A Comparative Analysis of the Determinants and Pricing of Liquidity in Floor and Electronic Trading Systems

TAYEH, MOHAMMAD,IBRAHIM,DIAB

بسم الله الرحمن الرحيم

وقل رب زدني علما

In the name of Allah, the Most Gracious, the Most Merciful

"And say: O my Lord! Advance me in knowledge."
(Surah Ta-Ha, 114)

A Comparative Analysis of the Determinants and Pricing of Liquidity in Floor and Electronic Trading Systems

By

Mohammad I. D. Tayeh

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Department of Economics and Finance

Durham Business School

University of Durham

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Abstract

In recent years many stock exchanges have moved away from floor-based to automated-based trading systems. However, the choice between these alternative trading systems is a major concern for stock exchange regulators and designers, and the impact of their merits on market characteristics (e.g. liquidity) is controversial. This thesis is motivated by the desire to shed light on this controversy, and therefore aims to offer a comparative analysis of various aspects of liquidity under floor and automated trading systems. More specifically, within the context of different trading systems (i.e. floor versus electronic), this thesis examines three empirical issues: firstly, the determinants of market-wide liquidity and its time-series behaviour; secondly, whether market-wide and firm-specific liquidity are priced in assets returns; and finally, whether the cross-sectional variations in firm-specific liquidity could be explained by the cross-sectional variations in information asymmetry and divergence of opinion.

The findings of this thesis can be summarized as follows. Firstly, market-wide liquidity is significantly influenced by market returns, market volatility, interest rate variables and the announcement of macroeconomic indicators. Market-wide liquidity also shows distinct day-of-the-week regularities and a distinct pattern around holidays. The impact of some factors on market-wide liquidity, and the time-series behaviour of market-wide liquidity on the floor trading system in some markets is higher than that on the electronic trading systems. Secondly, market-wide liquidity has a significant impact on assets returns, and after controlling for its effect, firm-specific liquidity has a significant effect on risk-adjusted returns. The liquidity premium required on market-wide and firm-specific liquidity, for some proxies of liquidity in some markets, is higher on an automated trading system than on a floor trading system. Finally, firm-specific liquidity is negatively related to the level of information asymmetry. However, the evidence for the impact of divergence of opinion on firm-specific liquidity is inconclusive; a higher level of divergence of opinion results in higher liquidity, which supports the optimistic view; and firm-specific liquidity decreases with divergence of opinion, which is consistent with the view that disagreement among investors is a source of risk. Additionally, after automation, the impact of information asymmetry (divergence of opinion) on firm-specific liquidity is greater (lesser) than that before automation.

Overall, this thesis demonstrates that the design and the structure of markets is closely linked to the latter's performance and that the change to automated trading systems has significant implications for liquidity. As such, this study should be a valuable reference point for stock exchanges that have introduced automation, or are considering doing so.

Declaration

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

Dedication

To my beloved parents,

Ibrahim and Fatima.

For your sincere prayers and encouragement.

You are a fountain of love and kindness,

I love you from the bottom of my heart.

To my brothers and sisters,

For your love and continual support.

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Chapter One
Introduction

The last two decades has witnessed the emergence of market microstructure as a new field within finance literature. Market microstructure "is concerned with the process by which investor's latent demands are ultimately translated into transactions" (Madhavan, 2000, p. 206). In the words of O'Hara (1997), market microstructure can also be defined as "the study of the process and outcomes of exchanging assets under explicit trading rules" (p. 1). The central theme of this area, in contrast to the efficient market hypothesis, is that due to different frictions, stock prices do not need to be equal to the full-information expectations of value (Madhavan, 2000). Therefore, market microstructure focuses on studying the process of price formation under different market frictions such as bid-ask spread and information asymmetry between traders.

This area has attracted the attention of several researchers and since its emergence it has grown and expanded quickly. As a result, there are already some useful studies that provide a valuable survey of the literature on market microstructure. For instance, Madhavan (2000) offers a distinctive account which categorizes issues examined in market microstructure into four categories: price formation and price discovery; market structure and design issues; information and disclosure, and the interface of market microstructure with other areas of finance[1].

This thesis takes the second and the fourth categories as its main focus. The published literature on market structure and design issues focuses on examining how different trading rules and mechanisms affect market quality and liquidity, while the literature on the interface of market microstructure with other areas of finance focuses on the quest for the link between market microstructure and other areas of finance such as asset pricing and corporate finance. The themes in this thesis are directly related to the on-going debates

[1] Other surveys include O'Hara (1997) which provides a detailed survey on the theoretical literature on market microstructure, Keim and Madhavan (1998) who offer an overview of the literature on the trading costs for institutional investors, and Biais et al. (2005) who survey the literature that focuses on price formation and market design.

(Madhavan, 2000, 2001; Jain, 2005; Huang and Chou, 2007) surrounding the implications of market structure on market performance and dynamics, and thus concentrate on the sub-field of market structure and design within the area of market microstructure, and in doing so examine and compare various issues under different market structures, especially floor versus electronic trading systems. Within this context, this thesis examines the determinants of liquidity and its implications on asset pricing. The latter issue will provide greater and stronger links between market microstructure and other areas of finance such as asset pricing areas.

One main reason for the rapid growth in market microstructure literature is the significant changes that have been adopted by many stock exchanges in their structure and design. These changes have affected the way in which market participants interact. Each structure determines the rules and the ways that affect price formation and the trading process, as well as the scope of information and strategic behaviour of traders (Biais et al., 2005). This ultimately affects the two main functions of financial markets, namely, liquidity and price discovery (O'Hara, 2003). The interest of academics and market participants such as exchange management, regulators and investors in enhancing their understanding of the effect of different market structures and trading mechanisms on market performance and characteristics has increased remarkably in recent times. This growing interest has stimulated the emergence of a large bulk of empirical research that mainly deals with examining the impact and the implications of specific trading mechanisms on market characteristics (such as liquidity and price efficiency) and compares market performance under different structures. For example, several papers have compared the trading costs of the continuous auction and dealership market (see Madhavan, 1992; Christie et al., 1994; Christie and Schultz, 1994; Huang and Stoll, 1996; Dutta and Madhavan, 1997 among others). Other studies such as Amihud et al. (1997) and Muscarella and Piwowar (2001) investigate the value effect for stocks moved from call auction trading to continuous trading. Additionally, some studies compare call auction and continuous auction with a special focus on the issue of informational efficiency, such as Amihud et al. (1990) and Amihud and Mendelson (1991) among others.

The adoption of electronic trading is one of the major changes that has occurred in market design and structure in recent years. Such a change has attracted the attention of several academics and exchange regulators and designers, as well as being the main focus of this thesis. This change (moving from floor to electronic trading system) is an important issue in market microstructure, and deserves thorough investigation for several reasons. Firstly, the use of electronic trading systems has grown rapidly due to advancing technology and stock market deregulation, to the extent that the fully automated trading systems' share in securities trading has expanded widely (Brockman and Chung, 2000; Ning and Tse, 2009). Many stock exchanges around the world have abandoned floor trading systems and have fully automated their trading systems, including the Swiss Stock Exchange, the London Stock Exchange, the Vienna Stock Exchange and the Amsterdam Stock Exchange. Some stock exchanges however, such as the New York Stock Exchange (NYSE) still maintain a floor trading system[2]. As exchanges move from floor to electronic trading systems, investigation of such structural changes in market structure is of particular interest to regulators and stock exchange designers. It is important to provide them with the required knowledge and understanding of how the automation of trading systems will affect market microstructure characteristics, especially liquidity, so they can decide whether to follow the same steps as other automated stock exchanges or maintain their traditional trading systems. Furthermore, such investigations will be also pertinent for countries which are yet to establish their stock exchanges and are yet to decide on which system to use.

Secondly, despite the extensive move towards the automation of trading systems, the issue of which trading system is the most suitable is far from resolved. There is ongoing controversy (Madhavan, 2000, 2001; Jain, 2005) concerning the relative merits of floor versus electronic trading systems, and to what extent these merits affect market characteristics such as liquidity and price efficiency. The proponents of floor trading argue that these systems are better than electronic systems. For example, professional relationships may evolve during floor trading because of repeated trading and result in the sharing of information about order flows, thus reducing the level of information asymmetry

[2] NYSE still maintains its floor trading because its members believe that the elimination of floor trading could result in worse prices for the public (Freund et al., 1997; Freund and Pagano, 2000).

and increasing liquidity (Venkataraman, 2001; Jain, 2005)[3]. Also, the role of human intermediaries (i.e. specialists and brokers) in floor trading systems could provide certain benefits for the trading process, through their quick reaction to different market conditions and the execution of sophisticated trading strategies, and thus reduce trading costs and market impact (Venkataraman, 2001). On the other hand, proponents of electronic trading systems argue that the latter is more efficient and may reduce problems associated with human error. In addition, these systems are able to attract new pools of liquidity by providing remote access to investors (see Freund et al., 1997; Freund and Pagano, 2000; Venkataraman, 2001; Jain, 2005). It appears important therefore to try to resolve some of this controversy by empirically examining and comparing automated trading systems with floor trading systems, in order to gain insight on the effects of the automation process on liquidity, on the implications for determinants of liquidity, and on the implications for liquidity on assets returns.

Although there is already a large number of empirical studies that examine the relative performance of floor trading systems versus electronic trading systems (see Shyy and Lee, 1995; Pirrong, 1996; Freund and Pagano, 2000; Venkataraman, 2001; Theissen, 2002a; Maghyereh, 2005; Ning and Tse, 2009 among others), they focus on investigating whether floor trading systems or electronic trading systems lead to higher liquidity, volatility and informational efficiency[4]. In other words, these studies enclose themselves within the typical perspective of comparison between different trading systems in relation to market quality. They compare the level of market characteristics such as liquidity, price efficiency and volatility before and after automation. What is presently lacking is a deeper understanding of the effect of the introduction of electronic trading systems on liquidity related issues such as the determinants and the time-series behaviour of market-wide liquidity; the importance of liquidity in asset pricing; and the implications of both information asymmetry between company managers and outsider investors, and divergence of opinion on firm-specific liquidity.

[3] Order flow is a stream of requests to trade that other traders make of the dealers (Harris, 2003) or which are submitted to the limit order book. Order flow is characterized by three parameters: order type (market or limit order), order direction (buy or sell) and order size (small or large) (see Domowitz et al. 2005).
[4] For a detailed review of the literature on floor and electronic trading systems, see section 2.2 in chapter two.

Besides the market structure issue, one of the main issues of market microstructure is liquidity, which represents the focal point of this thesis. Liquidity can easily be recognized but unfortunately is not that easy to define. Harris (2003) defines liquidity as "the ability to trade large size quickly, at low cost, when you want to trade" (p. 394)[5]. Interest in liquidity started with the seminal work of Demsetz (1968), who formalizes the bid-ask spread as the cost of immediacy (i.e. the cost of providing liquidity). His work attracted the attention of other researchers towards liquidity. At the beginning, the empirical research focused on liquidity at firm level (i.e. firm-specific liquidity) and examined its determinants (the factors affecting the cost of supplying liquidity) such as Tinic (1972), Benston and Hagerman (1974), Glosten and Milgrom (1985), Easley et al. (1996) among others. These studies depend on two paradigms in market microstructure theory to examine the determinants of stocks' liquidity and its cost components: the inventory model and the information asymmetry model. According to the inventory model, market makers maintain an optimal inventory level and they face risk when their inventory deviates from the optimal level as a result of accommodating order flow. Therefore, market makers post lower (higher) bid-ask spread when they have long (short) positions in order to maintain the inventory at the desired level (see Stoll, 1978b; Amihud and Mendelson, 1980; Ho and Stoll, 1981; O'Hara and Oldfield, 1986 among others). The second model assumes that market makers face two types of traders, uninformed (i.e. liquidity motivated) and informed traders and that they cannot distinguish between them. Consequently, market makers quote wider bid-ask spread to maximize the profit from liquidity motivated traders and minimize the loss to informed traders (see Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987 among others)[6].

Recently, a new strand of literature in market microstructure has emerged which focuses on examining the existence of a common component in liquidity (i.e. commonality in liquidity). This strand is motivated by the pioneering work of Chordia et al. (2000), which was then followed by Huberman and Halka (2001), and Hasbrouck and Seppi (2001) who

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[5] This definition reflects various dimensions of liquidity. See section 2.1 in chapter two for these dimensions and their definition.

[6] For a more comprehensive review and discussion of the literature on the inventory model and the information asymmetry model, see O'Hara (1997).

provide evidence on commonality in liquidity for the US markets[7]. These studies find that liquidity has a systematic common component and that the fluctuations of alternative measures of individual stock liquidity are correlated to market-wide liquidity. Consequently, the work on commonality shifts the focus of empirical research on liquidity of individual stocks toward liquidity at the aggregate level (i.e. market-wide liquidity), and paves the way for further empirical research in the market microstructure area[8]. For instance, the existence of a common component in liquidity sheds light on the importance of factors that could affect market-wide liquidity and what these factors could be. In recent years, only a few studies have examined market-wide liquidity and the underlying forces that are responsible for its time-series variation, particularly with regard to the US markets (NYSE, National Association of Securities Dealers Automated Quotations System (NASDAQ) and the American Stock Exchange (AMEX)) (see Chordia et al., 2001a; Fujimoto, 2003b; Van Ness et al., 2005).

Furthermore, the evidence of commonality not only attracted the attention of researchers towards specifying the factors that affect market-wide liquidity but also highlighted the importance of market liquidity on asset pricing, even though previously the literature had examined the relation between firm-specific liquidity and stock returns (see Amihud and Mendelson, 1986). In the last four decades, the area of asset pricing has witnessed remarkable developments since the emergence of Capital Asset Pricing Model (CAPM),

[7] Further work on commonality includes, for example, Coughenour and Saad (2004) who provide evidence on commonality in liquidity in NYSE and find that common market makers are one reason for liquidity commonality. Additionally, Domowitz et al. (2005) and Galariotis and Giouvris (2007) document the existence of liquidity commonality in the Australian and the London Stock Exchange respectively.

[8] Commonality in liquidity refers to the phenomenon in which time-series fluctuations (i.e. variations) in individual stock's liquidity are induced by common underlying factors or determinants (see Chordia et al., 2000). In other words, it is the proposition that the liquidity of individual stocks responds to the changes in market-wide liquidity or industry-wide liquidity (Brockman and Chung, 2002; Fabre and Frino, 2004). According to Chordia et al. (2000), its empirical manifestation is in the co-movement of the individual stock liquidity's variation with market liquidity's variation; where the latter is the cross-sectional average of all individual stocks' liquidity while excluding the liquidity of dependent stock from the average when estimating its sensitivity to changes in market liquidity (i.e. beta). This phenomenon, commonality in liquidity, is also referred to as systematic liquidity. This indicates that market-wide liquidity is one of the determinants of individual stocks' liquidity and any shock or variation in market-wide liquidity leads to a market-wide effect (i.e. liquidity co-movements or systematic variation). Consequently, market-wide liquidity i.e. the liquidity of the whole market can be considered as a state (i.e. systematic) variable that affects many stocks simultaneously (see Huberman and Halka, 2001). Throughout this thesis, the terms market-wide liquidity, market liquidity and aggregate liquidity are used interchangeably.

which was introduced by Sharpe (1964) and Lintner (1965) in an attempt to explain cross-sectional variation in stock returns. Extensive examination of this model eventually lead to other models in asset pricing such as intertemporal CAPM (ICAPM) (Merton, 1973), Arbitrage Pricing Theory (APT) (Ross, 1976) and consumption CAPM (CCAPM) (Breeden, 1979). These models attempted to identify the risk factors that could provide a better explanation for the cross-sectional variation in asset returns. In addition, some researchers looked at macroeconomic variables as risk factors in asset pricing models such as industrial production, inflation, spread in interest rates, corporate bond yields, input costs and money supply (see Chen et al., 1986). Others examined the implications of production and investment decisions of companies on asset pricing, such as Bossaerts and Green (1989), Cochrane (1991), and Naik (1994).

Moreover, the inability of CAPM to explain the cross-section of average returns on assets sorted by size and book-to-market ratio led to further developments in asset pricing represented by the work of Fama and French (1993). They provided a three factor model that was able to explain the cross-section return and capture the impact of stock characteristics such as size and the book-to-market ratio. Then, Carhart (1997) introduced the fourth factor model, which is the Fama-French three factor model augmented with the momentum risk factor, in an attempt to explain the momentum anomaly in asset pricing. Finally, asset pricing has witnessed a recent surge in interest in pricing models that account for the impact of liquidity on asset returns. However, the interest in liquidity and its importance in asset pricing started with the seminal work of Amihud and Mendelson (1986) who focus on firm-specific liquidity, as a characteristic of a stock, and its relation to asset prices. Very recently, after the evidence on commonality in liquidity had been documented in the US markets, the literature on liquidity and asset pricing, including that by Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005) among others, examines whether market-wide liquidity is a risk factor that is priced in the asset pricing model[9].

[9] Refer to section 3.2 in chapter three for a detailed review of the literature on liquidity and asset pricing.

Information asymmetry is another important issue of market microstructure concerns. The literature in market microstructure has largely focused on the information asymmetry between traders (i.e. informed and uninformed traders), and examined its implications on market microstructure related characteristics such as liquidity (see Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987; Admati and Pfleiderer, 1988; Glosten and Harris, 1988; Hasbrouck, 1991; Madhavan and Smidt, 1991 among others). Although the problem of information asymmetry could exist between various other groups such as shareholders, debt holders and managers, in this thesis we focus on the information asymmetry between company managers and the market (i.e. outside investors). The empirical research conducted so far on information asymmetry has largely focused on its relation in the process of valuing firms' assets and on examining the association between the change in the organizational form and the level of information asymmetry. For example, Nanda and Narayanan (1999), Krishnaswami and Subramaniam (1999), Gilson et al. (2001) among others examine the relation between spinoff and information asymmetry between company managers and the outside market. Draper and Paudyal (2008) examine the role of information asymmetry in bidders' gains[10]. In addition, the existence of information asymmetries between company managers and outside investors about a firm's value and its future prospects is expected to affect the level of disagreement among market investors. Investors often share the same common information about firms but they disagree about its meaning and in the way they interpret this information (i.e. divergence of opinion). However, the level of disagreement among investors depends on both the amount and the quality of information about the firm that is made available to investors (Harris and Raviv, 1993; Dische, 2002; Doukas et al., 2004; Moeller et al., 2006). Although there is a large bulk of empirical research on divergence of opinion, it focuses on examining the importance of divergence of opinion among investors in asset pricing such as Miller (1977), Ackert and Athanassakos (1997), Lee and Swaminathan (2000), Diether et al. (2002), Boehme et al. (2006), Doukas et al. (2004), Doukas and McKnight (2005) among others[11].

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[10] For more details on the literature on corporate actions and information asymmetry see section 4.2.1 in chapter three.
[11] See section 4.2.2 in chapter four for the literature on divergence of opinion and asset pricing.

Despite the growth in market microstructure literature in general, in the area of market structure and design, and in the area of the interface of market microstructure with other areas of finance such as asset pricing in particular, the literature still contains several gaps that this thesis attempts to fill.

First: in spite of the importance and the amount of research in the area of market structure and design, the ongoing developments and changes in financial markets' structure and design creates room for a considerable amount of future research in this area. However, the growing body of literature on market structure and design can be viewed as comparing and analyzing the impact of alternative market structures on market qualities such as liquidity and price efficiency. Thus, there is limited knowledge on how alternative market structures and designs could affect specific economic relations such as a market microstructure-related characteristic, liquidity, with its determinants, and the implications of liquidity on asset pricing. In particular, these issues to the best of our knowledge have not yet been examined and compared before and after the introduction of electronic trading systems.

Second: the existence of commonality in liquidity has attracted the attention of market microstructure literature towards the importance of market-wide liquidity. Chordia et al. (2000) argue that the evidence documented concerning commonality provides useful potential perspectives for further research. Their finding sheds light on different issues related to market liquidity that is particularly important and paves the way for future research. One such issue could be the attempt to identify the possible factors and macroeconomic influences that cause time-series variations in market-wide liquidity. In spite of researchers' interest such as Chordia et al. (2001a), Fujimoto (2003b) and Van Ness et al. (2005) in understanding market-wide liquidity in the US markets, our knowledge concerning which factors could be responsible for the time-series variation in market-wide liquidity and how market-wide liquidity behaves over time in other markets remains limited. Furthermore, the literature on this issue has not yet taken into consideration how different trading systems are able to affect market-wide liquidity, its determinants and its time-series behaviour.

Third: market microstructure does matter and it has important implications in other areas of finance. The interface of market microstructure literature with different areas of finance represents new opportunities for further future research and is still being written. One of the most interesting topics in this subfield of market microstructure is the effect of liquidity on asset pricing. Once again, the earlier literature focused on examining how liquidity level (i.e. firm-specific liquidity) is related to cross-sectional variation in asset returns (e.g. Amihud and Mendelson, 1986; Brennan et al., 1998; Datar et al., 1998 among others). They find illiquid stocks have higher expected returns. Since then, the literature has deviated its attention toward the importance of market liquidity in asset pricing and now examines whether market-wide liquidity is priced in stock returns or whether market-wide liquidity could be a priced state variable in the asset pricing model (e.g. Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006 among others). These studies find that systematic liquidity risk (i.e. market-wide liquidity) is a priced risk factor, and stocks with high sensitivity with aggregate market liquidity earn higher returns. However, none of the previous studies on liquidity and asset pricing has addressed the impact of liquidity in asset pricing in the context of alternative (floor and electronic) trading systems. Furthermore, previous literature looked at firm-specific liquidity and market-wide liquidity separately. Hence, the question that remains unanswered is if stocks pay a premium (i.e. higher expected return) for being less liquid, do they still pay another premium for their higher co-variation with market-wide liquidity? In other words, after accounting for a market-wide liquidity risk, is firm-specific liquidity priced in the cross-section returns? Furthermore, regardless of the developments in the use of conditional asset pricing models in asset pricing (see for example, Jagannathan and Wang, 1996; Ferson and Harvey, 1999; Lettau and Ludvigson, 2001; Avramov and Chordia, 2006b; Gomes et al., 2006 among others), literature on liquidity and asset returns that use conditional asset pricing models, where liquidity is one of the models' factors, in order to examine the pricing of liquidity, is very sparse.

Finally, notwithstanding the importance of the previous literature on market microstructure, it mainly focuses on examining the impact of information asymmetry between informed traders and uninformed traders on liquidity. However, the level of information asymmetry between corporate insiders (i.e. company managers) and outside investors could have very important implications on a microstructure characteristic of stock namely, liquidity, and thus provides an avenue of future research. Firms with high a level of information asymmetry are those where the managers have more information about a firm's value than outside investors do (Dierkens, 1991). This may expose outside investors to a high level of uncertainty about firms' future prospects, and thus increase the perceived risk of holding the stocks of such firms. In this case investors will avoid holding stocks with a high level of information asymmetry through reducing their trading activity and posting wider bid-ask spread. This ultimately will reduce stocks' liquidity. The impact of information asymmetry between company managers and outside investors on liquidity has been neglected so far and to the best of our knowledge, there are virtually no studies that explicitly examine the implications of information asymmetry between company managers and outside investors on firm-specific liquidity.

As well as information asymmetry, the issue of divergence of opinion among investors represents another potentially fruitful avenue of research in market microstructure. The disagreement in investors' opinions is expected to have important implications for firm-specific liquidity and thus could be recognized as one possible determinant of firm-specific liquidity. As mentioned previously, the literature on divergence of opinion among investors has extensively examined its importance in asset pricing, and thus the impact of divergence of opinion on firm-specific liquidity has not yet been explored in market microstructure literature.

This thesis sheds new light on some aspects in market microstructure such as market structure and design, and the interface of market microstructure with other areas of finance such as asset pricing. It investigates and compares various aspects of liquidity under different trading systems for a sample of European stock exchanges. Furthermore, by doing so, this thesis provides additional contributions to different aspects of other literature in market microstructure. More specifically, in relation to the issue of determinants of market-wide liquidity, this thesis explores the factors that affect the time-series variation in market-wide liquidity, as well as the time-series behaviour of market-wide liquidity (i.e. the regularities in market-wide liquidity during the week, around holidays and around the announcement of major macroeconomic indicators such as GDP, CPI and unemployment rates), before and after the automation of trading systems in stock exchanges that are smaller than the US markets: the Vienna Stock Exchange, the Swiss Stock Exchange, the Amsterdam Stock Exchange and the Frankfurt Stock Exchange. This provides the opportunity to assess the response of market-wide liquidity to different factors and examine its time-series behaviour under alternative trading mechanisms. Thus it will be possible to gain new insights from other non-US markets.

Furthermore, this thesis contributes to our knowledge of liquidity and asset pricing in several ways. First, it examines the role of liquidity in assets pricing before and after the automation of trading systems in the UK, Swiss and German markets. This study thus brings the two different areas of market microstructure together: the area of market structure and design and the area of the interface of market microstructure with other areas of finance. Second, this thesis significantly contributes to the literature on liquidity and asset pricing by employing the conditional asset pricing model of Avramov and Chordia (2006a) to examine the importance of liquidity in asset pricing. In this model, factor loadings are allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variables (i.e. short-term interest rate, term spread and default spread). Also, using individual stocks in this model provides the advantage of overcoming some of the problems that previous studies faced as a result of using portfolio construction techniques, such as data-snooping biases and loss of information that could result from sorting stocks into portfolios. Thus, this study is the first that uses individual stocks as test assets, within the context of a conditional asset pricing model, to examine the relation between liquidity and stock returns. In addition, this thesis undertakes a wider analysis by looking at both market-wide liquidity and firm-specific liquidity.

Finally, studies which explicitly investigate the relationship between firm-specific liquidity and the information asymmetry between corporate insiders and outside investors, and the relation of firm-specific liquidity and divergence of opinion among investors are virtually nonexistent. This thesis provides for the first time empirical evidence concerning the relation of firm-specific liquidity with information asymmetry and divergence of opinion for the UK, Swiss and German markets. In other words, for the aforementioned markets, this thesis examines whether the cross-sectional variation in information asymmetry and divergence of opinion could explain the cross-sectional variation in firm-specific liquidity. It also examines the impact of different trading systems on the implications for information asymmetry and divergence of opinion on firm-specific liquidity. This will draw out some important implications of how different trading systems could affect the level of information asymmetry and the disagreement among investors and, then, result in different impacts on firm-specific liquidity.

This thesis consists of five chapters including this one. Through chapters two, three and four, the thesis examines and compares three empirical issues, both before and after the automation of trading systems: the determinants of aggregate market liquidity (i.e. market-wide liquidity); the importance of liquidity in asset pricing; and the relation of liquidity to information asymmetry and divergence of opinion. These chapters have a similar structure and design: each chapter starts with a comprehensive review of the literature on the issue in question, presents the sample and discusses the methodology to be utilized, reports and discusses the empirical results, and summarizes the findings and draws conclusions.

Chapter two examines, before and after the automation of trading systems, the underlying forces and factors that are responsible for time-series variation in market-wide liquidity, and analyzes its time-series behaviour. To address these issues, the methodology of Chordia et al. (2001a) is applied before and after automation. The estimation method of Least Absolute Deviation is used to estimate the model, which allows us to control for the effect of outliers. In addition, the Least Trimmed Square method is used in the estimation process as a robust check. Both estimation methods provide qualitatively and quantitatively similar results. We utilize the Wald test to compare the impact of the factors on aggregate market liquidity and its time-series behaviour before and after automation. The results indicate that, either on both trading systems or under one trading period, market-wide liquidity is affected by different market variables such as concurrent market returns, recent market trends and market volatility. Also, it is affected by interest rate variables and the release of macroeconomic factors. In addition, liquidity shows distinct patterns during the week and around holidays. The most important finding is that before and after automation the impact of factors on market liquidity as well as the regularities in market liquidity are different, which means that trading systems play an important role in affecting both the response of market liquidity to its determinants and its time-series behaviour.

Chapter three investigates the relationship between liquidity, both market-wide liquidity and firm-specific liquidity, and assets returns under different trading systems (i.e. before and after the automation of trading systems). Unlike previous studies, the framework of Avramov and Chordia's (2006a) two-pass regression is utilized to examine this issue. As a first-pass time-series regression, the Fama-French three factor model augmented with liquidity factors is used as an asset pricing model. Following Chen et al. (1986), market-wide liquidity risk factors are derived as the innovations from autoregressive integrated moving average (ARIMA) models. Market-wide liquidity risk factors are measured by proportional bid-ask spread, turnover ratio and price impact. To estimate the time-series average of the second-pass cross-sectional regressions' coefficients, the Fama and MacBeth (1973) procedure is applied. The first-pass time-series regression allows us to examine the relationship between market-wide liquidity and individual assets returns, that is, whether market-wide liquidity is priced. Then, after adjusting the stocks' returns in the first-pass to risk factors, the second-pass cross-sectional regression allows us to examine whether firm-specific liquidity has any additional explanatory power to the cross-sectional variation in stock returns. The results show that both market liquidity and firm-specific liquidity have an important bearing on asset pricing under both floor and electronic trading systems, and their impact on asset returns before the automation of the trading system is different to their impact after automation.

Chapter four examines the relationship between firm-specific liquidity and both information asymmetry and divergence of opinion, and examines how moving from floor to electronic trading system could have impacted these relationships. To test these implications, this chapter uses both univariate and multivariate analysis. In univariate analysis we construct three equally-weighted portfolios on the basis of information asymmetry and divergence of opinion. However, the univariate analysis does not allow for the interaction between information asymmetry and divergence of opinion measures with other determinants of firm-specific liquidity (e.g. size, price and volatility), therefore, we use a multivariate regression framework. In multivariate analysis, a series of cross-sectional regressions are estimated and then the Fama and MacBeth (1973) procedure is used to estimate the time-series average of cross-sectional coefficients. This chapter also uses the ideas of Brennan et al.'s (1998) and Avramov and Chordia's (2006a) two-pass regressions, to allow for the impact of other information (i.e. market-wide and industry-wide information) on firm-specific liquidity in first-pass regression and then examines the relation of firm-specific liquidity with information asymmetry and divergence of opinion in the second-pass cross-sectional regressions. The purpose is to discover whether information asymmetry and divergence of opinion have any incremental explanatory power after allowing for market-wide and industry-wide information. A comparative analysis has been conducted for the univariate and multivariate analysis before and after automation, to find out how the impact of information asymmetry and divergence of opinion on firm-specific liquidity will be different between the two sub-periods. The t-test has been used to compare the results of univariate analysis, and the Wald test is applied to compare the coefficients of multivariate analysis between the two sub-sample periods. The results, in general, show that firms with low (high) levels of information asymmetry have high (low) liquidity. However, the evidence concerning the impact of divergence of opinion on liquidity is mixed. The results also show that the impact of information asymmetry and divergence of opinion on firm-specific liquidity is different across trading systems. However, after allowing for the market-wide and industry-wide information, the results show that both information asymmetry and divergence of opinion have no additional explanatory power. This implies that both market and industry factors are able to explain the cross-sectional variation in firm-specific liquidity, which puts into question the role of financial analysts and the value of the information they provide to investors in the market.

Finally, chapter five summarizes the findings of all the empirical chapters and discusses the policy implications of their results. It also provides some suggestions for future research.

Chapter Two
Determinants of Aggregate Market Liquidity

2.1 Introduction

Liquidity is considered one of the most important characteristics of financial markets, to the extent that liquid markets play an important role in reallocating investors' assets holdings, by allowing investors to trade and implement their trading strategies at low cost. A market is considered to be liquid when it accommodates the ability to trade a large size quickly, at low cost, when you wish to trade. This definition shows that market liquidity has several dimensions, which are: *Immediacy*, how quickly a trade of a given size can be arranged at a specific cost; *Width*, the cost of a trade that can be arranged at a given size; *Depth*, the size of a trade that can be executed at a specific cost; and *Resiliency*, the speed with which prices revert to previous levels following the trading of an uninformed trader (see Harris, 2003).

Despite the importance of liquidity in financial markets, it is likely to be affected by the markets' structure and design. Therefore, many stock exchanges have undergone dramatic change and restructuring in their trading arrangements in order to improve the liquidity of their trading systems. One of the most prominent features of the restructuring of stock exchanges has been the adoption of electronic trading systems (i.e. the move from floor to electronic trading systems). This change in trading systems is expected to affect liquidity due to the differences in the characteristics of floor and electronic trading systems, which may affect the mechanism for providing liquidity and its behaviour, and then results in different levels of liquidity under each trading system (see, Huang and Stoll, 1996; Freund and Pagano, 2000; Venkataraman, 2001 among others). As a result, if liquidity is expected to be affected by different trading systems, then different trading systems will have different implications on liquidity related issues such as the determinants of market-wide liquidity and its time-series behaviour. In other words, the move from floor to electronic trading systems is expected to have an impact upon the relationship between market-wide liquidity and its various determinants as well as an impact upon the time-series behaviour of market-wide liquidity. The major theme of this chapter therefore is to examine and compare under a different context of market structures (i.e. floor versus electronic trading systems) the determinants of market-wide liquidity and its time-series behaviour.

The issue of liquidity determinants has stimulated a lot of research in market microstructure, with the main focus on the examination of liquidity at the individual assets' level. That is, a considerable amount of studies have concentrated on examining the cross-sectional determinants of individual assets' liquidity such as Tinic (1972), Benston and Hagerman (1974), Branch and Freed (1977), Stoll (1978a), Easley et al. (1996), among others. These studies find that each security has its own liquidity which is affected by different factors such as price, trading volume, the number of trades, risk (volatility), competition and the number of market makers.

Recently, the emergence of the literature on commonality in liquidity such as Chordia et al. (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001), has shifted the attention of empirical research towards liquidity at the aggregate level (i.e. market-wide liquidity). These studies provide evidence of commonality in liquidity and find that different measures of firm-specific liquidity are correlated to aggregate market liquidity. Hence, they pave the way for further future empirical research concerning the factors and the underlying forces that could affect market-wide liquidity, as well as being concerned with the time-series behaviour of market-wide liquidity. As a result, some studies such as Chordia et al. (2001a), Fujimoto (2003b), Van Ness et al. (2005), and Chordia et al. (2005) have examined the factors that affect aggregate market liquidity and studied its time-series behaviour (e.g. examined the regularities in market-wide liquidity during the week and around holidays) for US markets (i.e. NYSE, NASDAQ and AMEX). They find that market-wide liquidity is affected by certain factors such as market return, volatility, and macroeconomic variables, and that market liquidity shows distinct regularities during the week, around the holidays and around the announcement of scheduled macroeconomic indicators such as GDP, CPI and unemployment.

Furthermore, the dramatic change in trading systems of many stock exchanges has motivated a large amount of empirical research on market structure and design. Consequently, researchers have focused their attention on an extensive examination of how such changes in market structure could influence market characteristics (such as liquidity and price discovery) and examine the superiority of one trading system over the other. For example, Shyy and Lee (1995) and Pirrong (1996) among others compare liquidity in a floor futures trading mechanism with an electronic futures trading mechanism, and show that liquidity in an electronic futures trading mechanism is higher than that in a floor trading mechanism. Theissen (2002a, 2002b), examines the transaction cost, the adverse selection costs and the issue of price discovery in the floor and electronic trading system on the Frankfurt Stock Exchange. He concludes that there is a difference in transaction costs and adverse selection costs between a floor and an electronic trading system, and finds that both trading systems contribute equally to price discovery. Venkataraman (2001) compares the execution costs between NYSE (a floor based trading structure) and the Paris Bourse (an automated trading structure) and shows that spreads are wider in Paris than in New York. Jain (2005) provides evidence that the firms' cost of equity has improved as a result of moving from a floor to an electronic trading system.

Notwithstanding the importance of these studies on determinants of market-wide liquidity, and despite the large amount of studies on market structure and design, studies that examine and compare the determinants of market-wide liquidity and its time-series behaviour under different market structures (i.e. floor versus electronic trading system) are virtually nonexistent. This chapter therefore, aims to examine and compare before and after the automation of trading systems the variation in market-wide liquidity, the factors that are responsible for the time-series variation in market-wide liquidity and its time-series behaviour (i.e. regularities in market-wide liquidity). This chapter will thus extend the empirical literature by filling the following gaps:

First, empirical studies on market structure and design so far have confined themselves to the typical perspective of comparison, between floor and electronic trading systems, in relation to market quality. That is, they compare different market characteristics such as liquidity, price discovery and volatility before and after the automation of the trading systems. Thus, our knowledge is limited on how the move from a floor to an electronic trading system could impact the relationship between market-wide liquidity and its determinants, and how this change affects the time-series behaviour of market-wide liquidity (i.e. the regularities in market-wide liquidity). This chapter therefore, contributes to our knowledge in this issue and extends the literature on market structure and design by investigating and comparing, under floor and electronic trading systems, the aggregate market liquidity, its time-series determinants (i.e. examining its relation with various determinants such as market variables and macroeconomic factors) and its time-series behaviour (i.e. studying the regularities in the time-series of market-wide liquidity during certain days of the week, around holidays and around the announcement of macroeconomic indicators).

Second, previous empirical work on the determinants of market-wide liquidity and its time-series behaviour is very sparse and is extensively focused on US markets (i.e. NYSE, NASDAQ and AMEX). Therefore, our knowledge on what factors could be responsible for the time-series variation in market-wide liquidity, and our knowledge of the time-series behaviour of market wide-liquidity in other markets is limited. Consequently, this chapter aims to fill this gap by investigating four European stock markets: the Swiss, Amsterdam, Vienna, and Frankfurt Stock Exchanges. These markets, compared to the US markets, are smaller. Also, these markets have witnessed a change in their trading system from a floor to an electronic trading system with the exception of the Frankfurt Stock Exchange, where both trading systems are working in parallel to each other. This may increase the likelihood of having different behaviour for market-wide liquidity and thus affect its relation to other determinants, which will provide us with different insights that are not possible to obtain in other markets.

Thus, this chapter addresses the following questions:

- *Does the daily variation in market-wide liquidity remain the same in floor and electronic trading systems?*

- *What are the factors that influence and determine market-wide liquidity in floor and electronic trading systems? How do these factors affect market-wide liquidity and to what extent within each trading system?*

- *Does the time-series of daily market-wide liquidity exhibit regularities (i.e. day-of-the-week effect, regularities around holidays and around scheduled macroeconomic announcements) on floor and on electronic trading systems? Do the same regularities exist under both trading systems?*

Apart from the scientific merits of these questions and the direct goal of providing a better understanding of market liquidity through addressing them, the findings of this chapter have implications for various parties. More specifically, comparing market liquidity and identifying the factors that influence market liquidity before and after the automation of trading systems are of interest to several market participants. For instance, it is important for investors to develop a better understanding of market-wide liquidity and its behaviour over time under different trading systems, so that they can gain extra insight into securities' pricing. The relationship between liquidity and stock returns was first addressed by Amihud and Mendelson (1986) who find a positive relationship between stock returns and illiquidity. Also, Chordia et al. (2000) argue that market-wide liquidity may affect asset prices. Thus, when the market becomes illiquid as a result of a shock, the investor will ask for higher returns for stocks with low liquidity following the market-wide shock, because these stocks are highly sensitive to the changes of market-wide liquidity. Amihud (2002) argues that if investors anticipate a low level of market liquidity, they will price stocks in a way that will allow them to generate higher expected returns. In this case, it will be important for investors, mutual funds, and portfolio managers to increase their understanding of the determinants of market liquidity and its behaviour within floor and electronic trading systems, so they can establish their trading strategies and formulate their portfolios in a way that enables them to achieve their target returns.

In addition, transaction cost is another issue concerning investors in stock markets[12]. In a liquid market the transaction costs are lower than those in illiquid markets. When investors buy/sell their shares at any given point in time, they will face transaction costs. As a result, investors prefer to trade with low transaction costs. Thus, the results of this chapter will be of some significance for investors, because they will provide investors with relevant insights that direct their trading decisions. For example, if the findings in this chapter show which trading system has more liquidity than the other and what the factors that influence the liquidity under each trading system are, investors will be able to estimate the transaction cost and then they will be able to trade effectively.

[12] Transaction costs include both explicit costs and implicit costs. Explicit costs are those that are easily identified by the accountant and include commissions, fees, and taxes. Implicit costs are the costs of trading that arise because traders generally have an impact upon prices and include bid-ask spread and market price impact (Harris, 2003). Here we refer to implicit transaction costs.

Moreover, this chapter has implications that are important for corporate finance policies. For example, for companies that are considering issuing stocks or considering an initial public offering (IPO), market liquidity is a critical component and an important input element in corporate policies and decisions. When investors buy new shares, more specifically IPO shares, they will be concerned about the expected liquidity and the uncertainty about its level, especially when shares start trading on the aftermarket. If shares are expected to be less liquid and their liquidity grows less predictable as well, one would also expect a greater amount of underpricing (Corwin et al., 2004). Therefore, according to the latter, a liquid market may reduce required underpricing and improve the future access to capital markets for firms considering issuing stocks by attracting analysts and/or investors. Conversely, if the market is characterized by being illiquid, this will result in the cancelling or failure of IPOs. Thus, by knowing under which trading system the market will be more liquid, and knowing what are the factors that will affect the change in market liquidity, firms will be able to identify the amount of liquidity that will be available, assess the degree of certainty about its level, and then formulate their decisions accordingly.

Finally, the findings of this chapter should have an important implication for stock exchanges' regulators and designers. That is, liquidity, as one of the most important characteristics of well-organized and functioning markets, represents a major concern of exchange organizations and regulators. They are interested in the optimal design of securities markets, which improves the quality of the market through increasing market liquidity and reducing the transaction costs, and thus attract more investors to trade and more companies to list their stocks. However, according to O'Hara (2003), some events (e.g. market crises such as the Asian crisis (1997), the Russian crisis (1998), and the bond market crisis (1998)) can cause liquidity problems in financial markets, thus stimulating a corresponding liquidity outflow to other markets. One example could be the "flight to liquidity" that is observed in the markets for emerging market debt or in bond markets. Such events, as Chordia et al. (2004) argue, shed light on regulatory concerns regarding liquidity crises. Therefore, the results of this chapter will help market designers and regulators to make the decisions that will improve market quality and liquidity. If after the automation of a trading system, market liquidity shows more variation in its level and becomes more sensitive to various determinants, then more regulations and policy procedures are required to maintain and improve liquidity on electronic trading systems. For example, the regulator may improve the performance of the electronic trading system, so that it guarantees the highest execution speed and thus low implicit and explicit transaction costs, and higher liquidity. On the other hand, if market liquidity becomes more stable after the automation of a trading system and it is less affected by different factors, then no further regulations are required.

The structure of this chapter is as follows. In the next section a review of the previous literature is considered. Section 2.3 discusses the research design, which covers the hypotheses developments, the methodology related to empirical investigation and the sample and data used in the empirical analysis. Section 2.4 presents the key findings and results, and finally in section 2.5, there are concluding remarks and a summary of the findings.

2.2 Literature Review

This section provides a review of the literature related to the determinants of liquidity and of the literature on market structure and design. Although there is a large bulk of research on market structure and design that deals with examining and comparing different market structures and settings, this section mainly concentrates on the portion of literature that examines the implications of floor and electronic trading systems.

2.2.1 Determinants of liquidity

A large amount of empirical work in market microstructure has been devoted to the examination of the determinants of the liquidity of individual assets. Demsetz (1968), Tinic (1972), Benston and Hagerman (1974), Branch and Freed (1977), Stoll (1978a), Easley et al. (1987), among others focus on identifying the determinants of liquidity for individual stocks in cross-section. They find that each security has a liquidity of its own that is affected by different factors such as price, trading volume, number of trades, risk (volatility), competition, the number of market makers, etc. More specifically, these studies find that firm-specific liquidity is positively related to stock price, trading volume, the number of traders, the number of market makers and is negatively related to trade size (order size) and volatility (i.e. risk).

Furthermore, the work of this chapter is considered to be related more to the work previously undertaken in the context of the London Stock Exchange by Draper and Paudyal (1997). They focus on examining the seasonality in trading activity and the bid-ask spread using monthly data for 345 firms. They find strong seasonality in trading activity. Their analysis shows that while institutional investors are active during January and April, individual investors are more active during March. In contrast, a bid-ask spread does not exhibit any seasonality except for portfolios with a large market value.

Recently, the evidence that has been discovered on commonality in liquidity in US markets by Chordia et al. (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001) has focused the attention of research towards the importance of market-wide liquidity. Consequently, a few recent studies have begun to investigate the issue of market-wide liquidity and the sources of its variation. Chordia et al. (2001a), for example, examine the time-series determinants of market-wide liquidity and its time-series behaviour in NYSE. They use high frequency data (intraday data) for a comprehensive sample of NYSE-listed stocks over an 11-year period, and construct time-series indices of market-wide liquidity measures over the sample period. The results of the time-series regressions show that both liquidity and trading activities are affected by short- and long-term interest rates, term spread, market volatility and recent market movements. The results also show strong day-of-the-week regularities in liquidity and trading activities; more specifically, trading activities and liquidity decline on Fridays, while Tuesdays display a different pattern. In addition, liquidity shows strong regularities around holidays. Finally, the results show that prior to the announcements related to GDP and the unemployment rate there was an increase in both market depth and trading activities.

As a part of their analysis, Huberman and Halka (2001) examine the time-series behaviour of liquidity proxies for 240 stocks listed in NYSE, using daily observations for each stock in the sample. Their results show that market liquidity is related to daily returns; more specifically, they find that negative daily returns bear a negative effect over spread variables and a positive one over depth variables. They also find that the daily changes in the term spread are positively correlated to the spread measures and negatively correlated to the depth measures, and the quality spread is insignificantly related to any of liquidity proxies, except the depth measures, which is positively correlated to quality spread. Their findings are consistent with the findings of Chordia et al. (2001a). However, Huberman and Halka (2001) find that risk variables (i.e. daily volatility in returns) are positively correlated to spread variables and negatively correlated to depth variables, which is inconsistent with the results of Chordia et al. (2001a) who find that spreads decrease when the market is volatile and market depth is unaffected by volatility.

Fujimoto (2003b) examines the time variation of market liquidity by studying the dynamic relation between market liquidity and various macroeconomic variables over the period from 1962 to 2001 for both NYSE and AMEX. In contrast to Chordia et al. (2001a), he uses daily data to construct monthly aggregate liquidity series using three proxies of liquidity (a proportional bid-ask spread, the price impact and return reversal), in addition to using the vector autoregression approach. Fujimoto finds that before the mid-1980s the influence of macroeconomic indicators on liquidity is stronger when the business cycle dynamics exhibit higher volatility. During the first half of the sample period, both monetary policy and inflation were important in explaining the variation in liquidity. Also, during the periods of negative shocks in supply-side inflation and the federal fund rate, and during the periods of positive shocks in non-borrowed reserves, market liquidity exhibited a significant improvement for a longer period of time. Furthermore, in addition to share turnover, the results show that market returns and volatility are the key determinants of liquidity, which are consistent with the results of Chordia et al. (2001a) and Huberman and Halka (2001). However, all of the determinants are affected by macroeconomic shocks. Therefore, he argues that the results of his study show that macroeconomic factors affect liquidity directly and indirectly through their effect on market returns, volatility, and share turnover. Finally, Fujimoto finds that market liquidity had become more resilient and less responsive to shocks at both the economic and market levels.

Van Ness et al. (2005) apply Chordia's et al. (2001a) methodology on the NASDAQ stock exchange. However, they examine market liquidity and its behaviour for the full sample period and during the bull and bear markets, taking into consideration the long-run impact of order handling rules. They use transaction data to construct daily series for aggregate market liquidity over the sample period from January 1993 to December 2002. Their results show that market liquidity and trading activity are related to contemporaneous market returns and are affected by interest rate variables (i.e. fed funds rate, the term spread, and the quality spread), but they are unrelated to market volatility. The latter finding is inconsistent with the findings of Chordia et al. (2001a), Huberman and Halka (2001) and Fujimoto (2003b). The results also show, consistent with Chordia et al. (2001a), that market liquidity exhibits a distinct day-of-the-week effect where liquidity declines on Fridays and increases on Thursdays. Finally, they find that spread measures are slightly influenced by macroeconomic announcements. Even though the results during the bull market are qualitatively similar to those for the whole period, the results of the bear market regressions show some differences i.e., the spreads during a bear market were affected by both interest rate changes and macroeconomic announcements.

Furthermore, the examination of the determinants of market liquidity has been extended to include bond markets in addition to equity markets. Chordia et al. (2005) study the common determinants of stock and bond liquidity and the effect of monetary shocks and money flows on transactions liquidity. Their study covers the period from 1991 to 1998, with intraday data for NYSE stocks and tick-by-tick data on-the-run Treasury notes with 10 years to maturity. They find that in both markets the weekly regularities in market liquidity are very similar; on Fridays the liquidity is very low compared with other days in the week, which is consistent with Chordia et al. (2001a) and Van Ness et al. (2005) who find that liquidity and trading activities decline on Fridays. Further, they conclude that both past liquidity and volatility are the most important variables in forecasting future liquidity. Also, across both stock and bond markets, they find a significantly positive correlation between the shocks of both liquidity and volatility which means that they are systemic in nature. In addition, the results show that unexpected relaxation in monetary policy is associated with improvements in stock market liquidity, which is consistent with the results of Fujimoto (2003b). Finally, they find that bond fund flows are capable of forecasting bond market liquidity.

In summary, the review thus far shows that the literature on the determinants of market-wide liquidity are very sparse, and have extensively focused on examining the factors that influence the times-series variation in market liquidity and studied its time-series behaviour in US markets (NYSE, NASDAQ, AMEX). The only study (Draper and Paudyal, 1997) that was carried out on another market (London Stock Exchange) focused on examining the seasonality in liquidity in that market. Furthermore, no study, to the best of our knowledge, has examined the determinants of market-wide liquidity and its time-series behaviour under a different context of market structure (i.e. floor versus electronic trading system). Thus, there is limited knowledge on how alternative trading systems could affect the relation of market-wide liquidity with its determinants and affect its time-series behaviour.

2.2.2 Market structure and design: floor versus electronic trading system

The heterogeneity in market structures and settings results in a huge amount of literature on market structure and design that make comparisons between alternative structures of stock markets (e.g. call versus continuous auction markets, quote-driven versus order-driven markets, and floor versus electronic markets). This literature mainly focuses on examining the impact of alternative trading mechanisms on market characteristics such as liquidity and price discovery. Despite the large amount of literature on market structure and design, this section focuses on a brief review of the literature on floor and electronic systems, which represents the main concern of this thesis[13].

Most of the previous empirical studies that compared floor trading systems with electronic trading systems examine different issues, utilizing different markets and different instruments. Shyy and Lee (1995), for example, compare floor trading at the London International Financial Future Exchange (LIFFE) and electronic trading at Deutsche Terminbrose (DTB) by investigating the intermarket relationship using the Bund futures contract[14]. They also compare the price-transmission and the informational asymmetry between these two trading systems. They use minute-by-minute transaction prices and bid-ask quotes for December 1993. Using Granger causality tests they find a unidirectional lead from DTB to LIFFE in price-transmission, and the informational asymmetry for Bund futures in DTB is lower than that in LIFFE.

[13] The literature on floor versus electronic trading system will be reviewed in this section and will represent the reference for other chapters in this thesis.

[14] Bund future contract is the most actively traded bond future contract which is based on the German government's 10-year bond (see Käppi and Siivonen, 2000).

Pirrong (1996) compares the liquidity supply mechanism on automated future trading mechanisms (DTB) and floor future trading mechanisms (LIFFE) using the Bund futures contracts over the period July 1992 to June 1993. Consistent with Shyy and Lee (1995), he finds that LIFFE has wider spreads than DTB but during high volatile periods DTB is deeper than LIFFE. Furthermore, Breedon and Holland (1998) evaluate the relative liquidity and the price discovery role of LIFFE and DTB. They use a full transaction record and minute-by-minute quotes for both the LIFFE and DTB over the period between 10th April and 2nd June 1995 for the June 1995 contract. They find that both markets are integrated and DTB has as much of a role in the underlying price discovery as LIFFE. Also, Breedon and Holland (1998) find that both markets are similar in terms of variable costs and the contribution to price formation, but they are different in terms of trade size (which is larger in floor trading systems) and in terms of the tendency of trading to move towards the floor trading systems (open outcry market) during volatile periods[15].

Moreover, some of the studies that compare the floor with the electronic trading systems tried to exploit the unique characteristics of some markets, which entail the co-existence of trading systems like the Frankfurt Stock Exchange. Grammig et al. (2001), for example, analyzed the preference of informed traders towards the two trading systems in the Frankfurt Stock Exchange, i.e. whether informed traders have a preference for the electronic trading system (anonymous trading) or for the floor system (non-anonymous trading). They use transaction data for the 30 stocks that constitute the DAX index across 44 trading days during June and July 1997. They find that informed traders prefer trading in the electronic trading system, and the probability of their trading is positively related to the bid-ask spread, especially, to the adverse selection component of the spread.

Theissen (2002a) examines the issue of transaction costs and adverse selection in non-anonymous floor trading and anonymous electronic trading systems. He uses transaction data for 30 stocks traded in both systems (these stocks constitute the DAX index) for a

[15] Frino et al. (1998) compare the cost of trading across DTB and LIFFE; Franke and Hess (2000) analyze the attractiveness of both floor and electronic trading systems by examining the informational differences between these trading systems. Huang (2004) compares the relative performance of Taiwan Futures Exchange (an electronic trading system) with the Singapore Exchange Derivatives Trading Limited (a floor trading system) where Taiwan stock index future contract is traded in both markets.

period of 42 days for two months (June and July 1997). He finds that the floor trading system is more competitive for less liquid stocks. The results also show that the differences between the bid-ask spreads in the two trading systems have a significant impact on market shares, and the reaction of quoted spread to volatility in an electronic trading system is more than that of the floor trading system. In addition, the adverse selection component of the spread is found to be larger on the electronic trading system, which supports the argument that the non-anonymous trading on the floor trading system is better suited to cope with adverse selection problems. Finally, his findings show that the realized spread, which has to cover the order processing costs, tends to be smaller on the electronic trading system. This is consistent with the hypothesis of higher operational efficiency of the electronic trading system. Moreover, Theissen (2002b) examines the process of price discovery in floor and electronic trading systems, using the same sample in Theissen (2002a). He finds that both trading systems contribute equally to price discovery when the estimation is based on transaction prices. However, using quote midpoints in the estimation model indicates that the electronic trading system contributes more to the process of price discovery[16].

Additionally, other studies compare trading systems that operate in different stock markets. For instance, Venkataraman (2001) compares the execution costs between NYSE (a floor based trading structure) and the Paris Bourse (an automated trading structure). He uses intraday data for matched stocks over one year from April 1997 to March 1998. He finds that the effective spread in NYSE is lower, even though the quoted spread measures on both exchanges are similar. Even after controlling for differences in relative tick size, adverse selection, and economic attribute, the execution costs in Paris remain higher compared to that in NYSE[17].

Finally, other studies in market structure and design have made a comparison between floor and electronic trading systems in the markets that experienced a shift from floor to electronic trading systems. For instance, Jain (2005) examines whether the move from

[16] Kirchner and Schlag (1998) and Freihube and Theissen (2001) also compare the floor and electronic trading systems in the Frankfurt Stock Exchange. The former identify the impact of market structure on the behaviour of prices and volume, and the latter analyze the quality of DAX index and MDAX index that are constructed from floor prices and electronic prices.

[17] Other examples include De Jong et al. (1995), who analyze the cost of trading French stocks in London SEAQ International and in Paris Bourse, and Frino and McCorry (1996) who compare the spreads between NYSE and the Australian Stock Exchange.

the floor trading system to the electronic trading system will lower the cost of equity for the listed firms as a result of improvements in liquidity and the informational environment. He uses monthly returns for 56 stock exchanges and annual returns for 15 additional markets from December 1969 to August 2001. According to the dividend growth model and the international CAPM, Jain finds that the automation of trading lowers the cost of equity as a result of improvements in liquidity and informational efficiency, and the decrease in cost of equity is more pronounced in emerging markets. Moreover, he finds a positive price reaction of 8.99% in listed stocks around the date of the announcement of the move to an electronic trading system[18].

Regardless of the large amount of empirical studies on market structure and design, especially on floor and electronic trading systems, these studies confine themselves to the general perspective of comparing market quality before and after the automation of trading systems. To date no study, to the best of our knowledge, has examined what the factors and economic forces that influence the time-series variation of market-wide liquidity are, as well as examining the time series behaviour of market-wide liquidity before and after the automation of trading systems.

To this end, this chapter aims to investigate and compare under a different context of market structure (i.e. floor versus electronic trading systems), the time-series variation in market-wide liquidity and indentify the underlying forces and factors (i.e. determinants) that are responsible for this time-series variation. Also, within this context, it aims to examine the time-series behaviour of market-wide liquidity (i.e. the regularities during the week, around holidays and around the announcement of macroeconomic indicators). This chapter addresses these issues for four European stock exchanges which are the Swiss Stock Exchange, the Amsterdam Stock Exchange, the Vienna Stock Exchange, and the Frankfurt Stock Exchange.

[18] Other examples include Naidu and Rozeff (1994) who compare market characteristics (i.e. liquidity, volatility, volume and efficiency) before and after the introduction of an electronic trading system at the Singapore Stock Exchange and Blennerhassett and Bowman (1998) who examine whether the shift to an electronic trading system reduces transaction costs at the New Zealand Stock Exchange.

2.3 Research Design

To address research questions, this section discusses how different characteristics of floor and electronic trading systems will affect the provision of liquidity. It also presents the dependent and independent variables and the justification for their inclusion in the empirical analysis, along with the developing and indentifying of the testable hypotheses. In addition, it discusses the methodology that is utilized to test the hypotheses and answer the research questions. Finally, it presents the sample and the data that are used in the empirical analysis with some descriptive statistics.

2.3.1 Market-wide liquidity under alternative trading systems, regression variables and hypotheses development

2.3.1.1 Trading systems and market liquidity

This section describes the different characteristics of floor and electronic trading systems and how they might affect the provision of liquidity and thus results in different levels of aggregate market liquidity.

The literature on market structure and design argues that different market structures could affect the behaviour of liquidity as well as the mechanism for providing liquidity (see Huang and Stoll, 1996; Freund and Pagano, 2000; Venkataraman, 2001 among others). This implies that the different characteristics of the trading systems (floor and electronic) may have different implications on liquidity and may result in a different level of market liquidity under each trading system. Therefore, it is expected that a market-wide liquidity may exhibit an asymmetric response to the factors that could affect its time-series variation and may show different regularities across a floor and an electronic trading system.

The effect of floor and electronic trading systems on market liquidity is expected to be different, and the issue of how both systems could affect liquidity is controversial. For instance, the degree of trading system anonymity is a potential determinant of market quality. In the case of floor trading (non-anonymous trading system), Venkataraman

(2001) argues that the liquidity of traditional floor based systems will increase because the degree of information asymmetry is expected to decline since all traders can share the information about order inflow and intrinsic value of the stock. Also, through the interaction among traders on a floor trading system, it would be easy to distinguish between informed traders and liquidity motivated traders, and then reduce the level of information asymmetry. This will improve liquidity by motivating more traders to trade, especially liquidity motivated traders, who possess no information and try to avoid trading with well informed traders. In addition, Theissen (2002a) argues that the lower degree of information asymmetry in floor trading may contribute to lower bid-ask spreads, which means more liquidity in the market. In contrast, the anonymity in an electronic trading system is expected to result in lower trading activities (i.e. lower trading volumes), especially at times of high information asymmetry. That is, during times of high information asymmetry, the knowledge of the counterparty of a trade becomes important for traders, especially liquidity motivated traders, to avoid being picked up by other informed traders. Since it is difficult to know the identities of market participants in the electronic trading system, most of the traders will avoid trading during the periods of higher information asymmetry. This will result in lower trading activity, and thus lower liquidity (see Kempf and Korn, 1998; Käppi and Siivonen, 2000; Theissen, 2002a). Furthermore, it is expected that floor trading systems will increase liquidity by attracting institutional investors who usually execute block trades. They prefer trading on a floor trading system because they can use a floor broker to execute their orders immediately thereby satisfying their liquidity needs (Venkataraman, 2001).

On the other hand, automated trading systems are expected to attract more liquidity into markets through their own characteristics compared with floor trading systems. For instance, Venkataraman (2001) argues that an automated trading system provides a large number of locations (i.e. remote access) from which the traders can access the system. This advantage of automated trading systems, as Theissen (2002b) points out, will result in an increase in the number of traders participating in trading activities and thereby increasing the level of liquidity. Furthermore, the efficiency of electronic trading systems with their high speed allows orders to be placed faster and to be executed immediately. This results in a higher quality of execution and attracts more traders and trading activities which, in turn, provides more liquidity to the market

(Freund and Pagano, 2000). Also, the advantage of electronic trading systems in offering higher operational efficiency compared with floor trading systems will affect the bid-ask spread. That is, such an advantage will result in a lower order processing cost component due to lower trading costs that result from faster order execution, facilitating the matching of buy and sell orders and a low cost of operations[19]. Therefore, the bid-ask spread will decline and then more liquidity will be attracted to the market.

In summary, since the two types of markets have different advantages/disadvantages, their superiority, in terms of liquidity, cannot be established theoretically. Consequently, the issue of whether floor or electronic trading system offers better liquidity becomes an empirical question. Therefore, it is important to examine empirically, on balance, whether market-wide liquidity increases or decreases after the introduction of electronic trading system, leading to a testable hypothesis that:

- H_1: *There is no significant difference in the average daily change in market liquidity before and after the introduction of an electronic trading system.*

2.3.1.2 The dependent variables (measures of liquidity)

Measuring liquidity is quite difficult due to its versatile nature; according to Kyle (1985), it is a slippery and elusive concept. It is not observed directly, but rather it has different aspects that cannot be reflected in one measure (Amihud, 2002). There are many proxies for liquidity that have been used in the market microstructure literature, but there exists little consensus on quantifying liquidity.

The proxies of liquidity can be divided into two broad categories: *friction-measures*, which are also known as order-based measures, and capture the price of concession of immediacy, such as the bid-ask spread; or *activity-measures*, which are also known as trade-based measures, and reflect the extent of trading, such as depth, trading volume,

[19] With regard to inventory costs, Franke and Hess (2000) argue that there is a little reason to believe that these costs are different among floor and electronic trading systems. In contrast, Theissen (2002a) argues that inventory costs should be of a greater importance on the floor trading systems, where a single person, the Makler (i.e. specialists), supplies liquidity to the market.

trading value, and turnover ratio. Moreover, liquidity proxies can be classified into ex-ante and ex-post measures. *Ex-ante* measures can be computed prior to the trade (e.g. a bid-ask spread). Such measures indicate the opportunity cost of not trading and may predict the future liquidity through predicting the future order flows as the trader knows the trading cost before placing orders. *Ex-post* measures reflect liquidity information following the execution of the trade such as effective spread and trading activity measures, which include the number of transactions, the trading volume, the trading value, and the turnover ratio. These measures describe the characteristics of stock exchanges (see Kumar, 2003; Aitken and Comerton-Forde, 2003).

Apart from the well known measures of liquidity such as the bid-ask spread measures and trading activity measures, there are other measures of liquidity that are employed in the market microstructure literature in order to investigate liquidity. An example here is the *price impact*, which reflects the impact of order flows on prices and is also known as Kyle's lamda. In addition, Amihud (2002) refers to some measures of liquidity used by other studies, such as the *amortized effective spread*, which is used by Chalmers and Kadlec (1998) and is calculated from subsequent transactions and quotes. Another measure is the *probability of informed trading* introduced by Easley et al. (1996) as a measure of microstructure risk, which is calculated on the premises of intra-day transaction data.

To address the research questions, a construction of market-wide liquidity series that are long enough is required to capture the properties of market liquidity. Most liquidity measures require high frequency data (micro-data) on transactions and quotes for their calculation, which are not available in most markets around the world (e.g. effective bid-ask spread, market depth, amortized effective spread, etc), and even when such data is available the access to such data will be limited. Therefore, due to the involved nature of the task, we shall resort here to the employment of those liquidity measures that allow us a feasible examination of the issue. The next three sections delineate the liquidity measures that are used to create a market-wide liquidity series (i.e. the dependent variable).

2.3.1.2.1 Bid-ask spread

A bid-ask spread reflects the immediacy dimension of liquidity and it is widely used as a measure of liquidity in market microstructure literature[20]. Demsetz (1968) was the first to relate the spread to the cost of transaction (i.e. price of immediacy). Therefore, liquidity could be measured through estimating the cost of an order's immediate execution. The investor who wants to trade immediately will execute his order at the current bid or ask price when he wants to sell or buy. The bid (ask) price includes the concession (premium) for the immediate sale (purchase). Thus the spread (i.e. the difference between the bid and ask prices) is the normal measure of liquidity (Amihud and Mendelson, 1986). In addition, the bid-ask spread reflects three cost components: order processing costs, inventory costs, and information asymmetry costs. Thus, any liquidity shock could result in a higher inventory risk and increase the possibility of trading with an informed trader. This, in turn, will result in higher bid-ask spread and then lower liquidity (see Eckbo and Norli, 2002). Although the bid-ask spread is a common measure of liquidity in market microstructure literature (e.g. Amihud and Mendelson, 1986; Chordia et al., 2000; Venkataraman, 2001 among others), it is considered a noisy measure of liquidity, because large trades tend to occur outside the spread and small trades tend to occur inside the spread (see Brennan and Subrahmanyam, 1996 and references cited in).

Due to the data availability we calculate this measure and construct the market-wide spread using daily data. We use the daily quoted spread to construct a market-wide quoted spread and also a proportional quoted spread, which are calculated by the cross-sectional average of individual stocks' quoted and proportional quoted bid-ask spreads. More specifically, first, we calculate a firm-specific quoted bid-ask spread and a proportional quoted spread, which is the quoted bid-ask spread divided by the midpoint of the quote, for stock *i* in day *t* as follows:

$$\text{qspr}_{it} = ask_{it} - bid_{it} \tag{2.1}$$

[20] Bid-ask spread also reflects another dimension of liquidity which is the width (tightness) (see for example, Kumar, 2003).

$$\text{pqspr}_{it} = \sum_{i}^{j} (ask_{it} - bid_{it}) / ((ask_{it} + bid_{it}) / 2) \tag{2.2}$$

where ask_{it} is the ask price for stock i at day t and bid_{it} is the bid price for stock i at day t. Then the cross-sectional average of individual stocks' quoted spreads and percentage quoted spreads is computed each day to construct a market-wide liquidity series. The market-wide liquidity series of quoted spread and proportional quoted spread is computed as follows:

$$\text{QSPR}_{mt} = \left(1/N_i \right) \sum_{i}^{j} ask_{it} - bid_{it} \tag{2.3}$$

$$\text{PQSPR}_{mt} = \left(1/N_j \right) \sum_{i}^{j} (ask_{it} - bid_{it}) / ((ask_{it} + bid_{it}) / 2) \tag{2.4}$$

where N_j is the number of stocks included in the cross-sectional average in day t.

2.3.1.2.2 Trading activity measures

Trading activities measures include the trading volume (i.e. shares volume), the trading value (i.e. currency volume) and the turnover ratio. For each stock in our sample, we define the trading volume as the total number of the share volume traded during the day; the trading value as the number of shares traded during the day multiplied by the stock price; and the turnover ratio as the product of the division between the trading value and the market capitalization. Trading activity measures are considered good proxies for liquidity because they are highly associated with the bid-ask spread and other measures of liquidity. Additionally, in equilibrium, liquidity is correlated with the trading frequency; therefore, if liquidity cannot be observed directly while the turnover ratio can, then the latter can be used as a proxy for liquidity. More specifically, portfolios with higher expected holding periods are expected, in equilibrium, to include stocks with higher bid-ask spread. The fact that the market gross return must be an increasing function of the spread, suggests that the observed asset returns must be an increasing function of the expected holding period. Since the turnover ratio is the reciprocal of investor's holding period, the observed stock return must be a decreasing function of the turnover ratio of that stock (see Datar et al., 1998; Chen, 2005 and references cited in). In addition, these measures are attractive, simple to calculate using readily available data (e.g. daily data), and widely accepted among researchers as proxies for liquidity (see Brennan et al., 1998; Datar et al., 1998; Chordia et al., 2001b; Avramov and Chordia, 2006a among others).

Utilizing daily data on these measures, we construct the aggregate market liquidity series by computing the cross-sectional average of individual stocks' trading volume, trading value and turnover ratio each day. The market-wide series of trading volume, trading value and turnover ratio are computed as follows:

$$\mathrm{TVOL}_{mt} = \left(1/N_j \right) \sum_i^j VOL_{it} \tag{2.5}$$

$$\mathrm{TVALUE}_{\mathrm{mt}} = \left(1/N_j \right) \sum_i^j TValue_{it} \tag{2.6}$$

$$\mathrm{TOV}_{\mathrm{mt}} = \left(1/N_j \right) \sum_i^j TValue_{it}/MV_{it} \tag{2.7}$$

where VOL_{it} is the trading volume for stock i at day t, $TValue_{it}$ is the trading value for stock i at day t, MV_{it} is the market capitalization for stock i at day t, and N_j is the number of stocks included in the cross-sectional average in day t.

2.3.1.2.3 Price impact

The price impact is the impact of order flows on prices. That is, when buy- or sell-orders arrive at the market with specific quantities, any imbalance in orders will move prices up or down because such an imbalance could be interpreted as a result of an information asymmetry, and the orders will be executed at a higher or a lower price. Kyle (1985) developed a model where market makers are unable to distinguish between informed and uninformed traders (i.e. liquidity traders) and therefore choose to set prices that are an increasing function of the probability of trading with informed traders. This is expected to lead to an inverse relationship between the price impact and liquidity; in other words, the larger the price impact the less liquid the stock.

The price impact (known as Kyle's lambda) is used as a proxy for liquidity in order to capture the depth dimension of liquidity – the market's ability to absorb and execute large orders with a lower price impact. Fujimoto (2003b) argues that the price impact accurately captures the costs associated with large trades compared to the quoted bid-ask spread, which measures the cost of trades that are small enough to be executed in a single transaction. To measure the price impact, we use the Amihud's (2002) illiquidity ratio, which is defined as the ratio of daily absolute stock returns over the trading value. It can be interpreted as the daily price response associated with one dollar of trading volume, which is the inverse of the Amivest ratio (liquidity ratio) that is used in the market microstructure literature (such as Cooper et al., 1985; Amihud et al., 1997; Berkman and Eleswarapu, 1998). The intuition behind the illiquidity ratio is that if a stock is less liquid, the value of the illiquidity ratio will be higher, which means that a stock's price moves a lot in response to little volume. Therefore, illiquidity ratio follows Kyle's (1985) concept of illiquidity, which is also defined as the response of price to the order flow (see Amihud, 2002). Furthermore, Hasbrouck (2005) finds that Amihud's (2002) illiquidity measure is the best proxy for the price impact; he finds that Kyle's lambda calculated from microstructure data is highly correlated with Amihud's illiquidity ratio, as their correlation is found to be 0.47. Finally, one major advantage of this measure over other measures of liquidity (for example amortized spread and effective bid-ask spread) is that it requires only daily data to be computed and can be used to construct a series that could span a long time period.

Therefore, following Amihud (2002) we employ the illiquidity ratio as a proxy for the price impact of a trade. This measure is first calculated for each stock in the sample, that is, the price impact for stock *i* at day *t* is given as follows:

$$\text{pimpact}_{it} = |R_{it}| \big/ TValue_{it} \tag{2.8}$$

where R_{it} is the return for stock i at day t and $TValue_{it}$ is the trading value for stock i at day t. Then, the cross-sectional average of the individual stocks' price impact is computed each day to construct a market-wide liquidity series as follows:

$$\text{PIMPACT}mt = \left(1/N_j \right) \sum_{i=1}^{j} \text{pimpact}_{\text{it}} \qquad (2.9)$$

N_j is the number of stocks included in the cross-sectional average in day t.

2.3.1.3 Explanatory variables (determinants of market liquidity)

This section aims to identify the factors that are expected to affect the time-series variation in market-wide liquidity, based on the main models of market microstructure. It also provides the theoretical explanation of the expected relations between these factors and market-wide liquidity through which several testable hypotheses are developed.

Since there is no specific theory for market liquidity (Huberman and Halka, 2001), the selection and the justification of the variables (factors) that expect to affect and determine market-wide liquidity is guided by the main two models in market microstructure: the information asymmetry model and the inventory model. Both explanations begin with the market makers, or dealers, who help in solving the problem of matching buyers with sellers by selling/buying on their own accounts. The origin of the information asymmetry model is accredited to Bagehot (1971) and formalized by Copeland and Galai (1983), then it is emphasized by Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), and Admati and Pfleiderer (1988) among others. Based on this model, stock markets are viewed as consisting of three types of traders: informed traders, liquidity traders, and market makers. The latter possess no superior information, but perform a crucial function in providing liquidity to the market. Dealers or market makers, when they trade, face both the informed traders and liquidity traders (noise traders), but they cannot distinguish between them. However, they make a profit from trading with liquidity motivated traders but lose money when they trade with informed traders. Therefore, dealers set spreads that maximize their profit from liquidity traders and minimize their losses to informed traders.

The inventory-based model is introduced by Demsetz (1968), and then is emphasized by Stoll (1978b), Ho and Stoll (1981), and Amihud and Mendelson (1980) among others. Based on this model, market makers should hold a target level of inventory (i.e. optimal level of inventory). However, their inventories deviate from their optimal levels as a result of the market makers' obligation to accommodate incoming orders. This forces market makers to either hold long or short positions, which will increase the risk and the cost of holding an undesirable level of inventory. Therefore, market makers always try to keep the optimal level of the inventory to maximize the expected average profit through adjusting the bid and ask prices after they trade. Consequently, market makers with long positions will set lower bid and ask prices to decrease the holding of excess inventory, and those with short positions will post higher bid and ask prices to cover the shortage in the inventory. Thus, a bid-ask spread represents a mechanism for market makers to manage their inventories and a compensation for any inventory holding risk.

2.3.1.3.1 Market variables

Market performance: Based on the inventory model, the main variables that will affect liquidity are expected to be those variables that affect inventory risk. Market performance is one of these variables. Chordia et al. (2001a) argue that changes in stocks prices and changes in market performance will affect market liquidity. Changes in stock prices could result in changes in investor expectations which stimulate them to change the composition of their portfolios. As a result their trading behaviour will change (increasing or decreasing their trading activities), which may affect the liquidity provided to the market. More specifically, when stock prices decline it will become costly to trade with these stocks, compared to the case when stock prices increase, therefore, the increase in trading cost will decrease the trading activities of investors, and hence decrease trading volume and then liquidity. On the other hand, the increase in stock prices will result in high stock returns, which will attract investors to participate in the stock market to increase their estimated profitability of stock market participation. Hence, the increased level of participation means a higher trading volume and thus higher liquidity (Griffin et al., 2004 and references cited in).

Moreover, the change in market performance is expected to influence market liquidity through affecting the inventory risk especially for market makers. That is, during a rising market, the level of the trading volume is expected to increase to the extent that market makers find it easier and quicker to adjust their inventory by laying off the imbalances. Since they can easily adjust their inventories, they will face less risk. Therefore, they will post tighter bid-ask spreads which lowers trading costs and thus increases liquidity. In contrast, in falling markets the level of the trading volume is expected to decline, and then it will be difficult for market makers to adjust their inventories which expose them to a higher inventory risk. In this case markets markers will post higher bid-ask spreads to avoid any additional inventory and thus reduce the potential inventory risk. This will reduce the liquidity provided to the market. Therefore, in a period of a rising market, liquidity is expected to be higher than in a period of a falling market. That is, market liquidity is expected to be positively related to concurrent market performance. Furthermore, for the reasons discussed in section 2.3.1.1, concerning the effect of the different characteristics of floor and electronic trading systems on market-wide liquidity, it is expected that the degree of the response of market-wide liquidity to the factors that affect its time-series variation will be different under both trading systems. In other words, this means that the extent of the impact of various determinants on market-wide liquidity will be different across trading systems. Therefore, based on the discussion in section 2.3.1.1, as market-wide liquidity will be higher or lower on one trading system compared with the other, it is likely that market returns will have either a weaker or stronger impact on market liquidity. Thus, the extent to which market return has an impact on market liquidity is an empirical issue. This leads us to the following testable hypotheses:

- *H_{2a}: Equity market return has a significant positive effect on market-wide liquidity.*

- *H_{2b}: There is no significant difference in the impact of equity market return on market-wide liquidity on floor and electronic trading systems.*

Recent market movements: Recent market history could be another possible factor that affects market-wide liquidity. Chordia et al. (2001a) argue that contrarian strategies and the different techniques of technical analysis involve past market moves, which create a link between trading activities and recent price trends (i.e. recent market moves).

According to Glaser and Weber (2009) this link has been fully explained by overconfidence theories, which argue that investors increase their trading activities level because they become overconfident as a result of higher returns. More specifically, the intuition behind the link between past returns and trading volume, according to Glaser and Weber (2009, p. 5), is as follows, "high total market returns make (some) investors overconfident about the precision of their information. Investors mistakenly attribute gains in wealth to their ability to pick stocks. As a result they underestimate the variance of stock returns and trade more frequently in subsequent periods because of inappropriately tight error bounds around return forecasts". This suggests that the trading volume will be lower after market losses and higher after market gains. Gervais and Odean (2001), Statman et al. (2006), and Glaser and Weber (2009) among others find that there is a strong positive relationship between past returns and trading volume. Therefore, following recent market losses (gains), inventory holding risk will be higher (lower) due to the fact that trading activities will be low (high) to the extent that investors / market makers find it more difficult (easy) to adjust their inventories.

In the light of this discussion, if trading volume is expected to be positively related to the past returns (i.e. recent market movements), then it is expected that market-wide liquidity will be positively related to market past returns. However, the impact of recent market movements upon market liquidity is likely to vary between floor and electronic trading systems. That is, recent market returns may have a stronger or weaker positive impact on market liquidity under one trading system compared with the other. This is due to the fact that market-wide liquidity is anticipated to be lower or higher on one trading system compared with the other. Thus, the extent of the impact of recent market returns on market liquidity across trading systems is an empirical question. This leads to the following testable propositions:

- H_{3a}: *Recent equity market return has a significant positive effect on market-wide liquidity.*

- H_{3b}: *There is no significant difference in the impact of recent equity market return on market-wide liquidity on floor and electronic trading systems.*

Market risk: According to the inventory model and the information asymmetry model, market risk (i.e. market volatility) is expected to affect liquidity negatively. More specifically, during periods of higher volatility the dealers will be unable to diversify their portfolios or have a portfolio with desirable risk-return characteristics. Therefore, they will post higher bid and ask prices to avoid any additional inventory and to earn a higher risk premium as compensation for any additional risk resulting from holding an undesirable inventory; higher volatility implies higher inventory risk and thus a wider bid-ask spread (i.e. lower liquidity). On the other hand, periods of higher volatility are normally characterized by a higher degree of information asymmetry (Theissen, 2002a). Therefore, it will be difficult for investors to value stocks accurately, because less information will be available during higher volatility periods (Harris, 2003). In this case, the level of information asymmetry will increase and thus increase the adverse selection cost component in the spread, which means a higher bid-ask spread and lower liquidity.

The empirical evidence supports the expected negative relationship between volatility and liquidity. Tinic (1972), Stoll (1978a), Menyah and Paudyal (1996) among others provide evidence that support the negative relationship between volatility and firm-specific liquidity. Also, Fujimoto (2003b) and Chordia et al. (2005) provide evidence that support the expected theoretical relationship between market volatility and market-wide liquidity. However, Chordia et al. (2001a) provide a mix of evidence about the relationship between market volatility and liquidity; they find that recent market volatility is associated with a decrease in trading volume and spreads, and Van Ness et al. (2005) find no relation between market volatility and aggregate market liquidity. Regardless of the inconclusive evidence concerning the relationship between market-wide liquidity and market volatility, it is expected that market-wide liquidity will be related negatively to market volatility. However, the impact of market volatility on market liquidity is likely to vary across trading systems. More specifically, as market-wide liquidity is anticipated to be higher or lower on one trading system compared with the other, as a result of the different characteristics of both trading systems, the degree of response of market-wide liquidity to market volatility is expected to be either weaker or stronger on one trading system compared with the other. Therefore, the extent of the impact of market volatility upon market liquidity remains an empirical issue leading to the following testable hypotheses:

- H_{4a}: *Equity market volatility has a significant negative effect on market-wide liquidity.*

- H_{4b}: *There is no significant difference in the impact of market volatility on market-wide liquidity on floor and electronic trading systems.*

2.3.1.3.2 Economic variables (short-term interest rate, term spread, and default spread)

Economic conditions are also among the variables that are expected to affect market liquidity to the extent that favourable economic states are likely to be related to increasing trading activities, reduced inventory risks, and improved liquidity (Fujimoto 2003b). The short-term interest rate, the default spread, and the term spread could be used as good indicators for the economic states. These three financial variables are known to be closely related to future economic growth and represent good indicators of the current health of the economy (see Chen, 1991; Fujimoto, 2003b). That is, as stated in Chen (1991), Fama and French (1989) observe that the short-term rate (Treasury bill) tends to be low in a business contraction. In addition, the default spread, which is implicitly included in the pricing of securities, is affected by the health of the economy and the term spread is related to the expected growth of GNP and consumption; when the future output is expected to increase, the consumption will decrease and borrowing will increase, thus the interest rate will increase (Chen, 1991).

The changes in the short-term interest rate, the default spread, and the term spread are expected to affect market liquidity. Market liquidity is expected to decrease (increase) with a short-term interest rate and default spread (term spread). More specifically, Chordia et al. (2001a) argue that market frictions such as short selling restrictions and margin requirements imply that liquidity should depend on interest rates. So by reducing margin costs and the cost of financing inventory, a decrease in the short-term rate will motivate trading activity which then increases market liquidity. Fujimoto (2003b) points out that a higher short-term rate means a restrictive monetary situation, which may lead to a change in expectations about future economic growth and thus affect the perceived risk of holding inventory. In addition, an increase in the quality spread (default spread) is expected to increase the holding inventory risk and then decrease liquidity. That is, an increase in quality spread means a higher company's perceived risk. Thus, the investors / dealers will avoid carrying such risky stocks to avoid any additional inventory risk by quoting a high bid-ask spread and reduce their trading activities, which then reduce liquidity. Further, the increase in the term spread will affect liquidity because investors will reallocate their wealth between debt and equity instruments which, as a result, will increase trading activities (see Chordia et al., 2001a).

