Trading Behaviour, Price Discovery and Volatility in Competing Market Microstructures

Andrew Ellul

London School of Economics and Political Science

Submitted in partial fulfilment of the requirements of the degree of Doctor in Philosophy

University of London

June 2001

Trading Behaviour, Price Discovery and Volatility in Competing Market Microstructures

Thesis Abstract

The first chapter investigates the price and volatility impacts produced by block trades in an inter-market environment with different microstructures. A sample of European cross-traded securities is employed to investigate whether large trades executed on the foreign market (London Stock Exchange's SEAQ-I market) produce any impacts on the securities' home markets and analyse whether different market microstructures matter. The price impact in the home markets is detected before the large trade is executed on SEAQ-I and proceeds in a protracted fashion, implying that substantial pre- and post-positioning is undertaken by London market makers through the home markets. The new equilibrium price on the home market is reached before the trade information is published on SEAQ-I. Large trades are also found to cause higher price volatility in auction trading systems than in a hybrid market microstructure.

The second and third chapters analyse the formation of quoted and effective spreads and their components in three different market microstructures. The results show that quoted and effective spreads generated by a hybrid system (Deutsche Börse's IBIS system) are lower than those generated by both the pure auction system (Paris Bourse's CAC system) and the dealership system (London Stock Exchange SEAQ market). Traders on a hybrid mechanism face the lowest costs and this result holds even when we control for (a) the level of market concentration in liquidity provision, and (b) company-specific news. However, the adverse selection component of the spread is significantly higher in an auction trading system compared to both the dealership and the hybrid trading system.

This fifth chapter investigates (a) whether, in a hybrid trading mechanism, voluntary market makers provide a higher level of price stabilisation than limit order traders even if they do not have any obligation to keep orderly markets, (b) the strategic interactions between the limit order book and market makers, and (c) the behaviour of the order flow at times of price uncertainty. We analyse these issues using high frequency data from the London Stock Exchange which has adopted a hybrid market microstructure. We find that prices on the dealership system track the security's true value more efficiently. The dealership system can transact higher volumes with lower price volatility. This evidence suggests that market makers provide price stabilisation, even if they have no binding obligation to do so, thus improving the market's quality. In terms of trading behaviour, we find that in a hybrid trading mechanism, traders are not encouraged to provide liquidity on the order book through limit orders as price uncertainty increases. Instead orders migrate to the dealership system for execution.

Acknowledgments

My first debt of gratitude goes to John Board, for his comments and suggestions together with his patience in listening to my research ideas and questions. Indeed, his assistance and encouragement date back to the period when I was a student reading for the MSc in Accounting and Finance. I have also learnt a huge deal from the feedback and ideas provided by Marco Pagano and David Webb, both of whom have been unsparing with their time.

During the course of my PhD I have benefitted enormously from comments made by various academics and market participants whom I have met in seminars, conferences or other academic activities. In particular, I would like to thank Utpal Bhattacharya, Geoffrey Booth, Margaret Bray, Vicente Cunat, Frank de Jong, Ian Domowitz, Larry Harris, Craig Holden, Jan P. Krahnen, Hung Neng Lai, Ananth Madhavan, Jose Marin, Narayan Naik, Theo Nijman, Bob Nobay, Richard Payne, Rafael Repullo, Enrique Sentana, Hyun Song Shin, Erik Thyssen, Alan Timmerman, Ian Tonks, Pradeep Yadav and Stephen Wells. All of them contributed with valuable ideas and much appreciated criticism.

I have presented most of this work in various seminars in different Universities, Business Schools and Associations' Annual Meetings. These occasions generated substantial feedback which led to subsequent improvements in my work. In view of this, I would like to show my gratitude to participants in seminars at CEMFI, London Business School, Kelley School of Business, Financial Markets Group lunchtime seminars, Said Business School, City Business School, Bocconi University, Pennyslvania State University, Michigan State University, Italian Exchange, Tilburg University, University of Amsterdam, University of Frankfurt, Pompeu Fabra University, York University, Warwick University and Scottish Institute for Research in Investment and Finance (University of Stratchylde). I have also presented papers based on some of the Chapters at the Annual Meetings of the European Finance Association (Helsinki and London), the Financial Management Association (Barcelona and Edinburgh) and LACEA (Rio de Janeiro).

This work would not have been possible without the supply of high frequency data from different Exchanges. I would like to thank Luca Filippa (Italian Exchange), Thorsten Ludecke and Hartmut Schmidt (German Exchange), Matthew Leighton (London Stock Exchange) and Bernard Perrot (Bourse de Paris) for making data sets available.

Finally I would like to thank all my colleagues and friends in the Department of Accounting and Finance and in the Financial Markets Group (FMG) for their encouragement and for entertaining my ideas for more than four years. I will always cherish the friendship of FMG students and researchers, such as Max Bruche, Andrea Caggese, Vicente Cunat, Robert Kosowski, Raoul Minetti and Alex Muermann. I will also remember the support given to me by a handful of good friends, like George Abela, Joseph Attard, David Fabri, Elena Ivleva, Carla Musella, Carlo, Paola and Guido Pagano and Lino Spiteri. I would also like to thank the administrative staff in the Department of Accounting and Finance, especially Mary Comben and Dorothy Richards, and the staff at the FMG.

Finally, I would like to thank my family, especially my mother, for their constant support throughout the years. Without their understanding it would have been much harder to start and finish the work presented here.

Contents

List of Tables

List of Figures

Chapter 1. Introduction

Competition between Exchanges for order flow and listings has intensified over the last few years. Major Exchanges have gone through reforms aimed at improving the efficiency and the attractiveness of their trading systems. We have witnessed rounds after rounds of reforms in market designs. Nowhere have such reforms been as wide-ranging as in the case of European Exchanges. The different market microstructures adopted by the major Exchanges have provided an important laboratory allowing us to investigate how different trading systems impact on markets' quality. Price discovery processes, liquidity provision, short term price volatility, order migration, trading costs and spread formation are some of the issues that can be fruitfully addressed by investigating the different trading environments.

These reforms have brought to the fore the old debate of fragmentation against centralisation of trading. The general principle has always been that, like any other market, centralisation of trading and trade information should lead to a comprehensive improvement in markets' quality. Liquidity-motivated and informed-motivated traders would like to participate in a market where they can obtain the best execution under prevalent market conditions. Arguably, this can be obtained through a centralised market where information from different investors is pooled together to obtain the best prices possible. But is a centralised market necessarily better than a fragmented market? Can a centralised market cater for all the different types of investors participating in the trading process? Is a centralised market an equilibrium outcome when Exchanges compete for order flow?

Evidence shows that the ideal of a centralised market has frequently been tempered, slowly but surely, across the different Exchanges through their efforts to attract order flow and the competition that results to attract a whole gamut of heterogenous traders. These different trading requirements are leading to different market set-ups and different trading platforms that need to be fully investigated.

On one hand, this has entailed some modifications to trading rules that, for example, temper transparency rules for large traders (one such example is the Paris Bourse where hidden orders are allowed). On the other hand, there has been the creation of alternative markets competing under one roof, creating *de facto* a hybrid trading system. The example of the London Stock Exchange (the "LSE"), where an order book system competes with a dealership-based system, is explicitly used in this work to analyse liquidity provision under the two microstructures.

The issue of the optimal trading system, between a quote-driven (dealership) and an order-driven (auction-based), in terms of liquidity provision and social welfare has yet to be conclusively answered. This remains a controversial issue even though in the last decade many Exchanges started adopting auction-based trading modes. The main difficulty lies in the fact that liquidity characteristics, such as depth, breadth and resilience, are not only influenced by the trading mechanisms employed but also by (a) the level of competition between dealers and other liquidity providers allowed in the market place (which is largely a decision adopted by a single Exchange and could be independent of the microstructure chosen), and (b) by the self-reinforcing beliefs (appearing in the models of Pagano, 1989, and Admati and Pfleiderer, 1988) where liquidity begets more liquidity. Furthermore, empirical work undertaken in this field has suffered from the well-known cross-market liquidity comparison problems: are the results being driven by the trading mechanism or are they the product of concentration in the market of liquidity provision?

The wide-ranging debate among market practitioners, regulators and academics regarding the benefits of screen-based trading systems and automated order execution systems, together with the appropriate role of mandatory (or voluntary) dealers is still going on. While major markets have introduced or enhanced screen-based trading, there has been a re-appraisal of the contributions that dealers can make in terms of improving market quality.

