0729	0.1750	0.1200	0.1106	-0.0380	0.9967 **	0.0462	2.5599
		(-1.563)	(-0.846)	(-1.221)	(0.614)	(1.309)	(0.841)	(0.807)	(-0.329)	(19.266)	(0.504)	
	R_F	0.2993 *	0.1944	-0.0743	0.0938	-0.3260 *	-0.1853	0.0337	-0.0329	0.9437 **	0.1944 *	8.6229
		(2.103)	(1.280)	(-0.506)	(0.751)	(-2.317)	(-1.233)	(0.233)	(-0.270)	(17.326)	(2.013)	
VOF	R_S	0.0238	0.0623	-0.1381	-0.2084	-0.0399	-0.0553	0.1348	0.2467	1.0495 **	-0.0882	4.5667
		(0.173)	(0.420)	(-0.943)	(-1.591)	(-0.290)	(-0.376)	(0.933)	(1.921)	(14.891)	(-1.260)	
	R_F	0.4654 **	0.1869	-0.0648	-0.1970	-0.4615 **	-0.1929	0.0570	0.2266	1.0443 **	-0.0092	14.6455 **
		(3.298)	(1.230)	(-0.433)	(-1.470)	(-3.278)	(-1.283)	(0.386)	(1.725)	(14.482)	(-0.129)	
VOW	R_S	-0.0362	-0.0299	0.0472	0.0786	0.0780	0.0191	-0.0603	-0.0235	0.9281 **	-0.0684	0.9576
		(-0.301)	(-0.235)	(0.380)	(0.723)	(0.657)	(0.153)	(-0.494)	(-0.221)	(18.888)	(-0.862)	
	R_F	0.3752 **	0.0972	-0.0225	0.0884	-0.3194 *	-0.1078	-0.0152	-0.0227	0.8821 **	0.0920	11.4006 *
		(2.940)	(0.720)	(-0.171)	(0.767)	(-2.539)	(-0.813)	(-0.118)	(-0.201)	(16.934)	(1.095)	

Notes: This table reports the VECM estimates and Granger causality tests results for the model (3.5a) and (3.5b):

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

* and ** denote significant levels of 5% and 1%, respectively.

Figures in the parenthesis (.) are the t statistics.

Granger causality tests are based on the Wald tests of (H_{01}: $\beta_{SI} = 0$) and (H_{02}: $\alpha_{FI} = 0$); the tests statistics are $\chi^2(4)$ distributed.

t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $B_{t-1} = \beta' X_{t-1} = S_{t-1} - F_{t-1}$ is restricted to be the lagged basis in all cases; $R_{SIF,t-1}$ is the lagged stock index returns.

See the equations (3.5a) and (3.5b) in the text for the definitions of the remaining terms.

Table 3.12: Summary Results of VECM_Period 1

Code	Lead-lag Relationship: Stock Leads	Lead-lag Relationship: Futures Leads	Error Correction: Stock Adjusts	Error Correction: Futures Adjusts		Common Factor Weights: Stock (θ_S)	Common Factor Weights: Futures ($\theta_F = 1-\theta_S$)
AA	√	x	–	–		0.454	0.546
AGN	√	x	–	+		0.990	0.010
AHL	x	x	–	–		0.549	0.451
ALV	√	x	–	+		0.624	0.376
AXA	x	x	–	+		0.979	0.021
AZN	√	x	–	–		0.948	0.052
BAR	x	x	–	–		0.782	0.218
BNP	√	x	–	–		0.661	0.339
BPA	x	x	–	–		0.461	0.539
BTL	x	√	–	+		0.750	0.250
BVA	√	x	–	–		0.563	0.437
CA	√	x	–	–		0.784	0.216
CGE	x	x	–	+		0.958	0.042
CSG	√	x	–	–		0.674	0.326
DBK	√	x	–	+		0.998	0.002
DCY	√	x	–	–		0.622	0.378
DTE	√	x	–	+		0.602	0.398
ENI	x	x	–	+		0.837	0.163
ENL	x	x	–	+		0.981	0.019
EOA	√	x	–	+		0.674	0.326
ERC	√	√	+	+		0.572	0.428
FTE	√	x	–	–		0.682	0.318
GEN	√	x	–	–		0.554	0.446
GXW	x	x	–	–		0.351	0.649
HAS	x	x	–	–		0.379	0.621
HNM	x	x	–	–		0.585	0.415
ING	x	x	–	–		0.864	0.136
LLO	√	x	+	–		0.001	0.999
MUV	√	x	–	–		0.625	0.375
NDA	x	x	–	–		0.893	0.107
NES	√	x	–	+		0.843	0.157
NOV	√	x	–	+		0.959	0.041
PHI	x	x	–	–		0.828	0.172
RBO	√	x	+	–		0.147	0.853
RD	x	x	–	–		0.759	0.241
ROG	√	x	–	–		0.222	0.778
SCH	x	x	+	–		0.333	0.667
SHB	√	√	–	–		1.000	0.000
SHE	√	√	–	–		0.001	0.999
SIE	√	x	–	+		0.832	0.168
TEF	√	x	–	–		0.804	0.196
TI	x	x	–	–		0.001	0.999
TIM	√	x	–	–		0.330	0.670
TLI	x	x	–	–		0.575	0.425
TOT	x	√	–	–		0.892	0.108
UBS	√	x	–	–		0.505	0.495
UC	√	x	+	–		0.284	0.716
VIV	√	x	–	–		0.001	0.999
VOF	x	x	–	+		0.814	0.186
VOW	√	x	+	+		0.531	0.469
√	30	5	+ 6	16	Mean	0.621	0.379
x	20	45	– 44	34			

Notes: The bivariate Vector Error Correction Model (3.5a) and (3.5b) is run for each 50 pairs of cointegrated stock and futures prices

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

A "√" indicates that the lagged cross-coefficients (β_{Si} or α_{Fi}) in equations are jointly significant at the 5% level (i.e., Recjection of H_{01} or H_{02}).
A "+" indicates that the error-correction coefficient (γ_S or γ_{Fi}) in equations is significant at the 5% level (i.e., Recjection of H_{03} or H_{04}).
The (θ_S) and (θ_F) is the price discovery contributions (i.e., weight in the common long memory factor) of stock and futures, respectively.
The calculations of the price discovery contributions [(θ_S) and (θ_F)] are based on the formula (3.8) in the text.

Table 3.13: Summary Results of VECM_Period 2

Code	Lead-lag Relationship		Error Correction		Common Factor Weights	
	Stock Leads	Futures Leads	Stock Adjusts	Futures Adjusts	Stock (θ_S)	Futures ($\theta_F = 1-\theta_S$)
AA	√	x	+	−	0.036	0.964
AGN	√	x	+	+	0.674	0.326
AHL	√	√	−	−	0.717	0.283
ALV	√	x	−	−	0.244	0.756
AXA	√	x	−	−	0.497	0.503
AZN	x	x	−	−	0.731	0.269
BAR	√	x	−	−	0.811	0.189
BNP	x	x	−	−	0.933	0.067
BPA	√	x	−	−	0.009	0.991
BTL	√	x	−	−	0.784	0.216
BVA	√	x	−	−	0.459	0.541
CA	x	x	−	−	0.425	0.575
CGE	x	x	−	−	0.822	0.178
CSG	√	x	−	−	0.457	0.543
DBK	√	x	−	+	0.001	0.999
DCY	√	x	−	−	0.001	0.999
DTE	x	x	−	−	0.590	0.410
ENI	√	x	−	+	0.001	0.999
ENL	x	x	−	−	0.001	0.999
EOA	x	√	−	−	0.635	0.365
ERC	√	x	−	−	0.827	0.173
FTE	√	x	−	−	0.834	0.166
GEN	√	x	−	−	0.459	0.541
GXW	x	x	−	−	0.595	0.405
HAS	√	x	−	+	0.931	0.069
HNM	√	x	−	−	0.317	0.683
ING	√	x	−	+	0.996	0.004
LLO	x	x	−	−	0.001	0.999
MUV	√	x	−	−	0.172	0.828
NDA	√	√	−	−	0.440	0.560
NES	√	x	−	−	0.713	0.287
NOV	√	x	+	−	0.208	0.792
PHI	√	x	−	+	0.894	0.106
RBO	x	x	−	−	0.745	0.255
RD	√	x	−	−	0.972	0.028
ROG	√	x	−	−	0.686	0.314
SCH	√	x	−	−	0.556	0.444
SHB	√	x	−	−	0.839	0.161
SHE	√	x	−	−	0.548	0.452
SIE	√	√	−	−	0.669	0.331
TEF	x	√	−	−	0.626	0.374
TI	x	x	+	+	0.960	0.040
TIM	√	x	+	−	0.001	0.999
TLI	√	x	−	−	0.172	0.828
TOT	x	√	−	−	0.896	0.104
UBS	√	x	−	−	0.112	0.888
UC	√	x	+	−	0.382	0.618
VIV	x	x	−	+	0.808	0.192
VOF	√	x	−	−	0.001	0.999
VOW	√	x	−	−	0.574	0.426
√	36	6	+ 6	8	Mean 0.515	0.485
x	14	44	− 44	42		

Notes: The bivariate Vector Error Correction Model (3.5a) and (3.5b) is run for each 50 pairs of cointegrated stock and futures prices

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SF,t-1} + \varepsilon_{F,t}$$

A "√" indicates that the lagged cross-coefficients (β_{Si} or α_{Fi}) in equations are jointly significant at the 5% level (i.e., Recjection of H_{01} or H_{02}).
A "+" indicates that the error-correction coefficient (γ_S or γ_F) in equations is significant at the 5% level (i.e., Recjection of H_{03} or H_{04}).
The (θ_S) and (θ_F) is the price discovery contributions (i.e., weight in the common long memory factor) of stock and futures, respectively.
The calculations of the price discovery contributions [(θ_S) and (θ_F)] are based on the formula (3.8) in the text.

Table 3.14. Descriptive Statistics of USF Share in Price Discovery_Period 1 & 2 and Z-test

	Mean	*Z-test*	Std Deviation	25th percentile	Median	75th percentile
A: Introduction Period						
France (7)	0.2918		0.3362	0.0748	0.2163	0.3285
Germany (8)	0.3115		0.1518	0.2867	0.3757	0.3826
Italy (6)	0.5020		0.3669	0.2334	0.5582	0.7043
Netherlands (6)	0.2593		0.2022	0.1449	0.2067	0.3986
Spain (3)	0.4331		0.2357	0.3162	0.4368	0.5519
Sweden (5)	0.2751		0.2059	0.1066	0.4153	0.4252
Switzerland (5)	0.3596		0.2904	0.1572	0.3260	0.4951
UK (10)	0.5366		0.3478	0.2263	0.5800	0.8018
Whole Sample (50)	**0.3788**		**0.2858**	**0.1638**	**0.3568**	**0.5283**
B: Maturity Period						
France (7)	0.2551	⇓ <0.2482>	0.2000	0.1349	0.1780	0.3477
Germany (8)	0.6392	↑ <-2.8600> ***	0.2870	0.3985	0.5912	0.8705
Italy (6)	0.6993	↑ <-0.9103>	0.3837	0.5602	0.8085	0.9990
Netherlands (6)	0.2851	↑ <-0.1538>	0.3577	0.0473	0.1946	0.3151
Spain (3)	0.4531	↑ <-0.1381>	0.0841	0.4089	0.4438	0.4926
Sweden (5)	0.4810	↑ <-1.2607>	0.3017	0.1734	0.5598	0.6827
Switzerland (5)	0.5649	↑ <-1.1534>	0.2723	0.3143	0.5425	0.7922
UK (10)	0.4844	⇓ <0.3260>	0.3688	0.2253	0.3373	0.8560
Whole Sample (50)	**0.4848**	**↑ <-1.7280> ***	**0.3258**	**0.1980**	**0.4181**	**0.7831**

Note This table presents the cross-sectional descriptive statistics of the USF share in price discoevry estimated on the basis of VECM adjusment coefficients in equations (3.5a) and (3.5b) and as given by formular (3.8). The sample consist of a total of 50 USFs including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Non-parametric Wilcoxon signed rank test (Z-test) is used to examine whether the mean value of (θ_F) in the introduction period is significantly lower.

< > Wilcoxon Z-test statistics

*, **, *** Significant at 10%, 5% and 1% level, respectively.

↑ = significant hiher share in price discovery ; ⇓ = significant lower share in price discovery

Table 3.15: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period_Unrestricted

Code	Dep Var	α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test ($H_{01}: \beta_{S,i}=0$)			
		α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test ($H_{02}: \alpha_{F,i}=0$)	β_0	β_2	β_1
AA	R_S	-0.0837	-0.0584	0.0871	0.1579 **	0.0288	-0.0053	-0.1347 *	-0.1619 **	1.1074 **	-0.1063 **	11.5501 *	1	-0.9975 **	-0.0102
		(-1.370)	(-0.892)	(1.365)	(2.887)	(0.467)	(-0.081)	(-2.118)	(-2.991)	(50.696)	(-2.643)			(-83.407)	(-0.296)
	R_F	0.4230 **	0.1484 *	0.2226 **	0.1954 **	-0.4400 **	-0.1820 **	-0.2502 **	-0.2072 **	1.0610 **	0.0323	57.5490 **			
		(6.631)	(2.171)	(3.340)	(3.420)	(-6.826)	(-2.669)	(-3.766)	(-3.665)	(46.509)	(0.768)				
AGN	R_S	0.0050	-0.0216	-0.0081	0.0055	-0.0003	-0.0019	-0.0026	-0.0043	1.5151 **	-0.0017	0.3081	1	-0.9610 **	-0.0838 **
		(0.216)	(-0.981)	(-0.395)	(0.299)	(-0.022)	(-0.136)	(-0.215)	(-0.494)	(52.984)	(-0.095)			(-201.177)	(-6.564)
	R_F	0.1441	0.1067	0.1154	0.0038	-0.1722 **	-0.1322 *	-0.0870	-0.0454	1.4335 **	0.8151 **	4.3281			
		(1.656)	(1.303)	(1.514)	(0.056)	(-2.871)	(-2.480)	(-1.952)	(-1.408)	(13.473)	(12.001)				
AHL	R_S	-0.1632	-0.2432 *	-0.3354 **	-0.0989	0.1959 *	0.3176 **	0.2492 *	0.1272	1.2043 **	0.0102	12.7367 *	1	-0.9365 **	-0.0725
		(-1.616)	(-2.276)	(-3.145)	(-0.984)	(1.988)	(3.054)	(2.393)	(1.305)	(18.592)	(0.586)			(-20.995)	(-0.656)
	R_F	0.2226 *	-0.1345	-0.2688 *	-0.0787	-0.1571	0.2075	0.1933	0.1189	1.0874 **	0.0210	12.7738 *			
		(2.083)	(-1.189)	(-2.381)	(-0.739)	(-1.506)	(1.886)	(1.754)	(1.153)	(15.863)	(1.135)				
ALV	R_S	-0.0504	-0.1874 **	-0.0769	-0.0522	0.1062 *	0.1735 **	0.0678	0.0074	1.2815 **	0.0189	13.4673 **	1	-0.9147 **	-0.3756 **
		(-1.294)	(-3.793)	(-1.551)	(-1.292)	(2.497)	(3.420)	(1.356)	(0.192)	(49.867)	(1.890)			(-45.709)	(-3.880)
	R_F	0.6938 **	0.2740 **	0.1042 *	-0.0280	-0.5897 **	-0.2539 **	-0.1183 *	-0.0285	1.0434 **	0.0415 **	316.0065 **			
		1(6.713)	(5.204)	(1.974)	(-0.651)	1(-3.009)	(-4.698)	(-2.220)	(-0.691)	(38.099)	(3.903)				
AXA	R_S	0.1037 **	-0.0358	-0.0263	-0.0368	-0.0013	-0.0073	-0.0012	0.0124	1.2822 **	-0.0009	1.1307	1	-1.0128 **	0.0450
		(4.292)	(-1.480)	(-1.089)	(-1.523)	(-0.097)	(-0.532)	(-0.087)	(0.905)	(35.106)	(-0.312)			(-13.707)	(0.204)
	R_F	0.1763 **	-0.0027	0.0108	-0.0872	-0.0303	-0.0212	-0.0003	0.0150	1.2250 **	0.0400 **	13.3537 **			
		(3.212)	(-0.049)	(0.197)	(-1.587)	(-0.970)	(-0.680)	(-0.011)	(0.480)	(14.770)	(6.276)				
AZN	R_S	-0.0956	-0.0336	-0.0008	-0.1279	0.1590	-0.0597	-0.0012	0.1130	0.8312 **	0.0197	7.3292	1	-0.9984 **	-0.0107
		(-0.819)	(-0.273)	(-0.006)	(-1.333)	(1.344)	(-0.483)	(-0.010)	(1.186)	(24.023)	(0.221)			(-217.869)	(-0.296)
	R_F	0.4605 **	0.3606 **	0.2219	-0.0356	-0.3886 **	-0.4351 **	-0.2146	0.0339	0.7571 **	0.1818 *	19.2650 **			
		(3.937)	(2.925)	(1.901)	(-0.371)	(-3.278)	(-3.511)	(-1.836)	(0.355)	(21.832)	(2.032)				
BAR	R_S	0.0544 *	-0.0509 *	0.0163	-0.0289	0.0198 *	-0.0022	-0.0151	-0.0025	1.1704 **	-0.0032	6.6049	1	-0.4157 **	-3.6090 **
		(2.509)	(-2.352)	(0.751)	(-1.330)	(2.023)	(-0.222)	(-1.549)	(-0.256)	(36.867)	(-1.952)			(-2.691)	(-3.578)
	R_F	0.1249	-0.0653	-0.1666 *	-0.0432	0.0081	-0.0011	-0.0145	0.0030	1.0969 **	0.0060	11.4739 *			
		(1.861)	(-0.974)	(-2.482)	(-0.643)	(0.269)	(-0.036)	(-0.479)	(0.099)	(11.161)	(1.193)				
BNP	R_S	0.1165 **	-0.0613 *	-0.0083	0.0344	-0.0530 **	0.0069	0.0060	-0.0250	0.9230 **	-0.0021	9.8066 *	1	-0.8843 **	-0.4710
		(4.254)	(-2.227)	(-0.302)	(1.251)	(-2.768)	(0.359)	(0.315)	(-1.313)	(35.724)	(-1.345)			(-2.806)	(-0.371)
	R_F	0.2510 **	-0.0569	0.0111	-0.0145	-0.0882 *	0.0017	0.0175	-0.0185	0.8370 **	0.0037	26.5259 **			
		(4.992)	(-1.125)	(0.220)	(-0.288)	(-2.510)	(0.049)	(0.496)	(-0.529)	(17.643)	(1.275)				
BPA	R_S	0.0290	-0.0176	-0.0796	-0.0126	-0.0592	-0.0365	0.0571	0.0307	0.8443 **	-0.1325	0.8800	1	-0.9914 **	-0.0530 *
		(0.242)	(-0.139)	(-0.653)	(-0.123)	(-0.492)	(-0.287)	(0.466)	(0.297)	(29.591)	(-1.521)			(-274.195)	(-2.350)
	R_F	0.4875 **	0.2213	-0.0164	0.0569	-0.5148 **	-0.2689 *	-0.0039	-0.0248	0.7950 **	0.0399	19.9152 **			
		(4.014)	(1.723)	(-0.133)	(0.544)	(-4.217)	(-2.083)	(-0.031)	(-0.237)	(27.485)	(0.452)				
BTL	R_S	-0.1661 **	-0.0780	0.0612	0.1451 **	0.1852 **	0.0659	-0.1266 *	-0.1250 *	0.9839 **	0.0027	26.1424 **	1	-0.8376 **	-0.8590 **
		(-3.106)	(-1.444)	(1.132)	(2.718)	(3.633)	(1.281)	(-2.457)	(-2.439)	(22.994)	(0.297)			(-17.111)	(-3.238)
	R_F	-0.0342	-0.0348	0.0183	0.1275 *	0.0541	0.0153	-0.1108	-0.0931	0.8848 **	0.0235 *	5.3231			
		(-0.578)	(-0.584)	(0.306)	(2.162)	(0.960)	(0.269)	(-1.946)	(-1.642)	(18.707)	(2.348)				
BVA	R_S	-0.1209	-0.1778 **	-0.0979	-0.0899	0.1419 *	0.1844 **	0.0819	0.0890	1.3212 **	-0.1052	9.3018	1	-0.9986 **	-0.0051
		(-1.846)	(-2.669)	(-1.559)	(-1.760)	(2.109)	(2.720)	(1.281)	(1.733)	(71.336)	(-1.879)			(-298.167)	(-0.626)
	R_F	0.3495 **	0.0968	0.0754	0.0484	-0.3005 **	-0.0921	-0.0695	-0.0527	1.2413 **	0.1267 *	36.5735 **			
		(5.321)	(1.449)	(1.197)	(0.945)	(-4.452)	(-1.355)	(-1.083)	(-1.023)	(66.833)	(2.257)				
CA	R_S	-0.1059	-0.0062	0.0196	-0.1584 *	0.0589	-0.0119	-0.0274	0.1396	0.7981 **	-0.0673	6.5282	1	-0.9953 **	-0.0167
		(-1.170)	(-0.064)	(0.211)	(-2.051)	(0.640)	(-0.124)	(-0.294)	(1.828)	(29.958)	(-1.012)			(-182.155)	(-0.807)
	R_F	0.3991 **	0.2265 *	0.1300	-0.0745	-0.4116 **	-0.2574 **	-0.1128	0.0556	0.7386 **	0.1031	24.2103 **			
		(4.402)	(2.354)	(1.397)	(-0.962)	(-4.464)	(-2.666)	(-1.208)	(0.726)	(27.668)	(1.547)				
CGE	R_S	-0.1080	0.0452	0.0513	0.2060 **	0.1151	-0.0054	-0.0348	-0.1773 **	1.4453 **	0.1120	16.3913 **	1	-1.0040 **	0.0122 **
		(-0.905)	(0.428)	(0.578)	(3.098)	(0.994)	(-0.053)	(-0.410)	(-2.824)	(25.488)	(0.895)			(-1053.350)	(5.162)
	R_F	0.0275	0.1407	0.1493	0.2366 **	-0.0107	-0.1228	-0.1378	-0.2079 **	1.3348 **	0.8914 **	13.7334 **			
		(0.211)	(1.220)	(1.539)	(3.253)	(-0.085)	(-1.103)	(-1.486)	(-3.028)	(21.520)	(6.513)				
CSG	R_S	-0.1540 *	0.0628	0.1008	0.0926	0.1764 *	0.0051	-0.0939	-0.1180	1.5000 **	0.0008	10.5293 *	1	-0.9480 **	-0.1876
		(-2.027)	(0.714)	(1.143)	(1.221)	(2.336)	(0.059)	(-1.078)	(-1.582)	(39.273)	(0.045)			(-25.598)	(-1.331)
	R_F	0.4555 **	0.3975 **	0.2540 **	0.1002	-0.4287 **	-0.3284 **	-0.2450 **	-0.1345	1.5015 **	0.0212	38.8046 **			
		(5.983)	(4.507)	(2.876)	(1.318)	(-5.664)	(-3.755)	(-2.808)	(-1.798)	(39.233)	(1.219)				
DBK	R_S	-0.0507	-0.0559	-0.0363	-0.0734	0.0439	0.0373	0.0422	0.0514	1.1150 **	-0.0628	1.7130	1	-0.9975 **	-0.0111
		(-0.890)	(-0.924)	(-0.634)	(-1.657)	(0.754)	(0.621)	(0.755)	(1.225)	(54.153)	(-1.330)			(-206.635)	(-0.551)
	R_F	0.5738 **	0.3825 **	0.1838 **	-0.0354	-0.5102 **	-0.3789 **	-0.1593 **	0.0144	0.9527 **	0.1588 **	100.2525 **			
		(9.188)	(5.766)	(2.928)	(-0.729)	(-7.990)	(-5.741)	(-2.598)	(0.312)	(42.170)	(3.067)				
DCY	R_S	-0.0596	-0.0274	0.0543	-0.0066	0.0602	0.0032	-0.0180	0.0366	1.0300 **	-0.0608	3.7561	1	-0.9865 **	-0.0508
		(-1.206)	(-0.507)	(1.035)	(-0.149)	(1.182)	(0.060)	(-0.346)	(0.849)	(45.248)	(-1.874)			(-92.231)	(-1.308)
	R_F	0.4901 **	0.3159 **	0.1994 **	0.0713	-0.4241 **	-0.3235 **	-0.1569 **	-0.0325	0.8892 **	0.0613	85.1943 **			
		(9.220)	(5.440)	(3.532)	(1.505)	(-7.740)	(-5.555)	(-2.799)	(-0.702)	(36.328)	(1.756)				
DTE	R_S	-0.0695	-0.0946	-0.1122	-0.0883	0.0451	0.0625	0.0496	0.0970 *	1.1002 **	-0.1128	4.5371	1	-1.0013 **	0.0041
		(-0.983)	(-1.341)	(-1.731)	(-1.770)	(0.627)	(0.887)	(0.776)	(2.026)	(37.141)	(-1.735)			(-289.175)	(0.433)
	R_F	0.4659 **	0.2522 **	0.1281	-0.0084	-0.4130 **	-0.2526 **	-0.1767 **	0.0282	0.9258 **	0.2136 **	52.3653 **			
		(6.522)	(3.540)	(1.956)	(-0.166)	(-5.678)	(-3.548)	(-2.734)	(0.584)	(30.927)	(3.250)				
ENI	R_S	-0.0461	-0.0457	-0.0098	-0.0116	0.0242	0.0126	-0.0040	0.0086	0.8067 **	0.0029	3.2670	1	-1.0429 **	0.1719
		(-1.868)	(-1.852)	(-0.396)	(-0.470)	(1.517)	(0.792)	(-0.251)	(0.542)	(29.956)	(1.762)			(-5.851)	(0.352)
	R_F	0.0215	-0.0101	-0.0210	-0.0457	0.0025	-0.0027	0.0040	0.0131	0.7477 **	0.0130 **	1.4386			
		(0.467)	(-0.221)	(-0.457)	(-0.995)	(0.085)	(-0.091)	(0.136)	(0.441)	(14.924)	(4.315)				
ENL	R_S	-0.0632 *	-0.0044	0.0044	-0.0291	-0.0204	-0.0037	0.0001	0.0221	0.7527 **	0.0003	4.0679	1	-1.2112 **	0.4392
		(-2.491)	(-0.173)	(0.173)	(-1.158)	(-1.354)	(-0.247)	(0.006)	(1.463)	(29.354)	(0.163)			(-4.478)	(0.901)
	R_F	-0.0033	0.0171	0.0061	-0.0052	-0.0518	0.0151	-0.0125	0.0180	0.6351 **	0.0132 **	0.1353			
		(-0.062)	(0.327)	(0.116)	(-0.100)	(-1.656)	(0.481)	(-0.400)	(0.575)	(11.955)	(3.725)				

Table 3.15: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period_Unrestricted (continued)

Code	Dep Var	α_{S1} / α_{F1}	α_{S2} / α_{F2}	α_{S3} / α_{F3}	α_{S4} / α_{F4}	β_{S1} / β_{F1}	β_{S2} / β_{F2}	β_{S3} / β_{F3}	β_{S4} / β_{F4}	δ_S / δ_F	γ_S / γ_F	Wald test (H_{01}: $\beta_{F,i}=0$) / Wald test (H_{02}: $\alpha_{F,i}=0$)	β_0	β_2	β_1
EOA	R_S	-0.1617 **	-0.0567	-0.0271	0.0890	0.0632	0.0475	0.0171	-0.0884	0.6818 **	-0.0718	6.5001	1	-0.9952 **	-0.0196
		(-2.844)	(-0.959)	(-0.481)	(1.857)	(1.083)	(0.795)	(0.298)	(-1.841)	(30.510)	(-1.660)			(-180.784)	(-0.884)
	R_F	0.2876 **	0.1714 **	0.0786	0.1060 *	-0.3296 **	-0.1847 **	-0.0667	-0.1055 *	0.5236 **	0.1358 **	26.6468 **			
		(4.869)	(2.790)	(1.340)	(2.129)	(-5.440)	(-2.978)	(-1.120)	(-2.115)	(22.558)	(3.023)				
ERC	R_S	0.0445	0.0975	-0.2522 **	-0.2413 **	-0.0083	-0.1467 *	0.1890 **	0.2222 **	1.8163 **	0.0206 **	25.1186 **	1	-0.9436 **	-0.1320
		(0.672)	(1.423)	(-3.679)	(-3.636)	(-0.132)	(-2.215)	(2.853)	(3.490)	(29.068)	(2.665)			(-19.992)	(-0.962)
	R_F	0.3373 **	0.1172	-0.2204 **	-0.2641 **	-0.3167 **	-0.1592 *	0.1728 *	0.2605 **	1.8046 **	0.0305 **	44.3131 **			
		(4.737)	(1.591)	(-2.992)	(-3.702)	(-4.651)	(-2.237)	(2.427)	(3.805)	(26.867)	(3.683)				
FTE	R_S	0.0163	-0.1427	0.1123	0.0613	0.0737	0.1187	-0.0747	-0.0472	1.2141 **	-0.0152 **	3.4599	1	-0.6212 **	-1.1070 **
		(0.178)	(-1.483)	(1.170)	(0.671)	(0.796)	(1.224)	(-0.772)	(-0.514)	(25.083)	(-3.344)			(-5.581)	(-3.065)
	R_F	0.3706 **	0.0430	0.2459 *	0.1101	-0.2705 **	-0.0544	-0.1987 *	-0.0851	1.1468 **	-0.0142 **	22.6271 **			
		(4.035)	(0.445)	(2.546)	(1.198)	(-2.904)	(-0.558)	(-2.042)	(-0.922)	(23.563)	(-3.111)				
GEN	R_S	0.0097	-0.0295	-0.0650	0.0771	0.0656	0.0076	0.0320	-0.0643	1.0189 **	-0.1727 *	2.9105	1	-0.9985 **	-0.0034
		(0.106)	(-0.326)	(-0.771)	(1.119)	(0.713)	(0.083)	(0.379)	(-0.942)	(40.968)	(-2.095)			(-482.869)	(-0.523)
	R_F	0.4153 **	0.1876 *	0.0591	0.1391 *	-0.3265 **	-0.2049 *	-0.0700	-0.1339 *	0.9681 **	0.1510	27.7089 **			
		(4.610)	(2.098)	(0.709)	(2.044)	(-3.592)	(-2.274)	(-0.839)	(-1.986)	(39.392)	(1.854)				
GXW	R_S	-0.1902	-0.1558	0.1533	0.0441	0.1815	0.0648	-0.1784	-0.0536	0.8192 **	-0.1419	8.5414	1	-0.9952 **	-0.0337
		(-1.551)	(-1.225)	(1.276)	(0.441)	(1.470)	(0.507)	(-1.474)	(-0.533)	(28.056)	(-1.470)			(-358.782)	(-1.683)
	R_F	0.3097 *	0.1796	0.3289 **	0.1003	-0.3220 *	-0.2668 *	-0.3558 **	-0.0978	0.7651 **	0.0554	11.6487 *			
		(2.485)	(1.389)	(2.693)	(0.988)	(-2.564)	(-2.054)	(-2.892)	(-0.956)	(25.773)	(0.565)				
HAS	R_S	-0.1258	-0.0328	0.0258	0.0739	0.1319	0.0075	0.0054	-0.0190	0.8309 **	-0.0802 *	4.2620	1	-0.9726 **	-0.1841 *
		(-1.801)	(-0.440)	(0.352)	(1.128)	(1.865)	(0.100)	(0.073)	(-0.287)	(36.011)	(-2.144)			(-74.982)	(-2.117)
	R_F	0.2834 **	0.1233	0.0506	0.1114	-0.2611 **	-0.1450	-0.0108	-0.0323	0.7980 **	0.0138	19.8113 **			
		(4.110)	(1.677)	(0.701)	(1.722)	(-3.738)	(-1.959)	(-0.148)	(-0.494)	(35.032)	(0.374)				
HNM	R_S	-0.0322	0.0080	0.0614	0.0266	-0.0706	-0.0628	-0.0874	-0.0625	0.6482 **	-0.1229	1.3019	1	-1.0058 **	0.0321
		(-0.341)	(0.084)	(0.702)	(0.374)	(-0.753)	(-0.673)	(-1.014)	(-0.918)	(20.207)	(-1.451)			(-235.358)	(1.414)
	R_F	0.4452 **	0.2829 **	0.2365 **	0.1198	-0.5365 **	-0.3491 **	-0.2575 **	-0.1297	0.6253 **	0.1924 *	21.6206 **			
		(4.570)	(2.906)	(2.624)	(1.636)	(-5.548)	(-3.626)	(-2.900)	(-1.848)	(18.913)	(2.203)				
ING	R_S	0.0104	0.0084	-0.0523 *	0.0117	0.0063	-0.0071	-0.0098	-0.0025	1.4110 **	-0.0016	0.6123	1	-0.9590 **	-0.1288
		(0.485)	(0.394)	(-2.453)	(0.547)	(0.359)	(-0.407)	(-0.557)	(-0.144)	(65.495)	(-0.813)			(-7.822)	(-0.330)
	R_F	0.0762	-0.0042	-0.0398	0.0283	-0.0402	-0.0070	-0.0065	-0.0100	1.3630 **	0.0094 **	5.2425			
		(1.949)	(-0.107)	(-1.018)	(0.724)	(-1.253)	(-0.219)	(-0.201)	(-0.313)	(34.580)	(2.632)				
LLO	R_S	0.0485	-0.0461	0.0820	0.0585	-0.0149	0.0140	-0.0923	-0.0612	1.1036 **	-0.0542 *	3.3261	1	-0.9933 **	-0.0465
		(0.822)	(-0.736)	(1.319)	(1.017)	(-0.247)	(0.221)	(-1.468)	(-1.062)	(35.748)	(-2.157)			(-73.984)	(-0.555)
	R_F	0.4056 **	0.0190	0.0736	0.0740	-0.3472 **	-0.0786	-0.0715	-0.0956	1.0132 **	0.0069	52.1238 **			
		(6.608)	(0.292)	(1.139)	(1.237)	(-5.545)	(-1.194)	(-1.094)	(-1.597)	(31.582)	(0.266)				
MUV	R_S	0.0159	-0.1556 *	-0.1258 *	-0.0868	0.0672	0.1620 **	0.1040	0.0704	1.2187 **	0.0033	7.2373	1	-0.9723 **	-0.1101
		(0.313)	(-2.473)	(-2.015)	(-1.739)	(1.276)	(2.592)	(1.706)	(1.506)	(44.590)	(0.137)			(-80.931)	(-1.873)
	R_F	0.8221 **	0.4103 **	0.1423 *	0.0554	-0.6873 **	-0.3782 **	-0.1887 **	-0.0654	1.0285 **	0.0454	237.5078 **			
		1(4.619)	(5.883)	(2.058)	(1.002)	1(-1.779)	(-5.458)	(-2.794)	(-1.261)	(33.960)	(1.723)				
NDA	R_S	-0.2179 **	-0.1314	-0.1559	-0.0179	0.1305	0.0948	0.1206	-0.0301	0.8732 **	-0.0284	5.0748	1	-1.0023 **	0.0094
		(-2.715)	(-1.555)	(-1.884)	(-0.242)	(1.600)	(1.108)	(1.440)	(-0.401)	(25.805)	(-0.606)			(-130.679)	(0.307)
	R_F	0.1780 *	0.0302	-0.1101	-0.0247	-0.2488 **	-0.0649	0.0563	-0.0232	0.8475 **	0.0863	9.5957 *			
		(2.259)	(0.363)	(-1.355)	(-0.341)	(-3.107)	(-0.773)	(0.685)	(-0.315)	(25.512)	(1.874)				
NES	R_S	-0.1735 **	-0.1517 *	-0.1471 *	-0.1386 *	0.1380 *	0.0889	0.0973	0.1302 *	0.7127 **	-0.0032	8.3963	1	-0.9910 **	-0.0536
		(-2.577)	(-2.146)	(-2.170)	(-2.449)	(2.064)	(1.263)	(1.454)	(2.374)	(32.473)	(-0.062)			(-125.779)	(-1.179)
	R_F	0.3490 **	0.1511 *	0.0198	-0.0701	-0.3881 **	-0.1914 **	-0.0560	0.0591	0.6480 **	0.1853 **	31.6038 **			
		(4.942)	(2.038)	(0.278)	(-1.182)	(-5.533)	(-2.592)	(-0.798)	(1.028)	(28.142)	(3.456)				
NOV	R_S	0.0000	0.0306	0.0280	0.1169	0.0037	-0.0556	-0.0941	-0.0848	0.7637 **	-0.1010	2.6572	1	-0.9925 **	-0.0314
		(-0.000)	(0.366)	(0.355)	(1.817)	(0.046)	(-0.666)	(-1.207)	(-1.361)	(35.853)	(-1.466)			(-159.264)	(-1.242)
	R_F	0.5017 **	0.3463 **	0.1908 *	0.1667 **	-0.4900 **	-0.3630 **	-0.2358 **	-0.1191	0.7444 **	0.1533 *	40.8889 **			
		(6.228)	(4.186)	(2.447)	(2.619)	(-6.082)	(-4.393)	(-3.058)	(-1.932)	(35.304)	(2.249)				
PHI	R_S	-0.0476	0.0926	0.1139	0.0875	0.0224	-0.1274	-0.0999	-0.0907	1.4321 **	-0.0197	3.5561	1	-0.9971 **	-0.0080
		(-0.403)	(0.779)	(1.037)	(1.016)	(0.189)	(-1.070)	(-0.910)	(-1.060)	(48.458)	(-0.185)			(-412.019)	(-1.058)
	R_F	0.4317 **	0.3605 **	0.2405 *	0.1175	-0.4540 **	-0.3882 **	-0.2171	-0.1178	1.3609 **	0.2957 **	12.8189 *			
		(3.540)	(2.939)	(2.123)	(1.322)	(-3.721)	(-3.159)	(-1.917)	(-1.334)	(44.617)	(2.692)				
RBO	R_S	-0.1786 *	-0.0727	0.0253	0.1286	0.1884 *	0.0610	-0.0566	-0.1502 *	1.1202 **	-0.0653	13.2850 **	1	-1.0028 **	0.0205
		(-2.319)	(-0.873)	(0.315)	(1.931)	(2.413)	(0.728)	(-0.695)	(-2.214)	(37.719)	(-1.313)			(-57.371)	(0.159)
	R_F	0.3568 **	0.1981 *	0.1569 *	0.1964 **	-0.3243 **	-0.2328 **	-0.1836 *	-0.2041 **	1.0732 **	0.0538	27.5121 **			
		(4.658)	(2.389)	(1.963)	(2.966)	(-4.176)	(-2.791)	(-2.269)	(-3.025)	(36.329)	(1.087)				
RD	R_S	-0.0426	-0.0427	0.0301	0.0261	0.0201	0.0018	-0.0138	0.0009	0.7062 **	-0.0002	2.2182	1	0.7092	-5.4846
		(-1.682)	(-1.684)	(1.186)	(1.030)	(1.218)	(0.107)	(-0.839)	(0.053)	(36.361)	(-0.305)			(0.426)	(-0.865)
	R_F	0.0453	-0.0190	0.0782	0.0106	0.0226	-0.0072	-0.0216	0.0069	0.6653 **	-0.0015	3.4071			
		(0.903)	(-0.378)	(1.555)	(0.211)	(0.691)	(-0.219)	(-0.661)	(0.211)	(17.291)	(-1.168)				
ROG	R_S	-0.0866	-0.2026 *	0.0127	-0.0677	0.1147	0.1636	0.0441	0.0986	0.8964 **	-0.1422	4.7426	1	-0.9966 **	-0.0172
		(-0.885)	(-2.024)	(0.136)	(-0.872)	(1.174)	(1.645)	(0.476)	(1.305)	(34.390)	(-1.758)			(-313.063)	(-1.123)
	R_F	0.4569 **	0.2323 *	0.2855 **	0.0807	-0.4258 **	-0.2746 **	-0.2297 *	-0.0480	0.8713 **	0.0681	25.3128 **			
		(4.576)	(2.274)	(2.991)	(1.019)	(-4.270)	(-2.705)	(-2.427)	(-0.622)	(32.758)	(0.825)				
SCH	R_S	-0.1408 *	-0.1503 *	-0.0786	-0.0418	0.1532 *	0.1220	0.0759	0.0536	1.3569 **	-0.1724 **	5.3939	1	-0.9937 **	-0.0145 *
		(-2.087)	(-2.192)	(-1.228)	(-0.804)	(2.245)	(1.771)	(1.185)	(1.028)	(72.589)	(-2.981)			(-347.809)	(-2.351)
	R_F	0.2875 **	0.1334	0.0257	0.0161	-0.2528 **	-0.1551 *	-0.0271	-0.0083	1.2875 **	0.0959	21.7121 **			
		(4.270)	(1.949)	(0.403)	(0.309)	(-3.712)	(-2.255)	(-0.424)	(-0.160)	(68.996)	(1.661)				
SHB	R_S	-0.0745	-0.2640 **	-0.1211	0.0638	0.0304	0.2101 **	0.0910	-0.0791	0.6396 **	-0.0032	11.0073 *	1	-1.0037 **	0.0189
		(-0.982)	(-3.347)	(-1.569)	(0.909)	(0.395)	(2.627)	(1.163)	(-1.124)	(25.938)	(-0.072)			(-101.454)	(0.383)
	R_F	0.2606 **	-0.1299	-0.1260	0.0268	-0.3081 **	0.0896	0.0754	-0.0453	0.6133 **	0.1200 **	28.9717 **			
		(3.479)	(-1.669)	(-1.654)	(0.387)	(-4.060)	(1.134)	(0.976)	(-0.652)	(25.196)	(2.755)				

Table 3.15: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period_Unrestricted (continued)

		α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_{01}: $\beta_{Si}=0$)			
Code	Dep Var	α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_{02}: $\alpha_{Fi}=0$)	β_0	β_2	β_1
SHE	R_S	0.2568	0.2350	0.2263	0.0390	-0.2422 *	-0.2219	-0.2094	-0.0268	0.9239 **	0.0089	6.7921	1	-0.8695 **	-0.9301 **
		(1.944)	(1.680)	(1.619)	(0.296)	(-2.068)	(-1.792)	(-1.696)	(-0.231)	(11.957)	(0.316)			(-22.370)	(-3.837)
	R_F	0.6867 **	0.4805 **	0.3656 *	0.1153	-0.6216 **	-0.4408 **	-0.3303 *	-0.0832	0.8715 **	0.0234	23.9991 **			
		(4.528)	(2.991)	(2.279)	(0.762)	(-4.626)	(-3.102)	(-2.331)	(-0.625)	(09.827)	(0.726)				
SIE	R_S	-0.0262	0.0243	-0.0132	-0.0525	0.0157	-0.0440	-0.0041	0.0302	1.1844 **	0.0057	5.5091	1	-1.1028 **	0.4156
		(-0.982)	(0.861)	(-0.466)	(-1.924)	(0.608)	(-1.664)	(-0.154)	(1.217)	(52.456)	(1.584)			(-12.559)	(1.158)
	R_F	0.3370 **	0.0978 *	0.0079	-0.0578	-0.2067 **	-0.1023 **	-0.0180	0.0270	0.9840 **	0.0223 **	89.7704 **			
		(9.251)	(2.537)	(0.203)	(-1.554)	(-5.868)	(-2.835)	(-0.499)	(0.798)	(31.967)	(4.572)				
TEF	R_S	-0.1136 *	-0.1740 **	-0.0862	-0.0404	0.1452 **	0.1466 **	0.1076 *	0.0078	1.2241 **	-0.0060 **	12.9589 *	1	-0.2537	-1.7357 **
		(-2.367)	(-3.214)	(-1.592)	(-0.833)	(2.987)	(2.732)	(2.015)	(0.165)	(64.394)	(-3.615)			(-1.230)	(-3.357)
	R_F	0.4407 **	0.1162 *	0.1558 **	0.0690	-0.3709 **	-0.1314 *	-0.1256 *	-0.1028 *	1.1941 **	-0.0065 **	91.2361 **			
		(8.992)	(2.102)	(2.818)	(1.392)	(-7.467)	(-2.396)	(-2.302)	(-2.128)	(61.496)	(-3.800)				
TI	R_S	-0.0006	-0.0108	0.0233	0.0490 *	-0.0085	-0.0023	0.0084	0.0064	1.1387 **	-0.0063 **	1.2004	1	-0.1089	-0.7426 **
		(-0.027)	(-0.490)	(1.062)	(2.218)	(-0.679)	(-0.182)	(0.668)	(0.512)	(32.291)	(-2.875)			(-0.961)	(-3.893)
	R_F	0.0136	-0.0255	0.0076	0.0814	-0.0181	-0.0096	0.0104	0.0193	0.9014 **	-0.0017	3.0041			
		(0.270)	(-0.508)	(0.151)	(1.612)	(-0.632)	(-0.337)	(0.362)	(0.673)	(11.193)	(-0.333)				
TIM	R_S	-0.0845	-0.1127 *	0.0337	0.0709	0.0346	0.0848	-0.0397	-0.0564	1.0679 **	-0.0810 **	7.2297	1	-0.8890 **	-0.1576 **
		(-1.880)	(-2.352)	(0.708)	(1.602)	(0.770)	(1.766)	(-0.830)	(-1.288)	(40.119)	(-5.022)			(-38.259)	(-4.270)
	R_F	0.3168 **	0.0535	0.1005	0.0548	-0.3698 **	-0.0795	-0.0821	-0.0345	0.9921 **	-0.0362 *	46.2237 **			
		(6.468)	(1.025)	(1.939)	(1.135)	(-7.546)	(-1.517)	(-1.574)	(-0.722)	(34.180)	(-2.060)				
TLI	R_S	-0.1734	-0.3639 **	-0.1312	-0.1887	0.1304	0.2516 *	0.0828	0.1643	0.9695 **	0.1317 *	5.0648	1	-1.0353 **	0.1421 **
		(-1.427)	(-2.884)	(-1.065)	(-1.676)	(1.056)	(1.971)	(0.663)	(1.447)	(23.485)	(2.021)			(-86.923)	(3.365)
	R_F	0.2404 *	-0.0531	0.0748	-0.0838	-0.2744 *	-0.0663	-0.1234	0.0596	0.9401 **	0.2052 **	8.1145			
		(2.006)	(-0.427)	(0.616)	(-0.755)	(-2.253)	(-0.527)	(-1.003)	(0.532)	(23.097)	(3.194)				
TOT	R_S	-0.2081 *	0.0393	0.1596	0.1466 *	0.2090 *	-0.1451	-0.1771 *	-0.1452	0.6441 **	0.0062	20.4904 **	1	-0.9965 **	-0.0175
		(-2.574)	(0.456)	(1.888)	(1.960)	(2.527)	(-1.668)	(-2.072)	(-1.925)	(28.284)	(0.143)			(-103.086)	(-0.357)
	R_F	0.2177 **	0.2080 *	0.2087 *	0.1684 *	-0.1931 *	-0.2964 **	-0.2024 *	-0.1692 *	0.5819 **	0.0951 *	20.4904 **			
		(2.694)	(2.419)	(2.471)	(2.254)	(-2.336)	(-3.410)	(-2.371)	(-2.244)	(25.574)	(2.208)				
UBS	R_S	-0.0035	-0.0120	0.0473	-0.0217	0.0676	-0.0354	-0.0592	0.0346	1.1136 **	-0.0291	4.4780	1	-0.9881 **	-0.0518
		(-0.060)	(-0.192)	(0.759)	(-0.377)	(1.181)	(-0.581)	(-0.977)	(0.622)	(48.402)	(-1.367)			(-48.443)	(-0.573)
	R_F	0.4119 **	0.1423 *	0.1662 *	0.0418	-0.3347 **	-0.1901 **	-0.1680 **	-0.0341	1.1271 **	0.0144	48.9009 **			
		(6.710)	(2.172)	(2.549)	(0.695)	(-5.593)	(-2.982)	(-2.650)	(-0.587)	(46.844)	(0.647)				
UC	R_S	-0.0564	-0.0995	-0.0446	0.0116	0.0849	0.0457	0.0270	-0.0028	0.9480 **	-0.1114 **	2.4546	1	-1.0030 **	0.0040
		(-1.031)	(-1.770)	(-0.811)	(0.235)	(1.522)	(0.795)	(0.481)	(-0.055)	(34.565)	(-3.098)			(-85.439)	(0.236)
	R_F	0.2773 **	0.0137	-0.0113	-0.0089	-0.2565 **	-0.0492	-0.0014	0.0203	0.9068 **	0.0499	33.6407 **			
		(5.102)	(0.245)	(-0.206)	(-0.181)	(-4.624)	(-0.861)	(-0.026)	(0.404)	(33.252)	(1.395)				
VIV	R_S	0.1068	-0.1130	0.2898 *	0.2199 *	0.0224	0.0152	-0.3241 *	-0.3245 **	1.1857 **	-0.3607 *	14.7771 **	1	-0.9997 **	0.0010
		(0.690)	(-0.747)	(2.101)	(1.999)	(0.144)	(0.100)	(-2.323)	(-2.934)	(22.939)	(-2.488)			(-827.390)	(0.249)
	R_F	0.5181 **	0.1325	0.4344 **	0.2412 *	-0.3952 **	-0.2238	-0.4690 **	-0.3285 **	1.1584 **	0.0080	29.3995 **			
		(3.419)	(0.895)	(3.217)	(2.239)	(-2.585)	(-1.500)	(-3.434)	(-3.033)	(22.889)	(0.056)				
VOF	R_S	-0.0870	-0.1153	0.0166	0.1345	0.0961	0.0785	-0.0881	-0.1254	1.2546 **	-0.1225	4.9734	1	-0.9964 **	-0.0158
		(-0.763)	(-0.981)	(0.151)	(1.517)	(0.836)	(0.664)	(-0.796)	(-1.399)	(32.428)	(-1.277)			(-280.591)	(-0.907)
	R_F	0.4240 **	0.2340	0.2068	0.2611 **	-0.4073 **	-0.2761 *	-0.2817 *	-0.2475 **	1.1540 **	0.0996	19.6225 **			
		(3.643)	(1.949)	(1.845)	(2.884)	(-3.469)	(-2.289)	(-2.493)	(-2.704)	(29.214)	(1.016)				
VOW	R_S	-0.0430	-0.1819 **	-0.1127	-0.0351	0.0934	0.1593 *	0.0971	0.0732	0.9405 **	-0.1426 *	6.7136	1	-0.9996 **	-0.0017
		(-0.675)	(-2.811)	(-1.869)	(-0.723)	(1.459)	(2.454)	(1.615)	(1.564)	(37.786)	(-2.510)			(-217.945)	(-0.099)
	R_F	0.4456 **	0.1251	0.0211	0.0687	-0.3734 **	-0.1266	-0.0589	-0.0123	0.7893 **	0.1684 **	62.2957 **			
		(6.529)	(1.805)	(0.327)	(1.323)	(-5.442)	(-1.819)	(-0.914)	(-0.244)	(29.602)	(2.767)				

Notes: This table reports the VECM estimates and Granger causality tests results for the unrestricted version of model (3.5a) and (3.5b):

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

* and ** denote significant levels of 5% and 1%, respectively.

Figures in the parenthesis (.) are the t statistics.

Granger causality tests are based on the Wald tests of (H_{01}: $\beta_{Si}=0$) and (H_{02}: $\alpha_{Fi}=0$); the tests statistics are $\chi^2(4)$ distributed.

t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $B_{t-1} = \beta' X_{t-1}$ is NOT restricted to be the lagged basis in all cases; $R_{SIF,t-1}$ is the lagged stock index returns.

See the equations (3.5a) and (3.5b) in the text for the definitions of the remaining terms.

Table 3.16: Summary Results of VECM_FULL Period_Unrestricted

Code	Lead-lag Relationship		Error Correction			Common Factor Weights	
	Stock Leads	Futures Leads	Stock Adjusts	Futures Adjusts		Stock (θ_S)	Futures (θ_F = 1-θ_S)
AA	√	√	+	−		0.233	0.767
AGN	x	x	−	+		0.998	0.002
AHL	√	√	−	−		0.672	0.328
ALV	√	√	−	+		0.688	0.312
AXA	√	x	−	+		0.979	0.021
AZN	√	x	−	+		0.902	0.098
BAR	√	x	−	−		0.654	0.346
BNP	√	√	−	−		0.635	0.365
BPA	√	x	−	−		0.231	0.769
BTL	x	√	−	+		0.897	0.103
BVA	√	x	−	+		0.546	0.454
CA	√	x	−	−		0.605	0.395
CGE	√	√	−	+		0.888	0.112
CSG	√	√	−	−		0.965	0.035
DBK	√	x	−	+		0.717	0.283
DCY	√	x	−	−		0.502	0.498
DTE	√	x	−	+		0.654	0.346
ENI	x	x	−	+		0.820	0.180
ENL	x	x	−	+		0.979	0.021
EOA	√	x	−	+		0.654	0.346
ERC	√	√	+	+		0.598	0.402
FTE	√	x	+	+		0.001	0.999
GEN	√	x	+	−		0.467	0.533
GXW	√	x	−	−		0.281	0.719
HAS	√	x	+	−		0.147	0.853
HNM	√	x	−	+		0.610	0.390
ING	x	x	−	+		0.855	0.145
LLO	√	x	+	−		0.114	0.886
MUV	√	x	−	−		0.933	0.067
NDA	√	x	−	−		0.752	0.248
NES	√	x	−	+		0.983	0.017
NOV	√	x	−	+		0.603	0.397
PHI	√	x	−	+		0.938	0.062
RBO	√	√	−	−		0.452	0.548
RD	x	x	−	−		0.001	0.999
ROG	√	x	−	−		0.324	0.676
SCH	√	x	+	−		0.357	0.643
SHB	√	√	−	+		0.974	0.026
SHE	√	x	−	−		0.725	0.275
SIE	√	x	−	+		0.797	0.203
TEF	√	√	+	+		0.001	0.999
TI	x	x	+	−		0.001	0.999
TIM	√	x	+	+		0.001	0.999
TLI	x	x	+	+		0.609	0.391
TOT	√	√	−	+		0.939	0.061
UBS	√	x	−	−		0.331	0.669
UC	√	x	+	−		0.309	0.691
VIV	√	√	+	−		0.022	0.978
VOF	√	x	−	−		0.448	0.552
VOW	√	x	+	+		0.541	0.459
√	42	13	+ 14	26	Mean	0.567	0.433
x	8	37	− 36	24			

Notes: The unrestricted vesrion of Vector Error Correction Model (3.5a) and (3.5b) is run for each 50 pairs of cointegrated stock and futures prices

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

A "√" indicates that the lagged cross-coefficients (β_{Si} or α_{Fi}) in equations are jointly significant at the 5% level (i.e., Recjection of H_{01} or H_{02}).
A "+" indicates that the error-correction coefficient (γ_S or γ_{Fi}) in equations is significant at the 5% level (i.e., Recjection of H_{03} or H_{04}).
The (θ_S) and (θ_F) is the price discovery contributions (i.e., weight in the common long memory factor) of stock and futures, respectively.
The calculations of the price discovery contributions [(θ_S) and (θ_F)] are based on the formula (3.8) in the text.

Table 3.17: VECM Adjustment Coefficients and USF Share in Price Discovery_FULL Period_Unrestricted

	Mean	Std Deviation	25th percentile	Median	75th percentile
A : Cointegrating vector					
β_0	1.0000	0.0000	1.0000	1.0000	1.0000
β_2	-0.9021	0.3006	-0.9997	-0.9952	-0.9507
β_1	-0.3105	0.9650	-0.1312	-0.0185	0.0003
B : Adjustment coefficients					
γ_s	-0.0473	0.0802	-0.1042	-0.0174	0.0007
γ_f	0.1026	0.1713	0.0140	0.0476	0.1335
C: USF share in price discovery					
France (7)	0.4187	0.4151	0.0862	0.3649	0.6866
Germany (8)	0.3142	0.1368	0.2632	0.3291	0.3740
Italy (6)	0.5705	0.4093	0.2684	0.6121	0.9219
Netherlands (6)	0.3838	0.4086	0.0829	0.2362	0.6573
Spain (3)	0.6984	0.2769	0.5481	0.6426	0.8208
Sweden (5)	0.2913	0.1615	0.2476	0.3898	0.3909
Switzerland (5)	0.3589	0.3242	0.0354	0.3971	0.6690
UK (10)	0.5149	0.2964	0.2928	0.5500	0.7562
Whole Sample (50)	0.4333	0.3108	0.1534	0.3903	0.6743

Note This table presents the cross-sectional descriptive statistics of the USF share in price discoevry estimated on the basis of VECM adjusment coefficients in equations (3.5a) and (3.5b) and as given by formular (3.8). The sample consist of a total of 50 USFs including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland.

Table 3.18: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period_Without SIF

Code	Dep Var	α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	γ_S	Wald test (H_{01}: $\beta_{S,i}=0$)
		α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	γ_F	Wald test (H_{02}: $\alpha_{F,i}=0$)
AA	R_S	-0.1849	-0.1140	0.1740	0.5068 **	0.1713	0.0360	-0.2563 *	-0.4765 **	-0.1373	29.5490 **
		(-1.641)	(-0.940)	(1.471)	(5.029)	(1.503)	(0.298)	(-2.173)	(-4.771)	(-1.891)	
	R_F	0.3313 **	0.0993	0.3090 **	0.5314 **	-0.3087 **	-0.1463	-0.3698 **	-0.5103 **	-0.0046	36.5473 **
		(2.989)	(0.832)	(2.655)	(5.361)	(-2.754)	(-1.229)	(-3.187)	(-5.194)	(-0.065)	
AGN	R_S	-0.0225	0.0038	-0.0889 *	0.0346	0.0438	0.0218	0.0156	0.0085	0.0447	3.6034
		(-0.554)	(0.097)	(-2.342)	(0.989)	(1.740)	(0.910)	(0.736)	(0.532)	(1.786)	
	R_F	0.4116 **	0.3539 **	0.1904 *	0.1029	-0.4103 **	-0.3192 **	-0.2091 **	-0.1029 **	0.4771 **	30.3306 **
		(4.709)	(4.153)	(2.335)	(1.371)	(-7.592)	(-6.204)	(-4.604)	(-2.993)	(8.873)	
AHL	R_S	-0.0979	-0.1689	-0.3143 *	0.0110	0.1630	0.2687 *	0.1752	0.0013	0.0158	6.3904
		(-0.846)	(-1.377)	(-2.564)	(0.095)	(1.441)	(2.248)	(1.464)	(0.012)	(1.554)	
	R_F	0.2864 *	-0.0637	-0.2466 *	0.0227	-0.1911	0.1600	0.1238	0.0035	0.0189	12.0041 *
		(2.423)	(-0.508)	(-1.968)	(0.193)	(-1.654)	(1.311)	(1.012)	(0.031)	(1.815)	
ALV	R_S	-0.0894	-0.2207 *	-0.1337	-0.0754	0.1176	0.2341 **	0.1290	0.0561	0.0246 *	7.0224
		(-1.324)	(-2.558)	(-1.543)	(-1.067)	(1.585)	(2.641)	(1.476)	(0.828)	(2.386)	
	R_F	0.6728 **	0.2522 **	0.0604	-0.0464	-0.5876 **	-0.2069 **	-0.0678	0.0137	0.0293 **	140.0237 **
		1(1.011)	(3.230)	(0.770)	(-0.726)	(-8.757)	(-2.579)	(-0.858)	(0.224)	(3.144)	
AXA	R_S	0.0724 *	0.0044	-0.0567	-0.0061	-0.0038	-0.0231	-0.0036	0.0135	-0.0032	1.9501
		(2.107)	(0.128)	(-1.650)	(-0.176)	(-0.192)	(-1.183)	(-0.185)	(0.690)	(-0.798)	
	R_F	0.1461 *	0.0354	-0.0185	-0.0581	-0.0326	-0.0364	-0.0026	0.0160	0.0382 **	7.7562
		(2.452)	(0.594)	(-0.311)	(-0.974)	(-0.961)	(-1.071)	(-0.078)	(0.471)	(5.452)	
AZN	R_S	-0.1147	-0.1264	-0.0454	-0.2213	0.1815	0.0200	0.0158	0.2158	-0.0196	7.4190
		(-0.844)	(-0.868)	(-0.326)	(-1.918)	(1.315)	(0.136)	(0.113)	(1.884)	(-0.202)	
	R_F	0.4673 **	0.2947 *	0.1939	-0.1139	-0.3921 **	-0.3808 **	-0.2115	0.1210	0.1154	17.6698 **
		(3.531)	(2.076)	(1.429)	(-1.013)	(-2.917)	(-2.666)	(-1.556)	(1.084)	(1.226)	
BAR	R_S	0.0175	-0.0667 *	-0.0394	-0.0170	0.0149	0.0130	-0.0297 *	-0.0028	-0.0005	6.2786
		(0.550)	(-2.100)	(-1.240)	(-0.534)	(1.041)	(0.908)	(-2.079)	(-0.196)	(-0.492)	
	R_F	0.0942	-0.0760	-0.2151 **	-0.0287	0.0028	0.0122	-0.0290	0.0018	0.0037	12.8999 *
		(1.339)	(-1.081)	(-3.057)	(-0.406)	(0.089)	(0.386)	(-0.917)	(0.057)	(1.807)	
BNP	R_S	0.0831 *	-0.0614	0.0051	0.0457	-0.0403	-0.0008	-0.0191	-0.0297	0.0001	3.7425
		(2.104)	(-1.544)	(0.129)	(1.151)	(-1.460)	(-0.030)	(-0.690)	(-1.081)	(0.047)	
	R_F	0.2210 **	-0.0567	0.0235	-0.0041	-0.0766	-0.0052	-0.0052	-0.0227	0.0053	16.5675 **
		(3.912)	(-0.997)	(0.414)	(-0.071)	(-1.940)	(-0.131)	(-0.132)	(-0.576)	(1.785)	
BPA	R_S	-0.1823	-0.1252	-0.2032	-0.1167	0.1382	0.0297	0.1302	0.1834	-0.0083	3.0565
		(-1.193)	(-0.767)	(-1.287)	(-0.872)	(0.897)	(0.181)	(0.821)	(1.366)	(-0.079)	
	R_F	0.3039 *	0.1317	-0.1243	-0.0360	-0.3432 *	-0.2173	0.0573	0.1146	0.1358	7.0057
		(2.021)	(0.819)	(-0.800)	(-0.273)	(-2.264)	(-1.342)	(0.367)	(0.868)	(1.312)	
BTL	R_S	-0.2017 **	-0.0466	0.0484	0.0883	0.1741 **	0.0393	-0.1576 *	-0.0557	0.0073	16.1137 **
		(-3.152)	(-0.721)	(0.747)	(1.382)	(2.850)	(0.638)	(-2.553)	(-0.908)	(1.171)	
	R_F	-0.0604	-0.0013	0.0118	0.0810	0.0400	-0.0124	-0.1422 *	-0.0340	0.0180 **	2.2109
		(-0.902)	(-0.019)	(0.175)	(1.213)	(0.626)	(-0.192)	(-2.204)	(-0.531)	(2.749)	
BVA	R_S	0.0604	-0.0505	-0.0241	-0.0392	-0.0632	0.0506	-0.0539	0.0923	-0.2283	2.5520
		(0.411)	(-0.334)	(-0.168)	(-0.334)	(-0.417)	(0.328)	(-0.368)	(0.781)	(-1.890)	
	R_F	0.5415 **	0.2329	0.1566	0.1027	-0.5146 **	-0.2342	-0.2087	-0.0561	-0.0174	16.5732 **
		(3.872)	(1.617)	(1.145)	(0.919)	(-3.572)	(-1.596)	(-1.499)	(-0.499)	(-0.152)	
CA	R_S	0.0290	0.0727	0.0767	-0.0222	-0.1140	-0.0589	-0.1370	0.0410	-0.0384	3.3359
		(0.244)	(0.573)	(0.624)	(-0.218)	(-0.941)	(-0.462)	(-1.111)	(0.405)	(-0.446)	
	R_F	0.5283 **	0.3031 *	0.1856	0.0532	-0.5759 **	-0.3044 *	-0.2169	-0.0373	0.1237	21.3442 **
		(4.578)	(2.464)	(1.558)	(0.538)	(-4.909)	(-2.465)	(-1.817)	(-0.380)	(1.482)	
CGE	R_S	-0.2499	-0.0503	-0.0311	0.1774 *	0.2466	0.0715	0.0219	-0.1023	0.2239	10.5194 *
		(-1.825)	(-0.407)	(-0.293)	(2.196)	(1.862)	(0.601)	(0.216)	(-1.345)	(1.596)	
	R_F	0.0109	0.1390	0.1318	0.2400 **	-0.0020	-0.1373	-0.1430	-0.1679 *	0.8574 **	10.9483 *
		(0.076)	(1.079)	(1.193)	(2.846)	(-0.015)	(-1.106)	(-1.356)	(-2.114)	(5.857)	
CSG	R_S	-0.0364	0.2002	0.1143	0.0296	0.0697	-0.0918	-0.1573	-0.0937	0.0293	2.5789
		(-0.306)	(1.448)	(0.825)	(0.248)	(0.588)	(-0.669)	(-1.149)	(-0.798)	(1.287)	
	R_F	0.5773 **	0.5373 **	0.2691	0.0381	-0.5387 **	-0.4269 **	-0.3090 *	-0.1099	0.0432	26.6955 **
		(4.842)	(3.882)	(1.939)	(0.318)	(-4.538)	(-3.107)	(-2.253)	(-0.935)	(1.892)	
DBK	R_S	-0.1276	-0.1246	-0.2755 **	-0.1754 *	0.1126	0.1372	0.2704 **	0.1474	0.0360	7.9676
		(-1.231)	(-1.129)	(-2.646)	(-2.170)	(1.062)	(1.250)	(2.657)	(1.923)	(0.421)	
	R_F	0.5100 **	0.3254 **	-0.0195	-0.1221	-0.4532 **	-0.2948 **	0.0349	0.0961	0.2405 **	44.1822 **
		(5.271)	(3.160)	(-0.201)	(-1.618)	(-4.575)	(-2.878)	(0.367)	(1.343)	(3.014)	
DCY	R_S	-0.1534	-0.1484	-0.1022	-0.0769	0.1542	0.1360	0.1063	0.1496 *	-0.0003	6.7615
		(-1.900)	(-1.672)	(-1.182)	(-1.057)	(1.847)	(1.526)	(1.236)	(2.105)	(-0.006)	
	R_F	0.4169 **	0.2174 **	0.0685	0.0129	-0.3498 **	-0.2140 *	-0.0530	0.0636	0.1031 *	31.7838 **
		(5.461)	(2.591)	(0.838)	(0.187)	(-4.430)	(-2.540)	(-0.652)	(0.946)	(2.149)	
DTE	R_S	-0.2559 *	-0.2989 **	-0.3514 **	-0.1824 *	0.2062 *	0.2708 **	0.2500 **	0.1920 **	-0.0164	10.5013 *
		(-2.508)	(-2.937)	(-3.763)	(-2.526)	(1.984)	(2.665)	(2.709)	(2.771)	(-0.175)	
	R_F	0.3112 **	0.0817	-0.0723	-0.0871	-0.2798 **	-0.0789	-0.0092	0.1075	0.2921 **	22.4750 **
		(3.294)	(0.867)	(-0.836)	(-1.302)	(-2.908)	(-0.838)	(-0.108)	(1.675)	(3.361)	
ENI	R_S	-0.0521	-0.0346	-0.0289	0.0360	0.0238	-0.0035	-0.0134	0.0114	0.0005	2.0851
		(-1.614)	(-1.071)	(-0.894)	(1.116)	(1.139)	(-0.165)	(-0.644)	(0.548)	(0.211)	
	R_F	0.0155	-0.0002	-0.0390	-0.0018	0.0031	-0.0167	-0.0038	0.0166	0.0125 **	0.7297
		(0.311)	(-0.003)	(-0.783)	(-0.037)	(0.095)	(-0.519)	(-0.119)	(0.515)	(3.348)	

Table 3.18: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period_Without SIF (continued)

Code	Dep Var	α_{S1} / α_{F1}	α_{S2} / α_{F2}	α_{S3} / α_{F3}	α_{S4} / α_{F4}	β_{S1} / β_{F1}	β_{S2} / β_{F2}	β_{S3} / β_{F3}	β_{S4} / β_{F4}	γ_S / γ_F	Wald test ($H_{01}: \beta_i = 0$) / Wald test ($H_{02}: \alpha_{F_i} = 0$)
ENL	R_S	-0.0537	-0.0204	-0.0096	-0.0174	-0.0252	-0.0104	-0.0029	0.0121	0.0003	2.2655
		(-1.615)	(-0.614)	(-0.290)	(-0.529)	(-1.273)	(-0.527)	(-0.146)	(0.610)	(0.105)	
	R_F	0.0036	0.0022	-0.0069	0.0036	-0.0556	0.0097	-0.0147	0.0099	0.0145 **	0.0274
		(0.064)	(0.040)	(-0.125)	(0.066)	(-1.677)	(0.294)	(-0.444)	(0.298)	(3.283)	
EOA	R_S	-0.1716 *	-0.1790 *	-0.0053	0.1709 **	0.0356	0.1374	-0.0765	-0.1662 **	-0.0497	15.3625 **
		(-2.262)	(-2.271)	(-0.071)	(2.671)	(0.456)	(1.722)	(-0.997)	(-2.590)	(-0.865)	
	R_F	0.2817 **	0.0788	0.0964	0.1694 **	-0.3517 **	-0.1162	-0.1389	-0.1651 **	0.1504 **	25.3912 **
		(3.998)	(1.076)	(1.374)	(2.850)	(-4.857)	(-1.568)	(-1.950)	(-2.770)	(2.823)	
ERC	R_S	0.1419	0.0970	-0.3464 **	-0.1279	-0.0622	-0.1279	0.2480 **	0.1033	0.0305 **	13.2424 *
		(1.596)	(1.053)	(-3.762)	(-1.436)	(-0.730)	(-1.437)	(2.786)	(1.209)	(3.502)	
	R_F	0.4353 **	0.1168	-0.3142 **	-0.1512	-0.3702 **	-0.1395	0.2327 *	0.1432	0.0372 **	35.2366 **
		(4.706)	(1.219)	(-3.281)	(-1.632)	(-4.180)	(-1.507)	(2.513)	(1.612)	(4.108)	
FTE	R_S	-0.1364	-0.1958	0.0653	-0.0264	0.2019	0.1578	-0.0311	0.0727	0.0145	4.8525
		(-1.217)	(-1.657)	(0.554)	(-0.236)	(1.776)	(1.325)	(-0.262)	(0.646)	(1.544)	
	R_F	0.2242 *	-0.0086	0.2004	0.0267	-0.1478	-0.0166	-0.1570	0.0281	0.0175	7.9856
		(2.031)	(-0.074)	(1.725)	(0.242)	(-1.320)	(-0.141)	(-1.342)	(0.253)	(1.892)	
GEN	R_S	0.0575	0.0992	-0.0768	0.2239 *	0.0037	-0.1053	0.0477	-0.1815	-0.1260	7.5363
		(0.423)	(0.725)	(-0.596)	(2.118)	(0.027)	(-0.762)	(0.370)	(-1.731)	(-1.070)	
	R_F	0.4943 **	0.3353 *	0.0663	0.2889 **	-0.4183 **	-0.3372 *	-0.0730	-0.2553 *	0.1521	25.1684 **
		(3.768)	(2.536)	(0.533)	(2.829)	(-3.154)	(-2.529)	(-0.586)	(-2.521)	(1.338)	
GXW	R_S	-0.2625	-0.2061	0.1060	-0.0907	0.2556	0.1252	-0.1199	0.0926	-0.0755	7.6571
		(-1.724)	(-1.289)	(0.697)	(-0.714)	(1.664)	(0.778)	(-0.782)	(0.724)	(-0.663)	
	R_F	0.2594	0.1459	0.2939 *	-0.0203	-0.2697	-0.2233	-0.3101 *	0.0338	0.0951	8.2032
		(1.730)	(0.926)	(1.962)	(-0.162)	(-1.783)	(-1.409)	(-2.054)	(0.268)	(0.847)	
HAS	R_S	-0.3222 **	-0.2477 *	-0.0143	-0.0382	0.2807 **	0.1841	0.0058	0.1146	0.0112	10.6305 *
		(-3.245)	(-2.337)	(-0.137)	(-0.409)	(2.780)	(1.721)	(0.055)	(1.212)	(0.217)	
	R_F	0.0973	-0.0818	0.0127	0.0041	-0.1195	0.0245	-0.0099	0.0966	0.0963	3.4837
		(1.008)	(-0.794)	(0.125)	(0.045)	(-1.217)	(0.236)	(-0.096)	(1.051)	(1.910)	
HNM	R_S	0.0952	0.1037	0.0909	0.0814	-0.1663	-0.1274	-0.1437	-0.1177	-0.1517	3.6341
		(0.875)	(0.944)	(0.888)	(0.976)	(-1.543)	(-1.174)	(-1.427)	(-1.474)	(-1.586)	
	R_F	0.5897 **	0.3915 **	0.2763 **	0.1787 *	-0.6512 **	-0.4283 **	-0.3236 **	-0.1892 *	0.1379	28.9768 **
		(5.351)	(3.518)	(2.664)	(2.113)	(-5.959)	(-3.894)	(-3.170)	(-2.336)	(1.423)	
ING	R_S	-0.0062	0.0247	-0.1156 **	-0.0022	0.0263	-0.0072	0.0033	0.0232	0.0006	0.9647
		(-0.138)	(0.551)	(-2.580)	(-0.049)	(0.713)	(-0.195)	(0.090)	(0.629)	(0.157)	
	R_F	0.0607	0.0120	-0.1004	0.0153	-0.0212	-0.0074	0.0059	0.0145	0.0108 *	4.7290
		(1.111)	(0.221)	(-1.842)	(0.280)	(-0.473)	(-0.164)	(0.131)	(0.324)	(2.319)	
LLO	R_S	0.0315	-0.1212	-0.0450	-0.0223	-0.0572	0.1304	-0.0140	0.0361	-0.0379	4.7333
		(0.373)	(-1.351)	(-0.506)	(-0.271)	(-0.663)	(1.437)	(-0.155)	(0.437)	(-1.108)	
	R_F	0.3945 **	-0.0465	-0.0399	0.0020	-0.3902 **	0.0251	-0.0023	-0.0081	0.0150	29.6329 **
		(4.771)	(-0.530)	(-0.458)	(0.024)	(-4.621)	(0.283)	(-0.026)	(-0.101)	(0.450)	
MUV	R_S	0.0131	-0.1971 *	-0.2411 *	-0.2008 *	0.0640	0.2309 *	0.2272 *	0.2038 **	0.0260	9.4281
		(0.167)	(-1.963)	(-2.396)	(-2.486)	(0.782)	(2.311)	(2.312)	(2.690)	(1.294)	
	R_F	0.8411 **	0.3919 **	0.0564	-0.0349	-0.7107 **	-0.3361 **	-0.0954	0.0423	0.0378 *	146.3698 **
		1(1.297)	(4.100)	(0.589)	(-0.454)	(-9.121)	(-3.536)	(-1.020)	(0.586)	(1.976)	
NDA	R_S	-0.3525 **	-0.3121 **	-0.2917 **	0.0446	0.3105 **	0.3210 **	0.2095	-0.0891	-0.0330	16.7268 **
		(-3.442)	(-2.898)	(-2.762)	(0.471)	(2.990)	(2.949)	(1.956)	(-0.929)	(-0.550)	
	R_F	0.0477	-0.1449	-0.2418 *	0.0360	-0.0745	0.1541	0.1422	-0.0808	0.0815	10.2122 *
		(0.476)	(-1.376)	(-2.341)	(0.390)	(-0.734)	(1.449)	(1.359)	(-0.861)	(1.393)	
NES	R_S	-0.1572	-0.0770	-0.1524	-0.1171	0.1208	0.0485	0.0742	0.1423	0.0638	4.9110
		(-1.671)	(-0.775)	(-1.592)	(-1.463)	(1.289)	(0.488)	(0.785)	(1.833)	(0.922)	
	R_F	0.3762 **	0.2280 *	0.0214	-0.0471	-0.4146 **	-0.2359 *	-0.0820	0.0678	0.2296 **	20.4369 **
		(4.077)	(2.338)	(0.227)	(-0.600)	(-4.510)	(-2.423)	(-0.883)	(0.890)	(3.382)	
NOV	R_S	0.0675	0.0593	-0.0495	0.0721	-0.0305	-0.0517	-0.0237	-0.0468	-0.0615	0.4042
		(0.563)	(0.478)	(-0.422)	(0.752)	(-0.254)	(-0.417)	(-0.205)	(-0.504)	(-0.619)	
	R_F	0.5800 **	0.3837 **	0.1219	0.1268	-0.5348 **	-0.3675 **	-0.1727	-0.0846	0.1751	27.3245 **
		(4.937)	(3.157)	(1.061)	(1.348)	(-4.537)	(-3.022)	(-1.518)	(-0.928)	(1.797)	
PHI	R_S	-0.2920	-0.2595	-0.2461	0.0912	0.2667	0.2351	0.2253	-0.0954	0.1521	4.8158
		(-1.412)	(-1.238)	(-1.265)	(0.595)	(1.287)	(1.118)	(1.157)	(-0.626)	(0.834)	
	R_F	0.2175	0.0393	-0.0924	0.1257	-0.2392	-0.0566	0.0833	-0.1265	0.4355 *	4.6658
		(1.077)	(0.192)	(-0.487)	(0.839)	(-1.183)	(-0.276)	(0.438)	(-0.850)	(2.445)	
RBO	R_S	-0.4518 **	-0.3142 *	-0.1059	0.0332	0.4131 **	0.3136 *	0.0152	-0.0347	-0.0306	16.4285 **
		(-3.967)	(-2.545)	(-0.888)	(0.336)	(3.574)	(2.527)	(0.126)	(-0.345)	(-0.415)	
	R_F	0.0954	-0.0331	0.0313	0.1052	-0.1095	0.0089	-0.1152	-0.0938	0.0867	3.2462
		(0.859)	(-0.275)	(0.269)	(1.091)	(-0.972)	(0.073)	(-0.978)	(-0.955)	(1.204)	
RD	R_S	-0.0348	-0.0516	-0.0300	0.0681	0.0171	0.0116	-0.0181	0.0030	0.0003	1.3702
		(-0.958)	(-1.419)	(-0.826)	(1.875)	(0.723)	(0.490)	(-0.764)	(0.126)	(0.427)	
	R_F	0.0515	-0.0284	0.0206	0.0493	0.0200	0.0022	-0.0255	0.0089	0.0012	2.0190
		(0.922)	(-0.509)	(0.369)	(0.883)	(0.548)	(0.061)	(-0.701)	(0.247)	(1.064)	
ROG	R_S	0.0591	-0.1214	-0.0738	-0.1910	-0.0493	0.1194	0.0561	0.1929	0.0093	5.3949
		(0.419)	(-0.836)	(-0.542)	(-1.689)	(-0.350)	(0.827)	(0.416)	(1.751)	(0.081)	
	R_F	0.6075 **	0.3180 *	0.2060	-0.0367	-0.5939 **	-0.3240 *	-0.2223	0.0416	0.2038	22.0331 **
		(4.331)	(2.203)	(1.522)	(-0.326)	(-4.238)	(-2.257)	(-1.655)	(0.379)	(1.788)	

Table 3.18: Estimates of the VECM and Granger Causality Tests for Stock and Futures Returns_FULL Period_Without SIF (continued)

Code	Dep Var	α_{S1} / α_{F1}	α_{S2} / α_{F2}	α_{S3} / α_{F3}	α_{S4} / α_{F4}	β_{S1} / β_{F1}	β_{S2} / β_{F2}	β_{S3} / β_{F3}	β_{S4} / β_{F4}	γ_S / γ_F	Wald test (H_{01}: $\beta_{Si}=0$) / Wald test (H_{02}: $\alpha_{Fi}=0$)
SCH	R_S	-0.3018 *	-0.0261	0.0300	-0.1018	0.2838	-0.0193	-0.0725	0.1615	0.0454	10.8694 *
		(-1.999)	(-0.168)	(0.206)	(-0.861)	(1.852)	(-0.124)	(-0.499)	(1.359)	(0.361)	
	R_F	0.1523	0.2646	0.1379	-0.0361	-0.1451	-0.3013 *	-0.1759	0.0902	0.2790 *	4.6023
		(1.053)	(1.785)	(0.991)	(-0.318)	(-0.988)	(-2.020)	(-1.263)	(0.793)	(2.314)	
SHB	R_S	-0.1020	-0.2336 *	-0.1400	0.0906	0.0675	0.2035 *	0.0887	-0.1112	-0.0144	7.2384
		(-1.050)	(-2.311)	(-1.416)	(1.008)	(0.686)	(1.986)	(0.885)	(-1.233)	(-0.256)	
	R_F	0.2347 *	-0.1004	-0.1437	0.0529	-0.2732 **	0.0827	0.0726	-0.0766	0.1086 *	15.7686 **
		(2.473)	(-1.017)	(-1.488)	(0.602)	(-2.843)	(0.826)	(0.742)	(-0.869)	(1.971)	
SHE	R_S	0.1856	0.1971	0.2522	0.0607	-0.1812	-0.1869	-0.2396	-0.0345	0.0043	5.1278
		(1.340)	(1.336)	(1.709)	(0.436)	(-1.475)	(-1.433)	(-1.838)	(-0.281)	(0.600)	
	R_F	0.6279 **	0.4512 **	0.3950 *	0.1393	-0.5711 **	-0.4133 **	-0.3629 *	-0.0932	0.0063	19.9992 **
		(4.020)	(2.715)	(2.375)	(0.887)	(-4.125)	(-2.810)	(-2.470)	(-0.674)	(0.782)	
SIE	R_S	0.0209	0.0237	-0.1079 *	-0.0527	0.0064	-0.0209	0.0569	0.0596	0.0069	3.2808
		(0.436)	(0.469)	(-2.131)	(-1.081)	(0.138)	(-0.441)	(1.202)	(1.342)	(0.878)	
	R_F	0.3732 **	0.0946	-0.0733	-0.0598	-0.2125 **	-0.0812	0.0343	0.0524	0.0276 **	62.2515 **
		(7.592)	(1.820)	(-1.408)	(-1.193)	(-4.471)	(-1.669)	(0.706)	(1.148)	(3.428)	
TEF	R_S	0.0959	0.1934	0.0529	0.0064	-0.0908	-0.2301 *	-0.0891	-0.0082	0.0082	4.4689
		(0.964)	(1.729)	(0.471)	(0.064)	(-0.902)	(-2.076)	(-0.804)	(-0.084)	(1.164)	
	R_F	0.6430 **	0.4740 **	0.2918 **	0.1153	-0.6000 **	-0.4990 **	-0.3184 **	-0.1196	0.0120	45.9420 **
		(6.557)	(4.300)	(2.633)	(1.159)	(-6.040)	(-4.566)	(-2.913)	(-1.234)	(1.733)	
TI	R_S	-0.0021	-0.0224	0.0331	0.1228 **	0.0047	0.0053	0.0075	0.0020	0.0007	0.3715
		(-0.071)	(-0.748)	(1.108)	(4.110)	(0.273)	(0.309)	(0.441)	(0.119)	(0.918)	
	R_F	0.0101	-0.0371	0.0130	0.1377 **	-0.0078	-0.0038	0.0096	0.0157	0.0021	7.5472
		(0.192)	(-0.704)	(0.246)	(2.617)	(-0.261)	(-0.126)	(0.319)	(0.524)	(1.665)	
TIM	R_S	-0.0777	-0.1942 *	0.0000	0.1707 *	0.0450	0.1352	0.0279	-0.1116	-0.0005	6.9631
		(-1.099)	(-2.568)	(-0.000)	(2.442)	(0.635)	(1.780)	(0.368)	(-1.609)	(-0.023)	
	R_F	0.3300 **	-0.0170	0.0728	0.1501 *	-0.3656 **	-0.0368	-0.0224	-0.0877	0.0262	31.4585 **
		(4.703)	(-0.226)	(0.974)	(2.162)	(-5.191)	(-0.488)	(-0.297)	(-1.273)	(1.297)	
TLI	R_S	-0.0621	-0.2258	-0.0956	-0.1304	0.0158	0.1387	0.0235	0.1001	0.0135	1.3529
		(-0.444)	(-1.504)	(-0.640)	(-0.944)	(0.111)	(0.914)	(0.155)	(0.719)	(0.366)	
	R_F	0.3943 **	0.1166	0.1353	-0.0112	-0.4321 **	-0.2123	-0.2073	-0.0186	0.0309	8.9494
		(2.867)	(0.791)	(0.923)	(-0.083)	(-3.091)	(-1.424)	(-1.396)	(-0.136)	(0.855)	
TOT	R_S	-0.1537	0.1587	0.2011	0.1763	0.1040	-0.2716 *	-0.2561 *	-0.1351	0.0395	13.9638 **
		(-1.485)	(1.443)	(1.858)	(1.842)	(0.983)	(-2.442)	(-2.342)	(-1.399)	(0.716)	
	R_F	0.2670 **	0.3159 **	0.2461 *	0.1952 *	-0.2878 **	-0.4104 **	-0.2735 **	-0.1598	0.1250 *	13.2282 *
		(2.680)	(2.982)	(2.362)	(2.117)	(-2.825)	(-3.832)	(-2.598)	(-1.718)	(2.355)	
UBS	R_S	0.0233	-0.0420	-0.0513	-0.0384	0.0719	0.0472	-0.0530	0.0317	0.0296	1.3338
		(0.220)	(-0.372)	(-0.458)	(-0.371)	(0.697)	(0.430)	(-0.485)	(0.316)	(0.776)	
	R_F	0.4393 **	0.1120	0.0664	0.0251	-0.3302 **	-0.1062	-0.1614	-0.0367	0.0735	17.1241 **
		(4.065)	(0.971)	(0.579)	(0.236)	(-3.131)	(-0.946)	(-1.445)	(-0.359)	(1.883)	
UC	R_S	-0.1157	-0.1167	-0.0674	0.1365	0.1939 *	0.0552	0.0669	-0.0840	-0.1048 *	10.0413 *
		(-1.500)	(-1.471)	(-0.870)	(1.958)	(2.468)	(0.681)	(0.845)	(-1.181)	(-2.063)	
	R_F	0.2205 **	-0.0028	-0.0332	0.1105	-0.1525 *	-0.0403	0.0365	-0.0576	0.0562	15.3031 **
		(2.930)	(-0.037)	(-0.440)	(1.624)	(-1.989)	(-0.509)	(0.472)	(-0.830)	(1.134)	
VIV	R_S	-0.0123	-0.0942	0.2645	0.2172	0.1060	-0.0088	-0.3669 *	-0.2895 *	-0.2453	11.1159 *
		(-0.068)	(-0.525)	(1.608)	(1.647)	(0.579)	(-0.049)	(-2.206)	(-2.184)	(-1.475)	
	R_F	0.4273 *	0.1703	0.4233 **	0.2458	-0.3396	-0.2669	-0.5247 **	-0.3018 *	0.0882	14.0495 **
		(2.407)	(0.972)	(2.632)	(1.906)	(-1.897)	(-1.512)	(-3.227)	(-2.329)	(0.543)	
VOF	R_S	-0.3789 *	-0.3659 *	-0.0352	-0.0611	0.3348 *	0.3069	-0.1042	0.0876	-0.0268	14.2297 **
		(-2.532)	(-2.335)	(-0.239)	(-0.511)	(2.215)	(1.950)	(-0.700)	(0.725)	(-0.223)	
	R_F	0.1747	0.0181	0.1690	0.0867	-0.2071	-0.0806	-0.3065 *	-0.0573	0.1624	4.4328
		(1.197)	(0.118)	(1.174)	(0.744)	(-1.405)	(-0.525)	(-2.113)	(-0.487)	(1.384)	
VOW	R_S	-0.1296	-0.2428 *	-0.1614	0.0263	0.1924 *	0.1958 *	0.1302	0.0234	-0.0420	5.2727
		(-1.370)	(-2.524)	(-1.801)	(0.365)	(2.023)	(2.029)	(1.457)	(0.336)	(-0.499)	
	R_F	0.3740 **	0.0749	-0.0192	0.1206	-0.2912 **	-0.0967	-0.0315	-0.0543	0.2514 **	33.2464 **
		(4.158)	(0.819)	(-0.225)	(1.759)	(-3.220)	(-1.053)	(-0.371)	(-0.820)	(3.141)	

Notes: This table reports the VECM estimates and Granger causality tests results for the model (3.5a) and (3.5b) excluding the lagged index futures returns :

$$R_{S,t} = \sum_{i=1}^{4} \alpha_{S,i} R_{S,t-i} + \sum_{i=1}^{4} \beta_{S,i} R_{F,t-i} + \gamma_S B_{t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{4} \alpha_{F,i} R_{S,t-i} + \sum_{i=1}^{4} \beta_{F,i} R_{F,t-i} + \gamma_F B_{t-1} + \varepsilon_{F,t}$$

* and ** denote significant levels of 5% and 1%, respectively.

Figures in the parenthesis (.) are the t statistics.

Granger causality tests are based on the Wald tests of (H_{01}: $\beta_{Si}=0$) and (H_{02}: $\alpha_{Fi}=0$); the tests statistics are $\chi^2(4)$ distributed.

t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $B_{t-1} = \beta' X_{t-1} = S_{t-1} - F_{t-1}$ is restricted to be the lagged basis in all cases; $R_{SIF,t-1}$ is the lagged stock index returns.

See the equations (3.5a) and (3.5b) in the text for the definitions of the remaining terms.

Table 3.19: Summary Results of VECM_FULL Period_Without SIF

Code	Lead-lag Relationship		Error Correction		Common Factor Weights	
	Stock Leads	Futures Leads	Stock Adjusts	Futures Adjusts	Stock (θ_s)	Futures ($\theta_F = 1-\theta_s$)
AA	√	√	–	–	0.001	0.999
AGN	√	x	–	+	0.914	0.086
AHL	√	x	–	–	0.544	0.456
ALV	√	x	+	+	0.544	0.456
AXA	x	x	–	+	0.922	0.078
AZN	√	x	–	–	0.855	0.145
BAR	√	x	–	–	0.890	0.110
BNP	√	x	–	–	0.982	0.018
BPA	x	x	–	–	0.942	0.058
BTL	x	√	–	+	0.711	0.289
BVA	√	x	–	–	0.001	0.999
CA	√	x	–	–	0.763	0.237
CGE	√	√	–	+	0.793	0.207
CSG	√	x	–	–	0.596	0.404
DBK	√	x	–	+	0.870	0.130
DCY	√	x	–	+	0.997	0.003
DTE	√	√	–	+	0.947	0.053
ENI	x	x	–	+	0.961	0.039
ENL	x	x	–	+	0.981	0.019
EOA	√	√	–	+	0.752	0.248
ERC	√	√	+	+	0.550	0.450
FTE	x	x	–	–	0.547	0.453
GEN	√	x	–	–	0.547	0.453
GXW	x	x	–	–	0.557	0.443
HAS	x	√	–	–	0.895	0.105
HNM	√	x	–	–	0.476	0.524
ING	x	x	–	+	0.947	0.053
LLO	√	x	–	–	0.284	0.716
MUV	√	x	–	+	0.592	0.408
NDA	√	√	–	–	0.712	0.288
NES	√	x	–	+	0.783	0.217
NOV	√	x	–	–	0.740	0.260
PHI	x	x	–	+	0.741	0.259
RBO	x	√	–	–	0.739	0.261
RD	x	x	–	–	0.793	0.207
ROG	√	x	–	–	0.956	0.044
SCH	x	√	–	+	0.860	0.140
SHB	√	x	–	+	0.883	0.117
SHE	√	x	–	–	0.595	0.405
SIE	√	x	–	+	0.801	0.199
TEF	√	x	–	–	0.595	0.405
TI	x	x	–	–	0.762	0.238
TIM	√	x	–	–	0.982	0.018
TLI	x	x	–	–	0.696	0.304
TOT	√	√	–	+	0.760	0.240
UBS	√	x	–	–	0.713	0.287
UC	√	√	+	–	0.349	0.651
VIV	√	√	–	–	0.265	0.735
VOF	x	√	–	–	0.858	0.142
VOW	√	x	–	+	0.857	0.143
√	34	14	+ 3	21	Mean 0.716	0.284
x	16	36	– 47	29		

Notes: The Vector Error Correction Model (3.5a) and (3.5b), without index futures returns, is run for each 50 pairs of cointegrated stock and futures prices

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \varepsilon_{F,t}$$

A "√" indicates that the lagged cross-coefficients (β_{Si} or α_{Fi}) in equations are jointly significant at the 5% level (i.e., Recjection of H_{01} or H_{02}).
A "+" indicates that the error-correction coefficient (γ_S or γ_{Fi}) in equations is significant at the 5% level (i.e., Recjection of H_{03} or H_{04}).
The (θ_S) and (θ_F) is the price discovery contributions (i.e., weight in the common long memory factor) of stock and futures, respectively.
The calculations of the price discovery contributions [(θ_S) and (θ_F)] are based on the formula (3.8) in the text.