In general, a high short-term rate, a high default spread, and a low term spread usually synchronize with recessionary states, which may represent increased inventory risks due to low trading activities during the recession. This in turn will lead investors to ask for a higher risk premium to compensate for a higher inventory risk through quoting a higher bid-ask spread which will reduce liquidity (Fujimoto, 2003b). It is therefore expected that the short-term interest rate and the default spread (term spread) will be negatively (positively) related to market liquidity. However, the impact of interest rate variables on market-wide liquidity is expected to be different before and after the automation of trading systems, due to the differences in the characteristics of both trading systems, which results in different levels of market liquidity across trading systems. That is, based on the discussion in section 2.3.1.1, as market liquidity is likely to increase or decrease after the automation of trading systems, it is therefore expected that the impact of interest rate variables on market-wide liquidity will be weaker or stronger after the automation of trading systems. Hence, the extent of the impact of interest rate variables upon market-wide liquidity is an empirical issue. This suggests the following testable hypotheses:

- H_{5a}: *Market-wide liquidity is negatively affected by the short-term interest rate and the default spread, and is positively affected by the term spread.*

- H_{5b}: *There is no significant difference in the impact of interest rate variables on market-wide liquidity on floor and electronic trading systems.*

2.3.1.3.3 Regularities in aggregate market liquidity (day-of-the-week effect, holiday effect)

The motivation for trading and the behaviour of the traders in the market plays an important role in determining the patterns of market-wide liquidity. It is therefore expected that there may be a day-of-the-week effect on market liquidity. Traders in financial markets are trading either to satisfy their liquidity needs (liquidity traders) or to act on some special information (informed traders). Both traders differ in timing their trade and in the amount of shares they want to trade, which may result in concentrated trading within a particular time. This will result in a different level of trading through the week, and thereby a different level of liquidity. More specifically, when informed traders have precise and more private information and decide to trade, the discretionary liquidity traders may choose to refrain from trading and decide to delay their trades. Since the informational advantage of informed traders is short lived, the decision of liquidity traders to delay their trades will leave the market with less liquidity and make it easier for the market makers to know the reasons behind informed traders' trading. Consequently, the trading volume will decline and thereby reducing the liquidity. Furthermore, with the trading break over the weekend, this may produce a severe adverse selection problem at the beginning of the week (on Monday). Therefore, it is more likely for liquidity motivated traders to defer their transactions and thus the trading volume on Monday will be the lowest of any day of the week (see Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990, 1993). Also, Chordia et al. (2001a) argue that changes in investors' mood or sentiments over the week may cause some systematic seasonal pattern in trading activity.

Market liquidity is also expected to show a particular pattern around holidays, since holidays are often considered as another form of market closing similar to weekends. Such patterns in liquidity are expected to result from the divergence of investors' trading behaviour around holidays. This could be explained by the inventory adjustment process; investors with a short position are expected to have more loss than those with a long position, therefore, they will be reluctant to take any short positions before a holiday. This will result in a lower selling pressure prior to a holiday, which will lead to a positive pre-holiday return and then a lower trading volume. As a consequence, market liquidity will be lower prior to holidays (see Fabozzi et al., 1994). In addition, Harris (2003) argues that during holidays liquidity tends to dry up and it will be difficult to trade a large size near holidays when many traders are not working. This is because most people are paying attention to other things during holidays. Thus, market-wide liquidity is anticipated to show a particular pattern during the week and around holidays. However, this pattern is expected to vary across trading systems, due to the different levels of market-wide liquidity that result from the different characteristics of both floor and electronic trading systems. That is, since market liquidity is likely to be higher or lower on the electronic trading system compared with the floor trading system, or vice versa, market-wide liquidity is anticipated to show either weaker or stronger regularities on one trading system compared with the other. Therefore, the nature of the regularities in market-wide liquidity on the floor and electronic trading system is an empirical issue. This leads to the following testable propositions:

- H_{6a}: *Aggregate market liquidity exhibits distinct regularities (i.e. the day-of-the-week effect and regularities around holidays).*

- H_{6b}: *The regularities in aggregate market liquidity on floor trading systems are expected to be the same as those on electronic trading system.*

2.3.1.3.4 Announcements of scheduled macroeconomic indicators (GNP, CPI and unemployment)

Many market participants believe that the announcement of scheduled macroeconomic news such as a Consumer Price Index (CPI), the employment rate, and the Gross Domestic Product (GDP) have a major impact on financial markets. Ederington and Lee (1993) argue that the announcements of such macroeconomic indicators are viewed as signalling the possible change in the demand for credit and foreign exchange or because market participants believe that these are important variables which the Federal Reserve takes into consideration in setting monetary policy, and thus their news release could affect financial markets. Further, Parbhoo et al. (2006) argue that news announcements of the unemployment rate, money supply growth and the consumer price index are more closely watched economic indicators and are well documented, offering insights into the future direction of the interest rate, the intrinsic health of the economy and the performance of financial markets[21].

It is expected that the announcement of macroeconomic news will affect market liquidity, and thus market liquidity is expected to show a distinct regularity around scheduled macroeconomic announcements. The release of macroeconomic news may stimulate investors to acquire private information through updating and revising their expectations, which in turn increases the trading activity (see Kim and Verrecchia, 1991; Wang, 1994). Furthermore, Fleming and Remolona (1999) argue that the impact of the release of a macroeconomic announcement on prices and liquidity comes in two stages. In the first stage, the release of a major macroeconomic announcement induces sharp simultaneous price changes, which causes a dramatic increase in the bid-ask spread. They argue that it is inventory control that drives the spread. That is, due to the inventory risks of sharp price changes, market makers evidently widen the bid-ask spread or withdraw their quotes. In the second stage, trading volume will increase and persist along with high price volatility and moderately wide bid-ask spreads. This is driven by a residual disagreement among investors about the meaning of information, which may arise from the differential in investors' private views including those based on dealers' knowledge of order flows.

Despite the argument about the effect of the announcement of macroeconomic indicators on stock markets, it is expected that such an announcement would be significantly related to the time-series variation in market-wide liquidity, and thus market-wide liquidity is expected to exhibit a pattern around the release of macroeconomic indicators. However, this pattern is likely to be different across trading systems due to the different levels of market-wide liquidity that result from the different characteristics of floor and electronic trading systems. Specifically, market-wide liquidity is anticipated to be higher or lower on one trading system compared with the other. This is expected to affect the pattern of market-wide liquidity around the announcement of macroeconomic indicators, which is likely to be weaker or stronger on

[21] Chordia et al. (2001a) do not support the use of proxies for firm-specific information (e.g. dummies for earnings announcement dates) as determinants of market liquidity, because such dates are not well coordinated across companies and information about earnings is often conveyed to the market before the official earnings announcement date.

one trading system compared with the other. This leads to the following testable hypotheses.

- H_{7a}: *Market-wide liquidity is affected by the announcement of macroeconomic variables such as GDP, CPI, and unemployment, and shows a particular pattern around these announcements.*

- H_{7b}: *The impact of the announcement of macroeconomic indicators is the same under each trading system.*

2.3.2 Data

The sample of this chapter includes four stock exchanges, whose choice was guided by the objective of this research, which is comparing and examining the determinants of market-wide liquidity and its time-series behaviour before and after the automation of the trading system. Thus, the selection of the sample focuses on stock markets which have undertaken change in their trading systems (i.e. have adopted an electronic trading system rather than a floor trading system). These markets are: the Swiss Stock Exchange (SSE), the Amsterdam Stock Exchange (ASE), the Vienna Stock Exchange (VSE) and the Frankfurt Stock Exchange (FSE). These markets are characterized by being smaller than the US and UK markets that were the main focus of previous studies. Further, the trading system in these markets (the Frankfurt Stock Exchange aside) have moved from a floor trading system to an electronic trading system, while in the Frankfurt Stock Exchange a new electronic trading system has been introduced to work in parallel to the existing floor trading system, where the same stocks are traded under both systems[22]. The composition of our sample is further expected to mitigate against the potential for the presence of the home bias in our analysis, since both trading systems included in the analysis are related to the same market[23]. In addition to this, our

[22] For the purpose of the discussion of empirical results, we sometimes refer to the floor trading system in the Frankfurt Stock Exchange as pre-automation or before automation, and to the electronic trading system in the Frankfurt Stock Exchange as post-automation or after automation.
[23] In contrast, Venkataraman (2001) compares the execution costs between the floor trading system and the electronic trading system using two stock exchanges (NYSE to proxy for floor trading and the Paris Bourse to proxy for electronic trading). The author acknowledges the difficulties in taking into account many factors resulting from country differences such as insider trading laws, the degree of competition for order flow, and the overall trading volume between both markets, NYSE and Paris Bourse.

analysis will bear the extra advantage through employing the German market (the Frankfurt Stock Exchange). More specifically, testing the impact of different trading systems (floor versus electronic) using the Frankfurt Stock Exchange will have great advantage over the testing for the impact of the switch of trading systems in markets where the electronic system replaced the floor one. The issue here is that the number of stocks traded changes with time and this means that for those markets where the electronic system replaced the floor one, we will be effectively estimating the impact based upon two different stock-samples (pre-transition; post-transition); however, in the case of the Frankfurt Stock Exchange, the simultaneous coexistence of both systems allows us to investigate the impact of different trading systems on the premises of the same stock-pool. This will present the opportunity for a potentially controlled experiment of two trading systems characteristics: floor trading versus electronic trading.

The data set under consideration ranges from September 1989 to December 2005. Since we were able to identify the exact date of change for all the markets, the sample period for each market will be different, contingent with the date of automation (see table 2.1). September 1989 represents the earliest start date of data for the Amsterdam Stock Exchange, whereas December 2005 is the latest date for data collection for the Frankfurt Stock Exchange. For each market, (Frankfurt aside), we use data for the five years before automation and for the five years following it. For the Frankfurt Stock Exchange we obtained a data set for both trading systems for eight years spanning from January 1998 to December 2005.

For each market, this research includes all stocks (dead and active) to mitigate against the potential estimation problems accruing from survivorship bias. Daily data for all stocks were obtained from Datastream. The data obtained includes the following variables: the closing bid prices, the ask prices, the closing prices, the trading volume, and the market value. These variables are processed to obtain the following proxies of liquidity, which were discussed in section 2.3.1.2, such as: the quoted spread, the percentage quoted spread, the trading volume, the trading value, the turnover ratio and the price impact. For some markets such as the Amsterdam Stock Exchange and the Vienna Stock Exchange, spread measures are not included in the analysis due to data availability constraints.

In addition, we collected data on the price indices of the four exchanges included in our sample using Datastream market indices, which have a representative sample of stocks covering the majority of market capitalization in each market. These price indices have been used to calculate market return. Data about interest rates (short-term interest rates, long-term interest rates on government bonds, and long-term interest rates on corporate bonds) were obtained either from Datastream or from other sources such as the central bank of some countries such as Germany (Deutche Bundes Bank) and Austria (Austrian National Bank) [24]. Moreover, data about holidays in each country included in our sample has been obtained from the following web site; www.timeanddate.com. Finally, in order to find how the announcement of macroeconomic indicators affect aggregate market liquidity, we were able to obtain the data regarding the announcement dates of the major macroeconomic indicators (i.e. GDP, CPI, and Unemployment) only for Germany for the whole sample period from the Germany Federal Statistical Office.

2.3.3 Descriptive statistics

Table 2.2 reports the descriptive statistics of the basic market liquidity measures for all stock exchanges for the two sub-samples periods before and after the automation of their trading systems, except for the FSE where it reports the descriptive statistics for both trading systems that are working in parallel to each other.

The results show that after the automation of a trading system, average trading volume increased in all markets except in SSE where it decreases by 0.302. Also, trading value increased in all markets after the automation except in SSE and VSE. Further, on average, the turnover ratio has been decreased in all markets after the introduction of an electronic trading system except in VSE where it is increased from 1.902 to 2.076. However, in contrast to ASE, the price impact measure experiences an increase in VSE and FSE after the automation of the trading system, but remains the same on both trading systems in SSE. In relation to spreads measures, which are only available for SSE and FSE, both measures (quoted spread and proportional quoted spread) increase after the introduction of an electronic trading system only in SSE, while in FSE only the quoted spread decreased by 0.117 after automation.

[24] See appendix 2A for the descriptive statistics of interest rate variables.

As indicated by the coefficient of variation, the trading volume and the trading value show a lower degree of variation after the automation of the trading system in SSE and FSE, but in ASE only the trading volume has lower variability[25]. While the turnover ratio shows high variability in SSE and VSE in an electronic trading system, the variability in the turnover ratio decreases in other markets. That is, the coefficient of variation for turnover ratio in SSE and VSE increases to 0.510 and 1.301 respectively during an electronic trading period compared with 0.370 and 0.514 respectively during a floor trading period. However, the price impact shows lower variability after the change only in SSE and ASE. Regarding the spread measures, both the quoted spread and the proportional quoted spread have a higher coefficient of variation under an electronic trading system in SSE, they are 0.287 and 0.265 respectively compared with 0.173 and 0.194 under a floor trading system. In FSE only the proportional quoted spread shows higher variability on an electronic trading system, which is 0.651 compared to 0.347 on a floor trading system. In sum, these results show that the move toward an automated trading system results in a change in the level of market liquidity as well as causing a change in the variability of market liquidity.

Table 2.3 represents the summary statistics for the absolute values of daily percentage changes in all market-wide liquidity measures for all markets included in our analysis. The average absolute daily change of the trading volume and the trading value is lower after the automation of trading systems in SSE and ASE compared to other markets. However, the average absolute daily change of turnover ratio increases in VSE after the automation, that is, it increased by 0.222. The average absolute daily change of price impact increases on an electronic trading system in FSE and decreases in other markets. In relation to spread measures, the average absolute daily change for both a quoted bid-ask spread and a proportional quoted bid-ask spread decreases in SSE after the automation of a trading system while they increase in FSE on the electronic trading system.

The pair-wise correlations among changes in the liquidity proxies for all markets are reported in table 2.4. One might have expected a negative relation between trading

[25] Coefficient of variation is measured as the ratio of the standard deviation to the mean, and is considered a useful statistic for comparing the degree of variation from one data series to another, even if the means are significantly different from each other (see http://www.investopedia.com/terms/c/coefficientofvariation.asp).

activity measures and both spreads and price impact measures, and a positive relation among trading activity measures. In SSE, the correlation among trading activity measures is positive and significant at a 1% level of significance under both trading systems. On a floor trading system, the correlations between the quoted spread and trading activity measures (trading volume, trading value, and turnover ratio) are positive and insignificant which is unexpected. This is inconsistent with Chordia et al. (2001a) and Van Ness et al. (2005) who find a negative correlation between spreads and trading activity measures. However, the correlation between a quoted spread and trading activity measures after the introduction of an electronic trading system becomes negative and only significant with the turnover ratio at a 1% level of significance. Also, the results show a significant negative correlation between the price impact and the turnover ratio (trading volume and trading value) on a floor (electronic) trading system at a 10% level of significance or better. Also, price impact has a significant positive correlation with the quoted spread (proportional quoted spread) on a floor (electronic) trading system at a 1% (5%) level of significance.

In ASE, on both trading systems, the correlation coefficients among trading activity measures is positive and significant at a 1% level of significance as expected. In addition, price impact has a negative and significant correlation at a 10% level of significance with a turnover ratio on a floor trading system, but it has a negative and significant correlation at a 1% level of significance with all trading activity measures on an electronic trading system. Also, in VSE the correlation coefficient among trading activity measures are positive and significant at a 1% level of significance before and after automation. After the automation of a trading system, price impact has a negative significant correlation at 10% level of significance with the trading value. Finally, in FSE, the results show a positive significant correlation at a 1% level of significance among trading activity measures under both trading systems. Although the correlation coefficients of the changes in market-wide quoted spread and proportional quoted spread with trading activity measures on a floor trading system are negatively significant at a 10% level of significance or better, they are quite low. This is consistent with the results of both Chordia et al. (2001a) and Van Ness et al. (2005). In contrast, on the electronic trading system, the correlation coefficients between spreads measures and trading activity measures are positively significant at a 5% level of significance or better. Finally, price impact only has a significant correlation with trading activity measures under the floor trading system.

Table 2.5 reports the autocorrelation for the percentage change in market-wide liquidity measures out to a lag of five trading days for the two sub-samples periods, before and after the automation of a trading system for SSE, ASE, and VSE, and for the floor trading system and the electronic trading system in FSE. The results show that on both trading systems in SSE, all the liquidity series show a significant negative first-order autocorrelation. There is even evidence of a negative high-order autocorrelation (up to a third and fourth lag) in some liquidity series. Although trading volume and trading value series on an electronic trading system in ASE show significantly negative fourth-order autocorrelation at a 1% level of significance, their fifth-order coefficients are positively significant at a 10% level of significance or better. This indicates the presence of a weekly seasonality. However, both the turnover ratio and the price impact series on both trading systems in ASE show significant negative autocorrelation up to the first lag and the second lag respectively. Regarding VSE, the trading volume, the trading value, and the turnover ratio series show negatively significant second-order autocorrelation at a 5% level of significance or better on a floor trading system, while they show negatively significant first-order autocorrelation on an electronic trading system. Furthermore, the price impact series exhibits significantly negative second-order autocorrelation at a 1% level of significance only on an electronic trading system. Finally, in FSE the results show that all liquidity series show a pattern. More specifically, the trading volume series shows a higher order autocorrelation on a floor trading system than on an electronic trading system while the turnover ratio series shows a higher order autocorrelation on an electronic trading system. However, the trading value, the quoted bid-ask spread and the proportional quoted spread series show the same pattern on both trading systems, with the spreads series showing a higher order autocorrelation than a trading value. In sum, the results suggest that the pattern of autocorrelation in liquidity series in all markets indicates that there is a potential presence of a weekly seasonal effect (i.e. day-of-the-week effect).

Comparing our results of autocorrelation with those for Chordia et al. (2001a) and Van Ness et al. (2005) for NYSE and NASDAQ respectively, we find that our results show that there is a statistically significant negative first-order autocorrelation for all the series in all markets, which is consistent with the results of those two studies. Negative autocorrelation might be expected, because most of these series are likely to be stationary. Also, consistent with Chordia et al. (2001a) and Van Ness et al. (2005), we find evidence of negative second-order autocorrelation but ours is stronger especially in the case of spreads measure. However, in contrast to Chordia et al. (2001a) and Van Ness et al. (2005), we find that the markets included in our sample appear to have autocorrelation with longer lags for some of the liquidity series. For example, Chordia et al. (2001a) report significant autocorrelation with lags of two days for change in quoted spreads in NYSE, and Van Ness et al. (2005) report significant autocorrelation with lags of four days for the same measure in Nasdaq. On the other hand, we find that in both SSE and FSE, autocorrelations exhibit lags of four and five days respectively. This indicates that market-wide liquidity in our sample is highly persistent. Moreover, the negative autocorrelation in some of the trading activity measures in some markets, either before or after the automation, exhibit longer lags (i.e. for two, three or four days) compared with those in NYSE which is for two days as in Chordia et al. (2001a).

2.3.4 Methodology

This section provides a discussion of the methods applied in this chapter to answer our research questions. It explains the parametric and non-parametric tests used to compare the daily changes in aggregate market liquidity before and after the automation of a trading system. It also discusses the estimation methods used to estimate the parameters of the regression model to examine the determinants of aggregate market liquidity. Finally, it presents the test of equality of the regressions' parameters between floor and electronic trading systems in order to find out whether the impact of various factors on market-wide liquidity has changed as a result of the introduction of electronic trading systems.

2.3.4.1 Comparative analysis

We compare the daily changes in aggregate market liquidity between the floor and electronic trading system using univariate analysis. In this approach we use both the parametric test (t-test) and nonparametric test (Mann-Whitney test), which are used to compare the mean (median in case of the nonparametric test) of daily changes in market-wide liquidity between floor and electronic trading systems. The t-test statistic for the difference in the means of daily changes in market liquidity is calculated as follows:

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{\sqrt{s^2{}_{n-1,1} / n_1 + s^2{}_{n-1,2} / n_2}} \tag{2.10}$$

where $\bar{x}_1, \bar{x}_2$, are the samples means; $\bar{x}_1$ is the average of a liquidity measure on a floor trading system and $\bar{x}_2$ is the average of the same liquidity measure on an electronic trading system. $s^2{}_{n-1,1}, s^2{}_{n-1,2}$ are the variance for the liquidity measure on a floor and an electronic trading system respectively. *N* is the number of observations. This formula is applied when there are equal observations under each trading system.

In calculating the standard t-test statistic, the assumption of normality distribution is assumed to hold. However, when the assumption of normality of t-test (parametric test) is violated, one can think of employing the analogous nonparametric test[26]. This kind of test has fewer or less rigorous assumptions than its parametric analogue. In other words, if the distribution of changes in market liquidity violates the assumption of normality, we will employ a nonparametric test of statistical significance for the changes in liquidity measures between floor and electronic trading systems. The Wilcoxon-Mann-Whitney rank sum test will be used in this case, which is the most commonly employed analogous nonparametric test for a t-test. It is slightly less powerful than the t-test when the assumptions for the t-test are met, but much more powerful when the assumptions of the t-test are seriously violated. In other words, this test makes no assumption about the distribution of the underlying series. The Wilcoxon-Mann-Whitney test is employed with ordinal (rank-order) data, by transforming the original interval/ratio observations into a rank-order format. By doing so the information is scarified, in other words, the rank-order provides no information about the amount of the difference between adjacent ranks (Sheskin, 2003). This test works as follows: it examines the equality of the centres of location of two samples to infer whether they are from the same population. The first

[26] When one or more of the assumptions of the t-test are violated, most researchers still prefer to use the t-test instead of its nonparametric analog. The justification for that is that many results of empirical studies have demonstrated that under most conditions a parametric test is reasonably robust (Sheskin, 2003).

step involves ordering all the observations of liquidity measures on floor and electronic systems in a combined series and assigning ranks to each regime (Jain, 2005). These ranks are then summed separately for floor and electronic samples. The test statistic U is the one of the sample with the higher sum of ranks.

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - \sum R \tag{2.11}$$

where U is the Mann-Whitney statistic, n_1 and n_2 is the number of observations under the floor and electronic trading system respectively, and $\sum R$ is the sum of ranks. However, in the case of a large sample (i.e. large number of observations) the above equation will give a very large value of a Mann-Whitney statistic (U statistic). In this case it will be difficult to compare the calculated U statistics with the critical U obtained from the tables, since the tables of U distribution is limited to a certain sample size. Consequently, the normal distribution can be employed to approximate the Mann-Whitney U statistics using the following equation:

$$Z = \frac{U - \frac{n_1 n_2}{2}}{\sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}}} \tag{2.12}$$

The second term in the numerator of equation (2.12) represents the expected value of U, while the denominator represents the expected standard deviation. Under the null hypothesis of no change, the expected value E(U) and its standard deviation σu are approximately normally distributed N(0,1). Although there is no agreement on the size of the sample that justifies the use of normal approximation of the Mann-Whitney distribution, it is generally stated that the normal approximation could be used when the sample size is larger than the sample size documented in the tables of U distribution (see Sheskin, 2003).

In summary, the univariate analysis using the t-test (Mann-Whitney test) provides evidence whether the difference in the mean (median) of daily changes in aggregate market liquidity, the difference before and after the introduction of an electronic trading system, is significant or not.

2.3.4.2 Multivariate analysis – regression framework

To examine the determinants of market-wide liquidity, we follow the method of Chordia et al. (2001a). The main approach is based on the idea of estimating several time-series regression of market-wide liquidity measures on various potential determinants. This model addresses the relationship between market-wide liquidity and its possible time-series determinants, which is discussed in section 2.3.1.3, and captures any potential behavioural aspects of market-wide liquidity. This model is estimated during the two sub-sample periods, before and after the automation of a trading system. The empirical model is as follows:

$$
\begin{aligned}
Y_{it} = {} & \alpha + \beta_1 MKT +_{it} + \beta_2 MKT -_{it} + \beta_3 MA5MKT +_{it} + \beta_4 MA5MKT -_{it} \\
& + \beta_5 |MA5MKT|_{it} + \beta_{6-9} D_{it} + \beta_{10} HOL_{it} + \beta_{11} SHRATE_{it} \\
& + \beta_{12} TERSPREAD_{it} + \beta_{13} QULSPREAD_{it} + \beta_{14} GDP(0)_{it} \\
& + \beta_{15} GDP(1-2)_{it} + \beta_{16} UNP(0)_{it} + \beta_{17} UNP(1-2)_{it} \\
& + \beta_{18} CPI(0)_{it} + \beta_{19} CPI(1-2)_{it} + \varepsilon_{it} \qquad (2.13)
\end{aligned}
$$

The dependent variable Y_{it} is the daily changes in aggregate market liquidity which is measured by the trading volume, the trading value, the turnover ratio, the price impact, the quoted spread, and the proportional quoted spread. α, β_1 … β_{19} are unknown parameters to estimate, ε_{it} is the time varying disturbance term. The explanatory variables included in equation (2.13), which are discussed in section 2.3.1.3, are defined according to Chordia et al. (2001a), as follows:

- MKT+ (MKT-): the daily market return if it is positive (negative) and zero otherwise; it is the signed concurrent daily return of the market which is a proxy for market performance (i.e. rising market and falling market).

- MA5MKT+ (MA5MKT-): the past five trading-day daily market return if it is positive (negative) and zero otherwise; it is the signed five-day moving average of past returns which is a proxy for recent market returns (i.e. recent market movements).

- MA5| MKT|: the past five trading-day moving average of a daily absolute market return, which is a proxy for recent market volatility.

- D_{it} (Monday-Thursday): indicator variables for days of the week; 1 if the trading day is Monday, Tuesday, Wednesday, or Thursday, and zero otherwise.

- HOL: indicator variables for holidays; 1 if a trading day satisfies the following conditions (1) if any holiday falls on a Friday then the preceding Thursday, (2) if it falls on a weekend or on a Monday, then the following Tuesday, (3) if it falls on another weekday then the preceding and following days, and 0 otherwise.

- SHRATE: the first difference in short-term rate (1-month or 3-month Treasury Bills).

- TERSPREAD: the daily change in the difference between the yield on a constant maturity 10-year Treasury bond and short rate.

- QULSPREAD: the daily change in the difference between the yield on highly rating bond or better corporate bond yield index and the yield on 10-year Treasury bond.

- GDP (0): indicator variables for the day of the announcement of GDP; 1 on the day of a GDP announcement and zero otherwise.

- GDP (1-2): indicator variables for the two days preceding the announcement of GDP; 1 on the two trading days prior to a GDP announcement and zero otherwise.

- UNP (0), UNP (1-2), CPI (0), and CPI (1-2) are defined as for GDP but for unemployment and Consumer Price Index announcements respectively.

2.3.4.2.1 The methods of estimation

Ordinary Least Square method (OLS) is the most widely used technique to find the best estimate of the coefficients in the regression model (equation (2.13)). This estimation method consists of minimizing the sum of squared residuals. According to the Gauss-Markov theorem, OLS is always the best linear unbiased estimator and if the residuals are normally distributed, then this procedure is the uniformly minimum variance unbiased estimator. In addition, under the normality assumption of the residuals, the inference procedures such as hypothesis test, confidence intervals and prediction intervals are powerful. However, when this assumption is violated the fit of the regression model, the parameter estimates, and inferences can be flawed. The violation of a normality assumption can occur as a result of the presence of outliers in a data set (Adnan et al., 2001). When the data are contaminated with outliers, the OLS will provide in-resistant (unstable) results. That is, the presence of the outliers will inflate the error variance and stretch the confidence interval, consequently the estimation cannot be asymptotically consistent which causes a bias in the parameter estimate. These consequences of outliers when applying OLS are due to the fact that OLS does not always find the outliers, because it is based on the sample mean and covariance matrix which are themselves affected by outliers. This is known as masking outliers. Also, OLS has 0% breakdown value, which means that even when there is an arbitrarily small percentage of outliers (bad observations) the coefficients of OLS may change to any value at all from $-\infty$ to $+\infty$ (see Rousseeuw and Zomeren, 1990; Zaman et al., 2001; Yaffee, 2002) [27].

As a result of these weaknesses with the OLS estimation method, a robust regression has been used to estimate the equation (2.13). Many authors have developed several robust regressions, which replace the criterion in OLS (minimizing the sum of squared errors) with one that is less sensitive to outliers such as least absolute deviations or least median of squares. Such robust regression is used to detect outliers and provide stable results in the presence of outliers through limiting the influence of outliers (Yaffee, 2002; Chen, 2002).

[27] Breakdown value could be defined as "a measure of the proportion of contamination that a procedure can withstand and still maintain its robustness" (Chen, 2002, p. 1).

In this research the Least Absolute Deviation (LAD) method is applied to estimate equation (2.13). This estimation method replaces the least sum of square criterion in OLS with least absolute deviation. That is, it aims to minimize the sum of absolute values of errors (Mutan, 2004). The robust regression LAD is able to detect outliers in the data set more efficiently than OLS. More specifically, LAD has a higher breakdown value compared with OLS; its breakdown point of the sample median is 50%. This means that LAD will provide estimators that can resist the effect of nearly 50% of contamination in the data (Rousseeuw, 1984). In addition to using LAD, as a robust check, the Least Trimmed Square (LTS) method is also used. This estimation method minimizes the least sum of squares as with OLS, but the only difference is that the largest squared residuals are not used in the summation (Mutan, 2004). It also has the same breakdown value as LAD, but its objective function is smoother, which makes LTS less sensitive to local effects. Furthermore, its statistical efficiency is better because its estimator is asymptotically normal (Rousseeuw and Van Driessen, 2006).

2.3.4.2.2 Comparing the estimated regression's coefficients before and after the automation

To investigate how the change from a floor trading system to an electronic trading system could affect the impact of various determinants on market liquidity and affect the time-series behaviour of market liquidity, the Wald-test is used. That is, the Wald test is used to test the coefficients equality restriction for the regressions estimated on a floor trading system and on an electronic trading system. In other words, we test whether the coefficient of the regression model estimated on a floor trading system is equal to the same coefficient of the regression model estimated on an electronic trading system (i.e. $\beta_{1F} = \beta_{1E}$). The formula for Wald test statistic is as follows:

$$W = m' \{Var[m|x]\}^{-1} m \qquad (2.14)$$

where m is the covariance matrix of the difference vector, and $\{Var[m|x]\}$ is the covariance matrix (see Green, 2003).

2.4 Empirical Results

This section presents and discusses the findings that are related to the comparison of the variation in market-wide liquidity, the determinants of aggregate market liquidity and its time-series regularities (i.e. time-series behaviour of market-wide liquidity) before and after the automation of a trading system. The results are reported first for the comparative analysis and then for the time-series regressions of market-wide liquidity on various potential determinants[28].

2.4.1 The daily changes in market-wide liquidity before and after the automation of the trading system

In order to examine whether the average daily changes in market liquidity will be the same on floor and electronic trading systems, we use both a parametric (t-test) and a nonparametric (Mann-Whitney) test. The nonparametric test has been applied because of the violation of normality assumption in market-wide liquidity series. The Jarque-Bera statistic for a normality test, as reported in appendix 2C, shows that all liquidity series are not normally distributed. Furthermore, as mentioned previously in section 2.3.4.1, in the case of a large sample the calculated Mann-Whitney statistic will be very large and difficult to compare with its critical value, therefore the normal approximation of the Mann-Whitney test is used[29]. The results of parametric and non parametric tests (normal approximation of Mann-Whitney) for the daily changes in market-wide liquidity are shown in table 2.6 in panel A and B respectively for all markets using equally weight liquidity measures. A significantly positive (negative) difference in average daily changes in market-wide liquidity indicates that the variation in market-wide liquidity is higher (lower) on a floor trading system and vice versa.

The empirical results of a t-test show that, in SSE, the average daily changes in all liquidity measures, except for price impact, show a significant decline at 1% and within a 10% level of significance. This implies that variation in market-wide liquidity is less

[28] See appendix 2B, which provides a summary of the testable hypotheses and whether they are supported or rejected, along with the reasons based on the empirical results of this section.

[29] In the interest of space the values of Mann-Whitney statistics (U statistics) are not reported here.

on an electronic trading system compared with that on a floor trading system. In the case of ASE and VSE, only the daily change in the turnover ratio shows respectively a significant decline and a significant increase in market-wide liquidity variation at a 1% level of significance. Furthermore, in contrast to SSE, the difference in the average daily change in spread measures in FSE is negatively significant at a 5% level of significance. This indicates that the variation in market-wide liquidity is higher in FSE's electronic system compared with the electronic trading system in SSE. This implies that the introduction of an electronic trading system in SSE provides more stability in market-liquidity compared with a floor trading system in FSE. These results reject the first hypothesis and indicate that the variation in market-wide liquidity on a floor trading system is different from that on an electronic trading system. However, the majority of t-test statistics, which are statistically insignificant, are in support of the first proposition. This implies that the introduction of an electronic trading system does not cause any change in the variation in market-wide liquidity, that is, market-wide liquidity remains stable across different trading systems.

Further, the results of a nonparametric test (the normal approximation of Mann-Whitney rank sum tests) that are reported in panel B for all markets show that the obtained z-values are statistically insignificant[30]. This means that there is no statistically significant difference in the daily changes of market-wide liquidity. Consequently, the results of nonparametric tests are consistent with the insignificant results of the t-test and thus accept the first hypothesis that the daily change in aggregate market liquidity is not different across trading systems. Once again, this means that moving to the electronic trading system away from the floor trading system does not affect the variability in aggregate market liquidity, and thus it is the same before and after automation.

2.4.2 Determinants of aggregate market liquidity

To find out what are the factors and the underlying forces that are responsible for the time-series variation in market-wide liquidity and to examine the time-series behaviour of market-wide liquidity, the time-series regression (equation (2.13)) has been estimated

[30] As a robust check we used another nonparametric test (Kruskal-Wallis). Its results were qualitatively and quantitatively similar to those provided by Mann-Whitney and its normal approximation. See appendix 2D.

before and after automation. Because of data availability constraint for the announcement of the scheduled macroeconomic indicators, equation (2.13) has been estimated without the indicator variables for these announcements[31]. Prior to the estimation of the regression model, all the time-series included in the regression model (including all aggregate market liquidity proxies, market return, volatility, and interest rate variables) have been tested for stationarity by performing an Augmented Dickey-Fuller and Phillips-Perron test. We allow for an intercept and use Akaike information criterion to guide selection of the lags. The unit root hypothesis (non-stationary) has been rejected for all of these series. The probability value (p-value) is less than 1% (see the results in appendix 2E). Then, the Least Absolute Deviation (LAD) is used as the estimation method to control for the impact of outliers, which could affect the precision of the estimation in case Ordinary Least Squares has been used. Further, as a robust check, the equation (2.13) has been re-estimated using another robust estimation method: Least Trimmed Squares (LTS). The results of both estimation methods (i.e. LAD and LTS) are qualitatively and quantitatively similar; therefore, in the discussion we focus on the results obtained by LAD[32]. Finally, a comparison of the estimated coefficients has been conducted to compare the impact of the various determinants on market-wide liquidity before and after the automation of trading systems. The empirical results of time-series regressions and the results of the Wald test that compare the estimated coefficients between pre- and post-automation periods for SSE, ASE, VSE, and FSE are reported in table 2.7 and in table 2.8 panel A, B, C, and D respectively. The next sub-sections provide a detail discussion of the empirical results concerning the relationship of market-wide liquidity with its possible determinants and on the time-series behaviour of market-wide liquidity.

2.4.2.1 Market performance

The results show that for all markets, in most cases, there is a distinctly symmetric response of trading activities measures to an up and down market (MKT+, MKT -) before and after automation. The coefficient of an up market (down market) is positively (negatively) related to trading activity measures and it is significant at a 1%

[31] The data on the announcement of macroeconomic indicators (i.e. GDP, CPI, and Unemployment) are only available for the Frankfurt Stock Exchange, therefore the estimation of equation (2.13) with these variables will be discussed later in this section.

[32] In the interest of space the results obtained by LTS are not reported here.

level of significance in the majority of cases. This means that aggregate market liquidity increases in both up and down market conditions. However, the increase in market liquidity when a market declines is an unexpected result, because the inventory holding risk is expected to be high during this period, which may result in lower trading activities. This indicates that any uncertainty in the market is followed by higher trading activity. These results are consistent with the results of Chordia et al. (2001a) and Van Ness et al. (2005), who find that market liquidity also shows symmetric response to up and down market in NYSE and NASDAQ respectively. But they are inconsistent with Fujimoto (2003b) who finds that liquidity is positively related to market performance (i.e. it increases (decreases) when market return increases (decreases)). While the significant positive coefficient of an up market provides support to the hypothesis H_{2a}, the significant negative coefficient of a down market does not.

The estimated coefficient of down market in both price impact and spared regressions provide further support to the hypothesis H_{2a}. Either on both trading systems or on one trading system, the coefficient of down market is negatively significant at a 1% and 5% level in most of the price impact (spreads) regressions for SSE, ASE and VSE (SSE and FSE). This means that market liquidity declines in a down market, which is consistent with the results of Chordia et al. (2001a) and Van Ness et al. (2005) who find a significant negative relation between a down market and spread measures. The decline of market liquidity in a down market, as shown by price impact and spreads regressions, is an expected one. This implies that dealers/investors become more concerned about inventory accumulation during the period of a declining market; therefore, they try to avoid trading with other parties by posting a wider bid-ask spread. In addition, as many traders try to avoid trading in falling markets, there are other traders who try to sell their holding. This will result in a large amount of orders flowing to the market without being filled. Consequently, the market's ability to absorb and accommodate incoming orders will decline and thus lower liquidity.

The results thus far show that market liquidity is affected by market conditions (i.e. up market and down market) either on both trading systems or on one trading system. This emphasizes the importance of investigating how the automation of trading systems could affect the impact of market performance on market-wide liquidity. In general, whenever the coefficient of any of the determinates of market liquidity are significant both before and after automation, the coefficient, while having the same sign, has an impact on market-wide liquidity that is significantly different in two sub-sample periods as indicated by the significant Wald test statistic. More specifically, the significant Wald statistics, reported in table 2.8, show that the size of the coefficients of an up market and a down market, in the absolute value, decreased significantly after the introduction of an electronic trading system in the majority of regression in SSE, ASE and VSE. By contrast, the size of the coefficients increased on the electronic trading system in FSE compared with the floor trading system. This implies that in SSE, ASE, and VSE, market liquidity shows less response to the change in market conditions during the electronic trading period. This rejects the hypothesis H_{2b} that the impact of market returns on market-wide liquidity is not different between floor and electronic trading systems.

2.4.2.2 Recent market movements

With regard to market trends variables, it is expected that aggregate market liquidity will be positively related to recent market moves. That is, market liquidity is expected to increase (decrease) following a recent increase (decrease) in market returns. In contrast, the results show that on either both or one trading system, most of the coefficients of a recently rising market (MA5MKT+) (a recently falling market (MA5MKT-)) are statistically negative (positive) at a 1% and 5% level of significance, and some others are within a 10% level of significance in trading activity regressions for all markets (SSE, VSE and FSE). This means that market liquidity shows a symmetric response to the recent market trends, that is, market liquidity decreases in both a recently rising market and a recently falling market. This provides partial support to the hypothesis H_{3a} in terms of a positive relation between market liquidity and a recently falling market. This implies that investors are less confident about the precise nature of their information and overestimate the variance of stock returns, and thus trade less frequently in the periods following a recently rising market which reduces market liquidity. Our results are consistent with the results of Chordia et al. (2001a) who find that a recently falling market causes a decrease in trading activity in NYSE, but inconsistent with Van Ness et al. (2005) who find no relation between the market trends and any liquidity measures.

In addition, the results also show that the coefficients of recently raising and falling markets are insignificant in spreads and price impact regressions in all markets, and do not support our hypothesis H_{3a}, however, they are consistent with the results of Van Ness et al. (2005). Furthermore, the significant results of the Wald test show that the size of recently rising and recently falling market coefficients, in trading value (trading volume) regression in SSE (VSE), decreased significantly after automation. This implies that recent market trends have more impact on market liquidity on a floor trading system compared with that on an electronic trading system. In contrast, in ASE the impact of a recently rising market becomes significant after automation in trading activity regressions. This does not provide support to our hypothesis H_{3b} that the impact of recent market trends on market-wide liquidity is not different across different trading systems.

2.4.2.3 Market volatility

It is expected that market liquidity will decline during periods of higher volatility, and thus it is expected that market volatility will be negatively (positively) related with trading activity (price impact and spreads) measures. Consistently, the estimated coefficients of recent market volatility (MA5 |MKT|) in trading activity regressions have the expected sign and are statistically significant at a 1% level of significance or lower in all markets either on both or just one trading system. This means that high levels of market volatility is associated with low trading activity due to a higher expected inventory risk during this time. This implies that most of the investors/dealers, who try to keep their portfolios at an optimal level, prefer to avoid trading during a high volatility period to avoid any additional inventory risk, which will be added to their portfolios if they trade. This will result in reducing the level of trading activity and thus reducing market liquidity. Our results are consistent with those of Chordia et al. (2001a), Fujimoto (2003b) and Chordia et al. (2005) who find a negative relationship between volatility and liquidity, but inconsistent with Van Ness et al. (2005) who find that recent market volatility is unrelated to any liquidity proxies in NASDAQ stock exchange. Our results also provide support to the hypothesis H_{4a} that market volatility is negatively related to market liquidity.

In contrast, the relationships between market volatility and both price impact and spread measures are unexpected and thus do not provide support to the hypothesis H_{4a}. More specifically, market volatility is negatively significant at a 5% level of significance in spreads regression on electronic trading systems for SSE, but it is weakly significant (at a 10% level of significance) in the price impact regression on floor trading systems for ASE. This means that market liquidity increases during high volatility periods. This is inconsistent with the findings of Huberman and Halka (2001) and Chordia et al. (2005), but it is consistent with the finding of Chordia et al. (2001a) who find a negative relation between volatility and spread. This implies that investors/dealers, who have inventory imbalance in their portfolio, will be unable to adjust their inventory during a high volatility period, because of the low level of trading activity following recent market volatility. Consequently, investors/dealers are forced to quote a lower bid-ask spread in order to attract more investors to trade and thus adjust their inventory imbalance.

Additionally, in SSE, ASE and VSE, the overwhelming results of the Wald test show that the impact of recent market volatility on aggregate market liquidity is more on a floor trading system compared with that on an electronic trading system. That is, in trading activity and price impact regressions, the size of a recent market volatility coefficient is significantly larger on a floor trading system compared with that on an electronic trading system. In contrast, the impact of market volatility on aggregate market liquidity is more on the electronic trading system in FSE. This implies that the introduction of an electronic trading system has affected the degree of a market-wide liquidity response to market volatility, to the extent that market liquidity shows less variability during the periods of higher volatility on an electronic trading system for SSE, ASE and VSE compared with FSE. Thus, these results reject our hypothesis H_{4b} that the impact of market volatility on market liquidity is not different on alternative trading systems.

2.4.2.4 Interest rate variables

The empirical results show that interest rate variables have a significant effect upon market-wide liquidity. More specifically, in FSE the short-term interest rate has a significant negative influence on trading volume and turnover ratio (trading value) on an electronic trading system (on both trading systems) at a 1% level of significance or lower. This indicates that market-wide liquidity decreases with a short-term interest rate, which implies that an increase in short-term rates could reduce trading activity because of an increase in the cost of margin trading and the cost of financing inventory. Our results are consistent with the findings of Chordia et al. (2001a, 2005), but inconsistent with the results of Fujimoto (2003b) who finds that average market liquidity is significantly higher when a short-term rate is high. This provides support to our hypothesis H_{5a} that market-wide liquidity will be negatively affected by a short-term interest rate. In addition, the impact of the short-term interest rate on market-wide liquidity in FSE on an electronic trading system is different than that on a floor trading system. That is, after automation the coefficient of the short-term interest rate becomes significant in both trading volume and turnover ratio regressions, and its size increases in trading value regression. This may indicate that after automation the investors become more concerned about the cost of financing inventory. Thus, the significant results of the Wald test reject the hypothesis H_{5b}, that the impact of the short-term interest rate on market liquidity is not different before and after automation.

On both trading systems or on one trading system, the results also show that an increase in treasury bonds relative to the short rate (term spread) is accompanied by decreased (increased) market liquidity in FSE and ASE (SSE). More specifically, the coefficients of term spread has a significant negative (positive) effect on trading activity (price impact) in FSE and ASE (ASE), and has a significant negative effect on a proportional quoted spread in SSE. The latter finding provides support to the hypothesis H_{5a}, which expects a positive relation between market liquidity and term spread, while the former findings are against expectations and does not support the hypothesis. The negative relation between proportional spread and term spread in SSE indicates that investors post a lower bid-ask spread to liquidate their equity holdings and move their investments to debt instruments in order to invest in higher yield long-term Treasury Bonds. In contrast, the negative (positive) relationship between trading activity (price impact) and term spread implies that investors, during the period of a higher term spread, trade more in debt instruments rather than pay attention to reallocate their wealth between debt instruments and an equity market, which leaves the latter with less trading activity. This will result in lower liquidity in an equity market. Also, leaving the equity market with less trading activity may reduce the market's ability to absorb orders and thus results in a higher impact of order flow. However, the positive relation between market liquidity and term spread in SSE, compared with that in FSE and ASE, is inconsistent with the findings of Chordia et al. (2001a) and Fujimoto (2003b) who find that liquidity declines with term spread. Furthermore, the impact of the term spread on market-wide liquidity is different between floor and electronic trading systems. After the automation of the trading system, the coefficient of term spread in proportional bid-ask spread (price impact) regression in SSE (ASE) becomes insignificant. This does not provide support to hypothesis H_{5b} that the impact of the term spread on market liquidity is not different between floor and electronic trading systems.

With regard to quality spread (i.e. default spread), the results show that market-wide liquidity decreases with the quality spread in VSE and FSE either on both trading systems or on one trading system. The coefficient of quality spread is negatively related to the turnover ratio in VSE, and negatively (positively) related to trading activity measures (proportional bid-ask spread) in FSE. This implies that an increase in the long-term interest rate on corporate bonds relative to long-term Treasury Bond yields could increase the perceived risk of holding inventory, and thereby decrease liquidity. In other words, when the interest rate on corporate bonds increases this might increase the risk related to stocks, and then investors try to avoid trading in such stocks by lowering trading activity and by increasing a bid-ask spread. In fact, the results show that liquidity increases with the quality spread in SSE. The coefficient of the quality spread is significantly negative (positive) at a 5% level of significance or better in proportional bid-ask spread (trading value) regression in a pre- (post-) automation period. This implies that the increase in the long term interest rate on corporate bonds will increase the perceived risk of holding inventory, and thus force the investors/dealers to remove risky assets from their portfolios by quoting a lower bid-ask spread to attract trading. These results are inconsistent with the results of Chordia et al. (2001a) and Van Ness et al. (2005) who find that default spread unrelated to market liquidity. However, the positive relation between market liquidity and the quality spread in SSE is consistent with the results of Fujimoto (2003b). Overall, our results provide partial support to our proposition H_{5a} in terms of the negative relation between liquidity and quality spread in ASE and FSE.

Finally, the results show that the impact of quality spread on market liquidity is different between floor and electronic trading systems. More specifically, the impact of quality spread on a floor trading system is more than that on an electronic trading system for SSE and FSE. In most cases, the coefficient of quality spread is significant in trading activity and proportional bid-ask spread (proportional bid-ask spread) regressions before the automation of a trading system in FSE (SSE). In contrast, the coefficient of quality spread becomes significant in turnover ratio regression after the automation of the trading system in VSE. These results reject the hypothesis H_{5b} that there is no difference in the impact of quality spread on market liquidity between a floor and an electronic trading system. In sum, the results generally show that all interest rate variables have a significant impact on market-wide liquidity and their impact on market liquidity is different under the different context of trading systems.

2.4.2.5 Day-of-the-week effect

Turning our attention to the daily behaviour of market-wide liquidity during the week, the results show that, in all markets, market liquidity exhibits distinct day-of-week regularities. More specifically, the day-of-week dummies for Monday are negative and significant in trading activity regressions at a 5% level of significance or better in all markets. Also, the coefficient of Monday is positively (negatively) significant in price impact (spread) regressions in all markets (FSE) at a 1% and 5% level of significance in most cases, and within 10% level of significance in a few cases. Apart from the negative coefficients of Monday in spared regression in FSE, other results indicate that market liquidity declines on Mondays either on both or one trading system. This result is consistent with the results of Van Ness et al. (2005) in NASDAQ, but inconsistent with the findings of Chordia et al. (2001a) and Chordia et al. (2005) who find that liquidity increases on Mondays in NYSE. The decline of liquidity on Mondays is expected and implies that the degree of information asymmetry among investors is high after the weekend, which encourages some traders (i.e. liquidity traders) to defer their trading to another day during the week. These results provide support to our postulated hypothesis H_{6a} that market liquidity shows a day-of-the-week effect.

In most cases market-wide liquidity increases on Tuesday in all markets on either both or one trading system. The majority of the results show that the coefficient of Tuesday is positively (negatively) significant in trading activity (price impact and spread) regressions at a 5% level of significance or better in most cases, which provides further support to the hypothesis H_{6a}. This implies that the level of information asymmetry declines in the second day of trading in the week, and thus increases trading activities in all markets in our sample. These results are consistent with the findings of Chordia et al. (2001a), Chordia et al. (2005) and Van Ness et al. (2005) with regard to NYSE and NASDAQ.

In contrast to VSE, market-wide liquidity keeps increasing on Wednesdays in SSE, ASE and FSE as shown by a significantly positive (negative) coefficient of Wednesday in trading activity (price impact and spread) regressions. This implies that the level of information asymmetry in SSE, ASE and FSE continues to decline and thus attracts more trading. These results provide further support to our hypothesis H_{6a} and are consistent with the results of Chordia et al. (2001a), Chordia et al. (2005) and Van Ness et al. (2005).

Furthermore, the results regarding the day-of-the-week dummy for Thursday also provide further support for hypothesis H_{6a}. That is, on Thursdays market liquidity continues to increase in SSE on an electronic trading system and in FSE on a floor trading system, as shown by the negatively (positively) significant coefficient of a Thursday in spread (trading value) regressions in both markets (FSE). This is consistent with the results of Chordia et al. (2001a) and Van Ness et al. (2005). In contrast, market-wide liquidity declines on a Thursday in ASE and VSE on either one or both trading systems. The coefficient of Thursday is significantly negative at a 1% and 5% and within a 10% level of significance in trading activity regressions. This may imply that the information asymmetry in ASE and VSE is higher on a Thursday and thus attracts less trading.

The regression intercepts are most likely to reflect the impact of Fridays (when the four days-of-the-week dummies are zero). The results provide a mix of evidence on the behaviour of liquidity on Fridays in each market as well as cross markets. More specifically, in contrast to FSE, market-wide liquidity increases on Fridays in SSE, ASE and VSE either on both or on one trading system. The constant is positively significant in trading activity regressions at a 1% and 5% level of significance in most cases and within a 10% level of significance in other cases. In contrast, market liquidity in all markets declines on Fridays as shown by the constant, which is positively significant at a 5% level of significance or better in spread and price impact regressions. This may imply that some investors are keen to trade to lay off the imbalance in their inventories, in order to avoid the expected higher inventory costs that they could face by holding inventory over the weekend. At the same time, other investors may post wider bid-ask spreads because they are reluctant to trade to avoid any additional inventory risk. Our results, that market liquidity declines on Fridays, are consistent with the results of Chordia et al. (2001a), Van Ness et al. (2005) and Chordia et al. (2005). Overall, the results of the indicators variables for the day of the week show that market-wide liquidity exhibits a strong day-of-the-week effect on both trading systems.

The evidence of the day-of-the-week effect in market-wide liquidity highlights the importance of looking at how different the regularities are before and after automation. The majority of the results show that the pattern of market-wide liquidity is different before and after automation. More specifically, the results show that some coefficients of day-of-the-week dummies either become insignificant or significant after automation, such as the coefficient of Tuesday, Wednesday and Thursday in price impact (spreads) regressions in ASE (FSE). Furthermore, the significant results of the Wald test in table 2.8 indicate that some of the coefficients of day-of-the-week dummies have significantly increased or decreased in size after automation. For example, the coefficient of Monday in trading activity (spreads) regressions in SSE (FSE) has decreased (increased) after the introduction of the electronic trading system. This strongly rejects the hypothesis H_{6b}, which states that the regularities in market liquidity on a floor trading system are not different from that on an electronic trading system.

2.4.2.6 The effect of holidays

The results show that market-wide liquidity exhibits a distinct pattern around holidays either on both or on one trading system. More specifically, with the exception of VSE, market-wide liquidity either decreases or increases in the other markets around holidays. For example, the results show that market-wide liquidity declines around the holidays in SSE and ASE. The coefficient of holidays' dummies is significantly negative (positive) at least at a 5% level of significance in trading activity (spreads and price impact) regressions in SSE and ASE (SSE). In contrast, the period around holidays in FSE is one of increasing liquidity. The coefficient of holidays' dummies is positive and weakly significant (at a 10% level of significance) in trading activity regressions, but it is significantly negative at a 5% level of significance in spread regression. This means that investors in SSE and ASE, in contrast to FSE, avoid trading before the holiday in order not to hold any positions, especially short positions. It might also mean that investors pay attention to other things around a holiday and thus it makes trading difficult as many investors are not working, which may result in reducing liquidity in these markets. Also, the higher bid-ask spreads in SSE around a holiday indicate the reluctance of investors to hold additional inventory prior to a holiday by quoting a higher bid and ask prices, which means lower liquidity. Our evidence that market liquidity declines around holidays in SSE and ASE is consistent with the findings of Chordia et al. (2001a), Van Ness et al. (2005), Chordia et al. (2005). Thus, our results provide further support to our proposition H_{6a} that aggregate market liquidity exhibits a distinct pattern around holidays.

Furthermore, the pattern of market liquidity around holidays is different before and after automation. After automation, the coefficient of holiday's dummy becomes insignificant as in the price impact and trading activity regressions in SSE and FSE respectively. However, the coefficient of a holiday's dummy become significant after the automation in spreads (turnover ratio) regressions in SSE and FSE (ASE). This implies that investors, after automation, become more able to trade and manage their holdings before the holidays. This could be due to the remote access advantage of the electronic trading system that does not require any physical attendance of investors to carry out their trades. These results reject the hypothesis H_{6b} which states that the patterns of market liquidity around holidays are not different before and after automation.

2.4.2.7 Announcement effect of macroeconomic indicators

This section discusses the results of estimating an equation (2.13) with the indicator variables of the announcement of macroeconomic indicators. This equation is estimated only for the Frankfurt Stock Exchange on the floor and electronic trading system, because the information on the announcement of macroeconomic indicators (i.e. GDP, CPI, and unemployment) is only available for that market. The estimated results are reported in table 2.9, and the results of the Wald test that compare the estimated coefficients between pre- and post- periods are reported in table 2.10.

The results obtained after including the indicator variables in equation (2.13) are qualitatively and quantitatively similar to those obtained by estimating the same equation without the indicator variables, except with some differences in terms of significance or sign. For example, in the new results, the short-term rate becomes insignificant on the floor trading system in trading value regression; the term spread becomes significant at a 5% on floor trading system in turnover ratio regression after it was significant at a 10% level; and day-of-the-week dummies either become significant at a 10% or a 5% level of significance after they were significant at either a 5% or a 10% level of significance in price impact and spread regressions.

The results, generally, show that there is a significant relation between the announcement of macroeconomic indicators and aggregate market liquidity. In other words, market-wide liquidity shows regularities around and on the day of the announcement of macroeconomic indicators. For example, the results show that aggregate market liquidity decreases prior to a GDP announcement on an electronic trading system. The coefficient of the dummy for the two days prior to the announcement of GDP is positively significant at a 5% level of significance in price impact regression. These results are inconsistent with those of Chordia et al. (2001a) who find that trading activities increase prior to the announcement of GDP. This may imply that uncertainty is high before the announcement and investors are not confident about their information, therefore, they tend to reduce their trading activity. This then reduces the market’s ability to absorb and accommodate the submitted orders, which increases the price impact of orders. Also, on the day of the announcement of GDP market-wide liquidity declines on the floor trading system. The coefficient of the day of the announcement of GDP is significantly positive at a 1% and a 10% level of significance in quoted bid-ask spread and proportional quoted bid-ask spread regressions respectively. The decline of liquidity on the day of an announcement is an unexpected result, because on that day the investors are expected to be fully informed and they have updated their expectations accordingly, which will affect their trading behaviour. However, what could be happening is that a disagreement concerning the information still exists among investors, which might affect the degree of uncertainty to the extent that they post higher bid-ask spreads. Alternatively, on the day of the announcement the inventory risk is expected to be higher because of the sharper price changes which force investors to quote a wider bid-ask spread. Our results are inconsistent with the results of Van Ness et al. (2005) and Chordia et al. (2005) who find no relation between liquidity measures and a macroeconomic announcement. Even so, our results provide support to our testable hypothesis H_{7a} that market-wide liquidity is affected by the announcement of macroeconomic variables.

The results concerning the effect of the announcement of CPI also provide partial support to the hypothesis H_{7a}. That is, aggregate market liquidity is not affected before the announcement of CPI by two days, however, on the day of the announcement of CPI, the results show that liquidity increases as indicated by a positively (negatively) significant coefficient in trading value (price impact) regression on an electronic (floor) trading system. Our result is inconsistent with the result of Chordia et al. (2001a) and Van Ness et al. (2005) who find that the announcement of CPI does not seem to influence market liquidity. This implies that inflation has not been particularly easy to predict in Germany compared to the USA.

Finally, market-wide liquidity increases prior to the announcement of unemployment as well as on the day of the announcement of unemployment, which provides further support to the proposition H_{7a}. The results show that the coefficient of two days prior to the announcement (day of the announcement) is negatively (positively) significant at a 1% and 5%, and within a 10% level of significance in proportional quoted spread (trading activity) regressions on floor (both) trading system. An increase of liquidity prior to the announcement of an unemployment rate as indicated by a lower bid-ask spread on a floor trading system may imply that the inventory risks are lower prior to the announcement because of the absence of sharp price changes. However, the increase in liquidity on the day of the announcement indicates that there is disagreement among investors on the meaning of the information which drives their trading activity up. Our results are consistent with those of Chordia et al. (2001a) who find that market liquidity increases prior to the announcement of unemployment in NYSE.

After the automation of the trading system, the results also show that the influence of macroeconomic announcements on market liquidity has changed, which rejects the hypothesis H_{7a} that the impact of the announcement of macroeconomic indicators on market liquidity is the same before and after automation. For example, the impact of the day of the announcement of CPI and unemployment, in trading value and turnover ratio regressions, becomes significant on an electronic trading system. This implies that the knowledge about macroeconomic indicators becomes important during the electronic trading period. This may be due to the absence of the advantage of sharing information in an electronic trading system, which may affect the trading behaviour of investors. In contrast, after the automation, the impact of the day of the announcement (two days of the announcement) of GDP and CPI (unemployment), in spreads and price impacts (proportional bid-ask spread) regressions, becomes insignificant on an electronic trading system. This indicates that, even though the announcement of macroeconomic indicators has impacted the trading behaviour of investors, it does not affect the cost of transactions and the cost of providing liquidity on electronic trading systems.

2.5 Conclusion

Although there are a large number of studies that have examined the cross-sectional determinants of liquidity of an individual stock, studies that have examined the factors that affect time-series variation in aggregate market liquidity are very sparse, and in particular, no study, to the best of our knowledge, has examined the determinants of market-wide liquidity and its times-series behaviour before and after the automation of trading systems. Therefore, this chapter extends the literature on market structure and design by examining and comparing before and after the introduction of an electronic trading system, the variation (i.e. change) in aggregate market liquidity, the factors that affect the time-series variation in market-wide liquidity and its time-series behaviour. A comparative analysis of market-wide liquidity has been undertaken before and after automation. Then, the methodology of Chordia et al. (2001a) has been applied to examine the determinants of market-wide liquidity and its time-series behaviour for four European stock markets, namely; the Swiss Stock Exchange (SSE), the Amsterdam Stock Exchange (ASE), the Vienna Stock Exchange (VSE), and the Frankfurt Stock Exchange (FSE). We use daily data for all stocks traded in these markets including dead stocks to avoid any survival bias in our results. The sample period for all markets (FSE aside) spans a period of ten years, five years before and five years after automation. In the case of FSE, where both a floor trading system and electronic trading system are working in parallel to each other, the sample period is extended for eight years.

By examining whether the variation in market-wide liquidity is different before and after automation, the results overwhelmingly provide evidence that the average daily changes in market-wide liquidity is not significantly after automation. The majority of the results of the t-test are statistically insignificant. Also, the results of non-parametric tests provide evidence that strongly support the findings of the t-test, which means that the daily changes in market-wide liquidity is the same before and after automation.

With regard to determinants of aggregate market liquidity, the results show that market liquidity is strongly related to concurrent markets either on both or on one trading system for all markets. That is, market liquidity increases in both an up and down market on floor and electronic trading systems. However, the influence of market returns (concurrent market return) on market-wide liquidity is greater on a floor trading system in all markets, except for FSE, where the impact of a concurrent market return over market liquidity is more on an electronic trading system. Recent market trends are related to aggregate market liquidity in all markets, but are strongly associated with market-wide liquidity in FSE on both trading systems. In addition, the results show that in all markets, recent market volatility negatively affects market-wide liquidity. This is demonstrated particularly by the negative coefficients of recent market volatility in all trading activity regressions. In contrast, the relation between recent market volatility and price impact in ASE and spread measures in SSE is unexpected. That is, both price impact and spread decrease with market volatility, which is consistent with the findings of Chordia et al. (2001a) in NYSE. However, the impact of recent market volatility on market liquidity is more on a floor trading system in all markets, except in the FSE, where its impact over liquidity is more on an electronic trading system.

The results also show that the changes in key interest rate variables (i.e. short-term rate, the term spread, and the quality spread) significantly influence market liquidity. Short-term rate and quality spread negatively affect market liquidity. However, term spread has a significantly positive (negative) effect on market liquidity in SSE (FSE and ASE). Also, the impact of interest rate variables on market liquidity on a floor trading system is different than that on an electronic trading system. For example, in FSE, a short term interest rate has a greater influence on market liquidity on an electronic trading system compared with that on a floor trading system, and the impact of both term spread and quality spread is more on a floor trading system in SSE, ASE and FSE.

In addition, there is a persistent day-of-the-week effect in all markets. That is, liquidity shows a strong day-of-the-week effect, which is different on both trading systems. More specifically, liquidity declines on Mondays in SSE, ASE, and VSE. In FSE, the results provide mixed evidence. That is, most of the trading activity and price impact measures show that market-wide liquidity declines on Mondays while spread measures show the opposite. Market-wide liquidity increases on Tuesdays and on Wednesdays in SSE, ASE and in FSE, while it increases only on Tuesdays in VSE. Moreover, on Thursdays the results are mixed: the liquidity either increases on that day in some markets (such as SSE and FSE) or decreases in other markets (such as ASE and VSE). Finally, on Fridays the liquidity in both ASE and VSE increase as shown by the positively significant constant in trading activity regressions, while in SSE and FSE it decreases as shown by the positively significant constant in spread regressions. Furthermore, market-wide liquidity shows a distinct pattern around holidays. In contrast to FSE, market-wide liquidity decreases around holidays in both SSE and ASE, but it does not show any particular pattern around holidays in VSE. The results also show that the regularities of market-wide liquidity during the week and around holidays are different before and after automation.

Consistent with Chordia et al. (2001a), but inconsistent with Van Ness et al. (2005) and Chordia et al. (2005), we find that macroeconomic announcements have some impact on market liquidity. That is, by examining the influence of the announcement of macroeconomic indicators on liquidity in FSE, the results show that prior to the announcement (on the day of announcement) of GDP, market-wide liquidity declines on an electronic (floor) trading system. In contrast, prior to and on the day of the announcement of unemployment, market liquidity increases on a floor trading system and on both trading systems respectively. Finally, on the day of announcement of CPI, market liquidity increases on the electronic (floor) trading system as shown by the significantly positive (negative) coefficient of the indicator variable in trading value (price impact) regression. Despite the significant impact of the announcement of macroeconomic indicators on market-wide liquidity, their impact on market-wide liquidity on a floor trading system is different than that on an electronic trading system.

To conclude, this chapter finds that aggregate market liquidity is affected by different factors such as concurrent market returns, recent market trends, and market volatility on both floor trading systems and electronic trading systems. Also, it shows that in some markets there is a significant influence of interest rate variables on market liquidity. Liquidity, in all markets, shows distinct patterns during the week (i.e. day-of-the-week effect) as well as around holidays. In addition, in the case of FSE, the results show that market-wide liquidity is affected by the release of information about major macroeconomic indicators such as GDP, CPI and unemployment, and thus shows a pattern around the announcement of macroeconomic indicators. Finally, the results provide evidence that the impact of the determinants of market-wide liquidity and its time-series behaviour is different across trading systems. That is, some factors have strong influence on market liquidity on a floor trading system and others have strong influence during an electronic trading period. This means that trading systems play a major role in affecting market liquidity and its relation with the factors that are responsible for its time-series variation.

Table 2.1

Dates of introduction of the electronic trading system and the sample period before and after automation

This table shows the stock exchanges that comprise our sample, the date of the introduction of the electronic trading system, the source of information about the date of the automation for each stock exchange and the sample period breakdown for each exchange before and after the automation of the trading system.

The Exchange	Date of Automation	Source of information	Sample period	
			Before Automation	After Automation
Swiss	2-August-1996	http://www.swx.com/swx/review_en.html	2-8-1991 to 1-8-1996	3-8-1996 to 2-8-2001
Amsterdam	30- September-1994	Lexis Nexis News retrieval services	30-9-1989 to 29-9-1994	1-10-1994 to 30-9-1999
Vienna	28-June-1996	Lexis Nexis News retrieval services	28-6-1991 to 27-6-1996	29-6-1996 to 28-6-2001
Frankfurt	28-November- 1997	info@deutsche-boerse.com	1/1/1998 to 30/12/2005 for both systems	

Table 2.2
Descriptive statistics of market-wide liquidity

These are descriptive statistics for time series of market-wide liquidity measures. The series are constructed by the cross-sectional average of individual stocks' liquidity measures for each market for the two sub-samples periods, during a floor trading system (before automation), and during an electronic trading system (after automation), with the exception of the Frankfurt Stock Exchange where the series are constructed for the floor trading system and the electronic trading system that are operating parallel to each other. The variables are defined as follows: Quoted bid-ask spread (QSPR): is the ask price minus the bid price, proportional quoted spread (PQSPR): the quoted bid-ask spread divided by the midpoint of the quote (in percent), trading volume (TVOL): the total share volume during the day, trading value (TVALUE): the total currency volume which is calculated by multiplying the trading volume by the daily closing price, turnover ratio (TOV): turnover measure of trading activities which is calculated by dividing trading value over the market capitalization, price impact (PIMPACT): the ratio of absolute return to trading value. All the variables are equally-weighted.

Panel A: Swiss stock exchange (SSE)												
	TVOL (000)		TVALUE		TOV		PIMPACT		QSPR		PQSPR	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	8.993	8.691	1781.803	1376.657	2.293	1.806	1.820E-04	1.820E-04	11.855	16.400	0.037	0.040
Median	8.258	8.294	1647.574	1203.834	2.201	1.576	1.530E-04	1.580E-04	11.754	14.918	0.037	0.038
Std. Dev. [a]	7.057	2.786	852.569	653.941	0.849	0.920	1.630E-04	1.020E-04	2.053	4.699	0.007	0.011
C of V[b]	0.785	0.321	0.478	0.475	0.370	0.510	0.896	0.560	0.173	0.287	0.194	0.265
Minimum	0.350	2.586	33.227	244.203	0.164	0.229	0.000	0.000	3.000	9.439	0.012	0.021
Maximum	208.600	20.420	8347.650	4648.634	15.242	13.383	0.003	0.002	34.037	37.082	0.064	0.095

Panel B: Amsterdam stock exchange (ASE)												
	TVOL (000)		TVALUE		TOV		PIMPACT		QSPR		PQSPR	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	166.007	371.074	1514.724	6406.675	21.939	3.985	6.210E-04	3.130E-04	-----------[c]	-----------	----------[d]	-----------
Median	154.839	363.431	1339.892	5937.982	9.329	3.557	4.730E-04	2.540E-04	-----------	-----------	-----------	-----------
Std. Dev.	67.813	117.426	638.236	3308.872	75.823	4.100	6.240E-04	2.380E-04	-----------	-----------	-----------	-----------
C of V	0.408	0.316	0.421	0.516	3.456	1.029	1.005	0.760	-----------	-----------	-----------	-----------
Minimum	7.372	66.683	146.285	685.715	1.094	0.931	0.000E+00	5.250E-05	-----------	-----------	-----------	-----------
Maximum	618.373	1315.311	5604.162	23214.620	2235.382	132.764	0.014	0.003	-----------	-----------	-----------	-----------

[a] Standard deviation.

[b] Coefficient of variation, which is the standard deviation divided by the mean.

[c, d] Spreads measures are not available for ASE.

Table 2.2 (Continued)

Panel C: Vienna stock exchange (VSE)												
	TVOL (000)		TVALUE		TOV		PIMPACT		QSPR		PQSPR	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	15.058	28.749	960.475	803.840	1.902	2.076	3.400E-04	1.327E-03	-----------[c]	-----------	----------[d]	-----------
Median	13.288	26.086	786.321	666.206	1.641	1.677	3.060E-04	8.420E-04	-----------	-----------	-----------	-----------
Std. Dev. [a]	8.090	29.207	608.902	542.250	0.976	2.701	1.840E-04	1.535E-03	-----------	-----------	-----------	-----------
C of V[b]	0.537	1.016	0.634	0.675	0.514	1.301	0.541	1.157	-----------	-----------	-----------	-----------
Minimum	1.138	3.013	114.281	55.209	0.627	0.346	1.560E-06	0.000E+00	-----------	-----------	-----------	-----------
Maximum	65.977	950.800	3975.726	8652.280	7.203	47.979	0.002	0.021	-----------	-----------	-----------	-----------
Panel D: Frankfurt stock exchange (FSE)												
	TVOL (000)		TVALUE		TOV		PIMPACT		QSPR		PQSPR	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	86.357	151.466	2611.054	5613.472	1.841	1.487	0.006	0.017	0.561	0.444	0.034	0.043
Median	15.277	141.215	184.539	4626.939	0.918	1.407	0.003	0.005	0.519	0.350	0.032	0.033
Std. Dev.	239.082	80.805	8746.311	3456.830	2.943	0.523	0.009	0.031	0.298	0.224	0.012	0.028
C of V	2.769	0.533	3.350	0.616	1.598	0.351	1.335	1.778	0.531	0.504	0.347	0.651
Minimum	2.855	14.865	27.664	747.079	0.171	0.355	1.350E-05	1.360E-06	0.164	0.147	0.014	0.008
Maximum	3917.667	811.517	203757.100	37558.870	52.720	4.051	0.058	0.547	1.420	1.407	0.080	0.147

[a] Standard deviation.

[b] Coefficient of variation, which is the standard deviation divided by the mean.

[c, d] Spreads measures are not available for VSE.

Table 2.3

Absolute percentage daily changes in market-wide liquidity measures

These are descriptive statistics for absolute values of daily percentage changes in the variables described in table 2.2. The summary statistics presented here for each market for the two sub-sample periods, during a floor trading system (before automation), and during an electronic trading system (after automation), with the exception of the Frankfurt Stock Exchange where the averages are constructed for the floor trading system and for an electronic trading system that are operating parallel to each others. A preceding Δ denotes the daily percentage change in the variable.

Panel A: Swiss stock exchange (SSE)												
	∣Δ TVOL∣		∣Δ TVALUE∣		∣Δ TOV∣		∣Δ PIMPACT∣		∣Δ QSPR∣		∣Δ PQSPR∣	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	0.306	0.180	0.301	0.179	0.237	0.196	0.663	0.367	0.088	0.061	0.072	0.048
Median	0.187	0.145	0.195	0.146	0.163	0.149	0.299	0.266	0.061	0.050	0.050	0.038
Std. Dev. [a]	0.906	0.161	1.419	0.169	0.476	0.227	5.835	0.470	0.153	0.052	0.161	0.045
Minimum	4.160E-04	5.280E-04	8.060E-05	8.230E-05	5.760E-05	4.230E-06	1.990E-04	4.530E-04	2.310E-05	5.570E-06	1.550E-04	1.740E-05
Maximum	20.482	1.535	47.447	2.503	10.396	4.159	197.555	8.741	3.190	0.494	4.367	0.520
Panel B: Amsterdam stock exchange (ASE)												
	∣Δ TVOL∣		∣Δ TVALUE∣		∣Δ TOV∣		∣Δ PIMPACT∣		∣Δ QSPR∣		∣Δ PQSPR∣	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	0.285	0.228	0.274	0.228	1.205	0.279	0.586	0.554	-----------[b]	-----------	----------[c]	-----------
Median	0.199	0.169	0.196	0.172	0.516	0.170	0.359	0.359	-----------	-----------	-----------	-----------
Std. Dev.	0.766	0.248	0.710	0.253	3.689	1.144	1.190	0.802	-----------	-----------	-----------	-----------
Minimum	1.600E-04	3.400E-04	2.320E-04	3.920E-05	1.060E-03	2.770E-04	3.620E-04	2.160E-06	-----------	-----------	-----------	-----------
Maximum	18.578	4.413	22.381	4.922	83.164	38.600	20.572	10.677	-----------	-----------	-----------	-----------

[a] Standard deviation.

[b, c] Spreads measures are not available for ASE.

Table 2.3 (Continued)

Panel C: Vienna stock exchange (VSE)												
	$\lvert\Delta$ TVOL$\rvert$		$\lvert\Delta$ TVALUE$\rvert$		$\lvert\Delta$ TOV$\rvert$		$\lvert\Delta$ PIMPACT$\rvert$		$\lvert\Delta$ QSPR$\rvert$		$\lvert\Delta$ PQSPR$\rvert$	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	0.373	0.411	0.356	0.395	0.240	0.462	0.746	0.707	----------- [b]	-----------	---------- [c]	-----------
Median	0.254	0.228	0.232	0.246	0.169	0.248	0.323	0.439	-----------	-----------	-----------	-----------
Std. Dev. [a]	0.485	2.888	0.486	1.532	0.291	1.640	8.086	0.953	-----------	-----------	-----------	-----------
Minimum	0.000E+00	2.490E-04	7.010E-05	5.890E-04	5.300E-06	6.630E-04	7.360E-04	6.720E-04	-----------	-----------	-----------	-----------
Maximum	7.538	99.986	5.718	49.928	3.596	42.314	274.666	9.120	-----------	-----------	-----------	-----------
Panel D: Frankfurt stock exchange (FSE)												
	$\lvert\Delta$ TVOL$\rvert$		$\lvert\Delta$ TVALUE$\rvert$		$\lvert\Delta$ TOV$\rvert$		$\lvert\Delta$ PIMPACT$\rvert$		$\lvert\Delta$ QSPR$\rvert$		$\lvert\Delta$ PQSPR$\rvert$	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Mean	0.164	0.217	0.185	0.233	0.163	0.160	0.610	0.636	0.065	0.111	0.042	0.086
Median	0.105	0.148	0.118	0.161	0.105	0.112	0.232	0.322	0.051	0.075	0.034	0.058
Std. Dev.	0.280	0.380	0.359	0.404	0.302	0.200	4.534	1.460	0.053	0.143	0.036	0.099
Minimum	1.040E-04	6.450E-05	7.630E-05	2.200E-04	1.120E-04	1.440E-04	3.890E-04	7.130E-04	7.840E-06	0.000E+00	8.280E-06	2.730E-06
Maximum	5.980	9.256	8.360	10.046	6.904	3.049	128.761	37.998	0.511	3.455	0.493	2.113

[a] Standard deviation.

[b, c] Spreads measures are not available for VSE.

Table 2.4
Correlations of simultaneous daily percentage changes in market-wide liquidity measures

These are correlations among daily percentage changes in the variables described in table 2.2. The correlations between variables are reported for each market for the two sub-sample periods, during a floor trading system (before automation), and during an electronic trading system (after automation), with the exception of the Frankfurt Stock Exchange where the correlation coefficients between variables are reported for the floor trading system and for an electronic trading system that are operating parallel to each other. A preceding Δ denotes the daily percentage change in the variable.

Panel A: Swiss stock exchange (SSE)						
	Liquidity measures	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR
Floor trading	ΔTVALUE	0.753***				
	ΔTOV	0.565***	0.282***			
	ΔPIMPACT	-0.029	0.006	-0.094***		
	ΔQSPR	0.042	0.038	0.020	0.115***	
	ΔPQSPR	0.008	-0.005	0.004	0.012	0.585***
Electronic trading	ΔTVALUE	0.829***				
	ΔTOV	0.562***	0.555***			
	ΔPIMPACT	-0.055*	-0.069**	-0.022		
	ΔQSPR	-0.017	-0.027	-0.062**	0.031	
	ΔPQSPR	0.005	-0.010	-0.012	0.057**	0.608***

Panel B: Amsterdam stock exchange (ASE)				
	Liquidity measures	ΔTVOL	ΔTVALUE	ΔTOV
Floor trading	ΔTVALUE	0.925***		
	ΔTOV	0.131***	0.177***	
	ΔPIMPACT	-0.032	-0.035	-0.054*
Electronic trading	ΔTVALUE	0.977***		
	ΔTOV	0.207***	0.143***	
	ΔPIMPACT	-0.078***	-0.081***	-0.078***

***, **, * Correlation is significant at the 0.01, 0.05, and 0.10 level respectively.

Table 2.4 (Continued)

Panel C: Vienna stock exchange (VSE)						
	Liquidity measures	ΔTVOL	ΔTVALUE	ΔTOV		
Floor trading	ΔTVALUE	0.817***				
	ΔTOV	0.660***	0.742***			
	ΔPIMPACT	0.000	0.013	0.011		
Electronic trading	ΔTVALUE	0.965***				
	ΔTOV	0.068**	0.115***			
	ΔPIMPACT	-0.042	-0.047*	0.028		
Panel D: Frankfurt stock exchange (FSE)						
	Liquidity measures	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR
Floor trading	ΔTVALUE	0.946***				
	ΔTOV	0.695***	0.558***			
	ΔPIMPACT	0.063***	0.053**	0.048**		
	ΔQSPR	-0.070***	-0.062***	-0.042*	-0.024	
	ΔPQSPR	-0.058***	-0.054**	-0.079***	-0.001	0.424***
Electronic trading	ΔTVALUE	0.989***				
	ΔTOV	0.801***	0.779***			
	ΔPIMPACT	-0.031	-0.033	-0.031		
	ΔQSPR	0.114***	0.110***	0.071***	-0.033	
	ΔPQSPR	0.072***	0.064***	0.047**	-0.117***	0.436***

***, **, * Correlation is significant at the 0.01, 0.05, and 0.10 level respectively.

Table 2.5

Autocorrelations of market-wide liquidity measures.

This table presents the autocorrelation coefficients in the daily percentage changes in the variables described in table 2.2. The autocorrelation coefficients are reported for each market for the two-samples periods, during a floor trading system (before automation), and during an electronic trading system (after automation), with the exception of the Frankfurt Stock Exchange where the autocorrelation coefficients are reported for the floor trading system and for an electronic trading system that are operating parallel to each other. Note that all variables in this table are measured as daily percentage changes – signified by the prefix Δ. Numbers with boldface type indicate that the coefficient is marginally statistical significant.

Panel A: Swiss stock exchange (SSE)							
		Constant	AR-1	AR-2	AR-3	AR-4	AR-5
Δ TVOL	Floor trading	0.110***	-0.113***	-0.026	-0.019	-0.002	0.012
	Electronic trading	0.021***	-0.471***	-0.385***	-0.259***	-0.193***	-0.002
ΔTVALUE	Floor trading	0.111**	**-0.050***	-0.010	-0.001	-0.007	0.001
	Electronic trading	0.019***	-0.522***	-0.390***	-0.286***	-0.247***	-0.003
ΔTOV	Floor trading	0.063***	-0.216***	-0.073**	-0.014	-0.034	0.032
	Electronic trading	0.029***	-0.423***	-0.163***	-0.126***	-0.042	0.084**
ΔPIMPACT	Floor trading	0.392**	-0.014	-0.001	0.000	-0.004	-0.001
	Electronic trading	0.110***	-0.336***	-0.130***	-0.077**	-0.025	-0.031
ΔQSPR	Floor trading	0.010***	-0.375***	-0.175***	**-0.058***	-0.027	0.016
	Electronic trading	0.003***	-0.403***	-0.195***	-0.125***	-0.138***	-0.037
Δ PQSPR	Floor trading	0.007***	-0.845***	-0.222***	-0.200***	-0.185***	-0.070
	Electronic trading	0.002	-0.299***	-0.159***	-0.070**	-0.095***	-0.027
Panel B: Amsterdam stock exchange (ASE)							
		Constant	AR-1	AR-2	AR-3	AR-4	AR-5
ΔTVOL	Floor trading	0.066***	-0.151***	**-0.049***	-0.025	-0.024	0.020
	Electronic trading	0.041***	-0.410***	-0.230***	-0.107***	-0.134***	0.054*
ΔTVALUE	Floor trading	0.067***	-0.121***	-0.034	-0.015	-0.021	0.032
	Electronic trading	0.042***	-0.404***	-0.217***	-0.089***	-0.109***	0.073**
ΔTOV	Floor trading	0.787***	-0.137***	-0.049	0.024	-0.011	0.155***
	Electronic trading	0.088**	-0.067**	-0.002	0.010	-0.004	-0.004
ΔPIMPACT	Floor trading	0.236***	-0.229***	-0.066**	-0.009	0.004	0.004
	Electronic trading	0.208***	-0.298***	-0.071**	-0.013	0.012	0.001

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5 (Continued)

Panel C: Vienna stock exchange (VSE)							
		Constant	AR-1	AR-2	AR-3	AR-4	AR-5
Δ TVOL	Floor trading	0.110***	-0.303***	-0.093***	-0.049	-0.058*	-0.017
	Electronic trading	0.148***	-0.436***	-0.122	-0.113	-0.091	-0.126
ΔTVALUE	Floor trading	0.100***	-0.325***	-0.061**	-0.014	-0.027	-0.037
	Electronic trading	0.139***	-0.321***	-0.063	-0.048	-0.060	-0.066
ΔTOV	Floor trading	0.050***	-0.349***	-0.155***	-0.044	-0.026	-0.035
	Electronic trading	0.215***	-0.074**	-0.020	-0.001	0.002	0.134***
ΔPIMPACT	Floor trading	0.197***	-0.005	0.000	-0.002	0.000	-0.001
	Electronic trading	0.324***	-0.316***	-0.086***	-0.003	0.027	-0.045
Panel D: Frankfurt stock exchange (FSE)							
		Constant	AR-1	AR-2	AR-3	AR-4	AR-5
Δ TVOL	Floor trading	0.032***	-0.262***	-0.084***	-0.060***	-0.030	-0.012
	Electronic trading	0.049***	-0.254***	-0.086***	0.012	-0.044*	0.037
ΔTVALUE	Floor trading	0.040***	-0.230***	-0.079***	-0.038	-0.015	0.017
	Electronic trading	0.055***	-0.255***	-0.089***	0.001	-0.045*	0.034
ΔTOV	Floor trading	0.033***	-0.216***	0.071***	-0.026	-0.012	0.002
	Electronic trading	0.026***	-0.440***	-0.218***	-0.102***	-0.069***	0.043*
ΔPIMPACT	Floor trading	0.431**	-0.026	0.033	0.002	0.402***	0.022
	Electronic trading	0.303***	-0.161***	0.001	0.042*	0.016	0.042*
ΔQSPR	Floor trading	0.003***	-0.547***	-0.354***	-0.211***	-0.165***	-0.086***
	Electronic trading	0.012***	-0.443***	-0.201***	-0.112***	-0.074***	-0.024
ΔPQSPR	Floor trading	0.002***	-0.396***	-0.235***	-0.166***	-0.126***	-0.023
	Electronic trading	0.009***	-0.403***	-0.252***	-0.155***	-0.070***	-0.023

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6

Parametric and nonparametric tests for the daily change in market-wide liquidity

This table represents the results of the analysis of the difference between the daily change in aggregate market liquidity of the floor trading system and the daily change in aggregate market liquidity of the electronic trading system using the parametric test (t-test) in Panel A and nonparametric test (Wilcoxon-Mann-Whitney rank sum test) in Panel B for all markets included in our sample. The analysis uses market-wide liquidity variables described in Table 2.2. All the variables are equally-weighted and they are measured as daily percentage changes – signified by the prefix Δ.