Most of the work on screen-based trading (for example by Glosten, 1994, Domowitz and Wang, 1994, Bollerslev, Domowitz and Wang, 1997) shows that, under normal market conditions, these systems incorporate information into prices more rapidly than dealership-based system and the quality of these markets (measured by liquidity and transaction costs) is not worse that dealership markets. However, these results do not seem to hold when considering adverse market conditions (when return volatility increases) or at times when information arrival is very intense.

The debate that has taken place in the mid 1990s over the reforms in both the LSE and NASDAQ testifies for this process of ongoing interactions between different market stakeholders in their search for a trading platform that generates the optimal execution package.

Another important development has been the emergence of cross-listing and cross-quoting of large capitalisation firms in different markets creating a trading process that fragments in different parallel markets: (a) the home market, and (b) the foreign market. These parallel markets can influence the equilibrium in various ways: (i) there are various sources, rather than just one, of price formation; (ii) liquidity fragments in different markets (and whether this fragmentation increases or lowers liquidity must be investigated); and (iii) there is a competing market place that can be used by informed and liquidity traders to execute their orders. As a result, one major question that arises in a parallel market set-up is whether the fragmentation of trading leads also to informational fragmentation where one market leads the other(s) in terms of impounding of price-sensitive information.

One can say that academia has provided a significant impetus to these debates through various theoretical and empirical models. However, it has to be said that a great deal remains to be done in terms of testing the myriad of theoretical models that have been proposed over the last two decades. One major criticism directed at these models has been the limited use that policy makers can make of these models in order to understand, explain and predict market behaviour under, for example, a fragmented vs. centralised set-up. These models can become somewhat more complex when (a) competition between Exchanges is taken into account, or (b) when the same security trades on parallel markets.

Arguably, the issue of trading on parallel markets and their interaction has become a pressing need since (a) many Exchanges are introducing multiple trading platforms within their organisation, and (b) many securities are being traded on two or more Exchanges leading to questions of market integration and institutional trading across the different markets.

One of the major objectives of this work is to empirically investigate traders' behaviour, liquidity provision and price discovery processes when the same security trades on two different trading platforms. Indeed, the theoretical and empirical contributions made in the past to investigate traders' behaviour and price discovery processes within a single Exchange is substantial. With the availability of high frequency data, empirical work has been carried out in various aspects of the trading process. However, work that concentrates on multiple markets has not been fully developed and a substantial number of areas remain to be addressed.

This work investigates the trading mechanisms used by different European

Exchanges, namely the Paris Bourse, Deutsche Börse, LSE, and the Italian Exchange. These four markets have different market microstructures which will be extensively used for the analysis. Prior to October 1997, the LSE was purely a dealership market. After the reforms enacted in October 1997, the LSE has a combination of order book-based trading and dealership-based trading. The Paris Bourse and Italian Exchange are considered to be pure order book-based systems.

The Integriertes Börsenhandels- und Informations-System - the IBIS system - the electronic trading system which was used by the Deutsche Börse and has now been replaced by the XETRA system is considered to be a hybrid trading system, combining both auction and dealership characteristics.[1]

In view of the different market microstructures explained above, a number of questions are asked. They range from liquidity provision and competition between Exchanges when the same security trades on different markets, to the cost of trading in different market microstructure to the comparative advantage of different liquidity providers and price efficiency under a hybrid trading system. The securities considered in these different markets are, in general, the biggest firms by market capitalisation and the most liquid by number of trades and volume transacted.

This effort is important because it considers a number of issues in various

[1] The following are the most important IBIS features which made it a hybrid mechanism: (a) most of the entries were quotes, implying that most market participants (with the exception of public traders) acted as market makers even if there was no obligation for them to provide two-way quotes throughout the trading day; (b) up to six quotes on each side were allowed and, based on these entries, the system maintained an open book; (c) proprietary trading by bank traders, *kursmakler,* and *freimakler* was allowed; (d) the platform provided an algorithm for trades bigger than the size of the best bid or ask to be executed by electronically accepting lower ranking bids or offers; (e) the system, unlike the screen-based platform used by the Paris Bourse, was not able to automatically execute matched orders. Given this trading architecture, execution risk on IBIS was minimised since there was limited uncertainty regarding the transaction price, the volume or the execution time.

market microstructure set-ups, using very rich datasets from different (European) Exchanges, leading to comparative results that are of interest from the academic, regulatory and market participants viewpoints.

This thesis consists of four self-contained research projects which share a common theme and a subject matter, although such issues are investigated in different markets and employing different empirical methodologies. The main theme that runs throughout the work presented in this thesis focuses on the organisation of financial markets and how their market microstructure influences the way trading occurs and the relationships between the different traders, the price discovery process, spread formation, liquidity provision, traders' strategies, trade location, etc.

This Chapter provides a brief outline of the research questions and a summary of the main results obtained in each Chapters. It also provides the major contributions made to the literature.

1.1 Large Trades' Impacts Across Markets

Chapter 2 considers institutional investors' trading by focusing on the price and volatility impacts generated by large trades in an inter-market set-up.

Orders submitted by institutional traders are attracting widespread attention because of their potential market impact. We analyse the impact of such trades in the context of cross-quoted securities, where the same security is traded on two separate markets with different order types migrating to different markets.

The emerging practice of cross quoting securities has provided traders with the possibility of trading the same security on different markets with different trading mechanisms. Theoretical models (Pagano, 1989 and Pagano and Röell, 1992) have demonstrated that different types of traders tend to concentrate their trades in different markets. This implies that trading systems, rather than innocuous features of the price discovery process, can bear substantial influence on that same process.

Related to the analysis of how different market microstructures attract heterogenous traders with different trading needs, there is the issue of how block trades are transacted in such a trading set-up. Large trades represent an important part of the institutional investors' business and account for a substantial part of the total volume transacted on equity Exchanges.

A fundamental question raised by large trades is the trade information contained in these trades. Existing literature (Burdett and O'Hara, 1987) has shown that trade size can be interpreted as a signal for the information held by the trader. In view of this, even the information related to the existence of a large trade to be executed can be valuable for the trading community.

There are a number of empirical studies dealing with large trades executed both on the LSE and the New York Stock Exchange. One of the first studies of large trades on the LSE was carried out by Gemmill (1996) who found that block purchases and sales produce a statistically significant permanent price impact although the sales' impacts were almost statistically insignificant. These results imply that large trades do have an information content and this provides an information advantage to those aware of such trades.

There are a number of questions related to the execution of large trades, such as the trading behaviour of informed traders, the price impact that they generate in the market, the optimal trade size that will minimize the price impact, the type of market microstructure that can handle large trades without disrupting "orderly" markets and the transparency regime that should be adopted by an Exchange.

The issue of how large trades are executed and their impact on price and volatility levels become somewhat more interesting when trading in cross-quoted securities is considered. The first question that needs to be asked in this case is which market attracts large trades and why.

If it is the case that it is only one market that attracts such trades, then it is pertinent to ask whether the large trade's impacts are confined to one single market or whether they are likely to spill over from one market to another. If it is the latter, then we have a richer set of investigations to undertake.

European equity markets are in several aspects ideal for such an analysis. European cross-quoted securities, listed on their home market and quoted on LSE's SEAQ-I market, form a sizeable group. These companies provide an ideal scenario since the trading mechanisms used in the home markets differ than those used in the foreign market. A sample of French, German and Italian cross-quoted securities that are listed in their home market and quoted on the LSE is used in this analysis.

1.1.1 Major Results

The most significant results obtained from analysing the way large trades are worked by SEAQ-I market makers are the following:

(a) large trades executed on SEAQ-I produce a permanent impact on the price levels in the home markets with the impact being larger in the case of order books (continuous auction systems) and lower in a trading system that combines auction and dealership characteristics.

This implies that there are some information leakages that occur before the trade is executed, possibly due to market makers' pre-positioning behaviour in the home markets. Another result worth noticing is that there is sufficient time after the trade's execution over which trading profits (before transaction costs) can still be earned by those market participants who know about the existence of the large trade before it is published by the LSE;

(b) evidence on the relationship between trade size and price impact indicates that very large trades are actually liquidity-motivated, rather than information-motivated. The permanent price impacts demonstrate that the price impacts are not necessarily increasing in trade size;

(c) generally speaking, the price impact is implemented or almost finished by the time the LSE publishes the trade information, implying that any asymmetric information that arises from a large trade is fully utilised by market participants, at least those who are aware of the large trade, before the LSE publishes the relevant trading information;

(d) finally, volatility tests computed for the three home markets indicate that return volatility around the time when a block trade is executed is higher in home markets that use continuous auction trading systems compared to what takes place in a hybrid system that contains substantial dealership characteristics. This result can imply that, as hypothesized by Madhavan (1992), the strategic behaviour of market participants which is present in the continuous auction markets produces a higher level of return volatility following the news of a large order compared to the volatility actually generated in a trading system that provides dealership liquidity.

