On the functioning and dynamics of stock market indices and the interaction of international markets: an investigation of the London stock exchange

Santamaria, Daniel

ON THE FUNCTIONING AND DYNAMICS OF STOCK MARKET INDICES AND THE INTERACTION OF INTERNATIONAL MARKETS:

An Investigation of the London Stock Exchange

By

Daniel Santamaria

A thesis submitted for the Doctor of Philosophy in Finance

University of Durham

Department of Economics and Finance

May 2000

To my parents and family
with love

ACKNOWLEDGEMENTS

To begin with, I want to take this opportunity to give my love and appreciation to mum and dad. Not only they gave me unlimited encouragement in the writing of the thesis, but the endless sacrifices they made throughout my life so that I could take advantage of the opportunities opened to me. My appreciation to them for telling me "pull your socks up son" and for being SO PATIENT with me. My love and appreciation extends to my brother Paul, Helen, little Ben and my godson Big Joe for their continued support and encouragement throughout the writing of the thesis.

I want to pay special tribute to my supervisor, Professor Tony Antoniou, not only for his expert guidence, but also for his kindness, consideration and understanding through the difficult times during the writing of the thesis.

I also want to extend my thanks to my old supervisor Dr Ian Garrett of Manchester University, for his helpful contribution to fruitful discussions and expert guidence, despite making endless trips from Manchester.

I want to thank my friends at Durham, especially to two of my best mates, Kostas Vorloou and Paris Frangoulis who were always there for me during good times and bad times. Thanks are also due for Julie Bushby.

I also want to extend my special thanks to Leo and Malvina for their generosity, for their unlimited interest and encouragement in my work.

Finally, I want to dedicate this thesis to my family in Spain and Cuba and especially, to my cousin Luis, who tragically passed away during the final stages of the thesis.

Daniel Santamaria

May 2000

CONTENTS

CONTENTS - *contd.*

CONTENTS - *contd.*

CONTENTS - *contd.*

CONTENTS - *contd.*

CONTENTS - *contd.*

LIST OF TABLES

LIST OF TABLES - *contd.*

LIST OF FIGURES

LIST OF FIGURES - *contd.*

Daniel Santamaria

ON THE FUNCTIONING AND DYNAMICS OF STOCK MARKET INDICES AND THE INTERACTION OF INTERNATIONAL MARKETS:

An Investigation of the London Stock Exchange

A thesis submitted for the Doctor of Philosophy in Finance

May 2000

ABSTRACT

This thesis presents four empirical studies on the functioning and dynamics of stock market indices. The first issue investigates the relationship between market anomalies and the variance of non-trading and trading period index returns. The results reveal the existence of this relationship that the study concludes is indicative of the prominent role of private information as the driving force behind price changes. As a second issue, the thesis addresses the empirical question concerning volatility patterns of index returns at the beginning and end of trading and whether variance differentials are attributable to the way the market processes information. Unlike previous investigations that focus on the behaviour of prices under different market regimes, the study investigates and concludes that the dynamics surrounding the information processing of the market adequately explains this phenomenon. Third, the thesis re-examines the volume-volatility relationship by decomposing trading volume into expected and unexpected components. Despite observing a positive relationship between both variables, the use of volume itself as a means of forecasting changes in index values do not hold for UK data. Finally, the thesis investigates the extent to which asymmetries govern the transmission of volatility across national stock markets. The results confirm the existence of an asymmetric component induced by extreme uncommon shocks such as the October 1987 Crash and by an additional half day's trading in Tokyo. The overall consensus running through the thesis is that changes in index values is indicative of the arrival and utilisation of information as opposed to mispricing caused by the actions of uninformed noise traders.

INTRODUCTION

The objective of this thesis is to investigate the functioning and dynamics of stock market indices and the interactions amongst national markets. One can encapsulate the subject area by the following statement

> *"Information leads to changes in expectations, which in turn leads to changes in prices. Because volatility is the product of unanticipated price movements, it is closely related to information." (Bookstaber & Pomerantz, 1989, p.38)*

When considering the functioning and dynamics of the stock market at national and international level, the above sentence mirrors the common theme of the thesis. That is, the theoretical and empirical question concerning the dynamics surrounding the processing of information in financial markets. Information itself possesses a number of characteristics that is a by-product of national and international stock market dynamics. The notion that information arrives in the market in clusters, which according to the above statement causes a clustering of price changes. In addition, the difference in information content determines whether it induces trading and hence, impact on price volatility. This assertion is dependent on how well informed the market is before the release of information, which in turn reflects on the amount of trading that takes place as traders revise their expectations. Related with the issue of information content is the market's perception of information itself. Usually, one identifies the market's perception of news in terms of whether a piece of information is good news or bad news. An argument explored in the thesis is the notion forwarded by DeBondt & Thaler (1985) that

> *"Research in experimental psychology suggests that, in violation of Bayes' Rule, most people tend to "overreact" to unexpected and dramatic news events." (P.793, 1985)*

where one views the word, "overreaction" in terms of extreme price movements, depicted as a fall in price in reaction to bad news. The final characteristic of information is the assertion that it takes time for stock prices to reflect new information once it arrives in the market. Given the tendency for information to cluster, its impact on trading activity and hence volatility, reflects a revision of prices as the market continues to assess the impact of the information cluster. The volatility persistence as a result, becomes more profound, the longer it takes for the market to analyse the impact of the information cluster. The characteristics of information listed above are such that it is equally applicable to national and international stock market interactions.

Despite the volume of literature in this subject matter, the majority of studies focused on the experience of the US markets. The aim of the thesis is to address some of the gaps that are inevitable in the literature by investigating this subject area on UK data. In addition, the thesis has the dual purpose of modifying the methodologies employed by these studies and uncovering new phenomena, either ignored or not recognised in the literature. Although the subject area focuses mostly on the FTSE-100 Price Index, the nature of the forthcoming studies is such that the thesis provides evidence on other FTSE price indices (the FTSE-250 and FTSE-350 Indices) and the Tokyo and New York markets.

The centrepiece of the thesis is the presentation of four separate empirical studies on the functioning and dynamics of stock market indices. Given the restrictions imposed on the availability of UK data, the thesis treats each study as a separate investigation even though the issues are related on a theoretical level. The objective of the first study is to investigate the relationship between market anomalies and the variance of index returns during non-trading and trading hours. The aim of the second study is to model volatility patterns at the beginning and end of trading and whether the difference in the behaviour of returns is attributable to the way the market disseminates information. The objective of the third investigation is to re-examine the joint dynamics between trading volume and volatility. The central issue addressed is whether volume driven by surprises contains more information and thus is most likely to proxy the information flow than the current information set. Furthermore, the study investigates the impact of asymmetries on the volume-volatility relationship. Finally, the objective of the fourth study is to investigate the extent to which asymmetries govern the transmission of volatility across international markets. In addition, the investigation tackles the empirical question of whether asymmetries in the volatility transmission mechanism are induced by extreme uncommon shocks such as the October 1987 Crash and by weekend trading in Tokyo. The key issue in these chapters is the relationship between information and volatility and how this information affects stock index values both at domestic and international level. Furthermore, the usefulness of the ensuing investigations is that it focuses and develops on areas identified by academics and is of interest to regulatory institutions.

Chapter One briefly introduces the history of the London Stock Exchange (LSE) and it's underlying stock indices[1] followed by a review of the literature on market models. The review is restricted to market models because the LSE operates a dealership market regime that relies heavily on the market maker. From the review, the chapter identifies the four areas of research listed in the previous page and summaries the relevant empirical literature.

Chapter Two provides an overview of the conditional heteroscedastic models as the prominent methodology in the thesis. The chapter places emphasis on highlighting the inadequacies of standard regression analysis by reviewing the literature on the distributional properties of financial time series data. A review of key papers reveals non-normality and non-linear dependencies caused by the time varying nature of statistical moments. As a consequence, this motivates the use of the Generalised Autoregressive Conditional Heteroscedastc (GARCH) type models as the core methodology from Chapter

[1] The chapter will restrict the review on underlying stock indices to those used in the thesis.

Four to Chapter Six of the thesis. In addition, the evidence serves to increase the awareness of the need to address the problem of serial dependencies in the data. This is an issue of paramount importance when utilising the Heteroscedastic Regression Model (HRM) in Chapter Three. Finally, the chapter provides a review of the ARCH family of models.

As a first line of investigation, Chapter Three examines the relationship between market anomalies and the variance of index returns on the FTSE-100 during non-trading and trading hours. Given that ARCH models cannot detect such relationships, the methodology utilised is the HRM using ordinary least squares (OLS). In recognition of the shortfalls faced with traditional regression analysis, the study addresses the problem of serial dependencies in the data by regressing returns on an autoregessive process prior to performing the HRM. For comparison purposes, the HRM provides regression estimates on the mean and variance for each trading day of the week along with variance ratios computed on the basis of the estimates. The most compelling result is the revealing of a relationship between the negative non-trading weekend effect and the variance of index returns. Although index returns are more volatile during trading hours, the results show how differences in the variance of non-trading and trading period returns narrow significantly in the presence of the weekend effect. Considering these findings, the study concludes that private information as opposed to public information and noise trading is the driving force behind the behaviour of index returns.

Chapter Four explores the dynamics that govern the behaviour of index return volatility at the beginning and end of trading. The motivation of this investigation is the Amihud & Mendelson (1987) study on stock return volatility under different trading regimes. Given the London market operates a dealership regime, a study of this nature is not possible using UK data. However, unlike previous investigations that focus on the magnitude of volatility, this study models the time varying nature of volatility using the Exponential GARCH (EGARCH) introduced in Chapter Two. This approach constitutes one of two innovations to the study given that the EGARCH serves the useful purpose of discriminating the impact of good news and bad news on conditional volatility. As a consequence, this entertains the prospect of attributing differences in volatility at opposite times of the day to the degree of asymmetry in returns. Within this framework, a second contribution of the study is the investigation of whether the dynamics surrounding the process of information is responsible for differences in the time varying nature of volatility. It is for this purpose that the study uses the Vector Autoregressive (VAR) approach with the view of performing Impulse Response Analysis on the basis of the conditional variance generated by the EGARCH. In performing this analysis on daily returns by day of the week, the FTSE-100 is more volatile at close of trading. Using impulse responses, the higher volatility at the close is attributable to the failure of the market to return to pre-shock levels following a random shock. This, the study concludes is indicative of inefficiencies in the dynamics that govern the processing of random shocks.

Chapter Five re-investigates the joint dynamics between trading volume and volatility using GARCH analysis on the FTSE-100, FTSE-250 and FTSE-350 Indices. The proposition of three indices provides inferences on whether the composition of the index impacts on the significance and nature of the volume-volatility relation. Furthermore, the study makes two additional contributions to the literature. The first contribution is the proposal of EGARCH models to investigate heteroscedastic versus volume effects. If volume fails to remove EGARCH effects, this leads to the interesting proposition of whether asymmetries impact the volume-volatility relationship. This is possible by using the GARCH model as a benchmark and tool of comparison with the EGARCH analysis. According to the results, there is no evidence of an association between asymmetries and the size of the volume effect, although trading volume helps explain more the GARCH process when using the more complex exponential heteroscedastic approach. The second contribution lies in the treatment of trading volume in which expected and unexpected components are extracted from volume data. In doing so, one can determine whether surprises contains more information and hence, further impact on volume and volatility than current information. The results in this thesis suggest this.

Chapter Six uses recent developments in the bivariate-EGARCH methodology to investigate the extent to which asymmetries govern the transmission of volatility across national indices. The emphasis of the study and one investigated in the initial analysis is the assertion that volatility transmissions are a manifestation of the magnitude and sign of the shock of the last market to trade. Within this context, the centrepiece of the study is the investigation of the following issue: *whether asymmetries in the transmission of volatility are induced by negative, uncommon shocks such as the October 1987 Crash and by an extra half day of trading in Tokyo on some weekends.* Given the nature of the subject area, the study uses daily data on the Tokyo, London and New York stock markets. In using bivariate-EGARCH models, the objective is to extract more information on the mechanism that governs the transmission of volatility than is possible with the GARCH approach. In brief, the results report evidence of volatility spillovers that are more profound in the presence of an asymmetric component. In addition, the findings suggest that asymmetries in the volatility transmission mechanism are induced by extreme uncommon shocks and by weekend trading in Tokyo.

Finally, Chapter Seven provides a summary of the studies undertaken and concludes the thesis. In addition, the chapter points out the implication of the results and lists areas of research identified in the studies that warrant further investigation in the future.

CHAPTER ONE

I. THE ECONOMICS OF THE MARKET MECHANISM

I.1 INTRODUCTION

The objective of this section is to provide an overview on the London Stock Exchange and the underlying stock indices that represents the performance of UK companies. Furthermore, this section provides a critique on the theoretical models that describes the functioning of the market. It is from the review, that the chapter identifies four areas of research that underpins the nature of the subject matter in the thesis.

The London Stock Exchange, the third largest equity market in the world, undertook structural reforms during the 1980's that cumulated in "Big Bang" on October 27, 1986. Amongst the key changes, involved the abolition of the traditional roles of jobbers and brokers and allowing members within the exchange to perform the role of market maker. Other changes included the liberalisation of commission charges and the introduction of a computerised system in quoting prices known as SEAQ for UK stocks and SEAQ International for non-UK stocks. Despite drastic structural changes undertaken by the exchange, the London market retained one key feature of its former trading system, its dealership regime. It is within this framework that the chapter provides a review of the dealership market models to identify areas of research for the purpose of the thesis.

Hence, this section proceeds as follows. Part I.2.1 provides a brief history of the London Stock Exchange along with a list of FTSE price indices launched by the exchange and the Faculty of Actuaries in part I.2.2. Given the LSE's retention of its dealership structure, part I.3.1 reviews the market models, followed by a list of issues for consideration in part I.3.2.

I.2 ABOUT THE UK STOCK MARKET

I.2.1 A Brief History of the London Stock Exchange

The origin of the London Stock Market dates back from the coffee houses in London during the 17th century. Its primary function was to act as a financial intermediary by offering individuals the opportunity to invest or raise money brought and sold shares in joint-stock companies. The attractiveness of financial intermediaries lies in its primary activities which is

> *"to create assets for savers and liabilities for borrowers which are more attractive to each other than would be the case if the parties had to deal with each other directly."*[2]

As their numbers increased, so did the number of intermediaries for investors. In 1760, after their expulsion from the Royal Exchange, 150 brokers created a new establishment at Jonathan's Coffee House where they met to undertake the process of buying and selling shares. By 1773, the members voted to change

[2] Howells & Bain, Financial Markets and Institutions (Longman London and New York, 1990) p.3.

the name of Jonathan's Coffee House to the Stock Exchange. The development of these financial intermediaries was such that by the 19th century, there were in excess of 20 stock exchanges in operation throughout the country. Although these exchanges operated independently of London, the increasing interrelationships between national economies and stock markets culminated in its eventual amalgamation in 1973.

The London Stock Exchange (LSE) became the first stock market in Europe to announce and implement major structural changes in the daily running of the market. On October 27, 1986, the LSE began a series of restructuring reforms of its domestic equity market, nicknamed 'Big Bang'. Some of the changes include the abolition of restrictions on member firms owned by outside corporations, which enables members to raise more capital to compete with competition from overseas. The process of buying and selling securities was simplified by eliminating the need to deal with third parties. Other changes include abolishing the voting rights of members and allowing firms to charge commission to their clients on a negotiable basis.

However, one of the most fundamental changes resulting from Big Bang is the opening of dealership to the competition by member firms. This was possible by eliminating the traditional roles of jobbers[3] and brokers and allowing members to act as market makers committed in the process of making bid and ask prices. Under this system, members as market makers buy and sell shares

[3] Jobbers are dealers who receive customer orders through single-capacity brokers.

for their own account and must quote two way prices on the stocks to which they assign to during the mandatory quote period.[4] Their primary objective is to set a price that represents an unbiased estimate of the expected value of the asset and trade a quantity that clears the market.

Trading itself went through substantial changes from face-to-face contact on the trading floor towards the use of telephones and computers in separate dealing rooms. The introduction of SEAQ for UK stocks and SEAQ International for non-UK stocks enabled share price information to be displayed in broker's offices throughout the UK.

The reforms announced under Big Bang served to increase the competitiveness of the LSE because it accounted for the needs of market participants better than European exchanges.[5] Being available on the phone on a continuous basis, market makers in the LSE provided a greater degree of immediacy than that of the European call auction exchanges. Moreover, market makers who themselves are member firms, commit large amounts of capital to provide a deep market ready to trade large blocks of stock. The competitiveness of the LSE was further enhanced by a 50% reduction in stamp duty on UK equity trades and its abolition on non-UK equity trades, thus providing London with an explicit transaction cost advantage.

---

[4] Market makers are obliged to trade on their quotes up to a quantity known as the Normal Market Size of the stock. On larger transactions, market makers can (and do) trade on a negotiated price.

[5] See Steil, <u>The European Equity Markets, The State of the Union and an Agenda for the Millennium</u>, A Report of the European Capital Markets Institute.

One of the most recent changes has been the launching of the Stock Exchange Electronic Trading Service (SETS) on October 20, 1997 to replace the quote driven market maker system. This is an electronic order book, applicable to stocks listed on the FTSE-100 index only. Under SETS, the matching of bid and ask prices leads to the automatic execution of orders against one another on screen with the intention to increase the speed and efficiency of the London market. However, stocks that move out of the FTSE-100 remain in SETS and stocks initially traded outside continue to operate under the quote driven market maker system.

I.2.2 The London Stock Exchange Indices

Despite the substantial changes implemented in the LSE since Big Bang, one key feature retained by the London market is its dealership structure. The following introduces a cluster of indices developed and launched by the LSE within the dealership market regime. The LSE constructed a "UK index series" along the lines of the major capitalisation blocks and industry sectors of the UK market. Its primary objective is to provide investors with a benchmark for assessing the performance of these sectors. Given that the thesis focuses on the FTSE-100, FTSE-250 and FTSE-350 price indices, this section restricts the review to these indices.

In partnership with the Financial Times and the Institute and Faculty of Actuaries, the LSE launched a number of comprehensive and complementary stock indices. Its purpose was to provide investors a measure of the performance of major capital and industry sectors in the UK market. In 1984 saw the development of the Footse (FTSE) 100 Index. This measures the performance of the 100 largest UK companies listed in the LSE based on market capitalisation. Other than performing this function, the FTSE 100 serves as the basis for futures and traded options on the London International Financial Futures and Options Exchange (LIFFE). As a guide to the performance of medium size companies, the LSE launched the FTSE-250 Index in October 1992. The index comprises of 250 of the largest UK companies after those listed on the FTSE-100 along with the availability of exchange-traded futures. The introduction of the FTSE-250 Index coincided with the launch of the FTSE-350. The index combines all the companies listed on the FTSE-100 and FTSE-250 Indices and serves the primary function as a benchmark for investors whose interests lie in the actively traded large and medium sized companies. One of the key features of the FTSE-350 is the calculation of real-time indices for each industry sector as a measure of industry performance across the UK market on a daily basis. Known as industry baskets, this serves the useful purpose of allowing investors to assess the effect of, and respond faster to the arrival of market-wide information. The LSE also launched other indices that include: FTSE SmallCap, FTSE All Share, FTSE Fledgling, FTSE-350 Higher Yield, FTSE-350 Lower Yield and finally the FTSE AIM.

Table 1.1 compares the size of the LSE with other major stock exchanges throughout the world during 1997. This includes domestic market capitalisation values along with turnover figures for domestic and international stocks and the number of new companies listed, both UK and non-UK. According to the statistics, the LSE is the largest market in Europe and the third largest in the world behind the Tokyo and New York markets. Furthermore, the LSE is the only exchange where trading volume on non-UK stocks is larger than domestic stocks. This is not surprising given the abolition of stamp duty.[6] By contrast, the two largest exchanges, New York and Tokyo both report lower levels of turnover on non-domestic stocks that constitutes a small fraction of the trading volume in domestic stocks.[7]

For illustrative purposes, figure 1.1 and 1.2 plots trading volume by turnover and end of day index prices on the FTSE-100, FTSE-250 and FTSE-350 Indices between 1988 and 1997. Notice that owing to the non-availability of the data, the figures plot trading volume for the FTSE-250 and FTSE-350 indices from September 31, 1992. The figures clearly show a progressive upward trend in trading volume that coincides with similar upward trends in

[6] Note that foreign equity turnover on the LSE is subject to double counting of trades that are executed via the domestic equity market trading mechanisms. Hence, one should treat turnover data with caution. See Steil, The European Equity Markets, The State of the Union and an Agenda for the Millennium, A Report of the European Capital Markets Institute.

[7] This reflects a lower transaction cost in the domestic market in relation to the foreign market. [See Barclay, Litzenburger & Warner (1990)]

Table 1.1

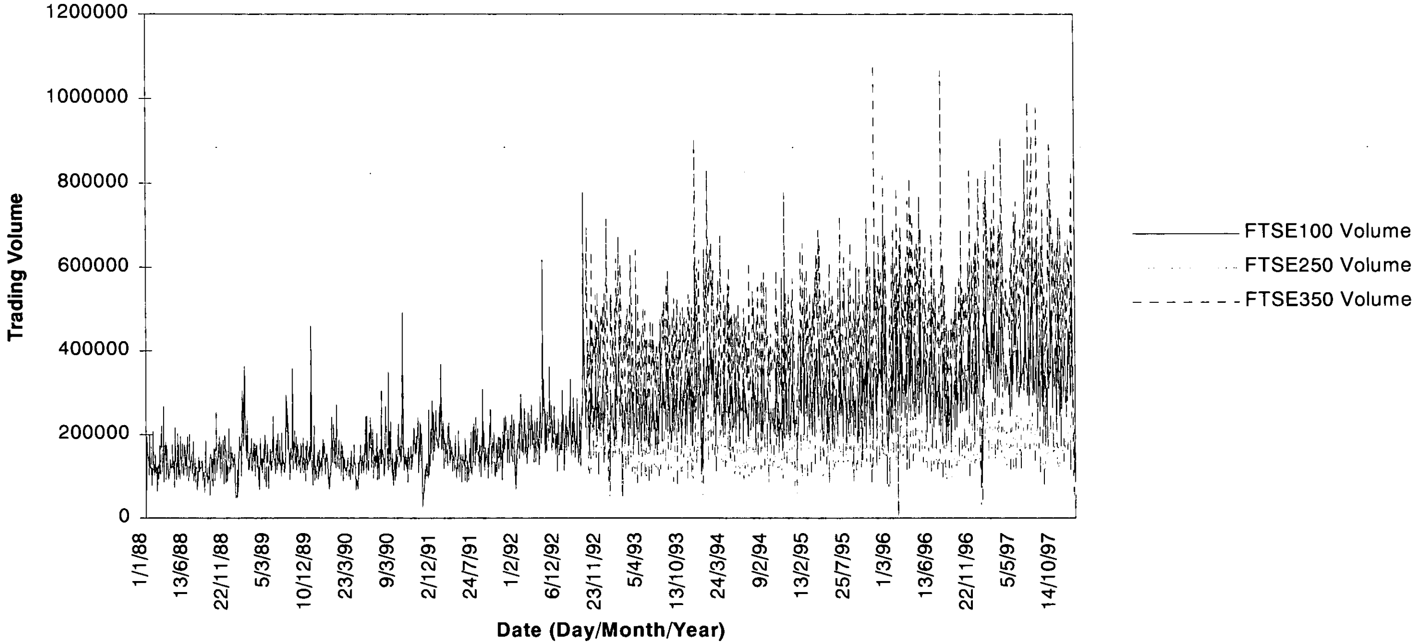
International Comparisons on Market Size at December 31, 1997

Exchange	Domestic Market Capitalisation (£m)	Turnover for 1997 (£m) Dom	Int	New Companies Listed Dom	Int
Australian	178,853	107,427	786	1,159	60
Brussels	82,768	17,261	2,679	141	140
London	1,251,425	523,857	721,617	2,465	526
Hong Kong	250,544	294,596	365	638	20
Luxembourg	20,372	598	12	56	288
Madrid	141,789	248,312	-	385	4
New York	5,463,413	2,266,014	294,943	2,691	356
Singapore	64,563	20,597	-	303	53
Tokyo	1,287,476	497,300	773	1,805	60
Toronto	358,126	186,218	339	1,362	58

Key words: Dom = Domestic, Int = International
Source: London Stock Exchange Fact File 1998

Figure 1.1

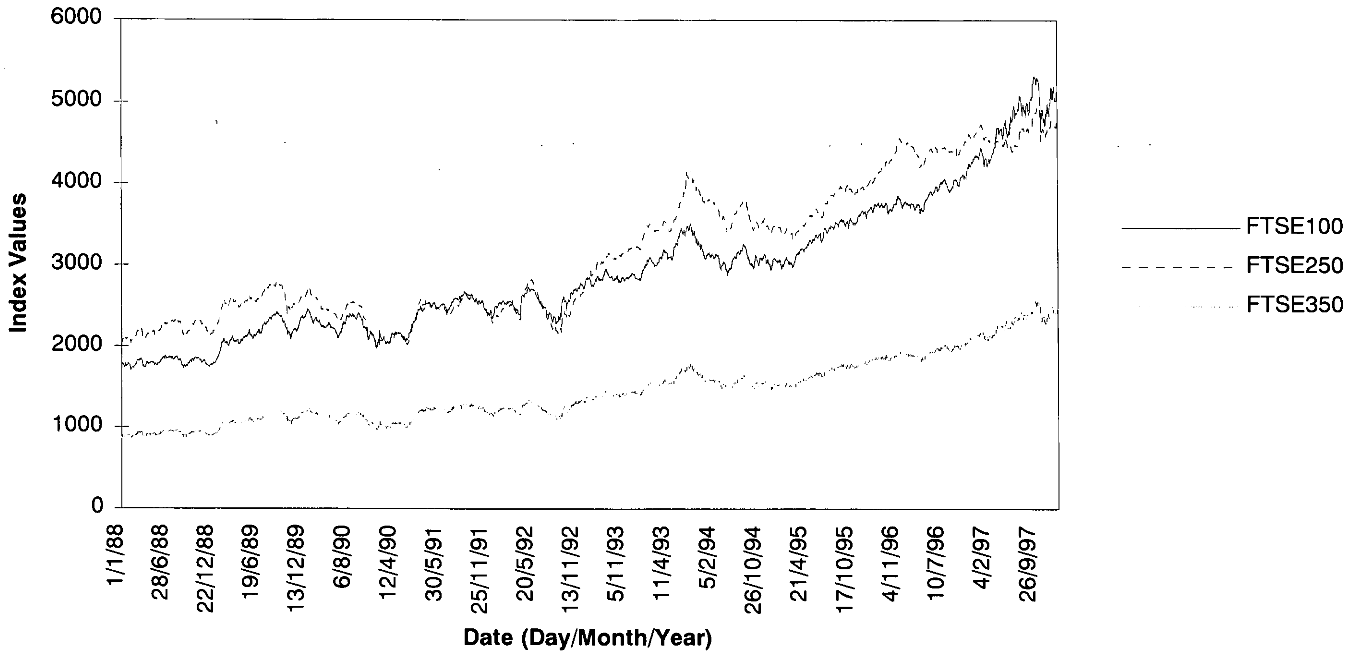
Trading Volume by Turnover Between 1988 and 1997



Source: Datastream International

Figure 1.2

FTSE Index Values Between 1988 and 1997



Source: Datastream International

the index values of all three indices. Moreover, this collaborates with the view of an increasingly competitive market since the reforms of Big Bang in 1986.

To provide intuition behind the figures, table 1.2 provides statistics on the percentage change in index values and trading volumes for the indices. These statistics are based on the values of the last trading day of the year. It is evident from the statistics that the upward trend in both index values and trading volume on an annual basis is not uniform. In the majority of cases, an annual increase (decrease) in trading activity from the previous year coincides with an annual increase (decrease) in the value of the index. However, there are instances where the annual change in both variables has opposite signs. This is most apparent for 1996. The nature of this relationship has been an issue of interest for researchers and one recognised in the thesis. Next, part I.3 provides a critique on the theoretical literature of market models.

Table 1.2

Year on Year Percentage Changes in Index Values
and Trading Volume

	FTSE 100		FTSE 250		FTSE 350	
Year	Index	Volume	Index	Volume	Index	Volume
1988	-	-	-	-	-	-
1989	35%	120%	22%	-	32%	-
1990	-12%	-41%	-20%	-	-14%	-
1991	16%	144%	12%	-	15%	-
1992	14%	-49%	21%	-	16%	-
1993	20%	14%	32%	7%	23%	11%
1994	-10%	-12%	-8%	6%	-10%	-5%
1995	20%	281%	15%	-24%	19%	147%
1996	12%	-77%	12%	-14%	12%	-68%
1997	25%	42%	7%	15%	21%	33%

Note: - refers to the non-availability of data.
The year-on-year percentage changes based on end of year index and volume figures.
Data supplied by Datastream International.

I.3 STOCK MARKET DYNAMICS

I.3.1 A Review on Theoretical Models

Theoretical models demonstrating how stock markets operate constitutes part of the noisy rational expectations literature.[8] The theoretical literature itself is diverse in nature because it conforms either to the market-clearing framework or the market-making framework. Given that the LSE operates a dealership market regime, this section restricts the review of the theory to market making models. The recent work of Kyle (1985), Admati & Pfleiderer (1988) and Foster & Viswanathan (1994) provided a structural link between information, trading volume and volatility. All models envisage a dealership market that consists of informed traders, liquidity traders and a market maker. Both informed and liquidity traders place market orders of quantities they wish to trade. For the former, the quantity traded is on the basis of their information set and is independent of current and future trades of liquidity traders.[9] On the other hand, the quantity traded by liquidity traders is independent from current and past trades of informed and liquidity traders. On this basis, the market maker will set a price and trade the quantity that clears the market based on information consisting of the combined trades of informed and liquidity traders, both past and present. Consequently, the price set represents an unbiased estimation of the expected liquidation value of the asset. Hence on

[8] Dupont (1997).

[9] The market model assumes that the informed trader is a profit maximiser and acts in a monopolistic fashion. Foster & Viswanathan (1994) provides some intuition behind this assumption by postulating that some informed traders are better informed than others. They conclude that those in possession of more information not known by other traders are monopolists in the asset market.

average they earn normal profits. However, the most intriguing aspect of these models is the inability of the market maker to discriminate the trades of informed and liquidity traders. The implication of this is that liquidity trading provides cover for the activities of informed traders in the pursuit of profit maximisation. Informed traders will trade on the basis of their information set along with the order flow. By the end of the period, the market releases the liquidation value of the asset and the asset holders are paid.

Kyle (1985) envisages a market where trading takes the form of a sequence of auctions. He begins with the assumption that the trades of informed traders x_t during period T is dictated by:

$$x_t = X_t(p_1, \ldots\ldots, p_t, v) \qquad t = 1,2,3,\ldots\ldots.,T \tag{1.1}$$

where

X_t = the trading strategy employed by the informed trader;

v = the underlying value of the asset based on fundamentals;

$p_1, \ldots\ldots p_t$ = past prices of the asset traded by the trader.

In addition, he shows that in equilibrium, the market maker must observe the combination of current and past trades of noise traders and informed traders as his information set:

$$y_t = x_t + u_t \tag{1.2}$$

where

x_t = represents trades of informed traders during trading period t;

u_t = represents trades of noise traders during trading period t;

y_t = the combined order flow of informed traders and noise traders.

Hence, Kyle postulates that the market maker will set the clearing price on the basis of

$$p_t = P_t[y_t] \tag{1.3}$$

where P_t is the pricing rule of the market marker. Within the framework of a continuous market, Kyle demonstrates how traders face the problem of how intensively they should trade on the basis of information. To illustrate this, he defines the dynamics of a market where the quantity traded by informed traders, the price set by market makers and the information content of prices takes the form:

$$x_t = \beta_t[v - p_t]t_t \tag{1.4a}$$

$$p_t = \lambda_t(y_t) \tag{1.4b}$$

$$\sum{}_t = var(v|x_1 + u_1, \ldots\ldots, x_t + u_t) \tag{1.4c}$$

where β_t measures how intensive informed traders trade on the basis of private information; $[v - p_t]$ is the information set observed by informed traders in submitting an order; t_t is the exchange trading period; λ_t and $\sum{}_t$ measures market depth and the information content of prices respectively. In this model, an expected increase in market depth, (i.e., λ_t decreases) implies that informed traders will trade small quantities now on the basis of private information β_t and large quantities later. Consequently by adopting this trading strategy now, the cost of unprofitable trades will be low, thus encouraging traders to destabilise prices in the pursuit of abnormal profits. Although volatility will be high during exchange intervals, price destabilisation is temporary given that market depth is expected to increase.

In addition, Kyle shows how volatility throughout the trading day is attributable to the trading volume of noise traders. This possibility arises because market makers cannot discriminate the activities of noise and informed traders. However in equation (1.3), the noise-trading component is rational because the price set by the market maker is an unbiased estimate of the true price. Furthermore, Kyle's model demonstrates that in a continuous equilibrium, the importance of noise trading declines throughout the trading day. Paramount to this result is the concept of market resiliency. Kyle defines market resiliency as the ability of the market to correct itself from uninformative shocks. Hence in a continuous equilibrium, the constant revealing and impounding of private information imply that $\beta_t \to \infty$ towards the close of trading. As a consequence, Kyle concludes that the activities of informed traders will ultimately determine the price at the close given the positive correlation of informed trades from interval to interval.

In related work, Admati & Pfleiderer (1988) extend Kyle's model by envisaging a market where the activities of discretionary liquidity traders induce a high concentration of trades at the beginning and end of trading. Unlike the noise traders in Kyle's model, discretionary liquidity traders have a degree of discretion over the timing of their trades depending on their strategy whilst not possessing any information. In their model, the rate of public information is constant and the magnitude of liquidity trading is the same in all periods. As a consequence, price volatility and trading volume can only be a reflection of changes in the strategic behaviour of traders.

In their model, they show how both informed and discretionary traders prefer to cluster their trades in periods when their trading has little effect on prices. That is, when the market is thick. The concentration of trades causes both trading volume and volatility to be high. The intuition behind this is simple: discretionary traders will trade where expected transaction costs are minimal and this trading encourages informed traders to trade. Assuming that information is endogenous, the greater the number of informed traders there are, the more intensive the competition becomes amongst these traders. This will ultimately reduce the cost of trading thereby improving the welfare of discretionary traders and intensifying the forces that lead to the concentration of trading.

Like Kyle using λ_t to denote market depth, the authors postulated that an increase in the variance of liquidity trading will lead to a decline in the value of λ_t, thus encouraging informed trading. Intuitively, this result is consistent with Kyle's proposition that in times when the market is thick and expected to "thin out," informed traders will trade large quantities on the basis of private information. However the essential finding is that this is indicative of the dominant role of discretionary traders in inducing more trading. It is from this assertion that Admati & Pfleiderer demonstrates the importance of concentrated discretionary liquidity trading on price volatility. To show this, they express the information content of prices and price variability alike at time t as:

$$q_t = var\left(\tilde{\Omega}_{t+1} \mid \tilde{p}_t\right) \tag{1.5a}$$

$$r_t = var\left(\tilde{p}_t - \tilde{p}_{t-1}\right) \tag{1.5b}$$

where q_t is the information content of prices. The notation q_t is explainable in terms of the signal received by informed traders regarding the release of public information in the next period $\tilde{\Omega}_{t+1}$ conditional on current price $\tilde{p}_t$. r_t is the variance of price changes. Within this framework, the authors argue that q_t is higher during periods of concentrated liquidity trading associated with higher return variance r_t. In this model, such a result is indicative of the attraction of more informed traders generating information to be impounded into prices. This effect is more profound when information is diverse. Consequently, they envisage a market where high liquidity trading has a multiplying effect on overall trading. However it is important to note that volatility is not indicative of the trading volume of liquidity traders because the variance of prices is independent of the variance of liquidity traders. Instead like Kyle's model, the trading volume of informed traders causes volatility.

Foster & Viswanathan (1994) provides an asymmetric trading model based on the proposition that some informed traders are better informed than others.

Unlike the Admati & Pfleiderer model, market dynamics are governed by the activities of informed traders as opposed to discretionary liquidity traders. The intuition behind this approach is to overcome the limitations of the Kyle and Admati & Pfleiderer models by relaxing the assumption that informed traders possess common information. Such a proposition leads to the interesting question of how informed traders learn each other's information by observing the order flow. This is of crucial importance because it provides inferences about the role of public and private information and allows changes in the strategic behaviour of traders.

Like Admati & Pfleiderer, trading volume and volatility are highest at the beginning and end of the trading period, however for different reasons. To guarantee expected profits, the objective of well informed traders are to minimise the ability of lesser traders to learn from the order flow. This is possible by trading aggressively on common information during early trading hours. As the amount of common information declines, well informed traders will trade more intensively on additional private information not possessed by the lesser trader. Nevertheless a change in the strategic behaviour of traders arises because of the inclusion of common and additional private information unlike the Kyle and Admati & Pfleiderer models. Deviating further from earlier models, Foster & Viswanathan find the role of common and private information is dependent on the amount of trading hours. They demonstrate that the longer the trading interval becomes, the more aggressive well informed traders will trade on the basis of common information at the start of trading.

Within this framework, the informed trader can change strategy by trading heavily on private information not known to other traders at the end of trading. Therefore, contrary to the Kyle and Admati & Pfleiderer models, changes in trading hours can cause volatility.

Kim & Verrecchia (1991) introduce the notion that the impact of public information on price volatility is dependent on the quality of private information acquired before the release of the announcement. In saying this, they identified a two-way relationship. The quality of the announcement anticipated before release encourages the acquisition of private information, and the quality of private information acquired determines the informational content of the announcement at the time of release. In their model, price volatility following the release of costless public information is indicative of the acquisition of low quality private information. Equally, price volatility can also reflect the acquisition of high quality private information traded upon before the release of the announcement. As a consequence, the release of public information will have little impact on the variance because the revision of expectations amongst traders is smaller. An important feature of their model is information asymmetry whereby the quality of private information acquired before the announcement differs considerably among traders. By assuming information asymmetry, their model recognises that traders differ in their risk aversiveness. Coupled with the cost of information, this implies that some traders can acquire quality private information whereas others cannot.

In addition, the Kim & Verrecchia analysis differs from the models discussed earlier in their treatment of trading volume. They view trading volume as a by-product of the heterogeneous belief revisions among traders following the release of public information. To begin with, Kim & Verrecchia define trading volume $\boldsymbol{TV}$ at trading period t as:

$$\boldsymbol{TV}_t = \boldsymbol{A}_t | p_t - p_{t-1} | \qquad t = 1,2,3......,T \qquad (1.6)$$

where $\boldsymbol{A}_t$ is the information asymmetry that averages the size of the information set of each trader in relation to the average quality of information possessed by each trader. $|p_t - p_{t-1}|$ is a measure of the revision in traders beliefs in terms of the change in price following the release of the announcement. It is within this framework that trading volume is attributable to the impact of public information that is on average, not large or small enough to lead to a convergence of all beliefs and price. By assuming that the expected quality of public information is unknown, the model predicts a positive relationship between price volatility and trading activity as traders continue to acquire private information prior to its release. Supposing that the quality of the announcement released is greater than expected by the market. In such a scenario, the reaction of both prices and trading volume is more profound given that the heterogeneous revision of beliefs amongst traders is greater.

I.3.2 Issues for Consideration

Although, the theoretical models reviewed in this section vary in nature, the common purpose of each one is to describe how a stock market operates within a market maker framework. The applicability of these models to the UK is possible given that the LSE operates a dealership market regime. It is from these models that a number of issues are identified for the purpose of the thesis.

Firstly, the notion of a relationship between market anomalies and the variance of non-trading and trading period index returns. A common feature of all market models is the assumption that private information is endogenously determined with public information held constant. The implication of this is twofold; first, the process of information complements with the potential for market anomalies. One documented phenomenon is the delayed release of negative information until after the close of trading[10] which affects trader expectations on price changes and thus, the timing of their sales and purchases. Second, the variance of returns will be greater during trading hours. This follows from the notion that the acquisition of private information impacts the variance through the actions of informed traders whilst holding the flow of public information constant.

The second issue to consider from the market models concerns the dynamics governing index return volatility at the beginning and end of trading. Although

[10] See the empirical studies cited and investigated by Peterson (1990).

all models posit a U-shaped pattern of volatility and trading activity, it is a by-product of the dynamics in the information processing of the market. By referring to the word "dynamics," one makes frequent references to changes in the strategic behaviour of traders (see Foster & Viswanathan (1994)) and the issue of market depth and resiliency (See Kyle (1985) and Admati & Pfleiderer (1988)). By positing a U-shape pattern of volatility, Kyle and Admati & Pfleiderer postulate that the market is thick and expected to "thin out" at the beginning and end of trading. In the Foster & Viswanathan model, this U-shape pattern is attributable to the utilisation of common and private information during these periods. As a consequence, the dynamics surrounding the processing of information are governed by the interrelationship between the strategic behaviour of traders and expectations on market depth.

A common feature of all models is the demonstration of a structural link between trading volume, the flow of information and volatility. The subject area has attracted much interest by researchers because an answer to this empirical question will improve our understanding about the joint dynamics between trading volume and volatility.[11] The thesis takes one step further by considering whether surprises contain more information content than current information and thus, further impact on trading volume and volatility. The Kim & Verrechia (1991) model provides intuition by considering the relationship between the quality of private information prior to the public announcement and the effects of the announcement itself on volume and volatility. In their

[11] See Section II.4 for a review of the literature.

model, they define surprises in terms of the information content of the announcement, which in turn is determined by the quality of private information gathered prior to its release. Therefore surprises are said to contain more information than expected news and thus, impact further on trading volume and volatility as expectations are revised.

The final issue to consider from the literature is the extent to which asymmetries plays an important role in the transmission of volatility across national stock markets. The nature of the study is such that it requires in addition, the inclusion of the Tokyo and New York markets. Although the market models reviewed can provide intuition behind market interdependencies, they fail to account for those relationships that are governed by the size and sign of innovations. Consequently, the view held and one initially investigated in the study is the underlying notion that the asymmetric transmission of volatility is a manifestation of information, both in sign and magnitude. Therefore, the issue identified from the market models is whether the following events induced asymmetries in the transmission of volatility across national markets:

I. Extreme negative shocks such as the October 1987 Crash;

II. An extra half-day of trading in Tokyo on some Saturdays.

The next section presents a review of the empirical literature. Given the volume of literature and its diversity, the review focuses on key papers on the areas of research outlined above.

II. A Review Of The Literature

II.1 Introduction

In section I, the review of the dealership market models identified four issues for investigation: the relationship between market anomalies and the variance of index returns during non-trading and trading hours; the dynamics governing the time varying nature of volatility at the beginning and end of trading; the volume-volatility relationship as driven by surprises against current information and; finally, the notion of asymmetries in the transmission of volatility across national stock markets.

The objective of this section is to review the literature on these issues. Apart from revealing the conclusions reached by these studies, the review serves the additional purpose of developing further the areas of research in the forthcoming investigations. Part II.2 reviews empirical studies on the process of information versus the process of trading. The nature of the subject area is such that the review considers two strands in the literature; firstly, evidence of market anomalies on US and non-US data and; second, evidence on the variance of trading and non-trading time returns. Part II.3 provides a review of studies on the volatility patterns at the start and end of trading along with evidence of asymmetries in returns. Given that the LSE operates a dealership market regime, the view held is to relate volatility differentials at opposite times of the day to the degree of asymmetry and information processing of the market. Part II.4 reviews the evidence on the volume-volatility relationship as driven by the flow of information. Finally, part II.5 focuses on key papers investigating the nature of international stock market interactions through price and volatility spillovers.

II.2 THE PROCESS OF INFORMATION AND TRADING

The behaviour of stock returns has been amongst the most investigated issues in finance. One of these is whether the process generating returns is continuous or restricted to trading hours. If the process is continuous, then the distribution of returns for Monday will differ from other days of the week. On the other hand, restricting the return generating process to trading hours, implies that the distribution of returns will exhibit the same shape across days of the week. An answer to this question will improve our understanding of the process of information and trading in generating changes in stock prices.

The question of whether the process generating returns is continuous or restricted to trading hours is well documented. Essentially, the literature divides into two interrelated areas. The first strand of evidence focuses on return anomalies in the first moments and the second deals with the variance of returns during trading and non-trading hours. Despite the volume of literature on this issue, previous studies have failed to demonstrate the relationship between market anomalies and the volatility differential in trading and non-trading time returns. Consequently, for the purpose of the thesis, the review serves the purpose of reviewing empirical studies on the behaviour of returns in their first and second moments.

II.2.1 Market Anomalies

The notion that expected returns for each day of the week should be the same is not a necessary condition for an efficient market. Despite this, in an efficient market, the activities of profit maximising traders ensure that such anomalies would be arbitraged away. Market anomalies observed in stock returns may be the reflection of the process of buying and selling based on traders expectations in the pursuit of profit maximisation. To elaborate further, traders on Fridays may delay their purchases until Monday when they expect stock prices to be lower. Conversely, sellers on Monday may delay their sales until Friday when prices are higher.

For the US market, a widely reported anomaly is the weekend effect where stock positions held over the two-day exchange holiday earn a statistically significant negative return. In testing the calendar time and trading time hypothesis, French (1980) reports a negative weekend effect based on daily returns on a portfolio that comprises all the companies listed on the S&P500 Index. Given the persisting nature of the weekend effect, French forwards the conclusion that this reflects a degree of market inefficiency.

In a related study, Rogalski (1984) investigates market anomalies by decomposing returns into trading and non-trading components. Using trading and non-trading index returns on the Dow Jones Industrial Average, he concludes that the weekend anomaly is a negative non-trading weekend effect. An implication of this result is to identify the origins of the weekend effect and to demonstrate the importance of opening index values in understanding the nature of the anomaly. Just as compelling is the revealing of a casual relationship between the non-trading weekend effect and the well-documented January effect. The nature of the relationship is such that the January effect dominates the non-trading weekend effect observed for the rest of the sample.

In another study, Peterson (1990) investigates whether seasonal patterns in returns is a reflection of anomalies in the reporting of earnings information. The motivation of this study is to document further evidence on the notion that firms tend to disclose positive earnings information earlier than negative information. In establishing this as the benchmark of his study, Peterson makes the useful distinction between reporting and non-reporting firms. The failure of firms to report earnings information implies that the information is likely to be negative. Using all companies listed on the CRSP daily returns file between 1980 and 1986, he finds anomalies of non-reporting returns similar to or marginally more profound than reporting returns. The implication of this finding is to question the assertion that the weekend effect is attributable to the delay in the release of negative information until after the close of trading.

In a recent study, Wang, Li & Erickson (1997) uses data on the NYSE, AMEX, Nasdaq and S&P Composite Index to show that the negative Monday effect occurs in the last two weeks of the month. The motivation of their study is twofold; firstly, to test the robustness of the weekend effect on different indices, using different sub-samples and controlling for the monthly effect. The other objective is to provide a fuller explanation behind the weekend effect. Despite the robustness of the weekend effect for the last two Mondays of the month, further investigtion using correlation analysis with the previous day's return and the impact of expiration days for stock options failed to provide an explanation behind this phenomenon.

For non-US studies, the literature is less extensive, although they provide an additional dimension by investigating whether seasonal patterns in other stock markets are independent to those revealed in the US. This is one issue addressed along with others by Jaffe & Westerfield (1985) in relation to the US, Japan, Canada, UK and Australia. Using daily stock returns for each of the markets, they report conclusive evidence of a weekend effect that is independent of the weekend effect observed in the US. Condoyanni, Hanlon & Ward (1987) later report similar findings using a larger number of markets.

In their study, Bell & Levin (1996) provide evidence of market anomalies using UK data. The motivation of their study relates to the identification of institutional features of the UK market that could explain the existence of market anomalies. By taking such a position, calendar regularities no longer appear to compromise market efficiency. Their findings are revealing by the isolation of three factors which, if accounted for properly, removes the weekend effect: the discontinuity in financing costs that are associated with the account settlement period; the "relative scarcity of funds while finance is held in banks' suspense and transmission accounts on Settlement day"[12] and; the decline in the transactions demand for money during non-trading periods including weekends.

Draper & Paudyal (1998) investigates the Monday effect by using an integrated regression model on two value weighted stock indices and 452 individual stocks traded on the LSE. The usefulness of the integrated regression model relates to its ability to capture both day-of-the-week effects along with seasonal and market factors. Consistent with the findings of previous studies, they report evidence of a negative Monday effect assuming that prices alone is considered. However, the incorporation of seasonal and market factors reveals that the average Monday return approximates the average return of other weekdays. Factors of importance included; fortnight of the month effect, account settlement day, ex-dividend day, the arrival of negative information on Fridays, trading activity and bid-ask spread. On the basis of these findings, the authors concluded that the results broadly support the trading time hypothesis for the weekend effect.

[12] Page 3, Bell & Levin (1996).

II.2.2 Trading and Non-Trading Time Variances

A well-documented phenomenon is the notion that equity returns are more volatile during trading hours. Oldfield and Rogalski (1980) postulate that daily returns exhibit a Autoregressive Jump Process that reflects the execution of trades. By contrast, a characteristic of non-trading returns is a single jump depicting the closing of the market. Therefore, the mean return is equal to one and the variance is zero. Although their model provides intuition behind this phenomenon, it fails to improve our understanding of the process of information in financial markets. Although the literature in this area is diverse, the primary objective of empirical studies is to test the validity of three competing hypothesis. First, the *Public Information Hypothesis,* which states that the scheduled release of information induces clustering of spot price volatility throughout the trading day. The official release of such information may not coincide with trading hours and as a consequence, the opening price will reflect a revision of expectations overnight. The result being, is the prediction that the variance of non-trading time returns equates trading time volatility.

Second, the *Private Information Hypothesis,* which states that a component of information impacts spot prices through the trading of informed investors. This process takes place during trading hours only, which implies that return volatility will be higher during trading than non-trading hours. Finally, some studies introduce the possibility that the irrational behaviour of traders may explain the behavioural characteristics of returns during trading and non-trading hours. Commonly termed as the *Noise Trading Hypothesis*, the trading activity of uniformed traders may induce mispricing. The additional volatility that follows is the correction of the pricing error by the market. As with the private information hypothesis, this process only takes place during trading hours.

Although the introduction of three competing hypothesis may explain the differential between trading and non-trading variance, no underlying explanation for this can be sought in its current form. Power (1970) provides useful intuition by relating volatility to the rate of information flow and noise trading. Ross (1989) derives a more restrictive version by linking the flow of information to stock market volatility:[13]

$$\sigma_p^2 = \sigma_s^2 \tag{1.7}$$

where

σ_p^2 = the variance of the change in stock prices;

σ_s^2 = the variance in the flow of information.

Equation (1.7) represents a non-arbitrage condition in which the variance of the change in price equates the variance in the flow of information relevant to the pricing of the asset. In forwarding such a hypothesis, Ross provides a simplistic explanation behind the behaviour of stock returns as driven by changes in the flow of information during trading and non-trading hours.

[13] To be examined in greater detail in Chapter Three.

II.2.3 Empirical Studies

Despite the consensus that the arrival of information has an impact on the variance of spot prices, there is disagreement on how this information affects volatility. Engle & Ng (1993) infer that the problem lies in the model specification used to measure volatility. Conversely, Antoniou & Holmes (1995) criticises previous studies for failing to acknowledge the link between information and volatility.

French & Roll (1986) investigates the behaviour of trading and non-trading returns by empirically testing the Public Information, Private Information and Noise Trading Hypothesis. Attention centred on the movement of stock returns on business days when the US market was closed, most notably on Wednesdays during the second half of 1968 and election days between 1962 and 1980. In computing variance ratios, they report convincing results that exchange holidays coincide with a low variance of returns. They find similar results when they compare two-day election returns with one-day returns for the same time period. On this basis, the study concludes that the data is consistent with the private information hypothesis. Although they acknowledge some evidence of noise trading, they find its impact on return variance is insignificant given that mispricing contributes between 4% and 12% variance in daily returns.

Harvey & Huang (1991) report mixed results using major currency futures on the International Money Markets (IMM) and the London International

Financial Futures Exchange (LIFFE). Their results are similar to those of French & Roll by reporting a concentration of variance in European cross rates during European trading hours. This they attribute to the concentration of informed trades when the market is most liquid. However, despite finding the US dollar more volatile during US trading hours, the study concludes this is a by-product of the arrival of public information as opposed to private information. Of paramount importance are two factors that the study based its conclusion. First, owing to its liquidity and 24 hour trading on the currency, they argue that the likelihood of an accumulation of traders possessing private information during US business hours is remote. In addition, the volatility of opening prices in the IMM is highest on days that coincide with major US economic announcements. This, they verify by tests on intra-daily variance equality that showed the strongest rejection of the null hypothesis occurring on Friday.

Jones, Kaul & Lipson (1994) provide further support for the public information hypothesis. In their study, they define non-trading periods as a scenario where traders endogenously decide not to trade when stock exchanges and businesses are open. The study makes a significant contribution to the literature by investigating the relationship between variance differentials across trading and non-trading periods and the size of the stock. They use NASDAQ - NMS stocks from the CRSP to construct five portfolios on the basis of market value to proxy the flow of information across securities. Their results reveal support for a positive relationship between variance ratios for weekdays and weekends and the size of the firm (i.e., the flow of information). In addition, their study makes a further contribution to the literature by determining which component of information is the driving force behind the positive relationship between variance and size. Using bid/ask spreads for this purpose, the study concludes that differences in return variance across portfolios are attributable to the rate of public information inflow.

Deviating from previous studies, Cheung & Kwan (1992) focus on the extent to which the dominant role of public information is restricted to the domestic market. Given the nature of the investigation, the authors opted to use data on the Toronto Stock Exchange (TSE) and New York Stock Exchange (NYSE). By comparing daily variance one and two days before, during and after exchange holidays in the US and Canada, the study investigates whether trading activity is abnormal on days when one of the exchanges is closed. They report results that fail to contradict the notion that the dominant role of public information is purely a domestic phenomenon. Upon closer inspection of the results, the most prominent conclusion is the finding that information from the US has a greater impact on the price volatility of other markets. Inferring from these findings, this is indicative of the dominance of the US market.

II.2.4 Summary of the Literature

Despite the volume of research on the return generating process, the literature to date has focused separately the issue of market anomalies and the variance of returns during trading and non-trading hours. It is the fact that previous studies have addressed these two areas separately that warrants an investigation of the anomaly-volatility relationship in this thesis. From the literature reviewed, the most documented finding is the revealing of a negative weekend anomaly that originates from the Friday close to the Monday open [Rogalski (1984)]. By contrast, there is less consensus on the driving force behind the behaviour of returns during trading and non-trading hours.

Due to the volume of literature on market anomalies, the review focused exclusively on the weekend effect. Previous studies have documented evidence of other seasonal patterns in returns in the form of the January effect and size effect of small stocks. [For instance, Keim (1983), Chan (1986) and more recently, Rathinasamy & Mantripragada (1996)] However, Dimson & Marsh (1999) using UK data from 1955 to 1997 reveal evidence questioning the robustness of the size effect in recent years whereby larger stocks reported higher abnormal returns since the launch of the Hoare Govett Smaller Companies Index in 1987.

A possible explanation behind the relationship between market anomalies and the variance of returns can be found in studies cited by Peterson (1990) in their attempt to investigate the timing in the release of negative earnings information. The assertion that traders on Friday postpone their purchases until Monday when they expect stock prices to be lower is a reflection of the expected release of negative information. The volatility that follows is indicative of the revision of expectations resulting from the release of this information over the weekend. Chapter Three investigates this issue further.