Table 3.20: VECM Adjustment Coefficients and USF Share in Price Discovery_WITH & WITHOUT SIF

	Mean	*Z-test*		Std Deviation	25^{th} percentile	Median	75^{th} percentile
A : Adjustment coefficients							
A.1 : WITH SIF (Firm-specific Information)							
γ_s	-0.0403			0.0622	-0.0724	-0.0119	0.0047
γ_f	0.0886			0.1202	0.0149	0.0481	0.1309
A.2 : WITHOUT SIF (Market-wide Information)							
γ_s	-0.0123			0.0760	-0.0324	0.0003	0.0155
γ_f	0.1144			0.1528	0.0177	0.0775	0.1473
B : USF share in price discovery							
B.1 : WITH SIF (Firm-specific Information)							
(θ_F)	0.3951			0.2336	0.2252	0.3917	0.5533
B.2 : WITHOUT SIF (Market-wide Information)							
(θ_F)	0.2840	⇓ 2.3713	**	0.2351	0.1115	0.2392	0.4071

Note This table presents the cross-sectional descriptive statistics of the USF share in price discoevry estimated on the basis of VECM adjusment coefficients in equations (3.5a) and (3.5b) and as given by formular (3.8). The sample consist of a total of 50 USFs including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland.

< > Wilcoxon Z-test statistics

*, **, *** Significant at 10%, 5% and 1% level, respectively.

↑ = significant hiher share in price discovery ; ⇓ = significant lower share in price discovery

Table 3.21: Descriptive Statistics and Correlations between Explanatory Variables

A : Descriptive statistics

	VolumeRatio	*TradeFrequency*	*SpreadRatio*	*Volatility*
Mean	0.7883	0.4389	1.1351	0.0225
Std. Deviation	0.9230	0.1545	0.3508	0.0071
25^{th} Percentile	0.2093	0.3241	0.9781	0.0172
Median	0.4350	0.4615	0.9882	0.0203
75^{th} Percentile	1.1003	0.5677	1.0517	0.0259

B : Pearson's correlation coefficients

	VolumeRatio		*TradeFrequency*	*SpreadRatio*	*Volatility*
VolumeRatio	1.0000				
TradeFrequency	0.3219	***	1.0000		
SpreadRatio	0.1260		0.1721	1.0000	
Volatility	-0.2147	*	-0.0444	0.0769	1.0000

Notes:
The table presents descriptive statistics and correlations between independent variables of our cross-sectional regressions. The relative trading volume of USF and stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. *, **, *** denote significance at 10%, 5%, and 1% respectively.

Table 3.22: Determinants of the USF Share in Price Discovery

Variable	Expected sign	Model 1		Model 2		Model 3		Model 4		Model 5	
Constant		-1.78587		-2.47576		-1.66589		-2.28974		-0.54857	
		(-0.535)		(-0.767)		(-0.483)		(-0.657)		(-0.165)	
MonthsListed	+	0.01089		0.02855		0.04785		0.03455		-0.00988	
		(0.184)		(0.469)		(0.817)		(0.615)		(-0.167)	
HomeMarket	+	1.46929	*	1.33829		1.31425	*	1.29681		0.03641	
		(1.850)		(1.440)		(1.680)		(1.530)		(0.043)	
VolumeRatio	+	0.38268	***								
		(3.160)									
TradeFrequency	+			0.07998							
				(0.048)							
SpreadRatio	-					-1.62420	***				
						(-3.190)					
Volatility	±							-0.10811			
								(-0.005)			
ContractSize	+									1.58276	***
										(4.290)	
Adjusted R^2		0.14		0.10		0.21		0.26		0.18	
Number of observations		50		50		50		50		50	

Notes:
The dependent variable is the logistic transformation of the USF share in price discovery estimated from the VECM adjustment coefficients. *MonthListed* is the number of months for which a USF has been listed in the EuronextLIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The relative trading volume of USFand stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. *, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 3.23: Determinants of the USF Share in Price Discovery_removed LHS Outliers (LLO & TIM)

Variable	Expected sign	Model 1		Model 2		Model 3		Model 4		Model 5	
Constant		-1.66292		-1.93108		-1.68591		-0.71654		-0.89571	
		(-0.523)		(-0.654)		(-0.526)		(-0.206)		(-0.281)	
MonthsListed	+	0.00736		0.01365		0.04284		0.01740		-0.00357	
		(0.131)		(0.250)		(0.779)		(0.303)		(-0.063)	
HomeMarket	+	0.81292	***	0.61867		0.68787	**	0.82645	***	-0.43494	
		(2.950)		(1.420)		(2.210)		(2.580)		(-1.110)	
VolumeRatio	+	0.40050	***								
		(3.940)									
TradeFrequency	+			0.61668							
				(0.423)							
SpreadRatio	-					-1.41253	**				
						(-2.450)					
Volatility	±							7.98386			
								(0.340)			
ContractSize	+									1.33635	***
										(4.770)	
Adjusted R^2		0.12		0.05		0.18		0.28		0.13	
Number of observations		48		48		48		48		48	

Notes:
The dependent variable is the logistic transformation of the USF share in price discovery estimated from the VECM adjustment coefficients. *MonthListed* is the number of months for which a USF has been listed in the EuronextLIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The relative trading volume of USFand stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. *, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 3.24: Determinants of the USF Share in Price Discovery_removed RHS outlier (ENI VolumeRatio)

Variable	Expected sign	Model 1	Model 2	Model 3	Model 4	Model 5
Constant		-1.93895	-2.24598	-0.97009	-1.09194	-0.57136
		(-0.577)	(-0.691)	(-0.281)	(-0.284)	(-0.172)
MonthsListed	+	0.01241	0.02553	0.03677	0.03484	-0.00946
		(0.208)	(0.417)	(0.625)	(0.534)	(-0.160)
HomeMarket	+	1.47231 *	1.40233	1.36715 *	1.52023 *	0.01195
		(1.860)	(1.500)	(1.760)	(1.780)	(0.014)
VolumeRatio	+	0.49580 **				
		(2.500)				
TradeFrequency	+		-0.14189			
			(-0.085)			
SpreadRatio	-			-1.73523 ***		
				(-3.840)		
Volatility	±				-0.02129	
					(-0.001)	
ContractSize	+					1.60673 ***
						(4.070)
Adjusted R^2		0.14	0.11	0.22	0.26	0.18
Number of observations		49	49	49	49	49

Notes:
The dependent variable is the logistic transformation of the USF share in price discovery estimated from the VECM adjustment coefficients. *MonthListed* is the number of months for which a USF has been listed in the Euronext.LIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The relative trading volume of USF and stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. *, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 3.25: Determinants of the USF Share in Price Discovery_Industry Dummies

Variable	Expected sign	Model 1	Model 2	Model 3	Model 4	Model 5
Constant		-3.21881	-2.89428	-3.09070	-1.99307	-2.21342
		(-0.893)	(-0.854)	(-0.875)	(-0.533)	(-0.573)
MonthsListed	+	0.00953	0.00096	0.04875	0.01931	-0.00038
		(0.152)	(0.015)	(0.803)	(0.289)	(-0.006)
HomeMarket	+	1.62116 *	1.18299	1.22220	1.45684	0.10112
		(1.820)	(1.210)	(1.500)	(1.590)	(0.126)
VolumeRatio	+	0.67139 ***				
		(3.060)				
TradeFrequency	+		1.03093			
			(0.554)			
SpreadRatio	-			-1.90701 ***		
				(-3.370)		
Volatility	±				-7.37787	
					(-0.338)	
ContractSize	+					1.46006 ***
						(4.330)
Resources (7/50)		0.35502	1.50401 **	1.90412 **	0.77929	0.95145
		(0.405)	(2.300)	(2.470)	(0.707)	(1.590)
Services (13/50)		1.79493 ***	1.97654 ***	1.86731 ***	2.03069 ***	1.38085 **
		(3.200)	(3.260)	(3.570)	(3.170)	(2.550)
ConsumerGoods (7/50)		0.67332	1.07737	1.03816	0.72870	0.81948
		(0.718)	(1.190)	(1.160)	(0.671)	(0.880)
Technology (2/50)		1.07152	1.00140	0.88364	1.56791	0.64748
		(0.937)	(0.848)	(0.725)	(1.270)	(0.589)
Financial (19/50)		1.57219 **	1.71599 **	2.05608 ***	2.11544 ***	1.39493 **
		(2.320)	(2.410)	(3.500)	(3.060)	(2.090)
Adjusted R^2		0.23	0.16	0.29	0.38	0.22
Number of observations		50	50	50	50	50

Notes:
The dependent variable is the logistic transformation of the USF share in price discovery estimated from the VECM adjustment coefficients. *MonthListed* is the number of months for which a USF has been listed in the Euronext.LIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The relative trading volume of USF and stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. We classify sample USFs in six indutry groups, according to the industry sectors of their underlying stocks. *Resources, Services, ConsumerGoods, Technology*, and *Financial* are dummies corresponding to five of these groups. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. *, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 3.26: Determinants of the USF Share in Price Discovery_Nontransformed LHS (Tobit Model)

Variable	Expected sign	Model 1		Model 2	Model 3		Model 4		Model 5	
Constant		0.34149		0.23027	0.29735		0.40564		0.56211	
		(0.757)		(0.471)	(0.623)		(0.837)		(1.241)	
MonthsListed	+	-0.00073		0.00208	0.00512		0.00280		-0.00436	
		(-0.089)		(0.215)	(0.592)		(0.306)		(-0.531)	
HomeMarket	+	0.17733	**	0.14804	0.14976	*	0.18993	**	-0.08845	
		(2.188)		(1.572)	(1.854)		(2.319)		(-0.927)	
VolumeRatio	+	0.07461	***							
		(3.229)								
TradeFrequency	+			0.04466						
				(0.185)						
SpreadRatio	-				-0.19114	***				
					(-3.248)					
Volatility	±						0.26707			
							(0.073)			
ContractSize	+								0.29220	***
									(4.461)	
Log Likelihood		6.55		4.22	6.51		9.84		8.69	
Number of observations		50		50	50		50		50	

Notes:
The dependent variable is the "nontransformed" USF share in price discovery estimated from the VECM adjustment coefficients. *MonthListed* is the number of months for which a USF has been listed in the Euronext.LIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The relative trading volume of USFand stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. *, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 3.27: Descriptive Statistics and Correlations between Explanatory Variables

A : Descriptive statistics

	USF Volume	Stock Volume	USF TradeFrequency	Stock TradeFrequency	USF Spread	Stock Spread	Volatility
Mean	150.69	24929.70	42.70	97.16	0.05	0.04	0.02
Std. Deviation	281.27	50378.10	15.11	0.65	0.03	0.01	0.01
25^{th} Percentile	18.13	4411.57	31.40	96.71	0.04	0.03	0.02
Median	38.90	9067.54	45.05	97.13	0.05	0.04	0.02
75^{th} Percentile	88.13	26905.72	55.51	97.66	0.06	0.05	0.03

B : Pearson's correlation coefficients

	USF Volume	Stock Volume	USF TradeFrequency	Stock TradeFrequency	USF Spread	Stock Spread	Volatility
USF Volume	1						
Stock Volume	0.546452 ***	1					
USF TradeFrequency	0.245984 **	0.133830	1				
Stock TradeFrequency	-0.051612	-0.239049 *	0.555866 ***	1			
USF Spread	-0.046114	0.029270	0.071292	0.317372 **	1		
Stock Spread	-0.187300	0.102412	-0.039754	0.304994 **	0.686476 ***	1	
Volatility	-0.187319	0.102405	-0.039805	0.304947 **	0.686484 ***	1.000000 **:	1

Notes:
The table presents descriptive statistics and correlations between independent variables of our cross-sectional regressions. The USF Volume and Stock Volume are the trading volume of USF and stock markets, respectively. USF TradeFrequency and Stock TradeFrequency are calculated as the average number of trading days over the whole sample period. The variables USF Spread and Stock Spread are the effective spread on these markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. *, **, *** denote significance at 10%, 5%, and 1% respectively.

Table 3.28: Determinants of the USF Share in Price Discovery_Separate RHS Variables

Variable	Expected sign	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant		-0.38260	-2.36116	-2.51522	42.56250 *	-2.30912	-2.28991	-2.28974	-0.54857
		(-0.109)	(-0.752)	(-0.780)	(1.720)	(-0.613)	(-0.657)	(-0.657)	(-0.165)
MonthsListed	+	-0.01272	0.02610	0.02963	0.07351	0.04729	0.03455	0.03455	-0.00988
		(-0.203)	(0.472)	(0.488)	(1.320)	(0.751)	(0.615)	(0.615)	(-0.167)
HomeMarket	+	1.29281	1.21492	1.34481	1.14834	1.20641	1.29682	1.29681	0.03641
		(1.570)	(1.330)	(1.450)	(1.340)	(1.450)	(1.530)	(1.530)	(0.043)
USF Volume	+	0.00164 ***							
		(2.650)							
Stock Volume	-		-0.00033						
			(-0.883)						
USF TradeFrequency	+			0.00031					
				(0.010)					
Stock TradeFrequency	-				-0.48800 ***				
					(-588.000)				
USF Spread	-					-22.34060 ***			
						(-3.360)			
Stock Spread	+						10.60240		
							(0.862)		
Volatility	±							-0.10811	
								(-0.005)	
ContractSize	+								1.58276 ***
									(4.290)
Adjusted R^2		0.17	0.11	0.10	0.13	0.20	0.11	0.26	0.18
Number of observations		50	50	50	50	50	50	50	50

Notes:
The dependent variable is the logistic transformation of the USF share in price discovery estimated from the VECM adjustment coefficients. *MonthListed* is the number of months for which a USF has been listed in the Euronext.LIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The USF Volume and Stock Volume are the trading volume of USF and stock markets, respectively. USF TradeFrequency and Stock TradeFrequency are calculated as the average number of trading days over the whole sample period. The variables USF Spread and Stock Spread are the effective spread on these markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. *, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 3.29: Multivariate GARCH Parameter Estimates

This table reports the parameter estimates for the augmented asymmetric BEKK GARCH (1,1)-X model (3.9):

$$H_t = C_0C_0' + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} + D_{11}'\xi_{t-1}\xi_{t-1}'D_{11} + E_{11}(Z_{t-1})^2 E_{11}' \qquad (3.9)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_t = \begin{bmatrix} \xi_{s,t} \\ \xi_{f,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{s,t},0\} \\ \min\{\varepsilon_{f,t},0\} \end{bmatrix}$; $Z_t = (P_{s,t} - P_{f,t})$; assuming $\varepsilon_t \backslash \Omega_t : N(0,H_t)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The above coefficients relating to the volatility transfers are indicated in **bold** characters.

Estimates are obtained using the BFGS numerical optimization algorithm and the method of quasi-maximum likelihood (QML). The robust standard error and associated t-statistics are calculated using the Bollerslev-Wooldridge (1992) approach. Figure in parentheses (.) indicate the robust t-statistics. A single (double) asterisk denotes significance at the 5% (1%) level. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
AA	0.0025 *	0.0025 *	0.0001	-0.3535 **	-0.3238	0.1127	0.2565	-1.3562 **	-0.5969 **	0.5440 **	-0.3917 **	-0.1879	-0.4662 **	-0.0840	0.1157	0.0573	3.2528	1.4426
	(2.175)	(2.537)	(0.111)	(-2.670)	(-1.507)	(1.144)	(1.366)	(-13.448)	(-8.784)	(7.991)	(-9.327)	(-1.223)	(-2.793)	(-0.813)	(0.752)	(0.059)	(0.711)	(0.115)
AGN	0.0099 **	0.0087 **	0.0002	0.5981 **	0.1520	-0.0062 **	0.4840 **	0.0231	0.5359 **	0.1170	-0.0329	0.1662	0.5312 **	0.0548	-0.2763 *	-0.0027 **	9.1313	64.4956 *
	(15.472)	(10.232)	(0.094)	(7.691)	(0.895)	(-5.421)	(3.408)	(0.181)	(3.109)	(1.871)	(-0.284)	(1.168)	(2.689)	(0.554)	(-2.367)	(-6.836)	(0.892)	(2.046)
AHL	0.0106 **	0.0095 **	0.0039 **	0.1430	-0.5694 **	0.0761	0.8760 **	1.9844 *	2.0935 *	-2.0133 *	-2.1228 *	-1.6158	-0.7332	1.6248	-0.1914	0.2316 **	0.1538 *	-0.0093
	(3.089)	(2.595)	(5.665)	(0.673)	(-2.603)	(0.452)	(4.181)	(2.213)	(2.285)	(-2.457)	(-2.555)	(-1.341)	(-0.631)	(1.125)	(-0.132)	(3.210)	(2.054)	(-0.187)
ALV	0.0022 **	0.0022 *	-0.0005	-0.2227 **	0.1504 *	0.0653	-0.3451 **	-0.8006 **	-1.5415 **	-0.1693 **	0.7504 **	-0.3342 **	-0.2113	0.3937 **	0.1608	0.0822 *	0.0085	-0.0871
	(3.053)	(2.477)	(-0.806)	(-2.945)	(2.185)	(0.930)	(-6.815)	(-11.223)	(-41.106)	(-3.392)	(15.581)	(-3.793)	(-1.469)	(3.796)	(0.908)	(2.247)	(0.063)	(-0.692)
AXA	0.0015 **	0.0069 **	0.0000	-0.1584 **	0.4297 **	0.0044	-0.6665 **	-0.9567 **	-0.4709 *	-0.0023	-0.4009	-0.3260 **	-0.5111 **	0.0022	0.1114	0.0004	0.1318	0.0000
	(3.055)	(3.890)	(0.000)	(-3.348)	(3.924)	(0.159)	(-6.466)	(-64.531)	(-2.023)	(-0.243)	(-1.693)	(-5.599)	(-2.629)	(0.432)	(0.600)	(0.375)	(1.804)	(0.000)
AZN	0.0017 **	0.0017 **	0.0000	0.1377 *	-0.1375 *	-0.1145	0.1005	0.0711 **	1.0165 **	0.9203 **	-0.0343 **	0.1395	0.0434	-0.3070 *	-0.1934	-8.6275 **	-8.7841 **	0.0000
	(6.061)	(5.747)	(0.000)	(1.983)	(-2.118)	(-1.804)	(1.310)	(4.705)	(78.487)	(60.146)	(-2.585)	(1.049)	(0.301)	(-2.192)	(-1.217)	(-3.087)	(-3.149)	(0.000)

Table 3.29: Multivariate GARCH Parameter Estimates (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
BAR	0.0093 **	0.0069 **	0.0000	0.6289 **	**1.0447** **	**-0.1276**	-0.5294 **	0.4736 **	**0.1085**	**-0.1154** *	0.5112 **	0.4313 *	**0.0471**	**0.1434**	0.5957 **	-0.0017 *	0.0352 *	0.0000
	(12.166)	(6.118)	(0.000)	(3.236)	**(7.725)**	**(-0.893)**	(-3.536)	(3.428)	**(0.511)**	**(-2.110)**	(4.309)	(2.168)	**(0.223)**	**(1.049)**	(4.367)	(-2.166)	(2.093)	(-0.000)
BNP	0.0011 *	-0.0026 **	0.0000	0.2240 **	**-0.4828** **	**-0.0405**	0.6620 **	0.9556 **	**0.5608** **	**0.0145**	0.4276 **	-0.1653 *	**-0.4150** *	**-0.0137**	0.2652	-0.0028	-0.0886 *	0.0000
	(2.500)	(-4.419)	(-0.000)	(4.207)	**(-4.115)**	**(-1.942)**	(7.345)	(43.863)	**(6.859)**	**(1.085)**	(5.111)	(-2.254)	**(-1.995)**	**(-1.191)**	(1.843)	(-1.752)	(-2.092)	(-0.000)
BPA	0.0056 *	0.0042 *	0.0015	0.6450	**0.1819**	**-0.3118**	0.1634	0.2826	**-0.2172**	**0.4971**	1.0499 **	0.3682	**-0.1387**	**-0.6414**	-0.0858	12.8732	13.1062	2.6634
	(2.341)	(1.986)	(1.721)	(1.853)	**(0.525)**	**(-0.946)**	(0.532)	(0.648)	**(-0.612)**	**(1.461)**	(3.489)	(0.753)	**(-0.298)**	**(-1.245)**	(-0.162)	(1.308)	(1.362)	(0.681)
BTL	0.0017 **	-0.0016 **	-0.0001	0.2024 **	**-0.7109** **	**-0.2263** **	0.5346 **	0.6016 **	**0.8960** **	**0.3931** **	0.0965	-0.0841	**0.3599** **	**0.1850** *	-0.3737 **	-0.0074	-0.1055 **	0.0553
	(4.798)	(-4.168)	(-0.085)	(3.559)	**(-3.879)**	**(-3.857)**	(3.452)	(4.671)	**(11.800)**	**(3.039)**	(1.300)	(-0.891)	**(3.089)**	**(2.005)**	(-2.997)	(-0.488)	(-2.724)	(0.748)
BVA	-0.0003	0.0003	0.0000	-0.0588	**-0.2177** **	**-0.1615** *	-0.0291	0.6757 **	**-0.3282** **	**0.3297** **	1.2304 **	0.1821	**0.1586**	**-0.0702**	-0.1703	0.4907	0.7271	-0.0038
	(-0.969)	(0.988)	(-0.017)	(-0.711)	**(-2.684)**	**(-1.969)**	(-0.350)	(18.488)	**(-8.353)**	**(6.867)**	(30.323)	(1.832)	**(0.986)**	**(-0.989)**	(-1.710)	(0.566)	(0.543)	(-0.009)
CA	0.0018 *	0.0024 *	0.0000	0.0749	**-0.0687**	**0.2177** *	0.3413 **	-0.4774 **	**0.5009** **	**-0.4762** **	-1.3980 **	-0.1094	**-0.0493**	**0.2532** **	0.0919	2.3924	0.0873	0.0000
	(1.994)	(2.330)	(0.000)	(1.119)	**(-0.618)**	**(2.293)**	(2.578)	(-10.742)	**(10.661)**	**(-9.544)**	(-26.699)	(-1.044)	**(-0.385)**	**(2.824)**	(0.920)	(1.443)	(0.070)	(0.000)
CGE	0.0051 **	0.0049 **	0.0000	0.3150	**0.6514** **	**-0.0841**	-0.3681 *	1.3745 **	**0.4981** **	**-2.1969** **	-1.4023 **	-0.0133	**-0.6715** *	**-0.1068**	0.6348 *	-0.0821	-0.0883	0.0000
	(4.280)	(4.430)	(0.000)	(1.838)	**(3.597)**	**(-0.549)**	(-2.155)	(44.622)	**(23.287)**	**(-37.089)**	(-33.389)	(-0.077)	**(-2.181)**	**(-0.631)**	(2.111)	(-0.263)	(-0.267)	(0.000)
CSG	0.0016	0.0005	0.0013 **	-0.0011	**0.2328** **	**0.2740** **	-0.0017	-0.8351 **	**-0.0438**	**-0.1196**	-0.9228 **	-0.3642	**0.1829**	**0.3839**	-0.3055 *	0.3668 **	0.0769	0.0832
	(1.934)	(0.524)	(3.329)	(-0.010)	**(2.873)**	**(3.072)**	(-0.019)	(-11.525)	**(-0.676)**	**(-1.564)**	(-14.036)	(-1.749)	**(1.319)**	**(1.953)**	(-2.238)	(3.688)	(0.483)	(0.617)
DBK	0.0019	0.0019	0.0000	0.1252	**-0.2089**	**0.0535**	0.3939 **	0.6545 **	**1.5227** **	**0.3178**	-0.6127 **	-0.3414	**-0.2150**	**0.2886**	0.0216	-0.0508	0.4911	-0.0086
	(0.816)	(0.823)	(-0.003)	(0.878)	**(-1.340)**	**(0.399)**	(3.369)	(2.769)	**(7.766)**	**(1.571)**	(-3.010)	(-1.406)	**(-0.949)**	**(1.521)**	(0.107)	(-0.015)	(0.097)	(-0.004)
DCY	0.0027	0.0044 **	0.0000	-0.1623 *	**0.3468** **	**-0.0029**	-0.5804 **	0.9101 **	**0.0459**	**0.0380**	0.8431 **	0.1006	**-0.1315**	**-0.3250** **	-0.1485	0.9044	-2.1966 **	0.0000
	(1.863)	(3.049)	(-0.000)	(-2.243)	**(3.658)**	**(-0.028)**	(-4.254)	(24.428)	**(0.864)**	**(0.825)**	(11.876)	(0.901)	**(-1.285)**	**(-2.728)**	(-0.907)	(1.006)	(-2.968)	(0.000)
DTE	-0.0020 **	-0.0015 *	0.0000	-0.0860	**-0.2140**	**0.3529**	0.4115 *	1.0114 **	**0.0661**	**-0.0932**	0.8853 **	-0.4034 **	**-0.2171** **	**0.1663**	-0.0839	0.1038	1.2171	0.0007
	(-2.850)	(-2.506)	(0.003)	(-0.389)	**(-1.130)**	**(1.607)**	(2.312)	(28.057)	**(1.673)**	**(-1.538)**	(17.279)	(-4.108)	**(-3.420)**	**(1.751)**	(-0.803)	(0.088)	(1.588)	(0.003)
ENI	0.0011 **	-0.0035 **	0.0007	-0.0085	**1.0114** **	**0.0756**	-0.7904 **	0.8953 **	**0.8340** **	**0.1066** *	0.0781	0.0057	**0.0426**	**-0.0666**	-0.1198	0.0122 *	-0.1335 *	0.0105
	(5.456)	(-4.445)	(0.176)	(-0.095)	**(6.778)**	**(1.823)**	(-6.917)	(26.867)	**(19.594)**	**(2.571)**	(1.475)	(0.193)	**(0.205)**	**(-0.960)**	(-0.496)	(2.207)	(-2.513)	(0.200)
ENL	0.0087 **	0.0075 **	0.0066 **	0.0018	**0.4409** **	**0.5062** *	0.0784	-0.1040	**-0.4717**	**-0.0560**	0.2112	0.8651 *	**0.0324**	**-0.7019**	-0.4143	0.0060	0.0519	-0.2299 *
	1(2.205)	(4.627)	(2.624)	(0.005)	**(2.740)**	**(2.089)**	(0.249)	(-0.182)	**(-0.486)**	**(-0.208)**	(0.509)	(2.273)	**(0.069)**	**(-1.665)**	(-0.965)	(0.220)	(0.338)	(-2.397)
EOA	0.0015 **	0.0016 **	0.0000	0.0064	**-0.2569** **	**-0.1988** **	0.0387	-0.1723	**0.8095** **	**1.0809** **	0.1995	-0.1503	**-0.2560** **	**0.0206**	0.2871 **	0.1453	-1.5250 **	0.0006
	(4.699)	(4.355)	(0.000)	(0.101)	**(-3.848)**	**(-3.623)**	(0.565)	(-0.515)	**(2.593)**	**(4.058)**	(0.625)	(-0.881)	**(-2.676)**	**(0.217)**	(4.810)	(0.344)	(-2.637)	(0.002)
ERC	0.0007	-0.0002	-0.0003	-0.0033	**0.2731**	**0.1318**	-0.3973	-0.9176 **	**-0.2262**	**-0.0753** **	-0.7673 **	0.0719	**0.4687** **	**-0.0055**	-0.3224 *	0.0242 **	0.0482	-0.0157
	(0.929)	(-0.153)	(-0.090)	(-0.048)	**(0.471)**	**(1.608)**	(-0.767)	(-116.757)	**(-1.817)**	**(-93.013)**	(-6.105)	(0.752)	**(3.359)**	**(-0.060)**	(-2.395)	(2.644)	(1.117)	(-0.323)
FTE	0.0015 **	0.0023 *	0.0017 **	-0.1486	**-0.6643** **	**0.2788** **	0.7097 **	1.3547 **	**1.9285** **	**-0.4141** **	-1.0864 **	0.4130 **	**0.2088**	**-0.1441**	0.1310	0.0863 *	0.1331	0.0974 **
	(4.165)	(1.976)	(3.936)	(-1.539)	**(-4.534)**	**(3.659)**	(4.784)	(230.232)	**(19.602)**	**(-58.773)**	(-12.510)	(4.240)	**(1.815)**	**(-1.611)**	(1.111)	(2.221)	(1.589)	(3.050)

Table 3.29: Multivariate GARCH Parameter Estimates (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
GEN	0.0008	0.0010	-0.0003	0.4107 **	0.3097	-0.1444	-0.0496	0.8557 **	-0.1287 *	0.1092 *	1.0705 **	-0.0553	-0.3147 *	-0.0396	0.2179	-2.8578	-5.5673	-1.5016
	(1.637)	(1.868)	(-0.912)	(2.960)	(1.382)	(-1.151)	(-0.236)	(15.600)	(-2.209)	(2.069)	(18.471)	(-0.399)	(-2.472)	(-0.383)	(1.559)	(-0.904)	(-1.176)	(-0.377)
GXW	0.0002	0.0002	0.0000	0.0209 **	0.0167	-0.0072	-0.0084	-1.0178 **	-0.0254 **	0.0196 **	-0.9733 **	-0.1145 **	-0.2002 **	0.1565 **	0.2654 **	-2.6683 *	2.0076	0.1314
	(1.649)	(1.299)	(-0.058)	(4.430)	(1.536)	(-1.787)	(-0.656)	(-1568.165)	(-143.307)	(69.055)	(-1387.502)	(-8.483)	(-27.532)	(9.858)	(15.459)	(-2.240)	(1.721)	(0.104)
HAS	0.0010 *	0.0033 **	0.0000	-0.0552	-0.4099 **	0.1421 *	0.5403 **	1.2007 **	1.4303 **	-0.2593 **	-0.6918 **	-0.0376	-0.6042 **	-0.2234 *	0.2485	2.4704	9.0704 **	0.0413
	(2.267)	(6.572)	(0.015)	(-0.874)	(-2.722)	(2.392)	(4.720)	(31.006)	(11.792)	(-5.100)	(-6.794)	(-0.457)	(-3.378)	(-2.461)	(1.388)	(1.620)	(2.948)	(0.017)
HNM	0.0079 **	0.0084 **	0.0000	0.2651	0.1919	0.4693 **	0.5495 **	0.2212	-0.6269 **	0.4101 *	1.1298 **	0.2129	-0.3564	-0.1312	0.6221	1.4155	-2.6541	0.0000
	(5.618)	(5.886)	(-0.000)	(1.649)	(1.073)	(2.616)	(2.829)	(1.659)	(-3.527)	(2.303)	(5.010)	(0.794)	(-1.090)	(-0.512)	(1.644)	(0.744)	(-0.974)	(-0.000)
ING	0.0017 **	-0.0028 **	0.0000	0.2659 **	-0.3808	-0.0100	0.7532 **	0.9186 **	0.5880 **	0.0232	0.3551 **	-0.2804 **	0.1866	0.0027	-0.2571	-0.0007	-0.1238	0.0000
	(3.896)	(-5.261)	(0.000)	(4.968)	(-1.565)	(-0.412)	(4.373)	(30.820)	(4.271)	(1.250)	(2.679)	(-2.949)	(0.787)	(0.275)	(-1.272)	(-0.419)	(-1.943)	(-0.000)
LLO	0.0009	-0.0012	0.0046 **	0.1749 *	-0.1210	0.0799	0.4189 **	-0.7486 **	-0.6209 *	-0.2206 *	-0.3028	0.1249	-0.4879	-0.0692	0.3141	1.5958	-1.7136	-2.0702 *
	(1.472)	(-0.914)	(5.084)	(2.320)	(-0.707)	(1.665)	(2.867)	(-7.791)	(-2.057)	(-2.506)	(-0.996)	(0.890)	(-0.859)	(-0.652)	(0.435)	(1.863)	(-1.712)	(-2.302)
MUV	0.0023 **	0.0023 **	0.0005 *	0.1425	0.3452 **	-0.2761 **	-0.4284 **	0.8496 **	1.6657 **	0.1153 **	-0.8121 **	-0.0857	0.2256 *	0.0415	-0.3568 **	0.4753 **	0.6443	0.6645 **
	(4.434)	(2.776)	(1.972)	(1.540)	(3.681)	(-3.721)	(-4.866)	(20.469)	(40.432)	(4.398)	(-36.327)	(-0.960)	(2.096)	(0.389)	(-2.881)	(2.857)	(1.038)	(3.318)
NDA	-0.0025 **	-0.0010	0.0017 **	0.5749 **	-0.5792 *	-0.4217	0.8748 **	0.8549 **	0.3393 **	0.0715	0.5814 **	-0.3993	-0.6702 *	0.0066	0.3034	-3.2966 *	1.0776	1.6205
	(-5.967)	(-1.334)	(3.405)	(2.649)	(-2.334)	(-1.911)	(3.586)	(9.742)	(3.834)	(0.785)	(6.098)	(-1.544)	(-2.156)	(0.031)	(1.119)	(-2.528)	(0.692)	(0.820)
NES	0.0011	0.0030 **	0.0000	0.0899	0.4309 **	0.0080	-0.1438	0.9473 **	0.1254	0.0242	0.7658 **	0.1316	-0.0804	0.1365	0.3623 **	-3.6562	2.0648	0.0009
	(1.467)	(4.715)	(-0.002)	(0.724)	(2.748)	(0.154)	(-1.123)	(14.832)	(1.715)	(0.264)	(8.910)	(1.538)	(-0.706)	(1.224)	(2.990)	(-1.609)	(0.708)	(0.001)
NOV	0.0034 **	0.0049 **	0.0000	0.3655	-0.2149	-0.4140 **	-0.0072	1.2477 *	1.2908 **	-0.5043	-0.8400	-0.5983 **	0.0631	0.2300	-0.4270 **	7.5250	17.8940 **	-0.0001
	(3.458)	(7.934)	(-0.000)	(1.650)	(-1.271)	(-3.081)	(-0.051)	(2.385)	(3.139)	(-0.673)	(-1.163)	(-3.382)	(0.374)	(1.358)	(-3.993)	(1.779)	(2.827)	(-0.000)
PHI	0.0013 **	0.0052 **	0.0000	0.1638 **	0.3230 **	0.1020 *	-0.1940 **	0.8928 **	1.1766 **	0.0695 **	-0.2481 **	-0.1920 *	-1.0562 **	0.1654	1.0651 **	-1.0315	9.7647 **	-0.0013
	(3.930)	(9.182)	(-0.000)	(3.755)	(6.084)	(2.037)	(-3.963)	(1154.077)	(14.439)	5(5.312)	(-2.654)	(-1.979)	(-6.548)	(1.711)	(6.133)	(-0.637)	(2.645)	(-0.000)
RBO	0.0013 **	-0.0005	0.0000	0.2694 **	-0.1075	-0.1681 *	0.1938 *	0.9346 **	0.1026 **	0.0548 *	0.8962 **	-0.0808	0.0606	0.1445 *	-0.1326 *	-7.3535 **	6.0855 **	-0.0193
	(3.985)	(-1.237)	(0.012)	(4.201)	(-1.357)	(-2.360)	(2.383)	(40.826)	(3.569)	(2.337)	(31.004)	(-1.485)	(1.422)	(2.371)	(-2.260)	(-5.077)	(2.604)	(-0.011)
RD	0.0008	-0.0019 *	0.0000	0.1942 **	-0.3646 **	-0.0040	0.6239 **	0.9751 **	0.9637 **	0.0015	0.0015	0.0027	-1.1611	-0.0035	2.2638 **	0.0009	-0.0001	0.0000
	(1.110)	(-2.028)	(-0.000)	(3.640)	(-3.571)	(-0.972)	(7.920)	(75.045)	(66.442)	(1.750)	(1.249)	(0.263)	(-1.492)	(-0.632)	(2.583)	(1.110)	(-0.043)	(-0.000)
ROG	0.0075 **	0.0080 **	0.0002	0.3817	0.0849	0.1625	0.4391	1.0583 **	0.3729	-1.0350 **	-0.6497 **	0.9105 **	1.0346 **	-0.9214 **	-0.8946 *	13.2981 *	13.4327	4.2335
	(11.439)	(11.435)	(0.428)	(1.053)	(0.245)	(0.445)	(1.295)	(5.385)	(1.660)	(-3.846)	(-2.665)	(3.459)	(3.229)	(-2.738)	(-2.029)	(2.037)	(1.520)	(0.882)
SCH	-0.0002	-0.0007	-0.0002	0.2818 **	0.0896	-0.1245 *	0.1203	0.9232 **	-0.0150	0.0619 *	0.9841 **	0.0053	0.2385 **	-0.1436	-0.2107 *	0.6083	-0.0040	-3.6967
	(-0.665)	(-1.226)	(-0.167)	(3.480)	(1.135)	(-2.370)	(1.447)	(31.714)	(-0.387)	(2.324)	(25.218)	(0.053)	(2.696)	(-1.900)	(-2.301)	(0.101)	(-0.000)	(-0.581)
SHB	0.0004	-0.0008	0.0028 *	-0.2226	0.2944 *	0.1956	-0.1187	0.3115	0.4277	0.6721	0.5166 *	0.0954	-0.1426	-0.4125	-0.1350	4.7552	-2.7144	1.0548
	(0.489)	(-0.261)	(2.137)	(-1.668)	(2.438)	(1.481)	(-1.024)	(0.850)	(1.679)	(1.919)	(2.165)	(0.492)	(-1.098)	(-1.876)	(-0.722)	(1.539)	(-1.493)	(0.710)
SHE	0.0083 **	0.0085 **	-0.0003	-0.4421	-0.1406	0.0009	-0.3286	0.1798	-0.8282 *	-0.1336	0.7328 **	2.9083 **	3.1496 **	-3.7016 **	-4.2008 **	0.0411	-0.0050	-0.0212
	(13.492)	(8.064)	(-0.211)	(-1.957)	(-0.389)	(0.005)	(-1.172)	(0.547)	(-2.465)	(-0.485)	(2.636)	(3.336)	(3.174)	(-3.609)	(-3.617)	(1.128)	(-0.128)	(-0.225)

Table 3.29: Multivariate GARCH Parameter Estimates (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
SIE	0.0004 **	0.0010 **	0.0000	-0.0698	0.2656 **	0.0148	-0.3242 **	-0.9869 **	-0.0420 **	-0.0108 **	-0.9437 **	0.0417	0.0261	-0.0002	0.0692	0.0152 **	-0.0672	0.0775 **
	(2.814)	(5.337)	(0.066)	(-1.753)	(5.255)	(0.884)	(-7.532)	(-336.496)	(-4.158)	(-6.993)	(-76.602)	(0.607)	(0.291)	(-0.034)	(1.259)	(3.245)	(-1.224)	(3.011)
TEF	0.0015	0.0035 **	0.0000	0.0724	0.4519 **	0.1738 **	0.0097	0.8930 **	1.1618 **	0.0503	-0.5767 *	-0.0375	0.2808 *	-0.0469	-0.3837 *	0.1079	0.1599 **	0.0001
	(1.477)	(4.738)	(-0.079)	(0.640)	(4.267)	(2.640)	(0.079)	(4.499)	(9.119)	(0.178)	(-2.353)	(-0.244)	(2.042)	(-0.224)	(-2.034)	(1.935)	(3.028)	(0.002)
TI	0.0089 **	0.0085 **	0.0036 **	0.5652 *	-0.1258	-0.8397 **	0.1137	-0.0095	0.0054	-0.0025	-0.0170	-0.4921	-0.2524 *	0.2779	-0.0282	0.0050 **	-0.0021 **	0.0323 *
	(20.867)	(17.462)	(11.528)	(2.228)	(-0.782)	(-3.135)	(0.552)	(-1.240)	(0.086)	(-0.062)	(-0.041)	(-1.822)	(-2.243)	(0.910)	(-0.299)	(6.445)	(-2.582)	(2.429)
TIM	0.0062 **	0.0093 **	0.0004	0.3561	-0.4679	-0.3199	0.5320 **	0.1625	0.2473	0.4576 *	-0.0177	0.0254	-0.0668	0.2669	0.4254 *	2.3324 **	2.4028 **	-0.4023
	(5.546)	(8.692)	(0.046)	(1.719)	(-1.633)	(-0.968)	(2.635)	(0.712)	(1.132)	(2.570)	(-0.108)	(0.199)	(-0.673)	(1.328)	(2.072)	(5.256)	(3.423)	(-0.044)
TLI	-0.0002	0.0008	-0.0001	-0.2253	0.3033 **	0.3734 *	-0.2415 *	0.2428	0.7925	0.7583 *	0.1865	-0.1289	0.2078	0.1701	-0.0731	-0.0914	2.9723	-0.4425
	(-0.308)	(1.580)	(-0.029)	(-1.456)	(3.376)	(2.327)	(-2.208)	(0.689)	(1.928)	(2.173)	(0.435)	(-1.145)	(1.178)	(0.983)	(-0.487)	(-0.087)	(1.456)	(-0.029)
TOT	-0.0016 **	-0.0013 **	-0.0004	0.2932 *	0.2496	-0.0204	-0.0415	0.9791 **	0.0372 *	-0.0294	0.9334 **	0.1844 *	0.0862	-0.1456 **	0.0315	0.7706	2.5613 **	-1.3846
	(-2.845)	(-2.842)	(-1.382)	(2.347)	(1.930)	(-0.242)	(-0.466)	(37.077)	(2.180)	(-0.989)	(39.775)	(2.230)	(0.922)	(-2.683)	(0.470)	(0.708)	(3.134)	(-1.374)
UBS	0.0016 *	0.0023 **	0.0000	0.3364 **	0.1355	-0.0300	0.1830 *	-0.8382 **	0.1358 **	-0.0899	-1.0037 **	0.3471 **	0.5672 **	-0.2798 *	-0.3483 **	1.3771 *	0.6901	1.4649 *
	(2.512)	(3.777)	(-0.043)	(4.762)	(1.526)	(-0.546)	(2.189)	(-24.038)	(3.131)	(-1.372)	(-14.948)	(2.597)	(4.052)	(-2.350)	(-2.881)	(2.072)	(0.702)	(2.211)
UC	-0.0009	0.0028 **	0.0000	0.0811	0.3074 **	0.2526 **	-0.0016	-0.0340	0.5864 **	0.9357 **	0.3812	0.1733	0.0115	0.0636	-0.0946	-3.8976 **	1.2798	-0.0002
	(-1.205)	(2.849)	(-0.000)	(0.847)	(4.235)	(3.950)	(-0.024)	(-0.123)	(2.781)	(4.151)	(1.564)	(1.330)	(0.106)	(0.492)	(-0.887)	(-3.741)	(1.800)	(-0.001)
VIV	0.0010	0.0009	0.0000	-0.2901	-0.3749 *	0.0410	0.1855	-1.0075 **	-0.0643	0.0435	-0.9114 **	-0.3113	-0.1514	0.2552	0.0079	-1.5521	-0.7982	0.0002
	(1.754)	(1.589)	(0.001)	(-1.480)	(-2.420)	(0.260)	(1.683)	(-27.056)	(-1.316)	(1.032)	(-18.044)	(-0.677)	(-0.361)	(1.275)	(0.038)	(-0.500)	(-0.142)	(0.000)
VOF	0.0030 **	-0.0004	0.0043 **	0.1749	-0.0640	0.1332	0.2702	0.4573 **	0.5061 **	0.4615 **	0.4316 **	-0.3978	-0.3501	0.7070	0.6663	-20.9163 **	23.8181 **	-10.0413
	(3.178)	(-0.173)	(5.252)	(0.561)	(-0.223)	(0.319)	(0.683)	(9.339)	(9.016)	(28.579)	(24.342)	(-1.339)	(-1.254)	(1.683)	(1.645)	(-3.135)	(3.350)	(-1.291)
VOW	0.0046 **	0.0042 **	0.0000	-0.0393	-0.3681 **	-0.1602	0.2250 **	0.8873 **	-0.0256	0.0059	0.9422 **	-0.4223 **	-0.4274	0.2076 **	0.2152	3.7304 *	1.1310	0.0000
	(4.920)	(4.234)	(-0.000)	(-0.306)	(-3.141)	(-1.795)	(2.741)	(28.020)	(-0.819)	(0.203)	(45.817)	(-4.267)	(-1.931)	(2.889)	(0.820)	(2.503)	(0.889)	(-0.000)

Table 3.30: Volatility Spillovers Joint Hypothesis Tests P-Values

This table reports the p-values associated with the Wald tests of the null hypotheses in the augmented asymmetric BEKK GARCH (1,1)-X model (3.9):

$$H_t = C_0 C_0' + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} + D_{11}' \xi_{t-1} \xi_{t-1}' D_{11} + E_{11} (Z_{t-1})^2 E_{11}' \qquad (3.9)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_t = \begin{bmatrix} \xi_{s,t} \\ \xi_{f,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{s,t}, 0\} \\ \min\{\varepsilon_{f,t}, 0\} \end{bmatrix}$; $Z_t = (P_{s,t} - P_{f,t})$; assuming $\varepsilon_t \setminus \Omega_t : N(0, H_t)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The above coefficients relating to the volatility transfers are indicated in **bold** characters.

Estimates are obtained using the BFGS numerical optimization algorithm and the method of quasi-maximum likelihood (QML). The robust standard error and associated t-statistics are calculated using the Bollerslev-Wooldridge (1992) approach. A single (double) asterisk denotes significance at the 5% (1%) level. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

	Null Hypotheses							
	Stock-to-USF Spillover		USF-to-Stock Spillover		Stock-to-USF Asym. Spillover		USF-to-Stock Asym. Spillover	
Stock	$H_{0,1}$: ($a_{1,2} = b_{1,2} = 0$)		$H_{0,2}$: ($a_{2,1} = b_{2,1} = 0$)		$H_{0,3}$: ($a_{1,2} = b_{1,2} = d_{1,2} = 0$)		$H_{0,4}$: ($a_{2,1} = b_{2,1} = d_{2,1} = 0$)	
AA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
AGN	0.0036	**	0.0000	**	0.0023	**	0.0000	**
AHL	0.0000	**	0.0168	*	0.0000	**	0.0306	*
ALV	0.0000	**	0.0030	**	0.0000	**	0.0022	**
AXA	0.0000	**	0.9665		0.0000	**	0.8110	
AZN	0.0000	**	0.0000	**	0.0000	**	0.0000	**
BAR	0.0000	**	0.0842		0.0000	**	0.1566	
BNP	0.0000	**	0.0780		0.0000	**	0.1002	
BPA	0.8122		0.3429		0.8542		0.4170	
BTL	0.0000	**	0.0003	**	0.0000	**	0.0008	**
BVA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
CA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
CGE	0.0000	**	0.0000	**	0.0000	**	0.0000	**
CSG	0.0148	*	0.0040	**	0.0170	*	0.0071	**
DBK	0.0000	**	0.2909		0.0000	**	0.3243	
DCY	0.0011	**	0.6485		0.0004	**	0.0290	*
DTE	0.2466		0.2624		0.0000	**	0.0004	**
ENI	0.0000	**	0.0111	*	0.0000	**	0.0000	**
ENL	0.0011	**	0.0685		0.0000	**	0.0641	

Table 3.30: Volatility Spillovers Joint Hypothesis Tests P-Values (continued)

Stock	Null Hypotheses							
	Stock-to-USF Spillover $H_{0,1}$: $(a_{1,2} = b_{1,2} = 0)$		USF-to-Stock Spillover $H_{0,2}$: $(a_{2,1} = b_{2,1} = 0)$		Stock-to-USF Asym. Spillover $H_{0,3}$: $(a_{1,2} = b_{1,2} = d_{1,2} = 0)$		USF-to-Stock Asym. Spillover $H_{0,4}$: $(a_{2,1} = b_{2,1} = d_{2,1} = 0)$	
EOA	0.0003	**	0.0000	**	0.0000	**	0.0000	**
ERC	0.1817		0.0000	**	0.0008	**	0.0000	**
FTE	0.0000	**	0.0000	**	0.0000	**	0.0000	**
GEN	0.0785		0.1161		0.0000	**	0.0747	
GXW	0.0000	**	0.0000	**	0.0000	**	0.0000	**
HAS	0.0000	**	0.0000	**	0.0000	**	0.0000	**
HNM	0.0006	**	0.0092	**	0.0000	**	0.0242	*
ING	0.0000	**	0.0541		0.0000	**	0.1001	
LLO	0.0009	**	0.0014	**	0.0029	**	0.0044	**
MUV	0.0000	**	0.0000	**	0.0000	**	0.0001	**
NDA	0.0006	**	0.0193	*	0.0007	**	0.0462	*
NES	0.0096	**	0.9651		0.0239	*	0.0225	*
NOV	0.0072	**	0.0076	**	0.0193	*	0.0109	*
PHI	0.0000	**	0.0000	**	0.0000	**	0.0000	**
RBO	0.0005	**	0.0355	*	0.0015	**	0.0076	**
RD	0.0000	**	0.2089		0.0000	**	0.0062	**
ROG	0.2518		0.0003	**	0.0036	**	0.0000	**
SCH	0.5028		0.0318	*	0.0019	**	0.0157	*
SHB	0.0505		0.0422	*	0.1116		0.0575	
SHE	0.0257	*	0.8741		0.0006	**	0.0026	**
SIE	0.0000	**	0.0000	**	0.0000	**	0.0000	**
TEF	0.0000	**	0.0300	*	0.0000	**	0.0670	
TI	0.7056		0.0006	**	0.0492	*	0.0008	**
TIM	0.2595		0.0151	*	0.4252		0.0129	*
TLI	0.0033	**	0.0577		0.0095	**	0.0248	*
TOT	0.0077	**	0.6109		0.0035	**	0.0206	*
UBS	0.0035	**	0.3614		0.0000	**	0.0048	**
UC	0.0001	**	0.0000	**	0.0000	**	0.0000	**
VIV	0.0078	**	0.5846		0.0165	*	0.3103	
VOF	0.0000	**	0.0000	**	0.0000	**	0.0000	**
VOW	0.0010	**	0.0618		0.0000	**	0.0045	**
Cannot be rejected		9		18		3		11
Rejected		41		32		47		39

Table 3.31: Volatility Responses to a Lagged Cross-Market Shock/News

	Effect of Past Stock News on Current USF Volatility		Effect of Past USF News on Current Stock Volatility	
	GOOD News $\varepsilon_{S,t-1} > 0$	BAD News $\varepsilon_{S,t-1} < 0$	GOOD News $\varepsilon_{F,t-1} > 0$	BAD News $\varepsilon_{F,t-1} < 0$
Code	$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \setminus \varepsilon_{F,t-1} = 2a_{12}^2 \varepsilon_{S,t-1}$	$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \setminus \varepsilon_{F,t-1} = 2a_{12}^2 \varepsilon_{S,t-1} + 2d_{12}^2 \xi_{S,t-1}$	$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \setminus \varepsilon_{S,t-1} = 2a_{21}^2 \varepsilon_{F,t-1}$	$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \setminus \varepsilon_{S,t-1} = 2a_{21}^2 \varepsilon_{F,t-1} + 2d_{21}^2 \xi_{F,t-1}$
AA	0.0105	-0.0322	0.0013	-0.0020
AGN	0.0023	-0.0305	0.0000	-0.0003
AHL	0.0324	-0.0862	0.0006	-0.2646
ALV	0.0023	-0.0067	0.0004	-0.0159
AXA	0.0185	-0.0446	0.0000	0.0000
AZN	0.0019	-0.0021	0.0013	-0.0107
BAR	0.1091	-0.1094	0.0016	-0.0037
BNP	0.0233	-0.0405	0.0002	-0.0002
BPA	0.0033	-0.0052	0.0097	-0.0509
BTL	0.0505	-0.0635	0.0051	-0.0085
BVA	0.0047	-0.0073	0.0026	-0.0031
CA	0.0005	-0.0007	0.0047	-0.0112
CGE	0.0424	-0.0875	0.0007	-0.0018
CSG	0.0054	-0.0088	0.0075	-0.0222
DBK	0.0044	-0.0090	0.0003	-0.0086
DCY	0.0120	-0.0138	0.0000	-0.0106
DTE	0.0046	-0.0093	0.0125	-0.0152
ENI	0.1023	-0.1025	0.0006	-0.0010
ENL	0.0194	-0.0195	0.0256	-0.0749
EOA	0.0066	-0.0132	0.0040	-0.0040
ERC	0.0075	-0.0294	0.0017	-0.0017
FTE	0.0441	-0.0485	0.0078	-0.0098
GEN	0.0096	-0.0195	0.0021	-0.0022
GXW	0.0000	-0.0040	0.0000	-0.0025

Table 3.31: Volatility Responses to a Lagged Cross-Market Shock/News (continued)

	Effect of Past Stock News on Current USF Volatility		Effect of Past USF News on Current Stock Volatility	
	GOOD News $\varepsilon_{S,t-1} > 0$	BAD News $\varepsilon_{S,t-1} < 0$	GOOD News $\varepsilon_{F,t-1} > 0$	BAD News $\varepsilon_{F,t-1} < 0$
Code	$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \setminus \varepsilon_{F,t-1} = 2a_{12}^2 \varepsilon_{S,t-1}$	$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \setminus \varepsilon_{F,t-1} = 2a_{12}^2 \varepsilon_{S,t-1} + 2d_{12}^2 \xi_{S,t-1}$	$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \setminus \varepsilon_{S,t-1} = 2a_{21}^2 \varepsilon_{F,t-1}$	$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \setminus \varepsilon_{S,t-1} = 2a_{21}^2 \varepsilon_{F,t-1} + 2d_{21}^2 \xi_{F,t-1}$
HAS	0.0168	-0.0533	0.0020	-0.0070
HNM	0.0037	-0.0164	0.0220	-0.0237
ING	0.0145	-0.0180	0.0000	0.0000
LLO	0.0015	-0.0253	0.0006	-0.0011
MUV	0.0119	-0.0170	0.0076	-0.0078
NDA	0.0335	-0.0785	0.0178	-0.0178
NES	0.0186	-0.0192	0.0000	-0.0019
NOV	0.0046	-0.0050	0.0171	-0.0224
PHI	0.0104	-0.1220	0.0010	-0.0038
RBO	0.0012	-0.0015	0.0028	-0.0049
RD	0.0133	-0.1481	0.0000	0.0000
ROG	0.0007	-0.1078	0.0026	-0.0875
SCH	0.0008	-0.0065	0.0015	-0.0036
SHB	0.0087	-0.0107	0.0038	-0.0208
SHE	0.0020	-0.9940	0.0000	-1.3702
SIE	0.0071	-0.0071	0.0000	0.0000
TEF	0.0204	-0.0283	0.0030	-0.0032
TI	0.0016	-0.0080	0.0705	-0.0782
TIM	0.0219	-0.0223	0.0102	-0.0174
TLI	0.0092	-0.0135	0.0139	-0.0168
TOT	0.0062	-0.0070	0.0000	-0.0022
UBS	0.0018	-0.0340	0.0001	-0.0079
UC	0.0094	-0.0095	0.0064	-0.0068
VIV	0.0141	-0.0164	0.0002	-0.0067
VOF	0.0004	-0.0127	0.0018	-0.0518
VOW	0.0136	-0.0318	0.0026	-0.0069
Average Volatility Responses	0.0153	-0.0459	0.0056	-0.0522
	1.53%	-4.59%	0.56%	-5.22%

Table 3.32: Diagnostic Tests of the Asymmetric BEKK GARCH (1,1)-X Model

Code	Dep Var	Mean	Variance	Skewness	Excess Kurtosis	Jarque-Bera	Q(4)	$Q^2(4)$	Sign-Bias (t-test)	Negative-Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F test)
AA	R_s	0.0363	0.9826	-0.0785	1.1714 **	61.3470 **	3.0293	3.1121	-0.9334	-0.2095	2.2141 *	6.3872
				(0.299)	(0.000)	(0.000)	(0.082)	(0.078)				(0.094)
	R_f	0.0056	1.0000	-0.1991 **	2.2536 **	230.0121 **	0.5928	4.3959 *	-0.0119	-0.6726	2.2152 *	8.6760 *
				(0.008)	(0.000)	(0.000)	(0.441)	(0.036)				(0.034)
AGN	R_s	-0.0262	0.9808	0.1414	4.5207 **	901.0439 **	2.5710	3.6109	0.5598	0.5693	-0.4041	1.6545
				(0.061)	(0.000)	(0.000)	(0.109)	(0.057)				(0.647)
	R_f	0.0609	0.9405	10.8099 **	248.8012 **	2739059.1996 **	4.7882 *	0.0201	-0.5628	0.3596	-0.1206	0.4002
				(0.000)	(0.000)	(0.000)	(0.029)	(0.887)				(0.940)
AHL	R_s	-0.0026	0.9523	-3.2232 **	53.7204 **	128563.2721 **	10.9366 **	0.0993	0.9119	-0.0436	-0.1434	1.1951
				(0.000)	(0.000)	(0.000)	(0.001)	(0.753)				(0.754)
	R_f	0.0076	0.9593	29.5409 **	924.9755 **	37727501.8063 **	8.9935 **	0.1890	0.8079	0.2634	-0.2349	1.1883
				(0.000)	(0.000)	(0.000)	(0.003)	(0.664)				(0.756)
ALV	R_s	-0.0039	1.0054	-0.0526	1.5213 **	117.2445 **	7.8956 **	2.6424	-0.2616	0.3423	1.0377	1.4089
				(0.456)	(0.000)	(0.000)	(0.005)	(0.104)				(0.703)
	R_f	0.0176	0.9793	-0.0258	1.1598 **	67.9548 **	15.9711 **	4.2905 *	0.3319	-0.0678	0.8473	2.1230
				(0.714)	(0.000)	(0.000)	(0.000)	(0.038)				(0.547)
AXA	R_s	-0.0122	0.9820	-0.1523 *	1.3188 **	92.3636 **	68.2705 **	1.6368	0.3710	-1.0280	0.8997	3.4376
				(0.031)	(0.000)	(0.000)	(0.000)	(0.201)				(0.329)
	R_f	0.0028	0.8661	-0.3399 **	1.9635 **	217.6722 **	79.9415 **	1.8988	-0.0775	-0.4428	0.8528	1.4891
				(0.000)	(0.000)	(0.000)	(0.000)	(0.168)				(0.685)
AZN	R_s	0.0032	1.0135	-0.1276	5.2022 **	1425.3427 **	2.8242	0.5748	0.0775	1.1446	1.1085	4.2386
				(0.065)	(0.000)	(0.000)	(0.093)	(0.448)				(0.237)
	R_f	0.0258	1.0101	-0.1694 *	5.5251 **	1609.9342 **	4.3958 *	0.7167	-1.0518	1.8096	0.8267	3.3322
				(0.014)	(0.000)	(0.000)	(0.036)	(0.397)				(0.343)
BAR	R_s	-0.0136	0.9710	0.0177	2.0985 **	217.3147 **	18.5546 **	25.3708 **	-1.0004	1.3123	0.5077	1.7845
				(0.804)	(0.000)	(0.000)	(0.000)	(0.000)				(0.618)
	R_f	-0.0188	0.9526	-3.3274 **	53.1260 **	141421.6635 **	39.3470 **	0.0373	-1.0295	0.3697	0.2611	1.2162
				(0.000)	(0.000)	(0.000)	(0.000)	(0.847)				(0.749)
BNP	R_s	0.0107	0.9924	-0.0316	1.6551 **	135.3318 **	63.8904 **	8.3184 **	0.0926	-1.5938	1.3862	7.4922
				(0.657)	(0.000)	(0.000)	(0.000)	(0.004)				(0.058)
	R_f	0.0053	0.9549	-2.2687 **	32.0811 **	51789.4659 **	67.3602 **	0.0663	1.4183	-0.5605	0.0066	3.0837
				(0.000)	(0.000)	(0.000)	(0.000)	(0.797)				(0.379)
BPA	R_s	0.0054	0.9767	0.0525	4.4499 **	1040.9775 **	5.5791 *	6.4844 *	-0.5242	-1.1402	1.0318	4.5978
				(0.447)	(0.000)	(0.000)	(0.018)	(0.011)				(0.204)
	R_f	0.0215	0.9910	-0.0816	4.0109 **	846.6338 **	3.8359	5.4093 *	-0.3728	-0.9956	1.0819	3.7581
				(0.238)	(0.000)	(0.000)	(0.050)	(0.020)				(0.289)
BTL	R_s	-0.0154	1.0022	0.1008	2.7812 **	392.0220 **	4.7630 *	2.6145	-0.9025	-0.9535	-0.5824	6.7337
				(0.153)	(0.000)	(0.000)	(0.029)	(0.106)				(0.081)
	R_f	-0.0065	1.0055	-0.0745	4.4741 **	1010.3223 **	11.9274 **	0.3095	-0.7988	-0.2240	0.2942	1.4328
				(0.290)	(0.000)	(0.000)	(0.001)	(0.578)				(0.698)
BVA	R_s	0.0111	0.9915	0.3147 **	1.6941 **	161.1254 **	8.0272 **	4.2815 *	0.7334	-1.4792	0.0067	2.6428
				(0.000)	(0.000)	(0.000)	(0.005)	(0.039)				(0.450)
	R_f	-0.0401	1.0005	0.2237 **	1.1825 **	78.8498 **	13.1097 **	6.5307 *	0.4482	-1.6819	0.7864	5.4224
				(0.002)	(0.000)	(0.000)	(0.000)	(0.011)				(0.143)
CA	R_s	-0.0352	0.9833	0.2587 **	3.5105 **	621.1595 **	13.2857 **	3.1774	0.0360	-0.7286	0.5176	1.2858
				(0.000)	(0.000)	(0.000)	(0.000)	(0.075)				(0.732)
	R_f	-0.0171	0.9889	0.3711 **	4.5191 **	1034.6599 **	11.0961 **	2.9963	0.8133	-0.5721	-0.1721	0.8692
				(0.000)	(0.000)	(0.000)	(0.001)	(0.083)				(0.833)
CGE	R_s	-0.0433	0.9452	-0.6098 **	7.2878 **	2868.7477 **	7.2224 **	1.9198	0.6993	0.0550	0.1076	1.2899
				(0.000)	(0.000)	(0.000)	(0.007)	(0.166)				(0.732)
	R_f	0.0057	0.9969	-0.4398 **	8.6142 **	3939.4783 **	5.0272 *	2.1824	1.6817	-0.5176	-0.3538	3.7793
				(0.000)	(0.000)	(0.000)	(0.025)	(0.140)				(0.286)
CSG	R_s	-0.0070	0.9821	-0.3271 **	2.1571 **	222.7248 **	9.9357 **	4.5963 *	0.1462	-0.5418	1.1894	3.1058
				(0.000)	(0.000)	(0.000)	(0.002)	(0.032)				(0.376)
	R_f	0.0018	0.9927	-0.1443	1.7412 **	136.5503 **	10.7639 **	10.6293 **	1.5746	-0.9784	1.1802	10.4301 *
				(0.056)	(0.000)	(0.000)	(0.001)	(0.001)				(0.015)
DBK	R_s	0.0015	0.9957	0.2390 **	1.9314 **	208.0008 **	8.3439 **	2.8613	-0.3466	-1.0365	0.8444	3.3703
				(0.001)	(0.000)	(0.000)	(0.004)	(0.091)				(0.338)
	R_f	-0.0053	0.9770	0.1286	1.7296 **	160.6470 **	3.4833	5.1067 *	-0.9477	-0.2077	1.2441	2.7461
				(0.063)	(0.000)	(0.000)	(0.062)	(0.024)				(0.432)
DCY	R_s	-0.0026	0.9969	0.5449 **	4.0872 **	882.7097 **	2.8788	1.3569	-2.4091	0.9162	2.9658	10.0548 *
				(0.000)	(0.000)	(0.000)	(0.090)	(0.244)				(0.018)
	R_f	0.9960	6.0161	0.3101 **	4.2979 **	930.2352 **	9.5753 **	0.7847	-1.5053	0.5444	1.7022	3.5277
				(0.000)	(0.000)	(0.000)	(0.002)	(0.376)				(0.317)
DTE	R_s	-0.0657	0.9953	0.0418	0.7084 **	26.7337 **	10.9120 **	0.5052	-1.7605	1.9204	1.9913 *	5.3895
				(0.545)	(0.000)	(0.000)	(0.001)	(0.477)				(0.145)
	R_f	-0.0364	1.0040	0.0208	1.3031 **	89.3107 **	3.8709 *	2.3328	-2.6587 **	1.7146	2.2452 *	7.4759
				(0.763)	(0.000)	(0.000)	(0.049)	(0.127)				(0.058)
ENI	R_s	0.0459	1.0091	-0.3843 **	1.7664 **	194.9753 **	0.1987	16.7700 **	-0.5041	-1.0635	2.9159 **	14.7444 **
				(0.000)	(0.000)	(0.000)	(0.656)	(0.000)				(0.002)
	R_f	0.0599	0.9526	0.3280 **	7.6375 **	3087.3996 **	0.7719	0.5221	0.7614	-1.1745	0.0564	1.7811
				(0.000)	(0.000)	(0.000)	(0.380)	(0.470)				(0.619)
ENL	R_s	0.0046	0.9625	-0.3553 **	2.3210 **	297.5596 **	1.2236	4.9802 *	-0.5323	1.2143	0.5158	1.5563
				(0.000)	(0.000)	(0.000)	(0.269)	(0.026)				(0.669)
	R_f	0.0663	0.9651	0.1373	8.9013 **	4005.1052 **	3.1144	6.7419 **	0.1138	0.2486	2.2670 *	8.1856 *
				(0.051)	(0.000)	(0.000)	(0.078)	(0.009)				(0.042)

Table 3.32: Diagnostic Tests of the Asymmetric BEKK GARCH (1,1)-X Model (continued)

Code	Dep Var	Mean	Variance	Skewness	Excess Kurtosis	Jarque-Bera	Q(4)	$Q^2(4)$	Sign-Bias (t-test)	Negative-Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F test)
EOA	R_s	0.0498	0.9910	0.0953	1.3868 **	96.6670 **	7.8168 **	1.8677	0.5918	-0.6015	0.0839	0.7614
				(0.181)	(0.000)	(0.000)	(0.005)	(0.172)				(0.859)
	R_f	0.0434	1.0033	0.0610	1.2472 **	77.4685 **	6.2774 *	3.6978	0.4340	-1.4561	-1.0686	3.6160
				(0.392)	(0.000)	(0.000)	(0.012)	(0.054)				(0.306)
ERC	R_s	0.0071	0.9727	0.0072	3.7467 **	615.3324 **	10.1740 **	10.5655 **	0.2574	-2.1067 *	1.9234	12.4950 **
				(0.925)	(0.000)	(0.000)	(0.001)	(0.001)				(0.006)
	R_f	0.0182	0.9615	-0.1683 *	5.1933 **	1187.1679 **	6.3084 *	3.4544	-0.1226	-1.0468	1.8640	6.7239
				(0.026)	(0.000)	(0.000)	(0.012)	(0.063)				(0.081)
FTE	R_s	-0.0527	0.9941	0.1578 *	1.3782 **	105.0359 **	9.6059 **	5.8353 *	-0.2399	-0.7738	1.4429	4.4133
				(0.022)	(0.000)	(0.000)	(0.002)	(0.016)				(0.220)
	R_f	-0.0445	0.9880	0.1612 *	1.4947 **	122.8500 **	8.6192 **	7.5906 **	-1.1050	0.1954	2.7314 **	8.5842 *
				(0.020)	(0.000)	(0.000)	(0.003)	(0.006)				(0.035)
GEN	R_s	-0.0304	0.9827	0.0785	1.3145 **	88.5102 **	8.4242 **	10.5126 **	0.1951	-1.4960	1.6689	8.5075 *
				(0.265)	(0.000)	(0.000)	(0.004)	(0.001)				(0.037)
	R_f	0.0110	0.9887	-0.0173	1.1624 **	68.2932 **	7.0243 **	8.1920 **	0.0964	-1.5144	2.1235 *	11.7845 **
				(0.806)	(0.000)	(0.000)	(0.008)	(0.004)				(0.008)
GXW	R_s	-0.0163	1.0132	0.1877 **	3.0057 **	482.0789 **	3.9001 *	5.2346 *	0.1101	-1.8951	1.6177	9.9053 *
				(0.007)	(0.000)	(0.000)	(0.048)	(0.022)				(0.019)
	R_f	-0.0003	0.9983	0.1443 *	3.3208 **	583.7911 **	2.5954	5.8975 *	0.0470	-2.2046 *	1.2643	10.4652 *
				(0.037)	(0.000)	(0.000)	(0.107)	(0.015)				(0.015)
HAS	R_s	-0.0079	1.0303	-0.7572 **	8.1310 **	3594.1841 **	7.4129 **	2.8957	-1.6134	-0.2542	1.6119	5.1844
				(0.000)	(0.000)	(0.000)	(0.006)	(0.089)				(0.159)
	R_f	-0.0133	0.9723	-0.5646 **	5.6942 **	1770.6034 **	9.4607 **	2.1600	-0.9207	-0.0632	0.7232	1.4146
				(0.000)	(0.000)	(0.000)	(0.002)	(0.142)				(0.702)
HNM	R_s	-0.0007	0.9718	0.0348	8.0361 **	2830.9288 **	1.9696	3.0465	1.9724 *	0.1446	-1.6049	6.6423
				(0.645)	(0.000)	(0.000)	(0.160)	(0.081)				(0.084)
	R_f	0.0241	1.0051	-0.3873 **	9.9959 **	4406.0225 **	1.8087	1.9228	2.4462 *	-0.0963	-1.6074	8.4317 *
				(0.000)	(0.000)	(0.000)	(0.179)	(0.166)				(0.038)
ING	R_s	0.0070	0.9833	0.1264	2.5051 **	333.0702 **	14.2309 **	1.4225	0.2862	-1.7276	-0.2852	4.0682
				(0.067)	(0.000)	(0.000)	(0.000)	(0.233)				(0.254)
	R_f	-0.0018	0.9532	-1.2190 **	11.2418 **	6952.4522 **	18.3638 **	0.2385	-0.9267	-0.1716	0.3247	1.5866
				(0.000)	(0.000)	(0.000)	(0.000)	(0.625)				(0.662)
LLO	R_s	0.0055	1.0090	-0.1826 **	1.9518 **	198.7960 **	8.6431 **	3.1130	-1.2154	1.2324	3.1688 **	11.5773 **
				(0.010)	(0.000)	(0.000)	(0.003)	(0.078)				(0.009)
	R_f	-0.0281	0.9910	-0.2539 **	2.4282 **	310.2601 **	4.4053 *	2.3356	0.2573	-0.1388	1.2443	3.3371
				(0.000)	(0.000)	(0.000)	(0.036)	(0.126)				(0.343)
MUV	R_s	-0.0268	0.9937	-0.2832 **	2.1907 **	258.1215 **	5.6921 *	6.2565 *	0.0693	-1.5809	1.1281	6.1596
				(0.000)	(0.000)	(0.000)	(0.017)	(0.012)				(0.104)
	R_f	-0.0081	0.9988	-0.1083	2.1081 **	226.4118 **	6.9165 **	7.1132 **	-0.4226	-1.4074	0.5724	4.8416
				(0.124)	(0.000)	(0.000)	(0.009)	(0.008)				(0.184)
NDA	R_s	0.0363	0.9638	0.3530 **	5.0655 **	1146.5777 **	7.0262 **	0.3577	0.9885	-0.8063	-0.6112	1.0216
				(0.000)	(0.000)	(0.000)	(0.008)	(0.550)				(0.796)
	R_f	0.0517	0.9565	0.6145 **	6.0625 **	1677.2789 **	3.6158	0.8410	-0.2763	0.5900	-0.0286	0.4275
				(0.000)	(0.000)	(0.000)	(0.057)	(0.359)				(0.934)
NES	R_s	0.0085	0.9974	-0.3797 **	3.2416 **	485.8609 **	5.2060 *	0.9182	-0.4349	-0.2775	1.6960	4.0021
				(0.000)	(0.000)	(0.000)	(0.023)	(0.338)				(0.261)
	R_f	-0.0222	0.9820	-0.6116 **	3.8916 **	729.4230 **	2.1036	1.0256	-1.7202	0.6984	2.1613 *	4.9493
				(0.000)	(0.000)	(0.000)	(0.147)	(0.311)				(0.176)
NOV	R_s	-0.0131	0.9884	0.1006	2.3733 **	248.6769 **	2.3047	5.0615 *	-1.4702	1.6403	3.1629 **	11.0363 *
				(0.183)	(0.000)	(0.000)	(0.129)	(0.024)				(0.012)
	R_f	-0.0294	0.9761	0.1301	2.0876 **	194.0013 **	3.3347	4.7421 *	-2.0600 *	1.5872	2.0483 *	5.3883
				(0.085)	(0.000)	(0.000)	(0.068)	(0.029)				(0.145)
PHI	R_s	-0.0031	1.0048	-0.1170	2.6039 **	307.5841 **	4.4590 *	6.4339 *	-0.9009	0.6064	1.1221	1.3306
				(0.117)	(0.000)	(0.000)	(0.035)	(0.011)				(0.722)
	R_f	0.0234	0.9928	0.0171	3.1730 **	453.0978 **	5.9946 *	13.5180 **	-0.9915	0.4771	0.9078	1.1649
				(0.819)	(0.000)	(0.000)	(0.014)	(0.000)				(0.761)
RBO	R_s	-0.0039	1.0060	-0.4654 **	3.7104 **	721.9073 **	8.6293 **	5.8398 *	-0.0757	-1.7762	0.4617	5.3736
				(0.000)	(0.000)	(0.000)	(0.003)	(0.016)				(0.146)
	R_f	-0.0064	1.0251	-0.5500 **	4.2900 **	967.6279 **	10.4680 **	3.9809 *	0.5097	-1.9758 *	0.1296	4.8489
				(0.000)	(0.000)	(0.000)	(0.001)	(0.046)				(0.183)
RD	R_s	-0.0011	0.9950	-0.6552 **	6.3037 **	2178.0214 **	6.4371 *	2.9011	1.1776	-2.1978 *	0.2921	6.6274
				(0.000)	(0.000)	(0.000)	(0.011)	(0.089)				(0.085)
	R_f	0.0346	1.0107	-3.7341 **	59.1914 **	187016.8170 **	0.9417	0.5498	0.5301	-2.6317 **	-0.2230	7.5717
				(0.000)	(0.000)	(0.000)	(0.332)	(0.458)				(0.056)
ROG	R_s	0.0331	0.9916	0.6965 **	3.7403 **	698.2864 **	2.5263	5.1645 *	-0.1607	0.0226	-0.8623	1.3773
				(0.000)	(0.000)	(0.000)	(0.112)	(0.023)				(0.711)
	R_f	0.0205	0.9891	0.5440 **	3.2924 **	527.0173 **	3.4630	8.4784 **	0.2741	-0.5247	-0.6856	0.7031
				(0.000)	(0.000)	(0.000)	(0.063)	(0.004)				(0.872)
SCH	R_s	0.0021	1.0070	-0.0358	1.1659 **	71.6875 **	3.3068	7.8294 **	-0.4112	-1.8217	0.7501	7.7011
				(0.604)	(0.000)	(0.000)	(0.069)	(0.005)				(0.053)
	R_f	-0.0265	1.0058	-0.2122 **	1.2462 **	91.0600 **	6.7859 **	4.0462 *	0.1872	-1.0604	-0.3388	1.5965
				(0.002)	(0.000)	(0.000)	(0.009)	(0.044)				(0.660)
SHB	R_s	0.0242	1.0049	-0.0952	1.2571 **	70.8547 **	11.0505 **	1.5621	-0.8664	0.3049	1.3339	1.8545
				(0.208)	(0.000)	(0.000)	(0.001)	(0.211)				(0.603)
	R_f	0.0242	1.0085	-0.3292 **	2.5752 **	309.6923 **	9.3917 **	6.0735 *	-2.0933 *	0.0150	2.5553 *	8.8554 *
				(0.000)	(0.000)	(0.000)	(0.002)	(0.014)				(0.031)

Table 3.32: Diagnostic Tests of the Asymmetric BEKK GARCH (1,1)-X Model (continued)

Code	Dep Var	Mean	Variance	Skewness	Excess Kurtosis	Jarque-Bera	Q(4)	$Q^2(4)$	Sign-Bias (t-test)	Negative-Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F test)
SHE	R_s	-0.0261	0.9901	3.4247 **	56.8425 **	161713.5718 **	2.3854	0.2010	-0.0087	1.0597	0.0149	1.6975
				(0.000)	(0.000)	(0.000)	(0.122)	(0.654)				(0.637)
	R_f	-0.0482	0.9769	3.7767 **	61.4424 **	189056.3438 **	1.1241	0.0994	-0.2124	0.3418	-0.0079	0.1316
				(0.000)	(0.000)	(0.000)	(0.289)	(0.752)				(0.988)
SIE	R_s	-0.0083	1.0022	-0.0688	1.4191 **	106.8116 **	6.8547 **	22.7865 **	-1.6154	-0.0039	3.7960 **	17.0804 **
				(0.319)	(0.000)	(0.000)	(0.009)	(0.000)				(0.001)
	R_f	-0.0070	0.9497	-0.1800 **	3.0252 **	487.6696 **	40.5065 **	2.8639	0.1558	-0.7396	0.7602	1.9227
				(0.009)	(0.000)	(0.000)	(0.000)	(0.091)				(0.589)
TEF	R_s	-0.0358	0.9910	0.1020	3.2654 **	562.4291 **	8.5876 **	3.5660	1.0281	0.1018	0.1953	3.0217
				(0.140)	(0.000)	(0.000)	(0.003)	(0.059)				(0.388)
	R_f	-0.0363	0.9883	-0.1453 *	3.1472 **	524.8557 **	3.1760	12.2663 **	-0.1207	0.0548	-0.1504	0.0964
				(0.035)	(0.000)	(0.000)	(0.075)	(0.000)				(0.992)
TI	R_s	-0.0418	0.9791	-0.9298 **	9.9529 **	5386.4126 **	9.3201 **	2.1343	0.5444	0.2986	-0.1893	0.8399
				(0.000)	(0.000)	(0.000)	(0.002)	(0.144)				(0.840)
	R_f	-0.0182	0.9849	-11.0626 **	268.4422 **	3811937.8698 **	10.1043 **	0.0131	-0.9013	0.1478	0.0960	1.0038
				(0.000)	(0.000)	(0.000)	(0.001)	(0.909)				(0.800)
TIM	R_s	-0.0592	0.9923	-0.1292	4.1877 **	793.6161 **	6.7272 **	0.4962	0.0699	0.0870	1.4704	3.7262
				(0.083)	(0.000)	(0.000)	(0.009)	(0.481)				(0.293)
	R_f	-0.0222	0.9910	-0.8823 **	8.8444 **	3666.9468 **	2.8279	0.1743	-1.1793	0.5346	1.1956	1.7546
				(0.000)	(0.000)	(0.000)	(0.093)	(0.676)				(0.625)
TLI	R_s	-0.0084	1.0067	0.0534	4.0425 **	716.8026 **	1.0311	5.1817 *	-1.6304	-0.4955	2.4197 *	9.0088 *
				(0.480)	(0.000)	(0.000)	(0.310)	(0.023)				(0.029)
	R_f	0.0081	1.0007	0.0997	4.2698 **	800.8863 **	0.6953	4.4875 *	-1.6702	-0.2330	2.7552 **	9.9789 *
				(0.188)	(0.000)	(0.000)	(0.404)	(0.034)				(0.019)
TOT	R_s	0.0388	0.9946	-0.1155	1.4621 **	115.1292 **	11.7057 **	6.8363 **	1.8629	-1.6222	-0.9090	3.8676
				(0.094)	(0.000)	(0.000)	(0.001)	(0.009)				(0.276)
	R_f	0.0371	0.9909	-0.1731 *	1.5842 **	138.1614 **	7.9763 **	6.8015 **	2.3907 *	-1.7636	-1.1450	6.0211
				(0.012)	(0.000)	(0.000)	(0.005)	(0.009)				(0.111)
UBS	R_s	0.0036	0.9890	-0.1440	1.4384 **	94.3291 **	4.9710 *	2.1010	0.2683	-1.4275	0.2124	2.9168
				(0.057)	(0.000)	(0.000)	(0.026)	(0.147)				(0.405)
	R_f	0.0133	1.0038	-0.2170 **	1.9354 **	172.4367 **	8.9815 **	1.2016	0.0285	-0.2207	1.1596	2.3625
				(0.004)	(0.000)	(0.000)	(0.003)	(0.273)				(0.501)
UC	R_s	0.0174	0.9698	0.0239	1.5151 **	116.0318 **	3.2118	5.7259 *	-1.4475	0.8385	2.4779 *	6.1358
				(0.735)	(0.000)	(0.000)	(0.073)	(0.017)				(0.105)
	R_f	0.0119	0.9885	0.0350	2.5891 **	338.7671 **	1.3149	4.9138 *	-0.3415	-0.2334	1.5620	3.3533
				(0.620)	(0.000)	(0.000)	(0.252)	(0.027)				(0.340)
VIV	R_s	-0.0682	0.9778	-0.5519 **	4.0994 **	889.1644 **	42.0384 **	2.8093	-0.1207	-1.9346	-0.4934	6.9405
				(0.000)	(0.000)	(0.000)	(0.000)	(0.094)				(0.074)
	R_f	-0.0364	0.9865	-0.4447 **	3.5051 **	645.1197 **	39.5174 **	2.1443	-0.3073	-1.3286	0.3069	3.6025
				(0.000)	(0.000)	(0.000)	(0.000)	(0.143)				(0.308)
VOF	R_s	-0.0402	0.9930	-0.4073 **	5.4143 **	1575.0877 **	2.7422	3.2442	-0.7248	1.1628	-0.1252	1.9348
				(0.000)	(0.000)	(0.000)	(0.098)	(0.072)				(0.586)
	R_f	-0.0116	0.9929	-0.4132 **	5.7228 **	1756.6621 **	2.7389	3.1183	0.0382	0.7296	0.1685	0.9433
				(0.000)	(0.000)	(0.000)	(0.098)	(0.077)				(0.815)
VOW	R_s	-0.0026	0.9879	0.2251 **	2.4713 **	311.2904 **	0.6696	4.7902 *	-1.8640	0.9570	2.8290 **	8.0844 *
				(0.002)	(0.000)	(0.000)	(0.413)	(0.029)				(0.044)
	R_f	-0.0035	0.9715	0.2675 **	2.2706 **	268.4721 **	1.2045	10.2991 **	-1.7558	1.0069	3.4655 **	12.1497 **
				(0.000)	(0.000)	(0.000)	(0.272)	(0.001)				(0.007)

Notes: *, ** Significant at 5% and 1% level, respectively

(.) = p-values

Jarque-Bera is the Jarque and Bera (1980) normality test, with propbability value in parentheses.

Q(4) and $Q^2(4)$ are respectively the Ljung-Box Q statistics at lag 4 of the standardized and square standardized residuals.

The Engle and Ng (1993) diagnostic tests (i.e., Sign-Bias, Negative-Size Bias, Positive-Size Bias, and Joint Test) are obtained from the estimation of the following regression model:

$$Z_t^2 = a + b_1 S_t^- + b_2 S_t^- \varepsilon_{t-1} + b_3 S_t^+ \varepsilon_{t-1} + v_t$$

where Z_t^2 is the standardized residuals, S_t^- is a dummy variable that takes a value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise; and S_t^+ is a dummy variable that takes a value of unity if $\varepsilon_{t-1} > 0$ and zero othe

Individual t-statistics are t-tests for the estimated coefficient (i) b_1 in Sign Bias Test (ii) b_2 in Negative-Size Bias Test and (iii) b_3 in Positive-Size-Bias Test. The F-statistics is the joint test that $b_1 = b$

Table 3.33: Multivariate GARCH Parameter Estimates_Student t Distribution

This table reports the parameter estimates for the augmented asymmetric BEKK GARCH (1,1)-X-student t model:

$$H_t = C_0C_0' + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} + D_{11}'\xi_{t-1}\xi_{t-1}'D_{11} + E_{11}(Z_{t-1})^2 E_{11}'$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_t = \begin{bmatrix} \xi_{s,t} \\ \xi_{f,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{s,t},0\} \\ \min\{\varepsilon_{f,t},0\} \end{bmatrix}$; $Z_t = (P_{s,t} - P_{f,t})$; assuming $\varepsilon_t \backslash \Omega_t$: $student-t(0,H_t,v)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The above coefficients relating to the volatility transfers are indicated in bold characters. v represents the parameter estimates of the student-t distribution (i.e, shape of the distribution).