1.1.2 Contribution to Literature

This chapter contributes to the market microstructure literature in a number of ways. A number of empirical studies (Holthausen *et al.*, 1987 and 1990, Board and Sutcliffe, 1995, Gemmill, 1996, Madhavan and Cheng, 1997) have dealt with the impact of large trades in a one-market set-up, but there appears to be no study of the inter-market effects of the execution of large trades. The possibility of market segmentation, where large trades migrate to the foreign market, raises the question as to the impacts of large trades (in this study, these trades are executed on SEAQ-I) on the price and volatility levels in home markets. Since different market mechanisms are considered, the nature and extent of such inter-market impacts allow us to infer some conclusions on whether microstructure difference do matter.

This work sheds light on the impact of market participants' behaviour in one equity market on the price and volatility levels in a different market. An interesting feature is that a substantial number of London market makers in European cross-quoted securities are major Continental banks (for example, Paribas, Deutsche Bank and IMI) having simultaneous access to both the home market and SEAQ-I which means that they can combine these different markets in their trading strategies.

A related issue is the provision of liquidity for these large trades. Although institutional investors do not go to the home markets for the execution of their trades, the market makers providing liquidity in London are re-balancing their positions using the home market through a protracted trading strategy aimed at minimising the price impacts.

Issues of financial regulation are closely related to the analysis carried out in this Chapter. In particular, analysing the evolution of price impacts pattern around the time when the large trade is executed can contribute towards a critical evaluation of the effects of the LSE's one-hour publication delay, introduced to protect market-makers who provide liquidity and immediacy for large trades, on the price adjustment process in the home markets.

1.2 Market Frictions

Chapters 3 and 4 investigate the measure of market frictions - the bid-ask spread - and its formation in three different market microstructures. A very important issue related to the debate on the best trading mechanism revolves around the level and evolution of trading costs in different market microstructures. These trading costs directly reflect the level of frictions in financial markets.

"Friction could be measured by how long it takes optimally to trade a given amount of an asset. Alternatively, it can be measured by the price concession needed for an immediate transaction. The two approaches converge because the immediate price concession can be viewed as the payment required by another trader, such as a dealer, to buy (or sell) the asset immediately and then dispose of (acquire) the asset according to the optimal policy." (Stoll, 2000)

All types of traders are interested in minimising their trading costs. Although financial regulators have mainly focused on trading costs for small investors, it is evident that they are becoming increasingly more aware of the impact of such costs on the performance of pension funds, mutual funds, etc., since these institutional investors are becoming increasingly important to policy makers.

Trading costs measure frictions in markets and it is important to investigate the sources of these frictions. As Stoll (2000) states, "understanding the sources of the spread is important for policy. If the source of the spread is real friction, improvements in trading systems can narrow the spread. If the source is monopoly rents, increased competition will narrow the spread. If the source is differential information delays for some traders vis-a-vis others, improvements in speed and greater parity of traders will reduce spreads. If the source is private information, improvements in disclosure will reduce spreads." (Stoll, 2000)

The major purpose of this Chapter is to explore the possible links between the mark-up charged by the suppliers of liquidity in different markets - the bid-ask spread - and market structures. This analysis is carried out through an empirical investigation of the trading costs (both quoted and effective spreads) in a multiple dealer market set-up (London Stock Exchange's SEAQ system), a pure limit order book market set-up (Paris Bourse's CAC system) and a screen-based hybrid trading system (Deutsche Börse's IBIS platform).

These three systems differ in terms of information dissemination (pre- and post-trade transparency), level of competition, cost structure and institutional design.

But should different market microstructures influence the levels and formation of the spreads? Existing literature, making use of the differences between the "traditional" dealership versus auction systems, provides a positive answer. Hybrid trading systems are getting more attention and their attributes, in terms of liquidity provision, price formation and spread levels, are being investigated. One such paper is the Viswanathan and Wang (1998) where they reach the conclusion that "when the cutoff point (in terms of trade size) is chosen appropriately, the hybrid limit-order book/dealership market generates higher trading profits for the customer than the pure dealership market" (Viswanathan and Wang, 1998).

The issue relating to the level of execution costs is receiving substantial attention from both academics and regulators. NASDAQ has undergone a number of reforms, aimed at increasing competition and reducing transaction costs. Barclay *et al.* (1997) find that trading costs on NASDAQ fell after the reforms. The same appears to have happened on the LSE since the introduction of the limit order book in October 1997, although spreads at the open have widened (Naik and Yadav, 1999).

These studies show that different trading architectures are likely to influence the behaviour of liquidity suppliers, whether market makers in a dealership market or limit order traders in an order driven system. The different behaviour is likely to impact the bidding strategy in different trading systems, influencing (a) the gross profits of liquidity suppliers, and (b) components of the bid ask spreads due to adverse selection, employing the various methodologies (Huang and Stoll,1996, George *et al.*, 1991, Booth *et al.*, 1995, Madhavan *et al.*, 1997 and Huang and Stoll, 1997) which have been proposed so far.

In view of these developments, this Chapter analyses the absolute levels of the spread and its components developing in different systems, considering, for the first time, two screen-based systems that differ in terms of the interaction between public traders and designated dealers.

Another interesting issue considered here is whether the level of dealer competition and dealers' market power can contribute towards our understanding of trading costs. Indeed, the major difficulty in such type of work lies with the fact that liquidity characteristics are not only influenced by the trading mechanisms adopted by single Exchanges but also through (a) the level of competition between dealers and other liquidity providers allowed in the market place, and (b) traders' self-reinforcing beliefs (captured by Pagano, 1989) where liquidity begets more liquidity. Furthermore, empirical work undertaken in this field has suffered from the well-known cross-market liquidity comparison problems: are the results being driven by the trading mechanism or are they the product of concentration in the market of liquidity provision?

1.2.1 Major Results

The results obtained in this Chapter show that SEAQ market makers post spreads that are much wider than those posted by CAC and IBIS dealers. When effective spreads are investigated, we find that these are also wider on

SEAQ compared with the other two markets. In addition, both the quoted spreads and the effective spreads on IBIS, for most trade locations, are the tightest when compared to all the other systems, implying that a hybrid system produces spreads that are narrower than both a dealership and an auction system. A closer analysis of trading shows that competition between different liquidity providers is highest on the hybrid system. We find that the hybrid type of trading appears to generate the lowest effective spreads and such result holds even after controlling for (public) news arrival and market competition. This means that market microstructure effects do matter in terms of explaining the levels of the effective spreads generated by the different markets.

But what are the sources of these different spreads? The presence of private information held by some traders has been argued to be an important source of such trading frictions. But can the difference in spreads be attributed to the presence of private information? And how do different liquidity providers behave when they fear that they might lose against superior informed traders?

To answer these questions, Chapter 3 investigates the components of the bid-ask spread, with a particular focus on the adverse selection segment. It is found that the adverse selection component of the spread is highest for order book systems (CAC-traded securities) and lowest on a dealership system (SEAQ-traded securities). This result implies that, in the first place, it is not higher adverse selection in dealership markets that are responsible for wider spreads in such markets. Secondly, it confirms that a number of trading practices, such as preferencing and internalisation of the order flow, allow liquidity suppliers on dealership systems to get "to know the order flow" better and hence to protect themselves better against adverse selection.

1.2.2 Contribution to Literature

Chapters 3 and 4 contribute to our knowledge of the sources of the spread. Understanding the sources of the spread is an important issue not only for traders, who would like to strategically time their trades in order to get the best prices, but also for policymakers in terms of choosing the optimal market design that can generate the lowest trading costs.

The empirical results found in Chapters 3 and 4 provide a confirmation of the Viswanathan and Wang (1998) hypothesis that a well-calibrated hybrid trading system dominates both dealership and order book systems.

The surprising result from this Chapter is that the hybrid system, IBIS, adopted by the German Börse and predecessor of XETRA, generated spreads which are generally lower than those on the order book-based system. This result is important for policy makers and regulators because it shows that interacting the order book with designated dealers can actually improve liquidity and markets' quality. The main issue then becomes finding the right balance between the order book and the role of dealers and fine-tuning this balance is likely to be an arduous task.

1.3 Price Efficiency in a Hybrid Market

Chapter 5 analyses the trading behaviour of liquidity providers in the order book and voluntary market makers in a dealership system when both these platforms interact together in a hybrid market mechanism. It is becoming increasingly common for Exchanges to give traders a choice between alternative trading mechanisms, with Exchanges adopting a hybrid type of trading platform, where auction-based and dealership-based systems interact together.