II.3 PRICE VOLATILITY AT THE OPEN AND CLOSE OF TRADING

One of the issues for consideration in the thesis concerns an investigation into the dynamics governing index return volatility at the open and close of trading. The literature to date is restrictive in scope and mostly focuses on whether differences in price volatility are a by-product of the market regime in operation. The main contributors in this issue are Garbade & Silber (1979) and Mendelson (1982, 1987) where they define market regimes in terms of the operation of a clearing-house and a dealership market. Pagano & Roell (1990) provides the most comprehensive overview on the subject. Their study serves the dual purpose of reviewing the merits, in theory and practice, of different trading systems and the implications for the performance and competitiveness of the European markets. The first empirical paper on the subject is Amihud & Mendelson (1987) for US stocks. Following this, is the Amihud & Mendelson (1989) study on the Tokyo Stock Exchange and Amihud, Mendelson & Murgia (1989) in relation to the Italian market: both studies cited by Pagano & Roell in their review. However, an investigation of this nature is not possible using UK data given that the LSE operates a dealership market regime. Consequently, the review on the literature focuses on US studies given its proximity to the operation of the UK market.

A related issue concerns the degree of asymmetry in returns at the start and end of trading. In this context, one describes the asymmetric effect in terms of the market reaction to the arrival of good news and bad news. When bad news arrives, this causes an unexpected drop in price that increases predictable volatility in excess of an unexpected increase in price caused by the arrival of good news. By taking into consideration the asymmetric effect, one probes deeper into the understanding of market dynamics by attributing differences in volatility to the overreaction (under-reaction) to bad (good) news at opposite periods of the trading day.

Given the absence of literature covering this issue directly, the review serves two purposes; firstly, to summarise the evidence on volatility patterns at opposite times of the day and secondly; to introduce and review the findings on the phenomena of the asymmetric effect in stock returns.

II.3.1 Evidence on Volatility Differentials

A problem envisaged in making empirical comparisons of two trading regimes is that it is difficult to attribute changes in the behaviour of stock prices to the trading mechanism when assets are traded in different environments. To overcome this difficulty, previous studies made the distinction between open-to-open and close-to-close returns. This is possible by viewing the opening transactions as representing the outcome of a clearing-house procedure and transactions at the close dictated by prices set by the market maker.

Amihud & Mendelson (1987) uses open-to-open and close-to-close returns on 30 NYSE stocks that comprise the Dow Jones Industrial List between February 8, 1982 and February 8, 1983. Although they focus on observed returns, the authors argue that the source of the volatility differential is the noise component that they assume to be endogenously determined by the trading mechanism. Using measures of dispersion, they find stock prices more volatile at the start of trading. What makes this result intriguing is how the variance of close-to-close returns is subject to bid-ask bias that increases the significance of the noise component in returns. However, these findings suggest on balance, that the magnitude of noise induced at the open is greater in significance.

Stoll & Whaley (1990) confirm the phenomena that the variance of open-to-open returns is greater than close-to-close returns. The study makes a significant contribution to the literature by examining the effects of market structure on volatility as attributable to the strategic behaviour of traders. They find frequently traded stocks are likely to be opened by a clearing- house procedure that exhibits higher variance and evidence of price reversals. The authors view this as a reflection of abnormal trading volume and delays at the open with the latter reflecting the strategic behaviour of the specialist. However, in using trading volume data at the open, close and during the trading day, the authors seem to have in mind a test of the joint dynamics between trading volume and volatility. The results lend support to this view, in which daytime volume causes an increase in the variance of close-to-close returns whereas volume and delays at the start of trading induce volatility of open-to-open returns. In summing up, the investigation concludes that the latter dominated the former.

In a later study, Park (1993) questions the findings of previous studies by arguing that the measure of volatility employed induces bid-ask bias. Although Amihud & Mendelson and Stoll & Whaley previously acknowledged the potential of bid/ask bias, they infer that this is not significant enough to dominate the volatility of open-to-open returns. However, by comparing the performance of natural and temporal measures of volatility, Park reports some striking results. In using the standard definition of volatility, he finds volatility revealing a U-shape pattern using intra-daily data. The implication of this result is to cast doubt on the interpretation that the difference in volatility patterns at the beginning and end of trading is indicative of the operation of different trading regimes. This view has additional credibility by the removal of the U-shape pattern using the temporal measure of volatility. Instead, this finding is suggestive of the efficient utilisation of information into prices as opposed to the trading regime in operation.

II.3.2 Evidence on Asymmetries in Stock Returns

French, Schwert & Stambaugh (1987) provide useful inferences on the relationship between the arrival of unanticipated information and returns. For instance, they postulate and find a negative relationship between returns and the unpredictable component of volatility, defined as the difference between predicted variance and actual variance of returns. If surprises increase investor uncertainty and there is a positive relation between expected risk premium and predictable volatility, they conclude that the discount rate for future cash flows will rise, thus reducing the present value of the stock and hence, its stock price.

Crucial to the issue of return asymmetries is the Uncertain Information Hypothesis (UIH), introduced by Brown, Harlow & Tinic (1988). In their study, they present a more viable and testable alternative to the Efficient Market Hypothesis (EMH) of Fama (1970). The basis of the UIH is the notion that investors change their demand and supply of inventories and hence the stock price before the consequence of an announcement is known. Consequently, this model defines surprises in terms of the arrival of new information, regardless of whether it is good news or bad news. Although the model maintains the assumption of rational and instantaneous use of information, the UIH deviates from the EMH on two fronts. First, investors are risk averse and secondly, the model recognises the importance of surprises, whether it be good news or bad news in which the common effect is to increase uncertainty. Implicit to this assertion is the assumption that traders have incomplete information before hand.

Within the framework of the UIH, the market will overreact to bad news given the dominance of risk aversive investors and the increased uncertainty. As the uncertainty induced by the surprise diminishes, prices will reverse up to a level where the post announcement expected return equates the pre announcement expected return. On the other hand, positive news leads to an initial rise in price followed by further price rises as the uncertainty diminishes. As with the effects of negative news, subsequent price rises after the initial stock market reaction is indicative of risk averse investors demanding a higher required rate of return as compensation for the increased uncertainty.

One of the most important contributors in this area is Campbell & Hentschel (1992) by introducing the concept of volatility feedback. Volatility feedback is an appealing concept because it is not sensitive to the non-normality in stock returns, thus accounting for the more complex nature of stock price reaction following a shock. The intuition behind this is the notion that volatility and the required rate of return will be lower in future following the arrival of no news, thus raising the stock price. If a piece of bad news arrives at the market regarding future dividends, this will increase future expected volatility. An increase in expected volatility raises the required rate of return, hence reducing the stock price. On the other hand, the arrival of bad news will increase the required rate of return and decrease the stock price, however the volatility effect will amplify the negative impact of the information. In other words, the market overreacts to the arrival of bad news.

II.3.3 Summary of the Literature

As an empirical question, stock market behaviour at the beginning and end of trading has received less attention. Despite some attempts to address this issue, these studies are restrictive in nature because it observes the size of the price change as opposed to the time varying nature of volatility. In addition, by paying attention on the market mechanism in operation, the literature fails to consider the dynamics governing the processing of information at the beginning and end of trading. Hence, Chapter Four of the thesis treats this as an empirical question in relation to UK data.

Focusing on the literature to date, a number of conclusions arise from the studies reviewed. Firstly using US data, open-to-open returns are more volatile than close-to-close returns. The finding that the market is more volatile at the start of trading coincides with the outcome of a clearing-house procedure. Second, a well-documented result is the revealing of asymmetries in stock returns.

Despite evidence of higher volatility at the commencement of trading, there is little consensus as to the source of the volatility differential. Amihud & Mendelson (1987) attributes differences in volatility to the mispricing component. Stoll & Whaley (1990) concludes that abnormal trading volume along with delays at the open explains the higher variability of prices at the commencement of trading. Given the inconclusiveness identified with this issue, the thesis focuses on the way market traders process information using impulse responses on the variance at the open and close of trading.

II.4 INFORMATION, TRADING VOLUME AND VOLATILITY

One of the most important questions to arise from the contribution of Ross (1989) and the equality condition of equation (1.7) is how to model the flow of information. Previous studies have highlighted the importance of this issue despite having different objectives. Darret & Rahman (1995) argued that jump volatility could be the result of the frequent flow of information. Antoniou & Holmes (1995) attributed increases in stock price volatility following the onset of futures trading to increases in the flow of information.

To begin with, traders trade in response to the arrival of information and as risk aversive agents engage in rebalancing portfolios. Given that market equilibrium represents the sum of individual demand and supply schedules of traders, the arrival of information leads to a revision of expectations that brings about disequilibrium. Through trading, the complex process of correcting individual excess demand or supply generates a new equilibrium price. Within this framework, the process of revision leads to a positive relationship between price volatility and trading volume driven by the arrival of information.

The volume of research in this area is diverse, yet there are two broad strands in the literature. The first, tests the volume-volatility relationship based on the traditional regression analysis. The second strand, tests for heteroscedasticity in the data that is explainable in terms of the informational role of volume. Although the nature of the studies varies considerably, all have the common objective of investigating the relationship between trading volume and volatility. As a consequence, this review focuses on a number of key papers.

II.4.1 On the Relation Between Trading Volume and Volatility

The most comprehensive review of the theory and empirical work is Karpoff (1987). Although he summarises the literature on the subject, Karpoff provides some interesting propositions, a number of which are taken up in this thesis. In citing the findings of previous studies, Karpoff reports overwhelming evidence of a positive relationship between trading volume and volatility, although the strength of the correlation varied depending on the data.

In their paper, Gallant, Rossi & Tauchen (1992) provide a though investigation of the volume-volatility relationship based on NYSE data between 1928 and 1987. The motivation behind their study is to address empirical issues not accounted for in previous studies, namely the generation of a volume-volatility relationship that is jointly stationary. This they achieve by adjusting log price changes and trading volume for anomalies and any deterministic trends in the data. The study makes a significant contribution to the existing literature by viewing the volume-volatility issue as a two-way relationship. Empirical testing on the stationary volume-volatility relationship reveals by-directional causality between trading volume and price changes. In addition, they observed a positive association between risk and return after conditioning on lagged volume.

Bessembinder & Seguin (1993) further examine the volume-volatility relationship using eight physical and financial futures data between May 1982 and March 1990. The main contribution of the study lies in their treatment of trading volume. Namely, the decomposition of volume into expected and unexpected components that correlates separately with volatility. The implication of this approach is to invite the prospect of determining whether volume induced by shocks contains more information and hence, a more profound impact on volatility than volume driven by expected information. Using regression analysis, they report a positive contemporaneous correlation between volume and volatility where surprises have between two and thirteen times greater impact on volatility. In addition, the study provides results on whether the volume-volatility relationship is asymmetric, an issue first identified by Karpoff (1987). Although they find an asymmetric relationship between volume and volatility, positive surprises accounted for 76% greater volatility.

Daigler & Wiley (1998) extend the Bessembinder & Seguin study by focusing on the volume-volatility relationship driven by four separate components of volume determined by the activities of the following participants. They include market makers, financial institutions acting as clearing members, floor traders and the general public.[14] They utilised the approach of Bessembinder & Seguin (1993) on five financial futures contracts to find a positive volume-volatility

[14] The authors view "the general public" in terms of off-the-floor participant such as individual speculators, hedgers and managed funds.

relationship driven by the activities of the general public. This they argue follows from the notion that those who are not active on the trading floor have wider heterogeneous beliefs. As a consequence, the study infers that the arrival of information generates enough trading to induce volatility with this component of volume.

II.4.2 Modelling the Volume-Volatility Relation using GARCH

One of the most cited studies in this area is Lamoureux & Lastrapes (1990). The objective of their study is to investigate the extent to which GARCH effects govern in relation to the flow of information, defined in terms of the stochastic mixing variable. Since this is unobservable, the study uses contemporaneous volume as a proxy for the rate of information, thus entertaining the notion that the variance of returns is conditional on the stochastic mixing variable. They estimated GARCH (1,1) models on daily returns and volume for twenty actively traded stocks from the Standard and Poor Stock Price Records. The results report a GARCH effect without the inclusion of volume in the variance equation, thus indicating evidence of volatility persistence following the arrival of information. However, GARCH effects disappear when contemporaneous volume is included as an explanatory variable. In all cases, the volume term is significant, which leads to the interpretation that it can proxy the flow of information and explain the variance of returns. One of the shortfalls with this approach and one acknowledged by the authors is the potential for simultaneity bias when using contemporaneous volume to explain price volatility.[15] Although the authors attempted to overcome this problem by introducing lagged trading volume into the ARCH model, this was found to have little explanatory power.

In related work, Sharma, Mougoue & Kamath (1996) investigates GARCH versus volume effects using market data of the NYSE between 1986 and 1989. Unlike Lamoureux & Lastrapes, they entertain the notion that market-wide information as opposed to firm-specific factors can be the driving force behind the volume-volatility relationship. Contrary to the findings of Lamoureux & Lastrapes, the inclusion of volume fails to remove GARCH effects. Although they interpreted the use of volume as helping to explain GARCH effects, the authors concluded that factors other than volume contribute to the heteroscedasticity in index returns.

Foster (1994) examines the relationship between volume, the flow of information and volatility using closing prices of nearby futures contracts of Brent Crude. In viewing GARCH analysis as merely a test of whether volume can proxy the flow of information, this study additionally proposes the utilisation of the Generalised Method of Moments (GMM) to model the volume-volatility relationship. In focusing on GARCH analysis, he finds that volume fails to proxy the flow of information, irrespective of whether it is contemporaneous or lagged. However, the GMM results reveal a

[15] Simultaneity bias is a model specification bias that arises when volume is endogenously determined by the GARCH system. Chapter Five discusses this issue in greater detail.

contemporaneous relationship between volume and volatility driven by a common factor, assumed to be the flow of information.

II.4.3 Summary of the Literature

The notion of a positive relationship between trading volume and volatility is well documented. A subject area of this nature is of interest to both academics and practitioners given that it can provide inferences on the degree of market efficiency and information on the regulatory requirements of the market. Although the literature in this area is extensive, it comprises of two broad strands. The first group of studies attempted to test the nature of the volume-volatility relationship and the second strand, tested the assumption that the flow of information is the driving force behind this relationship.

Despite overwhelming evidence of a positive correlation between trading volume and volatility, there is less consensus on the driving force behind this relationship. With the exception of Lamoureux & Lastrapes (1990), investigations using GARCH analysis have reached the conclusion that trading volume fails to proxy the flow of information. Instead some infer that other factors not endogenosly determined within the GARCH system contributes to the heteroscedastic nature of returns. One possibility is the activity of noise traders. In response to the inconclusiveness of previous studies, a theme considered in the thesis is the decomposition of trading volume into expected and unexpected components, first proposed by Bessembinder & Seguin (1993).

The implication of this approach is twofold. Firstly, to determine whether volume induced by surprises is a better proxy for the flow of information than volume reflecting current information. Secondly, if volume fails to proxy the information flow, this leads to the question of whether surprises help explain more the heteroscedastic nature of the data than current information. It is from the lack of consensus in this area that the thesis aims to make a significant contribution to the literature. Chapter Five addresses this issue in detail.

II.5 VOLATILITY TRANSMISSION ACROSS MARKETS

The final empirical question to consider in the thesis is the issue of asymmetries in the transmission of volatility across national stock markets. A well-established argument is the notion that traders in any given market utilises information generated domestically and from other stock markets. Provided that the information generated by other markets are of relevance to the pricing of domestic securities, this type of market behaviour is a by-product of the increasing globalisation of financial markets. An understanding of the nature of stock market interactions enables investors to develop and carry out more sophisticated hedging and trading strategies. Moreover, knowledge on the relationship amongst national markets provides regulatory institutions information on the regulatory requirements of the market.

Ripley (1973) identifies several theoretical explanations accounting for the link between national stock markets. The relationship between stock prices in two countries could be indicative of national incomes behaving at unison. The intuition behind this is the notion that the behaviour of national income determines future expectations of the economy and future economic development determines the ability of investors to purchase equities. The involvement of countries in currency areas can explain the linkage between stock markets that requires harmonisation of fundamental economic variables between nations. Consequently, this encourages similar patterns of exchange rate expectations for those involved. The existence of a dominant financial centre in a multinational area may enhance the relationship between national stock markets by allowing within-area capital flows, thus reducing interest rate differentials between countries. Given that interest rate changes affects the performance of national stock markets, equalisation of national interest rates will harmonise the relationship of equity prices. Another factor that determines the relationship between stock markets is the actions of MNC's in issuing new stock to be listed in foreign markets. For instance, stocks of MNC's listed in major stock markets such as Tokyo, London and New York are subject to almost around the clock trading. Assuming that there are no barriers in the movement of capital, the likelihood is such that market expectation regarding the future of these companies should be similar in the markets where the stocks are listed.

The literature in this field is very diverse, with early studies focusing on the mechanisms that transmit price changes from one market to the other. The introduction of ARCH and GARCH models has served to highlight the limitations of early studies. Most notably, the failure of traditional regression analysis to model market interdependencies through the variance and covariance. For the purpose of the thesis, the review considers both strands of the literature in which the key papers reviewed mirror the nature of the ensuing investigation.

II.5.1 Evidence on Price Spillovers

A common theme running through studies who investigate price spillovers is the importance of the lead-lag relationship between national markets. A lead-lag relationship signals unexploited arbitrage opportunities which goes against the spirit of an efficient international market. Early studies investigated market interdependencies in the light of extensive capital controls, especially Agmon (1972), Ripley (1973) and Panton, Lessig & Joy (1976). In general, the evidence from these studies suggests a low correlation among national stock markets. Hilliard (1979) discovered how cross correlation amongst national stock markets is dependent on the size of the lead-lag relationship that in turn depends on the time zone the markets operate.

Eun & Shim (1989) uses a nine-vector autoregressive (VAR) model on daily returns to investigate the extent to which the New York market affects the world's markets and the speed of transmission. Consistent with the hypothesis of Halliard, the highest correlation values coincide with markets that operated in the same time zone. Hence, the potential for price spillovers is greater. In addition, they found the most influential market to be the US that explained on average 16.78% of the variance of other countries against 2.15% for the UK. To determine the speed of news transmission from the US to other markets, the authors simulate reactions of the estimated VAR models. Consistent with the findings of previous studies, the study concludes that the geographical location of other markets dictates the speed of transmission as hypothesised by Hilliard.

Malliaris & Urrutia (1992) use the Granger methodology to investigate the effects of the October 1987 Crash on market interdependencies for six major stock markets. In using this approach, they perform unidirectional and bi-directional causality tests on pre-crash, month of crash and post-crash samples using data from May 1, 1987 to March 31, 1988. They discover feedback effects and lead-lag relationships restricted to the month of the crash. Furthermore, they find an increase in contemporaneous causality in the month during the crash and in the post-crash sample. As a consequence, these findings lend support against the notion that the October 1987 Crash originated from New York. Instead, the authors conclude that it reflected an international crisis affecting all markets simultaneously.[16]

Arshanpalli & Doukas (1993) use cointegration theory to investigate the integrating or segmenting effect of the October 1987 Crash on the stock markets of Germany, UK, France and Japan with respect to the US. In

[16] This is consistent with the findings of Roll (1988) using twenty-three national stock markets. He finds that nineteen out of the twenty-three stock markets experienced declines in excess of twenty per cent. The Asian markets excluding Japan were the first to decline, followed by the European markets, then the US and lastly, by Japan.

performing the analysis for the whole sample, they report cointegration of all markets with respect to the US, except for the German market. To isolate the impact of the Crash, the authors constructed pre and post Crash sub-samples to conclude that the shock had an integrating effect on the markets with respect of the US. Further, in performing error correction tests, they discover long run relationships between the US and European indices, thus suggesting cross border efficiency. The results also detect a one-way relationship between the US and European markets in which a shock from the US has an significant impact on the European indices, but not vice versa. Finally, with respect to the Japanese market, the results indicate a lack of integration in relation to other indices.

II.5.2 Evidence on Volatility Spillovers

Although the literature reviewed thus far focuses on the lead-lag relationship between markets, these studies are subject to a number of limitations. Most obvious, is their failure to recognise market interdependencies in the variance and covariance. As a consequence, markets may not respond in the same direction to a shock originating from the leading market. Moreover, they fail to investigate the time varying nature of market interdependencies that fluctuates markedly during stress periods. The failure to consider this is a reflection of the restrictions imposed using the traditional regression approach.[17]

[17] Chapter Two examines this issue at greater length.

The introduction of the Autoregressive Conditional Heteroskedascity (ARCH) by Engle (1982) and Generalised ARCH by Bollerslev (1986) has enabled researchers to shift their emphasis towards investigating volatility spillovers in international markets. Volatility spillovers is indicative of the degree of integration among national markets where investors having access to differing sets of information can extract information from the behaviour of stock prices in other markets.[18] Stock price movements of other indices are seen as public information that allows domestic traders to make inferences on the information set of other agents in foreign markets.

Hamao, Masulis & Ng (1990) use close-to-open and open-to-close returns to test the hypothesis that volatility from one market has a positive transmitting effect on the opening price of the next market to trade. Using GARCH-M models on daily and intra-daily prices, they report spillover effects from New York and London to Tokyo. However, the transmission of volatility on the other markets is smaller. By introducing a surprise term, the authors discover that an unexpected change from the foreign market has a significant spillover effect on the conditional mean of trading and non-trading index returns in the domestic market. In relation to the impact of a second foreign market when the domestic market is closed, all indices reveal support for the hypothesis that the volatility of open-to-close returns has a positive and significant effect on the opening price of the next market to trade.

[18] Furthermore, in a paper by Engle, Ito & Lin (1992), they discover the source of the spillover effect attributable to shifts toward deterministic and stochastic policy co-ordination.

Hogen & Melvin (1994) use a Meteor Shower GARCH model to investigate the relationship between volatility spillovers and the heterogeneous expectations across traders. In using Yen/Dollar exchange rates of four major markets, their results reveal that the source of the volatility spillover rests on the heterogeneous expectations of traders about the expected announcement. However, the announcement itself impacts on the conditional mean. They report similar findings for the post announcement GARCH estimates. As a consequence, the study concludes that new information causes changes in exchange rates that does not imply increases in exchange rate variations on a global scale.

Another contributor to the ongoing debate on stock market interdependencies is Koutmos & Booth (1995). The study cites as one of its main contributions the modelling of price and volatility spillovers as a Multivariate-EGARCH (MEGARCH) process. This approach has the useful property of isolating potential asymmetries in the volatility transmission mechanism. As a consequence, their methodology is consistent with the notion that price and volatility spillovers represent manifestations of global news generated by one market that is evaluated in magnitude and sign by the next market to trade. It is from this assertion, that the study identifies the central issue of investigation in the thesis. Using open-to-close returns on the New York, Tokyo and London markets, they report evidence of volatility spillovers that are more profound when the transmission of volatility has an asymmetric component. This implies that additional volatility spills over to the next market when information generated from the last market to trade is negative. The study also rigorously tests for market interdependencies by performing MEGARCH analysis on pre and post October 1987 Crash samples. On the basis of MEGARCH parameters, they report evidence pointing towards ever increasing interaction between national stock markets since the crash.

II.5.3 Evidence on Saturday Trading in Tokyo

In parallel with the issue of volatility spillovers, is the impact of weekend trading in one market on the relationship between national stock markets. The literature in this area is limited to the contributions of Barclay, Litzenberger & Warner (1990) and Puffer (1991). Both studies examine the impact of Saturday trading in Tokyo on the Tokyo and New York stock markets. The purpose of their investigations is to document further evidence on the driving force behind stock return volatility, paying particular attention on the relationship between private information and the variance. As a consequence, they treated the return generating process as an international phenomenon unlike the studies reviewed in Section II.2.

The driving force behind the Barclay, Litzenberger & Warner study is the relationship between trading volume and volatility, driven by the arrival of private information. Unlike investigations of this nature that use regression analysis and GARCH models, they utilise the variance ratio methodology. Despite the generality of the study, one of its main contributions is to highlight the potential of a bi-directional relationship between the Tokyo market and other markets caused by weekend trading. Hence, the selection of daily data for eight Japanese stocks listed in the US from July 1982 to January 1989 and 21 internationally listed US stocks in Tokyo between January 1980 and December 1986. In using the variance ratio approach, the authors provide evidence of additional volatility spillovers from the Tokyo market to Japanese stocks listed in New York, but not vice versa. This they attribute to a lack of trading on foreign stocks in Tokyo.

In a related study, Puffer (1991) investigates the transmission of information generated by Saturday trading at a macro level. As in Barclay *et al* (1990), the author utilises the variance ratio approach, but on daily opening and closing prices on the Dow Jones Industrial Average and Nikkei Average. On the basis of variance ratios for the whole sample, private information from Saturday trading has a transmitting effect on New York returns from the Friday close to the Monday open. Puffer concludes that this is attributable to a number of factors. First, the interdependencies of the Japanese and American economies imply that market-wide information from Tokyo will impact the New York market. Secondly, the portfolios of many investors comprise of Japanese and US stocks. Hence, any information that leads investors to rebalance their holdings of Japanese stocks may force them to alter their holdings of US stocks.

II.5.4 Summary of the Literature

Numerous studies have investigated market interdependencies since the seventies. The early literature focused on the relationship between national markets by examining price spillovers using traditional regression analysis. However, the development of ARCH and GARCH models allowed the prospect of examining market interactions through the variance and covariance. In addition, ARCH and GARCH models provide an extra dimension by allowing market interdependencies to vary overtime. This represents another key feature ignored by early studies given the restrictions imposed on the traditional regression approach.

As a final issue for consideration, Chapter Six examines the degree of asymmetries in the volatility transmission mechanism and whether this is induced by extreme uncommon shocks and by weekend trading in Tokyo. Given the nature of the forthcoming study, the volume of literature is such that the review is restrictive in scope. A common feature of early studies is the demonstration of a relationship between the correlation of national markets and the time zone in which the markets operate. Studies focusing on the October 1987 Crash demonstrate using price changes that this correlation increases during volatile conditions. As a consequence, it is useful to examine market relationships through the variance and covariance, including and excluding the Crash period.

In addition, the review focused on the impact of Saturday trading in Tokyo on the Tokyo and New York markets. The evidence suggests that weekend trading in Tokyo has a spillover effect on the New York market. However unlike previous studies, this thesis takes the view that weekend trading can induce spillover effects in both directions. In addition, this relationship depends on the size and sign of the innovation and the dynamics that govern the transmission of volatility across markets.

CHAPTER TWO

CONDITIONAL HETEROSCEDASTIC MODELS:

AN OVERVIEW

2.1 INTRODUCTION

The objective of this chapter is to examine the GARCH family of models and its use for the purpose of the thesis. To provide the motivation and justification for the use of these models, the chapter starts by focusing on the problems faced with conventional econometric models in its failure to capture the underlying generating process. For this reason, the next section begins by considering the statistical properties of time series data along with a review of the literature. A review of key papers provides overwhelming evidence of serial dependencies in the data and non-normality in the form of fat tails. As a consequence, the literature review has a dual purpose for the direction of the thesis. The first is to highlight the necessity to solve the problem of serial dependencies when using the Heteroscedastic Regression Model (HRM) in Chapter Three. The restrictions imposed of no serial dependencies and homoscedasticity in the error term means that the HRM is subject to the same shortfalls as conventional econometric models.

The second objective is to present evidence in the literature as a means of justifying the use of the conditional heteroscedastic model as the core methodology from Chapter Four to Chapter Six of the thesis. GARCH type models can remove systematic changes in the variance that accounts for much of the fat tails by allowing heteroscedasticity in the variance. Unlike standard regression models, the GARCH does not assume homoscedasticity, but instead is treated as a special case of the model. Consequently, these models allow the distribution of the data to exhibit fat tails and hence, are more able to describe the empirical distribution of financial data.

The chapter will proceed as follows. The next section considers the statistical properties of financial time series data along with a review of the literature. Section 2.3 introduces the univariate conditional heteroscedastic models. The overview extends to a multivariate setting in section 2.4 followed by an explanation of the estimation procedures in section 2.5. Finally, section 2.6 provides a summary and conclusion.

2.2 THE STATISTICAL PROPERTIES OF TIME SERIES DATA

The statistical properties of speculative prices and hence stock returns have implications for a number of financial models. For many years, the stylised fact about the evolution of price returns is the notion that financial prices follow a random walk. The fundamental model of stock price dynamics is the random walk model. Define Δp_t in terms of the logarithmic change in spot prices:

$$\Delta p_t = p_t - p_{t-1} \tag{2.1}$$

where p_t is the logarithm of the spot price at time *t*. If Δp_t is *statistically independent*, that is, it is unrelated to *n* past observations $\left(\Delta p_{t-1}, \Delta p_{t-2}, \Delta p_{t-3}, \ldots\ldots\ldots \Delta p_{t-n}\right)$, then Δp_t follows a random walk. The random walk model enhances our understanding of stock price movements using the "efficient markets" theory, which states that a change in price from one period to the next is purely random.[19] It is from this assertion, that the independence assumption has an economic meaning. The second condition that forms the basis of the random walk model is the identically distributed assumption. This ensures that the first two moments, the mean and variance do not vary over time and conform to a fixed probability distribution. This implies that changes in speculative prices over time is purely random and is consistent with the fundamentally important assumption that security returns follow a normal distribution. Crucial to the maintenance of a normal distribution in returns is the assumption of stationarity in the mean and variance.[20]

With conventional econometric models, the independently and identically distributed (i.i.d) properties are of paramount importance. This arises from the fundamental assumptions of zero mean, constant variance and zero covariance in the disturbance term that ensures that the estimates are unbiased and efficient. For larger samples, the i.i.d conditions enable consistency in the estimates where the estimator approximates its true value as the sample size

[19] Note that the Random Walk Model forms the benchmark of Fama's (1970) Efficient Market Hypothesis.
[20] To further elaborate, stationarity is defined in terms of constant statistical moments over periods of time.

increases. Given the importance of the i.i.d conditions for traditional regression models, the remainder of this section reviews the literature on the distributional properties of returns. By gauging the evidence, one can draw inferences on the usefulness of conventional models for purposes of forecasting or policy analysis. Owing to the volume of research, the literature review focuses on key papers by paying attention to the following issues; the independence assumption and the shape of the distribution.

2.2.1 Evidence on the Independence Assumption

To investigate the independence assumption, previous studies tested for serial correlation in changes in price. These investigations date back to the important contributions of Mandelbrot (1963) and Fama (1965). They report evidence of autocorrelation in daily stock returns at short lags, although the size of the autocorrelations is too small to have any economic meaning. As a consequence, the condition of a lack of autocorrelation in stock returns is widely accepted as a justified approximation. Commonly termed in the literature as linear dependencies, this is attributable to various market anomalies. For instance, the existence of a common market factor, infrequent trading on some stocks, the ability of the market to process information and day-of-the-weeks effects could explain observed serial dependencies at short lags.

However, one cannot make the assertion that a lack of autocorrelation in speculative price changes is sufficient to prove serial independence. Some investigations find stock returns governed by non-linear processes that allow successive price changes to relate through the second moments. First reported by Mandelbrot (1963), he finds evidence of returns exhibiting non-linear dependencies by observing a clustering of speculative price changes.[21] Later studies provide more convincing evidence in their rigorous challenge to the identical and independence assumptions. Hsieh (1988) rejects the null hypothesis that the distribution of Δp_t in equation (2.1) is independent and identically distributed for five currencies between 1974 and 1983. This he attributes to changes in the means and variance. In a later paper, Hsieh (1989) utilises a GARCH model on five currencies to reveal evidence of non-linear dependencies in exchange rate data. Akgiry (1989) uses the same conditional heteroscedastic model on daily stock returns to report evidence of statistical dependencies that are more profound than previously reported. Yang & Brorsen (1993) apply the same methodology and the BDS test statistic on US commodity prices and stock index futures. They reveal rejections of the i.i.d assumption for all original data series where the source of the rejection is the non-linear dependencies in daily price changes.

One source of non-linear dependencies in speculative price changes is the deterministic process that resembles a random walk. Another explanation and

[21] A clustering of price changes is characterized by large price changes followed by further changes of either direction.

one identified and reported by Hsieh (1989) is the notion that speculative price changes describe "non-linear stochastic functions of their own past." (Page 340) Until the introduction of Conditional Heteroscedastic Models, researchers could not investigate whether stock returns exhibit successive price changes related through the variance. In brief, this class of models can remove systematic changes by allowing heteroscedasticity in the variance. Section 2.3 introduces the conditional heteroscedastic model in greater detail.

2.2.2 Evidence on the Shape of the Distribution

The assumption of normally distributed observations is of paramount importance to the modelling and testing procedures in traditional regression analysis. Other than the i.i.d conditions, normality in the distribution of returns is a necessary requirement to generate precision of the estimates. This however, is offset by overwhelming evidence suggesting the contrary. A well-documented characteristic is the existence of fat tails or leptokurtosis in the distribution that exceeds those of the normal. Other than reporting autocorrelation in returns, Mandelbrot (1963) and Fama (1965) both find evidence of leptokurtosis in daily stock return data. The dataset exhibits leptokurtosis when daily changes in prices have more observations around the means and in the extreme tails than that of a normal distribution. In later studies, Akgiry (1989) uses the Kiefer-Salmon (1983) tests for zero excess kurtosis and normal skewness on 6030 daily returns on value-weighted and equally weighted indices. They reveal convincing evidence that the data cannot accept the null hypothesis of zero excess kurtosis. Hsieh (1989) reports similar findings using five major currencies between January 1974 and December 1983.

Given the overwhelming evidence of leptokurtosis in the distribution of returns, researchers have attempted to address the source of the phenomena. Fama (1965) infers that this may be attributable to non-stationarity in the distribution caused by the time varying nature of the first two moments, the mean and variance. Although Fama provided evidence to the contrary, he only tested for non-stationarity in the means. However, studies focusing on non-stationarity in the variance report more convincing evidence. [Mandelbrot (1963)] Akgiry (1989) uses the autocorrelation function to demonstrate how significant autocorrelation coefficients in the absolute and squared residual returns explain the existence of fat tails and peakness in the distribution of returns. Studies conclude that the conditional dependency in the variance causes fatter tails in the unconditional distribution in excess of the conditional. The notion of fat tails and non-stationarity in the second moments is the existence of volatility clustering in the dataset. It is from this assertion that motivated the development of conditional heteroscedastic models. As mentioned earlier, the objective of these models is to remove the systematically changing variance from the data that accounts for much of the leptokurtosis in the distribution of returns. Essentially, these models allow the distribution in the data to exhibit leptokurtosis and hence, are more able to describe the empirical distribution of financial data. The most popular are the

Autoregressive Conditional Heteroscedastic (ARCH) models first introduced by Engle (1982) and the Generalised ARCH (GARCH) later developed by Bollerslev (1986).

2.2.3 A Note on the Multivariate Distribution of Returns

So far, the focus of the review has been on the properties of univariate time series data. However, much financial analysis concerns the relationship between two or more time series. Examples include option prices and volatility, the rate of returns of different assets in a portfolio, index values of different markets and so forth. With overwhelming evidence pointing towards non-normality in univariate returns and the violation of the i.i.d conditions, there is no reason for the multivariate distribution of returns to be multivariate normal and stationary.

The empirical literature provides further evidence against normality and stationarity in the distribution of multivariate data. In testing the Capital Asset Pricing Model with time varying covariance, Bollerslev, Engle and Wooldridge (1988) fail to accept the null hypothesis that the conditional variance-covariance matrix is not autoregressive. This they discover using quarterly data on six month Treasury Bills, twenty year Treasury Bonds and stocks from 1959 to 1984. Koutmos & Tucker (1996) provide further evidence pointing towards this conclusion using daily closing prices and settlement prices on the S&P 500 Index and S&P 500 futures contract. Inferences are drawn from the correlation coefficient of returns between the spot and futures market before, during and after stress periods.[22] It is against this background that motivates the use of the bivariate conditional heteroscedastic model in Chapter Six.

2.2.4 *A Brief Summary of the Evidence*

A review of empirical research on financial time series data reveals conclusive evidence that violates the assumptions of serial independence and normality in the distribution of returns. In addition, the non-normality in the distribution of univariate data is such that there is no reason for the multivariate distribution of returns to be multivariate normal and stationary. As a consequence, the restrictions imposed of no serial dependencies and homoscedasticity in traditional regression models makes it impossible to make use of this information in the dataset. As a result, reviewing the literature has highlighted the importance of addressing the problem of serial dependencies when employing the Heteroscedastic Regression Model (HRM) in the next chapter. Moreover, the evidence warrants the attention and utilisation of the conditional heteroscedastic model for the purpose of the thesis. Hence, the next section provides a comprehensive review.

[22] In their investigation, the stress period referred to, was the October 1987 Crash.

2.3 UNIVARIATE CONDITIONAL HETEROSCEDASTIC MODELS

2.3.1 *ARCH and GARCH Models*

Despite evidence of volatility clustering in speculative price changes, the success of the conditional heteroscedastic model depends on its ability to capture the information present in the existing dataset, i.e., serial dependencies and heteroscedasticity. The restrictions imposed on traditional regression models makes it impossible to make use of this information when estimating time varying variance and covariance.

The conditional heteroscedastic model that allows the variance to vary as new information becomes available is the GARCH family of models. The GARCH stems from the invaluable contribution of Engle (1982) Autoregressive Conditional Heteroscedasticity (ARCH). This differs from traditional regression models by treating homoscedasticity as a special case of the model. Essentially, the intuition behind the introduction of ARCH is to overcome the limitations of the classical regression model. The problem levelled against regression analysis is their failure to capture the true nature of the underlying generating process. For example, the residuals u_t may not be random as assumed by linear regression models, but the result of a non-linear process. As mentioned in section 2.2, excess kurtosis is attributable to the conditional dependency in the second moments with the implication that the unconditional distribution will have fatter tails in excess of the conditional. The ARCH seeks to circumvent this problem by representing the error variance as a time series that evolves as a linear function of the lagged squared errors. Suppose that the return denoted as y_t is modelled as:

$$y_t = \phi' x_t + \varepsilon_t \tag{2.2}$$

where x_t is a vector with impact on the conditional mean y_t and ϕ represents the vector of parameters that corresponds to x_t. Conditional on the information set ξ_{t-1}, the error term ε_t of equation (2.2) is normally distributed with zero mean and variance h_t. That is

$$\varepsilon_t | \xi_{t-1} \sim N(0, h_t) \tag{2.3}$$

where

$$E(\varepsilon_t) = 0 \tag{2.4}$$

and

$$h_t = \alpha_0 + \alpha_i \sum_{i=1}^{q} \varepsilon_{t-i}^2 \tag{2.5}$$

Equation (2.5) represents a ARCH(q) process where the parameters are $\alpha_0 > 0$ and $\alpha_i \geq 0$. The term α_0 is the constant and ε_{t-i}^2 represents the news coefficient. The dependent variable h_t represents the conditional variance of ε_t where h_t is time varying if $\alpha_i > 0$. Homoscedasticity is a special case when it restricts α_i to be zero and the conditional variance h_t as a constant. Further, the ARCH process of equation (2.5) has the appealing property of allowing the error term ε_t to be serially uncorrelated but not necessarily independent. The implication of this is that it enables the model to predict changes in the volatility of the series.

Bollerslev (1986) provides a more generalised representation of the ARCH in equation (2.5) by the inclusion of a lagged conditional variance term. Conditional on the information set at time t, denoted as α_0, the distribution of the disturbance is assumed to be

$$\varepsilon_t | \xi_t \sim N[0, h_t] \tag{2.6}$$

where the conditional variance h_t is defined as

$$\begin{aligned} h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_{t-2}^2 + \ldots \\ &\ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \ldots\ldots + \beta_p h_{t-p} \end{aligned} \tag{2.7}$$

By defining the following

$$w_t = \left[1, \varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \ldots\ldots, \varepsilon_{t-q}^2, h_{t-1}, h_{t-2}, \ldots\ldots, h_{t-p}\right] \tag{2.8}$$

and the coefficients to be estimated

$$\delta = \left[\alpha_0, \alpha_1, \ldots\ldots, \alpha_q, \beta_1, \beta_2, \ldots\ldots\ldots, \beta_p\right]' = \left[\alpha', \beta'\right]' \tag{2.9}$$

then

$$h_t = \delta' w_t \tag{2.10}$$

The conditional variance as specified in equation (2.10) follows an Autoregressive Moving Average or ARMA(p,q) process. This is a Generalised-ARCH (p,q) model, where p represents the order of the autoregressive part and q is the order of the moving average. Bollerslev (1986) demonstrates the appealing property of the Generalised-ARCH (GARCH) by showing how it performs at least as well or even better with smaller number of terms than an ARCH model of a higher order. The GARCH (p,q) model in its simplest form is represented as:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 + \sum_{k=1}^{p} \beta_1 h_{t-k} \tag{2.11}$$

where the conditional variance today h_t is dependent on yesterday's news innovation ε^2_{t-i} and the conditional variance lagged one period back h_{t-k}. This can reflect the impact of old information where h_{t-k} is a function of ε^2_{t-i-1} and h_{t-k-1}. The use of the lagged conditional variance implies that today's volatility is known immediately after yesterday's market closure. Hence, it is a measure of volatility persistence. The terms α_1 and β_1 describes the nature of volatility and is a measure of the impact of last period's errors and variance on current volatility. Note that both parameters do not complement each other, thus avoiding the possibility of simultaneity bias in the GARCH system. The parameter α_0 defined as the constant, acts as a floor that prevents the variance from dropping below that level.

A useful attribute of the GARCH model is that it invites the prospect of testing two hypotheses. Firstly, testing the significance of the parameters to determine the nature of volatility and second, whether α_1 and β_1 sum to unity. Acceptance of this hypothesis indicates the presence of an Integrated GARCH (IGARCH) process, which is a specification characterised by a nonstationary variance. As a consequence, shocks in the innovation term ε^2_{t-i} will have a permanent effect on the conditional variance. As such, one can view the model in terms of the variance that is equivalent to a unit root test of the conditional mean.

2.3.2 Exponential GARCH Models

Despite the apparent success of ARCH and GARCH, these models cannot capture some important features of the data.[23] An important characteristic of the dataset is the asymmetric effect discovered by French, Schwert & Stambaugh (1987), Nelson (1990) and Schwert (1990). The asymmetric effect stipulates that the arrival of bad news causes an unexpected drop in price which in turn increases predictable volatility that exceeds an unexpected increase in price caused by the arrival of good news.[24] In a series of returns, one can identify the asymmetric effect by observing price movements that fall further than the highest price rise. Another limitation of the GARCH process concerns the non-negative constraints imposed on the coefficients α_0, α_i and β_1 of equation (2.11) to ensure that h_t remains positive for all t with a probability of one.

Nelson (1990) introduced an approach designed to capture the asymmetric component in returns. Defined as the Exponential-GARCH (EGARCH) model, he expresses the model specification as

$$h_t = exp\left\{\alpha_0 + \sum_{i=1}^{q} \alpha_i ln(h_{t-i}) + \alpha_k \sum_{k=1}^{p} \eta_{t-k}\right\} \tag{2.12}$$

[23] Engle & Ng (1993) and Lee & Brorsen (1997) highlight this by testing the performance of the GARCH model against other GARCH specifications.

[24] This follows from evidence of negative correlation in stock returns with changes in volatility. [See Black (1976)] One of the major limitations of GARCH models is that it considers only the magnitude of a shock and cannot discriminate between negative and positive shocks.

in which η_{t-k} is defined as

$$\eta_{t-k} = \left[\left(\frac{|\varepsilon_{t-k}|}{\sqrt{h_{t-k}}} - \sqrt{\frac{2}{\pi}}\right) + \theta_1\left(\frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}}\right)\right] \tag{2.13}$$

where α_0, α_i, α_k and θ_1 are the coefficients to estimate. $ln(h_{t-i})$ is the natural logarithm of the lagged conditional variance that replaces h_{t-k} in the GARCH specification of equation (2.11). The term η_{t-k} is the news coefficient that replaces ε_{t-i} in the GARCH where the first term is the size effect and θ_1 captures the asymmetric component. If θ_1 is negative and significantly different from zero, then past errors will have a greater impact on current variance than analogous positive errors. Hence, equation (2.12) expresses h_t as a function of both the magnitude and sign of lagged errors. Other than extracting more information on the underlying generating process, the EGARCH in addition imposes no restrictions on the sign of the coefficients.

A rival model to the EGARCH is the Quadratic GARCH model proposed by Engle (1990) and applied by Campbell & Hentschel (1992) in modelling the No News is Good News Effect. In testing the performance of various GARCH processes, Engle & Ng (1993) find that the EGARCH specification outperformed the Quadratic GARCH because the latter underestimated the volatility associated with negative shocks.

2.4 MULTIVARIATE HETEROSCEDASTIC MODELS

The conditional variance of one asset is likely to be related to its past history and other volatilities. The trend adopted in empirical studies is to engage in the expansion of univariate GARCH specifications into a multivariate setting. A multivariate conditional heteroscedastic model is most appropriate when modelling the co-movement among assets in a portfolio, or the time varying market interdependencies through the first and second moments. This approach accounts for the non-normality in the multivariate distribution of speculative price changes. Empirical studies reviewed in the previous chapter served to highlight the limitations of conventional econometric analysis in modelling the interactions between two or more time series. As a consequence, extending the model in this way has given ARCH a more prominent use in empirical finance.

To begin with, define returns in the first moments as:

$$y_t = \Phi'_t \beta + \varepsilon_t \qquad \varepsilon_t | \xi_{t-1} \sim N(0, H_t) \tag{2.15}$$

where the error term $\varepsilon_t = (\varepsilon_1, \varepsilon_m)$ is a $m \times 1$ vector of forecast errors conditional on the information set ξ_{t-1} that is normally distributed with zero mean and the conditional covariance matrix H_t. Returns in their second moments is defined as a multivariate GARCH(p,q) process:

$$vech(H_t) = \Gamma_i + A_k vech(\varepsilon_{t-k}, \varepsilon'_{t-k}) + Bvech(H_t) \tag{2.16}$$

where Γ_i is a $n \times 1$ vector of constants and A and B are $(n \times n)$ matrix polynomials of order p and q respectively. The term $vech(.)$ depicts the stacking operator of the lower part of the symmetric matrix. For example, a bivariate model estimated on two time series has $vech(H_t) = (h_{1,t}, h_{2,t}, h_{12,t})$.

A problem inherited with the estimation of the bivariate GARCH of equation (2.16) is the large number of parameters to be estimated. This poses a formidable challenge when maximising the log likelihood function.[25] From equation (2.16), there are $\frac{n(n+1)}{2} + \frac{(p+q)n^2(n+1)^2}{4}$ parameters to estimate. For instance, taking the simple case of a bivariate model, where $p = q = 1$ and $n = 2$, there are 21 GARCH parameters to estimate. For this reason, much attention has focused on reducing the number of unknown parameters. Many studies have followed the approach suggested by Bollerslev (1990) in which he imposes the restriction of constant correlation in the conditional covariance.[26] Hence, the restriction imposed on H_t is:

$$h_{12,t} = \rho\sqrt{h_{1,t}h_{2,t}} \tag{2.17}$$

where ρ is the conditional correlation coefficient which is restricted as a constant. This has the appealing property of allowing the conditional variance $(h_{1,t}, h_{2,t})$ and the conditional covariance $(h_{12,t})$ to vary over time despite the restriction imposed on the correlation coefficient.

The multivariate GARCH has been employed by previous studies investigating the time varying risk premia in foreign exchange markets (see Malliaropulos

[25] See Pagan (1996).
[26] See Koutmos & Booth (1995), Koutmos & Tucker (1996) and Malliaropulos (1997).

(1997) and others) and modelling the conditional beta on the basis of the Capital Asset Pricing Model (CAPM) (see Bollerslev, Engle & Wooldridge (1988). However, as with the univariate GARCH, the multivariate GARCH suffers the same short comings. For instance, the non-negative constraints imposed on the GARCH coefficients and the existence of asymmetries in the data. As a consequence, this has motivated the extension of the univariate EGARCH specification into a multivariate setting. First introduced by Koutmos & Booth (1995) and Koutmos & Tucker (1996), the underlying principle of this approach is to view dynamic interactions as manifestations of the impact of innovations, whether it is positive or negative. This they make possible by allowing changes in the variance and covariance to reflect the evaluation of innovations with respect to magnitude and sign. Assume two markets, *i* and *k*, and let $y_{i,t}$ be the returns at time *t*, market *i*. The multivariate EGARCH model is written as:

$$y_{i,t} = \Phi'_{i,0}\beta + \sum_{k=1}^{2} \beta_{i,k}\varepsilon_{k,t-1} + \varepsilon_t \qquad \text{for } i,k = 1,2 \qquad (2.18a)$$

$$h_{i,t} = exp\left\{\omega_{i,0} + \sum_{i=1}^{2} \alpha_i ln(h_{i,t-1}) + \sum_{k=1}^{2} \beta_{i,k} f_k(\Pi_{k,t-1})\right\} \qquad (2.18b)$$

where *i*, *k* = 1,2. $h_{i,t}$ is the conditional variance, $\beta_{i,k}$ is a measure of the volatility spillover effect and $\Pi_{k,t}$ is the standardised innovation from market *k* expressed as

$$\Pi_{k,t} = \frac{\varepsilon_t}{h_t} \qquad (2.19)$$

and

$$f_k\left(\Pi_{k,t-1}\right) = \left(\left|\Pi_{k,t-1}\right| - E\left(\left|\Pi_{k,t-1}\right|\right) + \theta_k \Pi_{k,t-1}\right) \tag{2.20}$$

where the first part of the innovation coefficient $\left|\Pi_{k,t-1}\right| - E\left(\left|\Pi_{k,t-1}\right|\right)$ is the size effect and the asymmetric term is θ_k. As with the univariate EGARCH, asymmetries are present in the data when θ_k is negative and significantly different from zero. In this model, the presence of asymmetries reinforces the volatility spillover effect $\beta_{i,k}$. As a consequence, a positive $\beta_{i,k}$ coefficient along with a negative θ_k implies that a negative shock originating from market k will have a greater impact on the volatility of market i than a positive shock. In this scenario, market interdependencies are said to be asymmetric.

2.5 ESTIMATING THE ARCH FAMILY OF MODELS

An efficient and very popular approach of estimating ARCH models is the Maximum Likelihood. The likelihood function assumes that the conditional density is normal, thus defining the logarithmic likelihood of a sample in terms of the summation of individual normal conditional densities. For instance, take a process y_t in which the two statistical moments, the mean and variance are stable and drawn from a normal distribution. The log likelihood function is expressed as:

$$ln(\Theta) = -\left(\frac{T}{2}\right) ln(2\pi) - \left(\frac{T}{2}\right) ln\,\sigma^2 - \left(\frac{1}{2}\sigma^2\right) \sum_{t=1}^{T} \left(Y_t - \mu\right)^2 \tag{2.21}$$

where $ln(\Theta)$ is the natural logarithm of the likelihood function for $t = 1,...T$. The procedure to maximise the likelihood function of equation (2.21) requires evolving the $ln(\Theta)$ to find the optimal value of the two parameters σ^2 and μ. This is possible by restricting the first order partial derivatives to zero and solving for the values of σ^2 and μ that generates maximum values of $ln(\Theta)$. By replacing the terms σ^2 and $Y_t - \mu$ with h_t and ε_t^2 respectively, the likelihood function of equation (2.21) becomes

$$ln(\Theta) = -\left(\frac{T}{2}\right) ln(2\pi) - \left(\frac{T}{2}\right) ln(h_t) - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{h_t} \tag{2.22}$$

which is an iterative procedure where $\Theta = (\alpha_0, \alpha_i, \beta_k, \phi)$ represents the GARCH parameters and h_t is the conditional variance. Unfortunately ARCH processes are highly non-linear, thus rendering invalid the assumption of normal conditional densities. However, there are numerical approaches that can maximise the likelihood function of (2.22) to obtain the vector Θ. Although Engle (1982) proposes a scoring algorithm to maximise the likelihood function, a more popular approach is the Berndt, Hall, Hall and Hausman (1974) BHHH algorithm. This approach utilises the covariance of the analytic gradients for each observation to form H. It has the advantage of being easy to compute and guarantees non-negative definite as long as the number of observations exceeds the total number of parameters. Other algorithms used include the Newton approach that differs from the BHHH algorithm because it uses analytic second derivatives to form H.

The usefulness of the maximum likelihood approach relates to the fact that it can jointly estimate the conditional mean and variance whilst allowing exogenous variables to impact the mean equation. Hence, it will be extensively used from Chapter Four to Chapter Six in the thesis.

2.6 SUMMARY AND CONCLUSIONS

The motivation of this chapter is to provide an overview of the conditional heteroscedastic models as the core methodology in the thesis. The literature review on the properties of financial time series data provided the intuition behind the use of these models. The consensus reached by previous studies concerns the violation of the i.i.d conditions caused by non-linear dependencies that allow successive price changes to relate through the second moments. Focusing on the shape of the distribution, a well-documented characteristic is the existence of fat tails that are attributable to non-stationarity of the mean and variance. The implication of these findings is to identify issues of paramount importance in the thesis. First, the existence of fat tails and the violation of i.i.d conditions serve to highlight the necessity to solve the problem of serial dependencies before utilising the Heteroscedastic Regression Model in the next chapter. Secondly, evidence of time varying statistical moments in the data motivates the use of the GARCH family of models from Chapter Four to Chapter Six of the thesis.

In the forthcoming investigations, the core methodology to be used is the EGARCH model. The choice of approach is partly in response to the failure of the GARCH to capture asymmetries in the data along with restrictions imposed on the sign of the GARCH parameters. The ability of the bivariate- EGARCH to extract more information on the interactions between national markets motivates its use in Chapter Six. Furthermore, in the most comprehensive review on the performance of GARCH models, Engle & Ng (1993) find that EGARCH out performed all other GARCH specifications using daily returns on the Japanese TOPIX index. This general conclusion is one supported by Lee & Brorsen (1997) using Deutsche Mark spot prices.

CHAPTER THREE

MARKET ANOMALIES AND THE VARIANCE OF THE FTSE-100 INDEX RETURNS DURING NON-TRADING AND TRADING HOURS

3.1 INTRODUCTION

The objective of this chapter is to investigate the relationship between market anomalies and the variance of FTSE-100 index returns during non-trading and trading periods. As discussed in Chapter One, market anomalies reflect the process of buying and selling based on trader expectations. As a consequence, this complements well with the prevailing explanations behind the behaviour of returns; the process of information and the process of trading hypothesis. For the former, the arrival of information causes traders to revise their perceptions on expected stock prices, thus inducing the anomaly. In the meantime, high variances over certain days are a reflection of the arrival of more information fundamental to the pricing of the index. In this scenario, there is no social cost attached to such volatility. The quicker and more accurately stock returns reflect new information, the more the efficient allocation of resources. In contrast, the process of trading produces the opposite scenario. Although trading on new information induces volatility, it may also lead to mispricing whereby traders overreact or under-react to each other's trades. Even though this increases intra-daily variances as the market corrects the mispricing, noise trader expectations are not conditional on information. As a consequence, this eliminates the systematic behaviour of returns and hence, the potential for market anomalies. Therefore, volatility induced in this way leads to the misallocation of resources.

This study performs four levels of investigation. To begin with, index returns are modeled in the first and second moments. This is followed by robustness testing of market anomalies in the return series using F-tests. Variance ratio analysis is then utilised to investigate the variance differential of non-trading and trading period returns. Finally, the investigation considers the importance of the noise-trading component in the variance using a modified variance ratio test.

Within this framework, the study analyses the impact of exchange holidays. This includes two-day, (normal weekend) three-day, (Bank Holiday) four-day, (Easter Holiday) Christmas and New Years Day exchange holidays.[27] The methodology proposed is the Heteroscedastic Regression Model (HRM). By using the HRM, the investigation examines the behaviour of non-trading and trading period returns through the first and second moments. The implication of using this approach is to allow the observation of a casual relationship between market anomalies and the variance of returns. Finally, the study computes variance ratios on the basis of significant variance estimates from the HRM. Given that this is a technique commonly used by previous studies, it enables one to make comparisons with the results of past investigations.