Swiss stock exchange (SSE)

Panel A: Parametric test (statistical t-test)

Liquidity measures		Δ TVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Mean	Floor trading	0.103	0.103	0.061	0.366	0.013	0.011
Mean	Electronic trading	0.024	0.024	0.033	0.103	0.002	0.001
Difference		0.078	0.079	0.028	0.263	0.011	0.010
t-statistic		2.822***	1.914*	1.615*	1.582	1.920*	1.869*

Panel B: Nonparametric test (Mann-Whitney Rank Sum Tests)

Z-statistic	-0.235	-0.096	-0.253	-0.102	-0.487	-0.600

Amsterdam stock exchange (ASE)

Panel A: Parametric test (statistical t-test)

Liquidity measures		Δ TVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Mean	Floor trading	0.082	0.073	0.756	0.251	-----------[a]	-----------[b]
Mean	Electronic trading	0.045	0.046	0.090	0.221	-----------	-----------
Difference		0.037	0.027	0.666	0.030	-----------	-----------
t-statistic		1.496	1.173	5.926***	0.670	-----------	-----------

Panel B: Nonparametric test (Mann-Whitney Rank Sum Tests)

Z-statistic	-0.612	-0.371	-0.709	-0.102	-----------	-----------

Vienna stock exchange (VSE)

Panel A: Parametric test (statistical t-test)

Liquidity measures		Δ TVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Mean	Floor trading	0.116	0.108	0.054	0.438	-----------	-----------
Mean	Electronic trading	0.173	0.145	0.204	0.318	-----------	-----------
Difference		-0.057	-0.037	-0.150	0.120	-----------	-----------
t-statistic		-0.670	-0.756	-3.006***	0.515	-----------	-----------

Panel B: Nonparametric test (Mann-Whitney Rank Sum Tests)

Z-statistic	-0.057	-0.006	-0.175	-0.049	-----------	-----------

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[a, b] Spreads measures are not available for ASE and VSE.

Table 2.6 (Continued)

Frankfurt stock exchange (FSE)							
Panel A: Parametric test (statistical t-test)							
Liquidity measures		Δ TVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Mean	Floor trading	0.030	0.038	0.031	0.360	0.003	0.002
	Electronic trading	0.048	0.053	0.026	0.312	0.014	0.009
Difference		-0.018	-0.016	0.005	0.048	-0.011	-0.008
t-statistic		-1.495	-1.155	0.555	0.447	-2.476**	-2.423**
Panel B: Nonparametric test (Mann-Whitney Rank Sum Tests)							
Z-statistic		-0.736	-0.649	-0.288	-0.370	-0.184	-0.961

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7

Determinants of aggregate market liquidity, equally weighted time series regressions estimated by LAD

This table represents the regressions of changes in market-wide liquidity measures on market movements, interest rate variables, day of the week, and holidays for each country included in our sample. These regressions are estimated under both floor and electronic trading systems, using equally weighted market-wide liquidity measures. The results are estimated by Least Absolute Deviation (LAD) method. All dependent variables are measured as daily percentage change in market-wide daily average liquidity proxies that are described in table 2.2 (Δ denote the daily percentage change in the variables). The independent variables are MKT+ (MKT-): the daily market return if it is positive (negative) and zero otherwise; MA5MKT+ (MA5MKT-): the past five trading-day daily market return if it is positive (negative) and zero otherwise; MA5| MKT|: the past five trading-day average of daily absolute market return (all the return variables are expressed as percentages); SHORTRATE: the first difference in short-term rate; TERSPREAD: the daily change in the difference between the yield on 10-year government treasury bond and short rate; QULSPREAD: the daily change in the difference between the yield on highly rating bond or better corporate bond yield index and the yield on 10-year government Treasury bond; (Monday-Thursday): 1 if the trading day is Monday, Tuesday, Wednesday, or Thursday, respectively, and zero otherwise. Holidays: 1 if a trading day satisfies the following conditions (1) if any holiday falls on Friday then the preceding Thursday, (2) if it falls on weekend or on a Monday, then the following Tuesday, (3) if it falls on another weekday then the preceding and following days, and 0 otherwise. The t-statistic values (not reported here) are corrected for autocorrelation and heteroskedasticity.

Table 2.7 (Continued)

Panel A: Swiss stock exchange (SSE)												
Dependent Variables	Δ TVOL				ΔTVALUE				ΔTOV			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	0.041*	0.025	-0.004	0.017	0.021	0.023	-0.005	0.016	0.026	0.021	0.004	0.017
MKT+	23.808***	2.940	10.145***	1.334	24.835***	2.506	10.342***	1.370	14.279***	2.314	8.126***	1.409
MKT-	-10.705***	2.572	-3.962***	1.344	-14.524***	1.758	-3.824***	1.224	-4.147*	2.204	-2.171	1.342
MA5MKT+	-7.470	4.678	-5.157**	2.436	-9.538**	4.476	-4.875**	2.308	-5.277	4.185	-4.416*	2.553
MA5MKT-	8.096	5.618	4.811	3.154	10.320**	5.215	5.059	3.225	5.659	4.606	5.710*	3.027
MA5ǀMKTǀ	-13.579***	3.758	-4.607**	1.949	-15.223***	3.278	-5.127**	2.017	-7.259**	3.250	-3.190*	1.872
SHORTRATE	-0.080	0.211	-0.099	0.222	-0.233	0.234	-0.082	0.194	-0.063	0.177	-0.272	0.243
TERMSPREAD	0.053	0.160	-0.041	0.177	-0.150	0.192	0.002	0.155	0.104	0.132	-0.179	0.195
QUALITYSPREAD	0.201	0.166	0.042	0.077	-0.075	0.219	0.125**	0.050	-0.064	0.152	-0.036	0.098
MONDAY	-0.212***	0.024	-0.117***	0.018	-0.204***	0.022	-0.116***	0.017	-0.197***	0.020	-0.113***	0.018
TUESDAY	0.121***	0.027	0.131***	0.019	0.147***	0.025	0.155***	0.019	0.127***	0.024	0.111***	0.020
WEDNESDAY	0.006	0.025	0.056***	0.019	0.034	0.024	0.052***	0.016	0.020	0.021	0.050**	0.020
THURSDAY	-0.011	0.023	-0.011	0.018	0.017	0.022	-0.006	0.017	0.019	0.020	-0.001	0.020
HOLIDAYS	-0.141***	0.049	-0.104**	0.044	-0.113**	0.054	-0.123***	0.040	-0.122***	0.037	-0.134***	0.051
R-squared	0.006		0.142		0.002		0.155		0.063		0.069	
Adjusted R-squared	-0.004		0.133		-0.009		0.146		0.053		0.059	
S.E. of regression	0.953		0.223		1.453		0.227		0.514		0.289	
Durbin-Watson stat	2.192		2.606		2.084		2.650		2.318		2.699	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.7 (Continued)

Panel A: Swiss stock exchange (SSE) (continued)												
Dependent Variables	ΔPIMPACT				ΔQSPR				ΔPQSPR			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	0.041	0.044	0.028	0.037	0.007	0.010	0.014**	0.006	0.004	0.007	0.010**	0.004
MKT+	2.152	4.721	-0.128	2.548	0.072	0.967	0.192	0.456	-1.048	0.766	-0.071	0.338
MKT-	-17.563***	6.857	-5.175*	2.779	-1.678*	0.955	-1.984***	0.464	-1.711**	0.811	-2.447***	0.321
MA5MKT+	8.225	8.365	-4.009	4.680	1.573	1.842	0.455	0.858	0.265	1.396	-0.290	0.615
MA5MKT-	1.773	10.283	0.746	5.694	-0.498	2.104	-0.443	0.873	0.071	1.537	-0.099	0.763
MA5|MKT|	-6.502	6.492	-1.012	4.401	-1.374	1.676	-1.395**	0.656	-0.352	1.047	-1.076**	0.488
SHORTRATE	-0.037	0.322	-0.375	0.441	0.034	0.086	0.039	0.079	-0.092	0.058	-0.038	0.068
TERMSPREAD	0.203	0.236	-0.080	0.358	-0.004	0.073	0.076	0.065	-0.077*	0.045	0.029	0.058
QUALITYSPREAD	-0.359	0.356	0.107	0.173	0.003	0.087	0.000	0.040	-0.147***	0.049	0.020	0.029
MONDAY	0.097**	0.049	0.141***	0.041	0.016*	0.009	-0.010	0.007	0.016**	0.007	-0.005	0.005
TUESDAY	-0.091**	0.043	-0.067*	0.037	-0.030***	0.009	-0.028***	0.006	-0.017**	0.007	-0.027***	0.005
WEDNESDAY	-0.022	0.042	-0.028	0.038	-0.012	0.009	-0.020***	0.007	-0.007	0.007	-0.015***	0.005
THURSDAY	-0.026	0.041	-0.022	0.038	-0.004	0.008	-0.016**	0.007	-0.006	0.007	-0.017***	0.005
HOLIDAYS	0.215**	0.084	-0.004	0.058	0.018	0.014	0.023**	0.011	0.001	0.012	0.024**	0.011
R-squared	-0.004		0.002		-0.001		0.046		0.001		0.092	
Adjusted R-squared	-0.014		-0.008		-0.012		0.036		-0.010		0.082	
S.E. of regression	5.902		0.590		0.177		0.079		0.177		0.063	
Durbin-Watson stat	2.027		2.582		2.121		2.683		1.818		2.544	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.7 (Continued)

Panel B: Amsterdam stock exchange (ASE)																
Dependent Variables	Δ TVOL				ΔTVALUE				ΔTOV				ΔPIMPACT			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	0.041*	0.024	0.061***	0.020	0.038*	0.024	0.059***	0.020	0.316***	0.092	0.040*	0.022	0.144***	0.055	0.045	0.048
MKT+	24.989***	2.969	12.788***	1.464	25.585***	2.698	13.678***	1.536	-8.124	8.469	11.346***	1.540	6.786	5.731	-2.979	3.106
MKT-	-16.358***	3.297	-10.159***	1.306	-16.241***	3.110	-8.932***	1.351	-2.816	7.564	-2.822**	1.364	-21.058***	7.218	-8.090**	3.716
MA5MKT+	-6.800	4.572	-6.626***	2.588	-4.949	4.601	-5.896**	2.535	-2.939	16.002	-6.365**	2.686	12.899	10.759	0.435	7.485
MA5MKT-	7.874	6.201	4.483	3.094	6.417	6.122	3.823	3.007	2.424	20.780	3.622	3.170	-9.703	11.912	0.069	6.846
MA5|MKT|	-16.117***	3.824	-10.215***	1.890	-17.428***	3.642	-10.619***	1.860	1.228	17.176	-6.515***	2.123	-17.388*	9.129	-1.527	4.613
SHORTRATE	0.069	0.287	-0.167	0.253	-0.093	0.281	-0.266	0.261	-0.066	0.909	-0.329	0.345	0.708	0.626	-0.014	0.938
TERMSPREAD	0.035	0.252	-0.179	0.173	-0.158	0.265	-0.239	0.170	-0.475	0.920	-0.544**	0.222	1.194*	0.632	-0.007	0.465
QUALITYSPREAD	0.347	0.237	0.254	0.191	0.190	0.237	0.113	0.191	-0.481	0.847	0.116	0.236	0.174	0.580	-0.414	0.488
MONDAY	-0.288***	0.022	-0.293***	0.022	-0.290***	0.021	-0.288***	0.022	-0.321***	0.086	-0.150***	0.023	0.053	0.064	0.114**	0.057
TUESDAY	0.170***	0.025	0.139***	0.024	0.181***	0.024	0.146***	0.024	0.042	0.102	0.094***	0.024	-0.166***	0.052	-0.030	0.053
WEDNESDAY	0.040*	0.022	0.028	0.020	0.048**	0.022	0.035*	0.020	0.001	0.092	0.035	0.022	-0.133***	0.051	0.013	0.056
THURSDAY	-0.008	0.023	-0.038*	0.021	-0.008	0.022	-0.036*	0.021	-0.182**	0.089	-0.011	0.023	-0.152***	0.052	-0.018	0.054
HOLIDAYS	-0.144***	0.056	-0.134***	0.038	-0.175***	0.063	-0.115***	0.040	-0.233	0.173	-0.153***	0.045	0.132	0.177	0.140	0.128
R-squared	0.041		0.228		0.050		0.222		-0.015		0.003		0.013		-0.013	
Adjusted R-squared	0.031		0.220		0.040		0.213		-0.025		-0.008		0.002		-0.024	
S.E. of regression	0.800		0.295		0.742		0.300		3.855		1.179		1.301		0.960	
Durbin-Watson stat	2.212		2.510		2.229		2.512		2.136		2.113		2.346		2.482	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.7 (Continued)

Panel C: Vienna stock exchange (VSE)																
Dependent Variables	Δ TVOL				ΔTVALUE				ΔTOV				ΔPIMPACT			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	0.172***	0.062	0.119***	0.032	0.125**	0.053	0.093***	0.032	0.077**	0.034	0.124***	0.035	0.112	0.071	0.209***	0.060
MKT+	35.814***	4.776	16.684***	2.682	37.584***	5.363	18.152***	2.952	23.969***	3.354	9.030***	3.452	2.631	5.276	1.707	4.572
MKT-	-28.241***	5.181	-13.193***	2.291	-22.200***	4.637	-11.092***	2.573	-15.988***	3.163	-5.241	3.294	-9.333*	5.744	-5.557	4.206
MA5MKT+	-17.847**	6.986	-8.175*	4.709	-11.189	6.795	-11.293**	5.072	-5.621	4.859	-3.226	6.235	-3.903	10.866	-8.920	10.100
MA5MKT-	14.554*	8.761	7.046	5.173	6.437	8.003	9.828*	5.864	7.971	5.339	4.524	6.473	-1.333	13.904	-2.291	8.728
MA5|MKT|	-24.038**	9.640	-11.050***	3.273	-27.628***	8.708	-9.422**	4.122	-18.396***	5.706	-4.760	4.498	-10.296	12.718	-6.736	7.359
SHORTRATE	-0.012	0.943	-0.526	0.748	-0.855	0.986	-0.420	0.755	-0.487	0.717	-0.898	0.885	0.560	1.512	-1.187	1.695
TERMSPREAD	-0.350	0.891	-0.452	0.587	-1.113	0.920	-0.489	0.593	-0.541	0.701	-1.003	0.786	0.664	1.477	-1.855	1.607
QUALITYSPREAD	0.278	0.938	-0.067	0.641	-1.006	0.967	-0.298	0.638	-0.186	0.759	-1.319*	0.806	0.929	1.467	-2.560	1.708
MONDAY	-0.403***	0.056	-0.299***	0.033	-0.317***	0.049	-0.264***	0.033	-0.200***	0.031	-0.188***	0.039	0.080	0.068	-0.098	0.072
TUESDAY	0.034	0.055	0.016	0.037	0.062	0.050	0.050	0.037	0.018	0.031	-0.025	0.042	0.004	0.065	-0.159**	0.070
WEDNESDAY	-0.119**	0.053	-0.101***	0.033	-0.097**	0.046	-0.084**	0.034	-0.059*	0.031	-0.127***	0.037	-0.016	0.061	-0.023	0.071
THURSDAY	-0.129**	0.053	-0.086**	0.035	-0.048	0.045	-0.050	0.036	-0.031	0.029	-0.085**	0.037	-0.003	0.062	-0.088	0.068
HOLIDAYS	0.073	0.066	0.059	0.070	0.017	0.067	0.077	0.063	0.096	0.060	0.000	0.065	-0.034	0.098	0.208	0.134
R-squared	0.132		0.051		0.103		0.035		0.104		-0.009		-0.002		-0.026	
Adjusted R-squared	0.118		0.040		0.089		0.024		0.090		-0.021		-0.018		-0.037	
S.E. of regression	0.599		0.609		0.603		0.679		0.352		1.717		9.892		1.171	
Durbin-Watson stat	2.491		2.439		2.523		2.422		2.614		2.133		2.016		2.481	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.7 (Continued)

Panel D: Frankfurt stock exchange (FSE)												
Dependent Variables	Δ TVOL				ΔTVALUE				ΔTOV			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	-0.011	0.011	-0.018	0.013	-0.020*	0.012	-0.019	0.014	-0.002	0.010	-0.016	0.011
MKT+	5.097***	0.694	7.856***	0.726	6.945***	0.806	8.932***	0.796	3.997***	0.664	7.399***	0.732
MKT-	-4.268***	0.666	-6.851***	0.644	-5.108***	0.715	-6.351***	0.717	-2.570***	0.596	-4.733***	0.590
MA5MKT+	-2.354*	1.316	-3.504**	1.498	-3.264**	1.457	-4.052**	1.664	-1.029	1.299	-2.349*	1.315
MA5MKT-	4.348***	1.335	3.852***	1.467	4.418***	1.559	3.822**	1.577	2.380*	1.268	3.009**	1.425
MA5|MKT|	-2.814***	0.940	-5.369***	0.950	-4.111***	1.078	-5.592***	1.029	-1.982**	0.887	-4.238***	0.845
SHORTRATE	-0.136	0.103	-0.407***	0.133	-0.195*	0.119	-0.440***	0.144	-0.102	0.099	-0.306***	0.106
TERMSPREAD	-0.197**	0.097	-0.368***	0.125	-0.272**	0.112	-0.404***	0.134	-0.178*	0.093	-0.328***	0.099
QUALITYSPREAD	-0.163**	0.074	-0.145	0.101	-0.205***	0.073	-0.141	0.104	-0.132*	0.073	-0.167***	0.064
MONDAY	0.005	0.013	-0.179***	0.014	0.002	0.014	-0.192***	0.015	0.028**	0.012	-0.097***	0.012
TUESDAY	-0.003	0.012	0.176***	0.015	0.025*	0.013	0.192***	0.017	-0.042***	0.012	0.090***	0.012
WEDNESDAY	0.022*	0.012	0.097***	0.013	0.038***	0.013	0.101***	0.015	0.008	0.011	0.058***	0.011
THURSDAY	0.019	0.012	0.019	0.014	0.036***	0.013	0.020	0.015	0.001	0.012	0.016	0.012
HOLIDAYS	0.048	0.030	0.012	0.043	0.054*	0.033	0.008	0.046	0.058*	0.034	0.017	0.040
R-squared	0.016		0.010		0.017		0.100		0.016		0.119	
Adjusted R-squared	0.010		0.093		0.010		0.094		0.010		0.113	
S.E. of regression	0.322		0.414		0.400		0.441		0.340		0.240	
Durbin-Watson stat	2.465		2.372		2.406		2.364		2.459		2.646	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.7 (Continued)

Panel D: Frankfurt stock exchange (FSE) (continued)												
Dependent Variables	ΔPIMPACT				ΔQSPR				ΔPQSPR			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	0.002	0.026	0.065	0.041	0.005	0.005	0.019**	0.008	0.007**	0.003	0.010	0.006
MKT+	2.527*	1.502	0.194	2.008	-0.035	0.280	-0.346	0.413	-0.300	0.192	-0.238	0.351
MKT-	-1.864	1.352	-2.448	2.054	-0.428	0.276	-0.948**	0.440	-0.906***	0.202	-1.623***	0.358
MA5MKT+	-1.706	2.943	4.953	4.496	0.434	0.655	0.893	0.879	-0.296	0.430	0.088	0.688
MA5MKT-	0.082	2.779	-1.708	4.500	-0.203	0.594	0.330	0.967	-0.284	0.391	-0.213	0.811
MA5|MKT|	-1.169	2.262	-0.961	3.364	-0.240	0.401	-0.515	0.654	-0.461	0.290	-0.798	0.516
SHORTRATE	0.124	0.268	0.156	0.358	0.001	0.055	0.016	0.078	-0.020	0.036	0.005	0.068
TERMSPREAD	0.194	0.256	0.074	0.353	-0.001	0.055	-0.028	0.076	-0.018	0.035	-0.039	0.067
QUALITYSPREAD	0.102	0.170	-0.111	0.206	0.014	0.045	0.003	0.064	0.050*	0.026	-0.064	0.053
MONDAY	0.087***	0.030	0.149***	0.046	-0.010*	0.006	-0.041***	0.009	-0.009**	0.004	-0.031***	0.007
TUESDAY	0.013	0.027	-0.102***	0.040	-0.017***	0.006	-0.017*	0.009	-0.016***	0.004	-0.005	0.007
WEDNESDAY	0.027	0.028	0.008	0.041	0.010**	0.006	-0.005	0.009	-0.002	0.004	0.004	0.007
THURSDAY	0.078***	0.030	-0.088**	0.041	-0.010*	0.006	-0.007	0.009	0.000	0.004	0.005	0.007
HOLIDAYS	-0.020	0.045	0.053	0.087	-0.005	0.013	-0.037**	0.018	-0.008	0.007	-0.009	0.014
R-squared	-0.004		-0.015		0.016		0.015		0.053		0.046	
Adjusted R-squared	-0.011		-0.022		0.010		0.009		0.047		0.039	
S.E. of regression	4.586		1.579		0.083		0.180		0.054		0.128	
Durbin-Watson stat	2.043		2.253		2.783		2.533		2.650		2.632	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.8
Wald test for the coefficients of equally-weighted time series regressions estimated by LAD

For the coefficients reported in table 3.7, this table represents the results of Wald test statistic that test the equality constraint between the variables' coefficients, which are estimated by LAD in liquidity regression, ΔTVOL, ΔTVALUE, ΔTOV, ΔPIMPACT, ΔQSPR and ΔPQSPR, before and after the automation of trading system for all stock markets included in our sample.

Panel A: Swiss stock exchange (SSE)						
Liquidity regression model	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Constant	7.128***	2.586*	1.543	0.123	1.361	2.256
MKT+	104.864***	111.875***	19.081***	0.800	0.068	8.341***
MKT-	25.169***	76.446***	2.168	19.868***	0.434	5.242**
MA5MKT+	0.902	4.084**	0.114	6.835***	1.699	0.812
MA5MKT-	1.084	2.661*	0.000	0.033	0.004	0.049
MA5|MKT|	21.178***	25.050***	4.723**	1.556	0.001	2.200
SHORTRATE	0.007	0.604	0.740	0.586	0.004	0.624
TERMSPREAD	0.281	0.964	2.107	0.622	1.525	3.343*
QUALITYSPREAD	4.265**	16.163***	0.082	7.246***	0.008	31.973***
MONDAY	28.089***	25.645***	22.057***	1.164	14.815***	19.285***
TUESDAY	0.266	0.149	0.715	0.396	0.066	4.823**
WEDNESDAY	7.395***	1.165	2.207	0.018	1.333	2.696*
THURSDAY	0.002	1.931	0.993	0.008	3.298*	6.067**
HOLIDAYS	0.715	0.068	0.057	14.080***	0.253	4.624**
Panel B: Amsterdam stock exchange (ASE)						
Liquidity regression model	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Constant	1.036	1.102	157.364***	4.150**	----------[a]	----------[b]
MKT+	69.416***	60.073***	159.930***	9.885***	-----------	-----------
MKT-	22.516***	29.285***	0.000	12.179***	-----------	-----------
MA5MKT+	0.005	0.140	1.628	2.773*	-----------	-----------
MA5MKT-	1.201	0.745	0.143	2.037	-----------	-----------
MA5|MKT|	9.752***	13.405***	13.302***	11.821***	-----------	-----------
SHORTRATE	0.874	0.440	0.579	0.592	-----------	-----------
TERMSPREAD	1.526	0.224	0.097	6.682***	-----------	-----------
QUALITYSPREAD	0.233	0.163	6.398**	1.451	-----------	-----------
MONDAY	0.054	0.009	54.856***	1.153	-----------	-----------
TUESDAY	1.680	2.213	4.765**	6.638***	-----------	-----------
WEDNESDAY	0.368	0.431	2.250	6.925***	-----------	-----------
THURSDAY	1.916	1.745	55.645***	6.041**	-----------	-----------
HOLIDAYS	0.064	2.209	3.177*	0.004	-----------	-----------

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

[a, b] Spreads measures are not available for ASE.

Table 2.8 (continued)

Panel C: Vienna stock exchange (VSE)						
Liquidity regression model	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Constant	2.693*	0.972	1.781	2.626*	----------[a]	----------[b]
MKT+	50.895***	43.320***	18.728***	0.041	-----------	-----------
MKT-	43.130***	18.632***	10.646***	0.806	-----------	-----------
MA5MKT+	4.219**	0.000	0.148	0.247	-----------	-----------
MA5MKT-	2.107	0.334	0.284	0.012	-----------	-----------
MA5|MKT|	15.744***	19.509***	9.189***	0.234	-----------	-----------
SHORTRATE	0.471	0.332	0.215	1.061	-----------	-----------
TERMSPREAD	0.030	1.108	0.346	2.456	-----------	-----------
QUALITYSPREAD	0.289	1.230	1.973	4.174**	-----------	-----------
MONDAY	10.034***	2.515	0.090	6.165**	-----------	-----------
TUESDAY	0.214	0.090	1.066	5.481**	-----------	-----------
WEDNESDAY	0.269	0.139	3.271*	0.010	-----------	-----------
THURSDAY	1.467	0.002	2.025	1.562	-----------	-----------
HOLIDAYS	0.043	0.895	2.174	3.236*	-----------	-----------
Panel D: Frankfurt stock exchange (FSE)						
Liquidity regression model	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Constant	0.336	0.005	1.624	2.346	2.918*	0.151
MKT+	14.455***	6.242**	21.597***	1.349	0.568	0.032
MKT-	16.083***	3.004*	13.462***	0.081	1.401	4.011**
MA5MKT+	0.589	0.224	1.006	2.194	0.272	0.313
MA5MKT-	0.115	0.143	0.195	0.158	0.305	0.008
MA5|MKT|	7.223***	2.068	7.128***	0.004	0.177	0.429
SHORTRATE	4.111**	2.913*	3.683*	0.008	0.037	0.132
TERMSPREAD	1.869	0.965	2.274	0.116	0.117	0.096
QUALITYSPREAD	0.032	0.381	0.302	1.077	0.031	4.588**
MONDAY	170.484***	156.315***	110.553***	1.853	11.816***	10.166***
TUESDAY	136.610***	97.356***	116.035***	8.408***	0.005	2.657*
WEDNESDAY	30.919***	17.806***	19.435***	0.229	2.665*	0.822
THURSDAY	0.000	1.108	1.655	16.303***	0.131	0.446
HOLIDAYS	0.685	0.982	1.047	0.688	3.292*	0.002

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

[a, b] Spreads measures are not available for VSE.

Table 2.9

Determinants of aggregate market liquidity, equally-weighted time series regressions with the announcement of macroeconomic indicators, estimated by LAD

This table represents the regressions of changes in market-wide liquidity measures on market movements, interest rate variables, day of the week, holidays, and the indictors variable for the day of announcement and for the two days preceding the announcement about GDP, CPI, and unemployment for the **Frankfurt Stock Exchange only**. These regressions are estimated under both floor and electronic trading systems, using equally weighted market-wide liquidity measures. The results in this table are estimated by Least Absolute Deviation (LAD) method. All dependent variables are measured as daily percentage change in market-wide daily average liquidity proxies that are described in table 2.2 (Δ denote the daily percentage change in the variables). The independent variables are MKT+ (MKT-): the daily market return if it is positive (negative) and zero otherwise; MA5MKT+ (MA5MKT-): the past five trading-day daily market return if it is positive (negative) and zero otherwise; MA5| MKT|: the past five trading-day average of daily absolute market return; SHORTRATE: the first difference in short-term rate; TERSPREAD: the daily change in the difference between the yield on 10-year government treasury bond and short rate; QULSPREAD: the daily change in the difference between the yield on highly rating bond or better corporate bond yield index and the yield on 10-year government Treasury bond; (Monday-Thursday): 1 if the trading day is Monday, Tuesday, Wednesday, or Thursday, respectively, and zero otherwise. Holidays: 1 if a trading day satisfies the following conditions (1) if any holiday falls on Friday then the preceding Thursday, (2) if it falls on weekend or on a Monday, then the following Tuesday, (3) if it falls on another weekday then the preceding and following days, and 0 otherwise. The t-statistic values (not reported here) are corrected for autocorrelation and heteroskedasticity.

Table 2.9 (Continued)

Dependent Variables	Δ TVOL				ΔTVALUE				ΔTOV			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	-0.011	0.011	-0.021	0.013	-0.022*	0.012	-0.023	0.015	0.000	0.010	-0.016	0.011
MKT+	5.132***	0.696	7.851***	0.730	6.959***	0.808	8.892***	0.794	4.013***	0.667	7.407***	0.731
MKT-	-4.308***	0.668	-6.839***	0.643	-5.111***	0.715	-6.294***	0.717	-2.587***	0.601	-4.760***	0.593
MA5MKT+	-2.338*	1.331	-3.562**	1.514	-3.272**	1.468	-4.182**	1.670	-0.960	1.305	-2.396*	1.323
MA5MKT-	4.363***	1.334	3.849***	1.469	4.367***	1.563	3.856**	1.578	2.413*	1.273	3.011**	1.434
MA5|MKT|	-2.807***	0.938	-5.357***	0.950	-4.121***	1.078	-5.524***	1.024	-1.968**	0.887	-4.230***	0.845
SHORTRATE	-0.141	0.104	-0.395***	0.134	-0.190	0.119	-0.427***	0.143	-0.108	0.099	-0.311***	0.106
TERMSPREAD	-0.200**	0.097	-0.357***	0.126	-0.265**	0.112	-0.392***	0.134	-0.184**	0.093	-0.333***	0.099
QUALITYSPREAD	-0.162**	0.074	-0.138	0.102	-0.199***	0.073	-0.132	0.105	-0.136*	0.074	-0.169***	0.064
MONDAY	0.005	0.013	-0.181***	0.014	0.001	0.014	-0.193***	0.015	0.030**	0.012	-0.098***	0.012
TUESDAY	-0.004	0.012	0.171***	0.016	0.022*	0.014	0.186***	0.017	-0.042***	0.012	0.087***	0.013
WEDNESDAY	0.021*	0.012	0.093***	0.014	0.036***	0.013	0.098***	0.015	0.008	0.011	0.056***	0.011
THURSDAY	0.017	0.012	0.017	0.014	0.035***	0.013	0.017	0.015	-0.002	0.012	0.013	0.012
HOLIDAYS	0.048	0.030	0.013	0.043	0.055*	0.033	0.010	0.046	0.059*	0.034	0.018	0.040
GDP (0)	-0.009	0.031	-0.017	0.032	-0.026	0.032	-0.007	0.032	0.031	0.029	0.030	0.030
GDP (1-2)	0.019	0.021	0.032	0.024	0.029	0.026	0.023	0.025	0.002	0.020	0.022	0.019
CPI(0)	0.000	0.017	0.028	0.020	0.006	0.018	0.039*	0.021	0.004	0.015	0.002	0.015
CPI(1-2)	-0.012	0.012	0.000	0.014	0.006	0.013	0.004	0.016	-0.012	0.012	-0.008	0.012
UNP(0)	0.033*	0.018	0.046**	0.019	0.034*	0.018	0.054**	0.021	0.010	0.017	0.028*	0.015
UNP(1-2)	-0.006	0.013	0.007	0.015	0.004	0.014	0.010	0.017	-0.013	0.013	-0.003	0.013
R-squared	0.017		0.100		0.018		0.100		0.017		0.120	
Adjusted R-squared	0.007		0.091		0.008		0.091		0.008		0.112	
S.E. of regression	0.322		0.415		0.401		0.442		0.341		0.240	
Durbin-Watson stat	2.464		2.369		2.405		2.360		2.459		2.643	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.9 (continued)

Dependent Variables	ΔPIMPACT				ΔQSPR				ΔPQSPR			
Trading system	Floor		Electronic		Floor		Electronic		Floor		Electronic	
Explanatory variables	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	-0.002	0.026	0.066	0.042	0.006	0.005	0.020**	0.009	0.008**	0.003	0.011*	0.007
MKT+	2.671*	1.487	0.410	2.013	-0.055	0.278	-0.344	0.415	-0.297	0.191	-0.254	0.351
MKT-	-2.110	1.345	-2.750	2.061	-0.438	0.276	-0.948**	0.440	-0.907***	0.204	-1.609***	0.361
MA5MKT+	-1.480	2.925	5.802	4.485	0.361	0.652	0.861	0.883	-0.258	0.426	0.089	0.698
MA5MKT-	-0.183	2.769	-2.090	4.480	-0.195	0.598	0.395	0.967	-0.258	0.389	-0.181	0.811
MA5|MKT|	-1.456	2.245	-1.374	3.364	-0.243	0.401	-0.478	0.657	-0.460	0.288	-0.782	0.518
SHORTRATE	0.113	0.266	0.134	0.358	-0.006	0.054	0.006	0.079	-0.023	0.037	0.001	0.069
TERMSPREAD	0.184	0.254	0.061	0.353	-0.007	0.054	-0.036	0.077	-0.020	0.035	-0.042	0.068
QUALITYSPREAD	0.098	0.169	-0.115	0.203	0.013	0.043	0.000	0.065	0.051*	0.027	-0.067	0.053
MONDAY	0.081***	0.029	0.148***	0.046	-0.010*	0.006	-0.041***	0.009	-0.008*	0.004	-0.031***	0.007
TUESDAY	0.015	0.028	-0.099**	0.040	-0.017***	0.006	-0.019**	0.009	-0.015***	0.004	-0.005	0.007
WEDNESDAY	0.030	0.028	0.007	0.041	0.010*	0.006	-0.006	0.009	-0.002	0.004	0.004	0.007
THURSDAY	0.089***	0.031	-0.079*	0.042	-0.012**	0.006	-0.010	0.009	-0.001	0.004	0.003	0.007
HOLIDAYS	-0.024	0.046	0.049	0.088	-0.005	0.014	-0.037**	0.017	-0.008	0.007	-0.009	0.014
GDP (0)	-0.051	0.068	-0.134	0.088	0.053***	0.014	0.047	0.030	0.016*	0.009	0.007	0.018
GDP (1-2)	0.071	0.056	0.205**	0.088	-0.012	0.011	0.001	0.015	-0.005	0.006	0.000	0.013
CPI(0)	-0.100**	0.045	-0.033	0.063	-0.007	0.010	-0.011	0.012	0.005	0.005	0.004	0.009
CPI(1-2)	0.040	0.033	-0.003	0.045	0.007	0.006	-0.007	0.009	-0.004	0.004	-0.009	0.008
UNP(0)	-0.029	0.039	-0.020	0.056	-0.010	0.009	0.021	0.013	-0.004	0.006	0.008	0.011
UNP(1-2)	0.018	0.033	-0.047	0.042	-0.004	0.007	-0.006	0.010	-0.011***	0.004	-0.006	0.008
R-squared	-0.004		-0.015		0.024		0.017		0.057		0.046	
Adjusted R-squared	-0.014		-0.025		0.015		0.008		0.048		0.037	
S.E. of regression	4.593		1.581		0.083		0.180		0.054		0.128	
Durbin-Watson stat	2.043		2.253		2.786		2.533		2.653		2.631	

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Table 2.10
Wald test for the coefficients of equally-weighted time series regressions with the announcement of macroeconomic indicators estimated by LAD

For the coefficients reported in table 3.9, this table reports the results of Wald test statistic that test the equality constraint between the variables' coefficients, which are estimated by LAD in liquidity regression, ΔTVOL, ΔTVALUE, ΔTOV, ΔPIMPACT, ΔQSPR and ΔPQSPR, on floor and electronic trading system for Frankfurt Stock Exchange only.

Liquidity regression model	ΔTVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Constant	0.588	0.001	1.945	2.609*	2.963*	0.141
MKT+	13.891***	5.919**	21.567***	1.262	0.487	0.015
MKT-	15.519***	2.719*	13.434***	0.096	1.341	3.788*
MA5MKT+	0.654	0.297	1.179	2.636*	0.320	0.247
MA5MKT-	0.122	0.105	0.174	0.181	0.372	0.009
MA5|MKT|	7.199***	1.876	7.176***	0.001	0.128	0.387
SHORTRATE	3.628*	2.755*	3.635*	0.003	0.022	0.122
TERMSPREAD	1.544	0.893	2.235	0.122	0.142	0.099
QUALITYSPREAD	0.052	0.401	0.264	1.103	0.044	4.839**
MONDAY	174.220***	157.877***	111.853***	2.082	11.633***	10.495***
TUESDAY	126.424***	91.214***	106.046***	7.982***	0.032	2.115
WEDNESDAY	28.635***	16.815***	18.142***	0.319	3.029*	0.659
THURSDAY	0.001	1.393	1.667	16.158***	0.051	0.409
HOLIDAYS	0.631	0.934	1.065	0.688	3.479*	0.001
GDP (0)	0.062	0.346	0.003	0.887	0.044	0.274
GDP (1-2)	0.291	0.048	1.063	2.321	0.825	0.124
CPI(0)	2.057	2.291	0.008	1.132	0.128	0.008
CPI(1-2)	0.753	0.013	0.118	0.913	2.230	0.400
UNP(0)	0.427	0.907	1.460	0.025	5.509**	1.358
UNP(1-2)	0.679	0.139	0.577	2.415	0.045	0.319

***, **, * Coefficients significantly different from zero at 1%, 5%, 10% level respectively.

Appendix

Supplementary Empirical Information

Appendix 2A
Debt explanatory variables

This table represents the descriptive statistics for the interest rate variables, Short term rate: the interest rate on 1-month or 3-month Treasury bills, Term spread: the yield spread between the yield on a constant maturity 10-years Treasury bond and short term interest rate, Quality spread: the yield spread between the yield on highly rating bond or better corporate bond yield index and the yield on 10-years Treasury bond. The descriptive statistics are provided for each market during a floor trading system (before automation), and during an electronic trading system (after automation), with the exception of the Frankfurt Stock Exchange where the descriptive statistics are provided for floor trading system and electronic trading system which are operating parallel to each other. For each market, panel A represents the descriptive statistics for the level in interest rate variables; panel B represents the descriptive statistics for the absolute value of daily first difference.

Swiss stock exchange (SSE)						
	Short Rate		Term Spread		Quality Spread	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Panel A: Interest rates levels						
Mean	4.938	2.102	0.197	1.241	0.258	0.428
Std. Dev.	2.190	0.825	1.410	0.659	0.210	0.295
Median	4.310	1.880	0.030	1.370	0.220	0.460
Maximum	9.470	3.590	2.740	2.480	0.820	1.050
Minimum	1.630	0.940	-2.590	-0.180	-0.410	-0.160
Panel B:Absolute Values of Daily First Differences						
Mean	0.042	0.029	0.053	0.036	0.016	0.016
Std. Dev.	0.049	0.039	0.067	0.047	0.053	0.055
Median	0.030	0.020	0.040	0.020	0.000	0.000
Maximum	0.470	0.660	0.720	0.680	0.670	0.700
Minimum	0.000	0.000	0.000	0.000	0.000	0.000

Amsterdam stock exchange (ASE)						
	Short Rate		Term Spread		Quality Spread	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Panel A: Interest rates levels						
Mean	8.027	3.515	-0.193	1.902	-0.033	0.270
Std. Dev.	1.574	0.719	0.894	0.660	0.110	0.142
Median	8.570	3.340	-0.395	2.040	-0.060	0.274
Maximum	9.920	5.600	2.410	3.240	0.304	0.562
Minimum	4.820	2.570	-1.450	0.490	-0.257	-0.092
Panel B:Absolute Values of Daily First Differences						
Mean	0.025	0.010	0.030	0.031	0.023	0.028
Std. Dev.	0.034	0.021	0.032	0.031	0.023	0.026
Median	0.010	0.003	0.020	0.020	0.017	0.021
Maximum	0.380	0.386	0.280	0.346	0.198	0.214
Minimum	0.000	0.000	0.000	0.000	0.000	0.000

Appendix 2A(Continued)

Vienna stock exchange (VSE)						
	Short Rate		Term Spread		Quality Spread	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Panel A: Interest rates levels						
Mean	6.537	3.695	0.773	1.566	-0.502	-0.371
Std. Dev.	2.246	0.649	1.740	0.796	0.412	0.455
Median	5.608	3.547	0.379	1.526	-0.537	-0.289
Maximum	9.867	5.140	3.431	3.208	0.339	0.523
Minimum	3.100	2.570	-1.553	0.194	-1.287	-1.189
Panel B:Absolute Values of Daily First Differences						
Mean	0.011	0.008	0.028	0.031	0.029	0.029
Std. Dev.	0.030	0.021	0.038	0.032	0.033	0.027
Median	0.000	0.002	0.015	0.021	0.019	0.021
Maximum	0.517	0.386	0.351	0.357	0.323	0.297
Minimum	0.000	0.000	0.000	0.000	0.000	0.000

Frankfurt stock exchange (FSE)			
	Short Rate	Term Spread	Quality Spread
Panel A: Interest rates levels			
Mean	3.057	1.373	0.661
Std. Dev.	0.918	0.687	0.560
Median	3.069	1.428	0.587
Maximum	5.750	3.623	2.804
Minimum	1.340	-0.911	-0.451
Panel B:Absolute Values of Daily First Differences			
Mean	0.056	0.074	0.036
Std. Dev.	0.133	0.130	0.048
Median	0.010	0.034	0.025
Maximum	1.160	1.175	0.887
Minimum	0.000	0.000	0.000

Appendix 2B

The testable hypotheses, their acceptance or rejection, and the justification

Hypothesis	Status (accepted/ rejected)	The reason
$H_{1:}$ There is no significant difference in the average daily change in market liquidity before and after the introduction of an electronic trading system.	Accepted	The difference in the average daily change in market liquidity between floor and electronic trading system is insignificant.
H_{2a}: Equity market return has a significant positive effect on market-wide liquidity.	Accepted	The up market (down market) is significantly and positively (negatively) related to trading activity (bid-ask spread and price impact) measures.
H_{2b}: There is no significant difference in the impact of equity market return on market-wide liquidity on floor and electronic trading system.	Rejected	The size of the coefficients of up market and down market is significantly different across trading systems.
H_{3a}: Recent equity market return has a significant positive effect on market-wide liquidity.	Accepted	The recently falling market is significantly and positively related to trading activity measures.
H_{3b}: There is no significant difference in the impact of recent equity market return on market-wide liquidity on floor and electronic trading systems.	Rejected	The size of the coefficients of recently raising market is significantly different across trading systems.
H_{4a}: Equity market volatility has a significant negative effect on market-wide liquidity.	Accepted	Market volatility is significantly and negatively related to trading activity measures.
H_{4b}: There is no significant difference in the impact of market volatility on market-wide liquidity on floor and electronic trading systems.	Rejected	The size of the coefficients of market volatility is significantly different across trading system.
H_{5a}: Market-wide liquidity is negatively affected by the short-term interest rate and the default spread, and is positively affected by the term spread.	Accepted	Short-term interest rate and quality spread have significant negative (positive) effect on trading activity (bid-ask spread) measures, and term-spread has significant negative effect on bid-ask spread measures.
H_{5b}: There is no significant difference in the impact of interest rate variables on market-wide liquidity on floor and electronic trading systems.	Rejected	The size of the interest rate variables' coefficients is significantly different across trading system / some of the coefficients become significant or insignificant after automation.

Appendix 2B (Continued)

H_{6a}: Aggregate market liquidity exhibits distinct regularities (i.e. the day-of-the-week effect and regularities around holidays).	Accepted	Mondays accompany a significant decrease in market liquidity, on Friday market liquidity shows mix pattern, and other days of the week tend to be accompanied by increased market liquidity. Also, market liquidity either significantly increases or decreases around holidays.
H_{6b}: The regularities in aggregate market liquidity on floor trading systems are expected to be the same as those on electronic trading system.	Rejected	The size of the coefficients of some of the day-of-the-week dummies and holiday's dummy is significantly different across trading system / some of the day-of-the-week and holiday dummies' coefficients become significant or insignificant after automation.
H_{7a}: Market-wide liquidity is affected by the announcement of macroeconomic variables such as GDP, CPI, and unemployment, and shows a particular pattern around these announcements.	Accepted	Market liquidity either significantly increases or decreases around the announcement of macroeconomic indicators.
H_{7b}: The impact of the announcement of macroeconomic indicators is the same under each trading system.	Rejected	Some of the coefficients of the announcement dummies become significant or insignificant after automation.

Appendix 2C
Normality test

This table reports the results of the normality test for all market liquidity series for all markets during a floor trading system and during an electronic trading system, using Jarque-Bera test for normality. All the Jarque-Bera statistic values are statistically significant at 1% level of significance; the null hypothesis of normal distribution has been rejected.

	Δ TVOL		ΔTVALUE		ΔTOV		ΔPIMPACT		ΔQSPR		ΔPQSPR	
	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading	Floor trading	Electronic trading
Panel A: Swiss stock exchange (SSE)												
Jarque-Bera	5110784	823	44125437	7476	1407559	66158	55434763	119152	755790	283	6061165	1849
Panel B: Amsterdam stock exchange (ASE)												
Jarque-Bera	6974365	39742	19322452	76009	2501943	44598162	920566	41293	-----------[a]	-----------	----------[b]	-----------
Panel C: Vienna stock exchange (VSE)												
Jarque-Bera	34040	64562951	24459	34204869	12272	6877169	59139459	7439	-----------	-----------	-----------	-----------
Panel D: Frankfurt stock exchange (FSE)												
Jarque-Bera	870334	1705840	2458947	1707755	2061417	58378	24826060	3637748	232	445847	1334	112255

[a, b] Spreads measures are not available for ASE and VSE.

Appendix 2D
Nonparametric tests Kruskal-Wallis

This table represents the results of the analysis of the difference between the daily change in aggregate market liquidity of the floor trading system and the daily change in aggregate market liquidity of the electronic trading system, using other nonparametric tests (Kruskal-Wallis) as a robust check to the results of Mann-Whitney test. The analysis uses market-wide liquidity variables as described in Table 2.2. All the variables are equally-weighted and they are measured as daily percentage changes – signified by the prefix Δ. All the results of Kruskal-Wallis statistic are insignificant which support the acceptance of the first hypothesis of no change.

	Δ TVOL	ΔTVALUE	ΔTOV	ΔPIMPACT	ΔQSPR	ΔPQSPR
Panel A: Swiss stock exchange (SSE)						
Kruskal-Wallis	0.055	0.009	0.064	0.010	0.237	0.360
Kruskal-Wallis (tie-adj.)	0.055	0.009	0.064	0.010	0.237	0.360
Panel B: Amsterdam stock exchange (ASE)						
Kruskal-Wallis	0.375	0.138	0.502	0.010	-----------[a]	----------[b]
Kruskal-Wallis (tie-adj.)	0.375	0.138	0.502	0.010	-----------	-----------
Panel C: Vienna stock exchange (VSE)						
Kruskal-Wallis	0.003	0.000	0.031	0.002	-----------	----------
Kruskal-Wallis (tie-adj.)	0.003	0.000	0.031	0.002	-----------	-----------
Panel D: Frankfurt stock exchange (FSE)						
Kruskal-Wallis	0.541	0.421	0.083	0.137	0.034	0.924
Kruskal-Wallis (tie-adj.)	0.541	0.421	0.083	0.137	0.034	0.924

[a, b] Spreads measures are not available for ASE and VSE.

Appendix 2E
Unit root test for dependent and explanatory variables

This table represents the results of the unit root test to test for stationarity using both Augmented Dickey-Fuller (DF) and Phillips-Perron (PP) tests. These tests allow for intercept and the selection of the lags is guided by Akaike Information criterion. For each market, the test has been done to all liquidity variables (i.e. dependent variables) in panel A and for the explanatory variables in Panel B, for the two sub-samples periods, during a floor trading system and electronic trading system, with exception of the Frankfurt Stock Exchange where the test has been done for independent variables under the floor trading system and electronic trading system, and for explanatory variables for the period where both systems working parallel to each other.The t-statistics for both tests are statistically significant at 1% level of significance.

	Floor trading		Electronic trading	
	DF	PP	DF	PP
	t-Stat	t-Stat	t-Stat	t-Stat
Swiss stock exchange (SSE)				
Panel A: Unit root test for dependent variables				
Δ TVOL	-38.367	-38.474	-7.434	-87.095
ΔTVALUE	-36.060	-36.067	-5.201	-85.999
ΔTOV	-28.329	-43.289	-3.930	-56.587
ΔPIMPACT	-35.203	-35.203	-23.993	-50.344
ΔQSPR	-18.713	-40.032	-15.911	-64.247
ΔPQSPR	-13.788	-37.993	-16.631	-51.896
Panel B: Unit root test for independent variables				
MKT+	-12.622	-33.455	-4.516	-34.849
MKT-	-15.221	-33.472	-5.296	-34.449
MA5MKT+	-9.188	-11.705	-10.993	-13.275
MA5MKT-	-11.624	-11.166	-7.345	-13.394
MA5|MKT|	-4.273	-8.433	-3.309**	-7.181
SHORTRATE	-26.959	-32.780	-31.263	-31.159
TERMSPREAD	-9.580	-36.719	-7.393	-33.438
QUALITYSPREAD	-13.916	-63.312	-12.351	-57.161
Amsterdam stock exchange (ASE)				
Panel A: Unit root test for dependent variables				
Δ TVOL	-12.863	-49.294	-4.982	-58.632
ΔTVALUE	-13.073	-41.395	-4.917	-57.389
ΔTOV	-4.296	-33.934	-5.471	-37.566
ΔPIMPACT	-29.782	-47.067	-23.356	-49.522
Panel B: Unit root test for independent variables				
MKT+	-34.353	-34.358	-3.675	-33.911
MKT-	-15.564	-35.376	-5.612	-35.237
MA5MKT+	-10.655	-11.348	-6.828	-14.846
MA5MKT-	-10.101	-12.554	-7.827	-14.427
MA5|MKT|	-4.312	-9.757	-2.588*	-6.467
SHORTRATE	-17.907	-29.297	-13.309	-30.557
TERMSPREAD	-14.792	-33.352	-24.638	-38.111
QUALITYSPREAD	-13.851	-80.268	-12.522	-101.767

Appendix 2E (Continued)

	Floor trading		Electronic trading	
	DF	PP	DF	PP
	t-Stat	t-Stat	t-Stat	t-Stat
Vienna stock exchange (VSE)				
Panel A: Unit root test for dependent variables				
Δ TVOL	-45.803	-48.593	-10.056	-9.917
ΔTVALUE	-27.947	-48.031	-19.452	-19.078
ΔTOV	-18.542	-49.811	-12.287	-37.355
ΔPIMPACT	-18.646	-34.176	-46.333	-47.016
Panel B: Unit root test for independent variables				
MKT+	-15.568	-29.839	-5.949	-32.330
MKT-	-8.414	-30.408	-6.338	-38.093
MA5MKT+	-7.379	-10.642	-11.687	-12.607
MA5MKT-	-7.332	-10.921	-6.477	-12.912
MA5|MKT|	-3.979	-8.512	-3.485	-7.396
SHORTRATE	-10.984	-33.307	-6.611	-32.450
TERMSPREAD	-32.683	-32.584	-24.360	-37.107
QUALITYSPREAD	-10.588	-28.537	-7.410	-39.217
Frankfurt stock exchange (FSE)				
Panel A: Unit root test for dependent variables				
Δ TVOL	-6.147	-58.870	-8.645	-58.260
ΔTVALUE	-6.375	-56.425	-8.593	-58.528
ΔTOV	-32.354	-56.037	-9.498	-72.136
ΔPIMPACT	-48.247	-48.247	-8.510	-53.181
ΔQSPR	-15.167	-121.084	-28.384	-79.828
ΔPQSPR	-13.309	-76.310	-17.510	-74.848
Panel B: Unit root test for independent variables				
	DF		PP	
MKT+	-5.618		-48.769	
MKT-	-4.566		-48.996	
MA5MKT+	-10.235		-17.140	
MA5MKT-	-8.821		-16.815	
MA5|MKT|	-3.342**		-8.768	
SHORTRATE	-12.390		-83.947	
TERMSPREAD	-10.548		-72.309	
QUALITYSPREAD	-48.055		-48.053	

Chapter Three
Liquidity and Assets Pricing

3.1 Introduction

Traditional asset pricing theory is based on the assumption of frictionless financial markets and considers them to be perfectly liquid, which assumes that investors do not pay any transaction costs (Luttmer, 1996). Consequently, traditional asset pricing theory does not take into account the role of liquidity in asset pricing. Recently, considerable attention has been directed towards liquidity (i.e. either firm-specific liquidity or market-wide liquidity) and its importance in asset pricing, and, hence a large amount of theoretical and empirical literature on liquidity and asset returns has emerged linking the area of market microstructure and asset pricing.

However, liquidity is likely to be a function of market structure and design. In the previous chapter it was shown that market-wide liquidity varies over time, and its response to its time-series determinants is different before and after the automation of a trading system. It was also shown that although market-wide liquidity exhibits some regularities (e.g. day-of-the-week effect), these regularities are different before and after automation. Therefore, the fact that many stock markets have adopted significant changes in their trading arrangements could also possibly affect liquidity and its relationship to asset returns. More specifically, many stock exchanges have moved away from a floor-based to an electronically-based trading system. This revolution in trading systems is expected to affect liquidity: the mechanism which provides liquidity, and the behaviour of liquidity will be affected by the varying characteristics of floor and electronic trading systems, which then may result in different levels of liquidity under each system (see, Huang and Stoll, 1996; Freund and Pagano, 2000; Venkataraman, 2001 among others)[33]. Of course, investors looking to increase the value of their stocks prefer a trading system which provides the highest liquidity, otherwise they would discount stocks more heavily when liquidity is low to reduce their value and earn higher expected returns. Consequently, if liquidity is expected to be affected by different trading systems, then different trading systems (i.e. floor versus electronic trading

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[33] See section 3.3.2 for more details on how floor and electronic trading systems could result in different levels of liquidity.

systems) will have different implications on the relationship between liquidity and asset returns (i.e. pricing of liquidity). This chapter therefore aims to investigate the pricing of market liquidity and firm-specific liquidity before and after the automation of trading systems.

There is an extensive literature that examines, theoretically and empirically, the relationship between liquidity and asset returns. Some studies, such as Amihud and Mendelson (1986), Heaton and Lucas (1996), Brennan and Subrahmanyam (1996), Brennan et al. (1998), Datar et al. (1998), Chordia et al. (2001b), Lo et al. (2004) among others, examine whether firm-specific liquidity is related to expected returns. That is, these studies examine whether illiquid stocks (i.e. stocks with higher bid-ask spread, lower turnover, higher price impact) offer investors a higher premium. Their findings generally show that stocks with lower liquidity earn higher expected returns. More recent literature has concentrated on the importance of market-wide liquidity in asset pricing rather than firm-specific liquidity[34]. This shift in attention has been driven by Chordia et al. (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001) who provide strong evidence for commonality in US markets and find that fluctuations in various measures of liquidity correlate significantly with market-wide liquidity. Their findings raise concerns about whether market-wide liquidity is a systematically-priced risk factor, and shed light on the possible role that market liquidity risk could play in explaining asset prices. Therefore, some theoretical and empirical studies (e.g. Lustig, 2005; Holmstrom and Tirole, 2001; Huang, 2003; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Chen, 2005 among others) have analyzed the impact of market-wide liquidity shocks on asset pricing and examined whether expected stock returns are related to their sensitivity to market-wide liquidity at the cross-sectional level. These studies find that market-wide liquidity is a priced risk factor and the stocks that show lower sensitivity to market-wide liquidity have lower expected stock returns.

Despite the large number of studies on liquidity and asset pricing, no study, to the best of our knowledge, has examined and compared the pricing of liquidity under floor and

[34] Firm-specific liquidity is the level of liquidity as an attribute of individual stock. That is, the individual stock will either be highly liquid or less liquid. Market-wide liquidity is market systematic liquidity as a state variable or undiversifiable risk factor, that its innovations have effects that are pervasive across common stocks (see for example, Pastor and Stambaugh, 2003; Sadka, 2006).

electronic trading systems[35]. Further, the previously mentioned studies on liquidity and assets returns have examined the liquidity-return relationship through focusing on either firm-specific or market-wide liquidity. Very few studies have considered a combination of market-wide and firm-specific liquidity in the liquidity-return relationship. The two notable exceptions are Acharya and Pedersen (2005) and Korajczyk and Sadka (2008), who either examine the pricing of market liquidity risk while controlling for liquidity level, or vice versa. Also, the literature on liquidity and asset pricing has generally been restricted to using unconditional asset pricing models rather than conditional ones. One notable exception is Martínez et al. (2005) who investigated whether aggregate liquidity is priced in the Spanish market using both unconditional and conditional asset pricing models. However, in Martínez et al. (2005) factor loadings are scaled by aggregate book-to-market ratio, and, thus their conditional model has been transformed into a scaled one, which can be interpreted as an unconditional multifactor model. Furthermore, in their analysis they use portfolios as tested assets rather than individual stocks. Finally, the literature on liquidity and asset pricing has extensively focused on investigating whether market-wide or firm-specific liquidity is priced on US markets such as the NYSE, NASDAQ, and AMEX, with little attention directed towards other markets. US markets are considered the most liquid in the world and thus what has been found in US markets may not be pertinent to other markets (see Bekaert et al., 2007; Galariotis and Giouvris, 2007).

Therefore, this chapter aims to extend the empirical literature on liquidity and asset pricing in the following ways:

First, while many stock markets have adopted changes in their structure, studies that examine whether and to what extent liquidity is priced before and after the automation of the trading system are virtually nonexistent. Thus, we know very little about how moving from traditional floor trading to electronic trading can impact upon liquidity and how this in turn could result in different pricings of liquidity. Market microstructure literature has documented strong evidence regarding the impact of different market structures on the quality of financial markets in terms of liquidity, and has shown that

[35] Also, to the best of our knowledge, none of the studies that compare floor and electronic trading systems, which have been reviewed in section 2.2.2, have examined the pricing of liquidity under both trading systems.

different market structures imply different liquidity behaviour. For example, Venkataraman (2001) finds that liquidity in the floor-trading system is higher than in the electronic-trading system. Amihud et al. (1997) find a significant change in asset values as a result of improving liquidity for stocks moved from call trading to continuous trading on the Tel Aviv Stock Exchange, i.e. shifting the trading of stocks from one trading system to another might affect their liquidity. So, if changes in market structure such as moving from a floor to an electronic trading system result in differences to both market and stock liquidity, then it is expected that there will be a difference in the required return by investors before and after the introduction of electronic trading. Furthermore, Avramov and Chordia (2006a) argue that "liquidity may be more of a trading phenomenon that is unrelated to the state of the economy. Liquidity is likely to be a function of market design, competition amongst liquidity suppliers, and the degree of information asymmetry in financial markets" (p. 1005). This has been confirmed in the previous chapter. So this chapter contributes to our knowledge concerning the impact of different trading systems (floor versus electronic) on the importance of liquidity in asset pricing, and thus provides a further and stronger link between the areas of market microstructure and asset pricing.

Second, literature on liquidity and asset pricing that uses conditional asset pricing models is very sparse. We will employ the two-stage conditional asset pricing model of Avramov and Chordia (2006a) to examine whether aggregate market liquidity constitutes a priced risk factor, and whether firm-specific liquidity generates an additional premium after controlling for market-wide liquidity. In this model, the factor loadings, in the first-pass time-series regression, are allowed to vary with a firm's size and book-to-market ratio as well as with business cycle variables. Also, by using individual stocks, data snooping biases and any loss of information that may result when stocks are sorted into portfolios, can be avoided[36].

Finally, our knowledge about the importance of liquidity in markets other than in the US is very limited. This provides us with a great opportunity to provide out-of-sample evidence in other markets. Thus, this research will focus on three main European markets: the UK (London Stock Exchange; LSE), Swiss (Swiss Stock Exchange; SSE)

[36] For detailed discussion of the features of this conditional asset pricing model, see section 3.3.1.1.

and German (Frankfurt Stock Exchange; FSE). These markets have major differences in their structure and are considered smaller than US ones. In US markets, stocks are traded under one trading system (e.g. floor trading system in NYSE), but stocks on the London Stock Exchange and the Swiss Stock Exchange are moved from floor to electronic trading system. On the Frankfurt Stock Exchange, stocks may either be traded electronically through the electronic trading system XETRA or on a floor trading system. Thus, these unique features across markets imply that the nature of liquidity will be different in each market. Moreover, specialists in US markets (i.e. NYSE) are obliged to provide liquidity to smooth trading in particular securities, while dealers and Maklers in the UK and German markets respectively may trade for their own accounts but are not obliged to provide liquidity[37]. The heterogeneity in market structure leads to differences in the conditions under which liquidity is provided across stock exchanges included in our sample. Therefore, examining whether and to what extent market-wide and firm-specific liquidity are priced before and after the automation of these markets, will provide new insight into the importance of liquidity in asset pricing.

Hence, this research addresses the following questions:

- Is aggregate market liquidity a priced risk factor under the change in market structures (i.e. before and after the introduction of automated trading systems)? If so, does the pricing of aggregate market liquidity differ before and after the automation of trading systems?

- Does firm-specific liquidity have any additional premium before and after the introduction of automated trading systems? If so, does this premium differ before and after the automation of trading systems?

Investigating liquidity, both market-wide and firm-specific, in asset pricing is important because illiquid stocks with higher transaction costs are traded at a discount (e.g. Amihud and Mendelson, 1986) and tend to have a high return sensitivity to market liquidity and thus higher expected returns (e.g. Acharya and Pedersen, 2005). Also, the existence of commonality across individual stocks' liquidity fluctuations implies that

[37] Makler are known as Amtlicher Kursmakler whose position resembles that of the NYSE specialist (see Grammig et al., 2001; Theissen, 2002a, 2002b).

market-wide liquidity constitutes a source of nondiversifiable systematic risk that could be priced. Finally, market-wide liquidity represents a major source of concern especially during market slumps. For example, during the 1987 stock market crash, the 1997 Asian crisis and the 1998 long-term capital market crisis, most financial markets suffered sharp declines in liquidity, which resulted in "flight-to-liquidity", as observed in the markets of debt securities. Therefore, the findings of this chapter should be of interest to individual investors, portfolio managers, financial managers (corporate finance), and financial market designers and regulators. Investors need to know whether market-wide liquidity is priced, and whether any additional premium is likely to be required for carrying stocks with different levels of liquidity. Understanding the securities' pricing process can lead investors to carry market-wide liquidity risk with greater efficiency. Amihud and Mendelson (1986) were the first to establish the return-liquidity relationship and find that they are negatively related. In addition, Chordia et al. (2000) point out that market liquidity could affect asset pricing, and that investors will therefore expect a higher return from holding stocks that are highly co-varied with market liquidity.

In the area of portfolio management, mutual funds and portfolio managers frequently re-balance their portfolios to meet investors' liquidity needs. Frequent re-balancing of portfolios exposes managers to transaction costs, which prevents profitable implementation of portfolio strategies. That is, profitability of momentum strategies is related to transaction costs, which may raise the issue of whether the returns on these strategies can be related to the time-variation of market liquidity. In cases where the unanticipated variations of liquidity have a systematic component, then trading strategies' returns (e.g. momentum returns) could be considered as a compensation for market-wide liquidity risk (see Sadka, 2006). Therefore, the findings of this research will help portfolio managers make decisions on which is more important for trading strategies, market-wide or firm-specific liquidity, and then help them in developing trading strategies and ensure their effective implementation. If liquidity is taken into consideration in portfolio constructions, a considerable profit could be achieved for momentum strategies, the reason being that momentum strategy profits are sensitive to market liquidity risk (see Korajczyk and Sadka, 2004; Sadka, 2006).

This chapter also has implications for corporate finance. It suggests new understanding of what may be required to improve a stock's liquidity. If the stock is less liquid, its returns will be highly sensitive to market liquidity and investors will ask for higher returns: the company will incur a higher cost of capital. Thus, it may be that financial managers will be required to devise financial policies to improve stock liquidity.

Finally, the findings of this chapter should benefit stock exchange regulators and may provide a useful reference for those that have introduced or are considering introducing an electronic trading system. It may also help regulators' decision-making in improving market liquidity, since maintaining a well-designed and highly liquid market keeps as many traders in the market as possible. If, for example, after the introduction of electronic trading systems, the market liquidity is highly priced and investors seek higher premium then more regulatory provisions can be introduced to improve the liquidity of electronic trading systems. That is, the regulators may implement new policy procedures to improve the mechanism of supplying liquidity in electronic trading systems. For example, they may decide to introduce designated market makers to support the operations of the electronic trading system and thus provide additional liquidity, especially for small and mid cap stocks for which the electronic systems may not be suitable. On the other hand, if the introduction of electronic trading systems results in higher liquidity, and thus a lower premium is paid to investors, then the automation of trading systems can be considered successful. Consequently, stock exchanges considering introducing electronic system can be assured of the possibility of increased liquidity.

The next section of this chapter reviews the literature concerning the relationship between liquidity and stock returns. Section 3.3 discusses the hypotheses development, methodology employed to undertake the analysis, and the data that is utilized in the empirical analysis. The empirical results are then discussed in section 3.4. Finally, section 3.5 concludes the chapter.

3.2 Literature Review

Numerous theoretical and empirical studies have been devoted to the importance of liquidity in assets pricing. These studies examine liquidity premia by testing whether firm-specific liquidity or market-wide liquidity is priced in asset pricing. Approaches using different liquidity measures, methodologies and asset pricing models, have been employed to examine these issues. The empirical issue which still needs further investigation, however, is whether both market-wide and firm-specific liquidity are priced under different market structures (i.e. before and after the automation of trading systems)[38].

3.2.1 Liquidity and assets returns – Theoretical studies

A growing body of theoretical studies have developed models to explain the liquidity-return relationship. These studies, to start with, explained the effect of firm-specific liquidity on asset returns by examining the impact of transaction costs on assets prices. However, there is controversy among these studies. From one theoretical point of view, some studies argue that liquidity has a significant effect on asset returns. These studies are based on the argument that the liquidity premium of less liquid assets depends on the investors' holding horizon. Thus, in equilibrium, investors with a longer holding horizon will choose to hold assets with higher transaction costs (i.e. assets with higher bid-ask spread) to maximize their net of transaction costs returns. When investors choose to hold less liquid assets with greater transaction costs they will discount them by a greater amount. So the size of illiquidity discount will increase and asset prices decrease, which in turn increases the expected returns. For instance, Amihud and Mendelson (1986) develop an equilibrium model where investors with a longer holding horizon hold assets with larger spreads (clientele effect), and these assets yield higher expected returns[39]. Therefore, investors with a long holding horizon will receive higher expected returns from carrying illiquid assets. Heaton and Lucas (1996) introduce a

[38] See section 2.2.2 for the review of the studies on market structure and design, especially with regard to floor and electronic trading systems.

[39] Clientele effect assumes that investors have different liquidity plans or expected holding periods. Thus, in equilibrium, investors with longer holding periods choose to hold illiquid stocks (i.e. stocks with higher bid-ask spread), while liquid stocks (i.e. stocks with low bid-ask spread) are allocated to investors with shorter holding periods (see Amihud and Mendelson, 1986).

model where investors face both systematic and unsystematic labour income shocks and trade frequently to reduce the unsystematic one. They find, because of frequent trading, that transaction costs play an important role and there are both direct and indirect effects of transaction costs on equity premium, where the former is dominant when transaction costs are large. Finally, Lo et al. (2004) find that small fixed transaction costs have a significant impact on asset returns by suggesting a continuous equilibrium model of asset prices and trading volume with fixed transaction costs and heterogeneous investors.

In sharp contrast, Constantinides (1986) develops a general equilibrium model where investors trade to rebalance their portfolios. According to this model, investors can avoid transaction costs by reducing their trading in assets with higher transaction costs. Consequently, investors' expected utility of the future consumption will be insensitive to deviations of the asset proportions from those proportions which are optimal in the absence of transactions costs. Thus, a very small liquidity premium is required as a compensation for these deviations. In other words, transaction costs have small effects on assets returns. A similar result in terms of the impact of transaction costs on asset returns has been found by Vayanos (1998) and Vayanos and Vila (1999) who assume an economy with overlapping generations, where the investors trade to accommodate lifetime consumption.

In the last few years, a few theoretical studies have directed their attention towards market-wide liquidity risk and have explained its role in asset returns based on the solvency constraints argument. They argue that many investors will require higher expected returns to hold less liquid stocks in the face of market-wide liquidity shock. More specifically, during the recession the liquidity shocks will be strong and the investors' idiosyncratic income risk will increase as well. So, investors with low-wealth and high income draws will face solvency constraints. As borrowing by those investors to facilitate consumption will be impossible, they will be forced to liquidate some of their assets to raise cash. If investors hold stocks that are illiquid and highly sensitive to market liquidity, then liquidation will take place when liquidity is low, because the decline in investors' wealth is related to the decline in liquidity. Liquidation will be costly, especially during periods of low liquidity, and when investors' wealth decreases and their margin utility is high. Therefore, stocks whose returns are highly co-varied with market-wide liquidity will have a sharp decline in their prices and their current returns so they are expected to pay higher returns in the future. That is, investors will require a systematic liquidity premium for stocks that are highly positively sensitive to market liquidity. For instance, Holmstrom and Tirole (2001) develop a liquidity-based asset pricing model that assumes a risk-neutral consumer and where the variation in liquidity demand at the corporate level is the driving force. In their model, they find that stocks' expected return is related to stocks' sensitivity to market-wide liquidity. Huang (2003) develop a model in an economy, where the agents who can invest in illiquid and liquid assets face sudden liquidity shocks and have a random holding period. Under this model, liquidity has a significant effect on asset returns when the agents face a borrowing constraint. Finally, Lustig (2005) in his model argues that liquidity shocks (i.e. liquidity risk) are induced by solvency constraints during an economic recession. He finds a strong relationship between aggregate liquidity and risk premia where investors ask for higher expected returns on stocks to compensate for business cycle-related liquidity risk.

To summarize, despite the controversy about the impact of liquidity at firm-specific level over stock return, the theoretical literature, in general, shows that both firm-specific and market-wide liquidity have an impact on stock returns. However, the majority of empirical studies, as we will see in the next section, provide evidence supporting the theorists.

3.2.2 Liquidity and returns - Empirical evidence

3.2.2.1 Firm-specific liquidity and asset returns

Most of the empirical studies that examine the relationship between liquidity as a firm-specific characteristic and stock returns, provide evidence in favour of the theory that stocks with low liquidity levels, represented by high bid-ask spread, high price impact, low turnover, and low trading volume, earn higher expected returns. These studies use a wide variety of liquidity measurements and base their analyses either on using the return on portfolios formed, based on some criteria such as size, book-to-market ratio or beta, or on using the return of individual stocks.

Amihud and Mendelson (1986), in their seminal work, test whether less liquid stocks with high bid-ask spread have higher expected returns. By using monthly returns and yearly quoted bid-ask spreads on NYSE stocks from 1961–1980 with a pooled (cross-sectional and time-series) methodology, Amihud and Mendelson provide much support for their prediction. They find that the average portfolio risk-adjusted returns increase with bid-ask spread. This result is robust after controlling for firm size. However, Eleswarapu and Reinganum (1993) question the results of Amihud and Mendelson (1986) and examine seasonality in the liquidity-return relationship. Their study uses the same proxy of liquidity as Amihud and Mendelson (1986) for NYSE stocks but for a longer sample period, from 1961-1990. Eleswarapu and Reinganum employ the Fama and MacBeth (1973) methodology rather than following Amihud and Mendelson's (1986) methodology, arguing that the later methodology restrains a constant market premium, possibly resulting in spurious effects of spread. The authors find no evidence in favour of Amihud and Mendelson's (1986) propositions. They also find that liquidity premium exhibits strong seasonality. That is, the relationship between liquidity and returns is confined to the month of January. These results are robust when Eleswarapu and Reinganum (1993) re-examine the return-liquidity relationship after relaxing Amihud and Mendelson's portfolio selection criteria[40].

In contrast, other studies shed light on the importance of liquidity through examining the impact of adverse selection on asset pricing. For example, Brennan and Subrahmanyam (1996) use, instead of bid-ask spread, both variable and fixed cost components of transaction costs, to test whether liquidity due to information asymmetry affects asset returns[41]. The authors argue that bid-ask spread is a noisy measure, because many large trades tend to occur outside the spread while small trades occur inside the spread. They apply the methods of Glosten and Harris (1988) and Hasbrouck (1991) to segregate transaction costs into both components. Compared with others, this study uses both intraday data over the period 1984-1988 and monthly returns for the period from 1984-1991 for NYSE and AMEX stocks. However, in asset pricing, this

[40] Amihud and Mendelson (1986) require eleven years of complete return data for a stock to be included in the analysis. This requirement, according to Eleswarapu and Reinganum (1993), removes smaller stocks from the analysis and causes a bias in documenting the size effect. Thus, Eleswarapu and Reinganum relax this requirement by using three years of return data, so the number of stocks included in the portfolio increased and, as a result, the portfolios include smaller size firms with larger bid-ask spread.
[41] A variable component depends on the amount of informed trading and noise trading, while a fixed component is related to inventory maintenance and order processing.

sample period is considered short when compared to other studies[42]. Similarly to Amihud and Mendelson (1986) but unlike Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996) apply the generalized least squares (GLS) method on pooled data to avoid the errors-in-variables problem that results from applying Fama-MacBeth's (1973) procedure. The regression analysis indicates that cost components, both fixed and variable, have significant premiums. However, their findings add little support for Amihud and Mendelson's model. More specifically, they find a positive and concave (at a decreasing rate) relationship between the variable cost component and stock returns, and a positive and convex (at an increasing rate) relationship between the fixed cost component and stock returns. The latter relationship is inconsistent with the proposition of Amihud and Mendelson (1986) (i.e. horizon clientele effect). This might be, as the authors argue, because of an incorrect estimate in fixed cost parameters, or it might be due to an incomplete adjustment for the risk using the Fama-French three factors model. The results also show, inconsistently with Eleswarapu and Reinganum (1993), that the liquidity-return relationship does not exhibit any seasonality. This might be, as Brennan and Subrahmanyam (1996) argue, due to different sample periods or due to the ability of the Fama-French model to absorb any seasonality.

The studies described above run their analyses using the returns on portfolios constructed by sorting stocks on different criteria (e.g. size, liquidity measure, and firm's beta). Such procedures (portfolio formation), according to Brennan et al. (1998), are used to moderate problems that could result from estimating betas as independent variables in a two-step estimation procedure or to enable the estimation of the covariance matrix of residual returns when a one-step estimation procedure is used. However, the portfolio formation procedure could result in two problems. First, possible loss of information when stocks are sorted into portfolios. Second, a data snooping bias that frequently exists in portfolio-based asset pricing tests (see Brennan et al. (1998) and references cited in). Therefore, recent empirical studies on liquidity and asset pricing focus on the return of individual stocks in examining the relationship between a stock's liquidity and its returns. They also use trading activity measures (e.g. trading volume, trading value and turnover ratio) as proxy for liquidity, rather than the bid-ask spread measure, which is considered a noisy proxy for liquidity. These measures are an

[42] Amihud et al. (2005) argue that tests of assets pricing require data that extend over a long time period to increase the power of the tests.

important determinant of liquidity, and are based on daily data that could be made available over a longer period, therefore providing a powerful test of the liquidity hypothesis.

Brennan et al. (1998), for example, focus on individual stocks and used dollar trading volume as a measure of liquidity. They examine whether expected stock returns could be explained by liquidity as well as by a number of firm characteristics such as size, book-to-market ratio, price, dividend yield, and past returns. They use monthly data for NYSE, AMEX, and NASDAQ stocks from 1966-1995, and estimate the risk-adjusted return using the Connor and Korajczyk (1988) approach and the Fama and French (1993) three factor model. Despite a risk-adjusted approach, Brennan et al. find that stock returns are strongly and negatively related to volume, consistent with the notion that liquidity is priced in asset pricing. This is also consistent with the findings of Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) who find a negative return-liquidity relationship, but is inconsistent with the results of Eleswarapu and Reinganum (1993).

In addition, Datar et al. (1998) provide an alternative test to Amihud and Mendelson's (1986) model using turnover ratio as a proxy for liquidity. They use monthly data on returns and trading volume for NYSE stocks from 1962-1991. In contrast to Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) but similar to Brennan et al. (1998), Datar et al. (1998) employ Fama and MacBeth’s (1973) procedure. The regression results are supportive of Amihud and Mendelson’s predictions; in other words, the results show that the cross-section stock returns are a decreasing function with turnover ratio. This confirms the notion that high liquid stocks pay lower returns, which is consistent with the findings of Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Brennan et al. (1998). Further, their results still hold after a number of robust checks such as controlling for other variables (i.e. size, book-to-market ratio, and firm beta), using a trimmed dataset, and dividing the dataset into two halves[43]. Their results also show, in contrast to Eleswarapu and Reinganum (1993) but consistent with Brennan and Subrahmanyam (1996), that liquidity does not show any seasonal pattern and that its effects exist throughout the year. That is, there is no

[43] They trim the lowest 1% and the highest 1% observations of turnover rate because the range of the turnover rate is very large. The turnover rate varies from 0.0013% to 110%.

evidence for January seasonality. This contradiction in results could be, as the authors argue, a result of using a different proxy for liquidity.

In contrast to other studies, Chordia et al. (2001b) not only focus on investigating the relationship between liquidity and returns, but also examine whether the variability in firm-specific liquidity is positively associated with stocks' expected returns. They propose that the risk-averse investor avoids variability in liquidity and will require higher returns for stocks with greater variability in liquidity. They use dollar volume (as in Brennan et al., 1998) and turnover rate (as in Datar et al., 1998) as liquidity measures. The study employs monthly data on NYSE and AMEX common stocks for the period from 1966-1995, and the methodology of Brennan et al. (1998), which focuses on individual stocks rather than portfolios. Their reported results are consistent with both theory and results of previous studies (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Brennan et al., 1998; Datar et al., 1998), in terms of the negative relationship between stock returns and liquidity. However, the results are unexpected with regard to the relationship between variability in liquidity and a stock's returns: stocks with higher fluctuations in liquidity have lower expected returns. This result still holds after controlling for size, book-to-market ratio, momentum, price level and dividends yield, and following some checks for robustness (such as using different definitions of variability in liquidity (e.g. coefficient of variation and conditional volatility), conducting separate tests for NYSE, AMEX, and NASDAQ, and controlling for returns predictive variables (e.g. term spread, default spread and short-term rate)).

3.2.2.2 Market-wide liquidity and assets returns

Recently, the research on liquidity and asset pricing has advanced by shifting its attention towards aggregate market liquidity and its importance in asset pricing. This focus is motivated by the evidence for the existence of commonality in liquidity (e.g. Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001). These studies show that if liquidity is expected to vary systematically, then it is expected that stocks with returns that are positively and highly correlated with market-wide liquidity will pay higher expected returns. Therefore, rather than investigating firm-specific liquidity, studies have evolved to examine whether market-wide liquidity, as a state variable, is a priced risk factor.

To address this issue, studies of aggregate market liquidity put forward different assets pricing models augmented with liquidity risk factors such as CAPM and Fama-French Factor models. They also use different measures of market-wide liquidity as proxies for the liquidity factor. These studies provide evidence in support of a systematic liquidity risk being a priced risk factor in either a time-series or in a cross-sectional framework.

3.2.2.2.1 Time-series test of market-wide liquidity

Amihud (2002) examines the time-series relationship between market expected and unexpected illiquidity and market excess returns. He develops a new measure of illiquidity, which could be defined as the ratio of a stock's absolute daily return to its daily trading value, and applies it to NYSE stocks between 1964 and 1997. This measure is considered an approximate measure of the price impact of order flow. The results show that expected market illiquidity has a positive and significant effect on ex ante stock excess return, while unexpected illiquidity has a negative and significant effect on contemporaneous stock return. This effect remains significant after controlling for the default yield premium and the term yield premium. In addition, both expected and unexpected market illiquidity have strong effects on the returns of small stock portfolios.

Along the same lines, Fujimoto (2003a) applies Amihud's (2002) methodology and conducts a time-series test for the liquidity-return relationship. However, he uses four monthly time-series market liquidity measures constructed on stocks from NYSE and AMEX for the period 1962-2002. Consistent with Amihud (2002), he finds a strong contemporaneous relationship between market return and market liquidity, that is, a significant negative effect of illiquidity shocks on current excess returns. However, he extends the test for the liquidity-return relationship in different economic conditions, and finds an asymmetric response of market return to illiquidity shocks. That is, the effect of illiquidity shocks on market returns is stronger during a recession period.

3.2.2.2.2 Cross-sectional test of market-wide liquidity

Examining the empirical studies that provide evidence for whether market-wide liquidity is a priced systematic risk factor in the cross-section, the studies examine whether a stock's expected returns are related to their sensitivity to the fluctuations in market-wide liquidity. For example, Pastor and Stambaugh (2003), examine the relationship between market-wide liquidity and asset returns by focusing on the price impact aspect of liquidity, and provide evidence that aggregate market liquidity is a priced risk factor. They develop a measure of market-wide liquidity based on volume related return reversal, using daily data on NYSE and AMEX stocks from 1966-1999. While this measure could be imprecise at the individual level, its market-wide average is estimated more precisely[44]. However, the results show that expected stock returns are cross-sectionally related to the sensitivities of returns to fluctuations in aggregate liquidity. That is, liquidity betas for stocks, which are the sensitivity to innovations in aggregate liquidity, play an important role in asset pricing. They find that during the sample period the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5% annually, after controlling for the exposure to the market return as well as size, value and momentum factors.

Further, Acharya and Pedersen (2005) develop a model that counts for pricing of liquidity risk while controlling for liquidity level. In contrast to Pastor and Stambaugh (2003), they separate liquidity risk into three parts; namely, the covariance between stock liquidity and market liquidity, the covariance between stock return and market liquidity, and the covariance between stock liquidity and market return. Acharya and Pedersen (2005) use Amihud's (2002) illiquidity ratio as a measure of illiquidity. This ratio is calculated from daily data on NYSE and AMEX stocks over the period 1962-1999. They show that a stock's return decreases in the covariance between the stock's return and the market illiquidity, and in the covariance between a stock's illiquidity and market returns; but is increasing in the covariance between a stock's illiquidity and market illiquidity. Although their results are consistent with those of Pastor and Stambaugh (2003), the amount of liquidity premium that Acharya and Pedersen (2005)

[44]As Liu (2006) argues, one possible reason for Pastor and Stambaugh's (2003) liquidity measure being imprecise at the individual stock level is that the estimation of this measure is based on using at least 16 daily observations over the month. Therefore, if a stock's number of trading days is less than 16 through the month, its liquidity measure cannot be estimated.

find is lower than that of Pastor and Stambaugh (2003): the liquidity premium is 1.1% in the former compared with 7.5% in the latter. This could be due, as the authors argue, either to using different liquidity measures, different sorting criteria, or to not controlling for the level of liquidity as in Pastor and Stambaugh (2003). However, Acharya and Pedersen (2005) point out that their results are imprecisely estimated because of inherent collinearity between the level of liquidity and liquidity risk.