These developments raise a number of fundamental questions regarding the strategic interaction between traders and the subsequent impacts on markets' quality. The provision of liquidity in different market microstructures is carried out by different dealers - limit order traders in order book-based systems and market makers (mandatory or voluntary) in dealership-based systems.

It is evident that investigating price efficiency and volatility is important since risk averse traders are assumed to care about price and execution uncertainty.

It is expected that strategic behaviour between traders differ across different market microstructures which would, in turn, generate different volatilities in the systems. Recent developments in market microstructure have analysed the interaction of different traders in the market, such as informed traders and liquidity traders (Admati and Pfleiderer, 1988, Easley and O'Hara, 1992, Lyons, 1995), traders with heterogeneous beliefs (Morris, 1994), and traders that herd on specific types of information (Froot *et al.*, 1992). Such considerations are important for the analysis of the order flow, its size, frequency and direction and impact on price stability.[2]

Price stability is considered to be an externality closely related to the provision of liquidity. The question as to whether public traders alone, acting through the order book, can supply the optimal amount of price stabilisation or whether dealers can "do the job" better has yet to be resolved.

Furthermore, one has to consider the impact of liquidity provision on price stability. If the presence of a market maker is found to dampen excessive price volatility, then this will improve the market's quality (generating less inefficient prices) and will, in turn, increase traders' participation in the

[2]The analysis of intradaily volatilities has already received a substantial level of attention through theoretical and empirical research (See Cohen, Maier, Schwartz and Whitcomb, 1978, Goldman and Beja, 1979, Roll, 1984, Kyle, 1985, Hasbrouck, 1988, Hasbrouck and Ho, 1987, Admati and Pfleiderer, 1988, Foster and Viswanathan, 1988, Stoll, 1978).

market, leading to higher volumes transacted.

We plan to investigate these issues by considering order flow dynamics taking place on LSE which, in October 1997, changed its trading environment (for the most liquid securities) from a pure dealership mechanism to a hybrid trading system based on an order book and voluntary dealers providing liquidity off the book. The trading regime change was expected to improve transparency in the market and enhance the bargaining power of investors vis-a-vis dealers, leading to lower trading costs of public investors. One major consequence resulting from these changes was that the mandatory obligations of market makers, enforced prior to the reform, ceased to exist. After the reform, dealers for the FTSE 100 index securities are entirely voluntary in terms of liquidity provision.

This Chapter investigates (a) which type of liquidity provision set-up, in a hybrid trading system, generates the highest price efficiency, taking into consideration market depth and breadth, (b) the strategic interactions between the limit order book and the dealers, and (c) how the order flow behaves at times of price uncertainty.

Such analysis has been hampered by the fact that Exchanges have, until recently, adopted one trading system and hence the price discovery process for a particular security could not be compared across different trading mechanisms. To investigate these issues,we use the FTSE 100 index's securities listed on the LSE, which are now traded on two parallel trading systems - an order driven system and a dealership system. This environment provides an ideal place for the analysis of transaction price efficiency, trading behaviour on the two systems and the strategic interaction between them.

1.3.1 Major Results

The results contained in this Chapter show that prices on the dealership system track the security's true price more efficiently. The analysis is undertaken by extracting the price volatility, measured as the deviation of the transaction prices on both the order book and the dealership system from the true "system-wide" price. The latter is calculated using a state-space model that extracts the information content from the order flow. Within a hybrid trading system, it is found that a dealership system is more robust than an order book system in that it can transact higher volumes with lower price volatility. This evidence suggests that dealers, acting in a hybrid trading system, provide price stabilisation, even if they have no binding obligation to do so, thus improving the market's quality.

However, there are various ways in which the order book contributes to the price discovery process. For example, the order book appears to be contributing through order imbalances that are formed; in essence, order imbalances are found to contain useful trade information for traders' strategies. Existing literature has found that the benefits from introducing the order book is the narrowing of spreads leading to benefits to small traders's transaction costs (See Naik and Yadav, 1999, for the LSE evidence). The result obtained in this Chapter is that the order book serves other purposes, besides producing lower transaction costs, considered important for traders' strategies. This evidence ties in with the results obtained by Harris and Panchapagesan (1999) for the New York Stock Exchange.

As far as strategic interaction between the two systems is concerned, this Chapter shows that in a hybrid trading system large trades are directed to the dealership system where liquidity is provided by the dealers and this routing takes place even when the order book is relatively full and can accommodate such trades. On the other hand, medium sized trades are directed to the auction system through a trading strategy aimed at picking up the best possible prices on the other side of the market.

In terms of trading behaviour, we find that within a hybrid architecture, as price uncertainty increases traders are not encouraged to provide liquidity on the order book through limit orders. Instead orders migrate to the dealership system for execution there. This re-affirms the dealers' contribution to the trading process and their role becomes vital in times of price uncertainty.

1.3.2 Contribution to Literature

This Chapter makes a number of contributions to the market microstructure debate, especially in terms of market designs. The trading mechanism used by the LSE makes various market microstructure comparisons possible. Furthermore, the data set made available by the LSE is particularly interesting since it contains high frequency data which can be fruitfully used to analyse (a) the order flow and its impact on volatility rather than the usual opening and closing prices which have been used up to now; and (b) the application of recent developments in the analysis of high frequency data to the systematic study of market microstructure. The data available is among the first of its kind that makes available to researchers both the order flow going on the book and off the book. The NYSE, which has a similar organisation to LSE, has rarely made available the data related to the upstairs market. Hence, the LSE dataset provides us with a complete picture of the order flow, rather than just one segment.

The Chapter provides also a useful insight into the contribution made by dealers towards price stabilisation. The results should lead to a re-evaluation of the dealers' role in promoting orderly markets. There is also a dynamic analysis of market making, in the sense that the role of dealers is investigated under various market conditions, mainly adverse conditions, for example when price volatility increases.

1.4 Conclusion

This study aims at investigating various issues related to the trading process and the price discovery process under different market microstructures. One major theme running through this work is the issue of parallel markets (whether they are physically fragmented in (a) different countries, or (b) housed under one roof and operated by the same Exchange authority) and how they interact between them.

Most theoretical models in the market microstructure field are modelled to investigate the case of a single Exchange. Extending these models to consider multiple markets tends to increase considerably their complexity. The price discovery process in such models would have to contemplate the numerous ways in which informed traders can use their superior information across different markets with transparency regimes that vary substantially across markets. In such a set-up, the strategies open to both informed and liquidity traders increase exponentially. This level of complexity can explain why it has been difficult to construct a general model of trade in multiple (parallel) markets that can be fruitfully used by all parties involved to generate explanations and predictions in the way markets operate.

It is because of the difficulties encountered by theory that empirical work can generate useful results that can be used to understand better the trading processes in a world where cross-listings are becoming, slowly but surely, the norm (at least for large capitalisation stocks). This study is aimed at this direction, mainly in understanding (a) how different market microstructures can influence trading processes, and (b) how parallel markets interact with each other in terms of liquidity provision, price formation and trade migration.

One of the major objectives of this research is to indicate directions that further theoretical work can adopt in the future in the field of parallel markets.

Chapter 2.Inter-market Impacts Generated by Large Trades

2.1 Introduction

The practice of cross-quoting securities provides traders with the possibility of trading the same security on different markets with different trading mechanisms. Related to the analysis of how different market microstructures attract different traders, there is the issue of how block trades are transacted in this trading environment. Large trades represent an important part of the institutional investors' business and account for a substantial part of the total volume transacted on equity Exchanges and hence merit special attention.

Furthermore, large trades are important because they have been found to contain price-sensitive information. A major study of large trades on the LSE, carried out by Gemmill (1996), finds that block purchases and sales generate statistically significant permanent price impacts. These results imply that large trades do have a substantial information content, providing an information advantage to those aware of such large orders.

Investigating execution of large trades in an inter-market trading environment presents an exciting issue given the amount of cross-border trading carried out by institutional investors. European equity markets provide an interesting environment where a fruitful analysis on the interaction of different trading mechanisms can be undertaken since cross-quoted securities, listed on their home market and quoted on London's SEAQ-I market, form a sizeable group. Trading in these securities could take place through different trading modes: Continental European equity markets are either largely auction-based systems or pure-hybrid systems while SEAQ-I, the London Stock Exchange's electronic price dissemination system for international securities, is often described as a dealership market.