[27] Except for Good Friday, Christmas and New Years Day, all other national holidays in the UK fall on Mondays. This invites the prospect not possible in previous studies of testing the effects of extended exchange holidays on the behaviour of UK stock index returns.

Moreover, the combination of the HRM and variance ratio tests enables the observation of a relationship between market anomalies and differences in the variance of non-trading and trading time returns.

In brief, this study reveals results that are consistent with the findings of previous investigations using US data. One of the most significant is the existence of a negative non-trading weekend effect that coincides with the highest non-trading period variance. Using robustness tests on index returns in their second moments, the impact of a weekend exchange holiday on UK returns greatest on the first day of trading after the holiday. Variance ratio tests performed, consistently show index returns more volatile during trading hours. However, the difference in the variance during trading and non-trading hours narrow significantly when the variance ratio includes the high non-trading weekend variance. As a consequence, the results observe a relationship between negative anomalies and an increase in the size of the variance ratio. The implication of this finding is to cast serious doubt on the importance of noise trading in determining index values throughout the trading day. This, the study justifies by using variance ratios to test the noise trading component in the variance. On the basis of these findings, the study concludes that private information is the principle explanation behind the existence of market anomalies and high trading-time variances.

The chapter will proceed as follows; the next section provides a theoretical discussion on the process of information and trading as the prevailing explanations behind the behaviour of returns. Section 2.3 intuitively explains the phenomena that return variances behave differently during trading and non-trading hours. Section 2.4 introduces the HRM for this type of analysis along with variance ratio tests. Section 2.5 presents the data and descriptive statistics for non-trading and trading period returns. In response to evidence reviewed in Chapter Two, section 2.6 addresses the empirically important issue of serial dependencies in index returns. Section 2.7 tests for market anomalies in returns in their first and second moments. Section 2.8 employs variance ratio analysis to investigate the variance differential of non-trading and trading period returns. In addition, the section tests the existence of the noise-trading component using a modified variance ratio test. Section 2.9 provides a summary and conclusion.

3.2 THEORETICAL CONSIDERATIONS

3.2.1 The Issue of Market Anomalies

To begin with, it is useful to intuitively explain the underlying relationship between market anomalies and differences in the variance of non-trading and trading time returns. In theory, market anomalies reflect the process of buying and selling driven by trader expectations in the pursuit of profit maximisation. The origins of the well-documented weekend effect relate to the notion that when faced with a two-day exchange holiday, traders on Friday may delay their purchases until the following Monday when they expect stock prices to be lower. On the other hand, sellers with the expectation of lower prices may postpone their sales until Friday when they expect stock prices to be higher. As such, the issue of market anomalies complements well with the process of information and trading hypothesis.

The relationship between market anomalies and the process of information nests on the notion that the accumulation of information over non-trading hours leads to downward expectations of stock prices at the commencement of trading. Peterson (1990) provides the intuition behind this proposition by investigating the potential for delays in the release of negative information until after the close of trading. By contrast, under the process of trading, traders overreact or under-react to each other's trades, thus leading to the mispricing of stocks. Although this increases intra-daily volatility as the market corrects the mispricing there is no potential for market anomalies as noise trader expectations are not conditional on current information.

The rest of this section introduces formally the process of information and trading hypothesis as the centre-piece of the study.

3.2.2 The Process of Information

The process of information divides into public and private components. As introduced in the literature survey of Chapter One, the *Public Information Hypothesis* states that the schedule release of announcements induces clustering of spot prices throughout the trading day. Examples of public information include macroeconomic news, company financial reports, tender offers and so forth. Given that the release of public information may take place outside trading hours, this will lead to a revision of market expectations reflected in non-trading variances. In addition, no one can trade on the information before release and once known, it affects stock prices at the same time. Consequently, if public information is the driving force behind high return variances, then market closures should not have any impact on the behaviour of index returns.

On the other hand, private information can only affect spot prices by the actions of informed traders. As a consequence, high trading time variances will decline when the stock market closes. The gathering of private information mostly takes place during trading hours. French & Roll (1986) attributes this to a number of factors. Firstly, to the greater quantity of private information produced during market operations and secondly; the benefits of generating private information are greater during trading periods which one can act upon faster and conveniently. One reason for this is related to the concept of perfect competition where the activities of informed traders reduce the cost of trading whilst generating more information. However, informed traders may possess information not known by other traders, thus enhancing the benefits of acquiring more private information. The idea being is that well-informed traders will have the ability to change trading strategies that maximise their expected profits. Despite the acquisition of most private information when the markets are open, traders continue to acquire information outside trading hours. Given that private information only affects prices during trading, any information generated when the markets are closed will not be acted upon until trading commences.

It is important to note here that the two information hypotheses, although tested for separately, are interrelated on a theoretical level. As introduced in Chapter One, Kim & Verrechia (1991) describes how the impact of public information is dependent on the quality of private information acquired prior to the release of the announcement. In their model, high return variances induced by the release of costless public information is indicative of the acquisition of low quality private information. In contrast, the failure of public information to affect the variance is a reflection of the acquisition of high quality private information traded on prior to the release of the announcement. As a consequence, their model envisages the notion that the validity of the public information hypothesis is dependent on how well informed the market is at the time of release.

3.2.3 The Process of Trading

A third possible explanation behind the behaviour of returns is the process of trading in which traders overreact to each other's trades. Commonly termed as the *Noise Trading Hypothesis*, this stipulates that trading induces noise where a component of returns is negatively autocorrelated. Consequently, the reversal of pricing errors occurring during trading hours induces higher variance of intra-daily returns. Like the private information hypothesis, noise trading arises endogenously during trading hours. The implication is such that high trading time variances will decline when the market closes.

The importance of the noise-trading component can largely reflect the quality of information that arrives in the market. Although the systematic component in prices can be explainable in terms of the quality of information, random fluctuations observed could indicate the amount of noise induced by trading. An important contributor in this area is Powers (1970) who examine the impact of futures trading on the information content of prices. He defines the variance of returns in terms of

$$\sigma_r = \sigma_s + \sigma_e \tag{3.1}$$

where

σ_r = variance of returns;

σ_s = the variance denoting the arrival of quality information and;

σ_e = the variance of the random component denoting noise trading.

Powers postulates that futures trading will reduce the importance of the noise-trading component because one of its primary functions is to uncover information that would not have been generated in the spot market. Although Powers only focuses on the unsystematic component of prices, he concludes that the impact of noise trading has declined in importance. This he attributes to the role of futures trading in improving the quality and flow of information.

Schleifer & Summers (1990) considers the noise-trading hypothesis as a scenario where excess variance of returns is a reflection of changes in investor sentiment. In their analysis, the behaviour of noise traders is dependent on their beliefs and sentiments not fully reflected by fundamentals. These changes can be a response to pseudo-signals such as the advice of brokers that investors perceive to carry information regarding future returns. Therefore, it follows that the arrival of poor quality information means that they will rely more on pseudo-signals as opposed to news regarding fundamentals.

The role of noise trading as a component in high trading time variances varies considerably in the theoretical literature. Kyle (1985) argues that the importance of the noise-trading component in volatility depends on the degree of market resiliency. As mentioned in Chapter One, Kyle defines resiliency in terms of the ability of the market to correct itself from uninformative shocks. Assuming the constant revealing of private information into prices in a continuous equilibrium, Kyle's model predicts that the importance of noise trading will decline throughout the trading day. Consequently, any pricing errors will be corrected for by the next day and hence, the covariance of returns across trading days becomes negative. In such a scenario, the noise-trading component is temporary and the impact of market closure would be a permanent loss of variance. To make the noise-trading hypothesis a testable proposition, the investigation will assume that the noise-trading component is temporary.

3.2.4 *The Volatility of Stock Returns and the Flow of Information*

One of the most important issues in this subject area is the underlying relationship between information and volatility. An invaluable contributor in this area is Ross (1989) who posits the notion that the rate of change in price equates the rate of change in the information flow. In making this assertion, he provides simple intuition behind the variance differential during non-trading and trading hours. Ross begins by setting out a number of conditions to derive the notation that equates the flow of information to spot price volatility. He envisages a market where there is no mispricing and hence, no arbitrage opportunities. Furthermore, he assumes that this is sustainable. On this basis, Ross forwards the notion that the price of an asset p follows a Martingale and is generated by a process of information s (1989, p.5, Lemma 1):

$$\frac{dp}{p} = \mu_p dt + \sigma_p dz_p \tag{3.2}$$

$$\frac{ds}{s} = \mu_s dt + \sigma_s dz_s \tag{3.3}$$

where the price of the asset and the information process has mean μ_p and μ_s respectively. σ_p is the standard deviation of prices, σ_s represents the flow of information and z is standard normal with zero mean and constant variance of one, i.e. $z \sim N(0, 1)$.

Equation (3.2) and (3.3) stipulates that asset prices and the process of information is a function of the rate of its mean and variance or standard deviation. Ross proves that if s follows a lognormal process, it can be used to predict values of s at a future date T so that asset prices will be such that $p(T)$ equates $s(T)$. That is, the drift in s is constant thus enabling Ross to set $\mu_s = 0$. Finally, using Itos Lemma, Ross demonstrates how expected returns satisfy the following security market line equation (SML) (1989, p.5, theorem 1):

$$\mu_p - r = -\text{cov}(p,q) \tag{3.4}$$

where

r = the risk free rate of interest and;

q = the pricing standard.[28]

Ross introduces equation (3.4) to solidify the no-arbitrage assumption through the incorporation of an asset pricing model, which is essentially an inseparable hypothesis to the efficient markets paradigm. Consequently, if expected returns does not satisfy the SML, investors can earn abnormal returns. Hence, the no-arbitrage condition breaks down and the market is inefficient, thus invalidating the asset pricing model.

By defining the liquidation value of the asset v as $v \equiv qs$ and through a process of differentiation, Ross formulates the following pricing relationship:

$$p = se^{[\mu_s - r + \text{cov}(q,s)(T-t)]} \tag{3.5}$$

In differential form, equation (3.5) becomes

$$\frac{dp}{p} = \frac{ds}{s} - [\mu_s - r + \text{cov}(q,s)]dt \tag{3.6}$$

[28] The pricing standard q in equation (3.4) is based on an asset pricing model.

By rearranging and substituting equations (3.2) and (3.4) into (3.6), he derives prices as being generated by

$$\mu_p dt + \sigma_p dz_p = [r - \mathrm{cov}(q, s)]dt + \sigma_s dz_s \tag{3.7}$$

in which the component μ_s is absent in equation (3.7). This follows from the notion that if s follows a lognormal process then $\mu_s = 0$. The reduced form of equation (3.7) implies that

$$\sigma_p dz_p = \sigma_s dz_s \tag{3.8}$$

which enables Ross to arrive at the final result that equates the variance of prices to the flow of information:

$$\sigma_p^2 = \sigma_s^2 \tag{3.9}$$

Equation (3.9) represents the no-arbitrage condition in which the variance of the change in price equates the variance or flow of information regarding factors, relevant to the price determination of the asset. The implication of condition (3.9) is that if prices are more volatile during trading hours, then the information flow must be highest when the markets are open.

The contribution of Ross provides more than just a conceptual link between information and volatility. Instead, it has served to tie up the volatility and efficiency literature. Although the equality condition of equation (3.9) is empirically impossible to test, the Ross Martingale condition has gone further than the efficiency literature in providing intuition behind the behavioural patterns of non-trading and trading period returns.

3.3 THE TRADING AND NON-TRADING PHENOMENON

A well-documented phenomenon is that asset prices are more volatile during trading hours than non-trading hours. French & Roll (1986) commented from their preliminary findings that on an hourly basis, the variance is between thirteen and one hundred times higher when the markets are open. Oldfield & Rogalski (1980) summarised this phenomenon intuitively by arguing

> *"There are reasons to assume that the return sequence when an organized market is formally open may differ from the return sequence during closed periods. For example, during a trading day, stock prices fluctuate as orders are executed. During nights, weekends, holidays, and holiday-weekends, there are no transactions, but a share's value from close to open on the next trading day may still change to reflect revised rational expectations about a firm's productivity. In fact, capital changes and important news items are usually announced after the stock exchange closes." (1980, p.729)*

Although neglected until recently, this issue has gained in importance because a solution to this phenomenon could provide a deeper understanding of how financial markets process information into prices.[29] Jones, Kaul & Lipson (1994) infer that the above definition of a trading and non-trading period assumes continuous trading until it's close. As a consequence, Oldfield &

[29] See French & Roll (1986).

Rogalski discount the impact of infrequent trading that arises when traders endogenously decide not to trade. Subsequently, the relationship between information and volatility is no longer conditional on trading activities dictated by the ability of traders to trade. As a result, this leans towards the proposition that traders will employ trading strategies involving the use of information that depend on expected profits and/or transaction costs.

One of the main objectives of this study is to empirically test for differences in the variance of returns during non-trading and trading time hours. An important contributor in this area is Oldfield & Rogalski (1980) in which developed a theory of common stock returns based on an autoregressive (AR) jump process.[30] Known as the Multiple Component Jump Process (MCJP), this comprises an underlying stochastic process and a separate jump process identified for overnights, holidays, weekends and holiday-weekends. In their model, actual transactions cause the jump process, where the size of the jumps may be autocorrelated. To elaborate further, changes in price are a reflection of the execution of trades that is temporary since an AR process assumes prices are stationary. The MCJP predicts that returns during trading hours will be more volatile than non-trading periods. Of paramount importance to this conclusion are two assumptions; first, returns are independently and identically distributed (i.i.d) across non-trading and trading periods. Second, the number of transactions that take place during the trading day is not constant, thus

[30] The intuition behind this is a new distribution theory of common stock returns developed in an earlier paper by Oldfield, Rogalski & Jarrow (1977).

allowing one to model the unconditional returns. As a consequence, trading period returns is a by-product of multiple jumps as a reflection of the execution of trades. On the other hand, as there are no transactions during non-trading hours, a single jump generates a return that represents a revision of expectations following the release of news after trading hours.

3.4 HETEROSCEDASTIC REGRESSION MODELS AND VARIANCE RATIO ANALYSIS.

3.4.1 The Model

For the purpose of the study, the core methodology proposed is the Heteroscedastic Regression Model (HRM). This procedure is similar to the approach used by Schwert (1990) and Jones, Kual & Lipson (1994). The main characteristic of the HRM is that models the return in the first and second moments. This requires regressing returns on day of the week and exchange holiday dummies and then saving the residuals. From the mean equation, the residuals are squared to compute the variance series. Using the variance as the dependent variable, the squared residuals are then regressed on the same day of the week and holiday dummies. Other than generating variance estimates, this approach identifies market anomalies that one can use to observe a relationship between the variance and day of the week and holiday effects. Further, in using

Ordinary Least Squares (OLS), this method will generate consistent estimators of the parameters.[31]

In modelling returns in the first moments, the procedure differs from previous studies by the inclusion of three-day, four-day, Christmas and New Year's Day exchange holiday dummies in the conditional mean equation:

$$R_{it} = \alpha_1 D_{M_t} + \dots\dots\dots\dots\dots + \alpha_5 D_{F_t} \\ + \alpha_6 D_{3D_t} + \alpha_7 D_{4D_t} + \alpha_8 D_{XMAS_t} + \alpha_9 D_{NY_t} + \varepsilon_{it} \qquad (3.10)$$

where R_{it} is the non-trading and trading period return on index i in time period t and D_{M_t} to D_{F_t} represent dummy variables from Monday to Friday; $D_{M_t} = 1$ if day t is a Monday and equal to zero otherwise.[32] Similarly, D_{T_t} to D_{F_t} represent Tuesday to Friday dummies respectively. $D_{i3_t}, D_{i4_t}, D_{XMAS_t}$ and D_{NY_t} dummies capture the impact of extended exchange holidays. These are denoted as three-day, four-day, Christmas and New Year exchange holidays along with the first day of trading after the holiday.[33] Intuitively, equation (3.10) defines returns as the expected return captured by day of the week and exchange holiday dummies. As with classical regression models, this relies on the assumption that the residual returns $\varepsilon_{i,t}$ are i.i.d for reliable coefficient estimates.

[31] See Pagan & Schwert (1990). This is of paramount importance because it implies that the estimates will be unbiased whereby there is no systematic tendency to either underestimate or overestimate the true value.
[32] It is worth emphasising that D_{M_t} is different from other days in that it represents a two-day exchange holiday and the first day of trading after the holiday.
[33] To capture the effect of national holidays, $D_{i3_t} = 1$, if day t is a Tuesday (i.e. a three-day exchange holiday to be followed by the first day of trading) and zero otherwise. This also applies for the dummy variable representing the four-day Easter holiday. For both Christmas and New Year's Day, D_{XMAS_t} and D_{NY_t} takes the value of one if day t is the exchange holiday followed by the first day of trading and zero otherwise.

The next stage is to generate variance estimates for each day of the week. To begin with, this requires saving and squaring the residuals ε_{it} from equation (3.10) to obtain $\hat{\varepsilon}_{it}^2$.[34] Modelling returns in the second moments involves the estimation of the following variance regression:

$$\hat{\varepsilon}_{it}^2 = \beta_1 D_{M_t} + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_5 D_{F_t}$$
$$+ \beta_6 D_{3D_t} + \beta_7 D_{4D_t} + \beta_8 D_{XMAS_t} + \beta_9 D_{NY_t} + v_{it} \qquad (3.11)$$

where β_1 is the dummy coefficient for the variance during the non-trading weekend and the first day of trading on Monday. Likewise, $\beta_2, \ldots\ldots, \beta_5$ are non-trading and trading period dummy coefficients for Tuesday to Friday and; β_6, β_7, β_8 and β_9 measures the variance during three-day, four-day, Christmas and New Year exchange holidays along with the first day of trading.

The usefulness of estimating the HRM of equation (3.10) and (3.11) is that it models the impact of exchange holidays separately from other weekdays along with the first day of trading. This is a useful distinction to make given that the behaviour of returns over the exchange holiday and on the first day of trading may differ from other weekdays. The prevailing explanation behind this relates to the accumulation of information during the exchange holiday. This will impact the opening price as the market revises its expectations on the basis of the new information. In addition, the generation of variance estimates for each day of the week allows the observation of volatility patterns that provides inferences on the dynamics of the market.

[34] See Davidian & Carroll (1987).

3.4.2 Variance Ratio Analysis

In conjunction with the HRM, this study proposes variance ratio analysis to analyse the behaviour of index returns across non-trading and trading periods. The use of variance ratios essentially determines the extent to which the variance of index returns is time varying. French & Roll (1986) and Harvey & Huang (1991) uses variance ratios to test the null hypothesis that hourly stock returns across non-trading and trading periods are constant. This they make possible by comparing two-day and three-day exchange holidays with a normal one-day return on the basis that one-day returns are independent. This is consistent with an essential property of the random walk hypothesis in which the variances are linear in the sampling period and returns $\boldsymbol{R_t}$ at time t are characterised by the following expression:

$$\boldsymbol{R_t} = \mu + \eta_t \tag{3.12}$$

where μ is the unconditional mean and η_t is the white noise term normally distributed with zero mean and variance σ^2_η. Assuming that returns do not contain errors caused by the bid-ask spread or overreaction of traders, equation (3.12) merely states that prices will follow a random walk $\left(cov(\eta_t, \eta_{t-k}) = 0\right)$. Hence, returns will be uncorrelated over time. Subsequently, the scenario envisaged is that the variance of returns will be linear to the measurement period. In relation to French & Roll (1986) and Harvey & Huang (1991), this implies that the variance of two-day returns should be twice the variance of a one day return. Taking this argument one step further, variance ratio tests have the desirable property of describing the stochastic evolution of prices over a period of time.

On the basis of significant variance estimates generated using equation (3.11), variance ratios are computed and defined as the ratio of non-trading period returns divided by returns during trading hours:

$$VR = \frac{\beta_{k,NT}}{\beta_{k,TD}} \qquad k = 1,\ldots\ldots\ldots\ldots,9 \tag{3.13}$$

where VR is the variance ratio, $\beta_{k,NT}$ is the variance of returns during non-trading hours and $\beta_{k,TD}$ is the variance of trading period returns.

3.4.3 Methodological Issues

In the previous chapter, the review on the literature demonstrates the problem of serial dependencies in daily and intra-daily data. In principle, both the arrival of information and noise trading can induce serial correlation in returns. The former can cause autocorrelation by changing the level of expected returns. However, the variability of expected returns are likely to be so small that the autocorrelation generated from this source will be unobservable. As for the latter, the potential for serial correlation arises on the assumption that market prices are related to the economic value of the stock. Hence, the process of correcting any mispricing caused by noise trading induces negative autocorrelations until the mispricing disappears.

In addition, there are two other factors that may induce serial correlation under the public information, private information and noise-trading hypothesis. The most important is the potential for *measurement* or *bid-ask bias*.[35] The source of bid-ask bias is the deviation of closing prices from its true value and essentially reflects the number of orders placed on one side of the market at the close. Transactions are either buyer initiated or seller initiated, and will cause negative serial dependence in successive price changes assuming no new information. Many studies have documented how bid-ask bias induces negative first order autocorrelation assuming that bid-ask errors are independently distributed over a period of time. Consequently, this will cause returns to resemble behaviour consistent with a first-order moving average process.

Serial dependencies in price changes may also arise as a consequence of nonsynchronous trading in which closing prices deviates from its true value if the last transaction is executed before the end of trading. Lo & MacKinlay (1988) investigates whether nonsynchronous trading causes spurious correlation in stock returns, where lagged volatility spillovers from large firms to small firms induces positive serial correlation in equally weighted stock returns. To provide intuition, the authors develop a non-trading model that distinguishes observed and virtual returns. They conclude that if an asset is traded infrequently, then observed returns defined as the accumulation of

[35] See Blume & Stambaugh (1983) in relation to the computation of returns using daily closing prices.

virtual returns over non-trading periods causes spurious induced correlation. However, the effect of nonsynchronous trading induced bias is usually minuscule in comparison with the bid-ask effect.[36][37]

In the case of UK data, index values are calculated on the basis of mid quotes and hence, theoretically are not susceptible to return autocorrelation caused by random bounce between bid and ask prices and nonsynchronous trading. However, the overwhelming evidence of serial dependencies reported in the previous chapter means that solving this problem is of paramount importance before estimating the HRM. Failure to adjust returns for serial dependencies may serve to induce spurious volatility, which reduces the reliability of the variance estimates and hence, the power of the variance ratio test. Therefore, section 3.6 provides autocorrelation test analysis using the Breusch-Godfrey (1978) procedure to identify serial correlation in returns.

3.5 DATA AND DESCRIPTIVE STATISTICS

3.5.1 The Data

The dataset consists of daily opening and closing index values on the FTSE-100 Index between January 1, 1988 to December 31, 1997. This is equivalent to 2609 observations of which the investigation adjusts for exchange holidays.

[36] See Blume & Stambaugh (1983).

[37] Lo & MacKinlay (1988) also arrive to this conclusion by performing autocorrelation tests on non-trading probabilities of between 10% and 50%. They find that when 10% of the stocks are infrequently traded, this induces a weekly autocorrelation of only 2.1%. When 50% of the stocks do not trade every day (which is unrealistic), this increases to only 17%, which suggests that bias induced by nonsynchronous trading is insignificant.

The data was downloaded from Datastream International. The FTSE-100 index consists of the 100 largest companies listed on the London Stock Exchange based on market capitalisation. Official trading hours are between 8:30am and 4:30pm, Monday to Friday, although there is very active trading outside these hours. To compute index returns during non-trading and trading hours, the study uses the procedure of Rogalski (1984). Given that the objective is to observe the behaviour of non-trading and trading period returns, the analysis restricts itself to the computation of close-to-open and open-to-close returns. Close-to-open returns R_t^{NT} are calculated as the ratio of the natural logarithm of today's opening price Po_t to the closing price of the last period to trade Pc_{t-1}.

$$R_t^{NT} = ln\left(Po_t / Pc_{t-1}\right) \tag{3.14}$$

where *ln* is the natural logarithm of prices. On the other hand, Rogalski calculates open-to-close returns R_t^T as the natural logs of the ratio of today's closing price Pc_t relative to today's opening index value Po_t.

$$R_t^T = ln\left(Pc_t / Po_t\right) \tag{3.15}$$

Essentially, the close-to-open return as defined in equation (3.14) represent changes in the logarithm of speculative price movements between the closing price of the last day of trading to the opening price of the current trading day. Likewise, the open-to-close return of equation (3.15) are a representation of changes in the logarithm of the opening price of the current day of trading to the closing price of the same trading day.

3.5.2 Descriptive Statistics

Table 3.1 presents the descriptive statistics for close-to-open and open-to-close returns on the FTSE-100 index for the whole sample. This includes the mean, variance, minimum and maximum values along with measures of skewness and kurtosis. P-values are in parentheses. To provide more reliable statistics, the analysis excludes weekdays coinciding with national holidays.[38] The statistics clearly show index returns more volatile during trading hours even though the measures of dispersion suggest that the extreme values are smaller. Although higher trading time variances is consistent with the results of French & Roll (1986) and Harvey & Huang (1991), the extreme values for close-to-open returns indicates that the market tends to experience greater revisions in price at the commencement of trading. In addition, although leptokurtosis is more evident for close-to-open returns, these findings add to the overwhelming evidence of the existence of fat tails reviewed in the previous chapter.

Table 3.2 shows a breakdown of the descriptive statistics by day of the week. Consistent with the findings of Rogalski (1984) and others[39], the sample mean provides the first indications of a significant negative non-trading weekend effect. In addition, the findings observe a casual relationship between the negative weekend effect and the variance. This finding indicates that negative

[38] Weekdays falling on exchange holidays are excluded by omitting zero returns that coincide with a national holiday.
[39] See the literature review of Chapter One.

Table 3.1

Descriptive Statistics on Close-to-Open and Open-to-Close Returns

Close-to-Open Returns [a]	
Sample Mean	0.016
Variance	0.249
Maximum	6.093
Minimum	-7.292
Skewness	-0.099
(p-value)	(0.04)
Kurtosis	39.631
(p-value)	(0.00)
Open-to-Close Returns [a]	
Sample Mean	0.028
Variance	0.523
Maximum	4.730
Minimum	-3.438
Skewness	0.138
(p-value)	(0.00)
Kurtosis	2.624
(p-value)	(0.00)

* Reject the null hypothesis that mean = 0 at the 0.05 level
[a] Returns multiplied by 10^2 for readability of the data.

Table 3.2

Descriptive Statistics for Close-to-Open and
Open-to-Close Returns by Day of the Week

Statistic	Mon	Tues	Wed	Thurs	Fri
Close-to-Open Returns					
Mean	-0.098*	0.095*	0.033	0.047*	-0.009
Variance	0.508	0.172	0.185	0.185	0.201
Maximum	6.093	2.168	1.542	4.393	5.284
Minimum	-7.292	-2.531	-2.550	-1.310	-1.887
Skewness	-1.156	0.207	-0.579	2.556	2.854
(p-value)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)
Kurtosis	38.694	5.955	4.838	24.032	38.646
(p-value)	(0.00)	(0.00)	0.00)	(0.00)	(0.00)
Open-to-Close Returns					
Mean	0.046	0.006	0.037	-0.001	0.052
Variance	0.595	0.499	0.455	0.488	0.589
Maximum	4.085	2.621	4.730	2.915	4.303
Minimum	-3.438	-2.515	-2.310	-3.103	-2.490
Skewness	-0.033	-0.002	0.659	-0.204	0.287
(p-value)	(0.77)	(0.99)	(0.00)	(0.06)	(0.01)
Kurtosis	2.993	1.037	4.486	1.700	2.755
(p-value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

* Reject the null hypothesis that mean = 0 at the 0.05 level

returns reflect the arrival of bad news, and the high variance representing market overreaction at the start of trading to this information. In contrast, positive overnight effects do not coincide with high overnight variances in relation to other weekdays. Once again, the descriptive statistics show index returns more volatile during trading hours for every weekday despite reporting smaller extreme values. In addition, the skewness and leptokurtosis is more prominent for close-to-open returns. In general, this leads to the conclusion that close-to-open returns deviate from normality to a greater degree than open-to-close returns as suggested by the higher measures of skewness and kurtosis.

3.6 SERIAL DEPENDENCIES IN FTSE-100 INDEX RETURNS

One cannot overemphasise the importance of addressing the problem of serial dependencies in stock returns. Blume & Stambaugh (1983) acknowledges that this is an issue of importance for any investigation using closing index values to compute daily returns. To determine whether the return series need adjustment, this study performs autocorrelation tests on close-to-open and open-to-close returns up to twelve lags using the Breusch-Godfrey (1978) procedure. The number of lags chosen is arbitrary. The Breusch-Godfrey procedure is a Langrange multiplier test for higher order serial correlation that tests the null hypothesis of no autocorrelation in daily returns. However, for the purpose of the study, the appealing property of this test is its application against the alternative hypothesis of u_t generated either by a AR(p) or MA(q) process.

To test the joint significance of the first p autocorrelations in the residuals requires the estimation of the following mean equation:

$$R_t = \alpha_1 + e_t \tag{3.16}$$

where R_t represents both return series at time t, and α_1 is the constant. The residuals e_t are saved and then used as a dependent variable to estimate the following:

$$e_t = \alpha + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots\ldots + \theta_{12} e_{t-12} \tag{3.17}$$

where $e_t = R_t - \alpha_1$ is the vector of OLS residuals, and $e_{t-1}, e_{t-2}, \ldots\ldots, e_{t-12}$, are the residuals lagged up to twelve periods. A value of nR^2 is obtained and compared to the χ^2 distribution with twelve degrees of freedom at the 0.05 level. Table 3.3 provides the results of the Breusch-Godfrey test up to lag 12 that includes chi-squared statistics for both return series in columns 2 and 3. t-statistics are in parentheses. For close-to-open and open-to-close returns, the results report an overwhelming rejection of the null hypothesis of serially uncorrelated returns. This consists of significant negative autocorrelations at lag 1 for both return series that becomes negative at lag 2 for close-to-open returns and positive for open-to-close returns. Consistent with the findings of Mandelbrot (1963), the main characteristic of both return series is the low autocorrelation coefficients. As consequence, it is difficult to gauge their economic significance.

Table 3.3

Daily Autocorrelations for the FTSE-100 Index Returns
Between January 1, 1988 to December 31, 1997.

Lag	Close-to-Open Returns	Open-to-Close Returns
1	-0.091	-0.073
	(-4.56)	(-3.64)
2	-0.076	0.078
	(-3.80)	(3.88)
3	-0.004	0.001
	(-0.18)	(0.04)
4	0.013	-0.010
	(0.66)	(-0.51)
5	0.031	0.015
	(1.54)	(0.73)
6	-0.003	-0.020
	(-0.16)	(-1.02)
7	-0.020	-0.079
	(-1.02)	(-3.97)
8	-0.004	0.018
	(-0.19)	(0.89)
9	0.005	0.018
	(0.26)	(0.89)
10	0.030	0.017
	(1.49)	(0.87)
11	-0.031	0.002
	(-1.57)	(0.12)
12	-0.006	0.034
	(-0.28)	(1.72)
$\chi^2(12)$	42.865	51.815

Chi-squared test statistic compared with a critical value of 21.0261.
t-statistics in parentheses

In acknowledgment of the problem of bias, previous studies employing the variance ratio methodology adjust the ratio as opposed to adjusting the return series.[40] Given the estimation of the HRM, this study represents a departure from previous investigations by adjusting returns before computing the variance ratio.

To adjust close-to-open and open-to-close returns, this study uses the procedure proposed by Akgiray (1989) which involves generating ordinary least squares (OLS) residuals from the following AR(2) process:

$$\boldsymbol{R}_t = \alpha_1 + \alpha_2 \boldsymbol{R}_{t-1} + \alpha_3 \boldsymbol{R}_{t-2} + \boldsymbol{e}_t \tag{3.18}$$

The primary objective of equation (3.18) is to remove systematic effects in the form of statistically significant higher order autocorrelations such as those reported in table 3.3. The order of the AR process ($\boldsymbol{R}_{t-1}$ and $\boldsymbol{R}_{t-2}$) depends on the order of the autocorrelation problem. Notice that the constant α_1 is included in the regression given that if returns are autocorrelated, the constant is the conditional mean. That is, conditional on past expected values.

Generating and testing the adjusted returns involves saving the residuals $\boldsymbol{e}_t$ from (3.18) and performing autocorrelation tests on the new series. Table 3.4 shows the autocorrelation test results on the adjusted series. According to the

[40] See Cho & Frees (1988), Kau & Nimalendran (1990), Schwert (1990) and Jones, Kual & Lipson (1994).

Table 3.4

Daily Autocorrelations on Adjusted Close-to-Open and Open-to-Close Returns.

Lag	Close-to-Open Returns	Open-to-Close Returns
1	0.001	0.011
	(0.05)	(0.37)
2	-0.002	0.024
	(-0.08)	(0.83)
3	-0.003	0.028
	(-0.17)	(0.97)
4	0.013	0.042
	(0.67)	(1.44)
5	0.031	-0.053
	(1.54)	(-1.82)
6	-0.008	-0.029
	(-0.38)	(-1.02)
7	-0.024	0.012
	(-1.20)	(0.41)
8	-0.005	0.042
	(-0.24)	(1.46)
9	0.008	0.019
	(0.40)	(0.64)
10	0.030	-0.024
	(1.50)	(-0.83)
11	-0.032	0.033
	(-1.61)	(1.13)
12	-0.001	-0.005
	(-0.05)	(-0.17)
$\chi^2(12)$	10.019	13.126

Chi-squared test statistic compared with a critical value of 21.0261.
t-statistics in parentheses

results, the autocorrelation tests cannot reject the null hypothesis of no serial dependencies in both return series. On the basis of the adjusted return series, the next section adopts the HRM to test for market anomalies in the first and second moments.

3.7 TESTING FOR MARKET ANOMALIES IN THEIR FIRST AND SECOND MOMENTS

3.7.1 *Testing for Market Anomalies*

The objective of this section is to model day of the week market anomalies and the variance of non-trading and trading period returns. There are two levels of investigation involved. The first, involves modelling returns in the first and second moments and secondly, robustness testing of market anomalies in the variance. To address these issues, this requires estimating the HRM of equations (3.10) and (3.11) on the adjusted return series. In estimated form, the two-step procedure is expressed as:

$$\begin{aligned} \boldsymbol{R}_{it} &= \boldsymbol{a}_1\boldsymbol{D}_{M_t} + \ldots\ldots\ldots\ldots\ldots\ldots\ldots + \boldsymbol{a}_5\boldsymbol{D}_{F_t} \\ &\quad + \boldsymbol{a}_6\boldsymbol{D}_{3D_t} + \boldsymbol{a}_7\boldsymbol{D}_{4D_t} + \boldsymbol{a}_8\boldsymbol{D}_{XMAS_t} + \boldsymbol{a}_9\boldsymbol{D}_{NY_t} + \varepsilon_{it} \end{aligned} \tag{3.19a}$$

$$\begin{aligned} \hat{\varepsilon}_{it}^2 &= \boldsymbol{b}_1\boldsymbol{D}_{M_t} + \ldots\ldots\ldots\ldots\ldots\ldots\ldots + \boldsymbol{b}_5\boldsymbol{D}_{F_t} \\ &\quad + \boldsymbol{b}_6\boldsymbol{D}_{3D_t} + \boldsymbol{b}_7\boldsymbol{D}_{4D_t} + \boldsymbol{b}_8\boldsymbol{D}_{XMAS_t} + \boldsymbol{b}_9\boldsymbol{D}_{NY_t} + v_{it} \end{aligned} \tag{3.19b}$$

where $\boldsymbol{a}$ and $\boldsymbol{b}$ represents the coefficients to be estimated. Table 3.5 displays the results that comprise of expected returns and variance estimates during non-trading and trading intervals. *t*-statistics are in parentheses. Consistent with earlier findings, there appears to be a negative non-trading weekend effect

Table 3.5

Expected Returns and Variance Estimates for Close-to-Open and Open-to-Close Returns on the FTSE-100

$$R_{it} = a_1 D_{M_t} + \ldots .. + a_5 D_{F_t} + a_6 D_{3Dt} + a_7 D_{4Dt} + a_8 D_{XMAS} + a_9 D_{NY} + \varepsilon_{it}$$

$$\hat{\varepsilon}^2_{it} = b_1 D_{M_t} + \ldots ... + b_5 D_{F_t} + b_6 D_{3DH_t} + b_7 D_{4DH_t} + b_8 D_{XMAS} + b_9 D_{NY} + v_{it}$$

	Close-to-Open Returns		Open-to-Close Returns	
Day of the Week	Mean Returns	Variance	Mean Returns	Variance
Monday	-0.115	0.508	0.015	0.581
	(-5.07)	(7.02)	(0.46)	(11.41)
Tuesday	0.073	0.138	-0.025	0.502
	(3.23)	(1.91)	(-0.77)	(9.85)
Wednesday	0.016	0.181	0.002	0.448
	(0.74)	(2.61)	(0.05)	(9.18)
Thursday	0.042	0.181	-0.026	0.476
	(1.95)	(2.62)	(-0.82)	(9.81)
Friday	-0.021	0.200	0.020	0.579
	(-0.95)	(2.87)	(0.64)	(11.82)
Three-day Holiday	0.159	0.191	-0.162	0.313
	(1.77)	(0.67)	(-1.24)	(1.56)
Four-day Holiday	-0.564	0.645	0.605	0.583
	(-3.64)	(1.30)	(2.67)	(1.67)
Christmas	0.177	0.036	0.699	0.235
	(1.14)	(0.07)	(3.08)	(0.68)
New Year	-0.108	0.230	-0.129	0.212
	(-0.66)	(0.44)	(-0.54)	(0.58)

The null hypothesis tested for this that $a = 0$ and $b = 0$ at the 0.05 level of significance which implies no market anomaly in the first and second moments.
t-statistics in parentheses.

in the first moments. Just as significant, is the revealing of a negative non-trading Easter weekend effect followed by a positive trading day effect on the first day of trading after the holiday. A positive trading day effect also occurs on the first day of trading after the Christmas holiday. These results are suggestive of the concentration of negative private information reflected in the opening price on the first day of trading after the holiday. Although citing previous studies, Peterson (1990) provides evidence of an anomaly in the release of information. That is, the early release of favorable earnings announcements and delays in unfavorable news until after the close of trading. Given that some trading takes place after UK hours and assuming that earnings information dominates the market, a similar conclusion is applicable to the FTSE-100 Index.

In observing both series of returns in their second moments, all the holiday effects except for the non-trading weekend effect are eliminated. The results imply this by the failure to reject the null hypothesis of $b = 0$ at the 0.05 level of significance. Moreover, the insignificance of the Tuesday to Friday dummies in the mean return has become significant in the second moments. This result suggests the existence of day of the week anomalies in the second moments, a finding not observed in previous studies. The results also indicate that index returns are significantly more volatile during trading hours, thus showing support for the private information and noise-trading hypothesis. Upon closer observation of the results, there appears to be a U-shape pattern of variances for trading period returns across days of the week. Monday's and

Friday's are the most volatile days with the quietest period occurring mid-week. The high variance on Mondays is indicative of the dissemination of private information accumulated over the weekend. On the other hand, the variance estimate for Friday's indicates a tendency for trades to cluster[41] before a two-day exchange holiday. Once again, the results show a casual relationship between expected returns and the variance where high variance estimates over the weekend coincide with the negative weekend effect. Once again, this is consistent with the private information hypothesis.

3.7.2 Testing the Robustness of the Variance Estimates

This investigation also provides F-test statistics to determine the robustness of market anomalies in both return series in their second moments. Using the adjusted close-to-open and open-to-close returns, the procedure proceeds from the general model estimated earlier

$$\hat{\varepsilon}_{it}^{2} = b_1 D_{M_t} + \ldots\ldots\ldots\ldots\ldots\ldots\ldots + b_5 D_{F_t} + b_6 D_{3D_t} + b_7 D_{4D_t} + b_8 D_{XMAS_t} + b_9 D_{NY_t} + v_{it} \qquad (3.20)$$

in which the restrictions imposed and tested for are:

H^1_0: $b_1 = 0$

H^2_0: $b_6 = 0$

---

[41] However, it is worth noting that Friday afternoon trading in London coincides with the release of most US macroeconomic news at the start of US trading. Although volatility spillovers is beyond the scope of this chapter, of importance to this interpretation is the responsiveness of UK stock prices to the release of public information in the US. There is evidence to suggest that the greatest price adjustment occurs in the first minute after the release of an announcement and takes several hours for volatility to return to its pre announcement level. [See Ederington & Lee (1993) in relation to interest rates and foreign exchange futures markets]

H^3_0: $b_7 = 0$

H^4_0: $b_8 = 0$

H^5_0: $b_9 = 0$

H^6_0: $b_6 = b_7 = 0$

H^7_0: $b_1 = b_6 = b_7 = 0$

H^8_0: $b_1 = b_6 = b_7 = b_8 = 0$

H^9_0: $b_1 = b_6 = b_7 = b_8 = b_9 = 0$

Acceptance of the null hypothesis implies that the restrictions imposed are valid. This will confirm that holiday periods have no effect on the nature of the return variance. To isolate the impact of exchange holidays on the nature of the variance, hypothesis H^1_0 to H^5_0 excludes both holiday periods and trading days that precede them where;

b_1 = Normal weekends

b_6 = Bank holiday weekends

b_7 = Easter holiday weekends

b_8 = Christmas holidays

b_9 = New Year holidays.

The hypothesis H^6_0 to H^9_0 tests the overall effect of exchange holidays. Table 3.6 presents the results that show *F*-test statistics on the restrictions imposed on the unrestricted model of equation (3.20). P-values are in parentheses. According to the results, the non-trading weekend effect is robust as implied by the overwhelming rejection of the null hypothesis at the 0.05 level. In addition, despite the observation of a non-trading weekend effect, the test

Table 3.6

Testing the Restrictions of the General Model During Exchange Holidays and Trading Times

Restrictions Imposed	Close-to-Open Returns	Open-to-Close Returns
	F-statistics	F-statistics
H^1_0: $b_1 = 0$	49.22*	130.11*
	(0.00)	(0.00)
H^2_0: $b_6 = 0$	0.45	2.42
	(0.50)	(0.12)
H^3_0: $b_7 = 0$	1.70	2.80
	(0.19)	(0.09)
H^4_0: $b_8 = 0$	0.01	0.46
	(0.94)	(0.50)
H^5_0: $b_9 = 0$	0.19	0.33
	(0.66)	(0.56)
H^6_0: $b_6 = b_7 = 0$	1.07	2.61
	(0.34)	(0.07)
H^7_0: $b_1 = b_6 = b_7 = 0$	17.12*	45.11*
	(0.00)	(0.00)
H^8_0: $b_1 = b_6 = b_7 = b_8 = 0$	12.84*	33.95*
	(0.00)	(0.00)
H^9_0: $b_1 = b_6 = b_7 = b_8 = b_9 = 0$	10.31*	27.22*
	(0.00)	(0.00)

* Reject the null hypothesis of valid restrictions imposed at the 0.05 level of significance.

statistic of 130.11 for open-to-close returns suggest that the impact of the weekend effect is greatest on the first day of trading after the weekend. The significance of the trading period Monday dummy further supports the private information hypothesis. Consistent with the findings of table 3.5, the results cannot reject the null hypothesis for other exchange holidays at the 0.05 level. This is not surprising given that national holidays occur infrequently, so that traders are not changing their trading strategies to take into account the extended weekends. Nevertheless, by imposing the restriction $b_1 = b_6 = b_7 = b_8 = b_9 = 0$, the test statistics support the overall conclusion that the holiday effect is most profound on the first day of trading.

3.8 VARIANCE RATIO TESTS

This study investigates further the difference in the variance of index returns during trading and non-trading hours using variance ratio tests. For illustrative purposes, figures 3.1(a) and 3.1(b) plots daily volatility values during non-trading and trading hours using the following expression for the standard deviation of returns:[42]

$$V_t = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(R_j - \bar{R}\right)^2} \tag{3.21}$$

where

V_t = the volatility series;

[42] See J. Hull, Options, Futures, and Other Derivative Securities (Prentice-Hall International Editions, 1989) p.88.

Figure 3.1(a)

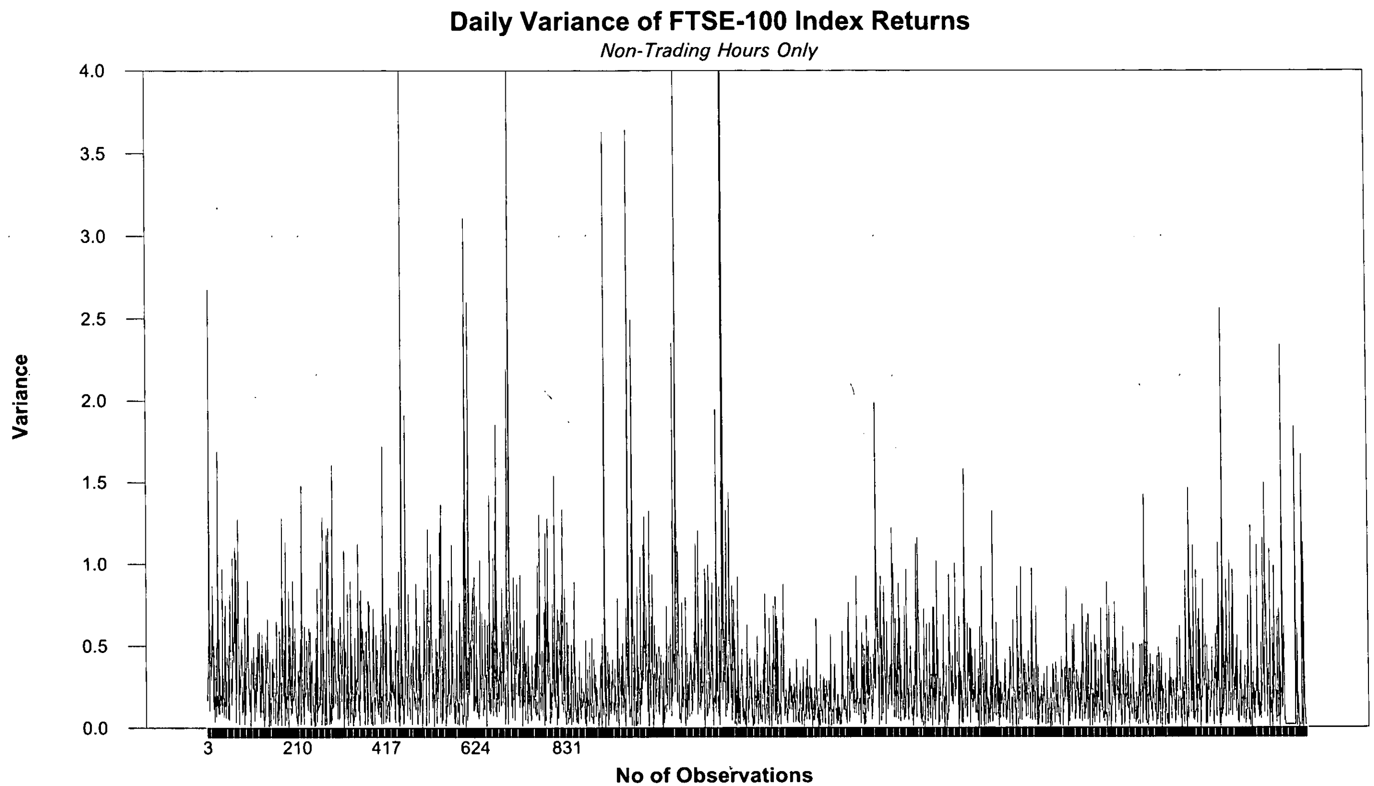
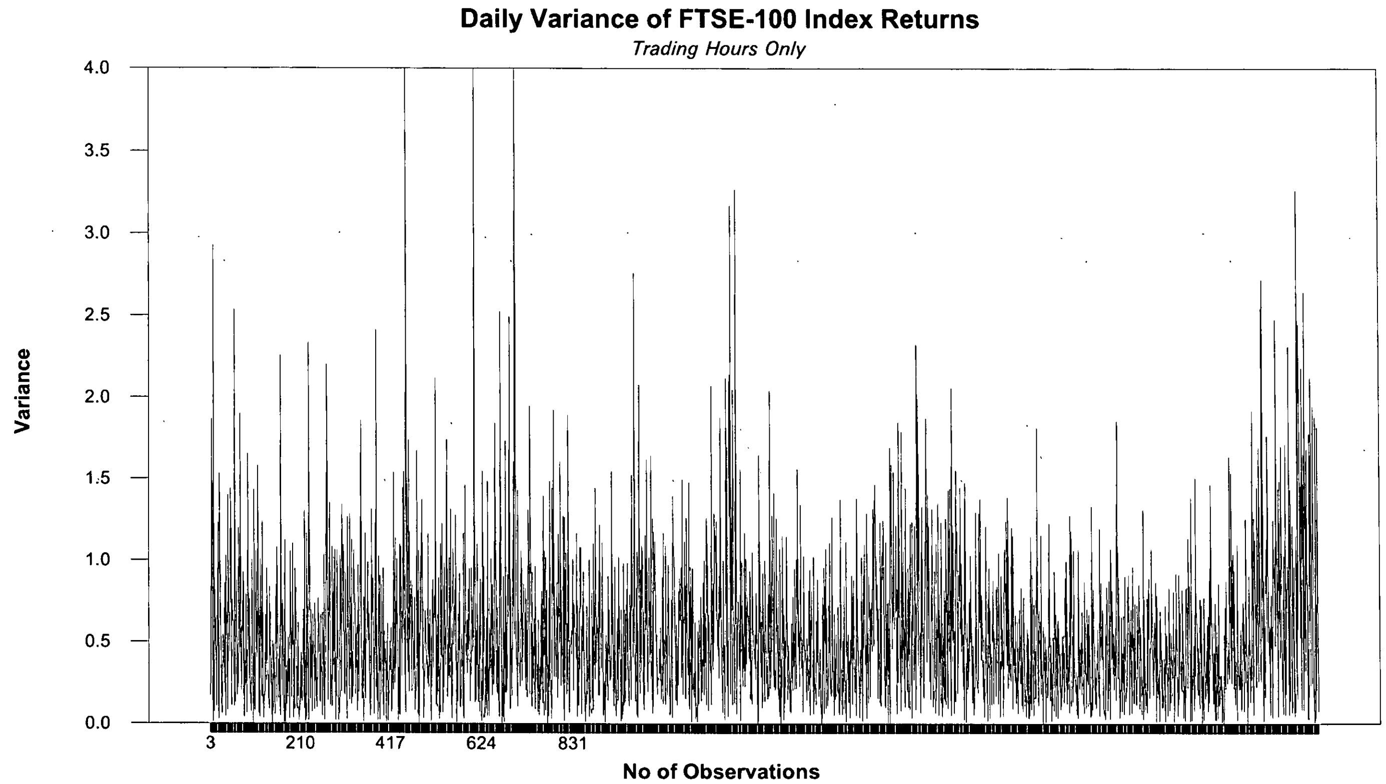

Daily Variance of FTSE-100 Index Returns
Non-Trading Hours Only
Variance
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
3
210
417
624
831
No of Observations

Figure 3.1(b)



Daily Variance of FTSE-100 Index Returns
Trading Hours Only
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Variance
3
210
417
624
831
No of Observations

N = the number of observations;

R_j = the index return at time j;

$\overline{R}$ = the mean return.

According to the graphs for the whole sample, index values appear to be more volatile during trading than non-trading hours.[43]

On the basis of significant variance estimates obtained from the HRM, the computation of variance ratios is the next step of the analysis. The hypothesis tested for assumes that the variance of returns is constant across non-trading and trading hours. Crucial to this hypothesis is the assumption that one-day returns are independent and hence, consistent with the essential property of the random walk model in which the variance is linear in the sampling period. Table 3.7 presents the test results which comprises of overnight and weekend ratios defined as:

(VR_O) = Overnight Ratio

$$VR_O = \frac{b_{2,NTT}}{b_{1,TM}}, \frac{b_{3,NTW}}{b_{2,TT}}, \frac{b_{4,NTTH}}{b_{3,TW}}, \frac{b_{5,NTF}}{b_{4,TTH}} \tag{3.22}$$

(VR_W) = Weekend Ratio

$$VR_W = \frac{b_{1,NTM}}{b_{j,TMF}} \tag{3.23}$$

[43] Owing to the adjustment of the data for national holidays, the graphs are labelled in terms of the number of observations as opposed to calendar dates in the horizontal axis.

where $b's$ are the significant coefficients estimated from equation (3.19b) and the variance of overnight returns under consideration are

$b_{2,NTT}$ = Monday-Tuesday *NTT*;

$b_{3,NTW}$ = Tuesday-Wednesday *NTW*;

$b_{4,NTTH}$ = Wednesday-Thursday *NTTH*;

$b_{5,NTF}$ = Thursday-Friday *NTF*.

Overnight variances are then divided by the variance of the last trading period to trade (i.e. from Monday to Thursday or $b_{1,TM},\ldots\ldots,b_{4,TTH}$). For the weekend ratio, $b_{1,NTM}$ is the non-trading weekend variance and $b_{j,TMF}$ is the variance of trading period returns on Monday,.......,Friday where $j = 1,\ldots.,5$. For comparison purposes with previous studies, the table also includes an additional row labeled "all days". This ratio measures the relative variance of non-trading period returns to trading returns for the five trading days put together. The procedure involves estimating the variance of five-day trading returns using the HRM approach:

$$R_{it} = a_0 + \varepsilon_{it} \tag{3.24a}$$

$$\varepsilon_{it}^2 = b_0 + v_t \tag{3.24b}$$

where a_0 and b_0 are the mean and variance estimates for all weekdays. Causal observation of the results in table 3.7 reveals an overwhelming rejection of the hypothesis that the variance is constant across non trading and trading hours. Consistent with previous studies, index returns are more volatile during trading hours as suggested by ratio values of ≤1 even though overnight periods are at least twice as long. The weekend ratio of 0.983 in the "all days" row compares

Table 3.7

Variance Ratio Test Statistics of Close-to-Open Returns
to Open-to-Close Returns

Day of the Week	(VR_O)	(VR_W)
All Days	*	0.983
Monday	0.238	0.873
Tuesday	0.360	1.011
Wednesday	0.404	1.135
Thursday	0.420	1.066
Friday	-	0.876

* No ratio is given for overnight returns given that this includes weekends.

with 1.107 reported by French & Roll (1986) and 1.685 by Harvey & Huang (1991) using close-to-close returns. Although the ratios confirm the findings of table 3.5, a different conclusion arises upon further examination of the weekend ratio. The ratio value of approximately equal to one from Monday to Friday indicates that the non-trading weekend effect reduces the volatility differential between non-trading and trading period returns. In addition, the statistics show an upside down U shape pattern on the size of the weekend ratio. The highest ratio value being on Wednesday coincides with the quietest day of the week. On the other hand, the most volatile days on Monday and Friday coincide with the lowest weekend ratio. As a consequence, the results reveal a relationship between the size of the variance ratio and the non-trading weekend effect.

3.8.1 Testing the Noise Trading Component in FTSE-100 Index Returns

Although the evidence presented thus far seems to support the private information hypothesis, one cannot discount the possibility that the high variance estimates during trading hours are indicative of the amount of noise trading. This proposition arises from the analysis of table 3.5 in that it fails to determine whether market closure cause a permanent loss of variance. Based on the assumption that mispricing is temporary, market closure and the permanent loss of variance are the characteristics that distinguish the private information from the noise-trading hypothesis.