In addition, evidence in favour of the notion that market-wide liquidity is a priced risk factor is provided from markets other than US ones. Martínez et al. (2005) analyze whether the expected returns on Spanish equities during the 1990s are cross-sectionally related with betas estimated relative to different liquidity measures. That is, in contrast to others, Martínez et al. use multiple measures to examine whether liquidity is priced. These liquidity measures are: Amihud's (2002) illiquidity ratio, Pastor and Stambaugh's (2003) return reversal, and the difference in the returns between portfolios of stocks with high sensitivity to changes in the relative bid-ask spread, and portfolios with low sensitivity to those changes. The analysis employs daily and monthly data for the period from 1991-2000 which is, compared with Pastor and Stambaugh (2003) and Acharya and Pedersen (2005), considered a very short period for asset pricing research. Consistent with the evidence documented for US markets, the results show that liquidity is priced in the Spanish market, especially when betas are estimated relative to the illiquidity ratio on either unconditional or conditional versions of liquidity-based asset pricing models. However, the other measures of systematic liquidity carry no premium, which is contradicted by the results of Pastor and Stambaugh (2003) who find that liquidity is priced using their measure.

Similarly to Brennan and Subrahmanyam (1996) who examine liquidity at firm-specific level, and in contrast to Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Martínez et al. (2005), Sadka (2006) measures liquidity by segregating price-impact components into fixed and variable cost components using the Glosten and Harris (1988) model. He investigates which component of liquidity is priced and which is important in explaining assets pricing anomalies (i.e. momentum and post-earning announcement drift). He focuses on market-wide measures of both the variable and the fixed components using intraday data for a sample of NYSE stocks during the period from 1983-2001. He uses the Fama-French three factors model augmented with liquidity factor and applies Fama and MacBeth (1973) procedure. The results show that liquidity is a priced risk factor, which is consistent with the findings of previous studies. However, in contrast to Brennan and Subrahmanyam (1996) who find that both components of firm-specific liquidity affect stock returns, Sadka (2006) finds that only the variable permanent component is priced.

Previous empirical studies, whether focusing on liquidity at individual firm level or at market-wide level, employ different liquidity measures. Each one of these measures reflects one dimension of liquidity. Therefore, in contrast to previous studies, Liu (2006) develops a new measure that captures multiple dimensions of liquidity[45]. This measure is the standardized turnover-adjusted number of zero daily trading volumes. Using daily and monthly data for all stocks on NYSE, AMEX, and NASDAQ over the period 1960-2003, the empirical results of CAPM, augmented with the liquidity factor, show a strong and significant liquidity premium over the sample period. The significant liquidity premium found indicates that liquidity is important for asset pricing, which is consistent with previous studies of US markets (such as Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006) and with Martínez et al. (2005) of the Spanish market.

Moreover, Chen (2005) and Korajczyk and Sadka (2008) argue that, although previous studies use alternative measures of liquidity, these measures reflect different facets of liquidity that are expected to be correlated (i.e. to share a common source of variation). Therefore, they, as an alternative, use the principle component analysis method of Connor and Korajczyk (1986) and the expectation maximization algorithm based method of Stock and Watson (1998), to extract from alternative liquidity measures a common measure of liquidity risk. Both of these studies examine whether this common measure of liquidity is priced. They find a consistent result with previous studies; they find that the common factor is significantly priced even though both studies used different data sets for different sample periods. Chen (2005) uses daily data for NYSE and AMEX over the period 1963-2002, while Korajczyk and Sadka (2008) use data of different frequencies for the period 1983-2000 for NYSE[46]. Although both studies find

[45] This measure captures dimensions of liquidity such as trading speed, trading quantity, and trading cost.
[46] Korajczyk and Sadka (2008) use intraday data for the estimation of liquidity measures and daily, monthly and annual data for the asset pricing analysis.

that the common factor (i.e. aggregate systematic liquidity) is priced, their results show that individual liquidity factors are not priced in the presence of the common factor. This means that the common factor was able to capture the priced component of other liquidity measures which might be priced in isolation. Furthermore, in contrast to Chen (2005), Korajczyk and Sadka (2008) examine the pricing of liquidity characteristics after controlling for liquidity risk, and they find some evidence that firm-specific liquidity is priced.

To summarize, reviewing the literature on firm-specific liquidity and market-wide liquidity, shows that liquid stocks (i.e. stocks with low bid-ask spread, high turnover ratio, and low price impact) pay lower returns, which confirms that liquidity as a firm characteristic is priced in asset returns. It also shows that market-wide liquidity is a priced risk factor and has an important bearing on asset pricing. However, none of the previous studies on liquidity and asset pricing have examined and compared the importance of liquidity in asset pricing under different market structure contexts (i.e. floor versus electronic trading systems). Further, studies that undertake empirical analysis of the liquidity-return relationship and take into consideration both market-wide liquidity and firm-specific liquidity are very sparse. Also, these studies give very little attention to using conditional asset pricing models in examining the liquidity-return relationship.

Therefore, this chapter investigates and compares the importance of liquidity (i.e. market-wide and firm-specific liquidity) in asset pricing under floor and electronic trading systems using the conditional asset pricing model of Avramov and Chordia (2006a), with reference to UK, Swiss and German markets, the three major markets in Europe. In other words, this research examines and compares whether market-wide liquidity is a priced risk factor, and whether firm-specific liquidity carries an additional premium after controlling for market-wide liquidity before and after the automation of trading systems based on the framework of Avramov and Chordia (2006a). The features of this conditional asset pricing model will be addressed in the next section.

3.3 Research Design

This section identifies the hypotheses to be tested and presents the methodology that is employed to address the research questions. It also presents the sample and the data employed in the analysis and discusses the measures of liquidity, and the construction of the liquidity risk factors.

3.3.1 Hypothesis developments

This section develops several testable hypotheses through providing the theoretical explanation for the rationale behind the relationship between liquidity and asset returns in the context of different market structures.

3.3.1.1 Liquidity and assets returns

The proposition is that market illiquidity is expected to have a significant negative effect on a current stock's excess return especially when higher future illiquidity is anticipated by investors. That is, if market liquidity is persistent (lower levels of market liquidity predict lower levels of market liquidity in future), this will result in higher expected stock returns and at the same time will result in lower current excess stock returns (i.e. positive contemporaneous return-liquidity relationship). This is due to the fact that if investors expect low market liquidity in future, they will react to the current illiquidity shocks by reducing current stock prices in order to earn a higher expected rate of return, which results in lower contemporaneous stock returns (see Amihud, 2002; Fujimoto, 2003a). Therefore, market liquidity as a risk factor is expected to be positively related to the current stock's excess returns.

Additionally, since illiquid stocks are expected to be traded at a discount because of their higher transaction costs, and tend to have a high return sensitivity to market liquidity (e.g. Amihud and Mendelson, 1986; Acharya and Pedersen, 2005), investors are expected to require higher expected returns on such stocks. This could be explained as follows: "consider, for example, any investor who employs some form of leverage and faces a margin or solvency constraint, in that if his overall wealth drops sufficiently, he must liquidate some assets to raise cash. If he holds assets with higher sensitivities to liquidity, then such liquidations are more likely to occur when liquidity is low, since drops in his overall wealth are then more likely to accompany drops in liquidity. Liquidation is costlier when liquidity is lower, and those greater costs are especially unwelcome to an investor whose wealth has already dropped and who thus has higher marginal utility of wealth. Unless the investor expects higher returns from holding these assets, he would prefer assets less likely to require liquidation when liquidity is low, even if these assets are just as likely to require liquidation on average" (Pastor and Stambaugh, 2003, p. 643).

To summarize, investors are expected to require a premium that compensates them for the risk of common systematic shocks including market-wide liquidity shocks and for holding illiquid stocks. However, if the variation in stock returns is completely explained by all risk factors, including a market-wide liquidity factor, then it is expected that liquidity as a firm characteristic will not have any additional impact on stock returns because its predicative power is captured by risk factors in the asset pricing model. This means that investors receive a premium only for bearing market-wide liquidity risk. On the other hand, if the known risk factors including market-wide liquidity risk are not sufficient to explain the variation in stock returns, then firm-specific liquidity will have a significant impact on risk-adjusted returns (i.e. explain the cross-sectional variation in risk adjusted returns). This means that investors will receive an additional premium for holding illiquid stocks. This leads to the first and second hypotheses:

H_1: In asset pricing aggregate market liquidity is a priced risk factor (i.e. has a significant positive effect on current stock's excess returns).

H_2: Firm specific liquidity has an additional premium (i.e. firm-specific liquidity is negatively and significantly related to risk-adjusted returns) after controlling for all risk factors including the market-wide liquidity risk factor.

3.3.1.2 Liquidity and assets returns under alternative trading systems

The proposition is that the introduction of an electronic trading system is expected to influence the relationship between market-wide liquidity and stock excess returns as well as influence the premium on firm-specific liquidity. Alternative market structures could have different implications on liquidity, and result in different levels of market-wide liquidity and firm-specific liquidity according to the trading system. As a result, the required rate of return on liquidity is expected to be different for floor and electronic trading systems. For example, the degree of trading system anonymity is a potential determinant of market quality. In the case of the floor trading system (i.e. non-anonymous trading system), Venkataraman (2001) argues that the liquidity of traditional floor based systems will increase, because the degree of information asymmetry is expected to decline since all traders can share the information about order inflow and the intrinsic value of the stock. Also, through the interaction among traders in a floor trading system, it would be easy to distinguish between informed traders and liquidity-motivated traders, thus reducing the level of information asymmetry. This will improve liquidity through motivating more traders to trade, especially liquidity-motivated traders who possess no information and try to avoid trading with well informed traders. In contrast, the high degree of information asymmetry in an anonymous electronic trading system will result in lower trading volume, especially during high volatility periods. This might be due to the fact that the knowledge of the identity of the other side of a trade is important during a period of high information asymmetry. Also during these periods the bid-ask spread will be very high, which means lower liquidity for an electronic trading system (see Kempf and Korn, 1998; Theissen, 2002a). Hence, it is expected that market-wide liquidity and firm-specific liquidity will be different for floor and electronic trading systems, and thus have a different impact on asset returns. Specifically, on the floor trading system market-wide and firm-specific liquidity are expected to be higher than that on the electronic trading system, and consequently they will have a lower impact on stock returns (i.e. have a lower premium) on the floor trading system.

On the other hand, the characteristics of automated trading systems are expected to attract more liquidity into markets than floor trading systems. Venkataraman (2001) argues that automated trading systems provide a large number of locations from which traders can access the system. All transactions are executed by remote access computers without the existence of traders. This advantage of automated trading systems, as Theissen (2002b) points out, will result in an increase in the number of participants in trading activities, filling submitted orders and thereby increasing the level of liquidity.

Moreover, the efficiency and high speed of such a trading system, compared with floor-based trading, allows fast placement and immediate execution of orders, resulting in a higher quality of execution that would attract more traders and trading activities. This also would provide more liquidity to the market (Freund and Pagano, 2000). Therefore, it is expected that both market-wide and firm-specific liquidity will be different for electronic and floor trading systems, and result in a different required rate of returns for each system. More specifically, it is anticipated that on the electronic trading system market-wide and firm-specific liquidity will be higher than that on the floor trading system, and thus their impact on stock returns (i.e. the required premium) will be lower on the electronic trading system.

All in all, the level of market liquidity and firm-specific liquidity is expected to be different under alternative trading systems (i.e. floor and electronic trading systems), and thus will affect their pricing in asset returns. However, no superiority in liquidity between floor and electronic trading systems can be established on the basis of the discussion above. As a result, it is not possible to have an unambiguous conclusion as to whether market-wide and firm-specific liquidity are higher or lower on one trading system compared with the other. Hence, the extent of pricing of market-wide liquidity and firm-specific liquidity in asset returns (i.e. whether market-wide and firm-specific liquidity have a stronger or weaker impact on asset returns), on the floor trading system compared with the electronic trading system is an empirical question. This will lead us to the third and fourth testable hypotheses:

$H_{3:}$ *Pricing of aggregate market liquidity (i.e. the relationship between market liquidity and stock excess returns) is not different before the introduction of an electronic trading system than after the introduction of an electronic trading system.*

$H_{4:}$ *The premium on firm-specific liquidity is not different before the introduction of an electronic trading system than that after the introduction of an electronic trading system.*

3.3.2 Empirical Methodology

This section discusses the methods applied to test the developed hypotheses and to answer the research questions. It explains the two-pass regression framework of Avramov and Chordia (2006a) that is employed in order to examine the pricing of both market-wide liquidity and individual stock liquidity before and after the automation of trading systems. It also explains the test of equality of regressions' parameters (i.e. estimated liquidity premium) between floor and electronic trading systems, to find out whether there is a difference in the pricing of market-wide liquidity and in the additional premium paid on firm-specific liquidity as a result of automation.

3.3.2.1 Conditional asset pricing framework

To examine whether market-wide liquidity and firm-specific liquidity are priced in asset returns, we used the two-pass cross-sectional regression based on the framework of Avramov and Chordia (2006a). The employment of this conditional model is motivated, in general, by the argument that conditional asset pricing models are reasonably successful and perform better than unconditional ones when allowance is made for time-varying risk premia (see Lettau and Ludvigson, 2001; Avramov and Chordia, 2006a among others).

In addition, Avramov and Chordia's (2006a) model is characterized by several features that distinguish it from other asset pricing models, especially those on liquidity and asset pricing. First, in the first-pass time-series regression of this framework, risk and expected returns are allowed to vary with conditional information. Indeed, previous studies have not allowed factor loadings to vary with firm characteristics (such as size and book-to-market ratio) and with business cycle variables in individual stocks. For example, Martínez et al. (2005) have examined the pricing of market liquidity using a conditional asset pricing model and have modelled the factor loadings as a function of market-wide information (i.e. aggregate market book-to-market ratio). Their procedure could be interpreted as an unconditional multifactor model, while in the Avramov and Chordia (2006a) framework such interpretation does not exist because firm level characteristics (i.e. size and book-to-market ratio) are not common among all test assets. Therefore, the product of multiplying risk factors with firm characteristics does not provide an additional risk factor in an unconditional representation. Also, firm size and book-to-market ratio provide information about a firm's risk and expected return (see Fama and French, 1992), therefore conditioning beta on these firm characteristics in this framework not only explain the variation in stock returns by common risk factors (i.e. market excess return, Fama-French factors and liquidity factor), but also by firm-level risk. Using size and the book-to-market ratio as conditioning variables is motivated by their separate role as determinants of beta. More specifically, the component of a firm's systematic risk, attributable to its growth option, represents a proxy for the risk of a firm's existing projects that could be captured by a firm's size and book-to-market ratio. In addition, allowing beta to vary with business cycle variables is motivated by the ability of these variables to capture investors' expectations about future market returns or business cycle conditions: they help in predicting future economic conditions and future market returns (see Avramov and Chordia, 2006a; and references cited in).

Secondly, another important feature of Avramov and Chordia's (2006a) model is the use of individual stocks, rather than portfolios constructed by sorting stocks on some criteria of interest such as size, book-to-market ratio and beta. Avramov and Chordia (2006a) argue that this is the first asset pricing framework using single securities in cross-sectional regressions where risk and expected returns are allowed to vary with conditioning information[47]. The focus on single securities helps to avoid the data snooping biases that exist in portfolio based asset pricing tests and also helps in avoiding any potential loss of information when stocks are sorted into portfolios.

Finally, compared with previous studies, the two-pass methodology allows us to examine both market-wide liquidity and firm-specific liquidity in asset pricing. That is, through the first-pass time-series regression we can find out whether aggregate market liquidity is priced, and from the second-pass cross-sectional regression we can find out whether individual stock liquidity has an additional premium (i.e. has an impact on stock expected returns) after controlling for the known risk factors including market liquidity risk. Therefore, this framework allows us to examine whether it is the market liquidity or liquidity as a firm characteristic, or both, that could be priced in asset pricing. Additionally, through the two stages regressions, time-series and cross-

[47] Both Brennan et al. (1998) and Chordia et al. (2001b) use individual stocks in their analysis, but they did not use conditional assets pricing models.

sectional regressions, this framework helps to avoid the collinearity problem that exists between market liquidity risk and firm-specific liquidity (i.e. level of liquidity), faced by previous studies such as Acharya and Pedersen (2005) and Korajczyk and Sadka (2008).

As in Avramov and Chordia (2006a), the empirical methodology of the two-pass conditional framework is discussed as follows. The returns are assumed to be generated by *Y*-risk factors model:

$$\tilde{R}_{it} = E_t(\tilde{R}_{it}) + \sum_{y=1}^{Y} \beta_{iy} \tilde{f}_{yt} + \tilde{\varepsilon}_{it} \tag{3.1}$$

where R_{it} is the return on security i at time t, E_t is the conditional expectations operator, f_{yt} is the unexpected return on the *y-risk* factor at time t, β_{iy} is the beta associated to the y^{th}-*risk* factor. Under the conditional version of *Y*-risk factors model, equation (3.1) could be written as follows:

$$\tilde{R}_{it} = E_{t-1}(\tilde{R}_{it}) + \sum_{y=1}^{Y} \beta_{iyt-1} \tilde{f}_{yt} + \tilde{\varepsilon}_{it} \tag{3.2}$$

β_{iyt-1} is the conditional beta corresponding to y^{th}-*risk* factor. The expected returns $E_{t-1}(\tilde{R}_{it})$ under the exact or equilibrium version of APT where the market portfolio is well diversified with respect to the factors, can be modeled as:

$$E_{t-1}(\tilde{R}_{it}) - R_{ft} = \sum_{y=1}^{Y} \lambda_{yt-1} \beta_{iyt-1} \tag{3.3}$$

where R_{ft} is the return on risk-free asset and λ_{yt-1} is the risk premium for factor y at time t. Substituting for $E_{t-1}(\tilde{R}_{it})$ in equation (3.2) from equation (3.3), the realized returns are given by:

$$\tilde{R}_{it} - R_{ft} = \sum_{y=1}^{Y} \beta_{iyt-1} \tilde{F}_{yt} + \tilde{\varepsilon}_{it} \tag{3.4}$$

where $\tilde{F}_{yt} = \tilde{f}_{it} + \lambda_{yt-1}$ is the sum of the factor innovation and its associated risk premium, and β_{iyt-1} is the conditional beta estimated by the first-pass time-series regression over the entire period. Then, the estimated risk-adjusted return on each security, $\tilde{R}^*_{it}$, for each month t is calculated as:

$$\tilde{R}^*_{it} = \tilde{R}_{it} - R_{ft} - \sum_{y=1}^{Y} \hat{\beta}_{iyt-1} \tilde{F}_{yt} \tag{3.5}$$

The risk adjustment procedure imposes the assumptions that the conditional zero-beta return equals the conditional risk-free rate, and that the APT factor premium is equal to the excess return on the factor. Next, from equation (3.5), the risk adjusted return represents the raw material for our estimation in the following cross-sectional regression:

$$\tilde{R}^*_{it} = c_{ot} + \sum_{m=1}^{M} c_{mt} Z_{mit-1} + \tilde{\varepsilon}_{it} \tag{3.6}$$

where Z_{mit-1} is the value of characteristic *m* for security *i* at time *t-1* and *M* is the total number of characteristics. The coefficients c_{mt} in equation (3.6) are estimated by using the standard Fama and MacBeth (1973) estimator. That is, we first estimate the vector of characteristics rewards c_t each month from Ordinary Least Square (OLS) regression:

$$\hat{c}_t = (Z'_{t-1} Z_{t-1})^{-1} Z'_{t-1} \tilde{R}^*_t \tag{3.7}$$

where Z_{t-1} is the vector of firm characteristics in month *t* and R^*_t is the vector of risk-adjusted returns. Then, the standard Fama and MacBeth (1973) estimators are the time series averages of these coefficients $\hat{c}_t$.

Note that, although the factors loading in first-pass regression are estimated with error, only the dependent variable (i.e. risk-adjusted return) is affected by this error. While there is no priori reason to believe that the errors in the estimated loadings will be correlated with the security characteristics Z_{t-1}, the factor loadings themselves will be correlated with the security characteristics. This implies that the Fama and MacBeth (1973) estimate of the coefficient vector $\hat{c}_t$ is unbiased. However, if the errors are correlated with the security characteristics, then the Fama and MacBeth (1973) estimators will be biased by an amount that depends upon the mean factor realizations and, hence, a purged estimator should be obtained to correct for the bias (see Brennan et al., 1998; Chordia et al., 2001b)[48]. In contrast, Avramov and Chordia (2006a) employed Shanken (1992) and Jagannathan and Wang (1998) approaches to correct the Fama and MacBeth (1973) standard errors attributable to the error in the estimation of factor loadings. In contrast to Jagannathan and Wang (1998), Shanken (1992) shows that the standard errors of the coefficients estimated by Fama and MacBeth (1973) are understated which increases the precision of the estimated coefficients. This is because standard errors ignore the additional variation induced by the estimation error in the factor loadings. However, Brennan et al. (1998) also show, by applying the correction of Shanken (1992), that the magnitude of the coefficient understatement in their sample is small and does not affect their basic conclusions. Also Chordia et al. (2001b) show that both the Fama and MacBeth procedure and the purged estimates give the same results. Therefore, in this research we use only the standard Fama and MacBeth estimator.

To formalize Avramov and Chordia's (2006a) conditional beta framework, equation number (3.6) could be written as follows:

$$\tilde{R}_{it} - [R_{ft} + \hat{\beta}(\theta, z_{t-1}, X_{it-1})\tilde{F}_t] = c_{ot} + c_t Z_{it-1} + \tilde{\varepsilon}_{it} \tag{3.8}$$

where X_{it-1} and Z_{it-1} are vectors of firm characteristics, z_{t-1} denotes a vector of business cycle variables, and θ represents the parameters that capture the dependence of β on the business cycle variables and the firm characteristics.

Under this conditional framework, the time variation in beta i.e. the modelling of beta (factor loading) as a function of firm characteristics and business cycle variables in the first-pass time-series regression can be described as follows. Let us assume that there is

[48] Brennan et al. (1998) and Chordia et al. (2001b) used a purged estimator developed by Black and Scholes (1974) which is the constant term from the regression of the month-by-month Fama-MacBeth estimates on the factor portfolio returns.

one risk factor; thus the conditional beta of security *i* ($\beta_{i,t-1}$ in equation 3.4) is modelled as:

$$\beta_{i.t-1} = \beta_{1,i} + \beta_{2,i}z_{t-1} + (\beta_{3,i}+\beta_{4,i}z_{t-1})Size_{i,t-1} + (\beta_{5,j,i}+\beta_{6,j,i}z_{t-1})BM_{i,t-1} \quad (3.9)$$

where Size and BM are the natural logarithm of market capitalization and book-to-market ratio at time *t-1*, and z_{t-1} is a macroeconomic variable (i.e. business cycle variable default spread, term spread, dividends yield and 3-month Treasury bill yield).

Also, in this conditional framework, time-varying alpha (i.e. asset pricing misspecification) will be considered, in which alpha could vary with the business cycle variables. Thus time-varying alpha could be modelled as follows:

$$\alpha_i = \alpha_1 + \alpha_2 z_{t-1} \quad (3.10)$$

Where z_{t-1} is a vector of macroeconomic variables (i.e. business cycle variables) at time *t-1*.

Under the Avramov and Chordia (2006a) framework, we employ the Fama-French three factors model augmented with liquidity risk factor as an asset pricing model:

$$R_{i.t} = \alpha_i + \sum_{j=i}^{3} \beta_{i,j,t-1}FF_{j,t} + \gamma_{i,t-1}LIQ_t + \mu_{i,t} \quad (3.11)$$

Therefore, the modelling of factor loading (i.e. beta) in the first-pass time-series regression will be as follows:

$$R_{i.t} = \alpha_{1,i,0} + \sum_{j=i}^{4} \alpha_{2,j,i}BC_{j,t-1} + \sum_{j=i}^{3} \beta_{1,j,i}FF_{j,t} + \sum_{j=i}^{3} \beta_{2,j,i}z_{t-1}FF_{j,t} + \sum_{j=i}^{3}(\beta_{3,j,i}+\beta_{4,j,i}z_{t-1})Size_{i,t-1}FF_{j,t} + \sum_{j=i}^{3}(\beta_{5,j,i}+\beta_{6,j,i}z_{t-1})BM_{i,t-1}FF_{j,t} + \gamma_{1,i}LIQ_t + \gamma_{2,i}z_{t-1}LIQ_t + (\gamma_{3,j,i}+\gamma_{4,j,i}z_{t-1})Size_{i,t-1}LIQ_t + (\gamma_{5,j,i}+\gamma_{6,j,i}z_{t-1})BM_{i,t-1}LIQ_t + \mu_{i,t} \quad (3.12)$$

where the R_{it} is the excess return on stock *i* at month *t, BC* is the vector of business cycle variables default spread, term spread, dividends yield and 3-month Treasury bill yield. *FF* is the vector of Fama-French three factors (i.e. market excess return, SMB and HML), *LIQ* is the liquidity risk factor. We have to emphasize that when beta is allowed to vary with macroeconomic variables z_{t-1}, the analysis has been conducted using default spread, term spread, dividends yield and 3-month Treasury bill yield separately in the time series regressions[49].

In the empirical examinations of the pricing of market-wide liquidity and firm-specific liquidity, betas in equation (3.12) are modelled under different conditional specifications. Although unconditional asset pricing models have been previously criticized in terms of their poor performance compared with their conditional counterparts, we include the estimation of the unconditional model to represent the benchmark for comparison purposes. Therefore, in addition to the unconditional asset pricing model, the following specifications have been estimated for the conditional model; (i) $\alpha_2 = \beta_{3\text{-}6} = \gamma_{3\text{-}6} = 0$, (ii) $\alpha_2 = \beta_2 = \beta_4 = \beta_6 = \gamma_2 = \gamma_4 = \gamma_6 = 0$, (iii) $\alpha_2 = 0$, (iv) $\beta_{3\text{-}6} = \gamma_{3\text{-}6} = 0$, (v) $\beta_2 = \beta_4 = \beta_6 = \gamma_2 = \gamma_4 = \gamma_6 = 0$ (vi) all coefficients depart from zero. To illustrate, the first-pass time-series regression for the (v) specification, for example, where beta is allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and alpha is time varying, is:

$$R_{i.t} = \alpha_{1,i,0} + \sum_{j=i}^{4} \alpha_{2,j,i} BC_{j,t-1} + \sum_{j=i}^{3} \beta_{1,j,i} FF_{j,t} + \sum_{j=i}^{3} \beta_{3,j,i} Size_{i,t-1} FF_{j,t} + \sum_{j=i}^{3} \beta_{5,j,i} BM_{i,t-1} FF_{j,t} + \gamma_{1,i} LIQ_t + \gamma_{3,j,i} Size_{i,t-1} LIQ_t + \gamma_{5,j,i} BM_{i,t-1} LIQ_t + \mu_{i,t} \quad (3.13)$$

In the second-pass cross-sectional regression, the risk-adjusted returns are regressed on firm specific variables (size, book-to-market ratio, liquidity and past raw returns):

$$R^*_{i,t} = \alpha_0 + \sum_{j=i}^{3} \psi_j FC_{j,i,t-1} + \sum_{j=i}^{3} \vartheta_j PCR_{j,i,t-1} + \varepsilon_{i,t} \quad (3.14)$$

where *FC* is a vector of firm characteristics *j* (j=3, firm size, book-to-market ratio, and liquidity measure (e.g. proportional bid-ask spread, turnover ratio, and price impact)). *PCR* are the past cumulative raw returns of stock *i* over the second through third (*RET2-3*), fourth through sixth (*RET4-6*), and seventh through twelfth (*RET7-12*) months prior

[49] A detailed discussion of these variables is provided in the sample section 3.3.3.

to the current month t. R^* is the risk-adjusted return which is equal to ($\alpha_{i,0}+\mu_{i,t}$) from equation (3.12).

For the purpose of testing the stated hypotheses, we estimated the model as described in equations (3.12) (the first-pass time-series regression) and equation (3.14) (the second-pass cross-sectional regression) for both pre- and post-automation periods. Then we test whether the coefficient of liquidity risk factor γ_1 in equation (3.12), and the coefficient of liquidity as a firm-characteristic ψ_t in equation (3.14) are equal to zero. Specifically, we test the null hypotheses that liquidity risk factors loading are insignificant in the first-pass time-series regression, and the firm liquidity characteristic is insignificant in the cross-sectional regression. If the known risk factors (and business cycle variables in case of time-varying alpha) are sufficient to explain the variation in stock returns, then the explanatory power of firm characteristics including liquidity, in the cross-sectional regression, should be insignificant. This means that the liquidity risk factor in the first-pass is priced and no additional premium is paid for liquidity as a firm characteristic. On the other hand, if the cross-sectional risk-adjusted return is still affected by the liquidity measures in the cross-sectional regression, after adjusting for Fama-French three factors and liquidity risk factor (and business cycle variables in case of time-varying alpha), then the coefficient of firm-specific liquidity should be significant. This means that an additional premium should be paid for carrying less liquid stocks even after taking into consideration the market-wide liquidity risk.

3.3.2.2 Comparing the liquidity premium before and after the automation of trading systems

To investigate the effect of the introduction of electronic trading systems on pricing of market-wide liquidity and firm-specific liquidity, we conduct a comparative analysis of the estimated liquidity coefficients between pre- and post-automation of trading systems. More specifically, to examine the influence of the automation of a trading system on the relationship between market-wide liquidity and excess stock return, we use the t-test to compare the cross-sectional averages of the individual coefficients of market liquidity risk factor estimated by first-pass time-series regression (equation (3.12)) before and after automation. That is, we test whether the cross-sectional average of the coefficients of market-wide liquidity risk factor on floor trading system γ_{1F} is expected to be equal to that on electronic trading system γ_{1E}. Additionally, to find out whether there will be a difference in the premium on firm-specific liquidity between pre- and post-automation, we use the Wald-test to test the coefficients equality restriction for the cross-sectional regressions (equation (3.14)) estimated on floor and electronic trading systems. In other words, we test whether the coefficient of the liquidity measures in the cross-sectional regression model estimated on a floor trading system is expected to be equal to the same coefficient of the regression model estimated on an electronic trading system (i.e. ψ_{tF} F = ψ_{tE}).

3.3.3 The sample

The sample includes all the stocks listed and subsequently delisted in the UK (the London Stock Exchange; LSE), Swiss (the Swiss Stock Exchange; SSE) and German (the Frankfurt Stock Exchange; FSE) stock markets. Examining the pricing of aggregate market liquidity and firm-specific liquidity in these markets is important for a number of reasons.

Firstly: these stock exchanges are among the most important in the world. They are considered among the major and biggest markets in Europe as well as in the world, they are respectively the second (fifth), third (ninth), and the fifth (fifteenth) in the Europe (World) by market capitalization[50]. Also, our empirical analysis employs a mixture of big and small markets. In other words, the Swiss market is considered smaller than the UK and German markets. Hence, investigating the Swiss Stock Exchange may give us some different results.

Secondly: UK and Switzerland have moved from the floor trading system to the electronic trading system, while in Germany (i.e. in the Frankfurt Stock Exchange) the electronic trading system has been introduced in parallel with the existing floor trading system. These unique changes in market structure may result in a change in the nature and the dynamic of liquidity in these markets. Previous studies such as Huang and Stoll (1996) and Fabre and Frino (2004) provide evidence that a different market structure

[50] Source: World Federation of Exchanges, domestic market capitalization, December 2007.

results in a different liquidity behavior across markets. Furthermore, Huang and Stoll (2001) argue that liquidity is endogenous to the market structure. Based on this, it would be impossible to automatically apply the findings of the research conducted in US markets to other markets. Therefore, examining the role of liquidity in asset pricing in other markets (i.e. London Stock Exchange, Frankfurt Stock Exchange and Swiss Stock Exchange) is considered important to provide out-of-sample evidence[51].

Our empirical analysis utilizes a data set for different sample periods. Since we were able to identify the exact date of the introduction of an electronic trading system for each market, the beginning and the end date of the sample period for each market is contingent on the date of automation (see table 3.1). Start date of sample periods for each market is also guided by data availability. That is, the sample period for UK data spans from October 1987 to October 2007, ten years prior and ten years after the introduction of an electronic trading system. The sample period for the German markets only spans ten years from January 1998 to December 2007 for each of the parallel trading systems. Finally, the sample period for the Swiss market runs from April 1990 to November 2002, which represents six years and four months before and after automation. This short sample period for the Swiss market is due to data availability restrictions, no data being available for more than 76 months before the automation date. In general, it may be recognized that our sample period is short compared to the available evidence on the pricing of liquidity. However, this does not represent a problem in itself. The results should be taken as valid for the period being examined, but be interpreted with more caution.

The basic data set consists of daily and monthly data for all stocks (dead and live), which are obtained from Datastream. The daily data for all stocks includes closing prices, bid prices, ask prices, trading volume and market value, which is used to construct the following liquidity measures: Proportional bid-ask spread, turnover ratio, and Amihud's (2002) illiquidity ratio (price impact). Monthly data include return index (which includes capital gains as well as dividend payment), book-to-market ratio, market value (size), and lagged returns, which are used for asset pricing analysis. The

[51] Although many stock exchanges have moved from floor to electronic trading systems, the availability of data confined our sample to these stock exchanges only; where the data is available over longer sample period.

time-series averages of the cross-sectional means, medians, and standard deviations of these variables are reported in table 3.2. The variables display considerable skewness. Therefore, we employ logarithmic transforms of all the variables except the lagged returns (proxy for momentum) because they may be zero. Also, following Avramov and Chordia (2006a), the firm characteristics for a given month were expressed as deviations from their cross-sectional means for that month and lagged by two months with respect to the excess returns and the risk-adjusted returns that are the dependent variables in regression models (equations (3.12) and (3.14)). Expressing firm characteristics as deviations from their cross-sectional average implies that the average security will have values of each non-risk characteristic that are equal to zero, so under both the null and the alternative hypotheses the security's expected returns will be determined solely by its risk characteristics. Also, lagging firm characteristics by one additional month is to preclude the possibility that a linear combination of the lagged return variables and other variables, that involve the price level, could provide a noisy estimate of the return in the previous month, thus leading to biases because of bid-ask spread effects and thin trading (see Brennan et al., 1998; Chordia et al., 2001b).

In addition, monthly data on market return indices and market dividends yields have been obtained from Datastream. Data on interest rate variables (i.e. business cycle variables) (short-term interest rate, long-term interest rate on government bond, and long-term interest rate on corporate bonds) were obtained from Datastream for each sample country, except for the data on long-term interest rates on corporate bonds for Germany and short-term interest rates for Switzerland which were obtained from Deutsche Bundes Bank and Bank of Switzerland respectively. Table 3.3 provides the details about definition, measurements and the source of these variables for each sample country.

With regard to Fama-French factors that are designed to mimic risk factors regarding size and book-to-market, we download the data on the two factors, small minus big (SMB) and high minus low (HML), for UK from the Stefan Nagel website for the period October 1987 to December 2001[52]. Then, we construct these factors for the rest of the sample period following Fama and French (1996) as follows. At the end of June

[52] We thank Stefan Nagel for providing the UK HML and SMB data, which is obtained from http://faculty-gsb.stanford.edu/nagel/Stefan%20Nagel's%20Data.htm.

of each year *t* all the stocks are sorted by their market capitalization. Then a breakpoint at the 70^{th} percentile of ranked market value is used to split stocks into two groups (small (S) and big (B)). Then all the stocks are allocated in an independent sorting to three book-to-market groups (low (L), medium (M), high (H)) based on the breakpoints for the bottom 40%, middle 20% and top 40% of the values of book-to-market ratio. We apply these breakpoints in constructing SMB and HML for the rest of the period in order to keep the consistency with the factors data obtained from Stefan Nagel's website. Dimson et al. (2003) argue that these breakpoints compared with those set by Fama and French (1996) (i.e. 50% market value and 30% / 70% book-to-market ratio) are applied to ensure the acceptable levels of diversification among portfolios. Then from the intersections of the two size and three book-to-market groups, six portfolios are formed (S/L, S/M, S/H B/L, B/M, B/H), where the value-weighted monthly returns are calculated from July of $year_t$ to June of $year_{t+1}$. SMB is the difference between the average of the returns on the three small-stocks portfolios and the average of the returns on the three big-stocks portfolios. HML is the difference between the average of the returns on the two high book-to-market ratio portfolios and the average of the returns on the two low book-to-market ratio portfolios. Every year in June, portfolios are reformed based on the new information on market capitalization and book-to-market ratio.

Also, Fama-French factors SMB and HML for Germany have been constructed following Fama and French (1996) as mentioned above, but by applying the same breakpoints set by Fama and French, which are 50% of market value (i.e. the size median) and the bottom 30%, middle 40% and top 30% of the values of book-to-market ratio. Finally, for Switzerland, data on SMB and HML factors have been obtained from the website of Ammann and Steiner[53]. Following Fama and French (1993), Ammann and Steiner (2007) construct these factors using a high quality dataset, taking into consideration the specific characteristics of the Swiss stock market such as the small number of stocks in the market. They find that the premiums of these factors are robust to the key assumptions of the construction methodology such as change in rebalancing horizon, the exclusion of small stocks, the use of more sub-portfolios and the application of an equally-weighted factor construction. They also find that these factors

[53] We thank Ammann and Steiner for providing the Switzerland HML and SMB data, which is obtained from their website www.ammannsteiner.ch.

have high explanatory power in a regression of excess portfolio returns on these factors, which is a confirmation of their relevance to the Swiss Stock Exchange.

3.3.4 Measures of market-wide liquidity

To construct market-wide liquidity proxies, we first start by defining the liquidity measure at the firm-specific level (i.e. measure liquidity for each individual firm). Then measures for aggregate market liquidity are calculated by taking the cross-sectional average across the sample stocks in the market. Following Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Sadka (2006) we calculate these aggregate measures on an equally-weighted basis. Using an equally-weighted average might be more appropriate than using value-weighted average. Because when value-weighted average is used, liquid firms (i.e. large cap stocks) will be overrepresented in the sample and the liquidity factor will be dominated by these firms (see Acharya and Pedersen, 2005; Liu, 2006). In constructing market-wide liquidity measures, we concentrated in our analysis on widely and mostly used measures of liquidity such as proportional bid-ask spread, turnover ratio, and price impact (Amihud's (2002) illiquidity ratio).The next three sub-sections discuss in detail the measures of individual stock liquidity and the calculation of market-wide liquidity proxies.

3.3.4.1 Bid-ask spread

The bid-ask spread is one of the most common and frequently used measures of liquidity. It reflects the immediacy dimension of liquidity. That is, according to Demsetz (1968), spread is the cost of supplying immediacy, and thus liquidity could be measured by estimating the cost of an order's immediate execution. It also results from inventory costs, order processing costs, and information asymmetry costs[54].

Since our objective is to construct liquidity factors that span a long time period this would be impossible with intra-day data which is unavailable for a long period in some markets. Therefore, we use the daily proportional quoted spread at firm-specific level to calculate the monthly average for each company. Then the monthly market-wide

[54] For further details on bid-ask spread, see section 2.3.1.2.1 in chapter two.

proportional quoted spread has been constructed by calculating the cross-sectional average of monthly individual stocks' proportional quoted bid-ask spreads. More specifically, the firm-specific proportional quoted spread (the quoted bid-ask spread divided by the midpoint of the quote) for stock *i* on day *d* in month *t* is given by:

$$\text{pqspr}_{i,d,t} = \left(ask_{i,d,t} - bid_{i,d,t}\right) / \left(\left(ask_{i,d,t} + bid_{i,d,t}\right) / 2\right) \tag{3.15}$$

where $ask_{i,d,t}$ and $bid_{i,d,t}$ are the ask price and the bid price for stock *i* on day *d* in month *t* respectively. Then the monthly proportional quoted spread for stock *i* in month *t* is given by:

$$\text{pqspr}_{it} = \left(1/D_{i,t} \right) \sum_{d=1}^{D} pqspr_{i,d,t} \tag{3.16}$$

where $D_{i,t}$ is the number of trading days for stock *i* at month *t*. Finally, the cross-sectional average of individual stocks' proportional quoted spreads is computed each month to construct a monthly market-wide liquidity series[55]. The market-wide liquidity series of proportional quoted spread is computed as follows:

$$\text{PQSPR}_{t} = \left(1/N_{j} \right) \sum_{n=1}^{N} pqspr_{i,t} \tag{3.17}$$

where N_j is the number of stocks included in the cross-sectional average in month *t*.

3.3.4.2 Turnover ratio

For each stock in our sample, the turnover ratio is given as the ratio of the trading value to the market capitalization. It is one of the trading activity measures that are frequently used as a proxy for liquidity, as it is highly associated with the bid-ask spread and other measures of liquidity. Also, the fact that turnover ratio is related to investors' holding

[55] Consistent with Amihud (2002), Eckbo and Norli (2002), Fujimoto (2003b), and Chen (2005), we remove the extreme observations at both ends of the cross-section before calculating aggregate market liquidity.

period indicates that it is related to liquidity, and thus one can use it as a proxy for liquidity[56].

To construct a market-wide turnover ratio, we start by defining turnover ratio at firm-specific level. More specifically, the firm-specific turnover ratio, which is the ratio of trading value to a firm's market capitalization for stock *i* on day *d* in month *t* is given by:

$$\text{tov}_{i,d,t} = TValue_{i,d,t} \big/ MV_{i,d,t} \tag{3.18}$$

where $TValue_{i,d,t}$ is the trading value for stock *i* on day *d* in month *t*, which is calculated as trading volume multiplied by the stock price. $MV_{i,d,t}$ is the market capitalization for stock *i* on day *d* in month *t*. Then the monthly turnover ratio for stock *i* in month *t* is given by:

$$\text{tov}_{it} = \left(1 \big/ D_{i,t} \right) \sum_{d=1}^{D} tor_{i,d,t} \tag{3.19}$$

where $D_{i,t}$ is the number of trading days for stock *i* at month *t*. Finally, as in the case of bid-ask spread, the cross-sectional average of individual stocks' turnover ratio is computed each month to construct a monthly market-wide liquidity series. The market-wide liquidity series of turnover ratio is computed as follows:

$$\text{TOV}_t = \left(1 \big/ N_j \right) \sum_{n=1}^{N} tor_{it} \tag{3.20}$$

where N_j is the number of stocks included in the cross-sectional average in month *t*.

[56] See section 2.3.1.2.2 in chapter two for more details on turnover ratio measure.

3.3.4.3 Price impact

Price impact is defined as the impact of order flows on stock prices. Compared with the bid-ask spread, the price impact accurately captures the costs associated with large trades. To measure the price impact, Amihud's (2002) illiquidity ratio is used, which is the ratio of daily absolute stock returns to the trading value. Illiquidity ratio is the inverse of the Amivest ratio (liquidity ratio) that is used in the market microstructure literature, and it follows Kyle's (1985) concept of illiquidity, which is defined as the response of price to the order flow (see Amihud, 2002)[57].

Thus, following Amihud (2002), illiquidity ratio is calculated for stock i on day d in month t as follows:

$$\text{pimpact}_{i,d,t} = \left|R_{i,d,t}\right| \big/ TValue_{i,d,t} \tag{3.21}$$

where $R_{i,d,t}$ and $TValue_{i,d,t}$ are the return and the trading value for stock i on day d at month t respectively. The monthly firm-specific price impact is given by:

$$\text{pimpact}_{i,t} = \left(1 \big/ D_{i,t} \right) \sum_{d=1}^{D} pimpact_{i,d,t} \tag{3.22}$$

where $D_{i,t}$ is the number of observations for stock i in month t. Then, the cross-sectional average of the monthly individual stock's price impact is computed each month to construct a monthly market-wide liquidity series as follows:

$$\text{PIMPACT}_{t} = \left(1 \big/ N_{j} \right) \sum_{n=1}^{N} pimpact_{i,t} \tag{3.23}$$

where N_j is the number of stocks included in the cross-sectional average in month t.

[57] For further details on price impact (Amihud's (2002) illiquidity ratio), see section 2.3.1.2.3 in chapter two.

Table 3.4 provides descriptive statistics for the time-series of the three aggregate market liquidity measures for all markets in our sample. As shown in panel A the average proportional quoted bid-ask spread in the LSE is around 7.6% on the electronic trading system, which is larger than the proportional quoted bid-ask spread on the floor trading system, which is nearly 4.4%. Similarly in other markets, the proportional quoted bid-ask spread in the SSE is 4.2% on the electronic trading system compared with 3.4% on the floor trading system, and it is 6.9% on the electronic trading system compared with 4.0% on the floor trading system in the FSE. The average monthly turnover in the LSE (FSE) on the electronic trading system is approximately 2.81 (1.28) compared with 2.47 (1.06) on the floor trading system. In contrast, turnover ratio on the floor trading system in the SSE is higher than that on the electronic trading system, it is 1.77 compared with 1.61. Finally, the average monthly price impact on electronic trading systems for all markets is higher than that on floor trading systems.

Panel B in table 3.4 shows the correlation between market liquidity series. We should expect these empirical measures to correlate. For proportional quoted bid-ask spread and price impact, high values represent less liquidity and for turnover high values represent high liquidity. Thus, we expect a positive correlation between bid-ask spread and price impact and a negative correlation of turnover ratio with bid-ask spread and price impact. The results in panel B show that the correlation coefficients in the LSE and the FSE on floor trading systems confirm all the expected correlations. However, the correlation coefficients of the turnover ratio with proportional bid-ask spread and with price impact are positive for LSE and for FSE on electronic trading, which are unexpected. Finally, the correlation coefficients between liquidity measures for SSE confirm all the expectations for floor and electronic trading systems.

3.3.5 Construction of liquidity risk factors

Following the calculation of market-wide liquidity proxies as shown in the previous section, we should use shocks or innovations of changes in market-wide liquidity series to construct the liquidity risk factors as in Pastor and Stambaugh (2003), and Acharya and Pedersen (2005) among others. The importance of using shocks or innovations is motivated by the rationale that shocks, unexpected variations, to the macroeconomic variable could be priced (see Chen et al., 1986; Sadka, 2006 and references cited in). Further, Pastor and Stambaugh (2003) argue that the failure to use liquidity innovations can contaminate risk measures, especially if there is a correlation between changes in liquidity and time variation in expected stock returns.

We could proceed by identifying and estimating the residuals of the autoregressive model as the unexpected innovations in the liquidity factor. However, according to Chen et al. (1986), if the change in a given series is not serially correlated, it can be used as innovation without alteration. That is, if the changes in the aggregate market liquidity series are not serially correlated, then they can be used as the liquidity risk factor: otherwise it could be necessary to estimate the innovations in aggregate changes in market liquidity as the residuals of a time-series model. Therefore, we estimate the autocorrelation in aggregate changes in market liquidity measures. The reported results of autocorrelation in panel C table 3.4 show that all market-wide liquidity series in the LSE, except the proportional bid-ask spread series on the floor trading system and the turnover ratio series on electronic trading system, are persistent. That is, they have statistically significant first-order serial correlation at 1%, and 5% level of significance. In the SSE only the turnover ratio series and price impact series show persistence during the floor trading period. The first-order serial correlation for these series is statistically significant at 10% and 1% level of significance respectively. Further, in the FSE, all market-wide liquidity series, apart from the proportional bid-ask spread series, are persistent. That is, they have statistically significant first-order serial correlation at a 5% level of significance or better in most cases. Some market-wide liquidity series in these markets show a significant higher order serial correlation (e.g. second-, third-, and fourth-order) at 1%, 5% and 10% levels of significance, for example, the turnover ratio on the floor trading system, and turnover ratio and price impact on the electronic trading system in the FSE. This means that they are highly persistent.

The persistence in some aggregate market liquidity series, as shown above, means that we cannot use these series directly as liquidity risk factors compared with non-persistence market-wide liquidity series, where the changes of these series could be used as innovations without alteration. To remove the persistence (i.e. remove the information which is tracked by lagged observations) and thus construct a time series of innovations, we model the aggregate changes in market liquidity into an autoregressive integrated moving average (ARIMA) model. Before proceeding with ARIMA model construction, the aggregate changes in market liquidity series have been tested for stationarity by performing the Augmented Dicky-Fuller test. We did not allow for intercept or trend and use information criteria (Akaike Information Criterion) to guide the selection of the lags. The results of the unit root test in Panel D in table 3.4 for all markets show that the unit root hypothesis (non-stationary) has been rejected for all series. The probability value (p-value) is either less than 1% or 5%. Then Box-Jenkins methods are used to determine the appropriate order of the autoregressive integrated moving average (ARIMA) model, which will be estimated to obtain the innovations of persistence aggregate market liquidity series.

Table 3.5 shows the order of ARIMA model for each of the persistence aggregate market liquidity series. The order of ARIMA model has been chosen based on the Bayesian Information Criterion. After estimating the ARIMA models and extracting the innovations of the persistence market-wide liquidity series, which represent the liquidity risk factor, the estimated innovations have been checked to see if they are serially correlated. The estimated autocorrelation results that are reported in table 3.6 panel A show that the estimated innovations are not serially correlated. That is, the first-order autocorrelation for all innovations in market liquidity is statistically insignificant. Also, panel B in table 3.6 shows the correlation coefficient between the innovations in market measures. For all markets and for both trading systems the results of correlations coefficients confirm the expected correlation between the innovations of market liquidity measures. In particular, the correlations between turnover and proportional bid-ask spread and price impact are negative, and they are positive between proportional bid-ask spread and price impact.

3.4 Empirical Results

This section presents and discusses the results of examining and comparing the pricing of market-wide liquidity and firm-specific liquidity before and after the automation of trading systems. The results are discussed first for the estimation of the first-pass time-series regression (equation (3.12)), which examines the pricing of market-wide liquidity. Then, this section reports the results of the second-pass cross-sectional regression (equation (3.14)), which examines the relationship between firm-specific liquidity and risk-adjusted returns. Both regressions have been estimated in the two sub-sample periods before and after automation, and then a comparative analysis has been conducted to compare the pricing of market-wide and firm-specific liquidity under different contexts of trading systems. In the first-pass time-series regression, we employed the Fama-French model augmented by market liquidity risk factor, which is measured by proportional bid-ask spread, turnover ratio, and illiquidity ratio (price impact). The first-pass regression is estimated using each of the liquidity factors separately. In the second-pass cross-sectional regression we use the same measures of liquidity but at individual stock level (i.e. firm-specific liquidity)[58].

3.4.1 Market-wide liquidity and firm-specific liquidity in the context of a conditional model

3.4.1.1 Market-wide liquidity

Table 3.7 summarizes the results of the first-pass time-series regression (equation (3.12)). It only reports the summarized results relating to the coefficients of market-wide liquidity risk factors[59]. The mean values of each of the market-wide liquidity coefficients in the pre- and post-automation of the trading system are presented. The table also gives the difference in the mean of the coefficients before and after automation, and the t-statistic of the null hypothesis that the mean value of the coefficients is equal before and after the introduction of the electronic trading system. Since the liquidity risk factor in the first-pass regression is represented by the innovations or the residuals of the proportional bid-ask spread, turnover ratio and price impact, higher values of proportional bid-ask spread and price impact and lower values of turnover ratio indicate lower liquidity. Thus, the estimated coefficients of proportional bid-ask spread and price impact are expected to be negative and those of turnover ratio to be positive. If market-wide liquidity is a priced risk factor and has a significant effect on stock excess returns, the mean value of the coefficients of market liquidity risk factor estimated from first-pass regression (equation (3.12)) will be

[58] See appendix 3A, which provides a summary of the testable hypotheses and whether they are supported or rejected, along with the reasons based on the empirical results of this section.

[59] Because the table is already voluminous, we do not report coefficients for the other risk factors in the first-pass regression.

statistically different from zero. That is, we test the hypothesis that the mean value of γ_i is equal to zero using a cross-sectional t-test following Chordia et al. (2000). Panel A shows the results of fixed beta (i.e. unconditional version model that has been estimated to represent a benchmark for comparison), in panel B beta is scaled by size and the book-to-market ratio, in panel C beta is allowed to vary with default spread, and in panel D beta is conditioned on size and book-to-market ratio, and also allows this conditioning to vary over time with business cycle variables (i.e. default spread)[60].

The results in Panel A show that, in all markets and during both sub-periods related to before and after automation, all the coefficients on market-wide liquidity risk factors have the expected sign, and most of them are statistically significant as indicated by their associated t-statistic. More specifically, the mean value of proportional bid-ask spread coefficients in all markets under both trading systems is negative as expected, and statistically significant on both trading systems in all markets except for Germany. The coefficient of turnover ratio is positive in all markets and statistically significant in pre- and post-automation in Germany and in pre- (post-) automation in Switzerland (UK). Finally, the mean value of the price impact coefficient has the predicted sign and it is statistically significant in pre- and post-automation in Switzerland and in pre- (post-) automation in Germany (UK). These results of all market-wide liquidity measures confirm the findings of previous studies such as Amihud (2002) and Fujimoto (2003a). They also support the first postulated hypothesis that market liquidity is a priced risk factor, that is, market-wide liquidity has a positive effect on stock excess returns. This means that any decrease in market-wide liquidity will result in lower current stock excess returns, because investors depress the current stock prices when they anticipate lower future market liquidity so they can earn higher expected returns.

The results thus far show that market-wide liquidity is an important priced risk factor in asset pricing on either one or both trading systems. This, however, leads us to investigate how the automation of the trading system could affect the relationship between market-wide liquidity and stock excess returns. In general, the t-test results represented in the last three columns in table 3.7 panel A, show that the introduction of

[60] The results of first-pass time-series regression in panel C and D are estimated using term spread, short-term interest rate, and dividends yield as conditional variables rather than default spread. The results obtained from this estimation are reported in appendix 3B and they are qualitatively similar to those obtained by using default spread.

the electronic trading system has impacted on the pricing of aggregate market liquidity. This implies that the change in market structure significantly results in changing market liquidity risk. More specifically, the t-test statistic shows that the size of the proportional bid-ask spread coefficients, in the absolute term, increases and decreases significantly after the introduction of the electronic trading system in UK and Germany respectively. That is, following automation, as market liquidity decreases in UK (Germany) stock excess returns decrease more (less). This suggests that market-wide liquidity became more (less) risky after the automation in UK (Germany). This implies that the immediacy of the market in filling investors' orders represents less concern to the investors during market liquidity shocks in Germany than in UK. Furthermore, post-automation, the influence of market-wide liquidity on stock excess-returns increases (decreases) in UK (Switzerland). The mean coefficient of turnover ratio increases (decreases) to 0.006 (0.004) post-automation. This means that the influence of market liquidity on stock excess returns becomes more (less) in UK (Switzerland), which may result in lower (higher) excess returns post-automation compared with the pre-automation period when market liquidity is low. In relation to the price impact, the results show that, only in Germany and after the introduction of the electronic trading system, the effect of market-wide liquidity risk on excess return decreases in the absolute term. The t-test statistic that compares the difference in the mean between the two trading systems is statistically significant at 5% level of significance. This implies that the market ability to absorb a large trading volume without or with minimum effect on stock prices increased during electronic trading, and thus market liquidity became less risky. All in all, the results show that the automation of the trading system has affected the relationship between market liquidity and stock excess returns, and results in market liquidity being more risky in the UK market compared with other markets in our sample. Thus, our results reject our third hypothesis that the effect of market-wide liquidity on stocks' excess returns before and after the automation of trading systems is not different.

In relation to the results in panel B, when beta is allowed to vary with firm characteristics (i.e. size and BM), they show that there is weak evidence of the effect of market liquidity on excess stock returns. Only the mean value of turnover ratio's coefficients in pre-automation UK and post-automation Germany, and the mean value of price impact's coefficient post-automation Switzerland are statistically significant, as indicated by their associated t-statistics. This provides very weak support to the first hypothesis that market-wide liquidity is a priced risk factor. In addition, the results reveal weak evidence that the introduction of the electronic trading system has affected the market liquidity-return relationship. In contrast to the UK, in post-automation Germany, the influence of market liquidity on excess stock returns increased as shown only by the increase in the mean value of the turnover ratio coefficients. Despite the weak evidence, it does not support the third hypothesis that the introduction of the electronic trading system does not affect the relationship between market liquidity and stock excess returns.

In sharp contrast, the results in panel C show that, when beta is allowed to vary with business cycle variables (i.e. default spread), there is strong evidence of a significant relationship between market liquidity and excess stock return. More specifically, there is clear evidence for pricing market-wide liquidity, with the mean value of proportional bid-ask spread being negatively and statistically significant at 1% and at 10% level of significance in pre- and post-automation UK and for the floor trading system in Germany respectively. This also is supported with the mean value of turnover ratio being positively significant at 1% level of significance in post-automation UK and Switzerland and for both trading systems in Germany, and with price impact being negatively and statistically significant at 10% and 1% level of significance in post-automation UK and Switzerland respectively. These results are consistent with the findings of Amihud (2002) and Fujimoto (2003a) and provide further support to the first postulated hypothesis that market liquidity is priced in asset returns. In addition, these results indicate once again that investors will react to negative liquidity shocks by depressing current stock prices in order to earn a higher expected return in future. These findings also imply that investors pay more attention to business cycle variables to predict market liquidity and to assess their liquidation needs, because market liquidity will be low and the probability of liquidation is expected to be higher when economic conditions deteriorate.

Furthermore, t-test results reported in panel C show that the introduction of the electronic trading system appears to have affected the relationship between market liquidity and excess stock returns. This implies that structural changes in markets' trading systems may significantly alter the liquidity of the markets and its risk. More specifically, the automation of the trading system seems to have significantly influenced the impact of market turnover ratio and price impact on excess stock returns. Prior to automation neither of these measures were significant for either UK or Switzerland, but they became significant after automation. Even though the mean value of turnover ratio coefficients in Germany is significant for both trading systems, its size increases after automation. This may indicate that after the automation of the trading system, market liquidity becomes more important as a risk factor, and investors become more concerned with the level of market trading activities and its ability to absorb large trading quantities. Thus, our results do not support the third proposition regarding the impact of the automation of the trading system on the relationship between market liquidity and stock excess returns.

Finally, when beta is allowed to vary with firm characteristics (i.e. size and BM) and with business cycle variables (i.e. default spread), the results in panel D do not provide evidence that market liquidity is a priced risk factor. Specifically, none of the coefficients of market liquidity measures are statistically significant either before or after the automation of the trading system. Also, the results show that the introduction of the electronic trading system has no significant impact on the liquidity-return relationship. Thus, the results under this specification of asset pricing model do not support the first hypothesis, but they provide support to the third hypothesis, that the pricing of market-wide liquidity is not different before and after automation.

Thus far the findings of the first-pass regression reveal that market-wide liquidity is a priced risk factor and that it is an important state factor in an asset pricing model on either one or both trading systems. These results are robust using different market-wide liquidity measures and using the unconditional and conditional version (i.e. when beta is allowed to vary with business cycle variables) of an asset pricing model.

3.4.1.2 Firm-specific liquidity

To find out whether liquidity as a firm-specific characteristic carries an additional premium, we examine the results of the second-pass cross-sectional regression (equation (3.14)). If the risk factors in the first-pass time-series regression are insufficient in explaining the variation in excess stock returns, the explanatory power of firm-specific liquidity should be significant. This implies that liquidity as a firm characteristic is related to the cross-section of individual risk-adjusted returns and it does carry an additional premium.

The coefficients of the second-pass cross-sectional regression model (equation. (3.14)) estimated in pre- and post-automation periods along with the Wald test results are reported in table 3.8. Panel A shows the results of fixed beta (i.e. unconditional version); in panel B, beta is scaled by size and the book-to-market ratio; in panel C, betas are allowed to vary with default spread; and in panel D beta is conditioned on size and the book-to-market ratio and also this conditioning is allowed to vary over time with business cycle variables (i.e. default spread)[61]. Although we applied different specifications of beta modelling, the results under different specifications are qualitatively similar with very few differences in terms of significance. To put it another way, the different specifications of beta modelling to examine whether liquidity as a firm characteristic carries an additional premium make relatively little difference in the results. Therefore, we focus our discussion of the empirical results of the second-pass cross-sectional regression on those reported in panels A (unconditional model) and B (where beta are allowed to vary with size and book-to-market ratio). We also highlight the differences in the results that are reported in panels C and D compared with those reported in panel A, which represents the benchmark case.

In both models (panels A and B), the results show that the coefficient on proportional bid-ask spread is significantly negative at 1% level of significance for both sub-sample periods related to pre- and post-automation in UK, but that this coefficient is statistically insignificant for other markets. Hence, under both unconditional and conditional asset pricing models, firm-specific liquidity on both trading systems in the UK carries an additional premium. However, the significantly negative relationship between proportional bid-ask spread and risk-adjusted return in UK is unexpected. This contradicts the argument that stocks with higher transactions costs (i.e. higher bid-ask spread) should earn a higher expected return. Instead it implies that investors will

[61] The results of second-pass cross-sectional regression reported in panel C and D are estimated using term spread, short-term interest rate, and dividends yield as condition variables in first-pass time-series regression rather than default spread. The results obtained from this estimation are reported in Appendix 3C and they are qualitatively similar to these obtained by using default spread.

receive a premium for carrying stocks with low bid-ask spread. Therefore, the sign of bid-ask spread is inconsistent with its role as a measure of transaction costs. This could be due to the fact that bid-ask spread is a noisy measure of liquidity or it is proxying for risk variables relating to price or firm size that are not captured by the Fama-French model (Brennan and Subrahmanyam, 1996). Further, this evidence is inconsistent with the positive spread-return relationship found by Amihud and Mendelson (1986) and with negative relations between return and liquidity as found by Brennan et al. (1998), Datar et al. (1998), Chordia et al. (2001b) among others. But, it is consistent with the findings reported by Eleswarapu and Reinganum (1993) and Brennan and Subrahmanyam (1996) using US data. The significant negative relation between proportional bid-ask spread and risk-adjusted returns in UK provides partial support to the second hypothesis in terms of the significant relationship between bid-ask spread and expected returns, but not in terms of coefficient sign, which is expected to be positive.

In contrast, the insignificance of liquidity premium (i.e. coefficient of proportional quoted spread) for both Switzerland and Germany indicates that the risk factors in first-pass regression capture the influence of firm-specific liquidity. This implies that investors only receive a premium on bearing market liquidity risk in Switzerland and Germany. Insignificant results in both Switzerland and Germany are inconsistent with the results of the Amihud and Mendelson (1986) who find positive spread-return relationships. Thus, the prediction of the Amihud and Mendelson (1986) model does not hold in these markets. This could be, as Eleswarapu (1997) argues, due to the fact that quoted spreads are not a better proxy for the cost of transacting in these markets. These results are inconsistent with our prediction and thus do not provide support to the second hypothesis that firm-specific liquidity has an additional premium.

With regard to turnover ratio, the results in panels A and B show that the impact of turnover ratio on risk-adjusted return in UK is captured by risk factors in the asset pricing model in the first-pass regression, and thus, liquidity carries no additional premium. In contrast, the coefficient of turnover ratio is significantly negative at a 5% level of significance or better in most cases in Switzerland and Germany on either both or one trading system. This implies that besides the premium that is required to compensate investors on market liquidity risk in Switzerland and Germany, investors ask for an additional premium for holding less liquid stocks. These results are consistent with the argument that asset returns must be a decreasing function of turnover ratio, and consistent with the results of Datar et al. (1998) using risk-unadjusted returns, and with the results of Brennan et al. (1998), Chordia et al. (2001b) and Avramov and Chordia (2006a) using an asset pricing model to adjust return for risk. Thus, the significant results of turnover ratio in the Swiss and German markets provide further support to the second postulated hypothesis.

The insignificant impact of turnover ratio on risk-adjusted return in the UK does not support the second hypothesis, and implies that there is no additional premium on firm-specific liquidity. In contrast to Avramov and Chordia (2006a), the risk factors in our first-pass time-series regression were able to capture the impact of turnover ratio. That is, the coefficient remains insignificant in all models (unconditional and conditional ones) in pre- and post-automation periods, except in the case when beta is allowed to vary with firm characteristics and with default spread during the electronic trading period (panel D). In comparison, Avramov and Chordia (2006a) were unable to capture the impact of turnover ratio on risk-adjusted returns even by using different versions of a conditional asset pricing model. They argue that the failure of their models in capturing the impact of liquidity could be "… that liquidity is more than of trading phenomenon, unrelated to the state of economy. Liquidity is likely to be a function of market design, competition amongst liquidity suppliers, and the degree of information asymmetry or the lack thereof" (Avramov and Chordia, 2006a, p1036). Thus, the inconsistency in our findings with that of Avramov and Chordia (2006a) as well as the difference in our results among the markets in our sample may be explained by the differences in market structure between UK and US markets and between UK and Switzerland and Germany in our sample.

Finally, when firm-specific liquidity is measured by price impact (i.e. illiquidity ratio), the results of cross-sectional regression show that liquidity as a firm-characteristic has an additional premium either on a floor or electronic trading system for each of the markets in our sample. More specifically, under the unconditional model, the coefficient of price impact is negative but weakly significant (at a 10% level of significance) for the electronic trading system in the UK market. This result is inconsistent with the findings of Brennan and Subrahmanyam (1996) who find that both variable and fixed components of price impact are significantly positively related to excess returns. The significant negative coefficient of price impact provides partial support to the second hypothesis. That is, the significant relation between price impact and risk adjusted returns implies that firm-specific liquidity has an additional premium after controlling for all risk factors, but the negative sign is against expectation. This once again means that investors pay a premium for holding stock with a higher price impact (i.e. less liquidity stocks).

In contrast, under both models, the estimated coefficients of price impact are positively significant at 5% and 10% in Switzerland (Germany) in the pre- (post-) automation period, which provides further support to the second postulated hypothesis. These results are consistent with the argument that less liquid stocks with higher price impact pay higher returns. This is consistent with the findings of Brennan and Subrahmanyam (1996) and other previous studies in terms of a negative liquidity-return relationship. This implies that the possibility that stocks' prices will be affected by large quantity of trading represents a concern, and hence an additional source of risk for investors who trade on the electronic (floor) trading system in Germany (Switzerland). To summarize, the significant negative (positive) relationship between risk adjusted returns and turnover ratio (price impact) in the Swiss and German markets, provides evidence that supports the second postulated hypothesis: liquidity as a firm characteristic has an additional premium after controlling for all risk factors including market-wide liquidity risk factor for floor and electronic trading systems.

The results thus far reveal that firm-specific liquidity carries an additional premium and plays an important role in asset pricing on either one or both trading systems. This highlights the importance of examining how the introduction of electronic trading system could affect this additional premium on liquidity. The results of the Wald test that compare the estimated coefficients between pre- and post-automation periods are reported in table 3.8. Whenever the coefficients of firm-specific liquidity, while having the same sign, are significant both pre- and post-automation, the coefficients have an impact on risk adjusted return that is significantly different in two sub-periods, as indicated by the significant Wald test statistic. The evidence for whether the introduction of an automated trading system has impacted on the premium of liquidity is mixed among liquidity measures. However, in general, the results for the pre- and post-automation periods show that the introduction of electronic trading appears to affect the additional premium required by investors on firm-specific liquidity. This implies that the introduction of the electronic trading system may significantly change the level of firm liquidity and thus affect its pricing in assets returns.

More specifically, although the coefficient of proportional bid-ask spread is significant and negative during both sub-sample periods for the UK under both models, only under the unconditional model does the Wald test statistic show that the size of the coefficient decreases significantly post-automation. This indicates a decrease in the effect of liquidity on risk-adjusted returns. These results do not support the fourth hypothesis that the premium on firm-specific liquidity will not be different before and after automation. In contrast, the Wald test results for turnover ratio support our prediction. That is, the automation of the trading system does not seem to have influenced the impact of turnover ratio on risk-adjusted returns. Even though the coefficients of turnover ratio in both models (in unconditional model) under both trading systems in Switzerland (Germany) are negatively significant, their impact on risk-adjusted return is insignificantly different as indicated by the insignificant Wald test statistic. This indicates that after the introduction of the electronic trading system, the level of stock trading activity does not change, which results in the same level of liquidity as before automation. Thus, firm-specific liquidity as proxied by turnover ratio is the same, and carries equal premiums under both trading systems. In relation to the price impact, the results show that its effect on risk-adjusted return is different across trading systems, which is against the fourth postulated hypothesis that the premium in firm-specific liquidity is not different across trading systems. That is, the coefficient of price impact becomes significant post-automation under the unconditional model (both models) for UK (Germany), but it becomes insignificant after the automation of the trading system in both models for Switzerland. The influence of price impact on risk-adjusted return is greater in the post- (pre-) automation period in UK and Germany (Switzerland).

Panels C and D in table 3.8 report respectively the Fama-MacBeth coefficients estimated when beta is allowed to vary with default spread and when the relationship of betas with size and book-to-market is allowed to vary over the business cycle with default spread. Overall the results presented in these panels are qualitatively similar to those reported previously in panels A and B, with some difference in terms of significance. More specifically, the results in panel C, when risk factors in first-pass regression are scaled by default spread, show that the coefficient of price impact in UK and Germany and the coefficient of turnover in Switzerland on an electronic trading system are no longer significant. This provides weak support to the second hypothesis that liquidity as a firm-characteristic carries an additional premium. This also suggests that under this conditional specification the known risk factors including market-liquidity risk in the first-pass regression were able to capture the influence of some measures of firm-specific liquidity. Additionally, in panel D, when the relationship between betas and size as well as book-to-market is allowed to vary over the business cycle with default spread, the results show that the coefficient of turnover ratio during the electronic trading period becomes negative and weakly significant at a 10% level of significance in UK. Also, the effect of price impact on risk-adjusted returns becomes insignificant (significant) in UK and Germany (Switzerland). The significance of firm-specific liquidity coefficients under this specification are consistent with the notion that all risk factors in first-pass time-series regression do not explain the variation in stock excess returns. This provides further support to the second hypothesis: firm-specific liquidity is negatively and significantly related to risk adjusted returns which thus have an additional premium after controlling for all risk factors.

Finally, the results in panels C and D show that there is a difference in liquidity premium before and after automation. For example, in panel C, the Wald test statistic reveals that the coefficient of proportional bid-ask spread in the UK is statistically different in the two sub-samples periods, and the coefficient of turnover ratio and price impact in Switzerland become insignificant in the post-automation period. Also, in panel D, the coefficient of turnover ratio in the UK and the coefficient of price impact in Switzerland become significant in the post-automation period. These results reject the fourth hypothesis, which states that the liquidity premium is not different between trading systems.

To summarise, we find a significant relationship between risk-adjusted return and different measures of liquidity in cross-sectional regression, on either one or both trading systems using different specifications of conditional asset pricing models. Panels A, B and D show strong evidence compared to panel C. In spite of this, the findings are consistent with the notion of a liquidity premium in asset prices. In other words, liquidity as a firm-specific characteristic has an additional premium after controlling for all risk factors including market liquidity risk. In addition, we find that the liquidity premium is different between the two trading systems, which implies that the introduction of the electronic trading system has influenced the impact of firm-specific liquidity on risk-adjusted returns.

Having examined the cross-sectional relationship between risk-adjusted return and liquidity after controlling for size, book-to-market ratio and momentum variables, it is worthwhile to highlight the role of these variables in the second-pass regression. The results in all panels show that the coefficients of size are positive but insignificant in most cases. This might be as a result of the presence of liquidity variables in the cross-sectional regression and with firm size serving as proxy for liquidity (see Amihud and Mendelson, 1986). This is consistent with the results of previous studies such as Amihud and Mendelson (1986), Brennan et al. (1998), Chordia et al. (2001b) and Avramov and Chordia (2006a). With regard to the book-to-market ratio, our results show that value effect is prominent in all regressions for all markets under both floor and electronic trading systems. The coefficients of book-to-market ratio are positive and statistically significant at 1% and 5% level of significance. Our results are consistent with those of Brennan et al. (1998), Datar et al. (1998), Chordia et al. (2001b) and Avramov and Chordia (2006a) using US data. Finally, the coefficients of past returns (momentum variables) are positive and statistically significant at all different levels of significance in most cases for all markets. These findings are consistent with those of Brennan et al. (1998), Chordia et al. (2001b) and Avramov and Chordia (2006a).

3.4.2 Market-wide liquidity and firm-specific liquidity in the context of conditional model and time-varying alpha

By using conditional models with time-varying risk premiums, the findings provide evidence that is consistent with a liquidity premium in asset prices, that is, it has been shown that market liquidity is priced and firm-specific liquidity has an additional premium. However, does a conditional model with time-varying risk premium and with time-varying asset pricing misspecification (time-varying alpha) lead to the same conclusion? That is, does the accounting for time-varying alpha affect the relationship between market liquidity and excess stock returns? Does that also show that liquidity premiums vary with the business cycle? To find out whether previous results hold, this section presents the results of estimating the conditional asset pricing model with time-varying alpha. That is, the first-pass time-series regression (equation (3.12)) has been modified to account for time-varying alpha. Then we estimate the first-pass regression and the second-pass cross-sectional regression (equation (3.14)) where beta is allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variables (i.e. default spread). This section presents first the results of estimation first-pass time-series regression that examine the pricing of market-wide liquidity. Following that it reports the results of second-pass regression that examine the relationship between firm-specific liquidity and risk-adjusted returns.

3.4.2.1 Market-wide liquidity

Table 3.9 presents a summary of the results of the first-pass time-series regression (equation (3.12)). It reports the summary results relating to the coefficients of market-wide liquidity risk factors[62]. The mean values of each market-wide liquidity coefficients estimated by the first-pass regression (equation (3.12)) in the pre- and post-automation of trading systems are reported. The table also gives the difference in the mean of the coefficients before and after the automation of trading systems, and the t-statistic of the null hypothesis that the mean value of the coefficients is equal before and after automation. The structure of this table follows that of table 3.7[63]. The results reported in this table are qualitatively and quantitatively similar to those reported in table 3.7 with very few differences in terms of the significance and the sing of the mean value of individual market liquidity coefficients.

Overall, the results support our previous evidence that market-wide liquidity has a significant effect on excess stock returns during the two sub-sample periods, and that the introduction of the electronic trading system has impacted on this relationship. More

[62] Because the table is already voluminous, we do not report coefficients for the other risk factors in the first-pass regression.

[63] The results of first-pass time-series regression in panels C and D are estimated using term spread, short-term interest rate, and dividends yield as conditional variables rather than default spread as a condition variables. The results obtained from this estimation are reported in appendix 3D and they are qualitatively similar to those obtained by using default spread.

specifically, the results in panel A show in most cases the coefficients of market-wide liquidity are significant and have the expected sign, which provides clear evidence that market-wide liquidity is a priced risk factor. This is supported with the mean value of individual coefficients of proportional bid-ask spread being negatively significant for UK and Switzerland during pre- and post-automation, and for Germany on its floor trading system. Also, it is supported with the mean value of turnover ratio's coefficients being positively significant on the electronic (floor) trading system for the UK (Swiss) market and under both trading systems for the German market, and with the mean value of price impact's coefficient being negatively significant in post- (pre-) automation UK (Germany) and in the two sub-periods for Switzerland. This indicates that market-wide liquidity has a positively significant impact on current excess stock return, and thus supports the first hypothesis that market-wide liquidity is a priced risk factor. Further, there is clear evidence that the introduction of an electronic trading system has influenced the relationship between market-wide liquidity and excess stock return. Most of the t-statistics which compare the mean value of the coefficients of market liquidity risk between floor and electronic trading systems, are statistically significant at 1% and 10% level of significance, which rejects the third hypothesis.

Furthermore, the results in panel B table 3.9 are consistent with those reported in panel B table 3.7. That is, when beta is allowed to vary with firm characteristics, the evidence that market liquidity is significantly affecting excess stock returns is very weak. Also, the results show that the introduction of an electronic trading system does not influence this relationship. These results do not strongly support the first hypothesis that market-wide liquidity is a priced risk factor, but do support the third hypothesis that the automation of the trading system does not have a significant impact on the pricing of market liquidity. In contrast, the results in panel C, when beta is allowed to vary with business cycle variables such as default spread, provide strong support to the first hypothesis and reject the third hypothesis. The results provide robust evidence that market-wide liquidity is a priced risk factor and that the automation of the trading system has an influence on the relationship between market-wide liquidity and stock excess returns. This may imply that conditioning beta on business cycle variables has an influence on the relationship between market liquidity and stock returns. This means that market liquidity is related to macroeconomic status and investors pay attention to macroeconomic predictive variables in predicting market liquidity to assess their future liquidation needs especially when the economy in recession. Finally, when beta is allowed to vary with both firm characteristics and business cycle variables, there is no evidence that market liquidity is a priced risk factor and there is no evidence that the impact of market liquidity on excess stock returns is different before and after the automation of the trading system. The majority of the mean values of individual market liquidity coefficients, and the t-statistics that compare the means between the two trading systems, are statistically insignificant as indicated by their associated t-value. These results do not support the first, however, they accept the third testable hypothesis.

To summarize, the results of employing both unconditional and conditional models with time-varying alpha provide robust evidence that market-wide liquidity is a priced risk factor, especially when beta is fixed and when it is allowed to vary with business cycle variables. Further, under these specifications, the results show that the pricing of market-wide liquidity on a floor trading system is different from that on an electronic trading system.

3.4.2.2 Firm-specific liquidity

The coefficients of the two-pass cross-sectional regression model (equation (3.14)) are reported in table 3.10. The structure of this table follows that of table 3.8[64]. Overall, the results reported in table 3.10 provide evidence that liquidity as a firm characteristic carries an additional premium on both floor and electronic trading systems, after adjusting excess stock returns to the known risk factors including market liquidity risk. They also show that the introduction of the electronic trading system has an impact on the influence of firm-specific liquidity on risk-adjusted returns, that is, the liquidity premium is different between the two trading systems.

More specifically, the results in panel A show that even though that there is weak evidence of liquidity premiums in the UK the evidence provided from other markets strongly indicates that there is a premium on individual firm liquidity. That is, when

[64] The results of second-pass cross-sectional regression reported in panels C and D are estimated using term spread, short-term interest rate, and dividends yield as condition variables in first-pass time- series regression rather than default spread. The results obtained from this estimation are reported in Appendix 3E and they are qualitatively similar to these obtained by using default spread.

alpha varies with business cycle variables, most of the liquidity coefficients in the UK are statistically insignificant. This may imply that capturing the impact of liquidity on the cross-section of expected returns unrelated to the business cycle in the UK may suggest an existence of business cycle pattern within liquidity. That is, liquidity is related to the state of the economy. This evidence is inconsistent with the findings of Avramov and Chordia (2006a) using US data. In contrast, liquidity variables' coefficients (i.e. proportional bid-ask spread, turnover ratio and price impact) in Switzerland and Germany under both trading systems are statistically significant at least at the 5% level of significance and have the predicted sign. That is, the coefficients of proportional bid-ask spread and price impact (turnover ratio) in both Switzerland and Germany are significantly positive (negative). This means that less liquid stocks with higher bid-ask spread, higher price impact and low turnover pay higher returns. This provides strong support for the second hypothesis that firm-specific liquidity has an additional premium, even though the results for UK provide weak support. Our results are consistent with those of Amihud and Mendelson (1986), Datar et al. (1998), Brennan et al. (1998), Chordia et al. (2001b) among others.

Furthermore, the results of the Wald test statistic in panel A reject the fourth hypothesis, and indicate that there is a difference in liquidity premium between pre- and post-automation periods. More specifically, the statistically significant Wald test statistics at 1% level of significance indicate that the coefficients of firm-specific liquidity have a significant different impact on risk-adjusted return in the two sub-sample periods for Switzerland and Germany. The estimated coefficients of liquidity variables are higher in absolute terms pre-automation, compared with those post-automation in Switzerland; but in Germany the opposite is true. This implies that the investors become less concerned about the liquidity level of individual firms after (before) the introduction of an electronic trading system in Switzerland (Germany), and thus ask for less (more) liquidity premiums.

Moreover, panel B in table 3.10 shows the Fama-MacBeth coefficient estimates with time-varying alpha and when the beta is allowed to vary with firm characteristics (i.e. size and book-to-market ratio). The results are qualitatively similar to those in panel A especially for Switzerland and Germany. With regard to the UK, the results in panel B compared with those in panel A show strong evidence of a liquidity premium. Most of the liquidity coefficients in the UK are statistically significant at the 10% level of significance or better either under one or both trading systems. The significance of the coefficients of firm-specific liquidity in this specification implies that risk factors in the first-pass are unable to explain the variation in stock-excess returns. This provides strong support to the second proposition that liquidity as firm characteristics has an additional premium after controlling for the known risk factors. Further, for most cases in all markets, the Wald statistic is statistically significant at 5% level of significance or better. This implies that the additional premium that the investors required for holding less liquid stock is different before and after the automation of the trading system. This also rejects the fourth postulated hypothesis that firm-specific liquidity does not have a different premium between the two trading systems.

Additionally, the results reported in panel C are qualitatively similar to those reported in panel A and those in panel D are qualitatively similar to those reported in panel B with very few differences in terms of coefficients' significance. But, in the case of the UK market compared with other markets, the results in panels A and C, in contrast with those in panels B and D, show that the impact of liquidity on a cross-section of expected returns unrelated to the business cycle in UK became insignificant in most cases. This may suggest that the known risk factors in the first-pass regression, in the case of the results in panels A and C, were able to capture the impact of liquidity as a firm characteristic and thus no additional premium was being paid for carrying illiquid stocks.

With regard to the controlling variables in the second-pass cross-sectional regression, the results in table 3.10 in all panels show that, in the UK and Switzerland, the coefficient of firm size is negative and statistically significant. This is consistent with the findings of Avramov and Chordia (2006a). In contrast, the firm size in Germany has a positive impact on expected cross-sectional returns and it is significant in most cases. This is consistent with the findings of Brennan et al. (1998) and Chordia et al. (2001b) who find positive significant size effect. Furthermore, the results show that the value affect is strongly present in the data. In all panels of the table 3.10, the coefficient of book-to-market ratio is positive and significant in most cases in UK and Germany, which is inconsistent with the results of Avramov and Chordia (2006a). However, the results in the case of Switzerland show that the impact of book-to-market ratio on expected returns is negative in most cases especially in panels A to C and positive in others. The change in sign of book-to-market ratio from positive to negative, compared with the results reported in table 3.8, could be due to the change of the dependent variable in cross-sectional regression, which is the asset mispricing purged of the business cycle variation in the case of time varying alpha (see Avramov and Chordia, 2006a). Furthermore, even though the examination of the impact of momentum variables on expected stock returns lies outside the framework of this research, our results show interesting evidence. In the presence of time-varying alpha, compared with the results in table 3.8, the coefficients of past returns RET2-3, RET4-6 and RET7-12 are positive and insignificant in most cases. This evidence is consistent with that of Avramov and Chordia (2006a) using US data and supports their argument that the momentum is not explained by using a rational asset pricing model, or it may not represent a compensation for risk: but this may suggest that the profit of momentum strategies could vary with the business cycle.

In summary, under different specifications of conditional asset pricing models with time varying alpha, the results provide evidence that firm-specific liquidity has a significant effect on risk adjusted return, and, hence it has an additional premium before and after the automation of the trading systems in both Switzerland and Germany. In relation to the UK, even though there is evidence regarding the premium of firm-specific liquidity, especially when beta is allowed to vary with firm characteristics and with firm characteristics and business cycle variables, the evidence is very weak. Further, the results also show that the automation of the trading system has impacted upon liquidity premium, that is, the liquidity premium is significantly different between the two sub-sample periods relating to pre- and post-automation of a trading system.