There is the common belief among European equity markets participants that, for these cross-quoted securities, the liquidity offered by SEAQ-I market and the Continental Exchanges is different. The emerging view is that SEAQ-I serves as a "wholesale" market whereas Continental Exchanges could be seen as "retail" markets. SEAQ-I is held to provide a higher level of depth where it is easier to execute large orders than the home markets, which are often seen to provide an advantage for smaller transactions. These views are also supported by empirical evidence carried out in the early 1990s, when SEAQ-I lacked any form of post-trade transparency and where trades executed in this market where reported to the LSE but never published.

This Chapter finds that, notwithstanding substantial changes in Continental European Exchanges aimed at facilitating the execution of large trades, the average size of SEAQ-I trades remains, generally speaking, much larger than the average size of trades executed on the Paris Bourse's CAC system, Deutsche Börse's IBIS system (predecessor of the present XETRA system) and the Italian Exchange. This means that SEAQ-I remains the preferred place for the execution of large trades, leaving smaller, retail-oriented trades for the Continental European Exchanges.

The possibility of such market segmentation raises the question as to the impacts of large trades executed in London on the price and volatility levels in home markets. This study focuses on French, German and Italian securities which are cross-quoted in London and as such should produce interesting results as far as inter-markets effects are concerned in that the trading system in place is materially different in each home market.

The period under consideration is the first six months of 1996 which coincides with time when the LSE started enforcing the publication of trades executed on SEAQ-I. Until 1995, there was no obligation whatsoever to publish prices of SEAQ-I trades and this could have explained why SEAQ-I was the preferred market for large trades. This Chapter shows that it does not appear that the change in the publication regime has decreased SEAQ-I attractiveness for institutional investors.

The major objectives of this Chapter are (a) to assess the price and volatility impacts produced by large trades executed in London on the home markets and how these effects vary according to the type of market microstructure utilised; (b) to estimate the speed of adjustment for the price to reach the new equilibrium level after a large trade; (c) given the ability to undertake 'protected trades' in London and in view of the possible pre-positioning undertaken by London market makers, to evaluate whether information of a large trade leaks to the respective home market before the trade is published on SEAQ-I; and (d) to appraise whether delaying the publication of a large trade produces a smoother price adjustment, delays the price's adjustment speed to the new equilibrium price level and causes less volatility in the home market.

The different equity markets used for this study have been chosen on the basis of their trading mechanisms and level of trading sophistication which should satisfy the need of analysing price impacts in different market microstructure set-ups. Both the Paris Bourse and the Italian Exchange (henceforth the "IE") are auction markets and both operate through a screen-based system. In contrast, the trading system used in the German market provides an interesting case of trading fragmentation as IBIS - the screen-based trading system that executes approximately 60% of the daily volume for the DAX 30 securities - is combined with floor-trading for a number of hours during the trading day. Although there were substantial disagreements regarding IBIS's true trading typology, there was some consensus that it was best described as a hybrid mechanism with both auction and dealership characteristics combined together.

This work is also designed to shed light on the impact of market participants' behaviour in one equity market on the price levels in a different market. There are various ways in which dealers on one Exchange can use another Exchange for trading purposes. For example, they may use it as a source of information or as an alternative channel for the execution of orders. There is also another subtle way in which dealers can use the parallel market: taking large orders in one market and working them in both markets in order to find the best sources of liquidity. This can be particularly true of London market makers in working large orders for cross-quoted securities. For example, Board and Sutcliffe (1995) have already found that London market makers carry out pre- and post-positioning when they receive a large order for UK securities (traded on SEAQ, the market for UK listed securities). If the same type of behaviour is adopted for cross-quoted securities, we can have a situation where the pre- and post-positioning takes place on both the London market and the home markets.

An interesting feature is that a substantial number of London market makers in European cross-quoted securities are major Continental banks (for example, Paribas, Deutsche Bank and IMI) which have simultaneous access to both the home market and SEAQ-I. The use of both markets is illustrated by Jacquillat and Gresse (1995) that show how London market makers tend to use the Paris market to rebalance their trading positions.

It is expected that the inventory positioning carried out by London market makers on Continental Exchanges will generate a price impact in these Exchanges in addition to the possible impacts created by the information contained in the large trade. The analysis of the evolution of price impacts pattern around the time when the large trade is executed can contribute towards a critical evaluation of London's one-hour publication delay's effects on the price adjustment process in the home markets. Moreover, the issue of whether or not large orders on SEAQ-I are observed by the Continental Exchanges before they are eventually executed and the relevant information is published by the LSE presents some important academic, practical and regulatory issues.

The rest of this Chapter is organised as follows. Section 2 and 3 present the literature review and the hypothesis to be tested in this Chapter while Section 4 reviews the methodologies employed to investigate price and volatility impacts produced by large trades. Section 5 presents the results obtained from both the event study, that considers only a limited sample of total large trades executed, and a regression model that investigates the full sample of large trades considering volume effects.

2.2 Literature Review

The literature reviewed in this Section goes through (a) work carried out on the execution of large trades and their impact; (b) the development and evolution of SEAQ-I through time; and (c) the fragmentation of the order flow across different markets together with a review of the major differences between dealership-based and auction-based markets.

2.2.1 Large Trades

The impact generated by large trades has attracted interests from several quarters. One major issue that has been analysed within the context of the LSE has been the transparency regime adopted by the Exchange authorities for large trades. The argument used by the LSE to defend the lack of transparency accorded to large trades was based on two views: (a) first, that large trades do not contain price-relevant information, and hence any price impact is likely to be temporary in nature, rather than permanent, and (b) market makers providing liquidity for large orders must be allowed to re-balance their inventories after executing the large trade in relative opaqueness.

A number of empirical studies have rejected the LSE's argument on the basis that large trades were found to produce permanent price impacts besides a temporary one. The first major study of large trades on the LSE was carried out by Gemmill (1996) who found that block purchases and sales produce a statistically significant permanent price impact although the sales' impacts were almost statistically insignificant. These results imply that large trades do have an information content and this provides an information advantage to those aware of such trades.

Gemmill finds that prices' adjustment speed to the new permanent price level is the same whether trade publication is immediate, has a 90 minute delay or a 24 hours delay. Such evidence rejects the hypothesis that delayed publication produces a smoother adjustment process. This evidence shows that, although large trades possess price information and knowledge of the trade gives an advantage to the parties involved in that trade, information about the order execution leaks to the marketplace before it is published by the LSE.

Board and Sutcliffe (1995) find that large trades executed on the LSE produce a permanent price impact which 'accord with the prior expectations that large Customer buys signify good news, while large Customer sells indicate bad news' (Board and Sutcliffe 1995). In fact, large purchase trades of alpha securities (in the 3 X NMS bracket) were found to produce a permanent price impact of +0.230% while large sale trades of alpha securities produce a permanent price impact of -0.179%. The authors find that SEAQ market makers often engage in pre-positioning before a large trade is executed. In the case of liquid stocks, the pre-positioning took more than three hours to be completed. The level of pre- and post-positioning decreases as the trade size increases.

2.2.2 SEAQ-I: Impact and Evolution

The introduction and evolution of SEAQ-I has attracted wide interest, not only from a regulatory point of view, but also from academia and market participants, given the order flow migrating from European Exchanges towards this market. This trading set-up, where large capitalisation securities are traded on parallel markets with different transparency regimes, has provided an ideal environment for the investigation of various aspects of the trading process.

There are numerous studies analysing the integration between SEAQ-I and Continental Exchanges and the many factors that led to SEAQ-I's success, which are discussed below. One important trend that emerged was the migration of large trades, made by institutional investors, to SEAQ-I. Evidence of this was presented by de Jong *et al.* (1995) who found that the mean and median size of a sample of French cross-quoted securities trades in London were approximately ten times those of trades executed on the Paris Bourse. In addition, using the same sample, very few transactions occurring in Paris exceeded the Normal Market Size (NMS) while almost half of the London trades exceeded NMS.

Pagano and Röell (1990), who were among the first to start analysing the order flow fragmentation between home markets and SEAQ-I, document the different levels of transaction costs and spreads across the major European

Exchanges. When they undertake a direct comparisons of the best bid and ask quotes between the Paris Bourse and SEAQ-I, they find that the former is consistently generating lower spreads than SEAQ-I. However, this advantage does not seem to be maintained when order sizes increase which, in itself, indicate the difference between tightness and depth on different markets.