Table 3.8 presents the variance ratio test results. To investigate the noise trading component in the variance requires a modification of the variance ratio to include relative trading period variances in weeks that follow national holidays to the variances in a normal five-day trading week. Weeks following three-day and four-day exchange holidays are separated from normal trading weeks. This creates a sub-sample of 81 observations for weeks following a four-day exchange holiday; 121 observations following a three-day holiday and 2260 observations following normal weekends. The analysis excludes weeks coinciding with Christmas and New Year holidays given the low number of observations. To compute the variance ratio for "all days" requires estimating the HRM of equation (3.24) on weeks following an exchange holiday and a normal five-day trading week. The b_0's are the variance estimates of interest.

$$VR_{TW3} = VR_{TW4} = \frac{b_{0,TF}}{b_{0,MF}} \tag{3.25}$$

where VR_{TW3} and VR_{TW4} are the variance ratios that extract the noise trading component in the variance for three-day and four-day exchange holidays respectively. The term $b_{0,TF}$ is the variance of trading period returns for weeks following a three-day and four-day exchange holiday (i.e. Tuesday to Friday) and $b_{0,MF}$ is the variance for a normal five-day trading week. Table 3.8 also report variance ratios defined as the relative trading period variance in weeks following exchange holidays to a one-day trading day variance during a normal week:

$$VR_{TW3} = VR_{TW4} = \frac{b_{0,TF}}{b_{1,TM}}, \frac{b_{0,TF}}{b_{2,TT}}, \frac{b_{0,TF}}{b_{3,TW}}, \frac{b_{0,TF}}{b_{4.TTH}}, \frac{b_{0,TF}}{b_{5,TF}} \tag{3.26}$$

where the coefficients b_1 to b_5 are the variance estimates for trading period returns first reported in table 3.5. Under all variance ratio tests, the private information hypothesis is said to be valid if the ratios VR_{TW3} and VR_{TW4} are ≥1. On the other hand, under the noise-trading hypothesis, the ratios must be ≤1. This follows from the assumption that any mispricing is temporary and corrected for by the next trading day.

On this occasion, the results from the variance ratio test draw mixed conclusions. There is some evidence of a noise-trading component in stock index returns as indicated by the variance ratio of less than one. This implies that the lost variance resulting from longer market closure is not recovered. However, the test statistics restrict this finding to weeks following a four-day exchange holiday. On the other hand, variance ratios of greater than one occurs for weeks following a three-day exchange holiday. Given that three-day exchange holidays occur more frequently, these results provide additional evidence in favour of the private information hypothesis.

Table 3.8

Variance Ratio Test Statistics for Weeks Following National Holidays in Relation to Normal Five-Day Trading Weeks

Day of the Week	3 Day Holiday (VR_{TW3})	4 Day Holiday (VR_{TW4})
All Days	1.188	0.746
Monday	1.059	0.665
Tuesday	1.227	0.770
Wednesday	1.376	0.864
Thursday	1.293	0.812
Friday	1.063	0.668

3.9 SUMMARY AND CONCLUSIONS

The objective of this chapter is to examine the relationship between market anomalies and the variance of index returns during non-trading and trading hours. Four levels of investigation were performed in this study, ranging from modelling returns in the first and second moments towards testing for the noise-trading component in the variance.

The motivation of this study is purely academic, and coincides with an increasing awareness that a solution to this phenomenon will provide us with a deeper understanding of how information is processed in financial markets. Empirical research in this area coincided with the development of the market model from Kyle (1985) and others. The interest generated from the introduction of these models served to enhance the role of information versus trading debate as the primary determinants governing the behaviour of returns during trading and non-trading hours.

The methodology proposed is the Heteroscedastic Regression Model (HRM). Unlike previous investigations, the HRM in this study includes exchange holiday dummies in the conditional mean and variance equation. Furthermore, whilst yielding consistent estimators of the parameters, this method additionally entertained the prospect of observing a relationship between market anomalies and the variance of returns. Apart from using the HRM, the computation of variance ratio tests provides an additional dimension to the analysis. Within this framework, the combination of variance ratio analysis with the HRM allows the investigation to investigate a relationship between market anomalies and the size of the variance ratio of non-trading and trading period returns.

Descriptive statistics on close-to-open and open-to-close returns reveal a number of consistencies with previous studies. Most notable, is the existence of a negative non-trading weekend effect along with high trading time variances. In addition, the descriptive statistics report the early signs of a relationship between the negative weekend effect and high weekend variances. It is from this association that the study related the weekend effect to the accumulation of negative information, whereas the high variance demonstrates the response of the market to this information.

In response to a review of key papers in the previous chapter, the analysis addresses the issue of serial dependencies in the data. Using the Breusch & Godfrey (1978) procedure, the test statistics highlight the problem of serial dependencies for both close-to-open and open-to-close index returns. Using the approach proposed by Akgiray (1989), the OLS residuals obtained from an AR(2) process is sufficient to correct for higher order serial dependencies for both return series.

The results presented in the main investigation concentrated on modelling the behaviour of close-to-open and open-to-close returns in their first and second moments. By using index returns adjusted for serial dependencies, two conclusions stand out. For instance, the revealing of a non-trading weekend effect in the mean and higher variance estimates for trading period returns. The latter finding is consistent with the results of French & Roll (1986) and Harvey & Huang (1991) using close-to-close returns. Although variance ratio analysis consistently reveals higher variances during trading hours, it found little evidence of a noise-trading component in trading time volatility.

The main implication of this study is that it has succeeded in asking more questions about the scope of previous studies. For instance, robustness tests on the variance estimates suggested that the impact of the negative weekend effect is most profound on the first day of trading. In addition, the idea of a relationship between the size of the variance differential and the nature of the anomaly requires further investigation. According to the mean and variance estimates *a* and *b*, the negative weekend effect tends to amplify weekend volatility, thus narrowing the variance differential between the return series using the weekend ratio. This contrasts with the impact of positive anomalies. Taken together, the study concluded that private information is most likely to be the driving force behind high trading time variances.

The implication of this study for the individual investor is that it provides useful inferences on the risk-ness of the market on a daily basis. According to the results, the FTSE-100 index tends to be riskier on Monday and Friday during a normal five day trading week. It therefore follows that a decision on whether an investor should remain in the market during volatile periods is related to the market efficiency argument. This is of paramount importance because investor perception that the market is dominated by noise-traders would mean that they will lack confidence in the market. As a consequence, they will leave the market to avoid losses caused by unwarranted adverse changes in the index price. According to the Efficient Market Hypothesis, the result would be a misallocation of resources. However, the findings in this study suggest the contrary given evidence in support of the private information hypothesis. Despite higher volatility levels at the beginning and end of the trading week, the perception of investors that informed traders dominates the market reduces the likelihood that they will lose confidence in the market.

CHAPTER FOUR

THE VOLATILITY OF INDEX RETURNS AT THE OPEN AND CLOSE OF TRADING: AN EMPIRICAL INVESTIGATION OF THE FTSE-100 INDEX

4.1 INTRODUCTION

The volatility of index returns observed at the open and close of trading has generated less interest. However, some attention has focused on comparing the opening transactions that represent the outcome of a clearing-house and the closing transactions that characterises the operation of a dealership market.[44] However, an investigation of this nature using UK data is not possible because the London stock market operates a dealership market regime. Hence, unlike previous studies that focus on different trading structures, this study considers an alternative approach. That is, that the behaviour of index returns at the beginning and end of trading is indicative of the dynamics that govern the information processing of the market. This involves investigating differences in both the size and sign of the innovations along with the importance of old news. In addition, the study considers the dynamic responses to random shocks in their duration and timing to further understand how markets process information.

[44] See the review of the literature in Chapter One.

The objective of this chapter is to investigate the behaviour of index return volatility at the beginning and end of trading. In undertaking such a study, the investigation provides an empirical framework for assessing volatility induced by the dynamics of the market. Two methodologies are proposed to this effect. The first methodology considered is the Exponential-GARCH (EGARCH) of Nelson (1990) to examine differences in the time varying nature of volatility. Monte Carlo Simulation will then be used to simulate the way the conditional variance responds to a shock in the conditional volatility. This leads to the proposal of the second methodology in this study; the Vector Autoregressive (VAR) model of Sims (1980). From the VAR, one can compute the Impulse Response Function using the simulation process. Within this empirical framework, the investigation is able to determine whether the behaviour of index return volatility at opposite times of the day is a direct consequence of the nature and dynamics of the market.

The study presents conflicting results. By estimating EGARCH on daily data, index returns are more volatile at the start of trading. However, an EGARCH analysis performed on daily returns by day of the week indicates that the market is most volatile at the close of trading for most weekdays. In both cases though, this is attributable to changes in the flow of information and reaction of the market to the innovation. Applying impulse response analysis by day of the week reveal that the failure of the market to return to its pre-shock level explains why index values are more volatile at the close of trading. This is despite the finding that the market is more sensitive to random shocks at the start of trading. On the basis of these results, the study provides two conclusions. First, one can interpret the high impulse response at the start of trading to the perception of the market that random shocks are bad news. Secondly, the failure of the market to return to pre shock levels may reflect the activities of better informed traders continuing trading on the basis of additional information only known to them.[45] This proposition relies on the notion that the random shock does not alter the expectations of better informed traders and hence, their trading pattern.

The chapter will proceed as follows. The next section provides a theoretical discussion of the issues. Section 4.3 introduces the EGARCH and VAR methodologies and its usefulness for this type of analysis. Section 4.4 presents the data used and some descriptive statistics. Section 4.5 reports the EGARCH estimates on daily returns and daily returns by day of the week. Section 4.6 displays the VAR and impulse response results followed by a summary and conclusion in section 4.7.

4.2 THEORETICAL DISCUSSION

4.2.1 Changes in the Flow of Information and Volatility

A possible explanation behind differences in volatility patterns relates to the rate of information flow at the beginning and end of trading. As first mentioned in Chapter One, one of the most important contributors in this area

[45] See Foster & Viswanathan (1994).

is Ross (1989). He introduces the notion that the rate of change in stock prices equates the rate of change in the flow of information. However, in its current form, the equality condition of equation (1.7) is too simplistic for the purpose of this study. To consider the notion that volatility at opposite times of the day is attributable to changes in the flow of information, it is of paramount importance to examine the role of private information. As discussed in the previous chapter, private information drives price volatility through the actions of informed traders. The key assumption made in this hypothesis lies in the distinction between public information and private information. That is, that no one can trade on the information before release and once known, it affects stock prices at the same time. This implies that traders cannot utilise additional private information until trading commences. Consequently, this leads to the expectation that volatility will be higher at the start of trading given the accumulation of private information during non-trading hours.[46]

4.2.2 Theoretical Models

The market models introduced in Chapter One provides useful intuition into the behavioural patterns of volatility at the beginning and end of trading. The recent work of Kyle (1985), Admati & Pfiederer (1988) and Foster & Viswanathan (1994) has provided a structural relationship between information, trading volume and volatility. Despite the diverse nature of these

[46] The key assumption made in reaching this conclusion is that the flow of public information is constant. This follows from the notion that public information is a by-product of business activities as opposed to the process of trading, hence it is relegated as of secondary importance.

models, their analysis provides useful intuition in this study by describing the dynamics that govern the information processing of the market.

According to Kyle, differences in volatility patterns at opposite periods of the day reflects the problem faced by informed traders of how intensively they should trade on the basis of private information. How intensively traders trade is in turn determined by their expectations on market depth. This is of paramount importance in this model because market depth provides information on the capacity of the market to absorb trades of market participants without having a large effect on price. Another key factor within this framework is market resiliency. Kyle's model concludes that the activities of informed traders will ultimately explain price volatility at the close of trading since their trades is positively correlated from interval to interval. However, this relies on the assumption of a continuous equilibrium where the market constantly reveals and incorporates information into prices.

Admati & Pfleiderer (1988) makes the assertion that the market is most volatile at the beginning and end of trading. This, they attribute to the concentration of trades at both periods. As discussed in Chapter One, the key feature of their model is the notion that both informed and discretionary traders prefer to cluster their trades in periods when their trading has little impact on prices. That is, when the market is thick and expected transaction costs are minimal. In such a scenario, they envisage a market where the trading activity of discretionary traders encourages informed trading. As a consequence, the high variances at the open and close of trading reflect the increased concentration of trading in response to trader expectations of even lower transaction costs.

Foster & Viswanathan (1994) envisages a U-shaped pattern of volatility by allowing informed traders to learn from each other's information by observing the order flow. Within this framework, the dissemination of common information causes high trading period variances at the start of trading. As common information becomes disseminated into prices, the informed trader will trade more intensively on additional private information not possessed by lesser traders, thus increasing volatility at the close. It therefore follows that the difference in volatility patterns at the beginning and end of trading is a reflection of the activities of informed traders and the degree to which some traders are better informed than others.

4.3 METHODOLOGY

Owing to the nature of the subject area, this study proposes two methodologies. The first methodology considered is the Exponential-GARCH (EGARCH) approach of Nelson (1990). This approach allows one to model the time varying nature of volatility at the beginning and end of trading. As discussed in Chapter Two, the usefulness of the EGARCH relates to its ability to extract more information from the data by capturing the asymmetric component in index returns.

Using the conditional variance series from the EGARCH estimates, the investigation employs the Vector Autoregressive (VAR) model of Sims (1980) as the second methodology proposed in this study. The VAR approach widens the scope of the analysis by modelling intra-market dependencies in the conditional variance and is ideal for investigating the Impulse Response Function. With the use of daily variances, one can simulate the way the conditional variance responds to a random shock of one day, two days and up to ten weeks ahead. The usefulness of impulse response analysis lies in its ability to model timing and duration in terms of how the market responds to a random shock by day of the week. Monte Carlo simulation is used to assess the significance of the results.

4.3.1 EGARCH Methodology

A review of key papers in Chapter Two revealed some stylised facts relating to the existence of fat tails and the violation of the i.i.d assumptions. Subsequently, this is a useful starting point when considering the time varying nature of volatility at opposite periods of the trading day. A useful strategy to adopt is to consider daily returns y_t as the product of the following:

$$y_t = \sigma_t \varepsilon_t \tag{4.1}$$

where ε_t is i.i.d with zero mean and a variance of one and σ_t is the deterministic part of y_t that represents the random variable assumed to be independent of ε_t. Assuming that σ_t^2 is i.i.d, equation (4.1) becomes:

$$E\left(y_t^k\right) = E\left(\sigma_t^k\right)E\left(\varepsilon_t^k\right) \tag{4.2}$$

in which if the error term ε_t is n.i.d then the model of equation (4.2) will exhibit excess kurtosis:

$$E\left(y_t^4\right) = 3E\left(\sigma_t^4\right) \geq 3\left[E\left(\sigma_t^2\right)\right]^2 = 3\sigma^4 \tag{4.3}$$

The appealing feature of these models relates to its ability to interpret the random variable σ_t as representing the flow of information arriving at any point in time. Consistent with the Ross (1989) Martingale condition, this implies that volatility reflects the rate of flow of "news" that arrives in the market. However, this is an over-simplistic assertion to hypothesise given that these models cannot discriminate between positive and negative information. Hence, the usefulness of the EGARCH model for this type of analysis.

The EGARCH specification restricts the conditional volatility of a time series to be dependent upon the logarithm of the lagged conditional variance α_1, the magnitude α_2 and sign θ_1 of the lagged errors. The EGARCH representation for daily index returns is expressed as in equation (2.12):

$$\begin{gathered}\Delta SP_t = \eta_t + \varepsilon_t \\ \varepsilon_t \left|\left(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots\right) \sim N\left(0, h_t\right),\right. \\ h_t = exp\left\{\alpha_0 + \sum_{i=1}^{q} \alpha_1 ln\left(h_{t-1}\right) + \alpha_2 \sum_{i=1}^{p} \Theta_{t-1}\right\}\end{gathered} \tag{4.4}$$

where ΔSP_t is the change in spot prices at time t, η_t is the mean conditional on past information and Θ_{t-1} is the innovation term as defined in equation (2.13).

By employing the EGARCH in this capacity, the objective is to observe the size of the asymmetric component in the data. As a result, the EGARCH can extract information on whether the market is more sensitive to negative news depending on the time of day. Given that this study also considers intra-market dependencies in the conditional variance and the impact of random shocks and market timing, the next stage introduces the Vector Autoregressive (VAR) methodology in detail.

4.3.2 Vector Autoregressive (VAR) Analysis

To consider the dynamics of intra-market dependencies, it is necessary to set up a system of simultaneous equations where there are at least as many equations as dependent variables. The Vector Autoregressive Model is an unconstrained reduced form of a dynamic simultaneous equation model that expresses a vector of endogenous variables as linear functions of their own and each other's lagged values. First introduced by Sims (1980), the VAR is a generalisation of the univariate AR representation. To model an N variable system using a vector autoregressive model is expressed as

$$Y_t = \sum_{s=1}^{L} \Phi_s Y_{t-n} + u_t \qquad E(u_t, u'_t) = \sum \tag{4.5}$$

which in expandable form is equivalent to

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2}, \ldots\ldots\ldots\ldots, + \Phi_n Y_{t-n} + u_t \tag{4.6}$$

where Y_t is $(N \times 1)$ column vector of conditional volatility for each day of the week. The $\Phi_1, \ldots, \Phi_n$ are $(N \times N)$ parameter matrices and u_t represents a vector i.i.d process in which $\sum$ is a $(N \times N)$ matrix that shows the variance and contemporaneous co-variances for individual elements of u_t. The disturbance term is vector valued, which is assumed to be independent over time, but may be contemporaneously correlated at the same point in time. Take the j*th* day of the week as the dependent variable and the i*th* day of the week as the independent variable. The ij*th* element of Φ_n is a measurement of the impact that a change in the conditional variance on the i*th* day of the week would have on the conditional volatility on the j*th* day of the week in n periods. Therefore, a negative (positive) significant coefficient implies that the variance on the j*th* day of the week is expected to decrease (increase) following an increase in volatility on the i*th* day of the week.

The model of equation (4.6) is an unrestricted VAR that allows all the variables in the N system to interact in a linear fashion with their own and other past values in the system. Moreover, in using historical values to forecast the quantitative effect that each variable has on its own and other variables, the specification of the VAR can be seen as a generalisation of a dynamic system. The N system of equations in (4.6) is estimated by ordinary least squares (OLS) given that coefficient estimates are efficient and consistent if each equation has the same number of independent variables.[47]

[47] See Zellner (1962).

Assuming that the process is stationary, the VAR model of equation (4.6) can be expressed in terms of a moving average representation:

$$Y_t = E(Y) + \sum_{n=0}^{\infty} A_n u_{t-n} \tag{4.7}$$

where

Y = the M-variate stochastic process;

$E(Y)$ = the deterministic part of Y_t;

u_t = the innovation process for Y.

More elaborately, $E(Y)$ is a $(N \times 1)$ vector representing the conditional volatility of the i*th* day of the week as a linear projection of all past conditional volatilities in the system. Regarded as the innovation process, u_{t-n} is a $(N \times 1)$ vector that represents unexpected changes in volatility at time *t-n*. Of interest here is the role that A_n plays in understanding how the system responds to a random shock in the conditional variance on the i*th* day of the week. Defined as $(N \times N)$ symmetric matrix, A_n can be expressed as:

$$A_n = \frac{\partial Y_{t+n}}{\partial u_t} \tag{4.8}$$

The symmetric matrix of equation (4.8) measures the sensitivity of the market on the i*th* day of the week to a one unit shock in the conditional volatility on the j*th* day of the week, holding other volatilities in the system constant.

The method employed in simulating the dynamics that govern intra-market dependencies is the Monte Carlo Simulation. Simulating requires setting

$u_{j,t} = \mathbf{1}$ along with other u_t's as well as $Y_{t-1} = Y_{t-2} = \ldots = Y_{t-n} = \mathbf{0}$. This is repeated for $j = 1,\ldots,s$ to obtain realisations of the A matrix for n periods for the ij*th* element of A. It is this process that defines the impulse response function.

4.3.3 Impulse Response Analysis

The impulse response function is a valuable tool in describing the reaction of the market in the future to a shock on today's conditional variance, holding other current and past volatilities constant. Consider a simple bivariate VAR model consisting of the volatility of index returns on the i*th* and j*th* day of the week, denoted as $Y_{i,t}$ and $X_{j,t}$ respectively:

$$\begin{aligned} Y_{i,t} &= \eta_1 + \Phi_1 Y_{i,t-1} + \Phi_2 X_{j,t-1} + u_{i,t} \\ X_{j,t} &= \eta_2 + \Phi_1 X_{j,t-1} + \Phi_2 Y_{i,t-1} + u_{j,t} \end{aligned} \tag{4.9}$$

The model of equation (4.9) is a VAR(1) specification given that the variables in the system have a lag order of one. A change in the innovation $u_{i,t}$ will immediately change the value of i*th* day of the week volatility $Y_{i,t}$. It will also change all future values of Y and X since lagged Y appears in both equations. Assuming that the innovations $u_{i,t}$ and $u_{j,t}$ are uncorrelated, the interpretation of the impulse response is straightforward. $u_{i,t}$ is the innovation for Y and $u_{j,t}$ is the innovation for X. The impulse response functions for $u_{j,t}$ measures the impact of a one standard deviation shock on current and future volatility on the i*th* and j*th* day of the week (Y and X). The innovations $u_{i,t}$ and $u_{j,t}$ are however, usually correlated, so that they have a common component that cannot be associated with a specific variable. A common, but arbitrary method of dealing with this issue is to attribute all the impact of any common component to the variable that comes first in the VAR system. In this case, the common component of $u_{i,t}$ and $u_{j,t}$ is $u_{i,t}$ given that the innovation $u_{i,t}$ precedes $u_{j,t}$. Hence, $u_{i,t}$ becomes the Y and X innovation, which is transformed to remove the common component. More technically, the errors must be orthogonalised so that the innovations $u_{i,t}$ and $u_{j,t}$ become a diagonal matrix defined as

$$E\left(u_{1,t}, u_{2,t}^{T}\right) = \Omega \tag{4.10}$$

meaning that the innovation processes contained in the error term $u_{ij,t}$ should be orthogonal to each other. For the purpose of this study, the errors are orthogonalised using the Choleski factorisation. This is a popular method of transforming the covariance matrix of the resulting innovations in the VAR residuals into a vector of orthogonal innovations defined as e_t:

$$E\left(e_{i,t} e_{j,t}\right) = 0 \qquad \text{where } i \neq j \tag{4.11}$$

To transform the error terms, a $(N \times N)$ lower matrix defined as V is chosen, and the orthogonalised innovations e_t are obtained to satisfy the following:

$$e = uV^{-1} \tag{4.12}$$

where the innovation u_t has an identity covariance matrix such that

$$Eee^{T} = \Omega \tag{4.13}$$

and

$$VV^T = \Omega \tag{4.14}$$

Upon making the transformation of the orthogonalised innovation and replacing u_t with $e_t V$, equation (4.7) can be rewritten as follows:

$$Y_t = \sum_{n=0}^{\infty} A_n V e_{t-n} \tag{4.15}$$

By defining $B_n = A_n V$, equation (4.15) becomes

$$Y_t = \sum_{n=0}^{\infty} B_n e_{t-n} \tag{4.16}$$

which omits the mean term $E(Y)$ of equation (4.7) given that it is of no importance to the simulation process. The i,j*th* component of B_n represents the impulse response of the market on the i*th* day of the week to a shock of one standard error on the j*th* day of the week. Hence, the elements of B_n are said to be *impact multipliers*. Assuming that the vector Y of the conditional volatility for each day of the week is stationary, then impulse responses should tend towards zero as *n* becomes large.

The advantages of using orthogonalised innovations are two fold. Firstly, given that they are uncorrelated, it is very simple to compute the variances or linear combinations of them. Furthermore, it is misleading to examine the impact of a random shock in isolation because historically, the variance is correlated with several other volatilities. Orthogonalisation takes into consideration any co-movement amongst the variables. This arises in the use of the Choleski factorisation given that it imposes a Wold causal chain in the

VAR system. This implies that a random shock will have a contemporaneous effect on all other variables and a shock occurring on the second variable will have the same effect on all variables except for the first one and so on.

4.4 DATA AND DESCRIPTIVE STATISTICS

The dataset in this study comprises of daily opening and closing index values on the FTSE-100 Index from January 1, 1988 to December 31, 1997. Once again, the dataset was downloaded from Datastream International. Open-to-open and close-to-close index returns are computed as the ratio of the natural logarithms of today's opening and closing prices relative to the opening and closing prices of the previous day of trading:

$$R_{O,t} = log\left(P_{O,t}/P_{O,t-1}\right) \tag{4.17a}$$

$$R_{C,t} = log\left(P_{C,t}/P_{C,t-1}\right) \tag{4.17b}$$

where P_O and P_C are opening and closing prices used to compute open-to-open $R_{O,t}$ and close-to-close returns $R_{C,t}$ respectively. The problem with using opening index values is that datastream does not report opening prices that coincide with national holidays. To overcome this problem, the closing price of the last trading day is used to generate zero returns during national holidays.

Table 4.1 provides the descriptive statistics for both return series. This includes the mean, variance, minimum and maximum values along with measures of skewness and kurtosis. The statistics also provide Ljung-Box Q tests for higher

Table 4.1

Descriptive Statistics on Open-to-Open
and Close-to-Close Returns

Open-to-Open Returns	
Sample Mean	0.042*
Variance	0.930
Maximum	10.397
Minimum	-7.234
Skewness	0.490
(p-value)	(0.00)
Kurtosis	8.907
(p-value)	(0.00)
L-B $Q(12)$	74.815
(p-value)	(0.00)

Close-to-Close Returns	
Sample Mean	0.042*
Variance	0.640
Maximum	5.440
Minimum	-4.140
Skewness	0.062
(p-value)	(0.199)
Kurtosis	2.146
(p-value)	(0.00)
L-B $Q(12)$	26.759
(p-value)	(0.01)

*Reject the null hypothesis that mean = 0 at the 0.05 level
L-B = Ljung-Box Q-statistic are chi-square distributed
$Q(12)$ test statistic compared with critical value of 21.0261

order serial correlation up to lag twelve. P-values are in parentheses. Consistent with the findings of Amihud & Mendelson (1987), index returns are more volatile at the start of trading. According to the measures of dispersion, the extreme values are greatest for index returns at the open. The range from a low of -7.234 to a high of 10.397 for open-to-open returns compares with the range -4.140 to 5.440 for close-to-close returns.

In finance theory, one of the most applied hypotheses tested for is the validity of the i.i.d assumptions and normality in the distribution of returns. As reviewed in Chapter Two, previous studies provide evidence that the distribution of returns exhibits fat tails and rejects the i.i.d assumptions. This conclusion is borne out by the descriptive statistics in table 4.1. The Ljung-Box *Q*-statistics reports evidence of serial dependencies in both return series. However, significant autocorrelations are more profound for open-to-open returns. In addition, the distribution of open-to-open returns exhibits a greater degree of skewness and leptokurtosis. This implies that trading periods in opposite times of any given day coincides with changes in the probability distribution of index returns. Figures 4.1(a) and 4.1(b) confirm this finding using the histogram of residual returns. The figures clearly show that the distribution of both return series fails to satisfy the identically and independence conditions. Given the failure of the i.i.d assumptions and the non-normality in the distribution of index returns, this motivates the use of the conditional heteroscedastic model of the EGARCH in the next section.

Figure 4.1(a)

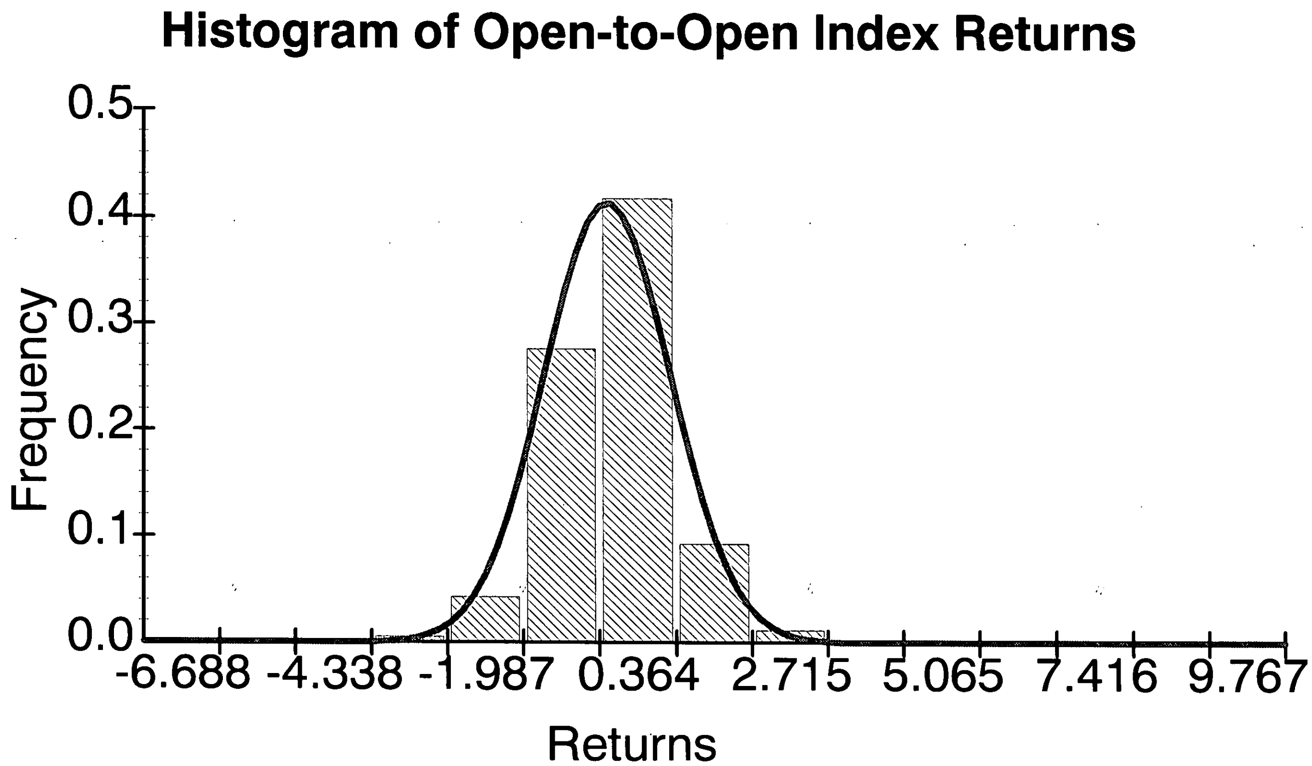
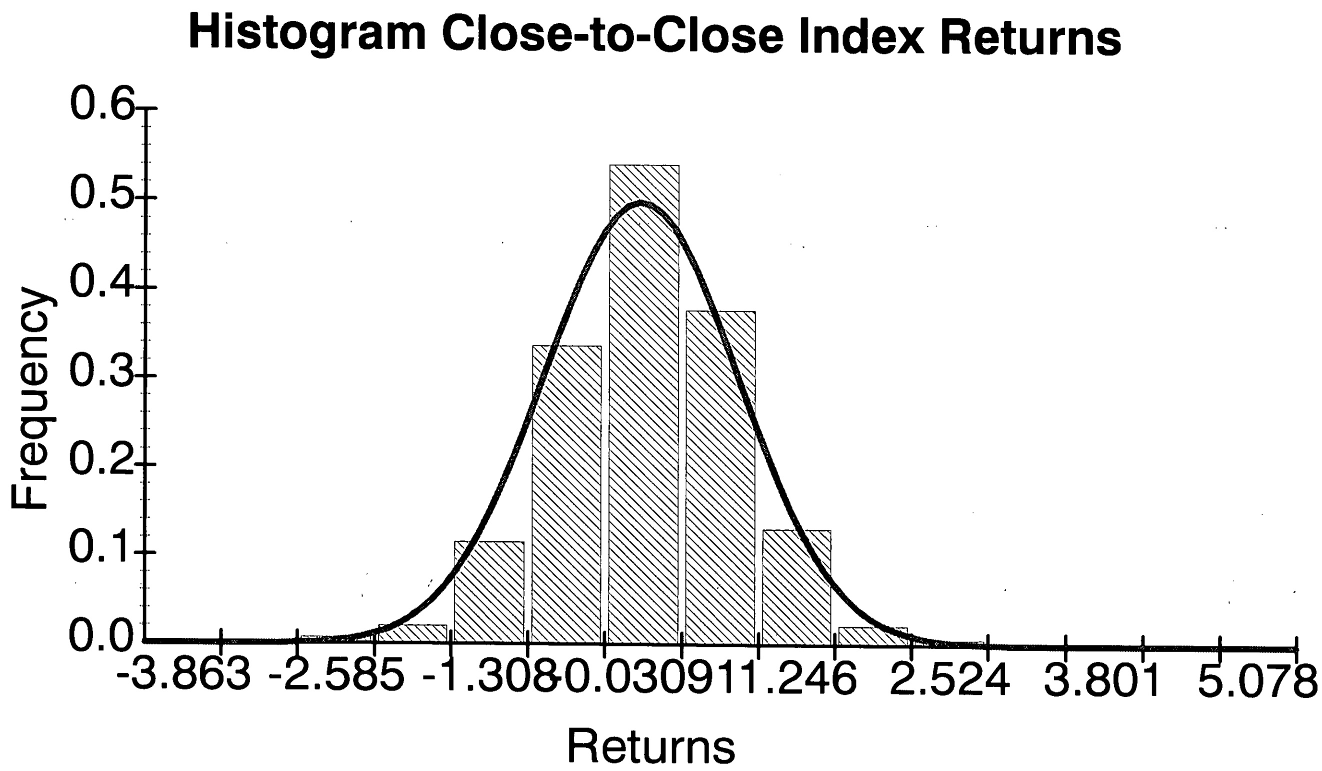

Histogram of Open-to-Open Index Returns
Frequency
0.5
0.4
0.3
0.2
0.1
0.0
-6.688 -4.338 -1.987 0.364 2.715 5.065 7.416 9.767
Returns

Figure 4.1(b)



Histogram Close-to-Close Index Returns
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Frequency
-3.863
-2.585
-1.308
-0.03091
1.246
2.524
3.801
5.078
Returns

4.5 EGARCH MODELLING

To model the time varying nature of volatility at the beginning and end of trading, the study utilises the following EGARCH specification:

$$R_t = \eta + \varepsilon_t \tag{4.18a}$$

$$h_t = exp\left\{a_0 + a_1 \log\left(h_{t-1}\right) + a_2 \xi_{t-1}\right\} \tag{4.18b}$$

where ξ_{t-1} is the information component and R_t represents daily open-to-open and close-to-close index returns at time t. Should residual returns continue to exhibit serial dependencies,[48] an AR(1) term will be included in the conditional mean so that equation (4.18a) becomes:

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t \tag{4.19}$$

where ϕ is the AR coefficient. To maximise the log likelihood function of equation (2.22), the study will use the Berndt, Hall, Hall & Hausman (1974) (BHHH) algorithm.

Table 4.2 provides summary statistics for the conditional variance h_t of open-to-open and close-to-close index returns respectively. According to the descriptive statistics, the highest variation over time appears to occur at the beginning of trading. This is borne out by the variance range from a low of 0.270 to a high of 6.101 for open-to-open returns against 0.247 to 1.994 for close-to-close returns.

[48] Section 4.5.1 discusses this issue in greater depth.

Table 4.2

Descriptive Statistics on the Conditional Variance (h_t):
Open-to-Open and Close-to-Close Returns

Open-to-Open Returns	
Sample Mean	0.896*
Variance	0.240
Maximum	6.101
Minimum	0.270
Skewness	3.672
(p-value)	(0.00)
Kurtosis	24.952
(p-value)	(0.00)

Close-to-Close Returns	
Sample Mean	0.634*
Variance	0.064
Maximum	1.994
Minimum	0.247
Skewness	1.599
(p-value)	(0.00)
Kurtosis	3.806
(p-value)	(0.00)

*Reject the null hypothesis that mean = 0 at the 0.05 level.

Table 4.3 shows EGARCH estimations on open-to-open and close-to-close returns along with *t*-statistics in parentheses. The results raise a number of important points related to the nature of volatility at the beginning and end of trading. First and foremost, the EGARCH coefficient estimates a_1, a_2 and θ_1 are statistically different from zero for both return series, thus indicating the presence of EGARCH effects. This suggests that the market discriminates positive and negative shocks irrespective of the time of day. However, according to the results, EGARCH parameters experience statistically significant changes from the beginning to the end of trading. For instance, the coefficient values for a_0 and a_2 is higher for open-to-open returns. This indicates that in an ARCH representation, index returns are more volatile at the beginning of trading. A lower a_1 coefficient value for returns at the open indicates that the market relies less on old news as traders respond faster to the accumulation of information outside trading hours. Hence, the higher a_2 coefficient value. Although the market is more sensitive to the arrival of bad news at the close, (as indicated by θ_1) the high volatility at the start of trading appears to be attributable to changes in the flow of information and the reaction of the market to innovations. Figure 4.2 provides confirmation that index returns are more volatile at the start of trading. This plots the conditional variance of index returns at the open and the close of trading based on EGARCH estimates generated by equation (4.18). The upper line represents the conditional variance at the start of trading and the lower line plots the variance at the close.

Table 4.3

EGARCH (1,1) Estimations of Open-to-Open and Close-to-Close Returns

(A) $$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

(B) $$h_t = exp\{a_0 + a_1 \log(h_{t-1}) + a_2 \xi_{t-1}\}$$

EGARCH Coefficients	Open-to-Open	Close-to-Close
η	0.036	0.038
	(2.14)	(2.61)
ϕ_1	-0.111	-
	(-6.07)	-
a_0	-0.151	-0.139
	(-10.02)	(-6.82)
a_1	0.978	0.980
	(252.44)	(184.26)
a_2	0.143	0.125
	(10.31)	(6.93)
θ_1	-0.183	-0.239
	(-3.68)	(-3.50)
Diagnostic Tests of the EGARCH Residuals		
Ljung-Box $Q(12)$	9.271	18.191
(p-value)	(0.68)	(0.11)
ARCH $Q^2(12)$	7.644	11.863
(p-value)	(0.81)	(0.46)

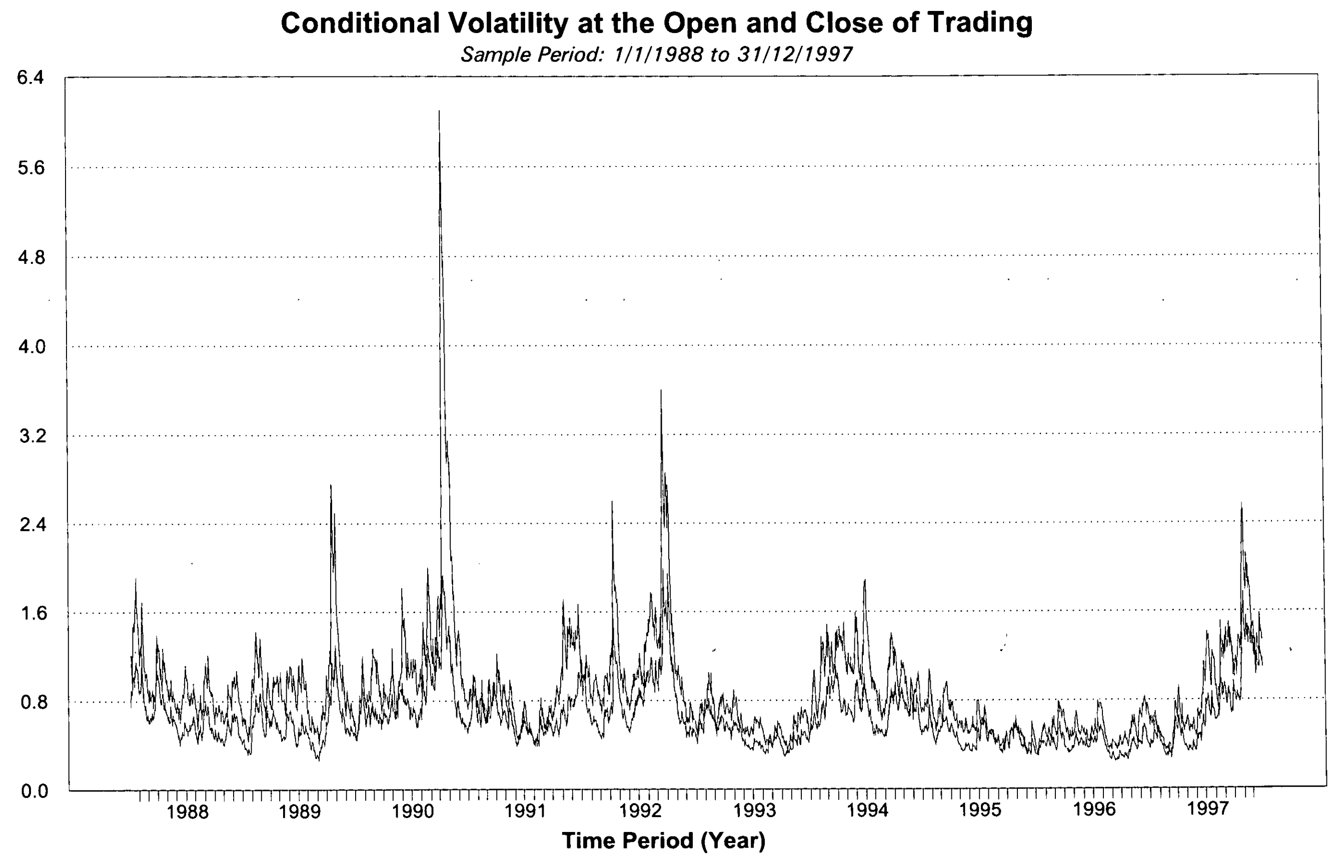
Significance tests at the 0.01 and 0.05 level

Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom

The analysis only reports ϕ_1 coefficients if the EGARCH fails to capture serial correlation in the data based on innovations generated by equation (4.18a).

t-statistics in parentheses for the EGARCH coefficients.

Figure 4.2


Conditional Volatility at the Open and Close of Trading
Sample Period: 1/1/1988 to 31/12/1997
6.4
5.6
4.8
4.0
3.2
2.4
1.6
0.8
0.0
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
Time Period (Year)

4.5.1 *Diagnostic Tests of the EGARCH*

Table 4.3 also presents diagnostic tests on the statistical adequacy of the EGARCH, based on the Ljung-Box (1978) *Q*-statistic for serial correlation and the ARCH test of Engle (1982) for heteroscedasticity. These tests establish whether the EGARCH is representative of the data in capturing the presence of serial dependencies and heteroscedasticity. The null hypothesis tested is of no autocorrelation and the existence of homoskedascity in the EGARCH residuals. The residual returns ε_t of the mean equation (4.18a) are standardised using the conditional variances h_t generated by the EGARCH of (4.18b):

$$z_t = \frac{\varepsilon_t}{\sqrt{h_{t-1}}} \tag{4.20}$$

where z_t is the standardised residual return. Based on the adjusted residuals z_t, the Ljung-Box *Q*-statistic is computed as a test for autocorrelation:

$$Q = T'(T'+2)\sum_{i \le k} \frac{1}{T'-i}\hat{\rho}_i^2 \tag{4.21}$$

where T' is the number of observations after being differenced d times $T' = T - d$ and k is the number of lags. Acceptance of the null hypothesis of no serial dependencies implies that the residuals follow a white noise. To determine whether the EGARCH captures heteroscedasticity in the data requires squaring the standardised residual returns z_t to perform the ARCH test. As mentioned in Chapter Two, the ARCH is a useful tool of measuring the tendency for large residual returns to cluster together. As such, the

ARCH(q) procedure as the second diagnostic test of the EGARCH is expressed as:

$$z_t^2 = \alpha_0 + \alpha_i \sum_{i=12}^{q} z_{t-12}^2 \tag{4.22}$$

which essentially regresses the squared standardised residual returns against its lags. For the purpose of the study, squared residuals up to lag twelve is used where the number of lags chosen is arbitrary. Both tests have a chi-square distribution χ^2. Using chi-squared statistics at the 0.01 and 0.05 level of order twelve, the critical values of 26.2170 and 21.0261 are compared with the Q-statistics of table 4.3. According to the test results, the models are successful in capturing serial dependencies and heteroscedasticity in both return series.

4.5.2 EGARCH Analysis by Day of the Week

To investigate further the time varying nature of volatility at the beginning and end of trading, the study adopts an alternative analysis by re-estimating EGARCH models on daily index returns by day of the week. To perform the analysis, requires sorting open-to-open and close-to-close index returns according to day of the week. This generates ten variables, each with 522 observations in both sets of series for Monday to Friday.[49]

Table 4.4 provides EGARCH estimates for open-to-open and close-to-close returns by day of the week along with diagnostic test statistics in table 4.5. The

[49] The study considered using weekly open-to-open and close-to-close returns for each day of the week. However, the estimation of EGARCH models fails to capture asymmetries in returns and hence, important information in the data.

results reports three cases in which EGARCH parameters a_1, a_2 and θ_1 are statistically different from zero, thus indicating the presence of EGARCH effects. This compares with four cases reported for close-to-close returns. In addition, the findings provide useful inferences on the origins of the non-trading weekend effect reported by French (1980). The presence of GARCH and EGARCH effects for Monday open-to-open and close-to-close returns indicate that the non-trading weekend effect originates at the close. This is consistent with the empirical evidence cited by Peterson (1990) that the market tends to release negative information after the close of trading.

Finally, by focusing on the parameters of the EGARCH model, the coefficients a_0, a_1, a_2, θ_1 experience statistically significant changes on a daily basis. Contrary to earlier findings, index returns are generally more volatile at the end of trading. According to Kyle's (1985) analysis, the size of the news coefficient a_2 along with higher volatility estimates is indicative of the high information content of prices as informed traders dictate the behaviour of the market. Alternatively, according to Foster & Viswanathan (1994), these findings are a reflection of two interrelated forces. Firstly, the degree of informativeness of well informed traders in relation other traders and second; the dissemination of additional private information by better informed traders. Of crucial importance to the second point is the notion that any events taking place does not alter their expectations formed on the basis of additional private information.

Table 4.4

EGARCH (1,1) Estimations of Open-to-Open and Close-to-Close Index Returns by Day of the Week

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = exp\left\{a_0 + a_1 \, log\left(h_{t-1}\right) + a_2 \xi_{t-1}\right\}$$

Coefficients	Mon	Tues	Wed	Thur	Fri
			Open-to-Open Returns		
η	-0.046	0.116*	0.039	0.095*	0.016
	(-0.86)	(2.88)	(1.00)	(2.47)	(0.42)
ϕ_1	-	-	-	-	-
	-	-	-	-	-
a_0	-0.064*	-0.174*	-0.402*	-0.227*	-0.261*
	(-2.12)	(-3.77)	(-5.29)	(-5.70)	(-3.29)
a_1	0.943*	0.944*	0.814*	0.931*	0.880*
	(66.28)	(31.65)	(15.47)	(32.57)	(17.49)
a_2	0.078*	0.158*	0.338*	0.193*	0.232*
	(2.32)	(3.97)	(5.03)	(5.85)	(3.30)
θ_1	0.803	-0.653*	-0.295*	-0.609*	-0.084
	(1.62)	(-3.74)	(-2.73)	(-4.56)	(-0.56)
			Close-to-Close Returns		
η	-0.054	0.097*	0.080*	0.034	0.021
	(-1.52)	(3.07)	(2.53)	(1.03)	(0.54)
ϕ_1	-	-	-	-	-
	-	-	-	-	-
a_0	-0.293*	-0.448*	-0.237*	-0.271*	-0.080
	(-3.52)	(-3.34)	(-2.02)	(-4.59)	(-1.25)
a_1	0.937*	0.797*	0.918*	0.945*	0.914*
	(26.94)	(8.29)	(13.70)	(31.49)	(21.64)
a_2	0.264*	0.309*	0.178*	0.236*	0.049
	(3.69)	(3.61)	(2.01)	(5.05)	(0.89)
θ_1	-0.480*	-0.520*	-0.444*	-0.353*	1.654
	(-4.78)	(-4.28)	(2.35)	(-4.22)	(0.69)

* Denotes significance at the 0.05 level
t-statistics in parentheses for the EGARCH coefficients.

Table 4.5

Diagnostic Test Statistics of the EGARCH

	Open-to-Open Returns	
	Ljung-Box $Q(12)$	ARCH $Q^2(12)$
Monday	15.049	2.424
	(0.24)	(0.99)
Tuesday	18.592	9.170
	(0.10)	(0.69)
Wednesday	13.797	5.605
	(0.31)	(0.93)
Thursday	16.481	7.400
	(0.17)	(0.83)
Friday	12.139	4.201
	(0.43)	(0.98)

	Close-to-Close Returns	
	Ljung-Box $Q(12)$	ARCH $Q^2(12)$
Monday	15.426	11.021
	(0.22)	(0.53)
Tuesday	13.835	17.001
	(0.31)	(0.15)
Wednesday	12.105	4.510
	(0.44)	(0.97)
Thursday	8.325	8.446
	(0.76)	(0.75)
Friday	23.237	6.270
	(0.03)	(0.90)

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed with 12 degrees of freedom
P-values are in parentheses

4.6 VAR ANALYSIS

4.6.1 Estimating the VAR System by Day of the Week

Using the conditional variance generated by the EGARCH in table 4.4, the study utilises VAR analysis by day of the week. By using the VAR in this capacity, one is able to model the transmission of volatility from one day to the next. Given the restrictive use of the VAR in finance, it is not possible to use the results in this study for comparison purposes.

Estimating the VAR requires setting up a system of simultaneous equations that contains as many equations as dependent variables. Given that this analysis investigates the way the market process information at the beginning and end of trading, the following system of equations are estimated:

$$\begin{aligned}
h_{M,t} &= \alpha_1 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s} \\
h_{T,t} &= \alpha_2 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s} \\
h_{W,t} &= \alpha_3 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s} \\
h_{TH,t} &= \alpha_4 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s} \\
h_{F,t} &= \alpha_5 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s}
\end{aligned} \tag{4.23}$$

where $h_{M,t-s},.....h_{F,t-s}$ represent the conditional variance from Monday to Friday at time t-s lags.[50] Table 4.6 presents the results from the five variable VAR system of equation (4.23). This provides VAR estimates for Monday to

[50] Before performing the VAR analysis, the number of lags s introduced into the system was predetermined using the Akaike Information Criterion and the Schwertz Bayesian Criterion. In applying both tests on the conditional variance of open-to-open and close-to-close returns, the results find lag one to be the appropriate lag order in the VAR system.

Table 4.6

VAR Estimates for the Conditional Variance of Open-to-Open and Close-to-Close Returns

$$h_{M,t} = \alpha_1 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s}$$
$$h_{T,t} = \alpha_2 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s}$$
$$h_{W,t} = \alpha_3 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s}$$
$$h_{TH,t} = \alpha_4 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s}$$
$$h_{F,t} = \alpha_5 + b_1 h_{M,t-s} + b_2 h_{T,t-s} + b_3 h_{W,t-s} + b_4 h_{TH,t-s} + b_5 h_{F,t-s}$$

	α	b_1	b_2	b_3	b_4	b_5	$\overline{R}^2$
Open-to-Open Returns							
Mon	0.087*	0.918*	0.042	-0.014	0.022	-0.023	0.86
	(0.032)	(0.020)	(0.036)	(0.025)	(0.021)	(0.021)	
Tues	0.051*	0.001	0.904*	0.000	0.014	0.018	0.84
	(0.019)	(0.011)	(0.021)	(0.015)	(0.012)	(0.012)	
Wed	0.130*	0.024	0.018	0.790*	-0.010	0.006	0.63
	(0.037)	(0.022)	(0.041)	(0.029)	(0.024)	(0.024)	
Thur	0.050	0.064*	-0.057	0.049	0.846*	-0.009	0.77
	(0.034)	(0.021)	(0.039)	(0.027)	(0.023)	(0.022)	
Fri	0.020	0.046*	0.020	0.037	0.005	0.852*	0.77
	(0.035)	(0.021)	(0.039)	(0.027)	(0.023)	(0.023)	
Close-to-Close Returns							
Mon	-0.006	0.869*	0.001	0.056	0.070*	0.028	0.85
	(0.028)	(0.022)	(0.026)	(0.040)	(0.023)	(0.030)	
Tues	0.097*	0.030	0.713*	-0.013	0.037	0.037	0.58
	(0.032)	(0.025)	(0.030)	(0.045)	(0.026)	(0.034)	
Wed	0.026	-0.000	0.001	0.900*	0.023*	0.020	0.85
	(0.013)	(0.011)	(0.013)	(0.019)	(0.011)	(0.014)	
Thur	-0.005	0.060*	0.008	0.103*	0.841*	0.007	0.80
	(0.031)	(0.024)	(0.029)	(0.044)	(0.025)	(0.033)	
Fri	0.076*	0.030	-0.000	0.052	-0.010	0.837*	0.73
	(0.023)	(0.018)	(0.022)	(0.032)	(0.019)	(0.024)	

* Significant coefficient values at the 0.05 level
Standard errors in parentheses

Friday along with standard errors in parentheses and the coefficient of determination. As expected, the coefficient of its own lagged conditional variance is high and significantly different from zero for both open-to-open and close-to-close variances. There is some evidence that volatility from other days of the previous week is relevant to current volatility using close-to-close returns. Given the use of the conditional variance, these findings lead to the conclusion that old news at opposite times of the trading day plays an important role behind the volatility of today's index returns. The adjusted coefficient of determination is quite high, thus validating the methodology employed in explaining intra-market volatility spillovers.

4.6.2 Impulse Response Analysis by Day of the Week

The five variable autoregressive system just estimated and reported in table 4.6 is difficult to interpret, especially when examining the size of the coefficients on the regression equations. Interpretation is further complicated by cross correlation feedbacks along with the fluctuation of estimated coefficients on successive lags. Hence, it is misleading to employ the common econometric practice of inferring the long run equilibrium behaviour by summarising the distributed lag relations. An alternative and more useful approach is to consider the system's response to random shocks in each of the five equations and the extent to which these shocks continue to have an impact on the system.

With the estimation of the five variable VAR system, one can now compute an impulse response analysis. Impulse response invites the prospect of analysing the reaction of the market to random shocks on a specific day using the simulated responses of the estimated VAR system. In using daily variances by day of the week, impulse response analysis can capture the impact of a random innovation on that day and on subsequent days of the week. Table 4.7 presents the impulse response of one week, five weeks and ten weeks ahead at the open and close of trading. The top half of the table is the impulse response of open-to-open variance whereas the bottom half represents the response of the variance at the close.

Of interest in the impulse responses are the variations in the velocity to which the effects of innovations are transmitted across days of the week along with duration and the rate of decay. Although the results report an increase in systematic volatility on the day of the shock, there is a marked decline in the increase of one-day volatility in subsequent days. Closer examination of the impulse response reveals that the market is more sensitive to a random shock at the start of trading for four out of the five days.

In addition, there is some evidence of an inverse relationship in the dynamic responses across days of the week. That is, an increase in the variance on the day of the innovation is followed by a reduction in volatility in the days after the shock. However, the decline in volatility levels is comparatively small. Although the market appears to be more sensitive to random shocks at the start

Table 4.7

Impulse Response to a Shock in the Conditional Variance of Open-to-Open and Close-to-Close Returns

Shock on		Impulse Response on				
	Weeks	*Mon*	*Tues*	*Wed*	*Thur*	*Fri*
Mon	1	0.171	0.041	0.004	-0.005	-0.002
	5	0.126	0.029	0.014	0.023	0.025
	10	0.086	0.022	0.014	0.031	0.034
Tues	1	0.000	0.090	0.023	0.010	0.004
	5	0.010	0.061	0.014	-0.005	0.010
	10	0.013	0.037	0.008	-0.008	0.012
Wed	1	0.000	0.000	0.194	0.034	0.013
	5	-0.005	0.003	0.074	0.037	0.023
	10	-0.005	0.005	0.022	0.021	0.016
Thur	1	0.000	0.000	0.000	0.180	-0.004
	5	0.011	0.007	-0.003	0.092	0.001
	10	0.015	0.008	-0.002	0.041	0.004
Fri	1	0.000	0.000	0.000	0.000	0.186
	5	-0.012	0.009	0.002	-0.006	0.098
	10	-0.014	0.010	0.002	-0.010	0.043
Mon	1	0.102	0.009	0.002	0.015	0.001
	5	0.063	0.011	0.003	0.024	0.008
	10	0.040	0.010	0.005	0.023	0.008
Tues	1	0.000	0.116	-0.003	0.013	-0.003
	5	0.002	0.031	-0.001	0.008	-0.002
	10	0.002	0.006	-0.000	0.004	-0.001
Wed	1	0.000	0.000	0.049	-0.005	-0.004
	5	0.008	-0.001	0.033	0.012	0.005
	10	0.015	0.002	0.021	0.018	0.008
Thur	1	0.000	0.000	0.000	0.110	-0.002
	5	0.020	0.008	0.006	0.058	-0.002
	10	0.023	0.008	0.008	0.033	0.001
Fri	1	0.000	0.000	0.000	0.000	0.083
	5	0.007	0.006	0.005	0.003	0.041
	10	0.009	0.005	0.006	0.006	0.019

of trading, it is difficult to judge from the impulse responses the rate of decay and duration of the innovation. As a consequence, the next stage of the analysis uses simulated confidence intervals on the conditional variance of open-to-open and close-to-close returns.