3.5 Conclusion

Despite the vast literature on liquidity and asset pricing, it has generally restricted itself to examining whether firm-specific liquidity or market-wide liquidity is priced in assets returns. Literature that undertakes empirical analysis which examines and compares the pricing of market-wide liquidity and firm-specific liquidity in different contexts of trading systems (i.e. before and after the automation of trading systems) is virtually nonexistent. Therefore, this chapter extends the literature and examines whether and to what extent market-wide liquidity and firm-specific liquidity are priced in asset pricing before and after the automation of a trading system within the context of a conditional asset pricing model. In addressing this issue for the three major European markets namely, the UK, Switzerland and Germany, it is possible to gain valuable insights about the pricing of both market and firm-specific liquidity that might be impossible to obtain by looking at other markets. We used daily and monthly data for all stocks traded in these markets. The sample period for the UK extended over twenty years (ten years pre-, ten years post-automation); for twelve years and eight months for Switzerland (six years four months pre-, the same post-automation); and within Germany, ten years for each trading system. In contrast to other studies that examine liquidity in asset pricing, we apply the conditional model of Avramov and Chordia (2006a) to the underlying markets in our sample, where factor loadings in this model are allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variables.

For the definition of a particular liquidity factor, following Chen et al. (1986), we used the innovations from a time-series model for the factor to represent the market-wide liquidity risk. Market-wide liquidity measures are constructed as the cross-section average of firm-specific liquidity measures, which are presented by using proportional bid-ask spread, turnover ratio and Amihud's (2002) illiquidity ratio (i.e. price impact). For each liquidity factor augmented in Fama-French's three factor model under the conditional framework of Avramov and Chordia (2006a), we apply the Fama and MacBeth (1973) procedure to estimate the time-series average of the second-pass cross-sectional regressions' coefficients. To address the research issue relating to the pricing of market-wide liquidity and firm-specific liquidity under different trading systems, the first-pass and the second-pass regressions in the framework of Avramov and Chordia (2006a) are estimated for the two sub-sample periods relating to before- and after-the automation of trading system.

The results provide evidence that market-wide liquidity is priced under both trading systems. More specifically, the results show that there is significant negative impact of market-illiquidity on stock excess return on either one or both trading systems. The evidence appears to be strong when beta is fixed and when it is allowed to vary with default spread. However, while the evidence that market liquidity is priced is weak when beta varies with firm characteristics, there is no significant evidence on pricing market liquidity when beta varies with both firm characteristics and default spread. The same results are obtained in the case of the asset pricing model with time-varying alpha. This appears to suggest that investors become more concerned about market liquidity when the economy is sour, and they pay much attention to macroeconomic predictive variables to predict market liquidity and assess their future liquidation needs, especially when market liquidity plunges during bad economic conditions. In addition, there is clear evidence that the introduction of electronic trading has impacted the relationship between market-wide liquidity and stock excess return. That is, the impact of market-wide liquidity is different pre- and post-automation. Within the post-automation period, market liquidity exhibits a strong impact on excess return for UK in most cases compared with Switzerland and Germany, where market liquidity has a strong impact on excess return pre-automation. This implies that market-wide liquidity presents a greater source of risk to investors after the automation of the trading system in the UK compared with Switzerland and Germany.

Examination of any possible additional premium on firm-specific liquidity after controlling for the known risk factors including market liquidity risk, suggests the existence of such a premium. More specifically, the results show that in most cases and under different specifications of the pricing model, firm-specific liquidity has a significant impact on risk-adjusted returns before and after the automation of the trading system. This implies that risk factors in the first-pass regression were unable to explain the variation in stock excess return, thus firm-characteristics including liquidity have significant explanatory power. This appears to be dominated most of the time for Switzerland and Germany in the case of asset pricing model with time-vary alpha. Furthermore, the results also show that the automation of the trading system has an influence the premium on firm-specific liquidity. That is, the effect of liquidity as a firm characteristic on risk-adjusted returns seems to be different before and after the automation of the trading system. This implies that moves towards electronic trading results in changes in the level of liquidity for individual stocks, which then results in a difference in the premium on firm-specific liquidity before and after the automation of the trading system.

Overall, the findings provide useful insights and reveal that market liquidity is a priced risk factor in both trading systems and, in some cases, either before or after automation. In addition, the results show that after controlling for known risk factors include market liquidity risk, firm-specific liquidity has an additional premium either on both trading systems, before or after the automation of the trading system. This means that both market-wide liquidity and firm-specific liquidity are priced and important in asset pricing. This result supports the evidence provided by previous studies based on US market data. Furthermore, the pricing of liquidity has been affected by the introduction of electronic trading. Both the pricing of market liquidity and the additional premium on firm-specific liquidity are different between floor and electronic trading.

This chapter contributes to the existing literature by: first, examining the role of liquidity (be it market-wide or firm specific) in asset pricing under different contexts of market structures (i.e. floor versus electronic trading systems). That is, it investigates whether and to what extent liquidity is priced before and after the automation of trading systems, an issue that has not been explored yet. Thus, it provides a further and stronger link between the area of market microstructure and the asset pricing area. Second, it extends the existing literature on liquidity and asset pricing by examining whether market-wide liquidity and firm-specific liquidity are priced using the conditional asset pricing model of Avramov and Chordia (2006a). Finally, it provides out-of-sample evidence by exploring whether liquidity is priced in markets other than the US such as the UK, Switzerland and Germany.

The finding that liquidity is important in asset pricing suggests that liquidity risk is a promising direction for future research: for example, to explore the importance of market liquidity in asset pricing in markets other than equity markets, such as fixed income markets for which there is a dearth of evidence.

Table 3.1

Dates of introduction of the electronic trading system and sample period before and after automation

This table shows the stock exchanges that comprise our sample, the date of the introduction of the electronic trading system, the source of information about the date of the automation for each stock exchange and the sample period breakdown for each exchange (before and after the automation of the trading system).

The Exchange	Date of Automation	Source of information	Sample period	
			Before Automation	After Automation
London	27-Oct.-1997	http://www.londonstockexchange.com	Oct. 1987 to Sept. 1997	Nov. 1997 to Oct. 2007
Swiss	2-Aug. -1996	http://www.swx.com/swx/review_en.html	April 1990 to July 1996	Aug. 1996 to Nov. 2002
Frankfurt	28-Nov. - 1997	info@deutsche-boerse.com	Jan. 1998 to Dec. 2007 for both trading systems	

Table 3.2
Summary statistics

This table presents the time-series average of cross-sectional means, medians, and standard deviations during the period, floor trading and electronic trading systems for UK, Switzerland and Germany. Prop. Bid-ask is the proportional bid-ask spread calculated by dividing the quoted bid-ask spread over the midpoint of quoted bid-ask spread. Turnover is the trading value divided by market capitalization. Price impact (illiquidity ratio) is the ratio of absolute return to trading value. Size represents the market capitalization expressed in millions. BM is the book-to-market ratio. RET2-3, RET4-6 and RET7-12 are the past cumulative raw returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month, respectively.

UK (London Stock Exchange)						
	Floor trading system			Electronic trading system		
	Mean	Median	StdDev.	Mean	Median	StdDev.
Prop.Bid-Ask	0.0462	0.0283	0.0543	0.0780	0.0440	0.1041
Turnover	2.6910	2.0592	3.3960	3.1424	1.8255	6.0591
Price Impact	0.0006	0.0000	0.0030	0.0070	0.0002	0.0921
Size	0.3452	0.0274	1.4364	0.8449	0.0370	5.1966
BM	0.6704	0.5735	2.1678	0.7773	0.5541	4.3012
Ret2-3	-0.0024	0.0004	0.1614	-0.0084	-0.0042	0.2082
Ret4-6	0.0008	0.0058	0.1998	-0.0125	-0.0037	0.2583
Ret7-12	0.0119	0.0267	0.2910	-0.0244	0.0021	0.3807
Switzerland (Swiss Stock Exchange)						
	Floor trading system			Electronic trading system		
	Mean	Median	StdDev.	Mean	Median	StdDev.
Prop.Bid-Ask	0.0389	0.0224	0.0685	0.0518	0.0207	0.1209
Turnover	1.9734	1.0527	3.6342	2.0308	0.8968	7.3491
Price Impact	0.0006	0.0001	0.0023	0.0033	0.0001	0.0356
Size	0.6181	0.1124	2.2271	0.6283	0.2030	2.1539
BM	1.7913	0.8851	6.2237	1.3312	0.6904	5.0308
Ret2-3	-0.0055	0.0003	0.1433	0.0045	0.0034	0.1621
Ret4-6	-0.0105	-0.0014	0.1708	0.0141	0.0116	0.1961
Ret7-12	-0.0153	-0.0019	0.2404	0.0285	0.0296	0.2811
Germany (Frankfurt Stock Exchange)						
	Floor trading system			Electronic trading system		
	Mean	Median	StdDev.	Mean	Median	StdDev.
Prop.Bid-Ask	0.0433	0.0273	0.0526	0.0848	0.0237	0.1888
Turnover	2.5238	0.8304	12.3342	1.6228	0.6185	4.0285
Price Impact	0.0480	0.0018	0.3463	1.0588	0.0017	11.0442
Size	1.3347	0.0812	6.1201	2.1907	0.3179	7.3718
BM	2.6563	0.5591	10.4144	2.8059	0.5859	10.2337
Ret2-3	-0.0166	-0.0097	0.2279	-0.0209	-0.0091	0.2661
Ret4-6	-0.0223	-0.0115	0.2813	-0.0287	-0.0111	0.3170
Ret7-12	-0.0374	-0.0099	0.4084	-0.0520	-0.0174	0.4397

Table 3.3

Definition, measurement and sources of macroeconomic variables (i.e. business cycle variables)

This table shows the data used to calculate the macroeconomic variables; short-term yield, dividends yield, default spread and term spread as well as their definitions. It also shows the source of data on interest rates and dividend yield.

Country	Short-term Financial Securities	Long-term Government Bonds	Corporate Bonds	Market Dividends Yield
UK	3-month Treasury bills	UK 20 Years Government Redemption Yield	Corporate bonds rate	Dividend yield on Financial Times All Share Price Index
Switzerland	Call Money Rate*	Long Term Government Bond Yield (10 years maturity)	Corporate bonds rate	Dividend yield on Germany DS-market constituents
Germany	3-month FIBOR	Long Term Government Bond Yield (9-10 years maturity)	Corporate bonds rate*	Dividend yield on Germany DS-market constituents

*the data on corporate bonds for Germany are obtained from the website of Deutche Bundes Bank, and the data on Call Money Rate for Switzerland are obtained from Bank of Switzerland, otherwise all the data are obtained from Datastream.

Macroeconomic variables (short-term yield, dividends yield, default spread (quality spread), and term spread) are measured as follow:

1- Short-term yield (YLD): is measured by the rate of return on short-term financial securities.
2- Dividends yield (DIV): is measured by dividend on value-weighted broad based market index.
3- Default spread (DEF): is measured as the difference between the yield on corporate bonds and the yield on long-term government bonds.
4- Term spread (TERM): is measured as the difference between the yield on long-term bonds and the yield on short-term financial securities.

Table 3.4
Aggregate market liquidity and the change in aggregate market liquidity

For each market in our sample (London Stock Exchange, Swiss Stock Exchange, and Frankfurt Stock Exchange) and during the two sub-periods, floor trading system and electronic trading system, this table represents descriptive statistics and correlation coefficients for the aggregate market liquidity measures in panel A and panel B respectively. Panel C and Panel D represent the autocorrelation and unit root test for the change in market liquidity respectively. The market liquidity measures are defined as follows: proportional bid-ask spread (PQSPR): the quoted bid-ask spread divided by the midpoint of the quote, turnover ratio (TOV): turnover measure of trading activities which is calculated by dividing trading value over the market capitalization, and Price impact (illiquidity ratio) (PIMPACT): the ratio of absolute return to trading value. The aggregate market liquidity measures are given by the cross-sectional average of the firm-specific liquidity measures. All market liquidity series are equally-weighted.

UK/ London Stock Exchange (LSE)						
	Floor Trading			Electronic Trading		
Liquidity Measures	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Panel A: Descriptive statistics for time-series of aggregate market liquidity.						
Mean	4.4316	2.4682	0.0004	7.5530	2.8101	0.0029
Median	4.5501	2.4019	0.0004	7.5072	2.7891	0.0028
Std. Dev.	1.6732	0.5761	0.0003	1.4860	0.6300	0.0018
Maximum	8.1737	4.6678	0.0013	11.6236	4.3016	0.0091
Minimum	1.8471	1.5597	0.0000	5.1341	1.4386	0.0006
Panel B: Correlations for time-series of aggregate market liquidity.						
PQSPR	1.0000			1.0000		
TOV	-0.5888	1.0000		0.1619	1.0000	
PIMPACT	0.8196	-0.5799	1.0000	0.8949	0.0885	1.0000
Panel C: Autocorrelations for the change in the time-series of aggregate market liquidity.						
AR(1)	0.0761	-0.2455**	-0.3898***	0.4019***	-0.0679	-0.4619***
AR(2)	-0.1326	-0.2705***	-0.2691***	0.0001	-0.0809	-0.0694
AR(3)	-0.0051	-0.1447	-0.1467	-0.0504	-0.3025***	-0.0459
AR(4)	0.0285	-0.1127	-0.2027*	-0.0570	0.0992	-0.0318
AR(5)	0.0395	-0.0070	0.1888*	0.0839	-0.2921***	-0.0564
Panel D: Unit root test for the change in the time-series of aggregate market liquidity.						
Test-statistic	-9.0377***	-10.1912***	-15.2150***	-7.1624***	-3.8388***	-17.3625***

Table 3.4 (continued)

Switzerland /Swiss Stock Exchange (SSE)						
	Floor Trading			Electronic Trading		
Liquidity Measures	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Panel A: Descriptive statistics for time-series of aggregate market liquidity.						
Mean	3.4045	1.7734	0.0004	4.2444	1.6065	0.0007
Median	3.2923	1.6900	0.0003	4.1579	1.4982	0.0005
Std. Dev.	0.7441	0.5385	0.0002	0.9559	0.6263	0.0006
Maximum	6.1954	3.0510	0.0013	7.1902	3.6374	0.0029
Minimum	1.9934	0.8311	0.0001	2.5082	0.6786	0.0002
Panel B: Correlations for time-series of aggregate market liquidity.						
PQSPR	1.0000			1.0000		
TOV	-0.4723	1.0000		-0.1608	1.0000	
PIMPACT	0.7280	-0.4784	1.0000	0.4086	-0.5841	1.0000
Panel C: Autocorrelations for the change in the time-series of aggregate market liquidity.						
AR(1)	-0.1118	-0.2158*	-0.5784***	0.0008	-0.1145	-0.0707
AR(2)	-0.0335	-0.2727**	-0.2482*	-0.1145	-0.1734	0.1303
AR(3)	0.0046	-0.2004	-0.1410	-0.1294	-0.1262	-0.1717
AR(4)	-0.1603	-0.0354	-0.0571	-0.1336	-0.1566	-0.4472***
AR(5)	0.0037	-0.1637	-0.0818	-0.0306	-0.0604	0.0573
Panel D: Unit root test for the change in the time-series of aggregate market liquidity.						
Test-statistic	-8.9961***	-7.9767***	-13.5859***	-10.3588***	-9.1464***	-4.5937***

Table 3.4 (continued)

Germany/Frankfurt Stock Exchange (FSE)						
	Floor Trading			Electronic Trading		
Liquidity Measures	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Panel A: Descriptive statistics for time-series of aggregate market liquidity.						
Mean	3.9657	1.0578	0.0235	6.8523	1.2808	0.2349
Median	3.9410	0.8812	0.0195	6.7433	1.2827	0.2093
Std. Dev.	1.2809	0.5020	0.0245	4.5076	0.4010	0.2649
Maximum	7.4260	3.9227	0.1324	20.2709	2.1914	1.2413
Minimum	1.6971	0.4565	0.0000	0.9895	0.5536	0.0001
Panel B: Correlations for time-series of aggregate market liquidity.						
PQSPR	1.0000			1.0000		
TOV	-0.4617	1.0000		0.2704	1.0000	
PIMPACT	0.8591	-0.3874	1.0000	0.8699	0.2536	1.0000
Panel C: Autocorrelations for the change in the time-series of aggregate market liquidity.						
AR(1)	0.1413	-0.3019***	0.1811*	-0.2800***	-0.2259**	-0.2041**
AR(2)	-0.0680	-0.2910***	-0.0076	-0.0473	-0.3033***	-0.1575*
AR(3)	0.1190	-0.2792***	-0.0803	-0.0708	-0.1146	-0.2410**
AR(4)	-0.1241	-0.1169	-0.0991	-0.0870	-0.1493	0.1653*
AR(5)	0.1731*	-0.0354	0.1828*	0.0466	-0.1067	0.0944
Panel D: Unit root test for the change in the time-series of aggregate market liquidity.						
Test-statistic	-9.6872***	-10.1527***	-9.0419***	-14.0169***	-10.4122***	-9.5623***

***, **, and * denotes significance at 1%, 5%, and 10% respectively. Augmented Dicky-Fuller critical values at 1%, 5% and 10% are respectively -2.585, -1.944, and -1.615 for unit root test during floor and electronic trading system.

Table 3.5
ARIMA models order

This table shows the order of ARIMA models for the change in aggregate market liquidity series that show persistence (i.e. a significant first-order autocorrelation) as shown in Panel C in table 1 for all markets.

Sample period	Liquidity measure	London Stock Exchange (LSE)	Swiss Stock Exchange (SSE)	Frankfurt Stock Exchange (FSE)
Floor Trading	PQSPR	--------------	--------------	--------------
	TOV	(1,0,1)	(1,0,1)	(1,0,1)
	PIMPACT	(0,0,1)	(0,0,1)	(2,0,1)
Electronic Trading	PQSPR	(1,0,0)	--------------	(0,0,1)
	TOV	--------------	--------------	(1,0,1)
	PIMPACT	(2,0,1)	--------------	(3,0,0)

Table 3.6
Innovations of the change in aggregate market liquidity

This table represents the autocorrelations and correlation coefficients for the innovations of aggregate market liquidity measures in panel A and panel B respectively. The market liquidity measures are defined as follows: proportional bid-ask spread (PQSPR): the quoted bid-ask spread divided by the midpoint of the quote, turnover ratio (TOV): turnover measure of trading activities which is calculated by dividing trading value over the market capitalization, and Price impact (illiquidity ratio) (PIMPACT): the ratio of absolute return to trading value. The aggregate market liquidity measures are given by the cross-sectional average of the firm-specific liquidity measures. All market liquidity series are equally-weighted.

London Stock Exchange (LSE)						
	Floor Trading			Electronic Trading		
Liquidity Measures	PQSPR*	TOV	PIMPACT	PQSPR	TOV*	PIMPACT
Panel A: Autocorrelations in the innovations in the time-series of aggregate market liquidity.						
AR(1)	------	0.0428	0.0770	0.0081	------	-0.0513
AR(2)	------	-0.0610	-0.0697	0.0007	------	-0.0610
AR(3)	------	0.0851	-0.0159	-0.0508	------	-0.0324
AR(4)	------	0.0518	-0.1276	-0.0752	------	-0.0289
AR(5)	------	0.0406	0.2697***	0.0179	------	-0.0695
Panel B: Correlations for the innovations in the time-series of aggregate market liquidity.						
PQSPR	1.0000			1.0000		
TOV	-0.3637	1.0000		-0.2296	1.0000	
PIMPACT	0.4888	-0.1422	1.0000	0.6731	-0.0761	1.0000
Swiss Stock Exchange (SSE)						
	Floor Trading		Electronic Trading			
Liquidity Measures	PQSPR*	TOV	PIMPACT	PQSPR*	TOV*	PIMPACT*
Panel A: Autocorrelations in the innovations in the time-series of aggregate market liquidity.						
AR(1)	------	0.0303	-0.0418	------	------	------
AR(2)	------	-0.0805	0.0608	------	------	------
AR(3)	------	-0.0318	-0.0148	------	------	------
AR(4)	------	0.0980	0.0076	------	------	------
AR(5)	------	-0.0736	-0.0755	------	------	------
Panel B: Correlations for the innovations in the time-series of aggregate market liquidity.						
PQSPR	1.0000			1.0000		
TOV	-0.3947	1.0000		-0.1503	1.0000	
PIMPACT	0.1478	-0.0934	1.0000	0.5501	-0.0845	1.0000

Table 3.6 (Continued)

Frankfurt Stock Exchange (FSE)						
	Floor Trading			Electronic Trading		
Liquidity Measures	PQSPR*	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Panel A: Autocorrelations in the innovations in the time-series of aggregate market liquidity.						
AR(1)	------	0.0323	-0.0054	0.0019	0.0380	0.0417
AR(2)	------	-0.0274	0.0319	0.0326	-0.0891	0.0443
AR(3)	------	-0.0713	-0.0421	-0.0570	0.0882	-0.0247
AR(4)	------	0.0554	-0.0877	-0.0695	-0.0181	0.0849
AR(5)	------	0.0673	0.2154	0.0652	-0.0032	0.0234
Panel B: Correlations for the innovations in the time-series of aggregate market liquidity.						
PQSPR	1.0000			1.0000		
TOV	-0.2651	1.0000		-0.1078	1.0000	
PIMPACT	0.4734	-0.2638	1.0000	0.2925	-0.1058	1.0000

*The aggregate change in the liquidity series is not serially autocorrelated, thus, this series has not been modelled into ARIMA model to estimate the innovations. Instead the original series of aggregate change itself is used directly as innovations (see section 3.3.5 and references cited in for the discussion on this issue).

***, **, and * denotes significance at 1%, 5%, and 10% respectively.

Table 3.7
Statistics of individual coefficients of market liquidity risk factors estimated by conditional asset pricing model

Among the other risk factors and control factors, this table reports the cross-sectional average of the time-series slope coefficients of market-wide liquidity risk factors with their associated t-statistics. These coefficients are estimated by running the first-pass time-series regression (Eq. (3.12)) for each firm during the floor trading period and the electronic trading period. Liquidity risk factors include PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. "Pos" reports the percentage of positive slope coefficients, while "Sig" gives the percentage of the coefficients that are significant at 10% of significance or higher. The last three columns present the difference in the mean between electronic and floor trading systems with the t-value and p-value of the null hypothesis that the difference in the mean is equal to zero.

Panel A: Unconditional asset pricing model.

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.008	(-5.04)	42	27	-0.026	(-12.13)	38	16	-0.018	(-6.46)	0.000
	TOV	0.001	(0.72)	48	12	0.006	(4.25)	50	15	0.005	(2.88)	0.004
	PIMPACT	-0.003	(-1.04)	50	13	-0.003	(-3.78)	44	17	0.000	(-0.04)	0.968
Swiss Stock Exchange (SSE)	PQSPR	-0.014	(-5.91)	33	16	-0.011	(-6.12)	31	16	0.003	(1.09)	0.275
	TOV	0.021	(7.79)	72	21	0.004	(1.08)	54	10	-0.018	(-4.04)	0.000
	PIMPACT	-0.043	(-5.43)	34	26	-0.035	(-5.28)	35	21	0.008	(0.73)	0.466
Frankfurt Stock Exchange (FSE)	PQSPR	-0.012	(-4.83)	41	15	-0.001	(-0.72)	49	14	0.012	(4.20)	0.000
	TOV	0.029	(10.15)	61	18	0.028	(6.71)	56	16	-0.001	(-0.27)	0.790
	PIMPACT	-4.5E-04	(-2.94)	47	17	-3.2E-05	(-1.41)	44	11	4.2E-04	(2.55)	0.011

Panel B: Conditional asset pricing model, Beta varies with Size and BM.

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	0.161	(1.49)	48	17	0.192	(1.25)	47	15	0.031	(0.16)	0.876
	TOV	-0.223	(-2.12)	49	14	0.053	(1.23)	52	17	0.276	(2.63)	0.009
	PIMPACT	-0.154	(-1.11)	49	18	-0.161	(-1.25)	47	17	-0.007	(-0.03)	0.972
Swiss Stock Exchange (SSE)	PQSPR	-0.140	(-1.48)	41	18	-0.031	(-0.19)	48	13	0.110	(0.60)	0.551
	TOV	0.102	(0.78)	60	21	-0.035	(-0.36)	50	14	-0.137	(-0.84)	0.401
	PIMPACT	0.066	(0.13)	49	17	-0.491	(-1.82)	45	18	-0.557	(-0.95)	0.342
Frankfurt Stock Exchange (FSE)	PQSPR	0.179	(0.49)	48	15	-0.013	(-0.83)	53	19	-0.191	(-0.45)	0.652
	TOV	-0.062	(-0.95)	52	17	0.163	(1.75)	54	19	0.225	(2.04)	0.042
	PIMPACT	-0.001	(-0.26)	50	18	-0.001	(-1.13)	54	18	0.001	(0.14)	0.890

Panel C: Conditional asset pricing model, Beta varies with default spread (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.045	(-3.15)	44	15	-0.021	(-3.37)	46	12	0.024	(1.60)	0.110
	TOV	-0.004	(-0.64)	49	13	0.028	(5.79)	54	14	0.033	(4.03)	0.000
	PIMPACT	0.046	(2.60)	50	17	-0.006	(-1.76)	47	14	-0.053	(-3.00)	0.003
Swiss Stock Exchange (SSE)	PQSPR	-0.002	(-0.36)	51	12	-0.008	(-1.45)	38	16	-0.006	(-0.77)	0.444
	TOV	-0.010	(-1.40)	48	16	0.023	(2.61)	63	18	0.033	(2.91)	0.004
	PIMPACT	0.029	(1.25)	55	9	-0.054	(-4.60)	22	19	-0.082	(-2.97)	0.003
Frankfurt Stock Exchange (FSE)	PQSPR	-0.009	(-1.92)	45	12	-0.001	(-0.37)	46	11	0.009	(1.62)	0.106
	TOV	0.044	(7.18)	55	15	0.080	(7.37)	61	17	0.035	(2.92)	0.004
	PIMPACT	-0.001	(-1.58)	44	14	-2.77E-05	(-0.37)	42	16	0.001	(1.46)	0.145

Panel D: Conditional asset pricing model, Beta varies with Size, BM and default spread (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.730	(-1.22)	51	16	-0.332	(-1.05)	50	14	0.398	(0.63)	0.530
	TOV	-0.022	(-0.07)	50	15	0.068	(0.21)	51	15	0.091	(0.20)	0.843
	PIMPACT	-0.025	(-0.03)	51	16	0.031	(0.19)	51	15	0.057	(0.08)	0.933
Swiss Stock Exchange (SSE)	PQSPR	-0.695	(-0.98)	54	17	0.615	(0.48)	50	15	1.310	(0.88)	0.377
	TOV	-0.371	(-0.70)	47	14	-0.320	(-0.16)	44	13	0.051	(0.02)	0.981
	PIMPACT	0.052	(0.07)	54	17	-1.727	(-0.19)	53	15	-1.779	(-0.20)	0.844
Frankfurt Stock Exchange (FSE)	PQSPR	-0.400	(-0.82)	49	16	-0.003	(-0.04)	48	15	0.397	(0.69)	0.490
	TOV	-2.494	(-1.01)	49	18	0.282	(0.91)	57	15	2.777	(0.96)	0.336
	PIMPACT	-0.038	(-0.81)	44	16	-2.54E-04	(-0.28)	49	16	0.038	(0.69)	0.489

Table 3.8

Fama-MacBeth estimates with Fama-French factors and liquidity as risk factor

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficient estimates (Eq. (3.14)) for all securities in the UK, Switzerland and Germany. Panel A presents the estimates when the dependent variable is the risk-adjusted return using the unconditional Fama-French model augmented with liquidity factor. In panel B the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with firm characteristics (i.e. size and book-to-market ratio). In panel C the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with business cycle variables default spread. In panel D the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variable default spread. Liq. Risk Factor is the liquidity risk factor added to Fama-French three factor model, PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. *Floor* and *electronic* in the third column in each panel refers to the estimation done during the floor trading system and electronic trading system respectively. Size represents the logarithm of market capitalization; BM is the logarithm of book-to-market ratio; RET2-3, RET4-6, RET7-12 are the past cumulative raw returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month; Prop.Bid-ask is the proportional bid-ask spread calculated as the quoted bid-ask spread divided by the midpoint of the quoted bid-ask spread; Turnover is the turnover ratio measures as the trading value divided by the market capitalization; Price impact is the ratio of absolute return divided by the trading value. $\overline{R^2}$ is the time-series average of the monthly adjusted R^2. T-statistic (reported in parenthesis) are adjusted for autocorrelation and heteroscedasticity. W-stat. is the Wald test statistic. All coefficients are multiplied by 100. *, **, *** denotes significance at the 10, 5, 1% level.

Panel A: Risk adjusted return is unconditional.

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.308 (-2.97)***	-0.162 (-3.69) ***	0.499 (7.83) ***	2.160 (4.53) ***	1.565 (3.54) ***	1.169 (4.24) ***	-0.545 (-5.37) ***			2.32%
		Electronic	-0.737 (-5.91) ***	-0.021 (-0.45)	0.909 (10.42) ***	2.467 (6.25) ***	1.757 (5.39) ***	1.073 (4.97) ***	-0.273 (-2.64) ***			2.12%
	W-stat.		11.82***	8.82***	22.05***	0.60	0.35	0.20	6.86***			
	TOV	*Floor*	-1.084 (-5.46) ***	0.143 (3.07) ***	0.559 (6.09) ***	2.770 (4.44) ***	2.134 (3.06) ***	2.061 (4.34) ***		0.018 (0.19)		4.22%
		Electronic	-0.829 (-5.73) ***	0.115 (2.16) **	0.921 (10.95) ***	2.691 (5.98) ***	1.769 (5.76) ***	0.995 (4.33) ***		0.001 (0.02)		2.27%
	W-stat.		3.10*	0.26	18.49***	0.03	1.41	21.54***		0.08		
	PIMPACT	*Floor*	-1.233 (-3.46) ***	0.120 (1.22)	0.543 (6.05) ***	2.743 (4.01) ***	2.169 (3.13) ***	1.976 (3.95) ***			-0.003 (-0.04)	4.13%
		Electronic	-0.806 (-5.19) ***	0.040 (0.53)	0.913 (9.94) ***	2.441 (5.31) ***	1.844 (6.01) ***	1.137 (5.01) ***			-0.074 (-1.81) *	2.30%
	W-stat.		7.55***	1.12	16.25***	0.43	1.12	13.63***			3.01*	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.889 (-4.54) ***	0.079 (0.83)	0.395 (3.01) ***	3.149 (2.84) ***	2.209 (2.17) **	1.947 (2.44) **	0.215 (1.31)			5.16%
		Electronic	-0.317 (-1.34)	0.054 (0.50)	0.643 (4.29) ***	2.810 (2.06) **	1.789 (1.55)	1.311 (1.94) *	0.136 (0.94)			7.64%
	W-stat.		5.88**	0.06	2.73*	0.06	0.13	0.88	0.29			
	TOV	*Floor*	-0.856 (-4.09) ***	-0.046 (-0.59)	0.346 (3.02) ***	3.033 (2.74) ***	1.790 (1.95) *	1.810 (2.29) **		-0.178 (-2.33) **		4.42%
		Electronic	-0.406 (-1.67) *	0.036 (0.36)	0.711 (4.56) ***	3.756 (3.19) ***	2.337 (2.17) **	1.465 (2.08) **		-0.153 (-2.04) **		7.81%
	W-stat.		3.43*	0.67	5.49**	0.38	0.26	0.24		0.11		
	PIMPACT	*Floor*	-0.928 (-4.07) ***	0.131 (1.42)	0.401 (3.40) ***	3.051 (2.72) ***	2.348 (2.44) **	1.947 (2.45) **			0.163 (2.20) **	4.41%
		Electronic	-0.392 (-1.66)*	0.082 (0.91)	0.640 (4.12) ***	4.307 (3.63) ***	2.251 (2.10) **	1.565 (2.54) **			-0.026 (-0.37)	7.54%
	W-stat.		5.17**	0.29	2.36	1.12	0.01	0.39			6.99***	

Panel A (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.219 (-1.24)	0.092 (1.50)	0.442 (3.58)***	1.357 (2.45) **	1.865 (4.32) ***	0.845 (2.59) **	0.070 (0.58)			3.69%
		Electronic	-0.468 (-1.39)	0.502 (1.44)	0.657 (3.11) ***	2.040 (2.93) ***	1.487 (2.29) **	0.451 (0.95)	-0.021 (-0.13)			4.65%
	W-stat.		0.55	1.38	1.03	0.96	0.34	0.69	0.32			
	TOV	*Floor*	-0.151 (-0.73)	-0.120 (-1.83) *	0.691 (2.16) **	0.052 (0.04)	0.837 (0.89)	1.404 (1.17)		-0.242 (-1.78) *		3.21%
		Electronic	-0.514 (-2.10) **	0.104 (1.46)	0.652 (3.14) ***	1.800 (2.27) **	1.632 (2.66) ***	0.514 (1.09)		-0.240 (-3.08) ***		4.96%
	W-stat.		2.20	9.95***	0.04	4.88**	1.67	3.58*		0.00		
	PIMPACT	*Floor*	-0.048 (-0.21)	0.110 (0.68)	0.677 (2.15) **	-0.259 (-0.18)	1.183 (1.54)	1.531 (1.33)			0.119 (0.91)	3.91%
		Electronic	-0.475 (-1.91) *	0.228 (1.83) *	0.554 (2.53) **	1.712 (2.09) **	1.883 (2.96) ***	0.489 (1.00)			0.125 (1.78) *	5.11%
	W-stat.		2.95*	0.91	0.32	5.79**	1.21	4.59**			0.01	

Panel B: Risk adjusted return is conditional on size and BM.

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.404 (-4.69) ***	-0.131 (-3.33) ***	0.319 (5.89) ***	2.035 (4.36) ***	1.610 (3.70) ***	1.165 (4.30) ***	-0.508 (-5.96) ***			2.27%
		Electronic	-0.814 (-8.10) ***	-0.007 (-0.15)	0.703 (9.28) ***	2.892 (7.99) ***	2.007 (6.25) ***	1.298 (5.80) ***	-0.373 (-4.06) ***			2.30%
	W-stat.		16.66***	7.09***	25.73***	5.61**	1.53	0.35	2.15			
	TOV	*Floor*	-1.091 (-6.26) ***	0.163 (3.70) ***	0.438 (5.16) ***	2.391 (3.92) ***	2.363 (3.70) ***	1.669 (4.17) ***		0.041 (0.49)		3.79%
		Electronic	-0.942 (-7.76) ***	0.171 (4.04) ***	0.715 (9.51) ***	2.891 (6.65) ***	1.928 (6.30) ***	1.267 (5.53) ***		-0.048 (-0.93)		2.41%
	W-stat.		1.51	0.03	13.56***	1.32	2.03	3.08*		2.95*		
	PIMPACT	*Floor*	-1.321 (-4.22) ***	0.158 (1.73) *	0.439 (4.96) ***	2.558 (3.97) ***	2.250 (3.67) ***	1.772 (4.45) ***			-0.006 (-0.09)	3.94%
		Electronic	-0.936 (-7.03) ***	0.118 (1.85) *	0.674 (8.44) ***	2.698 (6.23) ***	2.014 (6.65) ***	1.252 (5.34) ***			-0.039 (-1.01)	2.40%
	W-stat.		8.35***	0.38	8.69***	0.10	0.61	4.94**			0.74	

Panel B (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.823 (-4.63) ***	0.032 (0.36)	0.212 (2.09) **	3.080 (2.99) ***	1.438 (1.70) *	1.941 (2.67) ***	0.083 (0.61)			4.47%
		Electronic	-0.303 (-1.55)	0.191 (2.09) **	0.483 (3.61) ***	3.526 (3.36) ***	0.988 (1.06)	1.469 (2.69) ***	0.137 (1.06)			7.72%
	W-stat.		7.10***	3.02*	4.09**	0.18	0.23	0.74	0.17			
	TOV	*Floor*	-0.755 (-4.10) ***	-0.071 (-1.02)	0.096 (1.06)	2.729 (2.88) ***	1.153 (1.40)	2.167 (3.12) ***		-0.207 (-3.38) ***		3.53%
		Electronic	-0.362 (-1.89) *	0.189 (2.13) **	0.446 (3.28) ***	4.041 (4.22) ***	1.731 (1.91) *	1.748 (3.36) ***		-0.149 (-2.42) **		7.70%
	W-stat.		4.23**	8.56***	6.65***	1.87	0.41	0.65		0.89		
	PIMPACT	*Floor*	-0.890 (-4.47) ***	0.095 (1.10)	0.217 (2.19) **	2.743 (2.90) ***	2.020 (2.50) **	1.965 (2.92) ***			0.138 (2.15) **	3.86%
		Electronic	-0.349 (-1.87) *	0.169 (1.95) *	0.441 (3.10) ***	4.816 (5.16) ***	1.220 (1.41)	1.664 (3.07) ***			-0.052 (-0.73)	7.41%
	W-stat.		8.33***	0.72	2.47	4.94**	0.85	0.31			7.00***	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.292 (-2.18) **	0.104 (2.10) **	0.262 (2.46) **	1.351 (2.61) ***	1.798 (4.43) ***	0.655 (2.26) **	0.052 (0.44)			3.51%
		Electronic	-0.362 (-1.31)	0.308 (1.42)	0.358 (2.09) **	1.645 (2.52) **	1.665 (2.74) ***	0.377 (0.85)	0.000 (0.00)			4.45%
	W-stat.		0.06	0.88	0.31	0.2	0.05	0.39	0.11			
	TOV	*Floor*	-0.327 (-1.88) *	-0.072 (-1.04)	0.308 (1.01)	-0.417 (-0.28)	0.358 (0.36)	1.227 (1.19)		-0.207 (-1.49)		3.43%
		Electronic	-0.656 (-3.48) ***	0.132 (2.51) **	0.373 (1.98) **	1.601 (1.99) **	2.052 (3.42) ***	0.511 (1.14)		-0.233 (-3.40) ***		4.86%
	W-stat.		3.04*	15.12***	0.12	6.32**	7.96***	2.56*		0.14		
	PIMPACT	*Floor*	-0.138 (-0.76)	0.079 (0.60)	0.415 (1.47)	-0.921 (-0.54)	0.744 (0.96)	1.063 (1.14)			0.046 (0.37)	3.04%
		Electronic	-0.526 (-2.73) ***	0.231 (2.06) **	0.314 (1.70) *	1.905 (2.40) **	2.099 (3.42) ***	0.506 (1.09)			0.115 (1.75) *	4.96%
	W-stat.		4.06**	1.85	0.30	12.65***	4.88**	1.43			1.09	

Panel C: Risk adjusted return is conditional on default spread (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.360 (-3.69) ***	-0.148 (-3.47) ***	0.490 (7.71) ***	1.843 (3.70) ***	1.447 (3.48) ***	1.085 (3.66) ***	-0.548 (-5.42) ***			2.41%
		Electronic	-0.705 (-6.45) ***	-0.035 (-0.76)	0.844 (9.29) ***	2.325 (5.48) ***	1.639 (4.78) ***	0.939 (4.07) ***	-0.273 (-2.73) ***			2.26%
	W-stat.		9.96***	5.84**	15.20***	1.29	0.31	0.40	7.61***			
	TOV	*Floor*	-1.072 (-5.70) ***	0.147 (3.25) ***	0.556 (6.11) ***	2.509 (3.69) ***	2.282 (3.41) ***	1.865 (4.00) ***		0.019 (0.21)		4.46%
		Electronic	-0.796 (-5.93) ***	0.108 (2.15) **	0.849 (9.92) ***	2.530 (5.44) ***	1.585 (4.98) ***	0.896 (3.58) ***		-0.008 (-0.14)		2.39%
	W-stat.		4.22**	0.58	11.70***	0.00	4.80	14.99***		0.23		
	PIMPACT	*Floor*	-1.196 (-3.81) ***	0.117 (1.28)	0.519 (5.77) ***	2.513 (3.56) ***	2.244 (3.35) ***	1.813 (3.71) ***			-0.017 (-0.23)	4.40%
		Electronic	-0.774 (-5.42) ***	0.045 (0.62)	0.822 (8.85) ***	2.261 (4.66) ***	1.688 (5.29) ***	0.979 (4.12) ***			-0.055 (-1.40)	2.36%
	W-stat.		8.73***	0.99	10.64***	0.27	3.04*	12.35***			0.94	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.829 (-4.39) ***	0.067 (0.73)	0.354 (2.81) ***	3.127 (2.85) ***	2.211 (2.13) **	1.953 (2.52) **	0.243 (1.53)			5.34%
		Electronic	-0.223 (-0.98)	0.050 (0.47)	0.404 (2.85) ***	3.165 (2.36) **	1.252 (1.06)	1.274 (1.94) *	0.125 (0.88)			8.54%
	W-stat.		7.11***	0.03	0.12	0.00	0.65	1.06	0.68			
	TOV	*Floor*	-0.964 (-4.91) ***	-0.079 (-1.10)	0.313 (2.88) ***	2.492 (2.28) **	1.866 (2.11) **	1.786 (2.31) **		-0.233 (-3.47) ***		4.55%
		Electronic	-0.217 (-0.96)	0.052 (0.51)	0.474 (3.32) ***	3.939 (3.46) ***	2.002 (1.84) *	1.121 (1.46)		-0.106 (-1.63)		9.30%
	W-stat.		10.93***	1.68	1.27	1.61	0.02	0.76		3.80*		
	PIMPACT	*Floor*	-0.891 (-3.96) ***	0.101 (1.10)	0.382 (3.38) ***	2.761 (2.38) **	2.234 (2.49) **	1.819 (2.34) **			0.148 (2.02) **	4.59%
		Electronic	-0.188 (-0.86)	0.036 (0.40)	0.460 (3.09) ***	4.416 (4.03) ***	1.732 (1.62)	1.616 (2.57) **			-0.051 (-0.73)	8.20%
	W-stat.		10.36***	0.51	0.28	2.28	0.22	0.10			7.97***	

Panel C (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.193 (-1.16)	0.098 (1.69) *	0.437 (3.53) ***	1.265 (2.39) **	1.825 (4.16) ***	0.747 (2.39) **	0.066 (0.56)			3.73%
		Electronic	-0.361 (-1.11)	0.445 (1.38)	0.639 (3.09) ***	2.049 (3.06) ***	1.374 (2.02) **	0.323 (0.68)	-0.067 (-0.43)			4.97%
	W-stat.		0.27	1.15	0.96	1.37	0.44	0.80	0.74			
	TOV	*Floor*	-0.249 (-1.32)	-0.070 (-1.10)	0.630 (2.20) **	0.582 (0.52)	1.345 (1.55)	1.052 (1.08)		-0.241 (-1.73) *		3.34%
		Electronic	-0.500 (-2.18) **	0.103 (1.45)	0.616 (3.06) ***	1.876 (2.39) **	1.542 (2.39) **	0.365 (0.81)		-0.220 (-2.91) ***		4.98%
	W-stat.		1.19	5.95**	0.01	2.73*	0.09	2.33		0.08		
	PIMPACT	*Floor*	0.008 (0.04)	0.074 (0.43)	0.685 (2.17) **	-0.155 (-0.11)	1.348 (1.66) *	1.411 (1.19)			0.078 (0.58)	4.04%
		Electronic	-0.471 (-1.95) *	0.200 (1.60)	0.562 (2.62) ***	1.748 (2.18) **	1.692 (2.59) **	0.467 (0.98)			0.095 (1.35)	5.36%
	W-stat.		3.95**	1.02	0.33	5.66**	0.28	3.95**			0.05	

Panel D: Risk adjusted return is conditional on size, BM and default spread (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.464 (-6.04) ***	-0.096 (-2.60) ***	0.231 (4.56) ***	2.008 (4.00) ***	1.714 (4.05) ***	1.220 (4.89) ***	-0.426 (-4.97) ***			2.63%
		Electronic	-0.764 (-9.32) ***	-0.035 (-0.86)	0.552 (8.45) ***	2.719 (7.16) ***	1.935 (6.38) ***	1.280 (5.46) ***	-0.435 (-5.70) ***			2.55%
	W-stat.		13.40***	2.28	24.13***	3.51*	0.53	0.07	0.01			
	TOV	*Floor*	-0.998 (-6.36) ***	0.150 (3.61) ***	0.318 (4.36) ***	1.976 (3.33) ***	2.547 (4.40) ***	1.491 (4.05) ***		0.028 (0.37)		4.14%
		Electronic	-0.909 (-9.23) ***	0.211 (5.99) ***	0.544 (8.60) ***	2.604 (6.11) ***	1.765 (6.24) ***	1.266 (5.45) ***		-0.082 (-1.80) *		2.56%
	W-stat.		0.81	2.97*	12.74***	2.17	7.66***	0.94		5.84**		
	PIMPACT	*Floor*	-1.074 (-4.24) ***	0.114 (1.49)	0.347 (4.34) ***	2.107 (3.55) ***	2.506 (4.56) ***	1.580 (4.23) ***			-0.010 (-0.15)	4.17%
		Electronic	-1.021 (-9.30) ***	0.176 (3.24) ***	0.577 (8.49) ***	2.706 (6.02) ***	1.989 (7.72) ***	1.199 (4.95) ***			-0.017 (-0.52)	2.65%
	W-stat.		0.23	1.27	11.46***	1.78	4.03**	2.47			0.04	

Panel D (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.882 (-6.02) ***	0.012 (0.16)	0.185 (2.31) **	3.074 (3.09) ***	1.719 (2.06) **	2.177 (3.27) ***	-0.066 (-0.69)			4.69%
		Electronic	-0.263 (-1.69) *	0.150 (1.79) *	0.412 (3.61) ***	3.881 (4.89) ***	1.049 (1.54)	1.426 (2.74) ***	0.037 (0.37)			7.71%
	W-stat.		15.86***	2.71*	3.94**	1.03	0.97	2.08	1.06			
	TOV	*Floor*	-0.868 (-5.76) ***	0.033 (0.54)	0.129 (1.65)*	2.430 (2.62) **	1.152 (1.64)	2.438 (3.93) ***		-0.166 (-3.71) ***		4.11%
		Electronic	-0.324 (-2.11) **	0.215 (2.68) ***	0.367 (3.12) ***	4.184 (4.95) ***	1.553 (2.05) **	1.629 (3.54) ***		-0.102 (-2.02) **		7.82%
	W-stat.		12.60***	5.15**	4.09**	4.30**	0.28	3.10*		1.60		
	PIMPACT	*Floor*	-1.006 (-5.68) ***	0.128 (1.71) *	0.250 (3.24) ***	2.613 (2.89) ***	1.673 (2.24) **	2.094 (3.69) ***			0.068 (1.26)	3.99%
		Electronic	-0.134 (-0.90)	0.097 (1.17)	0.335 (2.62) **	4.998 (6.08) ***	0.993 (1.48)	1.247 (2.28) **			-0.100 (-1.67) *	8.22%
	W-stat.		34.06***	0.14	0.44	8.41***	1.03	2.40			7.79***	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.305 (-2.62) ***	0.124 (2.98) ***	0.217 (2.16) **	1.290 (2.64) ***	1.379 (3.47) ***	0.724 (3.00) ***	0.032 (0.29)			3.47%
		Electronic	-0.007 (-0.02)	-0.016 (-0.09)	0.417 (2.67) ***	2.010 (3.29) ***	1.805 (3.12) ***	0.542 (1.36)	0.037 (0.28)			4.37%
	W-stat.		0.73	0.64	1.64	1.39	0.54	0.21	0.00			
	TOV	*Floor*	-0.453 (-3.29) ***	0.029 (0.57)	0.340 (1.67) *	0.533 (0.46)	1.029 (1.45)	0.685 (1.58)		-0.216 (-1.97) *		3.14%
		Electronic	-0.606 (-3.77) ***	0.115 (2.39) **	0.345 (2.02) **	1.114 (1.47)	1.867 (3.36) ***	0.605 (1.58)		-0.217 (-3.33) ***		4.57%
	W-stat.		0.90	3.20*	0.00	0.58	2.27	0.04		0.00		
	PIMPACT	*Floor*	-0.082 (-0.44)	0.084 (0.75)	0.504 (2.16) **	-0.607 (-0.45)	0.729 (0.96)	1.026 (1.32)			0.031 (0.29)	3.23%
		Electronic	-0.470 (-2.66) ***	0.190 (1.96) *	0.232 (1.40)	1.935 (2.69) ***	1.669 (2.98) ***	0.654 (1.62) *			0.069 (1.23)	4.76%
	W-stat.		4.82**	1.19	2.69	12.53***	2.82*	0.85			0.46	

Table 3.9
Statistics of individual coefficients of market liquidity risk factors estimated by conditional asset pricing model with time-varying alpha

Among the other risk factors and control factors, this table reports the cross-sectional average of the time-series slope coefficients of market-wide liquidity risk factors with their associated t-statistics. These coefficients are estimated by running the first-pass time-series regression (Eq. (3.12)) for each firm during the floor trading period and the electronic trading period. Liquidity risk factors include PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. "Pos" reports the percentage of positive slope coefficients, while "Sig" gives the percentage of the coefficients that are significant at 10% of significance or higher. The last three columns present the difference in the mean between electronic and floor trading systems with the t-value and p-value of the null hypothesis that the difference in the mean is equal to zero.

Panel A: Unconditional asset pricing model.

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**p-value**
London Stock Exchange (LSE)	**PQSPR**	-0.005	(-3.20)	45	25	-0.025	(-11.81)	38	17	-0.020	(-7.21)	0.000
	TOV	-3.83E-04	(-0.34)	47	12	0.006	(4.45)	50	15	0.007	(3.66)	0.000
	PIMPACT	-0.002	(-0.56)	51	13	-0.004	(-4.37)	43	17	-0.002	(-0.70)	0.483
Swiss Stock Exchange (SSE)	**PQSPR**	-0.015	(-6.44)	32	17	-0.011	(-6.30)	31	16	0.004	(1.44)	0.151
	TOV	0.021	(7.62)	73	20	0.004	(0.90)	52	11	-0.018	(-3.76)	0.000
	PIMPACT	-0.037	(-4.42)	35	25	-0.038	(-5.26)	34	22	-0.001	(-0.10)	0.921
Frankfurt Stock Exchange (FSE)	**PQSPR**	-0.011	(-4.53)	42	14	2.77E-06	(0.00)	50	12	0.011	(4.12)	0.000
	TOV	0.030	(10.03)	61	19	0.035	(7.73)	57	16	0.005	(0.92)	0.359
	PIMPACT	-4.53E-04	(-2.12)	44	15	-2.63E-05	(-1.08)	46	11	4.27E-04	(1.88)	0.061

Panel B: Conditional asset pricing model, Beta varies with Size and BM.

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**p-value**
London Stock Exchange (LSE)	**PQSPR**	-0.213	(-0.56)	48	16	-0.025	(-0.58)	46	16	0.188	(0.55)	0.584
	TOV	-0.360	(-2.04)	48	14	0.023	(1.09)	52	16	0.383	(2.41)	0.016
	PIMPACT	-0.064	(-0.15)	50	17	0.017	(0.83)	48	17	0.081	(0.21)	0.830
Swiss Stock Exchange (SSE)	**PQSPR**	-0.145	(-1.31)	41	16	-0.220	(-1.84)	45	15	-0.075	(-0.46)	0.646
	TOV	0.202	(2.95)	64	20	0.036	(0.46)	51	15	-0.167	(-1.61)	0.107
	PIMPACT	-0.232	(-1.20)	47	16	-0.391	(-1.25)	45	18	-0.159	(-0.43)	0.667
Frankfurt Stock Exchange (FSE)	**PQSPR**	0.144	(1.44)	48	15	-0.015	(-0.97)	50	14	-0.159	(-1.36)	0.174
	TOV	-0.117	(-1.14)	52	17	0.149	(1.61)	53	18	0.266	(1.85)	0.064
	PIMPACT	0.006	(0.89)	48	19	-0.002	(-1.37)	47	16	-0.008	(-0.97)	0.332

Panel C: Conditional asset pricing model, Beta varies with default spread (Business cycle variable).

Sock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.029	(-1.94)	44	17	-0.017	(-2.62)	47	12	0.013	(0.79)	0.427
	TOV	0.010	(1.48)	51	13	0.034	(6.80)	56	13	0.024	(2.95)	0.003
	PIMPACT	-0.006	(-0.33)	48	17	-8.82E-05	(-0.02)	50	13	0.006	(0.33)	0.738
Swiss Stock Exchange (SSE)	PQSPR	-0.002	(-0.44)	48	10	-0.002	(-0.36)	45	13	0.000	(0.03)	0.978
	TOV	-0.009	(-1.11)	49	18	0.023	(2.47)	65	18	0.032	(2.61)	0.009
	PIMPACT	0.058	(2.33)	61	12	-0.063	(-4.48)	23	22	-0.120	(-3.95)	0.000
Frankfurt Stock Exchange (FSE)	PQSPR	-0.012	(-2.03)	45	12	-0.001	(-0.57)	48	12	0.011	(1.67)	0.096
	TOV	0.052	(7.54)	58	16	0.091	(7.51)	62	17	0.039	(2.90)	0.004
	PIMPACT	-0.002	(-1.57)	43	15	7.94E-05	(0.39)	44	15	0.002	(1.54)	0.125

Panel D: Conditional asset pricing model, Beta varies with Size, BM and Default spread (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	0.156	(0.14)	50	15	0.325	(0.90)	50	14	0.169	(0.16)	0.871
	TOV	0.191	(0.51)	50	15	0.055	(0.25)	51	15	-0.136	(-0.33)	0.739
	PIMPACT	-0.284	(-0.26)	50	15	0.083	(0.45)	50	14	0.367	(0.38)	0.704
Swiss Stock Exchange (SSE)	PQSPR	0.599	(1.87)	55	14	-0.691	(-0.19)	53	18	-1.290	(-0.34)	0.733
	TOV	0.184	(0.31)	48	13	-5.950	(-0.78)	45	17	-6.134	(-0.78)	0.433
	PIMPACT	-0.873	(-0.78)	53	17	-22.976	(-1.59)	51	16	-22.100	(-1.49)	0.137
Frankfurt Stock Exchange (FSE)	PQSPR	0.254	(1.06)	50	16	-0.011	(-0.14)	49	18	-0.265	(-0.92)	0.356
	TOV	0.025	(0.10)	50	17	0.296	(0.86)	56	14	0.271	(0.67)	0.505
	PIMPACT	-0.045	(-1.42)	44	14	0.003	(1.00)	50	17	0.048	(1.31)	0.191

Table 3.10

Fama-MacBeth estimates with Fama-French factors and liquidity as risk factor and time-varying alpha

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficient estimates (Eq. (3.14)) for all securities in the UK, Switzerland and Germany. Panel A presents the estimates when the dependent variable is the risk-adjusted return using the unconditional Fama-French model augmented with liquidity factor. In panel B the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with firm characteristics (i.e. size and book-to-market ratio). In panel C the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with business cycle variables default spread. In panel D the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variable default spread. Liq. Risk Factor is the liquidity risk factor added to Fama-French three factor model, PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. *Floor* and *electronic* in the third column in each panel refers to the estimation done during the floor trading system and electronic trading system respectively. Size represents the logarithm of market capitalization; BM is the logarithm of book-to-market ratio; RET2-3, RET4-6, RET7-12 are the past cumulative raw returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month; Prop. Bid-ask is the proportional bid-ask spread calculated as the quoted bid-ask spread divided by the midpoint of the quoted bid-ask spread; Turnover is the turnover ratio measures as the trading value divided by the market capitalization; Price impact is the ratio of absolute return divided by the trading value. $\overline{R^2}$ is the time-series average of the monthly adjusted R^2. T-statistic (reported in parenthesis) are adjusted for autocorrelation and heteroscedasticity. W-stat. is the Wald test statistic. All coefficients are multiplied by 100. *, **, *** denotes significance at the 10, 5, 1% level.

Panel A: Risk adjusted return is unconditional.

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	0.367 (1.52)	-0.394 (-4.53) ***	1.640 (7.36) ***	1.683 (0.83)	0.968 (0.57)	-0.015 (-0.01)	1.054 (3.18) ***			8.53%
		Electronic	2.739 (12.5) ***	-0.177 (-0.74)	1.418 (4.39) ***	1.000 (0.21)	0.798 (0.18)	0.168 (0.04)	0.259 (0.52)			9.02%
	W-stat.		117.26***	0.84	0.47	0.02	0.00	0.00	2.50			
	TOV	*Floor*	-0.396 (-1.17)	-0.469 (-4.18) ***	1.688 (6.99) ***	1.657 (0.8)	0.256 (0.15)	-0.834 (-0.56)		-0.351 (-1.57)		8.72%
		Electronic	0.939 (3.82) ***	-0.206 (-0.85)	1.281 (3.96) ***	0.613 (0.13)	0.463 (0.11)	-0.338 (-0.08)		0.241 (0.98)		9.31%
	W-stat.		29.46***	1.17	1.59	0.05	0.00	0.01		5.84**		
	PIMPACT	*Floor*	-1.774 (-2.31) **	-0.443 (-1.74) *	1.697 (6.36) ***	2.073 (1.05)	0.633 (0.36)	-0.823 (-0.53)			-0.063 (-0.31)	8.80%
		Electronic	1.643 (5.93) ***	-0.067 (-0.20)	2.167 (5.62) ***	1.119 (0.22)	0.990 (0.22)	0.310 (0.07)			-0.151 (-0.93)	9.10%
	W-stat.		152.24***	1.23	1.49	0.04	0.01	0.07			0.29	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.578 (32.39) ***	0.048 (0.45)	0.980 (5.21) ***	4.996 (1.78) *	3.019 (1.04)	3.329 (1.66)*	1.141 (4.26) ***			8.77%
		Electronic	3.530 (14.81) ***	-1.166 (-8.64) ***	-2.128 (-6.12) ***	-0.915 (-0.25)	-1.073 (-0.30)	4.855 (1.67) *	-0.499 (-2.14) **			17.35%
	W-stat.		73.82***	80.77***	79.82***	2.57	1.27	0.27	49.34***			
	TOV	*Floor*	4.391 (21.37) ***	-0.397 (-2.89) ***	1.050 (5.56) ***	4.288 (1.68) *	2.569 (1.02)	1.798 (0.86)		-1.116 (-7.85) ***		9.33%
		Electronic	4.358 (16.48) ***	-1.425 (-9.38) ***	-2.353 (-6.25) ***	0.412 (0.11)	-0.317 (-0.09)	6.073 (2.09) **		-0.496 (-3.17) ***		18.08%
	W-stat.		0.01	45.80***	81.62***	1.04	0.60	2.16		15.68***		
	PIMPACT	*Floor*	3.803 (15.78) ***	0.745 (6.29) ***	0.903 (4.99) ***	5.026 (1.94) *	3.833 (1.53)	1.820 (0.91)			1.212 (10.34) ***	8.70%
		Electronic	3.377 (13.18) ***	-0.956 (-5.56) ***	-1.958 (-5.55) ***	1.265 (0.36)	-0.554 (-0.16)	5.224 (1.86) *			0.302 (2.57) **	17.21%
	W-stat.		2.76*	97.93***	65.83***	1.16	1.51	1.47			59.74***	

Panel A (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-3.407 (-11.23) ***	0.732 (5.20) ***	0.444 (2.65) ***	2.094 (0.91)	2.780 (1.29)	3.607 (1.98) **	2.983 (8.75) ***			7.02%
		Electronic	-4.228 (-6.05) ***	2.640 (6.35) ***	3.124 (7.44) ***	1.901 (0.96)	1.404 (0.83)	2.602 (1.60)	5.715 (14.51) ***			10.02%
	W-stat.		1.38	21.07***	40.68***	0.01	0.66	0.38	48.14***			
	TOV	*Floor*	-5.339 (-9.67) ***	-0.360 (-1.99) **	1.804 (2.07) **	0.039 (0.01)	4.858 (1.36)	8.046 (3.04) ***		-2.371 (-8.62) ***		8.81%
		Electronic	-5.106 (-13.8) ***	1.332 (10.12) ***	3.520 (8.33) ***	1.323 (0.64)	1.559 (0.84)	3.169 (1.91) *		-2.749 (-15.72) ***		10.62%
	W-stat.		0.40	165.35***	16.47***	0.38	3.14*	8.65***		4.68**		
	PIMPACT	*Floor*	-3.856 (-9.79) ***	1.676 (8.45) ***	1.944 (2.18) **	-1.498 (-0.38)	4.151 (1.21)	8.349 (3.00) ***			1.558 (7.15) ***	8.42%
		Electronic	-5.429 (-16.06) ***	4.158 (23.15) ***	3.462 (8.07) ***	2.055 (0.97)	2.014 (1.07)	3.664 (2.14) **			2.305 (15.82) ***	10.78%
	W-stat.		21.65***	190.88***	12.52***	2.81*	1.29	7.48***			26.33***	

Panel B: Risk adjusted return is conditional on size and BM.

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	0.955 (3.00) ***	-0.229 (-0.93)	1.689 (4.76) ***	8.956 (1.54)	8.354 (1.63)	3.504 (1.09)	2.700 (2.68) ***			6.12%
		Electronic	1.662 (3.83) ***	0.095 (0.38)	2.728 (6.07) ***	2.142 (0.43)	1.080 (0.22)	2.562 (0.60)	0.237 (0.36)			5.10%
	W-stat.		2.65*	1.71	5.35**	1.85	2.23	0.05	13.75***			
	TOV	*Floor*	0.046 (0.05)	-1.020 (-3.87) ***	1.478 (2.97) ***	-0.354 (-0.06)	10.571 (1.27)	5.519 (0.85)		-0.238 (-0.38)		6.91%
		Electronic	1.298 (2.93) ***	-0.458 (-1.59)	0.930 (2.11) **	-3.456 (-0.66)	-1.130 (-0.23)	0.908 (0.21)		0.641 (2.34) **		5.89%
	W-stat.		8.00***	3.82	1.54	0.35	5.60**	1.14		10.28***		
	PIMPACT	*Floor*	-0.099 (-0.10)	-1.405 (-2.84) ***	1.164 (4.51) ***	0.091 (0.03)	-0.867 (-0.39)	-2.664 (-1.37)			-0.681 (-1.88) *	6.42%
		Electronic	1.814 (4.59) ***	-0.325 (-1.15)	2.820 (8.73) ***	-0.283 (-0.06)	1.044 (0.22)	2.002 (0.48)			-0.408 (-2.38) **	5.31%
	W-stat.		23.39***	14.68***	26.25***	0.01	0.16	1.26			2.55	

Panel B (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.977 (32.69) ***	-0.225 (-1.72) *	-0.137 (-1.02)	3.021 (1.00)	-1.062 (-0.32)	-0.388 (-0.16)	0.812 (2.75) ***			8.69%
		Electronic	1.695 (6.25) ***	0.437 (1.35)	-0.762 (-2.41) **	-0.647 (-0.17)	-0.740 (-0.20)	4.357 (1.76) *	-0.568 (-1.43)			13.62%
	W-stat.		249.15***	4.16**	3.91**	0.91	0.01	3.67*	12.14***			
	TOV	*Floor*	5.660 (31.62) ***	-0.614 (-5.47) ***	-0.082 (-0.60)	2.757 (0.98)	0.272 (0.09)	-0.166 (-0.07)		-0.639 (-4.50) ***		6.35%
		Electronic	1.706 (6.22) ***	-0.206 (-0.64)	-0.641 (-2.26) **	1.359 (0.31)	1.411 (0.33)	7.287 (2.80) ***		-1.822 (-8.32) ***		14.97%
	W-stat.		207.81***	1.61	3.90**	0.10	0.07	8.17***		29.21***		
	PIMPACT	*Floor*	4.753 (20.06) ***	0.678 (5.01) ***	-0.474 (-3.75) ***	2.127 (0.77)	-0.001 (0.00)	-2.335 (-1.08)			0.926 (7.23) ***	5.42%
		Electronic	0.982 (3.10) ***	1.126 (3.04) ***	0.131 (0.46)	0.709 (0.18)	-0.002 (0.00)	5.262 (2.38) **			0.748 (5.38) ***	12.50%
	W-stat.		141.55***	1.46	4.48**	0.13	0.00	11.80***			1.64	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-2.180 (-11.50) ***	0.713 (5.96) ***	1.284 (5.32) ***	2.739 (1.22)	3.915 (1.81) *	4.844 (2.90) ***	3.987 (12.27) ***			5.98%
		Electronic	-2.080 (-3.45) ***	1.914 (4.97) ***	4.589 (10.15) ***	3.229 (1.66) *	3.343 (1.96) *	3.347 (2.23) **	5.505 (14.25) ***			10.88%
	W-stat.		0.03	9.71***	53.46***	0.06	0.11	1.00	15.44***			
	TOV	*Floor*	-4.772 (-11.41) ***	-0.629 (-3.16) ***	1.911 (1.90) *	1.598 (0.45)	6.508 (1.91) *	9.880 (3.71) ***		-2.486 (-9.96) ***		6.96%
		Electronic	-2.298 (-5.07) ***	0.464 (2.49) **	5.015 (9.23) ***	2.618 (1.30)	3.616 (1.90) *	3.789 (2.54) **		-2.424 (-21.78) ***		9.85%
	W-stat.		29.78***	34.38***	32.61***	0.25	2.3	16.62***		0.31		
	PIMPACT	*Floor*	-3.094 (-12.44) ***	1.549 (7.85) ***	2.067 (2.25) **	-0.754 (-0.20)	4.564 (1.47)	8.367 (3.48) ***			1.751 (8.33) ***	6.30%
		Electronic	-3.080 (-7.64) ***	3.110 (14.56) ***	3.314 (6.84) ***	4.005 (1.92) *	3.660 (1.95) *	3.304 (2.19) **			2.017 (18.12) ***	8.55%
	W-stat.		0.00	53.38***	6.62***	5.22**	0.23	11.22***			5.73**	

Panel C: Risk adjusted return is conditional on default spread (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	0.991 (3.96) ***	-0.528 (-6.61) ***	1.512 (7.00) ***	1.093 (0.54)	0.666 (0.38)	-0.486 (-0.33)	1.439 (4.64) ***			9.26%
		Electronic	3.180 (11.97) ***	-0.155 (-0.56)	0.955 (2.78) ***	0.244 (0.05)	0.327 (0.07)	0.353 (0.08)	0.121 (0.24)			8.23%
	W-stat.		67.93***	1.84	2.62	0.03	0.01	0.04	6.95***			
	TOV	*Floor*	-0.343 (-1.00)	-0.474 (-3.99) ***	1.694 (6.75) ***	1.020 (0.47)	0.263 (0.15)	-1.394 (-0.91)		-0.403 (-1.76) *		9.19%
		Electronic	1.379 (6.28) ***	-0.085 (-0.36)	1.037 (3.05) ***	0.072 (0.01)	-0.100 (-0.02)	-0.253 (-0.06)		0.293 (1.29)		8.85%
	W-stat.		61.50***	2.73*	3.74*	0.04	0.01	0.07		9.41***		
	PIMPACT	*Floor*	-1.507 (-1.86) *	-0.415 (-1.54)	1.876 (6.49) ***	1.417 (0.68)	0.287 (0.16)	-1.412 (-0.88)			0.051 (0.25)	9.40%
		Electronic	2.361 (8.69) ***	-0.061 (-0.20)	1.570 (3.83) ***	0.372 (0.07)	0.391 (0.08)	0.230 (0.05)			-0.096 (-0.65)	8.76%
	W-stat.		202.54***	1.32	0.55	0.04	0.00	0.13			0.98	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.754 (32.71) ***	-0.177 (-1.62)	0.974 (5.90) ***	4.956 (1.85) *	2.505 (0.83)	2.834 (1.31)	0.965 (3.26) ***			9.31%
		Electronic	4.097 (17.18) ***	-1.371 (-9.74) ***	-2.367 (-6.31) ***	-0.954 (-0.25)	-1.334 (-0.35)	5.893 (2.01) **	-0.625 (-2.62) **			16.77%
	W-stat.		48.25***	71.89***	79.22***	2.36	1.02	1.09	44.33***			
	TOV	*Floor*	5.343 (27.49) ***	-0.505 (-3.75) ***	1.048 (6.17) ***	3.681 (1.43)	2.400 (0.90)	1.421 (0.63)		-0.957 (-6.85) ***		9.55%
		Electronic	4.438 (16.03) ***	-1.537 (-9.60) ***	-2.515 (-6.04) ***	0.214 (0.05)	-0.449 (-0.11)	6.378 (2.13) **		-0.597 (-3.83) ***		18.47%
	W-stat.		10.69***	41.56***	73.17**	0.75	0.51	2.73*		5.32**		
	PIMPACT	*Floor*	5.523 (22.92) ***	0.368 (3.12) ***	1.014 (6.29) ***	5.054 (1.96) *	3.697 (1.35)	1.529 (0.68)			0.880 (6.94) ***	9.00%
		Electronic	4.312 (13.14) ***	-0.906 (-4.96) ***	-2.434 (-5.30) ***	0.803 (0.21)	-1.154 (-0.30)	6.591 (2.27) **			0.628 (5.19) ***	17.28%
	W-stat.		13.64***	48.58***	56.49***	1.19	1.63	3.03*			4.36**	

Panel C (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-2.980 (-10.15) ***	0.794 (5.82) ***	0.237 (1.44)	1.414 (0.62)	2.317 (1.10)	3.312 (1.85) *	3.066 (8.83) ***			6.68%
		Electronic	-3.243 (-3.53) ***	1.846 (2.78) ***	2.369 (5.74) ***	2.148 (1.04)	1.500 (0.83)	2.134 (1.32)	5.077 (14.40) ***			8.76%
	W-stat.		0.08	2.51	26.65***	0.13	0.21	0.53	32.54***			
	TOV	*Floor*	-5.630 (-12.14) ***	-0.206 (-1.14)	1.513 (1.77) *	0.464 (0.14)	4.426 (1.32)	7.101 (3.03) ***		-2.345 (-8.65) ***		9.02%
		Electronic	-5.792 (-15.52) ***	1.486 (10.84) ***	3.357 (8.05) ***	1.661 (0.78)	1.443 (0.77)	2.669 (1.61)		-2.468 (-14.68) ***		10.19%
	W-stat.		0.19	152.29***	19.57***	0.32	2.56	7.14***		0.53		
	PIMPACT	*Floor*	-3.552 (-8.45) ***	1.571 (8.04) ***	1.589 (1.69) *	-1.851 (-0.48)	4.182 (1.14)	8.244 (2.89) ***			1.431 (6.50) ***	7.66%
		Electronic	-4.091 (-13.17) ***	3.464 (18.65) ***	2.931 (6.73) ***	2.473 (1.11)	2.000 (1.03)	3.670 (2.17) **			2.013 (15.08) ***	9.36%
	W-stat.		3.01*	103.89***	9.49***	3.77*	1.25	7.31***			18.97***	

Panel D: Risk adjusted return is conditional on size, BM and default spread (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.070 (-0.24)	0.295 (1.02)	1.840 (3.34) ***	-2.136 (-0.62)	-3.720 (-1.12)	-0.818 (-0.30)	2.216 (2.86) ***			4.31%
		Electronic	2.925 (5.02) ***	1.310 (3.02) ***	1.895 (3.09) ***	0.037 (0.01)	0.621 (0.11)	1.156 (0.25)	2.636 (2.99) ***			3.38%
	W-stat.		26.39***	5.49**	0.01	0.13	0.62	0.18	0.23			
	TOV	*Floor*	0.510 (1.04)	-0.487 (-3.19) ***	2.020 (3.72) ***	0.445 (0.11)	-1.916 (-0.51)	-1.800 (-0.61)		-0.188 (-0.47)		6.57%
		Electronic	0.065 (0.23)	0.166 (0.56)	1.751 (4.61) ***	-1.314 (-0.24)	-0.049 (-0.01)	1.722 (0.36)		0.094 (0.32)		3.87%
	W-stat.		2.52	4.92**	0.50	0.10	0.12	0.56		0.95		
	PIMPACT	*Floor*	-2.058 (-1.72) *	-0.028 (-0.07)	2.699 (4.45) ***	0.955 (0.32)	0.014 (0.00)	0.485 (0.23)			0.429 (1.36)	8.06%
		Electronic	1.212 (3.91) ***	-0.791 (-1.33)	2.532 (6.68) ***	2.598 (0.43)	4.532 (0.75)	5.404 (1.02)			-0.940 (-2.72) ***	3.24%
	W-stat.		111.00***	1.65	0.19	0.07	0.56	0.86			15.75***	

Panel D (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.851 (38.13) ***	0.011 (0.09)	0.061 (0.28)	4.274 (1.29)	1.472 (0.46)	1.265 (0.54)	1.504 (5.77) ***			5.84%
		Electronic	2.741 (6.14) ***	1.203 (1.51)	2.725 (2.11) **	24.027 (2.37) **	16.377 (2.00) **	22.938 (3.67) ***	6.241 (3.66) ***			8.51%
	W-stat.		48.47***	2.25	4.25**	3.79*	3.30*	12.01***	7.72***			
	TOV	*Floor*	4.558 (25.79) ***	-0.304 (-2.43) **	0.808 (3.76) ***	2.852 (0.98)	1.735 (0.59)	0.831 (0.35)		-0.438 (-3.34) ***		4.48%
		Electronic	4.103 (11.54) ***	-1.942 (-6.93) ***	-0.977 (-2.16) **	7.365 (1.73) *	0.387 (0.09)	6.802 (2.15) **		0.407 (0.99)		7.50%
	W-stat.		1.64	34.20***	15.57***	1.13	0.10	3.56*		4.24**		
	PIMPACT	*Floor*	5.347 (24.7) ***	0.711 (5.11) ***	-0.060 (-0.36)	2.551 (1.00)	1.000 (0.35)	-1.335 (-0.60)			0.645 (5.03) ***	3.76%
		Electronic	2.983 (5.81) ***	0.916 (1.28)	0.898 (1.40)	17.022 (2.37) **	3.071 (0.50)	14.219 (2.94) ***			1.019 (1.89) *	8.45%
	W-stat.		21.24***	0.08	2.22	4.05**	0.11	10.35***			0.48	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-1.305 (-4.76) ***	0.732 (3.61) ***	0.457 (1.55)	1.425 (0.63)	2.554 (1.19)	3.742 (2.32) ***	4.077 (8.97) ***			3.97%
		Electronic	0.693 (0.62)	0.482 (0.51)	3.593 (6.88) ***	2.182 (1.04)	1.813 (0.95)	2.832 (1.82) *	4.867 (10.5) ***			8.11%
	W-stat.		3.17***	0.07	36.01***	0.13	0.15	0.34	2.90*			
	TOV	*Floor*	-3.788 (-10.37) ***	-0.797 (-4.74) ***	0.913 (1.05)	1.022 (0.34)	4.625 (1.64) *	6.787 (3.77) ***		-2.836 (-9.88) ***		4.79%
		Electronic	-1.272 (-3.14) ***	0.148 (0.80)	3.752 (6.63) ***	0.535 (0.24)	1.075 (0.55)	2.579 (1.58)		-2.012 (-12.81) ***		7.22%
	W-stat.		38.61***	26.01***	25.13***	0.05	3.27*	6.67***		27.48***		
	PIMPACT	*Floor*	-0.777 (-1.27)	1.150 (3.97) ***	0.613 (1.05)	-0.862 (-0.28)	1.348 (0.51)	5.703 (2.79) ***			1.659 (6.87) ***	0.01%
		Electronic	-0.801 (-2.00) **	2.965 (10.97) ***	2.870 (5.45) ***	2.686 (1.05)	1.700 (0.78)	3.229 (1.97) *			2.089 (11.68) ***	7.88%
	W-stat.		0.00	45.11***	18.37***	1.92	0.03	2.28			5.78**	

Appendix
Supplementary empirical information

Appendix 3A
The testable hypotheses, their acceptance or rejection, and the justification

Hypothesis	Status (accepted/ rejected)	The reason
H_1: In asset pricing aggregate market liquidity is a priced risk factor (i.e. has a significant positive effect on current stock's excess returns).	Accepted	Turnover ratio (proportional bid-ask spread and price impact) has a significant positive (negative) effect on current stock's excess returns.
H_2: Firm specific liquidity has an additional premium (i.e. firm-specific liquidity is negatively and significantly related to risk-adjusted returns) after controlling for all risk factors including the market-wide liquidity risk factor.	Accepted	Firm-specific turnover ratio (proportional bid-ask spread and price impact) has a significant negative (positive) effect on current stock's excess returns.
H_3: Pricing of aggregate market liquidity (i.e. the relationship between market liquidity and stock excess returns) is not different before the introduction of an electronic trading system than after the introduction of an electronic trading system.	Rejected	The size of the coefficients of market liquidity measures is significantly different across trading systems / some of the coefficients become significant or insignificant after the automation.
H_4: The premium on firm-specific liquidity is not different before the introduction of an electronic trading system than that after the introduction of an electronic trading system.	Rejected	The size of the coefficients of firm-specific liquidity measures is significantly different across trading systems / some of the coefficients become significant or insignificant after the automation.

Appendix 3B
Robust test: Statistics of individual coefficients of market liquidity risk factors estimated by conditional asset pricing model

Among the other risk factors and control factors, this table reports the cross-sectional average of the time-series slope coefficients of market-wide liquidity risk factors with their associated t-statistics. These coefficients are estimated by running the first-pass time-series regression (Eq. (3.12)) for each firm during the floor trading period and the electronic trading period. Liquidity risk factors include PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. "Pos" reports the percentage of positive slope coefficients, while "Sig" gives the percentage of the coefficients that are significant at 10% of significance or higher. The last three columns present the difference in the mean between electronic and floor trading systems with the t-value and p-value of the null hypothesis that the difference in the mean is equal to zero.

Panel C-1: Conditional asset pricing model, Beta varies with **term spread** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**p-value**
London Stock Exchange (LSE)	**PQSPR**	-0.026	(-6.25)	37	21	-0.022	(-6.63)	39	15	0.004	(0.83)	0.408
	TOV	-0.001	(-0.39)	47	14	0.011	(4.83)	53	17	0.012	(3.57)	0.000
	PIMPACT	-0.014	(-2.49)	48	15	-0.003	(-1.40)	46	16	0.011	(1.92)	0.055
Swiss Stock Exchange (SSE)	**PQSPR**	-0.011	(-3.83)	36	15	-0.026	(-4.02)	30	23	-0.015	(-2.26)	0.024
	TOV	0.020	(5.54)	69	23	-0.027	(-2.74)	40	13	-0.047	(-4.90)	0.000
	PIMPACT	-0.032	(-3.25)	44	15	-0.086	(-2.50)	39	24	-0.055	(-1.67)	0.095
Frankfurt Stock Exchange (FSE)	**PQSPR**	-0.022	(-3.97)	40	15	0.005	(2.16)	50	12	0.027	(4.33)	0.000
	TOV	0.025	(4.85)	58	18	0.009	(1.43)	49	14	-0.016	(-1.92)	0.055
	PIMPACT	-0.001	(-1.68)	46	13	3.10E-06	(0.06)	53	12	0.001	(1.58)	0.114

Panel C-2: Conditional asset pricing model, Beta varies with **yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**p-value**
London Stock Exchange (LSE)	**PQSPR**	-0.070	(-4.35)	39	20	0.009	(0.45)	47	13	0.079	(3.06)	0.002
	TOV	-0.027	(-2.79)	48	14	0.029	(1.75)	55	16	0.056	(2.86)	0.004
	PIMPACT	-0.037	(-1.81)	47	15	0.026	(2.70)	56	17	0.062	(2.84)	0.005
Swiss Stock Exchange (SSE)	**PQSPR**	0.014	(1.57)	60	12	-0.004	(-0.73)	51	14	-0.018	(-1.62)	0.106
	TOV	-0.020	(-2.08)	48	18	0.017	(1.60)	60	16	0.038	(2.58)	0.010
	PIMPACT	0.015	(0.53)	51	10	-0.047	(-3.17)	45	25	-0.062	(-1.80)	0.072
Frankfurt Stock Exchange (FSE)	**PQSPR**	0.005	(0.62)	54	13	-0.001	(-0.29)	50	13	-0.007	(-0.65)	0.513
	TOV	0.026	(2.28)	55	17	0.074	(4.11)	57	13	0.049	(2.33)	0.020
	PIMPACT	1.86E-04	(0.20)	47	15	8.46E-05	(0.66)	48	12	0.000	(-0.10)	0.918

Panel C-3: Conditional asset pricing model, Beta varies with **dividends yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.131	(-4.82)	39	22	-0.089	(-2.68)	44	14	0.041	(0.95)	0.343
	TOV	-0.004	(-0.23)	48	15	-0.015	(-0.66)	49	17	-0.011	(-0.38)	0.703
	PIMPACT	-0.080	(-2.10)	52	16	-0.020	(-1.41)	41	22	0.060	(1.51)	0.130
Swiss Stock Exchange (SSE)	PQSPR	0.013	(0.73)	56	22	0.018	(1.24)	58	12	0.005	(0.19)	0.849
	TOV	-0.039	(-1.74)	47	14	0.075	(3.28)	64	19	0.114	(3.53)	0.000
	PIMPACT	-0.246	(-3.94)	38	21	-0.057	(-0.91)	50	15	0.188	(2.09)	0.037
Frankfurt Stock Exchange (FSE)	PQSPR	0.001	(0.06)	48	15	0.010	(2.37)	53	18	0.009	(0.59)	0.552
	TOV	0.008	(0.42)	50	19	0.046	(1.28)	50	10	0.038	(0.97)	0.333
	PIMPACT	-0.003	(-2.40)	51	16	-1.26E-04	(-0.92)	50	18	0.003	(2.14)	0.032

Panel D-1: Conditional asset pricing model, Beta varies with **size, BM and term spread** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.237	(-0.55)	48	16	-0.346	(-1.21)	48	14	-0.109	(-0.22)	0.828
	TOV	0.283	(1.75)	52	14	0.364	(1.57)	52	15	0.081	(0.27)	0.788
	PIMPACT	-0.374	(-1.52)	50	17	-0.003	(-0.03)	49	16	0.371	(1.47)	0.142
Swiss Stock Exchange (SSE)	PQSPR	-0.129	(-0.78)	51	16	1.123	(0.94)	50	16	1.252	(1.03)	0.304
	TOV	0.154	(0.77)	57	15	-1.320	(-1.23)	45	19	-1.474	(-1.34)	0.182
	PIMPACT	-0.986	(-1.24)	50	16	2.167	(0.63)	53	18	3.154	(0.88)	0.377
Frankfurt Stock Exchange (FSE)	PQSPR	0.344	(0.81)	49	19	-0.023	(-0.43)	49	15	-0.367	(-0.74)	0.460
	TOV	-0.740	(-1.18)	50	16	-0.098	(-0.26)	50	19	0.643	(0.80)	0.421
	PIMPACT	-0.017	(-0.99)	48	15	0.001	(0.80)	48	19	0.018	(0.90)	0.368

Panel D-2: Conditional asset pricing model, Beta varies with **size, BM and yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-2.381	(-1.96)	50	15	-11.634	(-1.25)	50	15	-9.254	(-0.86)	0.390
	TOV	1.148	(1.15)	52	16	0.264	(0.29)	50	18	-0.884	(-0.65)	0.519
	PIMPACT	1.376	(0.45)	51	15	-1.352	(-1.10)	50	17	-2.729	(-0.91)	0.361
Swiss Stock Exchange (SSE)	PQSPR	1.010	(1.47)	56	16	-0.307	(-0.38)	47	12	-1.317	(-1.23)	0.218
	TOV	1.703	(1.65)	49	15	2.952	(1.21)	47	19	1.249	(0.47)	0.640
	PIMPACT	1.336	(0.79)	52	19	0.059	(0.02)	52	15	-1.278	(-0.44)	0.663
Frankfurt Stock Exchange (FSE)	PQSPR	-0.333	(-0.39)	48	16	0.064	(0.45)	51	15	0.396	(0.4)	0.692
	TOV	-1.982	(-0.87)	54	17	0.581	(0.55)	50	16	2.564	(0.91)	0.362
	PIMPACT	-4.15E-04	(-0.01)	48	14	-9.70E-05	(-0.04)	49	16	0.000	(0.00)	0.997

Panel D-3: Conditional asset pricing model, Beta varies with **size, BM and dividends yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-1.468	(-0.52)	51	15	-0.087	(-0.07)	50	14	1.380	(0.49)	0.627
	TOV	0.783	(0.63)	51	17	0.126	(0.12)	52	15	-0.656	(-0.41)	0.685
	PIMPACT	-1.532	(-0.74)	50	17	0.783	(0.77)	51	17	2.315	(1.08)	0.280
Swiss Stock Exchange (SSE)	PQSPR	-2.230	(-1.51)	49	20	-8.670	(-1.64)	44	13	-6.440	(-1.17)	0.244
	TOV	4.146	(1.84)	53	19	-11.583	(-1.87)	44	15	-15.730	(-2.37)	0.018
	PIMPACT	-4.203	(-0.55)	51	20	-16.212	(-1.5)	54	18	-12.010	(-0.91)	0.364
Frankfurt Stock Exchange (FSE)	PQSPR	-0.088	(-0.06)	52	16	-0.381	(-1.34)	51	15	-0.293	(-0.18)	0.855
	TOV	2.155	(0.66)	49	15	0.275	(0.14)	51	21	-1.880	(-0.45)	0.656
	PIMPACT	0.051	(0.44)	50	14	0.012	(1.50)	51	17	-0.039	(-0.29)	0.773

Appendix 3C

Robust Test: Fama-MacBeth estimates with Fama-French factors and liquidity as risk factor

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficient estimates (Eq. (3.14)) for all securities in the UK, Switzerland and Germany as a result of robust tests using different business cycle variables (such as term spread, short-term interest rate and dividends yield) as conditioning variables. Panel C-1, C-2, C-3 presents the estimates when the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with business cycle variables term spread, short-term interest rate and dividends yield respectively. In panel D-1, D-2, D-3 the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variable term spread, short-term interest rate and dividends yield respectively. Liq. Risk Factor is the liquidity risk factor added to Fama-French three factor model, PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. *Floor* and *electronic* in the third column in each panel refers to the estimation done during the floor trading system and electronic trading system respectively. Size represents the logarithm of market capitalization; BM is the logarithm of book-to-market ratio; RET2-3, RET4-6, RET7-12 are the past cumulative raw returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month; Prop. Bid-ask is the proportional bid-ask spread calculated as the quoted bid-ask spread divided by the midpoint of the quoted bid-ask spread; Turnover is the turnover ratio measures as the trading value divided by the market capitalization; Price impact is the ratio of absolute return divided by the trading value. $\overline{R^2}$ is the time-series average of the monthly adjusted R^2. T-statistic (reported in parenthesis) are adjusted for autocorrelation and heteroscedasticity. W-stat. is the Wald test statistic. All coefficients are multiplied by 100. *, **, *** denotes significance at the 10, 5, 1% level.