Estimates are obtained using the BFGS numerical optimization algorithm and the method of maximum likelihood (ML). Figure in parentheses (.) indicate the t-statistics. A single (double) asterisk denotes significance at the 5% (1%) level. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}	v
AA	0.0027 **	0.0012 **	0.0000	0.2699 **	0.4650 **	-0.0255	-0.4077 **	0.0121	0.8258 **	0.8824 **	0.1672	0.0737	-0.3080	-0.3091 **	-0.1121	1.0145	-3.3124 *	-0.0002	4.2161 **
	(6.207)	(3.100)	(0.000)	(3.035)	(5.159)	(-0.267)	(-5.608)	(0.083)	(5.273)	(6.796)	(1.008)	(0.554)	(-1.934)	(-2.932)	(-0.794)	(0.683)	(-2.261)	(-0.000)	(11.803)
AGN	0.0010 **	-0.0007 *	0.0000	0.0862 *	0.7797 **	0.0063	-0.7923 **	0.9831 **	0.2844 **	-0.0006	0.7109 **	0.2181 **	-0.0673	-0.0229	0.2662	0.0001	-0.0410	0.0000	5.4695 **
	(3.994)	(-2.205)	(-0.000)	(2.228)	(11.213)	(0.429)	(-14.034)	(154.089)	(8.405)	(-0.121)	(22.143)	(6.002)	(-0.304)	(-1.293)	(1.485)	(0.045)	(-0.327)	(-0.000)	(11.778)
AHL	0.0108 **	0.0076 **	0.0024 *	0.4280 **	1.0756 **	-0.0705	-0.7418 **	0.2683	0.5073 *	0.4750 *	0.3413	0.5832 *	0.1812	-0.1950	0.2284	0.1862 **	0.0901	-0.0586	3.0810 **
	(7.556)	(5.101)	(2.159)	(3.374)	(7.058)	(-0.629)	(-5.218)	(1.076)	(2.056)	(2.206)	(1.517)	(2.066)	(0.501)	(-0.804)	(0.734)	(3.669)	(1.921)	(-0.930)	(13.772)
ALV	0.0022 **	0.0026 **	0.0000	0.0301	-0.2649 **	0.1042	0.4569 **	0.9613 **	0.0242	-0.0026	0.9075 **	-0.4132 **	-0.4336 **	0.4180 **	0.3298 **	0.0752 **	0.0478	0.1230 **	5.6147 **
	(5.890)	(6.567)	(0.057)	(0.475)	(-4.085)	(1.628)	(7.017)	(32.968)	(0.835)	(-0.079)	(30.322)	(-5.211)	(-3.846)	(5.501)	(2.911)	(2.974)	(1.387)	(3.208)	(9.814)
AXA	0.0019 **	0.0017	0.0029 **	0.1929 **	-0.4423 **	-0.0336	0.4249 **	0.9411 **	0.4129 **	0.0236	0.5404 **	-0.3488 **	-0.0139	0.0404	-0.4895 **	-0.0019	0.0233	0.0318	3.9892 **
	(4.458)	(1.314)	(9.170)	(2.849)	(-4.965)	(-1.357)	(4.642)	(36.434)	(6.933)	(1.013)	(9.061)	(-5.420)	(-0.104)	(1.283)	(-4.275)	(-1.027)	(0.509)	(0.844)	(12.301)
AZN	0.0067 **	0.0062 **	0.0007 **	-0.1402	-0.6277 **	-0.0326	0.4461 *	0.7787 **	-0.0699	0.0786	0.9379 **	-0.9077 *	-0.4693	0.5724	0.1526	12.1674 *	12.7081 *	-4.0885	3.2926 **
	(5.571)	(5.260)	(3.280)	(-0.737)	(-3.221)	(-0.169)	(2.216)	(8.342)	(-0.774)	(1.000)	(11.837)	(-2.523)	(-1.343)	(1.444)	(0.399)	(2.149)	(2.336)	(-1.873)	(14.468)
BAR	0.0014 **	0.0017 **	0.0000	-0.0140	-0.1750 **	-0.0027	-0.0003	1.0031 **	0.0511 **	-0.0307 *	0.9164 **	0.3171 **	0.3742 **	0.0017	0.0006	0.0002	0.0002	0.0015 **	3.7807 **
	(3.504)	(3.684)	(-0.007)	(-0.324)	(-3.415)	(-0.450)	(-0.048)	(74.119)	(3.016)	(-2.203)	(57.933)	(6.446)	(5.720)	(0.270)	(0.082)	(0.593)	(0.376)	(6.471)	(13.219)
BNP	0.0018 **	0.0004	0.0032 **	-0.2638 **	0.3466 **	0.0907	-0.6146 **	0.8543 **	0.5850 **	0.1128	0.3707 **	-0.1679 *	-0.5477 **	-0.0403	0.3103	0.0036 *	-0.0068 *	-0.0039	3.9831 **
	(4.429)	(0.302)	(5.318)	(-3.076)	(3.033)	(1.053)	(-6.087)	(9.785)	(6.303)	(1.301)	(3.814)	(-1.991)	(-3.601)	(-0.777)	(1.678)	(2.386)	(-2.177)	(-0.511)	(12.976)
BPA	0.0019 **	0.0019 **	0.0000	-0.0095	0.3792 **	-0.1477 *	-0.5372 **	-1.0056 **	-0.0792 *	0.0279	-0.8980 **	-0.3869 *	-0.3147	0.3962 **	0.2889	-13.5467	-13.0589	0.0061	4.3911 **
	(3.201)	(3.366)	(-0.000)	(-0.149)	(3.122)	(-2.491)	(-4.884)	(-43.170)	(-2.545)	(1.167)	(-30.098)	(-2.088)	(-1.576)	(2.603)	(1.528)	(-0.943)	(-0.935)	(0.000)	(11.377)

Table 3.33: Multivariate GARCH Parameter Estimates_Student t Distribution (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}	ν
BTL	0.0008	0.0009	-0.0008 *	-0.1345 *	0.5238 **	0.2005 **	-0.4075 **	0.4444 **	1.2261 **	0.5522 **	-0.2387 **	0.0283	0.2303	0.0883	-0.2167	0.0293	0.0368	-0.0364	3.2898 **
	(1.217)	(0.624)	(-2.042)	(-2.063)	(6.460)	(3.438)	(-5.603)	(6.965)	(15.874)	(8.352)	(-3.187)	(0.328)	(1.426)	(1.330)	(-1.637)	(1.591)	(0.873)	(-1.882)	(15.033)
BVA	0.0004 *	0.0001	-0.0004 *	0.0122	0.1734 **	0.1802 **	0.0432	0.9136 **	-0.0551 **	0.0644 **	1.0197 **	-0.2908 **	-0.2301 **	0.1065	0.2012 *	3.9571	4.2927 *	0.0273	6.1218 **
	(2.257)	(0.420)	(-2.224)	(0.313)	(4.262)	(4.211)	(0.995)	(149.661)	(-21.236)	(19.157)	(119.138)	(-4.029)	(-3.174)	(1.213)	(2.541)	(1.888)	(2.180)	(0.019)	(9.676)
CA	0.0005	0.0017 **	0.0000	0.0196	-0.4950 **	-0.1389	0.3160 **	0.7729 **	1.4647 **	0.2219 **	-0.5445 **	0.1979 *	0.1140	-0.0536	0.1547	-0.5930	5.3619 **	-0.0035	4.7553 **
	(1.798)	(5.787)	(-0.000)	(0.219)	(-6.216)	(-1.663)	(3.998)	(2121.618)	(116.815)	(615.906)	(-32.182)	(2.001)	(0.957)	(-0.536)	(1.322)	(-0.354)	(2.584)	(-0.000)	(11.541)
CGE	-0.0003	0.0001	0.0000	-0.0028	0.0697	0.0694	0.0221	0.9593 **	-0.0168	0.0348	1.0098 **	0.1454 *	0.1645 *	-0.0276	-0.0965	0.2183	0.2228	0.0000	4.2067 **
	(-0.691)	(0.258)	(-0.153)	(-0.035)	(1.037)	(1.723)	(0.493)	(40.191)	(-0.613)	(1.464)	(37.323)	(2.356)	(2.028)	(-0.465)	(-1.479)	(1.556)	(1.858)	(0.000)	(14.371)
CSG	0.0018 **	0.0001	0.0000	-0.0381	0.3505 **	0.1940 *	-0.2344 *	0.1258 **	0.9380 **	0.8328 **	0.0721 **	-0.2746 *	0.0990	0.1379	-0.2719 *	0.2122 *	0.0517	-0.0001	3.9322 **
	(5.330)	(0.223)	(0.000)	(-0.379)	(3.627)	(2.066)	(-2.523)	(8.928)	(49.423)	(55.771)	(3.940)	(-2.189)	(0.764)	(0.961)	(-2.008)	(2.498)	(0.663)	(-0.000)	(12.035)
DBK	0.0019 **	0.0021 **	0.0000	0.2697 **	-0.0150	-0.1036 *	0.1911 **	-0.7467 **	-1.6085 **	-0.2265 **	0.7185 **	-0.3016 **	-0.4623 **	0.2245 **	0.4967 **	-0.5240	0.1848	0.0000	5.7163 **
	(4.003)	(4.569)	(0.000)	(4.284)	(-0.182)	(-2.013)	(2.600)	(-10.471)	(-25.810)	(-3.312)	1(0.777)	(-2.943)	(-4.906)	(2.886)	(6.580)	(-0.357)	(0.099)	(0.000)	(9.884)
DCY	0.0004	0.0000	0.0000	-0.0269	0.3723 **	0.1761 **	-0.2544 **	-0.9549 **	-0.0609 **	-0.0336 **	-0.9320 **	-0.0984	0.0253	0.0513	0.0680	0.5791 *	-0.6010	-0.0005	5.1546 **
	(1.024)	(0.094)	(0.001)	(-1.025)	(8.759)	(6.454)	(-5.824)	(-188.530)	(-3.815)	(-10.467)	(-61.548)	(-1.624)	(0.336)	(0.962)	(0.748)	(2.095)	(-1.706)	(-0.001)	(10.950)
DTE	0.0008 **	0.0004	0.0000	-0.2181 **	0.0643	0.0786	-0.2213 **	0.2154	1.1282 **	0.7821 **	-0.1761	0.0944	0.3520 **	0.0788	-0.1628	0.4810	0.1986	-0.0003	6.6737 **
	(3.293)	(1.530)	(-0.000)	(-3.649)	(1.030)	(1.276)	(-3.795)	(1.269)	(7.833)	(4.873)	(-1.048)	(1.347)	(4.706)	(1.034)	(-1.707)	(0.724)	(0.230)	(-0.000)	(9.604)
ENI	0.0011 **	0.0045 **	-0.0002	-0.0375	-0.7560 **	-0.1447 **	0.6053 **	0.8966 **	0.4998 **	0.0866 **	0.4078 **	0.1199	-0.2150	0.0383	0.4314 **	0.0037	-0.0287 **	-0.0050	3.8531 **
	(2.745)	(8.021)	(-0.045)	(-0.889)	(-11.629)	(-4.614)	(8.827)	(38.715)	(8.034)	(4.086)	(6.125)	(1.309)	(-1.414)	(0.459)	(2.997)	(1.523)	(-2.927)	(-0.136)	(14.766)
ENL	0.0090 **	0.0064 **	0.0009	0.0265	-0.6899 **	-0.2570 **	0.3715 **	0.6268 **	0.3230 **	-0.0458	0.4661 **	-0.5548 **	-0.0397	0.1818	-0.4528 **	0.0125 **	0.0068	0.0305 **	3.2777 **
	(11.980)	(6.002)	(0.495)	(0.269)	(-7.300)	(-2.846)	(3.649)	(8.673)	(4.688)	(-0.461)	(5.726)	(-4.146)	(-0.278)	(1.329)	(-3.138)	(2.596)	(0.875)	(5.193)	(13.905)
EOA	0.0015 **	0.0012 **	0.0000	0.0376	-0.2830 **	-0.2110 **	0.0989	-0.0360	0.9226 **	0.9745 **	0.0887	-0.1118	-0.2325 **	0.0477	0.2960 **	0.5348	-1.8364 *	0.0000	6.1964 **
	(4.675)	(3.772)	(0.000)	(0.662)	(-4.984)	(-3.941)	(1.680)	(-0.242)	(6.465)	(7.426)	(0.604)	(-0.828)	(-2.623)	(0.553)	(4.602)	(0.778)	(-2.566)	(0.000)	(9.223)
ERC	0.0021 **	0.0013	0.0019 **	0.1945 **	-0.4844 **	0.0004	0.6309 **	0.9076 **	0.2689 **	0.0706 **	0.7015 **	0.2535 **	0.3035 *	-0.2063 **	-0.1129	-0.0586 **	-0.0397	0.0259 **	3.6501 **
	(4.264)	(1.624)	(5.754)	(4.860)	(-15.570)	(0.007)	(10.999)	(157.523)	(14.663)	(20.422)	(45.300)	(3.009)	(2.533)	(-3.310)	(-1.425)	(-4.836)	(-1.917)	(4.048)	(12.547)
FTE	0.0023 **	0.0010 **	-0.0008	0.1424	-0.3712 **	0.0009	0.4453 **	0.1939 **	0.8819 **	0.7696 **	0.0938 **	0.4589 **	0.1821	-0.2284 *	0.1325	0.1600 **	0.0439	-0.0303	4.7631 **
	(7.563)	(2.664)	(-0.991)	(1.804)	(-4.326)	(0.012)	(5.561)	(4.782)	(43.218)	(18.381)	(3.951)	(4.140)	(1.561)	(-2.122)	(1.092)	(3.532)	(1.203)	(-0.256)	(11.897)
GEN	0.0002	0.0006 **	0.0000	-0.0096	-0.2131 **	0.1655 **	0.3270 **	0.9432 **	-0.0061	0.0419	0.9810 **	0.3514 **	0.2076 **	-0.2344 **	0.0153	-2.1182	1.4164	-0.0067	4.6949 **
	(0.874)	(2.763)	(-0.001)	(-0.139)	(-2.973)	(2.766)	(5.784)	(43.227)	(-0.249)	(1.914)	(42.026)	(4.616)	(2.683)	(-3.124)	(0.185)	(-0.767)	(0.424)	(-0.000)	(10.812)
GXW	-0.0005	-0.0005	0.0000	0.1933 **	-0.2462 **	-0.1226	0.2998 **	0.9811 **	0.0893 **	0.0137 **	0.9064 **	-0.1251	0.2437	0.0310	-0.3680 *	1.1758	-1.2089	-0.0001	3.8456 **
	(-1.435)	(-1.267)	(0.000)	(2.585)	(-2.854)	(-1.623)	(3.412)	(294.432)	(5.689)	(4.702)	(58.605)	(-0.849)	(1.557)	(0.217)	(-2.426)	(0.261)	(-0.150)	(-0.000)	(13.716)
HAS	0.0012 **	0.0012 **	0.0000	-0.1253	0.2224 **	0.0523	-0.3687 **	-0.3446 **	-1.2622 **	-0.6244 **	0.2893 **	0.2165 **	0.0435	-0.5310 **	-0.3403 **	-5.3638 **	-6.7725 **	0.0014	3.0845 **
	(4.596)	(4.109)	(0.001)	(-1.691)	(2.945)	(0.629)	(-4.939)	(-2.877)	(-11.296)	(-5.679)	(2.596)	(2.874)	(0.477)	(-6.214)	(-3.139)	(-3.096)	(-3.483)	(0.000)	(16.396)
HNM	0.0010 **	0.0001	0.0000	0.0708	-0.3040 **	-0.0755	0.2582 **	-0.1835 **	-0.9977 **	-0.8187 **	0.0089 **	-0.0386	-0.4004 **	-0.0625	0.4131 **	0.1827	-1.0953	0.0001	3.6059 **
	(5.484)	(0.756)	(-0.000)	(1.497)	(-5.219)	(-1.667)	(4.494)	(-334.401)	(-1065.027)	(-1321.849)	(11.737)	(-0.780)	(-6.324)	(-1.427)	(7.211)	(0.283)	(-0.990)	(0.000)	(14.777)
ING	0.0021 **	-0.0019 **	0.0000	0.3629 **	-0.5016 **	-0.1324 *	0.7060 **	0.7248 **	0.9838 **	0.2402 **	-0.0603	-0.2119 *	-0.5731 **	-0.0267	0.1339	-0.0032	-0.0143 **	0.0000	3.8243 **
	(4.792)	(-3.931)	(-0.000)	(5.204)	(-5.172)	(-2.419)	(8.891)	(8.073)	1(2.833)	(2.796)	(-0.650)	(-2.203)	(-4.097)	(-0.899)	(0.992)	(-1.015)	(-3.541)	(-0.000)	(13.374)

Table 3.33: Multivariate GARCH Parameter Estimates_Student t Distribution (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}	ν
LLO	0.0010 **	-0.0010	-0.0009	0.1341	**-0.6989** **	**0.0492**	0.7778 **	0.9368 **	**1.4297** **	**0.0495**	-0.4780 **	-0.0053	**0.1075**	**-0.0815**	-0.4124 *	-0.2436	-0.1365	2.0537 **	**3.2283** **
	(3.215)	(-1.053)	(-0.345)	(1.751)	**(-6.853)**	**(0.598)**	(5.782)	(8.566)	**(20.816)**	**(0.431)**	(-6.157)	(-0.089)	**(0.569)**	**(-1.314)**	(-2.215)	(-0.478)	(-0.057)	(2.688)	**(13.848)**
MUV	0.0057 **	0.0046 **	-0.0004	-0.3325 *	**-0.6103** **	**0.3676** **	0.7231 **	-1.0909 **	**-0.2902** **	**0.3284** **	-0.5512 **	0.4644 **	**0.2040**	**-0.7274** **	-0.4947 **	1.2320 **	1.5368 **	-0.8329 **	**4.9635** **
	(5.461)	(4.215)	(-1.000)	(-2.537)	**(-5.410)**	**(2.868)**	(6.406)	(-12.235)	**(-3.094)**	**(3.780)**	(-6.471)	(3.074)	**(1.118)**	**(-4.395)**	(-2.589)	(3.967)	(4.284)	(-5.038)	**(10.852)**
NDA	0.0032 **	0.0022 **	-0.0010	-0.3891 **	**0.3852** **	**0.2005**	-0.5340 **	-1.0019 **	**-0.3209** **	**0.0600**	-0.6395 **	-0.0007	**0.3103**	**0.3742** *	-0.0323	-0.9573	-2.5725	-2.9227	**3.0749** **
	(5.833)	(3.130)	(-1.663)	(-3.515)	**(2.744)**	**(1.959)**	(-4.217)	(-21.850)	**(-5.320)**	**(1.204)**	(-9.695)	(-0.005)	**(1.710)**	**(2.351)**	(-0.176)	(-0.530)	(-0.793)	(-1.557)	**(13.694)**
NES	0.0007 *	0.0022 **	0.0006	0.1662 **	**-0.2420** **	**0.0504**	0.4560 **	-0.9606 **	**-0.1841** **	**-0.0176**	-0.7628 **	-0.0107	**-0.0691**	**0.0501**	-0.0651	-3.0055 *	3.2387	3.1657	**4.0491** **
	(2.189)	(4.858)	(0.393)	(3.252)	**(-3.092)**	**(1.017)**	(6.665)	(-83.192)	**(-4.757)**	**(-1.478)**	(-18.464)	(-0.094)	**(-0.461)**	**(0.642)**	(-0.348)	(-2.295)	(0.670)	(0.427)	**(12.747)**
NOV	0.0012 *	0.0028 **	0.0000	-0.0210	**-0.4693** **	**0.2392** *	0.5526 **	0.1410	**0.7633** **	**0.8125** **	0.1280	-0.5996 **	**-0.4264** *	**0.3661** *	0.0345	-8.1132 *	7.3658	-0.0003	**4.0835** **
	(1.987)	(5.034)	(-0.000)	(-0.203)	**(-5.244)**	**(2.084)**	(5.812)	(0.416)	**(2.685)**	**(2.710)**	(0.456)	(-3.421)	**(-2.512)**	**(2.070)**	(0.197)	(-2.064)	(1.702)	(-0.000)	**(11.401)**
PHI	0.0003	0.0017 **	0.0000	0.1908 **	**-0.1241**	**0.0156**	0.2654 **	0.4336 **	**1.3191** **	**0.5405** **	-0.3168 **	-0.0439	**-0.4131** *	**0.0611**	0.4671 **	-1.6394	1.8563	-0.0129	**4.2062** **
	(1.021)	(5.083)	(-0.001)	(3.472)	**(-1.911)**	**(0.293)**	(4.030)	(28.971)	**(52.650)**	**(31.723)**	(-13.198)	(-0.297)	**(-2.310)**	**(0.583)**	(3.797)	(-0.716)	(0.729)	(-0.001)	**(12.995)**
RBO	0.0014	0.0016 *	0.0005	-0.2474 *	**0.3862** **	**0.0554**	-0.5631 **	-0.0573	**0.7789** **	**1.0209** **	0.1962	-0.2426	**0.0081**	**0.4645** **	0.1547	0.2204	-4.1779	-3.5952	**3.5234** **
	(1.516)	(2.290)	(1.878)	(-2.575)	**(4.184)**	**(0.516)**	(-5.777)	(-0.249)	**(3.446)**	**(4.618)**	(0.852)	(-1.912)	**(0.065)**	**(3.565)**	(1.062)	(0.052)	(-0.837)	(-0.416)	**(13.638)**
RD	0.0105 **	0.0106 **	0.0001	0.2556 *	**-0.3270** *	**-0.0854**	0.5849 **	-0.0009	**0.2337**	**-0.0006**	0.0284	-0.3069 **	**-0.4906** **	**-0.0400**	0.3264 *	0.0023	0.0015	0.0025	**3.8957** **
	(11.688)	(8.478)	(0.096)	(1.974)	**(-2.205)**	**(-0.765)**	(4.708)	(-0.003)	**(0.869)**	**(-0.014)**	(0.411)	(-2.606)	**(-2.910)**	**(-0.568)**	(2.391)	(1.217)	(0.742)	(0.749)	**(14.127)**
ROG	0.0044 **	0.0052 **	0.0003	0.0945	**-0.1068**	**0.1499**	0.4100 *	0.9752 **	**0.0427**	**-0.1381** **	0.7533 **	0.7014 **	**0.8462** **	**-0.3668**	-0.5972 *	9.8848	12.2540	5.0538 *	**4.2058** **
	(5.992)	(6.498)	(0.957)	(0.534)	**(-0.532)**	**(0.821)**	(2.057)	(17.305)	**(0.624)**	**(-3.118)**	(13.569)	(3.105)	**(3.079)**	**(-1.569)**	(-2.199)	(1.817)	(1.802)	(2.075)	**(11.562)**
SCH	-0.0002	-0.0007 *	0.0000	0.0900	**0.2872** **	**-0.0123**	-0.1433	0.6923 **	**-0.2961** **	**0.3171** **	1.2219 **	0.1631	**0.2261**	**0.0585**	-0.1015	11.9811 **	11.2725 **	0.0000	**6.1793** **
	(-0.616)	(-2.213)	(0.000)	(0.875)	**(3.002)**	**(-0.142)**	(-1.721)	(29.751)	**(-14.272)**	**(13.352)**	(57.917)	(1.380)	**(1.907)**	**(0.544)**	(-1.048)	(3.183)	(2.997)	(-0.000)	**(9.741)**
SHB	0.0021 **	0.0033 **	0.0000	-0.3784 **	**0.3806** **	**0.2834** *	-0.3834 **	-0.1824	**0.4328**	**1.1361** **	0.5050	0.1214	**-0.2870** *	**-0.5874** **	-0.1160	-2.6722	2.0856	0.0000	**3.2102** **
	(3.272)	(4.972)	(-0.000)	(-2.969)	**(3.102)**	**(2.189)**	(-3.397)	(-0.659)	**(1.567)**	**(4.314)**	(1.856)	(0.773)	**(-2.063)**	**(-3.556)**	(-0.765)	(-1.720)	(1.393)	(-0.000)	**(12.878)**
SHE	0.0055 **	0.0054 **	0.0024 **	-0.4387 **	**-0.8960** **	**0.4103** **	0.8239 **	1.2218 **	**0.5749** **	**-0.4437** **	0.2163	-0.6824 **	**-0.4313** *	**0.3391** **	0.0025	-0.0339	0.0051	0.0803 **	**4.5691** **
	(6.389)	(4.835)	(5.026)	(-4.785)	**(-8.358)**	**(5.329)**	(8.597)	(11.181)	**(2.922)**	**(-3.264)**	(1.075)	(-5.629)	**(-2.371)**	**(2.701)**	(0.013)	(-1.007)	(0.119)	(3.673)	**(12.171)**
SIE	0.0006 *	0.0013 **	0.0000	0.0564	**-0.3445** **	**0.0355**	0.4699 **	-1.0039 **	**-0.0883** **	**0.0147**	-0.8819 **	-0.1052 *	**-0.1581**	**-0.0076**	-0.0622	0.0118 **	0.0182	0.0244 *	**5.6157** **
	(2.369)	(4.358)	(0.016)	(1.574)	**(-6.704)**	**(0.912)**	(9.346)	(-116.317)	**(-6.230)**	**(1.304)**	(-51.703)	(-2.195)	**(-1.779)**	**(-0.373)**	(-0.720)	(2.812)	(1.252)	(2.150)	**(10.914)**
TEF	0.0024 **	-0.0002	0.0000	0.2368 **	**0.6880** **	**0.0689**	-0.4561 **	0.7727 **	**1.2376** **	**0.1037** **	-0.3508 **	-0.1377	**0.1884**	**0.2014**	0.0229	0.2105 **	0.1004 **	0.0000	**4.1050** **
	(17.845)	(-1.153)	(0.000)	(3.481)	**(9.606)**	**(0.902)**	(-6.010)	(109.847)	**(16.963)**	**(13.854)**	(-3.965)	(-1.236)	**(1.105)**	**(1.560)**	(0.117)	(7.677)	(3.030)	(0.000)	**(15.149)**
TI	0.0044 **	0.0062 **	0.0024 *	0.3885 **	**-0.3082** **	**-0.1016**	0.5044 **	0.7692 **	**0.2398** **	**0.0892**	0.4575 **	-0.2366 *	**-0.1480**	**0.0485**	-0.2367 *	0.0035 **	-0.0024	0.0046 **	**3.7461** **
	(2.800)	(3.643)	(2.190)	(5.645)	**(-4.958)**	**(-1.426)**	(7.425)	(9.278)	**(2.728)**	**(1.507)**	(4.625)	(-2.456)	**(-1.558)**	**(1.183)**	(-2.029)	(4.158)	(-1.396)	(3.521)	**(13.621)**
TIM	0.0070 **	0.0084 **	0.0000	-0.0670	**-0.7344** **	**-0.1350**	0.5540 **	0.6042 **	**-0.0745**	**0.0652**	0.4913 **	0.2184 *	**0.1091**	**0.1262**	0.2617	2.2183 **	2.7445 **	0.0000	**3.4824** **
	(5.359)	(9.644)	(0.000)	(-0.712)	**(-6.460)**	**(-1.640)**	(5.286)	(4.051)	**(-0.414)**	**(0.725)**	(3.847)	(2.189)	**(0.638)**	**(1.213)**	(1.614)	(4.431)	(6.486)	(0.000)	**(13.955)**
TLI	-0.0008	0.0001	0.0000	-0.3497 **	**0.3128** **	**0.3062** **	-0.4073 **	0.7740 **	**0.1507** **	**0.2208** **	0.8382 **	-0.0495	**-0.3658** *	**-0.0872**	0.2175	-2.1872 *	0.2541	0.0167	**3.8615** **
	(-1.313)	(0.204)	(0.013)	(-3.586)	**(3.204)**	**(3.258)**	(-4.456)	(16.619)	**(3.724)**	**(4.652)**	(20.514)	(-0.315)	**(-2.286)**	**(-0.507)**	(1.236)	(-2.144)	(0.246)	(0.011)	**(13.043)**
TOT	0.0011	0.0023 **	-0.0005	-0.3171 **	**0.1568**	**0.0937**	-0.2774 **	0.1660	**0.9199** **	**0.8066** **	0.0347	0.5177 **	**0.4364** **	**-0.3333** **	-0.1522	-2.8742	-0.4863	-0.9794	**4.5787** **
	(1.798)	(4.341)	(-0.242)	(-3.222)	**(1.622)**	**(1.049)**	(-3.103)	(0.623)	**(3.685)**	**(3.127)**	(0.133)	(4.720)	**(4.003)**	**(-3.302)**	(-1.356)	(-1.244)	(-0.154)	(-0.259)	**(12.677)**
UBS	0.0020 **	0.0023 **	0.0012 **	0.1534	**0.5559** **	**0.1470** *	-0.2282 **	1.0405 **	**0.2139** **	**-0.1218** *	0.6958 **	-0.4088 **	**-0.3909** *	**0.3297** **	0.4949 **	0.8849	1.2997	0.5044	**3.7926** **
	(4.894)	(4.011)	(6.804)	(1.820)	**(6.096)**	**(2.118)**	(-2.829)	(22.402)	**(3.972)**	**(-2.087)**	(11.051)	(-3.014)	**(-2.220)**	**(3.065)**	(3.653)	(1.685)	(1.900)	(1.448)	**(12.438)**
UC	0.0003	-0.0023 **	0.0000	-0.1898 **	**0.3389** **	**0.4103** **	-0.0870	0.7265 **	**0.0957** *	**0.2445** **	0.8584 **	-0.1506	**-0.1225**	**-0.1541**	0.0268	4.1827 **	-0.8036	0.0000	**4.2204** **
	(0.804)	(-6.031)	(-0.000)	(-2.828)	**(5.842)**	**(6.812)**	(-1.461)	(14.194)	**(2.205)**	**(4.809)**	(18.609)	(-1.203)	**(-1.386)**	**(-1.181)**	(0.303)	(4.792)	(-1.269)	(0.000)	**(12.899)**
VIV	0.0021 **	0.0018 **	0.0002	-0.1234	**-0.3728** **	**0.3678** *	0.5646 **	1.0146 **	**0.1079**	**-0.0615**	0.8557 **	0.6724 **	**0.4195** **	**-0.5807** **	-0.2381	-4.6152	-5.8529	1.1317	**4.4621** **
	(4.243)	(3.741)	(0.554)	(-0.881)	**(-2.739)**	**(2.529)**	(4.030)	(13.327)	**(1.525)**	**(-0.740)**	(11.528)	(4.380)	**(2.586)**	**(-3.863)**	(-1.491)	(-1.399)	(-1.398)	(0.394)	**(11.467)**
VOF	0.0008 **	0.0002	-0.0004 *	-0.0213	**0.1274** *	**0.1848** *	-0.0150	-0.9186 **	**0.0015**	**-0.0613** **	-0.9898 **	-0.4075 **	**-0.0840**	**0.2883** **	-0.0541	1.4477	1.4873	0.3431	**5.8717** **
	(2.806)	(0.802)	(-2.113)	(-0.277)	**(2.245)**	**(2.530)**	(-0.281)	(-50.565)	**(0.378)**	**(-3.491)**	(-174.848)	(-4.718)	**(-1.164)**	**(3.027)**	(-0.719)	(1.223)	(1.764)	(0.482)	**(10.792)**
VOW	0.0025 **	0.0030 **	0.0000	-0.2400 **	**-0.5314** **	**0.0356**	0.3413 **	-0.3681 **	**-1.3029** **	**-0.5868** **	0.3493 **	0.3026 **	**0.0679**	**-0.2030** *	0.0670	-3.9095 **	-3.1728 *	0.0000	**5.6379** **
	(18.763)	(15.641)	(0.000)	(-9.449)	**(-18.693)**	**(1.536)**	(14.737)	(-23.341)	**(-84.466)**	**(-62.700)**	(31.876)	(3.269)	**(0.627)**	**(-2.447)**	(0.692)	(-3.344)	(-2.354)	(-0.000)	**(9.480)**

Table 3.34: Volatility Spillovers Joint Hypothesis Tests P-Values_Student t Distribution

This table reports the p-values associated with the Wald tests of the null hypotheses in the augmented asymmetric BEKK GARCH (1,1)-X-student t model:

$$H_t = C_0C_0' + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} + D_{11}'\xi_{t-1}\xi_{t-1}'D_{11} + E_{11}(Z_{t-1})^2E_{11}'$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_t = \begin{bmatrix} \xi_{s,t} \\ \xi_{f,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{s,t},0\} \\ \min\{\varepsilon_{f,t},0\} \end{bmatrix}$; $Z_t = (P_{s,t} - P_{f,t})$; assuming $\varepsilon_t \backslash \Omega_t$: $student-t(0, H_t, \nu)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The above coefficients relating to the volatility transfers are indicated in bold characters. ν represents the parameter estimates of the student-t distribution (i.e, shape of the distribution).

Estimates are obtained using the BFGS numerical optimization algorithm and the method of maximum likelihood (ML). Figure in parentheses (.) indicate the t-statistics. A single (double) asterisk denotes significance at the 5% (1%) level. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

	Null Hypotheses			
	Stock-to-USF Spillover	**USF-to-Stock Spillover**	**Stock-to-USF Asym. Spillover**	**USF-to-Stock Asym. Spillover**
Stock	**$H_{0,1}$: ($a_{1,2} = b_{1,2} = 0$)**	**$H_{0,2}$: ($a_{2,1} = b_{2,1} = 0$)**	**$H_{0,3}$: ($a_{1,2} = b_{1,2} = d_{1,2} = 0$)**	**$H_{0,4}$: ($a_{2,1} = b_{2,1} = d_{2,1} = 0$)**
AA	0.0000 **	0.0000 **	0.0000 **	0.0000 **
AGN	0.0000 **	0.0884	0.0000 **	0.0060 **
AHL	0.0000 **	0.0145 *	0.0000 **	0.0348 *
ALV	0.0001 **	0.0986	0.0000 **	0.0000 **
AXA	0.0000 **	0.3921	0.0000 **	0.1630
AZN	0.0001 **	0.5394	0.0003 **	0.4878
BAR	0.0008 **	0.0673	0.0000 **	0.1189
BNP	0.0000 **	0.2446	0.0000 **	0.3611
BPA	0.0059 **	0.0393 *	0.0010 **	0.0032 **
BTL	0.0000 **	0.0000 **	0.0000 **	0.0000 **
BVA	0.0000 **	0.0000 **	0.0000 **	0.0000 **
CA	0.0000 **	0.0000 **	0.0000 **	0.0000 **
CGE	0.4001	0.1224	0.0000 **	0.0216 *
CSG	0.0000 **	0.0000 **	0.0000 **	0.0000 **
DBK	0.0000 **	0.0009 **	0.0000 **	0.0000 **
DCY	0.0000 **	0.0000 **	0.0000 **	0.0000 **
DTE	0.0000 **	0.0000 **	0.0000 **	0.0000 **
ENI	0.0000 **	0.0000 **	0.0000 **	0.0001 **
ENL	0.0000 **	0.0007 **	0.0000 **	0.0006 **

Table 3.34: Volatility Spillovers Joint Hypothesis Tests P-Values_Student t Distribution (continued)

Stock	Null Hypotheses							
	Stock-to-USF Spillover $H_{0,1}$: $(a_{1,2} = b_{1,2} = 0)$		USF-to-Stock Spillover $H_{0,2}$: $(a_{2,1} = b_{2,1} = 0)$		Stock-to-USF Asym. Spillover $H_{0,3}$: $(a_{1,2} = b_{1,2} = d_{1,2} = 0)$		USF-to-Stock Asym. Spillover $H_{0,4}$: $(a_{2,1} = b_{2,1} = d_{2,1} = 0)$	
EOA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
ERC	0.0000	**	0.0000	**	0.0000	**	0.0000	**
FTE	0.0000	**	0.0000	**	0.0000	**	0.0000	**
GEN	0.0006	**	0.0000	**	0.0001	**	0.0000	**
GXW	0.0000	**	0.0000	**	0.0000	**	0.0000	**
HAS	0.0000	**	0.0000	**	0.0000	**	0.0000	**
HNM	0.0000	**	0.0000	**	0.0000	**	0.0000	**
ING	0.0000	**	0.0175	*	0.0000	**	0.0440	*
LLO	0.0000	**	0.1914		0.0000	**	0.0118	*
MUV	0.0000	**	0.0003	**	0.0000	**	0.0000	**
NDA	0.0000	**	0.0062	**	0.0000	**	0.0000	**
NES	0.0000	**	0.2150		0.0000	**	0.2236	
NOV	0.0000	**	0.0145	*	0.0000	**	0.0327	*
PHI	0.0000	**	0.0000	**	0.0000	**	0.0000	**
RBO	0.0000	**	0.0000	**	0.0001	**	0.0000	**
RD	0.0761		0.7411		0.0012	**	0.8846	
ROG	0.6664		0.0032	**	0.0004	**	0.0000	**
SCH	0.0000	**	0.0000	**	0.0000	**	0.0000	**
SHB	0.0079	**	0.0001	**	0.0080	**	0.0001	**
SHE	0.0000	**	0.0000	**	0.0000	**	0.0000	**
SIE	0.0000	**	0.3672		0.0000	**	0.5487	
TEF	0.0000	**	0.0000	**	0.0000	**	0.0000	**
TI	0.0000	**	0.3211		0.0000	**	0.5170	
TIM	0.0000	**	0.2537		0.0000	**	0.3121	
TLI	0.0003	**	0.0000	**	0.0000	**	0.0000	**
TOT	0.0011	**	0.0069	**	0.0000	**	0.0004	**
UBS	0.0000	**	0.0000	**	0.0000	**	0.0000	**
UC	0.0000	**	0.0000	**	0.0000	**	0.0000	**
VIV	0.0229	*	0.0107	*	0.0062	**	0.0000	**
VOF	0.0800		0.0010	**	0.1017		0.0000	**
VOW	0.0000	**	0.0000	**	0.0000	**	0.0000	**
Cannot be rejected		4		13		1		9
Rejected		46		37		49		41

Table 3.35: VECM and Multivariate GARCH Parameter Estimates_Joint Estimation

This table reports the conditional variance-covariance parameter estimates from the joint estimation for the VECM-Asymmetric BEKK GARCH (1,1)-X model:

$$R_{S,t} = \alpha_{s0} + \sum_{i=1}^{p} \alpha_{Si} R_{S,t-i} + \sum_{j=1}^{q} \beta_{Sj} R_{F,t-j} + \gamma_S Z_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t} \qquad (3.5a)$$

$$R_{F,t} = \alpha_{F0} + \sum_{i=1}^{p} \alpha_{Fi} R_{S,t-i} + \sum_{j=1}^{q} \beta_{Fj} R_{F,t-j} + \gamma_F Z_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t} \qquad (3.5b)$$

where $R_{s,t}$ and $R_{f,t}$ denote the returns of stock and futures, which are equal to $\Delta P_{s,t}$ and $\Delta P_{f,t}$, respectively. We use the multivariate version of the Schwarz Bayesian criterion (Schwarz, 1978) to determine the numbers of lags in the model, p and q. The basis at time $t-1$, Z_{t-1} (calculated as $Z_{t-1} = P_{s,t-1} - P_{f,t-1}$), serves as the error correction term (ECT).

Given; $\varepsilon_t = \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{bmatrix}$, the time-series evolution of conditional covariance matrix, $H_{t} = \begin{bmatrix} h_{s,t} & h_{sf,t} \\ h_{sf,t} & h_{f,t} \end{bmatrix}$, is assumed to follow a asymmetric BEKK GARCH(1,1)-X process:

$$H_{t,t} = C_0 C_0' + A_{11}' \varepsilon_{t,t-1} \varepsilon_{t,t-1}' A_{11} + B_{11}' H_{t,t-1} B_{11} + D_{11}' \xi_{t,t-1} \xi_{t,t-1}' D_{11} + E_{11} (Z_{t,t-1})^2 E_{11}' \qquad (3.9)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_t = \begin{bmatrix} \xi_{s,t} \\ \xi_{f,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{s,t}, 0\} \\ \min\{\varepsilon_{f,t}, 0\} \end{bmatrix}$; $Z_{t} = (P_{s,t} - P_{f,t})$; assuming $\varepsilon_t \backslash \Omega_t : N(0, H_t)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The above coefficients relating to the volatility transfers are indicated in **bold** characters. Estimates are obtained using the BFGS numerical optimization algorithm and the method of quasi-maximum likelihood. Figure in parentheses (.) indicate the t-statistics. A single (double) asterisk denotes significance at the 5% (1%) level. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
AA	0.0044 **	0.0048 **	-0.0005	0.5181 **	**0.0787**	**0.0669**	0.4214	1.3727 **	**1.2287** **	**-1.1558** **	-0.5881 *	0.0610	**0.1976**	**-0.0633**	0.0564	3.9883	4.8014	-3.4327
	(5.098)	(5.807)	(-0.946)	(2.619)	**(0.352)**	**(0.389)**	(1.823)	(6.319)	**(4.292)**	**(-6.221)**	(-2.159)	(0.213)	**(0.920)**	**(-0.233)**	(0.189)	(1.938)	(1.140)	(-0.873)
AGN	0.0094 **	0.0100 **	-0.0001	0.5751 **	**0.3546**	**0.0554**	0.3019	0.0925 **	**-0.0728**	**0.1218** *	-0.0917 **	0.0012	**0.2466**	**0.0290**	-0.1541	0.0152	17.8895	59.6942 *
	(16.967)	1(5.530)	(-0.044)	(5.007)	**(1.653)**	**(0.486)**	(1.381)	(6.033)	**(-1.557)**	**(2.364)**	(-5.724)	(0.011)	**(1.425)**	**(0.632)**	(-1.332)	(0.199)	(1.771)	(2.295)
AHL	0.0124 **	0.0118 **	-0.0025 **	0.3659	**0.9989** **	**-0.2457**	-0.9741 **	1.7537 **	**1.7285** **	**-1.9341** **	-1.9616 **	-0.4115	**0.2304**	**0.2487**	-1.2234 **	0.2102 **	0.1671 *	-0.0497 **
	(9.169)	(8.302)	(-7.192)	(1.288)	**(4.770)**	**(-1.526)**	(-7.271)	(3.157)	**(3.013)**	**(-3.989)**	(-3.962)	(-1.573)	**(1.102)**	**(0.872)**	(-6.194)	(3.187)	(2.561)	(-2.719)
ALV	0.0023 **	0.0025 **	0.0000	0.2544 *	**-0.1419**	**-0.0753**	0.3540 **	0.5025 **	**1.3385** **	**0.4622** **	-0.4565 **	-0.4383 **	**-0.2634**	**0.4588** **	0.1865	0.0380	0.1468 **	-0.0017
	(3.642)	(4.169)	(-0.005)	(2.493)	**(-1.860)**	**(-0.749)**	(5.371)	(3.448)	**(10.913)**	**(3.319)**	(-3.336)	(-4.345)	**(-1.000)**	**(4.334)**	(0.684)	(1.172)	(3.998)	(-0.020)
AXA	0.0014 **	0.0005	-0.0030 **	0.0961	**-1.1396** **	**-0.0102**	1.1586 **	0.9624 **	**0.5521** **	**0.0027**	0.3849 **	0.3314 **	**0.4475** *	**-0.0018**	-0.0213	-0.0008	-0.0450	-0.1227
	(3.990)	(0.288)	(-4.165)	(1.431)	**(-3.733)**	**(-1.259)**	(5.639)	(90.575)	**(4.115)**	**(0.702)**	(3.029)	(6.807)	**(2.500)**	**(-1.342)**	(-0.149)	(-1.276)	(-0.502)	(-1.613)

Table 3.35: VECM and Multivariate GARCH Parameter Estimates_Joint Estimation (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
AZN	0.0013	0.0020 **	0.0014	-0.2267	**0.3637**	**0.2319**	-0.3165	-0.3037	**-1.0909**	**-0.6943**	0.1238	0.1106	**0.0575**	**-0.2918** **	-0.2027	-6.6823	-10.2027 *	-6.7384
	(1.810)	(3.756)	(1.838)	(-1.128)	**(1.559)**	**(1.376)**	(-1.563)	(-0.443)	**(-1.800)**	**(-1.008)**	(0.195)	(1.155)	**(0.570)**	**(-2.902)**	(-1.703)	(-1.550)	(-2.433)	(-1.220)
BAR	0.0064 **	0.0037 *	0.0000	0.4102 **	**0.7247** **	**0.0631**	-0.3164	0.5399 **	**1.0585** **	**0.1086** *	-0.2294	-0.6670 **	**0.1718**	**0.0800**	-0.6814 **	-0.0041 **	-0.0467 **	0.0000
	(4.074)	(1.963)	(-0.000)	(3.248)	**(8.096)**	**(1.661)**	(-1.913)	(2.783)	**(5.141)**	**(2.346)**	(-1.721)	(-5.046)	**(0.835)**	**(1.589)**	(-4.115)	(-3.556)	(-2.971)	(-0.000)
BNP	0.0012 **	-0.0012	0.0018	-0.1492 **	**-0.9530** **	**-0.0343**	0.6468 **	0.9504 **	**0.4861** **	**0.0186**	0.4679 **	-0.1884 **	**-0.0110**	**0.0018**	-0.1026	-0.0026	-0.0711	0.0448
	(3.053)	(-0.483)	(0.709)	(-2.630)	**(-5.350)**	**(-1.146)**	(3.852)	(33.161)	**(3.744)**	**(0.869)**	(3.943)	(-2.712)	**(-0.023)**	**(0.099)**	(-0.278)	(-1.217)	(-1.349)	(0.621)
BPA	0.0055 **	0.0042 **	0.0012	0.6452	**0.1431**	**-0.3149**	0.1995	0.2832	**-0.2530**	**0.4946**	1.0888 **	0.6542 *	**0.1711**	**-0.9299** **	-0.3892	12.1017	11.9095	2.7621
	(2.818)	(2.577)	(1.862)	(1.256)	**(0.439)**	**(-0.565)**	(0.564)	(0.455)	**(-0.535)**	**(0.986)**	(2.784)	(2.234)	**(0.784)**	**(-4.070)**	(-1.306)	(1.199)	(1.158)	(0.764)
BTL	0.0016 **	-0.0014 **	0.0002	0.2270 **	**-0.7885** **	**-0.2732** **	0.6264 **	0.5876 **	**0.9511** **	**0.4110** **	0.0317	-0.0273	**0.2127**	**0.1119** *	-0.2434	-0.0367 **	-0.0417 **	0.0009
	(3.360)	(-3.700)	(0.236)	(3.673)	**(-5.628)**	**(-3.947)**	(4.688)	(4.487)	**(10.471)**	**(3.214)**	(0.324)	(-0.533)	**(1.939)**	**(2.135)**	(-1.903)	(-4.131)	(-3.370)	(0.023)
BVA	0.0013	0.0016	0.0000	0.2192	**0.4250**	**-0.0195**	-0.2190	1.7433 **	**1.3269** **	**-1.5671** **	-1.7039 **	-0.0453	**0.0985**	**-0.3270**	-0.4313	3.1093	1.2323	-0.0017
	(1.523)	(0.937)	(-0.006)	(1.640)	**(1.137)**	**(-0.148)**	(-0.869)	(17.187)	**80(9.156)**	**(-4.412)**	(-6.784)	(-0.149)	**(0.246)**	**(-0.915)**	(-0.885)	(0.841)	(0.368)	(-0.005)
CA	0.0021	0.0027 *	0.0000	0.0732	**-0.0909**	**0.2379** *	0.3849 **	0.4744 **	**-0.4970** **	**0.4669** **	1.3828 **	0.1294	**0.0426**	**-0.3211** **	-0.1320	2.2238	-0.1184	0.0000
	(1.874)	(2.224)	(-0.000)	(0.995)	**(-0.928)**	**(2.540)**	(3.337)	(7.595)	**(-7.828)**	**(6.687)**	1(9.534)	(0.818)	**(0.221)**	**(-4.605)**	(-1.491)	(1.272)	(-0.096)	(-0.000)
CGE																		
CSG	0.0021 **	0.0011	0.0015 **	0.1372	**0.3009**	**0.2493** **	0.0617	-0.7856 **	**-0.0070**	**-0.1262**	-0.9161 **	-0.5099 **	**0.1855**	**0.4638** **	-0.3299 **	0.3581 **	0.0813	0.0843
	(4.400)	(1.726)	(3.689)	(1.435)	**(1.816)**	**(2.807)**	(0.266)	(-12.060)	**(-0.136)**	**(-1.558)**	(-20.484)	(-4.505)	**(0.896)**	**(3.354)**	(-4.000)	(3.257)	(0.511)	(0.628)
DBK	0.0029	0.0030	0.0000	0.0978	**-0.2957** **	**0.0740**	0.4574 **	-0.9307 **	**-0.0273**	**-0.0031**	-0.9030 **	0.5077 *	**0.2664**	**-0.4457**	-0.0847	0.2013	1.1809	0.0001
	(1.387)	(1.411)	(0.000)	(0.796)	**(-2.689)**	**(0.556)**	(3.683)	(-16.606)	**(-0.423)**	**(-0.090)**	(-23.908)	(2.001)	**(1.166)**	**(-1.763)**	(-0.348)	(0.118)	(0.664)	(0.000)
DCY	0.0032	0.0047 **	0.0000	-0.1858	**0.4378** **	**0.0063**	-0.6813 **	-0.9066 **	**-0.0873**	**-0.0235**	-0.7930 **	-0.1233	**0.2060**	**0.3671** *	0.0521	0.8444	-2.5032 **	0.0002
	(1.913)	(2.784)	(-0.000)	(-1.942)	**(3.164)**	**(0.041)**	(-4.373)	(-9.842)	**(-0.785)**	**(-0.289)**	(-8.546)	(-0.850)	**(0.659)**	**(2.101)**	(0.136)	(0.669)	(-2.633)	(0.000)
DTE	0.0013 **	0.0010 *	0.0000	0.1301	**-0.0673**	**0.0831**	0.2265 *	-1.0071 **	**-0.0518** *	**0.0530**	-0.9201 **	-0.3553 *	**-0.2405**	**0.1683** **	-0.0269	-0.0574	-0.8196	0.0000
	(2.934)	(2.257)	(0.000)	(0.917)	**(-0.758)**	**(0.481)**	(2.133)	(-38.324)	**(-2.134)**	**(1.085)**	(-23.794)	(-2.464)	**(-1.730)**	**(2.599)**	(-0.288)	(-0.074)	(-1.415)	(0.000)
ENI	0.0007	-0.0014	0.0025	0.2317 **	**-1.0973** **	**-0.1163** **	0.9543 **	0.9202 **	**0.6829** **	**0.0772** **	0.2717 **	-0.0179	**0.0285**	**0.0097**	-0.1041	0.0121 *	-0.1283 *	-0.0049
	(1.209)	(-0.398)	(1.004)	(4.424)	**(-6.651)**	**(-5.875)**	(6.507)	(88.712)	**1(0.021)**	**(9.164)**	(4.903)	(-0.399)	**(0.200)**	**(0.489)**	(-0.715)	(2.369)	(-2.534)	(-0.660)
ENL																		
EOA	0.0016 **	0.0016 **	0.0000	0.1284	**0.2762** **	**0.1066**	-0.0386	-0.2284 **	**0.7600** **	**1.1214** **	0.2458 **	-0.1235	**0.1624**	**0.1942**	-0.2424 *	-0.6685	-1.1014 **	0.0000
	(4.630)	(4.945)	(-0.000)	(1.661)	**(4.728)**	**(1.843)**	(-0.613)	(-34.945)	**(98.153)**	**(100.324)**	(27.298)	(-0.541)	**(0.813)**	**(1.828)**	(-2.558)	(-1.305)	(-3.148)	(-0.000)
ERC																		
FTE	0.0017 *	0.0024 *	-0.0021 **	-0.0038	**-0.6763** **	**0.1488**	0.7990 **	1.1364 **	**0.5802** **	**-0.1766** *	0.3770	-0.4318 *	**-0.4648**	**0.2115**	0.3754	0.1174 *	0.1612	-0.1169 **
	(2.134)	(1.990)	(-4.733)	(-0.027)	**(-3.649)**	**(1.395)**	(4.824)	(15.365)	**(3.162)**	**(-2.089)**	(1.927)	(-2.322)	**(-1.915)**	**(1.345)**	(-1.724)	(2.444)	(1.792)	(-3.802)

Table 3.35: VECM and Multivariate GARCH Parameter Estimates_Joint Estimation (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
GEN																		
GXW	0.0118 **	0.0119 **	0.0000	-0.0123	**-0.2671**	**0.3744**	0.5936 **	-0.4107	**0.5449** **	**0.3593** *	-0.5868 **	0.2331	**0.0101**	**0.0571**	0.3126	1.5251	0.9685	-0.0003
	(23.922)	(24.564)	(-0.000)	(-0.054)	**(-1.139)**	**(1.626)**	(2.755)	(-1.921)	**(2.644)**	**(2.033)**	(-3.227)	(1.390)	**(0.063)**	**(0.263)**	(1.564)	(0.174)	(0.101)	(-0.000)
HAS	0.0005	0.0028 **	0.0000	0.0115	**-0.3721**	**0.0806**	0.4956 *	0.9258 *	**1.2462** **	**0.0586**	-0.4104	-0.0315	**0.6460** **	**0.2662** *	-0.3119 *	-0.2435	7.3243	-0.0140
	(0.615)	(3.109)	(-0.003)	(0.128)	**(-1.518)**	**(0.707)**	(2.178)	(2.258)	**(5.532)**	**(0.129)**	(-1.221)	(-0.165)	**(3.343)**	**(1.999)**	(-2.103)	(-0.113)	(1.861)	(-0.002)
HNM	0.0081 **	0.0095 **	-0.0001	0.0053	**-0.4743**	**0.5431**	1.0699 **	0.7577 *	**0.2047**	**-0.0664**	0.3261	-0.1624	**-1.0022** *	**0.2410**	1.3484 **	-0.4376	-6.7136	-4.1195
	(4.059)	(8.672)	(-0.264)	(0.010)	**(-1.773)**	**(0.709)**	(2.606)	(2.483)	**(0.271)**	**(-0.597)**	(0.576)	(-0.801)	**(-2.378)**	**(0.893)**	(4.032)	(-0.172)	(-1.135)	(-1.481)
ING	0.0016 **	-0.0019	0.0013	-0.1668 **	**0.2194**	**0.0319**	-0.6039 **	-0.9287 **	**-0.4861** **	**-0.0195**	-0.4642 **	0.3832 **	**0.0511**	**-0.0093**	0.1914	-0.0001	-0.1161 *	0.0195
	(4.613)	(-1.067)	(0.305)	(-2.970)	**(1.566)**	**(1.106)**	(-3.957)	(-32.830)	**(-3.731)**	**(-0.959)**	(-3.835)	(4.917)	**(0.097)**	**(-0.379)**	(0.489)	(-0.121)	(-2.101)	(0.277)
LLO	0.0009	-0.0014	0.0040 **	0.2205 **	**-0.1249**	**0.0514**	0.4183 **	0.7384 **	**0.4118** *	**0.2231** **	0.5187 *	-0.0530	**0.1669**	**0.0421**	0.1246	1.9496 *	-1.2083	-2.0889 *
	(1.921)	(-1.129)	(3.781)	(3.727)	**(-1.515)**	**(0.980)**	(6.520)	(22.617)	**(1.962)**	**(9.622)**	(2.436)	(-0.604)	**(0.896)**	**(0.406)**	(0.496)	(2.248)	(-1.453)	(-1.966)
MUV																		
NDA	0.0031 **	0.0010	-0.0017 **	-0.4721 **	**-0.2819** *	**0.4617** **	-0.1086	0.2133 **	**0.3109** **	**0.7264** **	0.6073 **	0.0235	**0.6792** **	**0.2791**	-0.3983 *	3.5841	-1.0857	-2.2549
	(4.117)	(1.811)	(-2.690)	(-3.908)	**(-2.315)**	**(6.047)**	(-1.151)	(8.845)	**(28.730)**	**(54.610)**	(149.246)	(0.080)	**(3.840)**	**(1.103)**	(-2.516)	(1.729)	(-0.724)	(-1.346)
NES	0.0011 *	0.0029 **	0.0000	0.0757	**0.2443**	**-0.0044**	0.0554	0.9348 **	**0.1318**	**0.0369** **	0.7647 **	-0.1337	**-0.0219**	**-0.1525**	-0.2652	-4.2432	5.3431	-0.0085
	(2.442)	(4.112)	(-0.000)	(0.396)	**(0.219)**	**(-0.026)**	(0.050)	(50.401)	**(1.719)**	**(5.704)**	(6.092)	(-0.846)	**(-0.028)**	**(-1.085)**	(-0.297)	(-1.090)	(0.556)	(-0.000)
NOV																		
PHI	0.0013 *	0.0047 **	-0.0001	0.1875	**0.5261**	**0.0526**	-0.4316	-0.9138 **	**-1.1991** **	**-0.0539**	0.2619 *	0.1952 *	**1.1418** **	**-0.1699**	-1.1403 **	-1.1086	10.1062 *	-0.3975
	(2.080)	(5.950)	(-0.016)	(1.700)	**(1.879)**	**(0.710)**	(-1.638)	(-10.398)	**(-11.312)**	**(-0.605)**	(2.470)	(1.970)	**(6.971)**	**(-1.698)**	(-7.109)	(-0.680)	(2.185)	(-0.022)
RBO	0.0013 **	-0.0006 *	-0.0004	-0.2326 **	**0.2324** **	**0.2148** **	-0.2622 **	0.9194 **	**0.1234** **	**0.0751** **	0.8777 **	-0.0828	**0.0557**	**0.0110**	-0.0017	-8.3114 **	5.8881 **	3.3342
	(7.058)	(-2.160)	(-1.462)	(-3.787)	**(4.492)**	**(4.738)**	(-5.229)	(476.153)	**(220.060)**	**(201.104)**	(557.331)	(-1.280)	**(0.807)**	**(0.178)**	(-0.022)	(-8.874)	(3.932)	(1.402)
RD	0.0008	-0.0018 **	-0.0001	0.1999 **	**-0.2978** **	**-0.0069**	0.5858 **	0.9684 **	**0.8855** **	**0.0071** **	0.0873 *	-0.0124	**1.2072** **	**0.0193** **	-2.3360 **	0.0010	0.0007	0.0000
	(1.780)	(-2.637)	(-0.032)	(5.539)	**(-3.350)**	**(-1.861)**	(6.809)	(123.233)	**(22.152)**	**(7.684)**	(2.248)	(-1.133)	**(3.422)**	**(5.320)**	(-3.773)	(1.571)	(0.523)	(-0.013)
ROG	0.0055 **	0.0055 *	0.0000	0.2761	**0.5623**	**0.1341**	-0.0997	1.8829 *	**1.5223**	**-1.6423** *	-0.9915	0.9563 *	**1.0357** **	**-0.8447**	-1.0750 **	11.0150	13.7919	0.0002
	(2.844)	(2.198)	(0.000)	(0.477)	**(0.680)**	**(0.216)**	(-0.094)	(2.211)	**(1.017)**	**(-2.057)**	(-0.792)	(2.294)	**(3.475)**	**(-1.568)**	(-4.184)	(0.385)	(1.302)	(0.000)
SCH	0.0003	0.0008	0.0003	0.3557 **	**0.1779**	**-0.1534** **	0.0657	0.8995 **	**-0.0399**	**0.0752** *	0.9943 **	-0.0114	**-0.2614** **	**0.1639** *	0.2363 **	0.6403	-0.3437	4.9023
	(0.684)	(1.719)	(0.406)	(4.223)	**(1.931)**	**(-2.695)**	(0.720)	(24.380)	**(-0.887)**	**(2.141)**	(22.404)	(-0.127)	**(-2.869)**	**(2.326)**	(2.668)	(0.132)	(-0.030)	(1.738)
SHB	0.0008	0.0002	0.0029 **	-0.3558 *	**0.2587** *	**0.3274** *	-0.0888	0.5187 **	**0.2669** *	**0.4608** **	0.6754 **	0.0262	**-0.0802**	**-0.3565**	-0.2136	5.7701 **	-2.3205	0.6805
	(0.895)	(0.101)	(4.343)	(-2.415)	**(2.088)**	**(2.255)**	(-0.831)	(3.598)	**(1.978)**	**(3.332)**	(4.990)	(0.120)	**(-0.544)**	**(-1.658)**	(-1.097)	(2.578)	(-1.077)	(0.489)

Table 3.35: VECM and Multivariate GARCH Parameter Estimates_Joint Estimation (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}
SHE																		
SIE	0.0010 **	0.0007 *	0.0000	0.2341 **	**-0.3079 ****	**-0.0651 ****	0.4229 **	0.9742 **	**0.1032 ****	**0.0015**	0.8870 **	-0.0808	**-0.2152 ***	**-0.0296**	0.1260	-0.0021	-0.1419 **	0.0001
	(3.589)	(2.449)	(-0.001)	(5.800)	**(-6.141)**	**(-3.124)**	(10.817)	(120.919)	**(7.450)**	**(0.183)**	(65.121)	(-1.458)	**(-2.563)**	**(-1.236)**	(1.436)	(-0.264)	(-3.406)	(0.002)
TEF	0.0013	0.0034 **	0.0000	-0.0736	**-0.4527 ****	**-0.1668**	-0.0177	-0.7683 **	**-1.1008 ****	**-0.1951**	0.4630	-0.0795	**0.2561 ****	**0.0009**	-0.3669	0.1132 *	0.1618 **	0.0000
	(1.487)	(5.411)	(-0.000)	(-0.468)	**(-3.757)**	**(-1.753)**	(-0.125)	(-2.639)	**(-6.305)**	**(-0.539)**	(1.370)	(-0.570)	**(2.594)**	**(0.004)**	(-1.891)	(2.040)	(3.057)	(-0.000)
TI	0.0088 **	0.0082 **	-0.0023	-0.4661	**0.0527**	**0.6713**	0.2529	-0.0214	**-0.0630**	**-0.0440**	-0.1775	-0.5460 **	**0.4692 ***	**0.5434**	-0.6253 *	0.0051 **	-0.0045	0.0369 **
	(13.197)	(7.277)	(-1.799)	(-1.817)	**(0.463)**	**(1.854)**	(1.531)	(-0.276)	**(-0.624)**	**(-0.464)**	(-0.534)	(-4.283)	**(2.260)**	**(1.934)**	(-2.528)	(2.709)	(-1.197)	(10.973)
TIM	0.0075 **	0.0086 **	-0.0011	0.3257	**-0.6859 ***	**-0.5999 ***	0.4763	-0.2729	**0.2672**	**-0.1057**	-0.2927 *	-0.0289	**0.4157**	**-0.2031**	-0.7709 *	2.5607 **	2.5151 **	-1.5513
	(5.883)	1(3.495)	(-0.862)	(1.489)	**(-2.253)**	**(-2.133)**	(1.174)	(-0.831)	**(0.585)**	**(-1.484)**	(-2.504)	(-0.151)	**(1.144)**	**(-0.884)**	(-2.138)	(5.362)	(3.600)	(-1.872)
TLI	0.0058 **	0.0046 **	0.0003	-0.3007	**0.2801**	**0.7677 ****	0.1196	0.7177 **	**0.4624 ****	**0.0816**	0.3986 **	0.1242	**-0.3707 ****	**0.0516**	0.6262 **	4.1304 **	0.9108	2.5606
	(13.009)	(9.862)	(1.111)	(-1.786)	**(1.829)**	**(5.325)**	(0.785)	(8.716)	**(7.970)**	**(1.146)**	(8.519)	(1.350)	**(-3.362)**	**(0.626)**	(4.848)	(2.618)	(0.657)	(1.772)
TOT	0.0023 **	0.0027 **	-0.0004	0.1152	**-0.0008**	**0.2246**	0.3219	-0.8498 **	**0.1265**	**-0.0683**	-1.0245 **	-0.5235 **	**-0.5102 ***	**0.4282 ****	0.3275	0.4680	-1.1047	-1.4252
	(3.255)	(2.895)	(-1.330)	(0.600)	**(-0.003)**	**(1.125)**	(1.284)	(-10.199)	**(1.176)**	**(-0.770)**	(-9.198)	(-2.599)	**(-2.160)**	**(2.671)**	(1.676)	(0.320)	(-1.108)	(-0.775)
UBS	0.0019 **	0.0016 **	-0.0002	-0.0648	**-0.3264 ****	**-0.1023**	0.1264 *	1.2814 **	**0.4145 ****	**-1.7938 ****	-1.2780 **	-0.0034	**-0.1651**	**-0.0286**	-0.0344	-1.1570	-0.0865	1.6411
	(4.155)	(2.967)	(-0.485)	(-0.558)	**(-2.680)**	**(-1.952)**	(2.158)	(77.590)	**(21.846)**	**(-23.432)**	(-27.605)	(-0.011)	**(-0.837)**	**(-0.087)**	(-0.177)	(-1.227)	(-0.072)	(1.309)
UC	0.0007	-0.0030 **	0.0000	0.0658	**0.2673 ****	**0.3503 ***	0.1093	0.6569 **	**0.0579**	**0.2729 ****	0.8400 **	0.0227	**0.0508**	**-0.1276**	0.1520	5.0655 **	-1.1842	0.0000
	(0.971)	(-5.921)	(-0.000)	(0.407)	**(4.125)**	**(2.433)**	(1.600)	(10.195)	**(1.380)**	**(4.659)**	(18.275)	(0.079)	**(0.586)**	**(-0.528)**	(1.161)	(3.505)	(-1.438)	(-0.000)
VIV	0.0007	0.0019 **	0.0000	0.2159	**0.1900**	**-0.1536**	-0.3423	-0.0451	**0.6725 ****	**1.0017 ****	0.3011 **	0.1791	**0.5494 ****	**0.1411**	-0.2601	-7.7900 **	0.3269	0.0056
	(1.148)	(4.996)	(0.015)	(0.599)	**(0.958)**	**(-0.422)**	(-1.755)	(-0.330)	**(25.036)**	**(8.245)**	(12.542)	(1.310)	**(3.248)**	**(1.240)**	(-1.254)	(-3.177)	(0.121)	(0.005)
VOF	0.0019 **	0.0016 **	0.0000	-0.1014	**0.0690**	**0.2943 ****	0.0378	-0.9157 **	**0.0057**	**-0.0444 ****	-0.9823 **	0.2582 **	**0.1145**	**-0.0128**	0.1239	-2.6381	-2.0454	0.0002
	(4.155)	(3.113)	(-0.000)	(-1.049)	**(1.540)**	**(3.922)**	(0.815)	(-130.320)	**(1.746)**	**(-6.900)**	(-99.923)	(2.716)	**(1.272)**	**(-0.068)**	(0.893)	(-1.949)	(-1.721)	(0.001)
VOW	0.0040 **	0.0047 **	0.0000	-0.1977	**-0.6412 ****	**-0.0221**	0.4579 **	0.0160	**0.9501 ****	**0.8610 ****	-0.0131	0.4485 **	**0.3061 ***	**-0.2640 ***	-0.1073	-3.5529	-3.6079 *	0.0000
	(2.705)	(3.060)	(-0.000)	(-1.081)	**(-3.964)**	**(-0.196)**	(4.470)	(0.108)	**(6.522)**	**(6.232)**	(-0.082)	(3.142)	**(2.390)**	**(-2.336)**	(-1.106)	(-1.735)	(-2.523)	(-0.000)

Table 3.36: Volatility Spillovers Joint Hypothesis Tests P-Values_Joint Estimation

This table reports the p-values associated with the Wald tests of the null hypotheses in the VECM-Asymmetric BEKK GARCH (1,1)-X model:

$$R_{S,t} = \alpha_{S0} + \sum_{i=1}^{p} \alpha_{Si} R_{S,t-i} + \sum_{j=1}^{q} \beta_{Sj} R_{F,t-j} + \gamma_S Z_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t} \quad (3.5a)$$

$$R_{F,t} = \alpha_{F0} + \sum_{i=1}^{p} \alpha_{Fi} R_{S,t-i} + \sum_{j=1}^{q} \beta_{Fj} R_{F,t-j} + \gamma_F Z_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t} \quad (3.5b)$$

where $R_{S,t}$ and $R_{F,t}$ denote the returns of stock and futures, which are equal to $\Delta P_{S,t}$ and $\Delta P_{F,t}$, respectively. We use the multivariate version of the Schwarz Bayesian criterion (Schwarz, 1978) to determine the numbers of lags in the model, p and q. The basis at time $t-1$, Z_{t-1}(calculated as $Z_{t-1} = P_{S,t-1} - P_{F,t-1}$), serves as the error correction term (ECT).

Given; $\varepsilon_t = \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix}$, the time-series evolution of conditional covariance matrix, $H_{i,t} = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix}$, is assumed to follow a asymmetric BEKK GARCH(1,1)-X process:

$$H_{i,t} = C_0 C_0' + A_{11}' \varepsilon_{i,t-1} \varepsilon_{i,t-1}' A_{11} + B_{11}' H_{i,t-1} B_{11} + D_{11}' \xi_{i,t-1} \xi_{i,t-1}' D_{11} + E_{11} (Z_{i,t-1})^2 E_{11}' \quad (3.9)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_{i,t} = \begin{bmatrix} \xi_{i,S,t} \\ \xi_{i,F,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{i,S,t}, 0\} \\ \min\{\varepsilon_{i,F,t}, 0\} \end{bmatrix}$; $Z_{i,t} = (P_{i,S,t} - P_{i,F,t})$; assuming $\varepsilon_t \backslash \Omega_t : N(0, H_t)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The above coefficients relating to the volatility transfers are indicated in **bold** characters. Estimates are obtained using the BFGS numerical optimization algorithm and the method of quasi-maximum likelihood Figure in parentheses (.) indicate the t-statistics. A single (double) asterisk denotes significance at the 5% (1%) level. All the estimations are made using the RATS statistical software with its built-in GARCH instruction.

	Null Hypotheses							
	Stock-to-USF Spillover		USF-to-Stock Spillover		Stock-to-USF Asym. Spillover		USF-to-Stock Asym. Spillover	
Stock	$H_{0,1}$: ($a_{1,2} = b_{1,2} = 0$)		$H_{0,2}$: ($a_{2,1} = b_{2,1} = 0$)		$H_{0,3}$: ($a_{1,2} = b_{1,2} = d_{1,2} = 0$)		$H_{0,4}$: ($a_{2,1} = b_{2,1} = d_{2,1} = 0$)	
AA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
AGN	0.2070		0.0321	*	0.1724		0.0565	
AHL	0.0000	**	0.0003	**	0.0000	**	0.0002	**
ALV	0.0000	**	0.0026	**	0.0000	**	0.0000	**
AXA	0.0001	**	0.3453		0.0000	**	0.2242	
AZN	0.1751		0.3880		0.1696		0.0213	*
BAR	0.0000	**	0.0387	*	0.0000	**	0.0894	
BNP	0.0000	**	0.4349		0.0000	**	0.5911	
BPA	0.8633		0.5095		0.8834		0.0002	**
BTL	0.0000	**	0.0004	**	0.0000	**	0.0011	**
BVA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
CA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
CGE								
CSG	0.0439	*	0.0000	**	0.0001	**	0.0000	**

Table 3.36: Volatility Spillovers Joint Hypothesis Tests P-Values_Joint Estimation (continued)

	Null Hypotheses							
	Stock-to-USF Spillover		USF-to-Stock Spillover		Stock-to-USF Asym. Spillover		USF-to-Stock Asym. Spillover	
Stock	$H_{0,1}$: $(a_{1,2} = b_{1,2} = 0)$		$H_{0,2}$: $(a_{2,1} = b_{2,1} = 0)$		$H_{0,3}$: $(a_{1,2} = b_{1,2} = d_{1,2} = 0)$		$H_{0,4}$: $(a_{2,1} = b_{2,1} = d_{2,1} = 0)$	
DBK	0.0050	**	0.5965		0.0018	**	0.1121	
DCY	0.0067	**	0.9517		0.0003	**	0.1085	
DTE	0.0413	*	0.2829		0.0528		0.0423	*
ENI	0.0000	**	0.0000	**	0.0000	**	0.0000	**
ENL								
EOA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
ERC								
FTE	0.0004	**	0.1022		0.0001	**	0.2024	
GEN								
GXW	0.0104	*	0.0015	**	0.0216	*	0.0038	**
HAS	0.0000	**	0.4647		0.0000	**	0.0083	**
HNM	0.0064	**	0.2506		0.0001	**	0.3091	
ING	0.0002	**	0.5419		0.0003	**	0.5938	
LLO	0.0248	*	0.0000	**	0.0396	*	0.0000	**
MUV								
NDA	0.0000	**	0.0000	**	0.0000	**	0.0000	**
NES	0.1748		0.0000	**	0.1494		0.0000	**
NOV								
PHI	0.0000	**	0.7350		0.0000	**	0.1101	
RBO	0.0000	**	0.0000	**	0.0000	**	0.0000	**
RD	0.0000	**	0.0000	**	0.0000	**	0.0000	**
ROG	0.5911		0.0473	*	0.0002	**	0.0298	*
SCH	0.1345		0.0209	*	0.0000	**	0.0018	**
SHB	0.0603		0.0034	**	0.1317		0.0033	**
SHE								
SIE	0.0000	**	0.0001	**	0.0000	**	0.0001	**
TEF	0.0000	**	0.2144		0.0000	**	0.3712	
TI	0.8052		0.0288	*	0.0642		0.0000	**
TIM	0.0060	**	0.0363	*	0.0153	*	0.0421	*
TLI	0.0000	**	0.0000	**	0.0000	**	0.0000	**
TOT	0.4730		0.3136		0.0486	*	0.0533	
UBS	0.0000	**	0.0000	**	0.0000	**	0.0000	**
UC	0.0002	**	0.0000	**	0.0007	**	0.0000	**
VIV	0.0000	**	0.0000	**	0.0000	**	0.0000	**
VOF	0.1563		0.0000	**	0.0365	*	0.0000	**
VOW	0.0000	**	0.0000	**	0.0000	**	0.0000	**
Cannot be rejected		3		7		0		5
Rejected		40		36		43		38

Table 3.37: VECM Parameter Estimates and Granger Causality Tests for Stock and Futures Returns_Joint Estimation

Code	Dep Var	α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_0: $\beta_{S,i}=0$)
		α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_0: $\alpha_{F,i}=0$)
AA	R_S	-0.1797 **	-0.0181	0.1384 *	0.1376 *	0.1241 *	-0.0018	-0.1328	-0.0942	0.9734 **	-0.1032 **	7.7533
		(-3.331)	(-0.277)	(2.059)	(1.998)	(2.019)	(-0.027)	(-1.714)	(-1.322)	(30.836)	(-2.681)	
	R_F	0.3103 **	0.2081 **	0.2298 **	0.1648 *	-0.3473 **	-0.2234 **	-0.2104 **	-0.1351 *	0.9390 **	0.0049	31.2615 **
		(4.958)	(2.971)	(3.433)	(2.550)	(-4.733)	(-3.120)	(-2.695)	(-1.983)	(27.909)	(0.138)	
AGN	R_S	-0.0764	-0.0097	-0.0157	0.0094	0.0716	0.0214	0.0025	-0.0027	1.4855 **	0.0089	2.3723
		(-0.624)	(-0.164)	(-0.709)	(0.395)	(0.588)	(0.438)	(0.199)	(-0.742)	(28.803)	(0.388)	
	R_F	0.4203 **	0.2080 **	0.0728	0.0357	-0.3980 **	-0.1939 **	-0.0888 *	-0.0345	1.4397 **	0.2190	20.3254 **
		(4.339)	(2.962)	(1.591)	(0.848)	(-4.417)	(-2.958)	(-2.162)	(-1.209)	(28.676)	(1.639)	
AHL	R_S	-0.3306 **	-0.4426 **	-0.2757 **	-0.0861	0.2495 **	0.6301 **	0.2025 **	0.1168 **	0.9417 **	0.0214 **	78.6274 **
		(-7.835)	(-7.340)	(-4.798)	(-1.867)	(4.923)	(8.818)	(3.184)	(2.741)	(33.323)	(6.485)	
	R_F	0.2672 **	-0.0469	-0.0837	0.0342	-0.3316 **	0.2627 **	0.0033	0.0291	0.8264 **	0.0243 **	3262.9802 **
		(38.932)	(-1.033)	(-1.498)	(0.922)	(-229.684)	(4.981)	(0.056)	(0.835)	(511.543)	(7.824)	
ALV	R_S	-0.0391	-0.1160	-0.1048	-0.0569	0.0764	0.1101	0.1083 *	0.0133	1.1591 **	0.0079	5.6048
		(-0.883)	(-1.714)	(-1.881)	(-1.288)	(1.601)	(1.532)	(1.967)	(0.320)	(35.639)	(1.442)	
	R_F	0.7399 **	0.3503 **	0.2035 **	0.0652	-0.6751 **	-0.3546 **	-0.2126 **	-0.1176 *	1.1018 **	0.0105	291.4625 **
		(15.056)	(5.482)	(3.351)	(1.468)	(-13.175)	(-5.668)	(-3.356)	(-2.522)	(32.245)	(1.675)	
AXA	R_S	0.0535 *	-0.0419	-0.0535 **	-0.0372 *	-0.0036	-0.0015	0.0041	0.0117 *	1.1715 **	0.0001	8.6010
		(2.212)	(-1.823)	(-2.843)	(-2.117)	(-0.298)	(-0.209)	(1.350)	(2.563)	(31.459)	(0.053)	
	R_F	0.8258 **	0.4727 **	0.1297 *	-0.0004	-0.7601 **	-0.4954 **	-0.1432 **	0.0133	1.1617 **	-0.0031	71.0928 **
		(6.195)	(3.685)	(2.323)	(-0.018)	(-5.740)	(-3.691)	(-2.682)	(0.615)	(27.208)	(-0.094)	
AZN	R_S	-0.2446	-0.1103	-0.1465	-0.1381	0.2804 *	0.0503	0.1650	0.1102	0.8468 **	0.0829	9.2073
		(-1.893)	(-0.837)	(-1.271)	(-1.472)	(2.221)	(0.391)	(1.439)	(1.144)	(15.903)	(1.207)	
	R_F	0.3134 *	0.2156	0.0585	0.0008	-0.2689 *	-0.2606 *	-0.0374	-0.0302	0.7618 **	0.1317 *	6.6623
		(2.404)	(1.595)	(0.471)	(0.008)	(-2.110)	(-1.995)	(-0.296)	(-0.306)	(15.524)	(2.019)	
BAR	R_S	0.0444	-0.0995 **	0.0481 *	-0.0770 **	0.0785 **	0.0148	-0.0099	-0.0069	1.0959 **	-0.0007	14.8128 **
		(1.424)	(-3.597)	(2.079)	(-3.735)	(2.806)	(1.243)	(-1.820)	(-1.622)	(34.331)	(-1.129)	
	R_F	0.6408 **	0.1400 **	0.0730	-0.0910 **	-0.5343 **	-0.2350 **	-0.0404	0.0253	1.0963 **	0.0037 **	184.5105 **
		(11.971)	(2.976)	(1.667)	(-2.671)	(-9.798)	(-5.447)	(-1.314)	(1.158)	(36.558)	(2.964)	
BNP	R_S	-0.0178	-0.0611 *	-0.0332	0.0137	-0.0006	0.0052	0.0160	-0.0374 *	0.8581 **	-0.0017	10.9744 *
		(-0.478)	(-2.190)	(-1.025)	(0.433)	(-0.020)	(0.241)	(1.110)	(-2.558)	(26.719)	(-1.356)	
	R_F	0.6188 **	0.1992 **	0.0333	0.0461	-0.5895 **	-0.2495 **	-0.0410	-0.0673	0.8240 **	0.0165	55.7847 **
		(6.431)	(3.068)	(0.612)	(0.857)	(-6.713)	(-3.557)	(-0.785)	(-1.750)	(25.046)	(1.432)	
BPA	R_S	-0.1779 *	-0.0968	-0.1175	-0.0999	0.1431	0.0554	0.0826	0.1024	0.8366 **	-0.1758 **	4.4198
		(-2.111)	(-1.215)	(-1.215)	(-1.153)	(1.542)	(0.662)	(0.856)	(1.354)	(32.480)	(-4.225)	
	R_F	0.2675 **	0.1077	-0.0485	-0.0296	-0.2997 **	-0.1241	0.0141	0.0458	0.7778 **	-0.0359	37.1943 **
		(3.956)	(1.254)	(-0.621)	(-0.360)	(-3.775)	(-1.459)	(0.177)	(0.631)	(27.175)	(-0.962)	
BTL	R_S	-0.2532 **	-0.2430 **	-0.0008	0.1175 *	0.2434 **	0.1810 **	-0.0305	-0.0784	0.9321 **	0.0196 **	84.9530 **
		(-7.837)	(-6.765)	(-0.018)	(2.243)	(6.526)	(4.725)	(-0.683)	(-1.664)	(12.936)	(2.800)	
	R_F	0.3637 **	0.1780 *	0.1938 *	0.1885 **	-0.3606 **	-0.2232 **	-0.2515 **	-0.1782 **	0.9216 **	0.0145 *	53.4146 **
		(5.815)	(2.562)	(2.080)	(3.335)	(-6.150)	(-3.472)	(-3.125)	(-3.093)	(13.168)	(2.094)	
BVA	R_S	-0.1039	-0.2066 *	-0.1079	-0.0142	0.1233	0.1691	0.0846	-0.0012	1.2357 **	-0.0534	12.0096 *
		(-1.335)	(-1.997)	(-1.122)	(-0.161)	(1.906)	(1.562)	(0.890)	(-0.013)	(39.641)	(-1.499)	
	R_F	0.3980 **	0.0669	0.0510	0.0864	-0.3605 **	-0.0957	-0.0640	-0.1130	1.1840 **	0.0887 *	72.5194 **
		(7.579)	(0.908)	(0.729)	(1.089)	(-6.749)	(-1.341)	(-0.957)	(-1.431)	(28.078)	(2.412)	
CA	R_S	-0.1796 *	-0.0423	0.0724	-0.0149	0.1396 *	0.0203	-0.1272 *	0.0187	0.7126 **	-0.0441	52.8612 **
		(-2.402)	(-0.651)	(1.203)	(-0.243)	(1.984)	(0.320)	(-2.125)	(0.312)	(23.848)	(-0.595)	
	R_F	0.3362 **	0.2819 **	0.2720 **	0.0790	-0.3598 **	-0.3146 **	-0.3081 **	-0.0772	0.6652 **	0.1285	32.2928 **
		(4.573)	(3.911)	(4.281)	(1.336)	(-5.197)	(-4.334)	(-4.876)	(-1.294)	(21.557)	(1.477)	
CGE	R_S											
	R_F											
CSG	R_S	-0.1976 **	-0.1391	-0.1368	0.0020	0.2708 **	0.1653	0.1336	-0.0533	1.3106 **	0.0136	94.0738 **
		(-5.329)	(-0.792)	(-0.982)	(0.018)	(6.271)	(0.948)	(0.813)	(-0.449)	(90.904)	(0.707)	
	R_F	0.5593 **	0.3352 *	0.2163 **	0.1110 **	-0.4849 **	-0.2914 *	-0.2241 **	-0.1595 **	1.3268 **	0.0175	985844.7788 **
		(14.856)	(2.393)	(9.322)	(684.511)	(-15.435)	(-2.275)	(-10.118)	(-12.444)	(11348.645)	(0.971)	
DBK	R_S	-0.0304	-0.0182	-0.0097	-0.0167	0.0543	0.0214	0.0223	0.0033	1.0442 **	-0.1171 **	1.4336
		(-0.627)	(-0.321)	(-0.170)	(-0.377)	(1.126)	(0.376)	(0.362)	(0.073)	(32.461)	(-2.841)	
	R_F	0.5768 **	0.3368 **	0.1845 *	0.0151	-0.5166 **	-0.3335 **	-0.1690 *	-0.0444	1.0043 **	0.0817	87.0434 **
		(9.248)	(4.676)	(2.538)	(0.324)	(-8.275)	(-4.531)	(-2.270)	(-0.922)	(29.140)	(1.606)	
DCY	R_S	0.0091	-0.0361	0.0435	-0.0130	0.0262	0.0026	-0.0247	0.0226	0.9913 **	-0.1171 **	0.6413
		(0.124)	(-0.752)	(0.821)	(-0.281)	(0.401)	(0.055)	(-0.448)	(0.436)	(25.102)	(-2.642)	
	R_F	0.5722 **	0.3087 **	0.1459 *	0.0750	-0.5258 **	-0.3348 **	-0.1243	-0.0839	0.9088 **	-0.0070	105.9015 **
		(9.552)	(3.672)	(2.086)	(1.265)	(-8.440)	(-4.245)	(-1.615)	(-1.608)	(17.778)	(-0.285)	
DTE	R_S	-0.0566	-0.1497	-0.1500 *	-0.0964	0.0568	0.1241	0.0903	0.1030 *	0.8435 **	-0.1982 **	5.4677
		(-0.790)	(-1.703)	(-1.977)	(-1.709)	(0.771)	(1.548)	(1.164)	(2.055)	(25.755)	(-3.041)	
	R_F	0.4274 **	0.1608	0.0849	-0.0188	-0.3916 **	-0.1767 *	-0.1530	0.0260	0.7617 **	0.1218 *	58.1697 **
		(5.984)	(1.725)	(1.041)	(-0.345)	(-5.475)	(-2.025)	(-1.953)	(0.553)	(24.607)	(2.502)	
ENI	R_S	-0.0718 *	-0.0445	0.0194	-0.0101	0.0631 **	0.0315	-0.0104	-0.0142	0.8072 **	-0.0006	11.2539 *
		(-2.074)	(-1.617)	(0.745)	(-0.396)	(3.042)	(1.831)	(-0.677)	(-0.709)	(17.420)	(-0.202)	
	R_F	0.3442 **	0.1286 **	-0.0049	-0.0514 *	-0.3336 **	-0.1479 **	0.0125	0.0297	0.7858 **	0.0324 **	51.2448 **
		(5.566)	(2.737)	(-0.180)	(-2.576)	(-5.268)	(-3.067)	(0.436)	(1.652)	(20.131)	(3.572)	
ENL	R_S											
	R_F											

Table 3.37: VECM Parameter Estimates and Granger Causality Tests for Stock and Futures Returns_Joint Estimation (continued)

		α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_{01}: $\beta_{F,i}$=0)
Code	Dep Var	α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_{02}: $\alpha_{S,i}$=0)
EOA	R_S	-0.2153 **	-0.1137 *	-0.1171	0.0464	0.1260 *	0.1286 **	0.0489	-0.0948 *	0.5792 **	-0.1338 **	17.8768 **
		(-4.718)	(-2.278)	(-1.914)	(1.033)	(2.522)	(2.813)	(0.974)	(-2.145)	(15.285)	(-3.561)	
	R_F	0.2923 **	0.2005 **	0.0424	0.1135 *	-0.3745 **	-0.1877 **	-0.1068 *	-0.1770 **	0.4963 **	0.1358 **	39.3273 **
		(5.708)	(3.539)	(0.600)	(2.199)	(-7.098)	(-3.743)	(-1.967)	(-3.485)	(12.052)	(4.674)	
ERC	R_S											
	R_F											
FTE	R_S	0.0356	-0.0580	0.0524	-0.0350	0.0710	0.0018	-0.0380	0.0256	1.0316 **	0.0125	0.7485
		(0.394)	(-0.667)	(0.442)	(-0.369)	(0.759)	(0.020)	(-0.316)	(0.280)	(14.480)	(1.724)	
	R_F	0.5641 **	0.2498 **	0.2248	0.0932	-0.4666 **	-0.2988 **	-0.2026	-0.0991	0.9551 **	0.0143 *	36.3760 **
		(5.811)	(2.733)	(1.932)	(0.976)	(-4.702)	(-3.220)	(-1.693)	(-1.079)	(13.349)	(1.995)	
GEN	R_S											
	R_F											
GXW	R_S	-0.1357	-0.1496	0.1374	0.0549	0.0929	0.0499	-0.1835	-0.0684	0.7702 **	-0.1390	7.1664
		(-1.467)	(-1.303)	(1.344)	(0.702)	(0.978)	(0.459)	(-1.797)	(-0.921)	(25.155)	(-1.650)	
	R_F	0.3274 **	0.0895	0.2610 **	0.1146	-0.3608 **	-0.1805	-0.2974 **	-0.1120	0.7346 **	0.0229	28.6033 **
		(3.412)	(0.765)	(2.625)	(1.464)	(-3.665)	(-1.630)	(-2.952)	(-1.499)	(22.896)	(0.258)	
HAS	R_S	0.0049	-0.0347	-0.0305	0.0688	-0.0187	0.0088	0.0707	-0.0240	0.7321 **	0.0004	3.5235
		(0.078)	(-0.564)	(-0.567)	(1.258)	(-0.258)	(0.152)	(1.147)	(-0.441)	(25.804)	(0.016)	
	R_F	0.4306 **	0.1291	-0.0176	0.0976	-0.4447 **	-0.1467 *	0.0443	-0.0377	0.7211 **	0.0879 **	57.1562 **
		(5.589)	(1.759)	(-0.332)	(1.847)	(-5.389)	(-2.188)	(0.812)	(-0.718)	(23.707)	(3.085)	
HNM	R_S	-0.0124	0.0831	0.1229	0.0602	-0.0582	-0.1740	-0.1015	-0.0537	0.5430 **	-0.1895	4.1941
		(-0.161)	(0.679)	(0.987)	(0.577)	(-0.787)	(-1.315)	(-1.267)	(-0.456)	(11.800)	(-1.299)	
	R_F	0.4025 **	0.3711 *	0.2538	0.1421	-0.4672 **	-0.4659 **	-0.2442 *	-0.0717	0.5399 **	-0.0021	49.6871 **
		(5.028)	(2.294)	(1.408)	(1.245)	(-6.126)	(-2.704)	(-2.002)	(-0.573)	(10.361)	(-0.019)	
ING	R_S	-0.0164	-0.0164	-0.0641 **	0.0429 *	0.0263	0.0121	-0.0028	-0.0014	1.2375 **	-0.0015	6.3622
		(-0.601)	(-0.642)	(-3.420)	(2.459)	(1.203)	(0.765)	(-0.306)	(-0.258)	(35.864)	(-1.114)	
	R_F	0.4460 **	0.2376 **	0.0614	0.0837 **	-0.4196 **	-0.2335 **	-0.0992 *	-0.0186	1.1873 **	0.0274	152.5231 **
		(9.875)	(3.810)	(1.418)	(2.828)	(-8.857)	(-3.425)	(-2.302)	(-0.765)	(34.996)	(1.219)	
LLO	R_S	-0.0067	-0.0628	-0.0027	-0.0367	0.0563	0.0467	-0.0459	0.0006	0.9653 **	-0.0367	3.5987
		(-0.109)	(-1.152)	(-0.062)	(-0.743)	(1.002)	(1.076)	(-1.422)	(0.013)	(18.215)	(-1.664)	
	R_F	0.4205 **	0.0663	0.0074	-0.0165	-0.3521 **	-0.0968 *	-0.0500	-0.0320	0.8959 **	0.0172	44.0764 **
		(6.446)	(1.197)	(0.164)	(-0.316)	(-5.335)	(-2.212)	(-1.558)	(-0.588)	(17.289)	(0.975)	
MUV	R_S											
	R_F											
NDA	R_S	-0.1502	-0.0342	-0.1197	0.1725	0.0478	-0.0534	0.0734	-0.0881	0.7774 **	-0.1236 *	4.0604
		(-1.612)	(-0.367)	(-1.798)	(1.929)	(0.499)	(-0.573)	(1.163)	(-1.213)	(25.247)	(-2.487)	
	R_F	0.3735 **	0.3018 *	0.0474	0.2711 **	-0.4517 **	-0.3865 **	-0.0993	-0.1694 **	0.7750 **	0.0443	45.4757 **
		(2.637)	(2.249)	(0.501)	(4.303)	(-3.132)	(-3.058)	(-1.068)	(-2.977)	(22.840)	(1.070)	
NES	R_S	-0.0657	-0.0584	-0.0492	-0.0886	0.0192	0.0183	0.0337	0.0424	0.6383 **	-0.1054	0.4643
		(-0.462)	(-0.216)	(-0.508)	(-0.964)	(0.103)	(0.069)	(0.372)	(0.247)	(18.834)	(-1.698)	
	R_F	0.3688	0.2174	0.1288	-0.0204	-0.4280	-0.2713	-0.1405	-0.0322	0.5558 **	0.2372	15.9762 **
		(1.291)	(0.686)	(1.264)	(-0.279)	(-1.457)	(-0.945)	(-1.740)	(-0.231)	(11.619)	(0.959)	
NOV	R_S											
	R_F											
PHI	R_S	-0.1060 *	-0.0316 **	-0.1323 **	-0.0659 **	0.0908 *	0.0018	0.1218 **	0.0737 **	1.4257 **	0.0722 **	3732.7607 **
		(-2.200)	(-4138.651)	(-145.093)	(-22.475)	(1.975)	(1.081)	(40.993)	(18.155)	(169.952)	(8.952)	
	R_F	0.3779 **	0.2108 **	-0.0373	-0.1299 **	-0.3950 **	-0.2367 **	0.0323	0.1441 **	1.3613 **	0.3910 **	412.0400 **
		(10.069)	(10.111)	(-1.515)	(-4.711)	(-10.208)	(-11.800)	(1.389)	(4.786)	(131.313)	(6.392)	
RBO	R_S	-0.1991 **	-0.1077	0.0185	0.0740	0.1901 **	0.0977	-0.0804	-0.0972	1.0513 **	0.0362	13.4616 **
		(-2.959)	(-1.322)	(0.219)	(1.187)	(2.888)	(1.241)	(-0.952)	(-1.444)	(25.137)	(1.055)	
	R_F	0.3364 **	0.1786 *	0.1380	0.1628 **	-0.3408 **	-0.2062 **	-0.1961 *	-0.1770 **	1.0132 **	0.0507	78.6128 **
		(5.627)	(2.372)	(1.643)	(2.601)	(-5.612)	(-2.795)	(-2.237)	(-2.595)	(23.856)	(1.370)	
RD	R_S	-0.1085 **	-0.0450 **	0.0578 **	0.0732 **	0.0284	-0.0006	-0.0112	-0.0023	0.6562 **	0.0009 **	5.9611
		(-5.743)	(-4.001)	(3.787)	(7.877)	(1.675)	(-1.334)	(-1.101)	(-0.284)	(233.727)	(8.177)	
	R_F	0.2605 **	0.0929 **	0.1291 **	0.0648 **	-0.3042 **	-0.1482 **	-0.0578 **	0.0040	0.6089 **	0.0013 **	39101455.52 **
		(2672.380)	(7.038)	(212.106)	(59.134)	(-1635.488)	(-31.783)	(-5.998)	(0.803)	(5166.138)	(10.034)	
ROG	R_S	-0.1738	-0.1814	-0.1684	-0.0911	0.1871	0.1601	0.1978	0.0800	0.8893 **	-0.0876	723.7477 **
		(-0.310)	(-0.198)	(-0.241)	(-1.467)	(0.348)	(0.186)	(0.330)	(1.875)	(6.348)	(-0.793)	
	R_F	0.3458	0.2070	0.0698	0.0235	-0.3267	-0.2436	-0.0450	-0.0345	0.8540 **	0.1516	25.8979 **
		(0.946)	(0.278)	(0.147)	(0.160)	(-0.908)	(-0.384)	(-0.124)	(-0.253)	(5.789)	(1.368)	
SCH	R_S	-0.1025	-0.1040	-0.0731	-0.0308	0.0994	0.0665	0.0759	0.0278	1.2573 **	-0.1213 *	3.6199
		(-1.712)	(-1.800)	(-1.478)	(-0.743)	(1.698)	(1.186)	(1.585)	(0.658)	(52.313)	(-2.575)	
	R_F	0.3441 **	0.1884 **	0.0294	0.0481	-0.3141 **	-0.2072 **	-0.0271	-0.0515	1.1877 **	0.0449	51.3340 **
		(6.231)	(3.337)	(0.572)	(1.119)	(-5.649)	(-3.763)	(-0.535)	(-1.183)	(49.761)	(1.026)	
SHB	R_S	-0.2314	-0.3752 *	-0.1366	0.0152	0.1401	0.3256 *	0.1096	-0.0135	0.5907 **	0.0064	5.3517
		(-1.876)	(-2.432)	(-1.552)	(0.226)	(1.149)	(2.215)	(1.324)	(-0.178)	(20.397)	(0.130)	
	R_F	0.2237 *	-0.0530	-0.0446	0.0400	-0.3165 **	0.0151	0.0012	-0.0525	0.5697 **	0.1009 *	12.8294 *
		(2.270)	(-0.480)	(-0.619)	(0.485)	(-3.185)	(0.144)	(0.016)	(-0.603)	(21.143)	(2.382)	
SHE	R_S											
	R_F											

Table 3.37: VECM Parameter Estimates and Granger Causality Tests for Stock and Futures Returns_Joint Estimation (continued)

		α_{S1}	α_{S2}	α_{S3}	α_{S4}	β_{S1}	β_{S2}	β_{S3}	β_{S4}	δ_S	γ_S	Wald test (H_{01}: $\beta_{Si}=0$)
Code	Dep Var	α_{F1}	α_{F2}	α_{F3}	α_{F4}	β_{F1}	β_{F2}	β_{F3}	β_{F4}	δ_F	γ_F	Wald test (H_{02}: $\alpha_{Fi}=0$)
SIE	R_S	-0.0614 *	-0.0152	-0.0405	-0.0473	0.0994 **	0.0044	0.0392 *	0.0369	1.0583 **	0.0030	30.2230 **
		(-2.132)	(-0.552)	(-1.780)	(-1.919)	(3.460)	(0.153)	(1.990)	(1.512)	(41.956)	(0.515)	
	R_F	0.5848 **	0.3697 **	0.2324 **	0.0970 **	-0.5394 **	-0.3852 **	-0.2327 **	-0.1080 **	1.0199 **	0.0771 *	249.2015 **
		(14.345)	(8.393)	(7.620)	(2.920)	(-13.455)	(-9.277)	(-7.703)	(-3.603)	(38.537)	(2.342)	
TEF	R_S	-0.2271 **	-0.1632 **	0.0004	-0.0034	0.2583 **	0.1595 **	0.0142	-0.0066	1.1932 **	0.0072 *	21.4537 **
		(-3.467)	(-2.713)	(0.008)	(-0.066)	(3.862)	(2.672)	(0.256)	(-0.132)	(54.812)	(2.247)	
	R_F	0.3691 **	0.1910 **	0.2384 **	0.0611	-0.3119 **	-0.1804 **	-0.2264 **	-0.0792	1.1604 **	0.0112 **	48.7836 **
		(6.102)	(3.568)	(4.604)	(1.347)	(-5.139)	(-3.270)	(-4.406)	(-1.744)	(58.678)	(3.417)	
TI	R_S	-0.0572 *	-0.0728	-0.0662 *	0.0536 **	0.0322	0.0785	0.0789	0.0078 *	1.0223 **	-0.0002	19.1850 **
		(-2.021)	(-1.801)	(-2.458)	(3.380)	(1.853)	(1.895)	(1.523)	(2.358)	(23.459)	(-0.415)	
	R_F	0.4488 **	0.0998	-0.0626 *	0.0392 *	-0.4648 **	-0.0711	0.0633	0.0065 **	0.9171 **	0.0072 **	105.8880 **
		(4.988)	(0.520)	(-2.063)	(2.026)	(-5.105)	(-0.440)	(1.362)	(5.301)	(19.319)	(4.876)	
TIM	R_S	-0.1334 *	-0.1255 *	-0.0841	0.0394	0.0999	0.1112	0.0546	0.0082	1.0348 **	-0.0101	4.1112
		(-2.385)	(-2.113)	(-1.542)	(0.978)	(1.744)	(1.838)	(1.068)	(0.180)	(28.627)	(-0.592)	
	R_F	0.4377 **	0.1188	0.1448 *	-0.0261	-0.4419 **	-0.1068	-0.1486 *	0.0819	0.9612 **	-0.0083	58.0851 **
		(6.458)	(1.104)	(2.109)	(-0.590)	(-5.759)	(-1.085)	(-2.124)	(1.367)	(22.188)	(-0.329)	
TLI	R_S	-0.4072 **	-0.1851 **	-0.0106	-0.2139 **	0.3618 **	0.0587	-0.0267	0.1944 **	0.7819 **	0.0337 **	397.6618 **
		(-11.643)	(-5.929)	(-0.255)	(-10.554)	(11.057)	(1.798)	(-0.696)	(11.235)	(57.775)	(4.007)	
	R_F	0.1712 **	0.1912 **	0.1948 **	-0.1284 **	-0.2002 **	-0.3309 **	-0.2162 **	0.1112 **	0.7652 **	0.0490 **	970710.7459 **
		(572.461)	(61.665)	(31.192)	(-88.373)	(-293.352)	(-85.924)	(-43.313)	(249.022)	(1363.712)	(502.014)	
TOT	R_S	-0.2089 *	0.0378	0.1061	0.0685	0.2171 *	-0.1522 *	-0.1276	-0.0761	0.6546 **	-0.0578	18.3630 **
		(-2.082)	(0.498)	(1.103)	(0.489)	(2.117)	(-1.960)	(-1.247)	(-0.538)	(21.719)	(-1.235)	
	R_F	0.2239	0.2166 **	0.1804	0.0845	-0.1854	-0.3126 **	-0.1864	-0.0868	0.5936 **	0.0584	10.9469 *
		(1.810)	(2.669)	(1.531)	(0.560)	(-1.442)	(-4.029)	(-1.538)	(-0.571)	(19.804)	(1.246)	
UBS	R_S	-0.0825	-0.1035	-0.0529	0.0003	0.1181	0.0980	0.0305	0.0104	1.0694 **	0.0144	3.7771
		(-1.234)	(-1.482)	(-0.892)	(0.005)	(1.790)	(1.503)	(0.543)	(0.188)	(37.949)	(0.450)	
	R_F	0.4492 **	0.2073 **	0.1702 **	0.1254 *	-0.4089 **	-0.2101 **	-0.1794 **	-0.1144 *	1.0564 **	0.0453	39.3201 **
		(5.948)	(2.652)	(2.603)	(2.218)	(-5.456)	(-2.847)	(-2.928)	(-2.114)	(39.351)	(1.481)	
UC	R_S	-0.1076 *	-0.0952	-0.0784	0.0397	0.1587 **	0.1057 *	0.0250	-0.0345	0.8382 **	-0.1501 **	15.4011 **
		(-1.993)	(-1.781)	(-1.772)	(0.914)	(3.331)	(2.051)	(0.510)	(-0.812)	(15.700)	(-3.519)	
	R_F	0.2719 **	0.1066 **	0.0068	0.0692	-0.2154 **	-0.0949 *	-0.0630	-0.0585	0.8247 **	0.1297 **	36.9810 **
		(5.465)	(2.870)	(0.168)	(1.636)	(-4.374)	(-2.309)	(-1.300)	(-1.383)	(12.726)	(3.644)	
VIV	R_S	-0.0686	-0.2852 **	-0.0046	0.1092 **	0.1042	0.2704 **	-0.0085	-0.1255 **	1.0021 **	-0.0852	63.2560 **
		(-1.330)	(-4.547)	(-0.046)	(2.945)	(1.236)	(4.678)	(-0.085)	(-4.215)	(38.126)	(-1.223)	
	R_F	0.4134 **	-0.0014	0.1487	0.1772 **	-0.3715 **	-0.0003	-0.1464	-0.1872 **	0.9728 **	0.1817 **	98.6784 **
		(8.097)	(-0.054)	(1.339)	(4.536)	(-4.931)	(-0.010)	(-1.368)	(-5.009)	(41.923)	(2.764)	
VOF	R_S	-0.2166 *	-0.1502 *	-0.1514 **	-0.0413	0.2207 *	0.1572 *	0.0798	0.0322	1.0623 **	0.1690	29.7387 **
		(-1.965)	(-2.258)	(-2.577)	(-0.667)	(2.209)	(2.190)	(1.264)	(0.507)	(27.467)	(1.535)	
	R_F	0.3181 **	0.1396	0.0476	0.0782	-0.3136 **	-0.1265	-0.1249 *	-0.0974	0.9861 **	0.2695 *	18.4985 **
		(2.803)	(1.871)	(0.851)	(1.252)	(-3.056)	(-1.523)	(-2.096)	(-1.488)	(18.725)	(2.383)	
VOW	R_S	-0.0060	-0.0707	-0.0677	-0.0101	0.0636	0.0371	0.0589	0.0401	0.9121 **	-0.1808 **	2.1391
		(-0.099)	(-1.010)	(-1.281)	(-0.215)	(1.002)	(0.520)	(1.075)	(0.835)	(34.841)	(-3.663)	
	R_F	0.5105 **	0.1656 *	0.0681	0.0301	-0.4463 **	-0.2097 **	-0.0910	-0.0131	0.8851 **	0.1014	69.3514 **
		(7.240)	(2.137)	(1.011)	(0.545)	(-6.420)	(-2.652)	(-1.330)	(-0.244)	(29.445)	(1.960)	

Notes: This table reports the VECM estimates and Granger causality tests results from the joint estimation of for the VECM-Asymmetric BEKK GARCH (1,1)-X model:

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S Z_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F Z_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

$$H_{t,t} = C_0 C_0' + A_{11}' \varepsilon_{t,t-1} \varepsilon_{t,t-1}' A_{11} + B_{11}' H_{t,t-1} B_{11} + D_{11}' \xi_{t,t-1} \xi_{t,t-1}' D_{11} + E_{11}' (Z_{t,t-1})^2 E_{11}$$

$$C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \quad A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \quad E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$$

$$\xi_t = \begin{bmatrix} \xi_{1,t} \\ \xi_{2,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{1,t}, 0\} \\ \min\{\varepsilon_{2,t}, 0\} \end{bmatrix} \quad Z_{t} = (R_{S,t} - R_{F,t}) \quad \varepsilon_t \backslash \Omega_t : N(0, H_t)$$

* and ** denote significant levels of 5% and 1%, respectively.