4.6.3 Simulated Confidence Intervals on the Conditional Variance

The problem with the impulse responses of table 4.7 is how to observe the duration and rate of decay at opposite times of the day. To overcome this problem, confidence bands around these responses are computed as a robustness test of the impulse response. Confidence bands for a statistical estimator serves the useful purpose of quantifying its uncertainty and enables correct interpretation and employment of measurement information. Large confidence intervals around the impulse response call into question the credibility of the measurement information.

Confidence bands for the impulse responses are calculated using Monte Carlo simulation, simulated 5000 times. Figure 4.3(a) and 4.3(b) display the time paths of the dynamic responses of both variance series by day of the week. By providing simulated confidence intervals on the conditional variance, the objective is to graphically show how the market reacts to a random shock by day of the week.

Figure 4.3(a)

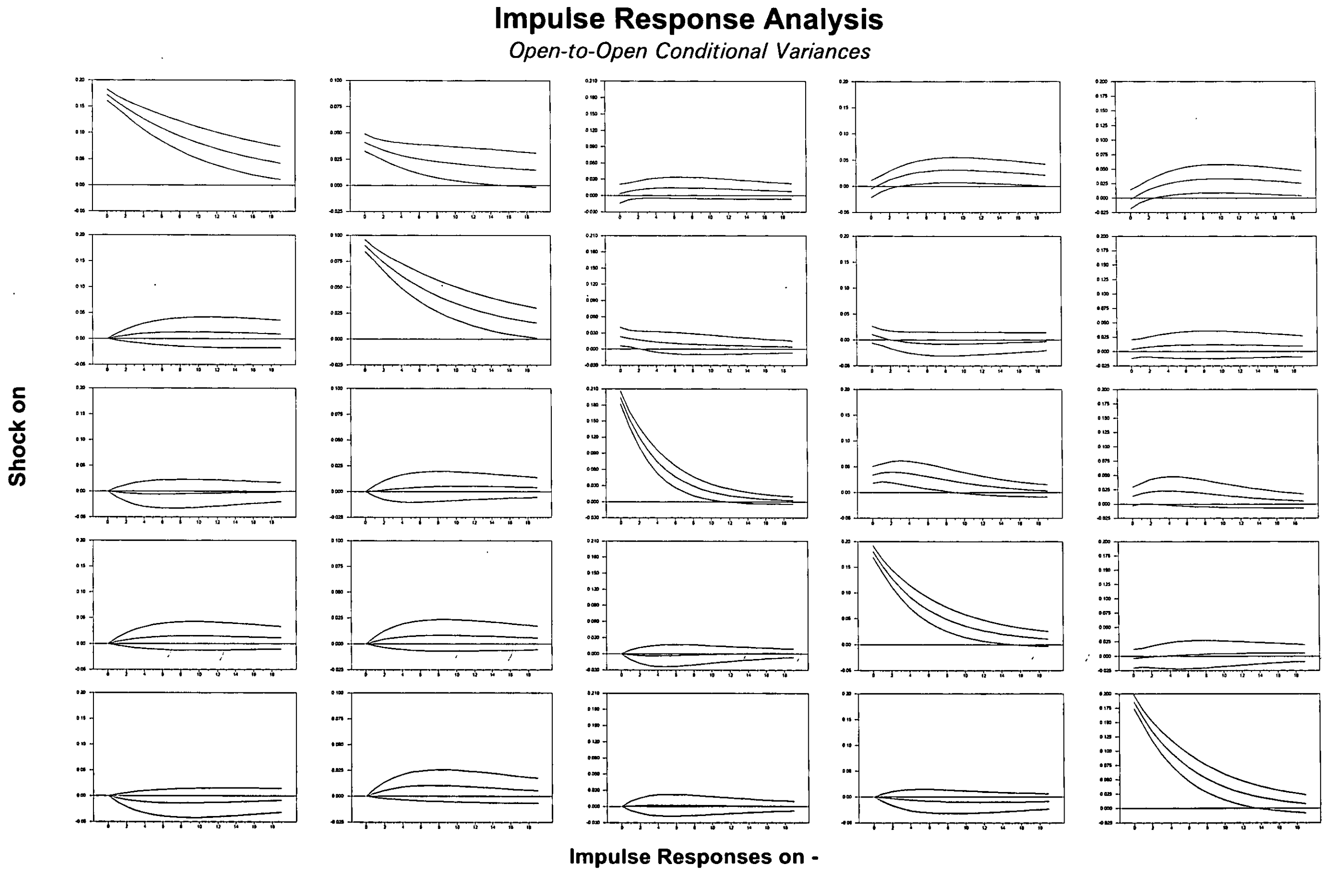
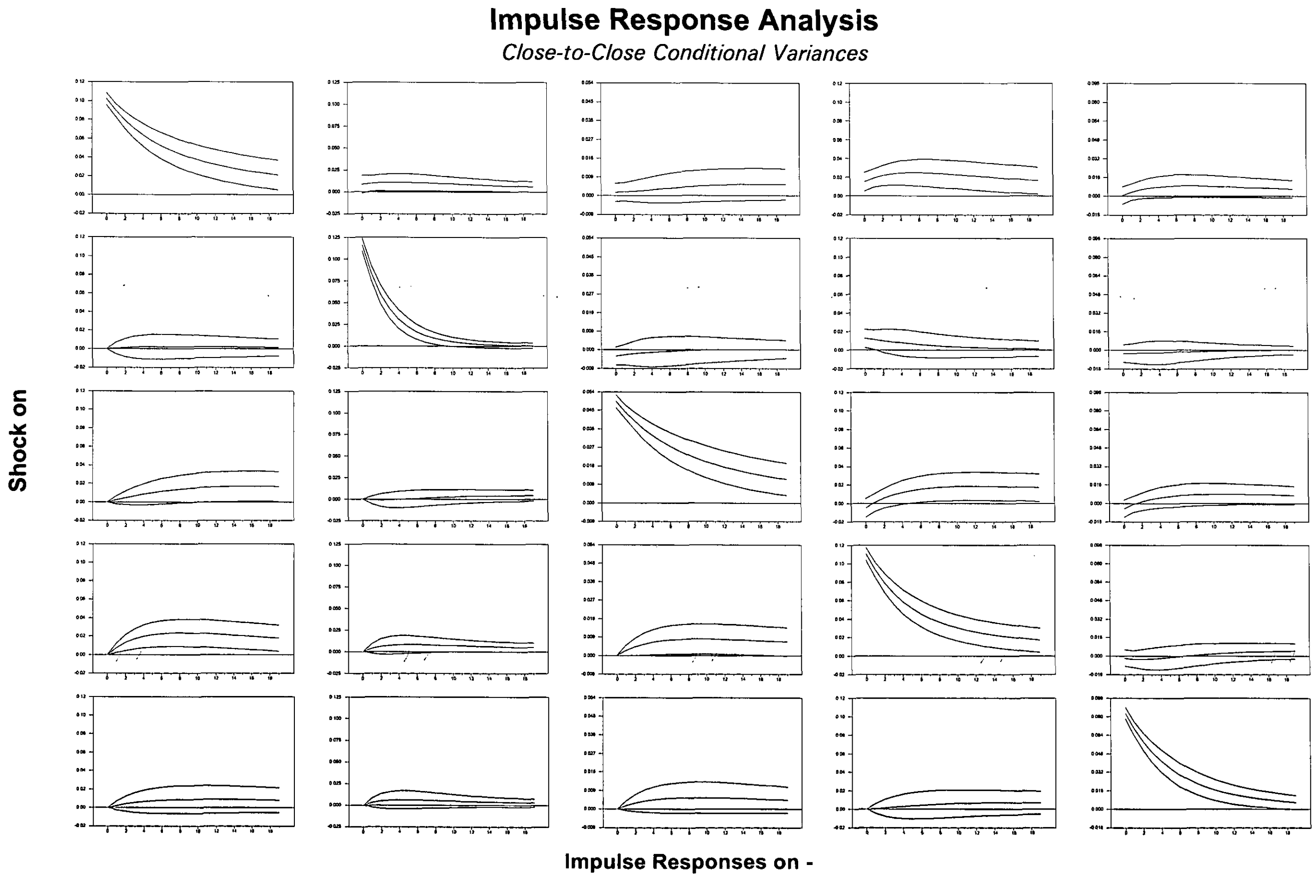

Impulse Response Analysis
Open-to-Open Conditional Variances
Shock on
Impulse Responses on -

Figure 4.3(b)


Impulse Response Analysis
Close-to-Close Conditional Variances
Shock on
Impulse Responses on -

In figures 4.3(a) and 4.3(b), there are five columns by five rows of graphs. On the vertical axis labelled "shock on" represents the day of the week in which an innovation occurred. Moving to the horizontal axis labelled "Impulse Responses on" represents the effects of the shock on days of the week following the innovation. Focusing on the graphs, the middle line is the impulse response to an innovation and the other two lines are the upper and lower confidence bands. Of interest in this type of analysis is the positioning of the confidence bands in relation to the horizontal axis. If at any time, the horizontal axis lies between the confidence bands, then the impulse response is zero. Conversely, if the horizontal axis is positioned above (below) the upper (lower) band, then the value of the impulse response equates the upper (lower) band.

There are a number of important observations made from the graphs. Firstly, index values appear to be more sensitive to random shocks at the start of trading for four out of the five days. Increases in volatility for most days are generally limited to the day of the week with which the random shock occurred for both variance series. However, closer examination of the graphs reveal more cases where a random shock originating at the start of trading leads to a statistically significant increase in the volatility in days following the shock. There is no evidence that index return variances respond negatively to random shocks.

Another interesting observation made with the graphs relates to duration and timing. More specifically, the graphs show an instantaneous increase in volatility for the Monday and Tuesday start of trading resulting from a shock on Monday. On the other hand, the impact of the Monday innovation on Thursday and Friday volatility at the open is not instantaneous, but lasts longer. The longest shock observed in this analysis is the Wednesday close even though the initial impact of the innovation is much smaller. It takes more than twenty weeks for the variance of Wednesday returns to return to its pre-shock level.

By examining the duration and rate of decay, one can observe the time it takes for the market to discount common volatility as a test of market efficiency. The faster the reaction of the market and the quicker the volatility reaches its pre-shock levels, the higher the degree of market efficiency. According to the impulse response on the day of the shock, the FTSE-100 Index appears to exhibit a greater degree of market efficiency at the start of trading.

The implication of the impulse response analysis presented is to provide evidence of a response differential depending on the time of day. According to the graphs, the market appears to discount the shock more rapidly into opening prices even though it is more sensitive to random innovations. These findings suggest that the market is more resilient at the beginning of trading and as such, contradicts Kyle's view of market resiliency that the activities of informed traders dominate the market at the close.

4.7 SUMMARY AND CONCLUSIONS

This chapter explores the dynamics that govern the behaviour of index return volatility at the beginning and end of trading. The nature of the investigation is such, that it considers the dynamics in the information processing mechanism of the market. As a consequence, this represents a significant departure from previous studies reviewed in Chapter One. This type of investigation is made possible by the events surrounding 'Big Bang' in October 1986; specifically, retaining the dealership structure within the London Stock Exchange. Other than modelling the time varying nature of volatility, the study also focuses on the impulse responses in their duration and timing.

To address these issues, the study utilises the EGARCH and Vector Autoregressive (VAR) methodologies to provide an empirical framework that allows further investigation into the dynamics of the market. As mentioned in Chapter Two, the usefulness of the EGARCH lies in its ability to capture asymmetries in the data. Furthermore, EGARCH modelling on daily open-to-open and close-to-close index returns entertains the prospect of examining the time varying nature of volatility at the open and close of trading. Given the restrictive nature of the initial investigation, the study extended the EGARCH analysis to daily returns by day of the week. This provides time varying conditional variances required to estimate the five variable VAR system used to compute impulse response analysis by day of the week.

Descriptive statistics on open-to-open and close-to-close returns provide early indications that index returns are more volatile at the start of trading. In addition, the measures of skewness and kurtosis along with the Ljung-Box Q-statistics consistently reveal further evidence of serial dependencies in the data and fat tails in the distribution of returns. Although this is consistent with previous studies reviewed in Chapter Two, these findings provided the motivation behind the use of the conditional heteroscedastic model in this study.

EGARCH analysis on open-to-open and close-to-close returns reveals conflicting findings. The estimation of EGARCH models on both return series consistently provides evidence of higher conditional variances at the beginning of trading. However, the re-estimation of EGARCH models on daily returns by day of the week indicates that the market is more volatile at the close of trading for most weekdays. Using the conditional variance by day of the week, the VAR analysis revealed some interesting findings through the impulse response function. Although the market is more sensitive to random shocks at the start of trading, the rate of decay is slower at the close. The longer time span required to discount random shocks may explain the higher volatility levels observed at the end of trading. Therefore, while the study concludes that the FTSE-100 index is more resilient at the beginning of trading, the slower rate of decay at the close reveals inefficiencies in the dissemination of random shocks.

From an academic perspective, the study highlighted some of the issues raised by the market models of Kyle (1985), Admati & Pfleiderer (1988) and Foster & Viswanathan (1994). For instance, the notion that the degree of market efficiency varies throughout the trading day can be indicative of the varying degrees of market resiliency envisaged by Kyle. According to the Foster & Viswanathan model, one can interpret the higher $\boldsymbol{a}_0$ and $\boldsymbol{a}_2$ coefficients at the close in terms of the activities of well informed traders. Using the conditional variance, the impulse response analysis provides added support to this interpretation by revealing a lower rate of decay at the end of trading. The intuition behind this conclusion is the notion of asymmetry in private information where better informed traders utilise additional information not possessed by lesser traders in the pursuit of higher profits.

CHAPTER FIVE

A GARCH EXAMINATION OF THE RELATIONSHIP BETWEEN TRADING VOLUME AND VOLATILITY ACROSS INDICES

5.1 INTRODUCTION

It is well documented in the finance literature that the relationship between trading volume and price volatility is positive. The arrival of new information into the market triggers trading until traders revise their expectations and prices reach a revised equilibrium. It is this process that links trading volume and price volatility as driven by a directing factor, the information flow. A considerable amount of interest generated concerns the role of trading volume that causes a positive correlation between volume and price volatility. Although the market models of Admati & Pfleiderer (1988) and Kim & Verrechia (1991) provide a positive relationship between information, volume and volatility, the nature of the models is consistent with two competing hypothesis; the Sequential Information Model of Copeland (1976) and the Mixture of Distributions Hypothesis of Clark (1973), Epps & Epps (1976) and Harris (1987). Although both hypotheses envisage a positive relationship between volume and volatility, they differ in the speed by which the market reaches a revised equilibrium price following new information. One contributor in this area of research is Blume, Easley & O'Hara (1994) who provides a model of information and volatility that focuses on the informational role of volume. Instead of describing the relationship between volume and volatility, their model demonstrates its applicability to technical analysis by addressing how it can explain market behaviour.

The objective of this chapter is to re-examine the relationship between trading volume and price volatility using the GARCH family of models. The study performs GARCH analysis on three stock indices within the London market: the FTSE-100, FTSE-250 and FTSE-350 Indices. In considering three indices, the aim is to examine whether the nature of the volume-volatility relationship changes with the composition of the index. The results in this chapter support this proposition.

In the light of key papers reviewed in the first chapter, the investigation makes a number of contributions to the literature. Unlike previous studies, this investigation proposes an Exponential-GARCH specification with the aim of addressing two issues. The first issue concerns testing EGARCH versus volume effects to determine whether volume proxies the information flow. Secondly, the failure of volume to eliminate EGARCH effects leads to the empirical question concerning the impact of asymmetries in index returns on the volume-volatility relationship. This is possible by utilising the GARCH model introduced in Chapter Two, as a benchmark and tool of comparison with the EGARCH analysis. The second main contribution of the study lies in the treatment of trading volume. Unlike previous investigations using GARCH analysis, this study extracts components of volume induced by current information and surprises.[51] The objective here is to investigate whether volume induced by surprises contains more information than volume driven by current information. Consequently, this leads to the following possible outcomes: firstly, volume effects are such that it eliminates the presence of GARCH and EGARCH effects (denoted as (E)GARCH thereafter). Secondly, volume driven by surprises (current information) explains more the (E)GARCH effects than volume generated by current information (surprises).

Other than contributing to the academic debate, investigations of this nature are useful in providing information on the regulatory requirements of the market. If increases in volume and volatility are not the outcome of a highly liquid and efficient market, it will lead to demands for regulation on trading practices and speculative activities. On the other hand, imposing regulations on trading activity will be harmful to the effective functioning of the market if increases in volume and volatility are the by-product of a highly liquid and efficient market.

The study finds that the nature of the volume-volatility relationship depends on the composition of the index and the component of trading volume used in the (E)GARCH process. The most conclusive result is the failure of trading volume to remove (E)GARCH effects. This means that both expected and unexpected components in volume are inadequate proxies for the flow of

[51] The motivation behind this is the Bessembinder & Seguin (1993) study who investigates the volume-volatility relationship using multivariate forecasting methods in which they decompose volume into expected and unexpected components.

information. In addition, this raises the suspicion that other variables outside the confines of the (E)GARCH system help explain index price volatility.

The chapter will proceed as follows. The next section provides a theoretical discussion on the relationship between trading volume and volatility. Section 5.3 presents the GARCH and EGARCH methodology with the inclusion of trading volume into the system. Section 5.4 describes the data and descriptive statistics followed by a preliminary analysis of the volume-volatility relationship in section 5.5. Section 5.6 presents and analyses the main empirical results. Finally, section 5.7 summarises and concludes the chapter.

5.2 THEORETICAL DISCUSSION

5.2.1 Models of Volatility, Trading Volume and Information

A review of market models in Chapter One demonstrates a positive relationship between trading volume and price volatility. The Admati & Pfleiderer (1988) model makes the proposition that traders use their discretion in choosing to trade when recent volume is large. This leads to the concentration of trading where the effect of volume on price volatility is dependent on recent levels of trading volume. Kim & Verrechia (1991) provides a direct analysis of the volume-volatility relationship driven by the information flow. In their model, the driving force behind high trading volume is the incentives of traders to gather information of relevance before the announcement. It is from this assertion that the model defines surprises in terms of the information content of the announcement that in turn, depends on the quality of private information acquired prior to its release.

Next, the theoretical discussion introduces two competing hypotheses behind the relationship between trading volume and volatility: the Sequential Information Model (SIM) and the Mixture of Distributions Hypothesis (MDH). Although both models postulate a positive relationship between trading volume and volatility, they differ in terms of the speed at which a new equilibrium price is attainable resulting from the arrival of new information. The MDH assumes that the market reaches a final equilibrium price immediately after the arrival of information. This differs somewhat from the SIM which allows incomplete equilibria before reaching a final equilibrium price as information is received and disseminated by one trader at a time.

5.2.2 *Sequential Information Hypothesis*

Copeland (1976) introduced the Sequential Information Model (SIM) which postulates the notion that information is received and utilised by one trader at a time or in a sequential fashion. The market reaches final equilibrium when all traders observe the same information set. As a consequence, prices may not change immediately in response to the arrival of new information. Instead, the scenario envisaged is a market where individual traders receive information and their trades in response to the signal leads to a number of incomplete equilibria. In this model, uninformed traders cannot infer the information content from the actions of informed traders. This is consistent with one of the key assumptions underpinning the asymmetric model of Foster & Viswanathan (1994) that allows informed traders to change their trading strategies after the dissemination of common information.

In focusing on key papers in this issue, some effort has gone into extending the SIM. Jennings & Barry (1983) modifies the SIM by allowing speculative activity on the part of informed traders. The implication of allowing informed traders to take a speculative position is to enable prices to adjust faster to the arrival of new information. Although they postulate a positive correlation between trading volume and volatility for an investor's trade, the overall relationship over time periods within a given trading day is ambiguous.

The key point in this type of study, are the implications of the SIM on the volume-volatility relationship. The sequential response to the arrival of information implies that price volatility is forecastable based on the knowledge of trading volume. As a consequence, the volume-volatility relationship is sequential, not contemporaneous.

5.2.3 Mixture of Distributions Hypothesis

The Mixture of Distributions Hypothesis (MDH) of Epps & Epps (1976) and Harris (1987) differs from the SIM in that final equilibrium is immediate in a world where new information induces trading activity to rebalance portfolios.

The motivation behind the MDH is the leptokurtosis exhibited in daily price changes that is attributable to random events of relevance in pricing the security. [Clark (1973)] Consequently, volatility within the confines of the MDH is dependent on the stochastic mixing variable, defined as the information flow. The idea of a positive relationship between the variance and trading volume originates from the notion that the market equilibrium price represents the sum of individual demand and supply schedules of traders. By defining the null price as the price at which the excess demand of the individual trader is zero, Epps & Epps (1976) argues that the flow of information generates disequilibrium between the null price and the market price. Subsequently, excess demand or supply resulting from new information induces further transactions and hence, price changes in order to rebalance portfolios. A restoration of the equality between the null price and the market price is the result.

The main implication of the above analysis is the joint distribution of daily price changes and trading volume. Within this framework, Harris (1987) analyses the MDH on the basis of two assumptions of paramount importance. Firstly, that daily changes in price and trading volume follow a joint bivariate normal distribution conditional on information events $\boldsymbol{n_t}$. By defining volatility and trading volume as the accumulation of price changes and volumes caused by the information flow $\boldsymbol{n_t}$, the outcome is a contemporaneous relationship between the variance and trading volume. The second assumption is that the arrival of information is random on any given day. This merely complements the first condition in which changes in price on any given day are driven by a stochastic mixing variable, i.e. flow of information (n_t). The implication of both assumptions is that the variance-covariance matrix of the conditional distribution will be proportional to the stochastic mixing variable n_t. Furthermore, it should follow that the variance-covariance matrix will be hetroscedastic given that n_t is stochastic.

Since prices and volume under the MDH are jointly distributed, the model traces simultaneous large volumes and price changes to a stochastic process defined as the flow of information. Intuitively, this implies that all traders are able to observe simultaneously excess demand and supply, along with price implications following the arrival of information relevant to pricing the security. Consequently, the shift to a new equilibrium price will be immediate whereby the null price of individual traders equates the market price.

5.2.4 The Role of Volume

A problem identified with the MDH lies in its failure to consider the precision or quality of n_t. Blume, Easley & O'Hara (1994) considers this issue by developing a model in which trading volume plays an informationally important role in an environment where traders receive pricing signals of differing quality. Of paramount importance is the assumption that the equilibrium price is non revealing given that pricing signals alone do not provide sufficient information to determine the underlying value. They treat trading volume as containing information on the quality of signals received by traders whereas prices alone do not. It is from this assertion that the model provides a link between trading volume, the quality of information flow and price volatility.

Their analysis is similar to the model developed by Kim & Verrechia in that precision of the signal plays an important role in determining trading activity and hence, volume. As a consequence, Blume *et al* scrutinises further the general hypothesis that volatility equates the flow of information inferred by the MDH. Consistent with the Kim & Verrechia analysis, the precision of information determines the reaction of traders and hence, volume and volatility. Although this implies the existence of a positive correlation between volume and volatility, n_t is no longer the driving force behind this relationship. For the MDH to hold, n_t must be of average precision to prevent a convergence of beliefs to induce trading activity.

To sum up, the Blume *et al* analysis provides an additional dimension to the MDH by providing a more refined test of the relationship between volume, volatility and the flow of information. Although they do not question the nature of the volume-volatility relationship, the use of trading volume as a proxy to n_t is under scrutiny.

5.3 METHODOLOGY

5.3.1 A Conditional Heteroscedastic Model for Volume and Volatility

The existence of ARCH effects follows from the notion that daily returns is determined by mixture of distributions where the stochastic mixing variable n_t represents the information flow. To further elaborate, trading volume and volatility driven by the stochastic flow of information, implies that changes in volume and volatility will change over time. Subsequently, this provides the motivation behind the use of the GARCH family of models for the purpose of the study. Lamourex & Lastrapes (1990) provides a framework of GARCH modelling that allows the stochastic mixing variable n_t to exhibit serial correlation. Beginning with the notion that the unexpected change in price during the day Ω_t is the summation of the intra-daily equilibrium price:

$$\varepsilon_t = \sum_{i=1}^{n_t} \phi_{i,t} \tag{5.1}$$

where Ω_t is drawn from a mixture of distributions and the flow of information determines the variance of each distribution. The term $\phi_{i,t}$ is the equilibrium price attained during the trading day. From equation (5.1), if the intra-daily equilibrium price increment $\phi_{i,t}$ is i.i.d with zero mean and variance σ^2, and n_t is sufficiently large, then:

$$\varepsilon_t | n_t \sim N(0, \sigma^2 n_t) \tag{5.2}$$

Given that the stochastic mixing variable exhibits serial correlation, define n_t as a autoregressive process:

$$n_t = \alpha_0 + \rho n_{t-p} + v_t \tag{5.3}$$

where

α_0 = the constant;

ρn_{t-p} = the autoregressive structure of lag order p;

v_t = the white noise term.

In equation (5.3), the autoregressive structure captures the persistence of innovations to the mixing variable. Based on the validity of the mixture model, Lamoureux & Lastrapes define the variance term as

$$\Omega_t = E\left(\varepsilon_t^2 | n_t\right) = \sigma^2 n_t \tag{5.4}$$

which they then substitute into a Moving Average representation in equation (5.5) to capture the persistence in the conditional variance, analogous when using a GARCH process:

$$\Omega_t = \sigma^2 \alpha_0 + \alpha_1 \Omega_{t-1} + \sigma^2 u_t \tag{5.5}$$

Essentially, the focus of this study is knowledge of the stochastic mixing variable n_t as the driving force behind the volume-volatility relationship. Given that the flow of information is unobservable, a proxy is required. As with previous investigations,[52] this study proposes trading volume as a proxy for the flow of information. Trading volume serves a useful purpose of providing inferences about the disequilibrium dynamics of asset markets. In addition, choosing volume as a mixing variable is consistent with both the SIM and MDH models. Moreover, Blume *et al* (1994) demonstrates how trading

[52] See Lamoureux & Lastrapes (1990), Najand & Yung (1991), Foster (1995) and Sharma, Mbodja & Kamath (1996).

volume provides useful inferences on the quality of the information signal that prices alone cannot infer.

The notion that trading volume is a proxy for the stochastic mixing variable consigns it to be exogenous in the conditional heteroscedastic model. As such, this model is represented as a GARCH process:

$$R_t = \eta + \varepsilon_{i,t} \tag{5.6a}$$

$$\varepsilon_t \big| (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t) \tag{5.6b}$$

where R_t is the rate of return and η is the mean coefficient of R_t. Given the inclusion of trading volume into the GARCH, the conditional variance h_t becomes a modified form of equation (2.11):

$$h_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-1}^2 + \sum_{k=1}^{q} \beta_k h_{t-1} + \gamma V_t \tag{5.7}$$

where V_t is trading volume. The summation of $\alpha_j + \beta_k$ measures the volatility persistence. As this approaches unity, shocks will have a more persisting effect on volatility. The conditional heteroscedastic model of equation (5.7) can determine whether the clustering of the information flow explains the presence of GARCH effects in the dataset. Within this framework, trading volume can proxy the flow of information only if the significance of the volume term γ eliminates the presence of GARCH effects (α_j and β_k). However, a problem inherited with equation (5.7) is the potential for simultaneity bias. This is a model specification problem that arises when trading volume and price volatility is a joint random function of the flow of information. As a consequence, trading volume is endogenously determined by the system and hence, will generate inconsistent estimates of the coefficients. This problem is overcome by lagging the volume term V_t in the GARCH specification.

$$h_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-1}^2 + \sum_{k=1}^{q} \beta_k h_{t-1} + \gamma V_{t-1} \tag{5.8}$$

By introducing the variable V_{t-1}, trading volume becomes exogenously determined in the model. The elimination of GARCH effects resulting from controlling volume is consistent with the joint hypothesis that it is attributable to the time varying flow of information.

5.3.2 *A Modified Test of the Volume-Volatility Relationship*

An innovative feature of this chapter is the proposal of the Exponential-GARCH (EGARCH) model of Nelson (1990) in this capacity. Given that daily returns is determined by a mixture of distribution, the ability of the EGARCH to extract more information from the data means that it provides more accurate readings of the volume-volatility relationship. Performing EGARCH analysis serves a dual purpose for this study. Firstly, it provides an intriguing challenge to the validity of the MDH by testing volume versus EGARCH effects. Secondly, the failure of volume to eliminate EGARCH effects leads to the empirical question concerning the impact of asymmetries on the volume-volatility relationship. Consequently, the EGARCH model of equation (2.12) is modified into a specification of the volume-volatility relationship:

$$h_t = exp\left\{ \alpha_0 + \sum_{j=1}^{q} \alpha_j ln(h_{t-1}) + \alpha_k \sum_{k=1}^{p} \Theta_{t-1} + \gamma V_{t-1} \right\} \tag{5.9}$$

where

Θ_{t-1} = the innovation that comprises the asymmetric term θ_1;[53]

V_{t-1} = trading volume lagged one period.

The EGARCH process of equation (5.9) defines the conditional volatility in terms of the logarithm of the lagged conditional variance α_1, the size and sign of the innovation α_2 θ_1 along with the trading volume γ. Support for the MDH occurs if $\gamma > 0$ and EGARCH effects disappear. Otherwise it is the (E)GARCH[54] process that arises from the time variation in returns that are attributable to the asymmetric effect and not trading volume proxying the flow of information.

5.4 DATA AND DESCRIPTIVE STATISTICS

5.4.1 Data and Summary Statistics

The dataset comprises of daily closing index values along with trading volume by turnover on the FTSE-100, FTSE-250 and FTSE-350 Indices. The FTSE-250 consists of 250 of the largest UK companies after those listed on the FTSE-100 Index. The FTSE-350 comprises of all companies listed on the FTSE-100 and FTSE-250 Indices. The sample period is September 30, 1992 to December 31, 1997 equivalent to 1371 daily observations. The data was downloaded from Datastream International where the availability of trading

[53] See equation (2.13) in Chapter Two for the definition.
[54] The term (E)GARCH is appropriate in this context because the alternative result to the MDH may see GARCH effects if the asymmetric component in returns is insignificant.

volume data on the FTSE-250 and FTSE-350 Indices restricted the starting date of the sample.

Table 5.1 displays summary statistics for all three close-to-close index return series. This includes the mean, variance, minimum and maximum values along with measures of skewness and kurtosis. Further, it provides Ljung-Box Q-statistics as a test for higher order serial correlation up to lag twelve. The descriptive statistics show that the sample mean is very small and significantly different from zero at the 0.05 level. Focusing on the measure of dispersion, the range between minimum and maximum values is greatest for the FTSE-250 index returns followed by the FTSE-100 and FTSE-350 indices. Judging from the measures of skewness and kurtosis, all index returns exhibit slight skewness to the left and excess kurtosis that is most profound for the FTSE-250 index. In sum, the returns on all three indices do not conform to a normal distribution. The Ljung-Box Q-statistics provides evidence of serial dependencies in all return series. Once again, the FTSE-250 index return series reports the greatest rejection of the null hypothesis of no autocorrelation. For illustrative purposes, figure 5.1(a) to 5.2(c) displays the sample autocorrelation coefficients up to 100 lags for both index and squared index returns. The autocorrelation patterns clearly show that index returns are not only non-normal, but cannot be independently and identically distributed (i.i.d). If this were the case, then both index returns and squared index returns would be i.i.d.

Table 5.1

Descriptive Statistics of Index Returns

	FTSE-100	FTSE-250	FTSE-350
Sample Mean	0.053*	0.052*	0.053*
Variance	0.567	0.255	0.456
Maximum	3.125	3.321	2.901
Minimum	-4.140	-5.147	-3.762
Skewness	-0.253	-0.782	-0.298
(p-value)	(0.00)	(0.00)	(0.00)
Kurtosis	1.416	12.607	1.715
(p-value)	(0.00)	(0.00)	(0.00)
L-B $Q(12)$	25.132	112.182	28.533
(p-value)	(0.01)	(0.00)	(0.00)

*Reject the null hypothesis that mean = 0 at the 0.05 level.
L-B = Ljung-Box Q-statistic are chi-square distributed
$Q(12)$ test statistic compared with critical value of 21.0261

Figure 5.1(a)

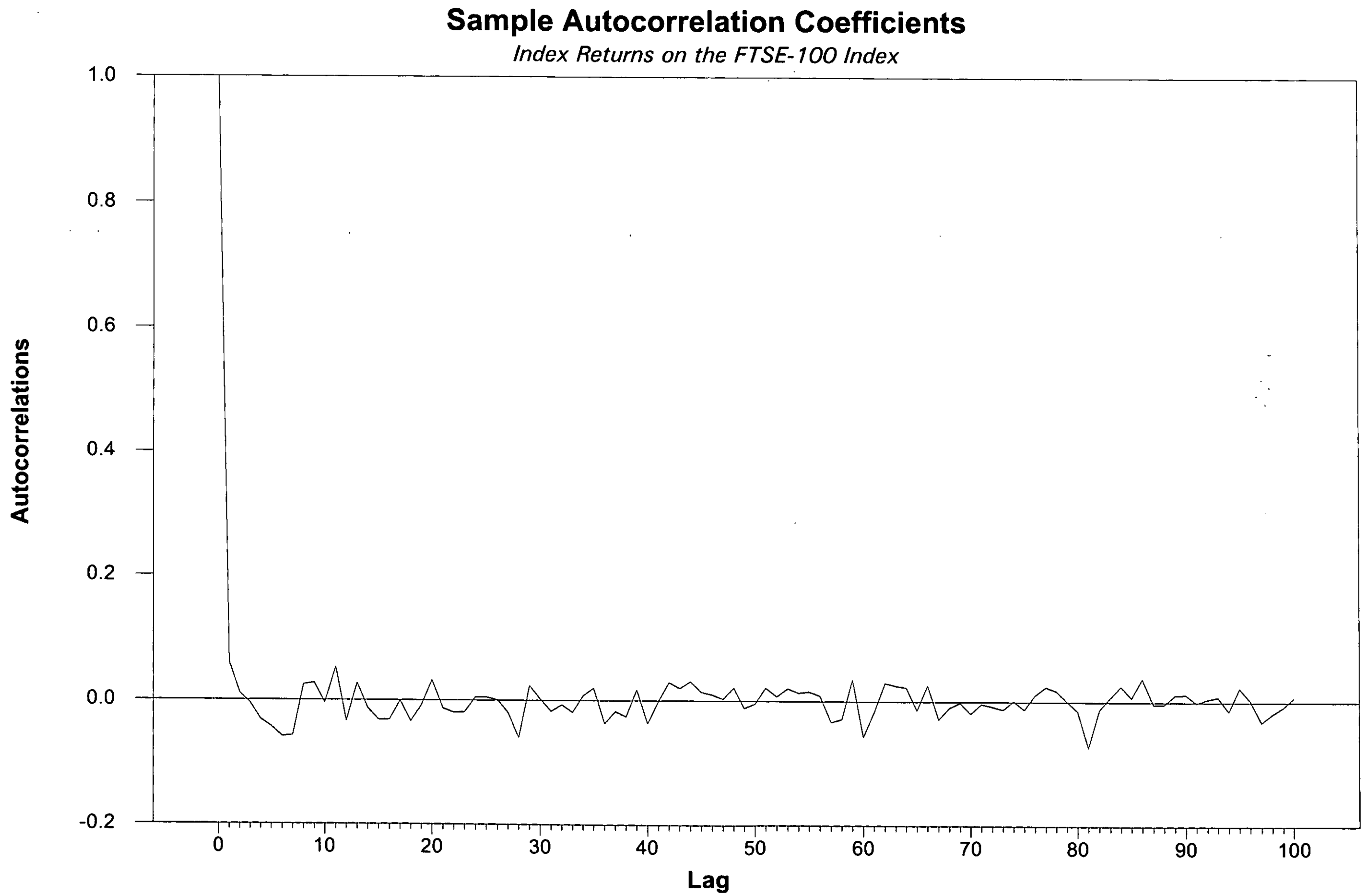

Sample Autocorrelation Coefficients
Index Returns on the FTSE-100 Index
Autocorrelations
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
10
20
30
40
50
60
70
80
90
100
Lag

Figure 5.1(b)

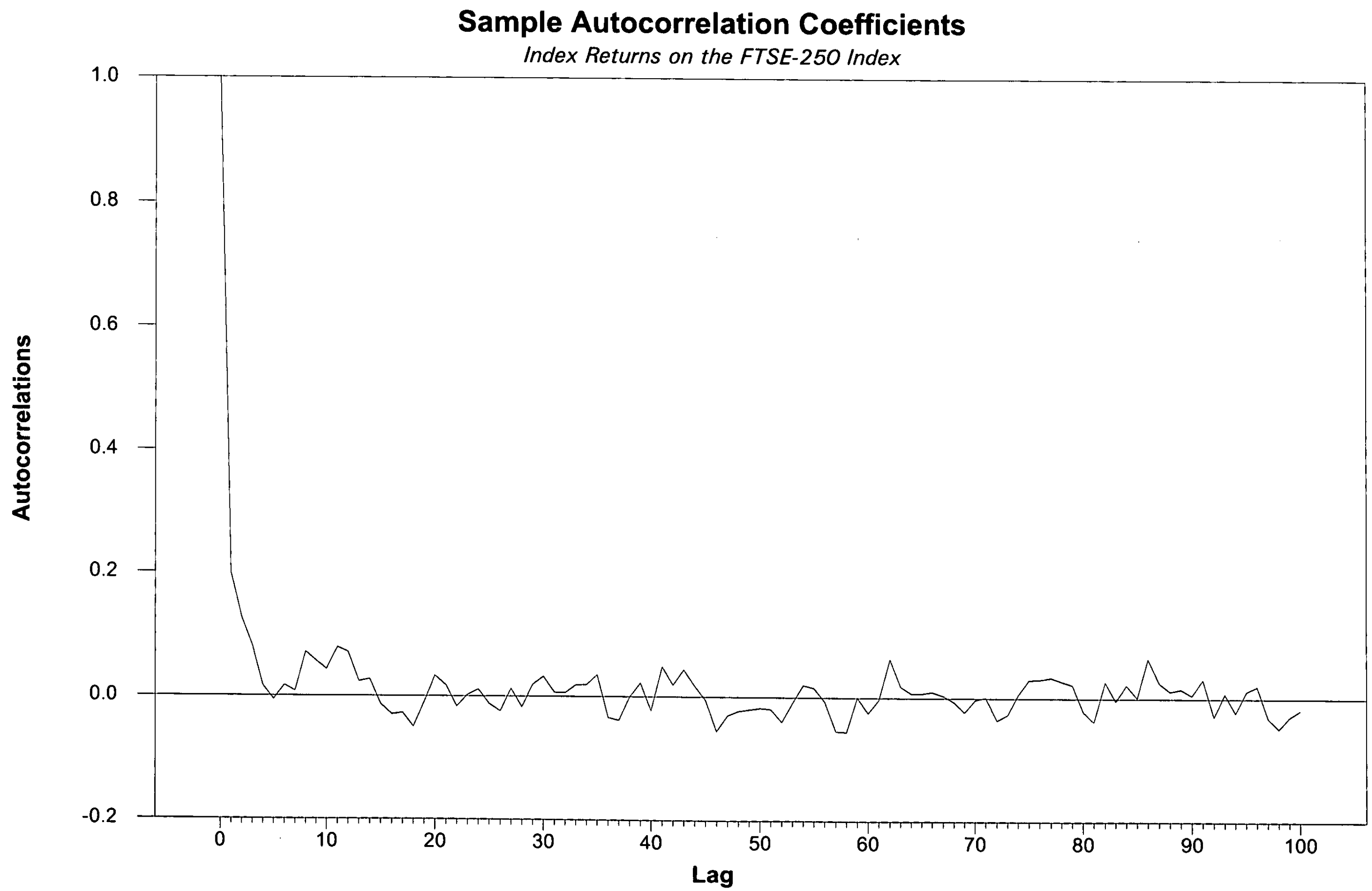

Sample Autocorrelation Coefficients
Index Returns on the FTSE-250 Index
Autocorrelations
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
10
20
30
40
50
60
70
80
90
100
Lag

Figure 5.1(c)

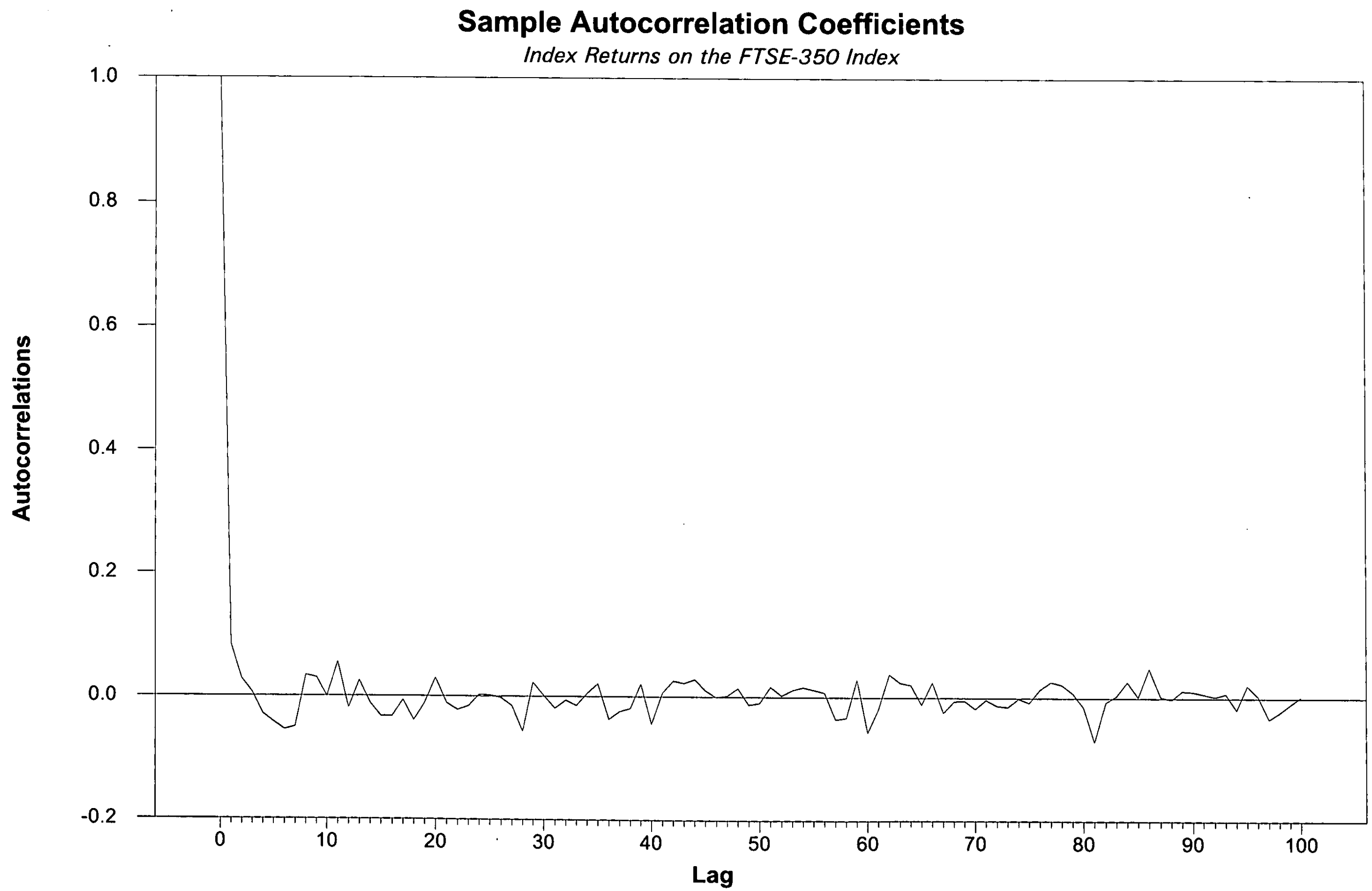

Sample Autocorrelation Coefficients
Index Returns on the FTSE-350 Index
Autocorrelations
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
10
20
30
40
50
60
70
80
90
100
Lag

Figure 5.2(a)

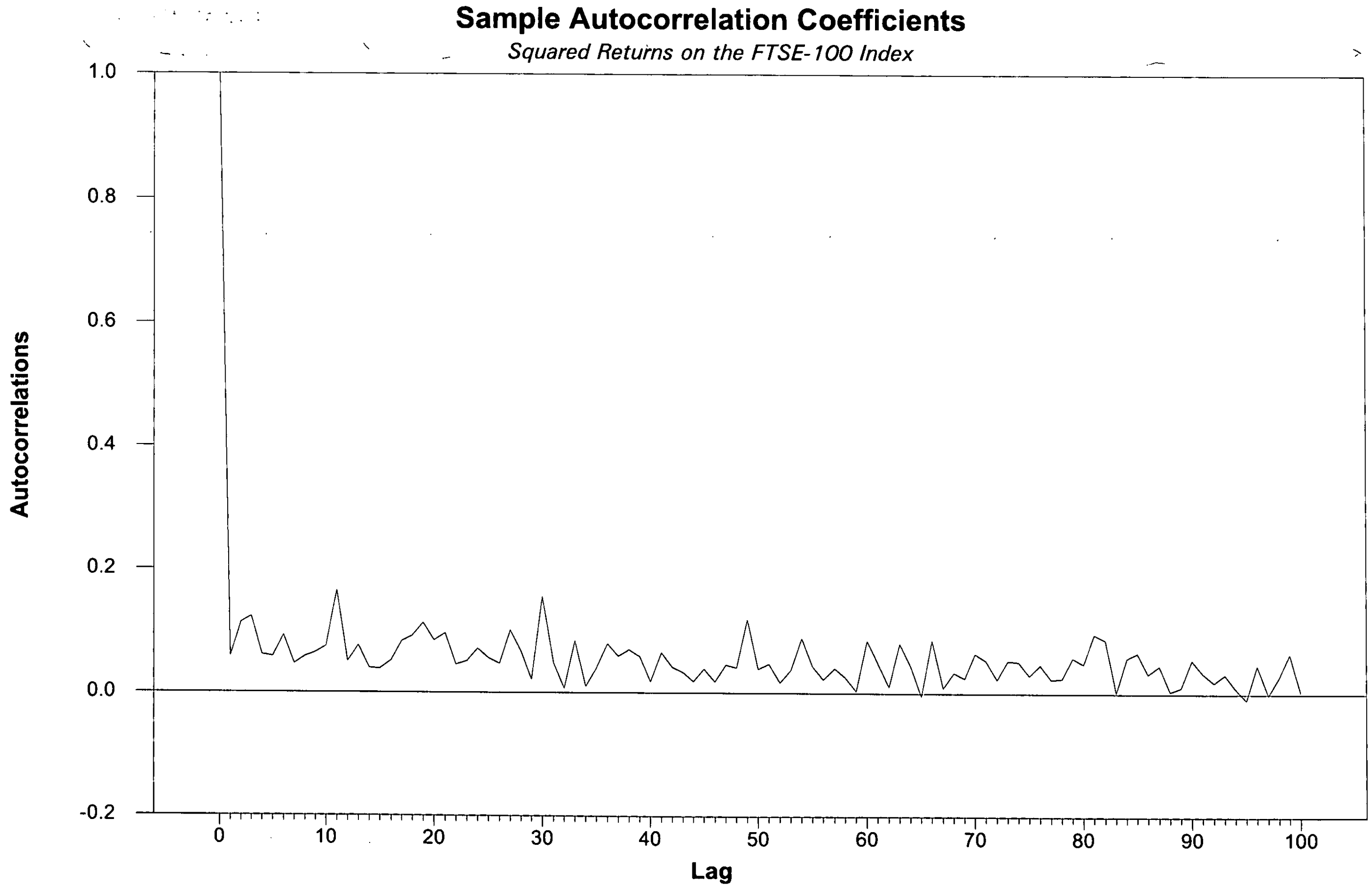

Sample Autocorrelation Coefficients
Squared Returns on the FTSE-100 Index
Autocorrelations
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
10
20
30
40
50
60
70
80
90
100
Lag

Figure 5.2(b)

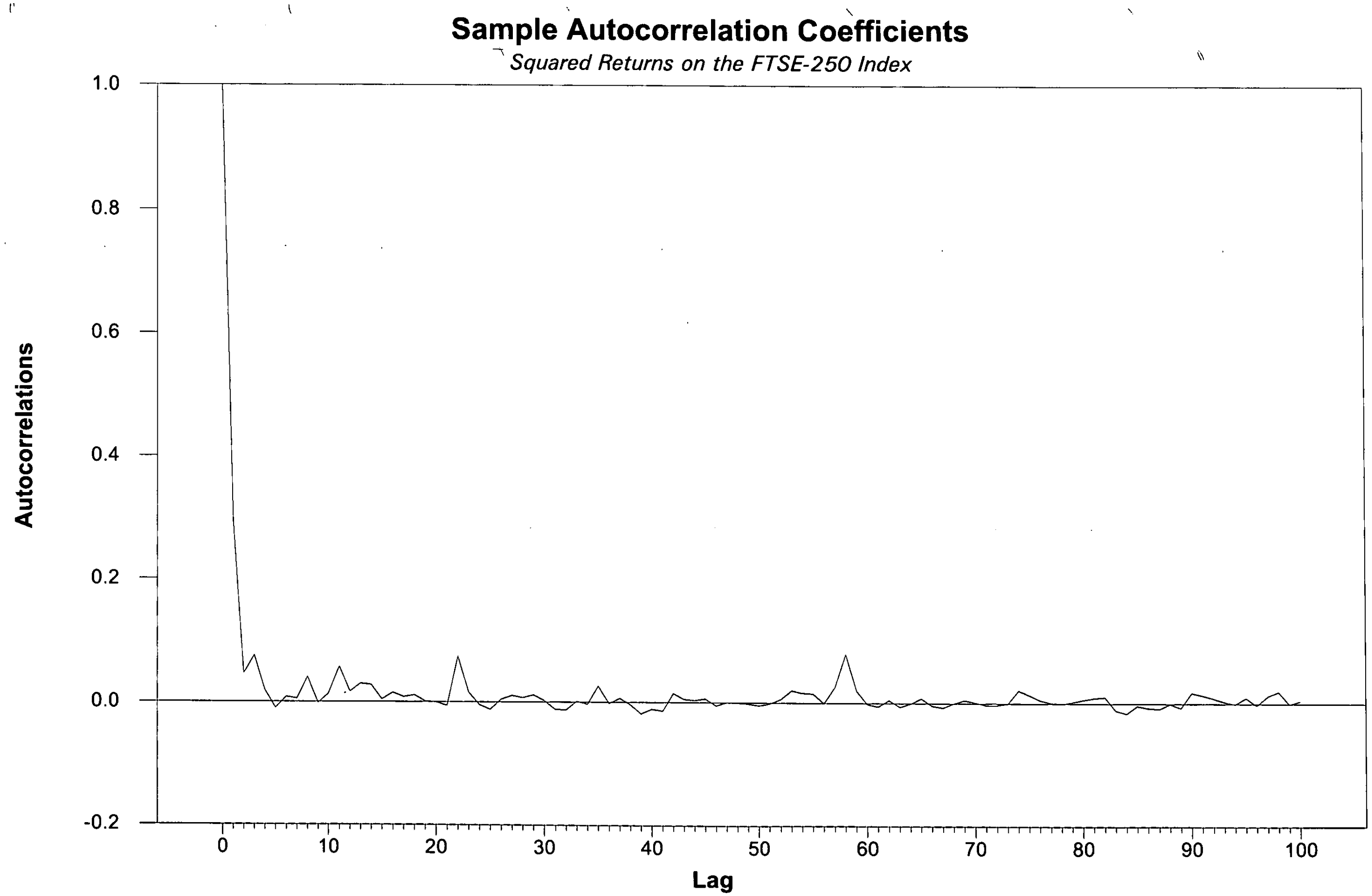
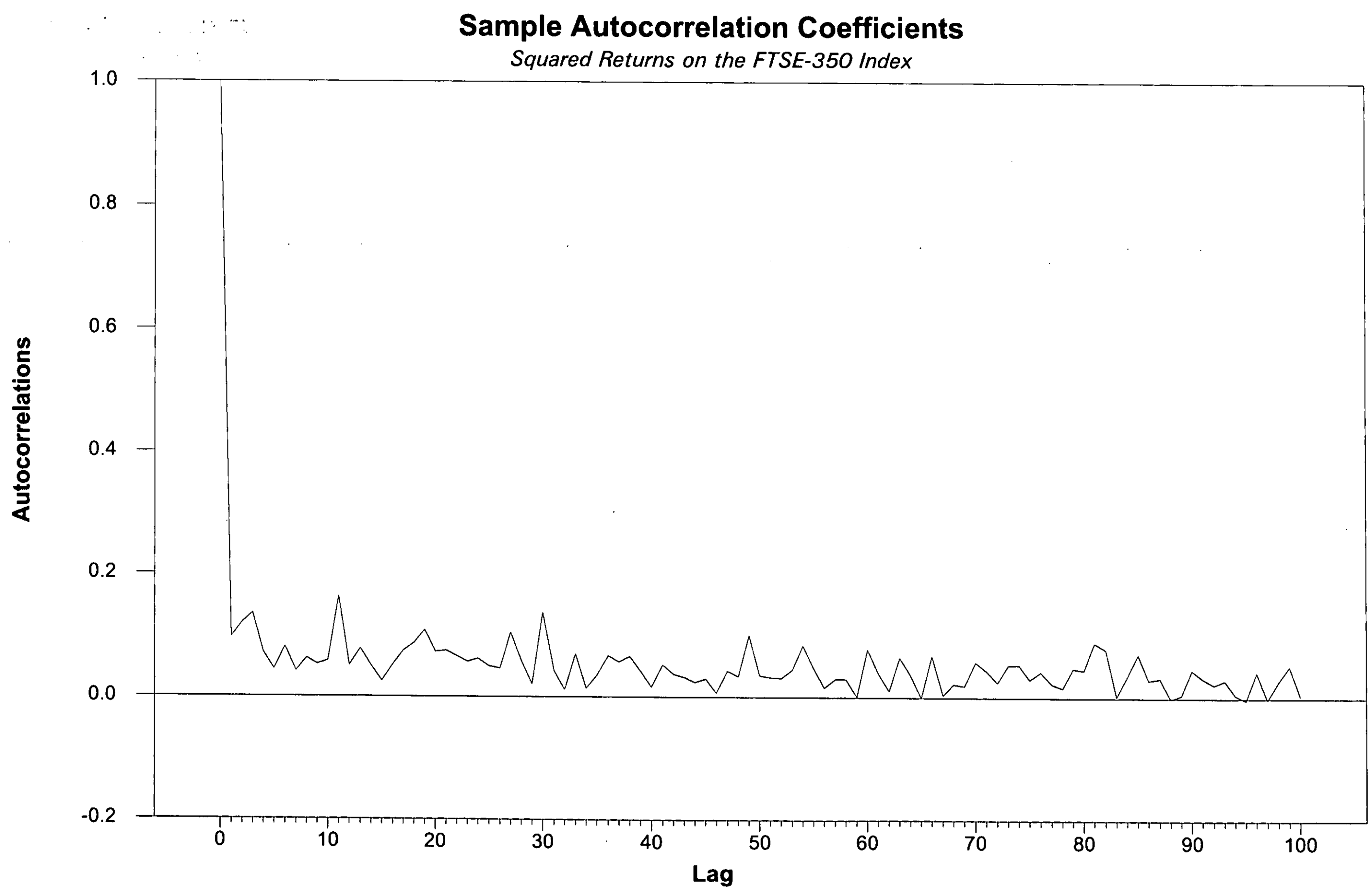

Sample Autocorrelation Coefficients
Squared Returns on the FTSE-250 Index
Autocorrelations
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
10
20
30
40
50
60
70
80
90
100
Lag

Figure 5.2(c)


Sample Autocorrelation Coefficients
Squared Returns on the FTSE-350 Index
Autocorrelations
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0
10
20
30
40
50
60
70
80
90
100
Lag

5.4.2 The Treatment of Trading Volume

This study focuses on trading volume in their first differences. The intuition behind using first differences is to relate price changes to changes in trading volume. The common characteristic of index returns and trading volume is that both series exhibit high autocorrelation. The descriptive statistics in table 5.2 confirm this finding using the Ljung-Box *Q*-Statistics for higher order serial correlation up to lag twelve.