Panel C-1: Risk adjusted return is conditional on **term spread** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.355 (-3.62) ***	-0.148 (-3.39) ***	0.483 (7.79) ***	1.720 (3.23) ***	1.371 (3.23) ***	1.110 (3.8) ***	-0.598 (-5.96) ***			2.63%
		Electronic	-0.764 (-6.27) ***	-0.005 (-0.12)	0.867 (10.46) ***	2.590 (6.64) ***	1.432 (4.02) ***	1.111 (4.93) ***	-0.341 (-3.59) ***			2.32%
	W-stat.		11.27***	9.85***	21.40***	4.98**	0.03	0.00	7.29***			
	TOV	*Floor*	-0.985 (-5.45) ***	0.116 (2.52) **	0.565 (6.42) ***	2.508 (3.82) ***	2.074 (3.08) ***	1.925 (4.18) ***		0.055 (0.62)		4.31%
		Electronic	-0.864 (-6.13) ***	0.171 (3.52) ***	0.864 (10.66) ***	2.765 (5.83) ***	1.400 (4.18) ***	1.075 (4.71) ***		-0.039 (-0.72)		2.49%
	W-stat.		0.74	1.28	13.60***	0.29	4.03**	13.85***		3.00*		
	PIMPACT	*Floor*	-1.051 (-3.26) ***	0.078 (0.83)	0.523 (5.93) ***	2.274 (3.37) ***	1.997 (2.94) ***	1.795 (3.89) ***			-0.027 (-0.35)	3.96%
		Electronic	-0.891 (-6.00) ***	0.114 (1.64) *	0.857 (9.85) ***	2.256 (4.66) ***	1.553 (4.66) ***	1.190 (4.86) ***			-0.052 (-1.28)	2.57%
	W-stat.		1.15	0.27	14.78***	0.00	1.78	6.11**			0.38	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.811 (-4.17) ***	0.048 (0.57)	0.349 (2.83) ***	2.857 (2.67) ***	1.809 (1.82) *	1.888 (2.38) **	0.174 (1.13)			5.19%
		Electronic	-0.243 (-1.18)	0.111 (1.14)	0.509 (3.62) ***	2.799 (2.08) **	1.466 (1.25)	1.429 (1.94) *	0.145 (1.05)			8.54%
	W-stat.		7.64***	0.43	1.31	0.00	0.09	0.39	0.04			
	TOV	*Floor*	-0.859 (-4.15) ***	-0.044 (-0.62)	0.305 (2.90) ***	2.509 (2.41) **	1.218 (1.38)	1.585 (2.01) **		-0.160 (-2.24) **		4.35%
		Electronic	-0.262 (-1.18)	0.091 (0.97)	0.532 (3.65) ***	3.409 (3.05) ***	2.235 (2.01) **	1.619 (2.16) **		-0.128 (-1.76) *		8.55%
	W-stat.		7.20***	2.09	2.43	0.65	0.83	0.00		0.19		
	PIMPACT	*Floor*	-0.902 (-4.00) ***	0.100 (1.16)	0.359 (3.17) ***	2.458 (2.32) **	1.574 (1.77) *	1.808 (2.34) **			0.099 (1.32)	4.32%
		Electronic	-0.266 (-1.26)	0.162 (1.66)*	0.517 (3.56) ***	3.905 (3.49) ***	1.791 (1.68) *	1.608 (2.38) **			0.019 (0.25)	8.43%
	W-stat.		9.09***	0.40	1.18	1.67	0.04	0.09			1.11	

Panel C -1(Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.243 (-1.47)	0.093 (1.56)	0.377 (3.04) ***	0.946 (1.70) *	1.638 (3.77) ***	0.800 (2.38) **	0.029 (0.23)			3.86%
		Electronic	-0.514 (-1.40)	0.533 (1.37)	0.599 (2.87) ***	1.321 (1.87) *	1.391 (2.22) **	0.355 (0.75)	-0.067 (-0.41)			4.78%
	W-stat.		0.55	1.28	1.13	0.28	0.15	0.88	0.34			
	TOV	*Floor*	-0.252 (-1.39)	-0.077 (-1.18)	0.566 (1.97) *	-0.576 (-0.44)	0.730 (0.80)	1.370 (1.15)		-0.238 (-1.86) *		3.56%
		Electronic	-0.525 (-2.28) **	0.112 (1.68) *	0.615 (2.92) ***	1.151 (1.45)	1.376 (2.26) **	0.689 (1.51)		-0.221 (-2.92) ***		5.12%
	W-stat.		1.41	8.08***	0.05	4.7**	1.13	2.23		0.05		
	PIMPACT	*Floor*	-0.077 (-0.37)	0.080 (0.52)	0.593 (2.01) **	-0.957 (-0.65)	1.004 (1.39)	1.555 (1.41)			0.072 (0.58)	3.75%
		Electronic	-0.542 (-2.28) **	0.243 (1.96) *	0.517 (2.37) **	1.111 (1.34)	1.656 (2.60) **	0.540 (1.14)			0.113 (1.68) *	5.25%
	W-stat.		3.82**	1.73	0.12	6.26**	1.05	4.62			0.37	

Panel C-2: Risk adjusted return is conditional on **Yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.383 (-4.01) ***	-0.143 (-3.31) ***	0.488 (7.86) ***	1.796 (3.48) ***	1.337 (3.18) ***	1.110 (3.76) ***	-0.596 (-6.01) ***			2.62%
		Electronic	-0.773 (-6.36) ***	-0.005 (-0.11)	0.905 (10.75) ***	2.724 (6.75) ***	1.550 (4.41) ***	1.122 (4.97) ***	-0.353 (-3.81) ***			2.42%
	W-stat.		10.32***	8.96***	24.50***	5.29**	0.37	0.00	6.87***			
	TOV	*Floor*	-1.003 (-5.45) ***	0.121 (2.59) **	0.576 (6.52) ***	2.621 (3.96) ***	2.071 (3.11) ***	1.931 (4.25) ***		0.055 (0.61)		4.28%
		Electronic	-0.892 (-6.37) ***	0.186 (3.78) ***	0.903 (10.97) ***	2.865 (5.83) ***	1.487 (4.58) ***	1.095 (4.71) ***		-0.051 (-0.96)		2.58%
	W-stat.		0.63	1.73	15.73***	0.25	3.24*	12.93***		3.95**		
	PIMPACT	*Floor*	-1.072 (-3.26) ***	0.086 (0.91)	0.536 (6.02) ***	2.320 (3.41) ***	1.984 (2.94) ***	1.790 (3.84) ***			-0.026 (-0.34)	3.98%
		Electronic	-0.920 (-6.22) ***	0.121 (1.76) *	0.900 (10.07) ***	2.414 (4.96) ***	1.657 (5.05) ***	1.257 (5.22) ***			-0.055 (-1.41)	2.65%
	W-stat.		1.05	0.26	16.59***	0.04	0.99	4.90**			0.56	

Panel C-2 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.799 (-4.34) ***	0.022 (0.25)	0.324 (2.64) ***	2.936 (2.74) ***	1.954 (2.00) **	1.729 (2.18) **	0.166 (1.08)			5.38%
		Electronic	-0.285 (-1.36)	0.096 (0.99)	0.623 (4.19) ***	2.458 (1.99) **	1.153 (1.03)	1.691 (2.46) **	0.177 (1.28)			8.15%
	W-stat.		6.05**	0.59	4.03**	0.15	0.51	0.00	0.01			
	TOV	*Floor*	-0.817 (-4.09) ***	-0.071 (-0.97)	0.262 (2.50) **	2.627 (2.51) **	1.406 (1.59)	1.488 (1.89) *		-0.157 (-2.30) **		4.49%
		Electronic	-0.397 (-1.82) *	0.081 (0.88)	0.670 (4.45) ***	3.156 (2.82) ***	2.206 (2.05) **	1.611 (2.17) **		-0.141 (-1.97) *		8.07%
	W-stat.		3.74*	2.69*	7.37***	0.22	0.55	0.03		0.05		
	PIMPACT	*Floor*	-0.824 (-3.81) ***	0.051 (0.59)	0.340 (3.13) ***	2.464 (2.29) **	1.749 (1.95) *	1.826 (2.37) **			0.092 (1.27)	4.48%
		Electronic	-0.363 (-1.79) *	0.121 (1.35)	0.588 (3.96) ***	3.946 (3.76) ***	1.715 (1.67) *	1.900 (2.96) ***			-0.004 (-0.06)	7.97%
	W-stat.		5.16**	0.60	2.79*	2.00	0.00	0.01			1.77	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.237 (-1.47)	0.096 (1.78) *	0.395 (3.27) ***	1.137 (2.03) **	1.754 (3.94) ***	0.954 (3.04) ***	0.049 (0.41)			3.78%
		Electronic	-0.460 (-1.37)	0.541 (1.42)	0.620 (3.13) ***	1.569 (2.34) **	1.494 (2.47) **	0.569 (1.24)	-0.031 (-0.19)			4.60%
	W-stat.		0.44	1.36	1.29	0.41	0.18	0.71	0.25			
	TOV	*Floor*	-0.130 (-0.69)	-0.086 (-1.33)	0.548 (1.91) *	-0.617 (-0.49)	0.895 (1.04)	1.378 (1.24)		-0.239 (-1.78) *		3.44%
		Electronic	-0.440 (-1.96) *	0.089 (1.41)	0.656 (3.21) ***	1.537 (1.91) *	1.506 (2.57) **	0.663 (1.47)		-0.236 (-3.17) ***		4.93%
	W-stat.		1.9	7.68***	0.28	7.19***	1.09	2.52		0.00		
	PIMPACT	*Floor*	-0.088 (-0.39)	0.115 (0.71)	0.632 (2.00) **	-0.727 (-0.49)	1.100 (1.54)	1.699 (1.45)			0.098 (0.74)	3.87%
		Electronic	-0.451 (-1.92) *	0.243 (1.98) **	0.594 (2.84) ***	1.307 (1.59)	1.757 (2.86) ***	0.684 (1.46)			0.131 (1.86) *	5.19%
	W-stat.		2.38	1.08	0.03	6.15**	1.15	4.70**			0.22	

Panel C-3: Risk adjusted return is conditional on **Dividends yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.423 (-4.71) ***	-0.138 (-3.43) ***	0.467 (7.41) ***	1.865 (3.63) ***	1.395 (3.26) ***	1.266 (4.79) ***	-0.572 (-6) ***			2.43%
		Electronic	-0.808 (-6.79) ***	0.005 (0.12)	0.895 (10.92) ***	2.547 (6.53) ***	1.678 (4.98) ***	1.073 (4.85) ***	-0.361 (-3.89) ***			2.33%
	W-stat.		10.48***	9.71***	27.30***	3.06*	0.70	0.76	5.18**			
	TOV	*Floor*	-1.005 (-5.02) ***	0.114 (2.42) **	0.547 (6.05) ***	2.817 (4.22) ***	2.241 (3.30) ***	2.139 (4.30) ***		0.058 (0.66)		4.40%
		Electronic	-0.900 (-6.49) ***	0.180 (3.85) ***	0.913 (11.19) ***	2.687 (5.45) ***	1.682 (5.31) ***	1.023 (4.26) ***		-0.036 (-0.66)		2.51%
	W-stat.		0.58	1.98	20.13***	0.07	3.12*	21.62***		3.06*		
	PIMPACT	*Floor*	-1.016 (-3.09) ***	0.048 (0.51)	0.513 (5.55) ***	2.929 (4.20) ***	2.206 (3.36) ***	2.106 (4.55) ***			-0.060 (-0.83)	4.03%
		Electronic	-0.954 (-6.50) ***	0.107 (1.55)	0.907 (10.18) ***	2.373 (4.74) ***	1.866 (6.02) ***	1.128 (4.80) ***			-0.067 (-1.65) *	2.56%
	W-stat.		0.18	0.73	19.56***	1.23	1.21	17.33***			0.03	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.874 (-4.62) ***	0.071 (0.72)	0.376 (2.93) ***	3.759 (3.66) ***	2.246 (2.22) **	1.880 (2.33) **	0.301 (1.79) *			6.01%
		Electronic	-0.364 (-1.63)	0.065 (0.62)	0.686 (4.72) ***	3.103 (2.88) ***	1.393 (1.27)	1.655 (2.69) ***	0.083 (0.59)			7.76%
	W-stat.		5.24**	0.00	4.55**	0.37	0.60	0.13	2.42			
	TOV	*Floor*	-0.813 (-4.2) ***	-0.078 (-1.11)	0.296 (2.77) ***	3.286 (3.19) ***	2.029 (2.21) **	1.687 (2.12) **		-0.197 (-2.81) ***		4.83%
		Electronic	-0.364 (-1.65)*	0.051 (0.52)	0.711 (4.69) ***	3.906 (3.95) ***	1.919 (1.78) *	1.655 (2.49) **		-0.118 (-1.69) *		7.81%
	W-stat.		4.17**	1.74	7.47***	0.39	0.01	0.00		1.29		
	PIMPACT	*Floor*	-0.910 (-4.23) ***	0.101 (1.11)	0.371 (3.38) ***	3.228 (3.07) ***	2.393 (2.39) **	1.998 (2.60) **			0.154 (2.14) **	4.75%
		Electronic	-0.421 (-1.92) *	0.063 (0.69)	0.701 (4.63) ***	4.494 (4.51) ***	1.720 (1.61)	1.687 (2.81) ***			-0.061 (-0.87)	7.91%
	W-stat.		4.96**	0.18	4.76**	1.61	0.40	0.27			9.38***	

Panel C-3 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.297 (-1.90) *	0.133 (2.59) **	0.403 (3.39) ***	1.513 (2.85) ***	1.784 (4.07) ***	0.579 (1.82) *	0.048 (0.40)			3.62%
		Electronic	-0.507 (-1.50)	0.524 (1.53)	0.615 (3.36) ***	2.278 (3.23) ***	1.328 (2.04) **	0.172 (0.40)	-0.018 (-0.12)			4.68%
	W-stat.		0.38	1.31	1.35	1.18	0.49	0.91	0.19			
	TOV	*Floor*	-0.251 (-1.26)	-0.062 (-1.00)	0.564 (1.96) *	0.317 (0.27)	0.327 (0.34)	1.002 (1.02)		-0.201 (-1.46)		3.36%
		Electronic	-0.623 (-2.78) ***	0.154 (2.65) ***	0.588 (3.00) ***	1.893 (2.29) **	1.250 (1.92) *	0.299 (0.66)		-0.232 (-3.05) ***		5.20%
	W-stat.		2.75*	13.87***	0.01	3.64*	2	2.43		0.17		
	PIMPACT	*Floor*	-0.088 (-0.39)	0.083 (0.50)	0.613 (1.96) *	-0.026 (-0.02)	0.397 (0.44)	1.240 (1.11)			0.054 (0.41)	3.72%
		Electronic	-0.566 (-2.41) **	0.2116 (1.76) *	0.5326 (2.67) ***	1.9696 (2.39) **	1.6073 (2.49) **	0.3824 (0.80)			0.0867 (1.24)	5.33%
	W-stat.		4.13**	1.15	0.16	5.86**	3.52*	3.24*			0.21	

Panel D-1: Risk adjusted return is conditional on size, BM and **Term spread** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.373 (-5.11) ***	-0.141 (-3.94) ***	0.235 (5.12) ***	1.636 (3.08) ***	1.556 (3.90) ***	1.245 (5.27) ***	-0.548 (-6.69) ***			2.61%
		Electronic	-0.818 (-9.39) ***	0.012 (0.30)	0.557 (8.07) ***	2.701 (7.52) ***	1.464 (4.88) ***	1.241 (6.66) ***	-0.410 (-5.45) ***			2.46%
	W-stat.		26.15***	14.99***	21.83***	8.79***	0.09	0.00	3.36*			
	TOV	*Floor*	-0.896 (-5.89) ***	0.115 (2.68) ***	0.311 (3.99) ***	2.137 (3.79) ***	2.526 (4.15) ***	1.459 (3.92) ***		-0.023 (-0.31)		4.17%
		Electronic	-1.029 (-9.77) ***	0.249 (7.06) ***	0.597 (8.85) ***	2.666 (6.51) ***	1.328 (4.52) ***	1.227 (6.41) ***		-0.108 (-2.19) **		2.55%
	W-stat.		1.59	14.50***	17.99***	1.67	16.61***	1.48		2.97*		
	PIMPACT	*Floor*	-1.191 (-4.98) ***	0.147 (2.02) **	0.331 (4.10) ***	2.073 (3.47) ***	2.323 (4.18) ***	1.387 (3.71) ***			0.018 (0.27)	4.00%
		Electronic	-1.091 (-9.01) ***	0.231 (3.91) ***	0.518 (7.53) ***	2.360 (5.25) ***	1.385 (5.15) ***	1.173 (5.91) ***			0.009 (0.22)	2.69%
	W-stat.		0.69	2.02	7.40***	0.41	12.18***	1.15			0.05	

Panel D-1 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.639 (-4.10) ***	0.013 (0.19)	0.155 (2.00) **	2.781 (3.72) ***	1.191 (1.60)	2.096 (3.03) ***	0.033 (0.33)			3.56%
		Electronic	-0.202 (-1.44)	0.200 (2.30) **	0.261 (2.35) **	2.709 (3.18) ***	0.949 (1.21)	1.321 (2.78) ***	0.009 (0.08)			7.52%
	W-stat.		9.65***	4.65**	0.91	0.01	0.10	2.67	0.05			
	TOV	*Floor*	-0.666 (-4.34) ***	0.031 (0.52)	0.172 (2.71) ***	2.768 (3.35) ***	1.398 (1.86) *	2.222 (3.32) ***		-0.152 (-3.2) ***		3.32%
		Electronic	-0.210 (-1.39)	0.248 (3.65) ***	0.202 (1.90) *	2.932 (3.24) ***	1.187 (1.76) *	1.590 (3.35) ***		-0.033 (-0.57)		7.47%
	W-stat.		9.10***	10.22***	0.08	0.03	0.10	1.77		4.18**		
	PIMPACT	*Floor*	-0.885 (-4.91) ***	0.108 (1.53)	0.226 (2.90) ***	2.141 (2.64) ***	1.579 (2.20) **	2.068 (3.41) ***			0.107 (1.79) *	3.65%
		Electronic	-0.207 (-1.46)	0.137 (1.63)	0.214 (1.88) *	4.322 (5.23) ***	0.762 (1.08)	2.014 (4.09) ***			-0.107 (-1.63)	7.15%
	W-stat.		22.88***	0.11	0.01	6.96***	1.35	0.01			10.70***	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.343 (-3.14) ***	0.111 (2.60) **	0.225 (2.28) **	0.942 (1.85) *	1.821 (4.50) ***	0.795 (3.08) ***	-0.084 (-0.76)			3.57%
		Electronic	-0.252 (-0.68)	0.147 (0.78)	0.278 (1.78) *	1.027 (1.80) *	1.786 (3.24) ***	0.225 (0.63)	0.005 (0.03)			4.17%
	W-stat.		0.06	0.04	0.11	0.02	0.00	2.55	0.36			
	TOV	*Floor*	-0.416 (-2.72) ***	0.013 (0.23)	-0.077 (-0.39)	-0.216 (-0.18)	0.483 (0.6)	0.256 (0.42)		-0.131 (-1.16)		3.96%
		Electronic	-0.653 (-3.96) ***	0.122 (2.46) **	0.219 (1.34)	1.104 (1.41)	1.911 (3.71) ***	0.515 (1.34)		-0.246 (-3.52) ***		4.93%
	W-stat.		2.07	4.81	3.27	2.86	7.70	0.46		2.70		
	PIMPACT	*Floor*	-0.205 (-1.30)	0.106 (0.91)	0.137 (0.63)	-1.342 (-0.81)	1.150 (1.84) *	0.914 (1.15)			0.048 (0.47)	2.83%
		Electronic	-0.551 (-3.18) ***	0.319 (3.03) ***	0.268 (1.53)	1.203 (1.53)	2.049 (3.56) ***	0.475 (1.16)			0.160 (2.60) **	4.94%
	W-stat.		3.99**	4.11**	0.57	10.42***	2.43	1.15			3.32*	

Panel D-2: Risk adjusted return is conditional on size, BM and **Yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.397 (-5.35) ***	-0.134 (-3.87) ***	0.232 (5.14) ***	1.666 (3.08) ***	1.577 (3.84) ***	1.177 (4.93) ***	-0.543 (-6.71) ***			2.64%
		Electronic	-1.026 (-11.22) ***	0.067 (1.44)	0.657 (9.61) ***	3.155 (7.39) ***	1.740 (5.26) ***	1.528 (7.04) ***	-0.438 (-5.35) ***			2.69%
	W-stat.		47.33***	18.59***	38.56***	12.17***	0.24	2.63*	1.66			
	TOV	*Floor*	-0.908 (-6.20) ***	0.123 (2.87) ***	0.346 (4.63) ***	2.036 (3.45) ***	2.551 (4.19) ***	1.678 (4.43) ***		-0.025 (-0.34)		4.14%
		Electronic	-1.127 (-10.64) ***	0.288 (8.22) ***	0.604 (9.19) ***	2.597 (5.83) ***	1.335 (4.73) ***	1.255 (6.13) ***		-0.160 (-3.42) ***		2.76%
	W-stat.		4.28**	22.16***	15.35***	1.59	18.55***	4.28**		8.34***		
	PIMPACT	*Floor*	-1.186 (-4.87) ***	0.152 (2.09) **	0.327 (4.12) ***	2.063 (3.42) ***	2.421 (4.30) ***	1.462 (3.79) ***			0.016 (0.25)	4.08%
		Electronic	-1.182 (-9.90) ***	0.268 (4.67) ***	0.558 (8.44) ***	2.453 (5.10) ***	1.545 (5.10) ***	1.265 (6.14) ***			0.021 (0.56)	2.81%
	W-stat.		0.00	4.09**	12.21***	0.66	8.33***	0.92			0.02	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.687 (-4.35) ***	-0.066 (-0.94)	0.086 (1.05)	2.843 (3.42) ***	1.259 (1.49)	2.026 (2.78) ***	-0.054 (-0.54)			4.23%
		Electronic	-0.124 (-0.88)	0.112 (1.55)	0.128 (1.15)	2.717 (3.22) ***	0.917 (1.17)	1.278 (2.59) **	0.160 (1.46)			7.78%
	W-stat.		15.93***	6.05**	0.15	0.02	0.19	2.30	3.81*			
	TOV	*Floor*	-0.685 (-4.32) ***	-0.011 (-0.19)	0.104 (1.68) *	2.550 (2.92) ***	1.346 (1.80) *	2.374 (3.57) ***		-0.166 (-3.40)***		3.73%
		Electronic	-0.187 (-1.20)	0.224 (3.44) ***	0.158 (1.41)	2.967 (3.35) ***	1.442 (2.03) **	1.163 (2.49) **		-0.112 (-1.91) *		7.24%
	W-stat.		10.20***	13.02***	0.22	0.22	0.02	6.72***		0.86		
	PIMPACT	*Floor*	-0.882 (-5.01) ***	0.040 (0.61)	0.153 (2.12) **	2.271 (2.73) ***	1.574 (1.96) *	2.146 (3.61) ***			0.064 (1.18)	3.68%
		Electronic	-0.161 (-1.09)	0.120 (1.60)	0.144 (1.26)	4.377 (5.18) ***	0.859 (1.14)	1.675 (3.84) ***			-0.033 (-0.52)	7.18%
	W-stat.		23.49***	1.14	0.01	6.20**	0.90	1.17			2.35	

Panel D-2 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.345 (-3.24) ***	0.113 (2.84) ***	0.204 (2.09) **	1.291 (2.52) **	1.673 (4.32) ***	0.757 (2.89) ***	-0.002 (-0.02)			3.60%
		Electronic	-0.325 (-1.12)	0.335 (1.32)	0.272 (1.73) *	1.630 (2.75) ***	1.980 (3.38) ***	0.366 (0.93)	0.061 (0.40)			4.48%
	W-stat.		0.00	0.76	0.18	0.33	0.27	0.99	0.17			
	TOV	*Floor*	-0.472 (-3.02) ***	0.001 (0.02)	-0.068 (-0.33)	0.053 (0.04)	1.075 (1.87) *	0.039 (0.08)		-0.164 (-1.27)		3.88%
		Electronic	-0.543 (-3.45) ***	0.103 (2.16) **	0.221 (1.29)	1.554 (2.11) **	2.211 (4.01) ***	0.778 (1.94) *		-0.286 (-4.41) ***		5.00%
	W-stat.		0.21	4.58**	2.84**	4.14**	4.24**	3.39*		3.53*		
	PIMPACT	*Floor*	-0.170 (-1.00)	0.061 (0.47)	0.256 (0.96)	-1.005 (-0.60)	1.139 (1.93) *	1.056 (1.14)			0.010 (0.08)	3.65%
		Electronic	-0.429 (-2.77) ***	0.279 (2.77) ***	0.344 (1.95) *	1.653 (2.22) **	2.275 (3.81) ***	0.535 (1.22)			0.167 (2.74) ***	5.00%
	W-stat.		2.80*	4.69**	0.25	12.74***	3.62*	1.41			6.66***	

Panel D-3: Risk adjusted return is conditional on size, BM and **Dividends Yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.487 (-7.23) ***	-0.098 (-2.79) ***	0.239 (5.03) ***	1.715 (3.68) ***	1.373 (3.87) ***	1.136 (4.20) ***	-0.507 (-6.36) ***			2.47%
		Electronic	-0.865 (-9.57) ***	0.033 (0.73)	0.606 (9.75) ***	2.737 (7.52) ***	1.912 (6.22) ***	1.157 (5.64) ***	-0.392 (-4.91) ***			2.60%
	W-stat.		17.49***	8.24***	34.92***	7.89***	3.08*	0.01	2.08			
	TOV	*Floor*	-1.006 (-7.31) ***	0.147 (3.88) ***	0.342 (4.32) ***	2.222 (3.86) ***	2.398 (4.01) ***	1.722 (4.41) ***		-0.019 (-0.27)		3.93%
		Electronic	-1.032 (-10.12) ***	0.232 (6.90) ***	0.607 (9.09) ***	2.600 (6.25) ***	1.836 (5.88) ***	1.233 (5.65) ***		-0.123 (-2.81) ***		2.71%
	W-stat.		0.06	6.32**	15.76***	0.82	3.24*	5.02**		5.64***		
	PIMPACT	*Floor*	-1.230 (-4.35) ***	0.161 (1.95) *	0.349 (4.11) ***	2.498 (4.20) ***	2.311 (4.22) ***	1.786 (4.52) ***			0.010 (0.16)	4.17%
		Electronic	-1.095 (-9.69) ***	0.208 (3.71) ***	0.596 (8.72) ***	2.700 (6.14) ***	1.961 (6.90) ***	1.249 (6.07) ***			0.011 (0.29)	2.66%
	W-stat.		1.44	0.71	13.05***	0.21	1.52	6.81***			0.00	

Panel D-3 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	-0.736 (-4.59) ***	0.037 (0.46)	0.177 (2.39) **	3.439 (4.33) ***	0.889 (1.13)	1.873 (2.69) ***	0.135 (1.30)			4.32%
		Electronic	-0.214 (-1.46)	0.099 (1.27)	0.166 (1.39)	3.423 (4.31) ***	0.941 (1.39)	1.320 (2.27) **	0.046 (0.45)			7.19%
	W-stat.		12.59***	0.65	0.01	0.00	0.01	0.91	0.76			
	TOV	*Floor*	-0.672 (-4.24) ***	-0.066 (-1.09)	0.060 (0.93)	2.683 (3.43) ***	1.139 (1.58)	2.221 (3.56) ***		-0.182 (-4.15) ***		3.81%
		Electronic	-0.311 (-2.08) **	0.086 (1.29)	0.232 (1.86) *	3.967 (5.24) ***	1.343 (2.03) **	1.473 (2.90) ***		-0.102 (-1.85) *		6.38%
	W-stat.		5.86**	5.22**	1.89	2.88*	0.10	2.17		2.09		
	PIMPACT	*Floor*	-0.848 (-4.79) ***	0.067 (0.84)	0.183 (2.29) **	2.640 (3.48) ***	1.288 (1.66)*	1.683 (2.73) ***			0.079 (1.36)	3.52%
		Electronic	-0.316 (-2.06) **	0.100 (1.26)	0.363 (2.93) ***	4.393 (5.65) ***	0.611 (0.93)	1.570 (3.38) ***			-0.034 (-0.54)	6.41%
	W-stat.		12.06***	0.17	2.11	5.09**	1.06	0.06			3.23*	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-0.256 (-2.33) **	0.142 (3.73) ***	0.102 (1.12)	1.502 (3.12) ***	1.629 (4.13) ***	0.462 (1.75) *	0.057 (0.53)			3.47%
		Electronic	-0.610 (-2.70) ***	0.329 (1.64) *	0.360 (2.25) **	1.695 (2.79) ***	1.638 (2.92) ***	0.369 (0.88)	0.033 (0.27)			4.12%
	W-stat.		2.46	0.87	2.61	0.1	0	0.05	0.04			
	TOV	*Floor*	-0.389 (-2.61) ***	-0.042 (-0.65)	-0.049 (-0.19)	-0.465 (-0.31)	0.467 (0.55)	0.585 (0.70)		-0.161 (-1.40)		3.91%
		Electronic	-0.566 (-3.48) ***	0.041 (0.90)	0.130 (0.82)	1.877 (2.50) **	2.006 (3.53) ***	0.658 (1.59)		-0.197 (-3.60) ***		4.85%
	W-stat.		1.18	3.34*	1.27	9.71***	7.32***	0.03		0.44		
	PIMPACT	*Floor*	-0.223 (-1.23)	0.051 (0.38)	-0.027 (-0.12)	-0.861 (-0.51)	0.909 (1.46)	0.750 (1.08)			0.023 (0.21)	4.05%
		Electronic	-0.457 (-2.64) ***	0.113 (1.31)	0.279 (1.65) *	2.020 (2.88) ***	1.540 (2.71) ***	0.475 (1.05)			0.088 (1.61) *	4.97%
	W-stat.		1.83	0.51	3.27*	16.89***	1.23	0.37			1.43	

Appendix 3D
Robust Test: Statistics of individual coefficients of market liquidity risk factors estimated by conditional asset pricing model with time-varying alpha

Among the other risk factors and control factors, this table reports the cross-sectional average of the time-series slope coefficients of market-wide liquidity risk factors with their associated t-statistics. These coefficients are estimated by running the first-pass time-series regression (Eq. (3.12)) for each firm during the floor trading period and the electronic trading period. Liquidity risk factors include PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. "Pos" reports the percentage of positive slope coefficients, while "Sig" gives the percentage of the coefficients that are significant at 10% of significance or higher. The last three columns present the difference in the mean between electronic and floor trading systems with the t-value and p-value of the null hypothesis that the difference in the mean is equal to zero.

Panel C-1: Conditional asset pricing model, Beta varies with **term spread** (Business cycle variable).

Stock Exchange	**Liq. Risk Factor**	**Floor Trading System**				**Electronic Trading System**				**Electronic minus Floor**		
		Mean	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**p-value**
London Stock Exchange (LSE)	**PQSPR**	-0.023	(-5.01)	38	19	-0.026	(-7.76)	39	14	-0.003	(-0.53)	0.597
	TOV	-0.002	(-0.59)	47	13	0.013	(5.31)	53	17	0.015	(3.79)	0.000
	PIMPACT	-0.011	(-1.92)	49	14	-0.005	(-2.33)	43	16	0.006	(0.99)	0.320
Swiss Stock Exchange (SSE)	**PQSPR**	-0.012	(-3.99)	34	16	-0.026	(-3.39)	31	26	-0.013	(-1.79)	0.074
	TOV	0.021	(5.53)	72	21	-0.026	(-2.24)	42	13	-0.048	(-4.22)	0.000
	PIMPACT	-0.031	(-2.79)	43	17	-0.089	(-2.45)	39	25	-0.059	(-1.68)	0.093
Frankfurt Stock Exchange (FSE)	**PQSPR**	-0.022	(-3.91)	40	16	0.008	(3.20)	52	12	0.030	(4.73)	0.000
	TOV	0.025	(4.41)	57	19	0.013	(1.95)	50	13	-0.012	(-1.41)	0.158
	PIMPACT	-0.001	(-1.80)	45	13	2.69E-05	(0.49)	52	12	0.001	(1.74)	0.082

Panel C-2: Conditional asset pricing model, Beta varies with **yield** (Business cycle variable).

Stock Exchange	**Liq. Risk Factor**	**Floor Trading System**				**Electronic Trading System**				**Electronic minus Floor**		
		Mean	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**Pos**	**Sig**	**Mean**	**t-value**	**p-value**
London Stock Exchange (LSE)	**PQSPR**	-0.060	(-3.20)	39	20	-0.018	(-0.87)	48	13	0.042	(1.49)	0.137
	TOV	-0.034	(-3.06)	47	12	0.041	(2.45)	56	16	0.075	(3.67)	0.000
	PIMPACT	-0.046	(-2.17)	48	15	0.021	(2.13)	56	17	0.068	(2.94)	0.003
Swiss Stock Exchange (SSE)	**PQSPR**	0.007	(0.71)	54	10	-0.007	(-1.15)	49	16	-0.014	(-1.11)	0.268
	TOV	-0.024	(-2.31)	47	17	0.024	(2.23)	60	15	0.048	(3.18)	0.002
	PIMPACT	-0.004	(-0.13)	50	9	-0.060	(-3.73)	41	24	-0.055	(-1.42)	0.155
Frankfurt Stock Exchange (FSE)	**PQSPR**	0.008	(0.92)	55	12	-0.004	(-0.69)	51	14	-0.012	(-1.11)	0.268
	TOV	0.011	(0.78)	54	16	0.081	(3.51)	57	14	0.069	(2.60)	0.009
	PIMPACT	0.001	(1.20)	48	13	-0.001	(-1.36)	50	12	-0.002	(-1.52)	0.129

Panel C-3: Conditional asset pricing model, Beta varies with **dividend yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-0.095	(-3.23)	40	22	-0.047	(-1.29)	45	14	0.048	(1.00)	0.316
	TOV	-0.027	(-1.28)	47	13	-0.033	(-1.41)	49	16	-0.006	(-0.19)	0.853
	PIMPACT	-0.044	(-1.14)	52	16	-0.024	(-1.48)	42	21	0.020	(0.49)	0.621
Swiss Stock Exchange (SSE)	PQSPR	-0.016	(-0.81)	49	21	0.025	(1.64)	57	12	0.041	(1.57)	0.117
	TOV	-0.023	(-0.94)	48	13	0.075	(2.89)	65	20	0.098	(2.73)	0.007
	PIMPACT	-0.201	(-3.18)	40	18	-0.071	(-1.14)	51	15	0.130	(1.45)	0.147
Frankfurt Stock Exchange (FSE)	PQSPR	-0.010	(-0.74)	47	15	-0.311	(-3.70)	54	21	0.021	(1.33)	0.182
	TOV	-0.001	(-0.07)	50	18	0.101	(2.07)	53	12	0.103	(2.03)	0.043
	PIMPACT	-0.003	(-2.57)	49	16	-0.001	(-1.32)	49	20	0.002	(1.44)	0.150

Panel D-1: Conditional asset pricing model, Beta varies with size, BM and **term spread** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	0.265	(0.57)	47	15	-0.018	(-0.11)	48	13	-0.283	(-0.63)	0.530
	TOV	0.663	(2.09)	52	13	0.092	(0.81)	51	14	-0.572	(-1.87)	0.061
	PIMPACT	-0.701	(-1.73)	50	16	-0.097	(-0.83)	48	14	0.604	(1.60)	0.109
Swiss Stock Exchange (SSE)	PQSPR	0.130	(1.07)	52	13	1.244	(0.90)	45	12	1.114	(0.79)	0.430
	TOV	0.062	(0.44)	55	13	-5.563	(-1.46)	48	16	-5.625	(-1.45)	0.148
	PIMPACT	-0.079	(-0.24)	51	12	0.298	(0.06)	52	18	0.377	(0.08)	0.940
Frankfurt Stock Exchange (FSE)	PQSPR	-0.121	(-0.73)	50	20	-0.060	(-1.13)	49	14	0.061	(0.31)	0.760
	TOV	0.130	(0.85)	50	16	0.002	(0.01)	51	18	-0.128	(-0.37)	0.714
	PIMPACT	-0.004	(-0.31)	47	15	0.004	(1.67)	49	20	0.008	(0.54)	0.589

Panel D-2: Conditional asset pricing model, Beta varies with size, BM and **yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-5.256	(-2.25)	49	15	-0.850	(-0.87)	50	14	4.406	(1.90)	0.058
	TOV	2.054	(1.12)	52	16	0.193	(0.25)	50	16	-1.862	(-1.01)	0.311
	PIMPACT	5.707	(1.98)	51	15	-0.089	(-0.12)	50	16	-5.796	(-2.19)	0.029
Swiss Stock Exchange (SSE)	PQSPR	0.652	(1.13)	52	18	-0.921	(-1.30)	47	13	-1.573	(-1.72)	0.087
	TOV	0.789	(1.04)	51	14	6.363	(1.32)	49	19	5.574	(1.12)	0.264
	PIMPACT	1.958	(1.22)	52	18	-3.580	(-1.09)	51	13	-5.537	(-1.50)	0.135
Frankfurt Stock Exchange (FSE)	PQSPR	0.179	(0.31)	48	15	0.169	(1.18)	50	15	-0.010	(-0.01)	0.988
	TOV	0.536	(1.60)	52	14	0.024	(0.02)	51	16	-0.512	(-0.51)	0.608
	PIMPACT	-0.047	(-0.99)	50	13	0.002	(0.74)	49	17	0.049	(0.88)	0.378

Panel D-3: Conditional asset pricing model, Beta varies with size, BM and **dividend yield** (Business cycle variable).

Stock Exchange	Liq. Risk Factor	Floor Trading System				Electronic Trading System				Electronic minus Floor		
		Mean	t-value	Pos	Sig	Mean	t-value	Pos	Sig	Mean	t-value	p-value
London Stock Exchange (LSE)	PQSPR	-2.904	(-0.44)	49	16	0.105	(0.06)	49	15	3.009	(0.50)	0.620
	TOV	-0.935	(-0.45)	50	16	0.470	(0.46)	52	14	1.405	(0.65)	0.517
	PIMPACT	-0.911	(-0.36)	51	16	-0.018	(-0.02)	50	16	0.894	(0.37)	0.712
Swiss Stock Exchange (SSE)	PQSPR	-0.431	(-0.55)	51	18	-8.562	(-1.58)	47	11	-8.131	(-1.45)	0.147
	TOV	1.806	(1.62)	53	18	-1.179	(-0.09)	43	13	-2.984	(-0.23)	0.821
	PIMPACT	1.922	(0.60)	52	17	9.391	(0.58)	56	18	7.469	(0.45)	0.655
Frankfurt Stock Exchange (FSE)	PQSPR	-0.331	(-0.49)	51	17	-0.136	(-0.55)	51	15	0.195	(0.24)	0.811
	TOV	-0.636	(-1.09)	48	16	0.772	(0.32)	49	19	1.408	(0.65)	0.513
	PIMPACT	-0.069	(-1.43)	50	16	0.004	(0.67)	51	16	0.072	(1.29)	0.198

Appendix 3E

Robust Test: Fama-MacBeth estimates with Fama-French factors and liquidity as risk factor and time-varying alpha

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficient estimates (Eq. (3.14)) for all securities in the UK, Switzerland and Germany. Panel C-1, C-2, C-3 presents the estimates when the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with business cycle variables term spread, short-term interest rate and dividends yield respectively. In panel D-1, D-2, D-3 the dependent variable is the risk-adjusted return when factor loadings (i.e. betas) are allowed to vary with firm characteristics (i.e. size and book-to-market ratio) and with business cycle variable term spread, short-term interest rate and dividends yield respectively. Liq. Risk Factor is the liquidity risk factor added to Fama-French three factor model, PQSPR is proportional bid-ask spread, TOV is the liquidity turnover ratio and PIMPACT is the price impact (Amihud's 2002 Illiquidity ratio). The construction of liquidity risk factors is explained in section 3.3.4. *Floor* and *electronic* in the third column in each panel refers to the estimation done during the floor trading system and electronic trading system respectively. Size represents the logarithm of market capitalization; BM is the logarithm of book-to-market ratio; RET2-3, RET4-6, RET7-12 are the past cumulative raw returns over the second through third, fourth through sixth, and seventh through twelfth months before the current month; Prop. Bid-ask is the proportional bid-ask spread calculated as the quoted bid-ask spread divided by the midpoint of the quoted bid-ask spread; Turnover is the turnover ratio measures as the trading value divided by the market capitalization; Price impact is the ratio of absolute return divided by the trading value. $\overline{R^2}$ is the time-series average of the monthly adjusted R^2. T-statistic (reported in parenthesis) are adjusted for autocorrelation and heteroscedasticity. W-stat. is the Wald test statistic. All coefficients are multiplied by 100. *, **, *** denotes significance at the 10, 5, 1% level.

Panel C-1: Risk adjusted return is conditional on **Term spread** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	1.148 (4.87) ***	-0.660 (-8.22) ***	1.633 (6.87) ***	1.268 (0.61)	0.789 (0.45)	-0.314 (-0.21)	1.208 (3.85) ***			9.42%
		Electronic	3.343 (15.54) ***	-0.274 (-1.07)	0.941 (2.74) ***	1.070 (0.21)	0.204 (0.04)	-0.038 (-0.01)	0.607 (1.17)			9.02%
	W-stat.		104.09***	2.25	4.07***	0.00	0.02	0.00	1.35			
	TOV	*Floor*	-0.370 (-1.00)	-0.530 (-4.33) ***	1.655 (6.68) ***	0.907 (0.42)	-0.078 (-0.05)	-1.439 (-0.93)		-0.495 (-2.00) **		9.04%
		Electronic	1.541 (6.55) ***	-0.598 (-2.36) **	0.476 (1.31)	0.994 (0.20)	0.259 (0.06)	-0.260 (-0.06)		0.543 (2.40) **		9.17%
	W-stat.		66.03***	0.07	10.62***	0.00	0.01	0.07		21.06***		
	PIMPACT	*Floor*	-1.785 (-2.08) **	-0.496 (-1.74) *	1.740 (6.40) ***	0.844 (0.40)	-0.155 (-0.09)	-1.576 (-0.98)			0.016 (0.08)	9.22%
		Electronic	2.651 (10.91) ***	-0.710 (-2.22) **	1.142 (2.66) ***	1.268 (0.24)	0.902 (0.19)	0.089 (0.02)			-0.248 (-1.66) *	8.82%
	W-stat.		333.18***	0.45	1.93	0.01	0.05	0.13			3.14*	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	6.044 (34.43) ***	-0.308 (-2.73) ***	0.825 (3.93) ***	3.302 (1.11)	1.261 (0.40)	2.254 (1.00)	0.511 (1.79) *			9.63%
		Electronic	3.829 (17.29) ***	-1.136 (-7.74) ***	-2.761 (-7.02) ***	0.012 (0.00)	-0.672 (-0.18)	5.788 (1.93) *	-0.656 (-2.57) **			18.33%
	W-stat.		100.03***	31.80***	83.14***	0.79	0.26	1.39	20.95***			
	TOV	*Floor*	5.648 (27.72) ***	-0.489 (-4.03) ***	0.864 (4.28) ***	3.194 (1.17)	1.676 (0.61)	1.169 (0.49)		-0.740 (-5.42) ***		9.57%
		Electronic	4.435 (15.63) ***	-1.360 (-9.50) ***	-2.389 (-6.21) ***	1.674 (0.45)	1.203 (0.32)	7.803 (2.64) ***		-0.216 (-1.51)		18.28%
	W-stat.		18.29***	37.02***	71.58***	0.17	0.02	5.02**		13.47***		
	PIMPACT	*Floor*	4.402 (18.2) ***	0.326 (2.79) ***	0.746 (4.02) ***	3.727 (1.37)	2.345 (0.88)	0.999 (0.45)			0.911 (7.47) ***	9.18%
		Electronic	3.715 (14.02) ***	-0.961 (-5.10) ***	-2.425 (-6.09) ***	1.744 (0.50)	0.001 (0.00)	5.992 (2.09) **			0.301 (2.30) **	17.99%
	W-stat.		6.74***	46.70***	63.42***	0.33	0.42	3.03*			21.68***	

Panel C-1 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-2.808 (-9.57) ***	0.629 (4.42) ***	0.561 (3.49) ***	2.080 (0.91)	2.892 (1.35)	3.430 (1.89) *	2.826 (8.25) ***			6.83%
		Electronic	-3.574 (-4.91) ***	2.578 (6.60) ***	3.301 (8.03) ***	1.543 (0.77)	1.506 (0.88)	2.275 (1.41)	5.811 (13.93) ***			9.77%
	W-stat.		1.11	24.94***	44.46***	0.07	0.65	0.51	51.21***			
	TOV	*Floor*	-4.840 (-8.09) ***	-0.297 (-1.73) *	1.832 (2.28) **	-0.581 (-0.15)	4.957 (1.39)	7.813 (2.96) ***		-2.106 (-7.18) ***		8.50%
		Electronic	-5.015 (-13.85) ***	1.354 (10.06) ***	3.735 (8.93) ***	1.359 (0.67)	1.863 (1.00)	3.436 (2.02) **		-2.677 (-15.73) ***		10.61%
	W-stat.		0.23	150.47***	20.73***	0.91	2.74*	6.59***		11.24***		
	PIMPACT	*Floor*	-2.963 (-5.55) ***	1.301 (6.49) ***	1.714 (2.27) **	-1.818 (-0.46)	3.724 (1.13)	7.736 (2.94) ***			1.334 (5.63) ***	7.24%
		Electronic	-4.590 (-15.05) ***	3.812 (21.14) ***	3.182 (7.24) ***	2.289 (1.08)	2.450 (1.25)	3.893 (2.23) **			2.195 (16.03) ***	9.89%
	W-stat.		28.47***	193.95***	11.16***	3.76*	0.42	4.83**			39.60***	

Panel C-2: Risk adjusted return is conditional on **Yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	1.072 (4.67) ***	-0.578 (-7.03) ***	1.600 (7.20) ***	1.320 (0.65)	0.792 (0.46)	-0.262 (-0.18)	1.267 (3.98) ***			9.29%
		Electronic	2.517 (12.90) ***	-0.150 (-0.58)	1.396 (4.17) ***	1.430 (0.29)	0.749 (0.16)	0.373 (0.09)	0.303 (0.56)			8.63%
	W-stat.		54.82***	2.76*	0.37	0.00	0.00	0.02	3.14*			
	TOV	*Floor*	-0.234 (-0.66)	-0.501 (-4.23) ***	1.589 (6.66) ***	0.954 (0.45)	-0.073 (-0.04)	-1.356 (-0.92)		-0.398 (-1.63)		8.78%
		Electronic	0.788 (3.89) ***	-0.343 (-1.44)	0.655 (1.84) *	0.943 (0.19)	0.332 (0.07)	-0.174 (-0.04)		0.301 (1.38)		9.02%
	W-stat.		25.40***	0.44	6.91***	0.00	0.01	0.08		10.33***		
	PIMPACT	*Floor*	-1.766 (-2.12) **	-0.456 (-1.66) *	1.764 (6.50) ***	1.090 (0.53)	0.071 (0.04)	-1.390 (-0.90)			0.008 (0.04)	9.15%
		Electronic	1.962 (8.64) ***	-0.420 (-1.33)	1.444 (3.30) ***	1.706 (0.33)	1.296 (0.28)	0.518 (0.12)			-0.219 (-1.43)	8.53%
	W-stat.		269.31***	0.01	0.54	0.01	0.07	0.18			2.21	

Panel C-2 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.225 (30.07) ***	-0.254 (-2.27) **	0.757 (3.82) ***	3.699 (1.33)	1.534 (0.51)	1.914 (0.89)	0.766 (2.65) ***			9.28%
		Electronic	3.781 (17.32) ***	-0.832 (-6.16) ***	-2.536 (-7.28) ***	0.209 (0.06)	-1.000 (-0.27)	5.765 (2.01) **	-0.720 (-3.21) ***			16.95%
	W-stat.		43.78***	18.32***	89.44***	0.94	0.48	1.80	43.92***			
	TOV	*Floor*	5.566 (28.11) ***	-0.608 (-4.61) ***	0.915 (5.22) ***	4.178 (1.58)	2.724 (1.01)	1.600 (0.69)		-0.819 (-5.92) ***		9.56%
		Electronic	4.637 (19.70) ***	-1.036 (-7.85) ***	-2.378 (-7.08) ***	1.119 (0.32)	0.792 (0.22)	6.866 (2.41) **		-0.271 (-1.91) *		17.39%
	W-stat.		15.58***	10.54***	96.06***	0.75	0.28	3.41*		14.90***		
	PIMPACT	*Floor*	4.005 (17.05) ***	0.258 (2.23) **	0.753 (4.92) ***	4.698 (1.78) *	3.361 (1.29)	1.340 (0.63)			0.975 (7.68) ***	8.85%
		Electronic	3.762 (16.47) ***	-0.604 (-3.80) ***	-2.665 (-7.76) ***	1.848 (0.54)	-0.511 (-0.15)	5.630 (2.01) **			0.290 (2.61) **	16.58%
	W-stat.		1.13	29.31***	98.98***	0.70	1.22	2.36			37.99***	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-2.639 (-10.30) ***	0.510 (4.19) ***	0.449 (2.74) ***	1.938 (0.84)	2.728 (1.27)	3.643 (2.00) **	2.818 (8.59) ***			6.76%
		Electronic	-3.280 (-5.39) ***	2.379 (7.24) ***	3.094 (7.32) ***	1.573 (0.81)	1.453 (0.88)	2.548 (1.61)	5.480 (14.12) ***			9.47%
	W-stat.		1.11	32.34***	39.21***	0.04	0.59	0.48	47.05***			
	TOV	*Floor*	-4.309 (-8.81) ***	-0.375 (-1.94) *	1.713 (1.98) **	-1.150 (-0.31)	4.702 (1.30)	7.910 (3.02) ***		-2.050 (-7.70) ***		8.40%
		Electronic	-4.765 (-13.14) ***	1.239 (8.70) ***	4.168 (10.19) ***	1.229 (0.60)	1.783 (0.94)	3.233 (1.90) ***		-2.629 (-16.81) ***		10.74%
	W-stat.		1.58	128.59***	36.02***	1.37	2.35	7.56***		13.71***		
	PIMPACT	*Floor*	-2.816 (-6.22) ***	1.351 (8.10) ***	1.934 (2.20) **	-1.412 (-0.36)	4.342 (1.25)	8.209 (2.97) ***			1.459 (6.82) ***	7.29%
		Electronic	-4.461 (-14.80) ***	3.524 (20.23) ***	2.940 (6.52) ***	2.079 (1.00)	2.160 (1.13)	3.759 (2.19) **			2.064 (16.02) ***	9.60%
	W-stat.		29.78***	155.71***	4.97**	2.84*	1.30	6.70***			22.05***	

Panel C-3: Risk adjusted return is conditional on **Dividend yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	1.069 (5.30) ***	-0.382 (-4.29) ***	1.801 (7.50) ***	1.526 (0.73)	1.053 (0.61)	0.130 (0.09)	1.190 (3.46) ***			8.45%
		Electronic	4.229 (15.91) ***	-0.138 (-0.59)	0.437 (1.13)	0.690 (0.14)	0.492 (0.10)	0.035 (0.01)	1.232 (2.16) **			8.47%
	W-stat.		141.46***	1.10	12.40***	0.03	0.01	0.00	0.01			
	TOV	*Floor*	0.218 (0.68)	-0.467 (-4.29) ***	1.604 (6.03) ***	1.514 (0.72)	0.226 (0.13)	-0.896 (-0.59)		-0.152 (-0.66)		8.37%
		Electronic	2.137 (8.18) ***	-0.494 (-2.00) **	0.795 (1.94) *	0.107 (0.02)	-0.144 (-0.03)	-0.476 (-0.11)		0.547 (2.36) **		9.00%
	W-stat.		53.90***	0.01	3.89**	0.08	0.01	0.01		9.05***		
	PIMPACT	*Floor*	-1.257 (-1.55)	-0.434 (-1.58)	1.895 (6.44) ***	2.051 (1.00)	0.441 (0.25)	-0.720 (-0.46)			-0.013 (-0.06)	8.99%
		Electronic	4.422 (14.36) ***	-0.960 (-2.92) ***	0.701 (1.52)	0.016 (0.00)	-0.098 (-0.02)	-0.476 (-0.10)			-0.445 (-3.07) ***	8.56%
	W-stat.		339.87***	2.57	6.72***	0.15	0.01	0.00			8.87***	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.759 (33.60) ***	-0.078 (-0.65)	0.263 (1.31)	4.012 (1.40)	0.605 (0.20)	-0.032 (-0.01)	1.246 (4.26) ***			8.96%
		Electronic	2.911 (12.09) ***	-1.150 (-8.27) ***	-2.178 (-6.16) ***	-0.173 (-0.05)	-1.060 (-0.30)	5.093 (1.84) *	-0.759 (-3.26) ***			16.04%
	W-stat.		139.85***	59.38***	47.62***	1.43	0.22	3.45*	74.17***			
	TOV	*Floor*	4.902 (27.01) ***	-0.466 (-3.69) ***	0.656 (3.78) ***	4.368 (1.68) *	1.610 (0.60)	0.221 (0.10)		-1.214 (-8.92) ***		7.93%
		Electronic	4.596 (19.35) ***	-1.427 (-9.37) ***	-2.716 (-6.80) ***	1.718 (0.47)	0.185 (0.05)	6.312 (2.11) **		-0.613 (-3.73) ***		17.58%
	W-stat.		1.66	39.79***	71.35***	0.53	0.15	4.16**		13.36***		
	PIMPACT	*Floor*	3.729 (16.19) ***	0.755 (6.39) ***	0.678 (4.61) ***	4.760 (1.72) *	2.168 (0.79)	-0.123 (-0.06)			1.023 (8.62) ***	6.86%
		Electronic	3.150 (12.65) ***	-1.053 (-5.83) ***	-2.050 (-5.96) ***	1.538 (0.45)	-0.882 (-0.25)	4.941 (1.78) *			0.187 (1.52)	16.31%
	W-stat.		5.41**	100.20***	62.94***	0.88	0.75	3.34*			45.98***	

Panel C-3 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-3.714 (-13.31) ***	0.824 (6.43) ***	0.163 (0.86)	2.369 (1.03)	2.863 (1.33)	3.393 (1.89) *	3.121 (9.23) ***			6.57%
		Electronic	-4.343 (-5.15) ***	2.409 (4.64) ***	2.124 (4.38) ***	2.640 (1.26)	1.403 (0.83)	2.014 (1.25)	5.674 (14.61) ***			9.10%
	W-stat.		0.56	9.31***	16.34***	0.02	0.75	0.73	43.24***			
	TOV	*Floor*	-6.060 (-11.87) ***	-0.153 (-0.80)	0.990 (1.24)	-0.090 (-0.03)	3.442 (1.12)	6.549 (2.88) ***		-2.249 (-9.01) ***		8.60%
		Electronic	-5.191 (-13.72) ***	1.250 (8.97) ***	3.072 (6.69) ***	1.629 (0.77)	1.136 (0.63)	2.813 (1.80) *		-2.788 (-15.86) ***		9.84%
	W-stat.		5.27**	101.36***	20.57***	0.66	1.65	5.73**		9.39***		
	PIMPACT	*Floor*	-4.620 (-10.65) ***	1.789 (9.22) ***	1.392 (1.51)	-1.384 (-0.35)	3.341 (1.02)	7.613 (2.83) ***			1.424 (6.74) ***	8.17%
		Electronic	-5.047 (-15.12) ***	3.850 (21.90) ***	2.863 (5.88) ***	2.489 (1.11)	1.555 (0.85)	3.403 (2.07) **			2.222 (16.31) ***	9.64%
	W-stat.		1.64	137.48***	9.14***	3.00*	0.95	6.58***			34.31***	

Panel D-1: Risk adjusted return is conditional on size, BM and **Term spread** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	0.525 (2.11) **	-0.316 (-2.03) **	0.682 (2.81) ***	0.887 (0.39)	2.311 (1.10)	2.573 (1.50)	2.514 (4.05) ***			5.21%
		Electronic	1.616 (3.91) ***	1.248 (2.66) ***	1.204 (2.15) **	-1.101 (-0.21)	-0.912 (-0.18)	2.326 (0.51)	2.246 (2.00) **			2.99%
	W-stat.		6.96***	11.14***	0.87	0.14	0.41	0.00	0.06			
	TOV	*Floor*	1.444 (2.97) ***	-0.965 (-6.20) ***	1.576 (3.89) ***	-0.182 (-0.06)	1.132 (0.47)	-1.408 (-0.72)		0.195 (0.57)		7.33%
		Electronic	-0.351 (-0.64)	-0.294 (-1.04)	1.685 (3.46) ***	2.712 (0.49)	2.493 (0.48)	3.867 (0.85)		0.928 (3.19) ***		3.15%
	W-stat.		10.71***	5.62**	0.05	0.27	0.07	1.35		6.34**		
	PIMPACT	*Floor*	-1.914 (-2.03) **	-0.501 (-1.66) *	1.811 (4.46) ***	0.653 (0.22)	0.842 (0.36)	-2.089 (-1.13)			0.152 (0.70)	7.13%
		Electronic	3.149 (5.12) ***	-0.578 (-1.76) *	1.306 (2.72) ***	-0.728 (-0.12)	-1.259 (-0.23)	1.590 (0.38)			-0.358 (-1.59)	2.82%
	W-stat.		67.76***	0.05	1.11	0.06	0.15	0.76			5.10**	

Panel D-1 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	6.728 (38.56) ***	-0.335 (-2.29) **	-0.050 (-0.29)	2.542 (0.82)	-1.627 (-0.49)	-1.173 (-0.45)	0.921 (3.79) ***			6.13%
		Electronic	3.745 (8.21) ***	-3.512 (-5.97) ***	2.077 (5.67) ***	12.197 (2.23) **	9.673 (1.69) *	9.225 (2.69) ***	1.563 (2.97) ***			12.92%
	W-stat.		42.81***	29.19***	33.68***	3.12*	3.89**	9.17***	1.49			
	TOV	*Floor*	5.564 (30.94) ***	-1.469 (-13.90) ***	-0.311 (-2.15) **	2.677 (0.96)	-0.091 (-0.03)	-0.368 (-0.14)		-0.947 (-8.15) ***		6.70%
		Electronic	1.972 (4.49) ***	0.477 (1.23)	-2.855 (-3.93) ***	-3.959 (-0.50)	-2.386 (-0.29)	9.468 (2.74) ***		-0.660 (-2.08) **		10.95%
	W-stat.		66.70***	25.39***	12.27***	0.69	0.08	8.13***		0.82		
	PIMPACT	*Floor*	5.845 (26.34) ***	0.029 (0.21)	0.110 (0.72)	1.702 (0.67)	-0.461 (-0.17)	-1.186 (-0.53)			1.048 (7.34) ***	5.02%
		Electronic	2.227 (6.24) ***	-0.792 (-1.66)*	1.069 (1.93) *	6.547 (1.77) *	3.430 (0.93)	5.544 (2.59) **			1.604 (4.55) ***	11.42%
	W-stat.		102.67***	2.97*	3.00*	1.71	1.11	9.90***			2.49	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-1.456 (-4.77) ***	0.526 (4.19) ***	1.805 (8.45) ***	3.802 (1.70) *	5.354 (2.45) **	4.943 (2.65) ***	3.574 (10.61) ***			5.39%
		Electronic	-0.076 (-0.09)	1.222 (1.89) *	6.434 (14.22) ***	2.116 (1.02)	4.127 (2.29) **	3.626 (2.26) **	5.439 (13.27) ***			10.63%
	W-stat.		2.75*	1.16	104.64***	0.66	0.46	0.67	20.7***			
	TOV	*Floor*	-5.390 (-15.42) ***	-0.398 (-1.77) *	1.958 (3.54) ***	1.001 (0.28)	5.150 (1.83) *	7.578 (3.40) ***		-2.171 (-8.71) ***		5.57%
		Electronic	-2.040 (-4.34) ***	0.232 (1.61)	7.296 (15.10) ***	3.174 (1.41)	5.032 (2.48) **	4.504 (2.46) **		-2.128 (-18.44) ***		11.45%
	W-stat.		50.91***	19.1***	121.98***	0.94	0.00	2.82*		0.14		
	PIMPACT	*Floor*	-1.667 (-3.66) ***	0.883 (4.06) ***	1.846 (4.02) ***	0.427 (0.13)	3.145 (1.17)	8.303 (3.89) ***			1.469 (6.45) ***	2.38%
		Electronic	-2.352 (-6.47) ***	2.845 (13.81) ***	3.708 (7.73) ***	4.352 (1.88) *	4.666 (2.30) **	4.069 (2.36) **			2.008 (15.54) ***	7.84%
	W-stat.		3.55*	90.74***	15.08***	2.88*	0.56	6.02**			17.46***	

Panel D-2: Risk adjusted return is conditional on size, BM and **Yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.276 (-0.84)	0.207 (0.78)	1.489 (5.27) ***	5.156 (1.62)	6.055 (2.20) **	4.675 (2.43) **	2.865 (3.55) ***			4.74%
		Electronic	0.913 (1.55)	0.998 (2.40) **	2.322 (6.21) ***	4.486 (0.77)	2.562 (0.47)	3.336 (0.69)	2.666 (2.04) **			2.67%
	W-stat.		4.08**	3.63*	4.97**	0.01	0.42	0.08	0.02			
	TOV	*Floor*	0.869 (1.89) *	-0.761 (-4.3) ***	1.242 (2.43) **	2.459 (0.68)	1.342 (0.45)	0.110 (0.04)		0.228 (0.66)		6.01%
		Electronic	-1.198 (-2.66) ***	-0.293 (-0.88)	1.849 (3.64) ***	4.923 (0.84)	4.174 (0.74)	5.631 (1.14)		1.637 (2.87) ***		3.31%
	W-stat.		20.99***	1.99	1.43	0.18	0.25	1.26		6.12**		
	PIMPACT	*Floor*	1.201 (0.84)	-1.340 (-2.75) ***	-2.572 (-1.97) **	-19.724 (-2.16) **	-14.982 (-2.59) **	-8.784 (-1.42)			0.398 (1.27)	7.02%
		Electronic	1.808 (3.61) ***	-1.546 (-3.06) ***	3.729 (9.14) ***	5.596 (0.99)	5.536 (1.09)	7.419 (1.73) *			-1.568 (-3.67) ***	2.56%
	W-stat.		1.47	0.17	238.31***	20.18***	16.21***	14.33***			21.15***	
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	5.980 (31.42) ***	-0.115 (-0.64)	-0.976 (-5.23) ***	2.386 (0.72)	-1.120 (-0.32)	-1.357 (-0.49)	0.826 (3.15) ***			7.84%
		Electronic	4.756 (11.00) ***	-2.685 (-5.68) ***	-1.775 (-2.22) **	5.469 (1.09)	4.231 (0.92)	14.480 (4.06) ***	0.138 (0.35)			12.87%
	W-stat.		8.02***	29.59***	0.99	0.38	1.35	19.73***	3.02*			
	TOV	*Floor*	5.253 (22.03) ***	-0.883 (-6.20) ***	-1.069 (-6.80) ***	1.501 (0.45)	-0.251 (-0.07)	-1.186 (-0.39)		-0.889 (-7.48) ***		6.58%
		Electronic	3.129 (5.54) ***	1.266 (3.27) ***	-1.932 (-1.98) *	1.492 (0.16)	0.746 (0.08)	12.662 (2.95) ***		0.379 (0.85)		8.63%
	W-stat.		14.13***	30.80***	0.78	0.00	0.01	10.38***		8.04***		
	PIMPACT	*Floor*	5.368 (23.72) ***	0.092 (0.54)	-0.753 (-5.03) ***	-0.036 (-0.01)	-1.797 (-0.63)	-2.698 (-1.17)			0.670 (5.13) ***	4.65%
		Electronic	4.515 (14.44) ***	-2.155 (-6.67) ***	1.993 (3.38) ***	2.076 (0.49)	2.351 (0.60)	9.705 (3.80) ***			-0.164 (-0.67)	8.28%
	W-stat.		7.45***	48.28***	21.63***	0.25	1.10	23.64***			11.44***	

Panel D-2 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-2.434 (-10.20) ***	0.356 (2.26) **	1.133 (4.97) ***	3.761 (1.64) *	4.472 (2.13) **	4.707 (2.95) ***	3.163 (8.61) ***			4.26%
		Electronic	-1.375 (-1.39)	1.506 (2.53) **	6.014 (11.84) ***	3.573 (1.77) *	4.257 (2.37) **	3.648 (2.49) **	5.497 (13.33) ***			11.19%
	W-stat.		1.15	3.72*	92.35***	0.01	0.01	0.52	32.04***			
	TOV	*Floor*	-5.634 (-14.08) ***	-0.101 (-0.49)	1.265 (3.07) ***	2.042 (0.62)	3.767 (1.48)	4.702 (2.35) **		-2.382 (-8.19) ***		3.59%
		Electronic	-2.544 (-4.72) ***	0.160 (0.82)	6.863 (11.06) ***	3.918 (1.75) *	5.258 (2.57) **	5.134 (2.92) ***		-1.984 (-17.21) ***		11.11%
	W-stat.		32.84***	1.81	81.44***	0.7	0.53	0.06		11.89***		
	PIMPACT	*Floor*	-1.310 (-1.42)	0.371 (1.00)	1.311 (2.57) **	2.524 (0.74)	4.825 (1.70) *	7.621 (3.36) ***			1.408 (5.46) ***	-0.19%
		Electronic	-3.864 (-12.99) ***	2.576 (11.91) ***	3.200 (6.13) ***	5.315 (2.14) **	4.629 (2.18)	4.282 (2.60) **			1.775 (11.61) ***	7.47%
	W-stat.		73.74***	104.03***	13.1***	1.26	0.01	4.1**			5.76**	

Panel D-3: Risk adjusted return is conditional on size, BM and **Dividends Yield** (business cycle variable).

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
London Stock Exchange (LSE)	PQSPR	*Floor*	-0.141 (-0.41)	-0.350 (-2.62) ***	0.674 (1.85) *	-1.935 (-0.93)	-1.308 (-0.68)	-0.934 (-0.55)	1.284 (2.24) **			4.24%
		Electronic	3.782 (8.33) ***	0.008 (0.03)	2.105 (5.48) ***	4.086 (0.71)	4.038 (0.77)	3.337 (0.68)	1.002 (1.05)			3.00%
	W-stat.		74.73***	1.42	13.86***	1.08	1.03	0.77	0.09			
	TOV	*Floor*	0.511 (0.72)	-0.524 (-2.36) **	0.178 (0.46)	-4.748 (-1.87) *	-0.702 (-0.27)	-0.984 (-0.46)		0.561 (1.70) *		5.27%
		Electronic	5.727 (7.46) ***	-0.724 (-1.98) **	-0.541 (-0.74)	-5.526 (-0.91)	-5.651 (-0.94)	-1.078 (-0.20)		0.859 (2.52) **		2.90%
	W-stat.		46.13***	0.30	0.96	0.02	0.68	0.00		0.76		
	PIMPACT	*Floor*	-0.888 (-0.91)	-0.428 (-1.33)	0.189 (0.47)	-4.974 (-1.85) *	-4.117 (-1.82) *	-3.615 (-2.09) **			0.114 (0.50)	6.04%
		Electronic	3.100 (3.69) ***	0.586 (1.04)	2.888 (3.17) ***	0.257 (0.04)	0.307 (0.05)	4.175 (0.73)			-0.274 (-0.67)	2.73%
	W-stat.		22.57***	3.24*	8.80***	0.56	0.43	1.85			0.91	

Panel D-3 (Continued)

Stock exchange	Liq. Risk Factor	Sample period	Intercept	Size	BM	RET2-3	RET4-6	RET7-12	Prop. Bid-ask	Turnover	Price impact	$\overline{R^2}$
Swiss Stock Exchange (SSE)	PQSPR	*Floor*	8.473 (47.94) ***	0.915 (6.08) ***	-0.897 (-6.20) ***	1.801 (0.45)	-2.606 (-0.70)	-3.739 (-1.22)	1.918 (6.32) ***			7.38%
		Electronic	0.615 (2.95) ***	0.726 (4.26) ***	0.561 (2.02) **	3.404 (0.78)	1.901 (0.50)	6.585 (2.54) **	-0.567 (-1.18)			7.31%
	W-stat.		1420.00***	1.24	27.51***	0.14	1.40	15.82***	26.50***			
	TOV	*Floor*	6.551 (31.91) ***	0.292 (1.94) *	-0.458 (-1.98) **	-0.636 (-0.15)	-4.378 (-1.06)	-4.131 (-1.20)		-1.370 (-8.79) ***		5.26%
		Electronic	2.214 (7.84) ***	-0.306 (-1.28)	-3.954 (-6.28) ***	4.985 (0.91)	-0.136 (-0.02)	6.226 (1.96) *		-0.956 (-3.68) ***		8.10%
	W-stat.		236.05***	6.25**	30.82***	1.06	0.60	10.68***		2.54		
	PIMPACT	*Floor*	6.820 (31.65) ***	1.606 (8.15) ***	-1.752 (-12.56) ***	1.836 (0.56)	-2.223 (-0.73)	-4.285 (-1.85) *			1.278 (7.64) ***	5.05%
		Electronic	4.723 (9.66) ***	-2.228 (-5.25) ***	-2.117 (-3.54) ***	-1.685 (-0.22)	-2.373 (-0.32)	9.616 (2.41) **			-1.067 (-3.70) ***	8.25%
	W-stat.		18.38***	81.76***	0.37	0.21	0.00	12.14***			66.08***	
Frankfurt Stock Exchange (FSE)	PQSPR	*Floor*	-2.302 (-7.03) ***	0.472 (2.63) ***	2.195 (7.67) ***	5.397 (1.35)	7.446 (1.93) *	7.530 (2.39) **	1.927 (3.31) ***			4.25%
		Electronic	-3.463 (-4.96) ***	1.828 (3.02) ***	4.805 (11.43) ***	4.369 (1.88) *	2.682 (1.46)	2.410 (1.60)	4.758 (11.74) ***			6.19%
	W-stat.		2.76*	5.00**	38.57***	0.20	6.72***	11.5***	48.76***			
	TOV	*Floor*	-5.841 (-14.53) ***	0.043 (0.25)	2.017 (3.06) ***	1.243 (0.34)	6.606 (2.11) **	9.448 (4.06) ***		-2.798 (-11.87) ***		6.28%
		Electronic	-3.404 (-10.23) ***	1.252 (9.27) ***	5.829 (11.61) ***	1.858 (0.75)	1.440 (0.68)	2.693 (1.64)		-2.669 (-18.21) ***		6.85%
	W-stat.		53.65***	80.08***	57.7***	0.06	5.91**	16.88***		0.78		
	PIMPACT	*Floor*	-2.650 (-5.04) ***	2.196 (9.51) ***	0.652 (1.91) *	0.659 (0.19)	4.680 (1.64)	7.619 (3.85) ***			2.094 (10.54) ***	1.65%
		Electronic	-4.360 (-12.95) ***	3.620 (18.92) ***	4.915 (11.5) ***	5.575 (2.52) **	3.393 (1.74) *	3.905 (2.44) **			2.256 (19.91) ***	8.15%
	W-stat.		25.82***	55.38***	99.45***	4.95**	0.44	5.37**			2.04	

Chapter Four
Information Asymmetry, Divergence of Opinion and Firm-specific Liquidity

4.1 Introduction

In the previous chapter it was shown that illiquidity is positively related to expected return, that is to say, illiquid stocks offer higher returns to investors than liquid stocks. It was also shown that liquidity is priced differently before and after the automation of a trading system, which means that level of liquidity is different across trading systems. This chapter investigates what it is that affects firm-specific liquidity: in particular, whether information asymmetry and divergence of opinion affect firm-specific liquidity and thus cause a difference in the levels of liquidity across stocks on floor and electronic trading systems.

The literature in the area of market microstructure shows that liquidity is primarily a function of asymmetric information to the extent that a high level of information asymmetry results in lower liquidity. Information asymmetry may exist among various groups such as informed traders and market makers (i.e. dealers/specialists), managers and outside investors. This chapter takes as its focus the information asymmetry between company managers and outside investors, where company managers are expected to have more specific information about their firms' assets value and future prospects than the outside investors[65,66]. In such a situation, investors face a higher degree of uncertainty about a firm's value, which exposes them to a higher level of risk. This, in turn, is expected to increase the perceived inventory risk and lower stocks' liquidity. The opposite is true when

[65] Previous studies in market microstructure have extensively examined the effect of information asymmetry between informed traders and market makers on liquidity. Such studies include, for example, Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Admati and Pfleiderer (1988),Glosten and Harris (1988), Madhavan and Smidt (1991), Hasbrouck (1991) among others. These studies point out that liquidity will decline in markets with informed traders as a result of wide bid-ask spreads that are set up by market makers to recover their loss to well-informed traders from uniformed traders.

[66] When mentioned in this chapter, information asymmetry is between the company managers and the market (i.e. outside investors) unless otherwise indicated.

both company managers and investors are equally informed about the firm (i.e. there is a lower level of information asymmetry)[67].

Outside investors often share common information about firms, but disagree as to its meaning and interpretation, which results in divergence of opinion (Harris and Raviv, 1993; Dische, 2002; Doukas et al., 2004 among others). Divergence of opinion can be recognized as a potential determinant of stock liquidity. It may reflect uncertainty among investors about firms' future prospects and represent a potential source of risk (Doukas et al., 2004; Doukas and McKnight, 2005 and references cited in). Therefore, it is anticipated that investors will avoid trading in stocks where divergence of opinion is higher, which may result in lower stock liquidity. On the other hand, when there is a disagreement in opinion among investors about a firm's value, the market may be dominated by the beliefs of optimistic investors (see Miller, 1977) [68]. In this case, the optimistic investors will hold and trade in stocks with a higher dispersion among investors, because they believe that these stocks have higher valuations (see Diether et al., 2002; Boehme et al., 2006 among others). Not only may stock prices be pushed up by this, but trading activity and market depth of these stocks may be increased, thereby improving stocks' liquidity. So divergence of opinion can result in either less or more liquidity[69].

Furthermore, with many stock exchanges having moved from floor to electronic trading systems, it is expected that the dissemination of information about firms and their informational environment will be affected, and thus affect firm-specific liquidity[70]. More specifically, the different characteristics of floor and electronic trading systems such as the sharing of information and the speed and efficiency in executing orders, are anticipated to affect the level of information asymmetry between managers and investors and the degree of divergence in investors' opinion. For example, in contrast to an electronic trading

[67] For more detail on the effect of information asymmetry on firm-specific liquidity, see section 4.3.3.1.

[68] In Miller's (1977) model, pessimistic investors are not allowed to trade when they actually wish to sell short the stocks with dispersion in investors' opinion, therefore, optimistic investors will dominate the market.

[69] For more details on the relationship between divergence of opinion and firm-specific liquidity, see section 4.3.3.2.

[70] Theissen, 2002b, Handa et al. (2004) and Maghyereh (2005) argue that the introduction of electronic trading systems will improve the transmission of information to market participants compared with floor trading systems. However, this issue is controversial. See section 4.3.3.3 for more details.

system, sharing information about orders and firms' fundamental value on a floor trading system will improve the dissemination of information and thus reduce the level of information asymmetry. This will also enhance investors' informational level to the extent that they can update their beliefs adequately and adjust the interpretation of information, which will then reduce the disagreement in their opinions. This in turn is expected to affect the extent to which an information asymmetry and divergence of opinion have an impact on firm-specific liquidity, i.e. different trading systems will have different implications concerning the relationship of information asymmetry and divergence of opinion with firm-specific liquidity[71]. Therefore, this chapter aims to examine the impact of automation of trading systems on the implications of information asymmetry and divergence of opinion on firm-specific liquidity. The investigation of this issue in this chapter will yield insights concerning the extent to which variations in the level of information asymmetry and differences in investors' opinions may affect firm-specific liquidity within different contexts of market structure.

The importance of information asymmetry between managers and investors has been extensively examined in the literature, mainly focusing on its role in valuing firms' assets around corporate events. For example, Dierkens (1991) shows that, at an equity issue announcement, the drop in stock prices is positively related to information asymmetry. Krishnaswami and Subramaniam (1999) provide evidence of the positive relation between information asymmetry and abnormal returns for the diversified companies that engaged in a spin-off. Officer et al. (2006) find that with a higher level of information asymmetry about the target, the acquirer achieves a higher gain. Draper and Paudyal (2008) examine the role of information asymmetry in bidders' gains and show that firms with higher information asymmetry achieve a higher gain from early bidders. These studies generally conclude that firms with a higher level of information asymmetry have engaged in informational releasing events such as equity issuance, spin-off, and takeover to alleviate information asymmetries through attracting the attention of investors.

[71] For further details on the impact of floor and electronic trading systems on the relationship of information asymmetry and divergence of opinion with firm-specific liquidity, see section 4.3.3.3.

Additionally, some studies with more particular relevance to our study are those that focus on the relationship between the number of financial analysts and liquidity, such as Chung et al. (1995), Brennan and Subrahmanyam (1995) and Easley et al. (1998). The first two studies examine the relationship between financial analysts and liquidity assuming that financial analysts are informed traders, to the extent that larger adverse selection cost (i.e. lower liquidity) is expected for stocks with substantial analysts' coverage. Chung et al. (1995) find that stocks' liquidity decreases as the number of analysts following the stock increases. In contrast, Brennan and Subrahmanyam (1995) provide evidence that firms with many analysts have smaller adverse selection costs (i.e. higher liquidity), which is against the notion that financial analysts are informed traders. Consistent with the analysis of Brennan and Subrahmanyam (1995), Easley et al. (1998) find that the probability of informed-based trade is lower for stocks with many financial analysts. This provides evidence that the number of financial analysts is not an appropriate proxy for information-based trading, and any study using it as such would not capture the true relationship.

Furthermore, although the literature on divergence of opinion is extensive, it is mainly directed towards examining the relationship between divergence of opinion and stock returns. For example, Miller (1977) theorizes the relationship between stock returns and disagreement among investors. Ackert and Athanassakos (1997), Lee and Swaminathan (2000), Diether et al. (2002), Boehme et al. (2006) among others provide empirical evidence in support of Miller's (1977) theory that stock returns are negatively related to divergence of opinion. In contrast, Doukas et al. (2004) and Doukas and McKnight (2005), among others, report a positive relationship between dispersion in forecasts and future returns.

Despite this plethora of studies on information asymmetry, financial analysts, and divergence of opinions, studies that explicitly examine the implications of information asymmetry on firm-specific liquidity, and those that examine the relationship between divergent opinion and firm-specific liquidity are virtually nonexistent. In particular, no study, to the best of our knowledge, has examined the impact of a different context of market structure (i.e. floor and electronic trading systems) on the implications of information asymmetry and divergence of opinion on firm-specific liquidity[72]. By investigating this issue, this chapter extends the empirical literature in the following ways:

First, although the recent developments in information technology have led to dramatic changes in the structure of the trading systems of financial markets, our knowledge is limited on how the move from floor to electronic trading systems can impact the level of information asymmetries and the disagreement among investors and how this, in turn, could result in a different impact on firm-specific liquidity. This chapter, therefore, contributes to our knowledge on this issue and extends the literature on market structure and design by examining whether and to what extent the cross-sectional variation in information asymmetry and divergence of opinion could explain the cross-sectional variation in firm-specific liquidity before and after the automation of trading systems.

Second, prior studies restricted themselves either to investigating the role of information asymmetry between managers and outside investors in valuing risky assets, or in examining different empirical issues related to financial analysts. Further, the literature has extensively examined the importance of divergence of opinion in asset pricing; but has not examined, as we do in this chapter, the relationship between information asymmetry and firm-specific liquidity, and also the relationship between divergence of opinion and individual stock liquidity. So this chapter extends the existing literature by providing more useful and deep insights about the nature of these relationships.