Taking the analysis one step further, Pagano and Röell (1990) measure the depth on each market when they compare the trading for 16 cross-quoted securities in the two markets. They compare orders of the same size in the two markets, showing that the Paris Bourse market is both tighter and deeper. It must be noted, however, that Pagano and Röell do not take into account the fact that a substantial proportion of SEAQ-I trades are effectively executed at prices within the best spread which used to be displayed on the screen. Furthermore, this result is only obtained for orders whose size is equivalent to the market makers' maximum quoted volume in London; these orders are large by Paris levels but not considered so on London. In fact, Pagano and Röell (1990) do not consider the large trades on London, the main reason for such an omission being that these London trades do not find any comparables on the Paris Bourse.

This consideration prompts the authors to suggest that SEAQ-I's appeal may be due to the fact that market makers post prices for immediate transactions whereas on the Paris Bourse traders have to wait for their orders to execute.

In another study, Pagano and Röell (1991) investigate the degree of integration between SEAQ-I and the IE for cross-quoted securities on the two markets. The test used by the authors is based on the bid-ask spread that emerges on SEAQ-I for these securities. The pricing errors on the IE are found to occur in about 11 % of the cases, which is considered to be a high figure and these errors are found to induce an adjustment to SEAQ-I quotes. This type of analysis was also carried out by the same authors for French cross-quoted securities on SEAQ-I (Pagano and Röell, 1990).

The most important aspect of the study on Italian cross-quoted securities is the investigation of which market, out of the two parallel ones, produces the highest amount of price sensitive information for these securities. If, as many suggest, this is the home market, then we should be able to have evidence of this in the behaviour of SEAQ-I market makers in setting their quotes. The authors argue that SEAQ-I spreads should widen when the main source of information - in this case the IE - is closed and this should take place to compensate SEAQ-I market makers for the expected losses that they incur by trading with informed traders. The results show that the spread did indeed contract when the IE was open for trade, but the authors find that the effect was less pronounced than for the French cross-quoted securities. Furthermore, when the IE was closed completely for holidays, the SEAQ-I spread was either significantly smaller or indistinguishable from those days when both Exchanges operated.

Over the years, Continental Exchanges tried to reform their trading systems in a bid to stop orders flowing to SEAQ-I and, possibly, get back some of the orders directed to London. Over the years, market makers on SEAQ-I are thought to have changed their commitment to SEAQ-I in different ways. One visible change was that the quotes posted to the screen were perceived to be as starting points for the bilateral negotiation between the market maker and the trader. Firm quotes were, essentially, obtained through direct soliciting to market makers. Pagano and Steil (1995) argue that, following these various developments, London dealers rather than using their inventory to accommodate clients' trades, are increasingly operating directly on Continental

European equity markets and work orders through the local systems.

Jacquillat and Gresse (1995) are of the view that, given the recent performance of the SEAQ-I market, the main emerging economic role of SEAQ-I market makers is that of providing firm quotes for very large volumes, creating a wholesale market in conjunction with Continental Exchanges that are designed to attract the retail trading interests. This view would be compatible with London developing in a sort of an upstairs market where the very large trades, especially if they are liquidity-motivated, are executed in such a market. This development of SEAQ-I could be considered to be in line with the model proposed by Seppi (1990), which is discussed below.

2.2.3 Fragmentation of Order Flow

There are a number of models that consider under the conditions under which the order flow fragments between different markets. Two such models are by Freedman (1989) and Chowdry and Nanda (1991). In Chowdry and Nanda (1991) we have an analysis of the order flow fragmenting between two markets that are open simultaneously. The model considers both one and two periods to compare different order flow dynamics. The authors assume the existence of an informed trader who is capable of splitting her orders across different markets where they are executed simultaneously. The ability of liquidity traders to migrate from one market to another differs in (a) trader's size, and (b) across the time settings considered. In the one period setting, large liquidity traders are allowed to migrate but no splitting of orders across markets is allowed in the two-period setting. Furthermore, in the two period setting, the Chowdry-Nanda assumes that market makers in each market will only respond to prior orders received in their own market.

Chowdry and Nanda show that in the presence of competitive zero-profit market makers and liquidity traders, the informed trader will obtain a benefit from the opportunity to hide his information. If some small liquidity traders are also allowed to split their orders across markets, then in equilibrium there will be a concentration of orders in one market leading to an important result: the trade's expected price impact is minimised in an Exchange where there is a concentration of small noise traders.

By extending the model to a two-period setting, the authors show that any trade information flowing across markets will generate an increase in depth. This result is obtained because information sharing reduces the profits earned by informed traders in later periods. In this sense, the "rent" charged to liquidity traders, which is introduced in the model as a compensation to market makers for the loss they expect to incur when they trade with traders with superior information, can be reduced.

On the other hand, Freedman (1989) considers a somewhat simpler model where two markets are open sequentially and are temporally separated, but private information is long-lived. Another major difference with respect to the Chowdry and Nanda (1991) model is that liquidity traders cannot migrate from one Exchange to another.

In this model there is the opportunity to trade in the market that leads, providing the right incentives to some liquidity traders to take advantage of such a situation. At the same time, a number of informed traders are modelled to be active on both markets and this trading activity releases price-sensitive information. Freedman shows that when there is more than one informed trader operating in the markets, the home market's depth is always higher when there is a foreign market. Competition between the different informed traders leads to an increased volume of trade which causes market makers to incur losses due to information asymmetry, but the price will contain higher information.

Comparing the Chowdry and Nanda (1991) and the Freedman (1989) models, we can see that while in the former the informational effect produces an increase in depth, the latter provides an explanation rooted on the competitive forces unleashed by the traders to account for the increase in depth.

The set-up based on a mixture between liquidity-motivated and information-motivated traders, central to the models considered above, is avoided by Pagano (1989) when he investigates trading across multiple Exchanges. Pagano relies on utility maximisation as the only motivation driving trading and each trader behaves on the basis of his conjecture of how the other traders present in the market will act. In a two period setting, Pagano shows that traders select the most suitable market to submit their order to on the sole basis of the maximum expected utility *ex ante*. One major result obtained by Pagano is based on the self-fulfilling aspect of trading: agents will trade when they expect the market to be deeper. This results in an equilibrium where, keeping transaction costs equal across markets, all traders will migrate to a single Exchange. A conjectural equilibrium is also possible when transactions costs are not equal and this is an important result for our study: the larger trades may migrate to the market with the highest fixed costs, provided such a market appears to be deeper. This result is rooted in the impact of transaction costs on the trading positions of large and small traders. For the large traders, going to the most expensive but deeper market, means that they will incur a loss from transaction costs but this loss is outweighed by market depth which minimises the price impact due to a higher liquidity value.

Another model is by Seppi (1990) where a trader is given the choice between trading in the "upstairs" or going to the "downstairs" market. Seppi argues that a liquidity trader may use the "upstairs" market if he can credibly signal to the market makers that his trade is not information-based. In Seppi's (1990) model, a credible signal is provided by the commitment on the part of the liquidity trader not to 'bag the street'. Other signals could come in the form of implicit commitments or are provided by the trader's reputation. Arguably, such reputational signals can be used more effectively in a quote driven mechanism with market makers with whom traders can build a long-term trading relationship. Applying Seppi (1990) model to the developments taking place on SEAQ-I, we could argue that SEAQ-I is being used as an "upstairs" market, where market makers serve as a screening device and mitigate the adverse selection costs that are bound to arise from a large order.

Grossman (1992) explores a trading set-up which is similar, in spirit, to the Seppi (1990) model. Traders face a choice between going to a "downstairs" market or migrating to an "upstairs" market. In the former, there is an open-order trading environment whereas in the latter system prices are negotiated bilaterally. Going to the "upstairs" market entails additional search cost but these are offset by decreased volatility resulting from the familiar assumption that market makers on the "upstairs" market are better informed and are therefore in a better position to intermediate between the different traders. Due to the different costs in these two markets, in equilibrium trading may take place on both the "upstairs" and "downstairs" markets. The model contains also the feature of traders' self-reinforcing beliefs: where an Exchange is perceived to offer greater depth there will be a tendency for this belief to become fact.

Another strand of the literature that investigates order fragmentation is based on the different microstructures that are assumed to impact on traders' decision. Pagano and Röell (1991) argue that a risk averse trader would prefer dealership market over an auction type of trading because the former offers the advantage of removing execution risk from the trading process. The market maker provides immediacy and hence execution risk is removed (at a cost), but an order submitted to an auction system may need the arrival of a new limit order for it to execute, generating trading uncertainty.

Continuing in this vein, Pagano and Röell (1992) show that when traders possess some form of information advantage then market makers in a *centralised* environment will not have a large incentive to widen spreads. Such a centralised market, based on market makers intervention, will generate narrower spreads in equilibrium.

2.3 Institutional Background and Hypotheses

This Section provides a brief description of the institutional evolution of SEAQ-I and sets out the hypotheses to be tested in this Chapter.