Unlike previous investigations performing GARCH analysis, this study utilises the relationship between volume and volatility that is driven by current information and surprises. As a consequence, it is necessary to make a distinction between expected and unexpected components in trading volume. The expected component is the change in trading volume driven by the current information set. On the other hand, the unexpected component is the change in trading volume triggered by random shocks or surprises. Other than providing an added dimension to the investigation, decomposing trading volume into expected and unexpected components have implications on the model specification of the GARCH process. This follows from the notion that expected components are not endogenously determined by the stochastic part of the GARCH model. (i.e. the news coefficient α_j in equation (5.7)) However, the unexpected component is endogenously determined by the GARCH process and as a consequence, lagging the volume term is a necessity. The following provides a framework for extracting expected and unexpected

Table 5.2

Descriptive Statistics of the Trading Volume Series
(First Differences)

	FTSE-100	FTSE-250	FTSE-350
Sample Mean	-0.001	-0.001	-0.001
Variance	0.089	0.096	0.124
Maximum	1.150	2.335	4.648
Minimum	-1.376	-1.725	-4.829
Skewness	-0.044	0.083	-0.180
(p-value)	(0.51)	(0.22)	(0.01)
Kurtosis	1.280	3.636	50.806
(p-value)	(0.00)	(0.00)	(0.00)
L-B $Q(12)$	337.486	282.987	255.218
(p-value)	(0.00)	(0.00)	(0.00)

*Reject the null hypothesis that mean = 0 at the 0.05 level.
L-B = Ljung-Box Q-statistic are chi-square distributed
$Q(12)$ test statistic compared with critical value of 21.0261
Note: The volume series is defined as the natural logarithm of today's trading volume to the trading volume of the last period to trade.

components in volume based on a similar approach by Bessembinder & Segiun (1993). To begin with, consider the conditional mean equation on the three index return series:

$$R_t = \varphi + \sum_{i=1}^{n} \delta_i R_{t-i} + \sum_{j=1}^{5} \rho_j D_{MF_t} + \sum_{k=1}^{m} \mu_k D_{HOL_t} + u_t \tag{5.10}$$

where R_t is the close-to-close index return at time *t*. D_{MF_t} and D_{HOL_t} are day of the week and national holiday dummy coefficients. In equation (5.10), the residuals u_t represent unexpected returns that are scaled to generate daily standard deviation values $\hat{\sigma}_t$ as a measure of volatility:

$$\hat{\sigma}_t = u_t \sqrt{\pi/2} \tag{5.11}$$

To extract the expected component in trading volume requires estimating an autoregressive model on the trading volumes of all three indices to obtain the forecast errors:

$$dVOL_t = \rho_j dVOL_{t-1} + \varepsilon_t \tag{5.12}$$

where $dVOL_t$ is the trading volume in their first differences and ε_t is the forecast error. However, unlike the Bessembinder & Segiun approach, the procedure adopted here predetermines the number of autoregressive coefficients in equation (5.12) by using the Akaike Information Criterion and the Schwertz Bayesian Criterion.[55] The extraction of the expected component in volume requires the generation of the unexpected component. Given that the focus of the study are stock indices, the model employed is a restricted version to the one proposed by Bessembinder & Segiun:

[55] In performing the Akaike Information Criterion and Schwertz Bayesian Criterion on all three volume series, the results indicate a lag order of one.

$$\varepsilon_t = \alpha + \sum_{j=1}^{3} \phi_j \hat{\sigma}_{t-i} + \sum_{k=1}^{3} \gamma_k dVOL_{t-k} + v_t \qquad (5.13)$$

in which the dependent variable ε_t is the error term from equation (5.12), v_t is the unexpected component in trading volume and $\hat{\sigma}_{t-i}$ is the daily standard deviation lagged one period. The intuition behind the inclusion of $\hat{\sigma}_{t-i}$ is the notion that past volatilities can forecast trading volumes.[56] From equation (5.13), the expected component is defined as the difference between the trading volume in the first differences and the unexpected component:

$$dVOL_t - v_t \qquad (5.14)$$

Table 5.3(a) and 5.3(b) present summary statistics on the expected and unexpected components in trading volume. The statistics provide first indications that surprises induce greater variability in trading volume than forecastable volume. Furthermore, minimum and maximum values provide further indications of an asymmetric response to surprises and current information.

[56] See the article by Gallant, Rossi & Tauchen (1992) for evidence.

Table 5.3(a)

Descriptive Statistics on the Expected Component
of Trading Volume

	FTSE-100	FTSE-250	FTSE-350
Sample Mean	-0.001	-0.002	-0.001
Variance	0.010	0.008	0.014
Maximum	0.453	0.487	1.614
Minimum	-0.380	-0.672	-1.556
Skewness	0.034	-0.096	0.180
(p-value)	(0.61)	(0.15)	(0.01)
Kurtosis	1.300	3.573	51.633
(p-value)	(0.00)	(0.00)	(0.00)

*Reject the null hypothesis that mean = 0 at the 0.05 level.
Note: The expected component is defined as the difference between volume in their first differences $\boldsymbol{dVOL_t}$ at day t and the unexpected component v_t. See equation (5.14).

Table 5.3(b)

Descriptive Statistics on the Unexpected Component
of Trading Volume

	FTSE-100	FTSE-250	FTSE-350
Sample Mean	-0.002[a]	-0.003[a]	-0.002[a]
Variance	0.079	0.088	0.110
Maximum	1.101	1.848	3.034
Minimum	-1.391	-1.929	-4.924
Skewness	-0.237	-0.155	-2.034
(p-value)	(0.00)	(0.02)	(0.00)
Kurtosis	1.493	3.246	43.561
(p-value)	(0.00)	(0.00)	(0.00)

*Reject the null hypothesis that mean = 0 at the 0.05 level.
[a] Multiplied by 10^4 for readability.
Note: The unexpected component is computed as the difference between the forecast error and the lagged standard deviation of residual returns and volume in their first difference. See equation (5.13).

5.5 PRELIMINARY ANALYSIS ON THE VOLUME-VOLATILITY RELATIONSHIP

Figure 5.3(a) to 5.4(c) displays scatter diagrams that plot index returns against changes in trading volume driven by current information and by surprises. As a preliminary analysis, this invites the prospect of determining whether trading volume induced by surprises conveys more information and hence, impact further on index returns than volume driven by current information.

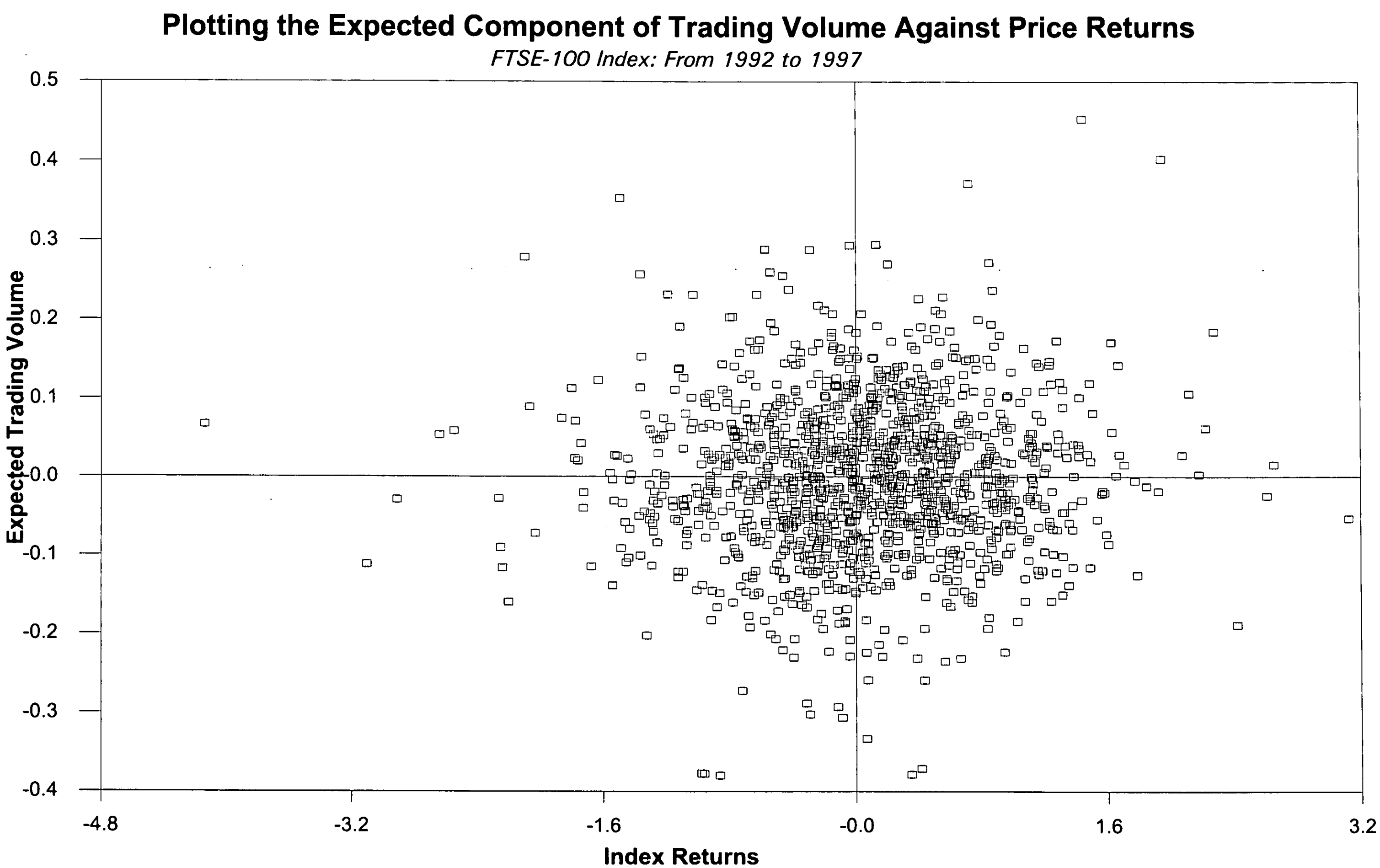
According to the scatter diagrams, the figures conform to a convex relationship between changes in trading volume and index returns. In their model of information and volume, Blume *et al* (1994) postulate that information precision and dispersion determines the nature of the relationship between trading volume and price changes. They introduce the notion that a V-shape relationship between trading volume and price changes is indicative of the arrival of high precision information. This V-shape pattern becomes more profound, the higher the precision of information.

In the analysis of Blume *et al,* information dispersion plays an important role in interpreting the relationship between trading volume and index returns as illustrated in figure 5.3(a) to 5.3(c). Unlike the V-shape pattern predicted in their model, the volume-index returns relationship displayed in the figures is indicative of a wide dispersion of information experienced in all three stock market indices. The implication of not detecting a V-shape pattern is that no inferences are possible on the precision of the information arrival. Given that the data cannot reveal a V-shape pattern of volume and index returns, the study assumes that the quality of information is fixed.

Figure 5.4(a) to 5.4(c) clearly illustrates that trading volume induced by surprises conveys information of relevance to pricing of all three indices. Inferring from the Blume *et al* model, the notion that surprises contains information is consistent with the lack of information precision observed in figure 5.3(a) to 5.3(c). The intuition behind this interpretation is the view that a lack of information precision in the expected component will mean that surprises will always convey information not known in the current information set. Hence the observation of a convex relationship between index returns and changes in volume caused by surprises.

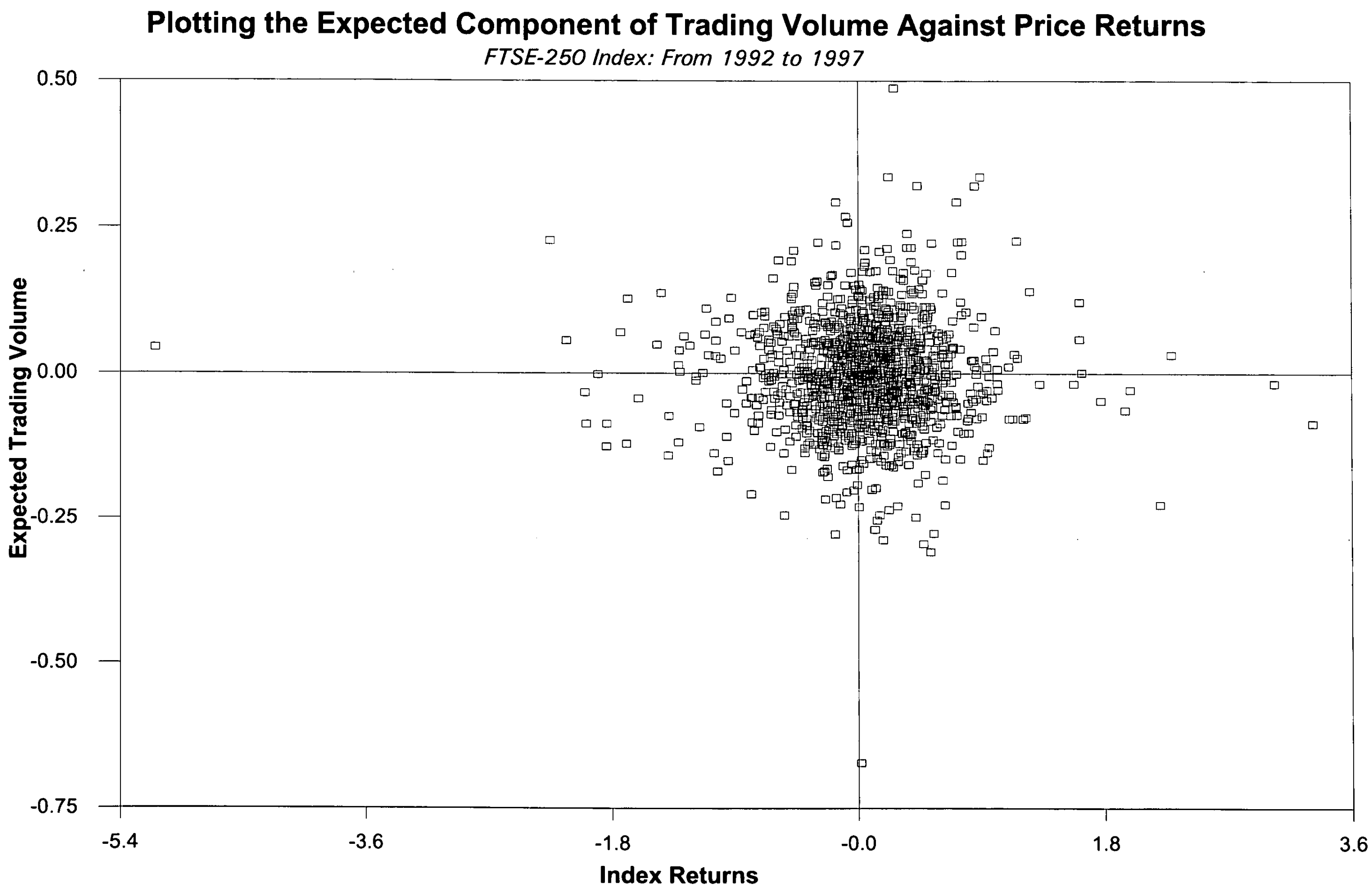
Another important observation raised by the scatter diagrams relates to the symmetry in the relationship between changes in trading volume and index returns. The preliminary evidence suggests that changes in trading volume are symmetric to the sign of the price change for all three indices.

Figure 5.3(a)



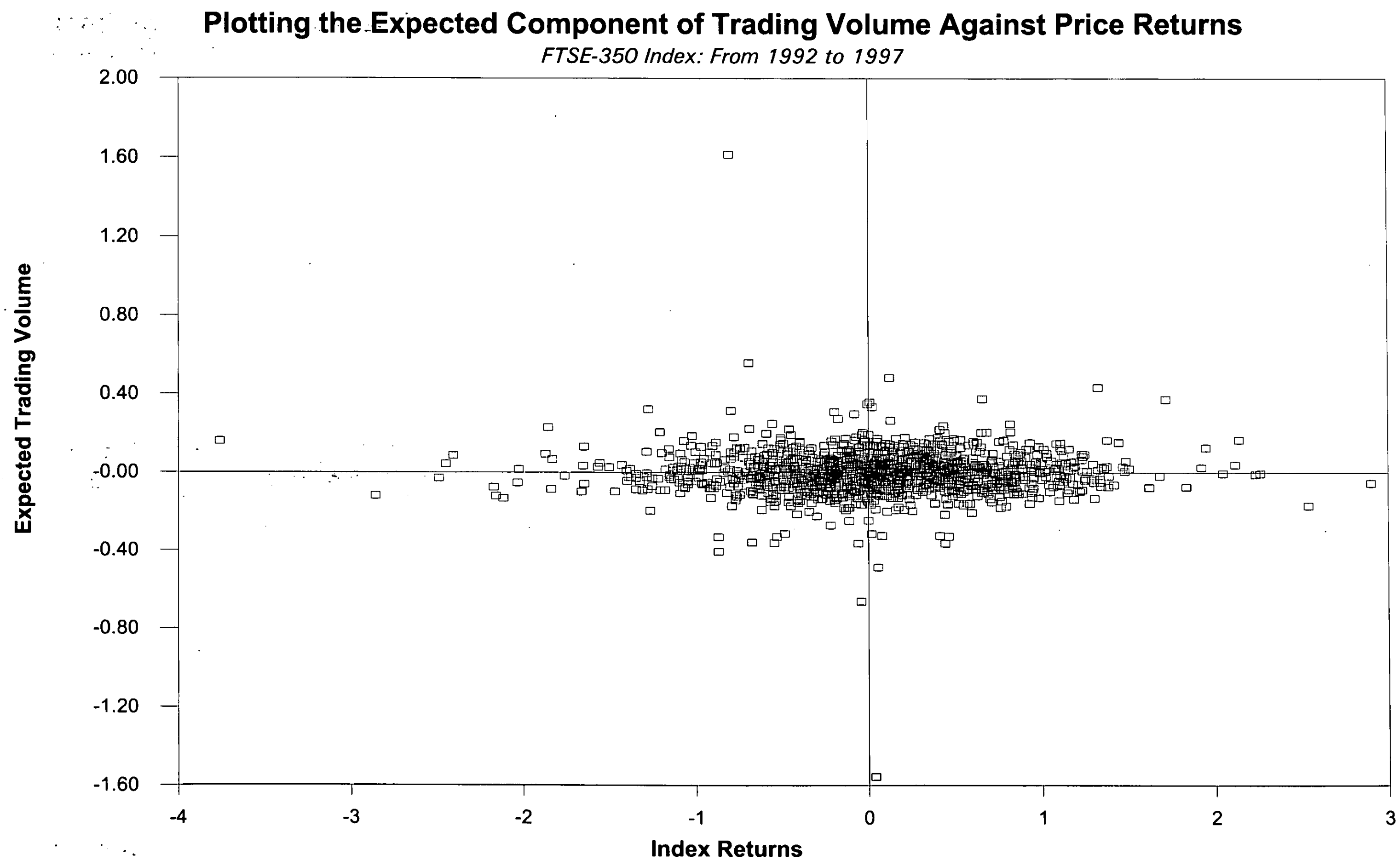
Plotting the Expected Component of Trading Volume Against Price Returns
FTSE-100 Index: From 1992 to 1997
Expected Trading Volume
0.5
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
-4.8
-3.2
-1.6
-0.0
1.6
3.2
Index Returns

Figure 5.3(b)



Plotting the Expected Component of Trading Volume Against Price Returns
FTSE-250 Index: From 1992 to 1997
Expected Trading Volume
Index Returns
0.50
0.25
0.00
-0.25
-0.50
-0.75
-5.4
-3.6
-1.8
-0.0
1.8
3.6

Figure 5.3(c)



Plotting the Expected Component of Trading Volume Against Price Returns
FTSE-350 Index: From 1992 to 1997
Expected Trading Volume
2.00
1.60
1.20
0.80
0.40
-0.00
-0.40
-0.80
-1.20
-1.60
-4
-3
-2
-1
0
1
2
3
Index Returns

Figure 5.4(a)

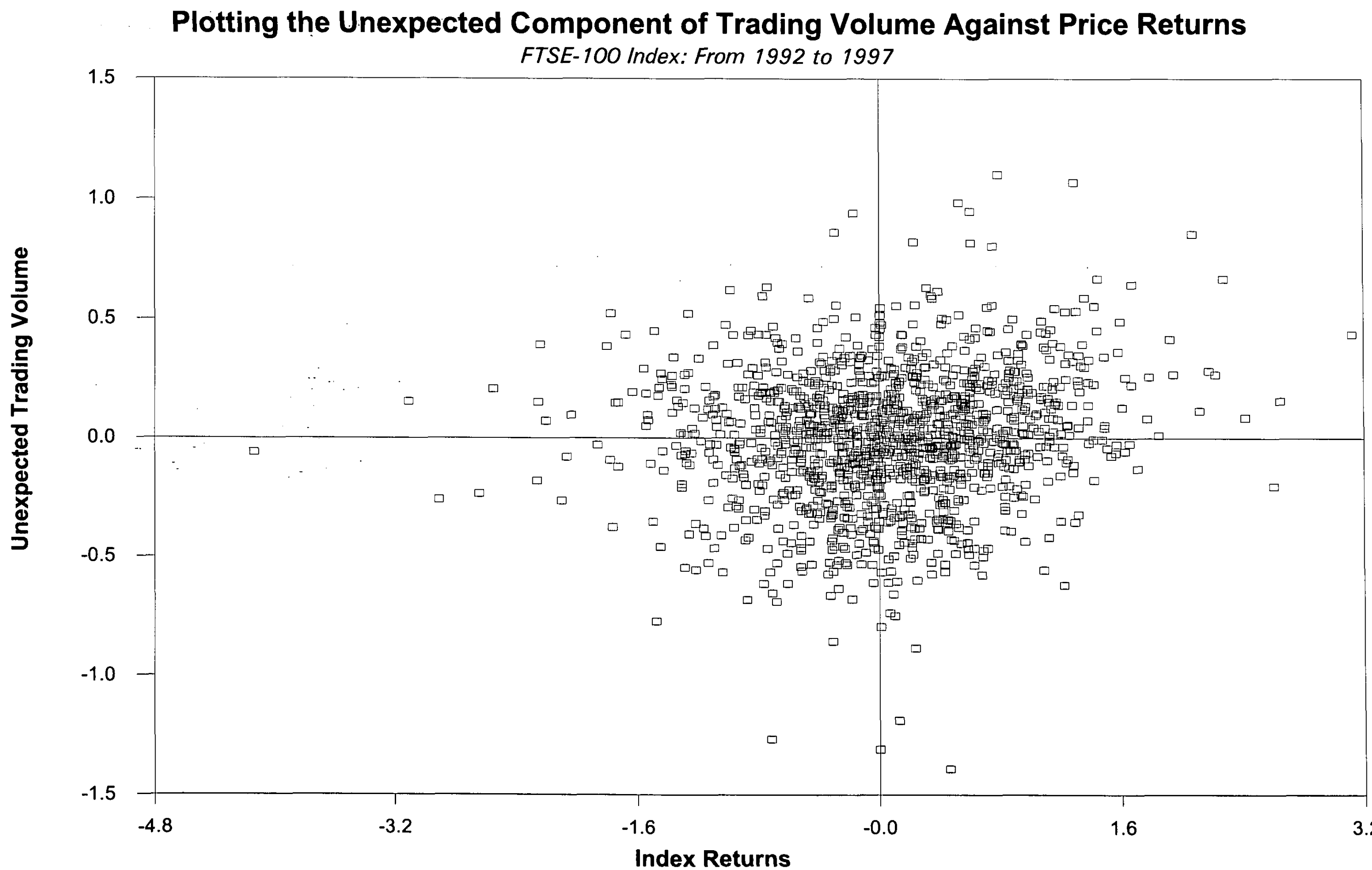

Plotting the Unexpected Component of Trading Volume Against Price Returns
FTSE-100 Index: From 1992 to 1997
Unexpected Trading Volume
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-4.8
-3.2
-1.6
-0.0
1.6
3.2
Index Returns

Figure 5.4(b)

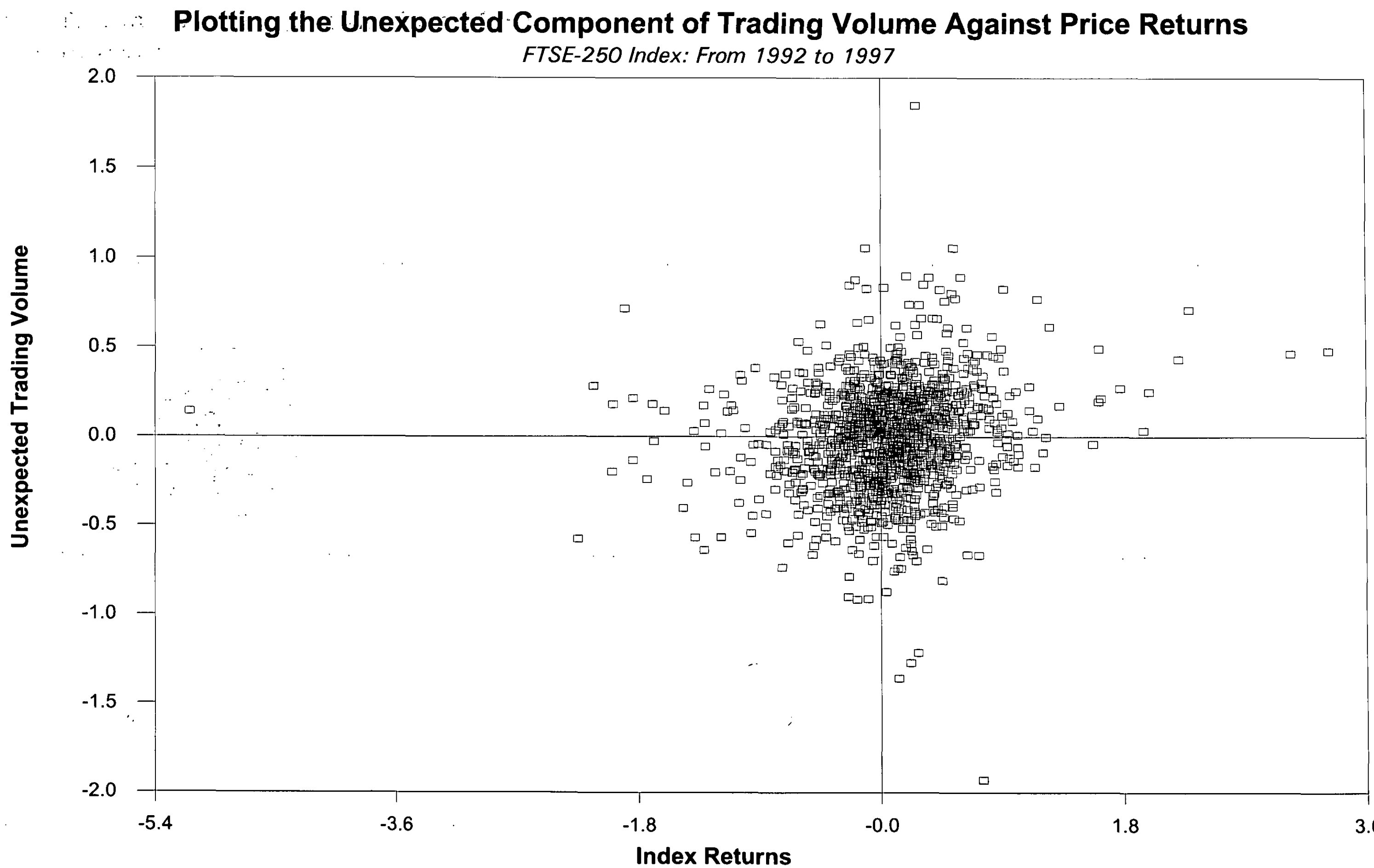
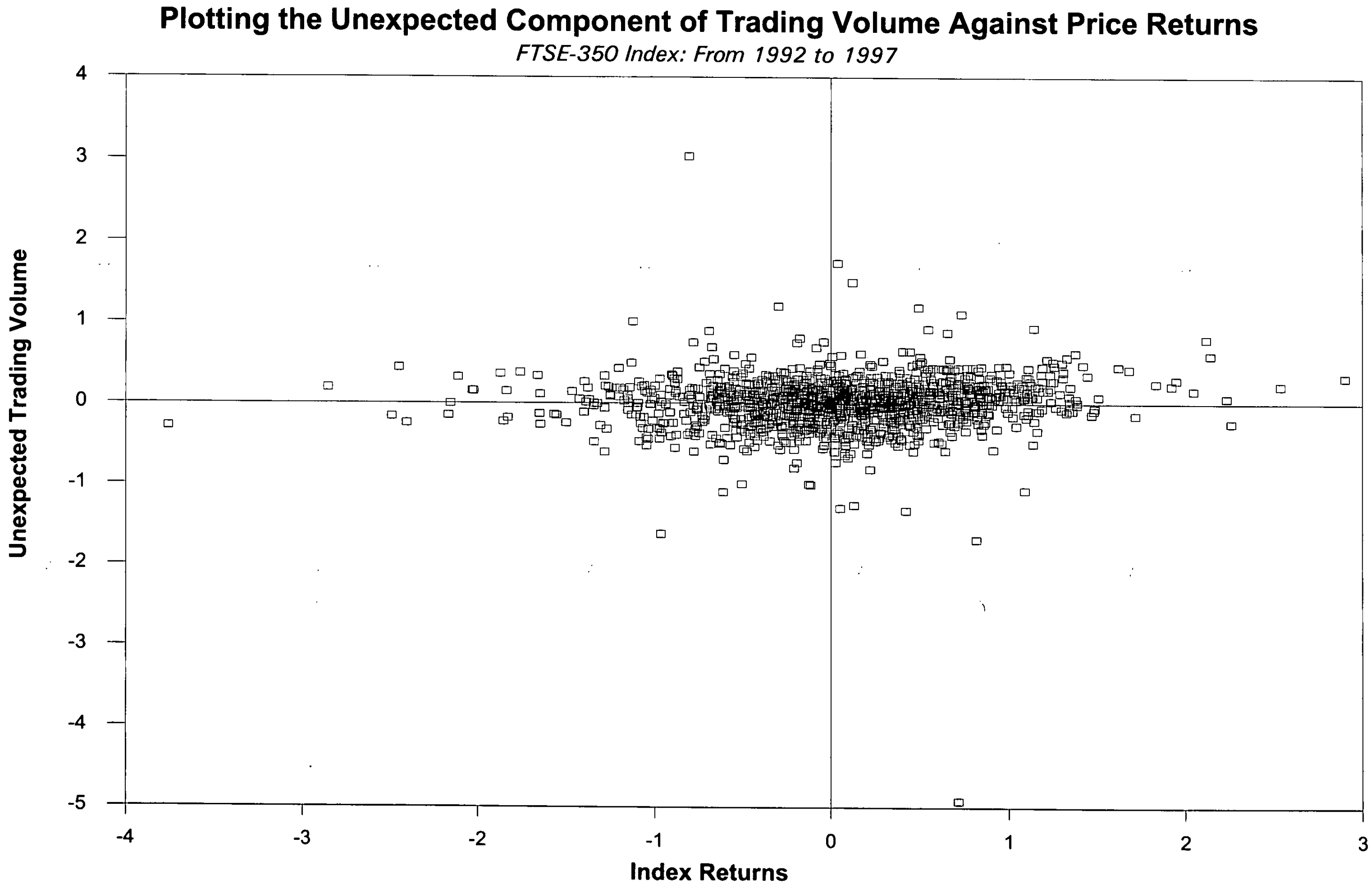

Plotting the Unexpected Component of Trading Volume Against Price Returns
FTSE-250 Index: From 1992 to 1997
Unexpected Trading Volume
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-5.4
-3.6
-1.8
-0.0
1.8
3.6
Index Returns

Figure 5.4(c)


Plotting the Unexpected Component of Trading Volume Against Price Returns
FTSE-350 Index: From 1992 to 1997
Unexpected Trading Volume
4
3
2
1
0
-1
-2
-3
-4
-5
-4
-3
-2
-1
0
1
2
3
Index Returns

5.6 EMPIRICAL RESULTS

5.6.1 GARCH Estimations

To begin with, the initial analysis focuses on the volume-volatility relationship using the following GARCH specification:

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + bh_{t-1} + \gamma V_t \qquad (5.15)$$

where

a_0 = the constant;

a_1 = the news coefficient;

b = the lagged conditional variance term;

γ = the volume coefficient.

As in the previous chapter, should residual returns continue to exhibit serial correlation, an AR(1) term will be included in the conditional mean that generates the error term ε_t. Furthermore, to solve the problem of simultaneity bias in the model specification, the volume term V_t is lagged one period back so that the GARCH model of equation (5.15) becomes

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + bh_{t-1} + \gamma V_{t-1} \qquad (5.16)$$

GARCH analysis in this study centres attention on a model specification that includes expected and unexpected components in volume. Table 5.4 presents GARCH estimations based on a restricted model that excludes trading volume V_t. *t*-statistics are in parentheses. In addition, the results present Ljung-Box $Q(12)$ and ARCH (12) statistics on the GARCH residuals as tests of the

Table 5.4

GARCH Estimations Without Trading Volume

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + bh_{t-1} + \gamma V_{t-1}$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + bh_{t-1}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.054	0.040	0.067
	(2.82)	(3.08)	(3.65)
ϕ_1	-	0.306	-
	-	(9.21)	-
a_0	0.003	0.033	0.046
	(1.47)	(6.95)	(5.03)
a_1	0.028	0.159	0.140
	(3.51)	(9.96)	(13.56)
b	0.966	0.697	0.772
	(88.26)	(21.88)	(37.59)
$a_1 + b$	0.994	0.856	0.912

Diagnostic Tests of the GARCH Residuals			
L-B $Q(12)$	20.451	20.798	25.763
(p-value)	(0.06)	(0.05)	(0.01)
ARCH $Q^2(12)$	21.129	9.527	30.812
(p-value)	(0.05)	(0.66)	(0.00)
Dickey Fuller Statistic	-0.691	-9.530	-11.199

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
Dickey Fuller test statistics compared with a critical value -2.8642 at the 0.05 level.
t-statistics in parentheses for the GARCH coefficients.

statistical adequacy of the models. According to the diagnostic analysis, the test results cannot reject the null hypothesis of no serial correlation and heteroscedasticity in the residuals.

In all cases, the GARCH parameters $\boldsymbol{a_1}$ and $\boldsymbol{b}$ are statistically different from zero, thus indicating the presence of GARCH effects. However, the GARCH estimates for the FTSE-100 index returns are a candidate for the near Integrated GARCH (IGARCH) process.[57] As discussed in Chapter Two, the presence of IGARCH effects implies that the conditional variance has memory and any shocks will have a permanent impact on volatility. As a test for IGARCH, table 5.4 also provides Dickey Fuller statistics that test the null hypothesis of nonstationarity and hence, an IGARCH process. In this case, the test findings cannot reject the null hypothesis at the 0.05 level, thus indicating that the conditional variance is nonstationary.

Turning to the GARCH parameters, the lagged conditional variance term $\boldsymbol{b}$ plays an important role in determining today's conditional variance of the FTSE-100 index. This provides evidence of volatility persistence which is not surprising given the presence of an IGARCH process. However, this interpretation differs for the other two indices. According to the GARCH coefficients $\boldsymbol{a_1}$ and $\boldsymbol{b}$, the FTSE-250 and FTSE-350 indices are more reactive to the arrival of new information.

[57] Near IGARCH arise where $a_1 + b$ is slightly less than one. This is well documented by Bollerslev (1987) and Ballie & Bollerslev (1989)

The analysis now proceeds to estimate the GARCH models of equations (5.15) and (5.16) that includes the expected component in volume. Table 5.5(a) and 5.5(b) present the results of the GARCH using contemporaneous and lagged trading volume. In all cases, the GARCH parameters $\boldsymbol{a_1}$ and $\boldsymbol{b}$ remain significantly different from zero despite the inclusion of the expected component. This contradicts the findings reported by Lamoureux & Lastrapes (1990) but is consistent with Najand & Yung (1991) and Sharma, Mougoue & Kamath (1996). In two out of the three indices, the expected component γ is statistically significant from zero only after lagging the volume term. As such, this observation indicates consistencies with the SIM of Copeland (1976) that postulates a lagged positive relationship between volume and volatility. The lack of a volume effect for the FTSE-100 index returns raises questions on the precision of the current information set. According to Kim & Verrechia (1991), this finding reflects the acquisition of low quality information forming the current information set.

These findings lead to the conclusion that the expected component in trading volume does not proxy the flow of information. The failure of volume to proxy the flow of information provides initial indications that variables other than trading volume help explain GARCH effects in index returns. In addition, this raises questions on the amount of information conveyed in forecastable volume. It is from this assertion that the analysis re-estimates the GARCH with the inclusion of trading volume driven by surprises.

Table 5.5(a)

GARCH Estimations With the Expected Component in Trading Volume

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = a_0 + a_1\varepsilon^2_{t-1} + bh_{t-1} + \gamma V_t$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.054	0.039	0.067
	(2.80)	(2.98)	(3.63)
ϕ_1	-	0.309	-
	-	(9.18)	-
a_0	0.004	0.036	0.046
	(1.46)	(6.96)	(5.13)
a_1	0.028	0.165	0.138
	(3.48)	(9.84)	(12.88)
b	0.966	0.682	0.775
	(86.94)	(20.36)	(37.95)
γ	0.052	0.075	0.155
	(0.31)	(1.38)	(1.05)
$a_1 + b$	0.994	0.757	0.913

Diagnostic Tests of the GARCH Residuals

Ljung-Box $Q(12)$	20.434	20.949	25.953
(p-value)	(0.06)	(0.05)	(0.01)
ARCH $Q^2(12)$	21.094	9.386	29.334
(p-value)	(0.05)	(0.67)	(0.00)
Dickey Fuller Statistic	-0.655	-9.79	-11.104

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
Dickey Fuller test statistics compared with a critical value -2.8642 at the 0.05 level.
t-statistics in parentheses for the GARCH coefficients.

Table 5.5(b)

GARCH Estimations With the Expected Component in Trading Volume Lagged one Period

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b h_{t-1} + \gamma V_{t-1}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.055	0.040	0.066
	(2.84)	(3.34)	(3.60)
ϕ_1	-	0.315	-
	-	(9.33)	-
a_0	0.003	0.039	0.050
	(1.36)	(7.67)	(5.22)
a_1	0.028	0.174	0.142
	(3.51)	(10.13)	(13.62)
b	0.966	0.659	0.759
	(89.27)	(20.33)	(35.62)
γ	0.087	0.166	0.260
	(0.48)	(3.97)	(7.20)
$a_1 + b$	0.994	0.833	0.901

Diagnostic Tests of the GARCH Residuals

Ljung-Box $Q(12)$	19.113	21.400	24.187
(p-value)	(0.09)	(0.04)	(0.02)
ARCH $Q^2(12)$	16.363	9.309	18.361
(p-value)	(0.18)	(0.68)	(0.11)
Dickey Fuller Statistic	-1.090	-10.247	-12.968

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
Dickey Fuller test statistics compared with a critical value -2.8642 at the 0.05 level.
t-statistics in parentheses for the GARCH coefficients.

Table 5.6(a) and 5.6(b) presents the GARCH results that include the unexpected component in trading volume. In all cases, the GARCH parameters remain significantly different from zero. Contrary to earlier findings, the unexpected component is significantly different from zero only when volume is contemporaneous. Despite the failure of volume to remove GARCH effects, the significance of the unexpected component for the FTSE-100 index appears to remove the presence of IGARCH, thus eliminating nonstationarity and hence, memory in the conditional variance.

In the light of earlier results, the higher γ coefficient values indicate that volume driven by surprises conveys more information of importance to the conditional variances than forecastable volume. However, one should treat these findings with caution given the potential for simultaneity bias in the GARCH system.

The overall conclusion thus far is that both components in trading volume are inadequate proxies for the information flow. It appears that the significance and nature of the volume-volatility relationship changes with the component of volume used and the composition of the index. The latter point is best illustrated in the comparisons made with the GARCH coefficients of the FTSE-100 and FTSE-250/FTSE-350 index returns.

Table 5.6(a)

GARCH Estimations With the Unexpected Component
in Trading Volume

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b h_{t-1} + \gamma V_t$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.048	0.036	0.066
	(2.46)	(2.92)	(3.57)
ϕ_1	-	0.303	-
	-	(9.42)	-
a_0	0.004	0.028	0.044
	(1.31)	(7.05)	(4.94)
a_1	0.032	0.149	0.135
	(3.43)	(10.20)	(13.25)
b	0.961	0.726	0.779
	(74.90)	(26.46)	(38.26)
γ	0.149	0.052	0.039
	(7.76)	(5.89)	(2.84)
$a_1 + b$	0.993	0.875	0.914

Diagnostic Tests of the GARCH Residuals

Ljung-Box $Q(12)$	20.835	19.653	25.385
(p-value)	(0.05)	(0.07)	(0.01)
ARCH $Q^2(12)$	19.466	9.961	31.709
(p-value)	(0.08)	(0.62)	(0.00)
Dickey Fuller Statistic	-3.528	-9.019	-10.980

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
Dickey Fuller test statistics compared with a critical value -2.8642 at the 0.05 level.
t-statistics in parentheses for the GARCH coefficients.

Table 5.6(b)

GARCH Estimations With the Unexpected Component in Trading Volume Lagged one Period

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b h_{t-1} + \gamma V_{t-1}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.055	0.039	0.055
	(2.83)	(3.01)	(3.15)
ϕ_1	-	0.308	-
	-	(9.20)	-
a_0	0.004	0.035	0.004
	(1.47)	(6.98)	(2.05)
a_1	0.028	0.163	0.030
	(3.59)	(9.89)	(4.01)
b	0.966	0.688	0.961
	(89.42)	(20.99)	(91.35)
γ	0.002	0.015	0.013
	(0.03)	(0.95)	(0.34)
$a_1 + b$	0.994	0.851	0.991

Diagnostic Tests of the GARCH Residuals			
Ljung-Box $Q(12)$	19.292	20.886	23.539
(p-value)	(0.08)	(0.05)	(0.02)
ARCH $Q^2(12)$	16.715	9.470	13.666
(p-value)	(0.16)	(0.66)	(0.32)
Dickey Fuller Statistic	-0.883	-9.684	-1.618

Significance tests at the 0.01 and 0.05 level

Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.

Dickey Fuller test statistics compared with a critical value -2.8642 at the 0.05 level.

t-statistics in parentheses for the GARCH coefficients.

5.6.2 EGARCH Estimations

The final stage of the analysis uses the following Exponential-GARCH process to investigate further the volume-volatility relationship

$$h_t = exp\{a_0 + a_1 \, log(h_{t-1}) + a_2\xi_{t-1} + \gamma V_t\} \qquad (5.17)$$

where ξ_{t-1} is the innovation term that incorporates the asymmetric coefficient θ_1. Once again, the problem of simultaneity bias in the EGARCH system is overcome by incorporating V_{t-1} into equation (5.17). Table 5.7 reports EGARCH results that exclude trading volume along with diagnostic test statistics. In only one case (FTSE-250 index) are all EGARCH parameters a_1, a_2 and θ_1 significantly different from zero. The presence of EGARCH effects for the FTSE-250 index returns is attributable to extreme observations in the data that are larger and more frequent (See the descriptive statistics of table 5.1). This is consistent with the notion postulated by Bollerslev, Chou & Kroner (1992) that the presence of EGARCH is a manifestation of a few extreme observations in the dataset.

According to the EGARCH coefficients, previous volatility a_1 plays a more important role on today's conditional variance when index prices follow a GARCH process (FTSE-100 and FTSE-350 indices). Although this suggests evidence of volatility persistence, the size of the a_1 coefficient indicates that traders rely on old news as an important piece of information. However, in the presence of asymmetries θ_1, the conditional variance of the FTSE-250 index is

Table 5.7

EGARCH Estimations Without Trading Volume

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = exp\{a_0 + a_1 \, log(h_{t-1}) + a_2 \xi_{t-1}\}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.049	0.038	0.051
	(2.59)	(2.87)	(2.97)
ϕ_1	-	0.331	-
	-	(10.97)	-
a_0	-0.127	-0.585	-0.141
	(-3.91)	(-11.59)	(-4.30)
a_1	0.985	0.864	0.981
	(151.88)	(44.70)	(141.81)
a_2	0.114	0.369	0.122
	(3.89)	(13.35)	(4.24)
θ_1	-0.207	-0.257	-0.178
	(-1.42)	(-6.06)	(-1.32)
Diagnostic Tests of the EGARCH Residuals			
Ljung-Box $Q(12)$	21.169	21.911	25.529
(p-value)	(0.05)	(0.04)	(0.01)
ARCH $Q^2(12)$	24.554	14.089	20.624
(p-value)	(0.02)	(0.30)	(0.06)

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
t-statistics in parentheses for the EGARCH coefficients.

better explained by the news coefficient a_2. Such a finding conforms to the notion that traders are more responsive to new information in view of the tendency to overreact to the arrival of negative innovations.

Following the same procedure as the GARCH analysis, the investigation moves on to estimate the EGARCH model that includes the expected component in volume. Table 5.8(a) and 5.8(b) displays the results using contemporaneous and lagged volume. Once again, the inclusion of volume fails to remove the presence of GARCH and EGARCH effects, thus leaving open the possibility that other factors besides volume explain the time varying nature of volatility. In all cases except for one, the expected component γ is insignificant irrespective of whether volume is lagged or contemporaneous. Once again, these findings raise questions on the quality of information that forms the trader's current information set.

Once again, the general failure of the expected component to proxy the flow of information questions the amount of information conveyed in forecastable volume. In the light of this conclusion, the final stage of the analysis involves re-estimating the EGARCH model with the inclusion of trading volume driven by surprises. Table 5.9(a) and 5.9(b) present EGARCH estimations that include the unexpected component in volume. Although the unexpected component fails to remove the presence of GARCH and EGARCH effects, the significance and size of the γ coefficient provide more evidence of a volume effect. This however only holds for contemporaneous volume. Once more,

Table 5.8(a)

EGARCH Estimations With the Expected Component in Trading Volume

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = exp\{a_0 + a_1 \log(h_{t-1}) + a_2 \xi_{t-1} + \gamma V_t\}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.049	0.037	0.051
	(2.57)	(2.80)	(2.97)
ϕ_1	-	0.333	-
	-	(10.95)	-
a_0	-0.128	-0.607	-0.142
	(-3.98)	(-11.54)	(-4.32)
a_1	0.984	0.857	0.981
	(153.32)	(42.36)	(141.24)
a_2	0.115	0.380	0.123
	(3.96)	(13.30)	(4.26)
θ_1	-0.218	-0.269	-0.171
	(-1.45)	(-6.07)	(-1.26)
γ	0.195	0.296	0.208
	(0.59)	(1.00)	(0.60)
Diagnostic Tests of the EGARCH Residuals			
Ljung-Box $Q(12)$	21.160	22.107	25.694
(p-value)	(0.05)	(0.04)	(0.01)
ARCH $Q^2(12)$	24.137	13.641	20.157
(p-value)	(0.02)	(0.32)	(0.06)

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
t-statistics in parentheses for the EGARCH coefficients.

Table 5.8(b)

EGARCH Estimations With the Expected Component in Trading Volume Lagged one Period

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = exp\{a_0 + a_1 \log(h_{t-1}) + a_2 \xi_{t-1} + \gamma V_{t-1}\}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.049	0.037	0.050
	(2.61)	(2.86)	(2.94)
ϕ_1	-	0.331	-
	-	(10.97)	-
a_0	-0.131	-0.587	-0.145
	(-4.00)	(-11.53)	(-4.42)
a_1	0.984	0.864	0.982
	(146.95)	(44.48)	(141.66)
a_2	0.117	0.369	0.125
	(3.97)	(13.24)	(4.34)
θ_1	-0.186	-0.254	-0.186
	(-1.26)	(-5.87)	(-1.45)
γ	0.092	0.117	0.729
	(0.22)	(0.36)	(2.04)

Diagnostic Tests of the EGARCH Residuals			
Ljung-Box $Q(12)$	19.981	21.911	23.854
(p-value)	(0.07)	(0.04)	(0.02)
ARCH $Q^2(12)$	15.878	14.030	11.546
(p-value)	(0.20)	(0.30)	(0.48)

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
t-statistics in parentheses for the EGARCH coefficients.

Table 5.9(a)

EGARCH Estimations With the Unexpected Component in Trading Volume

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = exp\{a_0 + a_1 \log(h_{t-1}) + a_2 \xi_{t-1} + \gamma V_t\}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.037	0.032	0.046
	(1.95)	(2.53)	(2.66)
ϕ_1	-	0.310	-
	-	(10.76)	-
a_0	-0.134	-0.489	-0.146
	(-3.75)	(-10.98)	(-4.20)
a_1	0.985	0.902	0.981
	(138.03)	(56.87)	(133.30)
a_2	0.120	0.328	0.126
	(3.74)	(12.49)	(4.16)
θ_1	-0.208	-0.241	-0.181
	(-1.42)	(-4.92)	(-1.34)
γ	0.500	0.433	0.243
	(9.60)	(7.87)	(4.86)

Diagnostic Tests of the EGARCH Residuals

Ljung-Box $Q(12)$	21.724	20.416	24.481
(p-value)	(0.04)	(0.06)	(0.02)
ARCH $Q^2(12)$	21.840	17.533	22.961
(p-value)	(0.04)	(0.13)	(0.03)

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
t-statistics in parentheses for the EGARCH coefficients.

Table 5.9(b)

EGARCH Estimations With the Unexpected Component in Trading Volume Lagged one Period

$$R_t = \eta + \phi_1 R_{t-1} + \varepsilon_t$$

$$h_t = exp\{a_0 + a_1 \log(h_{t-1}) + a_2 \xi_{t-1} + \gamma V_{t-1}\}$$

GARCH Coefficients	FTSE-100	FTSE-250	FTSE-350
η	0.049	0.037	0.052
	(2.60)	(2.81)	(3.00)
ϕ_1	-	0.333	-
	-	(10.94)	-
a_0	-0.133	-0.607	-0.149
	(-4.09)	(-11.57)	(-4.43)
a_1	0.984	0.857	0.979
	(150.25)	(42.47)	(135.98)
a_2	0.119	0.379	0.127
	(4.06)	(13.33)	(4.35)
θ_1	-0.196	-0.265	-0.160
	(-1.32)	(-5.95)	(-1.18)
γ	0.033	0.063	0.064
	(0.32)	(0.73)	(0.66)

Diagnostic Tests of the EGARCH Residuals			
Ljung-Box $Q(12)$	20.027	22.088	24.480
(p-value)	(0.07)	(0.04)	(0.02)
ARCH $Q^2(12)$	16.005	13.729	12.585
(p-value)	(0.19)	(0.32)	(0.40)

Significance tests at the 0.01 and 0.05 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom.
t-statistics in parentheses for the EGARCH coefficients.

these results should be treated with caution given the potential for simultaneity bias in the model specification. A consistent feature of these findings is the importance of old news in explaining today's conditional variance of all three price indices. Nevertheless, contemporaneous volume helps explain more the EGARCH effect than the GARCH results reported in table 5.6(a).

5.7 SUMMARY AND CONCLUSIONS

The objective of this chapter is to re-examine the relationship between trading volume and price volatility in relation to UK data. Consistent with previous investigations, the underlying issue in this study focused on whether heteroscedasticity in the returns process is explainable through the inclusion of trading volume as the stochastic mixing variable. For this reason, the study uses trading volume to proxy the flow of information. Although the GARCH methodology and the recent work on the informational role of volume are utilised for this purpose, this study makes two significant contributions to the literature reviewed in Chapter One. Firstly, the current investigation proposes the Exponential-GARCH methodology in this capacity to investigate whether the volume effect removes EGARCH effects. In failing this, the EGARCH analysis poses the empirical question of whether the volume effect is more evident in the presence of asymmetries. The second contribution lies in the treatment of volume. Unlike previous studies using GARCH, this investigation extracts information on the expected and unexpected components of trading volume. By extracting both components, the study can determine whether volume driven by surprises conveys more information and hence, impact further on price volatility than forecastable volume.

Preliminary results find early evidence that both expected and unexpected components convey information of relevance to the pricing of all indices. However, the results fail to provide information on the quality of the information signal. The (E)GARCH results reveal evidence of changes in the significance and nature of the volume-volatility relationship depending on the component of volume used and the composition of the index. On this basis, the study concludes that this is attributable to the size of the market responding differently to current information and surprises. Furthermore, in all cases, the volume term γ fails to eliminate the presence of (E)GARCH effects. A consequence of this finding is to leave open the possibility that other factors besides volume help explain the heteroscedastic nature of index returns. The implication of this result is that trading volume is an inadequate proxy for the flow of information.

The analysis reports important findings in response to issues raised by Bessembinder & Seguin (1993) warranting further research. In other words, a relationship between volume and volatility that is driven by current information and surprises. For instance, the significance of the expected component γ when including lagged trading volume presents evidence against the MDH of Epps & Epps (1976) and Harris (1987). On the other hand, the significance of the unexpected component when volume is contemporaneous leads to the interpretation that price volatility and volume represent a mixture of distribution. However, the elimination of the volume effect after including V_{t-1} into the (E)GARCH model raises the possibility that the contemporaneous volume-volatility relationship is attributable to simultaneity bias. Hence, one should exercise caution when interpreting the results.

In addition, the study reveals important findings to issues not identified in the literature; for instance, whether the volume effect is larger when trading is induced by surprises. The results indicate support for this hypothesis, which is most evident when using the EGARCH model. Furthermore, the lack of a volume effect when using the expected component raises questions on the precision of the current information set. According to the Kim & Verrechia (1991) model, this is indicative of the acquisition of low quality information forming the current information set. Finally, the EGARCH results suggest no evidence of a relationship between the existence of asymmetries and the size of the volume effect.

Other than making a number of contributions to the literature, the results in this study have practical implications on the regulatory requirements of the market. Given the failure of volume to proxy the flow of information, regulating trading practises to control the volume of trading may be harmful to the effective functioning of the market. This follows the notion that this reflects the operation of an efficient market where traders cannot use trading volume to forecast future changes in prices. Equally, this raises the suspicion that variables other than trading volume determines index price volatility outside the confines of the (E)GARCH systems. One possible factor is the amount of noise trading in the market. As a consequence, the imposition of regulatory controls in such a scenario may enhance the effective functioning of the market.