Figures in the parenthesis (.) are the t statistics.

Granger causality tests are based on the Wald tests of (H_{01}: $\beta_{Si} = 0$) and (H_{02}: $\alpha_{Fi} = 0$); the tests statistics are $\chi^2(4)$ distributed.

t-statistics and Wald tests are calculated using White's (1980) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $Z_{t-1} = Z' X_{t-1} = S_{t-1} - F_{t-1}$ restricted to be the lagged basis in all cases; $R_{SIF,t-1}$ is the lagged stock index returns

See the equations (3.5a) and (3.5b) and (3.9) in the text for the definitions of the remaining terms.

Table 3.38: Summary Results of VECM and Multivariate GARCH_Joint Estimation

Code	Lead-lag Relationship		Error Correction			Common Factor Weights	
	Stock Leads	Futures Leads	Stock Adjusts	Futures Adjusts		Stock (θ)	Futures (1-θ)
AA	√	×	+	−		0.046	0.954
AGN	√	×	−	−		0.961	0.039
AHL	√	√	+	+		0.531	0.469
ALV	√	×	−	−		0.571	0.429
AXA	√	×	−	−		0.001	0.999
AZN	×	×	−	+		0.614	0.386
BAR	√	√	−	+		0.835	0.165
BNP	√	√	−	−		0.909	0.091
BPA	√	×	+	−		0.001	0.999
BTL	√	√	+	+		0.426	0.574
BVA	√	√	−	+		0.624	0.376
CA	√	√	−	−		0.744	0.256
CGE							
CSG	√	√	−	−		0.562	0.438
DBK	√	×	+	−		0.411	0.589
DCY	√	×	+	−		0.001	0.999
DTE	√	×	+	+		0.381	0.619
ENI	√	√	−	+		0.981	0.019
ENL							
EOA	√	√	+	+		0.504	0.496
ERC							
FTE	√	×	−	+		0.533	0.467
GEN							
GXW	√	×	−	−		0.141	0.859
HAS	√	×	−	+		0.995	0.005
HNM	√	×	−	−		0.001	0.999
ING	√	×	−	−		0.948	0.052
LLO	√	×	−	−		0.318	0.682
MUV							
NDA	√	×	+	−		0.264	0.736
NES	√	×	−	−		0.692	0.308
NOV							
PHI	√	√	+	+		0.844	0.156
RBO	√	√	−	−		0.583	0.417
RD	√	×	+	+		0.602	0.398
ROG	√	√	−	−		0.634	0.366
SCH	√	×	+	−		0.270	0.730
SHB	√	×	−	+		0.941	0.059
SHE							
SIE	√	√	−	+		0.963	0.037
TEF	√	√	+	+		0.609	0.391
TI	√	√	−	+		0.967	0.033
TIM	√	×	−	−		0.001	0.999
TLI	√	√	+	+		0.593	0.407
TOT	√	√	−	−		0.502	0.498
UBS	√	×	−	−		0.759	0.241
UC	√	√	+	+		0.464	0.536
VIV	√	√	−	+		0.681	0.319
VOF	√	√	−	+		0.615	0.385
VOW	√	×	+	−		0.359	0.641
√	**42**	**20**	**+ 16**	**20**	**Mean**	**0.544**	**0.456**
×	**1**	**23**	**− 27**	**23**			

Notes: The VECM & Multivariate GARCH model in (3.5a), (3.5b) and (3.9) is run for each 50 pairs of cointegrated stock and futures prices

$$R_{S,t} = \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S Z_{t-1} + \delta_S R_{SIF,t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F Z_{t-1} + \delta_F R_{SIF,t-1} + \varepsilon_{F,t}$$

$$H_{i,t} = C_0 C_0' + A_{11}' \varepsilon_{i,t-1} \varepsilon_{i,t-1}' A_{11} + B_{11}' H_{i,t-1} B_{11} + D_{11}' \xi_{i,t-1} \xi_{i,t-1}' D_{11} + E_{11} (Z_{i,t-1})^2 E_{11}'$$

$$C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \quad A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \quad B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \quad E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$$

$$\xi_{i,t-1} = \begin{bmatrix} \xi_{i,S,t-1} \\ \xi_{i,F,t-1} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{i,S,t-1}, 0\} \\ \min\{\varepsilon_{i,F,t-1}, 0\} \end{bmatrix} \quad Z_{i,t} = \left(P_{i,S,t} - P_{i,F,t}\right) \quad \varepsilon_t \backslash \Omega_t : N(0, H_t)$$

A "√" indicates that the lagged cross-coefficients (β_{Si} or α_{Fi}) in equations are jointly significant at the 5% level (i.e., Recjection of H_{01} or H_{02}).
A "+" indicates that the error-correction coefficient (γ_S or γ_{Fi}) in equations is significant at the 5% level (i.e., Recjection of H_{03} or H_{04}).
The (θ_S) and (θ_F) is the price discovery contributions (i.e., weight in the common long memory factor) of stock and futures, respectively.
The calculations of the price discovery contributions [(θ_S) and (θ_F)] are based on the formula (3.8) in the text.

Figure 3.1: Trading Hours of the Markets (in GMT) - Stock and USFs

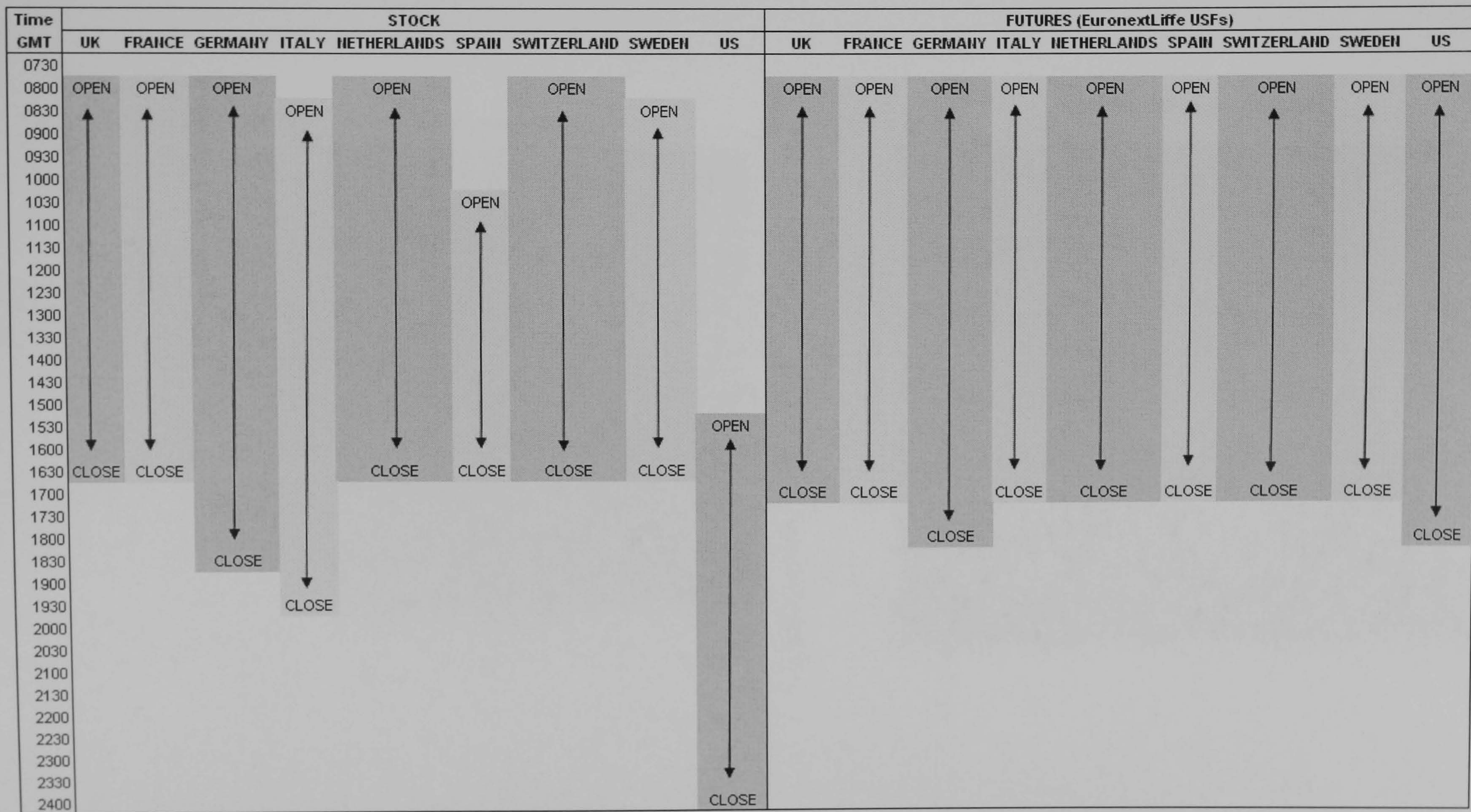


Figure 3.2: VECM Adjustment Coefficient in the Stock versus Futures Markets_FULL Period

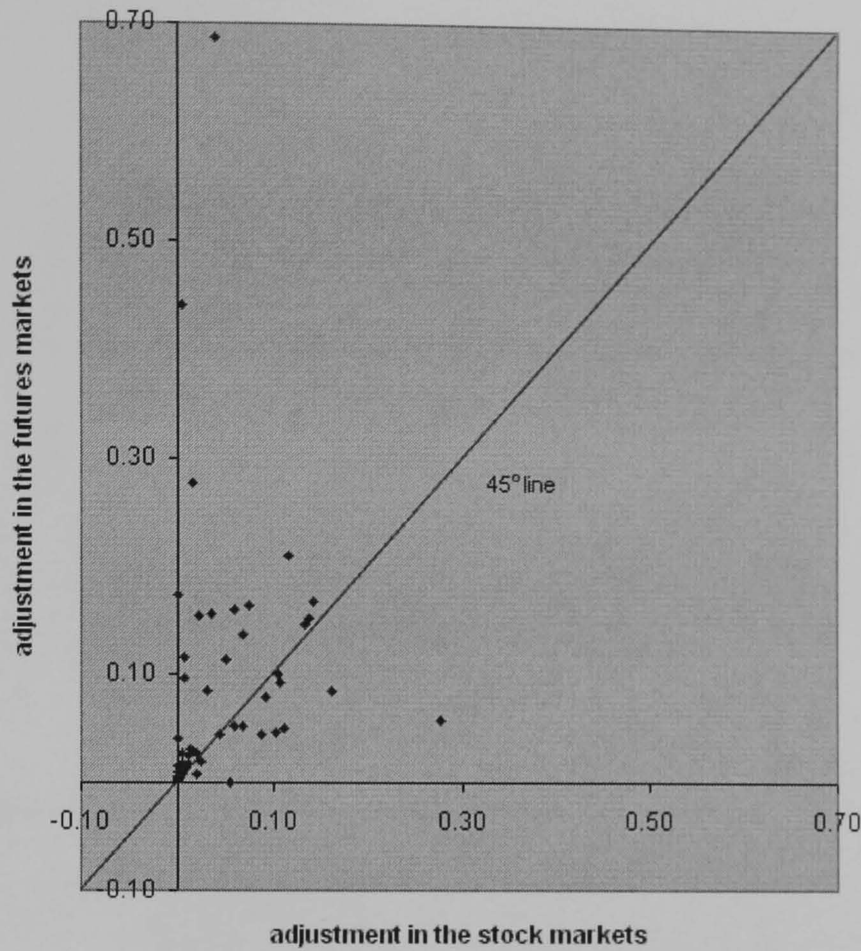


Figure 3.3: VECM Adjustment Coefficient in the Stock versus Futures Market_P1

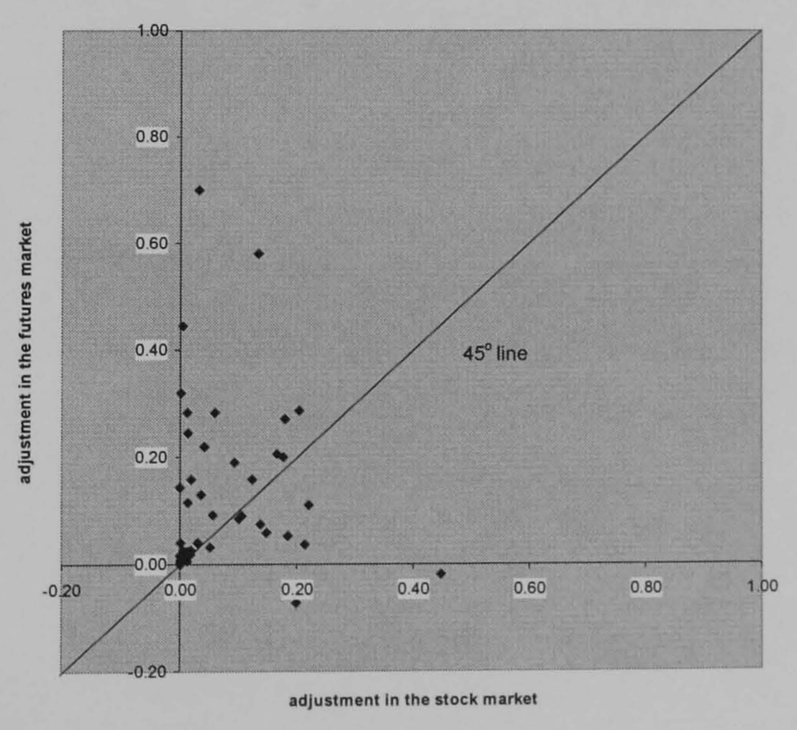


Figure 3.4: VECM Adjustment Coefficient in the Stock versus Futures Market_P2

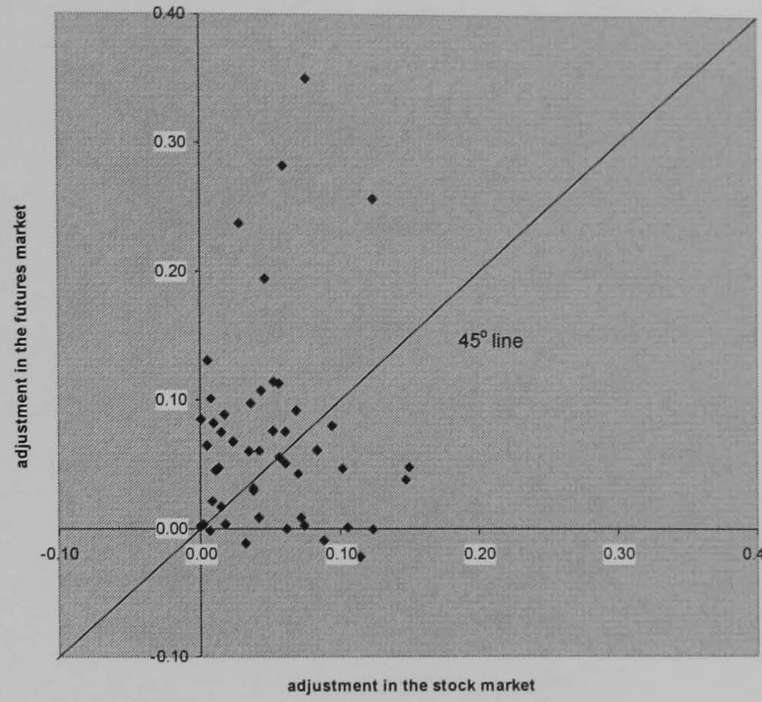


Figure 3.5: VECM Adjustment Coefficient in the Stock versus Futures Market_FULL Period_Unrestricted

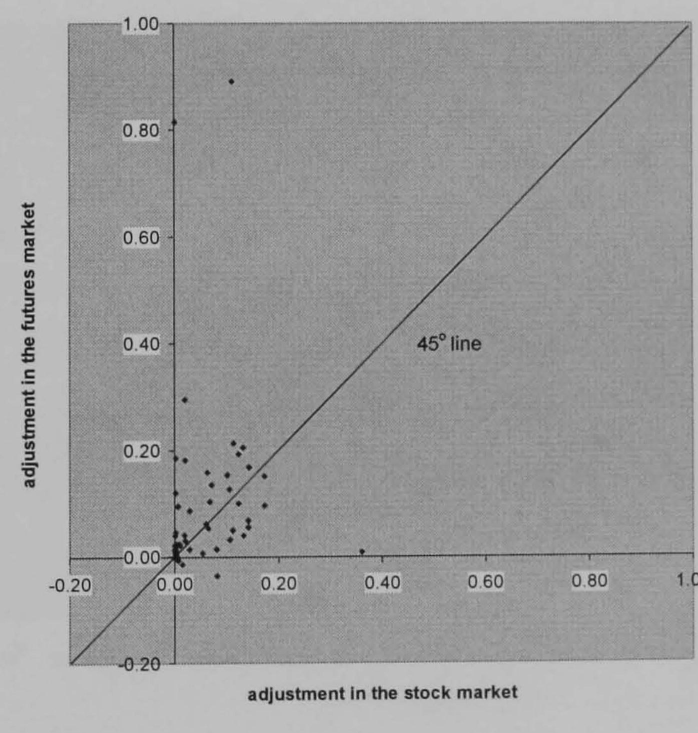


Figure 3.6: VECM Adjustment Coefficient in the Stock versus Futures Market_Without SIF

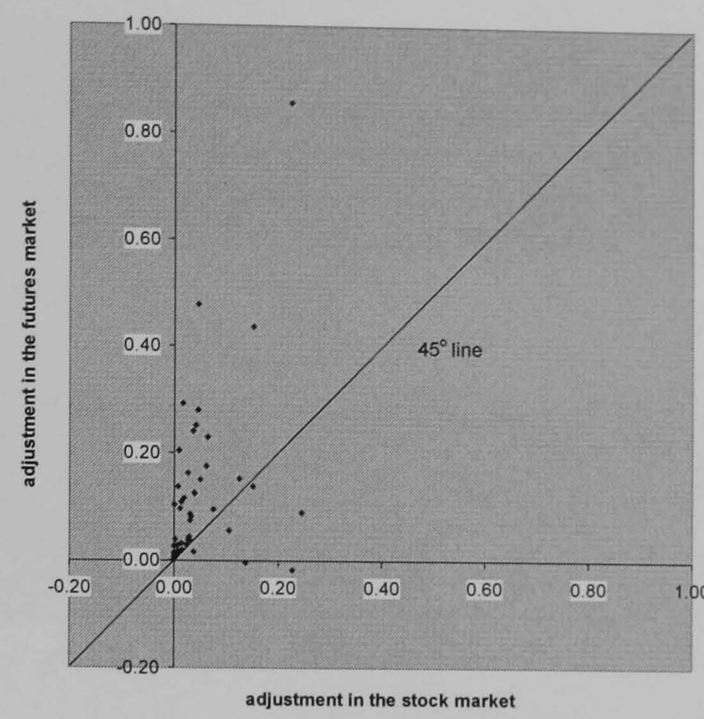


Figure 3.7: USF Price Discovery versus Volume

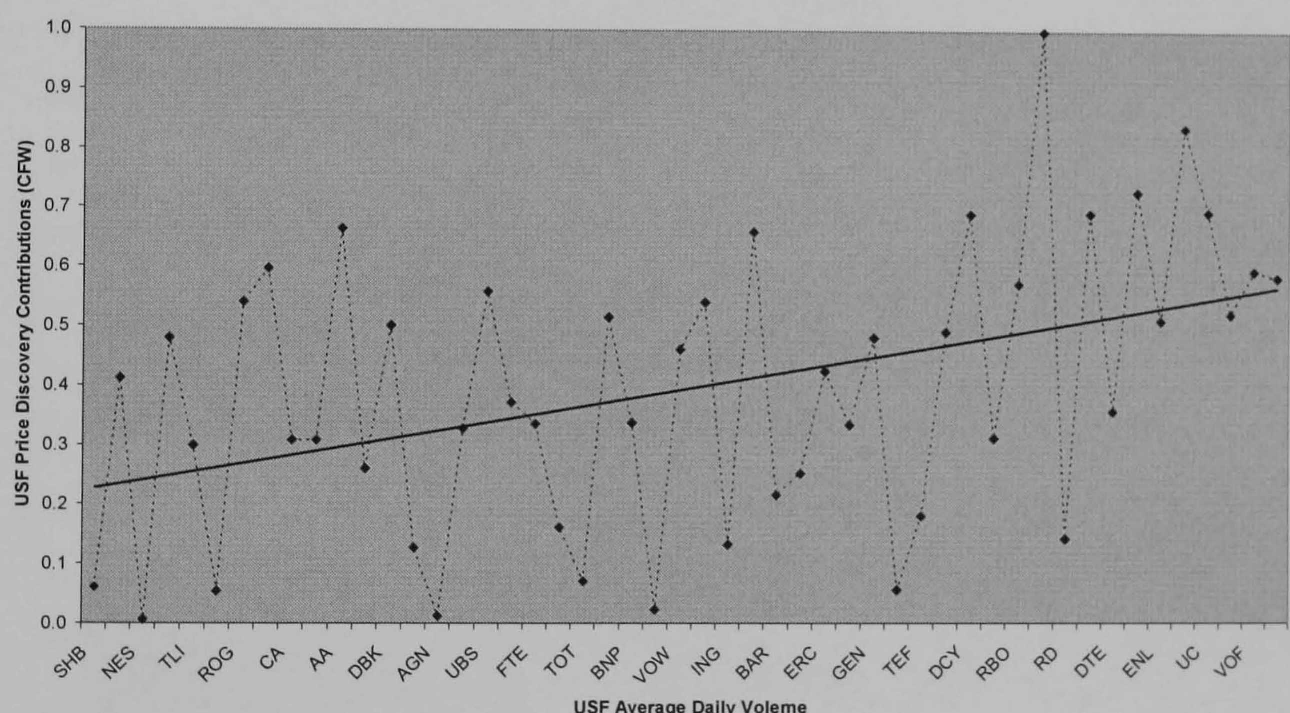


Figure 3.8: USF Price Discovery versus Spread

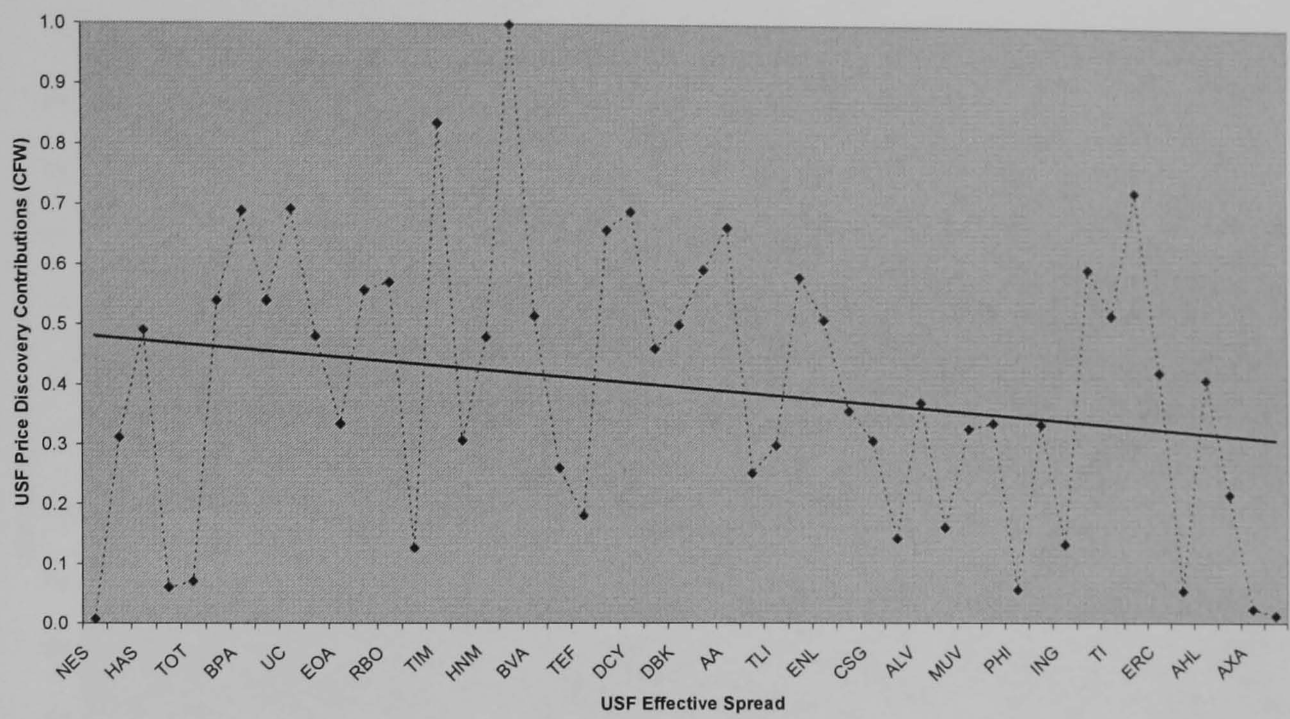


Figure 3.9: USF Price Discovery versus Volume Ratio

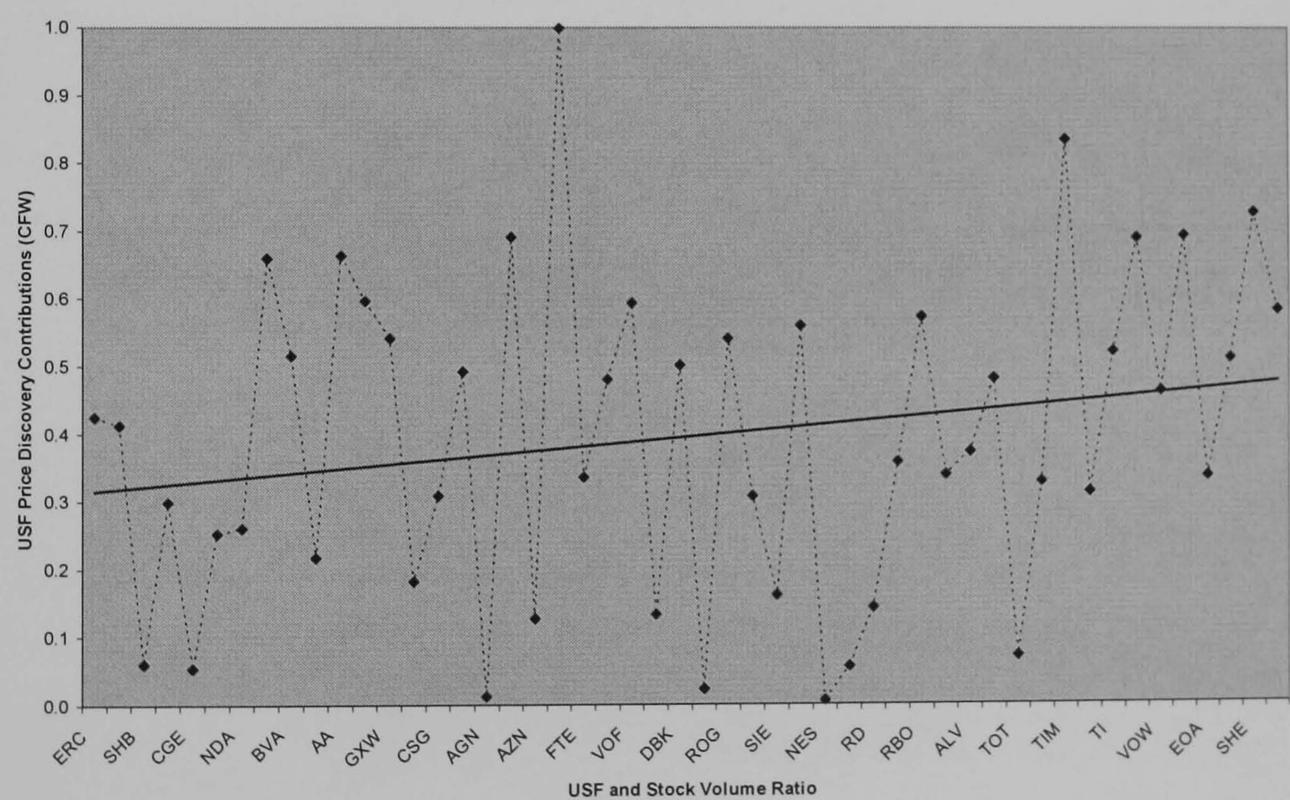


Figure 3.10: USF Price Discovery versus Spread Ratio

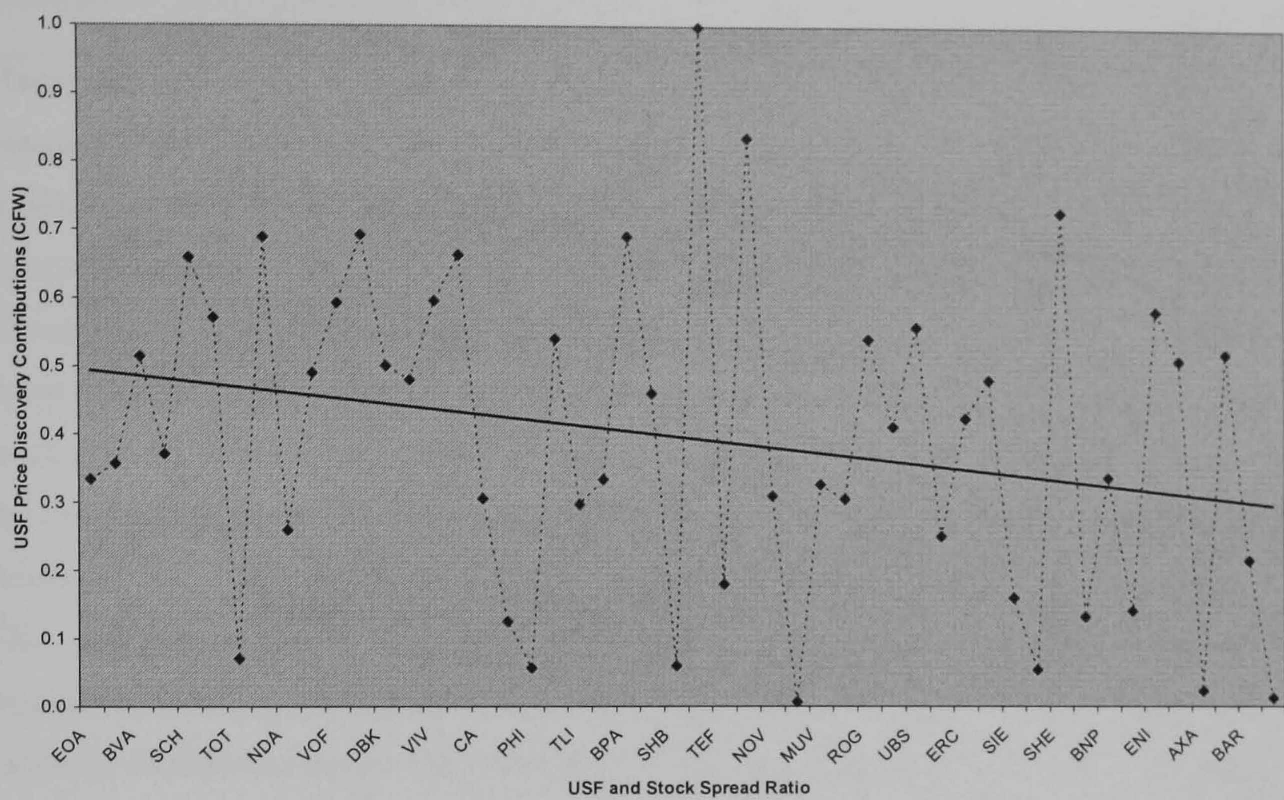
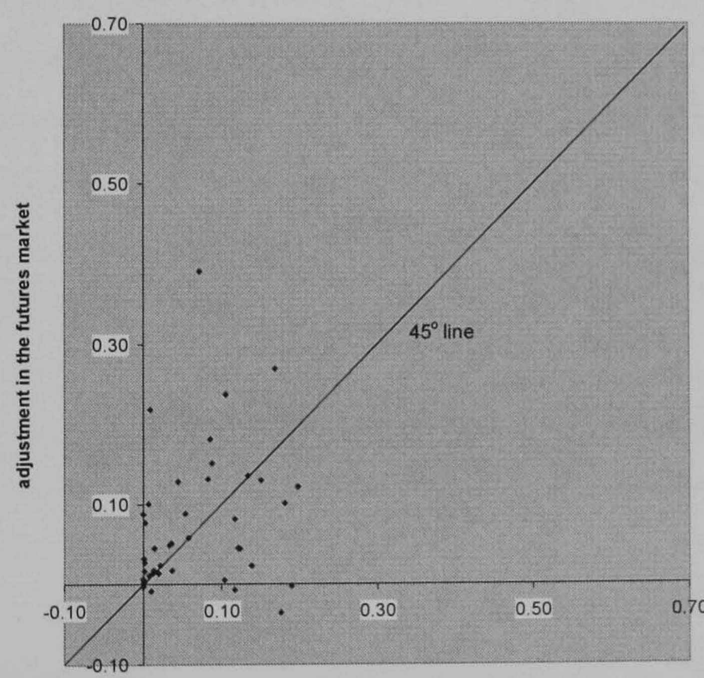


Figure 3.11: VECM Adjustment Coefficient in the Stock versus Futures Market_Joint Estimation



Appendix 3A: Overview of Main Contributions of Chapter 3

Existing Studies	This Study
Many studies consider the price discovery function of derivatives contracts, but no published work focus on SSF role in price discovery process.	First study to explicitly investigate the information transmission dynamics between the stocks and SSF in U.K. (i.e., Universal Stock Futures, USF).
Numerous studies have been devoted to price dynamics of cross-listed stocks and domestic stock markets, while some concentrate on the index and cross-listed stock index futures.	Examine the nature of "international" price discovery process across the cross-border single stock futures (e.g. USFs) and its underlying foreign stocks for the first time.
There is a 'learning curve' associated with derivatives contracts, their price discovery functions have been found to be improving over time; they tend to contribute more in the maturity period than the introduction period.	Address the issue of whether USFs price discovery contributions are different at the different stages of their development, and thus provide a direct answer to the learning curve / market-maturity hypotheses.
Due to the nature of stock index futures contracts, many studies found that they serve as the primary market for exploiting / discovery of the market-wide information that is expected to move market as a whole.	First study to directly compare the SSF futures ability in reflecting different type of information (i.e., Market-wide versus firm-specific news). It is believed that USFs facilitate the firm-specific information flow.
The amount of price discovery, and ultimately the degree of informed trading, in option markets is cross-sectionally related to the contemporaneous market conditions in both stock and option, such as trading volume, transaction costs, and volatility.	The large size of our sample enables us to explore the impact of several market microstructure (as well as contract design/specification) factors on the proportion of new information that is incorporated via USF markets.
The interaction of conditional variance (i.e., volatility-spillovers) has significant implications concerning the information transmission mechanism between stocks and derivatives markets.	First study to analyse the informativeness of USF by modelling the ways in which stock and USF interact through the second moments, and add to the long-lasting stabilising/destabilising debate.
It is commonly found that bad news raises market volatility by more than good news, and the price discovery role of derivatives is asymmetric across rising and falling markets.	Examine if the volatility-spillover patterns (and thus price discovery contribution of the USF contracts) vary depending on the information content (i.e., positive versus negative information).

Appendix 3B: The Impact of News on the Variance-Covariance Matrix

Given the time varying variance-covariance matrix, $H_t = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix}$, the time-series evolution of H_t, is assumed to follow a asymmetric BEKK GARCH (1.1)-X process:

$$H_t = C_0 C_0' + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} + D_{11}' \xi_{t-1} \xi_{t-1}' D_{11} + E_{11} (Z_{t-1})^2 E_{11}' \tag{3.9}$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$;

and, $\xi_t = \begin{bmatrix} \xi_{S,t} \\ \xi_{F,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{S,t}, 0\} \\ \min\{\varepsilon_{F,t}, 0\} \end{bmatrix}$; $Z_t = (P_{S,t} - P_{F,t})$.

Following Ng and Kroner (1998), the information at time t-1 and before is held constant, we evaluate the lagged elements of conditional variance-covariance matrix at their corresponding unconditional levels, e.g. $h_{S,t} = \sigma_S^2$. The objective is to evaluate more precisely the impact of an innovation at time t-1 of a market to the volatility of another market at time t. We specify market 1 to be the stock, market 2 to be futures.

1. Impact of News from USF market on Stock Market Volatility

Expanding model (3.9) for the (1,1) elements of H_t gives:

$$\begin{aligned} h_{S,t} &= c_{11}^2 + a_{11}^2 \varepsilon_{S,t-1}^2 + 2a_{11}a_{12}\varepsilon_{S,t-1}\varepsilon_{F,t-1} + a_{21}^2 \varepsilon_{F,t-1}^2 + b_{11}^2 h_{S,t-1} + 2b_{11}b_{12}h_{SF,t-1} \\ &+ b_{21}^2 h_{F,t-1} + d_{11}^2 \xi_{S,t-1}^2 + 2d_{11}d_{12}\xi_{S,t-1}\xi_{F,t-1} + d_{21}^2 \xi_{F,t-1}^2 \end{aligned} \tag{3.10}$$

The impact of "bad news" from USF market in period t-1 on the current stock market volatility at time t is given as:

$$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} = 2a_{11}a_{12}\varepsilon_{S,t-1} + 2a_{21}^2 \varepsilon_{F,t-1} + 2d_{21}^2 \xi_{F,t-1} + 2d_{11}d_{12}\xi_{S,t-1} \tag{3.11}$$

For simplicity, assume there is no news from stock market itself at time t-1, $\varepsilon_{S,t-1} = 0$, this reduces to:

$$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \backslash \varepsilon_{S,t-1=0} = 2a_{21}^2 \varepsilon_{F,t-1} + 2d_{21}^2 \xi_{F,t-1} \tag{3.12}$$

When there is "good news" from USF market in period t-1, $\varepsilon_{F,t-1} > 0$ and $\xi_{F,t-1} = 0$, the impact on the current stock market volatility at time t further reduces to:

$$\frac{\partial h_{S,t}}{\partial \varepsilon_{F,t-1}} \backslash \varepsilon_{S,t-1=0} = 2a_{21}^2 \varepsilon_{F,t-1} \tag{3.13}$$

Therefore, for a unit shock from USF to stock, the impact of a negative innovation exceeds the impact of good news by the quantity $2d_{21}^2$.

2. Impact of News from Stock market on USF Market Volatility

Similarly, expanding model (3.9) for the (2,2) elements of H_t gives:

$$\begin{aligned} h_{F,t} &= c_{12}^2 + c_{22}^2 + a_{12}^2\varepsilon_{S,t-1}^2 + 2a_{12}a_{22}\varepsilon_{S,t-1}\varepsilon_{F,t-1} + a_{22}^2\varepsilon_{F,t-1}^2 + b_{12}^2 h_{S,t-1} + 2b_{12}b_{22}h_{SF,t-1} \\ &+ b_{22}^2 h_{F,t-1} + d_{12}^2\xi_{S,t-1}^2 + 2d_{12}d_{22}\xi_{S,t-1}\xi_{F,t-1} + d_{22}^2\xi_{F,t-1}^2 \end{aligned} \tag{3.14}$$

The impact of "bad news" from stock market in period t-1 on the current USF market volatility at time t is given as:

$$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} = 2a_{12}a_{22}\varepsilon_{F,t-1} + 2a_{12}^2\varepsilon_{S,t-1} + 2d_{12}^2\xi_{S,t-1} + 2d_{12}d_{22}\xi_{F,t-1} \tag{3.15}$$

Again, for simplicity, assume there is no news from USF market itself at time t-1, $\varepsilon_{F,t-1} = 0$, this reduces to:

$$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \backslash \varepsilon_{F,t-1=0} = 2a_{12}^2\varepsilon_{S,t-1} + 2d_{12}^2\xi_{S,t-1} \tag{3.16}$$

When there is "good news" from stock market in period t-1, $\varepsilon_{S,t-1} > 0$ and $\xi_{S,t-1} = 0$, the impact on the current USF market volatility at time t further reduces to:

$$\frac{\partial h_{F,t}}{\partial \varepsilon_{S,t-1}} \backslash \varepsilon_{F,t-1=0} = 2a_{12}^2\varepsilon_{S,t-1} \tag{3.17}$$

Therefore, for a unit shock from the stock to USF, the impact of a negative innovation exceeds the impact of good news by the quantity $2d_{12}^2$.

It follows from the above that "bad news" from a market in period t-1 can raise the volatility of another market at time t, when the off-diagonal elements of D_{11} matrix (d_{12} and d_{21}) are significant. In this sense, no news, $\varepsilon_{S,t} = \varepsilon_{F,t} = \xi_{S,t} = \xi_{F,t} = 0$, is good news as it leads to minimum level of uncertainty (as proxied by volatility) in the following period (see, for instance, Campbell and Hentschel, 1992).

Chapter 4
The Hedging Performance of Universal Stock Futures

4.1 Introduction

In this thesis the prime concern is to examine the economic impact and performance of the newly established Universal Stock Futures (USF) contracts. To this end, chapters 2 and 3 have examined their impact on the underlying markets, and the price discovery role of these contracts. The research carried out in these two chapters demonstrates that USF trading did not undermine the underlying market, and futures served a useful social function by enhancing the information dissemination process. In this chapter we turn to an examination of the risk management function of USF markets by analysing the hedging performance of these contracts.

Market participants are confronted with various risks that arise from the ordinary conduct of their business. Derivatives markets (such as futures and options) provide an efficient way in which these risks may be transferred to other individuals who are willing to bear them. Hedging (i.e., the trading of derivatives with the objective of reducing or controlling future spot price risk) is a key function performed by derivatives markets, and their ability to transfer risk among different investors is often presented as the key justification for these markets (Garbade and Silber, 1983). According to Kolb (2000), the opportunity to control price risk through futures hedging is "...perhaps the greatest contribution of futures markets to society" (p.85). If price risk can be controlled efficiently through the futures markets then profitable investment opportunities involving a high level of risk can be pursued and, as a result, society as a whole benefits. Therefore, it is obvious that futures hedging plays an essential role in the economy.

The recent broad expansion in both the range and trading volume of futures markets has been accompanied by substantial interest in the theory and practice of hedging. For instance, since the introduction of stock index futures contracts in the early 1980s, the trading of index futures has been growing at a dramatic pace. It is believed that a major reason for its rapid growth is that it provides stock investors with a tool to hedge against stock price movements due to changes in market-wide conditions.[162] While hedging with index futures is useful and cost-effective in reducing market risk for a diversified portfolio, they may provide an inadequate hedge if the return profile of the stock exposure is significantly different from that of the index as a whole.[163]

In practice, many investors may have substantial undiversified exposure to individual stocks. For example, an investment bank that acquires shares of a firm through syndication may be subject to a covenant that restricts the sale of these shares. Similarly, a fund manager may have a large exposure to a stock that for some reasons he/she does not want to close out.[164] In many cases, investors may desire hedging against the price movements of a particular stock rather than the whole index.

---

[162] A considerable amount of empirical research has been directed towards examining the hedging effectiveness of stock index futures. The full list is too long to provide a census, but notable examples using stock index futures in U.S. includes studies by Figlewski (1984), Lindahl (1992), and Park and Switzer (1995). Examples of studies examining UK stock index futures include Lee (1994), Holmes (1995), and Butterworth and Holmes (2001). The authors who have addressed this issue in an international context are Yau (1993), Lypny and Powalla (1998), Pattarin and Ferretti (2004), Choudhry (2003, 2004), amongst others.

[163] Until recently the majority of studies that have examined the hedging effectiveness of index futures used the spot portfolios that mimic the index to evaluate the hedging performance of these financial instruments. However, in reality investors do not hold portfolios that match perfectly with the index. Butterworth and Holmes (2000, 2001) offer more realistic insights into the risk-reduction potential of the FTSE 100 and FTSE Mid-250 contracts by utilizing actual portfolios held by investment trust companies (ITC) as the underlying spot portfolios. They show that for ITCs both contracts offer a risk reduction of just 15-25%. This implies that previous studies that have examined index futures contracts in relation to their matching spot portfolios have clearly overstated their true risk reduction potential. Along the similar lines, Laws and Thompson's (2005) study strongly supports the former findings.

[164] Another instance in which investors may have concentrated holdings of a particular stock is when they received stock shares as part of a bonus or pension plan at their workplace. Brooks et al. (2006) also give some practical examples in which investors, particularly individuals, may have substantial exposures to single stocks, and thus illustrate the need for single-stock futures for hedging purposes.

According to Modern Portfolio Theory, the financial risk in owning a stock can be divided into two components: (1) market risk (systematic risk) and (2) firm-specific risk (unsystematic risk). Through diversification, an investor can *lower* her exposure to firm-specific risk, but not the market risk. Stock index futures are useful for transferring the market risk inherent in owning a portfolio. However, they may not always be an effective means to hedge firm-specific risk. Single-stock futures (SSF) are risk-shifting instruments that meet this specific need of market participants.[165]

Indeed, the question of firm-specific or idiosyncratic risk has recently attracted much attention from both academic and financial communities (Campbell et al., 2001; and Schwert, 2002). A growing number of studies have shown that there was an increase in the firm-level (i.e., unsystematic) volatility relative to the market volatility. For example, Campbell et al. (2001) is the first to provide a comprehensive study of idiosyncratic risk for U.S. stocks. They find that there was a noticeable increase in firm-level volatility relative to market volatility during the period from 1962 to 1997. Accordingly, correlations among individual stocks and the explanatory power of the market model for a typical stock declined. As a result, the hedging effectiveness of the market-wide instruments such as stock index futures for a single stock price risk significantly reduced, and the need for a *simple* derivative product that enables investors to efficiently hedge against increasing idiosyncratic risk is greater than ever. For many years, investors have relied on options to hedge their risk exposure in a particular stock; however, the fact that options markets are not readily understood lends to the calls for a relatively simpler product such as SSF for hedging purposes.

[165] Of course, as an alternative way to hedge against a potential fall in the stock price, investors could consider purchasing stock options. However, since options have more complicated pricing frameworks and often are not very transparent, investors would have to pay more transaction costs and margin outlays. In this context, single-stock futures represent a much cleaner and more efficient hedging tool than options (see Brooks et al., 2006).

Moreover, financial markets have become increasingly global over the last few decades; motivating more investors to invest internationally in order to receive better risk-return payoffs from global equity investing. When investing globally, however, there are substantial currency risks involved and thus hedging against the new risk from investing in non-domestic stocks becomes a major concern.

In response to these new market developments, in January 2001, LIFFE launched the single-stock futures contracts (under its brand name of Universal Stock Futures, USFs) on a total of 25 international shares trading in a dozen of different stock exchanges. These stocks are the leading stocks in their respective industry sectors and among the most actively traded shares in their respective stock exchanges. Two major considerations best account for the emergence of the USFs: first, it serves as a better tool than options/index futures to hedge against the non-systematic risk for individual stock; and second, cross-border futures can also reduce the currency risk for offshore investors due to the cash flow being limited to margin payment only.[166] As such, USFs should help with the 'cross-hedging' problem, particularly in relation to international portfolios and portfolios containing only a small number of stocks.

Of course, there are some other reasons for fund managers and investors to hold positions in the single-stock futures rather than trading the stock index futures alone. For instance, theoretically, the underlying stock index may not be mean-variance efficient because its weights on component stocks are fixed. If it is not efficient, then the beta of the portfolio (i.e., the regression coefficient of the portfolio against the stock index) may not properly represent the *true* systematic risk of the portfolio. Consequently, it may also not be appropriate to use the index futures as a sole source

[166] Also, due to the fact that all USFs and their underlying stocks are quoted/traded in the common local currency, any risk arises from the unexpected exchange rate movement is expected to be minimal.

to hedge against the systematic risk of a portfolio. In this case, the optimal portfolio (i.e. market portfolio) may be a combination of the stock market index and some other stocks. If the efficient frontier can be spanned by the index and a leading stock, then we know that the *true* systematic risk of a portfolio should be represented by the relationship between this portfolio and a certain 'combination' of the index and that leading stock. Therefore, it makes sense for the fund managers to trade both stock index futures and single-stock futures to hedge against the *true* systematic risk.[167]

Despite its popularity and the additional benefits provided by the new SSF contracts, to date academic studies of single-stock futures (such as USFs) are very limited, and in particular we could identify no study of hedging strategies and hedging effectiveness for these important new markets. This chapter presents the first attempt to fill the gap. More specifically, we address the following three important issues. First, we examine whether Universal Stock Futures (USFs) could serve as efficient risk management tools in hedging against the idiosyncratic risk of individual stock positions, and to contribute new evidence in this strand of literature regarding a futures market which has some unique characteristics. To address this issue, we first extend the most commonly used multivariate BEKK-GARCH model proposed by Engle and Kroner (1995) in order to develop an improved dynamic hedging strategy; and then evaluate the performance of such a hedging strategy by applying variance-reduction and utility-based performance evaluation criteria for both within-sample and out-of-sample periods. Second, we seek to demonstrate and explain the differences in the hedging effectiveness of USF contracts. To this end, we perform a cross-sectional analysis of factors affecting the hedging effectiveness of each USF. These factors include the contemporaneous market conditions (e.g. relative trading cost, market liquidity, and underlying volatility), futures specifications like 'contract

[167] The actual hedging efficiency of this hedging strategy (i.e. using simultaneously both USF and stock index futures contracts as the hedging instruments) is analysed in section 4.5.5.2.

size', the trading locations of underlying stocks, and the development stage of USFs. The regression analysis will demonstrate the relative strengths of the factors from these four different perspectives. Finally, we also investigate the *relative* hedging effectiveness of USF versus stock index futures, and assess the efficiency of creating USF portfolios in hedging those cash portfolios that containing only a few stocks. Since all the stocks on which USFs are written are also component stocks of the stock indices on which futures already exist, it may be also possible to use stock index futures (SIF) to hedge. Also, for those hedgers who hold more than one component stocks in their portfolio, multiple hedging by USFs may not be as effective as SIF since there are some correlations between the returns of the stocks and returns of the stock indices. To our knowledge, while these questions have been recognised as important issues, this is the first study to compare the *direct* hedging effectiveness of USF with the cross-hedging effectiveness of index futures contract.

Taken together, this chapter not only provides, for the first time, empirical evidence on the hedging performance of USF contracts but also contributes to the current understanding on the risk management role of futures markets in the following aspects. First, unlike stock index futures, the USF contracts are based on individual stocks which by definition can be directly traded and thus provide a unique opportunity to examine the hedging effectiveness of futures in which the underlying stock of the futures contract is exactly the same as the spot asset. This "matching nature" implies that USF may be a better hedging instrument in hedging the individual stock exposure than the market-wide instrument such as index futures. Our investigation of the *relative* hedging efficiency can thus provide a direct answer to this important issue. Second, our examination of USF hedging effectiveness over different time periods, and across several markets, could give important insights on the hedging effectiveness of futures markets at their different stages of development.

In addition, the cross-border USF contracts on the non-UK stocks allow us to shed some light to the performance of 'international' hedging, and assess the impact of trading locations of the underlying stocks on the hedging effectiveness of USFs. Third, the relatively large sample (i.e. 50 USFs) also permits us to examine the dominant characteristics that determine hedging efficiency of the futures markets by conducting a cross-sectional analysis. Empirical results will provide policy-makers insights on the importance of several factors in security design and market structures.

Finally, another important contribution of this chapter is to propose a new general multivariate GARCH model to estimate the dynamic hedge ratios, which incorporates time-varying volatility, volatility spillovers, the basis and asymmetric effects associated with the spot-futures covariance structure, while still allowing correlations between security returns to vary over time. Many recent studies have established the importance of (i) the deviation from the stock-futures equilibrium relationship (i.e. basis), (ii) the interdependence in conditional volatility, and (iii) the asymmetric pattern between spot and futures returns, on the variance-covariance structure in the cash-futures relationship which in turn have important implications concerning the estimations of optimal hedge ratios.[168] While some previous studies have employed models that capture one or more of these effects in the first and second moments of the stock and futures markets, there is no study that *simultaneously* allows for the above effects on the time-varying hedge ratio estimation process. Therefore, it is interesting to analyse whether the optimal hedging strategy constructed from a more flexible model that accounts for all these effects can produce a better hedging performance.[169]

---

[168] See, for example, Kavussanos and Nomikos (2000), Brooks et al. (2002), Meneu and Torro (2003), Choudhry (2004), Lien and Yang (2004), Lien (2005a), and Copeland and Zhu (2006).
[169] See Appendix 4A for an overview of the main contributions of this chapter to the current literature.

Findings of this chapter will benefit both the academic and financial communities. The latter includes investors (e.g., hedgers) in developing effective hedging and investment strategies, especially for those who trade globally in foreign stock markets and for those who hold portfolios containing only a small number of stocks. For example, if our empirical results indicate that USFs can provide market participants with an efficient and cost-effective means to hedge against the stock-specific risk, an investor can hedge the downward price of a biomedical company stock if the proposed new drug may have a chance of disapproval by a regulatory body. Market makers in the option markets can also implement their delta hedging strategy by using USFs, instead of the underlying stock, and save transaction costs as well as initial margin outlays. As the risk management function is often presented as the key justification for futures markets, the outcomes of our analysis will strengthen our understanding of the hedging function of single-stock futures in general, and for the specific case of USFs which remains relatively untested in the literature.

Additionally, the cross-sectional analysis on the determinants of USF hedging effectiveness will offer policy-makers and exchange executives important insights on the importance of several factors in security design and market structure that attract hedging demand in order to ensure the success of any new financial derivatives.[170] Finally, knowledge of the hedging effectiveness of LIFFE USF contracts could also provide useful references for other derivatives markets which have introduced and/or want to launch (international) single-stock futures. For instance, it may help the exchange executives and market regulators in emerging markets make decisions on whether similar derivative products should be listed in their markets as a means of enhancing the risk-sharing facility in the markets.

[170] It has been argued that a necessary but not sufficient condition for the success of a new futures contract is the existence of sufficient hedging demand for such a contract. If there is sufficient hedging demand for the contract, then the new contract is likely to succeed (see Working, 1953; Black, 1986).

The remainder of this chapter is organised as follows. Section 4.2 gives a brief review on the theory of hedging and minimum-variance hedge ratio (MVHR) methodology. Section 4.3 discusses time-varying hedge ratios and outlines the alternative model specifications that are used in estimating the conditional time-varying hedge ratios. Section 4.4 provides the descriptions of data. Section 4.5 presents the empirical results including preliminary unit root and cointegration tests, the estimations of the proposed new general BEKK-GARCH model, the within- and out-of-sample hedging effectiveness evaluations for different models, an analysis of the variations and determinants of hedging efficiency, and a comparison of USF and index futures hedging performance. Finally, section 4.6 concludes the chapter.

/ **4.2 Theories of Hedging and the Minimum-variance Hedge Ratios**

As discussed earlier, the major reason for the existence of derivatives market is to provide financial instruments for market participants to reduce the unwanted risk of price changes by transferring it to others who are more willing to bear the price risk.[171] Working (1953) argues that hedging is one of the most important social functions of futures markets. However, although hedging is believed to be the main reason for trading futures contracts, the objective of hedging has been proved controversial. This section sets out the alternative views of the purposes of hedging and, following that, presents the derivation of the minimum-variance hedge ratio.[172]

[171] This kind of exposure is called 'price risk' and is caused by the uncertainty of future price levels. However, it must note that there is another type of risk involved in hedging apart from the price risk. For instance, basis risk always occurs because of the short-run deviations of either spot or derivatives prices from their long-run equilibrium level. In this context, the basis risk (B) is defined as the variance of the difference between the spot price (S) and derivatives price (F) (i.e., B = S – F). The size of the basis risk depends mainly on the degree of correlation between spot and derivatives prices: the higher the correlation the less the basis risk. Since there is never a perfect correlation between spot and derivatives prices, the hedging in essence is an exchange of risk - swap price risk for basis risk. The behaviour and magnitude of basis has important implications to the hedgers and the effectiveness of hedges. For a hedge to be attractive, the basis risk should be significantly lower than the price risk.
[172] See Lien and Tse (2002) and Chen et al. (2003) for comprehensive reviews on futures hedging. Sutcliffe (1997) also contains a useful review of the literature on hedging stock indices with futures.

4.2.1 The Theories of Hedging

The origin of the term 'hedging' is unclear, but it appears to derive from the use of hedges to form a protective or defensive barrier around property (see Arditti, 1996). The objectives for hedging are as many as there are the potential risks in the market. In discussing hedge theory, Sutcliffe (1997) lists three main views of the nature and purpose of hedging: (i) the traditional risk minimisation view, where traders are seeking to reduce price risk; (ii) the profit maximisation view, where traders attempt to profit from the expected movements of the spot and futures price; and (iii) the portfolio approach, where traders try to reach a satisfactory risk-return trade-off by diversification. Each of these interpretations is considered next.

4.2.1.1 Risk Minimisation

Risk minimisation refers to an investor who is exposed to a risk and wishes to minimise or eliminate this exposure as his/her primary goal. This is normally achieved by taking an additional investment whose risk cancels out the initial risk. The investment of both the initial asset and the security used to offset the risk of this asset must be at equal magnitude. The hedge ratio (i.e. the number of derivatives contracts bought or sold divided by the number of spot contracts whose risk is being hedged) is simply one-to-one. In this case, the price of the derivatives contract and the price of the spot asset to be hedged are assumed to be perfectly correlated so that the losses on one position can be completely offset by the gains on the other position. In other words, this traditional view assumes that hedging will eliminate price risk. However, in reality, there is always a small amount of risk that remains unhedged when hedging with derivatives. A 'perfect' hedge will only occur when the risk of the additional investment exactly offset the initial risk. Unfortunately, the derivatives and spot prices do not move in unison due to a range of economic reasons.[173]

[173] For example, the asset whose price is to be hedged may not be exactly the same as the asset underlying the derivative contract, amongst others.

4.2.1.2 Profit Maximisation

Working (1953) was the first to challenge the traditional risk minimisation view of hedging, and to suggest that hedging in practice is undertaken not only for risk minimisation but also for other business related reasons such as profit maximisation. He argues, in the context of commodity futures, that

> "...hedging is not necessarily done for the sake of reducing risk. The role of risk-avoidance in most commercial hedging has been greatly overemphasized in economic discussions. Most hedging is done largely...because the information on which the merchant or processor acts leads logically to hedging. He buys the spot commodity because the spot price is low relative to the futures price and he has reason to expect the spot premium to advance." (Working, 1953, p.325)

Under this interpretation, the objective of a hedge is not to minimise risk, but to make a profit from movements in the relative prices of the spot asset and derivatives contract (i.e., speculation on the basis). Thus Working views hedging as a form of arbitrage and explicitly considers the speculative aspect of hedging. Many others have also endorsed Working's (1953) view and argued that traders hedge to increase their potential profits.

4.2.1.3 Portfolio Approach

Based on the earlier work of Johnson (1960) and Stein (1961), Ederington (1979) argues that a portfolio approach to hedging is superior to both the traditional one-to-one risk-minimising and the profit-maximising hedging interpretations. Under the mean-variance portfolio approach, the hedgers are assumed to be risk-averse and can hold different positions of the cash (long) and derivatives contracts (short) in his/her portfolio with the objective of maximising the expected value of the utility function. The investors buy or sell derivatives contracts in the same way they buy or sell any other portfolio of assets, according to their risk-return preferences. Therefore, a portfolio with assets and/or derivatives contracts can be entirely or partially hedged, depending on the risk and return the investor wants to sustain or earn. If an investor wants more earnings, he/she must also be willing take a higher risk. The portfolio strategies offer an opportunity for the hedger to select from a range of expected returns (i.e. diversify) because this approach does not require a cash portfolio to be fully hedged in order to lock in the existing returns (Howard and D'Antonio, 1991). This view of hedging incorporates both risk minimisation and profit maximisation as the objectives of hedgers and seems to have become more popular in practice.

4.2.2 The Minimum-variance Hedge

The earlier discussion demonstrates that, although alternative hedging strategies have been proposed to explain the purposes of hedging, the generally accepted view of hedging is that it is a means of protecting or insuring a position held in spot market. In spite of the restrictive assumption regarding attitudes to risk (i.e. infinite risk aversion), the risk-minimising approach provides a benchmark against which hedging effectiveness can be assessed and has been widely used in the literature (see Figlewski, 1984; Lindahl, 1992; Holmes, 1996; and Butterworth and Holmes, 2001). Therefore, the empirical analysis in this chapter is also undertaken on the basis that the primary purpose of hedging is to minimise the risk of a cash position.[174]

[174] Because traditional hedge theory deviates from a practical situation and maximisation hedge theory involves in speculative motivation (while fundamental finance assumes minimising risk as ordinary investors' hedging strategy), most hedging studies take variance minimisation hedge theory as the empirical framework. Exceptions include Junkus and Lee (1985) and Cecchetti et al. (1988) who used both risk minimisation and profit maximisation as the hedging objective in their empirical studies.

To achieve the risk minimisation objective, the hedger has to determine the number of futures contracts to buy or sell for each unit of spot asset on which he/she bears price risk (i.e. hedge ratio) that minimises the hedge portfolio risk. Johnson (1960), Stein (1961), and Ederington (1979) apply the principles of portfolio theory to demonstrate that the hedge ratio that minimises the risk of the hedged position is given by the ratio of the unconditional covariance between spot and futures price changes over the unconditional variance of futures price changes.

Assume that an individual has taken a long position in one unit of a particular stock and wants to secure his existing return by taking a short position in futures market.[175] The return on the hedged portfolio of stock and futures positions, ΔHP_t, is given by:

$$\Delta HP_t = \Delta S_t - h\Delta F_t \qquad (4.1)$$

where ΔHP_t is the change in the value of the hedged portfolio during time t; $\Delta S_t = S_t - S_{t-1}$ and $\Delta F_t = F_t - F_{t-1}$ are the changes in the logarithm of stock and futures prices between time t-1 and t, respectively; and h is the constant hedge ratio. Using the formula for the portfolio variance of two risky assets, the variance of the hedged portfolio returns, $Var(\Delta HP_t)$, is given by:

$$Var(\Delta HP_t) = Var(\Delta S_t) - 2hCov(\Delta S_t, \Delta F_t) + h^2 Var(\Delta F_t) \qquad (4.2)$$

where $Var(\Delta S_t)$, $Var(\Delta F_t)$, and $Cov(\Delta S_t, \Delta F_t)$ are the unconditional variance of the stock returns, the futures returns and their unconditional covariance, respectively. The optimal hedge ratio is the value of h that minimises the variance of the hedged

[175] Of course a hedge can be either short or long. A short (or selling) hedge involves selling futures contracts as a protection against a perceived decline in spot prices. For instance a shareholder, fearing that a stock price will fall, will always be a seller of futures. A long (or buying) hedge, on the other hand, involves buying futures as a protection against a price increase. For illustration purpose, we assume a short hedge in the minimum-risk framework.

portfolio returns (i.e. $\min_h[Var(\Delta HP_t)]$). Taking the partial derivative of equation (4.2) with respect to h , setting it equal to zero and solving for h . yields the minimum variance hedge ratio (MVHR), h^* , as follows:[176]

$$h^* = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)} \qquad (4.3)$$

In an *ex post* context, h^* is equivalent to the slope coefficient, β_1, in the regression:

$$\Delta S_t = \beta_0 + \beta_1 \Delta F_t + \varepsilon_t \quad ; \quad \varepsilon_t \sim iid(0, \sigma^2) \qquad (4.4)$$

Ederington (1979) shows that, within this specification, the degree of variance reduction achieved through hedging can be measured by the R^2 of equation (4.4) since it represents the percentage reduction in the variance of stock price changes. The higher R^2 value implies the greater efficiency of the minimum variance hedge.

However, several points need to be mentioned regarding to the above method of calculating MVHR. First, both β_1 and R^2 from equation (4.4) are *ex-post* measures of hedging effectiveness since they depend upon the previously explained correlation between the stock and futures prices, and as such they give an indication of the historical performance of the hedging strategy (i.e., the within-sample performance). In reality, hedgers use the historical hedge ratios to hedge a position in the future. Therefore, a more realistic way to evaluate the effectiveness of alternative hedging strategies is to use the out-of-sample framework (Butterworth and Holmes, 2000).

Second, the economic theory suggests that the prices of the spot asset and the derivatives contract are jointly / simultaneously determined (see, e.g., Stein, 1961). Estimating the spot and futures prices separately is subject to the 'simultaneous bias' and, as such, the estimated hedge ratio will be upward biased and inconsistent.

---

[176] As mentioned before, although the MVHR implicitly assumes infinite risk aversion, it is often used in empirical studies as it gives an unambiguous benchmark measure of hedging effectiveness.

Furthermore, equation (4.4) is potentially misspecified because it ignores the existence of a long-run cointegration relationship between spot and futures prices, and fails to capture the short-run dynamics by excluding relevant lagged variables (Engle and Granger, 1987). Omitting both long-run and short-run dynamics in the spot-future system will lead to downward bias on the estimated MVHR, which could possibly suffer from the problem of serial correlation in the regression residuals, $\{\varepsilon_t\}$. As a result, the futures position is less than optimal (see, for example, Herbst et al. 1992; Chou et al. 1996; Lien, 1996; and Lien, 2004, amongst others).[177]

Finally, the use of β_1 estimated from equation (4.4) as the MVHR (h^*) assumes that the covariance and the variance of futures returns remain constant over time. Clearly, this assumption is too restrictive and in contrast with the empirical evidence in different markets, which indicates that spot and futures are characterised by time-varying distributions (see, e.g. Park and Switzer, 1995). The findings of these studies suggest that the optimal (i.e. risk-minimising) hedge ratios should also be time-varying because the variance and covariance entering the MVHR calculations in equation (4.3) will adjust continuously as the new information arrives in the market.

The preceding discussion highlights the concerns regarding to the risk reduction properties of the MVHR, h^*, that are generated from equation (4.4). In order to address these problems, several empirical studies have modelled the spot and futures returns as a vector error-correction model (VECM) with the GARCH error structure. The VECM captures both short- and long-run relationships between spot and futures prices, while GARCH error structure permits the second moments of their distribution to change over time (see Gagnon and Lypny, 1997; Choudhry, 2003).

[177] Since these two biases work in opposite directions, one may hope that they will offset each other on average, even though such a coincidence cannot be assured (Lien and Tse, 2000).

4.3 Time-varying Hedge Ratios and Alternative Model Specifications

4.3.1 Time-varying Hedge Ratios

As demonstrated earlier, under the risk-minimisation framework, the MVHR can be estimated using equation (4.4) where returns from holding a spot contract (ΔS_t) are regressed on returns from holding a futures contracts (ΔF_t). The optimal hedge ratio (h^*) is equivalent to the slope coefficient (β_1) in this OLS regression. However, because the joint distribution of spot and futures returns is time-varying, the variance of the hedge portfolio returns, and thus hedge ratio, will also change through time as the new information arrives in the market and the information set is updated.

Given the above discussion, the variance of a hedged portfolio using a hedge ratio (h_t) conditional on the information set available at time t-1 (ψ_{t-1}) is as follows:

$$Var(\Delta HP_t/\psi_{t-1}) = Var(\Delta S_t/\psi_{t-1}) - 2h_t Cov(\Delta S_t, \Delta F_t/\psi_{t-1}) + h_t^2 Var(\Delta F_t/\psi_{t-1}) \qquad (4.5)$$

The optimal time-varying hedge ratio, h_t^*, which minimises the conditional variance of the hedged portfolio returns (i.e. $\min_{h_t}[Var(\Delta HP_t/\psi_{t-1})]$) is given by:

$$h_t^*/\psi_{t-1} = \frac{Cov(\Delta S_t, \Delta F_t/\psi_{t-1})}{Var(\Delta F_t/\psi_{t-1})} \qquad (4.6)$$

The conditional MVHR (h_t^*) of equation (4.6) is the ratio of the *conditional* covariance of spot and futures returns over the *conditional* variance of future returns. This ratio is similar to the conventional hedge ratio (h^*) in equation (4.4) except that conditional variance and covariance replace their unconditional counterparts. However, since the conditional moments change as the information set is updated, time-varying hedge ratio may provide superior risk reduction to the constant one. This study addresses this issue by comparing the hedging efficiency using h^* and h_t^*.

4.3.2 Alternative Model Specifications

To estimate the conditional MVHR (h_t^*) in equation (4.6), the bivariate VECM-GARCH models have been employed to account for the cointegrating relationship between stock and futures prices and the dynamic nature of their return distribution. The motivation behind using VECM-GARCH models in the context of futures hedge ratio estimation is that futures and stock prices react to the same information, and thus, have non-zero covariance conditional upon the available information set.[178] Alternative model specifications that we used in estimating h_t^* are considered in turn.

Let S_t and F_t denote, respectively, the logarithm of stock and USF prices at time t. The stock and USF returns are calculated as $R_{s,t} = S_t - S_{t-1}$ and $R_{F,t} = F_t - F_{t-1}$. The basis (i.e. spread) is defined as $B_t = S_t - F_t$. A bivariate error correction model (VECM) for the returns is specified as the following form:

$$R_{S,t} = \alpha_{S0} + \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \varepsilon_{S,t} \tag{4.7}$$

$$R_{F,t} = \alpha_{F0} + \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \varepsilon_{F,t} \tag{4.8}$$

This VECM specification contains information on both the short- and long-run adjustments to changes in stock-futures system. Specifically, B_{t-1} serves as the error-correction term to ensure that stock and USF prices never wander far from each other. The importance of incorporating a cointegrating relationship into the statistical modelling of spot and futures prices has been highlighted in many previous studies such as Kroner and Sultan (1993), Lien (1996), Choudhry (2003), and Lien (2004).

[178] A number of authors have fitted models accommodating both cointegration and conditional heteroscedasticity by using a variant of the VECM-GARCH family of models (see, for example, Lien et al., 2002; Moosa, 2003; Wang and Low, 2003; Floros and Vougas, 2004).

The conditional variance-covariance matrix of the residual vector, $\varepsilon_t = (\varepsilon_{S,t}, \varepsilon_{F,t})$, which is assumed to be conditionally normally distributed (i.e., $\varepsilon_t \backslash \psi_{t-1} \sim N(0, H_t)$), is denoted as:[179]

$$Var(\varepsilon_t / \psi_{t-1}) \equiv H_t = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix} \tag{4.9}$$

It is now well recognised that the variance of asset returns and the covariance among different asset returns are varying over time. To account for this statistical property, multivariate GARCH models are widely adopted to describe the dynamic behaviour of variance of spot and futures returns as well as the covariance between them.[180] Different model specifications/restrictions on the conditional variance-covariance matrix in multivariate GARCH model have been introduced to overcome the computational difficulty and to ensure a positive definite variance-covariance matrix. Each model has advantages and shortcomings, and may fit into one set of data better than others (see Kroner and Ng, 1998; and Bauwens et al., 2006 for the comprehensive reviews of many widely used multivariate GARCH models).

Similar to chapter 3, to estimate the conditional variance-covariance matrix of the stock and USF returns, $H_t = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix}$, we utilise the bivariate BEKK-GARCH (1,1) model first proposed by Engle and Kroner (1995) where the time-series evolution of H_t is described as follows:

[179] Of course, this can be further extended to cover more general error process like VECM-GARCH, with either t-distributed or skewed-t distributed shocks (see, e.g., Rao, 2000).
[180] Chan et al. (1991), Koutmos and Tucker (1996), Tse (1999), and So and Tse (2004), to name a few. However, most of these assume that the conditional correlation between spot and futures returns is constant through time. Although this assumption is implied in the cost-of-carry model and can overcome the computational difficulty, it is often rejected by the data (see, e.g., Tse and Tsui, 2002).

$$H_t = C_0 C_0' + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} \tag{4.10}$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$.

The innovations ε_t in model (4.10) are the unautocorrelated residuals obtained from our previous VECM in equations (4.7) and (4.8). We specify market 1 to be the stock, market 2 to be the futures. In this specification, there are two variance equations and one covariance equation, with a total of 11 parameters in the conditional variance-covariance system, H_t. The advantages of this specification are that it allows full interaction of conditional variances and covariance of two return series, and guarantees the covariance matrices are positive definite. Nevertheless, while this is perhaps one of the most general forms of the multivariate GARCH models and is widely used in the literature, it ignores the potential effect of the basis (i.e. deviation from stock-futures equilibrium prices) on the variance-covariance structure of a cointegrated system.

Therefore, our first modification to the BEKK model (4.10) is to incorporate the lagged squared basis term, $(B_{t-1})^2$, into the variance-covariance matrix (H_t) so that:

$$H_t = C_0 C_0' + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} + E_{11} (B_{t-1})^2 E_{11}' \tag{4.11}$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$;

and, $B_t = (S_t - F_t)$

This model allows the short-run deviation of stock-futures equilibrium price (i.e. basis) to impact the conditional variances and covariance, which in turn affect the estimation of optimal hedge ratio. We therefore term this model a 'BEKK-X model'.

The significance of incorporating the cointegrating relationship (as captured by the lagged squared basis term, $(B_{t-1})^2$) into the statistical modelling of the spot and futures variance-covariance system is emphasised by a number of previous studies. Lee (1994), for instance, applied a GARCH-X model to examine the predictive power of the basis/spread in forecasting exchange rate volatility. His results suggest that the exchange rates are more volatile and more difficult to predict when the basis/spread becomes larger. Ng and Pirrong (1994) also incorporated the squared basis as an explanatory variable into the conditional variance equations to describe the behaviour of metal spot and futures prices, and argued that the model that ignores the basis effect is misspecified. Zhong et al. (2004) investigated the hedging effectiveness of the Mexico IPC index futures contracts and found that the model which includes the basis effect has higher hedging efficiency.

More recently, Choudhry (2006) also extended the BEKK model for the conditional moments with an error correction term, ECT, (i.e. BEKK-X model) and found that it helps to reduce the variances of some commodity markets. Given the results of above studies, it would be interesting to analyse whether the optimal hedging strategy constructed from a model that accounts for basis effects by adding the lagged squared basis term, i.e. BEKK-X model (4.11), can provide a better fit to the data, and hence, produce a better hedging performance.[181]

[181] However, Sim and Zurbreugg (2000) replaced B_{t-1}^2 with $|B_{t-1}|$ in their GARCH-X model to examine the hedging effectiveness of KOSPI 200 futures contract during the Asian financial crisis period. Zhong et al. (2004) employed a similar method but replace B_{t-1}^2 with B_{t-1} to investigate the hedging effectiveness of Mexico IPC index futures contract. Nonetheless, our use of the lagged squared basis specification, rather than the lagged level or the lagged absolute value, is justified by the uniformly superior results and is also advocated by Lee (1994, p.377). Recently Lien and Yang (2006) further allow the basis to have asymmetric effects on variance-covariance system by separating it into positive and negative terms in examining the hedging effectiveness of six different currency futures. We also estimated a similar model as a robustness test.

Our second modification to the original BEKK model (4.10) is to introduce an asymmetry term, $D_{11}'\xi_{t-1}\xi_{t-1}'D_{11}$, into the variance-covariance matrix, H_t, so that:

$$H_t = C_0C_0' + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} + D_{11}'\xi_{t-1}\xi_{t-1}'D_{11} \qquad (4.12)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$;

and, $\xi_t = \begin{bmatrix} \xi_{S,t} \\ \xi_{F,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{S,t}, 0\} \\ \min\{\varepsilon_{F,t}, 0\} \end{bmatrix}$

This model allows for the asymmetries that may exist in the variance-covariance system of the stock and USF markets to enter into the conditional variances and covariance equations. We name it as 'AsymBEKK model' throughout the chapter.

The idea that the variance-covariance matrix may be asymmetric is not new.[182] Indeed, it is now widely accepted in literature that the 'bad news' about security return (negative innovation) raises the conditional variance and covariance by more than the equally sized 'good news' does.[183] Our asymmetric modification to the BEKK model (4.10) is also inspired by several studies. For instances, in their investigation of short-term interest risk hedging, Gagnon and Lypny (1995) show that greater risk reduction may be achieved by accounting for asymmetries in the spot-futures joint dynamics. Using a similar asymmetric BEKK-GARCH model, Brooks et al. (2002) examine the impacts of the asymmetric volatility response on the optimal hedge ratios and hedging effectiveness of the FTSE100 index futures. Their empirical results suggest that the asymmetric BEKK-GARCH model gives superior in-sample hedging performance, though the result of the simpler symmetric BEKK-GARCH model is not inferior in the out-of-sample period.

[182] There is a substantial body of literature which suggested that conditional volatility responds asymmetrically to news, especially at market level (see, for example, Black, 1976b; Christie, 1982). More recently, this phenomenon was also found to be pronounced at the individual firm level.

[183] Kroner and Ng (1998) identify three possible forms of asymmetries: (i) own-variance asymmetry, (ii) cross-variance asymmetry, and (iii) covariance asymmetry. The full range of possible asymmetries can be examined only through a multivariate approach (see Brooks et al., 2002).

However, the findings of Gagnon and Lypny (1995) and Brooks et al. (2002) are in contrast with those of Thomas and Brooks (2001) and Meneu and Torro (2003), who show that optimal hedge ratios are insensitive to the well-know asymmetric volatility and there is no significance difference in hedge effectiveness of the strategies derived from either symmetric or asymmetric GARCH models. In addition, the lack of sensitivity of hedge ratios to asymmetries is also recently confirmed by Copeland and Zhu (2006).[184] One of the possible reasons could be due to the fact that a ratio between the variance and covariance tends to compensate and make to eliminate the asymmetric effect if a proportion is maintained between both conditional second moments (see Meneu and Torro, 2003).

Recently Lien (2005a) presents a theoretical analysis for the effect of asymmetry on futures hedging, within the stochastic volatility framework. His analytical results indicate that the average hedge ratio increases with increasing degree of asymmetry. On the other hand, asymmetry seems to have little or no effect on hedging performance for both within-sample and out-of-sample cases. However, it should be noted that the asymmetric volatility model that Lien (2005a) considered suffers from several limitations such as constant correlation and the absence of spillover effects. The findings should be interpreted with cautions and the generality of results may be questionable. Since our AsymBEKK model incorporates both volatility spillover and the asymmetric effect associated with the spot-futures covariance structure, while allows correlations between two returns to vary over time, it enables us to examine the potential effect of asymmetry on futures hedging in a more general environment.

[184] Copeland and Zhu (2006) compare various dynamic hedge ratios with the standard OLS hedge ratio for futures contracts on the major stock index in six countries (Australia, Germany, Japan, Korea, UK and US). Their results suggest that the asymmetric GARCH refinement to computing minimum variance hedge ratios produces little or no improvement over OLS-based methods.

Finally, we further extend the original BEKK model (4.10) by adding *both* the lagged squared basis term, $(B_{t-1})^2$, and the asymmetry term, $D_{11}'\xi_{t-1}\xi_{t-1}'D_{11}$, into H_t, such that:

$$H_t = C_0C_0' + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} + D_{11}'\xi_{t-1}\xi_{t-1}'D_{11} + E_{11}(B_{t-1})^2E_{11}' \quad (4.13)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$;

and, $\xi_t = \begin{bmatrix} \xi_{S,t} \\ \xi_{F,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{S,t}, 0\} \\ \min\{\varepsilon_{F,t}, 0\} \end{bmatrix}$; $B_t = (S_t - F_t)$.

This augmented 'AsymBEKK-X' model is perhaps the most general form of the multivariate GARCH model which *simultaneously* incorporates the time-varying volatility, volatility spillovers, the basis and asymmetric effects on the spot-futures covariance structure while allowing correlations to vary over time. Moreover, this flexible model encompasses all BEKK models. Specifically, it reduces to original BEKK model (4.10) if the elements of D_{11} and E_{11} matrices are all set to zero; becomes BEKK-X model (4.11) when the elements of D_{11} matrix are equal zero; and reduces to AsymBEKK model (4.12) if the elements of E_{11} matrices are restricted to zero.[185]

In this chapter, we consider the hedging performance of the *dynamic* hedge ratios produced by the original BEKK, BEKK-X, AsymBEKK, as well as the most general AsymBEKK-X models, and compare them with the hedging effectiveness for the *constant* hedge ratios generated from both OLS and VECM regression models. For comparison purpose, performance of the unhedged position and naïve hedge ratio of one are also evaluated.

---

[185] Due to a large number of parameters involved in the estimation, we employ a two-step procedure to estimate our models. The first step is to apply VECM in equations (4.7) and (4.8) and then using residuals of VECM in the formulation of alternative BEKK GARCH (1,1) models in the second step. Before estimating mean equations, we use the Schwarz Bayesian criterion (Schwarz, 1978) to determine p, the number of lags in the mean equations. Tse (1999) mentions that, because the least squares estimator used in VECM is still unbiased and consistent even with the presence of heteroscedasticity, this two-step approach is asymptotically equivalent to a joint estimation of the VECM and GARCH models.

4.3.3 Measuring Hedging Effectiveness

To measure and compare the hedging effectiveness of each strategy, we compute the risk-reduction and its economic significance when the utility level is considered. Furthermore, we will distinguish between *ex-post* and *ex-ante* results by splitting the data sample in two parts. In the first one, the hedging performances are compared *ex-post* whereas in the second one an *ex-ante* approach is used.

4.3.3.1 The Risk Reduction

In order to evaluate the hedging performance of different hedging strategies, we compute the percentage reduction in the variance of the portfolio returns from these strategies over both within-sample and out-of-sample periods. More specifically, given the following variance of the hedged portfolio of each strategy:

$$Var(\Delta HP_t/\psi_{t-1}) = Var(\Delta S_t - h_t^* \Delta F_t/\psi_{t-1}) \qquad (4.14)$$

where h_t^* are the optimal (i.e. minimum-variance) hedge ratios produced by different models, the variance of each hedged portfolio is compared to the variance of the unhedged position (i.e. $Var(\Delta S_t)$ where $h_t^* = 0$ for all t), and then the variance reduction achieved through hedging is calculated as follows:

$$1 - \frac{Var(\Delta HP_t/\psi_{t-1})}{Var(\Delta S_t)} \qquad (4.15)$$

The larger the variance reduction, the higher the degree of hedging effectiveness. When h_t^* in equation (4.14) is the OLS hedge ratio of equation (4.4), β_1, this hedging effectiveness measure is same as the R^2 of equation (4.4) (see Ederington, 1979). This variance-based hedging effectiveness measure is widely used in the literature, even though it has been argued to be favouring the OLS hedge strategy.[186]

[186] Lien (2005b) emphasises the "inadequacy" of the Ederington effectiveness measure (4.15) to evaluate minimum-variance hedge ratios other than OLS. In fact, his analytical results demonstrate

4.3.3.2 The Utility-based Comparisons

The hedging effectiveness, in terms of variance reduction, is based on the assumption that the investor has infinite risk aversion and is willing to forgo infinite amount of return for a small benefit of risk reduction. In reality, however, the investors make their investment decisions based on the risk-return trade-off. From economic perspective, it is important to investigate whether the benefits from risk reduction outweigh the loss of earning from adopting a hedging strategy. One way to do this is to analyse the change of mean-variance utility functions.

To this end, we adopt a utility-based criterion to investigate how a hedger's utility has changed from using a variety of the hedging strategies for the out-of-sample period in order to better understand the economic significance of portfolio variance reduction. Following the standard approach (see, e.g., Kroner and Sultan, 1993; and Gagnon and Lypny, 1995), we restrict to a special case where investor has a mean-variance utility function. The expected utility for a hedging strategy is written as:

$$E\left[U(\Delta HP_t)/\psi_{t-1}\right] = E\left[\Delta HP_t/\psi_{t-1}\right] - \lambda Var(\Delta HP_t/\psi_{t-1}) \qquad (4.16)$$

where E is the expectation operator, ΔHP_t is the return of the hedged portfolio, ψ_{t-1} is the information set available at the beginning of the hedge, and λ is the degree of risk aversion which is assumed to be 4 (see, e.g., Koutmos and Pericli, 1998; and Chou, 1988; where this risk-aversion parameter is set as 4 and 4.5, respectively).[187]

---

that the OLS hedge will dominate all other hedging strategies, including those based on cointegration and/or GARCH, as long as they are judged on the unconditional variance criterion. However, his conclusion relies heavily on the assumption of no structural change over sample period. In this context, the failure of dynamic hedge to improve on OLS could be viewed as an indication that the structure is stable to justify rebalancing hedge (Copeland and Zhu, 2006).

[187] Note that the risk-minimisation hedge ratio is a special case of expected mean-variance utility maximisation hedge ratio when $\lambda = \infty$. To see this, expand the expected return and conditional variance term in equation (4.16), using equation (4.1) and (4.5), respectively, as $E(\Delta S_t/\psi_{t-1}) - h_t E(\Delta F_t/\psi_{t-1})$ and $Var(\Delta S_t/\psi_{t-1}) - 2h_t Cov(\Delta S_t, \Delta F_t/\psi_{t-1}) + h_t^2 Var(\Delta F_t/\psi_{t-1})$.

Different hedge ratios generated from different hedging models will lead to the different portfolio returns and variances, and thus, different level of expected utility. A hedging strategy can be considered as superior, in an economic sense, if its usage results in higher expected utility than using other hedging strategies.

4.3.3.3 The Relative Hedging Performance

To see more clearly the implications of the error correction mechanism, the time-varying volatility, the basis and asymmetric effects of the spot-futures covariance structure on the estimations of optimal hedge ratios and hence hedging effectiveness, we compute a measure on the *incremental* risk reduction to investigate the *relative* hedging performance between two different hedging strategies. For example, the importance of the asymmetries can be seen by the *additional* variance reduction of AsymBEKK model (4.12) over and above that achieved by the use of dynamic hedge based on the standard BEKK model (4.10). The improvement is calculated as:

$$1-\frac{Var(\Delta HP_t/AsymBEKK)}{Var(\Delta HP_t/BEKK)} \tag{4.17}$$

Positive (negative) value implies that AsymBEKK-based hedge has higher (lower) hedging effectiveness, in terms of variance reduction, than the BEKK-based hedge. Comparisons are also provided between other pairs of hedged portfolios, and for the changes in the level of utility of these portfolios derived from different strategies as:

$$\frac{EU(\Delta HP_t/BEKK)-EU(\Delta HP_t/AsymBEKK)}{\left|EU(\Delta HP_t/AsymBEKK)\right|} \tag{4.18}$$

The utility-maximising hedge ratio (i.e., $\underset{h_t}{Max}\left[E(\Delta HP_t/\psi_{t-1})-\lambda Var(\Delta HP_t/\psi_{t-1})\right]$) is then obtained by setting the second-order condition of above maximising objective: $h_t^*=\dfrac{-(\lambda/2)^{-1}E(\Delta F_t/\psi_{t-1})+Cov(\Delta S_t,\Delta F_t/\psi_{t-1})}{Var(\Delta F_t/\psi_{t-1})}$. If we have $\lambda=\infty$, the first term in the numerator is zero; and h_t^* is equivalent to the minimum-variance hedge ratio (MVHR) in equation (4.6).

4.4 Data Descriptions

The dataset we use is the same as those in the previous price discovery chapter. Specifically, daily closing prices of 50 individual stocks and their corresponding futures contracts are used.[188] The sample period spans almost five years from first day of each USF contract listed to December 30, 2005. All the days that either stock or futures markets were closed are removed. The number of observations for each USF contracts varies from 1060 to 1267. To prevent the thin markets and contract expiration effects, a single futures price series for each USF contract is constructed by using closing prices from the nearest contract with rolling over at the beginning of the delivery month to the next nearby contract.

Data sample is split into two periods. The first period covers from the first day of the sample to the day where there are 252 days left. The second period covers those last 252 days in the sample. Using the first sample, we estimate each model and then compare their within-sample hedging effectiveness. The out-of-sample performances are based on the last one year's worth of data (i.e. the last 250 returns observations).