Finally, this chapter provides new evidence, for the first time, on the implications of information asymmetry between company managers and outside investors and on the implication of divergence of opinion on firm-specific liquidity in European markets. Three main European markets are used to test this issue, namely the UK (London Stock Exchange; LSE), Swiss (Swiss Stock Exchange; SSE), and German (Frankfurt Stock Exchange; FSE). These markets have different attributes and major differences in their

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[72] Also, none of the studies on market structure and design, especially that on floor and electronic trading systems, which have been reviewed in section 2.2.2, have examined the relationship between information asymmetry and divergence of opinions and firm-specific liquidity before and after the automation of trading systems.

structure and are considered smaller than US markets, which were the main focus of previous studies. For example, unlike US markets where stocks are traded under one trading system (i.e. floor trading system), stocks in the UK and Swiss markets are shifted from floor to electronic trading systems. In the German market stocks may be traded either electronically through the electronic trading system XETRA or by the floor trading system. Thus, these different trading systems across markets, as discussed before, may affect the process of disseminating information produced by financial analysts which, in turn, may affect the implications of information asymmetry and divergence of opinion on firm-specific liquidity. Furthermore, institutional investors in NYSE hold approximately 82% of market shares compared with nearly 87.2%, 86.7% and 84.2% in the UK, German and Swiss markets respectively[73]. This difference in institutional investors' holdings may affect the number of financial analysts supplying information to the markets and, thus affect the level of information asymmetry and the degree of the divergence of opinion. Brennan and Tamarowski (2000) argue that institutional investors are likely to be significant users of analysts information, pointing out that "*institutional investors, by contrast, often require documented analyses by analysts and other third parties to justify their portfolio decisions*" (p. 29). Hence, investigating the relationship between information asymmetry and divergence of opinion with individual stock liquidity, before and after the automation for these major European markets will provide us with new insights that could not be obtained by looking at other markets.

To this end, the following questions will be addressed:

- Does the variation in the information asymmetry between the managers of the company and outside investors explain the cross-sectional variation in firm-specific liquidity?

[73] The source for the percentage of institutional ownership for US is Ho et al. (2004), while for LSE, FSE and SSE it is the Federation of European Securities Exchanges (FESE) http://www.fese.be/_lib/files/Share_Ownership_Survey _2007_Final.pdf.

- Does the variation in opinion among investors explain the cross-sectional variation in firm-specific liquidity?

- Does the impact of information asymmetry and divergence of opinion on firm-specific liquidity differ before and after the automation of trading systems?

The findings of this chapter should be of particular interest to many parties such as investors, companies, regulators and academics. An investigation of the relationship between information asymmetry, divergence of opinion and firm-specific liquidity will be important for investors because it sheds light on their trading behaviour and illuminates their trading decisions. Intuitively, investors prefer trading where there are low transaction costs and holding stocks that are less uncertain as to future prospects. For instance, if firms with high level of information asymmetry have lower liquidity, this indicates that trading in these firms' stocks will result in higher transaction costs (i.e. higher bid-ask spread). Easley et al. (1998) argue that stocks with low analysts' coverage will have a larger bid-ask spread. Furthermore, if the findings of this chapter show that stocks with a high level of analysts' disagreement because of high uncertainty about firms' future growth (Doukas et al., 2004) will be less liquid, this means that holding these stocks will expose investors to a higher level of risk. Therefore, investors will prefer to trade in stocks with a low level of information asymmetry (i.e. firms that are more transparent to the market) and with a low level of disagreement among investors.

Examining the implications of both information asymmetry and divergence of opinion on firm-specific liquidity could highlight the importance of companies' information disclosure policies and provide them with useful references for their decision making. For instance, it may help firms' executives make decisions on whether their information disclosure policy needs to improve. Thomas (2002) points out that firms with a high level of information asymmetry between managers and outside investors face problems in raising capital, have lower liquidity and, hence, a higher cost of capital. Therefore, if a low level of information asymmetry results in higher firm-specific liquidity, managers will decide to invest more in investor relations activities to improve the disclosure of information. This, in addition to improving a firm's liquidity, will reduce the cost of equity and increase the amount of capital raised by gaining easier access to capital markets. Krishnaswami and Subramaniam (1999) find that due to a low level of information asymmetry there was an improvement in the share price and an increase in the amount of capital raised by companies engaged in spin-off. Further, Dische (2002), Doukas et al. (2004) and Moeller et al. (2006) argue that the amount of information about a firm and its quality can affect the divergence in opinion among investors. Therefore, if the findings show that there is a significant relationship between divergence of opinion and individual stock liquidity, then firms could control the dispersion of earnings forecasts among investors in a such way that could benefit firms (Johnson, 2004) via improving their liquidity and, thus, reducing cost of equity.

In addition, the findings of this chapter should have some implications for exchange regulators and shed light on some regulatory concerns regarding the performance of trading systems. That is, exchanges' designers and regulators are responsible for ensuring that a trading system facilitates the process of information dissemination. Therefore, if, after the automation of trading systems, information asymmetry and the divergence of opinion have greater impact on firm-specific liquidity, then more regulations are required to improve the information diffusion of electronic trading systems. Otherwise, no further regulations are required.

Finally, the findings of this chapter are of central importance to academics and financial communities (i.e. investors and companies). They shed light on the nature of the role of financial analysts and emphasize the importance of the earnings forecast by financial analysts. Brennan and Subrahmanyam (1995) argue that financial analysts' activities are costly ones whose social benefits remain unexplored and Easley et al. (1998) argue that the role played by financial analysts in the market remains a puzzle not yet solved. Therefore, if firm-specific liquidity improved with low level of information asymmetry between firms and market (i.e. with substantial analysts coverage) and it is significantly affected by analysts' divergence of opinion, this will provide confirmation that the crucial role of financial analysts is to uncover and disseminate information about firms and highlight the importance and the creditability of their consensus about provided information. To this end, the discussion above emphasizes the need for more research to highlight the importance of the relationship of information asymmetry and divergence of opinion with individual stock liquidity.

The structure of this chapter is as follows. The next section provides a review of the literature related to information asymmetry and divergence of opinion. Section 4.3 presents the proxies for liquidity, information asymmetry, and divergence of opinion, describes the data and the sample that is utilized in the empirical analysis, develops the hypothesis and discusses the methodology employed to undertake the analysis. The empirical results are then discussed in section 4.4. Finally, section 4.5 concludes the chapter.

4.2 Literature Review

The literature that directly examines the association of liquidity with information asymmetry between managers and the market, and the association of liquidity with divergence of opinion is virtually nonexistent. Therefore, this section briefly reviews the empirical research undertaken to examine the relationship between information asymmetry and other issues such as corporate actions; the research on the role of financial analysts that is related to our study; and the research conducted to examine the effect of divergence of opinion on assets returns. This review of literature can be considered relevant to understanding the key issues of information asymmetry and divergence of opinion and their implications for liquidity[74].

4.2.1 Information asymmetry between managers and market

Company managers and outside investors are both assumed to have the same level of market-wide information; however, managers usually have the advantage and know more value-relevant, firm-specific information than outside investors which creates the information asymmetry problem between the two (see for example Dierkens, 1991). In this

[74] See section 2.2.2 for the review of the studies on market structure and design, especially with regard to floor and electronic trading systems.

case, managers with private and positive information about the firm will be motivated to attract the attention of the market towards it, to mitigate information asymmetry (Brennan and Hughes, 1991; Draper and Paudyal; 2008, among others). Managers normally do so by pushing their companies towards engaging in corporate actions such as equity issue, stock split, and takeover.

There is extensive empirical literature that examines the association between corporate actions requiring changes in organizational form and information asymmetry, and how the latter affects the value of the firm’s assets. For instance, Dierkens (1991) examines the interaction between information asymmetry and the issuing of new equity. He uses a sample of 197 firms that issued equity between 1980 and 1983. He shows that when there is an equity announcement, information asymmetry is significantly decreased. The results also show a negative relation between stock price and information asymmetry, and firms, therefore, time their equity issue announcement when the level of information asymmetry is low.

Furthermore, some diversified companies with liquidity constraints whose assets’ values are buried by a high level of information asymmetry, choose corporate spin-off to alleviate the asymmetric information about a firm’s value. Krishnaswami and Subramaniam (1999), for example, examine the information hypothesis which states that spin-off improves the value of a firm through mitigating the information asymmetry between managers and market regarding operating efficiency and profitability of the different divisions of the firm. They analyze a sample of 118 corporate spin-offs which were completed between 1979 and 1993, along with a control sample to control for firm-specific characteristics (e.g. size and industry classification) in their empirical tests. By using event study methodology in addition to univariate and multivariate analysis, they find that firms engaged in spin-off are those with higher information asymmetry. They report a significant decrease in the measure of information asymmetry after spin-off. In contrast to the control sample, they find that the abnormal return is larger for firms with a higher level of information asymmetry about their values. This is consistent with the theory that the mitigation of information asymmetry is an important factor in explaining spin-off gains. Finally, the results show that firms with liquidity constraints were able to raise more external capital after spin-off compared with the control sample.

In contrast, Thomas (2002) provides evidence which is at odds with the above research. He argues that corporate diversification is not necessarily related to a high level of information asymmetry, and information asymmetry that is related to one segment can be diversified away across other segments. In other words, the valuation errors that outsiders make are imperfectly correlated across multiple segments and may therefore be smaller for diversified firms. The sample that Thomas uses includes firms which have forecast data from I/B/E/S available for the end of fiscal years between July 1985 and June 1996. He finds that diversified firms, compared with focus firms, do not show a high level of information asymmetry between managers and the market. This implies that diversification provides a potential information benefit rather than exacerbates information asymmetries[75].

Further, Draper and Paudyal (2008) examine the proposition that managers where firms are undervalued and have an asymmetric information problem with the market, wish to reduce the information asymmetry and increase the value of their company's asset through attracting the attention of market participants by announcing takeover bids. They analyze 9,620 bids made by 1,630 UK companies between 1985 and 2003. The findings of both univariate and multivariate analyses are consistent with their prediction. More specifically, they find that bidders with high information asymmetry, compared with those with low information asymmetry, have higher announcement returns and larger gains. These findings are robust to alternative proxies for information asymmetry. The results also show that bidders with greater information asymmetry gain the most under all market conditions and for all relative deal size groups.

In summary, the review thus far suggests that firms that are missvalued (i.e. mainly undervalued) and have a higher cost of capital due to information asymmetry, undertake information-releasing events such as an equity issue, earning announcement, takeover, or

[75] Other studies such as Nanda and Narayanan (1999) and Gilson et al. (2001) among others provide evidence that is consistent with Krishnaswami and Subramaniam (1999). Clarke et al. (2004) provide evidence that is consistent with Thomas (2002).

company spin-off. Such events release valuable firm-specific information to the market through attracting the attention of financial analysts, who follow, analyze and disseminate information about the firm. This implies that firms with substantial financial analysts' coverage are those with low information asymmetry between company managers and outside investors.

4.2.2 Financial analysts and firm-specific liquidity

The role played by financial analysts has recently inspired a large amount of research[76]. However, a brief review of the key studies that examine the relationship between financial analysts and individual stock liquidity follows. Chung et al. (1995), for example, examine the relationship between financial analysts and bid-ask spread. They propose that market makers set up the bid-ask spread based on a belief that adverse selection risk is associated with the number of analysts following a stock. In other words, they expect a positive relation between financial analysts and a stock's bid-ask spread. They use intraday data for NYSE and AMEX on bid and ask prices for the period 1984-1988 and obtained data on financial analysts from I/B/E/S dataset. They find that stocks with greater analysts' coverage are those with a wider bid-ask spread, which is consistent with the view that the number of financial analysts is positively related to adverse selection costs, which makes market makers post higher bid and ask prices. Their result contradicts the notion that financial analysts are uninformed traders who only collect and disseminate information rather than creating private information.

Along the same lines, Brennan and Subrahmanyam (1995) estimate the effect of information-based trading on stock liquidity by examining the empirical link between financial analysts and adverse selection cost of transaction. They employ the number of analysts following a company as a proxy for informed trading and predict greater adverse

[76] Other studies have examined various empirical issues related to financial analysts. Hayes (1998) and Jackson (2005) examined the incentives for analysts to generate trade, Kim et al. (1997) and Branson et al. (1998) examined the response of stock price to the analysts' initial buy recommendation, and Irvine (2003) compared abnormal returns and liquidity around a recommendation of an analyst who is initiating coverage, to abnormal returns and liquidity around a recommendation by an analyst who already covers the stock.

selection costs for the firms with many analysts. For 1,508 stocks in NYSE, they use intraday and daily data of the year 1988, and data on the number of analysts for the year end 1987. The adverse selection cost, measured by Kyle (1985) lambda, is estimated by using both Glosten and Harris (1988) and Madhavan and Smidt (1991) procedures. However, the authors argue that neither measure of adverse selection costs is entirely appropriate because in NYSE both market and limit orders are allowed[77]. Inconsistent with their prediction, Brennan and Subrahmanyam find the firms being followed by a large number of analysts have more liquidity than those followed by few analysts. In other words, the adverse selection costs tend to decrease with the increase in analysts' coverage, which is at odds with the findings of Chung et al. (1995). Brennan and Subrahmanyam (1995) explain their results as due to enhanced competition among informed agents, resulting in information being quickly reflected in stock prices and thus deepening the market.

Employing financial analysts as a proxy for informed traders is inappropriate because their role focuses mainly on collecting, analyzing and disseminating information about firms. Therefore, the results of Brennan and Subrahmanyam (1995), in contrast with Chung et al. (1995), confirm this notion. However, Easley et al. (1998) argue that the puzzle about the role that the analysts play in financial markets remains unsolved. Therefore, Easley et al. develop a new approach to examining the informational role of analysts. That is, they investigate whether financial analysts provide private information to the market. They use intraday data during the sample period 1 October 1991 to 22 December 1991 and estimate the probability of informed trade for a sample of NYSE that varies in analysts' coverage. The results show, consistent with Brennan and Subrahmanyam (1995) but in contrast with Chung et al. (1995), that stocks with substantial analysts coverage have a low probability of informed trades. That is, even though stocks that are followed by more analysts have more information-based trade, the rate of uninformed trade in these stocks is greater. The findings also show that analysts do not provide or create any private information: private information events have the same probability across stocks with different analysts'

[77] Brennan and Subrahmanyam (1995) argue that the model of Glosten and Harris (1988) assumes that investors can place only unconditional market orders, while the model of Madhavan and Smidt (1991) explicitly assumes that informed traders condition their order flow on the price.

coverage. Finally, Easley et al. find that there is a relation between analysts and the reduction in the level of informed trading; therefore, the number of analysts following a firm cannot be used as a proxy for informed traders. Thus, the authors argue that any study (such as Brennan and Subrahmanyam, 1995 and Chung et al., 1995) which uses analysts' coverage as a proxy for informed trading cannot capture the true relationship.

Even though Brennan and Subrahmanyam (1995), Chung et al. (1995) and Easley et al. (1998) examine the relation between financial analysts and liquidity, none of them explicitly examine the implications of information asymmetry between company managers and outsider investors on firm-specific liquidity, which is the gap that this chapter aims to examine and fill.

4.2.3 Divergence of opinions

Turning our attention to the issue of divergence of opinion among investors, Harris and Raviv (1993) refer to divergence of opinion among investors as the situation where investors share common information about firms' future prospects and their growth opportunities, but they differ in the way they interpret this information. The issue of divergence among investors' opinions has attracted much attention from academics, and numerous studies have been devoted to examining its role in explaining the cross-section of stock returns. The literature has looked at the dispersion in investors' opinion and how it affects stock returns from two different points of view.

The first point of view, first developed by the seminal work of Miller (1977), states that under short sale constraint pessimistic investors are not allowed to trade (i.e. short the stocks): only optimistic investors will hold the stocks, so the prices will reflect a more optimistic valuation[78]. Whenever disagreement among investors about stocks' value is high, optimistic investors will place a heavy demand on stocks which, in turn, will increase stock prices and result in lower returns. In other words, divergence of opinion among investors is negatively related to stock returns. The work of Miller (1977) paves the way for

[78] We refer to this point of view throughout the thesis as the optimistic view.

further empirical work to test the valuation effect of divergence of opinions among investors. Diether et al. (2002), for example, examine the role of dispersion in analysts' forecasts (as proxy for divergence in opinion among investors) in explaining stocks cross-sectional returns for sample of NYSE, AMEX, and NASDAQ stocks from 1976 to 2000. They find evidence that stocks with low disagreement in opinion among investors earn higher returns than otherwise similar stocks, thereby providing support to Miller's hypothesis. In particular, they find that a portfolio of stocks with the lowest dispersion in investors' opinions outperform a portfolio of stocks with the higher dispersion in investors' opinions by 9.48% per year. These results are more pronounced for small stocks and stocks that have high book-to-market ratio and low momentum.

Consistent with Diether et al. (2002), Boehme et al. (2006) also provide evidence in support of the Miller effect. But in contrast to Diether et al. (2002), they test the overvaluation effect by using the two dimensions in Miller's hypothesis, which are short-sale constraint and divergence of investor opinion. By using a sample of NYSE and NASDAQ stocks from 1988-2002, they find that stocks subject to high divergence of investors' opinion and high short-sale constraints are overpriced. For these stocks, they report an annualized return of 21% which is greater than the return reported by Diether et al. (2002). Their findings also show that neither of these conditions, high divergence of investors' opinion and high short-sale constraints, is sufficient to produce overpricing.

The negative relationship between divergence of opinion and stock returns, reported by Diether et al. (2002) and Boehme et al. (2006) among others, shows that firms with high uncertainty about earnings do worse, which implies that instead of discounting uncertainty, investors pay a premium for it (see Johnson, 2004). This is inconsistent with the other point of view, the risk view, which posits that divergence of opinion among investors could be viewed as a potential source of risk. That is, since divergence of opinion presents highly uncertain, more volatile future prospects for a firm, investors should demand a higher expected rate of return on stocks with higher divergence of opinion among investors (see for example, Diether et al., 2002; Doukas and McKnight, 2005). Consequently, a positive relationship between divergence of opinion and stock returns is expected.

Doukas et al. (2004), for example, provide evidence that support the risk view. They examine whether divergence in opinion can explain the difference in the cross-sectional returns between value and growth stocks. They argue that investors will ask for higher expected returns when the disagreement among investors about stocks future price is high. By using a sample of NYSE, AMEX, and NASDAQ stocks from 1983 to 2001, they find that dispersion in analysts' forecast decreases as firm size increases and increases with book-to-market ratio. Their results show that divergence of opinion plays an important role in asset pricing since value stocks earn a higher return, which is considered a reward for greater dispersion in investors' opinion about a firm's future prospects. These results hold for alternative asset-pricing specifications.

Also, as part of their study, Doukas and McKnight (2005) provide evidence consistent with the notion that divergence of opinion among investors can be viewed as a proxy for risk. They used a sample of 13 European stock markets from 1988 to 2001, and find that stocks with high (low) dispersion in opinion earn higher (lower) expected returns. This result is consistent with the result of Doukas et al. (2004) but contradicts the result of Diether et al. (2002) and Boehme et al. (2006) among others, who report a negative relationship between stock returns and divergence in opinion among investors.

Overall, while there is much literature that examines the role of divergence of opinion, it mainly focuses on investigating the importance of divergence of opinion among investors in explaining the cross-sectional stock returns. None of the previous studies examine the implications of divergence of opinion among investors on firm-specific liquidity. To date the impact of divergence in investors' opinion on individual stock liquidity, and its role in explaining the cross-sectional variation in liquidity has been neglected in the microstructure literature.

To this end, this chapter sheds new light on not only the implications of information asymmetry and divergence of opinion on firms-specific liquidity, but also examines the impact of different market structures (i.e. floor versus electronic trading systems) on the relation between information asymmetry and divergence of opinion with firm-specific liquidity, for the biggest three European stock markets; specifically, the UK, the Swiss and the German markets. In other words, this research examines and compares whether the cross-sectional variation on firm-specific liquidity can be explained by the cross-sectional variation of information asymmetry and divergence of opinion before and after the automation of trading systems. Studies that attempt to highlight and examine this empirical issue, to the best of our knowledge, are virtually nonexistent.

4.3 Research Design

This section provides a discussion of the proxies for liquidity, information asymmetry and divergence of opinion that are employed in the empirical analysis. It also presents the sample and data, identifies the hypotheses to be tested and develops the methodology utilized to test the hypotheses.

4.3.1 Proxies for liquidity, information asymmetry and divergence of opinion

4.3.1.1 Proxies for liquidity

There are many measures of liquidity that have been used in the market microstructure literature. However, in our analysis in this chapter we focus on the most commonly used measures of liquidity, which are the same measures that are discussed in detail in previous chapter (section 3.3.4). These measures are: proportional bid-ask spread, turnover ratio, and price impact (Amihud's (2002) illiquidity ratio). For each one of these measures, we calculate it first on a daily basis using daily data, and then the monthly average is calculated by taking the average of daily observations for each company in a given month, as in equations (3.15) and (3.16), (3.18) and (3.19), (3.21) and (3.22) for proportional bid-ask spread, turnover ratio, and price impact respectively.

4.3.1.2 Proxies for information asymmetry

Information asymmetry can exist between different groups. However, this section presents the proxies for information asymmetry that mainly measure its level between company managers and outside participants (i.e. market). In our empirical analysis, we use two alternative measures: analysts' coverage (i.e. number of the analysts following a firm) and mean forecast error.

4.3.1.2.1 Analysts' coverage

Financial analysts play an important role in collecting, analyzing and disseminating information to the market about firms' future prospects. Firms that are followed by a large number of financial analysts have a lower level of information asymmetry between managers and the market: the market holds up-to-date information about firms' value and their future prospects. In contrast, firms that are followed by a small number of financial analysts face an information asymmetry problem between managers and the market, because less firm-specific information is available to the public (Draper and Paudyal 2008). We therefore use the number of analysts following a firm as a proxy for information asymmetry between the company managers and outside investors. For each stock, we set the analysts' coverage as equal to the number of analysts providing the Institutional Brokerage Estimate System (I/B/E/S) with their earnings estimate for one fiscal year. Wherever the number of analysts is not available, we set the analysts' coverage for that company equal to zero.

Previous studies such as Freeman (1987) and Bhushan (1989) provide evidence that the number of analysts following a firm is an increasing function of the firm's size. That is, both analysts' coverage and size are positively correlated, i.e. financial analysts have the incentive to focus on large firms. They find that generating information about large firms more profitable and large firms represent the interest of more investors (see for example, Freeman 1987; Bhushan, 1989; and Chung et al., 1995). Therefore, to control for the size effect on analysts' coverage, we made analysts' coverage orthogonal to firm size. More specifically, following Draper and Paudyal (2008) we regress analysts' coverage against firm size and use the residuals (ε_i) of the regression to measure the incremental analyst' coverage as follows:

$$Ln(1 + AC_{i,t}) = \propto + \beta_i Ln(1 + MV_{i,t}) + \varepsilon_{i,t} \tag{4.1}$$

where $AC_{i,t}$ is the number of analysts following a firm i at month t and $MV_{i,t}$ is the firm's market value and the error term ($\varepsilon_{i,t}$) represents the incremental analysts' coverage (IAC).

4.3.1.2.2 Mean forecast error

As a second measure for information asymmetry between company managers and outside investors, we use mean forecast error, calculated as the absolute ratio of the difference between the forecasted earnings per share and the actual earnings per share divided by the mean value of the forecasted earning per share. Krishnaswami and Subramaniam (1999) argue that the error in analysts' forecast will be larger when there is a high level of information asymmetry between managers and outside investors about a firm's value and cash flows. They also point out that Elton et al. (1984) find that approximately 84% of analysts' forecast error relate to inaccurate prediction of firm-specific factors. This suggests that using mean forecast error as a measure for information asymmetry will be appropriate. However, this measure may have some shortcomings: it may be correlated with a firm's earnings risk and, thus, a higher forecast error may result from volatile earnings rather than from a higher level of information asymmetry. Also, forecast error may include an optimistic component: analysts are overly optimistic with their forecasts at the beginning of the fiscal year, but tend to adjust their forecasts downward as the year approaches its end (see, Krishnaswami and Subramaniam, 1999 and references cited in).

4.3.1.3 Proxies for divergence of opinions

Financial analysts' level of consensus about a firm's future earnings is reflected by dispersion in analysts' earnings forecasts. Stocks with high dispersion in analysts' forecasts are those with a low level of consensus among financial analysts (i.e. those with a high level of divergence of opinion among investors) and vice versa. Therefore we use the dispersion in analysts' forecasts for one fiscal year as a proxy for the divergence of opinion among investors. Following Diether et al. (2002), Dische (2002), Boehme et al. (2006) among others, we measure dispersion in analysts' forecasts by the coefficient of variation, which is estimated by the standard deviation of the earnings forecasts divided by the absolute value of the mean of earnings forecasts as reported in I/B/E/S summary file. At least two analysts are required to obtain the coefficient of variation. This measure is intuitively appealing, and it has been extensively used in the literature that examines the relationship between divergence of opinion among investors and asset returns, such as Diether et al. (2002), Boehme et al. (2006) among others.

4.3.2 The sample

We utilize the same sample used in chapter two which includes all the stocks listed and subsequently delisted in the UK (London Stock Exchange; LSE), Swiss (Swiss Stock Exchange; SSE) and German (Frankfurt Stock Exchange; FSE) stock markets.

The primary data is taken from Datastream which consists of both daily and monthly data for all stocks (dead and live). The daily data includes bid prices, ask prices, trading volume, market value and closing prices. As discussed in the previous section, this daily data is used to calculate monthly-liquidity proxies: proportional bid-ask spread, turnover ratio, and Amihud's (2002) illiquidity ratio (price impact). Monthly data includes the stock return index (which includes capital gains as well as dividend payments), market return indices, industry return indices, size (market value) and stock prices. Also from Datastream, we have obtained data on 10 industrial economic sectors (based on Datastream level 2 classifications ICBIN).

Further, the data on analysts' earnings estimates is drawn from the Institutional Brokerage Estimate System (I/B/E/S) summary history file. The summary history file is derived from the detail file and it contains the number of estimates (i.e. number of forecasts) provided by financial analysts and the summary statistics for analysts' forecasts that include mean, median and standard deviation. I/B/E/S calculates these statistics on the third Thursday of each month using all the outstanding forecasts provided by financial analysts that month. For the countries included in the sample, I/B/E/S provides data on analysts' earnings forecasts since 1987. Data on stocks from both databases (i.e. Datastream and I/B/E/S) have been merged using the IBES ticker which is the common identifier between the two databases. The IBES ticker remains the same and does not change even when the company has changed its name or sedol. For stocks in I/B/E/S which do not have their match in Datastream by IBES ticker, because it is missing, have been matched using the information on companies' name and their sedol provided by the I/B/E/S company identification file[79]. That is, the match has been done based on the sedol and company name. Stocks which are in Datastream but not covered by I/B/E/S will have no data on analysts' earnings forecasts, however they are included in the analysis. For these stocks, we consider the number of analysts following a stock (i.e. analysts' coverage) equal to zero.

The sample period in this chapter has the same start date for all markets included in the analysis as in Chapter Two, which is guided by the availability of data, but it has been extended for all markets to the end of December 2008. However, the chapter utilized a data set for different sample periods based on the date of the introduction of the automated trading system (as shown in table 3.1 Chapter Two). That is, the sample period for UK data, which covers the floor and electronic trading periods, extends from October 1987 to December 2008. The sample period for the German markets only spans eleven years from January 1998 to December 2008 for each of the trading systems, which operate parallel to each other. Finally, the sample period for the Swiss market extends from April 1990 to December 2008.

Table 4.1 reports the time-series averages of the cross-sectional means, medians, and standard deviations of stocks characteristics. The variables display considerable skewness.

[79] The company identification file provides additional data for informational purposes. It is an event-driven file that records the changes in company's identification information such as official ticker, CUSIP/SEDOL, and company name (see the web site of WRDS http://wrds-web.wharton.upenn.edu/wrds/ds/ibes/idsum/contents.shtml).

Therefore, we employ logarithmic transforms of all the variables except the squared stock returns (proxy for stock return volatility measured as squared stock returns following Chordia et al. (2000)) because they may be equal to zero. In the case of analysts' coverage, we employ the natural logarithm of one plus the number of analysts following the firm, in order to include in the regression firms with zero analysts' coverage.

The descriptive statistics results show that the number of analysts following a firm in both the UK and Switzerland declines after moving to an electronic trading system, while in the German market, where both trading systems work parallel to each other, the number of analysts stays constant. More specifically, the mean of analysts' coverage in the UK and Switzerland on the floor trading system was nearly 6 and 9 analysts following a firm, and declined to nearly 4 and 7 analysts respectively, after moving to an electronic trading system. Further, in contrast to the UK market, both the mean of the error in analysts forecast (MFE) and the dispersion in analysts forecast (CV) declined in the Swiss market after moving to the electronic trading system. But in the German market, both MFE and CV are nearly equal under both trading systems. The results also show that after moving to an electronic trading system, the liquidity in the UK market declined as indicated by the increase in both the proportional bid-ask spread and the price impact, and as indicated by the decline in the turnover ratio. That is, proportional bid-ask spread and price impact increased to 8.4% and 0.016 during the electronic trading period compared with 4.9% and 0.001 respectively before, and turnover ratio decreased to almost 4 after the automation of the trading system compared with 20 during the floor trading period. Similarly to the UK, the results also show that liquidity for the electronic trading system in the German market is lower than that for the floor trading system. That is, both proportional bid-ask spread and price impact on floor trading systems are lower than proportional bid-ask spread and price impact on electronic trading systems: they are respectively 5.2% and 0.107 on floor trading compared with 8.7% and 3.616 on electronic trading systems. In contrast, the results in the Swiss market show the opposite: the firm-specific liquidity has increased after moving to the electronic trading system. The proportional bid-ask spread (turnover ratio) has decreased (increased) to 4.2% (13) after the move to the electronic trading system compared with 4.7% (4) before automation.

4.3.3 Hypotheses development

This chapter aims to examine whether the variation in firm-specific liquidity can be explained by both the variation in information asymmetry and the variation in divergence in opinions pre- and post-automation in the underlying markets. Therefore, in this section, we provide a theoretical explanation for the rationale and motivation behind these relationships and develop several testable hypotheses.

4.3.3.1 Information asymmetry and firm-specific liquidity

The level of information asymmetry between company managers and outside investors depends on the extent to which the information regarding the value and future prospects of a firm is made available to the public through an independent third party (i.e. financial analysts). Firms with few analysts' coverage have an information asymmetry problem between managers and outside investors, because the firm-specific information about the assets' value and future growth opportunities will only be available to the firm's managers. In this case, outside investors are expected to face greater firm-specific uncertainty (i.e. higher risk) (Dierkens, 1991; Krishnaswami and Subramaniam, 1999) by holding the firms' shares. The increased uncertainty (i.e. risk) due to less information available to outside investors could increase the perceived risk of holding inventory and thus reduce liquidity. Therefore, investors and market makers will be reluctant to hold the stocks of firms with a high level of information asymmetry through reducing their trading or posting wider bid-ask spread. This will result in lower market depth and thus reduce the liquidity.

On the other hand, if many analysts are following and covering a firm, then the information asymmetry gap between the company managers and outside investors will be reduced and both managers and outside investors will be equally informed about the intrinsic value of the firm's assets and future prospects. That is, substantial analysts' coverage will result in a large amount of firm-specific information being available in the market. In this case, the degree of uncertainty about the firm's future prospects and growth opportunities will be lower and, thus, the investors and market makers will not be reluctant to trade or hold the firms' shares because they will be less risky. In sum, this implies that the amount of risk faced by outside investors and market makers, which could be perceived as inventory holding risk, will be high for stocks with a high level of information asymmetry and thereby decrease firm-specific liquidity. Therefore, the level of information asymmetry between company managers and outside investors is expected to be negatively related to firm-specific liquidity. Expressed differently, it is expected that a higher level of information asymmetry will be associated with higher bid-ask spread and price impact and with lower turnover ratio. This leads to our first testable hypothesis:

H_1: information asymmetry between company managers and outsider investors has a significant negative effect on firm-specific liquidity.

4.3.3.2 Divergence of opinion and firm-specific liquidity

The empirical relation between divergence of opinion and firm-specific liquidity is particularly relevant in the light of the relation between firm-specific liquidity and the required rate of return (Amihud and Mendelson, 1986 among others), and also in the light of the relation between divergence of opinion and stock returns (Diether et al., 2002; Dische, 2002 among others). However, it is expected that divergence of opinion will have either a negative or positive effect on firm-specific liquidity, depending on whether divergence of opinion, manifested in the disagreement among financial analysts, can be viewed as a source of risk (see for example, Williams, 1977; Diether et al., 2002; Doukas et al., 2004; Doukas and McKnight, 2005 among others) or as a source of optimistic trading (see for example, Miller, 1977; Diether et al., 2002; Boehme et al., 2006 among others). More specifically, in the first view, disagreement among investors may reflect uncertainty about the firm's future prospects and its growth opportunities. That is, the higher the divergence of opinion among investors, the higher the uncertainty and vice versa. In this case, investors are expected to avoid trading in stocks with a higher level of divergence of opinion which may result in a lower trading volume and thus lower market depth. Also, market makers will post a higher bid-ask spread to avoid any additional inventory risk that they might face as a result of trading in stocks with a higher level of divergence of opinion.

Therefore, it is expected that divergence of opinion among investors will inversely affect firm-specific liquidity.

In the second view, when investors disagree in their opinions, the market will be dominated by the beliefs of optimistic investors: only optimistic investors are allowed to trade and pessimistic investors are not allowed to sell the stocks. Therefore, optimistic investors will place a large demand and push stock prices upwards because they believe that these stocks have a higher valuation (Diether et al., 2002). As a result the trading volume and market depth will increase for stocks with a high divergence of opinion. Further, market makers will post a lower bid-ask spread to attract trade and increase their holding of such stocks. Consequently, the increase in divergence of opinion among investors could increase firm-specific liquidity and, thus, it is expected that divergence of opinion will positively affect firm-specific liquidity. Since the discussion above predicts an ambiguous effect of divergence of opinion on firm-specific liquidity, the effect needs to be tested by empirical analysis. This will lead us to our second testable hypothesis:

H_2: Divergence of opinion among investors has an insignificant effect on firm-specific liquidity.

4.3.3.3 Information asymmetry, divergence of opinion and firm-specific liquidity under different contexts of trading systems

One of the major themes in this chapter is to compare the implications of information asymmetry and divergence of opinion on firm-specific liquidity in the context of different trading systems. It is expected that the latter may affect information dissemination process and thus affect firms' informational environment. Different characteristics of floor and electronic trading systems, such as information sharing and speed and efficiency in executing orders, may have impact on the level of information asymmetry between company managers and outside investors and on the divergence of opinion among investors. For example, on a floor trading system all investors can share information about order inflow and intrinsic value, through the professional relationships that emerge by frequent trading (Venkataraman, 2001). This may result in a faster diffusion of information about firms for a floor trading system and reduce the level of information asymmetry between managers and investors. This applies especially to firms followed by a small number of analysts (i.e. firms with high level of information asymmetry), as information about these firms is assumed to filter slowly to stock markets (Doukas and McKnight, 2005). In addition, this advantage is expected to alleviate the divergence of opinion among investors. That is, by sharing information about firms' intrinsic value, investors' knowledge and beliefs are updated adequately and thus their interpretation of information, which reduces the dispersion in their opinions. It is, therefore, expected that the impact of information asymmetry and divergence of opinion on firm-specific liquidity will be lower for a floor trading system than for an electronic trading one. This, in turn, will result in different levels of liquidity between floor and electronic trading systems for firms with the same level of information asymmetry and for firms with the same level of divergence in investors' opinion.

In contrast, the opposite could be true in the case of the electronic trading system. More specifically, the efficiency and high speed of the electronic trading system in placing and executing orders, compared with the floor trading system, (see for example, Freund and Pagano, 2000; Venkataraman, 2001; Theissen, 2002b) will attract more orders. Because more orders are placed and executed in the automated trading system, the prices become more informative (Huson and MacKinnon, 2003) through reflecting all the available information about firms. This will improve the informational environment of the firms through reducing the information asymmetry between company managers and outside investors. This will also help investors to adequately update their knowledge based on information already reflected in stock prices and, thus, reduce the divergence in their opinions. Hence, it is expected that the impact of information asymmetry and divergence of opinion on firm-specific liquidity will be lower for the electronic trading system. In sum, the level of information asymmetry between the company and outside investors and the degree of divergence in investors' opinions are both expected to be affected by different market structures (i.e. floor and electronic trading system) and this will affect their impact on firm-specific liquidity. However, the impact of information asymmetry and divergence of opinion on firm-specific liquidity is expected to be lower either on floor or electronic trading system. Therefore, the extent to which information asymmetry and divergence of opinion have an impact on firm-specific liquidity is an empirical issue. This will lead us to our third and fourth testable propositions:

H_3: There is no significant difference in the impact of information asymmetry on firm-specific liquidity before and after the introduction of an electronic trading system.

H_4: There is no significant difference in the impact of divergence of opinion among investors on firm-specific liquidity before and after the introduction of an electronic trading system.

4.3.4 Empirical methodology

In the light of the above discussion, this section seeks to empirically test the developed hypotheses, explaining the methodologies employed. It also discusses the comparative analysis that compares the average portfolio's liquidity as well as the estimated regressions' parameters between floor and electronic trading systems, to find out whether there is a difference in the impact of information asymmetry and divergence of opinion on firm-specific liquidity as a result of automation.

4.3.4.1 Univariate analysis

In order to draw conclusions about firm-specific liquidity for different classes of stocks, similar to the standard approach in asset pricing, we assign stocks to portfolios based on their characteristics, such as the level of information asymmetry (measured by analysts' coverage, mean forecast error, and incremental analysts' coverage) and divergence of opinion (measured by coefficient of variation). More specifically, in each month we sort stocks independently by their analysts' coverage, mean forecast error, incremental analysts' coverage and coefficient of variation. Then stocks are assigned into three equally-weighted portfolios, high, medium, and low, according to the level both of information asymmetry and of the divergence of opinion. Portfolios with a high level of information asymmetry between company managers and outside investors are those with stocks with low analysts' coverage and incremental analysts' coverage and with high mean forecast error. Portfolios with a high divergence of opinion among investors are those with stock with high coefficient of variation. After being assigned into portfolios, stocks are held for one month (i.e. portfolios are rebalanced monthly). For each portfolio, we calculate the monthly portfolio liquidity as the equally-weighted average of the liquidity of all stocks in the portfolio.

Furthermore, to draw a conclusion on how liquidity of portfolios with the same level of information asymmetry and portfolios with the same level of divergence of opinion will be different between floor and electronic trading systems, we conduct a comparison for average portfolios' liquidity across trading systems. In other words, the difference in average portfolio liquidity between portfolios with the same level of information asymmetry and between portfolios with same level of divergence of opinion across trading systems is tested for. The t-test to examine the difference in average portfolios' liquidity between trading systems is used.

4.3.4.2 Multivariate analysis

The estimation based on the univariate analysis, discussed in the previous section, will provide evidence concerning the implication of information asymmetry and divergence of opinion on firm-specific liquidity without allowing for interaction between these determinants and between other determinants of firm-specific liquidity. Therefore, to allow for this interaction, we use the multivariate analysis to provide further evidence concerning the implications of information asymmetry and divergence of opinion on firm-specific liquidity.

4.3.4.2.1 Cross-sectional framework

To examine the relationship between firm-specific liquidity and both information asymmetry and divergence of opinion, we run a series of cross-sectional regressions on a monthly basis. It could be simple to calculate the average for all variables in the sample period and then to estimate one single cross-sectional regression using the average values. But we apply the methodology of Fama and MacBeth (1973), which is widely used in cross-sectional analysis, by estimating monthly cross-sectional regressions, and then we calculate the time-series average of the estimated cross-sectional coefficients over time. Chordia et al. (2000) argue that this approach should improve the statistical precision. The cross-sectional regressions are estimated without, and with, controlling for the well known determinants of firm-specific liquidity such as firm size, price and return volatility.

More specifically, we estimate first an empirical model in the following form:

$$L_{i,t} = \propto\ + \beta_1 AC_{i,t} + \ \beta_2 MFE_{i,t} + \ \beta_3 CV_{i,t} + \varepsilon_{i,t} \tag{4.2}$$

where $L_{i,t}$ is the firm-specific liquidity measured by proportional bid-ask spread, turnover ratio and price impact, AC_{it} is analysts' coverage (i.e. the number of analysts following a firm) and, as mentioned previously, it is defined as the logarithm of one plus the number of analysts in order to include the firms for which there is no analysts' coverage in the regression model. $MFE_{i,t}$ is the mean forecast error in the analysts' earnings forecasts, $CV_{i,t}$ is the coefficient of variation and $\varepsilon_{i,t}$ is the error term. Then the model in equation (4.2) is estimated again while controlling for other factors that affect individual stock liquidity such as size, price and return volatility. That is, we estimate the empirical model of the form:

$$L_{i,t} = \propto\ + \beta_1 IAC_{i,t} + \ \beta_2 MFE_{i,t} + \ \beta_3 CV_{i,t} + \beta_4 size_{i,t} + \ \beta_5 P_{i,t} + \ \beta_6 Vol_{i.t} + \varepsilon_{i,t} \tag{4.3}$$

where $IAC_{i,t}$ is the incremental analysts' coverage derived from equation (4.1) to control for the size effect, $size_{i,t}$ is the market capitalization (i.e. market value) of the firm i at month t,

$P_{i,t}$ is stock price of the firm i at month t and $Vol_{i,t}$ is the return volatility measured as squared stock return following Chordia et al. (2000).

Then, the coefficients $\beta_1 - \beta_3$ in equation (4.2) and the coefficients $\beta_1 - \beta_6$ in equation (4.3) are estimated by using the standard Fama and MacBeth (1973) estimator. That is, we first estimate the vector of explanatory variables coefficients c_t each month from Ordinary Least Square (OLS) regression as follows:

$$\hat{c}_t = (\grave{X}_t X_t)^{-1} \grave{X}_t \tilde{L}_{i,t} \tag{4.4}$$

where $\hat{c}_t$ represents the coefficients $\beta_1 - \beta_3$ and the coefficients $\beta_1 - \beta_6$ in equations (4.2) and (4.3) respectively, and X_t is the vector of explanatory variables in both equation (4.2) and equation (4.3) in month t and $\tilde{L}_{i,t}$ is the vector of firm-specific liquidity. Then, the standard Fama and MacBeth (1973) estimators are the time-series averages of these coefficients $\hat{c}_t$.

4.3.4.2.2 The two-pass framework

The cross-sectional variation in firm-specific liquidity is expected to be affected by the different level of information that is available for both company managers and outside investors. In other words, information available to managers and outside investors could be divided into three levels of information, namely; market-wide, industry-wide, and firm-specific information. Dierkens (1991) argues that both managers and outside investors are equally informed about information at the wide level (i.e. market-wide and industry-wide information), but are not equally informed about firm-specific information. Thus, managers have more firm-specific information than outside investors which creates the problem of information asymmetry. Also, insufficient diffusion of information about a firm could result in disagreement among investors about a firm's future prospects. Therefore, investors will bear some of the uncertainty (i.e. risk) related to firm until the firm-specific information is disseminated to the market (see for example, Dierkens, 1991; Krishnaswami and Subramaniam, 1999). Until the firm-specific information becomes available to the market, and the level of information asymmetry is reduced and the investors update their beliefs and have a more informative consensus among themselves, the variation in firm-specific liquidity is expected to be affected by both market-wide and industry-wide information. Therefore, to examine the incremental impact of information asymmetry between the company managers and outside investors and the impact of divergence of opinion among investors on firm-specific liquidity, we have to control for the impact of other information (i.e. market-wide and industry-wide information) on firm-specific liquidity. This approach aims to discover whether firm-specific information has any incremental explanatory power after controlling the variation in firm-specific liquidity for market- and industry-wide information.

In order to examine the incremental explanatory power of information asymmetry and divergence of opinion among investors in the cross-sectional variation of firm-specific liquidity, we apply the idea of Brennan et al. (1998) and Avramov and Chordia (2006a): the two-pass regressions framework[80]. Their framework, which has been applied in asset pricing literature, is based on controlling the cross-sectional variation in stock returns for all risk factors in the first-pass regression (i.e. time-series regression), and then using the unexplained returns, which is the constant plus the residuals of first-pass regression, as a dependent variable in the second-pass regression (i.e. cross-sectional regression). We apply the same idea; however, for the purpose of the empirical analysis in this chapter, we employ the model of Chordia et al. (2000) as our first-pass time-series regression to control the variation in firm-specific liquidity for market-wide and industry-wide information. In the Chordia et al. (2000) model, individual stock liquidity is regressed on aggregate market and industry factors. Specifically, we run time-series regressions of firm-specific liquidity for each individual stock on market liquidity, industry liquidity, market return and industry return. By using aggregate measures (i.e. market factors and industry factors) we will control for the common component of liquidity that is not related to firm-specific information events (see Sadka and Scherbina, 2007 and references cited in). Then, we run cross-sectional regressions of the unexplained part of liquidity (i.e. constant plus residuals

[80] Both studies used the same regression framework (i.e. the two-pass regression): however, in contrast to Brennan et al. (1998), Avramov and Chordia (2006a) used a conditional framework.

from the first-pass regressions) as dependent variable on a set of explanatory variables that includes information asymmetry proxies and a divergence of opinion proxy.

The empirical methodology of the two-pass framework is explained as follows: first, the first-pass time-series regression will be as follows:

$$Li_{i,t} = \propto + \beta_1 MKTL_t + \beta_2 INDL_t + \beta_3 MKT_t + \beta_4 IND_t + \varepsilon_{i,t} \tag{4.5}$$

where $MKTL_t$ and $INDL_t$ are market liquidity and industry liquidity at the month t respectively. For each measure of liquidity, proportional bid-ask spread, turnover ratio and price impact, we construct the market liquidity (industry liquidity) by calculating the cross-sectional average of individual stocks' liquidity for all stocks in the sample (in the same industry). MKT_t and IND_t are, respectively, the market return and industry return at the month t. Market return and industry return are defined as the first difference of the natural logarithm of the monthly market return and industry return index respectively. The following specifications have been estimated for the first-pass regression (equation (4.5)): (i) $\beta_2 = \beta_3 = \beta_4 = 0$, (ii) $\beta_3 = \beta_4 = 0$, (iii) $\beta_4 = 0$, (iv) all coefficients depart from zero.

Next, from equation (4.5), the unexplained part of firm-specific liquidity (which is the sum of constant and residuals) represents the raw material for our estimation in the following cross-sectional regression:

$$UL_{i,t} = C_{0,t} + \sum_{m=1}^{M} C_{m,t} X_{m,i,t} + \varepsilon_{i,t} \tag{4.6}$$

where $X_{m,i,t}$ is the vector of explanatory variables that includes the proxy for information asymmetry and the proxy for divergence of opinion, and M is the total number of the explanatory variables. Equation (4.6) has been estimated without, and with, controlling for the determinants of firm-specific liquidity which are the firm size, price and return volatility. Once again, the coefficients $C_{m,t}$ in equation (4.6) are estimated by using the standard Fama and MacBeth (1973) estimator. That is, we first estimate the vector of characteristics rewards c_t each month from Ordinary Least Square (OLS) regression:

$$\hat{c}_t = (\grave{X}_t X_t)^{-1} \grave{X}_t \widetilde{UL}_{i,t} \tag{4.7}$$

where X_t is the vector of explanatory variables in equation (4.6) in month t and $\widetilde{UL}_{i,t}$ is the vector of the unexplained part of firm-specific liquidity. Then, the standard Fama and MacBeth (1973) estimators are the time-series averages of these coefficients $\hat{c}_t$.

For the purpose of testing the stated hypotheses, we estimated the empirical model as described in equations (4.2), (4.3), and (4.6) for both the pre-automation period and post-automation periods. Then we test whether the coefficients of information asymmetry measures and divergence of opinion measures are equal to zero. Specifically, we test the null hypotheses that the information asymmetry and divergence of opinion coefficients are insignificant in the cross-sectional regressions. In the case of the two-pass regressions framework, if the market-wide and industry-wide factors are sufficient to explain the variation in firm-specific liquidity, then, the explanatory power of information asymmetry measures and divergence of opinions measures in the cross-sectional regression should be insignificant. This means that market-wide and industry-wide factors, which control for market-wide and industry-wide information, are able to capture the impact of both information asymmetry and divergence of opinion. On the other hand, if the cross-sectional unexplained liquidity is still affected by the information asymmetry and divergence of opinion measures in the cross-sectional regression, after controlling for market-wide and industry-wide information, then the coefficient of information asymmetry and divergence of opinion should be significant. This means that firm-specific information is valuable and, thus, information asymmetry and divergence of opinion have incremental explanatory power even after taking into consideration the market-wide and industry-wide information.

4.3.4.2.3 Comparing estimated regressions' parameters before and after the automation of a trading system

To investigate the effect of the automation of the trading system on the impact of both information asymmetry and divergence of opinion on firm-specific liquidity, we conducted a comparative analysis of the estimated coefficients of information asymmetry and divergence of opinion pre- and post-automation of the trading system. More specifically, to examine the influence of the automation of a trading system on the relationship of information asymmetry and divergence of opinion with firm-specific liquidity, we used the Wald-test to test the coefficients equality restriction for the cross-sectional regressions (equations (4.2), (4.3), (4.6)) estimated on a floor trading system and on an electronic trading system. In other words, we tested whether the coefficient of the measures of information asymmetry and divergence of opinion in the cross-sectional regression model estimated on a floor trading system is expected to be equal to the same coefficient of the regression model estimated on an electronic trading system (i.e. $\beta_{1F} = \beta_{1E}$).

4.4 Empirical Results

This section presents and discusses the results of both univariate and multivariate analyses. The results are outlined first for univariate analysis, which is based on constructing portfolios based on information asymmetry and divergence of opinion. Following that, it reports the results of the cross-sectional regressions (i.e. multivariate analysis) that examine the variation in firm-specific liquidity, which is measured by proportional bid-ask spread, turnover ratio and price impact (Amihud’s 2002 illiquidity ratio). Both analyses have been conducted for the two sub-sample periods before- and after- the automation of a trading system, and a comparative analysis has then been applied to compare the effect of information asymmetry and divergence of opinion on firm-specific liquidity in different contexts of trading systems[81].

4.4.1 Univariate analysis

This sections starts with the portfolio analysis to examine the predictions, which state that stocks with a high level of information asymmetry have a lower liquidity, and those with a high level of divergence in opinion among investors are expected to have either lower or

[81] See appendix 4A, which provides a summary of the testable hypotheses and whether they are supported or rejected, along with the reasons based on the empirical results of this section.

higher liquidity. Table 4.2, panels A-D, reports the estimated equally-weighted average liquidity for the portfolios constructed on the basis of information asymmetry and on the basis of divergence of opinion. Stocks in the sample are ranked in ascending order based on analysts' coverage, incremental analysts' coverage and mean forecasting error (i.e. measures of information asymmetry), and based on the coefficient of variation (i.e. measure of divergence of opinion). Then, stocks are sorted into three equally-weighted portfolios: low, medium and high according to the ranking variables.

The results in table 4.2 panel A show that, in most cases, average portfolio liquidity, as measured by proportional bid-ask spread, price impact and turnover ratio, increase monotonically with the number of analysts following a firm under both trading systems. More specifically, both average proportional bid-ask spread and price impact decrease with the analysts' coverage. Thus, the results confirm the notion that stocks with low analysts' coverage (with a high level of information asymmetry) have statistically significant higher proportional bid-ask spread and price impact than stocks with high analysts' coverage (with a low level of information asymmetry). For example, in the UK market the proportional bid-ask spread (price impact) on the floor trading and electronic trading systems, respectively, is 5.4% and 7.3% (0.2 % and 0.6%) for stocks with low analysts' coverage, which is significantly higher than that for stocks with high analysts' coverage, 1.7% and 1.4% (0.005% and 0.010%). This is consistent with the results in the Swiss market and the German market. Furthermore, the turnover ratio shows a monotonic increase with analysts' coverage in all cases except on the floor trading system for both the UK and German markets. For example, in the Swiss market, stocks with large analysts' coverage, on both floor and electronic trading system, have significantly higher turnover ratio, 2.68 and 28.95 respectively, than stocks with a low analysts' coverage, 1.61 and 1.31. There is also a significant difference in the average liquidity among these portfolios: the F-statistics of the analysis of variance, that test the equality in the averages of two or more different groups, is statistically significant in the majority of cases at 1% and 5% significant level. These results imply that stocks with higher information asymmetry between managers and outsiders impose a higher level of uncertainty on investors. Consequently, the investors try to reduce their trading in these stocks and market makers post a wider bid-ask spread to avoid any additional inventory risk. Overall, the results provide support to the first prediction that information asymmetry is negatively associated with firm-specific liquidity on both trading systems.

Firm-specific liquidity is also examined by incremental analysts' coverage (IAC) which is estimated using equation (4.1). The purpose of employing IAC is to control for the effect of firm size on the number of analysts following a firm, and to evaluate the incremental value of analysts' coverage in reducing information asymmetry between manager and market (Draper and Paudyal, 2008). The results in table 4.2 panel B provide evidence which is consistent with that reported in panel A with regard to the pattern and the significance of proportional bid-ask spread and price impact measures. That is, the results also confirm that stocks with low IAC (with higher information asymmetry) have statistically significant higher proportional bid-ask spread and price impact than stocks with high IAC (with low information asymmetry). This provides additional support to the first hypothesis that firms with low information asymmetry have higher liquidity. In contrast, the results of turnover ratio provide weak support to this hypothesis. Only on the electronic trading systems for both the UK market and the German market, does turnover ratio show a monotonic increase with analysts' coverage. Otherwise turnover ratio decreases with an increase in analysts' coverage, which means that turnover ratio is higher for stocks with high information asymmetry. This may imply that, before the arrival of the firm-specific information to the market by financial analysts, informed traders try to take advantage of their information and trade profitably, which may increase the trading volume of stocks with higher information asymmetry.

The last measure for information asymmetry is based on the error in financial analysts' forecasts; the mean forecast error. Stocks with a high mean forecasting error are those with high information asymmetry between company managers and outside investors. The results based on this measure (table 4.2 panel C) in general show that firm-specific liquidity declines monotonically with the increase in mean forecast error on both trading systems. That is, consistent with evidence reported in previous panels (A and B), both proportional bid-ask spread and price impact increase as mean forecast error increases. For instance, for the UK market on the floor and electronic trading systems, proportional bid-ask spread (price impact) for stocks with low mean forecast error (low information asymmetry) is 2.3% and 2.8% (0.01% and 0.10%) respectively, while it is 4.4% and 6.5% (0.05% and 0.40%) for stocks with high mean forecast error (high information asymmetry). The results of proportional bid-ask spread and price impact for both the Swiss market and the German market are consistently similar. In contrast, the majority of turnover ratio results are inconsistent with our prediction. The average portfolio turnover ratio increases with mean forecast error. That is, firms with higher information asymmetry (high mean forecast error) have a higher turnover ratio (i.e. higher liquidity), which is against our prediction.

In summary, although the majority of turnover ratio results do not support our prediction, the evidence of a positive association of information asymmetry with both proportional bid-ask spread and price impact is strong and statistically significant and, thus provides strong support to the first hypothesis that firm-specific liquidity is negatively related to information asymmetry for both trading systems. The results are robust for alternative measures of information asymmetry.

Finally, to examine the relationship between firm-specific liquidity and divergence of opinion among investors, stocks are assigned to three portfolios based on the coefficient of variation (i.e. the measure of divergence of opinion). The results reported in table 4.2 panel D provide mixed evidence regarding this relationship. On the one hand, on both trading systems and for all markets, the average proportional bid-ask spread and average price impact increase with divergence of opinion. That is, firm-specific liquidity decreases with divergence of opinion. For instance, in the UK market, the proportional bid-ask spread (price impact) is 2.1% and 2.2% (0.01% and 0.04%) for stocks with a low divergence of opinion on floor and electronic trading systems respectively, which is significantly lower than stocks with a high divergence in opinion, 3.6% and 3.3% (0.04% and 0.10%). The results confirm the notion that divergence of opinion among investors is a source of risk and, therefore, investors and market makers are reluctant to trade and hold stocks with high dispersion in investors' opinion in order to avoid any additional risk which results in lower stock's liquidity. This contradicts the second hypothesis that firm-specific liquidity is not related to divergence in opinion among investors. Further, the analysis of variance confirms the existence of the difference in stocks' liquidity with different levels of divergence of opinion, the results of the F-statistic that test the equivalence in the average between two or more groups, in most cases, is statistically significant at 1% and 5% levels of significance.

On the other hand, the average portfolio turnover ratio in panel D increases with the divergence of opinion on both trading systems for the UK and the German markets, and only on the electronic trading system for the Swiss market. This means that firm-specific liquidity increases with divergence in investors' opinions. For example, the turnover ratio for stocks with a low divergence of opinion in the UK market on the floor and electronic trading systems, respectively, 2.6 and 3.7, is significantly lower than for stocks with a high divergence of opinion 3.5 and 4.7. This is also consistent with the results of the turnover ratio in the German market on both trading systems, and on the electronic trading system for the Swiss market. These results support the optimistic view of divergence of opinion: whenever there is disagreement in opinion among investors regarding the value of the firm, the market will be dominated by optimistic investors (see Miller, 1977 among others). However, the positive relationship between the turnover ratio and divergence of opinion could suggest that the turnover ratio is a better proxy for divergence of opinion. Doukas and McKnight (2005) point out that previous studies find a strong positive relationship between turnover ratio and dispersion in analysts' forecasts. However, our results do not support the second hypothesis that firm-specific liquidity is insignificantly related to divergence in investors' opinion. Overall, the results for the relationship between divergence of opinion and firm-specific liquidity are mixed. That is, the results of the proportional bid-ask spread and price impact provide strong and statistically significant evidence for a negative association between firm-specific liquidity and divergence of opinion, while the results of turnover ratio provide contradictory evidence.

The results of the univariate analysis thus far show that information asymmetry and divergence of opinion are significantly related to firm-specific liquidity on both trading systems. This leads us to investigate to what extent the relationship between firm-specific liquidity and both information asymmetry and divergence of opinion could be affected by the move towards an automated trading system. Therefore, we conduct a test to compare the average portfolio's liquidity between a floor and electronic trading system. For instance, the average liquidity of a portfolio of stocks with low analysts' coverage (high information asymmetry) on a floor trading system is compared with the average liquidity for the same portfolio on an electronic trading system. A statistically significant difference in the average portfolio liquidity implies that different trading systems have affected the level of information asymmetry and the level of divergence of opinion and thus their impact on firm-specific liquidity. A significantly negative (positive) difference in the average portfolio proportional bid-ask spread and price impact (turnover ratio) indicates that firm-specific liquidity is higher on an electronic trading system and vice versa.

The results of comparison tests are reported in table 4.3 panels A-D. In general, the great majority of the results show that the difference in the average liquidity of portfolios between electronic and floor trading systems is statistically significant at all levels of significance. The results of the portfolios constructed on the basis of analysts' coverage (panel A) show that the liquidity of stocks with high information asymmetry (low analysts' coverage) is lower (higher) on electronic trading system for the UK and the German markets (Swiss market). The difference in the average proportional bid-ask spread and price impact in the UK and the German markets (the Swiss market) is positive (negative) and only insignificant for price impact in the Swiss market. This implies that the floor trading system in the UK and Germany alleviates the information asymmetry problem for stocks with a high level of information asymmetry, which results in a higher stock liquidity compared with the electronic trading system. The difference in the turnover ratio for stocks with low analysts' coverage confirms this finding in the UK market, but not in the Swiss and German markets. In relation to the stocks with high analysts' coverage (low information asymmetry), the results in the UK and German markets are mixed. That is, the significant negative (positive) difference in the proportional bid-ask spread (turnover ratio) in the UK and German markets show higher liquidity on the electronic trading system for stocks with high analysts' coverage, while the positive difference in price impact shows the opposite. Further, stocks with high analysts' coverage in the Swiss market have higher liquidity on the electronic than on the floor trading system. The difference in proportional bid-ask spread and price impact is negatively significant at 1% and 10% level of significance respectively. Hence, the results do not support the third hypothesis that there is no difference in the impact of information asymmetry on firm-specific liquidity before and after the automation of a trading system.

Furthermore, the results based on incremental analysts' coverage (IAC), table 4.3 panel B, confirm the notion that the impact of information asymmetry on firm-specific liquidity is different under different trading systems. The results show that, in the UK and German markets, the difference in proportional bid-ask spread and price impact is significantly positive in most cases for stocks both with low IAC (high information asymmetry) and with high IAC (low information asymmetry). This indicates that the liquidity of stocks either with low IAC or high IAC is low on an electronic trading system. Once again, this implies that the level of information asymmetry between company managers and outsider investors on an electronic trading system is higher than on a floor trading system, which might be due to the sharing information advantage of the floor trading system. In contrast, the significantly negative differences in proportional bid-ask spread and price impact in most cases for the Swiss market indicate the opposite. That is, the results show that firm-specific liquidity is higher on an electronic trading system for stocks with either low or high IAC. Turnover ratio results provide further support for the results of proportional bid-ask spread and price impact in the German market, but they are inconsistent with other results in the case of the UK and Swiss markets. Regardless of the mixed evidence, the results reject the third hypothesis that the impact of information asymmetry on firm-specific liquidity is not different across trading systems.

The results of the final measure of information asymmetry, the mean forecasting error, are reported in table 4.3 panel C. The results provide further support to our findings in previous panels A and B. Under different trading systems, the impact of information asymmetry on firm-specific liquidity is different. More specifically, in contrast to the Swiss market, the significant positive difference in proportional bid-ask spread and price impact, in most cases, for the UK and German markets show that liquidity for stocks with low mean forecast error (low information asymmetry) and for stocks with high mean forecast error (high information asymmetry) is low on an electronic trading system. Once again, the results of turnover ratio contradict with the results of proportional bid-ask spread and price impact.

Finally, the results of comparing the average liquidity of portfolios with different levels of divergence of opinion between electronic and floor trading systems are reported in table 4.3 panel D. In general, the results show that the impact of divergence of opinion on firm-specific liquidity is different between floor and electronic trading systems. Stocks with low and high divergence of opinion are more liquid on the floor trading system than in the electronic trading system in the UK and German markets. The difference in the average portfolio price impact is significantly positive in both markets. In contrast, the liquidity of stocks with low and high divergence of opinion is higher on the electronic trading system in the Swiss market as shown by the significantly negative difference in the average portfolio proportional bid-ask spread. This implies that the floor trading system in both the UK and German markets is more effective in reducing the disagreement between investors, through their sharing of information and interaction advantage. However, the electronic trading system in the Swiss market seems to perform better for all stocks traded in the market. In contrast, the results of turnover ratio provide odd evidence in all markets and show that liquidity for stocks with the same level of divergence of opinion is low (high) on the electronic trading system for the Swiss (UK and German) market. Regardless of this, our findings do not provide support for the fourth hypothesis that the impact of divergence of opinion on firm-specific liquidity is indifferent across trading systems.

In sum, the results discussed above provide strong and statistically significant evidence, which shows that floor and electronic trading systems affect the level of information asymmetry between company managers and outside investors as well as affect the level of dispersion in opinion among investors, which then affects their relation with firm-specific liquidity. Further, the results, in general, show that in the UK and German markets the liquidity of stocks with different levels of information asymmetry and divergence of opinion will be higher on the floor trading system, while the Swiss market provides higher liquidity on the electronic trading system. This implies that the electronic trading system in the Swiss market is suitable and performs better for all stock compared with the electronic trading system in the UK and German markets.

4.4.2 Multivariate analysis

This section provides further investigation of the implications of information asymmetry and divergence of opinion on firm-specific liquidity using multivariate frameworks: the cross-sectional framework and the two-pass regressions framework. Both frameworks have been estimated during the two sub-sample periods before- and after the automation of the trading system, with and without controlling for the determinant of firm-specific liquidity (i.e. size, price and return volatility). Then a comparison of the estimated coefficients has been conducted to compare the impact of information asymmetry and divergence of opinion on firm-specific liquidity before and after the automation of a trading system.

4.4.2.1.1 Cross-sectional regression analysis

Table 4.4 shows the Fama-MacBeth (1973) coefficient estimates of the cross-sectional regression (equation (4.2)) in the pre- and post-automation periods along with the Wald test results. Panels A, B, and C report the results for the UK, Swiss and German markets respectively. Since firm-specific liquidity is measured by proportional bid-ask spread, price impact and turnover ratio, the higher (lower) the proportional bid-ask spread and price impact (turnover ratio), the lower the liquidity. Therefore, if information asymmetry and divergence of opinion are expected to negatively affect firm-specific liquidity, then the sign of the information asymmetry and divergence of opinion coefficients should be positive (negative) when firm-specific liquidity is measured by proportional bid-ask spread and price impact (turnover ratio). In all panels the results show that the coefficients on analysts' coverage, in proportional bid-ask spread and price impact regressions, are significantly negative at 1% level of significance during the two sub-sample periods in all markets. These results are inconsistent with the results of Chung et al. (1995), but they are consistent with the findings of Brennan and Subrahmanyam (1995) who find that the number of analysts following a firm is negatively related to price impact (i.e. estimated adverse selection cost component), and with Easley et al. (1998) who find that individual stock liquidity (measured by probability of information-based trading) is high for stocks where there are many analysts following a firm[82]. In addition, the results of turnover ratio regression provide consistent evidence, since the coefficient of analysts' coverage is significantly positive at 1% level of significance, except for Germany on the floor trading system which is negatively significant.

The overall results imply that the more analysts there are following a firm, the more firm-specific information will be available to the market, which will make investors better informed and certain about the future prospects of the firm. This will increase the trading activity of investors and market makers and thereby increase firm-specific liquidity. Further, the results on analysts' coverage provide confirmation that the main role of analysts' is to collect, analyze and disseminate information about firms, and not as proposed by Chung et al. (1995) and Brennan and Subrahmanyam (1995) that analysts are informed traders with informational advantage. That is, the greater the analysts' coverage, the lower the information asymmetry between company managers and the market. Our results of negative (positive) relations between analysts' coverage and both proportional bid-ask spread and price impact (turnover ratio) are consistent with the findings of univariate analysis and provide support for the first postulated hypothesis, that firm-specific liquidity is negatively related to information asymmetry between company managers and outsider investors on both trading systems.

Furthermore, the estimated coefficients of the mean forecast error (i.e. the other measure of information asymmetry) in both proportional bid-ask spread and price impact regressions provide further support for the first hypothesis. On both trading systems, the mean forecast error has a strong and positive impact, in most cases, on proportional bid-ask spread and price impact for the UK and Swiss markets. This confirms the intuition that firms with a high mean forecasting error (high information asymmetry) have lower liquidity. In contrast,

[82] Both studies, Brennan and Subrahmanyam (1995) and Easley et al. (1998), examine the relationship between liquidity and numbers of analysts, assuming that financial analysts are informed traders who may have informational advantage that could affect the information asymmetry between informed and uninformed traders.

on both trading systems for all markets, the positive and significant coefficient of mean forecasting error in turnover ratio regression indicates that firm-specific liquidity is higher for firms with a high mean forecasting error. This finding, once again, implies that when firms have high information asymmetry between managers and outsider investors, informed traders armed with superior information try to seize the advantage and trade quickly before more information gets released to the market. This will result in high trading levels and thus higher liquidity for firms with higher information asymmetry (i.e. high mean forecasting error). These findings are consistent with the findings of univariate analysis. Although the positive relationship between turnover ratio and the mean forecast error is against our prediction, the significant positive relationship between the mean forecast error and both proportional bid-ask spread and price impact provides further support for our first postulated hypothesis.

The results so far show that the cross-sectional variation in information asymmetry explains the cross-sectional variation in firm-specific liquidity for all markets and on both trading systems. This highlights the importance of examining how the introduction of the automated trading system could affect the impact of information asymmetry on firm-specific liquidity. The results of the Wald test that compares the estimated coefficients between pre- and post automation periods are reported in the last three columns in all panels. Whenever the coefficients of information asymmetry, while having the same sign, in all regressions are significant both before and after the automation of the trading system, the coefficients have an impact that is significantly different in the two sub-periods, as indicated by the significant Wald test statistic. The overwhelming results for all markets provide evidence that the impact of information asymmetry on firm-specific liquidity is different in the two sub-periods. More specifically, although the coefficients of analysts' coverage are significantly negative (positive) in proportional bid-ask spread and price impact (turnover ratio) regressions for all markets, the Wald test shows that in most cases the size of the coefficients significantly increased after the introduction of the electronic trading system. This indicates that information asymmetry between company managers and the outside market is more important on an electronic trading system, and represents a greater source of concern to investors than on a floor trading system. This, further, implies that analysts' coverage and the information provided by analysts to the market, become highly important in the absence of investors' ability to share information about firms.

In relation to the mean forecasting errors, the coefficient becomes insignificant after automation for the trading system in price impact (proportional bid-ask spread) regression for the UK (Swiss) market, while for the German market it is insignificant in both proportional bid-ask spread and price impact regression during the two sub-sample periods. The insignificance of the coefficient of mean forecasting error, in addition to the reduction in its size in price impact regression for the Swiss market after automation, indicates a decrease in its effect on firm-specific liquidity. These results are consistent with the findings of univariate analysis and confirm the notion that the impact of information asymmetry on firm-specific liquidity is different for floor and electronic trading systems, which rejects our third testable hypothesis.

In sum, the results so far show that the automation of a trading system appears to have an impact on the effect of information asymmetry on firm-specific liquidity. The results also show that the impact of information asymmetry is greater on an electronic trading system when measured by analysts' coverage; while the impact of information asymmetry is greater on a floor trading system when it is measured by mean forecasting error.

Turning our attention to the relationship between divergence of opinion and firm-specific liquidity, the results in all panels for all markets provide mixed evidence. More specifically, the coefficient of divergence of opinion, measured by coefficient of variation, is positively significant at 1% level of significance in proportional bid-ask spread and price impact for all markets during the two sub-sample periods. The results confirm the notion that firm-specific liquidity decreases with divergence of opinion. This implies that divergence of opinion among investors (manifested in disagreement among analysts) represents a source of risk and, thus, the greater the disagreement among investors the more uncertainty there is about a firm's future prospects and the more risk there is associated with the firm. In such a situation, investors are reluctant to trade and hold risky stock in order to avoid any additional inventory risk by posting higher bid-ask spread. This will result in low trading activity and, thus, lower market depth (i.e. higher price impact). These results are consistent with those of univariate analysis, and do not support our prediction that divergence of opinion has an insignificant impact on firm-specific liquidity.

In contrast, in all turnover ratio regressions for all markets during the two sub-sample periods, except for the Swiss market on the floor trading system, the coefficient of divergence of opinion is positive and significant at 1% level of significance. The results indicate that firm-specific liquidity increases as divergence of opinion increases. This is consistent with the optimistic view (i.e. non-risk view) about divergence of opinion: whenever investors disagree about a firm’s future prospects the market will be dominated by optimistic investors who trade and hold the firm’s stocks. The trading activity of optimistic traders will improve the liquidity of the firm. This evidence confirms the findings of univariate analysis and also rejects the second hypothesis that divergence of opinion has an insignificant impact on firm-specific liquidity.

In addition, the impact of divergence of opinion on firm-specific liquidity appears to have changed with the automation of the trading system, which rejects the fourth hypothesis that the impact of divergence of opinion on firm-specific liquidity is not different between trading systems. The results of the Wald test, which compare the estimated coefficients in the two sub-periods, are statistically significant in the majority of regressions. Even though the coefficient of divergence of opinion is significant for both the floor and the electronic trading systems, the Wald test shows that the size of the coefficient decreases significantly after the automation of the trading system. This indicates that the importance of divergence of opinion with regard to its effect on firm-specific liquidity has decreased during the electronic trading compared with floor trading system, because investors on floor-based trading can easily notice the disagreement among investors, which may result in high impact on firm-specific liquidity.

Overall, the results for the relationship between divergence of opinion and firm-specific liquidity are inconclusive. That is, the divergence of opinion among investors has either a negative or positive impact on firm-specific liquidity. Also its impact on firm-specific liquidity decreased during the electronic trading period compared with the floor trading one.

Table 4.5 shows the Fama-MacBeth (1973) coefficient estimates of the cross-sectional regression (equation (4.3)) after controlling for the other determinants of firm-specific liquidity such as size, price and return volatility. In this equation we use, instead of analysts' coverage, the incremental analysts' coverage as a proxy for information asymmetry between company managers and the outside market, because both the firm's size and analysts' coverage are positively correlated. We calculate the incremental analysts' coverage as the residuals of the equation (4.1).

The estimated coefficients, during the floor trading period, show that incremental analysts' coverage in most regressions has the expected sign and is statistically significant at 1% level of significance for the UK and Swiss markets, and it is only significant in proportional bid-ask spread regression in the German market. These results indicate that analysts' coverage still has a marginal contribution in reducing the information asymmetry between managers and outside investors, even after controlling for the effect of the firm's size. This means that the higher the incremental analysts' coverage the higher the firm-specific liquidity due to the low level of information asymmetry. In contrast, on an electronic trading system for all markets, none of the incremental analysts' coverage coefficients are statistically significant. This implies that, on the electronic trading system, firm size is a good proxy of analysts' coverage and that it does capture its effect. The implication of these findings is that, even though information about firms, especially large ones, could be available for all investors, the investors on a floor trading system also depend on the information collected, analyzed and disseminated by analysts in making their trading decisions. But, on an electronic trading system, because of the absence of investors' interaction and sharing of information, investors depend heavily on market capitalization (i.e. firm size) as an indication of the amount of information available to the market. This is consistent with the argument that firm's size is a good proxy for information asymmetry between company managers and outside investors. This may indicate that while the role of financial analysts, as well as the size of the firm, is important in the floor trading system in reducing information asymmetry, the role of market capitalization in presenting the level of information asymmetry is more important on an electronic trading system. However, these findings provide support for the first hypothesis: information asymmetry has significant negative impact on firm-specific liquidity.

In addition, after controlling for other determinates of firm-specific liquidity, the coefficient of mean forecasting errors remains significant in proportional bid-ask spread and turnover ratio (proportional bid-ask spread and price impact) regressions on a floor (electronic) trading system for the UK, and in proportional bid-ask spread regression on a floor trading system in the Swiss market. However, the significant and positive coefficient of mean forecasting error in proportional bid-ask spread and price impact regressions is consistent with the notion that firms with a high level of information asymmetry have lower liquidity and, thus, it is consistent with the first predictions. The insignificant impact of mean forecast error on the measures of firm-specific liquidity (i.e. proportional bid-ask spread, price impact, turnover ratio) may be captured by firm size, which implies again that the latter could be a better proxy for information asymmetry. The results show that in all panels, the impact of size on firm-specific liquidity is highly significant (at 1% level of significance) and has the expected sign in most of regressions on both trading systems. This means that large firms have a lower level of information asymmetry and, thus, higher liquidity, compared with small firms.

Finally, the results on the relationship between divergence of opinion and firm-specific liquidity in the UK market are consistent with those reported in panel A table 4.4. The results provide support for the risk view with the coefficients of divergence of opinion being positive in proportional bid-ask spread regressions on both trading systems, and for the optimistic view through the positive (negative) coefficient in turnover ratio (price impact) regression on both trading systems (floor). In other words, the evidence for the impact of divergence of opinion on liquidity in the UK market is inconclusive. However, it rejects the second hypothesis. In the Swiss market the evidence provides further support for the risk view as divergence of opinion is positively related to both proportional bid-ask spread and price impact on the floor trading system. However, the impact of divergence of opinion on the electronic trading system for the Swiss market is insignificant, which might also be due to the size effect. In contrast to the results reported in panel C table 4.4 for the German market, the estimated coefficients of divergence of opinion provide only further support to the non-risk view. The coefficient is negative and significant in price impact (proportional bid-ask spread and price impact) regression(s) in the pre- (post-) automated period and it is positive and significant in turnover ratio regression on both sub-periods. This implies that the German market is dominated by optimistic investors and that whenever investors disagree about the future prospects of a firm, its liquidity will improve. This shows that divergence of opinion is positively related to liquidity and thus rejects the second proposition.

Furthermore, the results also show that the impact of information asymmetry on firm-specific liquidity is different between the two trading systems, which reject the third hypothesis. For instance, the statistically significant Wald test statistics at 5% level of significance or better show that the impact of firm size (as a proxy of information asymmetry) is more important on the electronic (floor) trading system for the UK and German (Swiss) markets, and the impact of mean forecasting error is greater on the electronic trading system for the UK. Moreover, the coefficients of incremental analysts' coverage become insignificant after automation for all markets. This implies that investors on a floor trading system depend on the information provided by the analysts to improve their informational level about firms, while on an electronic trading system they depend on firm size. The results also show that the impact of divergence of opinion on firm-specific liquidity is different on both trading systems for all markets, which rejects the fourth hypothesis. The Wald test statistic reveals that the coefficient of divergence of opinion in proportional bid-ask spread and turnover ratio regressions on a floor trading system in the UK market is statistically different from that on an electronic trading system. The coefficient decreases in size during the electronic trading period in the UK market, which indicates that the effect of divergence of opinion is large on a floor trading system. Furthermore, the impact of divergence of opinion becomes insignificant (significant) after automation in proportional bid-ask spread and price impact (proportional bid-ask spread) regression in the Swiss (German) market.

To summarise, the results of both univarite and multivariate analysis (with and without controlling for the determinate of firm-specific liquidity) show that the cross-sectional variation in firm-specific liquidity is explained by the cross-sectional variation in information asymmetry. The evidence for the impact of divergence of opinion is inconclusive. The results also show that different market structures (i.e. different trading systems) appear to have affected the relationship between the variables that represent the focus of this chapter (information asymmetry, divergence of opinion and firm-specific liquidity) through affecting the process of disseminating information about firms.

4.4.2.1.2 Two-pass regression analysis

The results discussed in the previous section, based on the cross-sectional framework, overwhelmingly support the implication of information asymmetry on firm-specific liquidity: firms with a high level of information asymmetry between company managers and outside investors have lower liquidity. The results also provide mixed evidence for the impact of divergence of opinion on firm-specific liquidity: the divergence in opinion among investors could either positively or negative affect firm-specific liquidity. The results show that information asymmetry and divergence of opinion do not fully explain the variation in firm-specific liquidity. The adjusted R^2 for all regressions, without and with controlling for other determinants of firm-specific liquidity, ranges from 4.16% to 84.83% which is considered low. This may raise the possibility of other factors that could explain the variation in firm-specific liquidity. Therefore, this section aims to further examine the implications of information asymmetry and divergence of opinion on firm-specific liquidity after controlling for the impact of market-wide and industry-wide information using two-pass regressions framework. Although both company managers and outside investors have the same level of information about the market and industry, they have different level of firm-specific information. Therefore, we control for the impact of market-wide and industry-wide factors on the variation of firm-specific liquidity in the first-pass time-series regression and then, in the second-pass cross-sectional regression, we examine whether information asymmetry and divergence of opinion have any marginal explanatory power in explaining the cross-sectional variation in firms-specific liquidity, that is not captured by market-wide and industry-wide factors.

The coefficients of the second-pass cross-sectional regression model (equation (4.6)) without and with controlling for the other determinants of firm-specific liquidity, along with the Wald test results, are reported in table 4.6 panel A and panel B respectively. The regression model is estimated during the two sub-sample periods (before- and after the automation of the trading system). In the first-pass time-series regression, individual stock liquidity is regressed on market-wide and industry-wide factors under different specifications. In the first, individual stock liquidity is regressed on market liquidity. In the second, it regressed on market and industry liquidity, then on market liquidity, industry liquidity, and market return. Finally, it is regressed on market liquidity, industry liquidity, market return and industry return. If the factors in the first-pass time-series regression are insufficient in explaining the variation in firm-specific liquidity, the explanatory power of information asymmetry and divergence of opinion measures in the cross-sectional regression should be significant. This implies that information asymmetry and divergence of opinion play an important role in explaining the variation in firm-specific liquidity and that the firm-specific information provided to the market is valuable.

In the last three specifications of the first-pass regressions, we check for collinearity between market factors and industry factors, by calculating variance inflation factors (VIF) and correlation matrix. Whenever the value of VIF is equal to or above 10, this is an indication of high collinearity (see Gujarati, 2003 and the references cited in). The results show that for the majority of industries, there is collinearity between market liquidity and industry liquidity, and for all industries there is collinearity between market returns and industry returns[83]. Therefore, we made industry factors orthogonal to market factors. In other words, we regress industry factors against market factors and calculate the residuals of regression model.

[83] VIF is calculated as the inverse of one minus *R*-squared of the regression of one explanatory variable over all the other explanatory variables. Due to the lack of space, the tables for VIF and correlation coefficients are not reported as they are already voluminous.

Regardless of the different specifications of the first-pass time-series regression, the results are qualitatively and quantitatively similar. Therefore, we focus our discussion on the empirical results of the cross-sectional regression models estimated under the first specification (i.e. using market liquidity as an explanatory variable in the first-pass time-series regression) [84]. The results in panel A table 4.6, in general, show weak evidence for the impact of information asymmetry on firm-specific liquidity. More specifically, when market-wide information has been controlled for, firm-specific liquidity is not related to analysts' coverage for the UK and Swiss markets on both trading systems and for the German market on the electronic trading system only. This suggests that the explanatory power of analysts' coverage is captured by the factors in the first-pass time-series regression, and the cross-sectional variation in firm-specific liquidity is explained by market liquidity. These results are inconsistent with the results reported in table 4.4 in the previous section and do not support our first hypothesis. However, these findings confirm the Easley et al. (1998) view that financial analysts do not produce new information and that they rely on public, rather than private, information in making their recommendations. In contrast, mean forecast error has a significant impact on the cross-section of individual stock liquidity unexplained by wide-factors. The coefficient of mean forecast error is positively significant in proportional bid-ask spread and turnover ratio regressions for the UK (German) market on the floor and electronic trading systems respectively (only on an electronic trading system). This means that firm-specific liquidity measured by proportional bid-ask spread (turnover ratio) is low (high) for firms with a high mean forecasting error (i.e. high information asymmetry). Only the positive relationship between mean forecasting error and proportional bid-ask spread provides support for the first hypothesis that information asymmetry is negatively related to firm-specific liquidity.

The empirical results also show a weak negative effect of divergence of opinion among investors on firm-specific liquidity. In other words, the coefficient of divergence of opinion measure (coefficient of variation) is negatively significant at a 5% and weakly significant at a 10% level of significance in the turnover ratio regression on the electronic trading system,

[84] The results of the cross-sectional regressions estimated under other specifications of the first-pass time-series regression is reported in the Appendix 4B-4D.

for the UK and the German markets respectively. For the Swiss market, the coefficient of variation has a significant positive impact on price impact on both floor and electronic trading systems. These results imply that the factors in the first-pass (i.e. market liquidity) could not capture the impact of divergence of opinion among investors. In other words, investors may disagree on the meaning and in the interpretation of the information at both the wide-level and firm-level, however, only their disagreement about the firms' future prospects has an incremental explanatory power on the cross-sectional variation of firm-specific liquidity. Although the evidence is weak, it is consistent with the risk view; divergence of opinion among investors is a source of uncertainty about firms' future prospects and it is negatively related to liquidity, and thus does not support the second hypothesis.