CHAPTER SIX

ASYMMETRIC TRANSMISSION OF VOLATILITY BETWEEN STOCK MARKETS

6.1 INTRODUCTION

High trading time volatility arises due to the arrival process itself, that is, whether information arrives in clusters or in the dynamics that govern the market's response to this news. A well-documented argument is the notion that traders in any given market takes into consideration in their 'buy' and 'sell' decisions both domestically generated information and information produced by other stock markets. If information generated in foreign stock markets is relevant to the pricing of stocks in the domestic market, this is the product of an efficient international market. The increased globalisation of world economies through international trading and investments has been accompanied by the globalisation of financial markets. Investors can now consider the opportunities in all markets when making investment decisions given the ability of participants to trade in markets with the lowest regulatory standards and costs. Subsequently, the globalisation of financial markets has led to increased competition and co-operation amongst major financial centres.

This chapter examines the extent to which asymmetries govern the transmission of volatility across the Tokyo, London and New York markets between 1984 and 1997. The underlying notion of this study is to view the magnitude and sign of innovations as the driving force behind the relationship between national stock markets. While the Tokyo and London markets open and close in sequence, so does Tokyo and New York. However, there is a two-hour overlap between the start of New York trading and close of the London market. As a consequence, this study takes into account time zone differences when investigating market interdependencies. The objective of the study is to document additional evidence on the nature of price and volatility spillovers across national markets. Therefore, the initial part of the analysis investigates whether price and volatility spillovers reflect the evaluation of the size and sign of news by the next market to trade. Within this framework, the motivation of the study is the identification of additional issues raised by the market models reviewed in Chapter One: *whether asymmetries in the transmission of volatility are induced by extreme, uncommon events such as the October 1987 Crash and by an extra half-day of trading in Tokyo during some weekends.*

The first issue is in response to the proposition forwarded by Bollerslev, Chou & Kroner (1992) who argue that the asymmetric component in conditional volatility may be the product of extreme uncommon observations. The motivation behind the second issue lies in the Barclay, Litzenberger & Warner (1990) and Puffer (1991) studies in which they investigated the spillover effects of weekend trading in Tokyo using variance ratio methodology. In addition, there are two institutional features of the Tokyo market that warrants some explanation for its consideration in this investigation. Firstly, although the London and New York markets trade from Monday to Friday, the Tokyo market opened for a half day of trading on some Saturdays. Between August 1983 and July 1986, the Tokyo stock market was closed every second Saturday. This increased to the second and third weekends of each month from August 1986 to January 1989. From February 1989, weekend trading ceased completely. Secondly, trading in the Tokyo market takes place outside London and New York trading hours. This means that UK and US stocks listed in the Tokyo market are subject to almost around the clock trading. However, since transaction costs are lower in the domestic market for domestically listed stocks, trading volume will be low in foreign stocks in comparison.[58] This contrasts sharply with the UK market given the abolition of stamp duty on internationally listed stocks.[59]

One implication of undertaking this type of analysis is the larger sample period required to take into account the October 1987 Crash and weekend trading in Tokyo. To investigate whether these two events induced asymmetries in volatility transmissions, much attention will focus on two sub-samples of unequal length from January 1984 to January 1989 and February 1989 to December 1997.

The methodology proposed is the bivariate-EGARCH model introduced in Chapter Two of the thesis. The extension of EGARCH into a bivariate setting

[58] See Barclay, Litzenberger & Warner (1990).
[59] See table 1.1 in Chapter One on turnover figures for both domestic and internationally listed stocks.

allows one to model the asymmetric component in volatility transmissions between the Tokyo, London and New York markets. Moreover, this approach models price spillovers across markets, a common theme existing in previous studies. Therefore, for the purpose of this study, it is an ideal candidate.

This study finds evidence of an asymmetric component in the transmission of volatility where negative information originating from the last market to trade magnifies the volatility spillover to the next market. In addition, the importance of the asymmetric component is dependent upon the treatment of the October 1987 Crash and weekend trading in the bivariate-EGARCH model. The implication of the former leads one to conclude that the asymmetric component is a manifestation of extreme uncommon observations. On the other hand, weekend trading appears to induce asymmetries in the volatility transmission from Tokyo to London and New York, but not vice versa.

The chapter will proceed as follows; the next section examines how market dynamics and the nature of information can explain market interdependencies. Section 6.3 introduces the bivariate-EGARCH methodology and section 6.4 discusses the data and descriptive statistics. Section 6.5 presents the main results followed by a summary and conclusion in section 6.6.

6.2 THEORETICAL DISCUSSION

6.2.1 The Issue of Volatility Spillovers

One of the main characteristics of stock market dynamics is the tendency for volatility to cluster where turbulent periods are followed by tranquil periods. In addition, the volatility in one market can be attributable in part to the clustering of information in the last market to trade. Ito, Engle & Lin (1990) and Engle, Ito & Lin (1992) introduced the Heat Wave and Meteor Showers Hypothesis as two competing explanations behind the clustering of stock prices. The heat wave hypothesis stipulates that the clustering of stock prices is due to the arrival of country specific information. As a consequence, a large shock only affects the conditional variance of that country. In contrast, the meteor showers hypothesis postulates that a shock originating from the domestic market will have a spillover effect on other markets. Ito *et al* (1990) adequately describes this phenomenon using meteorological terminology

> *"Using meteorological analogies, we suppose that news follows a process like a heat wave so that a hot day in New York is likely to be followed by another hot day in New York but not typically by a hot day in Tokyo. The alternative analogy is a meteor shower which rains down on the earth as it rains. A meteor shower in New York will almost be followed by one in Tokyo." (p.526, 1990)*

The heat wave and meteor showers hypothesis has practical implications when considering the evolution of the relationship between major stock markets. In relation to the first issue in this study, the market that experiences extreme uncommon events followed by a clustering of prices is consistent with the heat wave hypothesis. In the next market to trade, the clustering of prices caused by the shock is attributable to the meteor showers theorem. According to the heat wave hypothesis, the second issue in this study has both empirical and theoretical implications. If the clustering of information revealed from weekend trading is domestic, it is likely to impact the volatility in that market on the same day and the next day of trading. As a consequence, there will be low correlation in the behavioural patterns of index returns across markets. The intuition behind this lies in the asymmetric information model of Kim & Verrecchia (1991). Their model assumes that a public announcement will have an effect on volatility only if the private information prior to its release at time t, is of average precision or quality. Consequently, their model predicts that volatility will be high at time t as private information is gradually disseminated into prices. This will be followed by another volatile day at time t+1 as traders revise their expectations following the release of the public announcement. This is an assumption that underpins the dynamics of the market that leads to the assertion that the clustering of volatility is attributable to the heat wave hypothesis.

On the other hand, the meteor showers hypothesis states that information revealed during trading in market i at time t, will have a spillover effect at the commencement of trading in market k either on the same day or at time $t+1$. For instance, worldwide news originating from Tokyo will have a spillover effect on the London and New York markets on the same day. Conversely, news originating from either London or New York will not have an impact on the Tokyo market until the next day. Although the market models of Kyle (1985) and Admati & Pfleiderer (1988) provide some intuition behind this phenomenon, the meteor shower effect could also represent a violation of market efficiency. Intuitively, meteor showers can be indicative of the domestic market's failure to fully incorporate its information into domestic stock prices. For instance, a shock originating from market i at time t may change market expectations of further shocks, i.e., a bandwagon effect. The failure of market i to disseminate information may encourage speculation to take place in market k at time $t+1$ in anticipation of further shocks when trading commences in market i. This argument assumes that information is not fully revealing in both markets.[60]

6.2.2 A Model of the Volatility Transmission Between Two Markets

The remainder of this section provides a theoretical framework to illustrate the transmission of information between two markets (i and k) using the contagion model of King & Wadhwani (1990). They envisage a scenario where information is of two types; first, news affecting both markets denoted as $\boldsymbol{\Phi}$

[60] See the contagion model introduced by King & Wadhwani (1990). Next in section 6.2.2 introduces a mechanism of volatility transmission that resembles a contagion model.

and second, country-specific news defined as Ω. To begin with, they define the process that generates price changes in both markets as:

$$SP_{i,t} - SP_{i,t-1} = \Phi_{i,t} + \alpha_{i,k} E_1(\Phi_{k,t}) + \Omega_{i,t} \qquad (6.1a)$$

$$SP_{k,t} - SP_{k,t-1} = \alpha_{k,i} E_2(\Phi_{i,t}) + \Phi_{k,t} + \Omega_{k,t} \qquad (6.1b)$$

where $SP_{i,t} - SP_{i,t-1} = \Delta SP_{i,t}$ and $SP_{k,t} - SP_{k,t-1} = \Delta SP_{k,t}$ is the percentage change in the spot price in markets *i* and *k* respectively. The terms E_1 and E_2 is the expectators operator conditional upon news revealed in both markets. Equations (6.1a) and (6.1b) states that the change in the spot price of market *i* provides information for the next market to trade *k* on the nature of the information revealed in market *i*. However in this model, there is a non-fully revealing component because some information is country-specific and hence, is irrelevant to the next market to trade. Consequently, agents in market *k* face the problem of determining the value of information observed in market *i* that is of relevance to them.

King *et al* provides a solution by defining $E_1(\Phi_{k,t})$ and $E_2(\Phi_{i,t})$ in equations (6.1a) and (6.1b) as

$$E_1(\Phi_{k,t}) = \Theta_2\left[\Delta SP_{k,t} - \alpha_{i,k} E_2(\Phi_{i,t})\right] \qquad (6.2a)$$

$$E_2(\Phi_{i,t}) = \Theta_1\left[\Delta SP_{i,t} - \alpha_{k,i} E_1(\Phi_{k,t})\right] \qquad (6.2b)$$

where Θ represents the variance of the information flow

$$\Theta = \frac{\sigma^2_{\Phi x}}{\sigma^2_{\Phi x} + \sigma^2_{\Omega x}} \qquad \text{where } x = i, k \qquad (6.3)$$

By substituting equations (6.2a) and (6.2b) into (6.1a) and (6.1b), they modify the process that generates changes in prices of both markets:

$$\Delta SP_{i,t} = \left(1 - \alpha_{i,k}\alpha_{k,i}\Theta_1\Theta_2\right)\left(\Phi_{i,t} + \Omega_{i,t}\right) + \alpha_{i,k}\Theta_2\Delta SP_{k,t} \qquad (6.4a)$$

$$\Delta SP_{k,t} = \left(1 - \alpha_{i,k}\alpha_{k,i}\Theta_1\Theta_2\right)\left(\Phi_{k,t} + \Omega_{k,t}\right) + \alpha_{k,i}\Theta_1\Delta SP_{i,t} \qquad (6.4b)$$

Note that the problem with the price generating process of equations (6.4a) and (6.4b) is that the parameters α and Θ cannot be identified separately. To overcome this, they define the α and Θ parameters for markets i and k in terms of

$$\beta_{i,k} = \alpha_{i,k}\Theta_k \qquad \text{where } \Theta_k = \Theta_2 \qquad (6.5a)$$

$$\beta_{k,i} = \alpha_{k,i}\Theta_i \qquad \text{where } \Theta_i = \Theta_1 \qquad (6.5b)$$

where β measures the elasticity of the change in price in market i in response to a shock from market k and vice versa. By defining the current information set π_x as

$$\pi_x = \Phi_x + \Omega_x \qquad \text{where } x = i, k \qquad (6.6)$$

and solving equations (6.4a) and (6.4b), the price generating process becomes:

$$\Delta SP_{i,t} = \pi_{i,t} + \beta_{i,k}\pi_{k,t} \qquad (6.7a)$$

$$\Delta SP_{k,t} = \pi_{k,t} + \beta_{k,i}\pi_{i,t} \qquad (6.7b)$$

From equations (6.7a) and (6.7b), the volatility of stock price changes in markets i and k respectively are

$$Var\left(\Delta SP_{i,t}\right) = \sigma^2_{\pi i} + \left(\beta_{i,k}\right)^2 \sigma^2_{\pi k} \qquad (6.8a)$$

$$Var\left(\Delta SP_{k,t}\right) = \sigma^2_{\pi k} + \left(\beta_{k,i}\right)^2 \sigma^2_{\pi i} \qquad (6.8b)$$

and the covariance of the two markets $Cov(\Delta SP_i, \Delta SP_{k,t})$ expressed as:

$$Cov(\Delta SP_i, \Delta SP_{k,t}) = \beta_{k,i}\sigma^2_{\pi i} + \beta_{i,k}\sigma^2_{\pi k} \qquad (6.9)$$

Within the framework of the contagion model just described, the investigation essentially focuses on changes in price volatility as a consequence of changes in the β parameter that are attributable to changes in the Θ term. In considering extreme uncommon shocks, the view taken is to observe these events in terms of the information content, thus impacting the value of β. On the other hand, by investigating the effects of weekend trading in one market, the assumption made is that the rate of information flow Θ changes.[61]

6.3 BIVARIATE-EGARCH METHODOLOGY

To investigate the asymmetric component in the transmission of volatility, the study utilises the bivariate-EGARCH model. To take into account time zone differences, the EGARCH model is adjusted so that the mean and variance in each market is conditional on domestically generated information and information revealed by the last market to trade. The motivation behind the use of the bivariate-EGARCH model lies in the number of advantages the bivariate setting has over the univariate approach. Although it improves the power and efficiency of tests for price and volatility spillovers, the bivariate-EGARCH serves the useful purpose of modelling spillovers as manifestations of the impact of worldwide information on any market. Given the inclusion of the

[61] This is based on the proposition of Ross (1989) that changes in stock price volatility is a reflection of changes in the information flow.

asymmetric term, the bivariate-EGARCH allows own market and cross-market innovations to have an asymmetric impact on the volatility of the next market to trade. This implies that news revealed through trading in one market is evaluated with respect to both size and sign by the next market. Hence, it is an ideal candidate for this study.

The EGARCH in its bivariate form enables one to model price spillovers[62] in the mean equation and volatility spillovers[63] of price changes in the second moments. In this type of study, the treatment of returns in the first moments is of paramount importance in modelling price spillovers given the difference in time zone at which these markets operate.[64] As a consequence, this study investigates market interdependencies in the mean by using a procedure that resembles the Granger specification of Malliaris and Urrutia (1992).

Suppose a global shock originates from Tokyo at time *t*, at 12:00 am GMT. Although the shock will immediately impact on Tokyo returns, it will also affect London and New York returns on the same day, 9 and 14.5 hours after the shock. To explain the adjustment of returns in the first moments, lets begin by defining market i as the last market to trade and market k as the current market in operation. In addition, define y_1, y_2, y_3 as index returns on the

[62] Price spillovers is a measure of the effect of an innovation originating from market i on the conditional mean of market k.
[63] Volatility spillovers is a measure of the effect of an innovation originating from market i, on the conditional volatility of market k.
[64] The intuition behind this is the notion that correlation between markets is dependent upon the time zone in which the markets operate, a common theme found with previous studies reviewed in Chapter One.

Tokyo, London and New York markets respectively. Therefore, London returns in the first moments are expressed as:

$$y_{2,t} = \delta_0 + \sum_{m=1}^{1} \phi_1 y_{i,t-m} + \sum_{n=1}^{1} \phi_2 y_{k,t-n} + \varepsilon_t \tag{6.10}$$

$$\varepsilon_t | (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_{k,t}),$$

where i,k = 1,2,3 (1 = Tokyo, 2 = London and 3 = New York), ε_t is the innovation at time t and $y_{i,t-m}$ measures the price spillover of the last market to trade, i.e. Tokyo. The term $y_{k,t-n}$ denotes lagged index returns on the London market. Similarly, the mean equation for New York returns is defined as:

$$y_{3,t} = \delta_0 + \sum_{m=1}^{1} \phi_{1,2} y_{i,t-m} + \sum_{n=1}^{1} \phi_3 y_{k,t-1} + \varepsilon_t \tag{6.11}$$

where the term $\phi_{1,2}$ indicates that a shock from Tokyo and London will impact the New York market on the same day. On the other hand, suppose a random shock originates from London on any given day. The shock will impact London and New York returns on the same day t and Tokyo returns on the following day at time t+1. Consequently to model price spillovers requires an adjustment for time zone differences so that Tokyo returns in the first moments are:

$$y_{1,t+1} = \delta_0 + \sum_{m=1}^{1} \phi_{2,3} y_{i,t-m} + \sum_{n=0}^{1} \phi_1 y_{k,t-n} + \varepsilon_t \tag{6.12}$$

in which $\phi_{2,3}$ implies that shocks originating from London and New York will have an impact on Tokyo index values the next day. Given the use of end of day index values, the same adjustment is made for modelling price spillovers from New York to London.

To investigate market interdependencies in the second moments requires the estimation of the following bivariate-EGARCH process:

$$h_{k,t} = exp\left\{\omega_{k,0} + \sum_{k=1}^{2} \alpha_k ln\left(h_{k,t-1}\right) + \beta_{i,k} \sum_{k=1}^{2} \Pi_{i,t-1}\right\} \tag{6.13a}$$

$$h_{i,k,t} = \rho_{i,k}\sqrt{h_{i,t} h_{k,t}} \tag{6.13b}$$

where $h_{i,k,t}$ is the conditional covariance defined as $Cov\left(\varepsilon_{i,t}, \varepsilon_{k,t} | \Psi_{t-1}\right)$ for i,k = 1,2,3. This represents a measure of the intra-daily lead/lag relationship and defines the conditional covariance in each market as the exponential of past own and cross market standardised innovations. The term $h_{k,t-1}$ is the lagged conditional variance and the innovation Π from market i is defined as:

$$\Pi_{i,t-1} = \left[\left(\frac{|\varepsilon_{i,t-1}|}{\sqrt{h_{i,t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \theta_i \left(\frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}}\right)\right] \tag{6.14}$$

The importance of equation (6.14) is that it captures the volatility spillover as a manifestation of the size and nature of the innovation from the last market to trade. Asymmetries are present when θ_i is negative and significantly different from zero whereas the coefficient $\beta_{i,k}$ is a measure of the volatility spillover across markets. Therefore, a positive $\beta_{i,k}$ that is significantly different from zero along with a negative θ_i indicates that bad news from market i has a greater impact on the volatility of market k than good news.

6.4 DATA AND PRELIMINARY RESULTS

6.4.1 The Dataset

The dataset used in this chapter consists of daily closing index values on the Nikkei 225 Stock Average, FTSE-100 and the Dow Jones 65 Composite Indices from January 1, 1984 to December 29, 1997. The data was downloaded from Datastream International. To undertake an investigation of this nature requires a larger sample than used in previous chapters to take into account the October 1987 Crash and weekend trading in Tokyo.[65] To investigate the source of asymmetries in the transmission of volatility, whether it is induced by the crash or by weekend trading, requires two sample periods of unequal length; January 1, 1984 to January 31, 1989 and February 1, 1989 to December 29, 1997. The first sub-sample takes into account the crash period and ends in January 1989 to coincide with the ceasing of weekend trading. The second sub-sample coincides with normal market conditions.

Despite the availability of opening index values for all indices, Datastream does not report index values for Saturday trading. As a consequence, this study computes close-to-close index returns as opposed to returns defined from the open to the close of trading. The trading times for the Tokyo market are midnight - 2:00 am and 4:00 am - 6:00 am GMT, which is prior to the commencement of trading in London (9:00 am - 5:00 pm) and New York (2:30

[65] Although the sample size includes Saturday trading in Tokyo, the stickiness of closing index values reported by Datastream restricted the starting date to January 1, 1984.

pm - 9:00 pm). The next subsection provides preliminary results to reveal information on each of the return series.

6.4.2 *Descriptive Statistics*

Table 6.1 presents summary statistics for daily close-to-close index returns of all three markets for the whole sample period. This includes the mean, variance, minimum and maximum values along with the skewness and kurtosis of the return series. The statistics also include the Ljung-Box (1978) test results for twelfth order serial correlation. P-values are in parentheses. With the exception of Tokyo index returns, the sample means of the remaining two markets are significantly different from zero. In addition, the index returns of all three markets exhibit negative skewness and leptokurtosis that is most profound for New York returns. Collaborating with the evidence reviewed in Chapter Two, the Ljung-Box Q-statistics detects evidence of serial dependencies in the index returns of all three markets.

Figure 6.1(a) to 6.1(c) provides visual inspection of Tokyo, London and New York data. This shows time series plots of continuously compounded index returns for the Nikkei 225 Average, FTSE-100 and Dow Jones 65 Composite Indices. The shaded part of the graph represents the time period that coincides with weekend trading in Tokyo between 1984 and 1989. Other than determining whether the i.i.d conditions hold, the graphs serve to justify the methodology used in this study. Apart from showing clear evidence of clustering in the dataset, of particular interest is the correlation of the clusters

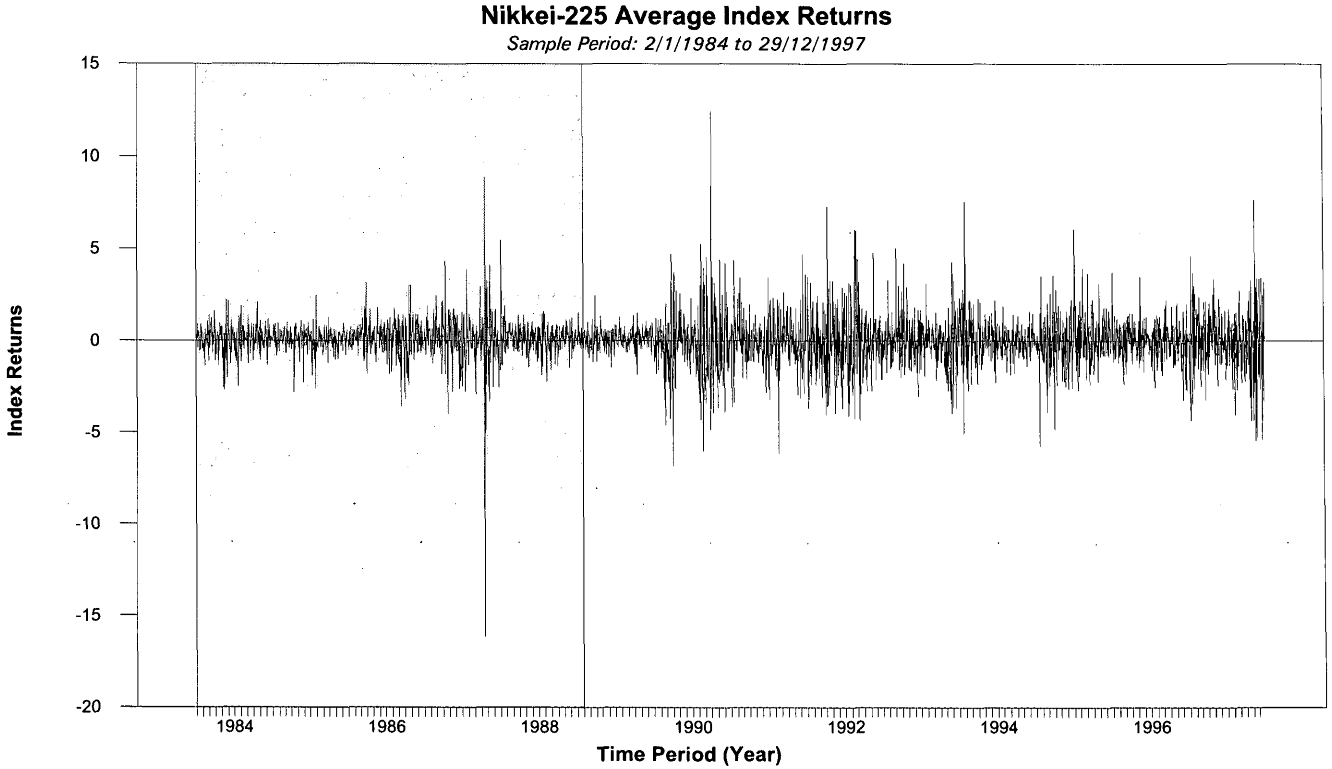
Table 6.1

Descriptive Statistics for Daily Close-to-Close Returns
Sample period: January 1, 1984 to December 29, 1997

	Tokyo	London	New York
Sample mean	0.012	0.048*	0.045*
Variance	1.644	0.830	0.871
Maximum	12.430	7.597	8.419
Minimum	-16.135	-13.029	-22.475
Skewness	-0.232	-1.420	-4.141
(p-value)	(0.00)	(0.00)	(0.00)
Excess kurtosis	13.019	21.854	98.791
(p-value)	(0.00)	(0.00)	(0.00)
L-B $Q(12)$	42.975	54.514	44.153
(p-value)	(0.00)	(0.00)	(0.00)

*Reject the null hypothesis that mean = 0 at the 0.05 level
L-B = Ljung-Box Q-statistic are chi-square distributed
$Q(12)$ test statistic compared with critical value of 21.0261

Figure 6.1(a)



Nikkei-225 Average Index Returns
Sample Period: 2/1/1984 to 29/12/1997
15
10
5
0
-5
-10
-15
-20
Index Returns
1984
1986
1988
1990
1992
1994
1996
Time Period (Year)

Figure 6.1(b)

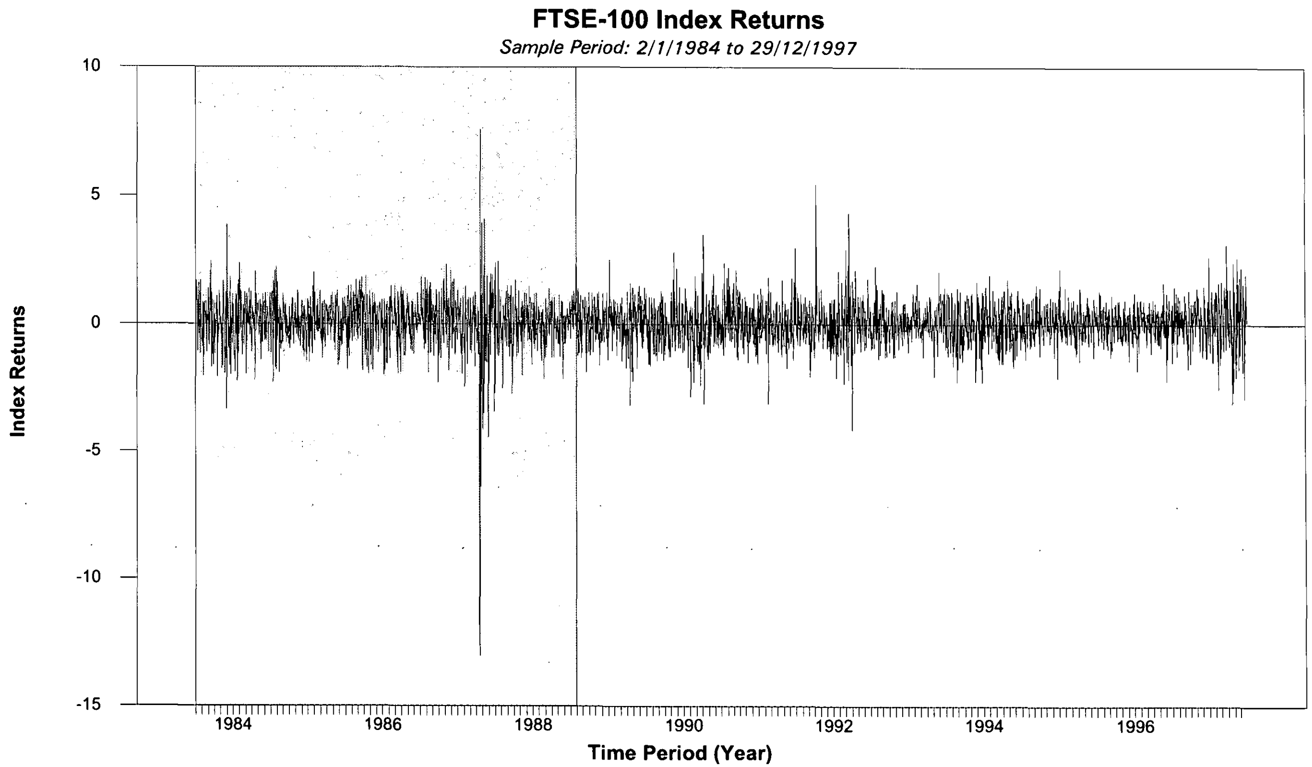

FTSE-100 Index Returns
Sample Period: 2/1/1984 to 29/12/1997
Index Returns
10
5
0
-5
-10
-15
1984
1986
1988
1990
1992
1994
1996
Time Period (Year)

Figure 6.1(c)

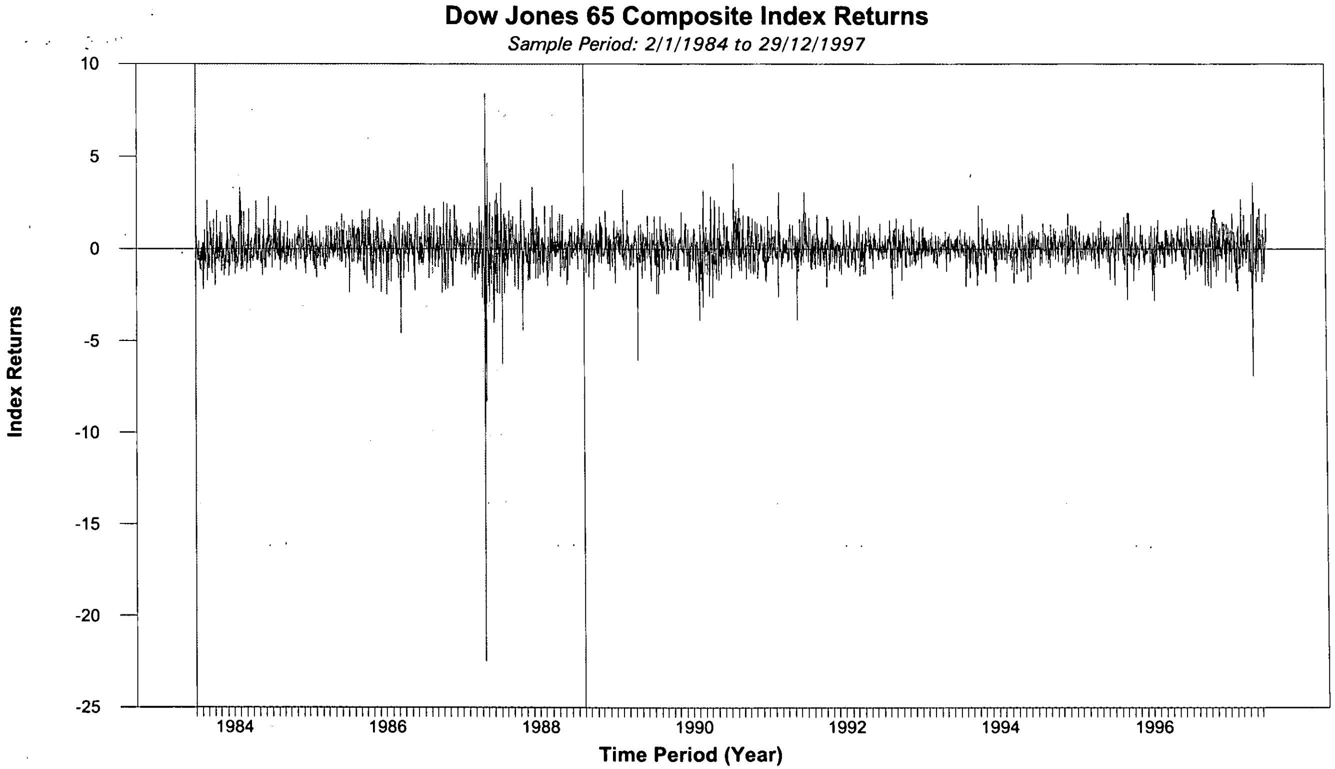

Dow Jones 65 Composite Index Returns
Sample Period: 2/1/1984 to 29/12/1997
10
5
0
-5
-10
-15
-20
-25
Index Returns
1984
1986
1988
1990
1992
1994
1996
Time Period (Year)

Table 6.2

Correlation Statistics for Index Returns

	$Corr(R_1, R_2)$ Ljung-Box Q-Statistic	P-values
	Whole Sample	
Tokyo & London	2124.212	(0.00)
Tokyo & New York	2106.675	(0.00)
London & New York	2956.326	(0.00)
	1984 to 1989	
Tokyo & London	971.770	(0.00)
Tokyo & New York	1133.260	(0.00)
London & New York	1136.839	(0.00)
	1989 to 1997	
Tokyo & London	1351.135	(0.00)
Tokyo & New York	1306.514	(0.00)
London & New York	1573.784	(0.00)

where R_1, R_2 are index returns for country 1 and 2 respectively.

between the return series. Table 6.2 confirms this finding using the Ljung-Box Q-statistics of the cross correlations between the three index return series over the entire sample period. In the light of these results along with evidence of volatility clustering, this motivates the use of the bivariate conditional heteroscedastic model as the ideal candidate for this study.

6.5 BIVARIATE-EGARCH ANALYSIS ON DAILY DATA

6.5.1 Bivariate-EGARCH Analysis on the Whole Sample

The initial part of the analysis aims to identify the existence of an asymmetric component in the transmission of volatility across national stock markets. As a starting point in using the bivariate-EGARCH model, the first step involves estimating the following mean equation to investigate market interdependencies through the first moments:

$$\boldsymbol{R}_{2,t} = \delta_k + \phi_i \boldsymbol{R}_{1,t-1} + \phi_k \boldsymbol{R}_{2,t-1} + \varepsilon_t \tag{6.15a}$$

$$\boldsymbol{R}_{3,t} = \delta_k + \phi_i \boldsymbol{R}_{1,t-1} + \phi_k \boldsymbol{R}_{3,t-1} + \varepsilon_t \tag{6.15b}$$

where $\boldsymbol{R}_1$, $\boldsymbol{R}_2$, $\boldsymbol{R}_3$ are daily index returns on the Tokyo, London and New York stock markets respectively. Equation (6.15a) and (6.15b) models the price spillover from Tokyo to London and New York. After adjusting for time zone differences, modelling a price spillover from London and New York to Tokyo requires the estimation of the regression:

$$\boldsymbol{R}_{1,t+1} = \delta_k + \phi_i \boldsymbol{R}_{2,t-1} + \phi_k \boldsymbol{R}_{1,t} + \varepsilon_t \tag{6.16a}$$

$$\boldsymbol{R}_{1,t+1} = \delta_k + \phi_i \boldsymbol{R}_{3,t-1} + \phi_k \boldsymbol{R}_{1,t} + \varepsilon_t \tag{6.16b}$$

Likewise, to model a price spillover from New York to London requires the same adjustment procedure described above. To investigate volatility spillovers, the second step requires the estimation of the following bivariate-EGARCH specification on index returns:

$$h_{k,t} = exp\left\{a_{k,0} + a_{i,k}\xi_{i,t-1} + \gamma_k log\left(h_{k,t-1}\right)\right\} \tag{6.17a}$$

$$h_{i,k,t} = \rho\sqrt{h_{i,t}h_{k,t}} \tag{6.17b}$$

where $h_{i,k,t}$ is the conditional covariance and $\xi_{i,t-1}$ is the information component from market i that includes the asymmetric term θ_i. Exhibit 6.1 provides a summary of the EGARCH coefficients to be estimated and the sequence of results presented throughout the remainder of the investigation.[66]

Exhibit 6.1

A Summary of the Bivariate-EGARCH Models Estimated

Model	Coefficients	$h_{k,t}$
From London to Tokyo:	$(\delta_{1,0}, \phi_{1,2}, \phi_{1,0}, a_{1,0}, a_{1,2}, \theta_{1,2}, \gamma_1)$	Tokyo Market
From Tokyo to London	$(\delta_{2,0}, \phi_{2,1}, \phi_{2,0}, a_{2,0}, a_{2,1}, \theta_{2,1}, \gamma_2)$	London Market
From New York to Tokyo	$(\delta_{1,0}, \phi_{1,3}, \phi_{1,0}, a_{1,0}, a_{1,3}, \theta_{1,3}, \gamma_1)$	Tokyo Market
From Tokyo to New York	$(\delta_{3,0}, \phi_{3,1}, \phi_{3,0}, a_{3,0}, a_{3,1}, \theta_{3,1}, \gamma_3)$	New York Market
From New York to London	$(\delta_{2,0}, \phi_{2,3}, \phi_{2,0}, a_{2,0}, a_{2,3}, \theta_{2,3}, \gamma_2)$	London Market
From London to New York	$(\delta_{3,0}, \phi_{3,2}, \phi_{3,0}, a_{3,0}, a_{3,2}, \theta_{3,2}, \gamma_3)$	New York Market

Note that market i,k = 1,2,3 where 1 = Tokyo, 2 = London and 3 = New York.

[66] Throughout the investigation, the analysis will present results according to the opening and closing times of the markets. Hence, the presentation of Tokyo, London and New York results respectively.

Table 6.3 contains the coefficient values of the bivariate-EGARCH model estimated over the whole sample. These results consider market interdependencies in their first and second moments by modelling price and volatility spillovers. Table 6.4 provides Ljung-Box and ARCH statistics as diagnostic tests of the statistical adequacy of the EGARCH models. The diagnostic test statistics reveal that the bivariate-EGARCH can account for most of the serial dependencies and heteroscedastic nature of the data.

The bivariate-EGARCH results in table 6.3 raise a number of important points. For instance, the correlation coefficient denoted as ρ appears to reflect the time zone differences in which the markets operate. The coefficient value of 0.089 for the Tokyo and New York markets contrasts with a correlation value of 0.342 between London and New York where there is a 2.5 hour overlap.

Focusing on market interdependencies in their first moments, there is some evidence of price spillovers. The ϕ coefficient is significantly different from zero for a price spillover from Tokyo to London and vice versa, thus indicating the presence of a bi-directional relationship between the two markets. In contrast, there is no evidence of price spillovers between Tokyo and New York and only one-directional spillovers from New York to London. In all cases, the ϕ coefficient is negative which leads to the conclusion that price changes caused by news in one market leads to a movement in price of the opposite direction in the next market to trade. As such, this finding raises the suspicion

Table 6.3

Bivariate-EGARCH Estimations on Daily Data. (Excluding Crash Dummy) - Sample Period: January 1, 1984 to December 31, 1997

	Tokyo Market		Tokyo Market		London Market
$\delta_{1,0}$	0.023	$\delta_{1,0}$	0.020	$\delta_{2,0}$	0.042
	(1.60)		(1.42)		(3.24)*
$\phi_{1,2}$	-0.034	$\phi_{1,3}$	0.028	$\phi_{2,3}$	-0.047
	(-2.15)*		(1.88)		(-3.23)*
$\phi_{1,0}$	0.048	$\phi_{1,0}$	0.038	$\phi_{2,0}$	0.071
	(2.70)*		(2.10)*		(4.07)*
$a_{1,0}$	-0.322	$a_{1,0}$	-0.348	$a_{2,0}$	-0.277
	(-22.56)*		(-23.51)*		(-13.63)*
$a_{1,2}$	0.322	$a_{1,3}$	0.348	$a_{2,3}$	0.251
	(24.91)*		(26.16)*		(13.30)*
θ_1	-0.098	θ_1	-0.092	θ_2	-0.274
	(-2.87)*		(-2.79)*		(-5.94)*
γ_1	0.960	γ_1	0.957	γ_2	0.939
	(336.12)*		(308.40)*		(122.46)*
	London Market		**New York Market**		**New York Market**
$\delta_{2,0}$	0.037	$\delta_{3,0}$	0.041	$\delta_{3,0}$	0.045
	(2.80)*		(3.19)*		(3.44)*
$\phi_{2,1}$	-0.028	$\phi_{3,1}$	-0.003	$\phi_{3,2}$	-0.006
	(-2.77)*		(-0.31)		(-0.48)
$\phi_{2,0}$	0.044	$\phi_{3,0}$	0.071	$\phi_{3,0}$	0.017
	(2.46)*		(3.57)*		(0.88)
$a_{2,0}$	-0.254	$a_{3,0}$	-0.234	$a_{3,0}$	-0.213
	(-10.63)*		(-17.11)*		(-15.33)*
$a_{2,1}$	0.231	$a_{3,1}$	0.213	$a_{3,2}$	0.193
	(10.52)*		(17.72)*		(15.54)*
θ_2	-0.269	θ_3	-0.043	θ_3	-0.089
	(-5.93)*		(-0.95)		(-1.92)
γ_2	0.946	γ_3	0.957	γ_3	0.957
	(130.82)*		(281.24)*		(283.41)*
$\rho_{1,2}$	0.210	$\rho_{1,3}$	0.089	$\rho_{2,3}$	0.342
	(13.73)*		(5.15)*		(25.35)*

* Denotes significance at the 0.05 level

Table 6.4

Diagnostic Test Statistics of the Bivariate-EGARCH
- Period: January 1, 1984 to December 31, 1997

		Ljung-Box Q(12)	ARCH $Q^2(12)$
Tokyo &	TKO	18.192	4.290
London		(0.11)	(0.98)
	LDN	27.289	33.876
		(0.01)	(0.00)
Tokyo &	TKO	17.659	3.684
New York		(0.13)	(0.99)
	NY	15.232	5.373
		(0.23)	(0.94)
London &	LDN	20.092	22.826
New York		(0.07)	(0.03)
	NY	33.133	7.201
		(0.00)	(0.84)

Significance tests at the 0.01, 0.05 and 0.005 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom
Chi-square critical value at 0.005 with 12 degress of reedom is 28.299
Key:
TKO = Tokyo
LDN = London
NY = New York

that information in one market is perceived differently by the next market to trade.

In relation to second order market interdependencies, there is more evidence of bi-directional relationships between the markets. The existence of volatility spillovers conforms to the Meteor Showers theorem of Engle, Ito & Lin (1990) and later investigated by Hogan & Melvin (1994). However, according to the significance of the theta θ_i coefficient, the results report bi-directional asymmetries for the Tokyo and London markets only. The asymmetric component is also present in volatility spillovers from New York to Tokyo and London. In all cases, the spillover effect $a_{i,k}$ is greater in the presence of an asymmetric component. This conforms to the notion that negative information originating from one market has a more profound impact on the volatility of the next market to trade. These results are consistent with the findings of Koutmos & Booth (1995) and the conclusion that both the size and the sign of the innovation play an important role in determining the degree of market interdependencies through the variance.

To probe further into the dynamics of the volatility transmission mechanism, the analysis isolates the extent to which negative information from one market magnifies the volatility effect of the next market to trade. This is possible by using a ratio statistic that resembles the one used by Koutmos & Tucker (1996)

$$RATIO = \frac{1}{\left({a_{i,k} + a_{i,k}\theta_i} \middle/ {a_{i,k} - a_{i,k}\theta_i} \right)} \tag{6.18}$$

where $a_{i,k} + a_{i,k}\theta_i$ is the proportion of the volatility spillover to market k that is attributable to negative information from market i and; $a_{i,k} - a_{i,k}\theta_i$ represents the proportion of the spillover to market k caused by positive innovations of a similar magnitude from market i. Table 6.5 presents the results of the test statistics.[67] The ratio values indicate that a decline in price from one market has a greater impact on the spillover effect to the next market than an increase in price of similar magnitude.

Furthermore, the extent to which negative information magnifies the spillover effect appears to be dependent on the time zone differences these markets operate. For instance, the coefficient values indicate that a decline in the Tokyo price increases the spillover effect to the London market by 1.735 times more than an upward movement in price of similar magnitude. This compares with a ratio value of 1.217 from London to Tokyo.

In addition, negative information originating from Tokyo and New York has a greater impact on the volatility spillover to the London market than if the negative innovation originated from London. This finding collaborates with the market leader role of the Tokyo and New York markets[68] and the fact that

[67] Note that the asterisk applies when the asymmetric term θ_i from the last market to trade is statistically insignificant. In other words, where volatility spillovers are symmetric in nature.

[68] See Schollhammer & Sand (1985), Eun & Shim (1989) and Koch & Koch (1991) on the market leader role of the US and Japanese markets.

Table 6.5

Impact of Negative Innovations on Volatility Spillovers

Innovation From	Spillover to: Tokyo	London	New York
Tokyo	-	1.735	*
London	1.217	-	*
New York	1.203	1.753	-

Note: These calculations are made on the basis on the following formula

$$RATIO = \frac{1}{\left({a_{i,k} + a_{i,k}\theta_i} \Big/ {a_{i,k} - a_{i,k}\theta_i} \right)}$$

which measures the extent to which negative news from market i has a greater impact on the volatility spillover to market k than positive news of similar size.

the turnover of non-UK stocks exceeds domestic stocks as a result of the abolition of stamp duty.[69] Therefore, based on the assumption that information generated is relevant to the performance of these stocks, the potential of a news spillover effect from Tokyo and New York to London is greater.

6.5.2 Bivariate-EGARCH Analysis on the October 1987 Crash

As a measure of the relationship between the markets, figure 6.2(a) to 6.2(c) plots the covariance based on the results presented in table 6.3. In all cases, the graphs show a positive relationship thus meaning that an increase in volatility in one market increases the volatility of the next market to trade. Moreover, the figures highlight the unstable nature of the correlation between markets during stress periods. The classic example is the October 1987 Crash as depicted by the sharp spike.

Given the impact of stress periods on the covariance of the markets, this section investigates further the dynamics surrounding the October 1987 Crash and inducement of asymmetries in the volatility transmission mechanism. To investigate whether the October 1987 Crash induces asymmetries in the transmission of volatility, requires the estimation of bivariate-EGARCH models with and without a crash dummy $\alpha_k D_C$ in the conditional mean of

[69] See table 1.1 for a snapshot of turnover figures for 1997.

Figure 6.2(a)

Covariance Between Tokyo and London Markets

Sample Period: January 1, 1984 to December 31, 1997

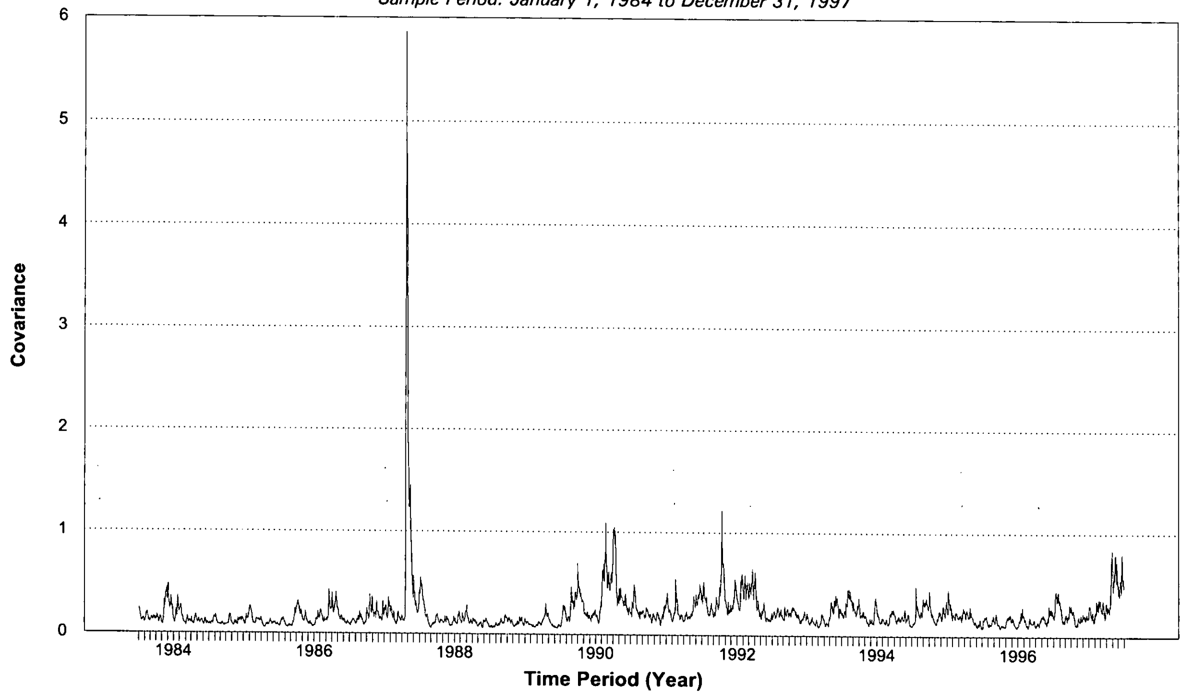
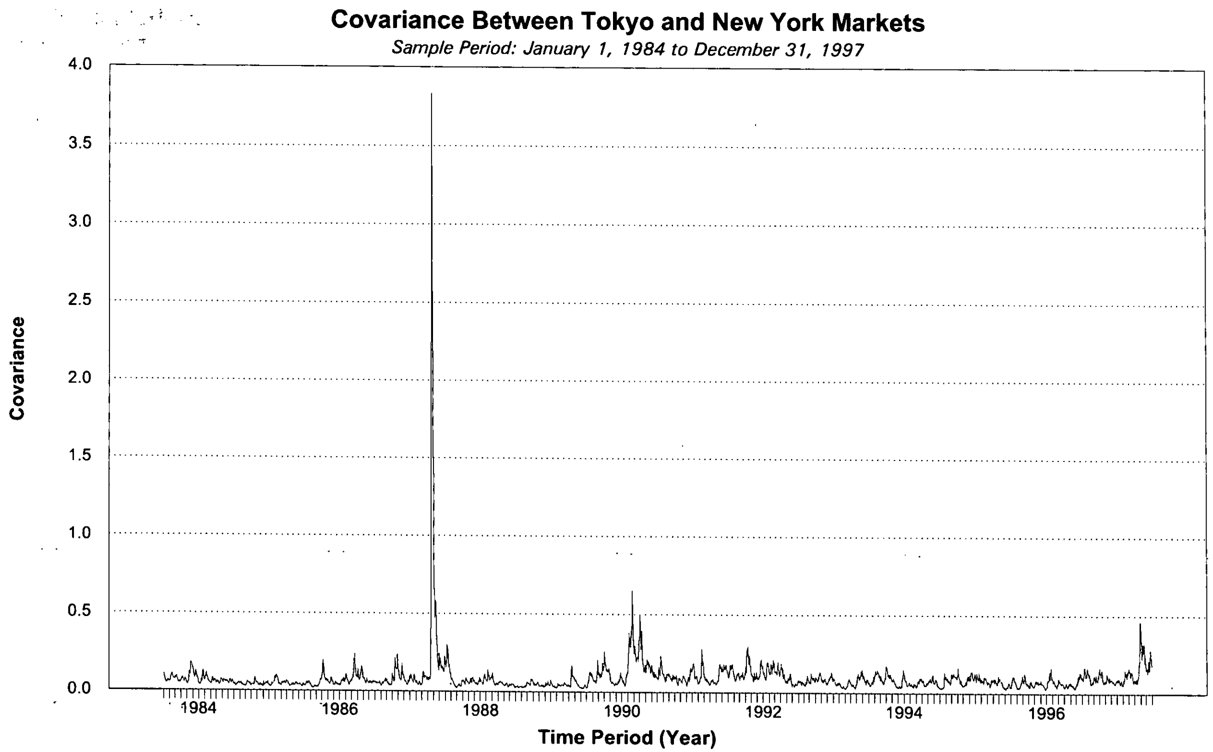
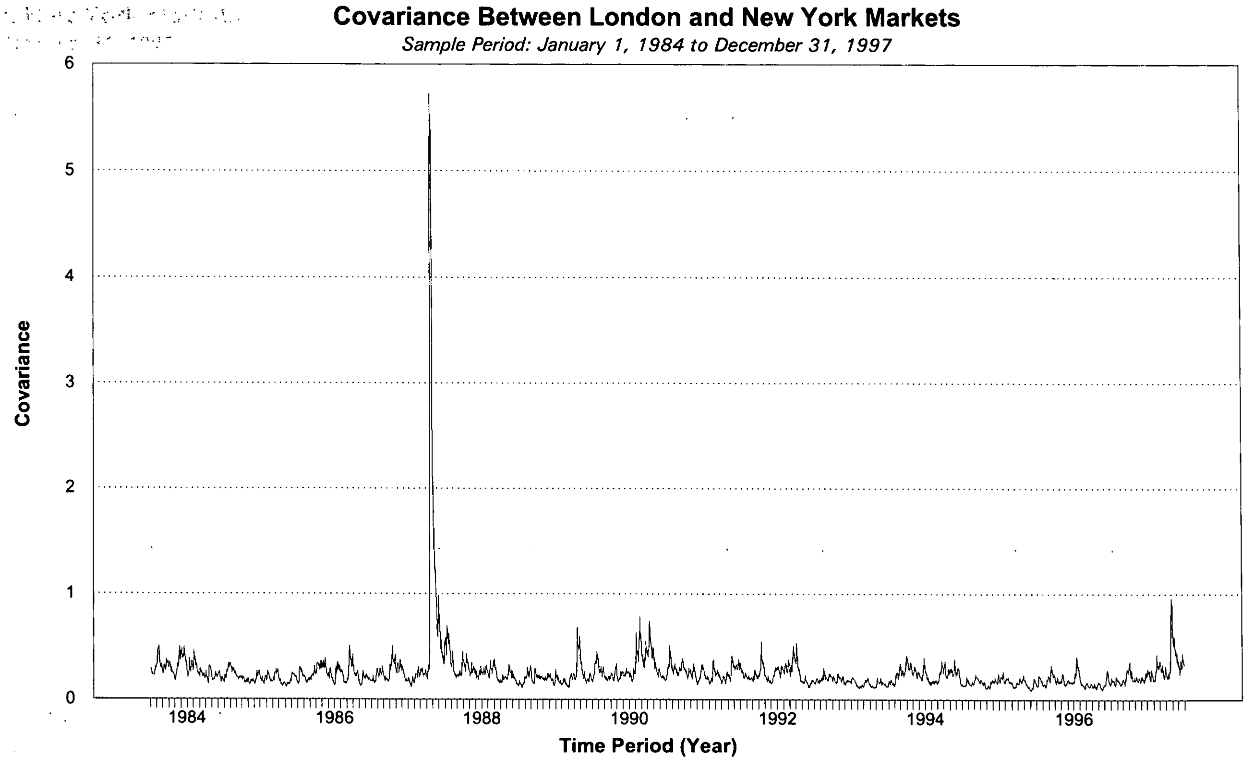


Figure 6.2(b)



Covariance Between Tokyo and New York Markets
Sample Period: January 1, 1984 to December 31, 1997
Covariance
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1984
1986
1988
1990
1992
1994
1996
Time Period (Year)

Figure 6.2(c)


Covariance Between London and New York Markets
Sample Period: January 1, 1984 to December 31, 1997
Covariance
0
1
2
3
4
5
6
1984
1986
1988
1990
1992
1994
1996
Time Period (Year)

equations (6.15) and (6.16).[70][71] Table 6.6(a) and 6.6(b) present the EGARCH results, with and without the dummy variable for all three markets over the sample period January 1, 1984 to January 31, 1989. Table 6.6(c) displays the results for the February 1, 1989 to December 29, 1997 sample period. Given that the second sample does not cover the crash period, the analysis excludes the crash dummy α_k from the mean equation. Finally, table 6.7 provides the diagnostic test statistics for serial correlation and heteroscedasticity.[72]

From the results presented in table 6.6(a) to 6.6(c), there is evidence of increasing market interdependencies through the covariance. In all cases, the correlation coefficient has increased from the 1984-1989 to the 1989-1997 sample, thus revealing growing market interdependence over a period of time. Turning to second moment market interdependencies, adjusting for the crash in the conditional mean induces bi-directional asymmetries in the volatility transmission mechanism. In the 1984-1989 sample, the results reveal six cases of EGARCH effects when adjusting for the crash in the conditional mean. This reduces to two cases after excluding the crash dummy. Table 6.6(c) reveals no evidence of asymmetries for the 1989-1997 sample. Taken together, these

[70] Adjusting for the crash follows the approach of Antoniou & Holmes (1995) in modelling returns in their first moments.
[71] The crash dummy variable takes the value of one on the day of the crash and zero otherwise.
[72] Although the bivariate-EGARCH can account for most of the serial dependencies and heteroscedasticity in the data, there are cases where one should exercise caution when interpreting the results.