Table 4.1 provides the summary statistics for the stock and USF returns and the basis for the within-sample estimation period. Since futures are the derivatives of stock, the statistics for the stock and futures should be closely correlated. From Table 4.1, we find that the means of all stock and futures returns are very close to zero, except stock NOV. For all stock and USF returns, the standard deviation is similar, indicating that futures market fluctuated more or less to the same extent as stock did. With a few exceptions, the basis has a larger absolute mean than its stock and futures returns and the majority of them are more stable than the returns. Nevertheless, the

[188] The list of these USFs and their underlying stocks is given in Table 3.2.

standard deviation of basis is larger than that of stock and futures returns in 17 cases, implying that the naïve one-to-one hedge strategy does not help to reduce risk.[189] Statistics for skewness and excess kurtosis indicate significant deviations from normality in all series, particularly in a number of futures return and basis series. As a result, the Jarque-Bera test statistics also provide clear evidence of significant departures from normality across all the stock returns, futures returns and basis series. Such deviations can be, to a considerable degree, attributed to the presence of conditional heteroscedasticity, or volatility clustering (see Bollerslev et al., 1992).

The Ljung-Box Q statistics for 12 lags show evidence of temporal dependencies in 72 percent (i.e., 72 out of 100) in the first moment of the time-series distributions, while for the squared returns, $Q^2(12)$ statistic is significant in almost all cases, implying that conditional heteroscedasticity is present in most returns series. This is also confirmed by the Lagrange Multiplier (LM) test of ARCH effects suggested by Engle (1982). Such dependencies can be modelled by GARCH type of models where the second moments are allowed to be time-varying. Accordingly, the use of time-varying variances and covariance in hedging decisions is expected to produce better results than those obtained under the assumption of constant second moments.

Also presented in Table 4.1 are the volatility specification test statistics of Engle and Ng (1993) for testing for asymmetries in the second moments of the returns series. The joint test statistic is significant in almost all instances verifying that volatility asymmetries are present across returns and need to be incorporated into the model. Thus, inclusion of an asymmetric term in the models (4.12) and (4.13) is justified.

[189] Our finding that the fluctuation in the basis was generally less than the range of fluctuations in the futures or stock returns is consistent with the literature where the basis is almost always more stable than the futures price or the cash price. Indeed, the relatively low variability of the basis is very important for hedgers as hedging is an exchange of price risk for basis risk.

4.5 Empirical Results

This section presents the empirical results of our investigation on the risk management function of USF contracts. We report the results in the following steps. The first subsection provides the preliminary unit root and cointegration tests for each pair of stock and futures series in order to confirm the cointegration of two prices series and thus provide justification to the error correction specifications. Then, we describe the estimation results for our VECM-AsymBEKK-X model (4.13) that is used to produce the dynamic hedge ratios for hedging the USF stock positions. In the third subsection we measure the hedging effectiveness of USF by applying both variance-reduction and utility-based performance evaluation criteria for the within-sample and out-of-sample periods. Subsequently, the time-series and cross-sectional variations in hedging efficiency are considered for certain periods / groups by means of sub-period / sub-sample analysis. Following that we examine the cross-sectional determinants of USF hedging performance. Finally, the last subsection investigates the *relative* hedging effectiveness of USF versus index futures and assesses the efficiency of creating USF hedge portfolio in hedging cash portfolio containing multiple stocks.

4.5.1 Unit Root and Cointegration Tests

In order to prevent spurious regression and cointegration problems, it is necessary to perform unit root and cointegration tests on their price and return series to verify stationarity before doing any further analysis. If the price series of stock and futures are non-stationary but the changes of prices are stationary, the cointegration concept becomes relevant in the subsequent empirical analysis. As in the previous chapter, we adopt the augmented Dickey-Fuller (ADF) test to perform unit root tests, and use Johansen's (1988) methodology to test for the possible cointegration relationship.

The results of testing both the unit roots and cointegration are reported in Table 4.2. As expected, the null hypotheses of a unit root for the price series are not rejected at the 1% level (except eight series at 10% level), indicating that most stock and futures prices are non-stationary. The unit root test is also applied to the changes of stock and futures prices (i.e., returns). The test statistics suggest that all the stock and futures return series are stationary. Overall, the ADF test results indicate that most stock and USF prices are non-stationary whereas all returns are stationary.

Johansen (1988) cointegration trace test statistics indicate a long-run equilibrium relationship between stock and futures prices in almost all instances, except for 9 cases where no cointegration relationship was found. In these cases, not surprisingly, the unit root statistics suggest the basis is non-stationary. Table 4.2 also shows that, when a cointegration relationship exists, the cointegrating vector is close to [1, 0, -1], and the basis is indeed found to be stationary.[190] Thus the basis (i.e. $B_t = S_t - F_t$) appears to be a good and meaningful summary for their cointegration relationships. The implication of this finding is that the short-run dynamics of price changes will, to some extent, be influenced by past deviations from the common stochastic trend.

Taken together, the unit root and cointegration tests results are generally consistent with current literature (see Kroner and Sultan, 1993; Koutmos and Pericli, 1998) suggesting that the stock and USF futures prices share a stable long-run relationship. This in turn supports our VECM specification in equations (4.7) and (4.8). However, for those stock and USF prices that are not cointegrated, a vector autoregressive (VAR) model is adopted instead.

---

[190] The finding that most cointegrating vectors are approximately equal to (1, 0, -1) supports the standard expectations model (i.e. 'Forward Unbiasedness Hypothesis') that the futures price is the average of all discounted expected spot prices, which also implies that the basis is a stationary process (Alexander, 2001).

4.5.2 Model Estimation and Diagnostics

4.5.2.1 Estimation Results

Table 4.3 reports the estimation results of the VECM equations in (4.7) and (4.8). When stock and USF prices are not cointegrated, a VAR model (i.e. VECM without the error correction term, B_{t-1}) is applied. Since the model contains a common set of regressors, without the loss of efficiency, each equation is separately estimated using Ordinary Least Squares (OLS) technique.[191] The multivariate version of Schwarz Bayesian criterion is adopted to determine the lags length in the mean equations.[192] Newey and West (1987) procedure is used to calculate consistent standard errors and associated t-statistics under the serially correlated and heteroskedastic error process.

VECM equations (4.7) and (4.8) produce a large number of coefficient estimates. However, several observations can be made across the mean equations in Table 4.3. First, the feedback effects between each pair of stock and USF markets are observed. That is, the lagged stock (futures) returns help predict current future (stock) returns. More specifically, when considering only statistical significant estimates, most of the lagged stock (USF) returns tend to have *positive* effects on current USF (stock) returns and *negative* effects on current stock (USF) returns. Each market exhibits, to some extent, a mean-reverting behaviour with a stronger degree occurring in the USF markets. Secondly, the lagged basis has a significant positive effect on the current futures returns for 26 out of 41 cointegrated markets (as indicated by significant γ_f) suggesting that futures prices tend to move closer to stock prices. In contrast, the effects of lagged basis on current stock returns are insignificant for 35 out of 41 cases

---

[191] It is well known in the literature on cointegration between conventional I(1) process that the OLS estimator of the cointegrating vector is super-consistent (see, for instance, Stock, 1987).

[192] Similar to our previous Johansen test results, the Schwarz Bayesian criterion indicates four lags in the VECM equations (4.7) and (4.8) for all but a few pairs of stock and futures returns. Therefore, for consistency, we again estimate all models with four lags.

(as shown by insignificant γ_S). This implies that USF market follows the movement of stock market in order to maintain the cointegration relationship.[193]

Overall, the above results suggest that stock market seems to be the 'dominant' market in the lead-lag relationship between stock and USF markets, although there is a bi-directional causality in many cases. This lead-lag pattern is consistent with what we have documented previously in chapter 3. As discussed in chapter 3, the fact that most USF contracts are traded far less frequently than their underlying stocks could cause the stock market to play the leading role in disseminating the new information.

Table 4.4 presents the Quasi-maximum likelihood (QML) estimates of our general AsymBEKK-X model (4.13) and their corresponding robust t-statistics. The convention in these estimates is that subscript 1 concerns the stock market and subscript 2 represents the USF market. The coefficients relating to the impact of the basis and asymmetries on variance-covariance matrix are indicated in **bold** character. Consistent with $Q^2(12)$ and ARCH(12) statistics (in Table 4.1), we find that there is some evidence of the ARCH and GARCH effects in the conditional variances of stock and futures markets (as captured by a_{11} & a_{22} and b_{11} & b_{22}, respectively), whereas the asymmetric responses to their own innovations are not as pronounced as Engle and Ng (1993) asymmetric volatility tests suggested (as indicated by d_{11} & d_{22}). However, the focus of this section is on the coefficients that describe the effects of asymmetries and basis on the variance-covariance matrix between these two markets, captured by off-diagonal elements of D_{11} and E_{11} matrix (indicated in **bold** characters).

[193] It should also be noted that, for 11 cases, the Johansen (1988) cointegration trace test statistics indicate the prevalence of cointegration relationships but the estimated error correction coefficients (as reported in Table 4.3) are not significant at the conventional levels. This surprising result may arise from the fact that the ECT is not the actual cointegration relationship identified by the statistical test.

As can be seen from Table 4.4, the estimates of the elements of D_{11} and E_{11} are significant in many instances, highlighting the importance of asymmetries and basis on the variance-covariance system. For example, the coefficients on the lagged squared basis (e_{11} & e_{22}) in the two variance equations indicate that the basis $(B_{t-1})^2$ is significant and affects the volatility of the stock (futures) market in 20 (9) cases. For other cases, however, the estimated coefficients are not significant. One possible reason for this may be because the basis is restricted to be the exact spread, $(S_t - F_t)$.

To test whether our general AsymBEKK-X model (4.13) provides a superior data characterisation compared to the BEKK, BEKK-X, and AsymBEKK models, we further performed a number of model specification tests. Specifically, we examine each of the three simpler BEKK models to determine whether they could be rejected against the more general AsymBEKK-X model, as indicated by Wald test statistics. The final three columns of Table 4.4 report the *P*-values of the Wald tests. The third last column of this table tests the restriction to be AsymBEKK model in which the good and bad news affect the variance-covariance of stock and futures differently, but ignores the effect of basis. For 14 out of 50 cases, this model cannot be rejected.

The final two columns of Table 4.4 show that both BEKK-X and BEKK models are rejected in favour of our modified general AsymBEKK-X model in all instances. Table 4.5 summarises the results of these restriction tests and reports the 'best-performing' model for each pair of stock and futures series. Of the four models, the general AsymBEKK-X model clearly dominates any other simpler models, though AsymBEKK model performs marginally better in 14 stock-futures pairs.

These multivariate GARCH model specification tests suggest that the pursuit of a model that allows for both basis and asymmetry effects on variance-covariance matrix (i.e. AsymBEKK-X model) is important and may yield superior hedging performance relative to a model which ignores one/both features which is manifest in the data. However, to examine how far hedging effectiveness can be improved by the use of a dynamic strategy generated from this general model, further investigation is required. One of the aims of this chapter is to demonstrate this improvement.

4.5.2.2 Diagnostic Tests

When modelling the conditional variance and covariance equations, it is essential to verify the specification is a statistically adequate representation of the data in hand. The diagnostic tests on the standardised residuals and squared standardised residuals of our general AsymBEKK-X model (4.13) indicate that it is well-specified and provides reasonably adequate descriptions of the daily stock and USF returns series.

As shown in Table 4.6, the means and variances of the standardized residuals fulfil the requirement of zero mean and unit variance. As these results satisfy the Bollerslev and Wooldridge (1992) moment conditions, we can be confident that our Quasi-maximum likelihood (QML) estimates are consistent. In addition, the skewness and excess kurtosis of standardized residuals are generally lower than the ones for the raw returns series (see Table 4.1), indicating that a large proportion of excess kurtosis in daily returns is attributable to the conditional heteroskedasticity. As a result of significant kurtosis and skewness, the normality hypothesis is also rejected by the Jarque-Bera tests in many series. Nevertheless, since we use QML estimation, non-normality is not crucial, as the standard errors are adjusted to take into account of this non-normality.

The estimated Ljung-Box Q(4) and $Q^2(4)$ statistics show that the residuals autocorrelations have decreased significantly from the raw returns (see Table 4.1). Moreover, the diagnostic tests suggested by Engle and Ng (1993) to detect volatility asymmetries show no evidence of any remaining asymmetry, with only 5 exceptions. Taken together, the results of these diagnostic tests again suggest that the dynamic hedge ratios based on the time-varying variance-covariance matrix of our general AsymBEKK-X model (4.13) could outperform other simpler models. We now turn to an examination of this important issue using USF data.

4.5.3 Hedge Ratios and Hedging Effectiveness

Following the estimations of the BEKK, BEKK-X, AsymBEKK, and the general AsymBEKK-X models, measures of the time-varying variances and covariance are extracted and then used to compute the conditional hedge ratios as in equation (4.6). For illustration, Figures 4.1 to 4.4 present the time-varying hedge ratios for AA, obtained from four different BEKK models, together with the conventional hedge ratio generated from the OLS model of equation (4.4). It can be seen that the conditional hedge ratios are clearly changing as new information arrives at market. Moreover, dynamic hedge ratios are relatively unstable with a few extremes (perhaps due to structural changes), particularly for those based on the AsymBEKK-X model.

4.5.3.1 Summary Statistics of Hedge Ratios

The descriptive statistics of the constant and time-varying hedge ratios are presented in Table 4.7. The constant hedge ratios generated from OLS equation (4.4) are smaller than that produced by VECM regression (4.7) and (4.8) for 45 of 50 stocks. On average, the OLS and VECM hedge ratios are 0.8281 and 0.8600, respectively.

This finding is consistent with the analytical results of Lien (1996, 2004) who demonstrate that the omission of cointegration relationship tends to produce a smaller hedge ratio. Nonetheless, across all 50 samples, the constant hedge ratios have a lower average value than their conditional counterparts. For the four time-varying models, AsymBEKK-X hedge ratios have higher average value than other three simpler models, although their average variability (STD) is not the smallest. The results of ADF unit root tests on the conditional hedge ratios reveal that, with a few exceptions, the time-varying hedge ratios are stationary implying that they are mean-reverting (i.e., impact of a shock to the series eventually becomes negligible).

4.5.3.2 Within-sample Hedging Effectiveness

This section investigates whether the basis and asymmetry effects on the variance-covariance system of stock and futures returns have any impact on the dynamic hedging strategies. For each stock, we evaluate the hedging effectiveness of dynamic hedging strategies generated from the BEKK model with four different specifications on the time-varying variances and covariance: (i) totally ignores the effects of both basis and asymmetry (i.e. BEKK), (ii) incorporates the asymmetry effects only (i.e. AsymBEKK), (iii) replaces the asymmetry effects with the basis effects instead (i.e. BEKK-X), and (iv) allowing both asymmetry and basis effects (i.e. AsymBEKK-X). In addition, we also compare the four dynamic hedging strategies with the constant hedging strategies based on either the OLS or the VECM regression models. Finally, the performance of the unhedged position and naïve hedge ratio of one are also evaluated.

Following the estimations of the model, we extract the time series of variances and covariance of stock and futures returns for each model specification and for each stock over the sample period. Then, the time-varying hedge ratios for each model and for each stock are calculated as in equation (4.6). Subsequently, a corresponding series of hedged portfolio returns is constructed by using the computed hedge ratios. To evaluate the hedging performance for a given strategy, the variances of hedged portfolio returns for each model specification and for each stock are then calculated. The percentage reduction in the variance of portfolio returns of equation (4.15) is subsequently applied to make the comparisons among different hedging strategies. The larger the percentage variance reduction, the higher the hedging effectiveness.[194]

Table 4.8 reports the portfolio variance along with the percentage variance reduction from adopting each hedging strategy. The results indicate that time-varying hedge ratios perform better, in terms of risk reduction, in 43 out of 50 stocks.[195] For the remaining 7 stocks, however, the constant OLS model outperforms the dynamic hedging strategies despite the superior statistical properties of conditional models.[196] It is also worth noting that some hedge ratios estimated by OLS/VECM provide extremely small level of risk reduction (see AGN, AXA, BAR, ENI, ENL and TI) and are well below the variance reduction provided by the BEKK-based hedge ratios.

---

[194] It is worth noting that using the variance reduction (instead of the standard deviation reduction) as a measure of hedging performance, the true extent of risk reduction may actually be overestimated. However, for consistency and comparison with the literature on futures hedging, we use the variance reduction as a measure of hedging performance.

[195] However, it should be noted that the superior performance of dynamic hedging may not hold when transaction costs are explicitly taken into account. The benefits, in terms of variance reduction, are based on the assumption that the dynamic hedge ratios are updated every period *irrespective* of transaction costs. In reality, however, there are transaction costs which rise proportionately with the frequency of portfolio re-balancing. Examination of the robustness of our results in the presence of transaction cost is worthy of further study, but is beyond the scope of this chapter.

[196] A number of recent studies also find that there are very little, or even negative, gains in variance reduction by using time-varying hedge ratios (see Alexander and Barbosa, 2005 and 2006; Copeland and Zhu, 2006) This suggests that additional complexity of specifying and estimating GARCH hedge ratios may be justified for some hedge positions but not for others. One possible reason may be because the underlying structure is too stable to justify the use of time-varying hedge ratios.

Nevertheless, the dynamic hedging strategies for these stocks also fail to eliminate as large proportion of the variability of the hedged portfolio as evidenced in other cases. The relatively poorer hedging performance of these USF contracts (mainly the cross-border contracts) reflects the fact that these futures prices do not capture accurately the fluctuations of their underlying stocks, perhaps due to the thin trading problem or the breakdown of cointegration relationship. In the light of the above evidence, LIFFE could promote more these futures contracts (especially cross-listed futures) to attract more volume in order to improve the hedging effectiveness of these contracts.

Among the dynamic hedging strategies, our general AsymBEKK-X model has the greatest hedging effectiveness (i.e. largest variance reduction) in 22 stocks, with an *average* percentage variance reduction of 82.87% (i.e. over 7 percentage points more than that achieved by OLS and VECM). The AsymBEKK model ranks second and provides greater variance reduction than alternative models in 11 stocks. Allowing for only basis effect, BEKK-X strategy also achieves better performance in 7 instances, but the standard BEKK performs the worst among conditional hedges. Moreover, we also find that the naïve hedge is the worst hedging strategy since it substantially increases portfolio variance compared to unhedged position, in 7 cases.

The 'superiority' of AsymBEKK-X model can also be clearly seen by the additional variance reduction over and above that achieved by using alternative hedges based on the constant and conditional models (as calculated similarly in equation (4.17)). Results in Table 4.9 indicate that there are incremental risk reductions from this strategy compared to other alternative models (at least 35 improvements obtained). The reduction is largest in comparison with the naïve hedge (i.e. 20.46% on average). The advantage of using AsymBEKK-X model based dynamic hedges rather than the conventional OLS hedges is 13% additional reduction in portfolio variance when we average across 50 sample stocks, ranging from -8.38% in ALV to 86.14% in AXA. The general improvements are also observed over other dynamic hedges, although the average incremental risk reduction is smaller than that evidenced in constant hedges. For example, if we adopt a standard BEKK model without considering the effects of asymmetry and basis to derive the optimal hedged strategy, an additional 7.26% risk will be incurred on average.

Overall, these findings suggest that, in the absence of transaction costs, the dynamic hedging is superior to static hedging in terms of total variance reduction; and the dynamic hedging strategy that incorporates both the basis and asymmetry effects on the time-varying variance-covariance in stock and futures markets can produce tangible benefits for investors who want or need to hedge individual stock exposure.

4.5.3.3 Out-of-sample Hedging Effectiveness

Recall that we split the sample into two periods. The first period covers from the first day of the sample to the day where there are 252 days left. The second period covers those last 252 days in the sample. Using the first sample period, we have estimated each model and compared their within-sample hedging effectiveness in last section. While the within-sample analysis of the hedging strategies gives an indication of their historical performance, investors are more concerned with how well they can perform in the future using alternative strategies. In this context, the out-of-sample performance is a more appropriate way to evaluate the effectiveness of conditional hedge ratios (see, Kavussanos and Nomikos, 2000; Butterworth and Holmes, 2000).

To this end, we conduct out-of-sample comparisons based on the last one year's worth of data (i.e. the last 250 returns) to further evaluate the performance of different hedge strategies. Specifically, we estimate alternative models using the first sample period, and then each model is re-estimated with a daily rollover in the second period. The optimal hedge ratios are subsequently constructed and the hedged portfolio returns are calculated. This rollover estimation is continued until the end of second period. As a result, a series of hedge ratios and a corresponding series of hedged portfolio returns for each model and each stock are obtained. Similar to the within-sample analysis, the out-of-sample hedging performance is also evaluated by computing the percentage reduction in the portfolio variance as in equation (4.15).

The results for the out-of-sample hedging effectiveness are presented in Table 4.10. Similar to the previous within-sample results, our general AsymBEKK-X model also seems to outperform the alternative hedging strategies in majority of stocks and produces the highest average risk reduction across the 50 sample socks (i.e. 82.38%). The out-of-sample results indicate that time-varying hedge ratios perform better than the constant counterparts once again, but only in 35 out of 50 stocks.[197] We also find that the hedging effectiveness generated from the naïve and conventional OLS hedge ratios have marginally improved comparing to their within-sample performance. Different from within-sample performance, BEKK-X model is ranked second instead and provides greater variance reduction than alternative models in 11 stocks. Standard BEKK is still the worst performed conditional hedges in reducing variance. For the percentage variance improvement (reported in Table 4.11), AsymBEKK-X strategy offer an *average* incremental risk reduction of 6.40%, 2.86%, and 2.36% when compared to BEKK, AsymBEKK, and BEKK-X strategy, respectively.

[197] The superior performance of dynamic hedging is consistent with the findings of previous studies. Several studies find that time-varying hedge lead to higher risk reduction than constant hedge for assets such as foreign currency (Kroner and Sultan, 1993) and stock index (Park and Switzer, 1995).

4.5.3.4 Utility Comparisons

From a portfolio theory point of view, hedging with futures can be considered as a portfolio problem in which the investor use futures contracts as one more asset to include in their portfolio set in order to maximise utility. However, the hedging effectiveness measure given in equation (4.15) is based on a strong assumption that the investors are infinitely risk-averse and are willing to forgo infinite amount of return for a small benefit of risk reduction. In practice, however, most investors tend to trade-off the risk and return of an investment as the appraisal criteria. From economic perspective, it is important to investigate whether the benefits from risk reduction outweigh the loss of earning from adopting a hedging strategy.

Therefore, to better understand the economic significance of portfolio variance reduction, we adopt an *ex ante* utility-based criterion to investigate how a hedger's utility can be improved by using the strategy generated by our AsymBEKK-X model. Consider a special case where a hedger has a mean-variance utility function, the expected utility for a hedging strategy is given by equation (4.16), repeated here for convenience:

$$E\left[U(\Delta HP_t)/\psi_{t-1}\right] = E\left[\Delta HP_t/\psi_{t-1}\right] - \lambda Var(\Delta HP_t/\psi_{t-1})$$

where E is the expectation operator, ΔHP_t is the return of the hedged portfolio, ψ_{t-1} is the information set available at the beginning of the hedge, and λ is the degree of risk aversion which is assumed to be 4 in this chapter.[198] Different hedge ratios generated from different hedging models will lead to the different portfolio returns and variances, and thus, different level of expected utility. A hedging strategy can be considered as superior if its usage results in higher expected utility than using others.

[198] We have also computed our results for λ values of 1, 8, 10 to see how sensitive our results to the aversion degree parameter. The results are qualitatively similar to those under assumption of λ = 4.

Table 4.12 reports the out-of-sample expected utility for each model and each stock examined. The results indicate that the dynamic hedging strategies based on our general AsymBEKK-X model (incorporating both basis and asymmetry impacts) outperforms others strategies and produces the highest total utility for 13 out of 50 stocks. It is also interesting to note that the difference of hedging performance (as compared through the expected utility level) between the constant hedges and other dynamic hedges becomes minimal. Another striking feature of the utility-based analysis is that the static hedging strategy derived from OLS model seems to perform almost as well as the dynamic hedging strategy generated by AsymBEKK-X model. This seems to be related to the typical problem of forecasting in financial markets: more complicated models, especially where involved large numbers of parameters, incorporates too much noise to deliver any improvement outside the sample period (see, e.g., Alexander and Barbosa, 2005, 2006; Copeland and Zhu, 2006). Nonetheless, if a hedger had adopted the strategies from the AsymBEKK-X model rather than from the OLS model, he/she would still have the utility increase in more than half of the hedged positions (i.e., 28 out of 50 instances), as indicated by the utility improvement results in Table 4.12.

Overall, the utility-based results for hedging performance suggest that the mean-variance expected utility-maximising hedgers can produce additional hedging benefits by exploiting the potential effects of basis and asymmetry on second moments and cross moments of stock and futures returns, corroborating the comparisons based on the variance-reduction criterion. The superior hedging performance of our general AsymBEKK-X model is not surprising given that it is better able to fit the data sample compared to other models (see section 4.5.2).

4.5.4 Variations and Determinants of Hedging Effectiveness

In the previous subsections, we have contributed new evidence to the futures hedging literature by examining the hedging effectiveness of Universal Stock Futures (USFs). Our empirical findings suggest that, on a total variance-reduction basis and expected utility-maximisation basis, most USFs have served as efficient risk management tools in hedging against the individual stock exposures. Moreover, we also find that the newly proposed dynamic hedging strategy that incorporates both the basis and asymmetry effects on the time-varying variance-covariance structure can produce tangible benefits for investors who want to hedge their exposure to a stock position.

Although our evidence is in favour of the hedging role of USF markets, there seems to be a considerable variation in the hedging effectiveness of these contracts across different underlying stocks. For example, in relation to the within-sample risk-reduction of AsymBEKK-X hedges (in Table 4.8), the hedging performances of 50 sample USF contracts vary significantly from 94.64% in TLI to just 19.57% in TI. We speculate that the trading conditions associated with individual stocks and futures (or markets), such as the trading systems and institutional differences of the markets at which underlying stocks being traded, the geographical origin of the underlying stock markets, the development stages of futures market, the trading characteristics such as relative liquidity and trading costs, and the futures contract features/designs, are the possible explanations for these variations.

As mentioned before, the special features of USF contracts provide us a unique opportunity to directly examine whether these factors could significantly affect the risk management role a futures market. For example, with underlying stocks trading in several different markets and countries, our USF sample enables us to investigate whether the USF hedging effectiveness could be influenced by the geographical origin of their underlying stock markets or the underlying stock trading locations. Moreover, it also allows us to investigate the extent to which the hedging performance of a futures market varies across the 'introduction/learning' and 'maturation' periods. These are the issues we wish to address next.

4.5.4.1 Cross-sectional and Time-series Variations

The first issue we wish to address is whether there is any significant variation in the hedging effectiveness of the USFs whose underlying stocks are being traded in the geographically-separated stock markets (that is, whether any 'country effect' exist?). We address this question by partitioning the within-sample hedging effectiveness of AsymBEKK-X model into eight USF groups according to their underlying stock markets location.

Table 4.13 presents the cross-sectional descriptive statistics on the estimated optimal hedge ratios (h_t^*) and hedging effectiveness measures (as given in equation (4.15)) for our entire USF sample, as well as for each of the USF group. The results reported in this table indicate that, while our whole USF sample (on average) reduces the hedged portfolio variance by 82.87% with the mean h_t^* value of 0.9114, there is a considerable variation in the hedging effectiveness of different USF groups. Specifically, hedging with USFs written on Germany and Italy stocks can only achieved less than 75% of average risk-reduction, although their mean h_t^* values are not necessarily the smallest. On the other hand, for those USFs whose underlying stocks are being traded in Spain, more than 90% average variance-reduction can be obtained through futures hedging. The average standard deviation of their hedging performance is 0.005, which is much less than that of other USF contracts. Since the eight markets considered in this study have considerable differences in their trading systems and market structures, the finding of significant variations in USF hedging efficiency across these markets is, perhaps, not very surprising. Overall, the results suggest that there is a 'country-effect' in the hedging effectiveness of different USF contracts, and that the geographical origin of its underlying stock may influence the efficiency of a futures contract in hedging against its underlying stock price risk.

The issue of whether the trading location of the underlying stocks could affect the hedging performance of USF contracts is further analysed by comparing the relative effectiveness of domestic and cross-listed USFs hedges (i.e. home-bias hypothesis). To this end, we employ a similar technique as in previous section but partition our entire USF sample into two groups: one includes the 10 USFs that trading on U.K. stocks and the other one includes all the USFs that are based on 40 European stocks. Cross-sectional descriptive statistics of the estimated optimal hedge ratios (h_t^*) are presented in Panel A of Table 4.14. The average minimum-variance hedge ratios among the U.K. USF contracts is slightly larger than that of European USF contracts, implying that hedging of domestic stock exposures may be more effective than the 'international' cross-border hedging. Comparison on average hedging effectiveness of these two different USF groups in Panel B of Table 4.14, lends further support to the dominance of the domestic USFs hedging. Specifically, the USF hedging in U.K. stocks has reduced more than 86% of average portfolio variance whereas for the cross-listed USFs, only 82% of average variance reduction can be achieved. Nonetheless, a non-parametric Wilcoxon signed rank test cannot reject the null hypothesis that the average hedging effectiveness of these two USF groups are equal.

Next, we extend our empirical analysis and further investigate the hedging functions of the USF markets over the different development stages. The following steps are involved in our analysis. First, the within-sample period of daily stock and USF prices is divided into two sub-periods, which are dictated by the different development stages of the markets. The first period is the initial introduction period and corresponding to the first two years of trading in our 50 USF samples. The second period covers the next two years of trading (i.e., maturity period). Then, the VECM-AsymBEKK-X model estimation and hedging effectiveness analysis, along the lines set out in section 4.5.3.2, are repeated and performed over the two sub-periods to investigate the temporal variability of the futures hedging performance. The cross-sectional descriptive statistics of USF hedging effectiveness for the introduction and maturity periods are presented in Panel A and B of Table 4.15, respectively. As a whole, the USF markets have 82.72% and 82.84% hedging effectiveness in the introduction (P1) and maturity (P2) sub-periods, comparable to the 82.87% in the full within-sample period. While the average hedging performance of 50 USF contracts appears to have increased slightly over the two sub-periods, the Wilcoxon Z-test shows that this small increase is statistically insignificant. We also find that, when the figures from Table 4.15 are broken down by country groups, most USFs have experienced some changes in their hedging efficiency although the majority of these are not statistically significant as indicated by the results of Z-tests.

View collectively, results of our sub-sample and sub-periods analyses indicate that there is some cross-sectional and time-series variation in USF hedging effectiveness. Differences in the underlying stocks trading location, market structure, and market maturity are likely causes of these variations. However, the results may also be driven by a set of different trading and contract design factors: any far reaching conclusions cannot be drawn at this stage. As discussed earlier, the relatively large size of our USF sample allows us to control for these factors and formally explore the cross-sectional determinants of USF hedging performance in the next section.

4.5.4.2 Cross-sectional Determinants of Hedging Effectiveness

The results from previous section suggest that the hedging effectiveness of USF markets is not equal across all the stocks in our sample. They vary considerably through time and across contracts or markets. In this section, we perform a set of OLS regressions in order to identify the factors affecting the level of USF hedging performance. What determines the effectiveness of USF hedging? This is the principal question we wish to address in this section. Most of previous studies were unable to address this important issue because in order to do so with any degree of confidence requires a fairly large sample. The relatively large size of our sample, 50 USFs in total, enables us to explore the determinants of futures hedging performance.

Before performing the formal cross-sectional regression analysis, it would be useful to see visually whether the hedging effectiveness of USF contracts is related to the observable market variables, such as the trading volume and spread. Therefore, we sorted the hedging effectiveness of 50 USF contracts by (i) trading volume, and (ii) effective spread, in an ascending order. Figures 4.5 and 4.6 illustrate the results. Inspecting these two figures, it appears that the hedging effectiveness of USFs (HE) is negatively related to both the trading volume and the trading costs in futures markets (as proxied by their effective spread).[199] This is corroborated by a correlation analysis. In particular, the correlation between the HE and the average daily trading volume is -0.354, and is -0.358 for the effective spread. On the basis of these, it seems to suggest that the hedging performance of a USF contract may be affected by both the liquidity and transaction cost of the markets.

[199] Figures 4.7 and 4.8 visualize the relationships between HE and the relative trading volume and spread ratio in stock and USF markets. Patterns are similar to the one observed in Figures 4.5 and 4.6.

In order to obtain more detailed insights into the cross-sectional determinants of USF hedging effectiveness, we perform a number of cross-sectional OLS regressions. The testing framework is similar to that in chapter 3 where the dependent variable is defined as the within-sample hedging effectiveness measure of USF contracts generated from AsymBEKK-X model, which is directly extracted from Table 4.8. We then regress these hedging effectiveness measures on a number of explanatory variables including factors related to the relative trading characteristics (i.e. *VolumeRatio*, *TradingFrequency*, *SpreadRatio*, and underlying *Volatility*), the futures specifications like '*ContractSize*', the trading locations of underlying stocks (i.e. *HomeMarket*), and the development stage of USF contracts (i.e. *MonthsListed*). The regression results will demonstrate the relative strengths of these factors in explaining the differences in the hedging effectiveness of 50 USF contracts.

Given the relatively high correlation between some of our explanatory variables (see Table 3.21), we run a set of regressions including the main explanatory variables separately in order to avoid multicollinearity problem. In addition, we used the Newey and West (1987) procedure to calculate the consistent standard errors (and the associated t-statistics) of the regression parameter estimates in order to adjust for the serially correlated and heteroskedastic error process. The estimated coefficients of a set of cross-sectional OLS regressions are reported in columns (3) through (7) of Table 4.16. In all five specifications, we control for both market maturity and country effects, as evidenced by our findings from the sub-sample and sub-period analysis. In general, we find evidence that hedging performance of a USF market is related to the relative trading volume and bid-ask spreads in the stock and futures markets, and is affected by the contract size of USF contracts.

In model (1), the coefficient of $VolumeRatio$ is negative and statistically significant at the 1 % level, implying that the lower the volume of trading in the USF in relation to stock, the higher hedging effectiveness of the futures market. This result is rather surprising, but in line with previous graphical evidence in Figure 4.7. One possible explanation for this result is the relatively low USF trading volume. When there is no trading for futures, which is not uncommon, the daily settlement price of USF is theoretically determined in reference to the closing stock price.[200] Therefore, it is not surprising to see that ex-post hedging effectiveness is greater for the thinly traded contracts than heavily traded contracts. For model (2), we include only the $TradeFrequency$ and also find it to be statistically significant indicating that the ratio of each paired markets trading days does provide explanatory power on the variation of USF futures hedging efficiency. The coefficient of $SpreadRatio$ in model (3) is highly significant and has a priori expected negative sign, which is consistent with the argument that the USF markets with relatively lower transaction costs tend to have greater hedging effectiveness.

From model (4), we find that the coefficient of variable $Volatility$ (as measured by the standard deviation of daily stock return) is positive but statistically insignificant, implying that USFs hedging effectiveness is not directly related to their underlying stocks volatility. Finally, we find support to our conjecture that hedging effectiveness of a USF contract is affected by not only the relative trading characteristics of stocks and futures markets, but also USF contract feature. The coefficient of $ContractSize$ in model (5) is negative and statistically significant, indicating that the smaller the size of USF contract, the greater the hedging efficiency of futures markets.

200 Examining the daily trading in each USF contract, we find that it is not uncommon to find not a single trade on a given day for some thinly traded USF contracts.

While the empirical analysis of this section is relatively casual, it highlights some interesting results and reveals that the variables measuring relative market quality such as the ratios of trading volume and bid-ask spread are major determinants of the degree of hedging effectiveness across USF contracts, and that, the hedging role of futures are more pronounced for the smaller sized USF contracts.

4.5.5 Relative Hedging Effectiveness of USF and Stock Index Futures

4.5.5.1 USF Contract *OR* Stock Index Futures

In this section, we compare the hedging effectiveness of USF on its underlying stock position and the cross-hedging effectiveness using the stock index futures (SIF). First the effectiveness of USF and SIF in reducing the price risk of spot positions is analyzed. Then the *relative* hedging effectiveness of these contracts is determined. The rationales for doing this analysis (i.e. comparing the *direct* hedging effectiveness of USF with *cross* hedging effectiveness of SIF contracts) are as follows: (i) all the stocks on which USFs are written are also the component stocks of stock indices on which futures already exist, it may be also possible to use index futures to hedge; (ii) for those hedgers who hold more than one component stocks in their portfolio, multiple hedging by USFs may not be as effective as by SIF since there are some correlations between the returns of the stocks and returns of the stock indices; and (iii) it is argued that stock index futures are the major competitor to USF in terms of its potential use by institutional investors. Previous research has suggested that SIF is an effective hedge instrument for a portfolio comprising of index component stocks. As such, the possibility of an effective cross-hedge with SIF challenges the viability of USFs.[201]

[201] The returns of following stock index futures were used to represent the stock index futures from the same country as the USF underlying stocks: (i) CAC40 for France, (ii) DAX for Germany, (iii)

Although it has been shown in previous sections that there is some difference in hedging efficiency between hedge ratios estimated using OLS and with other more sophisticated models (such as AsymBEKK-X model), we adopt the variance-minimizing hedge ratio estimated by OLS method because the main focus of this section is to compare the efficiency of USF and SIF in reducing stock price risk. Empirically this simple approach offers a convenient performance benchmark for comparison purposes. Also, due to its simplicity of understanding and estimation, OLS hedge is widely used by market players in practice (Brooks and Chong, 2001).

Therefore, we apply the OLS regression to estimate the minimum-variance hedge ratios for USF as well as those for SIF contract in hedging individual stock positions. The regression equations for the *direct* and *cross-hedging*, respectively, are given by:

$$R_S = \beta_{0,USF} + \beta_{1,USF} R_{USF} + \varepsilon_{USF} \tag{4.19a}$$

$$R_S = \beta_{0,SIF} + \beta_{1,SIF} R_{SIF} + \varepsilon_{SIF} \tag{4.19b}$$

where subscripts $_{USF}$ and $_{SIF}$ denote the usage of USF and SIF contract as the hedging instrument; $\beta_{1,USF}$ and $\beta_{1,SIF}$ are the minimum-variance/optimal hedge ratios (OHR).[202] Ederington (1979) demonstrates that the coefficient of determination from the OLS regressions, R^2, can be interpreted as the proportional reduction in the variance of spot price changes when the futures contract is used to construct the hedge portfolio with minimum risk. In this context, higher values of R^2 imply greater degree of *in-sample* hedging effectiveness (HE). However, a simple comparison of

MIB for Italy, (iv) AEX for Netherlands, (v) IBEX35 for Spain, (vi) OMX for Sweden, (vii) SMI for Switzerland, and (viii) FTSE100 for U.K. stocks. Their daily closing price series over the sample period are obtained from Datastream.

[202] As stated earlier, while the Ederington OLS methodology is simple and easy to use, the optimal hedge parameter estimates from the OLS technique will yield unbiased results only when the data satisfies the assumptions of homoskedasticity and no serial correlation. Preliminary regressions performed on the data reveal the presence of heteroskedasticity and autocorrelation. Therefore, the Newey and West (1987) procedure is employed to calculate consistent standard errors and t-statistics in order to mitigate the serially correlated and heteroskedastic error problems.

R^{2}'s cannot be a formal statistical test of *relative* hedging effectiveness of USFs and index futures. Therefore, we employ the procedure suggested by Nothaft et al. (1995) to compare statistically the hedging effectiveness of the USF and SIF contracts. Nothaft et al. (1995) proposed an *indirect* test on the equality of the residual where USF is the hedging instrument ($\hat{\varepsilon}_{USF,t}$) and the residual where SIF is the hedging instrument ($\hat{\varepsilon}_{SIF,t}$) in order to determine the statistical significance of observed difference in R^{2}'s of the two regressions (i.e. hedging effectiveness of two futures contracts). Since equations (4.19a) and (4.19b) have the same dependent variable (i.e. the stock price changes, R_S), $\hat{\varepsilon}_{USF,t}$ and $\hat{\varepsilon}_{SIF,t}$ are not independent; thus, the standard F-test on the null hypothesis that two residual variances are equal is invalid in this case.

To proceed with the test of the null hypothesis, $H_0 : \mathrm{var}(\hat{\varepsilon}_{USF,t}) = \mathrm{var}(\hat{\varepsilon}_{SIF,t})$, the following procedure is used instead. First, two transformation variables are constructed:

$$Z_{1,t} = \hat{\varepsilon}_{USF,t} + \hat{\varepsilon}_{SIF,t} \qquad (4.20a)$$

$$Z_{2,t} = \hat{\varepsilon}_{USF,t} - \hat{\varepsilon}_{SIF,t} \qquad (4.20b)$$

As a result of this transformation, the covariance between these two new variables establishes the following relationship between residual variances:

$$\mathrm{cov}(Z_{1,t}, Z_{2,t}) = \mathrm{var}(\hat{\varepsilon}_{USF,t}) - \mathrm{var}(\hat{\varepsilon}_{SIF,t}) \qquad (4.21)$$

Then, the test of $\mathrm{cov}(Z_{1,t}, Z_{2,t}) = 0$ is equivalent to the testing of the equality of residual variances, i.e., the original null hypothesis [$H_0 : \mathrm{var}(\hat{\varepsilon}_{USF,t}) = \mathrm{var}(\hat{\varepsilon}_{SIF,t})$].

Second, we regress $Z_{1,t}$ on $Z_{2,t}$ using the following OLS regression:

$$Z_{1,t} = \alpha_0 + \alpha_1 Z_{2,t} + u_t \qquad (4.22)$$

Since $\alpha_1 = \text{cov}(Z_{1,t}, Z_{2,t}) / \text{var}(Z_{1,t})$, $\alpha_1 = 0$ implies that $\text{cov}(Z_{1,t}, Z_{2,t}) = 0$ and thus $\text{var}(\hat{\varepsilon}_{USF,t}) = \text{var}(\hat{\varepsilon}_{SIF,t})$. Therefore, a t-test of significance of α_1 is an appropriate (and sufficient) test for the relative hedging effectiveness of the two futures contracts under study. Specifically, if α_1 is not significantly different from zero, then the two futures contracts achieve the same hedging effectiveness. If α_1 is significantly different from zero and it is positive, i.e., $\text{var}(\hat{\varepsilon}_{USF,t}) > \text{var}(\hat{\varepsilon}_{SIF,t})$, then SIF contracts is a more effective hedging instrument. In the case when α_1 is statistically negative, $\text{var}(\hat{\varepsilon}_{USF,t}) < \text{var}(\hat{\varepsilon}_{SIF,t})$, USF is a better hedging instrument.[203]

The optimal hedge ratios (OHR) and *in-sample* hedging effectiveness (HE) of the underlying stock using USF are reported in column 2 of Table 4.17 whereas the OHR and HE using the stock index futures (SIF) from the same country as the spot stock as the hedging instrument are reported in column 3 of Table 4.17. The last column of Table 4.17 reports the estimated parameter α_1 and t-statistic of the test on relative hedging effectiveness of the two futures contracts. The Newey and West (1987) procedure is used to calculate consistent standard errors and associated t-statistics under the serially correlated and heteroskedastic error process.

In line with expectation, empirical results from Table 4.17 indicate that hedging with USF has a better performance than hedging with stock index futures. For 41 out of our 50 (82%) individual stock positions, the hedge based on USF contracts has a

[203] Refer to Nothaft et al. (1995) for further discussion of the test of relative hedging effectiveness. Karagozoglu (1999) had successfully applied this statistical testing procedure to test the hedging effectiveness for the Explicit versus Implicit futures contracts.

higher hedging effectiveness (i.e. R^2), though the corresponding optimal hedge ratio (OHR) is not necessarily larger. Average across all 50 stocks in the sample, the hedging efficiency improves substantially by 43.54% [(0.757-0.527)/0.527] relative to hedging with SIF. However, before one could conclude that USFs have constantly outperformed the index futures, a statistical test of the significance of the differences in R^2 has to be performed. As stated earlier, this is equivalent to the test of the equality of variances of residuals from regressions with USF and SIF contracts (i.e. test of significance of the estimated parameter α_1). The last column of Table 4.17 shows that the estimate of α_1 is negative and significant at 10% level for 40 stocks. This significant and negative coefficient confirms that USF contract is a better hedging instrument than SIF contract in hedging individual stock position within our sample period.

One of the possible reasons for nine USF contracts fail to improve upon the ex-post hedging performance is that price movement of USF is affected by both corresponding spot stock and futures markets. In other words, a change in the price of an USF does not necessarily rely on its cash counterpart exclusively. The trading activities within the futures market such as the spread trading between the index futures and USF might also affect the price of an USF. Consequently, USF is not necessarily a better hedging instrument than index futures in all cases. Taking into account the transaction cost and liquidity for both USF and index futures markets, one might even favour index futures as the hedging instrument because many hedgers are concerned about the possible impact of large orders that can be executed in the market without suffering from a large price concession.

4.5.5.2 USF Contract *AND* Stock Index Futures

The empirical results from Table 4.17 suggest that the majority of USFs exhibit superior hedging effectiveness in reducing the firm-specific risk which is left largely unhedged if we hedge the individual stock position with stock index futures alone. Moreover, as discussed earlier, it may also not be appropriate to use the index futures as a sole source to hedge against the systematic risk of a portfolio. The optimal portfolio (i.e. market portfolio) may be a combination of the stock market index and some other stocks. If the efficient frontier can be spanned by the index and a leading stock, then we know that the *true* systematic risk of a portfolio should be represented by the relationship between this portfolio and a certain 'combination' of the index and that leading stock. Therefore, it makes sense for the fund managers to trade both stock index futures and single-stock futures to hedge against the *true* systematic risk. In other words, it is possible that hedging effectiveness of the individual stock exposure can be further improved by hedging with the index futures in addition to its USF contract since this hedging strategy may mitigate the market risk of a portfolio.

Utilizing the similar testing procedure in the previous section, this section analyses the hedging effectiveness of using simultaneously both USF and stock index futures (SIF) contracts, and compares the hedging efficiency of this strategy with that of hedging with the USF contract alone. On comparing the hedging effectiveness, we once again employ a statistical test based on the estimated parameter α_1 in order to infer whether hedging with both USF and SIF contracts is superior in reducing the variance of hedged portfolio prices.

Table 4.18 reports the optimal hedge ratios (OHR) and hedging effectiveness (HE) of using both USF and SIF as well as those for using USF contracts alone in hedging individual stock positions. From Table 4.18, it can be seen that controlling for the market risk with index futures does indeed improve the portfolio variance reduction. Adding the SIF contract to the hedged portfolio where only USF is used as hedging instrument leads to an improvement in hedging effectiveness for all 50 stocks, though the corresponding t-statistics of the test on relative hedging effectiveness of these two hedging strategies are not all statistically significant. Specifically, the *ex-post* hedging efficiency has been further improved by 10.12% [(0.833-0.757)/0.757] on average. The positive and significant α_1 coefficient shown in the last column of Table 4.18 confirms that hedging with stock index futures in addition to the USF contract could improve the hedging efficiency in hedging individual stock exposure. Given the fact that many previous studies have shown that hedging with multiple futures contracts can enhance the hedging performance of a single futures contract (DeMaskey, 1997), it is not surprising to see that the *ex-post* hedging effectiveness is greater for the multi-futures hedging than that of using a single USF contract.

4.5.5.3 Multiple USF Contracts *OR* Stock Index Futures

Until this point, we have test for the hedging effectiveness of USF in hedging its underlying stock position and compare it with cross-hedging effectiveness using the stock index futures by assuming that each portfolio consists of one spot stock only. Empirical results from previous sections suggest that USF exhibits superior hedging effectiveness in terms of R^2 for the individual stock exposure. Adding index futures contract to control for the market risk further improves the hedging effectiveness for market participants who hold only the underlying stock of USF in their portfolios. In reality, however, this is rarely the case. Investors may hold more than one stock in the portfolio, especially for institutional investors. Thus, using multiple contracts of USF to hedge against the exposure in a number of stocks in a diversified portfolio may not be optimal. Instead, using a broader based futures contract (such as the stock index futures) may be a better hedge against the covariance risk within the portfolio.

This section explores this possibility by constructing a number of cash portfolios consisting of three to ten USF underlying stocks, and testing the effect of hedging these "representative" portfolios with the equally-weighted USF portfolios on the variance reduction; then compared with that of hedging with index futures from the same trading location as the spot stocks. That is, we examine whether the formation of a portfolio of USFs creates a better hedge in hedging *multiple* stock exposures than hedging with index futures alone. The application of a portfolio approach in this section should provide useful information to both investors and market regulators. For instances, if our results show that the creation of such a hedge portfolio using multiple USFs leads to higher risk reduction than just using index futures, this indicates that it is possible for hedgers to create their own 'futures portfolio' to tailor to their stock portfolio held.[204] Further, it shows how effective the created hedge tool is for a certain cash portfolio size (from three up to ten USFs are used to hedge). Additionally, it should give the exchange executives important insights in determining the optimal futures contract size that would attract new investors to utilize futures for hedging purposes. This in turn may help regulators to make decisions on whether the smaller E-mini/narrow-based index futures should be introduced as a means of enhancing risk management role of futures markets.[205]

---

[204] It has to be recognised that such hedging approach may associated with higher transaction costs than using index futures alone. Also, the use of multiple USFs as the hedging instrument might still be too expensive for small retail investors, and for those with very large cash portfolio exposure where it may not be sufficient number of USF contracts to cover the whole range of stocks held.

[205] As a matter of fact, there are already a number of mini-sized index futures (i.e. E-mini futures) that have been trading in the S&P500, Nasdaq100, DJIA, FTSE 100, HSI, and many others.

Once again, utilizing the similar statistical testing procedure in the previous sections, we analyze the hedging effectiveness of using an equally-weighted portfolio of USFs and stock index futures (SIF) in hedging *multiple* stock exposures, and compare the relative hedging efficiency of these two hedging strategies.[206] On comparing the hedging effectiveness, we again employ a statistical test based on the estimated parameter α_1 in order to infer whether hedging with USF portfolios and SIF contracts is superior in reducing the variance of hedged portfolio prices.

Table 4.19 reports the optimal hedge ratios (OHR) and hedging effectiveness (HE) of using the portfolio of USFs as well as those for using SIF contracts alone in hedging *multiple* stock positions. The results from Table 4.19 indicate that hedging with a portfolio of USFs has a better performance than hedging with the stock index futures. For 7 out of our 8 representative portfolios, the in-sample hedge based on an equally-weighted portfolio USF contracts has a higher hedging effectiveness (i.e., R^2), though the corresponding optimal hedge ratio (OHR) is not necessarily larger. The majority of the hedge improvements are significantly different from zero at 5% level. Average across all 8 cash portfolios in the sample, the hedging efficiency improves by 17.88% [(0.892-0.757)/0.757] relative to hedging with the index futures. However, the positive α_1 coefficient for the UK stocks portfolio suggests that USF portfolio hedge is unlikely to improve the hedging efficiency in hedging the spot portfolios containing ten or more stocks. These results are generally consistent with the empirical findings by Chiu et al. (2005) who find that the small E-mini / narrow-based index futures are more effective in hedging the small-sized portfolios (i.e. usually contain about 5 stocks) than that of using the regular index futures.

[206] Eight representative portfolios are constructed in total. Each portfolio is based on the country in which the underlying stocks are traded: (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland.

4.5.5.4 Summary on Relative Hedging Effectiveness

Using OLS technique, this section investigates the *ex-post* hedging effectiveness of USF on its underlying stock position as well as for cross-hedging effectiveness using the stock index futures (SIF). On comparing hedging effectiveness, we emphasize that a statistical test has to be performed in order to infer whether USF is superior in reducing the variance of the stock prices. By simply comparing the regression R^{2}'s (i.e. coefficient of determination) is an inadequate test for the relative hedging effectiveness of the two futures contracts under study, and thus might be misleading. We employ the approach suggested by Nothaft et al. (1995) to conduct such a test and find the following results. First, as expected, hedging with USF has a better performance than hedging with index futures for individual stock positions. Second, hedging simultaneously with USF and index futures further improves hedging efficiency compared to hedging with only USF contracts. Finally, creating an equally-weighted USF portfolio to hedge *multiple* stock portfolios is also more effective than that of using index futures in hedging the small-sized portfolio.

4.6 Conclusions

In this chapter the hedging performance of Universal Stock Futures (USF) contracts has been examined for the period since their listings in 2001. In the introduction to this thesis it was suggested that hedging is the most important function of futures markets and is arguably the major justification for the existence of futures contracts. Given its popularity and the phenomenal growth of the volume of contracts traded (which has actually surpassed the volume of options contracts traded in LIFFE), it is surprising that the hedging effectiveness of the USF contract has not previously been addressed. This chapter presents the first attempt to fill the gap.

The examination of hedging performance and hedging effectiveness is undertaken in three stages. In its three main sections, this chapter considers the following issues. Firstly, we investigated whether, and to what extent, USF contracts have served as efficient risk management tools in hedging against the idiosyncratic risk of individual stock position. To address this issue, we proposed an improved dynamic hedging strategy to evaluate the USF hedging performance by applying variance-reduction and utility-based performance evaluation criteria for both within-sample and out-of-sample periods. Secondly, we performed a cross-sectional analysis to identify the factors that explain the differences in the hedging effectiveness of USF contracts. The factors we considered include the contemporaneous market conditions, futures contract specifications, trading locations of underlying stocks, and the development stage of USF contracts. Finally, we also compared the *relative* hedging effectiveness of USF versus stock index futures, and assessed the efficiency of creating a USF portfolio in hedging the cash portfolio containing only a small number of stocks.

4.6.1 Summary of Results

The major findings of our empirical analysis are summarized as follows:

1. Hedging Effectiveness: Our empirical findings suggest that, on a total variance-reduction basis and an expected utility-maximisation basis, the majority of USF contracts have served as efficient risk management tools in hedging against the individual stock exposures. Moreover, we find that the basis and asymmetry effects in the time-varying variance-covariance structure have important implications in the estimation of hedge ratio, and our proposed dynamic hedging strategy that incorporates both of these effects can produce additional hedging benefits for investors who want/need to hedge their exposure to a stock position.

2. Variations and Determinants of Hedging Effectiveness: The results of our sub-sample and sub-period analysis indicate that there is a cross-sectional and time-series variation in USF hedging effectiveness. In addition, the cross-sectional regression results reveal that the variables measuring relative market quality such as the ratios of trading volume and bid-ask spread are major determinants of the degree of hedging effectiveness across USFs. However, we also uncover clear evidence that the hedging role of futures is more pronounced for the smaller sized USF contracts. Thus we can reasonably infer that hedging efficiency of futures is driven by factors other than difference in trading costs and liquidity alone, contract design factor also seems to play an important role.

3. Relative Hedging Effectiveness of USF and Index Futures: By comparing the hedging effectiveness of USFs and the futures on several stock indices, we find that hedging with USF has a better performance than hedging with index futures for individual stock positions. In addition, hedging *simultaneously* with USF and index futures further improves hedging efficiency compared to hedging with only USF contracts. More importantly, creating an equally-weighted USF portfolio to hedge multiple stock portfolios is also more effective than that of using index futures in hedging the small-sized portfolio.

4.6.2 Implications of Findings

Taken together, the evidence presented in this chapter strongly suggests that most USF contracts are effective means by which to hedge individual stock price risk. This is not entirely surprising given the fact that the underlying stock of the futures contract is exactly the same as the spot assets. However, despite the risk management function are performed efficiently by most USFs, the risk-reduction ability of some USFs contracts is much lower than others and compared poorly to that evidenced in other commodity and financial futures markets. The poorer hedging performance is found to be the results of relatively lower trading volume and larger contract size in these contracts, which abstain users from using these futures to hedge their individual stock exposure. As a policy implication, this suggest that the LIFFE should first advertise more this derivative market through marketing campaigns in order to attract the much needed volume in these USFs, and second, reduce the size of these contracts to make them more accessible and attractive to the small retail investors. Awareness and increased trading activity should promote the hedging efficiency.

In addition, the comparison of alternative methods for computing more efficient hedge ratios indicates that time-varying hedge ratios generated from the flexible VECM-AsymBEKK-X models outperform both the constant hedge ratios and alternative specifications in reducing total portfolio risk. The implication of these results is that market agents can benefits from this general framework by computing superior hedge ratios and thus controlling more efficiently their stock price risk. However, in pursuing a dynamic hedging strategy it is necessary to take account of the additional costs that arise from frequent portfolio re-balancing. Therefore, the investor must weigh up the benefits of reducing risk by frequent changing of hedge ratios, against the increased costs associated with adopting such a dynamic strategy.

Finally, the finding that the creation of a hedge portfolio using multiple USFs leads to higher risk reduction than just using index futures, indicates that it is possible for hedgers to create their own 'futures portfolio' to tailor to their stock portfolio held. This in turn may help government regulators make decisions on whether the E-mini / narrow-based index futures should be introduced as a means of enhancing the risk-sharing opportunities in the markets.

Overall, the results shown here demonstrate that the introduction of the futures contract on individual stocks such as USF has given portfolio managers a valuable instrument by which to avoid risk without liquidating their spot position. They allow a better match for risk management purposes than do broad-based index futures and enable individual components of a portfolio to be hedged without having to change the make-up of the entire portfolio. These should give justification for other derivatives exchanges to launch similar single-stock futures as a means of improving the risk-shifting capacity in their markets.

4.6.3 Limitations and Direction of Future Research

Despite the effort to conduct this research as thorough and accurate as possible, several points need to be made with regard to the empirical results documented in this chapter. First, the superior hedging effectiveness shown in many USF contracts may be overstated due to thin trading or illiquidity. The reason is that when there is no trading for stock futures, which is not uncommon, the daily settlement price of the USF will be theoretically determined in reference to the closing stock price.[207] Therefore, it is not surprising to see that ex-post hedging effectiveness is greater for the thinly traded contracts than heavily traded contracts (as shown in section 4.5.4). Hence, to evaluate the usefulness of the futures contract in hedging an underlying exposure, one should consider not only the expected hedging effectiveness of the futures contract but also the liquidity of the contract. In the case of USFs, it should be noted that despite the fact that a futures contract may display superior hedging effectiveness for the underlying stock, liquidity could be the more important consideration in the hedging decision.

[207] As mentioned before, inspecting the daily trading activity in each USF contract, we find that it is not uncommon to find no single trade on a given day for some thinly traded USF contracts.

Second, the analysis in this chapter has not considered the issue of transaction costs. In reality, however, there are transaction costs which rise proportionately with the frequency of portfolio re-balancing. One motivating factor for future research lies in consideration of transaction costs. For instance, it would be interesting to see if the dynamic hedge ratios generated from the more flexible VECM-GARCH models (such as AsymBEKK-X model we proposed here) are superior to static ones in the presence of transaction costs.

Third, anther concern regarding the hedging efficiency of USF contract is that they are traded on relatively immature markets, which could lead to pricing anomalies that may affect our results. In practice, an alternative approach to hedge against individual stock position would be to create a *synthetic* long USF position by combining a long call and a short put with the same exercise price and expiration. Therefore, a comparison of the hedging effectiveness between these two approaches (i.e. *explicit* versus *implicit* futures hedging, see Karagozoglu, 1999) would be a worthwhile exercise. Finally, another obvious extension is the use of a longer sample period for estimating the hedge ratios and for determining hedging effectiveness. Our sample period is limited by the length of time that USF contracts have been trading. Of course, further research may also be conducted for different frequency of data, hedge horizons, single-stock futures markets, etc.

Table 4.1: Summary Statistics of Stock Returns, Futures Returns, and Basis

Code	Variables	N	μ	σ	S	K	JB	Q(12)	$Q^2(12)$	ARCH (12)	Sign-Bias (t-test)	Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F-test)
AA	Rs	809	-0.0003	0.0267	0.026	3.741	470.70 ***	37.669 ***	662.587 ***	34.294 ***	0.7802	-5.7797 ***	6.0640 ***	65.2233 ***
	Rf	809	-0.0003	0.0262	-0.001	4.102	565.79 ***	22.116 **	521.607 ***	28.514 ***	-0.4995	-5.7035 ***	4.7513 ***	51.8412 ***
	Basis	810	0.0024	0.0118	0.765	2.710	325.54 ***							
AGN	Rs	809	-0.0016	0.0356	-0.126	3.229	352.61 ***	47.198 ***	578.584 ***	35.621 ***	-1.7294 *	-8.3542 ***	3.4493 ***	75.2636 ***
	Rf	809	-0.0016	0.0989	0.108	305.110	3130300.00 ***	147.836 ***	201.361 ***	98.629 ***	5.4928 ***	0.1987	26.2713 ***	373.2388 ***
	Basis	810	-0.0254	0.0692	-24.190	648.980	14241000.00 ***							
AHL	Rs	809	-0.0020	0.0490	-9.976	206.750	1450700.00 ***	30.011 ***	2.916	0.454	0.8015	-0.4431	0.0646	1.4015
	Rf	809	-0.0022	0.0496	-10.005	203.310	1403300.00 ***	25.938 **	2.476	0.388	0.9430	-0.4314	0.1624	1.6397
	Basis	810	-0.1329	0.0678	1.365	-0.031	250.70 ***							
ALV	Rs	965	-0.0011	0.0294	-0.032	2.065	143.52 ***	21.058 **	475.148 ***	28.127 ***	-0.9457	-5.8804 ***	3.1804 ***	43.2134 ***
	Rf	965	-0.0012	0.0282	-0.243	2.235	175.93 ***	11.030	472.106 ***	24.881 **	-0.4977	-5.3986 ***	4.0548 ***	43.7071 ***
	Basis	966	-0.0620	0.0590	0.509	-1.527	113.27 ***							
AXA	Rs	965	-0.0005	0.0309	0.136	2.420	199.34 ***	25.804 **	505.634 ***	24.824 **	-1.2367	-7.6184 ***	5.4647 ***	80.8704 ***
	Rf	965	-0.0019	0.0548	-15.912	371.090	4664600.00 ***	4.329	0.035	0.003	-1.2814	-0.0610	-1.0551	1.8584
	Basis	966	-0.0516	0.2356	-5.067	23.739	22401.00 ***							
AZN	Rs	1016	-0.0004	0.0202	0.092	4.197	593.47 ***	31.111 ***	111.875 ***	7.156	-2.7578 ***	-4.9676 ***	1.9337 *	30.2841 ***
	Rf	1016	-0.0005	0.0198	0.303	4.971	843.34 ***	35.552 ***	117.601 ***	6.863	-1.7048 *	-4.6108 ***	3.1275 ***	31.5126 ***
	Basis	1017	-0.0018	0.0062	-0.167	7.722	2008.90 ***							
BAR	Rs	939	0.0001	0.0219	0.135	2.192	163.95 ***	35.489 ***	441.133 ***	23.670 **	-0.1615	-5.9224 ***	4.5902 ***	53.4182 ***
	Rf	939	-0.0014	0.0498	-20.546	522.240	9227600.00 ***	6.377	0.024	0.002	0.9618	0.0848	0.0699	1.2284
	Basis	940	-0.3595	0.6085	-0.867	-1.248	153.39 ***							
BNP	Rs	939	0.0001	0.0219	-0.056	4.156	581.16 ***	25.441 **	414.954 ***	21.577 **	0.4029	-4.5787 ***	3.1837 ***	32.3641 ***
	Rf	939	-0.0006	0.0320	-11.104	228.030	1765000.00 ***	9.433	0.023	0.002	0.9727	-0.6574	0.2602	2.0851
	Basis	940	-0.1469	0.2834	-1.188	-0.582	201.08 ***							
BPA	Rs	1016	-0.0001	0.0176	-0.418	1.889	143.47 ***	37.408 ***	244.396 ***	16.573	-1.1390	-6.8747 ***	2.8095 ***	53.9964 ***
	Rf	1016	-0.0002	0.0173	-0.505	1.947	161.77 ***	34.024 ***	224.485 ***	15.571	-1.4831	-6.5926 ***	2.8738 ***	49.6187 ***
	Basis	1017	-0.0003	0.0052	-0.138	0.578	13.80 ***							
BTL	Rs	965	-0.0005	0.0246	0.098	1.193	49.13 ***	23.670 **	221.535 ***	14.456	-1.9737 **	-5.5804 ***	1.8526 *	33.5212 ***
	Rf	965	-0.0009	0.0257	-1.072	9.845	3413.90 ***	28.018 ***	8.321	0.312	0.2237	-1.4576	2.5943 ***	9.2312 **
	Basis	966	-0.0493	0.1058	-1.528	0.614	326.70 ***							
BVA	Rs	939	-0.0002	0.0226	0.267	1.626	98.53 ***	16.634	392.971 ***	22.309 **	-0.3010	-4.8390 ***	3.5590 ***	36.2180 ***
	Rf	939	-0.0002	0.0216	0.226	1.280	61.97 ***	9.601	387.167 ***	21.894 **	1.1158	-3.2309 ***	3.3035 ***	25.2775 ***
	Basis	940	0.0016	0.0065	-0.563	5.342	1002.40 ***							
CA	Rs	939	-0.0006	0.0207	0.005	2.346	185.13 ***	28.138 ***	469.501 ***	26.769 ***	-1.0975	-7.0175 ***	4.5508 ***	65.3604 ***
	Rf	939	-0.0006	0.0203	-0.127	2.351	187.99 ***	23.290 **	422.318 ***	24.906 **	-0.7881	-6.4438 ***	5.0791 ***	63.0694 ***
	Basis	940	-0.0011	0.0082	1.575	8.539	2785.50 ***							
CGE	Rs	1016	-0.0017	0.0420	0.373	5.355	983.03 ***	20.029 *	121.066 ***	9.399	-1.6095	-5.6729 ***	1.5777	34.4856 ***
	Rf	1016	-0.0017	0.0460	0.785	15.350	8005.30 ***	15.984	153.381 ***	24.033 **	1.5507	-3.4674 ***	9.0553 ***	86.8390 ***
	Basis	1017	-0.0026	0.0159	-8.522	209.380	1483900.00 ***							
CSG	Rs	807	-0.0002	0.0282	-0.237	3.857	507.88 ***	35.020 ***	610.352 ***	26.006 **	0.0648	-6.7705 ***	3.4303 ***	59.5296 ***
	Rf	807	-0.0003	0.0285	-0.057	3.818	490.56 ***	29.813 ***	623.557 ***	29.126 ***	-0.3927	-7.3801 ***	3.2607 ***	66.5339 ***
	Basis	808	-0.0247	0.0300	-1.110	-0.473	173.25 ***							
DBK	Rs	1016	-0.0005	0.0249	-0.126	2.025	140.04 ***	10.826	383.011 ***	23.089 **	-1.1669	-6.3397 ***	2.7142 ***	46.5041 ***
	Rf	1016	-0.0005	0.0243	-0.117	2.519	215.26 ***	23.222 **	292.020 ***	14.462	-0.2580	-6.2583 ***	2.3493 **	48.6022 ***
	Basis	1017	0.0003	0.0105	0.766	3.803	565.32 ***							
DCY	Rs	939	-0.0005	0.0241	-0.006	1.212	49.39 ***	23.901 **	408.568 ***	28.846 ***	-0.4577	-5.9142 ***	2.1372 **	43.0004 ***
	Rf	939	-0.0005	0.0233	-0.005	1.188	47.48 ***	24.349 **	279.620 ***	18.572 *	0.2275	-4.1637 ***	1.4518	24.3954 ***
	Basis	940	0.0016	0.0147	2.010	5.651	1617.30 ***							
DTE	Rs	1016	-0.0008	0.0290	0.083	1.753	104.21 ***	29.360 ***	366.148 ***	22.211 **	-0.6480	-7.3765 ***	4.9519 ***	74.8187 ***
	Rf	1016	-0.0008	0.0276	0.072	1.451	71.48 ***	20.067 *	299.838 ***	17.425	1.6918 *	-3.5942 ***	5.9238 ***	47.6507 ***
	Basis	1017	-0.0010	0.0120	1.082	6.480	1569.60 ***							
ENI	Rs	1016	0.0003	0.0168	-0.439	1.401	91.95 ***	18.896 *	221.723 ***	16.162	1.0221	-4.8832 ***	3.9293 ***	40.3755 ***
	Rf	1016	0.0009	0.0267	14.254	323.270	3541300.00 ***	6.965	0.039	0.004	1.2821	0.8057	0.0293	1.7296
	Basis	1017	0.0463	0.2047	2.323	3.426	1120.60 ***							
ENL	Rs	967	0.0001	0.0161	-0.895	5.876	1268.60 ***	28.560 ***	142.450 ***	9.556	-0.4056	-4.4858 ***	2.4257 **	25.4311 ***
	Rf	967	0.0007	0.0275	16.172	382.230	4947900.00 ***	8.528	0.024	0.002	0.2021	-1.1657	0.0979	2.2892
	Basis	968	-0.0187	0.1829	2.727	5.505	2019.20 ***							
EOA	Rs	939	0.0002	0.0191	0.156	2.243	172.42 ***	33.041 ***	251.867 ***	14.816	1.4902	-3.1179 ***	4.7543 ***	32.6006 ***
	Rf	939	0.0002	0.0179	0.388	2.638	254.19 ***	28.948 ***	202.696 ***	13.994	-0.2652	-8.4820 ***	3.8087 ***	87.0525 ***
	Basis	940	0.0005	0.0114	1.250	3.644	656.67 ***							
ERC	Rs	807	-0.0006	0.0445	-0.065	4.405	653.05 ***	38.192 ***	198.514 ***	15.649	1.5370	-3.8557 ***	6.9865 ***	59.8697 ***
	Rf	807	-0.0010	0.0466	-0.663	8.164	2300.30 ***	19.356 *	258.501 ***	9.240	2.1134 **	-2.7758 ***	7.0450 ***	53.7805 ***
	Basis	808	-0.0822	0.1399	-1.210	-0.522	206.12 ***							
FTE	Rs	1016	-0.0012	0.0362	0.349	2.666	255.34 ***	9.408	588.441 ***	34.152 ***	0.5626	-6.3866 ***	8.5437 ***	102.6709 ***
	Rf	1016	-0.0014	0.0357	0.273	2.739	262.23 ***	11.051	438.872 ***	25.209 **	0.0029	-6.0926 ***	7.1326 ***	81.3952 ***
	Basis	1017	-0.0830	0.0725	0.727	-1.373	134.51 ***							
GEN	Rs	967	-0.0004	0.0187	-0.299	2.231	179.33 ***	27.792 ***	646.498 ***	32.837 ***	-0.2212	-9.1633 ***	4.9521 ***	102.6038 ***
	Rf	967	-0.0004	0.0182	-0.193	2.299	182.64 ***	19.129 *	587.404 ***	28.999 ***	0.1009	-8.2177 ***	4.9552 ***	88.4621 ***
	Basis	968	-0.0017	0.0055	0.536	5.232	958.99 ***							
GXW	Rs	1016	-0.0004	0.0179	0.128	2.533	217.90 ***	18.615 *	166.783 ***	13.705	-2.4569 **	-7.9235 ***	3.4010 ***	69.6147 ***
	Rf	1016	-0.0004	0.0176	0.145	3.062	318.16 ***	20.366 *	180.247 ***	15.263	-1.9654 **	-8.1914 ***	4.1276 ***	78.0965 ***
	Basis	1017	-0.0010	0.0053	0.037	1.396	65.74 ***							
HAS	Rs	1016	-0.0002	0.0161	-0.579	7.027	1705.20 ***	48.360 ***	86.869 ***	4.358	-1.1031	-3.6046 ***	0.5523	13.4626 ***
	Rf	1016	-0.0002	0.0156	-0.179	3.319	374.81 ***	47.517 ***	103.169 ***	4.850	-0.2909	-3.6576 ***	1.1921	16.5640 ***
	Basis	1017	0.0017	0.0091	0.855	1.254	151.24 ***							
HNM	Rs	807	0.0002	0.0193	0.191	5.335	961.90 ***	17.286	51.504 ***	4.906	0.0219	-4.3319 ***	1.2663	23.1303 ***
	Rf	807	0.0002	0.0205	-0.058	8.142	2229.30 ***	28.547 ***	150.400 ***	23.559 **	-1.3827	-8.0798 ***	1.4986	66.0616 ***
	Basis	808	-0.0019	0.0077	6.545	133.850	608190.00 ***							
ING	Rs	1016	-0.0006	0.0300	0.098	3.230	352.07 ***	27.518 ***	535.670 ***	33.637 ***	1.3073	-5.9425 ***	5.6646 ***	67.8205 ***
	Rf	1016	-0.0013	0.0365	-5.124	85.134	247240.00 ***	11.642	0.032	0.003	-0.3385	-0.5979	0.8487	1.5481
	Basis	1017	-0.0716	0.2149	-2.158	2.677	867.48 ***							
LLO	Rs	965	-0.0004	0.0210	0.027	1.840	113.89 ***	20.231 *	473.118 ***	23.189 **	-0.4725	-6.1499 ***	5.8840 ***	67.8358 ***
	Rf	965	-0.0004	0.0208	0.169	1.876	122.19 ***	18.616 *	375.622 ***	21.930 **	0.8245	-4.0357 ***	5.9387 ***	49.3091 ***
	Basis	966	0.0035	0.0152	2.098	4.250	1199.40 ***							
MUV	Rs	965	-0.0013	0.0293	-0.236	3.069	324.08 ***	19.915 *	454.667 ***	25.285 **	-2.3700 **	-9.0522 ***	3.6183 ***	87.1243 ***
	Rf	965	-0.0013	0.0296	-0.223	4.514	691.88 ***	31.288 ***	510.525 ***	27.237 ***	0.1100	-5.7980 ***	3.6705 ***	47.0337 ***
	Basis	966	-0.0351	0.0256	0.826	-0.021	91.86 ***							

Table 4.1: Summary Statistics of Stock Returns, Futures Returns, and Basis (continued)

Code	Variables	N	μ	σ	S	K	JB	Q(12)	$Q^2(12)$	ARCH (12)	Sign-Bias (t-test)	Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F-test)
NDA	Rs	807	0.0005	0.0223	-0.031	4.228	601.21 ***	26.932 ***	327.611 ***	20.495 *	-0.6892	-6.4007 ***	3.2075 ***	48.4541 ***
	Rf	807	0.0004	0.0217	0.082	4.578	705.56 ***	23.772 **	297.081 ***	19.216 *	-1.1960	-6.3554 ***	3.7106 ***	51.1539 ***
	Basis	808	-0.0002	0.0117	2.240	9.017	3408.80 ***							
NES	Rs	807	-0.0001	0.0141	0.090	4.827	784.52 ***	18.406	342.476 ***	23.885 **	0.0765	-4.4193 ***	4.3697 ***	37.5880 ***
	Rf	807	-0.0001	0.0143	-0.015	3.832	493.70 ***	27.137 ***	480.218 ***	33.055 ***	-0.1885	-6.0508 ***	6.9910 ***	77.7764 ***
	Basis	808	0.0015	0.0073	2.150	7.138	2334.70 ***							
NOV	Rs	807	-9.4719	0.0144	0.228	2.763	263.57 ***	23.631 **	239.994 ***	13.446	-0.2437	-2.9685 ***	3.1200 ***	18.2389 ***
	Rf	807	-0.0001	0.0145	0.468	3.233	380.75 ***	17.615	215.498 ***	12.883	-1.7192 *	-3.7629 ***	2.3991 **	20.2312 ***
	Basis	808	0.0005	0.0052	0.973	5.391	1104.50 ***							
PHI	Rs	835	-0.0004	0.0344	-0.005	0.948	30.22 ***	15.822	356.216 ***	18.701 *	-0.2452	-5.8399 ***	4.4996 ***	52.4487 ***
	Rf	835	-0.0004	0.0338	0.083	0.880	26.95 ***	9.716	307.690 ***	15.869	0.4106	-5.4313 ***	3.9648 ***	46.6605 ***
	Basis	836	-0.0016	0.0074	-0.586	9.325	2969.80 ***							
RBO	Rs	939	0.0001	0.0210	-0.084	2.798	264.10 ***	32.862 ***	480.235 ***	32.587 ***	-0.6631	-6.7228 ***	4.1344 ***	58.6796 ***
	Rf	939	0.0000	0.0202	0.050	2.928	288.67 ***	31.855 ***	431.020 ***	26.896 ***	-0.2521	-5.6869 ***	3.4301 ***	42.9380 ***
	Basis	940	-0.0007	0.0083	1.020	6.845	1715.20 ***							
RD	Rs	1016	-0.0004	0.0178	-0.524	3.196	380.41 ***	29.339 ***	299.972 ***	20.208 *	-0.0733	-6.7044 ***	2.3485 **	55.1232 ***
	Rf	1016	-0.0004	0.0174	-0.527	3.290	401.35 ***	21.336 **	253.806 ***	19.170 *	-0.1879	-6.5622 ***	2.4227 **	52.3714 ***
	Basis	1017	-0.6927	0.0071	0.998	1.506	210.22 ***							
ROG	Rs	807	0.0002	0.0166	-0.007	2.218	165.40 ***	9.739	374.208 ***	21.069 **	-0.4217	-5.5549 ***	3.8785 ***	43.6423 ***
	Rf	807	0.0001	0.0169	0.176	2.186	164.77 ***	9.873	346.911 ***	19.587 *	-0.2417	-4.4317 ***	3.8711 ***	33.3590 ***
	Basis	808	0.0007	0.0055	1.353	4.882	1047.60 ***							
SCH	Rs	1016	-0.0002	0.0233	0.105	1.641	91.97 ***	23.352 **	492.702 ***	28.526 ***	1.0979	-6.7823 ***	6.5924 ***	90.2043 ***
	Rf	1016	-0.0002	0.0225	0.266	1.669	103.21 ***	18.754 *	414.588 ***	21.813 **	1.9873 **	-4.8794 ***	6.2929 ***	65.8736 ***
	Basis	1017	0.0008	0.0066	0.105	1.145	45.56 ***							
SHB	Rs	807	0.0003	0.0160	0.015	3.194	343.14 ***	12.838	318.029 ***	23.696 **	-0.1788	-5.1308 ***	2.3173 **	31.2679 ***
	Rf	807	0.0003	0.0158	0.165	3.149	337.14 ***	15.128	331.317 ***	27.217 ***	-1.1393	-7.1784 ***	2.4138 **	54.9136 ***
	Basis	808	-0.0006	0.0088	2.586	8.414	3279.80 ***							
SHE	Rs	939	-0.0004	0.0180	-0.636	3.862	555.91 ***	24.161 **	318.805 ***	20.188 *	-0.1238	-7.0320 ***	2.3962 **	58.3205 ***
	Rf	939	-0.0003	0.0190	-0.799	6.145	1355.40 ***	30.926 ***	125.450 ***	11.901	1.9048 *	-3.0877 ***	5.2091 ***	36.1299 ***
	Basis	940	0.1528	0.0281	0.252	-0.509	17.22 ***							
SIE	Rs	1016	-0.0005	0.0268	0.153	0.489	11.20 ***	15.385	228.619 ***	10.835	0.0555	-4.8458 ***	3.1891 ***	35.4874 ***
	Rf	1016	-0.0009	0.0285	-1.809	23.263	18637.00 ***	14.431	2.944	0.058	0.9896	-0.5286	0.8147	2.2017
	Basis	1017	-0.0253	0.0983	-3.125	7.919	3422.00 ***							
TEF	Rs	1016	-0.0003	0.0215	0.276	2.078	155.42 ***	17.010	161.650 ***	9.648	-2.6936 ***	-6.6206 ***	1.5298	44.8300 ***
	Rf	1016	-0.0004	0.0215	0.395	2.720	269.75 ***	13.904	200.510 ***	16.522	-0.7901	-5.4757 ***	2.1279 **	37.1288 ***
	Basis	1017	-0.0780	0.0383	-0.010	-1.397	65.68 ***							
TI	Rs	1016	-0.0005	0.0234	-0.892	6.709	1620.30 ***	32.683 ***	113.621 ***	9.236	-0.4243	-5.3611 ***	2.4496 **	35.6431 ***
	Rf	1016	-0.0015	0.0418	-21.239	544.360	10025000.00 ***	2.925	0.025	0.002	1.0189	0.3828	0.0233	1.5099
	Basis	1017	-0.7392	0.5696	1.307	-0.045	229.87 ***							
TIM	Rs	837	-0.0005	0.0201	0.107	3.103	325.19 ***	26.377 ***	183.280 ***	12.187	-1.0280	-4.0491 ***	0.9912	17.9141 ***
	Rf	837	-0.0005	0.0202	-0.200	2.769	263.14 ***	38.268 ***	143.887 ***	11.020	-2.2697 **	-6.0185 ***	1.2933	36.5861 ***
	Basis	838	-0.0200	0.0238	0.388	-0.186	21.42 ***							
TLI	Rs	807	-0.0002	0.0265	0.392	6.257	1337.20 ***	22.445 **	158.734 ***	18.117	-3.6645 ***	-9.5373 ***	2.2147 **	86.4542 ***
	Rf	807	-0.0002	0.0262	0.394	6.484	1434.30 ***	22.568 **	169.553 ***	18.935 *	-3.3121 ***	-9.8440 ***	2.4788 **	92.2830 ***
	Basis	808	-0.0215	0.0060	0.667	6.899	1660.30 ***							
TOT	Rs	1016	0.0000	0.0172	-0.241	1.262	61.37 ***	31.999 ***	305.985 ***	20.665 *	-0.2939	-8.0905 ***	3.7765 ***	78.5740 ***
	Rf	1016	0.0000	0.0166	-0.165	1.455	74.86 ***	28.339 ***	267.042 ***	18.620 *	-1.2462	-9.0170 ***	4.0954 ***	91.7229 ***
	Basis	1017	-0.0001	0.0098	1.622	4.190	944.12 ***							
UBS	Rs	807	0.0003	0.0191	0.248	3.716	472.58 ***	28.442 ***	489.199 ***	27.932 ***	-0.1593	-6.3501 ***	5.4437 ***	65.1045 ***
	Rf	807	0.0003	0.0197	-0.005	5.284	938.80 ***	27.042 ***	381.913 ***	25.075 **	0.5803	-5.1115 ***	4.8314 ***	47.7929 ***
	Basis	808	-0.0043	0.0155	-0.244	0.705	24.76 ***							
UC	Rs	967	-0.0001	0.0183	0.174	4.740	759.49 ***	46.133 ***	432.156 ***	26.390 ***	0.1252	-6.7255 ***	6.8899 ***	85.6624 ***
	Rf	967	-0.0001	0.0177	0.331	4.927	830.86 ***	36.904 ***	340.346 ***	20.791 *	-0.6879	-5.7166 ***	5.5823 ***	60.2046 ***
	Basis	968	-0.0002	0.0110	2.441	8.505	3233.20 ***							
VIV	Rs	939	-0.0012	0.0375	-1.218	12.146	5159.60 ***	56.540 ***	324.018 ***	31.007 ***	-0.5077	-9.2411 ***	4.3790 ***	96.1915 ***
	Rf	939	-0.0012	0.0368	-1.388	12.868	5826.90 ***	52.140 ***	212.830 ***	21.298 **	0.1323	-6.3558 ***	3.9981 ***	54.2763 ***
	Basis	940	-0.0023	0.0083	-0.419	9.165	2848.00 ***							
VOF	Rs	1016	-0.0005	0.0255	0.300	0.998	45.61 ***	35.465 ***	185.113 ***	10.046	0.5013	-4.2610 ***	3.9629 ***	36.0686 ***
	Rf	1016	-0.0005	0.0247	0.260	0.991	42.11 ***	38.594 ***	178.917 ***	8.500	1.4169	-2.3528 **	3.7058 ***	21.8728 ***
	Basis	1017	-0.0024	0.0063	-4.144	59.795	122530.00 ***							
VOW	Rs	939	-0.0005	0.0237	-0.023	1.357	62.02 ***	26.656 ***	323.179 ***	20.551 *	-1.3550	-5.8790 ***	2.3865 **	38.9488 ***
	Rf	939	-0.0005	0.0233	-0.240	1.908	130.19 ***	30.347 ***	288.037 ***	19.670 *	-1.0572	-1.6210	0.1129	2.8213
	Basis	940	0.0006	0.0114	0.502	5.722	1134.90 ***							

Notes: *, **, *** Significant at 10%, 5% and 1% level, respectively

N = number of observation; μ = mean; σ = standard deviation; S = skewness; K = excess Kurtosis; JB = Jarque-Bera test for normality.

ARCH (12) test is the Langrange Multiplier [LM(12)] test for ARCH effects and distributed as a χ^2 with 12 degree of freedom.

Q(N) and Q^2(N) are the Ljung-Box Q statistics which are distributed as χ^2 with N degree of freedom where N is the number of lags.

The Ljung-Box statistics for N lags is calculated as $LB(N)=T(T+2)\sum(\rho_j^2/T-j)$ where ρj is the sample autocorrelation for j lags and T is the sample size.

The Engle and Ng (1993) volatility asymmetries tests (i.e., Sign-Bias, Negative-Size Bias, Positive-Size Bias, and Joint Test) are also reported.

Table 4.2: Unit Root and Cointegration Test Results

Code	Stock Name	Stock Price	Futures Price	Stock Return	Futures Return	Basis	Johansen Cointegration Trace Test Statistics (λ_{trace}) (H_0: r = 0)	Cointegrating vecor (1, β_1, β_2)
AA	ABN AMRO Holdings NV	-2.942	-2.905	-29.326 ***	-28.088 ***	-5.535 ***	35.50 ***	(1, -0.0012, -1.0005)
AGN	Aegon NV	-1.976	-2.485	-27.916 ***	-23.296 ***	-25.667 ***	121.18 ***	(1, -0.0706, -0.9651)
AHL	Koninklijke Ahold NV	-1.822	-2.080	-17.192 ***	-16.616 ***	-1.533	6.88	
ALV	Allianz AG	-0.975	-0.852	-30.641 ***	-29.372 ***	-1.354	18.55 *	(1, -0.2906, -0.9308)
AXA	Axa SA	-1.741	-3.771 **	-28.943 ***	-30.718 ***	-5.791 ***	46.69 ***	(1, -0.0631, -0.9735)
AZN	AstraZeneca plc	-2.394	-2.305	-24.542 ***	-24.103 ***	-4.769 ***	41.31 ***	(1, -0.0594, -0.9922)
BAR	Barclays plc	-2.302	-1.382	-29.633 ***	-29.924 ***	-1.731	10.97	
BNP	BNP Paribas SA	-2.568	-1.737	-29.090 ***	-29.879 ***	-1.905	11.69	
BPA	BP plc	-2.112	-2.048	-21.730 ***	-21.537 ***	-7.142 ***	43.36 ***	(1, -0.0471, -0.9924)
BTL	BT Group plc	-2.347	-1.867	-32.227 ***	-20.675 ***	-2.930 **	25.17 ***	(1, -1.2686, -0.7592)
BVA	Banco Bilbao Vizcaya Argentaria SA	-1.992	-1.884	-31.119 ***	-29.601 ***	-5.849 ***	55.64 ***	(1, -0.0131, -0.9952)
CA	Carrefour SA	-3.317 *	-3.219 *	-33.480 ***	-32.448 ***	-7.348 ***	43.16 ***	(1, -0.0244, -0.9933)
CGE	Alcatel SA	-2.118	-2.170	-32.172 ***	-33.655 ***	-28.416 ***	156.48 ***	(1, 0.0138, -1.0046)
CSG	Credit Suisse Group	-1.623	-1.557	-17.642 ***	-17.969 ***	-1.931	13.75	
DBK	Deutsche Bank AG	-2.220	-2.174	-32.651 ***	-30.230 ***	-6.384 ***	59.39 ***	(1, -0.0024, -0.9995)
DCY	DaimlerChrysler AG	-2.269	-2.148	-31.312 ***	-29.112 ***	-4.335 ***	31.51 ***	(1, -0.0626, -0.9832)
DTE	Deutsche Telekom AG	-2.511	-2.440	-34.399 ***	-20.764 ***	-10.480 ***	91.67 ***	(1, 0.0111, -1.0038)
ENI	Eni SpA	-2.825	-3.012	-33.136 ***	-31.714 ***	-3.104 **	26.13 ***	(1, -0.4403, -0.8295)
ENL	Enel SpA	-1.600	-3.139 *	-33.772 ***	-33.035 ***	-3.369 **	25.64 ***	(1, 0.4809, -1.2323)
EOA	E.ON AG	-1.221	-1.173	-35.770 ***	-33.814 ***	-8.026 ***	56.69 ***	(1, -0.0357, -0.9910)
ERC	Telefonaktiebolaget LM Ericsson AB	-1.631	-1.424	-25.692 ***	-27.269 ***	-1.773	21.51 **	(1, -0.1650, -0.9193)
FTE	France Telecom SA	-1.929	-1.901	-30.009 ***	-29.534 ***	-1.182	10.12	
GEN	Assicurazioni Generali SpA	-1.429	-1.391	-29.935 ***	-29.178 ***	-11.337 ***	83.31 ***	(1, -0.0036, -0.9984)
GXW	GlaxoSmithKline plc	-2.464	-2.388	-32.525 ***	-32.355 ***	-6.958 ***	45.63 ***	(1, -0.0372, -0.9947)
HAS	HSBC Holdings plc	-3.456 **	-3.355 *	-33.846 ***	-32.492 ***	-5.424 ***	35.79 ***	(1, -0.0506, -0.9927)
HNM	Hennes & Mauritz AB	-2.953	-2.743	-30.319 ***	-32.170 ***	-12.003 ***	83.05 ***	(1, 0.0364, -1.0066)
ING	ING Groep NV	-1.784	-1.911	-31.490 ***	-31.430 ***	-2.957 **	26.55 ***	(1, 0.7243, -1.2460)
LLO	Lloyds TSB Group plc	-1.972	-2.037	-31.945 ***	-31.976 ***	-4.706 ***	24.92 ***	(1, -0.0811, -0.9877)
MUV	Münchener Rücksversicherungs Gesellschaft AG	-1.364	-1.430	-28.893 ***	-28.708 ***	-1.440	13.16	
NDA	Nordea AB	-1.660	-1.603	-30.079 ***	-29.120 ***	-5.964 ***	30.78 ***	(1, 0.0225, -1.0057)
NES	Nestle SA	-2.175	-2.176	-29.715 ***	-30.522 ***	-5.448 ***	38.64 ***	(1, -0.0355, -0.9941)
NOV	Novartis AG	-2.748	-2.738	-27.354 ***	-27.568 ***	-7.704 ***	57.38 ***	(1, -0.0426, -0.9896)
PHI	Koninklijke Philips Electronics NV	-2.163	-2.123	-29.955 ***	-29.560 ***	-8.428 ***	67.53 ***	(1, -0.0066, -0.9974)
RBO	Royal Bank of Scotland Group plc	-3.725 **	-3.584 **	-32.894 ***	-31.160 ***	-7.223 ***	43.61 ***	(1, -0.0395, -0.9946)
RD	Royal Dutch Petroleum Company	-2.211	-2.209	-33.036 ***	-32.129 ***	-7.450 ***	37.76 ***	(1, 0.6936, -1.0003)
ROG	Roche Holding AG	-1.993	-2.023	-27.579 ***	-28.394 ***	-5.400 ***	34.70 ***	(1, -0.0292, -0.9940)
SCH	Santander Central Hispano SA	-2.189	-2.092	-33.031 ***	-31.260 ***	-9.560 ***	68.36 ***	(1, -0.0146, -0.9936)
SHB	Svenska Handelsbanken AB	-2.039	-2.013	-29.863 ***	-30.300 ***	-5.926 ***	36.24 ***	(1, 0.0187, -1.0036)
SHE	Shell Transport & Trading Company plc	-2.508	-2.654	-31.786 ***	-32.564 ***	-2.497	13.01	
SIE	Siemens AG	-2.404	-2.842	-31.044 ***	-29.370 ***	-3.889 ***	24.34 **	(1, 0.4750, -1.1194)
TEF	Telefonica SA	-2.129	-2.044	-31.430 ***	-30.805 ***	-1.691	11.72	
TI	Telecom Italia SpA	-2.222	-2.224	-13.583 ***	-32.012 ***	-0.794	12.21	
TIM	Telecom Italia Mobile SpA	-2.404	-2.395	-30.441 ***	-31.432 ***	-3.256 **	18.81 *	(1, -0.1331, -0.9024)
TLI	TeliaSonera AB	-2.791	-2.777	-29.495 ***	-22.275 ***	-7.486 ***	55.96 ***	(1, 0.0085, -0.9963)
TOT	Total Fina Elf SA	-2.606	-2.518	-33.733 ***	-24.959 ***	-5.584 ***	31.16 ***	(1, -0.0043, -0.9991)
UBS	UBS AG	-2.600	-2.270	-25.744 ***	-26.096 ***	-3.657 ***	24.62 ***	(1, -0.0484, -0.9882)
UC	UniCredito Italiano SpA	-2.864	-2.792	-29.916 ***	-29.620 ***	-7.568 ***	54.99 ***	(1, 0.0061, -1.0041)
VIV	Vivendi Universal SA	-1.221	-1.202	-20.210 ***	-20.387 ***	-10.611 ***	101.08 ***	(1, 0.0017, -0.9998)
VOF	Vodafone Group plc	-2.325	-2.307	-22.283 ***	-22.408 ***	-8.508 ***	84.39 ***	(1, -0.0136, -0.9967)
VOW	Volkswagen AG	-2.747	-2.682	-29.766 ***	-29.687 ***	-10.285 ***	71.21 ***	(1, 0.0041, -1.0013)

Notes: The following ADF test regressions are run for each series, Schwarz Bayesian criterion (Schwarz, 1978) is used to determine lag length k.

$$\Delta P_t = \alpha + \beta t + \gamma P_{t-1} + \sum_{i=1}^{k-1} \psi_i \ \Delta P_{t-i} + \mu_t \qquad \text{Prices series}$$

$$\Delta R_t = \alpha + \gamma R_{t-1} + \sum_{i=1}^{k-1} \psi_i \ \Delta R_{t-i} + \mu_t \qquad \text{Returns series}$$

$$\Delta \hat{s}_t = \gamma \hat{s}_{t-1} + \sum_{i=1}^{k-1} \gamma_i \ \Delta \hat{s}_{t-i} + \mu_t; \qquad \text{Basis series}$$

For brevity, this table only reports the ADF test statistic of each regression. The critical values of MacKinnon (1996) are used.