SEAQ-I's initial success in attracting institutional investors can be attributed to one major factor: London market makers provide a higher level of immediacy than the continuous auctions on the Continent which resulted in a deeper market where market makers are always ready to trade block trades.

Since the late 1980s, Continental European equity markets carried out a number of significant changes aimed at addressing needs of institutional investors and attract some of the order flow back from London. The major efforts were made mainly to facilitate the execution of large trades in the auction trading systems used by most of the Continental exchanges.

The Paris Bourse, for example, introduced the hidden order facility which provides for parts of a large order not to be placed in the limit order book and are hence rendered invisible to the market. The publication regime established by the Paris Bourse was also changed in order to provide higher protection to the execution of large orders.

Over the same period, SEAQ-I has experienced a number of changes that have transformed the nature of services it provides. Pagano and Steil (1995) find that market makers, who were initially committing capital to the system through their inventory, ceased to act as all-weather market makers. In addition, compared to the early 1990s, the bid-ask spreads quoted on the screens widened substantially, ceased to be firm and are now perceived as serving exclusively as an advertisement for the services provided by the market makers. Firm quotes can only be obtained by a direct contact with the market maker.

Tables 1-4 provide summary statistics that can help classify the trades' typology for cross-quoted securities executed on different markets. Trades in the home markets are much more frequent than those executed on SEAQ-I and this must be interpreted as a result of the different market microstructure in that a medium to large order is normally executed as an entire trade in a dealership market but could result in a number of smaller trades if executed through the limit order book. Trades on the Paris Bourse are 16.62 times more frequent than on SEAQ-I; trades on the IE are 17.07 times frequent than on SEAQ-I; and 8.11 times more frequent on IBIS than on SEAQ-I. For the London-executed trades, it could be noted that the distribution of their size is skewed with the mean being substantially larger than the median. The same can be said for the trades executed on the Paris Bourse, IBIS and the IE.

It is clear that trades on SEAQ-I are much larger than those executed on the home markets. The Tables show that the mean size of transactions in European cross-quoted securities executed on SEAQ-I is 19.839 times that

Table 1: **Trading of French cross-quoted securities on SEAQ-I and the Paris Bourse**

PANEL A: TRADING ON SEAQ-I

	Trade size			Trade size percentiles		
	Mean	Std. Dev.	Median	90th	95th	99th
Alcatel Alsthom	6059	33843	1400	10500	21886	65000
AXA	8460	21624	2391	20000	32000	85000
BNP	10760	43345	2530	21950	41200	116000
Elf Aquitaine	10244	61948	2000	15379	33000	125000
Michelin	10719	29850	2500	23707	46424	145000
Paribas	7988	36870	1700	15572	28000	106084
Peugeot	3099	14764	840	6425	11150	30500
Rhone-Poulenc	24409	73754	5500	60000	100300	248157
Societe General	4640	22178	1000	8000	16200	50664
Total	10177	39908	2500	20000	38607	121000
UAP	16638	62450	4000	35220	60000	200000

PANEL B: TRADING ON THE PARIS BOURSE

	Trade size			Trade size percentiles		
	Mean	Std. Dev.	Median	90th	95th	99th
Alcatel Alsthom	391	3071	100	974	1190	3200
AXA	582	2472	246	1200	2000	4785
BNP	343	3449	39	912	1250	3580
Elf Aquitaine	334	5116	30	878	1400	3464
Michelin	603	2467	182	1150	2040	5000
Paribas	465	5277	100	1000	1550	4734
Peugeot	312	3964	131	530	1000	2000
Rhone-Poulenc	505	3718	50	1031	2054	5000
Societe General	301	2706	70	600	1000	2150
Total	821	10342	250	1516	2468	6000
UAP	460	4189	83	1000	1946	4981

The Table reports summary statistics for the size of trades executed on SEAQ-I (Panel A) and on the Paris Bourse (Panel B) for a sample of French cross-quoted securities over the period January-June 1996.

Table 2: **Trading of German cross-quoted securities on SEAQ-I and the Deutsche Borse**

PANEL A: TRADING ON SEAQ-I

	Trade size			Trade size percentiles		
	Mean	Std. Dev.	Median	90th	95th	99th
Allianz	530	3818	100	800	1578	5500
BASF	2656	13184	760	4500	9680	34000
Bayer	2717	25984	531	4750	93000	28811
BMW	6669	13591	2000	17600	30000	72500
Commerzbank	2699	10032	1000	5000	10000	33000
Daimler-Benz	1858	6360	500	3000	5810	21600
Deutsche Bank	16126	125874	5000	23000	50000	197347
Dresdner Bank	60111	252657	5500	58140	287000	1036444
Lufthansa	2871	7812	1000	6000	10000	29000
Mannesman	1515	3513	500	3270	6000	18000
Volkswagen	2047	5636	500	4500	7620	28200

PANEL B: TRADING ON THE DEUTSCHE BÖRSE

	Trade size			Trade size percentiles		
	Mean	Std. Dev.	Median	90th	95th	99th
Allianz	306	180	200	600	600	1000
BASF	1431	849	1000	2000	2000	4000
Bayer	2720	4186	1000	7000	10000	20000
BMW	3036	3268	2000	60000	10000	14000
Commerzbank	1510	984	1000	2000	3000	5000
Daimler-Benz	1291	711	1000	2000	2000	4000
Deutsche Bank	8810	9000	9000	20000	20000	40000
Dresdner Bank	8737	7433	8000	20000	20000	40000
Lufthansa	1104	882	1000	2000	2000	4000
Mannesman	1284	689	1000	2000	2000	4000
Volkswagen	1324	917	1000	2000	2000	4000

The Table reports summary statistics for the size of trades executed on SEAQ-I (Panel A) and on the Deutsche Börse (Panel B) for a sample of German cross-quoted securities over the period January-June 1996.

Table 3: **Trading of Italian cross-quoted securities on SEAQ-I and on the Italian Exchange**

PANEL A: TRADING ON SEAQ-I

Figures for Panel A only are shown in 000

	Trade size			Trade size percentiles		
	Mean	Std. Dev.	Median	90th	95th	99th
Assicurazioni Generali	31	114	10	62	114	322
BCI	244	948	65	400	750	4787
Benetton Group	30	76	70	76	120	300
Credito Italiano	334	982	105	690	1180	3582
FIAT	196	514	60	432	520	2190
Istituto San Paolo	112	338	22	201	381	1741
Mediobanca	436	207	44	83	150	479
Olivetti	934	2410	277	2500	4000	8125
Pirelli	261	756	100	500	950	3000
STET	196	457	75	450	778	2000
Telecom Italia	346	1404	75	690	1211	2000

PANEL B: TRADING ON THE ITALIAN EXCHANGE

	Trade size			Trade size percentiles		
	Mean	Std. Dev.	Median	90th	95th	99th
Assicurazioni Generali	1506	9356	500	3000	5000	10000
BCI	7459	91237	2000	14000	22000	50000
Benetton Group	2372	13014	1000	5000	5000	12000
Credito Italiano	15589	157208	5000	27500	47500	100000
FIAT	9662	48808	5000	20000	30000	60000
Istituto San Paolo	3499	49427	1000	5000	7500	20000
Mediobanca	2333	5571	1000	5000	7000	15000
Olivetti	26126	67431	10000	50000	100000	200000
Pirelli	15146	36904	10000	30000	50000	100000
STET	12085	56945	5000	25000	37500	70000
Telecom Italia	20655	260563	7500	40000	50000	100000

The Table reports summary statistics for the size of trades executed on SEAQ-I (Panel A) and on the Italian Exchange (Panel B) for a sample of Italian cross-quoted securities over the period January-June 1996.