Table 6.6(a)

Bivariate-EGARCH Estimations on Daily Data. (Including Crash Dummy) - Sample Period: January 1, 1984 to January 31, 1989

	Tokyo Market		Tokyo Market		London Market
$\delta_{1,0}$	0.057	$\delta_{1,0}$	0.061	$\delta_{2,0}$	0.046
	(2.88)*		(3.22)*		(1.94)
α_1	-10.637	α_1	-11.29	α_2	-5.562
	(-14.03)*		(-20.54)*		(-10.99)*
$\phi_{1,2}$	-0.075	$\phi_{1,3}$	0.007	$\phi_{2,3}$	-0.096
	(-3.75)*		(0.35)		(-4.48)*
$\phi_{1,0}$	0.130	$\phi_{1,0}$	0.106	$\phi_{2,0}$	0.126
	(4.31)*		(3.29)*		(4.05)*
$a_{1,0}$	-0.497	$a_{1,0}$	-0.503	$a_{2,0}$	-0.487
	(-12.72)*		(-13.10)*		(-7.73)*
$a_{1,2}$	0.444	$a_{1,3}$	0.451	$a_{2,3}$	0.452
	(11.92)*		(12.33)*		(7.36)*
θ_1	-0.135	θ_1	-0.128	θ_2	-0.310
	(-2.11)*		(-2.15)*		(-4.12)*
γ_1	0.900	γ_1	0.904	γ_2	0.861
	(89.44)*		(94.92)*		(35.66)*
	London Market		**New York Market**		**New York Market**
$\delta_{2,0}$	0.049	$\delta_{3,0}$	0.059	$\delta_{3,0}$	0.058
	(2.01)*		(2.54)*		(2.46)*
α_2	-6.654	α_3	-19.870	α_3	-17.336
	(-28.83)*		(-17.22)*		(-5.98)*
$\phi_{2,1}$	-0.037	$\phi_{3,1}$	-0.012	$\phi_{3,2}$	-0.041
	(-1.35)		(-0.51)		(-1.75)
$\phi_{2,0}$	0.101	$\phi_{3,0}$	0.053	$\phi_{3,0}$	0.022
	(3.15)*		(1.64)		(0.72)
$a_{2,0}$	-0.454	$a_{3,0}$	-0.180	$a_{3,0}$	-0.169
	(-7.30)*		(-9.28)*		(-7.79)*
$a_{2,1}$	0.425	$a_{3,1}$	0.170	$a_{3,2}$	0.158
	(7.01)*		(9.33)*		(7.76)*
θ_2	-0.309	θ_3	-0.299	θ_3	-0.255
	(-4.04)*		(-4.06)*		(-3.37)*
γ_2	0.876	γ_3	0.983	γ_3	0.980
	(38.94)*		(245.93)*		(245.04)*
$\rho_{1,2}$	0.168	$\rho_{1,3}$	0.087	$\rho_{2,3}$	0.271
	(6.51)*		(2.77)*		(10.52)*

* Denotes significance at the 0.05 level.

Table 6.6(b)

Bivariate-EGARCH Estimations on Daily Data. (Excluding Crash Dummy) - Sample Period: January 1, 1984 to January 31, 1989

	Tokyo Market		Tokyo Market		London Market
$\delta_{1,0}$	0.043	$\delta_{1,0}$	0.046	$\delta_{2,0}$	0.056
	(2.09)*		(2.33)*		(2.25)*
$\phi_{1,2}$	-0.086	$\phi_{1,3}$	0.002	$\phi_{2,3}$	-0.099
	(-4.90)*		(0.12)		(-4.49)*
$\phi_{1,0}$	0.188	$\phi_{1,0}$	0.167	$\phi_{2,0}$	0.099
	(6.28)*		(5.35)*		(3.21)*
$a_{1,0}$	-0.627	$a_{1,0}$	-0.625	$a_{2,0}$	-0.424
	(-13.72)*		(-14.41)*		(-7.41)*
$a_{1,2}$	0.563	$a_{1,3}$	0.564	$a_{2,3}$	0.403
	(12.87)*		(13.58)*		(7.03)*
θ_1	-0.067	θ_1	-0.057	θ_2	-0.283
	(-0.98)		(-0.86)		(-3.49)*
γ_1	0.853	γ_1	0.859	γ_2	0.873
	(66.61)*		(71.65)*		(38.06)*
	London Market		**New York Market**		**New York Market**
$\delta_{2,0}$	0.061	$\delta_{3,0}$	0.047	$\delta_{3,0}$	0.053
	(2.35)*		(1.95)		(2.20)*
$\phi_{2,1}$	-0.021	$\phi_{3,1}$	0.026	$\phi_{3,2}$	-0.021
	(-0.72)		(0.98)		(-0.87)
$\phi_{2,0}$	0.054	$\phi_{3,0}$	0.061	$\phi_{3,0}$	0.009
	(1.68)		(1.77)		(0.26)
$a_{2,0}$	-0.386	$a_{3,0}$	-0.287	$a_{3,0}$	-0.262
	(-5.85)*		(-10.82)*		(-9.10)*
$a_{2,1}$	0.370	$a_{3,1}$	0.275	$a_{3,2}$	0.250
	(5.68)*		(11.62)*		(9.36)*
θ_2	-0.250	θ_3	-0.080	θ_3	-0.114
	(-3.02)*		(-1.30)		(-1.82)
γ_2	0.880	γ_3	0.960	γ_3	0.956
	(37.27)*		(138.43)*		(132.90)*
$\rho_{1,2}$	0.175	$\rho_{1,3}$	0.079	$\rho_{2,3}$	0.327
	(6.58)*		(2.44)*		(14.09)*

* Denotes significance at the 0.05 level.

Table 6.6(c)

Bivariate-EGARCH Estimations on Daily Data.
Sample Period: February 1, 1989 to December 29, 1997

	Tokyo Market		Tokyo Market		London Market
$\delta_{1,0}$	-0.024	$\delta_{1,0}$	-0.025	$\delta_{2,0}$	0.031
	(-1.13)		(-1.16)		(2.00)*
$\phi_{1,2}$	-0.012	$\phi_{1,3}$	0.047	$\phi_{2,3}$	-0.023
	(-0.46)		(1.86)		(-1.17)
$\phi_{1,0}$	-0.016	$\phi_{1,0}$	-0.026	$\phi_{2,0}$	0.048
	(-0.74)		(-1.13)		(2.29)*
$a_{1,0}$	-0.183	$a_{1,0}$	-0.190	$a_{2,0}$	-0.118
	(-10.49)*		(-10.57)*		(-6.05)*
$a_{1,2}$	0.186	$a_{1,3}$	0.192	$a_{2,3}$	0.106
	(11.04)*		(11.18)*		(6.06)*
θ_1	0.051	θ_1	0.068	θ_2	-0.095
	(0.83)		(1.13)		(-0.95)
γ_1	0.980	γ_1	0.980	γ_2	0.981
	(357.56)*		(352.26)*		(214.18)*
	London Market		**New York Market**		**New York Market**
$\delta_{2,0}$	0.030	$\delta_{3,0}$	0.040	$\delta_{3,0}$	0.040
	(1.93)		(2.53)*		(2.56)*
$\phi_{2,1}$	-0.034	$\phi_{3,1}$	-0.014	$\phi_{3,2}$	0.005
	(-3.08)*		(-1.27)		(0.31)
$\phi_{2,0}$	0.033	$\phi_{3,0}$	0.080	$\phi_{3,0}$	0.020
	(1.56)		(3.24)*		(0.87)
$a_{2,0}$	-0.127	$a_{3,0}$	-0.210	$a_{3,0}$	-0.189
	(-6.15)*		(-10.98)*		(-10.75)*
$a_{2,1}$	0.113	$a_{3,1}$	0.160	$a_{3,2}$	0.146
	(6.19)*		(9.68)*		(9.75)*
θ_2	-0.104	θ_3	0.146	θ_3	0.055
	(-1.08)		(1.27)		(0.48)
γ_2	0.979	γ_3	0.922	γ_3	0.931
	(190.87)*		(104.91)*		(107.15)*
$\rho_{1,2}$	0.224	$\rho_{1,3}$	0.103	$\rho_{2,3}$	0.351
	(12.41)*		(5.07)*		(19.51)*

* Denotes significance at the 0.05 level.

Table 6.7

Diagnostic Test Statistics of the Bivariate-EGARCH
- Period: January 1, 1984 to January 31, 1989

	Tokyo & London		Tokyo & New York		London & New York	
	TKO	LDN	TKO	NY	LDN	NY
	Period: January 1, 1984 to January 31, 1989 With Crash Dummy					
L-B $Q(12)$	26.391	27.103	23.592	40.675	29.515	61.029
(p-values)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
ARCH $Q^2(12)$	13.819	37.791	12.926	21.872	66.684	26.561
(p-values)	(0.32)	(0.00)	(0.39)	(0.04)	(0.00)	(0.01)
	Without Crash Dummy					
L-B $Q(12)$	4.653	25.648	43.134	21.215	25.531	41.593
(p-values)	(0.97)	(0.01)	(0.00)	(0.05)	(0.01)	(0.00)
ARCH $Q^2(12)$	11.861	20.249	11.539	26.476	20.529	26.170
(p-values)	(0.46)	(0.06)	(0.48)	(0.01)	(0.06)	(0.01)
	Period: February 1, 1989 to December 29, 1997					
L-B $Q(12)$	26.425	34.369	26.549	18.869	25.480	33.179
(p-values)	(0.01)	(0.00)	(0.01)	(0.09)	(0.01)	(0.00)
ARCH $Q^2(12)$	54.898	33.806	59.325	34.077	37.324	27.717
(p-values)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Significance tests at the 0.01, 0.05 and 0.005 level
Chi-square critical value at 0.005 with 12 degrees of freedom is 28.299
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom
Key:
TKO = Tokyo
LDN = London
NY = New York

findings provide conclusive evidence in support of Bollerslev, Chou & Kroner (1992) who argues that the presence of the asymmetric component in volatility represents a manifestation of extreme, uncommon observations.

In addition, the parameters of the EGARCH model $(a_{i,k}, \theta_i, \gamma_k)$ have undergone statistically significant changes for all indices over the two sample periods with and without the crash dummy. Comparison analysis of tables 6.6(a) and 6.6(b) reveals that volatility spillovers $a_{i,k}$ are generally more profound with the conditional mean unadjusted for the crash despite the presence of GARCH effects. This suggests that the crash accounts for much of the higher volatility spillover effect on individual markets. In relation to the findings presented in the early sample, volatility spillovers for the period 1989-1997 are less profound in the absence of asymmetries.[73] Given the existence of an asymmetric component in the early sample, this result is consistent with the findings of Koutmos & Booth (1995) who find volatility spillovers more profound in the presence of EGARCH effects.

Upon closer observation of the 1984-1989 sample the London market appears to be most sensitive to news originating from New York after adjusting for the crash. On the other hand, the Tokyo market appears to be most sensitive to news from New York without the crash dummy. The same conclusion applies to the 1989-1997 sample. These results contrast with the New York market

[73] In relation to the significance of the asymmetric component in the early sample, these results suggest that the "melt down" during the crash corrected the massive mispricing of the market, thus reducing the tendency for the markets to overreact to bad news.

that appears to be least sensitive to news originating from either Tokyo or London.

To provide further intuition into the dynamics of the volatility transmission mechanism, table 6.8 (see next page) provides ratio statistics on the basis of equation (6.18). The ratios are computed using the EGARCH coefficient values over the 1984-1989 and 1989-1997 samples, with and without the crash dummy. In comparison with the results provided in table 6.3 for the whole sample, the asymmetric component induced by the crash appears to have an even greater impact on the volatility spillover to the next market to trade. These findings collaborate with the general conclusion that the crash induces asymmetries and thus, further impact on the nature of volatility transmissions across markets.

6.5.3 Saturday Trading in Tokyo - A Consideration

Thus far, the empirical question answered in this study is whether the presence of an asymmetric component in volatility represents a manifestation of extreme, uncommon events. The final issue to consider is the notion that an extra half-day of trading in Tokyo induces asymmetries in the volatility transmission mechanism. The objective here is to probe further into the dynamics that govern the processing of information in the Tokyo market and the next two markets to trade. To entertain this prospect, the analysis includes a dummy variable (denoted as $\varphi_k D_{TW}$) in the conditional mean of equations

Table 6.8

Impact of Negative Innovations on Volatility Spillovers:
Adjusted with and without the Crash Dummy

Innovation From	Spillover to: Tokyo	London	New York
	Sample 1 with Crash Dummy		
Tokyo	-	1.894	1.853
London	1.312	-	1.684
New York	1.294	1.898	-
	Sample 1 without Crash Dummy		
Tokyo	-	1.667	*
London	*	-	*
New York	*	1.790	-
	Sample 2		
Tokyo	-	*	*
London	*	-	*
New York	*	*	-

Note: These calculations are made on the basis on the following formula

$$RATIO = \frac{1}{\left({a_{i,k} + a_{i,k}\theta_i} \middle/ {a_{i,k} - a_{i,k}\theta_i} \right)}$$

which measures the extent to which negative news from market i has a greater impact on the volatility spillover to market k than positive news of similar size.
Note:
Sample 1 = 1984 - 1989 sample
Sample 2 = 1989 - 1997 sample

(6.15) and (6.16) to capture weekend returns that coincide with Saturday trading in Tokyo.[74] The purpose of the exercise is to document any changes in the EGARCH coefficients that describe market interdependencies with and without an extra half day of trading in Tokyo. Hence, the investigation will analyse changes in the model coefficients in relation to the results reported in table 6.6(b).

Table 6.9 presents the bivariate-EGARCH results that include the weekend dummy, followed by diagnostic test statistics in table 6.10. According to the weekend dummy coefficient, Saturday trading in Tokyo appears to impact most the London market by generating significant negative returns. This contrasts sharply with the other markets by reporting small positive coefficient values for the Tokyo market and an insignificant effect on New York returns. These results raise a number of issues of importance; firstly, the failure of weekend trading to impact index returns in a uniform manner indicates that information generated in Tokyo is perceived differently in all three markets. Secondly, the insignificant impact of Saturday trading on New York returns poses questions on the potential effects of weekend trading inferred by Puffer (1991). However, the results do not discount the possibility of a spillover of firm specific information from Tokyo to New York.[75]

[74] The dummy variable takes the value of one when a Monday return follows weekend trading in Tokyo and zero otherwise.
[75] See Barclay, Litzenberger & Warner (1990).

Table 6.9

Bivariate-EGARCH Estimations Including Weekend Dummy.
Sample Period: January 1, 1984 to January 31, 1989

	Tokyo Market		Tokyo Market
$\delta_{1,0}$	0.030	$\delta_{1,0}$	0.041
	(1.39)		(1.91)
φ_1	0.097	φ_1	0.095
	(2.60)*		(2.30)*
$\phi_{1,2}$	-0.076	$\phi_{1,3}$	0.011
	(-4.06)*		(0.54)
$\phi_{1,0}$	0.183	$\phi_{1,0}$	0.137
	(6.14)*		(4.26)*
$a_{1,0}$	-0.634	$a_{1,0}$	-0.559
	(-13.78)*		(-14.72)*
$a_{1,2}$	0.571	$a_{1,3}$	0.504
	(12.96)*		(14.02)*
θ_1	-0.079	θ_1	-0.109
	(-1.16)		(-1.81)
γ_1	0.853	γ_1	0.885
	(71.12)*		(88.13)*
	London Market		**New York Market**
$\delta_{2,0}$	0.094	$\delta_{3,0}$	0.064
	(3.50)*		(2.54)*
φ_2	-0.239	φ_3	-0.045
	(-3.32)*		(-0.67)
$\phi_{2,1}$	-0.022	$\phi_{3,1}$	-0.100
	(-0.78)		(-10.59)*
$\phi_{2,0}$	0.059	$\phi_{3,0}$	0.064
	(1.86)		(4.33)*
$a_{2,0}$	-0.377	$a_{3,0}$	-0.621
	(-5.88)*		(-11.18)*
$a_{2,1}$	0.360	$a_{3,1}$	0.579
	(5.70)*		(18.71)*
θ_2	-0.255	θ_3	-0.313
	(-3.06)*		(-15.30)*
γ_2	0.887	γ_3	0.544
	(37.99)*		(20.72)*
$\rho_{1,2}$	0.180	$\rho_{1,3}$	0.075
	(6.83)*		(2.44)*

*Denotes significance at the 0.05 level.

Table 6.10

Diagnostic Test Statistics of the Bivariate-EGARCH

		Ljung-Box Q(12)	ARCH $Q^2(12)$
Tokyo &	TKO	4.366	11.546
London		(0.97)	(0.48)
	LDN	24.253	21.264
		(0.02)	(0.05)
Tokyo &	TKO	31.628	28.304
New York		(0.00)	(0.00)
	NY	22.916	36.2597
		(0.03)	(0.00)

Significance tests at the 0.01, 0.05 and 0.005 level
Both Ljung-Box and ARCH(12) tests are chi-square distributed, with 12 degrees of freedom
Chi-square critical value at 0.005 with 12 degrees of freedom is 28.299
Key:
TKO = Tokyo
LDN = London
NY = New York

Focusing on second moment market interdependencies, the EGARCH results show evidence of an asymmetric component in the volatility spillover from Tokyo to London and New York. Moreover, in comparing the findings with the results of table 6.6(b), the spillover effect from Tokyo to New York increased by 2.1 times[76] after including the weekend dummy. Taken together, these results indicate that weekend trading in Tokyo reveals information that traders in London and New York perceive to be negative. Furthermore, the dramatic increase in spillover effects from Tokyo to New York is in line with the general conclusions of Puffer (1991).

To extract further information on the importance of the asymmetric component from the Tokyo market, the analysis re-computes the ratio of equation (6.18). According to the coefficient estimates, a decline in Tokyo prices increases the volatility spillover to the London and New York markets by 1.683 and 1.909 times respectively. Once again, the ratio statistics collaborate with the general conclusion of Puffer (1991), that weekend trading in Tokyo increases the volatility of the next market to trade. However, unlike Puffer, the results provide inferences on the sign and magnitude of information in causing additional volatility spillovers generated by weekend trading.

[76] This increases to 3.4 times when compared with the results in table 6.6(a).

6.6 SUMMARY AND CONCLUSIONS

This chapter investigates the asymmetric volatility transmission across the Tokyo, London and New York markets. One of the objectives of the study is the documentation of additional evidence on the nature of market interdependencies. As a result, the initial line of investigation considers the notion that price and volatility spillovers are a manifestation of the size and sign of news evaluated by the next market to trade. Within this framework, the study investigated two issues that constitute its main contribution to the existing literature: whether extreme, uncommon shocks such as the October 1987 Crash and a extra half-day of trading in Tokyo induces asymmetries in the transmission of volatility across markets. As a consequence, this warranted a larger sample period than previously used in earlier chapters and the use of two sub-samples of unequal lengths from 1984 to 1989 and 1989 to 1997.

To investigate these issues, the analysis employs the extended bivariate version of the EGARCH model introduced in Chapter Two. In using the bivariate-EGARCH approach, the objective is to model market interdependencies in the first and second moments. In addition, the usefulness of this model lies in its ability to extract more information on the dynamics that govern the transmission of volatility across markets. Subsequently, this entertains the notion that negative news in the first market to trade will have a greater impact on the volatility of the next market to trade.

The first important observation made by the results is the presence of asymmetries in the transmission of volatility that tends to magnify the spillover effect across markets. In addition, the study provides evidence that asymmetries are induced after adjusting the bivariate-EGARCH model for the crash. These findings provide strong empirical support for the proposition that the asymmetric response of volatility to an innovation may be the result of large irregular negative shocks. Although the findings do not dispel the notion that negative returns are more common than positive returns, it casts doubt on the view that this causes asymmetries in stock returns to the same degree that the clustering of price movements causes volatility clustering.[77]

Furthermore, the investigation reveals evidence of significant changes in the nature of market interdependencies over the two sample periods. For instance, the presence of EGARCH effects along with more pronounced volatility spillovers in the 1984-1989 sample reduces to GARCH effects in the 1989-1997 sample period. In the early sample, the London market appears to be most sensitive to news originating from New York after adjusting for the crash. On the other hand, the Tokyo market appears to be most sensitive to news from New York without the crash dummy. The analysis reports similar findings in the later sample, despite the presence of a symmetric component in volatility transmissions. This contrasts with the New York market in which the study finds to be least sensitive to news originating from either Tokyo or London. These results are in accordance to the conclusions of previous studies

[77] See the volatility feedback effect introduced by Campbell & Hentschel (1992).

reviewed in Chapter One concerning the market leadership role played by the US.

In response to issues raised by Barclay, Litzenberger & Warner (1990) and Puffer (1991), the investigation tackled the empirical question of whether an extra half-day of trading in Tokyo induces asymmetries in the transmission mechanism. According to the EGARCH estimations, the degree of asymmetry in volatility transmissions is more profound and restricted to the spillover from Tokyo to London and New York. In making comparisons with earlier findings, the inclusion of weekend trading in Tokyo appears to impact most on the New York market by increasing the magnitude of the volatility spillover at least 2.1 times. This result collaborates with the finding that a downward movement in Tokyo prices approximately doubles the volatility spillover to New York than a positive movement of similar magnitude. The usefulness of these findings, other than providing consistencies with the results of previous studies, is the identification of the source of the increase in the volatility spillover.

Finally, from a practitioner's point of view, the results presented in this chapter has policy implications for individual markets planning institutional changes in the form of contagion effects. The trading of stocks over an additional half-day of trading in Tokyo *per se* affects stock prices in other markets. This is more profound when the contagion effect is asymmetric. Taking this issue further, it follows that an additional half day of trading induces more pronounced price jumps in London and New York. This conclusion is consistent with the contagion model of King & Wadhwani (1990). As a consequence, the policy implications of this study warrant further research on the subject matter for the purpose of identifying the regulatory requirements of the market.

CHAPTER SEVEN

CONCLUSION

7.1 A SUMMARY OF THE INVESTIGATIONS

"In a world of uncertainty, information becomes a useful commodity - acquisition of information to eliminate uncertainty should then be considered as an alternative to productive investment subject to uncertainty." (Hirshleifer, Investment, Interest and Capital, Prentice Hall, 1970)[78]

The assertion that information itself is a useful commodity and how it impacts on stock market indices is the underlying notion of the thesis and one borne out in the findings throughout. Despite the volume and diversity of the literature in this subject matter, the majority of studies focused mostly on the experience of the US market. As a consequence, one of the objectives of the thesis was to bridge some of the imbalances in the literature that is inevitable given the focus of attention to one market.

The nature of the investigations undertaken in this thesis is to some extent a by-product of the market regime in operation. The key feature retained by the London Stock Exchange (LSE) following 'Big Bang' is its dealership structure. As discussed in Chapter One, this structure relies heavily on the

[78] This quote is cited in Copland & Weston, Financial Theory and Corporate Policy (Third Edition, Addison-Wesley Publishing Company, 1992) p.330.

market maker whose activities involve buying and selling shares and quoting two-way prices on the stocks they are assigned to throughout the trading day. Such is the importance of market structures that Chapter One provides a critique of the market making models. This review has the dual purpose of identifying the empirical issues in the ensuing investigations and provides useful intuition behind the results.

In reviewing the literature on market making models, the thesis identifies four areas of research. The first issue considers the relationship between market anomalies and the variance of non-trading and trading period returns on the FTSE-100 Index. The second issue explores the dynamics that govern the behaviour of index return volatility at opposite periods of the trading day. Using three stock indices in the LSE, the third issue examines the joint dynamics of trading volume and volatility driven by surprises and current information. Finally, the thesis investigates the asymmetric transmission of volatility across markets and whether this is induced by extreme, uncommon shocks and by weekend trading in Tokyo. Although the research areas listed above are interrelated on a theoretical level, the thesis viewed each issue separately given the restrictions imposed on the availability of UK data.

The nature of the investigations listed above has served to highlight the importance of examining the core methodology of the thesis. The view held throughout, is to observe the choice of methodology as dictated by two interrelated empirical issues; firstly, the objective of the investigation itself and second, the usefulness of the approach against the overwhelming evidence of serial dependencies and non-normality in the distribution of speculative price changes. As a consequence, much of the emphasis in Chapter Two focused on the failure of conventional regression models to capture the true nature of the underlying generating process. It is for this reason that the thesis proposes the use of GARCH and EGARCH models from Chapter Four to Chapter Six in the thesis. Despite the use of the Heteroscedastic Regression Model (HRM) in Chapter Three, the review of key papers has served to highlight the necessity to adjust the data for serial dependencies before performing the analysis.

As was mentioned in the introduction, the underlying motivation of the thesis is the empirical and theoretical question concerning the dynamics surrounding the information processing in financial markets. The intuition behind this notion is to understand whether information fulfils its prescribed role in eliminating uncertainties that govern the functioning and dynamics of the market. The first line of investigation tested the above hypothesis against the alternative that renders the market dominated by the activities of noise traders. This was possible by examining the behaviour of index returns during non-trading and trading periods. In addressing this area of research in Chapter Three, the findings revealed consistencies with previous studies in that index returns are more volatile during trading hours. However, previous investigations have treated the identification of variance differentials in too simplistic manner by viewing the process of information and trading hypothesis as principle factors. In response, the view held in the study and one that constitutes a contribution to the existing literature, is the relationship between market anomalies and the variance of index returns. The existence of such a relationship is possible by the complementary nature of market anomalies with the process of information and trading hypothesis. As highlighted in Chapter Three, the results support the first hypothesis where the private information component is the driving force behind the behaviour of FTSE-100 Index returns.

A second line of investigation considered the dynamics that govern the behaviour of index return volatility at the beginning and end of trading. Chapter Four addresses this issue by paying attention to the time varying nature of volatility at the beginning and end of trading. Unlike previous studies that focus on different market structures as the centrepiece of their investigations, a similar study is not applicable to the UK given that the LSE operates a dealership market regime. For the purpose of the thesis, this allows differences in volatility patterns at opposite periods of the trading day to be attributable to the dynamics in the information processing of the market. Utilising EGARCH models introduced in Chapter Two provides inferences on volatility differentials that are driven by old news and the size and sign of recent information. The arguments proposed here goes beyond the use of EGARCH models towards modelling the duration and rate of decay of a shock at the open and close of trading. The results in this chapter revealed interesting findings not sought for in previous studies. Despite collaborative evidence that trading period variances are more volatile at the start of trading, the re-estimation of EGARCH models on daily returns by day of the week generated contrasting results. Furthermore, by using impulse response analysis on each day of the week, the higher volatility observed at the day's close relate to the failure of the market to return to pre-shock levels following a random shock.

Although the first two empirical studies focused on the one-dimensional relationship between information and volatility, Chapter Five examines whether the same relationship is two-dimensional. The study proposes that a two dimensional relationship between information and volatility is only possible if information affects prices through trading. Hence, this chapter re-examines the volume-volatility relationship as driven by the flow of information. Although the volume of literature in this subject area is extensive, the study makes two important contributions to the academic debate. The first contribution is the proposal of the EGARCH methodology in this capacity. Given that daily returns is determined by a mixture of distribution, the ability of EGARCH models to extract more information from the data means that it provides more accurate readings of the volume-volatility relationship. The investigation makes a further contribution by extracting information on the components of trading volume that are driven by surprises and current information. By treating volume in this way, the study can investigate whether surprises contain more information and thus, further increase volatility than current information. The initial conclusion reached is of a positive relationship between both variables that depends on the component of volume used and the composition of the index. However in all cases, trading volume fails to proxy the flow of information. One can view this in terms of the operation of an efficient market in which forecasting changes in prices based on changes in trading volume is not possible. An alternative explanation provided in the study is that this raises the suspicion that variables other than trading volume determines index price volatility outside the confines of the (E)GARCH systems.

The final line of investigation focused on the asymmetric transmission of volatility across the Tokyo, London and New York stock markets. The intuition behind this subject area relates to the notion that volatility transmissions across indices represent a manifestation of extreme movements. As a consequence, the chapter starts by investigating the extent to which asymmetries govern the transmission of volatility. Within this framework, the study proposes two issues that contribute to the literature: whether asymmetries in the transmission of volatility are induced by extreme, uncommon events such as the October 1987 Crash and by an extra half-day of trading in Tokyo during some weekends. The nature of the investigation warranted the use of the bivariate-EGARCH model. The usefulness of this approach relates to its ability to extract more information about the dynamics surrounding market interdependencies than is possible with the GARCH. As such, this is borne out by the results.

7.2 OVERALL IMPLICATION OF THE RESULTS

In studying the functioning and dynamics of stock market indices, this thesis has uncovered new phenomena within the framework of a dealership market structure. The uncovering new phenomenon borne out by the results has served to pose questions on the scope of previous studies. The overall consensus running through the thesis is that the arrival and dissemination of information is the driving force behind changes in index values as opposed to the activities of uninformed noise traders. In addition, the thesis reveals anomalies both in speculative price changes and the nature and flow of information. One obvious example is the relationship between market anomalies and index return variances observed in Chapter Three. The results suggest evidence of a non-trading weekend effect associated with the highest non-trading variances. This finding leans itself to the conclusion that an accumulation of negative private information leads to a downward revision of expected index values on Monday. Thus, revealing a new phenomenon not reported by previous studies. In addition, no investigation to our knowledge has provided variance estimates for the five trading days of the week along with holiday periods. As such, the results served the useful purpose of highlighting the implications of ignoring this type of analysis by providing conclusive findings. For instance, the revealing of a U-shape pattern of variances indicates the presence of two interrelated forces. Firstly, the Monday variance represents an acceleration of trades given the accumulation of private information over the weekend and second; the Friday variance reflects the execution of trades before the weekend. In addition, the difference in the variance of returns during trading and non-trading hours narrow significantly in the presence of the non-trading weekend effect. Once again, this underlines the importance of private information in the determination of index values.

Chapter Four highlighted a previously investigated phenomenon that concerns the behaviour of index return volatility at the beginning and end of trading. However, unlike previous studies, this is attributable to the dynamics governing the information processing of the market as opposed to the market structure. As a consequence, the centrepiece of the investigation was the identification of two sources of market volatility envisaged in the literature. According to the Efficient Market Hypothesis (EMH), the arrival of information induces trading, thus having an immediate impact on price volatility. The second explanation and one suggested by the results, relates to the inability of the market to process this information in a manner that conforms to the strict definition of the EMH. This is implied by the longer time span required for the market to discount the information especially at the close of trading.[79] Therefore, to pass judgement on whether a market is efficient is no longer a viable proposition to make. Instead, the findings justify the need to comment on the relative degrees of efficiency during the trading day.

Of direct interest to the regulatory authorities concerns the relationship between information, trading volume and volatility investigated in Chapter Five. The investigation served the useful purpose of providing information on

[79] In Chapter Four, the word "information" represented a random shock.

the nature and causes of volatility, two issues of paramount importance before the recommendation and imposition of regulatory controls. If the revealing of a positive volume-volatility relationship is indicative of an efficient market, the imposition of restrictions on trading activity may serve to harm the effective functioning of the market. An alternative conclusion also borne out by the results suggest that this is attributable to other factors not captured in the GARCH system. One possible factor to arise in the study is the dominance of noise traders. As a consequence, increased volume driven by the activities of noise traders will invoke demands for the imposition of restrictions on their trading activities. In such a scenario, the enforcement of regulations on trading activities may serve to improve the effective functioning of the market.

Finally, another useful area of research to policy makers is the findings presented in Chapter Six. Unlike previous studies that examine the October 1987 Crash on the degree of market interdependencies,[80] the thesis considers whether the presence of an asymmetric component is the product of extreme, uncommon events. The crash results suggest that an uncommon event of this magnitude appears to condition the market's differential response to negative and positive news.

Of particular interest to the regulatory authorities is the impact of an extra day of trading in one market on the domestic and international market. The results

[80] See Malliaris & Urrutia (1992) and Arshanpalli & Doukas (1993) in the literature review of Chapter One.

indicate that an additional half-day of trading in Tokyo induces asymmetries that is restricted to the next market to trade. In addition, the nature and causes of volatility determine whether changes in the number of trading days are beneficial to the effective functioning of the market. If volatility induced by an extra half day of trading reflects the dissemination of additional information, then allowing more trading time will be beneficial to the effective functioning of national and international markets. This conclusion is suggested by the results.

7.3 ISSUES FOR FUTURE RESEARCH

The four empirical studies in this thesis have raised areas of research, worthy of consideration in the future. For instance, the relationship between market anomalies and the variance of index returns in Chapter Three highlights a new phenomenon that is applicable to intra-daily data. An investigation of this nature will provide inferences on the origins of any anomaly and allow for the observation of intra-daily patterns in returns in the first and second moments. Moreover, one can utilise this type of analysis on intra-daily data by day of the week to determine any changes in the patterns.

The use of different data types is applicable in studying the dynamics of information processing in stock markets as investigated in Chapter Four. An obvious starting point is to use noon data in conjunction with daily opening and closing prices. With this type of analysis, one can observe the time varying nature of volatility over the three periods and the responsiveness of the market to random shocks using impulse response analysis. Given that the market models reviewed in Chapter One envisage a U-shape pattern of volatility, this analysis can confirm whether the behaviour of noon data is consistent with the inactivity of traders. Within this framework, the investigation can probe further into this issue by determining which day of the week the U-shape pattern is most profound and then performing the impulse response analysis. An analysis of this nature will serve the useful purpose of extracting more information on the dynamics surrounding the processing of information.

A re-examination of the volume-volatility relationship in Chapter Five is possible at a micro level by focusing on individual stocks along the lines of Lamoureux & Lastrapes (1990). However, unlike their study who uses twenty of the most actively traded stocks, one possible direction is the construction of portfolios that comprises of large, medium and small stocks. Future research in this direction is reminiscent of the study of Weigand (1996) who does precisely this. However, he considers information spillovers across different size portfolios using volume only. Nevertheless, this type of investigation within the framework envisaged in the thesis could determine whether surprises contain more information and thus, further impact on the portfolio of smaller stocks than larger stocks.

In summary, the issues raised by the thesis provide a useful starting point for future research.

BIBLIOGRAPHY

Admati, A.R. and P. Pfleiderer, (1988): "A Theory of Intraday Trading Patterns: Volume and Price Variability", *Review of Financial Studies,* Vol 1, pp.3 - 40.

Agmon, T. (1972): "The Relations Among Equity Markets: A Study of Share Price Co-movement in the United States, United Kingdom, Germany and Japan", *Journal of Finance*, Vol 27, pp.839 - 855.

Akgiray, V. (1989): "Conditional Heteroskedascity in Time Series of Stock Returns: Evidence and Forecasts", *Journal of Business*, Vol 62, No 1, pp.55 - 80.

Amihud, Y. & H. Mendelson, (1987): "Trading Mechanisms and Stock Returns: An Empirical Investigation", *Journal of Finance*, Vol 42, No 3, pp.533 - 553.

Antoniou, A. & A.J. Foster, (1992): "The Effects of Futures Trading on Spot Price Volatility: Evidence for Brent Crude Oil Using GARCH", *Journal of Finance & Accounting*, Vol 19, No 4, pp.473 - 484.

Antoniou, A. & P. Holmes, (1995): "Futures Trading, Information and Spot Price Volatility: Evidence for the FTSE 100 Stock Index Futures Contract Using GARCH", *Journal of Banking & Finance*, Vol 19, pp.117 -129.

Arshanpalli, B. & J. Doukas, (1993): "International Stock Market Linkages: Evidence from the Pre - and Post - October 1987 Period", *Journal of Banking and Finance*, Vol 17, pp.193 - 208.

Baillie, R. & T. Bollerslev, (1989): "Common Stochastic Trends in a System of Exchange Rates", *Journal of Finance*, Vol 44, pp.167 - 182.

Barclay, M.J., R.H. Litzenberger & J.B. Warner, (1990): "Private Information, Trading Volume, and Stock - Return Variances", *The Review of Financial Studies*, Vol 3, No 2, pp.233 - 253.

Becketti, S. & D.J. Roberts, (1990): "Will Increased Regulation of Stock Index Futures Reduce Stock Market Volatility?", *Economic Review*, pp.33 - 42.

Bell, D. & E. Levin, "Do Intra-Week Regularities in Stock Returns Undermine Efficient Market Theory? Some Evidence from the UK.", University of Sterling Working Paper, 1996.

Berndt, E., R. Hall & J. Hausman, (1974): "Estimation and Inference in Nonlinear Structural Models", *Annals of Economic and Social Measurement*, Vol 3, pp.653 - 665.

Bessembinder, H. & P.J. Seguin, (1993): "Price Volatility, Trading Volume, and Market Depth: Evidence from Futures Markets, *Journal of Financial and Quantitative Analysis*, Vol 28, No 1, pp.21 - 39.

Black, F. (1976): "Studies in Stock Volatility Changes", Proceedings of the 1976 Meetings of the Business and Economics Statistics Section, *American Statistical Association*, pp.177 - 181.

Blume, L., D. Easley & M. O'Hara, (1994): "Market Statistics and Technical Analysis: The Role of Volume", *Journal of Finance*, Vol 49, No 1, pp.153 - 181.

Blume, M.E. & R.F. Stambaugh, (1983): "Biases in Computed Returns. An Application to the Size Effect", *Journal of Financial Economics*, Vol 12, pp.387 - 404.

Bollerslev, T. (1986): "Generalised Autoregressive Conditional Hetroskedasticity", *Journal of Econometrics*, Vol 31, pp.307 - 327.

Bollerslev, T. (1987): "A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return", *The Review of Economics and Statistics*, pp.542 - 547.

Bollerslev, T. (1990): "Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalised ARCH Model", *The Review of Economics and Statistics*, Vol 72, pp.498 - 505.

Bollerslev, T., R.Y. Chou & K.F. Kroner, (1992): "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence", *Journal of Econometrics*, Vol 52, pp.5 59.

Bollerslev, T., R.F. Engle & J.M. Wooldridge, (1988): "A Capital Asset Pricing Model With Time-Vrying Covariances", *Journal of Political Economy*, Vol 96, No 1, pp.116 - 131.

Bookstaber R.M. & S. Pomerantz, (1989): "An Information-Based Model of Market Volatility", *Financial Analysts Journal*, November/December, pp.37 - 46.

Brown, K.C., W.V. Harlow & S.M. Tinic, (1988): "Risk Aversion, Uncertain Information, and Market Efficiency", *Journal of Financial Economics*, Vol 22, pp.355 - 385.

Campbell, J.Y. & L. Hentschel, (1992): "No News is Good News - An Asymmetric Model of Changing Volatility in Stock Returns", *Journal of Financial Economics*, Vol 31, No 3, pp.543 - 569.

Chan, K.C. (1986): "Can Tax-Loss Selling Explain the January Seasonal in Stock Returns?", *Journal of Finance*, Vol 41, pp.1115 - 1128.

Cheung, C.S. & C.C.Y. Kawn, (1992): "A Note on the Transmission of Public Information Across International Stock Markets", *Journal of Banking and Finance*, Vol 16, pp.831 - 837.

Cho, D.C. & E.W. Frees, (1988): "Estimating the Volatility of Discrete Stock Prices", *Journal of Finance*, Vol 43, No 2, pp.451 - 466.

Clark, P.K. (1973): "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices", *Econometrica*, Vol 41, pp.135 - 155.

Condoyanni, L., J. O'Hanlon & C.W.R. Ward, (1987): "Day of the Week Effects on Stock Returns: International Evidence", *Journal of Business and Accounting*, 14, No 2, pp.159 - 174.

Copland, Thomas.E. & J.Fred. Weston, "Financial Theory and Corporate Policy", Third Edition, Addison - Wesley Publishing Company, 1992.

Copeland T.E. (1976): "A Model of Asset Pricing Under the Assumption of Sequential Information Arrival", *Journal of Finance*, Vol 31, No 4, pp.1149 - 1168.

Daigler, R.T. & M.K. Wiley, (1998): "The Impact of Trader Type on the Futures Volatility-Volume Relation", *Forthcoming Journal of Finance, December 1999*, pp.1 - 30.

Darret, A.F. & S. Rahman, (1995): "Has Futures Trading Activity Caused Stock Price Volatility?", *The Journal of Futures Markets*, Vol 15, No 5, pp.537 - 557.

Davidian, M. & R.J. Carroll, (1987): "Variance Function Estimation", *Journal of American Statistical Association*, Vol 82, No 400, pp.1079 - 1091.

De Bondt, W.F.M. & R. Thaler, (1985): "Does the Stock Market Overreact?", *Journal of Finance*, Vol 40, pp.793 - 805.

Dimson, E. & P.Marsh, (1999): "Murphy's Law and Market Anomalies", *The Journal of Portfolio Management*, Winter, pp.53 - 69.

Draper, P. & K. Paudyal, "Monday Effect: An Integrated Approach", Glasgow Caledonian University, Working Paper, 1998.

Dupont, D. "Extracting Information From Trading Volume", Board of Governors of the Federal Reserve System, Working Paper, 1997.

Ederington, L.H. & J.H. Lee, (1993): "How Markets Process Information: News Releases and Volatility", *Journal of Finance*, Vol 48, No 4, pp.1161 - 1191.

Engle, R.F. (1982): "Autoregressive Conditional Hetroskedasticity With Estimates of the Variance of United Kingdom Inflation", *Econometrica*, Vol 50, No 4, pp.987 - 1007.

Engle, R.F. (1990): "Discussion: Stock Market Volatility and the Crash of 87", *Review of Financial Studies*, Vol 3, pp.103 - 106.

Engle, R.F. and V.K. Ng, (1993): "Measuring and Testing the Impact of News On Volatility", *Journal of Finance*, Vol 48, No 5, pp.1749 - 1778.

Engle, R.F., T. Ito & W.L. Lin, (1992): "Where does Meteor Shower Come From? The Role of Stochastic Policy Co-ordination", *Journal of International Economics*, Vol 32, pp.221 - 240.

Epps, T.W. & M.E. Epps, (1976): "The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distributions Hypothesis", *Econometrica*, Vol 44, No 2, pp.305 - 321.

Eun, C.C. & S. Shim, (1989): "International Transmission of Stock Market Movements", *Journal of Financial and Quantitative Analysis*, Vol 24, No 2, June 1987, pp.241 - 256.

Fama, E.F. (1965): "The Behaviour of Stock Market Prices", *Journal of Business*, Vol 38, pp.34 - 105.

Fama, E.F. (1970): "Efficient Capital Markets: A Review of Theory and Empirical Work", *Journal of Finance*, May 1970, pp.383 - 417.

Fama, E.F. (1991): "Efficient Capital Markets: II", *Journal of Finance*, Vol 46, No 5, pp.1575 - 1611.

Foster, A.J. (1995): "Volume-Volatility Relations for Crude Oil Futures Markets", *The Journal of Futures Markets*, Vol 15, No 8, pp.929 - 951.

Foster, F.D. & S. Viswanathan, (1994): "Strategic Trading With Asymmetrically Informed Traders and Long-Lived Information", *Journal of Financial and Quantitative Analysis*, Vol 29, No 4, pp.499 - 518.

French,K.R. (1980): "Stock Returns and the Weekend Effect", *Journal of Financial Economics*, Vol 8, pp.55 - 69.

French, F.R. & R. Roll, (1986): "Stock Return Variances - The Arrival of Information and the Reaction of Traders", *Journal of Financial Economics*, Vol 17, No 1, pp.5 - 26.

French, K.R., G.W. Schwert & R.F. Stambaugh, (1987): "Expected Stock Returns and Volatility", *Journal of Financial Economics*, Vol 19, pp.3 - 29.

Gallant, A.R., P.E. Rossi & G. Tauchen, (1992): "Stock Prices and Volume", *The Review of Financial Studies*, Vol 5, No 2, pp.199 - 242.

Garbade, K.D. & W.L. Silber, (1979): "Structural Organisation of Secondary Markets: Clearing Frequency, Dealer Activity and Liquidity Risk, *Journal of Finance*, Vol 34, No 3, pp.577 - 593.

Godfrey, L.G. (1978): "Testing Against General Autoregressive and Moving Average Error Models when the Regressors Include Lagged Dependent Variables", *Econometrica*, Vol 46, No 6, pp.1293 - 1301.

Greene, William.H. "Econometric Analysis", Second Edition, Prentice Hall, 1993.

Hamao, Y., R.W. Masulis & V. Ng, (1990): "Correlations in Price Changes and Volatility Across International Stock Markets", *The Review of Financial Studies*, Vol 13, No 2, pp.281 - 307.

Harris, L. (1987): "Transactions Data Tests of the Mixture of Distributions Hypothesis", *Journal of Financial and Quantitive Analysis*, Vol 22, No 2, pp.127 - 141.

Harvey, C.R. & R.D. Huang, (1991): "Volatility in the Foreign Exchange Currency Futures Market", *The Review of Financial Studies*, Vol 4, No 3, pp.543 - 569.

Hilliard, J.E. (1979): "The Relationship Between Equity Indices on World Exchanges", *Journal of Finance*, Vol 44, No 1, pp.103 - 114.

Hogen, K.C. & M.T. Melvin, (1994): "Sources of Meteor Showers and Heat Waves in the Foreign Exchange Market", *Journal of International Economics*, Vol 37, pp.239 - 247.

Howells, Peter.G.A. & Keith. Bain, "Financial Markets and Institutions", Longman London and New York, 1990.

Hsieh, D.A. (1988): "The Statistical Properties of Daily Foreign Exchange Rates: 1974-1983", *Journal of International Economics*, Vol 24, pp.129-145.

Hsieh, D.A. (1989): "Testing for Nonlinear Dependence in Daily Foreign Exchange Rates", *Journal of Business*, Vol 62, No 3, pp.339 - 368.

Hull, John. "Options, Futures, and Other Derivative Securities", Prentice-Hall International Editions, 1989.

Ito, T., R.F. Engle & W.L. Lin, (1990): "Meteor Showers or Heat Waves? Heteroskedastic Intra-daily Volatility in the Foreign Exchange Market", *Econometrica*, Vol 58, No 3, pp.573 - 70.

Jaffe, J. & R. Westerfield, (1985): "The Week-End Effect in Common Stock Retuns: The International Evidence", *Journal of Finance*, Vol 40, No 2, pp.433 - 454.

Jennings, R.H. & C. Barry, (1983): "Information Dissemination and Portfolio Choice", *Journal of Financial and Quantitative Analysis*, Vol 18, pp.1 - 19.

Jennings, R. & L. Starks, (1985): "Information Content and the Speed of Stock Price Adjustment", *Journal of Accounting Research*, Vol 23, No 1, pp.336 - 350.

Johnston, J. "Econometric Methods", Third Edition, McGraw-Hill, 1991.

Jones, C.M., G. Kaul & M.L.L. Lipson, (1994): "Information, Trading and Volatility", *Journal of Financial Economics*, Vol 36, pp.127 - 154.

Karpoff, J.M. (1987): "The Relation Between Price Changes and Trading Volume: A Survey", *Journal of Financial & Quantitive Analysis*, Vol 22, No 1, pp.109 - 126.

Kau, G. & M. Nimalendran, (1990): "Price Reversals - Bid-Ask Errors or Market Overreaction", *Journal of Financial Economics*, Volume 28, pp.67 - 93.

Keim, D.B. (1983): "Size Related Anomalies and Stock Return Seasonality: Further Empirical Evidence", *Journal of Financial Economics*, Vol 12, pp.13 - 32.

Kim, O. & R.E. Verrecchia, (1991): "Market Reaction to Unanticipated Announcements", *Journal of Financial Economics*, Vol 30, pp.273 - 309.

King, M.A. & S. Wadhwani, (1990): "Transmission of Volatility Between Stock Markets", *The Review of Financial Studies*, Vol 3, No 1, pp.5 - 33.

Koch, P.D. & T.W. Koch, (1991): "Evolution in Dynamic Linkages Across Daily National Stock Indexes", *Journal of International Money and Finance*, Vol 10, pp.231 - 251.

Koutmos, G. & G.G. Booth, (1995): "Asymmetric Volatility Transmission in International Stock Markets", *Journal of International Money and Finance*, Vol 14, No 6, pp.747 - 762.

Koutmos, G. & M. Tucker, (1996): "Temporal Relationships and Dynamic Interactions Between Spot and Futures Stock Markets" , *The Journal of Futures Markets*, Vol 16, No 1, pp.55 - 69.

Kyle, A.S. (1985): "Continuous Auctions and Insider Trading", *Econometrica*, Vol 53, pp.1315 - 1335.

Lamoureux, C.G. & W.D. Lastrapes, (1990): "Hetroscedasticity in Stock Return Data: Volume Versus GARCH Effects", *Journal of Finance*, Vol 45, No 1, pp.221 - 29.

Lee, J-H. & B.W. Brorsen, (1997): "A Non-Nested Test of GARCH vs. EGARCH Models", *Applied Economic Letters*, Vol 4, pp.765 - 768.

Ljung, G.M. & G.E.P. Box, (1978): "On a Measure of Lack of Fit in Time Series Models", *Biometrika*, Vol 67, pp.297 - 303.

Lo, A.W. & A.G. MacKinlay, (1988): "Stock Prices Do Not Follow Random Walks: Evidence From a Simple Specification Test", *The Review of Financial Studies*, Vol 1, No 1, pp.41 - 66.

London Stock Exchange, "Fact File 1998", London Stock Exchange Limited, Black Sun Plc, London, 1998.

Malliaris, A.G. & J.L. Urrutia, (1992): "The International Creash of October 1987: Causality Tests", *Journal of Financial and Quantitative Analysis*, Vol 27, No 3, pp.353 - 363.

Malliaropulos, D. (1997): "A Multivariate GARCH Model of Risk Premia in Foreign Exchange Markets", *Economic Modelling*, Vol 14, pp.61 - 79.

Mandelbrot, B. (1963): "The Variation of Certain Speculative Prices", *Journal of Business*, Vol 36, pp.314 - 419.

Mendelson, H. (1982): "Market Behaviour in a Clearing House", *Econometrica*, Vol 50, No 6, pp.1505 - 1524.

Mendelson, H. (1987): "Consolidation, Fragmentation, and Market Performance", *Journal of Financial and Quantitative Analysis*, Vol 22, No 2, pp.189 - 207.

Najand, M. & K. Yung, (1991): "A GARCH Examination of the Relationship Between Volume and Price Variability in Futures Markets", *The Journal of Futures Markets*, Vol 11, No 5, pp.613 - 621.

Nelson, D. (1990): "Conditional Heteroscedasticity in Asset Returns: A New Approach", *Econometrica*, Vol 59, pp.347 - 370.

Oldfield JR, G.S. & R.J. Rogalski, (1980): "A Theory of Common Stock Returns Over Trading and Non-Trading Periods", *Journal of Finance*, Vol 35, No 3, pp.729 - 751.

Oldfield JR, G.S., R.J. Rogalski & R.A. Jarrow, (1977): "An Autoregressive Jump Process For Common Stock Returns", *Journal of Financial Economics*, Vol 5, pp.389 - 418.

Pagan, A. (1996): "The Econometrics of Financial Markets", *Journal of Empiricial Finance*, Vol 3, pp.15 - 102.

Pagan, A.R. & G.W. Schwert, (1990): "Alternative Models for Conditional Stock Volatility", *Journal of Econometrics*, Vol 45, pp.267 - 290.

Pagano, M. & A. Roell, "Trading Systems in European Stock Exchanges", *Discussion Paper, LSE Financial Markets Group Discussion Paper Series*, No 75, 1990.

Panton, D.B., V.P. Lessig & D.M. Joy, (1976): "Comovement of International Equity Markets: A Taxonomic Approach", *Journal of Financial and Quantitative Analysis*, pp.415 - 432.

Park, H.Y. (1993): "Trading Mechanisms and Price Volatility: Spot Versus Futures", *The Review of Economics and Statistics*, pp.175 - 179.

Peterson, D.R. (1990): "Stock Return Seasonalities and Earnings Information", *Journal of Financial and Quantitative Analysis*, Vol 25, pp.187 - 201.

Pindyck, Robert.S. & Daniel.L. Rubinfield, "Econometric Models and Economic Forecasts", Forth Edition, McGraw-Hill International Editions, 1998.

Powers, M.J. (1970): "Does Futures Trading Reduce Price Fluctuations in the Cash Markets?", *The American Economic Review*, Vol 60, pp.460 - 464.

Puffer, M.K. (1991): "Private Information and Weekend Volatility in the Tokyo and New York Stock Markets", *Journal of Banking and Finance*, Vol 15, pp.407 - 423.

Ramanathan, Ramu. "Introductory Econometrics with Applications", Second Edition, The Dryden Press, Harcourt Brace Jovanovich College Publishers, 1992.

Rathinasamy, R.S. & K.G. Mantripragada, (1996): "The January Size Effect Revisted: Is it a case of Risk Measurement?", *Journal of Financial and Strategic Decisions*, Vol 9, No 3, pp.9 - 14.

Ripley, D.M. (1973): "Systematic Elements in the Linkage of National Stock Market Indices", *Review of Economics and Statistics*, Vol 55, pp.356 - 361.

Rogalski, R.J. (1984): "New Findings Regarding Day-of-the-Week Returns Over Trading and Nontrading Periods: A Note", *Journal of Finance*, Vol 41, No 5, pp.1603 - 1614.

Roll, R. (1988): "The International Crash of October 1987", *Financial Analysts Journal*, September/October, pp.19 - 35.

Ross, A. (1989): "Information and Volatility: The No-Arbitrage Martingle to Timing and Resolution Irrelevancy", *Journal of Finance*, Vol 44, pp.1 - 17.

Schollhamer, H. & O. Sand, (1985): "The Interdependence Among the Stock Markets of Major European Countries and the United States: An Empirical Investigation of the Interrelationships Among National Stock Prices Movements", *Management International Review*, Vol 25, pp.17 - 26.

Schwert, G.W. (1990): "Stock Volatility and the Crash of '87", *The Review of Financial Studies*, Vol 3, No 1, pp.77 - 102.

Sharma, J.L., M. Mbodja & R. Kamath, (1996): "Heteroskedasticity in Stock Market Indicator Return Data: Volume Versus GARCH Effects", *Applied Financial Economics*, Vol 6, pp.337 - 342.

Shleifer, A. & L.H. Summers, (1990): "The Noise Trader Approach to Finance", *Journal of Economic Perspectives*, Vol 4, No 2, pp.19 - 33.

Sims, C.A. (1980): "Macroeconomics and Reality", *Econometrica*, Vol 48, No 1, pp.1 - 48.

Steil, Benn. "The European Equity Markets, The State of the Union and an Agenda for the Millennium", A Report of the European Capital Markets Institute.

Stewart, Jon. "Econometrics", Philip Allan, 1991.

Stoll, H.R. & R.E. Whaley, (1990): "Stock Market Structure and Volatility", *The Review of Financial Studies*, Vol 3, No 1, pp.37 - 71.

Wang, K., Y.Li & J. Erickson, (1997): "A New Look at the Monday Effect", *Journal of Finance*, Vol 52, No.5, pp. 2171 – 2186.

Weigand, R.A. (1996): "Trading Volume and Firm Size: A Test of the Information Spillover Hypothesis", *Review of Financial Economics*, Vol 5, No 1, pp.47 - 58.

Yang, S.R. & B.W. Brorsen, (1993): "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroskedasticity or Chaos?", *The Journal of Futures Markets*, Vol 13, No 2, pp.175 - 191.

Zellner, A. (1962): "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests of Aggregation Bias", *Journal of American Statistical Association*, Vol 57, pp.348 - 368.