The λ_{trace} tests the null hypothesis that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r.

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{2} \ln(1 - \hat{\lambda}_i)$$

where $\hat{\lambda}_i$ is the estimated eigenvalues of the Π matrix. Critical values are taken from Osterwald-Lenum (1992, Table 1).

$\beta = (1, \beta_1, \beta_2)$ are the coefficient estiamtes of the cointegrating vector where the coefficient of S_t is normalised to unity, β_1 is the intercept term and β_2 is the coefficient on Ft.

*, **, *** Significant at 10%, 5% and 1% level, respectively.

Table 4.3: Estimates of the VECM/VAR for Stock and Futures Returns

Code	Dep Var	α_{s0}	α_{s1}	α_{s2}	α_{s3}	α_{s4}	β_{s1}	β_{s2}	β_{s3}	β_{s4}	γ_s
		α_{f0}	α_{f1}	α_{f2}	α_{f3}	α_{f4}	β_{f1}	β_{f2}	β_{f3}	β_{f4}	γ_f
AA	Rs	-0.0004	-0.1847	-0.1140	0.1878	0.5330 ***	0.1711	0.0350	-0.2750 *	-0.4963 ***	-0.1475
		(-0.398)	(-1.355)	(-0.784)	(1.333)	(4.507)	(1.242)	(0.241)	(-1.958)	(-4.237)	(-1.558)
	Rf	-0.0004	0.3438 **	0.1182	0.3383 **	0.5677 ***	-0.3204 **	-0.1654	-0.4034 ***	-0.5414 ***	0.0014
		(-0.461)	(2.570)	(0.828)	(2.447)	(4.893)	(-2.372)	(-1.162)	(-2.928)	(-4.711)	(0.015)
AGN	Rs	-0.0015	-0.0205	0.0062	-0.0905 **	0.0337	0.0407	0.0195	0.0138	0.0078	0.0408
		(-1.218)	(-0.418)	(0.132)	(-2.057)	(0.840)	(1.254)	(0.662)	(0.549)	(0.421)	(1.185)
	Rf	-0.0016	0.2470 **	0.2338 **	0.1124	0.0682	-0.2464 ***	-0.1960 ***	-0.1273 **	-0.0618	0.6819 ***
		(-0.604)	(2.349)	(2.330)	(1.190)	(0.792)	(-3.532)	(-3.093)	(-2.360)	(-1.558)	(9.223)
AHL	Rs	-0.0018	-0.1192	-0.2133	-0.3340 **	0.0355	0.1871	0.3180 **	0.1857	-0.0179	–
		(-1.065)	(-0.818)	(-1.410)	(-2.210)	(0.246)	(1.305)	(2.142)	(1.249)	(-0.127)	
	Rf	-0.0020	0.1902	-0.1624	-0.2936 *	0.0345	-0.0899	0.2620 *	0.1595	-0.0042	–
		(-1.151)	(1.289)	(-1.060)	(-1.918)	(0.236)	(-0.619)	(1.742)	(1.059)	(-0.030)	
ALV	Rs	-0.0010	-0.1069	-0.2309 **	-0.1416	-0.0765	0.1318	0.2467 **	0.1415	0.0554	0.0345 **
		(-1.044)	(-1.400)	(-2.377)	(-1.455)	(-0.966)	(1.574)	(2.471)	(1.441)	(0.730)	(2.078)
	Rf	-0.0012	0.6583 ***	0.2447 ***	0.0535	-0.0488	-0.5763 ***	-0.1967 **	-0.0575	0.0124	0.0406 ***
		(-1.399)	(9.559)	(2.793)	(0.610)	(-0.684)	(-7.629)	(-2.184)	(-0.649)	(0.182)	(2.711)
AXA	Rs	-0.0005	0.0751 *	0.0073	-0.0555	-0.0058	-0.0050	-0.0238	-0.0040	0.0130	-0.0038
		(-0.515)	(1.953)	(0.189)	(-1.443)	(-0.150)	(-0.230)	(-1.101)	(-0.183)	(0.603)	(-0.825)
	Rf	-0.0020	0.1492 **	0.0382	-0.0158	-0.0603	-0.0330	-0.0366	-0.0027	0.0159	0.0380 ***
		(-1.131)	(2.208)	(0.565)	(-0.234)	(-0.891)	(-0.868)	(-0.963)	(-0.071)	(0.420)	(4.753)
AZN	Rs	-0.0005	-0.0958	-0.1011	-0.0053	-0.1689	0.1525	-0.0133	-0.0309	0.1698	-0.0294
		(-0.813)	(-0.582)	(-0.592)	(-0.033)	(-1.290)	(0.913)	(-0.078)	(-0.192)	(1.306)	(-0.222)
	Rf	-0.0005	0.4591 ***	0.3056 *	0.2417	-0.0599	-0.3957 **	-0.3988 **	-0.2666 *	0.0754	0.1590
		(-0.813)	(2.878)	(1.844)	(1.555)	(-0.472)	(-2.445)	(-2.392)	(-1.710)	(0.598)	(1.242)
BAR	Rs	0.0001	0.0148	-0.0625 *	-0.0487	-0.0158	0.0154	0.0133	-0.0300 *	-0.0027	–
		(0.188)	(0.415)	(-1.754)	(-1.368)	(-0.442)	(0.980)	(0.848)	(-1.916)	(-0.174)	
	Rf	-0.0014	0.0970	-0.0729	-0.2356 ***	-0.0268	0.0035	0.0126	-0.0295	0.0021	–
		(-0.843)	(1.199)	(-0.902)	(-2.912)	(-0.329)	(0.097)	(0.354)	(-0.831)	(0.060)	
BNP	Rs	0.0000	0.0934 **	-0.0624	0.0090	0.0422	-0.0424	-0.0013	-0.0192	-0.0283	–
		(0.015)	(2.115)	(-1.402)	(0.202)	(0.949)	(-1.395)	(-0.043)	(-0.631)	(-0.935)	
	Rf	-0.0007	0.2329 ***	-0.0604	0.0286	-0.0100	-0.0776 *	-0.0049	-0.0057	-0.0213	–
		(-0.693)	(3.628)	(-0.934)	(0.443)	(-0.155)	(-1.759)	(-0.111)	(-0.129)	(-0.485)	
BPA	Rs	-0.0002	-0.2774	-0.1840	-0.2080	-0.1338	0.2227	0.0859	0.1241	0.2009	0.0142
		(-0.293)	(-1.557)	(-0.968)	(-1.136)	(-0.870)	(1.239)	(0.448)	(0.673)	(1.300)	(0.112)
	Rf	-0.0002	0.2145	0.0669	-0.1304	-0.0532	-0.2618	-0.1571	0.0516	0.1326	0.1702
		(-0.281)	(1.228)	(0.359)	(-0.726)	(-0.352)	(-1.485)	(-0.836)	(0.285)	(0.875)	(1.366)
BTL	Rs	-0.0007	-0.2117 ***	-0.0453	0.0499	0.0893	0.1861 ***	0.0375	-0.1624 **	-0.0549	0.0056
		(-0.914)	(-2.987)	(-0.633)	(0.697)	(1.264)	(2.758)	(0.550)	(-2.384)	(-0.811)	(0.739)
	Rf	-0.0011	-0.0722	-0.0006	0.0125	0.0818	0.0540	-0.0140	-0.1465 **	-0.0314	0.0165 **
		(-1.388)	(-0.972)	(-0.007)	(0.166)	(1.106)	(0.764)	(-0.196)	(-2.051)	(-0.442)	(2.093)
BVA	Rs	-0.0003	0.0852	-0.0316	-0.0138	-0.0384	-0.0879	0.0299	-0.0679	0.0941	-0.2848 *
		(-0.348)	(0.476)	(-0.175)	(-0.081)	(-0.281)	(-0.478)	(0.162)	(-0.394)	(0.685)	(-1.812)
	Rf	-0.0003	0.5400 ***	0.2404	0.1642	0.1090	-0.5137 ***	-0.2431	-0.2186	-0.0616	-0.0249
		(-0.364)	(3.176)	(1.402)	(1.021)	(0.841)	(-2.940)	(-1.391)	(-1.335)	(-0.472)	(-0.167)
CA	Rs	-0.0007	0.0035	0.0531	0.0498	-0.0372	-0.0961	-0.0419	-0.1101	0.0525	-0.0116
		(-1.040)	(0.025)	(0.361)	(0.350)	(-0.319)	(-0.686)	(-0.284)	(-0.774)	(0.455)	(-0.114)
	Rf	-0.0007	0.5184 ***	0.2906 **	0.1631	0.0437	-0.5729 ***	-0.2934 **	-0.1931	-0.0285	0.1574
		(-1.040)	(3.883)	(2.041)	(1.186)	(0.387)	(-4.228)	(-2.056)	(-1.403)	(-0.256)	(1.593)
CGE	Rs	-0.0015	-0.2255	-0.0234	-0.0085	0.1844 **	0.2179	0.0503	0.0039	-0.1072	0.1903
		(-1.163)	(-1.450)	(-0.169)	(-0.072)	(2.067)	(1.446)	(0.376)	(0.035)	(-1.278)	(1.174)
	Rf	-0.0016	-0.0231	0.1209	0.1251	0.2334 **	0.0284	-0.1138	-0.1314	-0.1582 *	0.8977 ***
		(-1.127)	(-0.142)	(0.832)	(1.015)	(2.500)	(0.180)	(-0.813)	(-1.116)	(-1.801)	(5.293)
CSG	Rs	-0.0002	-0.0651	0.2052	0.1325	0.0387	0.0945	-0.0936	-0.1786	-0.1059	–
		(-0.224)	(-0.452)	(1.217)	(0.785)	(0.270)	(0.659)	(-0.560)	(-1.072)	(-0.751)	
	Rf	-0.0004	0.5785 ***	0.5680 ***	0.3087 *	0.0450	-0.5425 ***	-0.4562 ***	-0.3524 **	-0.1204	–
		(-0.429)	(4.011)	(3.366)	(1.829)	(0.314)	(-3.779)	(-2.726)	(-2.112)	(-0.853)	
DBK	Rs	-0.0004	-0.1834	-0.1720	-0.3213 ***	-0.2051 **	0.1646	0.1836	0.3184 ***	0.1720 **	0.0997
		(-0.483)	(-1.467)	(-1.335)	(-2.694)	(-2.258)	(1.296)	(1.437)	(2.740)	(2.006)	(0.899)
	Rf	-0.0003	0.4278 ***	0.2709 **	-0.0626	-0.1467 *	-0.3773 ***	-0.2434 **	0.0790	0.1156	0.3599 ***
		(-0.461)	(3.689)	(2.269)	(-0.566)	(-1.743)	(-3.204)	(-2.054)	(0.733)	(1.455)	(3.499)
DCY	Rs	-0.0005	-0.2038 **	-0.2014 *	-0.1469	-0.1057	0.2010 **	0.1852 *	0.1468	0.1827 **	0.0320
		(-0.594)	(-2.148)	(-1.929)	(-1.453)	(-1.270)	(2.054)	(1.772)	(1.465)	(2.260)	(0.505)
	Rf	-0.0004	0.4069 ***	0.2081 **	0.0582	0.0015	-0.3410 ***	-0.2054 **	-0.0440	0.0796	0.1437 **
		(-0.561)	(4.562)	(2.119)	(0.612)	(0.019)	(-3.706)	(-2.091)	(-0.467)	(1.047)	(2.411)
DTE	Rs	-0.0008	-0.2918 **	-0.3391 ***	-0.3867 ***	-0.1997 **	0.2403 *	0.3097 **	0.2809 **	0.2070 ***	0.0077
		(-0.936)	(-2.221)	(-2.707)	(-3.471)	(-2.395)	(1.814)	(2.485)	(2.560)	(2.599)	(0.059)
	Rf	-0.0008	0.2183 *	0.0210	-0.1092	-0.1004	-0.1923	-0.0190	0.0252	0.1201	0.4304 ***
		(-0.914)	(1.802)	(0.181)	(-1.063)	(-1.306)	(-1.574)	(-0.165)	(0.249)	(1.636)	(3.597)
ENI	Rs	0.0003	-0.0580	-0.0329	-0.0336	0.0346	0.0227	-0.0045	-0.0145	0.0104	0.0004
		(0.540)	(-1.628)	(-0.922)	(-0.941)	(0.973)	(1.017)	(-0.204)	(-0.648)	(0.464)	(0.152)
	Rf	0.0010	0.0029	0.0048	-0.0406	-0.0060	0.0032	-0.0164	-0.0057	0.0147	0.0121 ***
		(1.154)	(0.052)	(0.085)	(-0.715)	(-0.107)	(0.090)	(-0.461)	(-0.162)	(0.414)	(2.898)
ENL	Rs	0.0001	-0.0525	-0.0168	-0.0102	-0.0273	-0.0271	-0.0098	-0.0044	0.0137	0.0004
		(0.191)	(-1.417)	(-0.453)	(-0.276)	(-0.741)	(-1.263)	(-0.455)	(-0.207)	(0.637)	(0.148)
	Rf	0.0007	0.0006	0.0095	-0.0013	0.0002	-0.0569	0.0096	-0.0164	0.0111	0.0152 ***
		(0.841)	(0.009)	(0.149)	(-0.020)	(0.004)	(-1.540)	(0.258)	(-0.445)	(0.300)	(3.077)

Table 4.3: Estimates of the VECM/VAR for Stock and Futures Returns (continued)

Code	Dep Var	α_{s0}	α_{s1}	α_{s2}	α_{s3}	α_{s4}	β_{s1}	β_{s2}	β_{s3}	β_{s4}	γ_s
		α_{f0}	α_{f1}	α_{f2}	α_{f3}	α_{f4}	β_{f1}	β_{f2}	β_{f3}	β_{f4}	γ_f
EOA	Rs	0.0002	-0.1740 **	-0.1848 **	-0.0047	0.1834 **	0.0170	0.1372	-0.0784	-0.1712 **	-0.0370
		(0.376)	(-1.980)	(-2.048)	(-0.054)	(2.561)	(0.189)	(1.509)	(-0.904)	(-2.397)	(-0.525)
	Rf	0.0003	0.2816 ***	0.0849	0.1111	0.1917 ***	-0.3687 ***	-0.1285	-0.1528 *	-0.1782 ***	0.1929 ***
		(0.476)	(3.478)	(1.021)	(1.407)	(2.905)	(-4.458)	(-1.534)	(-1.912)	(-2.709)	(2.973)
ERC	Rs	-0.0006	0.1437	0.1072	-0.3711 ***	-0.1289	-0.0594	-0.1383	0.2659 **	0.1068	0.0384 ***
		(-0.388)	(1.374)	(0.997)	(-3.459)	(-1.236)	(-0.596)	(-1.335)	(2.568)	(1.067)	(3.372)
	Rf	-0.0011	0.4065 ***	0.1107	-0.3443 ***	-0.1559	-0.3441 ***	-0.1309	0.2543 **	0.1506	0.0451 ***
		(-0.689)	(3.727)	(0.987)	(-3.077)	(-1.434)	(-3.307)	(-1.211)	(2.354)	(1.444)	(3.797)
FTE	Rs	-0.0010	-0.1450	-0.1977	0.0726	-0.0273	0.2121 *	0.1597	-0.0349	0.0755	–
		(-0.862)	(-1.148)	(-1.485)	(0.547)	(-0.216)	(1.655)	(1.192)	(-0.261)	(0.597)	
	Rf	-0.0012	0.2164 *	-0.0073	0.2115	0.0253	-0.1378	-0.0172	-0.1649	0.0312	–
		(-1.054)	(1.740)	(-0.056)	(1.619)	(0.204)	(-1.093)	(-0.130)	(-1.253)	(0.251)	
GEN	Rs	-0.0003	0.1270	0.1618	-0.0288	0.2801 **	-0.0679	-0.1720	-0.0030	-0.2358 *	-0.2331
		(-0.514)	(0.744)	(0.973)	(-0.188)	(2.267)	(-0.394)	(-1.025)	(-0.019)	(-1.919)	(-1.449)
	Rf	-0.0003	0.4937 ***	0.3526 **	0.0877	0.3336 ***	-0.4223 **	-0.3593 **	-0.0979	-0.3004 **	0.1450
		(-0.556)	(3.004)	(2.202)	(0.594)	(2.804)	(-2.546)	(-2.222)	(-0.661)	(-2.538)	(0.936)
GXW	Rs	-0.0004	-0.1985	-0.1650	0.1811	-0.0603	0.1911	0.0875	-0.2000	0.0574	-0.1426
		(-0.741)	(-1.160)	(-0.926)	(1.077)	(-0.433)	(1.105)	(0.487)	(-1.177)	(0.408)	(-1.063)
	Rf	-0.0004	0.3195 *	0.1911	0.3723 **	0.0124	-0.3321 *	-0.2663	-0.3951 **	-0.0045	0.0505
		(-0.777)	(1.901)	(1.092)	(2.253)	(0.091)	(-1.954)	(-1.510)	(-2.366)	(-0.033)	(0.384)
HAS	Rs	-0.0002	-0.3818 ***	-0.2393 *	0.0065	-0.0501	0.3392 ***	0.1738	-0.0193	0.1229	0.0158
		(-0.347)	(-3.287)	(-1.931)	(0.053)	(-0.460)	(2.865)	(1.388)	(-0.156)	(1.110)	(0.260)
	Rf	-0.0002	0.0386	-0.0775	0.0422	-0.0067	-0.0589	0.0192	-0.0423	0.1058	0.1008 *
		(-0.341)	(0.343)	(-0.645)	(0.356)	(-0.063)	(-0.513)	(0.158)	(-0.353)	(0.986)	(1.710)
HNM	Rs	0.0003	0.1683	0.1425	0.0981	0.0854	-0.2421 *	-0.1599	-0.1462	-0.1252	-0.2615 *
		(0.388)	(1.136)	(1.019)	(0.788)	(0.875)	(-1.646)	(-1.156)	(-1.196)	(-1.347)	(-1.755)
	Rf	0.0002	0.5259 ***	0.3572 **	0.2450 *	0.1697 *	-0.5901 ***	-0.3854 ***	-0.2880 **	-0.1800 *	0.2447
		(0.360)	(3.479)	(2.505)	(1.931)	(1.707)	(-3.933)	(-2.732)	(-2.310)	(-1.899)	(1.610)
ING	Rs	-0.0006	-0.0084	0.0270	-0.1178 **	-0.0037	0.0245	-0.0080	0.0036	0.0213	-0.0002
		(-0.623)	(-0.168)	(0.541)	(-2.359)	(-0.074)	(0.598)	(-0.195)	(0.087)	(0.521)	(-0.035)
	Rf	-0.0013	0.0569	0.0146	-0.1025 *	0.0138	-0.0212	-0.0080	0.0062	0.0124	0.0100 *
		(-1.119)	(0.931)	(0.240)	(-1.682)	(0.226)	(-0.424)	(-0.161)	(0.125)	(0.249)	(1.841)
LLO	Rs	-0.0004	0.0610	-0.1238	-0.0446	-0.0328	-0.0923	0.1295	-0.0176	0.0469	-0.0688
		(-0.657)	(0.603)	(-1.151)	(-0.420)	(-0.337)	(-0.894)	(1.190)	(-0.163)	(0.482)	(-1.406)
	Rf	-0.0005	0.4355 ***	-0.0466	-0.0479	-0.0162	-0.4395 ***	0.0218	0.0016	0.0122	0.0069
		(-0.772)	(4.393)	(-0.442)	(-0.459)	(-0.170)	(-4.341)	(0.204)	(0.015)	(0.128)	(0.144)
MUV	Rs	-0.0011	0.0215	-0.1820	-0.2278 **	-0.1941 **	0.0523	0.2149 *	0.2185 *	0.1990 **	–
		(-1.178)	(0.235)	(-1.583)	(-1.994)	(-2.135)	(0.546)	(1.876)	(1.957)	(2.337)	
	Rf	-0.0012	0.8465 ***	0.4114 ***	0.0742	-0.0257	-0.7200 ***	-0.3556 ***	-0.1090	0.0350	–
		(-1.334)	(9.742)	(3.771)	(0.685)	(-0.298)	(-7.930)	(-3.273)	(-1.030)	(0.434)	
NDA	Rs	0.0006	-0.3998 ***	-0.3708 ***	-0.3372 ***	0.0270	0.3578 ***	0.3762 ***	0.2533 **	-0.0766	-0.0237
		(0.732)	(-3.301)	(-2.916)	(-2.717)	(0.246)	(2.922)	(2.934)	(2.017)	(-0.688)	(-0.312)
	Rf	0.0006	0.0122	-0.1877	-0.2787 **	0.0224	-0.0379	0.1968	0.1772	-0.0708	0.1093
		(0.741)	(0.103)	(-1.508)	(-2.294)	(0.209)	(-0.316)	(1.568)	(1.442)	(-0.650)	(1.464)
NES	Rs	-0.0002	-0.2385 **	-0.1318	-0.1982 *	-0.1304	0.1965 *	0.0996	0.1094	0.1499 *	0.1325
		(-0.412)	(-2.092)	(-1.104)	(-1.742)	(-1.398)	(1.740)	(0.838)	(0.976)	(1.663)	(1.505)
	Rf	-0.0002	0.3301 ***	0.2282 *	0.0216	-0.0308	-0.3803 ***	-0.2399 **	-0.0866	0.0509	0.3104 ***
		(-0.415)	(2.962)	(1.955)	(0.195)	(-0.337)	(-3.444)	(-2.062)	(-0.790)	(0.578)	(3.606)
NOV	Rs	-0.0001	0.0548	0.0712	-0.0460	0.0585	-0.0129	-0.0549	-0.0313	-0.0227	-0.0540
		(-0.247)	(0.354)	(0.454)	(-0.314)	(0.494)	(-0.083)	(-0.351)	(-0.216)	(-0.197)	(-0.397)
	Rf	-0.0001	0.5396 ***	0.3793 **	0.1203	0.1110	-0.4882 ***	-0.3559 **	-0.1752	-0.0567	0.2320 *
		(-0.257)	(3.552)	(2.467)	(0.838)	(0.956)	(-3.208)	(-2.317)	(-1.233)	(-0.502)	(1.740)
PHI	Rs	-0.0004	-0.3838	-0.3205	-0.2627	0.1098	0.3540	0.2954	0.2384	-0.1181	0.2204
		(-0.350)	(-1.487)	(-1.250)	(-1.121)	(0.606)	(1.372)	(1.151)	(1.018)	(-0.656)	(0.918)
	Rf	-0.0004	0.0864	-0.0522	-0.1453	0.1230	-0.1138	0.0341	0.1341	-0.1289	0.5733 **
		(-0.360)	(0.343)	(-0.209)	(-0.636)	(0.696)	(-0.452)	(0.136)	(0.587)	(-0.734)	(2.448)
RBO	Rs	0.0001	-0.4654 ***	-0.3269 **	-0.1124	0.0286	0.4233 ***	0.3256 **	0.0205	-0.0306	-0.0630
		(0.148)	(-3.389)	(-2.241)	(-0.808)	(0.253)	(3.044)	(2.222)	(0.146)	(-0.266)	(-0.617)
	Rf	0.0001	0.0713	-0.0444	0.0271	0.1019	-0.0874	0.0198	-0.1128	-0.0886	0.1036
		(0.086)	(0.532)	(-0.312)	(0.199)	(0.924)	(-0.644)	(0.138)	(-0.822)	(-0.789)	(1.042)
RD	Rs	-0.0004	-0.2762 *	-0.1682	-0.0347	0.1518	0.2568 *	0.1183	-0.0147	-0.0908	-0.0762
		(-0.766)	(-1.898)	(-1.121)	(-0.236)	(1.149)	(1.737)	(0.779)	(-0.099)	(-0.678)	(-0.839)
	Rf	-0.0005	0.0894	-0.0614	0.0553	0.1487	-0.0951	0.0026	-0.0900	-0.0905	0.0511
		(-0.836)	(0.628)	(-0.418)	(0.384)	(1.152)	(-0.658)	(0.018)	(-0.617)	(-0.691)	(0.576)
ROG	Rs	0.0002	0.0064	-0.1905	-0.0992	-0.2053	0.0219	0.1907	0.0759	0.2058	0.0484
		(0.370)	(0.037)	(-1.058)	(-0.593)	(-1.523)	(0.126)	(1.065)	(0.456)	(1.563)	(0.330)
	Rf	0.0002	0.6075 ***	0.2832	0.2036	-0.0329	-0.5791 ***	-0.2899	-0.2325	0.0355	0.2603 *
		(0.378)	(3.519)	(1.588)	(1.228)	(-0.246)	(-3.356)	(-1.634)	(-1.409)	(0.272)	(1.788)
SCH	Rs	-0.0003	-0.2983 *	-0.0035	0.0492	-0.0919	0.2786	-0.0417	-0.0941	0.1532	0.0718
		(-0.359)	(-1.688)	(-0.020)	(0.294)	(-0.681)	(1.557)	(-0.231)	(-0.562)	(1.132)	(0.473)
	Rf	-0.0003	0.1484	0.2837 *	0.1561	-0.0321	-0.1450	-0.3219 *	-0.1963	0.0875	0.3284 **
		(-0.399)	(0.878)	(1.653)	(0.976)	(-0.249)	(-0.847)	(-1.866)	(-1.227)	(0.676)	(2.261)
SHB	Rs	0.0004	-0.2205 *	-0.3623 ***	-0.2683 **	-0.0039	0.1695	0.3342 ***	0.2137 *	-0.0334	0.0493
		(0.706)	(-1.867)	(-2.954)	(-2.250)	(-0.037)	(1.425)	(2.699)	(1.773)	(-0.312)	(0.671)
	Rf	0.0004	0.1388	-0.1907	-0.2395 **	0.0029	-0.1925 *	0.1751	0.1635	-0.0442	0.1828 **
		(0.752)	(1.205)	(-1.594)	(-2.059)	(0.028)	(-1.659)	(1.449)	(1.391)	(-0.423)	(2.551)

Table 4.3: Estimates of the VECM/VAR for Stock and Futures Returns (continued)

Code	Dep Var	α_{s0} / α_{f0}	α_{s1} / α_{f1}	α_{s2} / α_{f2}	α_{s3} / α_{f3}	α_{s4} / α_{f4}	β_{s1} / β_{f1}	β_{s2} / β_{f2}	β_{s3} / β_{f3}	β_{s4} / β_{f4}	γ_s / γ_f
SHE	Rs	-0.0004	-0.0250	0.0581	0.1592 *	0.0317	-0.0110	-0.0963	-0.2229 ***	0.0506	-
		(-0.689)	(-0.320)	(0.708)	(1.948)	(0.409)	(-0.146)	(-1.223)	(-2.844)	(0.687)	
	Rf	-0.0003	0.3588 ***	0.2629 ***	0.3039 ***	0.1093	-0.3879 ***	-0.3091 ***	-0.3398 ***	0.0112	-
		(-0.517)	(4.432)	(3.086)	(3.583)	(1.361)	(-4.986)	(-3.781)	(-4.176)	(0.147)	
SIE	Rs	-0.0004	0.0206	0.0257	-0.1091 *	-0.0550	0.0052	-0.0220	0.0567	0.0603	0.0063
		(-0.528)	(0.389)	(0.460)	(-1.946)	(-1.018)	(0.102)	(-0.420)	(1.086)	(1.232)	(0.712)
	Rf	-0.0009	0.3760 ***	0.0959 *	-0.0750	-0.0632	-0.2116 ***	-0.0816	0.0351	0.0533	0.0270 ***
		(-1.050)	(6.906)	(1.665)	(-1.300)	(-1.137)	(-4.026)	(-1.517)	(0.654)	(1.058)	(2.949)
TEF	Rs	-0.0003	0.1297	0.2550 *	0.0956	0.0363	-0.1325	-0.2957 **	-0.1321	-0.0401	-
		(-0.491)	(1.086)	(1.862)	(0.694)	(0.300)	(-1.091)	(-2.173)	(-0.972)	(-0.341)	
	Rf	-0.0006	0.7445 ***	0.6066 ***	0.4010 ***	0.1920	-0.7144 ***	-0.6355 ***	-0.4262 ***	-0.1954 *	-
		(-0.868)	(6.362)	(4.521)	(2.973)	(1.621)	(-6.004)	(-4.766)	(-3.199)	(-1.694)	
TI	Rs	-0.0004	-0.0043	-0.0237	0.0369	0.1309 ***	0.0035	0.0040	0.0074	0.0031	-
		(-0.611)	(-0.129)	(-0.713)	(1.110)	(3.942)	(0.186)	(0.213)	(0.399)	(0.167)	
	Rf	-0.0014	0.0077	-0.0414	0.0162	0.1468 **	-0.0073	-0.0044	0.0096	0.0177	-
		(-1.047)	(0.128)	(-0.693)	(0.272)	(2.462)	(-0.219)	(-0.133)	(0.289)	(0.531)	
TIM	Rs	-0.0005	-0.0964	-0.2211 **	-0.0093	0.1772 **	0.0507	0.1548 *	0.0423	-0.1190	-0.0011
		(-0.686)	(-1.125)	(-2.396)	(-0.101)	(2.116)	(0.590)	(1.675)	(0.460)	(-1.437)	(-0.035)
	Rf	-0.0005	0.3471 ***	-0.0056	0.0871	0.1592 *	-0.3898 ***	-0.0486	-0.0219	-0.0904	0.0364
		(-0.669)	(4.090)	(-0.061)	(0.961)	(1.917)	(-4.577)	(-0.530)	(-0.241)	(-1.100)	(1.219)
TLI	Rs	-0.0003	-0.2695	-0.3877	-0.1911	-0.1836	0.2154	0.2995	0.1179	0.1540	0.1679
		(-0.362)	(-1.108)	(-1.605)	(-0.858)	(-0.990)	(0.884)	(1.240)	(0.528)	(0.832)	(0.795)
	Rf	-0.0003	0.1410	-0.0620	-0.0312	-0.1156	-0.1848	-0.0323	-0.0399	0.0802	0.4376 **
		(-0.367)	(0.590)	(-0.261)	(-0.143)	(-0.635)	(-0.772)	(-0.136)	(-0.182)	(0.441)	(2.109)
TOT	Rs	0.0000	-0.1807	0.1625	0.2032 *	0.1905 *	0.1236	-0.2761 **	-0.2621 **	-0.1485	0.0435
		(0.052)	(-1.583)	(1.336)	(1.699)	(1.806)	(1.058)	(-2.245)	(-2.168)	(-1.393)	(0.718)
	Rf	0.0000	0.2455 **	0.3248 ***	0.2449 **	0.2080 **	-0.2730 **	-0.4194 ***	-0.2772 **	-0.1727 *	0.1277 **
		(0.037)	(2.237)	(2.777)	(2.129)	(2.050)	(-2.431)	(-3.546)	(-2.385)	(-1.685)	(2.193)
UBS	Rs	0.0003	-0.0071	-0.0737	-0.1102	-0.0508	0.1004	0.0823	-0.0066	0.0389	0.0509
		(0.424)	(-0.056)	(-0.545)	(-0.820)	(-0.411)	(0.814)	(0.625)	(-0.051)	(0.326)	(1.123)
	Rf	0.0002	0.4244 ***	0.0918	0.0153	0.0261	-0.3145 **	-0.0836	-0.1200	-0.0430	0.0921 **
		(0.303)	(3.287)	(0.664)	(0.112)	(0.207)	(-2.497)	(-0.622)	(-0.897)	(-0.353)	(1.988)
UC	Rs	-0.0001	-0.1877 **	-0.1963 **	-0.1275	0.1179	0.2709 ***	0.1343	0.1418	-0.0669	-0.1037 *
		(-0.182)	(-2.075)	(-2.110)	(-1.411)	(1.474)	(2.943)	(1.410)	(1.532)	(-0.817)	(-1.650)
	Rf	-0.0001	0.1740 **	-0.0563	-0.0828	0.0950	-0.1022	0.0124	0.0951	-0.0452	0.0735
		(-0.192)	(1.977)	(-0.622)	(-0.941)	(1.220)	(-1.140)	(0.134)	(1.055)	(-0.567)	(1.201)
VIV	Rs	-0.0015	0.2035	0.0606	0.3826 *	0.2751 *	-0.1081	-0.1662	-0.4847 **	-0.3505 **	-0.5281 **
		(-1.222)	(0.860)	(0.272)	(1.935)	(1.787)	(-0.453)	(-0.742)	(-2.425)	(-2.265)	(-2.223)
	Rf	-0.0015	0.5232 **	0.2431	0.4927 **	0.2785 *	-0.4336 *	-0.3436	-0.5950 ***	-0.3375 **	-0.0226
		(-1.237)	(2.260)	(1.116)	(2.547)	(1.849)	(-1.859)	(-1.569)	(-3.043)	(-2.230)	(-0.097)
VOF	Rs	-0.0006	-0.4740 **	-0.4369 **	-0.0728	-0.0646	0.4200 **	0.3678 *	-0.0760	0.0849	0.0480
		(-0.784)	(-2.324)	(-2.207)	(-0.410)	(-0.469)	(2.056)	(1.857)	(-0.426)	(0.612)	(0.242)
	Rf	-0.0006	-0.0371	-0.1193	0.0951	0.0680	-0.0088	0.0437	-0.2442	-0.0473	0.4280 **
		(-0.804)	(-0.188)	(-0.621)	(0.552)	(0.509)	(-0.044)	(0.227)	(-1.411)	(-0.351)	(2.223)
VOW	Rs	-0.0005	-0.1942 *	-0.3022 ***	-0.2080 **	0.0008	0.2538 **	0.2494 **	0.1745 *	0.0372	0.0198
		(-0.694)	(-1.774)	(-2.760)	(-2.061)	(0.010)	(2.322)	(2.275)	(1.738)	(0.482)	(0.197)
	Rf	-0.0005	0.2974 ***	0.0195	-0.0605	0.1018	-0.2222 **	-0.0469	0.0036	-0.0456	0.3465 ***
		(-0.645)	(2.886)	(0.189)	(-0.637)	(1.347)	(-2.158)	(-0.455)	(0.038)	(-0.627)	(3.653)

Notes: This table reports the VECM estimates for the model (4.7) and (4.8):

$$R_{S,t} = \alpha_{S0} + \sum_{i=1}^{p-1} \alpha_{Si} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Si} R_{F,t-i} + \gamma_S B_{t-1} + \varepsilon_{S,t}$$

$$R_{F,t} = \alpha_{F0} + \sum_{i=1}^{p-1} \alpha_{Fi} R_{S,t-i} + \sum_{i=1}^{p-1} \beta_{Fi} R_{F,t-i} + \gamma_F B_{t-1} + \varepsilon_{F,t}$$

Figures in the parenthesis (.) are the t statistics.

*, ** and *** denote significant levels of 10%, 5% and 1%, respectively.

t-statistics are calculated using Newey and West's (1987) heteroskedasticity consistent variance-covariance matrix.

The cointegrating vector $B_{t-1} = \beta' X_{t-1} = S_{t-1} - F_{t-1}$ is restricted to be the lagged basis in all cases.

The VAR model (i.e. VECM without the error correction term, B_{t-1}) are estimated for those stock-futures pairs that are not cointegrated.

Table 4.4: Quasi-Maximum Likelihood (QML) Estimates for Variance/Covariance Equations of AsymBEKK-X Model

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}	AsymBEKK	BEKK-X	BEKK
AA	-0.0020	-0.0039 ***	-0.0005	0.2903 **	0.1495	-0.1956	-0.1493	1.1482 ***	0.2582 ***	-0.2251 **	0.6761 ***	0.3308	0.4236	0.1016	-0.0028	-1.6274	-3.8197	0.6595	0.4653	0.0000 ***	0.0000 ***
	(-1.524)	(-7.449)	(-0.122)	(2.467)	(0.999)	(-1.131)	(-0.761)	(15.734)	(7.128)	(-2.223)	(14.948)	(1.210)	(1.548)	(0.374)	(-0.010)	(-0.911)	(-1.505)	(0.138)			
AGN	0.0020 ***	-0.0436 ***	0.0000	0.1344 ***	0.1340 *	-0.0009	-0.0002	0.9163 ***	0.1652	0.0284	0.7665 ***	0.4394 ***	0.4421 ***	-0.0150	-0.0246	0.0045	-0.0371	0.0000	0.0137 **	0.0000 ***	0.0000 ***
	(6.532)	(-3.548)	(0.000)	(3.233)	(1.946)	(-0.751)	(-0.004)	(47.500)	(1.336)	(1.616)	(6.222)	(9.729)	(3.599)	(-0.956)	(-0.222)	(1.291)	(-1.495)	(-0.000)			
AHL	-0.0023	0.0013	0.0000	0.2888	-0.1753	-0.4101	0.2212	-2.0674 ***	-2.3015 ***	2.7723 ***	2.9506 ***	-0.1865	-0.4813	0.0532	-0.0652	-0.1896	-0.1551	0.0000	0.8957	0.0000 ***	0.0000 ***
	(-0.445)	(0.278)	(0.001)	(0.602)	(-0.378)	(-0.887)	(0.429)	(-2.880)	(-3.310)	(4.601)	(5.008)	(-0.355)	(-1.008)	(0.081)	(-0.115)	(-0.776)	(-0.765)	(-0.002)			
ALV	0.0033 ***	0.0032 ***	0.0000	-0.1042	0.2061 ***	0.2178	-0.0491	1.0075 ***	0.0723	-0.0749 *	0.8653 ***	-0.5464 *	-0.3645	0.1829	0.0335	0.0313	0.0005	-0.0911 ***	0.0070 ***	0.0000 ***	0.0000 ***
	(4.175)	(4.238)	(-0.805)	(-1.227)	(2.958)	(0.997)	(-0.262)	(21.071)	(1.390)	(-1.852)	(19.491)	(-1.718)	(-1.207)	(0.474)	(0.085)	(0.629)	(0.010)	(-3.324)			
AXA	-0.0031 ***	0.0036	0.0000	0.1950 ***	-0.0399	-0.0017	0.0441	-0.9440 ***	-0.7782 **	0.0019	-0.1944	-0.3635 ***	0.1492	0.0076	-0.5207 ***	0.0021 ***	0.1399 *	0.0000	0.0004 ***	0.0000 ***	0.0000 ***
	(-2.971)	(1.292)	(-0.000)	(2.721)	(-0.280)	(-0.346)	(0.253)	(-35.488)	(-2.397)	(0.361)	(-0.581)	(-5.494)	(1.429)	(0.453)	(-6.112)	(2.607)	(1.920)	(0.000)			
AZN	0.0013 **	0.0019 ***	0.0000	-0.2041 **	0.0262	0.2351 **	-0.0325	-0.5199 ***	0.4261 ***	1.5204 ***	0.5471 ***	0.0125	0.0081	-0.2670 ***	-0.2466 ***	5.8263 *	4.9739	-0.0380	0.3717	0.0000 ***	0.0000 ***
	(2.485)	(4.216)	(0.012)	(-2.330)	(0.295)	(2.494)	(-0.421)	(-13.116)	(9.705)	(37.275)	(10.984)	(0.152)	(0.085)	(-2.986)	(-2.669)	(1.665)	(1.473)	(-0.012)			
BAR	0.0024 ***	0.0021 **	-0.0016 ***	-0.0889	0.0902 *	-0.0012	-0.0051	0.9721 ***	0.1320 ***	-0.0162	0.8236 ***	0.3546 ***	0.4631 ***	0.0015	-0.0038	-0.0002	0.0222	-0.0094	0.0000 ***	0.0000 ***	0.0000 ***
	(3.511)	(2.087)	(-3.127)	(-1.623)	(1.771)	(-0.535)	(-0.428)	(45.349)	(3.305)	(-1.092)	(21.187)	(5.934)	(6.178)	(0.598)	(-0.591)	(-0.437)	(1.494)	(-0.134)			
BNP	0.0018 ***	0.0006	0.0051 ***	-0.1517 **	0.2807	0.0233 ***	-0.4461 ***	0.9147 ***	0.8622 ***	0.0415 ***	0.0426 *	-0.3532 ***	-0.4553	-0.0016	-0.0029	-0.0081 **	0.0061	0.0911 *	0.0001 ***	0.0000 ***	0.0000 ***
	(3.428)	(0.169)	(4.958)	(-2.561)	(1.461)	(3.019)	(-4.597)	(79.260)	(20.622)	(3.563)	(1.719)	(-7.591)	(-1.596)	(-0.064)	(-0.010)	(-2.122)	(0.143)	(1.953)			
BPA	-0.0024 ***	-0.0026 ***	-0.0009 ***	0.5144 ***	0.5185 ***	-0.3561 ***	-0.4278 ***	0.9631 ***	0.0535	-0.0098	0.8996 ***	-0.3826 ***	-0.3932 ***	0.1142	0.0992	13.8639	7.8182	2.2420	0.2971	0.0000 ***	0.0000 ***
	(-7.213)	(-7.011)	(-4.514)	(6.468)	(5.473)	(-3.726)	(-4.078)	(7.889)	(0.442)	(-0.081)	(7.706)	(-2.719)	(-2.587)	(0.753)	(0.640)	(1.578)	(1.118)	(0.576)			
BTL	0.0016 ***	0.0019	-0.0034 ***	-0.1324 ***	0.5066 *	0.0285	-0.4935 **	0.8866 ***	1.2924 ***	0.0909 ***	-0.3610 ***	-0.2047 ***	-0.5509 ***	-0.0591	0.3854 **	0.0156	0.0853	-0.1727	0.0119 **	0.0000 ***	0.0000 ***
	(3.778)	(0.386)	(-3.494)	(-3.296)	(1.886)	(0.623)	(-2.273)	(166.408)	(12.505)	(22.528)	(-2.939)	(-3.228)	(-3.657)	(-1.044)	(2.523)	(0.733)	(0.371)	(-1.311)			
BVA	0.0006	0.0016 ***	0.0000	-0.0488	-0.1864	0.1146	0.1907	0.0301	0.9079 ***	0.9819 ***	0.0181	-0.1492	-0.0193	0.4646 ***	0.3712 ***	12.0793 ***	9.6114 **	0.0019	0.0151 **	0.0000 ***	0.0000 ***
	(1.214)	(3.486)	(-0.002)	(-0.171)	(-0.697)	(0.389)	(0.695)	(0.307)	(10.369)	(9.943)	(0.193)	(-0.880)	(-0.139)	(2.686)	(2.616)	(2.661)	(2.250)	(0.001)			
CA	0.0048 ***	0.0057 ***	-0.0002	0.4813 ***	0.6792 ***	-0.1835 **	-0.3482 ***	-0.6761 ***	0.2688 ***	-0.2184 ***	-1.1107 ***	-0.0104	-0.0212	0.4082 ***	0.3895	-2.1717	-4.8160 *	-2.3153	0.0020 ***	0.0000 ***	0.0000 ***
	(5.979)	(5.874)	(-0.548)	(4.781)	(6.300)	(-2.295)	(-3.365)	(-49.396)	(12.401)	(-5.713)	(-19.951)	(-0.076)	(-0.096)	(2.689)	(1.458)	(-1.531)	(-1.884)	(-0.925)			
CGE	-0.0023 *	-0.0025 *	0.0000	0.2726 *	0.2767 **	-0.0505	-0.0484	0.9080 ***	-0.0213 *	0.0635 ***	0.9891 ***	-0.3515	0.0583	0.3714 **	-0.1477 *	0.5845	0.5752	0.0000	0.4231	0.0000 ***	0.0000 ***
	(-1.736)	(-1.714)	(-0.001)	(1.833)	(1.997)	(-0.489)	(-0.468)	(78.676)	(-1.665)	(5.763)	(57.496)	(-1.554)	(0.601)	(1.965)	(-1.875)	(1.587)	(1.627)	(0.001)			
CSG	-0.0016 **	-0.0017 **	0.0001	-0.0861	-0.1748 **	0.0053	0.0590	0.9161 ***	-0.0689 **	0.0594 *	1.0355 ***	0.0225	-0.1258	0.2470	0.3950 **	0.8335 ***	0.8075 ***	0.0437	0.0025 ***	0.0000 ***	0.0000 ***
	(-2.298)	(-2.371)	(0.224)	(-1.057)	(-2.110)	(0.082)	(0.644)	(30.339)	(-2.131)	(1.793)	(29.132)	(0.134)	(-0.682)	(1.583)	(2.357)	(3.660)	(3.633)	(0.591)			
DBK	0.0038 ***	0.0040 ***	0.0000	-0.0090	0.3157 **	0.1302	-0.1570	-1.4526 ***	-0.5625 ***	2.2814 ***	1.4763 ***	0.7161 ***	0.6704 ***	-0.4994 ***	-0.5805 ***	-2.2421	-0.4331	-0.0002	0.6186	0.0000 ***	0.0000 ***
	(6.243)	(6.724)	(-0.000)	(-0.060)	(2.150)	(0.618)	(-0.755)	(-66.737)	(-46.259)	(56.028)	(68.605)	(9.827)	(6.931)	(-9.804)	(-9.028)	(-0.663)	(-0.150)	(-0.000)			
DCY	0.0023 ***	0.0025 ***	0.0000	-0.4035 ***	-0.2268 **	0.5149 ***	0.3769 ***	1.1540 ***	0.2231 ***	-1.9885 ***	-1.1693 ***	0.2349 **	0.4235 ***	0.1030	-0.2110 *	-0.8952	-0.4250	0.0000	0.6478	0.0000 ***	0.0000 ***
	(3.408)	(3.434)	(-0.000)	(-5.677)	(-2.133)	(6.220)	(3.419)	(115.277)	(19.744)	(-49.297)	(-47.895)	(2.053)	(4.104)	(0.718)	(-1.733)	(-0.835)	(-0.970)	(-0.000)			
DTE	0.0021 ***	0.0021 ***	0.0000	0.0705	0.2937 **	0.0863	-0.1486	0.9982 ***	0.0379 *	-0.0375	0.9277 ***	0.3722 ***	0.1585	-0.1206	0.0593	1.0409	1.0995	0.0000	0.8682	0.0000 ***	0.0000 ***
	(5.862)	(5.695)	(-0.000)	(0.507)	(2.448)	(0.642)	(-1.269)	(38.727)	(1.686)	(-1.401)	(40.383)	(2.673)	(1.075)	(-0.750)	(0.328)	(0.758)	(0.765)	(-0.000)			
ENI	0.0019 ***	-0.0024 ***	0.0000	0.2794 ***	-0.8948 ***	-0.1039 ***	1.0652 ***	0.8846 ***	0.8502 ***	0.0873 ***	0.0713 **	-0.0369	-0.2746	-0.1689 ***	0.0441	0.0098	-0.1370 **	0.0000	0.0001 ***	0.0004 ***	0.0000 ***
	(3.924)	(-3.609)	(0.000)	(5.923)	(-4.170)	(-2.745)	(4.552)	(63.395)	(26.428)	(6.826)	(2.180)	(-0.546)	(-0.911)	(-2.766)	(0.150)	(1.430)	(-2.191)	(0.000)			
ENL	0.0014 ***	0.0011	0.0079 ***	0.0445	0.5446 ***	0.0465	-0.4604 **	0.9775 ***	0.8335 ***	0.0007	0.0227	0.0125	-0.3837 *	0.1926 ***	0.2769	-0.0041 ***	0.0139	-0.2566 **	0.0020 ***	0.0002 ***	0.0000 ***
	(3.582)	(0.169)	(5.612)	(0.733)	(3.248)	(1.037)	(-2.389)	(109.939)	(16.950)	(0.261)	(0.466)	(0.217)	(-1.948)	(2.615)	(0.752)	(-3.051)	(0.062)	(-2.347)			

Table 4.4: Quasi-Maximum Likelihood (QML) Estimates for Variance/Covariance Equations of AsymBEKK-X Model (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}	AsymBEKK	BEKK-X	BEKK
EOA	0.0022 ***	0.0023 ***	0.0000	-0.0777	0.2099 **	0.2153 **	-0.0216	0.7317 ***	-0.1947	-1.6373 ***	-0.7673 ***	**-0.3135 *****	**-0.3416 *****	**-0.0140**	**0.1866 ***	**-2.8832 ****	**-0.6368**	**-0.0068**	0.0170 **	0.0000 ***	0.0000 ***
	(6.365)	(6.268)	(0.025)	(-0.540)	(2.413)	(2.573)	(-0.342)	(2.741)	(-0.724)	(-7.505)	(-2.934)	**(-3.475)**	**(-5.597)**	**(-0.107)**	**(1.886)**	**(-2.334)**	**(-0.641)**	**(-0.028)**			
ERC	0.0027	0.0010	0.0030	0.0463	0.7952 **	-0.0511	-0.9658 ***	0.8220 **	1.0504 ***	0.1753	-0.0888	**-0.1026**	**0.5804 ****	**0.0103**	**-0.5679 ****	**0.0224**	**0.0710**	**-0.0100**	0.0001 ***	0.0000 ***	0.0000 ***
	(1.127)	(0.118)	(0.538)	(0.204)	(2.491)	(-0.207)	(-2.629)	(2.114)	(3.694)	(0.444)	(-0.280)	**(-0.473)**	**(2.208)**	**(0.052)**	**(-2.168)**	**(1.007)**	**(1.063)**	**(-0.149)**			
FTE	0.0018 ***	0.0018	0.0024 ***	-0.1294	0.5007 ***	0.0030	-0.6883 ***	1.0652 ***	0.5723 ***	-0.0994	0.3875 ***	**0.3509 *****	**0.1421**	**-0.0954**	**-0.0441**	**0.0730**	**0.0941**	**0.0863 *****	0.0040 ***	0.0000 ***	0.0000 ***
	(3.040)	(1.118)	(5.296)	(-0.849)	(3.097)	(0.024)	(-4.637)	(10.580)	(4.205)	(-0.995)	(2.752)	**(3.664)**	**(0.486)**	**(-1.085)**	**(-0.152)**	**(1.588)**	**(1.054)**	**(2.743)**			
GEN	0.0013 ***	0.0018 ***	0.0000	0.3544 ***	0.4367 ***	-0.3298 ***	-0.3621 ***	-0.9326 ***	0.0212	-0.0283	-0.9721 ***	**-0.4841 *****	**-0.1707**	**0.1380**	**-0.1833**	**-6.5126 *****	**-7.9638 *****	**-0.0002**	0.0349 **	0.0000 ***	0.0000 ***
	(3.732)	(4.372)	(0.002)	(6.062)	(6.230)	(-4.154)	(-4.543)	(-28.982)	(0.491)	(-0.790)	(-20.365)	**(-4.685)**	**(-1.269)**	**(1.328)**	**(-1.381)**	**(-2.888)**	**(-2.910)**	**(-0.000)**			
GXW	0.0042 ***	0.0029 **	0.0016 ***	-0.2029	-0.0578	0.2064	0.0070	0.7068 ***	-0.0891	0.2396 **	1.0324 ***	**-0.3591 ****	**-0.0505**	**-0.0338**	**-0.3298 ***	**-27.1458 ***	**-7.7939**	**-2.3248**	0.0154 **	0.0000 ***	0.0000 ***
	(3.287)	(1.982)	(5.324)	(-0.715)	(-0.394)	(0.914)	(0.057)	(5.244)	(-0.737)	(2.051)	(10.497)	**(-2.236)**	**(-0.437)**	**(-0.154)**	**(-1.936)**	**(-1.946)**	**(-0.710)**	**(-0.799)**			
HAS	0.0013	0.0037 ***	0.0000	0.0826	-0.3085 **	-0.2181 **	0.1145	0.6335 *	1.0819 ***	0.3396	-0.1948	**0.1184**	**-0.3662 ***	**-0.4314 *****	**-0.0334**	**-0.3448**	**5.1759 *****	**0.0007**	0.0139 **	0.0000 ***	0.0000 ***
	(1.573)	(4.295)	(-0.001)	(0.888)	(-2.392)	(-2.373)	(0.573)	(1.786)	(3.687)	(0.913)	(-0.568)	**(0.598)**	**(-1.881)**	**(-2.615)**	**(-0.196)**	**(-0.168)**	**(2.888)**	**(0.000)**			
HNM	-0.0013 *	0.0017 ***	0.0000	-0.2292	0.6219 *	0.2204	-0.7360 **	0.8363 ***	0.7757 ***	0.1602	0.1793	**0.6795**	**-2.3929 ***	**-0.5567**	**2.8519 ****	**-0.6893**	**3.6152**	**0.0013**	0.9388	0.0000 ***	0.0000 ***
	(-1.815)	(2.752)	(0.000)	(-1.065)	(1.955)	(1.089)	(-2.457)	(5.188)	(4.960)	(0.961)	(1.037)	**(1.444)**	**(-1.884)**	**(-1.058)**	**(2.049)**	**(-0.461)**	**(0.633)**	**(0.002)**			
ING	0.0028 ***	-0.0012	0.0017	-0.0068	-0.3007 ***	-0.0271	0.4239 ***	0.9304 ***	0.5216 ***	0.0188	0.4404 ***	**-0.4453 *****	**0.0489**	**0.0203**	**-0.4259 *****	**0.0002**	**-0.1171 ***	**0.0151**	0.0000 ***	0.0000 ***	0.0000 ***
	(6.782)	(-0.766)	(0.518)	(-0.146)	(-2.721)	(-1.138)	(3.703)	(69.396)	(6.046)	(1.387)	(5.069)	**(-11.606)**	**(0.370)**	**(0.695)**	**(-3.603)**	**(0.048)**	**(-1.932)**	**(0.427)**			
LLO	0.0016 ***	0.0068 ***	-0.0016	0.1551 ***	-0.1015	0.0354	0.3336 ***	-1.0163 ***	-0.9506 ***	0.0659 ***	0.0706 ***	**0.0933**	**-0.1895**	**0.2239 *****	**0.3250 ***	**-1.4958 ***	**-0.5977**	**3.3029 ****	0.0343 **	0.0000 ***	0.0000 ***
	(5.569)	(6.260)	(-0.511)	(3.400)	(-1.086)	(0.838)	(4.464)	(-579.080)	(-35.331)	(127.526)	(5.899)	**(1.615)**	**(-1.441)**	**(3.861)**	**(1.741)**	**(-1.777)**	**(-0.229)**	**(2.096)**			
MUV	0.0039 ***	0.0038 ***	0.0002	-0.1138	0.2859 **	0.1243	-0.2094 *	1.1465 ***	0.2596 ***	-0.2540 ***	0.6543 ***	**0.3357 ****	**0.2490**	**0.1770**	**0.2313**	**-0.0806**	**0.3613**	**0.5655 ****	0.0001 ***	0.0000 ***	0.0000 ***
	(7.802)	(6.942)	(1.219)	(-0.915)	(2.355)	(0.999)	(-1.660)	(20.652)	(4.654)	(-3.877)	(10.555)	**(2.243)**	**(0.868)**	**(1.316)**	**(0.858)**	**(-0.246)**	**(1.138)**	**(2.528)**			
NDA	0.0026 *	-0.0026 *	0.0005	0.2338 **	-0.1621	-0.3544 ***	0.2043 **	0.3475 ***	0.3232 ***	0.6485 ***	0.6562 ***	**-0.1138**	**-0.2344**	**-0.1095**	**0.0303**	**0.9483**	**-2.3097**	**0.6325**	0.0892 *	0.0000 ***	0.0000 ***
	(1.867)	(-1.879)	(0.090)	(2.059)	(-1.530)	(-3.068)	(2.101)	(3.151)	(68.291)	(6.279)	(131.510)	**(-0.876)**	**(-1.234)**	**(-0.854)**	**(0.158)**	**(0.671)**	**(-1.562)**	**(0.135)**			
NES	0.0021 ***	0.0027 ***	0.0020 ***	-0.1488	-0.0097	0.1251	0.1966	0.9993 ***	0.2853 ***	-0.0552 ***	0.6242 ***	**-0.5138 ****	**-0.6418 ***	**0.1763**	**0.3562**	**-6.2558 ****	**-6.6490 ***	**8.6894 *****	0.0000 ***	0.0000 ***	0.0000 ***
	(4.304)	(3.619)	(5.874)	(-1.328)	(-0.063)	(1.341)	(1.380)	(46.732)	(3.350)	(-5.875)	(6.935)	**(-2.290)**	**(-1.778)**	**(0.669)**	**(0.840)**	**(-2.533)**	**(-1.875)**	**(3.909)**			
NOV	0.0027 ***	0.0009	0.0000	0.3309	0.1866	-0.4293	-0.0896	0.3207	0.8682	0.6469 **	0.0611	**0.4315**	**0.5073**	**-0.0672**	**-0.1595**	**-4.2764**	**-24.1887 *****	**0.0001**	0.0247 **	0.0000 ***	0.0000 ***
	(3.482)	(0.731)	(-0.000)	(1.014)	(0.913)	(-1.327)	(-0.326)	(1.014)	(1.531)	(2.041)	(0.097)	**(0.790)**	**(0.382)**	**(-0.114)**	**(-0.098)**	**(-0.287)**	**(-2.972)**	**(0.000)**			
PHI	0.0030 **	0.0077 ***	0.0000	0.1480	-0.4817 *	-0.2130	0.4811 *	1.1845 ***	1.3068 ***	-0.2265	-0.4123	**-0.1983**	**-0.2872**	**-0.1021**	**-0.0032**	**3.9274**	**11.9551 ****	**-0.0006**	0.1854	0.0000 ***	0.0000 ***
	(2.001)	(5.532)	(-0.000)	(0.567)	(-1.770)	(-0.686)	(1.669)	(2.748)	(3.230)	(-0.503)	(-0.946)	**(-1.125)**	**(-1.355)**	**(-0.561)**	**(-0.015)**	**(1.022)**	**(2.024)**	**(-0.000)**			
RBO	0.0037	0.0033 ***	0.0019 ***	-0.2226	0.1602	0.2464	-0.0408	0.1503	-0.6538	-1.0915	-0.2678	**0.0464**	**-0.0250**	**-0.4831**	**-0.3827**	**-3.9071**	**4.1611**	**-9.4766**	0.0006 ***	0.0000 ***	0.0000 ***
	(1.591)	(3.681)	(6.016)	(-0.716)	(0.323)	(0.577)	(-0.063)	(0.056)	(-0.251)	(-0.431)	(-0.100)	**(0.093)**	**(-0.044)**	**(-1.158)**	**(-0.712)**	**(-0.332)**	**(0.435)**	**(-0.753)**			
RD	-0.0278 ***	0.0185	-0.0069	0.3859 ***	0.0511	-0.1330	0.2742 **	-0.1966	-0.5947	-0.7624 *	-0.3240	**-0.0080**	**0.2541**	**-0.2487**	**-0.4024 ****	**0.0594 *****	**-0.0312**	**0.0138**	0.0003 ***	0.0000 ***	0.0000 ***
	(-3.116)	(1.350)	(-0.117)	(3.726)	(0.415)	(-1.217)	(2.345)	(-0.455)	(-1.477)	(-1.809)	(-0.805)	**(-0.048)**	**(1.381)**	**(-1.534)**	**(-2.057)**	**(3.094)**	**(-1.075)**	**(0.117)**			
ROG	0.0020 **	0.0021 **	-0.0004	-0.2909 **	-0.4133 ***	0.1832	0.2401 **	-0.6943 ***	0.2668 ***	-0.2812 ***	-1.2082 ***	**0.0974**	**0.0521**	**-0.3722 ****	**-0.3264 ***	**-14.1833 *****	**-9.7041 ****	**0.0243**	0.0059 ***	0.0000 ***	0.0000 ***
	(2.399)	(2.539)	(-0.657)	(-2.456)	(-4.222)	(1.393)	(2.423)	(-13.514)	(6.155)	(-4.974)	(-25.735)	**(0.700)**	**(0.348)**	**(-2.491)**	**(-1.957)**	**(-2.850)**	**(-2.106)**	**(0.016)**			
SCH	0.0006	0.0014 ***	0.0000	0.0766	-0.1067	0.2086	0.4247 ***	1.2557 ***	0.3301 ***	-0.3380 ***	0.5901 ***	**-0.5644 *****	**-0.7896 *****	**0.7655 *****	**0.9117 *****	**22.3233 *****	**22.6947 *****	**0.0044**	0.0020 ***	0.0000 ***	0.0000 ***
	(1.436)	(3.367)	(-0.003)	(0.562)	(-0.748)	(1.554)	(3.003)	(83.835)	(15.769)	(-24.932)	(26.099)	**(-24.190)**	**(-20.152)**	**(19.760)**	**(13.443)**	**(3.455)**	**(3.124)**	**(0.003)**			
SHB	0.0012	-0.0011	0.0020	-0.2118	0.0113	0.1660	0.1485 *	0.0139	0.1332	0.9544 ***	0.8218 ***	**0.2310**	**-0.2138**	**-0.5883 *****	**-0.0825**	**7.0433 ****	**-0.2812**	**1.9424**	0.0043 ***	0.0000 ***	0.0000 ***
	(0.754)	(-0.399)	(1.111)	(-0.868)	(0.124)	(0.623)	(1.655)	(0.070)	(0.789)	(5.104)	(5.001)	**(1.443)**	**(-1.548)**	**(-4.108)**	**(-0.631)**	**(2.258)**	**(-0.152)**	**(1.597)**			

Table 4.4: Quasi-Maximum Likelihood (QML) Estimates for Variance/Covariance Equations of AsymBEKK-X Model (continued)

Code	c_{11}	c_{21}	c_{22}	a_{11}	a_{12}	a_{21}	a_{22}	b_{11}	b_{12}	b_{21}	b_{22}	d_{11}	d_{12}	d_{21}	d_{22}	e_{11}	e_{21}	e_{22}	AsymBEKK	BEKK-X	BEKK
SHE	-0.0003	-0.0039 **	0.0000	-0.3801 ***	-0.2864 *	0.2275 ***	0.4049 ***	1.4066 ***	1.5693 ***	-0.5183 ***	-0.7802 ***	**0.2074**	**0.6907 *****	**0.1202**	**-0.2060**	**0.0210**	**-0.0519**	**0.0000**	0.0246 **	0.0000 ***	0.0000 ***
	(-0.217)	(-2.281)	(0.000)	(-4.859)	(-1.789)	(5.509)	(4.063)	(9.828)	(12.169)	(-2.956)	(-4.749)	**(1.088)**	**(3.243)**	**(0.751)**	**(-0.785)**	**(0.620)**	**(-1.106)**	**(0.000)**			
SIE	0.0006	0.0014 *	-0.0005	-0.1067 **	0.2145 ***	0.0152	-0.2295 ***	0.9741 ***	0.0498 **	0.0061	0.9274 ***	**-0.2625 *****	**-0.1172 ***	**0.0135**	**-0.1371 ****	**-0.0158**	**0.0989**	**-0.0266**	0.0437 **	0.0000 ***	0.0000 ***
	(0.821)	(1.863)	(-1.017)	(-2.033)	(3.695)	(0.413)	(-3.485)	(115.736)	(2.307)	(0.692)	(44.329)	**(-8.720)**	**(-1.782)**	**(0.777)**	**(-2.406)**	**(-1.575)**	**(1.108)**	**(-0.190)**			
TEF	0.0035 ***	0.0011 **	0.0000	-0.3136 **	0.0207	0.5428 ***	0.2301 *	-0.3541	0.2759	1.2834 ***	0.6778	**0.4753 ****	**0.5455 ****	**-0.2442**	**-0.4700 ****	**0.2617 *****	**0.1826 *****	**0.0000**	0.0039 ***	0.0001 ***	0.0000 ***
	(4.066)	(2.150)	(-0.001)	(-2.515)	(0.169)	(4.276)	(1.862)	(-0.882)	(0.668)	(3.230)	(1.594)	**(2.251)**	**(2.139)**	**(-1.306)**	**(-2.080)**	**(3.648)**	**(3.185)**	**(0.001)**			
TI	0.0113 ***	0.0104 ***	0.0033 ***	0.6066 ***	0.1273	-0.8385 ***	-0.0668	-0.0018	0.0035	-0.0051	0.0102	**-0.5286 ****	**-0.9366 *****	**0.1753**	**0.8357 *****	**0.0089 *****	**0.0014**	**0.0330 ****	0.0000 ***	0.0000 ***	0.0000 ***
	(20.937)	(21.298)	(13.531)	(3.145)	(0.579)	(-3.079)	(-0.265)	(-0.096)	(0.092)	(-0.414)	(0.421)	**(-1.978)**	**(-4.728)**	**(0.592)**	**(2.983)**	**(10.751)**	**(1.237)**	**(2.177)**			
TIM	0.0014	0.0053 ***	0.0000	0.0789	-0.6900 ***	-0.1532	0.6756 ***	-0.6549 ***	-0.9389 ***	-0.3258	0.0926	**-0.3395 *****	**0.3277**	**0.0237**	**-0.7708 ***	**0.9536 ***	**1.5946 ***	**0.0000**	0.0366 **	0.0000 ***	0.0000 ***
	(1.475)	(4.460)	(-0.000)	(0.423)	(-4.207)	(-0.792)	(3.510)	(-3.454)	(-6.053)	(-1.635)	(0.482)	**(-2.996)**	**(0.956)**	**(0.176)**	**(-1.894)**	**(1.922)**	**(1.888)**	**(-0.000)**			
TLI	0.0004	0.0040 *	0.0031	0.0605	-0.2078	-0.1224	0.0734	0.8114 ***	0.2474	0.1668	0.6976 ***	**0.4101**	**-0.0815**	**-0.6922**	**-0.2324**	**3.8450**	**-0.4619**	**-9.4691 *****	0.0010 ***	0.0000 ***	0.0000 ***
	(0.206)	(1.710)	(1.407)	(0.086)	(-0.295)	(-0.193)	(0.117)	(4.494)	(1.595)	(0.950)	(4.833)	**(0.538)**	**(-0.109)**	**(-0.902)**	**(-0.307)**	**(1.148)**	**(-0.085)**	**(-3.072)**			
TOT	-0.0003	-0.0036	0.0000	0.3574	-0.0900	-0.1392	0.2753	0.7384 ***	0.2964	0.2406	0.6329	**0.4921**	**0.5408 *****	**-0.3469 *****	**-0.3074 ****	**1.9509**	**-1.3701**	**-0.0003**	0.3399	0.0000 ***	0.0001 ***
	(-0.150)	(-1.485)	(-0.000)	(1.250)	(-0.240)	(-0.643)	(1.090)	(04.314)	(0.722)	(1.375)	(1.362)	**(1.608)**	**(3.242)**	**(-3.280)**	**(-2.034)**	**(0.871)**	**(-0.788)**	**(-0.000)**			
UBS	0.0026 *	0.0029	0.0000	-0.0060	0.2096	0.1640	0.0262	-3.0041 ***	-3.2718 ***	2.4637 ***	2.9699 ***	**0.2823**	**0.0485**	**0.1004**	**0.2823**	**1.3535**	**1.9410**	**-0.0859**	0.8088	0.0000 ***	0.0000 ***
	(1.725)	(1.420)	(0.015)	(-0.022)	(0.791)	(1.047)	(0.177)	(-30.045)	(-11.684)	(1990.280)	(19.278)	**(1.473)**	**(0.144)**	**(0.606)**	**(1.438)**	**(0.881)**	**(0.937)**	**(-0.015)**			
UC	0.0016 **	-0.0029 ***	0.0000	-0.2042	0.2424 ***	0.3541 ***	-0.0205	-0.6317 ***	-0.1623 ***	-0.3321 ***	-0.7794 ***	**0.3280 *****	**0.1657 ***	**0.0400**	**0.1451 ***	**3.5904 *****	**-1.2179**	**-0.0001**	0.0001 ***	0.0000 ***	0.0000 ***
	(2.018)	(-5.907)	(0.000)	(-1.419)	(3.649)	(4.354)	(-0.245)	(-7.529)	(-2.811)	(-4.131)	(-14.068)	**(4.441)**	**(1.802)**	**(0.480)**	**(1.784)**	**(4.705)**	**(-1.547)**	**(-0.000)**			
VIV	0.0027 ***	0.0027 ***	0.0000	0.1121	0.0959	-0.0242	0.0041	0.9773 ***	-0.0058	-0.0149	0.9719 ***	**-0.1906**	**-0.3257 ****	**-0.1269**	**0.0496**	**9.6873 *****	**10.0333 *****	**0.0002**	0.0054 ***	0.0000 ***	0.0000 ***
	(3.960)	(3.729)	(-0.003)	(0.795)	(0.667)	(-0.235)	(0.048)	(40.219)	(-0.256)	(-0.814)	(59.136)	**(-1.272)**	**(-2.082)**	**(-1.000)**	**(0.398)**	**(2.975)**	**(3.098)**	**(0.002)**			
VOF	0.0023 ***	0.0025 ***	0.0000	-0.0357	0.0283	0.1733 **	0.0702	-1.1203 ***	-0.1462 ***	0.1668 ***	-0.8234 ***	**-0.2097 *****	**-0.1458 ****	**-0.0980**	**-0.1288 ****	**-0.6407**	**-0.5438**	**0.0000**	0.3638	0.0000 ***	0.0000 ***
	(5.939)	(6.155)	(0.000)	(-0.472)	(0.607)	(1.970)	(1.308)	(-61.407)	(-9.616)	(8.411)	(-46.765)	**(-3.794)**	**(-2.382)**	**(-1.579)**	**(-2.248)**	**(-0.910)**	**(-1.221)**	**(-0.000)**			
VOW	0.0028 ***	0.0030 ***	0.0000	-0.2837 ***	0.0734	0.3127 **	0.0333	0.8909 ***	-0.0303	-1.7750 ***	-0.9382 ***	**-0.2815 *****	**-0.3816 *****	**-0.0142**	**0.1547**	**-2.9810**	**-2.4780**	**0.0000**	0.6751	0.0000 ***	0.0000 ***
	(4.355)	(4.525)	(-0.000)	(-3.051)	(0.668)	(2.337)	(0.222)	(6.802)	(-0.219)	(-16.606)	(-6.939)	**(-3.003)**	**(-3.156)**	**(-0.129)**	**(0.972)**	**(-1.118)**	**(-1.187)**	**(-0.000)**			

This table reports the parameter estimates for the augmented asymmetric BEKK GARCH (1,1)-X model (4.13):

$$H_t = C_0C_0' + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} + D_{11}'\xi_{t-1}\xi_{t-1}'D_{11} + E_{11}(Z_{t-1})^2E_{11}' \qquad (4.13)$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$; $D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$; $E_{11} = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$

and $\xi_t = \begin{bmatrix} \xi_{s,t} \\ \xi_{f,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{s,t}, 0\} \\ \min\{\varepsilon_{f,t}, 0\} \end{bmatrix}$; $Z_t = (P_{s,t} - P_{f,t})$; assuming $\varepsilon_t \setminus \Omega_t : N(0, H_t)$

The off-diagonal elements in A_{11} (B_{11}) matrix describes the innovations (volatility) spillovers between the stock and futures markets, while the off-diagonal elements of D_{11} matrix captures the asymmetric volatility responses of a market to another market's innovations. The coefficients relating to the asymmetries and basis effects (i.e. D_{11} and E_{11}) are indicated in **bold** characters. Estimates are obtained using the BFGS numerical optimization algorithm and the method of quasi-maximum likelihood (QML). The robust standard error and associated t-statistics are calculated using the Bollerslev-Wooldridge (1992) approach. All the estimations are made using the RATS statistical software with its built-in GARCH instruction. Figure in parentheses (.) indicate the robust t-statistics. *, ** and *** denote significant levels of 10%, 5% and 1%, respectively.

'Asym-BEKK', 'BEKK-X' and 'BEKK' are the Wald tests P-values for the restrictions $E_{11} = 0$, $D_{11} = 0$ and $E_{11} = D_{11} = 0$ respectively.

Table 4.5: Summary of BEKK GARCH (1,1) Model Specification Tests

	Asym-BEKK	BEKK-X	BEKK	Best Model
AA	FAIL	REJECT	REJECT	Asym-BEKK
AGN	REJECT	REJECT	REJECT	Asym-BEKK-X
AHL	FAIL	REJECT	REJECT	Asym-BEKK
ALV	REJECT	REJECT	REJECT	Asym-BEKK-X
AXA	REJECT	REJECT	REJECT	Asym-BEKK-X
AZN	FAIL	REJECT	REJECT	Asym-BEKK
BAR	REJECT	REJECT	REJECT	Asym-BEKK-X
BNP	REJECT	REJECT	REJECT	Asym-BEKK-X
BPA	FAIL	REJECT	REJECT	Asym-BEKK
BTL	REJECT	REJECT	REJECT	Asym-BEKK-X
BVA	REJECT	REJECT	REJECT	Asym-BEKK-X
CA	REJECT	REJECT	REJECT	Asym-BEKK-X
CGE	FAIL	REJECT	REJECT	Asym-BEKK
CSG	REJECT	REJECT	REJECT	Asym-BEKK-X
DBK	FAIL	REJECT	REJECT	Asym-BEKK
DCY	FAIL	REJECT	REJECT	Asym-BEKK
DTE	FAIL	REJECT	REJECT	Asym-BEKK
ENI	REJECT	REJECT	REJECT	Asym-BEKK-X
ENL	REJECT	REJECT	REJECT	Asym-BEKK-X
EOA	REJECT	REJECT	REJECT	Asym-BEKK-X
ERC	REJECT	REJECT	REJECT	Asym-BEKK-X
FTE	REJECT	REJECT	REJECT	Asym-BEKK-X
GEN	REJECT	REJECT	REJECT	Asym-BEKK-X
GXW	REJECT	REJECT	REJECT	Asym-BEKK-X
HAS	REJECT	REJECT	REJECT	Asym-BEKK-X
HNM	FAIL	REJECT	REJECT	Asym-BEKK
ING	REJECT	REJECT	REJECT	Asym-BEKK-X
LLO	REJECT	REJECT	REJECT	Asym-BEKK-X
MUV	REJECT	REJECT	REJECT	Asym-BEKK-X
NDA	REJECT	REJECT	REJECT	Asym-BEKK-X
NES	REJECT	REJECT	REJECT	Asym-BEKK-X
NOV	REJECT	REJECT	REJECT	Asym-BEKK-X
PHI	FAIL	REJECT	REJECT	Asym-BEKK
RBO	REJECT	REJECT	REJECT	Asym-BEKK-X
RD	REJECT	REJECT	REJECT	Asym-BEKK-X
ROG	REJECT	REJECT	REJECT	Asym-BEKK-X
SCH	REJECT	REJECT	REJECT	Asym-BEKK-X
SHB	REJECT	REJECT	REJECT	Asym-BEKK-X
SHE	REJECT	REJECT	REJECT	Asym-BEKK-X
SIE	REJECT	REJECT	REJECT	Asym-BEKK-X
TEF	REJECT	REJECT	REJECT	Asym-BEKK-X
TI	REJECT	REJECT	REJECT	Asym-BEKK-X
TIM	REJECT	REJECT	REJECT	Asym-BEKK-X
TLI	REJECT	REJECT	REJECT	Asym-BEKK-X
TOT	FAIL	REJECT	REJECT	Asym-BEKK
UBS	FAIL	REJECT	REJECT	Asym-BEKK
UC	REJECT	REJECT	REJECT	Asym-BEKK-X
VIV	REJECT	REJECT	REJECT	Asym-BEKK-X
VOF	FAIL	REJECT	REJECT	Asym-BEKK
VOW	FAIL	REJECT	REJECT	Asym-BEKK

Notes:

This table summarises the results of multivariate GARCH model specification tests of various BEKK GARCH (1,1) models. The best-performing models for each stock-futures pair, on the basis of Wald test statistic, are also reported in the last column. A 'REJECT' indicates that the model is rejected in favour of our modified AsymBEKK-X at the 10% significance level.

Table 4.6: Diagnostic Tests on the Standardised Residuals of Asymmetric BEKK GARCH (1,1)-X Model

Code	Dep Var	Mean	Variance	Skewness	Excess Kurtosis	Jarque-Bera	Q(4)	$Q^2(4)$	Sign-Bias (t-test)	Negative-Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F-test)
AA	Rs	-0.0066	0.9900	-0.1847 *	0.8695 **	29.86 **	1.9071	12.0431 **	0.2102	0.8130	-1.8816	7.0866
				(0.033)	(0.000)	(0.000)	(0.167)	(0.001)				(0.069)
	Rf	-0.0064	0.9999	-0.1741 *	0.6861 **	19.81 **	3.3087	7.5738 **	0.5702	0.1771	-0.7916	1.1619
				(0.044)	(0.000)	(0.000)	(0.069)	(0.006)				(0.762)
AGN	Rs	-0.0125	0.9954	-0.1148	0.3363	5.55	4.5909 *	7.5675 **	0.8967	0.8528	-1.2245	5.5527
				(0.185)	(0.053)	(0.062)	(0.032)	(0.006)				(0.136)
	Rf	0.0007	1.1016	20.4909 **	520.8922 **	9134397.91 **	0.3848	0.0016	0.9410	0.1896	-0.1880	1.9098
				(0.000)	(0.000)	(0.000)	(0.535)	(0.968)				(0.591)
AHL	Rs	-0.0079	0.9797	-3.2085 **	46.7401 **	74472.16 **	5.2880 *	0.1383	1.5314	-0.2703	-0.8443	2.6754
				(0.000)	(0.000)	(0.000)	(0.021)	(0.710)				(0.444)
	Rf	-0.0040	0.9806	-3.4076 **	48.7492 **	81067.38 **	5.3166 *	0.1451	1.1979	-0.0940	-0.6153	1.7277
				(0.000)	(0.000)	(0.000)	(0.021)	(0.703)				(0.631)
ALV	Rs	-0.0088	0.9709	-0.1247	0.3497 *	7.37 *	1.7876	4.4454 *	-0.5264	1.4259	0.4349	2.3624
				(0.115)	(0.028)	(0.025)	(0.181)	(0.035)				(0.501)
	Rf	0.0006	0.9907	-0.0472	0.0642	0.52	1.0472	2.5613	-0.1014	1.8114	0.4823	6.0254
				(0.551)	(0.686)	(0.771)	(0.306)	(0.110)				(0.110)
AXA	Rs	-0.0026	0.9870	-0.1131	0.4035 *	8.55 *	3.0451	3.2866	-2.3057 *	2.6584 **	0.6783	8.9582 *
				(0.154)	(0.011)	(0.014)	(0.081)	(0.070)				(0.030)
	Rf	-0.0092	0.9992	-0.3660 **	1.4768 **	108.56 **	7.6701 **	1.7059	-1.1449	1.9269	0.8832	3.7414
				(0.000)	(0.000)	(0.000)	(0.006)	(0.192)				(0.291)
AZN	Rs	-0.0052	1.0052	-0.3085 **	3.2192 **	452.15 **	3.7223	1.2834	-1.0650	-0.6271	-0.1860	5.0334
				(0.000)	(0.000)	(0.000)	(0.054)	(0.257)				(0.169)
	Rf	-0.0032	1.0012	-0.2754 **	3.5496 **	543.01 **	4.3874 *	2.0312	-1.9056	-0.2743	-0.3100	10.9189 *
				(0.000)	(0.000)	(0.000)	(0.036)	(0.154)				(0.012)
BAR	Rs	-0.0065	0.9904	-0.0423	1.3942 **	75.85 **	3.0404	1.7465	0.4737	-1.4898	-0.5430	2.6874
				(0.598)	(0.000)	(0.000)	(0.081)	(0.186)				(0.442)
	Rf	-0.0008	1.0117	-3.9726 **	60.6928 **	145654.64 **	16.1479 **	0.0335	1.0510	-0.0206	-0.3350	1.4737
				(0.000)	(0.000)	(0.000)	(0.000)	(0.855)				(0.688)
BNP	Rs	-0.0043	0.9933	-0.3528 **	1.9775 **	171.38 **	5.4495 *	1.4646	0.6418	0.1912	-0.3035	1.0341
				(0.000)	(0.000)	(0.000)	(0.020)	(0.226)				(0.793)
	Rf	-0.0039	0.9743	-2.4945 **	31.3913 **	39275.62 **	8.0475 **	0.1119	1.1115	-0.3356	-0.1607	1.7644
				(0.000)	(0.000)	(0.000)	(0.005)	(0.738)				(0.623)
BPA	Rs	0.0000	0.9925	-0.2100 **	0.3494 *	12.56 **	1.9443	2.8565	-0.3251	0.2752	0.9796	1.1695
				(0.007)	(0.024)	(0.002)	(0.163)	(0.091)				(0.760)
	Rf	0.0016	0.9919	-0.2503 **	0.5122 **	21.59 **	2.1425	3.0885	-0.7127	0.7590	1.6736	3.2795
				(0.001)	(0.001)	(0.000)	(0.143)	(0.079)				(0.351)
BTL	Rs	0.0038	0.9990	0.0182	0.4843 **	9.43 **	1.0058	10.5074 **	-0.9792	0.6022	0.5540	0.9765
				(0.819)	(0.002)	(0.009)	(0.316)	(0.001)				(0.807)
	Rf	0.0067	0.9880	-0.3060 **	2.7851 **	324.93 **	1.9410	0.8306	-1.6943	0.3082	1.2850	3.7352
				(0.000)	(0.000)	(0.000)	(0.164)	(0.362)				(0.292)
BVA	Rs	0.0049	0.9871	0.0218	0.1990	1.61	2.5164	4.2498 *	-0.4636	1.6328	-0.7686	5.5586
				(0.786)	(0.216)	(0.446)	(0.113)	(0.039)				(0.135)
	Rf	0.0020	0.9858	-0.0409	0.4563 **	8.35 *	1.3494	4.4783 *	0.8681	1.2800	-1.1657	7.7391
				(0.610)	(0.005)	(0.015)	(0.245)	(0.034)				(0.052)
CA	Rs	-0.0007	0.9773	0.0683	1.3080 **	67.24 **	1.6207	4.8602 *	-0.3561	0.4336	0.9432	1.0721
				(0.395)	(0.000)	(0.000)	(0.203)	(0.027)				(0.784)
	Rf	0.0025	0.9819	0.0564	1.4719 **	84.72 **	1.0149	2.6115	0.1393	0.0766	0.5425	0.7292
				(0.483)	(0.000)	(0.000)	(0.314)	(0.106)				(0.866)
COE	Rs	-0.0001	0.9962	0.0740	1.3373 **	76.18 **	1.5332	4.2812 *	-0.1364	-0.5774	-0.0798	0.8688
				(0.338)	(0.000)	(0.000)	(0.216)	(0.039)				(0.833)
	Rf	-0.0093	1.0037	0.3521 **	3.2389 **	462.33 **	1.0435	2.1085	-0.4828	0.0811	-0.3935	1.0915
				(0.000)	(0.000)	(0.000)	(0.307)	(0.146)				(0.779)
CSG	Rs	-0.0069	0.9944	-0.2348 **	0.8198 **	29.79 **	8.4399 **	3.4920	0.1876	-0.6438	0.3471	0.8928
				(0.007)	(0.000)	(0.000)	(0.004)	(0.062)				(0.827)
	Rf	-0.0021	0.9937	-0.1749 *	0.5869 **	15.58 **	9.5469 **	2.8416	1.2847	-0.3623	-0.2125	2.7369
				(0.044)	(0.001)	(0.000)	(0.002)	(0.092)				(0.434)
DBK	Rs	0.0014	0.9844	0.0996	0.9805 **	42.13 **	1.5757	3.3809	0.1813	-0.2914	-1.3486	2.6747
				(0.197)	(0.000)	(0.000)	(0.209)	(0.066)				(0.445)
	Rf	0.0091	0.9926	0.1374	0.8864 **	36.24 **	1.4274	3.0953	1.2709	-0.5130	-0.9052	1.8497
				(0.075)	(0.000)	(0.000)	(0.232)	(0.079)				(0.604)
DCY	Rs	0.0075	0.9839	-0.0285	0.3805 *	5.75	2.6978	9.1195 **	0.3301	0.2378	-1.7034	4.6254
				(0.722)	(0.018)	(0.056)	(0.100)	(0.003)				(0.201)
	Rf	0.0099	0.9843	-0.0130	0.6389 **	15.89 **	0.3232	7.1162 **	2.0861 *	-0.7371	-2.1665 *	5.9750
				(0.872)	(0.000)	(0.000)	(0.570)	(0.008)				(0.113)
DTE	Rs	0.0247	1.0000	0.0470	0.6747 **	19.53 **	4.7179 *	3.7901	0.5608	0.1944	-1.7169	4.1433
				(0.543)	(0.000)	(0.000)	(0.030)	(0.052)				(0.246)
	Rf	0.0235	0.9930	0.0960	0.6763 **	20.80 **	2.1276	1.0800	-0.4060	0.2747	-0.6490	1.6383
				(0.214)	(0.000)	(0.000)	(0.145)	(0.299)				(0.651)
ENI	Rs	-0.0005	1.0046	-0.4290 **	1.4893 **	124.32 **	0.6639	0.6150	1.1767	-0.0371	-0.4747	2.3254
				(0.000)	(0.000)	(0.000)	(0.415)	(0.433)				(0.508)
	Rf	0.0026	0.9817	0.3134 **	8.9330 **	3374.74 **	0.1428	0.8754	1.3587	0.1152	-0.8474	3.0483
				(0.000)	(0.000)	(0.000)	(0.706)	(0.349)				(0.384)
ENL	Rs	0.0158	0.9962	-0.7031 **	4.2849 **	814.35 **	1.1718	1.3357	0.0325	-0.1562	0.4013	0.3438
				(0.000)	(0.000)	(0.000)	(0.279)	(0.248)				(0.952)
	Rf	0.0097	0.9709	-0.2752 **	8.4564 **	2875.54 **	2.5384	1.3585	0.9102	-1.1091	-0.2433	1.5345
				(0.001)	(0.000)	(0.000)	(0.111)	(0.244)				(0.674)
EOA	Rs	0.0070	0.9945	-0.2975 **	1.0472 **	56.39 **	4.4186 *	1.4079	-0.0527	-1.2770	-1.0140	4.9183
				(0.000)	(0.000)	(0.000)	(0.036)	(0.235)				(0.178)
	Rf	0.0060	0.9937	-0.0589	0.4445 **	8.22 *	5.1525 *	7.0304 **	1.7301	-4.0011 **	-2.3576 *	19.7379 **
				(0.464)	(0.006)	(0.016)	(0.023)	(0.008)				(0.000)
ERC	Rs	-0.0012	0.9861	0.0572	2.2914 **	175.68 **	3.6615	4.5437 *	0.5418	-1.5276	0.2734	3.2720
				(0.509)	(0.000)	(0.000)	(0.056)	(0.033)				(0.352)
	Rf	0.0013	0.9925	-0.1550	3.4568 **	402.02 **	3.0833	2.2694	-0.3051	-0.3142	0.8283	1.1503
				(0.074)	(0.000)	(0.000)	(0.079)	(0.132)				(0.765)
FTE	Rs	-0.0167	0.9873	0.0574	0.1095	1.06	2.0117	4.4252 *	0.3066	0.4917	0.7356	2.6891
				(0.457)	(0.479)	(0.589)	(0.156)	(0.035)				(0.442)
	Rf	-0.0172	0.9921	-0.0005	0.2349	2.32	1.6691	2.8706	0.4471	0.2883	0.1499	1.2046
				(0.995)	(0.129)	(0.313)	(0.196)	(0.090)				(0.752)
GEN	Rs	0.0088	0.9860	-0.2809 **	1.2185 **	72.09 **	0.8725	15.0726 **	0.1103	0.0382	0.5040	0.6282
				(0.000)	(0.000)	(0.000)	(0.350)	(0.000)				(0.890)
	Rf	0.0080	0.9906	-0.1759 *	1.0723 **	51.00 **	2.2261	17.3383 **	-0.0394	0.4358	0.8725	1.6054
				(0.026)	(0.000)	(0.000)	(0.136)	(0.000)				(0.658)
GXW	Rs	-0.0199	1.0034	-0.4172 **	2.5287 **	298.40 **	1.1669	9.1705 **	0.5991	-1.7671	0.2612	4.3559
				(0.000)	(0.000)	(0.000)	(0.280)	(0.002)				(0.226)
	Rf	-0.0160	1.0012	-0.4862 **	3.1084 **	446.40 **	0.7547	8.8203 **	0.0640	-2.1754 *	0.1611	7.6141
				(0.000)	(0.000)	(0.000)	(0.385)	(0.003)				(0.055)
HAS	Rs	-0.0054	1.0082	-0.3452 **	3.3396 **	489.41 **	4.0826 *	1.1432	2.0649 *	-0.1142	-1.5250	6.5045
				(0.000)	(0.000)	(0.000)	(0.043)	(0.285)				(0.089)
	Rf	-0.0077	0.9848	-0.2673 **	2.7004 **	318.90 **	4.1227 *	1.0563	1.1398	0.6147	-0.9837	4.1209
				(0.001)	(0.000)	(0.000)	(0.042)	(0.304)				(0.249)
HNM	Rs	0.0049	1.0213	-0.0658	3.8170 **	486.83 **	0.8052	1.7092	1.2507	-1.5937	-1.1845	2.9414
				(0.448)	(0.000)	(0.000)	(0.370)	(0.191)				(0.401)
	Rf	0.0118	0.9549	-0.1785 *	4.7579 **	759.78 **	0.9626	1.8533	0.6053	0.1510	-0.4807	0.7842
				(0.040)	(0.000)	(0.000)	(0.327)	(0.173)				(0.853)
ING	Rs	-0.0004	0.9792	-0.2308 **	0.8231 **	37.48 **	6.9789 **	3.3110	0.2880	1.2581	-0.7543	4.3092
				(0.003)	(0.000)	(0.000)	(0.008)	(0.069)				(0.230)
	Rf	-0.0010	0.9991	-1.1624 **	10.1328 **	4548.28 **	3.9583 *	0.4724	-0.8317	0.6589	-0.0001	1.1795
				(0.000)	(0.000)	(0.000)	(0.047)	(0.492)				(0.758)
LLO	Rs	0.0049	0.9974	-0.0985	0.6027 **	16.07 **	5.0839 *	7.5022 **	-0.6551	1.1306	0.4996	1.2929
				(0.214)	(0.000)	(0.000)	(0.024)	(0.006)				(0.731)
	Rf	-0.0009	0.9765	-0.2467 **	1.1815 **	65.51 **	2.0410	0.7922	1.4784	-0.6687	-0.5326	2.6022
				(0.002)	(0.000)	(0.000)	(0.153)	(0.373)				(0.457)
MUV	Rs	-0.0049	0.9864	-0.2114 **	0.9010 **	39.58 **	0.9378	4.6110 *	-0.8032	1.7571	0.0168	3.7907
				(0.008)	(0.000)	(0.000)	(0.333)	(0.032)				(0.285)
	Rf	-0.0122	0.9864	-0.1301	0.8157 **	29.29 **	0.8868	2.5176	-1.2522	2.1113 *	1.5098	5.2797
				(0.100)	(0.000)	(0.000)	(0.346)	(0.113)				(0.152)

Table 4.6: Diagnostic Tests on the Standardised Residuals of Asymmetric BEKK GARCH (1.1)-X Model

Code	Dep Var	Mean	Variance	Skewness	Excess Kurtosis	Jarque-Bera	Q(4)	$Q^2(4)$	Sign-Bias (t-test)	Negative-Size-Bias (t-test)	Positive-Size-Bias (t-test)	Joint Test (F-test)
NDA	Rs	0.0177	0.9983	-0.1286	2.1610 **	158.07 **	1.6111	1.5222	-0.3194	-1.0266	0.2566	2.5333
				(0.138)	(0.000)	(0.000)	(0.204)	(0.217)				(0.469)
	Rf	0.0141	1.0024	0.0586	2.7605 **	254.78 **	0.7927	0.9556	-1.2755	-0.2071	1.1122	3.3812
				(0.499)	(0.000)	(0.000)	(0.373)	(0.328)				(0.336)
NES	Rs	0.0005	1.0013	-0.2962 **	1.6021 **	97.38 **	3.8647 *	1.9879	-0.5305	0.5172	0.0206	0.5330
				(0.001)	(0.000)	(0.000)	(0.049)	(0.159)				(0.912)
	Rf	0.0002	1.0152	-0.4305 **	2.1602 **	180.48 **	1.7281	4.0482 *	-1.5093	0.6663	1.1666	2.4486
				(0.000)	(0.000)	(0.000)	(0.189)	(0.044)				(0.485)
NOV	Rs	-0.0132	0.9987	-0.0839	1.5268 **	78.74 **	1.5904	3.1281	-0.6375	1.6198	0.6949	2.9760
				(0.334)	(0.000)	(0.000)	(0.207)	(0.077)				(0.395)
	Rf	-0.0147	0.9920	0.1037	1.3259 **	60.11 **	1.2369	5.3392 *	-0.9952	1.8525	0.5046	3.5025
				(0.232)	(0.000)	(0.000)	(0.266)	(0.021)				(0.320)
PHI	Rs	-0.0115	1.0091	-0.1263	0.2816	4.94	0.9367	9.1774 **	-0.4202	0.1951	-0.6360	1.6973
				(0.138)	(0.099)	(0.084)	(0.333)	(0.002)				(0.638)
	Rf	-0.0111	0.9915	-0.0996	0.2928	4.33	1.1011	6.1119 *	0.6377	-0.5212	-0.5676	0.4586
				(0.242)	(0.087)	(0.115)	(0.294)	(0.013)				(0.928)
RBO	Rs	-0.0073	0.9880	-0.1125	2.1065 **	174.46 **	2.8994	1.5426	0.6597	0.2076	-0.8081	1.3139
				(0.161)	(0.000)	(0.000)	(0.089)	(0.214)				(0.726)
	Rf	-0.0058	0.9966	-0.1458	2.3853 **	224.49 **	4.2918 *	1.0497	-0.5373	0.5662	-0.4058	1.3928
				(0.070)	(0.000)	(0.000)	(0.038)	(0.306)				(0.707)
RD	Rs	-0.0015	0.9904	-0.7445 **	3.1853 **	520.29 **	1.4200	2.2237	-0.9538	0.3400	-1.2799	8.0714 *
				(0.000)	(0.000)	(0.000)	(0.233)	(0.136)				(0.045)
	Rf	-0.0040	0.9906	-0.6962 **	3.0097 **	462.77 **	1.4049	2.9189	1.4331	-0.1320	-1.4658	3.3502
				(0.000)	(0.000)	(0.000)	(0.236)	(0.088)				(0.341)
ROG	Rs	-0.0024	0.9995	-0.0368	0.5686 **	10.97 **	1.4255	2.7272	-0.0451	0.5951	0.8519	1.7687
				(0.671)	(0.001)	(0.004)	(0.232)	(0.099)				(0.622)
	Rf	-0.0020	1.0041	-0.0153	0.4976 **	8.29 *	2.0616	3.0887	0.3854	0.7002	0.2764	2.2982
				(0.860)	(0.004)	(0.016)	(0.151)	(0.079)				(0.513)
SCH	Rs	-0.0019	0.9924	-0.1797 *	0.5805 **	19.62 **	3.7026	0.8953	1.7442	-0.6803	-1.7377	4.0128
				(0.020)	(0.000)	(0.000)	(0.054)	(0.344)				(0.260)
	Rf	0.0011	0.9970	-0.1698 *	0.6000 **	20.01 **	3.9440 *	1.3832	2.3597 *	-1.2365	-2.0088 *	6.0767
				(0.028)	(0.000)	(0.000)	(0.047)	(0.240)				(0.108)
SHB	Rs	-0.0042	1.0042	0.0023	0.7791 **	20.26 **	1.6116	2.4067	-0.3611	0.4542	0.2644	0.2162
				(0.978)	(0.000)	(0.000)	(0.204)	(0.121)				(0.975)
	Rf	-0.0077	1.0117	-0.0231	1.0487 **	36.78 **	3.2141	3.1273	-0.5996	0.2207	0.8965	0.8435
				(0.790)	(0.000)	(0.000)	(0.073)	(0.077)				(0.839)
SHE	Rs	0.0057	1.0012	-0.6960 **	2.7456 **	368.38 **	1.3729	4.0254 *	1.7403	0.1316	-0.3042	6.7203
				(0.000)	(0.000)	(0.000)	(0.241)	(0.045)				(0.081)
	Rf	0.0021	0.9883	-0.2138 **	2.2466 **	203.32 **	3.5839	7.7529 **	0.7978	0.1059	0.8344	4.5486
				(0.008)	(0.000)	(0.000)	(0.058)	(0.005)				(0.208)
SIE	Rs	0.0031	1.0022	0.0146	0.1083	0.53	0.2350	4.7915 *	1.1452	0.3935	-1.9171	6.2345
				(0.850)	(0.484)	(0.767)	(0.628)	(0.029)				(0.101)
	Rf	0.0017	0.9895	-0.1329	1.6999 **	124.58 **	3.3108	2.0286	-0.7364	0.7191	-1.0532	4.9740
				(0.085)	(0.000)	(0.000)	(0.069)	(0.154)				(0.174)
TEF	Rs	-0.0102	0.9972	0.0555	1.1048 **	51.89 **	2.2337	3.7895	0.4746	0.2245	-2.1176 *	6.3760
				(0.472)	(0.000)	(0.000)	(0.135)	(0.052)				(0.095)
	Rf	-0.0127	1.0015	-0.0943	0.6691 **	20.34 **	0.9377	6.8343 **	0.2405	-0.4849	-2.1385 *	7.2635
				(0.222)	(0.000)	(0.000)	(0.333)	(0.009)				(0.064)
TI	Rs	0.0002	0.9868	-0.5480 **	3.8580 **	676.91 **	5.2749 *	3.3280	-1.3203	0.0560	0.8480	2.6069
				(0.000)	(0.000)	(0.000)	(0.022)	(0.068)				(0.456)
	Rf	0.0098	0.9926	-12.0841 **	281.1990 **	3352231.78 **	4.0281 *	0.0183	-0.9048	0.2103	-0.3324	1.7485
				(0.000)	(0.000)	(0.000)	(0.045)	(0.892)				(0.626)
TIM	Rs	-0.0032	0.9979	0.0243	0.7647 **	20.33 **	5.3362 *	4.1415 *	0.1957	0.4074	-0.7012	1.1060
				(0.775)	(0.000)	(0.000)	(0.021)	(0.042)				(0.776)
	Rf	-0.0170	0.9567	-0.3287 **	2.3163 **	200.74 **	2.6071	0.6740	-0.4253	0.9474	0.0934	0.9930
				(0.000)	(0.000)	(0.000)	(0.106)	(0.412)				(0.803)
TLI	Rs	0.0058	0.9918	0.0529	2.8144 **	264.74 **	1.1540	2.7788	0.0266	-0.8288	0.1422	1.0816
				(0.542)	(0.000)	(0.000)	(0.283)	(0.096)				(0.782)
	Rf	0.0076	0.9796	0.0031	2.8466 **	270.44 **	1.7463	2.1309	0.1593	-0.7637	-0.0566	0.7240
				(0.971)	(0.000)	(0.000)	(0.186)	(0.144)				(0.868)
TOT	Rs	-0.0054	0.9883	-0.2998 **	0.4114 **	22.26 **	2.5287	8.3595 **	0.7562	-1.6150	-1.4265	4.3659
				(0.000)	(0.008)	(0.000)	(0.112)	(0.004)				(0.225)
	Rf	-0.0055	0.9725	-0.2484 **	0.3277 *	14.91 **	1.7103	5.4012 *	0.7695	-1.4194	-1.0525	2.5954
				(0.001)	(0.034)	(0.001)	(0.191)	(0.020)				(0.458)
UBS	Rs	-0.0141	0.9949	-0.1515	0.2213	4.70	7.5664 **	0.6619	0.0348	-0.3088	0.0953	0.1694
				(0.081)	(0.203)	(0.095)	(0.006)	(0.416)				(0.982)
	Rf	-0.0086	0.9894	-0.2867 **	0.4617 **	18.09 **	8.4066 **	1.9910	0.0984	0.0936	0.4938	0.6179
				(0.001)	(0.008)	(0.000)	(0.004)	(0.158)				(0.892)
UC	Rs	-0.0035	0.9888	-0.2646 **	1.5872 **	112.09 **	4.3356 *	12.3758 **	-1.4913	0.5532	3.8444 **	17.0609 **
				(0.001)	(0.000)	(0.000)	(0.037)	(0.000)				(0.001)
	Rf	-0.0055	0.9641	-0.1511	1.3686 **	78.66 **	1.6886	2.3229	-2.0199 *	1.2184	2.5729 *	6.7905
				(0.056)	(0.000)	(0.000)	(0.194)	(0.127)				(0.079)
VIV	Rs	0.0336	0.9837	-0.2729 **	1.7790 **	134.62 **	14.0001 **	3.4914	-0.7029	-0.5731	-0.5936	4.0604
				(0.001)	(0.000)	(0.000)	(0.000)	(0.062)				(0.255)
	Rf	0.0309	0.9696	-0.3021 **	1.9206 **	157.59 **	16.1429 **	3.5621	-0.1747	-0.6841	-0.5962	1.9077
				(0.000)	(0.000)	(0.000)	(0.000)	(0.059)				(0.592)
VOF	Rs	0.0095	1.0091	0.0800	0.4927 **	11.29 **	1.7096	4.0162 *	0.7217	0.3704	-0.8140	2.0966
				(0.300)	(0.001)	(0.004)	(0.191)	(0.045)				(0.553)
	Rf	0.0144	1.0002	0.0534	0.3896 *	6.87 *	2.0130	3.6365	1.4638	0.0912	-0.9781	4.5311
				(0.489)	(0.012)	(0.032)	(0.156)	(0.057)				(0.210)
VOW	Rs	-0.0044	0.9780	0.0889	1.1413 **	51.87 **	2.5451	3.5071	0.1769	0.4757	-1.3028	3.1674
				(0.268)	(0.000)	(0.000)	(0.111)	(0.061)				(0.367)
	Rf	-0.0028	0.9840	0.0593	0.9590 **	36.30 **	2.0657	1.6931	0.8273	-0.0011	-1.8340	4.1749
				(0.460)	(0.000)	(0.000)	(0.151)	(0.193)				(0.243)

Notes: *, ** Significant at 5% and 1% level, respectively

(.) = p-values

Jarque-Bera is the Jarque and Bera (1980) normality test, with propbability value in parentheses.