Furthermore, the introduction of electronic trading systems appears to affect the impact of information asymmetry on firm-specific liquidity. For instance, in the UK market, the impact of mean forecasting error in proportional bid-ask spread (turnover ratio) regression is significant (insignificant) before automation, but it became insignificant (significant) after automation. On the floor trading system, the impact of mean forecast error in proportional bid-ask spread and turnover ratio regressions was insignificant for the German market, but it is significant on the electronic trading system. These results reject our third prediction and show that the impact of information asymmetry on firm-specific liquidity is different across trading systems. Also, the impact of divergence of opinion on firm-specific liquidity, as appears in turnover ratio regression in the UK and German markets, is greater on the electronic trading system compared with the floor trading system where the coefficient is insignificant. Although the evidence is weak, it rejects the fourth hypothesis and indicates that the impact of divergence of opinion on firm-specific liquidity is different between floor and electronic trading systems.

Furthermore, the empirical estimates reported in panel B, while controlling for other determinants of firm-specific liquidity such as size, price, and return volatility, show that the impact of information asymmetry and divergence of opinion on firm-specific liquidity has been captured by market liquidity. The majority of the coefficients of information asymmetry measures and of divergence of opinion measures are insignificant especially for the Swiss and the German markets. Apart from that, the estimates for the UK market provide little evidence of the impact of information asymmetry and divergence of opinion on firm-specific liquidity. That is, the incremental analysts' coverage has a significant negative impact on proportional bid-ask spread during the two sub-periods (i.e. floor and electronic trading system), which is not expected given the existence of the size in the same equation. This significant effect of incremental analysts coverage might be due to the insignificant impact of a firm's size that captured by the factors in the first-pass regression. Also, the coefficient of mean forecast error has the expected sign in the proportional bid-ask spread regression; it is positively significant at 1% level of significance. These results suggest that a firm with a high level of information asymmetry is illiquid and, thus, provide further but weak support to the first hypothesis.

Once again, the evidence concerning the impact of divergence of opinion is inconclusive. More specifically, the significant negative relation between turnover ratio and coefficient of variation in the UK (German) market on both trading systems (on electronic trading system) is consistent with the risk view. That is, the higher the divergence of opinion the more the uncertainty faced by investors. This is also consistent with the significant positive relation between price impact and coefficient of variation on the floor trading system in the Swiss market. However, the significant negative relation between proportional bid-ask spread and coefficient of variation in the UK market on the floor trading system is consistent with the optimistic view, where the market will be dominated by optimistic traders who trade and increase their holding of stock with a high level of divergence of opinion. These results contradict the results reported in table 4.5 panel A, and reject the second hypothesis. Finally, the results provide mixed evidence on the impact of automation on the influence of information asymmetry and divergence of opinion on firm-specific liquidity. That is, some of the information asymmetry and divergence of opinion coefficients became insignificant after automation, which indicates that the impact of information asymmetry and divergence of opinion on liquidity is different. However, the insignificant Wald test in the case of significant coefficients for both sub-sample periods indicates that information asymmetry and divergence of opinion on both trading systems has the same impact on firm-specific liquidity.

Overall, the results of two-pass regression provide weak evidence concerning the impact of information asymmetry and divergence of opinion on firm-specific liquidity before and after automation. This may imply that market-wide information and industry-wide information play an important role in explaining the cross-sectional variation in firm-specific liquidity, and both information asymmetry between company managers and outside investors and the divergence of opinion have little incremental explanatory power in relation to the variations in cross-sectional liquidity.

4.5 Conclusion

This chapter represents the first empirical study that explicitly examines the implications of information asymmetry between company managers and outside investors, and the implications of divergence of opinion on firm-specific liquidity, before and after the automation of trading systems for the UK, Swiss and German markets.

We argued that firms with a high level of information asymmetry between company managers and outside investors should have lower liquidity, and that firms with a high level of divergence of opinion among investors could have either high liquidity or low liquidity, depending on whether divergence of opinion represents the dominant optimistic view in the market or whether it represents a source of uncertainty. We also argue that the impact of information asymmetry and divergence of opinion on firm-specific liquidity can be different before and after automation of trading systems. The overwhelming results of both univariate and multivariate analysis show that, in all markets in our sample under both floor and electronic trading systems, firm-specific liquidity is negatively related to information asymmetry. Specifically, liquidity of firms with greater information asymmetry between company managers and outside investors is significantly lower than liquidity of firms with low information asymmetry. Analysts' coverage is significant and negatively (positively) related to proportional bid-ask spread and price impact (turnover ratio) and mean forecast error is positively related to proportional bid-ask spread and price impact. This indicates that firms with substantial analysts' coverage and low forecast error (i.e. low information asymmetry) have higher liquidity than other firms. This is consistent with the notion that financial analysts increase the supply of information about a firm to the market, which reduces the uncertainty regarding the firm's future prospects and, consequently, investors and market makers will not be reluctant to trade or hold stocks that have low information asymmetry. These findings are robust after controlling for the impact of firm size. In contrast to the above findings, we find that the results of turnover ratio in portfolio analysis and in regression analysis show the opposite. That is, firms with a high level of information asymmetry have higher liquidity (i.e. high turnover ratio). This result supports the notion that informed traders try to take advantage of their private information regarding firms with high information asymmetry and trade profitability before information is disseminated to the market.

Further, our results provide inconclusive evidence concerning the relationship between divergence of opinion and firm-specific liquidity for all markets during both sub-sample periods, pre- and post-automation of the trading systems. The majority of the results clearly support the notion that divergence in investors' opinion can be viewed as a proxy for risk. In the univariate analysis, liquidity measured by proportional bid-ask spread and price impact declines monotonically with the divergence of opinion. Also, in the multivariate analysis, divergence of opinion is positively related to proportional bid-ask spread and price impact (i.e. negatively related to firm-specific liquidity). In contrast, the results of turnover ratio reflect the optimistic view of the divergence of opinion. That is, the average portfolio turnover ratio increases monotonically with divergence of opinion, and in the multivariate analysis the divergence of opinion is positively related to turnover ratio (i.e. positively related to firm-specific liquidity). The inconclusive evidence about this relationship stresses the need for future empirical research to confirm whether liquidity is positively or negatively related to divergence of opinion.

The results of the comparative analysis support the prediction that the impact of information asymmetry as well as the divergence of opinion on firm-specific liquidity is different across trading systems. For the portfolios that include stocks with the same level of information asymmetry, and stocks with the same level of divergence of opinion, the average portfolio liquidity across trading systems is different. In most cases, the univariate results of proportional bid-ask spread and price impact show that, in contrast to the Swiss market, the average portfolio liquidity for stocks with the same level of information asymmetry and with the same level of divergence of opinion, is higher on the floor trading system than that on the electronic trading system for the UK and German markets. However, the results of turnover ratio show the opposite. Further, the results of the Wald test, which compares the estimated parameters before and after the automation of a trading system, are also consistent with our prediction. Our findings imply that the informational environment is affected by whether the trading system is floor-based or electronically-based. It appears that the floor trading system is more efficient than the electronic one in disseminating information among investors, to the extent that information asymmetry between company managers and outside investors with regard to the same stock will be lower on a floor trading system than an electronic one, especially in the case of the UK and German markets. This also implies that investors on the floor trading system are quickly able to update their beliefs, and thus decrease disagreement among themselves with regard to companies' future prospects.

Furthermore, the explanatory power of the cross-sectional regressions ranges from 4.16% to 84.83%, which means that information asymmetry and divergence of opinion, along with other determinates of firm-specific liquidity, could not fully explain the cross-sectional variation of firm-specific liquidity. Therefore, further work as to the implications of information asymmetry and divergence of opinion on firm-specific liquidity has been conducted, after controlling, however, for the impact of other information (i.e. market-wide and industry-wide information) on the cross-sectional variation of firm-specific liquidity. We applied the idea of Brennan et al. (1998) and Avramov and Chordia (2006a) which is based on the two-pass regression framework. The findings of this analysis provide useful insights and question the importance of the information provided by financial analysts. The results provide overwhelming evidence that information asymmetry and divergence of opinion are not related to firm-specific liquidity. This suggests that the factors in the first-pass time-series regression were able to capture the impact of information asymmetry and divergence of opinion on firm-specific liquidity. These results question the type of information supplied to the market by financial analysts. Is this information considered public information? If so, what causes the variation in firm-specific liquidity when analysts disseminate information to the market or when the number of analysts following a firm increase? Do the behaviour and reactions of investors cause this variation? Such issues could be usefully researched.

Finally, it has been argued that a high level of information asymmetry between company managers and outside investors as well as the divergence of opinion could represent a source of risk due to the uncertainty about firms' future prospects. This could affect the inventory holding costs for investors and market makers. Therefore, another interesting extension of our analysis would be to examine the impact of information asymmetry and divergence of opinion on the cost components of bid-ask spread.

Table 4.1
Descriptive statistics

This table presents the time-series average of cross-sectional means, medians, and standard deviations during the two sub-sample periods, during the floor trading period and the electronic trading period, for UK, Switzerland and Germany. Measures of information asymmetry include: analyst's coverage (AC) is measured as the number of financial analysts reported earnings forecast to I/B/E/S. Mean forecasting error (MFE) is measured as the absolute ratio of the difference between the forecasted earnings per share and the actual earnings per share divided by the mean value of the forecasted earning per share. Incremental analysts' coverage (IAC) is estimated as the residuals of the equation (4.1). The measure of Divergence of opinion includes the coefficient of variation (CV) which is estimated by the standard deviation of the earnings forecasts divided by the absolute value of the mean of earnings forecasts as reported in I/B/E/S summary file. Measures of liquidity include: proportional bid-ask spread (PQSPR) is calculated by dividing the quoted bid-ask spread over the midpoint of quoted bid-ask spread, turnover ratio (TOV) is the trading value divided by market capitalization, and price impact (PIMPACT) is the ratio of absolute returns divided by trading value. Size represents the market capitalization expressed in millions. Price is the stock price at the end of month. Return volatility (VOL) is measured as the squared stock return.

Panel A: UK (London Stock Exchange)								
	Floor trading system				Electronic trading system			
Variables	N	Mean	Median	StdDev.	N	Mean	Median	StdDev.
AC	129	5.973	3.674	5.517	134	4.434	2.332	4.813
MFE	129	1.154	0.091	19.922	134	1.380	0.164	13.053
IAC	129	0.229	0.143	0.546	134	0.060	0.038	0.422
CV	129	0.203	0.053	1.383	134	0.274	0.070	1.899
PQSPR	129	0.049	0.031	0.057	134	0.084	0.049	0.111
TOV	129	19.516	2.124	399.109	134	3.812	1.686	32.208
PIMPACT	129	0.001	5.680E-05	0.006	134	0.016	3.912E-04	0.305
Size	129	0.428	0.047	1.588	134	0.840	0.034	5.653
Price	129	4.255	1.365	45.962	134	3.591	0.975	32.513
VOL	129	0.017	0.004	0.073	134	0.032	0.005	0.131
Panel B: Switzerland (Swiss Stock Exchange)								
	Floor trading system				Electronic trading system			
Variables	N	Mean	Median	StdDev.	N	Mean	Median	StdDev.
AC	79	9.057	6.576	7.904	149	6.749	4.886	6.725
MFE	79	1.012	0.161	5.356	149	0.811	0.183	3.048
IAC	79	0.155	0.004	0.448	149	0.014	-0.007	0.410
CV	79	0.504	0.140	2.512	149	0.242	0.105	0.714
PQSPR	78	0.047	0.022	0.096	149	0.042	0.018	0.094
TOV	79	3.882	1.430	19.615	149	13.040	0.860	175.111
PIMPACT	79	0.007	1.076E-04	0.082	149	0.007	1.028E-04	0.080
Size	79	0.650	0.120	2.340	149	1.077	0.257	3.892
Price	79	680.116	268.177	1790.790	149	579.842	186.001	1685.000
VOL	79	0.013	0.002	0.074	149	0.017	0.002	0.105

Table 4.1 (continued)

Panel C: Germany (Frankfurt Stock Exchange)								
	Floor trading system				Electronic trading system			
Variables	N	Mean	Median	StdDev.	N	Mean	Median	StdDev.
AC	132	7.629	3.170	9.145	132	7.658	3.223	9.138
MFE	132	1.756	0.342	6.921	132	1.789	0.345	7.247
IAC	132	0.042	0.027	0.440	132	0.089	0.078	0.491
CV	132	0.472	0.162	1.601	132	0.479	0.163	1.643
PQSPR	132	0.052	0.029	0.073	130	0.087	0.025	0.194
TOV	132	3.368	0.643	37.151	132	39.668	0.640	933.571
PIMPACT	132	0.107	0.003	1.145	132	3.616	0.002	59.689
Size	132	1.330	0.078	6.239	132	2.131	0.267	7.607
Price	132	44.570	11.031	164.888	132	31.288	11.280	112.558
VOL	132	0.041	0.006	0.202	132	0.065	0.008	0.391

Table 4.2
Information asymmetry, divergence of opinion and liquidity

This table reports the time-series means of monthly cross-sectional averages of liquidity measures for the portfolios formed on the basis of the level of information asymmetry and on the basis of the level of the divergence of opinions among investors. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts coverage (AC), incremental analysts' coverage (IAC) estimated using equation (4.1) and mean forecasting errors (MFE). Divergence of opinion is measured by coefficient of variation (CV). Under all measures of information asymmetry and divergence of opinion, stocks are sorted into three portfolios. High (low) analysts' coverage and incremental analysts' coverage (mean forecasting errors) refer to low information asymmetry between company managers and outsider investors. Low CV refers to low divergence in opinion among investors. Floor and Electronic refer to the estimation made during the floor trading system and electronic trading system respectively. Portfolios are equally weighted and rebalanced monthly. T-test is applied to test the null hypothesis that the time-series average of liquidity is equal to zero. F-Statistic, one-way analysis of variance is applied to examine the equivalence in the means of two or more portfolios. *, **, *** denotes the significance at 10%, 5%, 1% level respectively.

Panel A: Liquidity by Analysts' Coverage

		UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
		Liquidity Measures								
Analysts' Coverage		PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Floor	Low	0.054***	3.183***	0.002***	0.049***	1.609***	0.003	0.038***	1.256***	0.023***
	Medium	0.033***	3.164***	0.001***	0.027***	2.108***	2.385E-04***	0.028***	1.076***	0.006***
	High	0.017***	3.017***	4.790E-05***	0.013***	2.676***	8.825E-05***	0.012***	1.158***	0.001***
	F-Statistic	444.06***	0.25	58.09***	262.58***	24.41***	1.94	122.03***	0.61	17.81***
Electronic	Low	0.073***	2.392***	0.006***	0.028***	1.310***	0.001***	0.054***	1.432***	0.718***
	Medium	0.037***	3.051***	0.001***	0.016***	1.862***	2.131E-04***	0.028***	1.665***	0.429*
	High	0.014***	5.247***	9.554E-05***	0.010***	28.954***	6.006E-05***	0.010***	3.401***	0.010*
	F-Statistic	811.01***	252.78***	31.53***	126.82***	1.09	51.63***	66.61***	68.59***	3.06**

Table 4.2 (continued)

Panel B: Liquidity by Incremental Analysts' Coverage

		UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
		Liquidity Measures								
Incremental Analysts' Coverage		PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Floor	Low	0.056***	3.129***	9.154E-04***	0.086***	2.868***	0.014***	0.043***	2.690***	0.070***
	Medium	0.086***	260.384	0.003***	0.050***	6.365***	0.002***	0.077***	6.686***	0.236***
	High	0.038***	3.127***	5.313E-04***	0.033***	2.192***	0.010	0.039***	1.969***	0.050***
	F-Statistic	111.54***	2.09	21.89***	53.32 ***	24.93***	2.15	47.32***	10.94***	12.97***
Electronic	Low	0.076***	3.007***	0.016**	0.036***	28.727	0.005***	0.078***	1.706***	1.924***
	Medium	0.154***	9.474	0.042***	0.075***	10.218***	0.010	0.145***	198.006*	7.704
	High	0.073***	3.432***	0.007***	0.023***	1.979***	0.006***	0.059***	2.213***	3.800***
	F-Statistic	301.54***	0.98	3.54**	192.81***	1.54	0.35	56.23***	2.70*	0.80

Panel C: Liquidity by Mean Forecasting Error

		UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
		Liquidity Measures								
Mean Forecasting Error		PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Floor	Low	0.023***	2.649***	1.255E-04***	0.024***	1.998***	2.283E-04***	0.019***	1.097***	0.002***
	Medium	0.027***	2.692***	1.991E-04***	0.024***	2.202***	2.357E-04***	0.023***	1.151***	0.004***
	High	0.044***	3.275***	4.814E-04***	0.035***	2.192***	4.822E-04***	0.030***	1.102***	0.007***
	F-Statistic	146.310***	14.260***	69.890***	49.76 ***	1.21	37.07 ***	38.20***	0.07	10.65***
Electronic	Low	0.028**	3.624***	0.001**	0.015***	1.582***	2.458E-04***	0.018***	2.173***	0.005***
	Medium	0.037***	3.447***	0.004	0.017***	30.242	2.842E-04***	0.024***	2.224***	0.010***
	High	0.065***	3.342***	0.004***	0.022***	1.955***	4.965E-04***	0.030***	2.153***	0.390
	F-Statistic	112.240***	3.540**	1.27	25.62***	1.02	10.46***	20.49***	0.12	1.59

Table 4.2 (continued)

Panel D: Liquidity by Divergence of Opinions (CV)		UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
		Liquidity Measures								
Coefficient of Variation		PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Floor	Low	0.021***	2.595***	1.188E-04***	0.019***	2.422***	1.624E-04***	0.017***	1.209***	0.003***
	Medium	0.022***	2.868***	1.135E-04***	0.024***	2.232***	2.179E-04***	0.019***	1.105***	0.003***
	High	0.036***	3.480***	3.796E-04***	0.031***	2.090***	3.482E-04***	0.026***	1.400***	0.006***
	F-Statistic	153.99***	22.45***	25.20***	49.13***	1.92	26.89***	28.73***	0.96	6.12***
Electronic	Low	0.022***	3.653***	3.750E-04***	0.014***	1.866***	1.725E-04***	0.016***	2.196***	0.050**
	Medium	0.020***	4.489***	2.958E-04***	0.013***	34.361	1.513E-04***	0.018***	2.659***	0.586
	High	0.033***	4.717***	0.001***	0.018***	2.089***	3.126E-04***	0.025***	2.625***	0.097***
	F-Statistic	115.71***	28.00***	9.28***	11.75***	1.01	10.14***	13.13***	4.55**	1.75

Table 4.3

Test of difference in portfolios' liquidity means across trading systems

This table presents the differences in the liquidity means of the portfolios constructed on the basis of the level of information asymmetry and on the basis of the level of the divergence of opinion among investors. The differences represent the average portfolio liquidity for the electronic trading system minus the average portfolio liquidity for the floor trading system. Measures of liquidity, level of information asymmetry and divergence of opinion are as described in table 4.1. T-test is applied to test the null hypothesis that the difference in the mean is equal to zero. *, **, *** denote the significance at 10%, 5%, 1% level respectively.

Panel A: Difference in Portfolios' Liquidity by Analysts' Coverage

	UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
	Liquidity Measures								
Analysts' Coverage	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Low	0.018***	-0.791***	0.004***	-0.021***	-0.299***	-0.002	0.016***	0.176**	0.695***
Medium	0.005***	-0.112	0.001***	-0.011***	-0.245	-2.500E-05	4.000E-04	0.590***	0.422*
High	-0.003***	2.230***	4.760E-05***	-0.003***	26.278	-2.800E-05*	-0.002**	2.243***	0.010*

Panel B: Difference in Portfolios' Liquidity by Incremental Analysts' Coverage

	UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
	Liquidity Measures								
Incremental Analysts' Coverage	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Low	0.020***	-0.122	0.020*	-0.050***	25.859	-0.009***	0.035***	-0.984**	1.855***
Medium	0.068***	-250.910	0.040***	0.025***	3.853	0.008	0.068***	191.320	7.469
High	0.035***	0.306*	0.010***	-0.011***	-0.213*	-0.004	0.020***	0.244	3.750**

Panel C: Difference in Portfolios' Liquidity by Mean Forecasting Error

	UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
	Liquidity Measures								
Mean Forecasting Error	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Low	0.005***	0.975***	0.001**	-0.009***	-0.415***	1.750E-05	-0.001	1.076***	0.003*
Medium	0.011***	0.756***	0.004	-0.007***	28.040	4.840E-05	0.001	1.073***	0.006**
High	0.021***	0.066	0.004***	-0.013***	-0.236*	1.440E-05	3.000E-04	1.051***	0.383

Table 4.3 (continued)

Panel D: Difference in Portfolios' Liquidity by Divergence of Opinions (CV)									
	UK (London Stock Exchange)			Switzerland (Swiss Stock Exchange)			Germany (Frankfurt Stock Exchange)		
	Liquidity Measures								
Coefficient of Variation	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Low	0.001	1.058***	2.560E-04***	-0.005***	-0.555**	1.000E-05	-0.001	0.987***	0.048**
Medium	-0.002**	1.622***	1.820E-04***	-0.011***	32.128	-6.700E-05***	-0.001	1.554***	0.583
High	-0.003**	1.237***	6.800E-04***	-0.014***	-0.001	-3.600E-05	-3.000E-04	1.225***	0.091***

Table 4.4

Cross-sectional regression of individual stock liquidity to information asymmetry and divergence of opinion

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficients of equation (4.2) estimated for all securities in the UK, Switzerland and Germany during the two sub-sample periods, during the floor trading period and the electronic trading period, using the Fama and MacBeth (1973) procedure. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts' coverage (AC), incremental analysts' coverage (IAC) estimated using equation (4.1) and mean forecasting errors (MFE). Divergence of opinion is measured by coefficient of variation (CV). Adj. R^2 is the time-series average of the monthly adjusted R^2. Wald Stat. is the Wald test statistic applied to examine the equality between the coefficients estimated for floor and electronic trading systems. T-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively.

Panel A: UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-2.093 (-30.76)***	4.819 (45.05) ***	-9.171 (-51.04) ***	-1.904 (-31.93)***	4.562 (58.76) ***	-9.401 (-49.15) ***	10.03***	10.97***	1.45
AC	-0.665 (-38.53) ***	0.344 (11.86) ***	-2.483 (-74.33) ***	-1.148 (-23.61) ***	0.706 (21.54) ***	-3.111 (-55.84) ***	98.70***	122.21***	127.00***
MFE	0.035 (12.16) ***	0.023 (6.29) ***	0.039 (6.70) ***	0.029 (5.30) ***	0.030 (8.02) ***	0.016 (1.30)	1.17	3.81*	3.47*
CV	0.143 (21.93) ***	0.074 (7.76) ***	0.168 (6.90) ***	0.078 (11.20) ***	0.057 (11.97) ***	0.079 (4.17) ***	87.61***	11.44***	22.53***
Adj. R^2 (%)	47.01	8.36	51.02	51.13	21.30	56.07			

Panel B: Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-2.099 (-46.16)***	-0.890 (-11.17) ***	-5.519 (-32.58) ***	-3.056 (-13.59)***	-0.777 (-9.52) ***	-6.030 (-22.62) ***	18.12***	1.92	3.67*
AC	-0.799 (-72.86) ***	0.453 (24.70) ***	-1.694 (-71.1) ***	-0.606 (-14.35) ***	0.657 (15.87) ***	-2.169 (-14.32) ***	20.77***	24.30***	9.85***
MFE	0.033 (3.75) ***	0.059 (4.64) ***	0.075 (3.16) ***	0.026 (0.91)	0.038 (1.77) *	-0.075 (-2.30) **	0.06	0.96	21.09***
CV	0.130 (13.81) ***	-0.110 (-5.80) ***	0.206 (5.26) ***	0.128 (2.40) **	0.135 (4.61) ***	0.183 (7.11) ***	0.00	69.66***	0.81
Adj. R^2 (%)	42.53	6.70	43.35	24.38	9.84	37.45			

Table 4.4 (continued)

Panel C: Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-2.621 (-57.50) ***	-0.309 (-2.34) **	-4.113 (-20.97) ***	-2.451 (-21.67)***	-1.613 (-7.06) ***	-2.230 (-6.69) ***	2.26	32.54***	31.87***
AC	-0.736 (-31.19) ***	-0.226 (-2.95) ***	-1.922 (-41.1) ***	-0.940 (-22.24) ***	0.827 (12.43) ***	-3.195 (-34.76) ***	23.25***	250.55***	191.69***
MFE	-0.004 (-0.44)	0.037 (2.15) **	0.040 (0.95)	-0.007 (-0.81)	0.052 (4.02) ***	-0.015 (-0.60)	0.11	1.24	4.70**
CV	0.077 (9.88)***	0.150 (5.97) ***	0.139 (4.61) ***	0.064 (6.85) ***	0.088 (3.94) ***	0.194 (6.42) ***	1.89	7.51***	3.35*
Adj. R^2 (%)	57.26	14.72	54.21	57.71	21.76	64.05			

Table 4.5

Cross-sectional regression of individual stock liquidity to information asymmetry and divergence of opinion after controlling for other determinants of liquidity

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficients of equation (4.3) estimated for all securities in the UK, Switzerland and Germany during the two sub-sample periods, during the floor trading period and the electronic trading period, using the Fama and MacBeth (1973) procedure. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts' coverage (AC), incremental analysts' coverage (IAC) estimated using equation (4.1) and mean forecasting errors (MFE). Divergence of opinion is measured by coefficient of variation (CV). Size is the market capitalization. Price is the price of stock at the end of the month. Volatility is the stock's return volatility measured as squared stock return. Adj. R^2 is the time-series average of the monthly adjusted R^2. Wald Stat. is the Wald test statistic applied to examine the equality between the coefficients estimated during floor and electronic trading systems. T-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity. The coefficients of both PQSPR and PIMPACT regressions are multiplied by 100. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively.

Panel A: UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-1.559 (-24.57)***	5.198 (32.03) ***	-8.629 (-87.14) ***	-0.983 (-15.30)***	4.417 (54.24) ***	-7.587 (-50.65) ***	80.52***	91.85***	48.41***
IAC	0.026 (7.05) ***	0.055 (6.30) ***	-0.030 (-3.46) ***	-0.033 (-1.60)	0.019 (0.83)	-0.052 (-1.24)	8.34***	2.28	0.29
MFE	0.017 (8.74) ***	0.008 (2.25) **	0.004 (1.17)	0.027 (7.00) ***	0.002 (0.35)	0.016 (1.90) *	7.45***	1.26	1.95
CV	0.066 (17.5) ***	0.079 (9.87) ***	-0.029 (-2.83) ***	0.033 (3.55) ***	0.057 (8.13) ***	-0.007 (-0.30)	12.82***	9.75***	0.90
Size	-0.289 (-55.79) ***	0.066 (3.69) ***	-1.123 (-126.21) ***	-0.443 (-24.65) ***	0.252 (23.00) ***	-1.298 (-62.43) ***	73.60***	288.28***	71.05***
Price	-0.129 (-18.86) ***	-0.003 (-0.56)	-0.015 (-2.02) **	-0.092 (-14.29) ***	-0.042 (-5.27) ***	0.011 (1.43)	33.65***	23.49***	11.69***
Volatility	1.232 (10.67) ***	6.287 (11.15) ***	0.312 (0.65)	0.585 (4.88) ***	4.763 (15.48) ***	-0.262 (-1.42)	29.18***	24.57***	9.70***
Adj. R^2 (%)	68.92	11.07	77.05	75.70	25.58	84.83			

Table 4.5 (continued)

Panel B: Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-1.391 (-25.51)***	0.468 (1.45)	-3.317 (-17.81) ***	-2.466 (-11.06)***	1.406 (2.89) ***	-3.797 (-8.21) ***	23.23***	3.71*	1.07
IAC	-0.073 (-6.57) ***	0.244 (3.27) ***	-0.161 (-3.47) ***	0.306 (0.95)	-0.540 (-1.14)	0.755 (1.14)	1.39	2.72*	1.91
MFE	0.017 (2.42) **	-0.024 (-0.65)	0.019 (0.73)	0.025 (0.54)	0.040 (0.59)	-0.041 (-0.51)	0.03	0.89	0.55
CV	0.074 (10.37) ***	-0.051 (-0.53)	0.107 (1.81) *	0.428 (1.08)	-0.450 (-0.76)	0.750 (0.97)	0.81	0.46	0.70
Size	-0.465 (-67.21) ***	-0.121 (-2.75) ***	-0.949 (-39.54) ***	-0.339 (-20.34) ***	-0.020 (-0.43)	-1.082 (-23.84) ***	56.69***	4.60**	8.49***
Price	-0.002 (-0.53)	0.044 (1.00)	-0.171 (-6.48) ***	0.209 (1.11)	-0.420 (-1.24)	0.374 (0.90)	1.25	1.88	1.73
Volatility	0.963 (1.88) *	13.699 (9.33) ***	0.381 (0.38)	0.376 (0.85)	17.640 (11.14) ***	-5.763 (-6.03) ***	1.74	6.20**	41.36***
Adj. R^2 (%)	60.57	4.16	61.40	39.30	10.76	55.93			

Panel C: Germany (Frankfurt Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-2.266 (-46.5)***	0.485 (3.83) ***	-3.279 (-23.41) ***	-2.124 (-29.40)***	-1.254 (-8.32) ***	-1.054 (-6.76) ***	3.84**	133.01***	203.96***
IAC	-0.050 (-2.41) **	-0.181 (-1.65) *	0.180 (1.58)	0.002 (0.06)	-0.101 (-1.49)	0.087 (1.27)	2.81*	1.36	1.86
MFE	0.005 (1.34)	-0.030 (-1.40)	0.028 (1.32)	0.007 (1.10)	-0.021 (-1.04)	0.024 (1.26)	0.11	0.21	0.03
CV	0.000 (0.03)	0.081 (2.25) **	-0.083 (-2.43) **	-0.025 (-1.72) *	0.121 (3.19) ***	-0.089 (-2.75) ***	3.02*	1.15	0.04
Size	-0.332 (-36.1) ***	-0.216 (-6.66) ***	-0.914 (-28.41) ***	-0.413 (-26.58) ***	0.259 (10.38) ***	-1.425 (-60.41) ***	27.50***	361.66***	468.09***
Price	-0.014 (-1.51)	-0.080 (-1.55)	0.038 (0.68)	0.003 (0.31)	-0.090 (-3.68) ***	0.027 (1.07)	3.30*	0.18	0.16
Volatility	-0.319 (-2.02) **	10.741 (4.66) ***	-4.995 (-1.89) *	-0.396 (-1.92) *	7.373 (9.15) ***	-3.054 (-4.66) ***	0.14	17.48***	8.75***
Adj. R^2 (%)	68.57	33.12	70.28	70.90	18.39	80.12			

Table 4.6

Fama-MacBeth estimates of the cross-sectional regression with market liquidity as explanatory variable in the first-pass time-series regression

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficients for all securities in the UK, Switzerland and Germany during the two sub-sample periods, during the floor trading period and the electronic trading period, using the Fama and MacBeth (1973) procedure. Panel A presents the estimates of the second-pass cross-sectional equation (4.6) without controlling for the determinants of firm-specific liquidity, Panel B represents the estimates of the second-pass cross-sectional equation (4.6) after controlling for other determinants of firm-specific liquidity. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts' converge (AC), incremental analysts' coverage (IAC) estimated using equation (4.1) and mean forecasting errors (MFE). Divergence of opinions is measured by coefficient of variation (CV). Size is the market capitalization. Price is the price of stock at the end of the month. Volatility is the stock's return volatility measured as squared stock return. Adj. R^2 is the time-series average of the monthly adjusted R^2. Wald Stat. is the Wald test statistic applied to examine the equality between the coefficients estimated during floor and electronic trading system. T-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity. The coefficients of both PQSPR and PIMPACT regressions are multiplied by 100. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively.

Panel A: Estimates of the second-pass cross-sectional equation (4.6) without controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.033 (0.93)	0.141 (0.21)	0.003 (0.61)	0.050 (1.09)	-0.077 (-1.09)	0.170 (1.24)	0.14	9.42***	1.48
AC	-0.001 (-0.18)	-0.062 (-0.26)	-0.001 (-0.66)	0.029 (1.09)	0.019 (0.39)	0.022 (0.52)	1.27	2.80*	0.31
MFE	0.018 (5.33) ***	-0.006 (-0.43)	1.771E-04 (0.62)	0.006 (0.82)	0.023 (2.54) **	0.030 (1.19)	2.87*	10.63***	1.39
CV	-0.006 (-1.09)	-0.005 (-0.15)	-3.470E-04 (-0.57)	0.032 (1.03)	-0.031 (-2.52) **	0.034 (0.79)	1.50	4.37**	0.63
Adj. R^2 (%)	1.38	1.90	2.63	0.38	1.15	0.47			

Table 4.6 Panel A (continued)

Switzerland (Swiss Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.024 (0.26)	-0.128 (-0.97)	0.002 (0.61)	0.471 (0.88)	-0.09 (-0.70)	0.006 (1.09)	0.69	0.12	0.44
AC	0.006 (0.20)	0.045 (0.99)	6.768E-05 (0.06)	0.046 (1.29)	-0.01 (-0.15)	-0.001 (-0.36)	1.27	0.92	0.16
MFE	-0.003 (-0.18)	0.036 (1.25)	-4.190E-04 (-0.75)	0.121 (1.15)	-0.02 (-1.03)	-1.490E-04 (-0.28)	1.39	8.70	0.26
CV	0.027 (1.33)	-0.042 (-0.94)	0.002 (1.97)*	0.099 (0.74)	-0.01 (-0.37)	0.002 (1.76)*	0.29	2.25	0.00
Adj. R^2 (%)	0.90	-0.48	4.31	0.38	-0.22	-0.75			

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.037 (-1.73)*	-0.071 (-0.67)	0.073 (1.18)	0.013 (0.17)	-11.769 (-1.82)*	-2.136 (-0.07)	0.42	0.52	0.01
AC	-0.012 (-2.00)**	0.025 (0.48)	-0.021 (-1.10)	-0.004 (-0.16)	0.685 (0.16)	1.868 (0.21)	0.42	0.17	0.05
MFE	0.005 (0.95)	3.240E-04 (0.01)	-0.015 (-0.97)	0.026 (1.80)*	6.002 (1.74)*	-0.829 (-0.07)	3.03*	2.98*	0.01
CV	0.001 (0.14)	0.024 (0.28)	0.022 (1.38)	-0.012 (-0.65)	-10.750 (-1.80)*	0.516 (0.06)	0.48	4.88**	0.00
Adj. R^2 (%)	0.71	3.59	4.05	1.21	2.66	1.14			

Table 4.6 (continued)

Panel B: Estimates of the second-pass cross-sectional equation (4.6) with controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.063 (1.41)	-0.514 (-1.07)	-0.001 (-0.13)	0.031 (0.60)	-0.781 (-7.15)***	0.190 (1.36)	0.40	5.98**	1.86
IAC	-0.015 (-3.78)***	0.020 (0.44)	-3.530E-04 (-0.72)	-0.047 (-1.81)*	-0.013 (-0.3)	0.037 (0.92)	1.54	0.56	0.86
MFE	0.011 (3.88)***	-0.018 (-1.57)	2.063E-05 (0.08)	-0.007 (-0.53)	-0.008 (-0.85)	0.018 (1.17)	1.91	1.04	1.36
CV	-0.009 (-2.13)**	-0.068 (-1.69)*	-4.590E-04 (-0.74)	0.025 (1.04)	-0.055 (-3.23) ***	0.021 (0.67)	1.98	0.57	0.47
Size	-0.004 (-1.17)	-0.024 (-0.48)	-0.001 (-0.79)	-0.001 (-0.22)	0.038 (2.80) ***	-0.002 (-0.81)	0.66	21.06***	0.32
Price	-0.012 (-2.00)**	0.048 (1.64)	0.001 (1.03)	-0.002 (-0.23)	0.031 (1.66) *	-0.014 (-1.18)	1.74	0.79	1.51
Volatility	1.269 (3.15)***	23.420 (6.47)***	0.120 (2.32)**	0.716 (1.89)*	16.786 (8.60) ***	0.260 (1.01)	2.13	11.56***	0.29
Adj. R^2 (%)	5.63	7.49	5.63	2.83	7.57	1.70			

Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.025 (0.22)	1.115 (0.82)	-0.003 (-0.62)	0.209 (0.42)	-0.309 (-0.82)	-0.005 (-0.39)	0.14	14.35***	0.02
IAC	-0.021 (-0.66)	0.296 (1.11)	-0.001 (-1.11)	1.256 (1.45)	-0.203 (-0.73)	0.015 (1.35)	2.16	3.20*	2.06
MFE	-0.008 (-0.54)	-0.138 (-1.07)	-0.001 (-0.88)	-0.080 (-0.82)	0.024 (0.51)	-0.002 (-1.59)	0.55	11.67***	1.51
CV	0.025 (1.16)	0.337 (1.01)	0.002 (1.79)*	0.942 (1.15)	-0.370 (-1.02)	0.015 (1.13)	1.25	3.81*	1.03
Size	-0.006 (-0.41)	-0.174 (-0.95)	4.897E-06 (0.01)	-0.014 (-0.76)	0.055 (1.16)	-0.001 (-0.44)	0.19	23.46***	0.20
Price	0.005 (0.42)	0.140 (1.04)	0.001 (1.65)	0.342 (0.98)	-0.192 (-0.88)	0.007 (1.01)	0.93	2.34	0.86
Volatility	2.574 (1.43)	17.285 (2.68)***	0.304 (3.63)***	-0.931 (-1.45)	30.348 (8.65)***	0.082 (1.09)	29.71***	13.87***	8.66***
Adj. R^2 (%)	2.83	4.90	2.55	3.61	13.58	7.17			

Table 4.6, Panel B (continued)

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.027 (-1.14)	-0.322 (-2.14)**	0.079 (1.22)	0.079 (1.04)	-0.598 (-6.38)***	5.092 (0.63)	1.93	8.67***	0.38
IAC	0.008 (0.39)	0.110 (0.83)	-0.004 (-0.23)	0.035 (1.03)	0.107 (1.38)	-4.991 (-1.14)	0.62	0.00	1.30
MFE	0.002 (0.39)	0.018 (0.29)	-0.017 (-1.22)	0.017 (1.16)	0.045 (1.13)	-0.964 (-1.01)	1.02	0.46	0.99
CV	-0.004 (-0.46)	-0.071 (-0.77)	0.022 (1.31)	0.011 (0.46)	-0.126 (-2.04)**	2.315 (1.25)	0.40	0.80	1.52
Size	0.004 (1.33)	0.032 (1.17)	-0.006 (-1.01)	-0.008 (-0.75)	0.037 (2.26)**	0.379 (0.92)	1.23	0.12	0.88
Price	-0.011 (-1.02)	-0.059 (-0.88)	-0.008 (-0.42)	0.011 (0.42)	-0.014 (2.26)	-1.396 (-0.7)	0.70	4.49**	0.48
Volatility	-0.034 (-0.14)	8.810 (2.19)**	-0.752 (-1.13)	-0.317 (-0.77)	14.717 (6.56)***	-60.361 (-0.28)	0.47	6.93***	0.08
Adj. R^2 (%)	1.76	10.82	4.83	1.84	13.17	3.57			

Appendices

Supplementary empirical information

Appendix 4A

The testable hypotheses, their acceptance or rejection, and the justification

Hypothesis	Status (accepted/ rejected)	The reason
H_1: information asymmetry between company managers and outsider investors has a significant negative effect on firm-specific liquidity.	Accepted	Information asymmetry is significantly and negatively (positively) related to turnover ratio (proportional bid-ask spread and price impact).
H_2: Divergence of opinion among investors has an insignificant effect on firm-specific liquidity.	Rejected	Divergence of opinion has a significant effect on turnover ratio, proportional bid-ask spread and price impact.
$H_{3:}$ There is no significant difference in the impact of information asymmetry on firm-specific liquidity before and after the introduction of an electronic trading system.	Rejected	The size of the coefficients of information asymmetry measures is significantly different across trading systems / some of the coefficients become significant or insignificant after automation.
$H_{4:}$ There is no significant difference in the impact of divergence of opinion among investors on firm-specific liquidity before and after the introduction of an electronic trading system.	Rejected	The size of the coefficients of divergence of opinion measures is significantly different across trading systems / some of the coefficients become significant or insignificant after automation.

Appendix 4B
Fama-MacBeth estimates of the cross-sectional regression with market liquidity and industry liquidity as explanatory variables in the first-pass time-series regression

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficients for all securities in the UK, Switzerland and Germany during the two sub-sample periods, during the floor trading period and the electronic trading period, using the Fama and MacBeth (1973) procedure. Panel A presents the estimates of the second-pass cross-sectional equation (4.6) without controlling for the determinants of firm-specific liquidity. Panel B represents the estimates of the second-pass cross-sectional equation (4.6) after controlling for other determinants of firm-specific liquidity. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts' converge (AC), incremental analysts' coverage (IAC) estimated using equation (4.1), and mean forecasting errors (MFE). Divergence of opinion is measured by coefficient of variation (CV). Size is the market capitalization. Price is the price of stock at the end of the month. Volatility is the stock's return volatility measured as squared stock return. Adj. R^2 is the time-series average of the monthly adjusted R^2. Wald Stat. is the Wald test statistic applied to examine the equality between the coefficients estimated during floor and electronic trading systems. T-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity. The coefficients of both PQSPR and PIMPACT regressions are multiplied by 100. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively.

Panel A: Estimates of the second-pass cross-sectional equation (4.6) without controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.027 (0.84)	-0.372 (-1.06)	0.003 (0.81)	0.046 (1.07)	-0.085 (-1.35)	0.110 (1.07)	0.20	20.43***	1.08
AC	-0.001 (-0.18)	0.131 (1.08)	-0.001 (-0.46)	0.031 (1.14)	0.026 (0.64)	0.013 (0.43)	1.38	6.57**	0.20
MFE	0.018 (5.35)***	0.001 (0.08)	2.817E-04 (0.98)	0.006 (0.87)	0.022 (2.65)***	0.017 (1.05)	3.26*	6.28**	1.06
CV	-0.008 (-1.68)*	-0.005 (-0.15)	2.273E-04 (0.46)	0.032 (1.05)	-0.028 (-2.19)**	0.021 (0.68)	1.74	3.10*	0.46
Adj. R^2 (%)	1.13	1.71	2.57	0.33	0.90	0.34			

Appendix 4B, Panel A (continued)

Switzerland (Swiss Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.030 (0.38)	-0.017 (-0.16)	-0.024 (-1.26)	0.472 (0.91)	-0.127 (-1.27)	0.005 (1.12)	0.72	1.20	37.07***
AC	0.002 (0.06)	0.008 (0.20)	0.006 (1.43)	0.034 (0.94)	0.044 (1.41)	-0.001 (-0.42)	0.79	1.29	17.52***
MFE	-0.004 (-0.27)	0.035 (1.30)	-0.001 (-1.22)	0.114 (1.11)	-0.020 (-0.96)	-1.170E-04 (-0.23)	1.32	6.93***	3.11*
CV	0.026 (1.18)	-0.040 (-0.95)	-0.004 (-0.72)	0.098 (0.75)	0.007 (0.25)	0.002 (1.66)*	0.31	2.64	33.03***
Adj. R^2 (%)	0.73	0.87	3.83	0.14	0.16	-0.76			

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.038 (-1.80)*	0.017 (0.17)	0.011 (0.15)	0.024 (0.29)	-0.094 (-1.57)	-1.357 (-0.04)	0.57	3.44*	0.00
AC	-0.013 (2.23)**	0.017 (0.38)	-0.004 (-0.17)	-0.014 (-0.61)	0.004 (0.10)	1.845 (0.20)	1.36	0.11	0.04
MFE	0.007 (1.40)	-0.001 (-0.05)	-0.002 (-0.08)	0.016 (1.08)	0.049 (1.64)	-0.669 (-0.06)	0.40	2.84*	0.00
CV	0.001 (0.15)	0.058 (1.19)	-0.001 (-0.04)	-0.013 (-0.53)	-0.091 (-1.90)	0.537 (0.06)	0.33	9.70***	0.00
Adj. R^2 (%)	1.09	2.20	5.00	0.59	1.70	1.24			

Appendix 4B (continued)

Panel B: Estimates of the second-pass cross-sectional equation (4.6) with controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.058 (1.37)	-0.630 (-1.75) *	0.003 (0.60)	0.022 (0.44)	-0.772 (-7.52)	0.140 (1.16)	0.50	1.93	1.29
IAC	-0.014 (3.50) ***	0.016 (0.38)	2.720E-04 (0.47)	-0.047 (1.80)*	-0.006 (-0.15)	0.014 (0.50)	1.60	0.30	0.24
MFE	0.011 (3.81) ***	-0.011 (-0.93)	7.442E-05 (0.26)	-0.006 (-0.52)	-0.008 (-0.98)	0.008 (0.95)	2.05	0.16	0.88
CV	-0.011 (-2.65) ***	-0.066 (-1.69) *	1.392E-05 (0.03)	0.026 (1.09)	-0.052 (-3.04)***	0.013 (0.54)	2.40	0.62	0.30
Size	-4.000E-03 (-1.26)	0.014 (0.58)	-3.540E-04 (-0.75)	-8.120E-04 (-0.21)	0.039 (3.07)***	0.003 (1.06)	0.70	3.97**	1.43
Price	-0.011 (-1.95) *	0.026 (1.04)	-9.890E-05 (-0.15)	1.533E-04 (0.02)	0.031 (1.64)*	-0.017 (-1.09)	2.18	0.05	1.17
Volatility	1.255 (3.29)***	21.366 (6.51)***	0.085 (1.70)*	0.748 (2.08)**	16.329 (8.54)***	0.140 (0.38)	1.98	6.94***	0.02
Adj. R^2 (%)	4.89	6.16	5.69	2.53	7.03	1.53			

Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.048 (0.53)	1.067 (0.88)	-0.028 (-1.08)	0.220 (0.45)	-0.172 (-0.46)	-0.004 (-0.34)	0.12	10.91***	4.70**
IAC	-0.028 (-0.86)	0.203 (0.89)	0.002 (0.56)	1.196 (1.45)	-0.252 (-0.82)	0.014 (1.33)	2.19	2.19	1.39
MFE	-0.011 (-0.77)	-0.126 (-1.10)	-0.001 (-1.22)	-0.077 (-0.82)	0.024 (0.47)	-0.002 (-1.48)	0.50	8.60***	0.59
CV	0.027 (1.17)	0.307 (1.05)	-0.003 (-0.63)	0.876 (1.17)	-0.396 (-0.99)	0.014 (1.15)	1.28	3.06*	1.93
Size	-0.008 (-0.62)	-0.162 (-1.00)	0.003 (1.02)	-0.013 (-0.74)	0.035 (0.97)	-0.001 (-0.43)	0.08	29.51***	7.63***
Price	0.002 (0.21)	0.128 (1.09)	3.5E-05 (0.06)	0.312 (0.98)	-0.201 (-0.86)	0.006 (1.00)	0.95	1.99	1.00
Volatility	2.227 (1.40)	16.215 (2.59)	-0.042 (-0.08)	-1.579 (-2.05)**	30.644 (8.39)***	0.041 (0.67)	24.36***	15.61***	1.81
Adj. R^2 (%)	2.02	4.56	4.25	3.05	11.90	6.50			

Appendix 4B, Panel B (continued)

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.027 (-1.20)	-0.148 (-1.25)	0.030 (0.39)	0.050 (0.65)	-0.527 (-5.71)***	6.159 (0.88)	0.99	16.87***	0.77
IAC	0.015 (0.77)	-0.004 (-0.05)	0.025 (0.70)	0.017 (0.44)	0.056 (0.79)	-6.309 (-1.18)	0.00	0.71	1.41
MFE	0.004 (0.67)	0.013 (0.27)	-0.004 (-0.21)	0.014 (1.00)	0.034 (1.00)	-1.929 (-1.11)	0.54	0.39	1.24
CV	-0.002 (-0.16)	-0.018 (-0.34)	0.001 (0.04)	-0.028 (-1.19)	-0.103 (-2.10)**	4.422 (1.20)	1.22	3.02*	1.43
Size	0.005 (1.49)	0.027 (1.06)	-0.010 (-0.90)	0.005 (0.44)	0.024 (1.52)	0.142 (0.27)	0.00	0.04	0.08
Price	-0.011 (-0.95)	-0.069 (-1.08)	0.011 (0.36)	-0.047 (-1.3)	0.005 (0.23)	1.071 (0.29)	0.99	10.92***	0.08
Volatility	-0.095 (-0.43)	8.700 (2.47)**	-0.576 (-0.72)	-0.380 (-0.63)	14.421 (7.25)***	-261.921 (-0.75)	0.22	8.27***	0.56
Adj. R^2 (%)	1.98	7.73	5.23	1.42	9.20	3.62			

Appendix 4C
Fama-MacBeth estimates of the cross-sectional regression with market liquidity, industry liquidity and market return as explanatory variables in the first-pass time-series regression

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficients for all securities in the UK, Switzerland and Germany during the two sub-sample periods, during the floor trading period and the electronic trading period, using the Fama and MacBeth (1973) procedure. Panel A presents the estimates of the second-pass cross-sectional equation (4.6) without controlling for the determinants of firm-specific liquidity. Panel B represents the estimates of the second-pass cross-sectional equation (4.6) after controlling for other determinants of firm-specific liquidity. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts' coverage (AC), incremental analysts' coverage (IAC) estimated using equation (4.1) and mean forecasting errors (MFE). Divergence of opinions is measured by coefficient of variation (CV). Size is the market capitalization. Price is the price of stock at the end of the month. Volatility is the stock's return volatility measured as squared stock return. Adj. R^2 is the time-series average of the monthly adjusted R^2. Wald Stat. is the Wald test statistic applied to examine the equality between the coefficients estimated during floor and electronic trading systems. T-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity. The coefficients of both PQSPR and PIMPACT regressions are multiplied by 100. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively.

Panel A: Estimates of the second-pass cross-sectional equation (4.6) without controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.032 (1.05)	-0.484 (-1.35)	0.005 (1.25)	0.051 (1.09)	-0.101 (-1.63)	0.120 (1.24)	0.17	37.78***	1.40
AC	0.003 (0.39)	0.141 (1.21)	-0.001 (-0.86)	0.030 (1.17)	0.033 (0.77)	0.005 (0.18)	1.13	6.55*	0.05
MFE	0.018 (5.43)***	0.005 (0.38)	2.996E-04 (1.02)	0.011 (2.44)**	0.021 (2.09)**	0.015 (0.97)	2.82*	2.51	0.90
CV	-0.007 (-1.50)	-0.029 (-0.88)	2.937E-04 (0.60)	0.028 (1.01)	-0.025 (-1.90)*	0.021 (0.72)	1.59	0.09	0.50
Adj. R^2 (%)	1.10	1.69	2.48	0.33	0.75	0.30			

Appendix 4C, Panel A (continued)

Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.074 (0.88)	-0.006 (-0.06)	-0.017 (-0.52)	0.477 (0.96)	-0.069 (-0.67)	0.009 (1.90)*	0.65	0.37	31.18***
AC	-0.005 (-0.18)	-0.023 (-0.61)	0.007 (0.65)	0.047 (1.26)	0.009 (0.27)	-0.001 (-0.63)	1.93	0.92	24.83***
MFE	-0.003 (-0.23)	0.027 (1.04)	-0.005 (-0.87)	0.117 (1.16)	-0.024 (-1.12)	2.585E-04 (0.52)	1.41	5.49**	113.23***
CV	0.026 (1.14)	-0.037 (-0.95)	0.004 (0.94)	0.101 (0.81)	0.008 (0.27)	0.002 (2.29)**	0.36	2.45	5.38**
Adj. R^2 (%)	0.66	0.38	4.17	1.23	0.50	0.79			

Germany (Frankfurt Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.038 (-1.81)*	0.014 (-0.12)	-0.022 (-0.10)	0.048 (0.23)	-0.107 (-1.83)*	15.800 (0.48)	1.20	4.26**	0.23
AC	-0.013 (2.34)**	0.013 (0.30)	-0.002 (-0.03)	-0.017 (-0.70)	0.012 (0.31)	-3.181 (-0.31)	1.57	0.00	0.10
MFE	0.008 (1.74)*	0.013 (0.59)	-0.045 (-1.15)	0.002 (0.15)	0.045 (1.55)	-1.618 (-0.14)	0.14	1.23	0.02
CV	-0.001 (-0.12)	0.041 (0.99)	0.008 (0.23)	0.004 (0.14)	-0.084 (-1.87)*	0.257 (0.03)	0.03	7.70***	0.00
Adj. R^2 (%)	1.11	1.67	6.06	0.56	1.70	0.38			

Appendix 4C (continue)

Panel B: Estimates of the second-pass cross-sectional equation (4.6) with controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.072 (1.82)*	-0.735 (-2.11)**	0.003 (0.48)	0.017 (0.31)	-0.802 (-8.17)***	0.150 (1.28)	1.03	0.47	1.59
IAC	-0.014 (3.53)***	0.011 (0.27)	1.864E-04 (0.32)	-0.049 (1.98)**	-0.009 (-0.23)	0.016 (0.60)	2.04	0.26	0.35
MFE	0.011 (3.82)***	-0.008 (-0.73)	1.785E-04 (0.59)	-0.001 (-0.08)	-0.010 (-1.26)	0.007 (0.84)	1.98	0.06	0.68
CV	-0.009 (-2.39)**	-0.079 (-1.95)*	1.723E-04 (0.35)	0.023 (1.04)	-0.049 (-2.85)***	0.014 (0.61)	2.13	3.08*	0.36
Size	-0.002 (-0.75)	0.017 (0.74)	-0.001 (-2.14)**	-4.870E-04 (-0.13)	0.037 (2.50)**	-5.690E-05 (-0.02)	0.16	1.88	0.05
Price	-0.013 (-2.36)**	0.032 (1.36)	0.001 (1.11)	0.002 (0.27)	0.038 (2.00)**	-0.016 (-0.95)	3.68*	0.08	1.00
Volatility	1.251 (3.30)***	22.647 (6.26)***	0.087 (1.92)*	0.744 (2.09)	16.213 (8.45)***	0.190 (0.46)	2.04	11.24***	0.06
Adj. R^2 (%)	4.71	6.20	5.21	2.53	6.64	1.76			

Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.073 (0.76)	1.014 (0.82)	-0.019 (-0.65)	0.158 (0.36)	-0.202 (-0.51)	-3.890E-04 (-0.04)	0.04	9.58***	2.99*
IAC	-0.032 (-1.01)	0.206 (0.87)	-0.005 (-0.50)	1.141 (1.44)	-0.272 (-0.84)	0.013 (1.23)	2.18	2.17	2.94*
MFE	-0.010 (-0.67)	-0.131 (-1.10)	-0.005 (-0.78)	-0.080 (-0.86)	0.029 (0.54)	-0.002 (-1.32)	0.56	8.79***	5.03**
CV	0.028 (1.18)	0.312 (1.02)	0.004 (0.90)	0.800 (1.18)	-0.416 (-0.98)	0.015 (1.19)	1.29	2.95*	0.70
Size	-0.011 (-0.83)	-0.169 (-1.01)	2.712E-05 (0.01)	-0.017 (-0.93)	0.053 (1.56)	-0.001 (-0.79)	0.10	42.59***	0.66
Price	0.006 (0.64)	0.141 (1.15)	0.004 (0.77)	0.292 (0.98)	-0.222 (-0.91)	0.007 (1.04)	0.92	2.21	0.22
Volatility	2.298 (1.45)	16.155 (2.59)**	-0.436 (-0.95)	-1.104 (-1.61)	31.184 (8.27)***	0.025 (0.34)	24.59***	15.90***	39.53***
Adj. R^2 (%)	1.91	4.60	3.61	2.80	11.57	7.44			

Appendix 4C, Panel B (continued)

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.018 (-0.79)	-0.142 (-1.20)	-0.091 (-0.42)	0.054 (0.66)	-0.525 (-6.39)	19.273 (1.48)	0.77	21.78	2.21
IAC	0.013 (0.65)	0.005 (0.07)	0.129 (1.23)	0.031 (0.79)	0.041 (0.64)	-7.527 (-1.33)	0.22	0.31	1.84
MFE	0.004 (0.81)	0.031 (0.76)	-0.063 (-1.54)	0.002 (0.10)	0.031 (0.95)	-2.162 (-0.80)	0.04	0.00	0.61
CV	-0.003 (-0.30)	-0.039 (-0.91)	-0.006 (-0.15)	-0.012 (-0.51)	-0.104 (-2.15)**	4.298 (1.11)	0.15	1.78	1.24
Size	0.004 (1.42)	0.028 (1.10)	1.592E-04 (0.01)	0.007 (0.47)	0.027 (1.74)*	-1.222 (-0.93)	0.03	0.01	0.87
Price	-0.013 (-1.14)	-0.077 (-1.19)	-0.033 (-0.81)	-0.045 (-1.25)	-0.001 (-0.05)	1.834 (0.48)	0.80	10.39***	0.24
Volatility	-0.133 (-0.60)	8.671 (2.45)**	0.881 (0.62)	-0.241 (-0.42)	14.271 (7.18)***	-219.083 (-0.64)	0.03	7.93***	0.41
Adj. R^2 (%)	2.29	7.04	6.16	1.41	9.04	4.93			

Appendix 4D
Fama-MacBeth estimates of the cross-sectional regression with market liquidity, industry liquidity, market return and industry return as explanatory variables in the first-pass time-series regression

This table represents time-series averages of individual stocks' cross-sectional OLS regression coefficients for all securities in the UK, Switzerland and Germany during the two sub-sample periods, during the floor trading period and the electronic trading period, using the Fama and MacBeth (1973) procedure. Panel A presents the estimates of the second-pass cross-sectional equation (4.6) without controlling for the determinants of firm-specific liquidity, Panel B represents the estimates of the second-pass cross-sectional equation (4.6) after controlling for other determinants of firm-specific liquidity. All measures are as defined in table 4.1. Liquidity is measured by the proportional bid-ask spread (PQSPR), the turnover ratio (TOV), and the price impact (illiquidity ratio) (PIMPACT). Measures of information asymmetry include: analysts' coverage (AC), incremental analysts' coverage (IAC) estimated using equation (4.1) and mean forecasting errors (MFE). Divergence of opinion is measured by coefficient of variation (CV). Size is the market capitalization. Price is the price of stock at the end of the month. Volatility is the stock's return volatility measured as squared stock return. Adj. R^2 is the time-series average of the monthly adjusted R^2. Wald Stat. is the Wald test statistic applied to examine the equality between the coefficients estimated during floor and electronic trading systems. T-statistics (reported in parentheses) are corrected for autocorrelation and heteroscedasticity. The coefficients of both PQSPR and PIMPACT regressions are multiplied by 100. *, **, *** denotes significance at the 10%, 5%, and 1% level respectively.

Panel A: Estimates of the second-pass cross-sectional equation (4.6) without controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.034 (1.12)	-0.633 (-1.40)	0.002 (0.53)	0.054 (1.21)	-0.101 (-1.6)	0.110 (1.17)	0.21	70.43***	1.32
AC	0.002 (0.24)	0.161 (1.19)	-1.530E-04 (-0.12)	0.029 (1.09)	0.031 (0.69)	0.003 (0.09)	1.04	8.35***	0.01
MFE	0.020 (5.63)***	0.010 (0.85)	1.219E-05 (0.04)	0.011 (2.55)**	0.020 (1.90)*	0.012 (0.80)	3.50*	0.99	0.64
CV	-0.008 (-1.76)*	-0.062 (-1.68)*	0.001 (1.06)	0.027 (1.00)	-0.026 (-2.11)**	0.020 (0.68)	1.69	8.51***	0.44
Adj. R^2 (%)	1.08	1.82	2.67	0.33	0.77	0.24			

Appendix 4D, Panel A (continued)

Switzerland (Swiss Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.055 (0.65)	0.102 (0.68)	0.087 (1.18)	0.435 (0.95)	-0.030 (-0.3)	0.007 (1.35)	0.68	1.76	275.55***
AC	-0.005 (-0.18)	-0.051 (-1.03)	-0.021 (-1.08)	0.049 (1.25)	0.007 (0.23)	5.885E-05 (0.04)	1.89	3.50*	180.74***
MFE	-0.009 (-0.63)	0.012 (0.49)	-0.002 (-0.49)	0.112 (1.17)	-0.020 (-0.96)	4.315E-04 (0.87)	1.60	2.45	23.77***
CV	0.024 (0.99)	-0.014 (-0.38)	0.021 (1.7)*	0.091 (0.78)	0.016 (0.58)	0.002 (2.05)**	0.33	1.14	428.48***
Adj. R^2 (%)	0.62	1.45	1.76	1.17	0.67	0.95			

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.028 (-1.35)	0.041 (0.43)	-0.302 (-1.19)	0.074 (0.90)	-0.081 (-1.38)	17.042 (0.49)	1.53	4.33	0.24
AC	0.009 (1.58)	0.016 (0.35)	0.051 (0.69)	-0.019 (-0.74)	0.007 (0.18)	-4.016 (-0.37)	1.22	0.04	0.14
MFE	0.007 (1.60)	-0.001 (-0.05)	-0.032 (-0.48)	0.013 (0.83)	0.037 (1.43)	-3.683 (-0.30)	0.13	2.21	0.09
CV	-0.002 (-0.29)	0.067 (1.39)	-0.077 (-0.83)	-0.002 (-0.07)	-0.073 (-1.79)*	1.125 (0.12)	0.00	11.82***	0.02
Adj. R^2 (%)	0.65	1.91	6.22	0.65	1.70	0.79			

Appendix 4D (continued)

Panel B: Estimates of the second-pass cross-sectional equation (4.6) with controlling variables.

UK (London Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.070 (1.82)*	-0.852 (-2.06)**	-1.690E-04 (-0.03)	0.017 (0.33)	-0.790 (-8.01)***	0.130 (1.13)	1.08	0.39	0.42
IAC	-0.012 (3.27)***	-0.002 (-0.07)	-2.180E-04 (-0.37)	-0.051 (2.03)**	-0.005 (-0.12)	0.017 (0.64)	2.36	0.00	0.30
MFE	0.012 (4.18)***	-0.007 (-0.60)	-7.170E-05 (-0.24)	0.000 (-0.05)	-0.010 (-1.18)	0.005 (0.54)	2.43	0.12	0.34
CV	-0.011 (-2.63)***	-0.105 (-2.15)**	4.217E-04 (0.86)	0.021 (1.03)	-0.049 (-3.02)***	0.013 (0.60)	2.45	12.03***	0.31
Size	-0.002 (-0.8)	0.022 (0.86)	-0.001 (-1.31)	-0.001 (-0.33)	0.037 (2.58)**	-0.003 (-0.68)	0.04	1.13	0.51
Price	-0.012 (-2.3)**	0.031 (1.21)	0.001 (1.32)	0.003 (0.32)	0.037 (1.92)*	-0.011 (-0.65)	3.52*	0.08	0.27
Volatility	1.309 (3.63)***	21.665 (6.29)***	0.079 (1.83)*	0.764 (2.14)**	15.998 (8.37)***	0.300 (0.70)	2.34	8.78***	
Adj. R^2 (%)	4.61	5.82	4.67	2.49	6.55	1.65			

Switzerland (Swiss Stock Exchange)

	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	0.047 (0.48)	0.994 (0.81)	0.084 (1.09)	0.121 (0.3)	-0.157 (-0.4)	-0.002 (-0.19)	0.03	8.50***	60.27***
IAC	-0.029 (-0.87)	0.193 (0.90)	-0.012 (-1.4)	1.130 (1.44)	-0.273 (-0.87)	0.014 (1.34)	2.20	2.18	6.29**
MFE	-0.016 (-1.07)	-0.124 (-1.09)	-0.002 (-0.41)	-0.085 (-0.91)	0.029 (0.55)	-0.002 (-1.16)	0.55	8.31***	0.07
CV	0.025 (1.01)	0.292 (1.01)	0.020 (1.62)	0.778 (1.17)	-0.394 (-0.96)	0.014 (1.17)	1.27	2.80*	0.18
Size	-0.011 (-0.83)	-0.156 (-0.98)	-0.009 (-1.38)	-0.019 (-1.11)	0.042 (1.30)	-4.640E-04 (-0.41)	0.23	37.44***	55.96***
Price	0.007 (0.75)	0.120 (1.09)	0.002 (0.60)	0.290 (0.98)	-0.208 (-0.88)	0.006 (1.01)	0.92	1.92	0.41
Volatility	2.213 (1.38)	15.846 (2.54)**	-0.039 (-0.03)	-0.808 (-1.42)	31.150 (8.25)***	-0.025 (-0.51)	28.40***	16.41***	0.07
Adj. R^2 (%)	1.63	4.51	4.42	2.72	11.30	7.04			

Appendix 4D, Panel B (continued)

Germany (Frankfurt Stock Exchange)									
	Floor Trading system			Electronic Trading system			Wald Stat.		
Explanatory\Dependent	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT	PQSPR	TOV	PIMPACT
Constant	-0.016 (-0.69)	-0.137 (-1.16)	-0.278 (-0.95)	0.021 (0.24)	-0.502 (-7.17)	0.109 (0.76)	0.18	27.16	0.61
IAC	0.013 (0.72)	-0.017 (-0.22)	-0.268 (2.25)**	-0.011 (-0.27)	0.026 (0.44)	-0.096 (-2.04)**	0.34	0.55	4.43**
MFE	0.004 (0.75)	0.018 (0.4)	-0.048 (-0.69)	0.014 (1.04)	0.024 (0.82)	-0.026 (-0.81)	0.56	0.04	0.64
CV	-0.001 (-0.15)	-0.007 (-0.14)	-0.099 (-0.99)	-0.030 (-1.07)	-0.089 (-2.01)**	0.044 (1.11)	1.08	3.41*	1.28
Size	0.002 (0.66)	0.027 (1.06)	0.003 (0.10)	0.006 (0.41)	0.023 (1.52)	-0.006 (-0.53)	0.07	0.08	0.28
Price	-0.006 (-0.65)	-0.061 (-0.93)	-0.035 (-0.69)	-0.042 (-0.97)	0.008 (0.39)	0.029 (0.75)	0.69	10.59***	0.58
Volatility	-0.049 (-0.23)	8.926 (2.36)**	-1.310 (-0.60)	0.574 (0.84)	14.650 (7.42)***	-1.865 (-0.59)	0.82	8.40***	0.34
Adj. R^2 (%)	2.08	6.09	5.90	1.54	8.95	5.37			

Chapter Five
Summary and Conclusions

5.1 Overview

This thesis investigates empirically the effects of the introduction of automated trading systems on liquidity related issues. As indicated in the introduction, the movement towards automating trading systems in many stock exchanges, and the continuous debate on the benefits or otherwise of floor versus electronic trading systems, emphasizes the necessity for further empirical research. Therefore, this thesis has examined, both before and after automation, three empirical issues related to liquidity: identifying the determinants of time-series variation in market-wide liquidity and its time-series behaviour; the pricing of market-wide and firm-specific liquidity in asset returns; and finally, the relation of firm-specific liquidity with information asymmetry between company managers and outsider investors and with the divergence of opinion among investors.

Through exploring these issues, this thesis contributes to our knowledge in market microstructure, and in particular to the literature on market structure and design, through examining how changes in the structure of trading systems may affect the impact of underlying factors and economic forces on liquidity, and the implications of liquidity in asset pricing, for a sample of European stock exchanges. Furthermore, this thesis also contributes to our knowledge of the determinants of market-wide liquidity by providing out-of-sample evidence from four European stock exchanges, by examining the factors that are responsible for the time-series variation in market-wide liquidity and analyzing its time-series behaviour, in other markets such as the Swiss Stock Exchange, the Amsterdam Stock Exchange, the Vienna Stock Exchange and the Frankfurt Stock Exchange. It also contributes to the literature on liquidity and asset pricing, by providing out-of-sample evidence in relation to US studies by shedding light on the importance of liquidity in asset pricing for the UK, Swiss, and German markets. A further contribution of this thesis to the literature on liquidity and asset pricing is reflected in the methodology which investigates the pricing of both market-wide liquidity and firm-specific liquidity in asset returns using a conditional asset pricing model (i.e. the framework of Avramov and Chordia, 2006a). Finally, this thesis contributes to the literature on market microstructure and specifically to the literature on liquidity by providing, for the first time, new evidence concerning the implications of information asymmetry between a firm's managers and outsider investors and on the implications of divergence of opinion on firm-specific liquidity for the three major European stock markets: the UK, Swiss and German markets.

5.2 Summary of the Findings

As stated earlier, the objective of this thesis is to examine various empirical issues related to liquidity before and after the automation of trading systems. Chapter two identifies the factors and the underlying forces that are responsible for the time-series variation in market-wide liquidity, and investigates the time-series behaviour of market-wide liquidity (i.e. the regularities in market-wide liquidity during the week, around holidays and around the announcement of major macroeconomic indicators such as GDP, CPI and unemployment rates). This is explored for the Swiss Stock Exchange, the Amsterdam Stock Exchange, the Vienna Stock Exchange and the Frankfurt Stock Exchange. The determinants and their expected relationships to market-wide liquidity have been specified based upon theoretical paradigms in market microstructures (i.e. inventory and information asymmetry models). The results overwhelmingly confirm most of the predicted relationships. More specifically, the results show that, on either one or both trading systems, market variables are significantly related to market-wide liquidity: up market (down market) is positively (negatively) related to trading activity and down market is negatively related to bid-ask spreads and price impact measures, recently rising market and recently falling market (i.e. recent market trends) are respectively negatively and positively related to trading activity measures, and recent market volatility, in most cases, has a significantly negative effect on market liquidity. The findings also show that interest rate measures (i.e. short-term interest rate, the term spread, and the quality spread) significantly influence market liquidity. The short-term rate and the quality spread are negatively related to market liquidity. However, while the term spread has a significantly negative effect on market liquidity in the Swiss Stock Exchange, it has a significantly positive effect on market liquidity in the Amsterdam Stock Exchange and the Frankfurt Stock Exchange. With respect to the main objective, the evidence shows that the impact of these factors on market-wide liquidity is different before and after automation. That is, in most cases the impact of market-wide liquidity determinants such as concurrent market returns, recent market trends, volatility, term spread and quality spread, decreases after the automation of the trading system in all markets except the Frankfurt stock exchange, where the impact of these factors became more pronounced following its changeover.

Moreover, consistent with the results from US studies, the results show that there is a distinct day-of-the-week effect in market-wide liquidity in all markets. We find that while liquidity increases on Fridays only in the Amsterdam Stock Exchange and the Vienna Stock Exchange, it declines on Mondays in all markets. In addition, liquidity shows a distinct pattern around holidays. It declines (increases) around holidays in the Swiss Stock Exchange and the Amsterdam Stock Exchange (the Frankfurt Stock Exchange). Furthermore, the patterns of market-wide liquidity during the week and around holidays exist on either one or both trading systems. However, these patterns are different before and after automation. For example, on Mondays market liquidity on the floor trading system for all markets is lower than that on the electronic trading system. In addition, around holidays market liquidity is lower (higher) on the electronic trading system of the Amsterdam Stock Exchange (the Frankfurt Stock Exchange). Finally, with regards to the effect of the announcement of macroeconomic indicators, which has only been examined for the Frankfurt Stock Exchange where the data on the announcement of macroeconomic indicators is only available for that market, the results show that market-wide liquidity is influenced by the announcement of GDP, CPI and unemployment rates before and after automation, and their impact on market liquidity is different under both types of trading systems. For instance, market-wide liquidity decreases (increases) on a floor trading system on the day of the announcement of GDP (unemployment rate).

In relation to the second issue - the pricing of liquidity in asset returns - chapter three examines the importance of market-wide liquidity and firm-specific liquidity in asset pricing before and after automation. More specifically, this chapter examines whether market-wide liquidity is a priced risk factor, and whether firm-specific liquidity has any additional premium after controlling for all risk factors including market liquidity risk. Then, this analysis is extended to investigate how the changeover might affect the impact of liquidity on asset returns. To examine this issue, the model of Avramov and Chordia (2006a) has been estimated for the two sub-samples periods, pre- and post- automation. The findings provide evidence which suggests that, on either one or both trading systems, both market-wide and firm-specific liquidity have a significant impact on stocks' returns (i.e. are priced on asset returns). This implies that investors will ask for a premium for bearing market liquidity risk as well as for a premium for carrying less liquid stocks. Our results show that the impact of liquidity, market-wide and firm-specific, on stock returns during the floor trading period is different than that during the electronic trading period. For example, the results show that the impact of market liquidity on excess return is strong in the post-automation period for the UK market compared to the Swiss and German markets, where the impact of liquidity is strong in the pre-automation period. Furthermore, generally the premium on firm-specific liquidity in the Swiss market during floor trading is higher than that during electronic trading, while in the German market firm-specific liquidity has a higher premium on electronic trading systems. Finally, the results provide strong evidence that market liquidity is priced when beta is fixed (i.e. unconditional asset pricing model) and when beta is allowed to vary with default spread. However, the evidence is weak when beta is allowed to vary with firm-characteristics. This implies that investors become more concerned about liquidity if economic conditions have changed, because market liquidity is expected to be low and the probability for liquidation is expected to be higher when economic conditions turn sour.

Finally, chapter four examines the impact of information asymmetry between company managers and outside investors, and the implications of divergence of opinion on firm-specific liquidity pre- and post- automation. To the best of our knowledge, this is the first time that these implications are addressed and examined explicitly. We expect that stocks with a high level of information asymmetries and divergence of opinion could represent a high level of uncertainty about a firm's future prospects, and thus result in a high level of risk. This could affect both the inventory holding costs and information asymmetry costs for investors and market makers, which will then negatively affect firm-specific liquidity. The majority of the results for both univariate and multivariate analyses confirm our prediction regarding the relation between information asymmetry and firm-specific liquidity. The results show that, before and after automation, there is a significant negative relationship between the level of information asymmetry and firm-specific liquidity, i.e. there is no effect of automation on the relationship between information asymmetry and firm-specific liquidity. This implies that firms with a low level of information asymmetry between company managers and investors are those with high liquidity. In contrast, the results provide mixed evidence regarding the relationship between liquidity and divergence of opinion. We find that divergence of opinion is positively related to all measures of liquidity during the two sub-samples periods, before and after automation. That is, while the positive relation between divergence of opinion and both proportional bid-ask spread and price impact support the risk view of divergence of opinion, the positive relation between divergence of opinion and turnover ratio supports the optimistic view. Even though there is a significant relation between firm-specific liquidity and both information asymmetry and divergence of opinion under both trading systems, the results show that the impact of information asymmetry and divergence of opinion on firm-specific liquidity on floor trading systems is different from that on electronic trading systems. That is, the results show that in most cases for all markets, the impact of information asymmetry (divergence of opinion) on firm-specific liquidity on floor (electronic) trading systems is lesser than that on electronic (floor) trading systems. This implies that different trading systems could affect differently the informational environment of firms, and thus affect the impact of information asymmetry and divergence of opinion on liquidity.

We also examined whether information asymmetry and divergence of opinion that results from firm-specific information have any incremental effect on firm-specific liquidity, after allowing for the impact of both market-wide and industry-wide information. To examine this issue, the ideas of Brennan et al. (1998) and Avramov and Chordia (2006a) model have been used. In this model, stock excess returns are adjusted to risk factors through running time-series regression of stock excess returns on asset pricing risk factors. Then the unexplained variation in stock returns (i.e. risk adjusted returns), which is represented by the sum of the constant and the residual of first-pass time-series regressions, is used as a dependent variable in cross-sectional regressions. Through applying this approach, however, we control the variation in firm-specific liquidity for market-wide and industry-wide information by running time-series regression of firm-specific liquidity on market-wide and industry-wide factors. Then, the unexplained part of firm-specific liquidity is regressed in cross-sectional regression using a set of explanatory variables including information asymmetry and divergence of opinion proxies. The great majority of the results show that the impact of information asymmetry and divergence of opinion is statistically insignificant before and after automation of trading systems. This implies that market factors and industry factors were able to explain the variation in firm-specific liquidity, and thus capture the cross-sectional impact of information asymmetry and divergence of opinion proxies on firm-specific liquidity. This finding puts into question the role and the type of information provided by financial analysts: do they depend on firm-specific information or public information to provide recommendations to the market? Such a question deserves further investigation.

5.3 Implications

The findings of this thesis should be of particular interest to market participants such as investors, company managers and market designers and regulators. The results of our research should provide these parties with new insights into the implications of floor and electronic trading systems on liquidity and on its relation with its determinants and asset returns. In particular, the evidence in chapter two shows that market-wide liquidity is influenced by several factors, and that there is day-of-the-week regularities in market-wide liquidity. It also shows that the impact of factors on market-wide liquidity and the daily regularities in liquidity in floor trading systems is different than that in electronic trading systems. This finding will be useful for investor and portfolio managers and help to guide their trading strategies, to coincide their trading with the time and the place (i.e. either floor or electronic trading) in which market liquidity is expected to be high. This will help them to achieve higher profits through avoiding high transaction costs, which may result when the market becomes illiquid during adverse market and macroeconomic conditions.

This evidence, in addition to the evidence in chapter three on liquidity and asset pricing will help both investors and managers to manage their portfolios even more efficiently. The findings in chapter three indicate that market-wide liquidity and firm-specific liquidity are priced differently on floor trading systems compared to electronic trading systems. Therefore, portfolio managers and investors can know the amount of the premium required on market liquidity risk and firm-specific liquidity and thus guide their investment decisions, through balancing the expected trading costs against expected returns. Additionally, the work in chapter four on information asymmetry and divergence of opinion may also be a useful factor in the decision-making process of investors and portfolio managers who try to select the right stocks to trade in and hold in their portfolios. They will direct their attention towards selecting stocks that expose them to low levels of risk and uncertainty, which are the stocks with low levels of information asymmetry and divergence of opinion. In brief, the evidence provided in this thesis is expected to be of great importance and interest in the investment spectrum.

Company managers (i.e. financial managers) and policymakers are also expected to benefit from the findings of this thesis. For companies that are considering raising more external capital or going public, the access into financial markets and raising cash will be easier, and liquidity risk on the aftermarket for initial public offering will be lower during the time when the market is highly liquid. The findings of chapter two suggest that financial managers should base such decisions on some input variables such as market factors and macroeconomic variables, to decide the right time to gain access into the market. Also, the findings concerning the relationship between liquidity and asset returns could provide financial managers with new insights into the question of their financial management policies: if a firm's stocks are less liquid, financial managers are required to implement new liquidity-increasing financial policies to improve the liquidity of their stocks and thus reduce the firm's opportunity cost of capital.

A further policy implication of this thesis is related to corporate information disclosure policy. One of the corporate policies and decisions that financial managers could pay more attention to is the improvement of the information disclosure policy. A poor disclosure policy might be the reason for deteriorating stocks' liquidity, especially when investors are reluctant to hold or trade in stocks having low levels and poor quality firm-specific information being available to the market. Therefore, a firm's executives will make decisions to invest more in investors' relations activities in order to improve the quality of disclosure policy. This will result in a lower level of information asymmetry between company managers and outside investors and thus reduce the level of divergence of opinion among investors. Consequently, as shown by the evidence in the last chapter, this will improve a firm's liquidity, which ultimately leads to a lower cost of capital and then an increase in the amount of capital raised by gaining easy access to financial markets.

Finally, the empirical research carried out throughout this thesis shows that different trading systems have important implications on the market microstructure characteristic - liquidity, on its economic relation with the factors that are responsible for its time-series variation, on its relation with asset returns, and on its relation with information asymmetry and divergence of opinion. This provides useful references to exchange regulators and designers in other markets, which have already introduced or are considering introducing an electronic trading system, on the possible success of such a changeover, and whether further regulations and policy procedures are required to maintain the efficient functioning of the market within the new trading system. For example, if after the introduction of electronic trading systems, market-wide liquidity exhibits a strong response to other market factors and macroeconomic variables, or if market liquidity is highly priced and a higher premium is required by investors on stocks traded on the automated trading system, then more regulations are required to improve the mechanism of supplying liquidity in the new trading system, especially during the periods of a negative market and macroeconomic shocks. Furthermore, the difference in the impact of information asymmetry and divergence of opinion on firm-specific liquidity before and after the automation of trading systems, as shown in the last chapter, will help regulators to take the necessary actions to improve the informational efficiency of the trading system, where liquidity is highly influenced by information asymmetry and divergence of opinion.

5.4 Future Research

Although this thesis has investigated significant issues in relation to market structure and design and its implications for various market microstructure-related issues, there are some obvious issues awaiting future research that have not been addressed in this thesis due to space, time constraints and data availability restrictions. This section aims to provide some suggestions that could be helpful in enhancing the knowledge of both academics and practitioners concerning various issues related to market microstructure. For instance, in relation to the determinants of market-wide liquidity and its time-series behaviour, an examination of this issue for other financial markets, especially the emerging markets, could be an important extension of the research undertaken here. These markets are characterized by higher illiquidity (i.e. lower liquidity) and volatility. They have also undergone structural changes that may affect liquidity such as equity market liberalization, which may drive up liquidity (see Lesmond, 2005; Bekaert et al., 2007). This may affect the degree of response of market-wide liquidity to various factors and macroeconomic forces. This would enhance our understanding and provide additional verification of the underlying factors and economic forces that are responsible for the time-series variation in market-wide liquidity and its time-series behaviour, and in particular, could be of great importance for market participants and regulators.

The empirical analysis of chapter three (i.e. the second empirical chapter) could be extended to markets other than equity markets, such as bond markets. Studies that examine the role of liquidity in asset pricing for bond markets are rare, so our knowledge about the pricing for liquidity and its implications on expected returns in debt securities markets is limited. The availability of sufficient and reliable data that spans a long time period for other European markets or Asian markets could for example, provide new insights into the role of liquidity in asset pricing using the methodologies adopted here. The inclusion of a larger variety of markets would provide us with wider evidence of how liquidity will be priced in different markets with different institutional features that could possibly affect the mechanism of providing liquidity and thus its pricing process.

The research undertaken in this thesis concerning the impact of information asymmetry and divergence of opinion on firm-specific liquidity certainly has further scope for future research. It has been argued that the level of information asymmetry between company managers and outside investors (measured by the number of analysts following the firm) represents a source of risk (i.e. uncertainty about a firm's future prospects), which is perceived by investors in the form of high inventory risk. Thus, further research could analyze the impact of analysts following on the costs components of bid-ask spread, especially the inventory cost component and the information asymmetry component. This could provide further confirmation as to whether financial analysts are informed traders or only represent a channel for disseminating information about firms.

Finally, since this thesis analyses different issues relating to liquidity under different trading systems, similar research could be undertaken for alternative market structures such as quote-driven versus order-driven markets and call-auction versus continuous-auction mechanisms. In these alternative market structures, the provision and supply mechanism of liquidity is different and this could affect the relation of liquidity with its determinants and perhaps affect its impact on asset returns. Furthermore, due to the data availability, the analysis undertaken in this thesis has relied on using daily data. Thus, an obvious extension of the research undertaken in this thesis is that similar research could be conducted using high frequency data (i.e. transaction data).

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