Q(4) and $Q^2(4)$ are respectively the Ljung-Box Q statistics at lag 4 of the standardized and square standardized residuals.

The Engle and Ng (1993) diagnostic tests (i.e., Sign-Bias, Negative-Size Bias, Positive-Size Bias, and Joint Test) are obtained from the estimation of the following regression model:

$$Z_t^2 = a + b_1 S_t^- + b_2 S_t^- \varepsilon_{t-1} + b_3 S_t^+ \varepsilon_{t-1} + v_t$$

where Z_t^2 is the standardized residuals, S_t^- is a dummy variable that takes a value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise; and S_t^+ is a dummy variable that takes a value of unity if $\varepsilon_{t-1} > 0$ and zero otherwise.
Individual t-statistics are t-tests for the estimated coefficient (i) b_1 in Sign Bias Test (ii) b_2 in Negative-Size Bias Test and (iii) b_3 in Positive-Size-Bias Test. The F-statistics is the joint test that $b_1=b_2=b_3=0$.

Table 4.7: Summary Statistics of the Constant and Time-Varying Hedge Ratios

	Constant Hedge Ratios		Time Varying Hedge Ratios											
			MEAN				STD				ADF			
	OLS	VECM	BEKK	AsymBEKK	BEKK-X	AsymBEKK-X	BEKK	AsymBEKK	BEKK-X	AsymBEKK-X	BEKK	AsymBEKK	BEKK-X	AsymBEKK-X
AA	0.9537	0.9712	0.9441	0.9410	0.9464	0.9265	0.0695	0.0691	0.0722	0.0949	-18.466 ***	-8.440 ***	-14.156 ***	-3.839 ***
AGN	0.1242	0.2089	0.1849	0.1847	0.1859	0.3404	0.1418	0.1500	0.1411	0.2931	-2.658 *	-2.696 *	-2.652 *	-2.681 *
AHL	0.9552	0.9555	0.9299	0.9550	0.9480	0.9448	0.1255	0.1180	0.1037	0.1192	-24.761 ***	-17.630 ***	-34.472 ***	-25.401 ***
ALV	0.8818	0.9986	0.9917	1.0081	1.0275	1.0082	0.1019	0.0639	0.0931	0.0509	-8.075 ***	-8.424 ***	-5.530 ***	-6.218 ***
AXA	0.3040	0.3111	0.8269	0.8154	0.8772	0.8909	0.2221	0.2143	0.1721	0.1763	-8.936 ***	-9.454 ***	-6.055 ***	-6.468 ***
AZN	0.9738	0.9998	0.9957	1.0007	0.9987	0.9954	0.0501	0.0054	0.0391	0.0175	-7.096 ***	-5.323 ***	-5.050 ***	-5.426 ***
BAR	0.1733	0.1705	0.5715	0.5266	0.6730	0.6693	0.2392	0.1913	0.3730	0.3751	-17.267 ***	-20.806 ***	-1.728	-1.429
BNP	0.4595	0.4599	0.7025	0.7705	0.7627	0.7531	0.2510	0.2587	0.3414	0.3381	-31.467 ***	-29.769 ***	-1.823	-2.111
BPA	0.9869	0.9968	0.9743	0.9865	0.9856	0.9840	0.0517	0.0264	0.0407	0.0268	-4.202 ***	-9.467 ***	-7.282 ***	-7.856 ***
BTL	0.8523	0.8484	0.9172	0.8704	0.8947	0.9015	0.1300	0.1445	0.1435	0.1275	-7.551 ***	-18.801 ***	-4.550 ***	-4.740 ***
BVA	1.0001	1.0222	1.0085	1.0031	1.0081	1.0058	0.0493	0.0333	0.0466	0.0247	-4.551 ***	-4.794 ***	-5.194 ***	-4.624 ***
CA	0.9555	0.9904	0.9808	0.9792	0.9788	0.9788	0.0509	0.0547	0.0666	0.0676	-5.194 ***	-8.229 ***	-7.453 ***	-5.726 ***
CGE	0.8110	0.8911	0.9507	0.9303	0.9348	0.9421	0.1164	0.1363	0.1316	0.1206	-4.325 ***	-12.542 ***	-4.710 ***	-11.444 ***
CSG	0.9438	0.9662	0.9599	0.9606	0.9670	0.9660	0.0524	0.0358	0.0452	0.0409	-3.926 ***	-4.442 ***	-6.363 ***	-3.713 ***
DBK	0.9004	1.0042	0.9748	0.9782	0.9794	0.9765	0.0918	0.0474	0.0583	0.0514	-6.555 ***	-12.487 ***	-12.328 ***	-13.625 ***
DCY	0.9019	0.9724	0.9624	0.9671	0.9608	0.9648	0.0864	0.0809	0.0848	0.0627	-10.564 ***	-6.930 ***	-7.873 ***	-6.117 ***
DTE	0.8934	0.9981	0.9819	0.9891	1.0011	0.9849	0.0649	0.0492	0.0525	0.0456	-5.738 ***	-4.498 ***	-3.371 **	-4.251 ***
ENI	0.2905	0.2914	0.3444	0.6652	0.7970	0.7907	0.1182	0.3460	0.3096	0.3028	-4.634 ***	-28.577 ***	-3.859 ***	-3.825 ***
ENL	0.2883	0.2842	0.5354	0.6582	0.7580	0.7623	0.2631	0.2996	0.2586	0.2493	-8.704 ***	-23.065 ***	-4.019 ***	-4.779 ***
EOA	0.8891	0.9602	0.9405	0.9416	0.9386	0.9424	0.1103	0.0767	0.1120	0.0674	-7.328 ***	-6.117 ***	-7.351 ***	-4.963 ***
ERC	0.8961	0.9005	0.9454	0.9570	0.9462	0.9621	0.1014	0.1029	0.0938	0.0985	-18.505 ***	-17.237 ***	-17.178 ***	-15.832 ***
FTE	0.9771	0.9826	0.9478	0.9691	0.9710	0.9724	0.0952	0.0793	0.0770	0.0732	-15.033 ***	-17.127 ***	-16.815 ***	-17.803 ***
GEN	0.9693	1.0006	0.9689	0.9739	0.9619	0.9707	0.0717	0.0687	0.0698	0.0749	-4.758 ***	-3.663 ***	-5.280 ***	-3.570 ***
GXW	0.9773	0.9901	0.9927	0.9923	0.9917	0.9901	0.0422	0.0372	0.0407	0.0357	-6.032 ***	-9.983 ***	-5.779 ***	-7.601 ***
HAS	0.9786	0.9869	0.9574	0.9487	0.9485	0.9443	0.0975	0.0750	0.0986	0.0877	-10.597 ***	-10.339 ***	-6.354 ***	-10.907 ***
HNM	0.8317	0.9096	0.9703	0.8731	0.9558	0.9679	0.1392	0.2526	0.0857	0.0652	-11.440 ***	-8.450 ***	-8.902 ***	-16.664 ***
ING	0.6367	0.6351	0.6872	0.6735	0.8300	0.8369	0.2881	0.2720	0.2859	0.2948	-19.185 ***	-25.320 ***	-2.932 **	-3.433 **
LLO	0.9384	0.9601	0.8899	0.8921	0.8977	0.8797	0.1240	0.1219	0.1148	0.1530	-4.280 ***	-3.654 ***	-3.471 ***	-5.784 ***
MUV	0.8686	0.9772	0.9630	0.9666	0.9631	0.9653	0.1160	0.0709	0.0989	0.0693	-7.300 ***	-11.027 ***	-9.448 ***	-9.415 ***
NDA	0.9576	0.9649	0.9355	0.9284	0.9429	0.9327	0.0947	0.0882	0.0953	0.0915	-5.565 ***	-4.481 ***	-9.174 ***	-6.702 ***
NES	0.8722	0.9404	0.9255	0.9285	0.9306	0.9242	0.1019	0.0987	0.1159	0.1108	-11.307 ***	-11.183 ***	-12.105 ***	-7.477 ***
NOV	0.9186	0.9693	0.9855	0.9804	0.9786	0.9861	0.0837	0.0691	0.0904	0.0597	-9.673 ***	-20.229 ***	-9.349 ***	-14.398 ***
PHI	0.9852	1.0046	0.9886	0.9861	0.9863	0.9835	0.0576	0.0567	0.0426	0.0549	-10.721 ***	-6.720 ***	-4.163 ***	-5.160 ***
RBO	0.9714	0.9819	0.9781	0.9701	0.9728	0.9702	0.0667	0.0609	0.0880	0.0428	-12.251 ***	-10.192 ***	-85.006 ***	-5.166 ***
RD	0.9881	0.9915	0.9743	0.9623	0.9559	0.9575	0.0414	0.0540	0.0724	0.0567	-9.212 ***	-5.800 ***	-3.809 ***	-4.782 ***
ROG	0.9260	0.9718	0.9764	0.9756	0.9746	0.9681	0.0422	0.0285	0.0454	0.0486	-5.363 ***	-5.544 ***	-6.765 ***	-7.266 ***
SCH	0.9940	1.0157	1.0127	1.0112	1.0163	1.0086	0.0645	0.0421	0.0560	0.0486	-6.123 ***	-8.596 ***	-6.010 ***	-6.215 ***
SHB	0.9411	0.9662	0.9411	0.9444	0.9396	0.9428	0.0879	0.0681	0.1102	0.0741	-20.069 ***	-18.950 ***	-11.083 ***	-7.318 ***
SHE	0.8440	0.8704	0.8235	0.8292	0.8219	0.8283	0.1238	0.1063	0.1263	0.1030	-4.324 ***	-3.946 ***	-4.466 ***	-4.063 ***
SIE	0.7386	0.7785	0.8739	0.9221	0.9004	0.8964	0.1117	0.1997	0.2235	0.2209	-4.392 ***	-26.331 ***	-2.848 *	-3.448 ***
TEF	0.9495	0.9837	0.9847	0.9917	0.9826	0.9920	0.0474	0.0453	0.0586	0.0448	-5.715 ***	-11.255 ***	-10.977 ***	-13.002 ***
TI	0.1860	0.1799	0.2078	0.2080	0.4744	0.4432	0.2385	0.2399	0.3871	0.3938	-6.642 ***	-6.647 ***	-1.272	-1.206
TIM	0.8880	0.9145	0.8723	0.8648	0.8803	0.8786	0.1789	0.1689	0.1787	0.1953	-13.272 ***	-11.429 ***	-14.366 ***	-6.152 ***
TU	0.9843	0.9981	0.9885	0.9972	0.9945	0.9931	0.0519	0.0381	0.0582	0.0484	-10.593 ***	-14.928 ***	-18.879 ***	-9.584 ***
TOT	0.9760	0.9919	0.9794	0.9777	0.9702	0.9762	0.0643	0.0632	0.0643	0.0613	-7.662 ***	-9.019 ***	-6.499 ***	-7.206 ***
UBS	0.9212	0.9360	0.9462	0.9461	0.9506	0.9443	0.0911	0.0264	0.0442	0.0560	-11.489 ***	-7.851 ***	-6.460 ***	-8.302 ***
UC	0.9210	0.9378	0.8658	0.8470	0.8927	0.8231	0.1513	0.1248	0.1282	0.2405	-4.244 ***	-7.590 ***	-6.999 ***	-5.871 ***
VIV	0.9824	0.9974	0.9817	0.9713	0.9682	0.9658	0.0436	0.0361	0.0425	0.0443	-5.886 ***	-9.826 ***	-5.081 ***	-4.709 ***
VOF	0.9862	1.0020	0.9892	0.9880	0.9865	0.9860	0.0257	0.0293	0.0350	0.0337	-13.176 ***	-3.362 **	-5.919 ***	-8.747 ***
VOW	0.8603	0.9597	0.9534	0.9463	0.9577	0.9506	0.0868	0.0343	0.0896	0.0459	-8.604 ***	-8.432 ***	-10.491 ***	-8.727 ***
Average	**0.8281**	**0.8600**	**0.8837**	**0.8911**	**0.9113**	**0.9114**	**0.1063**	**0.1032**	**0.1161**	**0.1136**	**-9.508**	**-11.232**	**-9.274**	**-7.315**
Maximum	**1.0001**	**1.0222**	**1.0127**	**1.0112**	**1.0275**	**1.0086**	**0.2881**	**0.3460**	**0.3871**	**0.3938**	**-2.658**	**-2.696**	**-1.272**	**-1.206**
Minimum	**0.1242**	**0.1705**	**0.1849**	**0.1847**	**0.1859**	**0.3404**	**0.0257**	**0.0054**	**0.0350**	**0.0175**	**-31.467**	**-29.769**	**-85.006**	**-25.401**

Notes MEAN and STD are the mean and standard deviation of the hedge ratio series.
ADF is the Augmented Dickey Fuller test (Dickey and Fuller, 1981) on the level of the series. The ADF regressions include an intercept term; the lag length of the ADF test is determined by minimising Schwarz Bayesian criterion, SBC (Schwarz, 1978)

Table 4.8: Within-sample Hedging Effectiveness

	Portfolio Variance								Variance Reduction (%)						
	Unhedged	Constant Hedge			Time Varying Hedge				Constant Hedge			Time Varying Hedge			
		Naïve	OLS	VECM	BEKK	AsymBEKK	BEKK-X	AsymBEKK-X	Naive	OLS	VECM	BEKK	AsynBEKK	BEKK-X	AsynBEKK-X
AA	0.000713	0.000092	0.000090	0.000090	0.000090	0.000087	0.000090	0.000088	87.14	87.35	87.32	87.44	87.75 *	87.44	87.68
AGN	0.001267	0.008629	0.001116	0.001186	0.000681	0.000648	0.000676	0.000621	-581.06	11.93	6.38	46.22	48.83	46.63	50.96 *
AHL	0.002401	0.000160	0.000155	0.000155	0.000148	0.000138	0.000172	0.000137	93.33	93.53	93.53	93.81	94.23	92.83	94.29 *
ALV	0.000867	0.000261	0.000250	0.000261	0.000263	0.000265	0.000261	0.000271	69.87	71.15 *	69.90	69.67	69.42	69.94	68.73
AXA	0.000954	0.002133	0.000676	0.000676	0.000114	0.000111	0.000093	0.000094	-123.55	29.11	29.10	88.09	88.40	90.22 *	90.17
AZN	0.000410	0.000037	0.000037	0.000037	0.000038	0.000037	0.000038	0.000037	90.98	91.05	90.98	90.84	90.98	90.66	91.07 *
BAR	0.000480	0.002102	0.000405	0.000405	0.000170	0.000176	0.000149	0.000145	-338.03	15.53	15.53	64.47	63.40	68.95	69.69 *
BNP	0.000480	0.000563	0.000264	0.000264	0.000108	0.000093	0.000083	0.000083	-17.24	44.95	44.95	77.53	80.64	82.76 *	82.69
BPA	0.000312	0.000018	0.000018	0.000018	0.000018	0.000018	0.000018	0.000018	94.10	94.11	94.11	94.09	94.21 *	94.08	94.11
BTL	0.000606	0.000140	0.000126	0.000126	0.000112	0.000114	0.000119	0.000115	76.85	79.23	79.23	81.46 *	81.14	80.33	80.96
BVA	0.000512	0.000046	0.000046	0.000046	0.000047	0.000046	0.000047	0.000046	91.10	91.10 *	91.05	90.87	90.92	90.88	91.03
CA	0.000430	0.000052	0.000052	0.000052	0.000052	0.000051	0.000050	0.000051	87.81	88.00	87.89	87.84	88.18	88.28 *	88.23
CGE	0.001764	0.000448	0.000373	0.000386	0.000341	0.000266	0.000276	0.000262	74.59	78.87	78.10	80.65	84.90	84.33	85.15 *
CSG	0.000794	0.000071	0.000069	0.000069	0.000072	0.000070	0.000073	0.000069	91.03	91.36 *	91.31	90.93	91.19	90.79	91.32
DBK	0.000621	0.000147	0.000141	0.000148	0.000150	0.000143	0.000143	0.000141	76.28	77.23	76.20	75.83	76.92	76.90	77.29 *
DCY	0.000579	0.000145	0.000139	0.000142	0.000139	0.000139	0.000139	0.000140	75.06	75.96	75.50	75.97	75.98 *	75.93	75.88
DTE	0.000840	0.000239	0.000230	0.000239	0.000229	0.000231	0.000238	0.000235	71.57	72.60	71.60	72.73 *	72.55	71.63	72.00
ENI	0.000281	0.000579	0.000221	0.000221	0.000152	0.000105	0.000074	0.000072	-106.08	21.38	21.38	45.97	62.62	73.76	74.43 *
ENL	0.000259	0.000580	0.000196	0.000196	0.000136	0.000119	0.000093	0.000085	-123.99	24.33	24.32	47.34	54.16	64.10	67.12 *
EOA	0.000365	0.000114	0.000110	0.000112	0.000113	0.000112	0.000113	0.000110	68.64	69.73	69.28	68.98	69.17	69.13	69.92 *
ERC	0.001986	0.000264	0.000241	0.000241	0.000258	0.000219	0.000250	0.000209	86.70	87.88	87.88	86.99	88.98	87.41	89.47 *
FTE	0.001311	0.000093	0.000093	0.000093	0.000102	0.000088	0.000092	0.000087	92.89	92.94	92.94	92.26	93.28	93.02	93.34 *
GEN	0.000348	0.000037	0.000037	0.000037	0.000039	0.000037	0.000038	0.000037	89.33	89.42 *	89.33	88.77	89.25	89.11	89.33
GXW	0.000320	0.000025	0.000025	0.000025	0.000025	0.000024	0.000025	0.000025	92.29	92.34	92.32	92.31	92.35 *	92.31	92.35
HAS	0.000261	0.000027	0.000027	0.000027	0.000027	0.000027	0.000026	0.000027	89.60	89.64	89.63	89.81	89.59	89.86 *	89.77
HNM	0.000371	0.000093	0.000081	0.000084	0.000069	0.000077	0.000054	0.000067	74.94	78.14	77.45	81.40	79.37	85.40 *	81.81
ING	0.000898	0.000533	0.000357	0.000357	0.000200	0.000189	0.000088	0.000084	40.63	60.25	60.25	77.70	78.91	90.20	90.68 *
LLO	0.000442	0.000062	0.000060	0.000061	0.000058	0.000057	0.000058	0.000061	85.94	86.32	86.27	86.78	87.00 *	86.77	86.13
MUV	0.000857	0.000211	0.000196	0.000206	0.000200	0.000198	0.000195	0.000198	75.38	77.15	75.94	76.65	76.91	77.22 *	76.94
NDA	0.000500	0.000067	0.000066	0.000066	0.000065	0.000061	0.000062	0.000061	86.56	86.73	86.72	87.03	87.80	87.64	87.88 *
NES	0.000200	0.000048	0.000045	0.000046	0.000042	0.000041	0.000042	0.000040	75.93	77.60	77.12	78.79	79.51	78.95	80.15 *
NOV	0.000208	0.000031	0.000030	0.000031	0.000028	0.000028	0.000028	0.000028	84.92	85.59	85.33	86.64	86.71 *	86.40	86.56
PHI	0.001182	0.000074	0.000074	0.000075	0.000069	0.000067	0.000072	0.000069	93.70	93.73	93.69	94.20	94.30 *	93.90	94.19
RBO	0.000439	0.000054	0.000054	0.000054	0.000054	0.000053	0.000055	0.000052	87.71	87.79	87.78	87.79	88.02	87.56	88.16 *
RD	0.000318	0.000023	0.000023	0.000023	0.000023	0.000023	0.000023	0.000023	92.79	92.80	92.80	92.70	92.87	92.91 *	92.82
ROG	0.000277	0.000033	0.000031	0.000032	0.000033	0.000032	0.000032	0.000032	88.07	88.64 *	88.42	88.19	88.29	88.34	88.55
SCH	0.000544	0.000045	0.000045	0.000045	0.000046	0.000045	0.000045	0.000044	91.74	91.74	91.70	91.61	91.75	91.67	91.83 *
SHB	0.000257	0.000036	0.000035	0.000036	0.000035	0.000038	0.000034	0.000033	85.89	86.23	86.17	86.31	85.19	86.94	87.21 *
SHE	0.000323	0.000075	0.000066	0.000066	0.000063	0.000059	0.000064	0.000059	76.81	79.53	79.45	80.43	81.81 *	80.18	81.63
SIE	0.000722	0.000334	0.000278	0.000279	0.000277	0.000279	0.000219	0.000214	53.77	61.47	61.29	61.66	61.36	69.59	70.29 *
TEF	0.000462	0.000045	0.000044	0.000045	0.000043	0.000042	0.000042	0.000042	90.22	90.48	90.36	90.62	90.90	90.86	90.93 *
TI	0.000548	0.001645	0.000488	0.000488	0.000394	0.000394	0.000402	0.000441	-200.10	11.03	11.02	28.04	28.06 *	26.65	19.57
TIM	0.000404	0.000088	0.000083	0.000083	0.000078	0.000076	0.000080	0.000076	78.15	79.41	79.34	80.69	81.24 *	80.18	81.10
TLI	0.000701	0.000038	0.000038	0.000038	0.000036	0.000039	0.000037	0.000038	94.62	94.65	94.63	94.90 *	94.49	94.66	94.64
TOT	0.000296	0.000033	0.000033	0.000033	0.000034	0.000033	0.000033	0.000032	88.82	88.88	88.85	88.61	88.79	88.82	89.03 *
UBS	0.000364	0.000038	0.000036	0.000036	0.000037	0.000036	0.000036	0.000036	89.54	90.20 *	90.17	89.91	90.10	90.15	90.17
UC	0.000335	0.000071	0.000069	0.000069	0.000067	0.000068	0.000069	0.000066	78.78	79.36	79.33	80.04	79.81	79.28	80.39 *
VIV	0.001410	0.000105	0.000105	0.000105	0.000102	0.000102	0.000102	0.000101	92.54	92.57	92.55	92.75	92.80	92.79	92.84 *
VOF	0.000651	0.000055	0.000055	0.000056	0.000056	0.000056	0.000056	0.000056	91.48	91.50 *	91.47	91.44	91.43	91.42	91.44
VOW	0.000560	0.000170	0.000159	0.000165	0.000184	0.000159	0.000168	0.000161	69.64	71.53	70.57	67.22	71.59 *	69.95	71.35
Mean	**0.000649**	**0.000420**	**0.000154**	**0.000157**	**0.000118**	**0.000112**	**0.000109**	**0.000106**	**41.55**	**75.68**	**75.37**	**80.86**	**81.76**	**82.60**	**82.87 ***
Maximum	**0.002401**	**0.008629**	**0.001116**	**0.001186**	**0.000681**	**0.000648**	**0.000676**	**0.000621**	**94.62**	**94.65**	**94.63**	**94.90 ***	**94.49**	**94.66**	**94.64**
Minimum	**0.000200**	**0.000018**	**0.000018**	**0.000018**	**0.000018**	**0.000018**	**0.000018**	**0.000018**	**-581.06**	**11.03**	**6.38**	**28.04**	**28.06 ***	**26.65**	**19.57**
No. of " * "									**0**	**7**	**0**	**3**	**11**	**7**	**22**

Notes: This table presents in-sample comparisons of hedging performance under alternative model specifications.
Portfolio Variance is the variance of the hedged portfolio in equation (4.14). The results are rounded to 6 decimal places.
Variance Reduction is the variance reduction from the unhedged position with the use of the alternative models in equation (4.15). The results are rounded to 4 decimal places and reported as the percentage (%).
An asterisk (*) denotes the model with the largest variance reduction.

Table 4.9: Percentage Variance Improvement of AsymBEKK-X Hedge Compared to:

	Improvement of AsymBEKK-X over Other OHRs (%)					
	Constant Hedge			Time Varying Hedge		
	Naive	OLS	VECM	BEKK	AsymBEKK	BEKK-X
AA	4.18 *	2.62	2.85	1.93	-0.55	1.89
AGN	92.80 *	44.33	47.62	8.83	4.18	8.12
AHL	14.50	11.78	11.78	7.75	1.08	20.38 *
ALV	-3.78	-8.38	-3.89	-3.10	-2.25 *	-4.02
AXA	95.60 *	86.14	86.14	17.51	15.26	-0.47
AZN	1.05	0.32	1.03	2.58	1.10	4.40 *
BAR	93.08 *	64.12	64.12	14.69	17.19	2.38
BNP	85.24 *	68.56	68.56	22.98	10.62	-0.37
BPA	0.19	-0.09	0.07	0.38	-1.78	0.48 *
BTL	17.74 *	8.32	8.33	-2.73	-0.98	3.17
BVA	-0.80	-0.80	-0.30	1.68 *	1.17	1.57
CA	3.42 *	1.88	2.83	3.24	0.45	-0.44
CGE	41.57 *	29.72	32.19	23.26	1.65	5.22
CSG	3.18	-0.45	0.14	4.25	1.52	5.69 *
DBK	4.26	0.28	4.58	6.07 *	1.62	1.68
DCY	3.30 *	-0.32	1.58	-0.36	-0.41	-0.19
DTE	1.51 *	-2.21	1.38	-2.70	-2.02	1.28
ENI	87.59 *	67.47	67.47	52.67	31.58	2.52
ENL	85.32 *	56.55	56.55	37.56	28.27	8.41
EOA	4.07 *	0.62	2.07	3.03	2.42	2.55
ERC	20.82 *	13.10	13.12	19.08	4.42	16.35
FTE	6.38	5.70	5.74	14.02 *	0.94	4.63
GEN	-0.01	-0.85	0.02	4.98 *	0.76	2.04
GXW	0.72 *	0.08	0.29	0.46	-0.08	0.51
HAS	1.64	1.23	1.30	-0.44	1.68 *	-0.88
HNM	27.43 *	16.81	19.34	2.22	11.86	-24.60
ING	84.29 *	76.54	76.54	58.20	55.78	4.85
LLO	1.32 *	-1.36	-1.02	-4.97	-6.74	-4.82
MUV	6.30 *	-0.93	4.13	1.23	0.10	-1.25
NDA	9.84 *	8.68	8.72	6.58	0.65	1.91
NES	17.53 *	11.39	13.23	6.39	3.11	5.67
NOV	10.89 *	6.73	8.39	-0.56	-1.15	1.14
PHI	7.70	7.39	7.92 *	-0.11	-1.95	4.71
RBO	3.68	3.08	3.16	3.08	1.20	4.82 *
RD	0.46	0.27	0.29	1.71 *	-0.63	-1.22
ROG	4.05 *	-0.73	1.16	3.07	2.24	1.82
SCH	1.19	1.15	1.67	2.71 *	0.97	2.02
SHB	9.34	7.12	7.53	6.56	13.64 *	2.05
SHE	20.77 *	10.25	10.59	6.11	-1.00	7.30
SIE	35.73 *	22.89	23.25	22.51	23.11	2.29
TEF	7.21 *	4.72	5.88	3.32	0.25	0.69
TI	73.20 *	9.60	9.61	-11.77	-11.80	-9.66
TIM	13.51 *	8.21	8.52	2.15	-0.73	4.63
TLI	0.31	-0.14	0.21	-5.07	2.79 *	-0.30
TOT	1.80	1.33	1.54	3.63 *	2.08	1.83
UBS	6.06 *	-0.26	-0.03	2.59	0.73	0.20
UC	7.61 *	5.00	5.12	1.78	2.90	5.35
VIV	3.98 *	3.59	3.87	1.28	0.63	0.66
VOF	-0.43	-0.64	-0.36	0.06	0.08	0.23 *
VOW	5.61	-0.65	2.62	12.59 *	-0.87	4.63
Mean	**20.46 ***	**13.00**	**13.95**	**7.26**	**4.30**	**2.04**
Maximum	**95.60 ***	**86.14**	**86.14**	**58.20**	**55.78**	**20.38**
Minimum	**-3.78 ***	**-8.38**	**-3.89**	**-11.77**	**-11.80**	**-24.60**
No. of " + "	**46**	**36**	**45**	**40**	**35**	**38**
No. of " - "	**4**	**14**	**5**	**10**	**15**	**12**

Notes: This table compareds in-sample hedging performance of AsymBEKK-X based hedge ratios over other model specifications.
Improvement is measured as the variance reduction from the hedged position with the use of other models in equation (4.17).
The results are rounded to 4 decimal places and reported as the percentage (%).
An asterisk (*) denotes the model with the greatest improvement.
" + " denotes further variance reduction of AsymBEKK-X hedge over and above to that achieved by using other models.
" - " denotes additional variance of AsymBEKK-X hedge over and above to that achieved by using other models.

Table 4.10: Out-of-sample Hedging Effectiveness

Portfolio Variance

	Unhedged	Constant Hedge: Naive	Constant Hedge: OLS	Constant Hedge: VECM	Time Varying Hedge: BEKK	Time Varying Hedge: AsymBEKK	Time Varying Hedge: BEKK-X	Time Varying Hedge: AsymBEKK-X
AA	0.000088	0.000017	0.000016	0.000016	0.000016	0.000016	0.000016	0.000015
AGN	0.000155	0.000022	0.000047	0.000041	0.000055	0.000043	0.000033	0.000022
AHL	0.000258	0.000152	0.000136	0.000137	0.000098	0.000085	0.000426	0.000076
ALV	0.000133	0.000024	0.000023	0.000024	0.000020	0.000024	0.000020	0.000023
AXA	0.000149	0.000019	0.000022	0.000021	0.000020	0.000021	0.000021	0.000019
AZN	0.000126	0.000012	0.000011	0.000012	0.000012	0.000011	0.000011	0.000011
BAR	0.000116	0.000008	0.000083	0.000082	0.000024	0.000025	0.000009	0.000008
BNP	0.000107	0.000017	0.000037	0.000036	0.000025	0.000023	0.000019	0.000019
BPA	0.000138	0.000012	0.000012	0.000012	0.000008	0.000009	0.000010	0.000009
BTL	0.000137	0.000012	0.000012	0.000012	0.000012	0.000013	0.000011	0.000011
BVA	0.000067	0.000013	0.000013	0.000013	0.000012	0.000011	0.000013	0.000011
CA	0.000081	0.000011	0.000010	0.000010	0.000011	0.000011	0.000011	0.000011
CGE	0.000360	0.000012	0.000025	0.000016	0.000012	0.000012	0.000014	0.000012
CSG	0.000096	0.000024	0.000023	0.000023	0.000023	0.000022	0.000017	0.000021
DBK	0.000124	0.000011	0.000011	0.000011	0.000012	0.000011	0.000015	0.000011
DCY	0.000170	0.000033	0.000031	0.000032	0.000029	0.000030	0.000029	0.000031
DTE	0.000073	0.000024	0.000022	0.000024	0.000027	0.000024	0.000029	0.000026
ENI	0.000124	0.000030	0.000045	0.000045	0.000089	0.000051	0.000024	0.000030
ENL	0.000087	0.000036	0.000048	0.000048	0.000041	0.000039	0.000034	0.000032
EOA	0.000128	0.000020	0.000020	0.000019	0.000021	0.000019	0.000022	0.000021
ERC	0.000220	0.000079	0.000072	0.000072	0.000061	0.000055	0.000079	0.000044
FTE	0.000135	0.000013	0.000012	0.000012	0.000013	0.000012	0.000012	0.000013
GEN	0.000068	0.000016	0.000015	0.000016	0.000014	0.000014	0.000015	0.000014
GXW	0.000119	0.000003	0.000003	0.000003	0.000003	0.000003	0.000003	0.000003
HAS	0.000038	0.000015	0.000014	0.000015	0.000011	0.000012	0.000011	0.000011
HNM	0.000113	0.000014	0.000016	0.000015	0.000015	0.000016	0.000016	0.000040
ING	0.000096	0.000019	0.000020	0.000020	0.000029	0.000028	0.000018	0.000019
LLO	0.000091	0.000031	0.000030	0.000030	0.000027	0.000025	0.000027	0.000024
MUV	0.000110	0.000008	0.000008	0.000008	0.000008	0.000008	0.000008	0.000008
NDA	0.000110	0.000017	0.000017	0.000017	0.000021	0.000019	0.000019	0.000017
NES	0.000063	0.000014	0.000013	0.000013	0.000014	0.000013	0.000014	0.000013
NOV	0.000067	0.000027	0.000025	0.000026	0.000020	0.000025	0.000022	0.000020
PHI	0.000183	0.000021	0.000020	0.000021	0.000018	0.000018	0.000018	0.000018
RBO	0.000083	0.000009	0.000009	0.000009	0.000009	0.000009	0.000009	0.000009
RD	0.000108	0.001891	0.000293	0.000292	0.000097	0.000048	0.000100	0.000048
ROG	0.000134	0.000020	0.000018	0.000019	0.000020	0.000019	0.000019	0.000019
SCH	0.000081	0.000011	0.000011	0.000011	0.000011	0.000011	0.000011	0.000011
SHB	0.000096	0.000021	0.000020	0.000020	0.000021	0.000020	0.000022	0.000019
SHE	0.004652	0.000163	0.000042	0.000044	0.000042	0.000043	0.000044	0.000048
SIE	0.000105	0.000007	0.000009	0.000008	0.000007	0.000007	0.000009	0.000008
TEF	0.000061	0.000022	0.000020	0.000021	0.000019	0.000019	0.000019	0.000019
TI	0.000127	0.000025	0.000094	0.000095	0.000108	0.000109	0.000028	0.000026
TIM	0.000126	0.000051	0.000046	0.000046	0.000041	0.000038	0.000041	0.000042
TLI	0.000177	0.000028	0.000027	0.000028	0.000026	0.000022	0.000024	0.000024
TOT	0.000119	0.000009	0.000009	0.000009	0.000009	0.000009	0.000009	0.000009
UBS	0.000078	0.000018	0.000017	0.000017	0.000017	0.000016	0.000016	0.000016
UC	0.000130	0.000033	0.000031	0.000031	0.000031	0.000031	0.000035	0.000039
VIV	0.000112	0.000017	0.000017	0.000017	0.000015	0.000015	0.000015	0.000018
VOF	0.000150	0.000009	0.000009	0.000009	0.000009	0.000009	0.000009	0.000009
VOW	0.000179	0.000017	0.000015	0.000016	0.000017	0.000016	0.000016	0.000016
Mean	**0.000213**	**0.000063**	**0.000032**	**0.000032**	**0.000026**	**0.000024**	**0.000029**	**0.000021**
Maximum	**0.004652**	**0.001891**	**0.000293**	**0.000292**	**0.000108**	**0.000109**	**0.000426**	**0.000076**
Minimum	**0.000038**	**0.000003**	**0.000003**	**0.000003**	**0.000003**	**0.000003**	**0.000003**	**0.000003**
No. of "*"								

Variance Reduction (%)

	Constant Hedge: Naive	Constant Hedge: OLS	Constant Hedge: VECM	Time Varying Hedge: BEKK	Time Varying Hedge: AsymBEKK	Time Varying Hedge: BEKK-X	Time Varying Hedge: AsymBEKK-X
AA	81.27	82.40	82.07	81.54	82.27	81.68	82.56 *
AGN	85.75	69.49	73.60	64.40	72.33	78.83	86.03 *
AHL	41.12	47.33	47.04	61.91	66.95	-65.36	70.67 *
ALV	81.57	82.76	81.63	84.65	81.90	85.03 *	83.03
AXA	87.45	85.43	85.76	86.24	85.69	86.20	87.48 *
AZN	90.61	90.95	90.63	90.85	91.36	91.18	91.40 *
BAR	93.28 *	28.65	28.84	79.34	78.43	92.05	92.88
BNP	84.25 *	65.47	66.04	76.81	78.96	82.67	82.42
BPA	91.38	91.61	91.45	93.86 *	93.29	92.95	93.17
BTL	90.94	90.88	90.92	91.40	90.76	91.76 *	91.71
BVA	80.73	80.81	80.04	81.54	83.01	80.24	83.37 *
CA	87.07	87.36 *	87.16	86.38	87.03	86.84	85.91
CGE	96.74	93.02	95.58	96.74	96.79 *	96.11	96.76
CSG	75.02	76.61	76.14	76.00	77.61	82.57 *	78.15
DBK	91.21	91.23	91.20	90.65	91.48 *	87.90	90.89
DCY	80.85	81.86	81.37	82.67	82.63	83.04 *	81.68
DTE	67.38	69.79 *	67.42	62.84	67.42	59.85	64.31
ENI	75.40	63.30	63.65	28.11	58.56	80.83 *	75.57
ENL	58.94	45.53	45.54	52.87	55.31	61.06	63.52 *
EOA	84.68	84.74	84.86	83.56	84.90 *	82.80	83.55
ERC	64.06	67.27	67.08	72.24	74.86	64.18	80.05 *
FTE	90.71	90.91	90.87	90.38	90.81	91.01 *	90.45
GEN	77.11	78.41	77.16	79.47	79.60 *	77.53	79.51
GXW	97.26	97.29	97.29 *	97.27	97.24	97.10	97.28
HAS	60.33	62.33	61.68	70.36	68.76	69.89	71.06 *
HNM	87.30 *	86.15	87.02	86.83	86.08	86.32	64.85
ING	80.23	79.05	79.14	69.36	70.51	81.48 *	79.77
LLO	66.28	67.54	67.25	70.39	72.26	69.82	73.18 *
MUV	92.62	92.49	92.88	92.85	92.81	92.45	93.04 *
NDA	84.73	84.90 *	84.89	81.25	83.05	83.16	84.81
NES	77.58	79.24 *	78.89	78.04	78.99	77.28	78.93
NOV	60.19	63.50	61.78	69.68	62.81	67.87	70.35 *
PHI	88.67	88.80	88.58	89.90	89.90	89.97	90.36 *
RBO	88.79	89.02	88.97	88.88	88.78	89.18 *	89.04
RD	-1647.13	-170.22	-169.75	10.47	55.21	7.74	55.38 *
ROG	84.97	86.20 *	85.78	85.36	85.56	85.58	85.74
SCH	86.39	86.43	86.30	86.15	86.50	86.64 *	86.39
SHB	78.17	79.13	78.88	77.88	79.44	76.80	80.51 *
SHE	96.49	99.09 *	99.05	99.09	99.08	99.06	98.98
SIE	93.35 *	91.62	92.18	92.91	92.90	91.53	92.04
TEF	64.01	66.99	65.58	68.24	69.01 *	68.57	68.26
TI	80.11 *	25.77	25.16	15.05	14.42	78.16	79.13
TIM	59.54	63.88	63.25	67.50	69.54 *	67.27	66.75
TLI	84.44	84.61	84.50	85.53	87.41 *	86.20	86.40
TOT	92.38	92.47	92.42	92.46	92.28	92.49 *	92.46
UBS	76.41	78.58	78.25	78.66	79.31	79.97 *	79.57
UC	74.50	76.52 *	76.28	76.31	76.49	73.38	69.82
VIV	84.50	84.87	84.58	86.21	86.58 *	86.27	84.25
VOF	94.01	94.24 *	94.10	93.83	94.15	94.07	94.14
VOW	90.61	91.45 *	91.14	90.49	91.13	91.18	91.24
Mean	**46.69**	**73.35**	**73.24**	**77.91**	**80.04**	**78.41**	**82.38 ***
Maximum	**97.26**	**99.09 ***	**99.05**	**99.09**	**99.08**	**99.06**	**98.98**
Minimum	**-1647.13**	**-170.22**	**-169.75**	**10.47**	**14.42**	**-65.36**	**55.38 ***
No. of "*"	**5**	**9**	**1**	**1**	**8**	**11**	**15**

Notes This table presents out-of-sample comparisons of hedging performance under alternative model specifications.
Portfolio Variance is the variance of the hedged portfolio in equation (4.14). The results are rounded to 6 decimal places.
Variance Reduction is the variance reduction from the unhedged position with the use of the alternative models in equation (4.15). The results are rounded to 4 decimal places and reported as the percentage (%).
An asterisk (*) denotes the model with the largest variance reduction.

Table 4.11: Out-of-sample Percentage Variance Improvement of AsymBEKK-X Hedge Compared to:

	Improvement of AsymBEKK-X over Other OHRs (%)					
	Constant Hedge			Time Varying Hedge		
	Naive	OLS	VECM	BEKK	AsymBEKK	BEKK-X
AA	6.86 *	0.89	2.69	5.48	1.61	4.76
AGN	1.97	54.20	47.07	60.75 *	49.50	33.99
AHL	50.18	44.31	44.61	23.00	11.24	82.26 *
ALV	7.88 *	1.53	7.60	-10.57	6.25	-13.42
AXA	0.23	14.06 *	12.06	9.03	12.49	9.26
AZN	8.51 *	4.99	8.24	6.02	0.50	2.59
BAR	-5.88	90.02 *	90.00	65.55	67.00	10.46
BNP	-11.59	49.08 *	48.23	24.20	16.45	-1.46
BPA	20.85 *	18.65	20.13	-11.19	-1.77	3.24
BTL	8.52	9.15	8.76	3.59	10.33 *	-0.62
BVA	13.70	13.35	16.70 *	9.94	2.11	15.85
CA	-8.96	-11.41	-9.75	-3.45 *	-8.64	-7.03
CGE	0.62	53.65 *	26.77	0.76	-0.91	16.84
CSG	12.55 *	6.62	8.46	8.98	2.42	-25.33
DBK	-3.68	-3.82	-3.52	2.57	-6.88	24.70 *
DCY	4.32 *	-1.02	1.64	-5.69	-5.49	-8.02
DTE	-9.41	-18.13	-9.53	3.95	-9.54	11.11 *
ENI	0.68	33.44	32.79	66.01 *	41.05	-27.46
ENL	11.15	33.02 *	33.01	22.60	18.36	6.32
EOA	-7.42	-7.81	-8.69	-0.05	-8.94	4.37 *
ERC	44.50 *	39.05	39.42	28.14	20.65	44.32
FTE	-2.87	-5.07	-4.67	0.76 *	-3.92	-6.30
GEN	10.49 *	5.08	10.28	0.19	-0.43	8.81
GXW	0.64	-0.40	-0.48	0.50	1.32	6.18 *
HAS	27.05 *	23.17	24.48	2.37	7.36	3.90
HNM	-176.75	-153.76	-170.87	-167.01	-152.46 *	-156.95
ING	-2.35	3.43	3.00	33.96 *	31.39	-9.25
LLO	20.46 *	17.39	18.12	9.42	3.33	11.13
MUV	5.63	7.25	2.22	2.52	3.13	7.70 *
NDA	0.54	-0.61	-0.53	19.00 *	10.40	9.81
NES	6.05	-1.46	0.19	4.06	-0.26	7.28 *
NOV	25.52 *	18.78	22.43	2.20	20.28	7.72
PHI	14.94	13.91	15.60 *	4.54	4.54	3.86
RBO	2.21	0.23	0.68	1.46	2.36 *	-1.27
RD	97.45 *	83.49	83.46	50.17	0.39	51.64
ROG	5.11 *	-3.34	-0.28	2.60	1.24	1.11
SCH	0.00	-0.30	0.60	1.69 *	-0.85	-1.88
SHB	10.72	6.60	7.71	11.89	5.22	16.01 *
SHE	70.84 *	-12.75	-7.56	-12.36	-10.69	-8.85
SIE	-19.61	5.12	-1.68	-12.22	-11.99	6.03 *
TEF	11.81 *	3.84	7.80	0.06	-2.43	-0.99
TI	-4.94	71.89	72.11	75.43	75.61 *	4.46
TIM	17.83 *	7.96	9.53	-2.30	-9.14	-1.58
TLI	12.61 *	11.67	12.27	6.05	-7.97	1.44
TOT	1.08	-0.06	0.54	-0.01	2.36 *	-0.34
UBS	13.39 *	4.62	6.06	4.25	1.27	-2.01
UC	-18.35	-28.57	-27.23	-27.44	-28.38	-13.38 *
VIV	-1.60 *	-4.07	-2.12	-14.18	-17.32	-14.73
VOF	2.16	-1.72	0.71	5.01 *	-0.23	1.25
VOW	6.66	-2.49	1.10	7.84 *	1.18	0.60
Mean	**5.65**	**9.87**	**10.00 ***	**6.40**	**2.86**	**2.36**
Maximum	**97.45 ***	**90.02**	**90.00**	**75.43**	**75.61**	**82.26**
Minimum	**-176.75**	**-153.76**	**-170.87**	**-167.01**	**-152.46 ***	**-156.95**
No. of " + "	**36**	**32**	**37**	**38**	**30**	**31**
No. of " - "	**14**	**18**	**13**	**12**	**20**	**19**

Notes: This table compareds out-of-sample hedging performance of AsymBEKK-X based hedge ratios over other model specifications. Improvement is measured as the variance reduction from the hedged position with the use of other models in equation (4.17). The results are rounded to 4 decimal places and reported as the percentage (%).
An asterisk (*) denotes the model with the greatest improvement.
" + " denotes further variance reduction of AsymBEKK-X hedge over and above to that achieved by using other models.
" - " denotes additional variance of AsymBEKK-X hedge over and above to that achieved by using other models.

Table 4.12: Utility Comparisons for Out-of-Sample Hedging Performance

	Utility Comparison for Out-of-Sample Hedging Performance_Degree of Risk Aversion = 4 (%)						
	Constant Hedge			Time Varying Hedge			
	Naive	OLS	VECM	BEKK	AsymBEKK	BEKK-X	AsymBEKK-X
AA	-0.0258	-0.0208	-0.0226	-0.0138	-0.0222	-0.0214	-0.0121 *
AGN	-0.0285 *	-0.0590	-0.0569	-0.0560	-0.0295	-0.0337	-0.0665
AHL	-0.1519	-0.1332	-0.1340	-0.1032	-0.0919	-0.0886 *	-0.0958
ALV	-0.0251	-0.0085 *	-0.0247	-0.0344	-0.0226	-0.0266	-0.0346
AXA	-0.0188	0.0003	-0.0047	-0.0033	0.0017 *	-0.0217	-0.0020
AZN	-0.0122	-0.0072	-0.0113	0.0010 *	0.0007	-0.0021	-0.0022
BAR	-0.0073	-0.0730	-0.0761	0.0001 *	-0.0011	-0.0075	-0.0027
BNP	-0.0150	-0.0027	-0.0021	0.0002	0.0022 *	-0.0080	-0.0031
BPA	-0.0117	-0.0097	-0.0111	0.0070	-0.0014	-0.0061	0.0079 *
BTL	-0.0130	-0.0095	-0.0095	-0.0059 *	-0.0178	-0.0064	-0.0069
BVA	-0.0088	-0.0085	-0.0106	-0.0061	-0.0067	-0.0059	-0.0043 *
CA	-0.0097	-0.0084 *	-0.0098	-0.0111	-0.0088	-0.0173	-0.0117
CGE	-0.0125	-0.0288	-0.0181	-0.0119	-0.0056	-0.0079	-0.0045 *
CSG	-0.0244	-0.0139 *	-0.0172	-0.0184	-0.0146	-0.0165	-0.0257
DBK	-0.0106	-0.0020 *	-0.0105	-0.0115	-0.0118	-0.0093	-0.0223
DCY	-0.0315	-0.0216 *	-0.0278	-0.0431	-0.0263	-0.0264	-0.0599
DTE	-0.0229	-0.0265	-0.0228 *	-0.0258	-0.0334	-0.0236	-0.0383
ENI	-0.0207	0.0071 *	0.0067	0.0066	-0.0466	-0.0288	-0.0223
ENL	-0.0232	-0.0297	-0.0298	-0.0335	-0.0201 *	-0.0323	-0.0287
EOA	-0.0191	-0.0096	-0.0156	-0.0171	-0.0200	-0.0090	-0.0090 *
ERC	-0.0779	-0.0593 *	-0.0599	-0.0600	-0.1039	-0.0770	-0.0786
FTE	-0.0095 *	-0.0105	-0.0103	-0.0113	-0.0125	-0.0158	-0.0305
GEN	-0.0146	-0.0102	-0.0142	-0.0023	-0.0009	0.0012 *	-0.0172
GXW	-0.0039	-0.0014	-0.0024	-0.0009	-0.0020	-0.0017	-0.0007 *
HAS	-0.0222	-0.0191	-0.0199	-0.0123	-0.0155	-0.0122 *	-0.0130
HNM	-0.0120	-0.0021	-0.0062	-0.0069	-0.0031	0.0016 *	-0.0032
ING	-0.0182	-0.0123	-0.0134	-0.0001	0.0103 *	-0.0039	-0.0002
LLO	-0.0319	-0.0298	-0.0304	-0.0166 *	-0.0222	-0.0213	-0.0196
MUV	-0.0081	0.0035 *	-0.0056	-0.0068	-0.0049	0.0017	-0.0185
NDA	-0.0248	-0.0202	-0.0208	-0.0308	-0.0243	-0.0251	-0.0069 *
NES	-0.0107	0.0029	-0.0034	-0.0078	0.0078	0.0084 *	0.0060
NOV	-0.0262	-0.0180	-0.0223	0.0127	0.0190 *	-0.0019	0.0166
PHI	-0.0207	-0.0206 *	-0.0208	-0.0217	-0.0215	-0.0207	-0.0234
RBO	-0.0082	-0.0081 *	-0.0081	-0.0126	-0.0148	-0.0085	-0.0111
RD	-1.6230	-0.1900	-0.1901	-0.0223	-0.0033 *	-0.0052	-0.0206
ROG	-0.0197	-0.0052 *	-0.0123	-0.0168	-0.0073	-0.0098	-0.0137
SCH	-0.0132	-0.0125	-0.0145	-0.0041	-0.0103	-0.0108	-0.0038 *
SHB	-0.0198	-0.0147	-0.0164	-0.0150	-0.0181	-0.0152	-0.0063 *
SHE	-0.2299	-0.0303	-0.0368	-0.0407	-0.0389	-0.0437	-0.0146 *
SIE	-0.0149	-0.0101	-0.0163	-0.0038 *	-0.0118	-0.0140	-0.0116
TEF	-0.0040 *	-0.0046	-0.0044	-0.0081	-0.0083	-0.0101	-0.0071
TI	-0.0239 *	-0.1675	-0.1687	-0.1865	-0.1916	-0.0389	-0.0506
TIM	-0.0546	-0.0555	-0.0554	-0.0464	-0.0324 *	-0.0411	-0.0486
TUI	-0.0195	-0.0186	-0.0190	-0.0182	-0.0172 *	-0.0181	-0.0317
TOT	-0.0094	-0.0069	-0.0089	-0.0017	-0.0067	-0.0040	-0.0006 *
UBS	-0.0182	-0.0079	-0.0101	-0.0103	-0.0163	-0.0055 *	-0.0058
UC	-0.0313	-0.0133	-0.0168	-0.0088	-0.0174	-0.0208	-0.0078 *
VIV	-0.0174	-0.0163	-0.0172	-0.0148	-0.0117 *	-0.0146	-0.0120
VOF	-0.0094	-0.0097	-0.0097	-0.0082	-0.0098	-0.0112	-0.0072 *
VOW	-0.0177	-0.0068 *	-0.0137	-0.0192	-0.0209	-0.0125	-0.0168
Mean	**-0.0582**	**-0.0248**	**-0.0271**	**-0.0196**	**-0.0197**	**-0.0170**	**-0.0155 ***
Maximum	**-0.0039**	**0.0071**	**0.0067**	**0.0127**	**0.0190 ***	**0.0084**	**0.0166**
Minimum	**-1.6230**	**-0.1900**	**-0.1901**	**-0.1865**	**-0.1916**	**-0.0886 ***	**-0.0958**
No. of " * "	**4**	**12**	**1**	**5**	**9**	**6**	**13**
No. of " + "							
No. of " - "							

	Utility Improvement of AsymBEKK-X over Other OHRs_Degree of Risk Aversion = 4 (%)					
	Constant Hedge			Time Varying Hedge		
	Naive	OLS	VECM	BEKK	AsymBEKK	BEKK-X
AA	53.21	42.06	46.69	12.94	45.66	43.61
AGN	-133.22	-12.68	-16.73	-18.59	-125.47	-97.09
AHL	36.91	28.07	28.48	7.20	-4.30	-8.19
ALV	-38.22	-305.77	-40.54	-0.81	-53.62	-30.04
AXA	89.44	-685.68	57.72	39.82	-217.59	90.83
AZN	82.30	70.12	80.81	-311.87	-415.42	-4.41
BAR	63.20	96.32	96.47	-5381.31	-147.79	64.36
BNP	79.13	-14.89	-47.82	-1697.78	-241.38	60.99
BPA	167.67	181.67	171.51	12.81	649.47	230.31
BTL	46.65	26.79	26.74	-18.47	60.94	-7.84
BVA	51.61	49.45	59.55	29.75	35.71	27.56
CA	-20.30	-40.06	-19.61	-5.71	-33.63	32.08
CGE	64.31	84.45	75.34	62.43	20.85	43.51
CSG	-5.66	-85.80	-49.25	-39.55	-76.31	-55.57
DBK	-109.48	-1011.33	-112.33	-94.30	-89.01	-139.68
DCY	-90.55	-177.91	-115.74	-39.07	-128.25	-127.27
DTE	-67.14	-44.55	-68.13	-48.37	-14.46	-62.04
ENI	-8.02	-414.20	-432.93	-440.05	52.15	22.57
ENL	-23.74	3.38	3.77	14.35	-42.57	11.17
EOA	53.16	6.84	42.56	47.67	55.14	0.95
ERC	-0.99	-32.54	-31.33	-31.03	24.36	-2.14
FTE	-221.94	-190.56	-196.61	-169.85	-143.98	-93.26
GEN	-18.13	-68.93	-21.79	-640.58	-1826.80	-1578.46
GXW	81.87	51.06	71.14	20.52	65.92	58.70
HAS	41.20	31.73	34.48	-6.27	15.92	-6.75
HNM	73.60	-49.23	49.17	54.18	-3.80	-303.67
ING	99.06	98.61	98.72	-99.39	-101.67	95.61
LLO	38.43	34.07	35.38	-18.42	11.70	7.74
MUV	-127.29	-628.76	-230.39	-173.92	-278.26	-1206.14
NDA	71.97	65.68	66.60	77.42	71.46	72.34
NES	156.15	106.14	275.69	177.42	-22.51	-28.18
NOV	163.38	192.25	174.23	30.57	-12.72	985.34
PHI	-13.24	-13.77	-12.63	-7.96	-9.05	-13.32
RBO	-35.79	-36.80	-36.76	12.32	24.98	-29.81
RD	98.73	89.17	89.17	7.54	-527.55	-298.76
ROG	30.23	-166.75	-11.51	18.40	-87.38	-40.32
SCH	71.19	69.59	73.74	5.99	63.12	64.69
SHB	68.25	57.05	61.64	58.08	65.25	58.48
SHE	93.65	51.81	60.30	64.11	62.45	66.61
SIE	22.22	-15.14	29.06	-202.65	1.56	17.59
TEF	-78.51	-55.16	-62.76	12.27	13.76	29.54
TI	-111.52	69.78	70.00	72.86	73.58	-30.18
TIM	11.08	12.42	12.33	-4.69	-50.07	-18.23
TUI	-62.61	-70.16	-67.00	-74.37	-83.79	-74.65
TOT	93.69	91.40	93.30	64.78	91.15	85.00
UBS	68.15	26.68	42.63	43.85	64.50	-5.95
UC	75.05	41.08	53.47	11.63	55.14	62.51
VIV	30.87	26.26	29.97	18.46	-3.29	17.29
VOF	22.93	25.39	25.48	11.28	26.46	35.21
VOW	5.03	-145.46	-22.61	12.66	19.81	-34.29
Mean	**20.76**	**-50.74**	**10.79**	**-170.47**	**-61.39**	**-40.23**
Maximum	**167.67**	**192.25**	**275.69**	**177.42**	**649.47**	**985.34**
Minimum	**-221.94**	**-1011.33**	**-432.93**	**-5381.31**	**-1826.80**	**-1578.46**
No. of " * "						
No. of " + "	**32**	**28**	**31**	**27**	**24**	**25**
No. of " - "	**18**	**22**	**19**	**23**	**26**	**25**

Notes This table compareds out-of-sample utility of alternative hedge models and presents the Utility improvement of AsymBEKK-X based hedge ratios over other model specifications.
Improvement is measured as the utility changes from the hedged position with the use of other models in equation (4.18). The results are rounded to 4 decimal places and reported as the percentage (%).
An asterisk (*) denotes the model with the highest utility
" + " denotes utility improvement of AsymBEKK-X hedge over and above to that achieved by using other models.
" - " denotes utility reduction of AsymBEKK-X hedge from that achieved by using other models.

Table 4.13: Descriptive Statistics of OHRs and HE of USFs_8 Countries

		Mean	Std Deviation	25th percentile	Median	75th percentile
A :	**Optimal Hedge Ratios (OHRs)**					
	France (7)	0.9256	0.0821	0.9165	0.9658	0.9743
	Germany (8)	0.9611	0.0332	0.9485	0.9651	0.9786
	Italy (6)	0.7781	0.1799	0.7694	0.8069	0.8647
	Netherlands (6)	0.8316	0.2458	0.8593	0.9357	0.9543
	Spain (3)	1.0021	0.0089	0.9989	1.0058	1.0072
	Sweden (5)	0.9597	0.0235	0.9428	0.9621	0.9679
	Switzerland (5)	0.9577	0.0239	0.9443	0.9660	0.9681
	UK (10)	0.9149	0.1028	0.8852	0.9572	0.9855
	Whole Sample (50)	**0.9114**	**0.1298**	**0.8977**	**0.9598**	**0.9782**
B :	**Hedging Effectiveness (HE)**					
	France (7)	0.8878	0.0387	0.8669	0.8903	0.9151
	Germany (8)	0.7280	0.0340	0.7020	0.7167	0.7615
	Italy (6)	0.6866	0.2516	0.6894	0.7741	0.8092
	Netherlands (6)	0.8510	0.1691	0.8843	0.9175	0.9385
	Spain (3)	0.9126	0.0050	0.9098	0.9103	0.9143
	Sweden (5)	0.8820	0.0461	0.8721	0.8788	0.8947
	Switzerland (5)	0.8735	0.0441	0.8656	0.8855	0.9017
	UK (10)	0.8653	0.0736	0.8276	0.8896	0.9135
	Whole Sample (50)	**0.8287**	**0.1302**	**0.7801**	**0.8778**	**0.9100**

Notes:
This table presents the cross-sectional descriptive statistics of the optimal hedge ratios (OHRs) and the hedging effectiveness measures (HE) estimated on the basis of variance-covariance coefficients in AsymBEKK-X model (4.13) and as given by formula (4.6) and (4.15). The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland.

Table 4.14: Descriptive Statistics of OHRs and HE of USFs_Europe vs UK

		Mean	*Z-test*	Std Deviation	25th percentile	Median	75th percentile
A :	**Optimal Hedge Ratios**						
	A.1 : Home Market (10 UK Stocks)						
	OHRs	0.9149		0.1028	0.8852	0.9572	0.9855
	A.2 : Foreign Market (40 European Stocks)						
	OHRs	0.9105	⇓ <0.1122>	0.1368	0.9172	0.9598	0.9763
B :	**Hedging Effectiveness**						
	B.1 : Home Market (10 UK Stocks)						
	HE	0.8653		0.0736	0.8276	0.8896	0.9135
	B.2 : Foreign Market (40 European Stocks)						
	HE	0.8195	⇓ <1.4261>	0.1400	0.7667	0.8744	0.9074

Notes:
This table presents cross-sectional descriptive statistics of the optimal hedge ratios (OHRs) and the hedging effectiveness measures (HE) estimated on the basis of variance-covariance coefficients in AsymBEKK-X model (4.13) and as given by formula (4.6) and (4.15). The entire 50 USFs sample were split into two groups, one includes the 10 USFs that trading on U.K. stocks and the other one includes all the remaining USFs that basing on 40 European stocks. Non-parametric Wilcoxon signed rank test (Z-test) examines whether the mean value of OHRs and HE in European USFs is significantly higher.

< > Wilcoxon Z-test statistics

*, **, *** Significant at 10%, 5% and 1% level, respectively.

↑ = higher ; ⇓ = lower

Table 4.15: Descriptive Statistics for HE of USFs_8 Countries_P1 & P2

	Mean	Z-test	Std Deviation	25th percentile	Median	75th percentile
A : Introduction Period (P1)						
France (7)	0.8873		0.0485	0.8549	0.9005	0.9172
Germany (8)	0.7080		0.0391	0.6827	0.6908	0.7444
Italy (6)	0.6974		0.2664	0.7031	0.7785	0.8449
Netherlands (6)	0.8453		0.1975	0.8859	0.9198	0.9482
Spain (3)	0.9161		0.0035	0.9144	0.9164	0.9179
Sweden (5)	0.8905		0.0406	0.8868	0.8889	0.8900
Switzerland (5)	0.8798		0.0427	0.8677	0.8994	0.9064
UK (10)	0.8628		0.0857	0.8432	0.8877	0.9176
Whole Sample (50)	**0.8272**		**0.1405**	**0.7714**	**0.8852**	**0.9111**
B : Maturity Period (P2)						
France (7)	0.8881	↑ <-0.0355>	0.0389	0.8668	0.8695	0.9000
Germany (8)	0.7964	↑ <-4.7591> ***	0.0351	0.7636	0.8001	0.8202
Italy (6)	0.6209	⇓ <0.5636>	0.1990	0.4989	0.6623	0.7693
Netherlands (6)	0.8768	↑ <-0.3835>	0.0377	0.8471	0.8867	0.8945
Spain (3)	0.9000	⇓ <1.7260> *	0.0158	0.8920	0.8998	0.9078
Sweden (5)	0.8337	⇓ <1.2478>	0.0933	0.7801	0.7994	0.9151
Switzerland (5)	0.8430	⇓ <1.1658>	0.0562	0.8252	0.8598	0.8730
UK (10)	0.8765	↑ <-0.4142>	0.0597	0.8671	0.8849	0.9117
Whole Sample (50)	**0.8284**	↑ <-0.0497>	**0.1150**	**0.7905**	**0.8624**	**0.8968**

Notes:
This table presents the cross-sectional descriptive statistics of the hedging effectiveness measures (HE) estimated on the basis of variance-covariance coefficients in AsymBEKK-X model (4.13) and as given by formula (4.15). The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland.
Non-parametric Wilcoxon signed rank test (Z-test) examines whether the mean value of HE in Maturity period is significantly higher.
< > Wilcoxon Z-test statistics ; ↑ = higher ; ⇓ = lower
*, **, *** Significant at 10%, 5% and 1% level, respectively.

Table 4.16: Determinants of the USF Hedging Effectiveness

Variable	Expected sign	Model 1	Model 2	Model 3	Model 4	Model 5
Constant		1.14500 ***	1.05149 ***	1.33778 ***	1.21549 ***	1.04697 ***
		(4.650)	(3.870)	(4.950)	(4.720)	(6.310)
MonthsListed	+	-0.00520	-0.00252	-0.00530	-0.00771	-0.00370
		(-1.120)	(-0.470)	(-1.240)	(-1.530)	(-1.210)
HomeMarket	+	0.03807	0.08099 ***	0.04778 **	0.05531 *	0.17369 **
		(1.320)	(2.600)	(2.020)	(1.870)	(2.270)
VolumeRatio	-	-0.04401 ***				
		(-2.850)				
TradeFrequency	-		-0.22499 ***			
			(-2.600)			
SpreadRatio	-			-0.19714 ***		
				(-3.260)		
Volatility	±				1.37480	
					(0.792)	
ContractSize	-					-0.14684 *
						(-1.840)
F-statistics		2.66 *	1.71	7.69 ***	0.98	3.33 **
		(0.060)	(0.178)	(0.000)	(0.410)	(0.027)
Adjusted R2		0.15	0.10	0.33	0.06	0.18
Number of observations		50	50	50	50	50

Notes:
The dependent variable is the hedging effectiveness (HE) of the USF estimated on the basis of variance-covariance coefficients in AsymBEKK-X model (4.13), and as given by formula (4.15). *MonthListed* is the number of months for which a USF has been listed in the Euronext.LIFFE through December 30,2005. *HomeMarket* is a dummy variable that takes a value of one for the U.K. USFs and zero for the European USFs. The relative trading volume of USF and stock markets, *VolumeRatio*, is measured as the ratio USF volume to stock volume. *TradeFrequency* is calculated as the average number of USF trading days over the whole sample period relative to that of stock markets. The variable *SpreadRatio* is the ratio of effective spread on the USF and the stock markets. We measure stock volatility, *Volatility*, as the standard deviation of daily stock return. The dummy variable *ContractSize* is equal one for contracts written on U.K. and Italian based stocks which represent 1000 stocks and zero for others smaller size contracts. The sample consist of a total of 50 USFs contracts including (i) 10 USFs based on stocks traded in U.K., (ii) 7 USFs for stocks traded in France, (iii) 8 USFs for stocks traded in Germany, (iv) 6 USFs for stocks traded in Italy, (v) 6 USFs for stocks traded in Netherlands, (vi) 3 USFs for stocks traded in Spain, (vii) 5 USFs for stocks traded in Sweden, and (viii) 5 USFs for stocks traded in Switzerland. Adjusted t-statistics based on the heteroskedasticity-consistent covariance matrix as per Newey and West (1987) are in parentheses below the coefficients. The number in parentheses under F statistics is the probability value of significance (i.e. P-value).
*, **, *** denote significant at 10%, 5%, and 1% respectively.

Table 4.17: Relative Hedging Effectiveness of the Universal Stock Futures (USF) vs Stock Index Futures (SIF)

Spot Asset			Hedging Instruments: USF		Hedging Instruments: SIF		Relative Hedging Effectiveness	
Code	Stock Name	No. of Observations	OHR (β_{1USF})	HE (R^2)	OHR (β_{1SIF})	HE (R^2)	α_1	t-statistics
AA	ABN AMRO Holdings NV	809	0.954	0.873	1.133	0.724	-0.5083	-4.32 ***
AGN	Aegon NV	809	0.124	0.119	1.525	0.738	0.8990	11.60 ***
AHL	Koninklijke Ahold NV	809	0.955	0.935	1.218	0.249	-0.9099	-7.50 ***
ALV	Allianz AG	965	0.882	0.711	1.287	0.679	-0.0752	-0.58
AXA	Axa SA	965	0.304	0.291	1.270	0.499	0.4113	1.78 *
AZN	AstraZeneca plc	1016	0.974	0.910	0.842	0.330	-0.8769	-23.10 ***
BAR	Barclays plc	939	0.173	0.155	1.163	0.540	0.7437	6.54 ***
BNP	BNP Paribas SA	939	0.460	0.450	0.918	0.520	0.1299	0.37
BPA	BP plc	1016	0.987	0.941	0.834	0.425	-0.8861	-33.20 ***
BTL	BT Group plc	965	0.852	0.792	0.997	0.315	-0.7631	-3.36 ***
BVA	Banco Bilbao Vizcaya Argentaria SA	939	1.000	0.911	1.338	0.820	-0.4696	-4.74 ***
CA	Carrefour SA	939	0.955	0.880	0.802	0.443	-0.8210	-18.50 ***
CGE	Alcatel SA	1016	0.811	0.789	1.456	0.349	-0.7186	-2.77 ***
CSG	Credit Suisse Group	807	0.944	0.914	1.532	0.604	-0.8538	-12.30 ***
DBK	Deutsche Bank AG	1016	0.900	0.772	1.119	0.710	-0.1602	-1.67 *
DCY	DaimlerChrysler AG	939	0.902	0.760	1.028	0.654	-0.2594	-2.77 ***
DTE	Deutsche Telekom AG	1016	0.893	0.726	1.131	0.536	-0.3941	-3.95 ***
ENI	Eni SpA	1016	0.291	0.214	0.783	0.414	0.4945	1.27
ENL	Enel SpA	967	0.288	0.243	0.759	0.429	0.4029	1.92 *
EOA	E.ON AG	939	0.889	0.697	0.681	0.455	-0.4485	-5.58 ***
ERC	Telefonaktiebolaget LM Ericsson AB	807	0.896	0.879	1.845	0.449	-0.8278	-4.07 ***
FTE	France Telecom SA	1016	0.977	0.929	1.228	0.334	-0.9132	-16.60 ***
GEN	Assicurazioni Generali SpA	967	0.969	0.894	1.036	0.594	-0.7719	-12.30 ***
GXW	GlaxoSmithKline plc	1016	0.977	0.923	0.822	0.402	-0.8769	-34.30 ***
HAS	HSBC Holdings plc	1016	0.979	0.896	0.842	0.517	-0.8333	-17.80 ***
HNM	Hennes & Mauritz AB	807	0.832	0.781	0.643	0.292	-0.8323	-3.14 ***
ING	ING Groep NV	1016	0.637	0.603	1.424	0.777	0.4104	1.26
LLO	Lloyds TSB Group plc	965	0.938	0.863	1.102	0.527	-0.6883	-11.30 ***
MUV	Münchener Rücksversicherungs Gesellschaft AG	965	0.869	0.771	1.233	0.631	-0.2932	-2.93 ***
NDA	Nordea AB	807	0.958	0.867	0.874	0.400	-0.8677	-10.30 ***
NES	Nestle SA	807	0.872	0.776	0.699	0.499	-0.5951	-6.37 ***
NOV	Novartis AG	807	0.919	0.856	0.756	0.561	-0.7651	-6.97 ***
PHI	Koninklijke Philips Electronics NV	835	0.985	0.937	1.433	0.690	-0.7243	-12.40 ***
RBO	Royal Bank of Scotland Group plc	939	0.971	0.878	1.141	0.568	-0.7373	-11.50 ***
RD	Royal Dutch Petroleum Company	1016	0.988	0.928	0.701	0.533	-0.8270	-21.10 ***
ROG	Roche Holding AG	807	0.926	0.886	0.872	0.561	-0.8195	-12.90 ***
SCH	Santander Central Hispano SA	1016	0.994	0.917	1.364	0.811	-0.5552	-7.87 ***
SHB	Svenska Handelsbanken AB	807	0.941	0.862	0.632	0.407	-0.8523	-9.76 ***
SHE	Shell Transport & Trading Company plc	939	0.844	0.795	0.907	0.489	-0.5868	-4.26 ***
SIE	Siemens AG	1016	0.739	0.615	1.195	0.697	0.1832	0.75
TEF	Telefonica SA	1016	0.949	0.905	1.232	0.778	-0.5674	-5.50 ***
TI	Telecom Italia SpA	1016	0.186	0.110	1.159	0.465	0.8083	8.59 ***
TIM	Telecom Italia Mobile SpA	837	0.888	0.794	1.069	0.618	-0.4636	-4.30 ***
TLI	TeliaSonera AB	807	0.984	0.946	0.985	0.362	-0.9528	-35.00 ***
TOT	Total Fina Elf SA	1016	0.976	0.889	0.634	0.394	-0.8461	-25.10 ***
UBS	UBS AG	807	0.921	0.902	1.120	0.705	-0.6934	-7.22 ***
UC	UniCredito Italiano SpA	967	0.921	0.794	0.956	0.526	-0.6529	-5.68 ***
VIV	Vivendi Universal SA	939	0.982	0.926	1.179	0.291	-0.9648	-19.80 ***
VOF	Vodafone Group plc	1016	0.986	0.915	1.290	0.487	-0.7891	-8.94 ***
VOW	Volkswagen AG	939	0.860	0.715	0.939	0.565	-0.3253	-3.12 ***
Mean			**0.828**	**0.757**	**1.063**	**0.527**		
Maximum			**1.000**	**0.946**	**1.845**	**0.820**		
Minimum			**0.124**	**0.110**	**0.632**	**0.249**		
No. of " + "							**9**	**9**
No. of " - "							**41**	**41**

Notes:
This table presents the results of the test of relative hedging effectiveness for each USF and the stock index futures (SIF) from the same country as the underlying stock. The empirical results are based on the OLS regression (4.22):

$$Z_{1,t} = \alpha_0 + \alpha_1 Z_{2,t} + u_t ;$$

α_1 is the slope coefficient from the regression model; where $Z_{1,t} = \varepsilon_{USF} + \varepsilon_{SIF}$ and $Z_{2,t} = \varepsilon_{USF} - \varepsilon_{SIF}$; ε_{USF} and ε_{SIF} are the residuals of regressions when the hedging instrument is chosen to be the USF and the SIF contracts (i.e. $R_S = \beta_{0,USF} + \beta_{1,USF} R_{USF} + \varepsilon_{USF}$, $R_S = \beta_{0,SIF} + \beta_{1,SIF} R_{SIF} + \varepsilon_{SIF}$, respectively). Negative α_1 coefficient "-" implies that variance of residuals when the USF contract is used is less than the case when the SIF contract is used as the hedging instrument (i.e. USF contract is a better hedge than the SIF, in terms of the portfolio risk reduction). The Newey and West (1987) procedure is used to calculate consistent standard errors of the regression parameter estimates under the serial correlated and heteroskedastic error process. *, **, *** denote significant at 10%, 5% and 1% level, respectively.

Table 4.18: Relative Hedging Effectiveness of the Universal Stock Futures (USF) and BOTH USF & Stock Index Futures (SIF)

Spot Asset			Hedging Instruments					Relative Hedging Effectiveness	
			USF		USF AND SIF				
Code	Stock Name	No. of Observations	OHR (β_{1USF})	HE (R^2)	OHR (β_{1USF})	OHR (β_{1SIF})	HE (R^2)	α_1	t-statistics
AA	ABN AMRO Holdings NV	809	0.954	0.873	0.737	0.345	0.895	1	2.51 **
AGN	Aegon NV	809	0.124	0.119	0.039	1.469	0.749	1	9.62 ***
AHL	Koninklijke Ahold NV	809	0.955	0.935	0.918	0.208	0.941	1	1.69 *
ALV	Allianz AG	965	0.882	0.711	0.549	0.722	0.823	1	3.91 ***
AXA	Axa SA	965	0.304	0.291	0.180	1.054	0.587	1	2.94 ***
AZN	AstraZeneca plc	1016	0.974	0.910	0.921	0.144	0.917	1	2.25 **
BAR	Barclays plc	939	0.173	0.155	0.082	1.073	0.571	1	5.47 ***
BNP	BNP Paribas SA	939	0.460	0.450	0.299	0.671	0.672	1	2.07 **
BPA	BP plc	1016	0.987	0.941	0.935	0.106	0.945	1	2.63 ***
BTL	BT Group plc	965	0.852	0.792	0.773	0.306	0.815	1	1.51
BVA	Banco Bilbao Vizcaya Argentaria SA	939	1.000	0.911	0.747	0.401	0.926	1	2.65 ***
CA	Carrefour SA	939	0.955	0.880	0.878	0.144	0.889	1	2.27 **
CGE	Alcatel SA	1016	0.811	0.789	0.722	0.480	0.817	1	1.71 *
CSG	Credit Suisse Group	807	0.944	0.914	0.878	0.170	0.917	1	1.29
DBK	Deutsche Bank AG	1016	0.900	0.772	0.578	0.566	0.855	1	5.10 ***
DCY	DaimlerChrysler AG	939	0.902	0.760	0.621	0.483	0.830	1	4.35 ***
DTE	Deutsche Telekom AG	1016	0.893	0.726	0.679	0.506	0.791	1	3.80 ***
ENI	Eni SpA	1016	0.291	0.214	0.162	0.666	0.471	1	2.33 **
ENL	Enel SpA	967	0.288	0.243	0.183	0.640	0.517	1	3.49 ***
EOA	E.ON AG	939	0.889	0.697	0.708	0.316	0.766	1	4.40 ***
ERC	Telefonaktiebolaget LM Ericsson AB	807	0.896	0.879	0.826	0.314	0.886	1	0.85
FTE	France Telecom SA	1016	0.977	0.929	0.938	0.149	0.933	1	1.81 *
GEN	Assicurazioni Generali SpA	967	0.969	0.894	0.866	0.179	0.902	1	2.32 **
GXW	GlaxoSmithKline plc	1016	0.977	0.923	0.922	0.117	0.929	1	3.08 ***
HAS	HSBC Holdings plc	1016	0.979	0.896	0.903	0.122	0.902	1	1.98 **
HNM	Hennes & Mauritz AB	807	0.832	0.781	0.773	0.146	0.793	1	0.99
ING	ING Groep NV	1016	0.637	0.603	0.258	1.070	0.828	1	2.05 **
LLO	Lloyds TSB Group plc	965	0.938	0.863	0.810	0.288	0.883	1	3.41 ***
MUV	Münchener Rücksversicherungs Gesellschaft AG	965	0.869	0.771	0.621	0.589	0.852	1	4.34 ***
NDA	Nordea AB	807	0.958	0.867	0.899	0.126	0.872	1	1.30
NES	Nestle SA	807	0.872	0.776	0.723	0.229	0.807	1	3.16 ***
NOV	Novartis AG	807	0.919	0.856	0.818	0.137	0.864	1	1.35
PHI	Koninklijke Philips Electronics NV	835	0.985	0.937	0.857	0.271	0.946	1	2.57 **
RBO	Royal Bank of Scotland Group plc	939	0.971	0.878	0.855	0.235	0.889	1	2.55 **
RD	Royal Dutch Petroleum Company	1016	0.988	0.928	0.909	0.106	0.934	1	2.94 ***
ROG	Roche Holding AG	807	0.926	0.886	0.847	0.125	0.891	1	1.82 *
SCH	Santander Central Hispano SA	1016	0.994	0.917	0.782	0.347	0.928	1	3.47 ***
SHB	Svenska Handelsbanken AB	807	0.941	0.862	0.878	0.100	0.868	1	1.40
SHE	Shell Transport & Trading Company plc	939	0.844	0.795	0.702	0.320	0.833	1	2.42 **
SIE	Siemens AG	1016	0.739	0.615	0.389	0.805	0.794	1	2.69 ***
TEF	Telefonica SA	1016	0.949	0.905	0.754	0.314	0.917	1	2.47 **
TI	Telecom Italia SpA	1016	0.186	0.110	0.078	1.088	0.483	1	6.62 ***
TIM	Telecom Italia Mobile SpA	837	0.888	0.794	0.680	0.386	0.831	1	3.58 ***
TLI	TeliaSonera AB	807	0.984	0.946	0.962	0.061	0.947	1	1.61
TOT	Total Fina Elf SA	1016	0.976	0.889	0.909	0.111	0.897	1	3.58 ***
UBS	UBS AG	807	0.921	0.902	0.787	0.222	0.911	1	2.03 **
UC	UniCredito Italiano SpA	967	0.921	0.794	0.779	0.256	0.813	1	2.29 **
VIV	Vivendi Universal SA	939	0.982	0.926	0.966	0.066	0.926	1	0.97
VOF	Vodafone Group plc	1016	0.986	0.915	0.893	0.259	0.926	1	1.42
VOW	Volkswagen AG	939	0.860	0.715	0.629	0.443	0.789	1	4.16 ***
Mean			**0.828**	**0.757**	**0.692**	**0.389**	**0.833**		
Maximum			**1.000**	**0.946**	**0.966**	**1.469**	**0.947**		
Minimum			**0.124**	**0.110**	**0.039**	**0.061**	**0.471**		
No. of " + "								**50**	**50**
No. of " - "								**0**	**0**

Notes:
This table presents the results of the test of relative hedging effectiveness for using USF alone and for using the stock index futures (SIF) from the same country as the underlying stock as well as its USF as the hedging instrument. The empirical results are based on the OLS regression (4.22):

$$Z_{1,t} = \alpha_0 + \alpha_1 Z_{2,t} + u_t ;$$

α_1 is the slope coefficient from the regression model; where $Z_{1,t} = \varepsilon_{USF} + \varepsilon_{USF\&SIF}$ and $Z_{2,t} = \varepsilon_{USF} - \varepsilon_{USF\&SIF}$; ε_{USF} and $\varepsilon_{USF\&SIF}$ are the residuals of regressions when the hedging instrument is chosen to be the USF alone and both USF & SIF contracts (i.e. $R_S = \beta_{0,USF} + \beta_{1,USF}R_{USF} + \varepsilon_{USF}$, $R_S = \beta_{0,SIF} + \beta_{1,USF}R_{USF} + \beta_{1,SIF}R_{SIF} + \varepsilon_{USF\&SIF}$, respectively). Positive α_1 coefficient "+" implies that variance of residuals when only USF contract is used is more than the case when both USF & SIF contracts are used as the hedging instruments (i.e. hedging simultaneously with USF & SIF contracts is a better hedge than the USF alone, in terms of the portfolio risk reduction). The Newey and West (1987) procedure is used to calculate consistent standard errors of the regression parameter estimates under the serial correlated and heteroskedastic error process. *, **, *** denote significant at 10%, 5% and 1% level, respectively.

Table 4.19: Relative Hedging Effectiveness of a Portfolio of Universal Stock Futures (USF) and Stock Index Futures (SIF)_Country Portfolios

Spot Portfolios		Hedging Instruments				Relative Hedging Effectiveness	
		USF Portfolios		SIF			
Country (no. of stocks)	No. of Observations	OHR (β_{1USF})	HE (R^2)	OHR (β_{1SIF})	HE (R^2)	α_1	t-statistics
France (7)	936	0.897	0.865	1.064	0.615	-0.5568	-2.17 **
Germany (8)	938	1.070	0.893	0.924	0.756	-0.4848	-5.20 ***
Italy (6)	837	0.965	0.858	0.714	0.603	-0.7063	-5.73 ***
Netherlands (6)	806	1.246	0.883	0.741	0.696	-0.5262	-2.05 **
Spain (3)	939	1.004	0.951	1.315	0.929	-0.2435	-3.43 ***
Sweden (5)	807	0.952	0.924	0.996	0.703	-0.7093	-5.52 ***
Switzerland (5)	807	0.953	0.914	0.996	0.893	-0.2023	-1.28
UK (10)	937	0.915	0.852	0.994	0.859	0.0297	0.10
Mean		**1.000**	**0.892**	**0.968**	**0.757**		
Maximum		**1.246**	**0.951**	**1.315**	**0.929**		
Minimum		**0.897**	**0.852**	**0.714**	**0.603**		
No. of " + "						**1**	**1**
No. of " - "						**7**	**7**

Notes:
This table presents the results of the test of relative hedging effectiveness for using an equally-weighted portfolio of USFs and for using the stock index futures (SIF) from the same country as the underlying stock as the hedging instrument. The empirical results are based on the OLS regression (4.22):

$$Z_{1,t} = \alpha_0 + \alpha_1 Z_{2,t} + u_t;$$

α_1 is the slope coefficient from the regression model; where $Z_{1,t} = e_{USF} + e_{SIF}$ and $Z_{2,t} = e_{USF} - e_{SIF}$; e_{USF} and e_{SIF} are the residuals of regressions when the hedging instrument is chosen to be the USF and the SIF contracts (i.e. $R_S = \beta_0 + \beta_1 R_{USF} + e_{USF}$, $R_S = \beta_0 + \beta_1 R_{SIF} + e_{SIF}$, respectively). Negative α_1 coefficient "-" implies that variance of residuals when the portfolio of USF contracts is used is less than the case when the SIF contract is used as the hedging instrument (i.e. a portfolio of USF contracts is a better hedge than the SIF, in terms of the portfolio risk reduction). The Newey and West (1987) procedure is used to calculate consistent standard errors of the regression parameter estimates under the serial correlated and heteroskedastic error process. *, **, *** denote significant at 10%, 5% and 1% level, respectively.

Figure 4.1: Constant vs. Time-varying Hedge Ratios for AA_BEKK

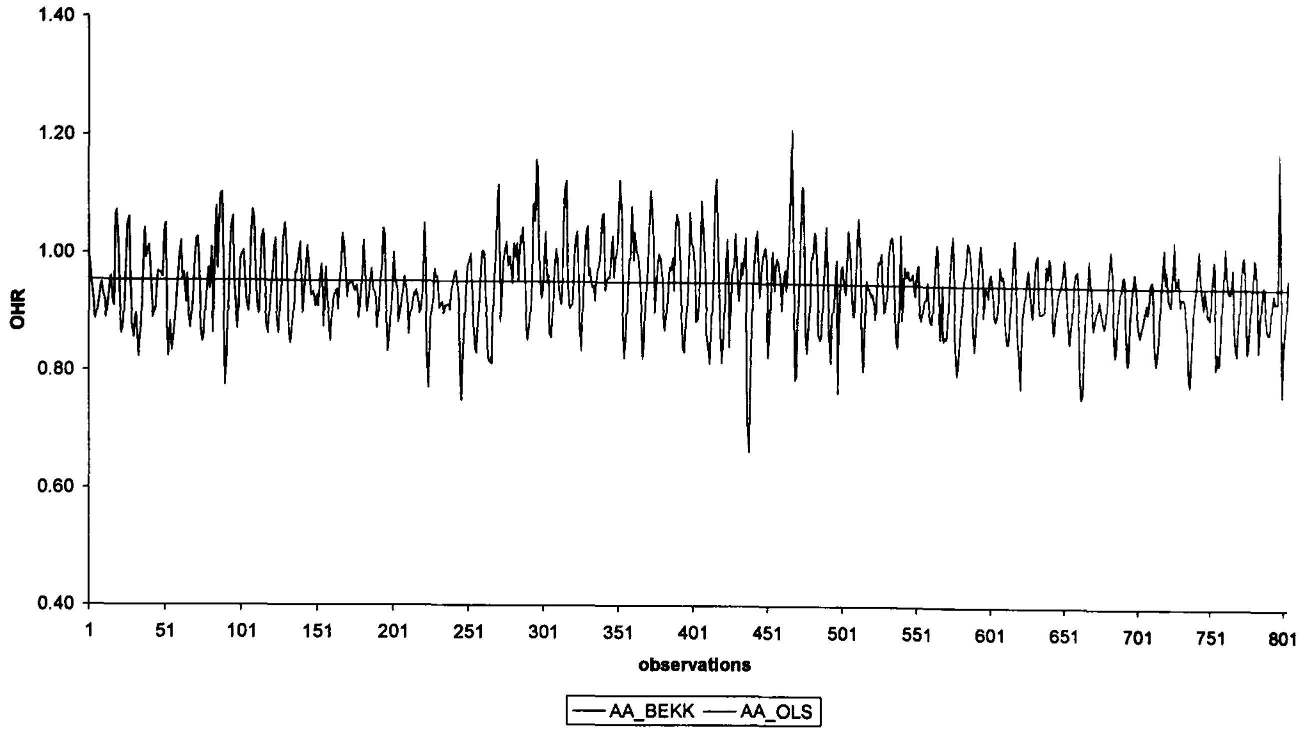


Figure 4.2: Constant vs. Time-varying Hedge Ratios for AA_BEKK-X

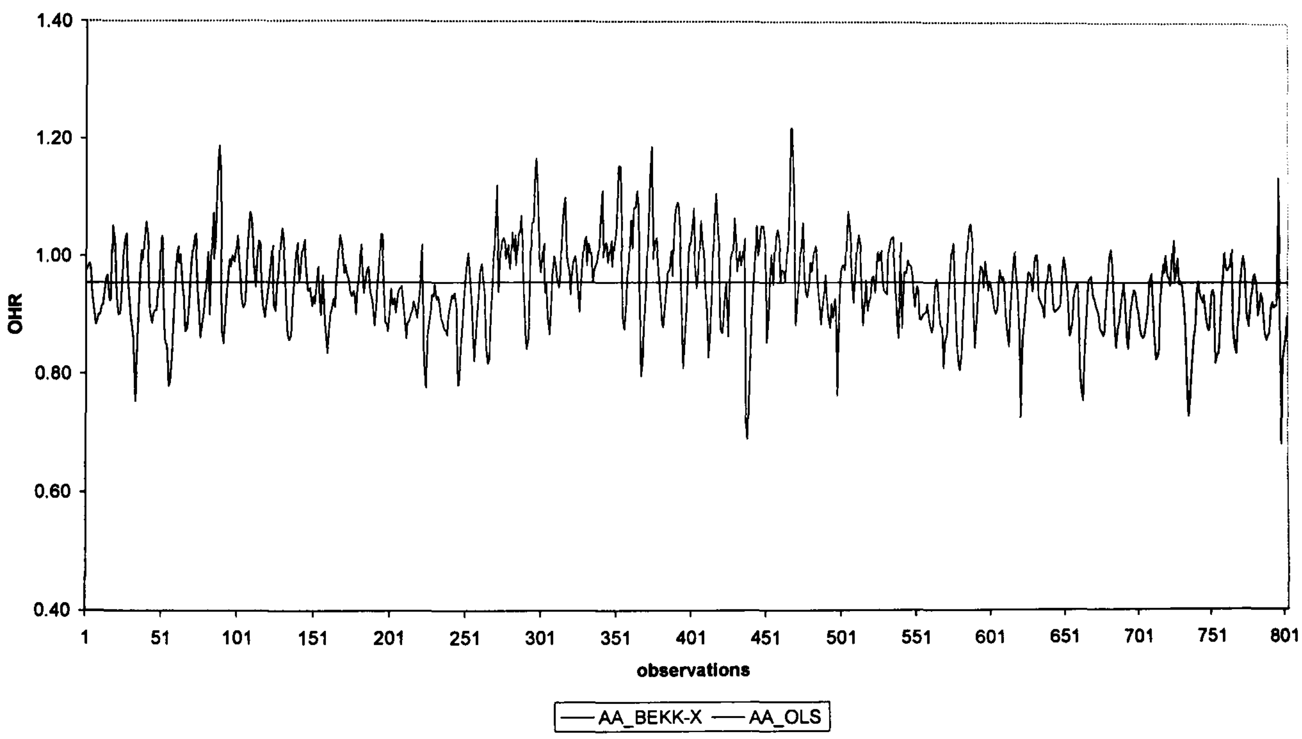


Figure 4.3: Constant vs. Time-varying Hedge Ratios for AA_AsymBEKK

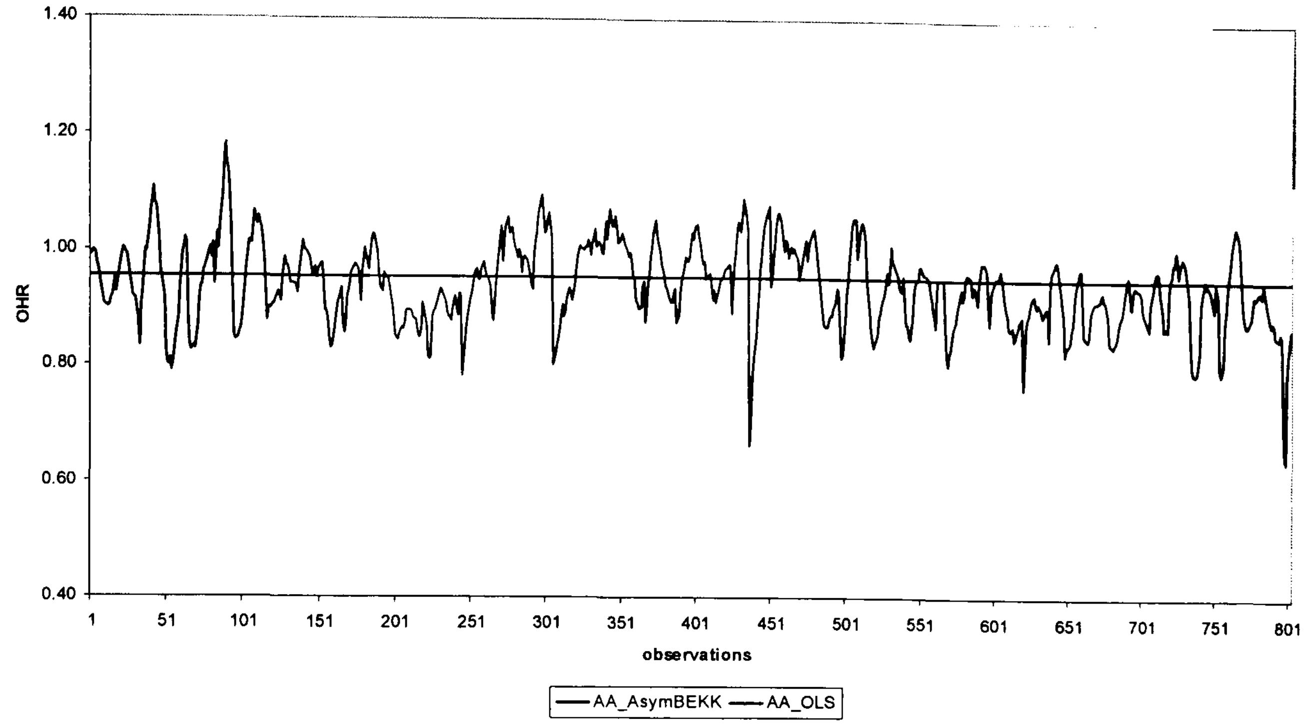


Figure 4.4: Constant vs. Time-varying Hedge Ratios for AA_AsymBEKK-X

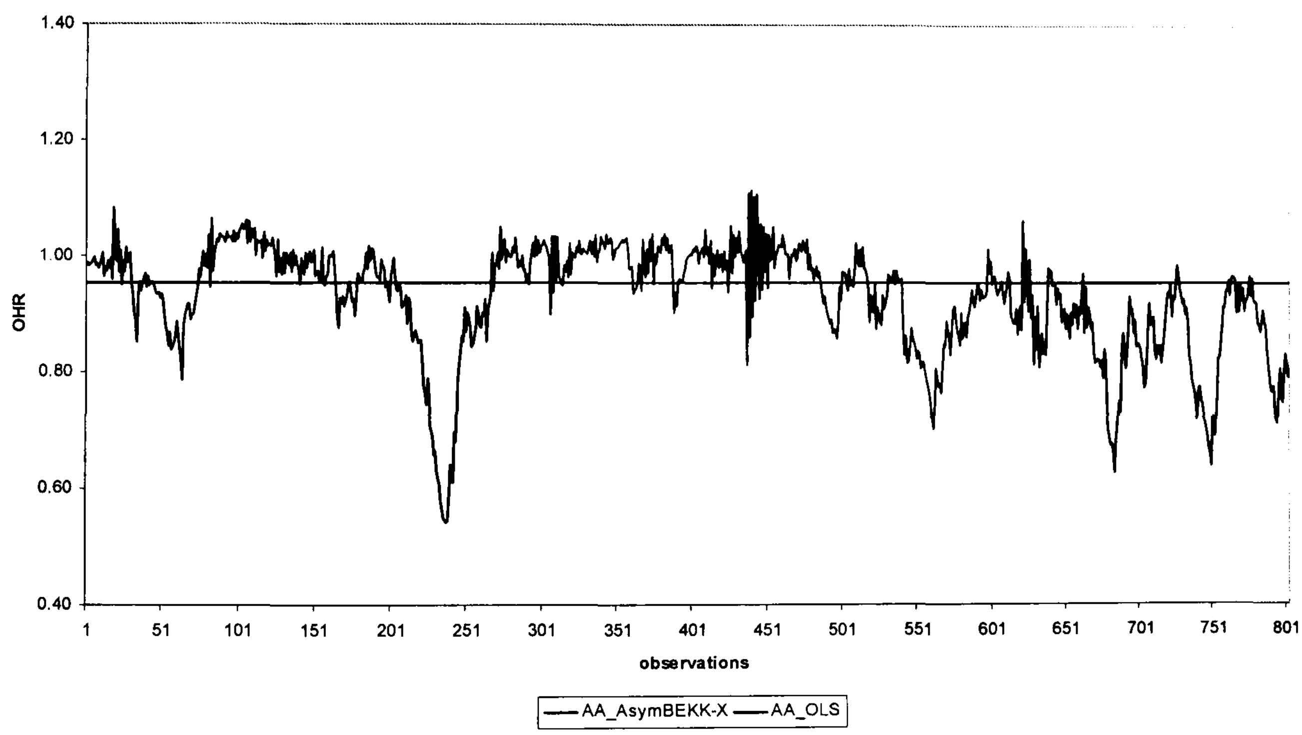


Figure 4.5: Hedging Effectiveness versus USF Volume

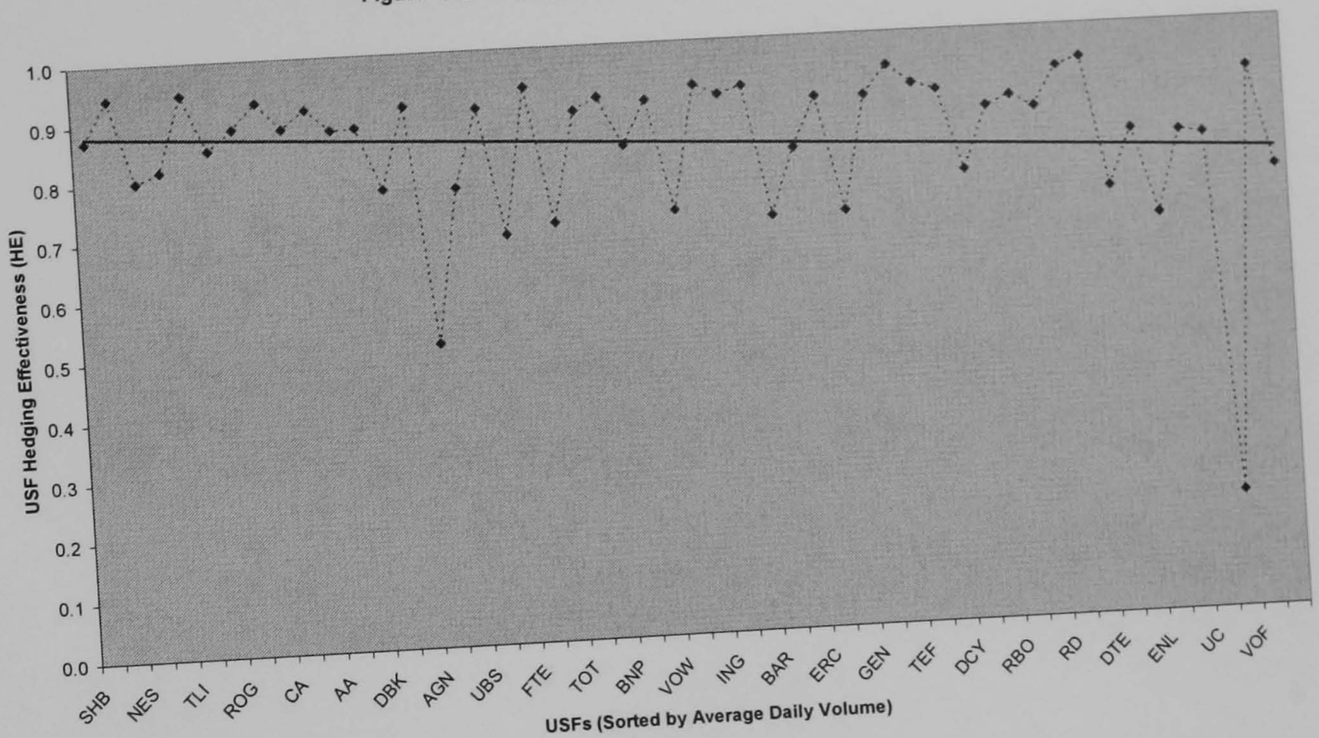


Figure 4.6: Hedging Effectiveness versus USF Spread

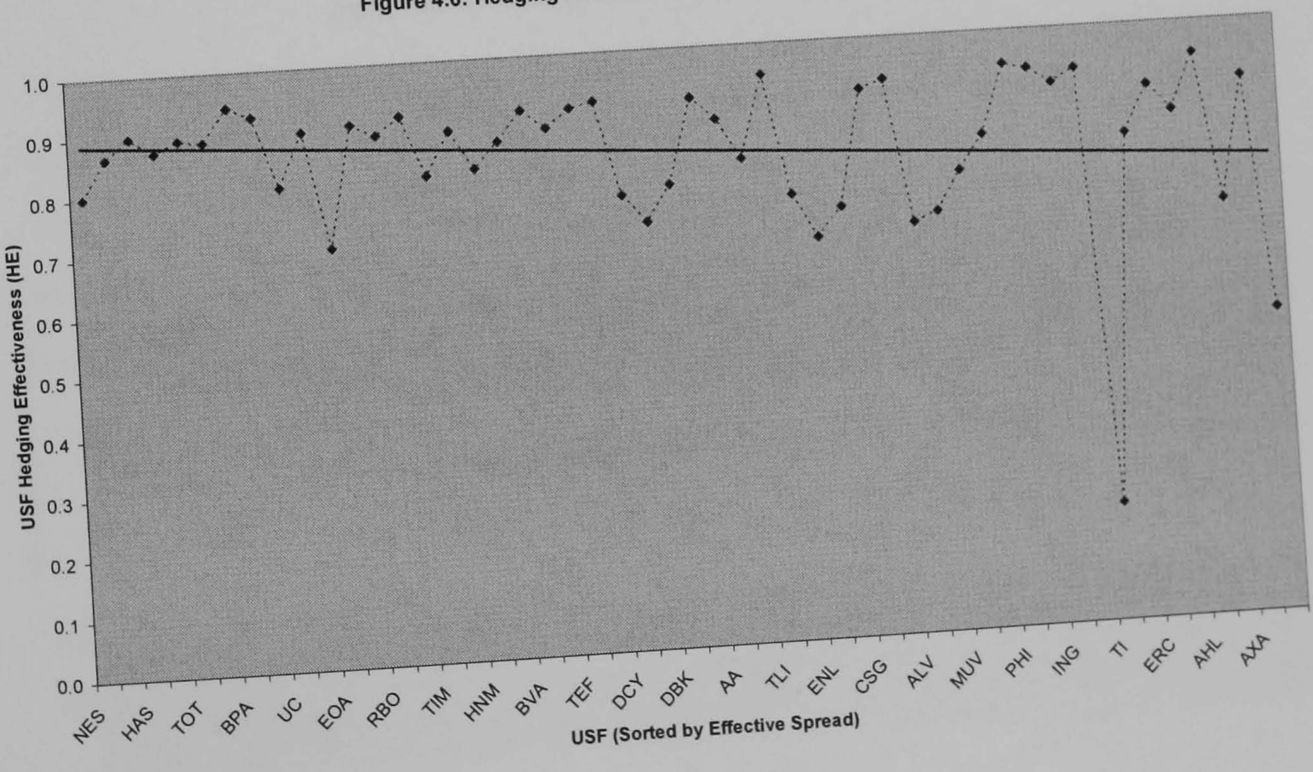


Figure 4.7: USF Hedging Effectiveness versus Volume Ratio

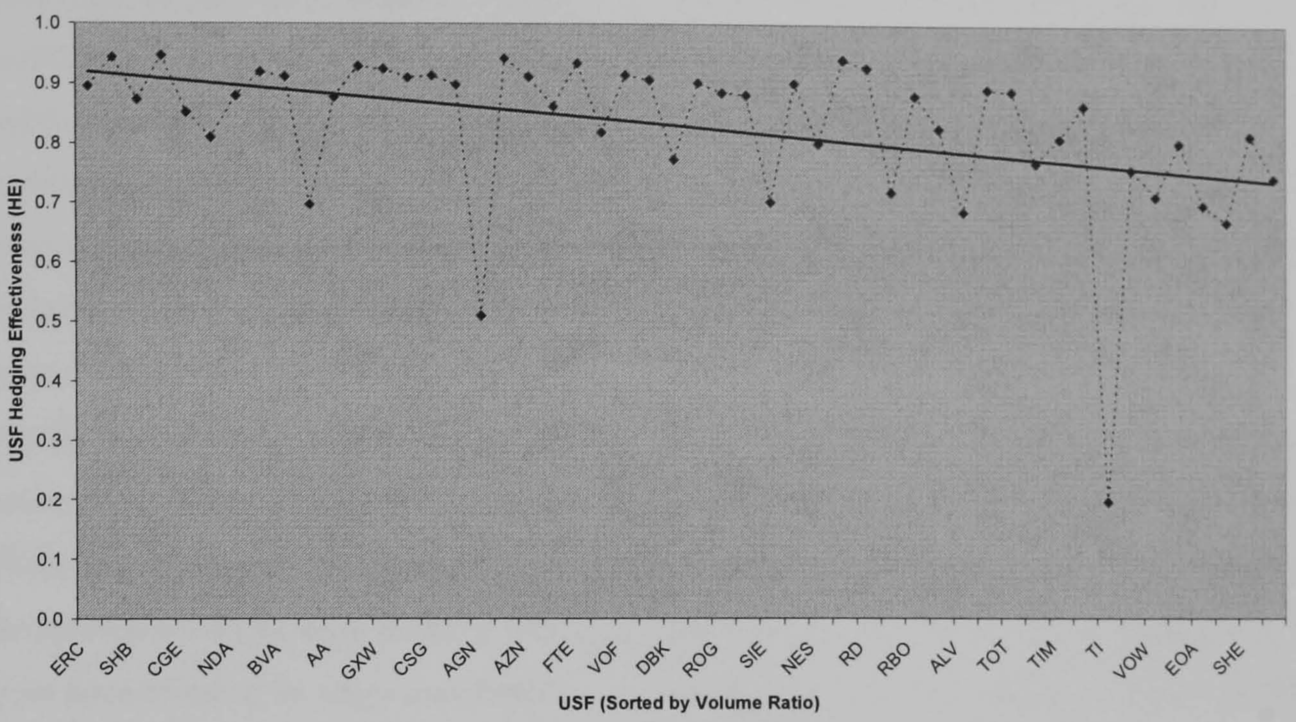
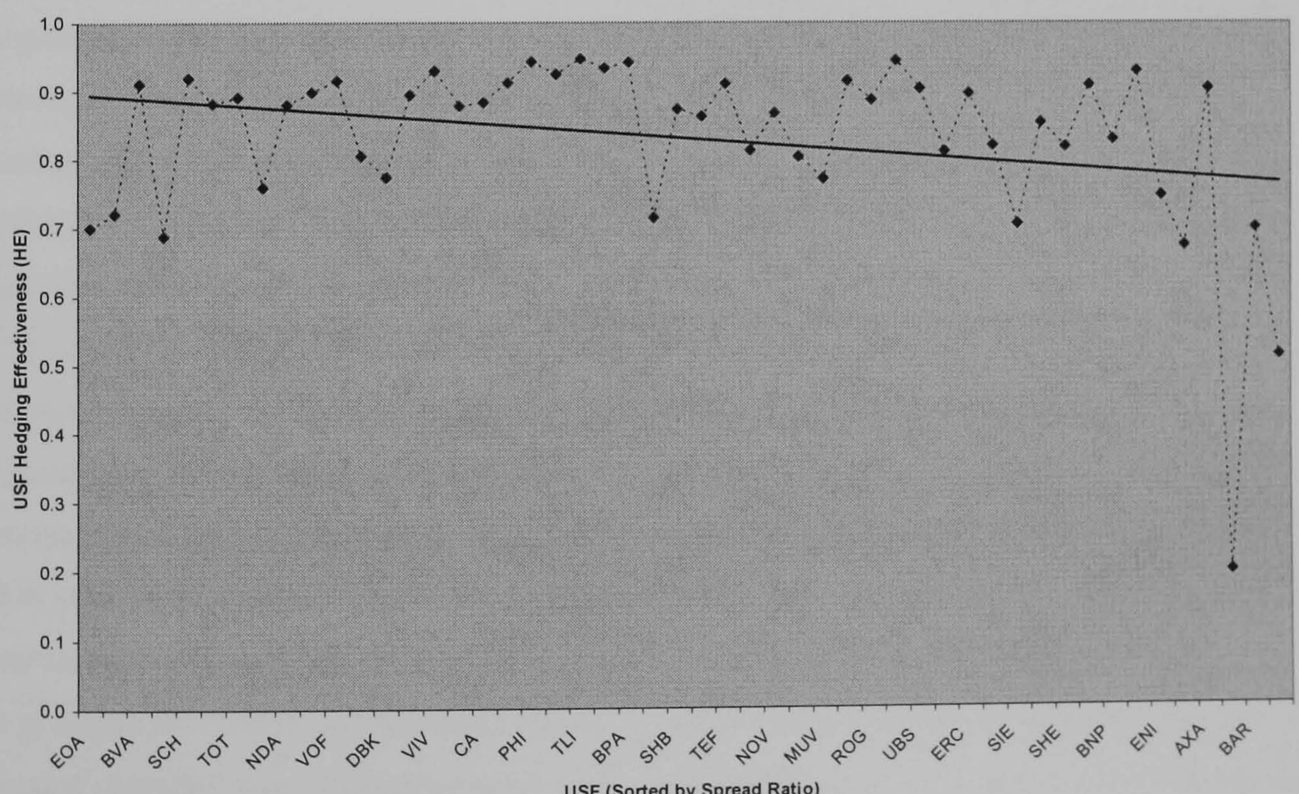


Figure 4.8: USF Hedging Effectiveness versus Spread Ratio



Appendix 4A: Overview of Main Contributions of Chapter 4

Existing Studies	This Study
Many studies have considered the hedging performance of derivatives contracts, but no published work focuses on the hedging function of SSFs.	First study to explicitly investigate the hedging effectiveness of SSF in the U.K. (i.e., Universal Stock Futures, USF).
Numerous studies have been devoted to hedging effectiveness of internationally cross-listed stock index futures, and concluded that trading location of underlying assets is important factor.	Examine the performance of "international" hedging using the cross-border single stock futures (e.g. USFs) for the first time, and assess the impact of the geographical origin of the underlying stocks on the performance.
There is a 'learning curve' associated with derivatives contracts, their hedging functions have been found to be vary considerably over time; they tend to be more effective risk management tools in the maturity period than the introduction period.	Address the issue of whether USFs hedging effectiveness is different at the different stages of their development, and thus provide a direct answer to the learning curve / market-maturity hypotheses.
The hedging effectiveness of futures contracts is closely related to the contemporaneous market conditions (such as trading volume, transaction costs, and volatility), and contract specifications like contract size and settlement methods.	The large sample size enables us to explore the impact of several market microstructure (as well as contract design/specification) factors on the effectiveness of hedging via USF markets.
The deviation from stock-futures equilibrium relationship (i.e., the basis / spread) has significant implications concerning each market volatility and co-movements, and thus affects the estimations of optimal hedge ratios and hedging effectiveness.	Investigate the effects of the basis / spread on optimal hedging strategies by incorporating the squared basis into the variances and covariance equations when estimating the optimal hedge ratios, and add new evidence on this important topic.
It is commonly found that bad news raises market volatility more than good news, and the models that allow the hedging ratio to be both time-varying and asymmetric tend to give superior hedging performance.	Examine if the optimal hedging strategy constructed from the models that account for both time-varying and asymmetric hedge ratios produce better hedging performance during the period when the USF markets are sufficiently mature.

Chapter 5
Conclusions and Further Research

5.1 Introduction

The general theme of research in this thesis is the investigation of the role and functioning of the Universal Stock Futures (USF) market and its impact on the underlying stock market. As indicated in the introduction to this thesis, the success of a futures contract is dependent upon the contract providing benefits to economic agents, over and above the benefits they can get from stock market alone. If no such benefits exist, then market participants have no reason to trade in the futures market which eventually leads to loss of trading interests. The two most important benefits of futures markets are price discovery and risk management functions, which are often presented as the justification for futures trading (see Garbade and Silber, 1983). From this perspective, if the success of any new futures contract is to be assessed, it is essential that detailed investigation be carried out as regard to the performance of this contract in its prescribed functions and its effect on the underlying market.

While a considerable amount of research has been directed towards examining the impact and performance of different financial and commodity futures markets, there is little evidence regarding the futures on single stocks such as USFs. Given their increasing usage and growing interest, it is somewhat surprising that the functioning of single stock futures (SSF) markets have received so little attention to date. Therefore, it is the objective of this thesis to fill this gap in the literature by providing a detailed analysis of the functioning of USF markets and their relationship with the underlying stock markets. In order to achieve this objective, this thesis presents three related empirical essays dealing with first, the impact of USF trading on the market dynamic and volatility of underlying stock, second the efficiency of USF markets with respect to their price discovery role, and third the risk management performance of futures markets through hedging. The motivation for investigating these issues derives from the fact that these are the most important benefits and major concern of any futures market, and hence the findings of the thesis are of particular importance to those involved in trading and regulating these markets. Moreover, with the investigation centred on USF contracts, this thesis extends the existing empirical evidence to a futures market in which the underlying stock of contract is exactly the same as the spot asset and has contracts listed on both domestic and foreign stocks. In addition to providing insights for the first time for USF markets, the thesis also refines the methodologies used in previous studies to draw more reliable inferences.

This purpose of this chapter is to provide the concluding remarks to the thesis. In the next section we summarise the main results of each chapter, while in section 5.3 we discuss the policy implications of our findings. Finally, section 5.4 presents some topics for future research which, due to space and time constraints, have not been investigated here.

5.2 Summary of Findings

In chapter 1, the two benefits (i.e. price discovery and risk management) that derivative markets in general, and futures markets in particular, provide to market participants are discussed; a brief description of the USF market is provided; and the contributions of this thesis to the literature are also identified.

Since the major concern surrounding the futures contracts is whether their introduction would enhance or harm the underlying markets, an obvious starting point for the empirical analysis of the functioning of USFs relates to their effect on the underlying stock market. Chapter 2 investigates this issue and finds that the impact of futures trading on the underlying market is a complex issue which has often been addressed with a simple question of whether or not the level of volatility has changed after the introduction of futures. As shown in Antoniou et al. (2005), the volatility effects of futures trading can be attributed to either destabilising speculation or improved information flows brought by futures. To clearly understand the influence of futures trading, therefore, it is necessary to adopt an approach which can distinguish between these different causes of changes in volatility levels. To this end, chapter 2 investigates the effect of USF trading utilising a heterogeneous trader model which allows consideration not only on underlying volatility, but also on the extent to which futures inhibit or promote feedback trading in the stock market.

The results suggest that the introduction of USF contracts has not had a detrimental effect on the underlying stock markets. While there are some changes in the underlying volatility level and nature, similar changes are also observed in the control stocks, suggesting that these changes are not induced by futures. It should, of course, be recognised that all the stocks on which USFs are written are also component stocks of the stock indices on which futures already exist, thus it may be expected that these stocks would be less affected by the introduction of USFs. Nevertheless, to the extent that USFs have impacted on wider market dynamics, the influence appears to have been positive, leading to a small reduction in feedback trading and improved efficiency following the onset of futures trading. In addition, the results also suggest that although there are differences in the pattern of market dynamics between industries they are not futures induced, highlighting the need for analysis of industry-based control sample before any policy implications are drawn.

As described in chapter 1, futures markets can be expected to play a beneficial economic role only if they successfully carry out their prescribed functions. The ability to expand and improve the information set available to market participants and the provision of hedging opportunities are the most important functions of futures trading. Chapters 3 and 4 investigate these two functions of USF markets. More specifically, chapter 3 looks at the part that the USF markets play in the price discovery process, and the factors that influence this role. The research is presented on three levels. The first of which examines the proportion of new information that is incorporated via the USF markets and finds that price discovery takes place in both stock and futures markets, although the USF markets on average play a relatively smaller role in the price discovery than their underlying stocks. The second phase of the analysis investigates the impact of several variables which may influence the role of futures in the price discovery process. The results suggest that the price contributions of USFs vary considerably over time and across firms, and are influenced by the geographical origin of underlying stock, the development stage of futures contract, the relative trading characteristics, the contract design and specifications, as well as the information types and content. The final stage of the analysis examines the volatility interdependence of the stock and USF markets and concludes that there is a bi-directional volatility spillover between two markets with a slightly stronger effect from the stock to the futures markets.

Finally, the risk management function of USF contracts is investigated in chapter 4. In addition to examining the effectiveness of constant and time-varying hedge ratios in reducing stock price risk, the research investigates the factors that explain the variations of hedging effectiveness across USF contracts, and assesses the relative hedging efficiency of USF and stock index futures. The major findings can be summarised as follows. First, both in- and out-of-sample test results suggest that the majority of USF contracts have served as efficient risk management tools in hedging against the individual stock exposures. Moreover, we find that the dynamic hedging strategy that incorporates both the basis and asymmetry effects in the variance-covariance structure can produce additional hedging benefits for investors who want to hedge their exposure to individual stock positions. Also the hedging effectiveness varies from one USF market to the other. The results of the cross-sectional analysis suggest that the differences in the underlying stock trading location, futures contract design, and market maturity are the most likely causes of these variations. As far as the *relative* hedging effectiveness is concerned, we find that hedging with USF has a better performance than hedging with index futures for the individual stock positions. In addition, hedging simultaneously with USF and index futures further improves hedging efficiency compared to hedging with only USF contracts. Also, an equally-weighted USF portfolio is also found to be more effective than the index futures in hedging the small-sized portfolio.

5.3 Policy Implications

The results of the research undertaken in this thesis should provide investors, exchange management, and regulators some insights into possible gains and losses associated with trading futures on single stocks. In particular, the evidence presented in chapter 2 clearly demonstrates that the introduction of USFs has not impacted negatively on the underlying markets. On the contrary, to the extent that futures have impacted on market dynamics, the influence appears to have been positive, leading to a small reduction in feedback trading and improved efficiency. This implies that the public concern over the adverse impact of futures trading is not fully justified and calls for further regulation on these markets (such as higher margins and restrictions on the issue of new contracts) is unwarranted and could even be counter-productive.

In addition, the findings regarding the price discovery function of USF contracts in chapter 3 indicate that USF markets on average provide a means of enhancing information dissemination and contribute to the discovery of new information about stock prices. Therefore, market participants can use information generated by futures prices to guide their investment decision in the underlying stock market. The finding that some stocks contribute relatively more to price discovery indicates that informed traders are more likely to choose this market to reveal their private information. From a policy perspective, this is particularly important as the knowledge of where informed traders choose to trade and the factors influencing their choices are highly relevant to regulators in preventing illegal insider trades. Moreover, the investigation into the impact of several variables which influence USF price discovery role should provide exchange management with a benchmark for designing new futures contracts that are more conductive to the timely dissemination of the new information.

The hedging analysis carried out in chapter 4 demonstrates that the majority of USF contracts perform the risk management function efficiently. This is not entirely surprising given the fact that the underlying stock of the futures contract is exactly the same as the spot assets. This matching nature implies that the correlation of the stock and futures prices should be high and thus the effectiveness of hedges will also be strong accordingly. Nonetheless, the risk-reduction ability of some USFs contracts are much lower than others and compared poorly to that evidenced in other commodity and financial futures markets. The poorer hedging performances are believed to be the results of relatively lower trading volume and larger contract size in these contracts, which abstain users from using these futures to hedge their individual stock exposure. As a policy implication, this suggests that LIFFE should first promote more this derivative market through marketing campaigns in order to attract the much needed volume in some USFs, and second, reduce the size of these contracts to make them more accessible and attractive to the small retail investors. An increase in awareness and trading activity of more investors may promote the hedging efficiency of these contracts. Additionally, the finding that the creation of a hedge portfolio using multiple USFs leads to higher risk reduction than just using index futures, indicates that it is possible for hedgers to create their own 'futures portfolio' to tailor to their stock portfolio held. This in turn may help government regulators make decisions on whether the E-mini / narrow-based index futures should be introduced as a means of enhancing the risk-sharing opportunities in the markets.

Overall, the research carried out in this thesis demonstrates that the USF contracts in general provide useful services to the economy by contributing to the information dissemination and risk-sharing process in the markets, and have no detrimental impact on the working of the underlying markets. This gives useful reference for investors, exchange management and regulators in other derivative markets (which have already introduced and/or plan to launch single stock futures) to the possible success of similar products in their markets, and for the evaluation of whether the public concern about the negative impact of SSF on underlying equity markets is warranted.

5.4 Suggestions for Further Research

The primary aim of the research in this thesis is to investigate the economic benefits and costs of introducing futures on single stocks and assist to settle the controversies surrounding these new derivative products. In the thesis we investigate the price discovery and risk management functions of the USF contracts. In addition, we also consider how the onset of futures trading has affected the underlying stock market. However, it should be recognised that while this thesis has examined what is seen to be the most important issues in relation to futures markets, there are related research questions of importance which have not been addressed here due to space and time constraints and availability of data. For example, this thesis has not examined the existence (or otherwise) of arbitrage opportunities or the pricing relationship between the stock and futures markets. Furthermore, due to the newness of USF contracts, the analysis of this thesis has placed considerable reliance on the data for period immediately after futures introduction. As volume of trade in USFs increases it will be possible to undertake analysis of several issues using more recent/frequent data. Therefore, the aim of this section is to suggest directions in which fruitful future research can be undertaken to improve / enhance our knowledge in the USF market.

Provided that sufficient and reliable data are available, an obvious extension of research undertaken in this thesis would involve undertaking similar investigations for other single stock futures (SSF) markets using the methodologies adopted here. This would enhance our understanding of the role and functioning of SSF contracts in general and provide investors and policy-makers with important information. Also, it would be interesting to further develop the research carried out in this thesis. Regarding the impact of USF trading on the underlying stock market, the investigation in chapter 2 suggests that there are there are differences in the pattern of market dynamics between industries. Therefore, an examination of why such differences exist is worthy of further study. Moreover, the current study could be also extended to consider other possible impacts of futures trading on the underlying market (such as the effects on diversification potential and liquidity) in order to provide more references to investors and regulators. In addition, useful information about the impact of USF futures trading may be retrieved by investigating the expiration-day effect using more frequent data, such as the minute-by-minute data.

There is also ample scope for further research in the price discovery performance of the market. Firstly, the empirical analysis of chapter 3 can be extended to the transactions in all of the relevant markets. Using the transaction data might help to overcome the non-synchronicity problem and allows us to identify more precise channels in which the new information transmit between each relevant markets. Examination of the simultaneous trading of stock futures, stock options and stocks is expected to contribute the knowledge in the area of linkages between equity derivatives and underlying markets. Secondly, another possible extension is to analyse the information flows within these markets in the periods immediately prior to announcements of the important corporate events. Thirdly, future research could also consider the impact of different investors trading activity (e.g. institutional investors) on proportion of price discovery in each market, and to address the question of from where and whom price discovery were initiated. In addition, as some recent studies suggest that futures contribution to information discovery is relatively larger in quiet periods than in volatile periods, it would be interesting to examine the USF price discovery role across the stable and volatile periods. Finally, future research could put more effort into explaining how the results documented here can be exploited to formulate profitable trading strategies in practice.

Turning next into the hedging performance of the market, one motivating factor for future research lies in consideration of transaction costs and see if the dynamic hedge ratios generated from the more flexible VECM-GARCH models are superior to static ones in the presence of transaction costs. Moreover, since a synthetic long USF position can be created by combining the call and put options with the same exercise price and expiration, the comparison of hedging effectiveness between these two approaches would also be a worthwhile exercise. In addition, as our sample period is limited by the length of time that USF contracts have been trading, another obvious extension is the use of a longer sample period for estimating the hedge ratios and for determining hedging effectiveness. Finally, further research may also be conducted for different frequency of data, hedge horizons, single-stock futures markets, etc.

References

Abhyankar, A.H., 1995, "Return Volatility Dynamics in the FTSE 100 Stock Index and Stock Index Futures Market," *Journal of Futures Markets*, 15, 457-458.

Admati, A.R. and Pfleiderer, P. 1988, "A Theory of Intraday Patterns: Volume and Price Variability," *Review of Financial Studies,* 1, 3-40.

Aggrawal, R. 1988, "Stock Index Futures and Cash Market Volatility," *Review of Futures Markets*, 7, 290 – 299.

Aitken, M., and Comerton-Forde, C. 2003, "How should Liquidity be Measured?" *Pacific-Basin Finance Journal,* 11, 45-59.

Anand A., and Karagozoglu A.K. 2006, "Relative Performance of Bid-ask Spread Estimators: Futures Market Evidence," *Journal of International Financial Markets, Institutions and Money,* 16, 231-245.

Alexander, C. 2001. "Market Models: A Guide to Financial Data Analysis", Chichester, UK: New York NY.

Alexander, C. and Barbosa, A. 2005, "Is Minimum Variance Hedging Necessary for Equity Indices? A Study of Hedging and Cross-Hedging Exchange Traded Funds," *ICMA Centre Discussion Papers in Finance DP2005-16*, University of Readings.

Alexander, C. and Barbosa, A. 2006, "Minimum Variance Hedging and Stock Index Market Efficiency," *ICMA Centre Discussion Papers in Finance DP2006-04*, University of Readings.

Alkeback, P. and Hagelin, N. 1998, "The Impact of Warrant Introductions on the Underlying Stocks, with a Comparison to Stock Options," *Journal of Futures Markets*, 18, 307 – 328.

Ang, J.S., and Cheng, Y. 2005a, "Financial Innovation and Market Efficiency: The Case of Single Stock Futures," *Journal of Applied Finance*, 15, 38-51.

Ang, J.S., and Cheng, Y. 2005b, "Single Stock Futures: Listing Selection and Trading Volume," *Finance Research Letters*, 2, 30-40.

Antoniou, A., and Holmes, P. 1995, "Futures Trading, Information and Spot Price Volatility: Evidence for the FTSE-100 Stock Index Futures Contract Using GARCH," *Journal of Banking and Finance,* 19, 117-129.

Antoniou, A., Holmes, P. and Priestly, R. 1998, "The Effects of Stock Index Futures Trading on Stock Index Volatility: An Analysis of the Asymmetric Response of Volatility to News," *Journal of Futures Markets*, 18, 151 - 166.

Antoniou, A., Koutmos, G. and Pericli, A. 2005, "Index Futures and Positive Feedback Trading: Evidence from Major Stock Exchanges," *Journal of Empirical Finance*, 12, 219 - 238.

Antoniou, A., Malliaris, A. and Priestley, R. 1999, "An Analysis of the Asymmetric Response of Stock Prices to News," *Working Paper No. 9905*, Durham University.

Arditti, F. 1996, "Derivatives: A Comprehensive Resource for Options, Futures. Interest Rate Swaps, and Mortgage Securities," Harvard Business School Press. Boston, Massachusetts.

Arshanapalli, B., and Doukas, J. 1993, "International Stock Market Linkages: Evidence from the Pre- and Post-October 1987 Period," *Journal of Banking and Finance,* 17, 193-208.

Ates, A., and Wang, H.K. 2005, "Information Transmission in Electronic versus Open-outcry Trading Systems: An Analysis of U.S. Equity Index Futures Markets," *Journal of Future Markets,* 25, 679-715.

Baillie, R.T., Booth, G., Yiuman, T., and Zabotina, T. 2002, "Price Discovery and Common Factor Models," *Journal of Financial Markets,* 5, 309-321.

Bauwens, L., Laurent, S., and Rombouts, J. 2006, "Multivariate GARCH Models: A Survey," *Journal of Applied Econometrics*, 21, 79-109.

Becketti, S. and Roberts, D. 1990, "Will Increased Regulation of Stock Index Futures Reduce Stock Market Volatility?," Federal Reserve Bank of Kansas City Economic Review, November-December, 33 – 46.

Bekaert, G., Garcia, M. and Harvey, C. 1995, "The Contribution of Speculators to Effective Financial Markets," *Research Project*, A Catalyst Institute Research Project.

Berndt, E., Hall, H., Hall, R. and Hausman, J. 1974, "Estimation and Inference in Nonlinear Structural Models," *Annuals of Economic and Social Measurement*, 4, 653 - 666.

Bessembinder, H. and Sequin, P. 1992, "Futures-Trading Activity and Stock Price Volatility," *Journal of Finance*, 47, 2015 – 2034.

Bessembinder, H., and Seguin, P. 1993, "Price Volatility, Trading Volume and Market Depth: Evidence from Futures Markets," *Journal of Financial and Quantitative Analysis*, 28, 21-39.

Bhar, R. 2001, "Return and Volatility Dynamics in the Spot and Futures Markets in Australia: An Intervention Analysis in a Bivariate EGARCH-X Framework," *Journal of Futures Markets,* 21, 833-850.

Black, D.G. 1986, "Success and Failure of Futures Contracts: Theory and Empirical Evidence," Salomon Brothers Centre, *Monograph* 1986-1.

Black, F. 1975, "Fact and Fantasy in the Use of Options," *Financial Analysts Journal,* 31, 36-41.

Black, F. 1976a, "The Pricing of Commodity Contracts," *Journal of Financial Economics,* 3, 167-179.

Black, F. 1976b, "Studies in Stock Price Volatility Change," *Proceedings of the 1976 Meeting of the Business and Economics Statistic Section, American Statistical Association,* August, 177-181.

Blair, B., Poon, S., and Taylor, S. 2002, "Asymmetric and Crash Effects in Stock Volatility for the S&P 100 Index and Its Constituents," *Applied Financial Economics,* 12, 319-329.

Board, J. and Sutcliffe, C. 1993, "The Effects of the Existence of Index Futures on UK Share Price Volatility," *Discussion Paper*, Department of Accounting and Management Science, University of Southampton, No. 93-66.

Board, J. and Sutcliffe, C. 1996, "The Dual Listing of Stock Index Futures: Arbitrage, Spread Arbitrage, and Currency Risk," *Journal of Futures Markets*, 16, 29-54.

Bohl, M. and Reitz, S. 2006, "Do Positive Feedback Traders Act in Germany's Neuer Market?" *Quarterly Journal of Business and Economics*, 45, 3 - 14.

Bollen, N. 1998, "A Note on the Impact of Options on Stock Return Volatility," *Journal of Banking and Finance*, 22, 1181 - 1191.

Bollen, N., Smith, T., and Whaley, R.E. 2003, "Optimal Contract Design: For Whom?," *Journal of Futures Markets,* 23, 719-750.

Bollerslev, T., 1990, "Modeling Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Approach," *Review of Economics and Statistics,* 72, 498-505.

Bollerslev, T., and Wooldridge, J. 1992, "Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances," Econometric Reviews, 11, 143-172.

Bollerslev, T., Chou, R. and Kroner, K. 1992, "ARCH Modeling in Finance," *Journal of Econometrics*, 52, 5 – 59.

Bollerslev, T., Engle, R., and Wooldrige, J. 1988, "A Capital Asset Pricing Model with Time Varying Covariance," *Journal of Political Economy,* 96, 116-131.

Bologna, P. and Cavallo, L. 2002, "Does the Introduction of Stock Index Futures Effectively Reduce Stock Market Volatility? Is the 'Futures Effect' Immediate? Evidence from the Italian Stock Exchange Using GARCH," *Applied Financial Economics*, 12 183 – 192.

Booth, G., Chowdhury, M., Martikainen, T., and Tse, Y. 1997, "Intraday Volatility in International Stock Index Futures Markets: Meteor Showers or Heat Waves?," *Management Science,* 43, 1564-1576.

Booth, G., Lin, J., Martikainen, T., and Tse, Y. 2002, "Trading and Pricing in Upstairs and Downstairs Stock Markets," *Review of Financial Studies,* 15, 1111-1135.

Booth, G., R.W. So., and Y. Tse, 1999, "Price Discovery in the German Equity Index Derivatives Markets," *Journal of Futures Markets,* 19, 619-643.

Brailsford, T. and Cusack, A. 1997, "A Comparison of Futures Pricing Models in a New Market: The Case of Individual Share Futures," *Journal of Futures Markets*. 5. 515 – 541.

Brooks, C. and Chong, J. 2001, "The Cross-Currency Hedging Performance of Implied versus Statistical Forecasting Models," *Journal of Futures Markets*, 21, 1043 – 1069.

Brooks, C., and Henry, Ó.T. 2000, "Linear and Non-Linear Transmission of Equity Return Volatility: Evidence from the US, Japan and Australia," *Economic Modelling*, 17, 497-513.

Brooks, C., Burke, S., and Persand, G. 2003, "Multivariate GARCH Models: Software Choices and Estimation Issues," *Journal of Applied Econometrics,* 18. 725-734.

Brooks, C., Davies, R., and Kim, S. 2006, "Cross Hedging with Single Stock Futures," *Working Paper,* University of Reading.

Brooks, C., Henry, Ó.T., and Persand, G. 2002, "The Effect of Asymmetries on Optimal Hedge Ratios," *Journal of Business*, 75, 333-352.

Brorsen, B. 1991, "Futures Trading, Transactions Costs and Stock Market Volatility," *Journal of Futures Markets*, 11, 153 – 163.

Butterworth, D. 2000, "The Impact of Futures Trading on Underlying Stock Index Volatility: The Case of the FTSE Mid 250 Contract," *Applied Economics Letters*. 7. 439 – 442.

Butterworth, D., and Holmes, P. 2000, "Ex ante Hedging Effectiveness of UK Stock Index Futures Contracts: Evidence for FTSE100 and FTSE Mid250 Contracts," *European Financial Management*, 6, 441-457.

Butterworth, D., and Holmes, P. 2001, "The Hedging Effectiveness of Stock Index Futures: Evidence for FTSE100 and FTSE Mid250 Indexes Traded in the UK," *Applied Financial Economics,* 11, 57-68.

Campbell J.Y., and Hentschel, L. 1992, "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns," *Journal of Financial Economics,* 31, 281-318.

Campbell, J.Y., Lettau, M., Malkiel, B., and Xu, Y. 2001, "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk," *Journal of Finance*, 56. 1 – 43.

Carlton, D. 1984, "Futures Markets: Their Purpose, Their History. Their Growth, Their Success and Failures," *Journal of Futures Markets*, 4, 237-271.

Cecchetti, S., Cumby, R., and Figlewski, S. 1988, "Estimation of the Optimal Futures Hedge," *Review of Economics and Statistics*, 70, 623 – 630.

Chakravarty, S., H. Gulen., and S. Mayhew, 2004, "Informed Trading in Stock and Option Markets," *Journal of Finance,* 59, 1235-1257.

Chan, K. and Karolyi, G. 1991, "The Volatility of the Japanese Stock Market: Evidence from 1977 to 1990," *Japanese Financial Market Research*, edited by W. Ziemba, W. Bailey and Y. Hamao, North-Holland, Amsterdam, 121 – 144.

Chan, K., 1992, "A Further Analysis of the Lead-Lag Relationship between the Cash Market and Stock Index Futures Market," *Review of Financial Studies,* 5, 123-152.

Chan, K., K.C. Chan., and G.A. Karolyi, 1991, "Intraday Volatility in the Stock Index and Stock Index Futures Markets," *Review of Financial Studies,* 4, 657-684.

Chang, E., Chou, R.Y., and Nelling, E.F. 2000, "Market Volatility and the Demand for Hedging in Stock Index Futures," *Journal of Futures Markets*, 20, 105-125.

Chatrath A., Chaudhry, M., and Christie-David, R. 2000, "Price Dynamics and Information Flows in Strategically-linked Debt Instruments: The NOB and MOB Constituents," *Journal of Business Finance and Accounting*, 27, 1003-1025.

Chatrath, A., and Song, F. 1998, "Information and Volatility in Futures and Spot Markets: The Case of the Japanese Yen," *Journal of Futures Markets,* 18, 201-223.

Chatrath, A., Christie-David, R., Dhanda, K.K., and Koch, T.W. 2002, "Index Futures Leadership, Basis Behavior, and Trader Selectivity," *Journal of Futures Markets,* 22, 649-677.

Chau, F., Holmes, P., and Paudyal, K. 2005, "The Impact of Single Stock Futures on Feedback Trading and the Market Dynamics of the Cash Market: The Case of Domestic and Cross-Border Universal Stock Futures," *Working Paper*, University of Durham.

Chaudhury, M. and Elfakhani, S. 1997, "Listing of Put Options: Is There Any Volatility Effect?," *Review of Financial Economics*, 6, 57 – 75.

Chen, S., Lee, C. and Shrestha, K. 2003, "Futures Hedge Ratios: A Review," *Quarterly Review of Economics and Finance*, 43, 433 – 465.

Cheng, Y. 2003, "Propensity Score Matching and the New Issues Puzzle," *Working Paper*, SSRN. Available at http://ssrn.com/abstract=421006

Cheung, Y., and Lai, K. 1993, "Finite Sample Sizes of Johansen's Likelihood Ratio Tests for Cointegration," *Oxford Bulletin of Economics and Statistics,* 55, 313-328.

Cheung, Y.W. and Ng, L.K. 1996, "A Causality-in-variance Test and its Application to Financial Market Prices," *Journal of Econometrics,* 72, 33-48.

Chiang, R., and Fong, W.M. 2001, "Relative Informational Efficiency of Cash, Futures, and Options Markets: The Case of an Emerging Market," *Journal of Banking and Finance,* 25, 355-375.

Chiu, C., Wu, P., Chen, C., and Cheng, W. 2005, "Hedging with Floor-Traded and E-mini Stock Index Futures," *Quarterly Journal of Business & Economics*, 44, 49 – 68.

Chou, R.Y. 1988, "Volatility Persistence and Stock Valuations - Some Empirical Evidence Using GARCH," *Journal of Applied Econometrics*, 3, 279 – 294.

Chou, W., Fan, K. and Lee, C. 1996, "Hedging with the Nikkei Index Futures: The Conventional Model versus the Error Correction Model," *Quarterly Review of Economics and Finance*, 36, 495 – 505.

Choudry, T. 2003, "Short-Run Deviations and Optimal Hedge Ratio: Evidence from Stock Futures," *Journal of Multinational Financial Management*, 13, 171 – 192.

Choudry, T. 2004, "Time-Varying Distribution and Hedging Effectiveness of Three Pacific-Basin Stock Futures," *International Review of Economics and Finance*, 13, 371 – 385.

Choudry, T. 2006, "Short-Run Deviations and Time-Varying Hedge Ratios: Evidence from Agricultural Futures Markets," *Working Paper*, EFMA 2006.

Christie, A. 1982, "The Stochastic Behavior of Common Stock Variance: Value, Leverage and Interest Rate Effects," *Journal of Financial Economics*, 10, 407-432.

Chu, Q.C., Hsieh, W.L., and Tse, Y. 1999, "Price Discovery on the S&P 500 Index Markets: An Analysis of Spot Index, Index Futures, and SPDRs," *International Review of Financial Analysis,* 8, 21-34.

Clark, P.K. 1973, "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices," *Econometrica,* 41, 135-159.

Collver, C.D. 2005, "Informed Trading in Option Market during the Earnings Announcement Periods," *Nova Southwestern University, Working Paper.*

Conrad, J. 1989, "The Price Effect of Option Introduction," *Journal of Finance*, 44, 487 – 498.

Copeland, L. and Zhu, Y. 2006, "Hedging Effectiveness in the Index Futures Market," *Working Paper*, Cardiff Business School, Investment Management Research Unit.

Copeland, T.E. 1976, "A Model of Asset Trading under the Assumption of Sequential Information Arrival," *Journal of Finance,* 31, 1149-1168.

Covrig, V., Ding, D.K., and Low, B.S. 2004, "The Contribution of a Satellite Market to Price Discovery: Evidence from the Singapore Exchange," *Journal of Futures Markets*, 24, 981-1004.

Cox, C. 1976, "Futures Trading and Market Information," *Journal of Political Economy,* 84, 1215-1236.

Crain, S.J. and Lee, J.H. 1995, "Intraday Volatility in Interest Rate and Foreign Exchange Spot and Futures Markets," *Journal of Futures Markets,* 15. 395-421.

Cuny, C.J. 1993, "The Role of Liquidity in Futures Market Innovations," *Review of Financial Studies*, 6, 57-78.

Damodaran, A. 1990, "Index Futures and Stock Market Volatility," *Review of Futures Markets*, 9, 442 – 457.

Damodaran, A. and Lim, J. 1991, "The Effect of Option Listing on the Underlying Stocks Return Process", *Journal of Banking and Finance*, 15, 647 - 664.

Damodaran, A. and Subrahmanyam, M. 1992, "The Effects of Derivative Securities on the Markets for the Underlying Assets in the United States: A Survey," *Financial Markets, Institutions & Instruments*, 1, 1 – 22.

Darrat, A., Rahman, S. and Zhong, M. 2002, "On the Role of Futures Trading in Spot Market Fluctuations: Perpetrator of Volatility or Victim of Regret?," *Journal of Financial Research*, 25, 431 – 444.

De Jong, F. 2002, "Measures of Contributions to Price Discovery: A Comparison," *Journal of Financial Markets,* 5, 323-327.

De Jong, F., and Nijman, T. 1997, "High Frequency Analysis of Lead-Lad Relationships between Financial Markets," *Journal of Empirical Finance,* 4, 259-277.

DeB Harris, F.H., McInish, T.H., and Wood, R.A. 2002, "Common Factor Components versus Information Shares: A Reply," *Journal of Financial Markets,* 5, 341-348.

DeB Harris, F.H., McInish, T.H., and Wood, R.A. 2002, "Security Price Adjustment across Exchanges: An Investigation of Common Factor Components for Dow Stocks," *Journal of Financial Markets,* 5, 277-308.

DeB Harris, F.H., McInish, T.H., Shoesmith, G. and Wood, R.A. 1995, "Cointegration, Error Correction and Price Discovery on Informationally-linked Security Markets," *Journal of Financial and Quantitative Analysis*, 30, 563 – 579.

DeMaskey, A. 1997, "Single and Multiple Portfolio Cross-Hedging with Currency Futures," *Multinational Finance Journal*, 1, 23 – 46.

Dennis, S. and Sim, A. 1999, "Share Price Volatility with the Introduction of Individual Share Futures on the Sydney Futures Exchange", *International Review of Financial Analysis*, 8:2, 153 – 163.

Detemple, J. and Jorion, P. 1990, "Option Listing and Stock Returns," *Journal of Banking and Finance*, 14, 781-801.

Dickey, D.A., and Fuller, W.A. 1981, "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root," *Econometrica,* 49, 1057-1072.

Dodd, R. 2000, "Primer: Derivatives," Available at: www.financialpolicy.org

Duffee, G. 1995, "Stock Returns and Volatility: A Firm Level Analysis," *Journal of Financial Economics*, 37, 399-420.

Dutt, H., and Wein, I. 2003, "On the Adequacy of Single Stock Futures Margining Requirements," *Journal of Futures Markets*, 23, 989-1002.

Dwyer Jr. G, Locke, P., and Yu, W. 1996, "Index Arbitrage and Nonlinear Dynamics between the S&P 500 Futures and Cash," *Review of Financial Studies,* 9, 301-332.

Easley, D., and O'Hara, M. 1987, "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics,* 19, 69-90.

Easley, D., O'Hara, M., and Srinivas, P.S. 1998, "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade," *Journal of Finance,* 53, 431-465.

Ederington, L. 1979, "The Hedging Performance of the New Futures Markets," *Journal of Finance*, 34, 157 – 170.

Edwards, F. 1988a, "Does Futures Trading Increase Stock Market Volatility?", *Financial Analysts Journal*, Jan/Feb, 63 - 69.

Edwards, F. 1988b, "Futures Trading and Cash Market Volatility: Stock Index and Interest Rate Futures", *Journal of Futures Markets*, 8, 421 - 439.

Edwards, F., and Ma, C. 1992, "Futures and Options," International Edition, *McGraw-Hill Book Co.,* Singapore.

Engle, R. 1982, "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation," *Econometrica*, 50, 987-1008.

Engle, R. 2002, "Dynamic Conditional Correlation – A Simple Class of Multivariate GARCH Models," *Journal of Business and Economics Statistics,* 20, 339-350.

Engle, R., and Granger C.W.J. 1987, "Co-integration and Error Correction: Representation, Estimation, and Testing," *Econometrica,* 51, 277-304.

Engle, R., and Kroner, K.F. 1995, "Multivariate Simultaneous Generalized ARCH," *Econometric Theory,* 11, 122-150.

Engle, R., and Ng, V. 1993, "Measuring and Testing the Impact of News on Volatility," *Journal of Finance,* 48, 1749-1778.

Engle, R., and Yoo, B.S. 1987, "Forecasting and Testing in Co-integrated Systems," *Journal of Econometrics,* 35, 143-159.

Eun, C.S., and Sabherwal, S. 2003, "Cross-border Listings and Price Discovery: Evidence from U.S.-Listed Canadian Stocks," *Journal of Finance,* 58 549-575.

Fama, E.F., 1970, "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, 25, 383-417.

Figlewski, S. 1984, "Hedging Performance and Basis Risk in Stock Index Futures," *Journal of Finance*, 39, 657-669.

Figlewski, S. 1987, "The Interaction between Derivatives Securities on Financial Instruments and the Underlying Cash Markets: An Overview." *Journal of Accounting, Auditing & Finance*, 2, 299-318.

Fleming, J., Ostdiek, B. and Whaley, R.E. 1996, "Trading Costs and the Relative Rates of Price Discovery in Stock, Futures and Options Markets," *Journal of Futures Markets*, 16, 353-387.

Floros, C. and Vougas, D. 2004, "Hedge Ratios in Greek Stock Index Futures Market," *Applied Financial Economics*, 14, 1125 – 1136.

Foerster, S. and Karolyi, G. 1998, "Multimarket Trading and Liquidity: A Transaction Data Analysis of Canada-U.S. Interlistings," *Journal of International Financial Markets, Institutions and Money*, 8, 393 – 412.

Foerster, S. and Karolyi, G. 1999, "The Effects of Market Segmentation and Investor Recognition on Asset Prices: Evidence from Foreign Stocks Listing in the United States," Journal of Finance, 54, 981 – 1013.

Franke, G., and Hess, D. 2000, "Information Diffusion in Electronic and Floor Trading," *Journal of Empirical Finance*, 7, 455-478.

French, K.R., and Roll, R. 1986, "Stock Return Variances: The Arrival of Information and the Reaction of Traders," *Journal of Financial Economics*, 17, 5-26.

Freris, A. 1990, "The Effects of the Introduction of Stock Index Futures on Stock Prices: The Experience of Hong Kong 1984 – 1987, *Pacific Basin Capital Markets Research*, edited by S.G. Rhee and R.P. Chang, North Holland, Amsterdam, 409 – 416.

Frino, A., and West, A. 2003, "The Impact of Transaction Costs on Price Discovery: Evidence from Cross-listed Stock Index Futures Contracts," *Pacific-Basin Finance Journal*, 11, 139-151.

Frino, A., Walter, T., and West, A. 2000, "The Lead-Lag Relationship between Equities and Stock Index Futures Markets around Information Releases," *Journal of Futures Markets*, 20, 467-487.

Fung, H., Leung, W.K., and Xu, E. 2001, "Information Role of U.S. Futures Trading in a Global Financial Market," *Journal of Futures Markets*, 21, 1071-1090.

Fung, J.K.W., and Draper, P. 1999, "Mispricing of Index Futures Contracts and Short Sales Constraints," *Journal of Futures Markets*, 19, 695-715.

Fung, J.K.W., Lien, D., Tse, Y., and Tse, Y.K. 2005, "Effects of Electronic Trading on the Hang Seng Index Futures Market," *International Review of Economics and Finance,* 14, 415-425.

Gagnon, L. and Lypny, G. 1995, "Hedging short-term interest risk under time-varying distributions," *Journal of Futures Markets*, 15, 767 – 783.

Gagnon, L. and Lypny, G. 1997, "The Benefits of Dynamically Hedging the Toronto 35 Stock Index," *Canadian Journal of Administrative Sciences*, 14, 69 – 78.

Garbade, K., and Silber, W. 1983, "Price Movements and Price Discovery in Futures and Cash Markets," *Review of Economics and Statistics,* 65, 289-297.

Gerety, M. and Mulherin, J. 1991, "Patterns in Intraday Stock Market Volatility, Past and Present," *Financial Analysts Journal*, 47, 71 – 79.

Geweke, J. 1982, "Measurement of Linear Dependence and Feedback between Multiple Time Series," *Journal of American Statistical Association*, 76, 363 – 373.

Gibson, R., and Zimmermann, H. 1994, "The Benefits and Risks of Derivative Instruments: An Economic Perspective," *Unpublished Manuscript,* Universite de Lausanne and Hochschule St. Gallen.

Glosten, L., Jagannathan, R., and Runkle, D. 1993, "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *Journal of Finance*, 48, 1779-1801.

Glosten, L.R., and Milgrom, P.R. 1985, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics,* 14, 71-100.

Gonzalo, J. 1994, "Five Alternative Methods of Estimating Long-run Equilibrium Relationship," *Econometrica,* 60, 203-233.

Gonzalo, J., and Granger, C. 1995, "Estimation of Common Long-memory Components in Cointegrated Systems," *Journal of Business and Economic Statistics*, 13, 27-36.

Goss, B. and Yamey, B. 1978, "The Economics of Futures Trading," 2nd ed, The Macmillan Press Ltd, London.

Grammig, J., Melvin, M., and Schlag, C. 2004, "The Role of U.S. Trading in Pricing Internationally Cross-Listed Stocks," *EFA 2004 Annual Conference Paper*, No 3267. Avaliable at SSRN: http://ssrn.com/abstract=567066

Grammig, J., Melvin, M., and Schlag, C. 2005, "Internationally Cross-Listed Stock Prices During Overlapping Trading Hours: Price Discovery and Exchange Rate Effects," *Journal of Empirical Finance*, 12, 139-164.

Granger, C.W.J. 1988, "Some Recent Developments in a Concept of Causality," *Journal of Econometrics,* 39, 199-211.

Greene, W. 1997, "Econometric Analysis," 3rd edition, *Prentice Hall International*, UK.

Greewich Associates (GA), 2005, "Securitization Market Investors Survey Cities Disclosure, Price Discovery as Primary Concerns," *Private Placement Letter,* April. p.6.

Grier, K.B., Henry, Ó.T., and Olekalns, N. 2001, "The Effects of Uncertainty on Macroeconomic Performance: The Importance of the Conditional Covariance Model," *University of Melbourne Discussion Paper*, No. 10/2001.

Grunbichler, A., Longstaff, F.A., and Schwartz, E.S. 1994, "Electronic Screen Trading and the Transmission of Information: An Empirical Examination," *Journal of Financial Intermediation,* 3, 166-187.

Gulen, H. and Mayhew, S. 2000, "Stock Index Futures Trading and Volatility in International Equity Markets," *Journal of Futures Markets*, 20, 661 - 685.

Hagelin, N. 2000, "Index Option Market Activity and Cash Market Volatility under Different Market Conditions: An Empirical Study from Sweden," *Applied Financial Economics*, 10, 597 – 613.

Hahn, R. and Tetlock, P. 2006, "A New Approach for Regulating Information Markets," *Journal of Regulatory Economics*, 29, 265 - 281.

Harris, L. 1989, "S&P500 Cash Stock Price Volatilities," *Journal of Finance*, 44, 1155 - 1175.

Harris, L. 1990, "Liquidity, Trading Rules and Electronic Trading System," *Salomon Centre Monograph series in Financial and Economics,* 4, New York University.

Harris, L. 2003, "Trading and Exchange," *Oxford University Press,* Oxford.

Harris, R. and Sollis, R. 2003, "Applied Time Series Modeling and Forecasting," *John Wiley & Son Ltd,* London.

Hasbrouck, J. 1995, "One Security, Many Markets: Determining the Contributions to Price Discovery," *Journal of Finance,* 50, 1175-1199.

Hasbrouck, J. 2003, "Intraday Price Formation in U.S. Equity Index," *Journal of Finance,* 58, 2375-2399.

Hatch, B.C. 2003, "The Intraday relation between NYSE and CBOE Prices," *Journal of Financial Research,* 26, 97-112.

Hemler, M.L., and Longstaff, F. 1991, "General Equilibrium Stock Index Futures Prices: Theory and Empirical Evidence," *Journal of Financial and Quantitative Analysis,* 26, 287-308.

Henry, Ó.T., and McKenzie, M. 2006, "The Impact of Short Selling on Price-Volume Relationship: Evidence from Hong Kong," *Journal of Business*, 79, 671-691.

Herbst, A., Swanson, P. and Caples, S. 1992, "A Re-Determination of Hedging Strategies using Foreign Currency Futures Contracts and Forward Markets," *Journal of Futures Markets*, 12, 93 – 104.

Hodgson, A. and Nicholls, D. 1991, "The Impact of Index Futures Markets on Australian Share Market Volatility," *Journal of Business Finance and Accounting*, 18, 267 – 280.

Hodgson, A., Masih, A., and Masih, R. 2003, "Price Discovery between Informationally Linked Markets during Different Trading Phases," *Journal of Financial Research,* 26, 77-95.

Holmes, P. 1995, "Ex Ante Hedge Ratios and the Hedging Effectiveness of the FTSE-100 Stock Index Futures Contract," *Applied Economics Letters*, 2, 56 – 59.

Holmes, P. 1996, "Stock Index Futures Hedging: Hedge Ratio Estimation, Duration Effects, Expiration Effects and Hedge Ratio Stability," *Journal of Business Finance and Accounting*, 23, 63 – 78.

Hong, H., and Rady, S. 2002, "Strategic Trading and Learning about Liquidity," *Journal of Financial Markets,* 5, 419-450.

Howard, C. and D'Antoniou, L. 1991, "Multiperiod Hedging Using Futures: A Risk Minimization Approach in the Presence of Autocorrelation," *Journal of Futures Markets*, 11, 697 – 710.

Huang, R.D. 2002, "The Quality of ECN and Nasdaq Market Maker Quotes," *Journal of Finance,* 57, 1285-1319.

Hung, M.W., Lee, C.F., and So, L.C. 2003, "Impact of Foreign-listed Single Stock Futures on the Domestic Underlying Stock Markets," *Applied Economics Letters*, 10, 567-574.

Hwang, S., and Valls, P. 2006, "Small Sample Properties of GARCH Estimates and Persistence," *European Journal of Finance*, Forthcoming.

Johansen, S. 1988, "Statistical Analysis of Cointegration Vectors," *Journal of Economics Dynamics and Control,* 12, 231-254.

Johansen, S., and Juselius, K. 1990, "Maximum Likelihood Estimation and Inference on Cointegration - with Applications to the Demand for Money," *Oxford Bulletin of Economics and Statistics,* 52, 169-211.

John, K., Koticha, A., Narayanan, R., Subrahmanyam, M.G. 2003, "Margin Rules, Informed Trading in Derivatives, and Price Dynamics," EFA 2003 *Annual Conference Paper,* No. 508. Available at SSRN: http://ssrn.com/abstract=424981

Johnson, L. 1960, "The Theory of Hedging and Speculation in Commodity Futures," *Review of Economic Studies*, 27, 139 – 151.

Johnson, P.M. 2005, "Perspectives: Solving the Mystery of Stock Futures," *Financial Analysts Journal*, 61, 80-82.

Junkus, J. and Lee, C. 1985, "Use of the Three Stock Index Futures in Hedging Decisions," *Journal of Futures Markets*, 5, 201 – 222.

Kamara, A., Miller, T. and Siegel, A. 1992, "The Effect of Futures Trading on the Stability of Standard and Poor 500 Returns," *Journal of Futures Markets*, 12, 645 – 658.

Kan, R., and Zhou, G. 2003, "Modelling Non-normality Using Multivariate t: Implications for Asset Pricing," *Working paper*, Olin School of Business, Washington University, St. Louis.

Karagozoglu, A. 1999, "Explicit versus Implicit Contracts: The Case of DIFF and CROSS Futures," *Financial Review*, 34, 101 – 118.

Karpoff, J.M. 1987, "The Relationship between Price Changes and Trading Volume: A Survey," *Journal of Financial and Quantitative Analysis,* 22, 109-126.

Kavussanos, M.G. and Nomikos, N. 2000, "Constant vs. Time-Varying Hedge ratios and Hedging Efficiency in the BIFFEX Market," *Transportation Research Part E*, 36, 229 – 248.

Kavussanos, M., Visvikis, L. and Batchelor, R. 2004, "Over-the-counter Forward Contracts and Spot Price Volatility in Shipping," *Transportation Research Part E*, 40, 273 - 296.

Kavussanos, M., and Visvikis, I. 2004, "Market Interactions in Returns and Volatilities between Spot and Forward Shipping Freight Markets," *Journal of Banking and Finance,* 28, 2015-2049.

Kearney, C., and Patton, A.J. 2000, "Multivariate GARCH Modeling of Exchange Rate Volatility Transmission in the European Monetary System," *Financial Review,* 41, 29-48.

Kempf, A. 1998 "Short Selling, Unwinding and Mispricing," *Journal of Futures Markets*, 18, 903-923.

Kim, D. and Kon, S. 1994, "Alternative Models for the Conditional Heteroscedasticity of Stock Returns," *Journal of Business*, 67, 563 – 598.

Kim, M., and Szakmary, A.C., and Schwarz, T.V. 1999, "Trading Costs and Price Discovery across Stock Index Futures and Cash Markets," *Journal of Futures Markets,* 19, 475-498.

Kim, M., Szakmary, A. and Mathur, I. 2000, "Price Transmission Dynamics between ADRs and Their Underlying Foreign Securities," *Journal of Banking and Finance*, 24, 1359 – 1382.

Koch, P. and Koch, T. 1993, "Index and Non-Index Stock Price Volatilities Around the 1987 Market Crash," *Journal of Business Research*, 26, 189 – 199.

Kodres, L. 1994, "The Existence and Impact of Destabilizing Positive Feedback Traders: Evidence from the S&P 500 Index Futures Market," *Working Paper*, SSRN.

Kolb, R.W. 2000, "Futures, Options, and Swaps," 3rd edition, *Blackwell Publishers Inc.*, USA.

Koutmos, G. 1997, "Feedback Trading and the Autocorrelation Pattern of Stock Returns: Further Empirical Evidence," *Journal of International Money and Finance*. 16, 625 - 636.

Koutmos, G. and Pericli, A. 1998, "Dynamic Hedging of Commercial Paper with T-Bill Futures," *Journal of Futures Markets*, 18, 925 – 938.

Koutmos, G. and Saidi, R. 2001, "Positive Feedback Trading in Emerging Capital Markets," *Applied Financial Economics*, 11, 291 - 297.

Koutmos, G. 1996, "Modeling the Dynamic Interdependence of Major European Stock Markets," *Journal of Business Finance and Accounting*, 23, 975-988.

Koutmos, G., and Tucker, M. 1996, "Temporal Relationships and Dynamic Interactions between Spot and Futures Stock Markets," *Journal of Futures Markets*, 16, 55-69.

Kroner, K.F., and Ng, V.K. 1998, "Modeling Asymmetric Comovements of Asset Returns," *Review of Financial Studies*, 11, 817-844.

Kroner, K.F., and Sultan, J. 1993, "Time-varying distributions and dynamic hedging with foreign currency futures," *Journal of Financial and Quantitative Analysis*, 28, 535-551.

Kurov, A., and Lasser, D. 2004, "Price Dynamics in the Regular and E-mini Futures Markets," *Journal of Financial and Quantitative Analysis*, 39, 365-384.

Kyle, A. 1985, "Continous Auctions and Insider Trading," *Econometrica*, 53, 1315-1335.

Laatsch, F. 1991, "A Note on the Effects of the Initiation of Major Market Index Futures on the Daily Returns of the Component Stocks," *Journal of Futures Markets*. 11, 313 – 317.

Lascelles, D. 2002, "Single Stock Futures: The Ultimate Derivative." Centre for the Study of Financial Innovation, *CSFI Publications*, 52, 1 - 23.

Laws, J. and Thompson, J. 2005, "Hedging Effectiveness of Stock Index Futures." *European Journal of Operational Research*, 163, 177 – 191.

Lee, C. and Tong, H. 1998, "Stock Futures: The Effects of Their Trading on the Underlying Stocks in Australia," *Journal of Multinational Financial Management*. 8, 285 – 301.

Lee, S. and Ohk, K. 1992, "Stock Index Futures Listing and Structural Change in Time-Varying Volatility," *Journal of Futures Markets*. 12. 493 – 509.

Lee, T., and Tse, Y. 1996, "Cointegration Tests with Conditional Heteroscedasticity," *Journal of Econometrics*, 73. 401-410.

Lee, T.H. 1994, "Spread and Volatility in Spot and Forward Exchange Rates," *Journal of International Money and Finance,* 13, 375-383.

Lehmann, B.N. 2002, "Some Desiderata for the Measurement of Price Discovery across Markets," *Journal of Financial Markets,* 5, 259-276.

Lien, D. 1996, "The Effect of the Cointegration Relationship on Futures Hedging: A Note," *Journal of Futures Markets*, 16, 773 – 780.

Lien, D. 2004, "Cointegration and the Optimal Hedge Ratio: The General Case," *Quarterly Review of Economics and Finance*, 44, 654 – 658.

Lien, D. 2005a, "A Note on Asymmetric Stochastic Volatility and Futures Hedging," *Journal of Futures Markets*, 25, 607 – 612.

Lien, D. 2005b, "A Note on Superiority of the OLS Hedge Ratio," *Journal of Futures Markets*, 25, 1121 – 1126.

Lien, D. and Tse, Y. 2000, "Hedging Downside Risk with Futures Contracts," *Applied Financial Economics*, 10, 163 – 170.

Lien, D. and Tse, Y. 2002, "Some Recent Developments in Futures Hedging," *Journal of Economic Surveys*, 16, 357 – 396.

Lien, D. and Yang, L. 2006, "Spot-Futures Spread, Time-Varying Correlations, and Hedging with Currency Futures," *Journal of Futures Markets,* 26, 1019 – 1038.

Lien, D., and Yang, L. 2004, "Alternative Settlement Specification and Australian Individual Share Futures Contracts," *Journal of International Financial Markets, Institutions, and Money*, 14, 473-490.

Lien, D., Tse, Y., Tsui, A. 2002, "Evaluating the Hedging Performance of the Constant Correlation GARCH Model," *Applied Financial Economics*, 12, 791 – 798.

Lindahl, M. 1992, "Minimum Variance Hedge Ratios for Stock Index Futures: Duration and Expiration Effects," *Journal of Futures Markets*, 12, 33 – 53.

Lockwood, L. and Linn, S. 1990, "An Examination of Stock Market Return Volatility during Overnight and Intraday Periods, 1964 – 1989," *Journal of Finance*, 45, 591 – 601.

Lypny, G. and Powalla, M. 1998, "The Hedging Effectiveness of DAX Futures," *European Journal of Finance*, 4, 345 – 355.

Maberly, E., Allen, D. and Gilbert, R. 1989, "Stock Index Futures and Cash Market Volatility," *Financial Analysts Journal*, 45, 75 – 77.

MacKinly, A.C., and Ramaswamy, K. 1988, "Index-Futures Arbitrage and the Behavior of Stock Index Futures Prices," *Review of Financial Studies,* 1, 137-158.

MacKinnon, J.G., 1996, "Numerical Distribution Functions for Unit Root and Cointegration Tests," *Journal of Applied Econometrics,* 11, 601-618.

Martens, M., 1998, "Price Discovery in High and Low Volatility Periods: Open Outcry versus Electronic Trading," *Journal of International Financial Markets, Institutions and Money,* 8, 243-260.

Martens, M., Kofman, P., and Vorst, T. 1998, "A Threshold Error Correction Model for Intraday Futures and Index Returns," *Journal of Applied Econometrics,* 13, 245-263.

Mayhew, S. 2000, "The Impact of Derivatives on Cash Markets: What Have We Learned?," *Working Paper*, Department of Banking and Finance, University of Georgia.

Mayhew, S. and Mihov, V. 2004, "How do Exchanges Select Stocks for Option Listing?", *Journal of Finance*, 59, 447 - 471.

McKenzie, M., Brailsford, T., and Faff, R. 2001, "New Insight into the Impact of the Introduction of Futures Trading on Stock Price Volatility," *Journal of Futures Markets,* 21, 237-255.

McKenzie, M.D., and Brooks, R.D. 2003, "The Role of Information in Hong Kong Individual Stock Futures Trading," *Applied Financial Economics,* 13, 123-131.

Meneu, V., and Torro, H. 2003, "Asymmetric Covariance in Spot-Futures Markets," *Journal of Futures Markets,* 23, 1019-1046.

Merton, R. 1973, "An Intertemporal Capital Asset Pricing Model," *Econometrica*, 41, 867 - 888.

Merton, R.C. 1990, "The Financial System and Economic Performance," *Journal of Financial Services Research,* 4, 263-300.

Merton, R. 1995, "A Functional Perspective of Financial Intermediation," *Financial Management,* 24, 23-41.

Miller, E.M. 1977, "Risk, Uncertainty, and Divergence of Opinion," *Journal of Finance*, 32, 1151-1168.

Miller, M.H. 1986, "Financial Innovation: The Last Twenty Years and the Next," *Journal of Financial and Quantitative Analysis*, 21, 459-471.

Moosa, I. 2003, "The Sensitivity of Optimal Hedge Ratio to Model Specification," *Financial Letters*, 1, 15 – 20.

Newey,W. and West, K. 1987, "A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703 – 708.

Ng, V., and Pirrong, S.C. 1994, "Fundamental and Volatility: Storage, Spreads, and the Dynamic of Metal Prices," *Journal of Business,* 67, 203-230.

Nothaft, F., Lekkas, V. and Wang, G. 1995, "The Failure of the Mortgage-Backed Futures Contract," *Journal of Futures Markets*, 15, 585 – 603.

O'Connor, M.L. 1999, "The Cross-sectional Relationship between Trading Costs and Lead/Lag Effects in Stock & Option Markets," *The Financial Review*, 34, 95-118.

O'Hara, M. 1995, "Market Microstructure Theory," *Blackwell Publisher.*

O'Hara, M. 2003, "Presidential Address: Liquidity and Price Discovery," *Journal of Finance*, 58, 1335-1354.

Odean, T. 1998, "Are Investors Reluctant to Realize Losses," *Journal of Finance*, 53, 1887-1934.

Osterwald-Lenum, M. 1992, "A Note with the Quantiles of the Asymptotic Distribution of the ML Cointegration Rank Test Statistics," *Oxford Bulletin of Economics and Statistics*, 54, 461-472.

Pagan, A. 1996, "The Econometrics of Financial Markets," *Journal of Empirical Finance*, 3, 15-102.

Park, T. and Switzer, L. 1995, "Time-Varying Distributions and the Optimal Hedge Ratios for Stock Index Futures," *Applied Financial Economics*, 5, 131 – 137.

Pattarin, F. and Ferretti, R. 2004, "The Mib30 Index and Futures Relationship: Econometric Analysis and Implications for Hedging," *Applied Financial Economics*, 14, 1281 – 1289.

Patton, A.J. 2006, "Modelling Asymmetric Exchange Rate Dependence," *International Economic Review*, 47, 527-556.

Pericli, A. and Koutmos, G. 1997, "Index Futures and Options and Stock Market Volatility," *Journal of Futures Markets*, 17, 957 – 974.

Pilar, C. and Rafael, S. 2002, "Does Derivatives Trading Destabilize the Underlying Assets? Evidence from the Spanish Stock Market," *Applied Economics Letters*, 9, 107 – 110.

Poteshman, A.M. 2006, "Unusual Option Market Activity and the Terrorist Attacks of September 11, 2001," *Journal of Business*, forthcoming.

Presidential Task Force Report on Market Machanisms, 1988.

Puttonen, V. 1993, "Short Sales Restrictions and the Temporal Relationship between Stock Index Cash and Derivative Markets," *Journal of Futures Markets*, 13, 645-664.

Rao, V. 2000, "Preference-Free Optimal Hedging Using Futures," *Economics Letters*, 66, 223 – 228.

Robinson, G. 1994, "The Effect of Futures Trading on Cash Market Volatility: Evidence from the London Stock Exchange," *Review of Futures Markets*, 13, 429 – 452.

Roll, R. 1984, "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market," *Journal of Finance,* 39, 1127-1139.

Roope, M., and Zurbruegg, R. 2002, "The Intraday Price Discovery Process between the Singapore Exchange and Taiwan Futures Exchange," *Journal of Futures Markets*, 22, 219-240.

Ross, S. 1989, "Information and Volatility: the No-arbitrage Martingale Approach to Timing and Resolution Irrelevancy," *Journal of Finance,* 44, 1-17.

Santoni, G. 1987, "Has Programmed Trading Made Stock Prices More Volatile?," Federal Reserve Bank of St. Louis Review, May, 18 – 29.

Schreiber, P.S., and Schwartz, R.A. 1986, "Price Discovery in Securities Markets," *Journal of Portfolio Management,* 12, 43-48.

Schwarz, G. 1978, "Estimation the Dimension of a Model," *Annals of Statistics,* 6, 461-464.

Schwarz, T.V., and Laatsch, F.E. 1991, "Dynamic Efficiency and Price Leadership in Stock Index Cash and Futures Markets," *Journal of Futures Markets,* 11, 669-683.

Schwarz, T.V., and Szakmary, A.C. 1994, "Price Discovery in Petroleum Markets: Arbitrage, Cointegration, and the Time Interval of Analysis," *Journal of Futures Markets,* 14, 147-167.

Schwert, G. 2002, "Stock Volatility in the New Millennium: How Wacky is Nasdaq?," *Journal of Monetary Economics*, 49, 3 – 26.

Sentana, E. and Wadhwani, S. 1992, "Feedback Traders and Stock Returns Autocorrelations: Evidence from a Century Daily Data," *Economic Journal*, 102, 415 – 425.

Shanno, D.F., and Phua, K.H. 1980, "Remark on algorithm 500, a Variable Metric Method for Unconstrained Minimization," *ACM Transactions on Mathematical Software,* 6, 618-622.

Shefrin, H., and Statman, M., 1985, "The Disposition to Sell Winners too Early and Ride Losers too Long: Theory and Evidence," *Journal of Finance,* 40, 777-791.

Silber, W. 1981, "Innovation, Competition and New Contract Design in Futures Markets," *Journal of Futures Markets*, 1, 123-155.

Sim, A. and Zurbruegg, R. 2000, "The KOSPI 200 and Dynamic Hedging Effectiveness During the Asian Financial Crisis," *Working Paper*, School of Banking & Finance, University of New South Wales.

Skinner, D. 1989, "Options Markets and Stock Return Volatility," *Journal of Financial Economics*, 23, 61 - 78.

So, R.W., and Y. Tse, 2004, "Price Discovery in the Hang Seng Index Markets: Index, Futures, and the Tracker Fund," *Journal of Futures Markets,* 24, 887-907.

Sorescu, S. 2000, "The Effect of Options on Stock Prices: 1973 to 1995." *Journal of Finance*, 55, 487 – 514.

St. Pierre, E. 1998, "The Impact of Option Introduction on the Conditional Return Distribution of Underlying Securities," *Financial Review*, 33, 105 – 118.

Stein, J. 1961, "The Simultaneous Determination of Spot and Futures Prices," *American Economic Review*, 51, 1012 – 1025.

Stein, J. 1987, "Information Externalities and Welfare-Reducing Speculation," *Journal of Political Economy*, 95, 1123 - 1145.

Stephan, J.A., and Whaley, R.E. 1990, "Intraday Price Changes and Trading Volume Relationships in the Stock and Stock Options Markets," *Journal of Finance*, 45, 191-220.

Stock, J.H. 1987, "Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors," *Econometrica*, 55, 1035-1056.

Stock, J.H., and Watson, M.W, 1988, "Testing for Common Trends," *Journal of the American Statistical Association*, 83, 1097-1107.

Stoll, H.R., and Whaley, R.E. 1990, "The Dynamics of Stock Index and Stock Index Futures returns," *Journal of Financial and Quantitative Analysis*, 25, 441-468.

Subrahmanyam, A. 1991, "A Theory of Trading in Stock Index Futures," *Review of Financial Studies*, 4, 17-51.

Sutcliffe, C. 1997, "Stock Index Futures: Theories and International Evidence," 2nd Edition, *Cambridge*, ITBP.

Swan, E.J. 2000, "Building the Global Market: A 4000 Year History of Derivatives," *Kluwer Law International Ltd*, London, U.K.

Tesar, L., and Werber, I. 1995, "Home Bias and Higher Turnover," *Journal of International Money and Finance*, 14, 467-492.

Theissen, E. 2002, "Price Discovery in Floor and Screen Trading Systems," *Journal of Empirical Finance*, 9, 455-474.

Theissen, E. 2005, "Price Discovery in Spot and Futures Markets: A Reconsideration," EFMA 2006 *Annual Conference Paper*, No. 202361.

Thomas, S. and Brooks, R. 2001, "GARCH-Based Hedge Ratios for Australian Share Price Index Futures: Does Asymmetry Matter?," *Accounting, Accountability and Performance*, 7, 61 – 76.

Tse, Y. 1999, "Price Discovery and Volatility Spillovers in the DJIA Index and Futures Markets," *Journal of Futures Markets*, 19, 911-930.

Tse, Y., and Xiang, J. 2006, "Market Quality and Price Discovery: Introduction of the E-mini Energy Futures," *Global Finance Journal*, 16, 164-179.

Tse, Y.K., and Tsui, A.K.C. 2002, "A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model with Time-varying Correlation," *Journal of Business and Economics Statistics,* 20, 351-362.

United States General Accounting Office, 2000. "CFTC and SEC Issues Related to the Shad-Johnson Jurisdictional Accord," Report to Congressional Requesters. Washington DC.

Wang, C. and Low, S. 2003, "Hedging with Foreign Currency Denominated Stock Index Futures: Evidence from the MSCI Taiwan Index Futures Market," *Journal of Multinational Financial Management*, 13, 1 – 17.

Wang, P., and Wang, P. 2001, "Equilibrium Adjustment, Basis Risk and Risk Transmission in Spot and Forward Foreign Exchange Markets," *Applied Financial Economics,* 11, 127-136.

Watt, W., Yadav, P. and Draper, P. 1992, "The Impact of Option Listing on Underlying Stock Returns: The UK Evidence," *Journal of Business Finance and Accounting*, 19, 485 – 503.

Wei, P., Poon, P., Zee, S. 1997, "The Effect of Option Listing on Bid-Ask Spreads, Price Volatility, and Trading Activity of the Underlying OTC Stocks," *Review of Quantitative Finance and Accounting*, 9, 165 – 180.

Whaley, R.E. 2003, "Derivatives," Chapter 19 in *Handbook of the Economics of Finance*, Elsevier, 1, Part 2, 1129-1206.

White, H. 1980, "A Heteroskedasticity-consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica,* 48, 817-838.

Working, H. 1953, "Hedging Reconsidered," *Journal of Farm Economics*, 35, 544 – 561.

Wu, G., and Xiao, Z. 2002, "A Generalized Partially Linear Model of Asymmetric Volatility," *Journal of Empirical Finance*, 9, 287-319.

Yadav, P.K., Pope, P.F., and Paudyal, K. 1994, "Threshold Autoregressive Modelling in Finance: the Pricing of Equivalent Assets," *Mathematical Finance*, 4, 205-221.

Yau, J. 1993, "The Performance of the Hong Kong Hang Seng Index Futures Contract in Risk Return Management," *Pacific-Basin Finance Journal*, 1, 381 – 406.

Young, P.L., and Sidney, C. 2003, "Single Stock Futures: A Trader's Guide," *John Wiley & Sons Ltd,* London, U.K.

Yu, S. 2001, "Index Futures Trading and Spot Price Volatility," *Applied Economics Letters*, 8, 183 – 186.

Zhong, M., Darrat, A.F., and Otero, R. 2004, "Price Discovery and Volatility Spillovers in Index Futures Markets: Some Evidence from Mexico," *Journal of Banking and Finance*, 28, 3037-3054.