Table 4: **Summary statistics for a sample of cross-quoted securities**

PANEL A: FRENCH CROSS-QUOTED SECURITIES	Trade frequency ratio	Trade size ratio
AGF	0.0414	59.7922
BNP	0.0459	31.3703
Elf Aquitaine	0.0531	30.6707
Eurotunnel	0.0205	37.7353
Rhone-Poulenc.	0.0308	48.3347
UAP	0.0306	36.1696
ALL FRENCH	0.0602	19.8395
PANEL B: GERMAN CROSS-QUOTED SECURITIES		
Bayer	0.1453	3.1029
Degussa	0.3082	2.7393
Deutsche Bank	0.2282	1.8304
Dresdner Bank	0.2107	6.8801
Hoechst	0.0348	12.4830
Volkswagen	0.1844	1.5461
ALL GERMAN	0.1233	2.9255
PANEL C: ITALIAN CROSS-QUOTED SECURITIES		
Alleanza	0.0431	17.9962
Ferruzzi Finanziaria	0.0433	254.6357
FIAT	0.0329	20.3032
Montedison	0.0481	40.6565
Olivetti	0.0439	35.7548
Telecom Italia	0.0492	16.7649
ALL ITALIAN	0.0585	32.6882

The Table analyses the number of trades for the cross-quoted securities (executed in the home and foreign markets) and the mean trade size. Trade frequency ratio is defined as

$$\frac{\text{Number of trades executed on SEAQ-I}}{\text{Number of trades executed in home market}}$$

Trade size ratio is defined as

$$\frac{\text{Mean size of trades executed on SEAQ-I}}{\text{Mean size of trades executed in home marketsize of}}$$

on Paris Bourse (for French securities), 32.688 times that on the IE (for Italian securities) and 2.9255 times that on IBIS (for German securities). The upper size percentiles (the Tables reproduce the size of the 90th, 95th and 99th percentile) confirm the size difference between the trades executed on SEAQ-I and the home markets.

The reason for SEAQ-I's attractiveness as a place to execute large trades is very much a disputed issue. Röell (1992) and Madhavan (1995) have shown that large trades tend to emigrate towards the market with the least onerous publication regime. However, although the changes introduced in January 1996 gave SEAQ-I a more onerous trade publication regime, the evidence shows that this has not led to the migration of large trades away from London.

On the other hand, Wells (1993) suggests that the London market's major competitive advantage is provided by the market makers' commitment of capital to the system which leads to higher liquidity for large trades when compared to that provided by continuous auction systems such as those in operation in Continental European exchanges.

2.3.1 Hypotheses Tested

Since no previous work has dealt with price impacts of large trades in an inter-market set-up, most of the theoretical and empirical background reviewed here is obtained from the existing literature that investigates LSE market makers' behaviour and execution of large trades in a single market set-up. Such literature could help disentangle some of the issues which relate to how market-markers carry out inventory management, an issue directly related to this Chapter's objectives.

Hypothesis 1: Large trades executed on SEAQ-I do not produce any price *impact in the home market before the trade's reported time on SEAQ-I.*

Hypothesis 2: Large trades executed on SEAQ-I do not generate any price impact in the home market after the trade is reported as executed on SEAQ-I.

A number of studies have found that large trades were found to produce a permanent price impact besides a temporary one. Gemmill (1996) finds that block purchases produce a statistically significant permanent price impact while block sales also produce permanent price impacts but these are almost statistically insignificant. This implies that large trades do have an information content and this provides an information advantage to those aware of such trades.

Board and Sutcliffe (1995) find that large trades executed on the LSE produce a permanent price impact which 'accord with the prior expectations that large Customer buys signify good news, while large Customer sells indicate bad news' (Board and Sutcliffe 1995).

Burdett and O'Hara (1987) state that "because block trades have predictable price effects, information as to the very existence of a trade can be valuable. The success of the block trader, therefore, depends on his being able to curtail knowledge of his syndication activities. This suggests that the trading process, itself, may generate information effects on security prices".

An interesting question is whether the price impact starts manifesting itself before the trade is actually reported as having been executed. This might be caused by any inventory pre-positioning carried out by SEAQ-I market makers through trading in the home markets.

Board and Sutcliffe (1995), investigating London-listed securities, find that market makers often engage in pre-positioning before a large trade is executed. In the case of liquid stocks, the pre-positioning took more than three hours to be completed.

In the case of European cross-quoted securities, the pre-positioning can either take place on the same SEAQ-I system or through the home markets. In addition, since 'protected trades'[3] are allowed on SEAQ-I it is expected that at least part of the pre-positioning associated with such trades takes place in the home markets. The suspicion that London market makers carry out inventory management for European cross-quoted securities in the home markets finds confirmation in Jacquillat and Gresse (1995). They argue that 'as a great deal of the block traded by SEAQ-I market makers are finally executed on the CAC, the CAC order book can be considered as an interdealer broker, taking advantage of commercially more aggressive UK based market makers' (Jacquillat and Gresse (1995)).

Hence, it is expected that the information content of a large trade executed in London will not be confined exclusively to the London market but also produces a price impact on the home market. The trading activity associated with pre-positioning is expected to act as a signal about the presence of a large order to be executed, the trade direction of which can be inferred by the type of inventory management carried out by the market maker.

In this way, the news of a large trade leaks to the market and information gets impounded in the prices (formed in the home markets) before the trade is actually reported as executed on SEAQ-I and before the relevant trade information is published on the SEAQ-I screens.

Hypothesis 3: The price impact produced by large trades is not an increasing function of the trade size.

[3] The LSE defines a protected trade as 'a transaction which is accepted by a member firm on the basis that the price or price and size at which the transaction is to be executed in the market is to be improved upon within a specified period'. The maximum period over which the protected trade remains valid is the end of the MQP following the receipt of the order. Protected trades are reported to the LSE and published through the same channels used for the other trades.

It is argued that pre- and post-positioning carried out by London market makers is an important channel through which the price impacts are produced in the home markets. Board and Sutcliffe (1995) find that the level of pre- and post-positioning decreases as the trade size increases. If rebalancing in home markets for large trades executed in London were to follow the same trading behaviour used by market makers on SEAQ[4], then price impacts should not increase with the trade size.

Jacquillat and Gresse (1995) argue that the main emerging economic role of SEAQ-I market makers is that of providing firm quotes for very large volumes. One possible implication of such an argument is that SEAQ-I market makers are willing to accommodate large orders, employing their inventory to provide the necessary depth, and then rebalancing their position slowly over time, rather than aggressively.

This behaviour is compatible with the emerging view that London is developing in an "upstairs" market where the very large trades are executed in such a market. In this way, the London market makers on SEAQ-I serve as a screening device and mitigate the adverse selection costs that are bound to arise from a large order.

This development of the LSE would be in line with Seppi (1990) who uses a model where a trader has the choice between trading in the upstairs or on the downstairs market. The liquidity trader may use the upstairs market if he can credibly signal to the block trader that his trade is not information-based. In Seppi's (1990) model, a credible signal is provided by the commitment on

[4]Board and Sutcliffe (1995) find that the mean number of trades which are pre-positioned represents 26.85% in the case of trades in the 10-20 X NMS bracket, decreases to 25.06% for trades in the 20-35 X NMS bracket and decreases further to 20.21% in the case of trades larger than 35 X NMS. The same trading behaviour takes place when post-positioning is considered with post-positioning representing 16.40% in the case of trades in the 10-20 X NMS bracket, 9.69% for trades in the 20-35 X NMS bracket and amounts only to 7.76% of all the trades larger than 35 X NMS.

the part of the liquidity trader not to 'bag the street'. Other signals could come in the form of implicit commitments or are provided by the trader's reputation. This model can be applied in the case of SEAQ-I.

A block trade originating from a liquidity trader should generate a lower price impact than one from an informed trader if the liquidity trader can credibly signal his status. There is also the consideration that even if market makers were willing to pre- and post-position the very large trades, they could effectively be hitting a liquidity barrier in the home markets as they off-load the large trade. Hence, fully aware of such problems, SEAQ-I's market makers could be off-loading very large volumes slowly rather than aggressively so that the overall price impact is minimised.

Hypothesis 4: Delaying trade publication does not hold the price from adjusting to its new equilibrium price in the home markets before the information is published on the LSE.

As from 1 January 1996, large trades reported as having been executed on SEAQ-I are published with a one hour delay in the case of trades in the size bracket 6 X NMS to 75 X NMS while those larger than 75 X NMS can be published up to five days after execution. This publication regime allows us to analyse whether the one hour delay enforced by the LSE does in fact prevent the price transacted in the home markets from adjusting to its new equilibrium level before the trade information is published.

In a different context, Gemmill (1996) finds that prices' adjustment speed to the new permanent price level following a large trade is the same whether trade publication is immediate, has a 90 minute delay or a 24 hours delay, also rejecting the hypothesis that delayed publication produces a smoother adjustment process. This evidence shows that information leaks to the marketplace before it is published by the Exchange authorities. This leaves limited, if any, advantage to the trade parties to use their information.

This publication regime also allows an analysis on whether the one hour publication delay produces a smooth price adjustment process in the home markets.

Hypothesis 5: Volatility produced by large trades is not higher in auction markets (CAC and IE) than in hybrid trading systems (IBIS).

Madhavan (1992) analyses a quote driven system and an order driven mechanism where the former is an extension of the Glosten (1989) model which utilises competing market makers while the latter is an extension of the Kyle (1989) model. The market makers in the quote driven system provide bid and ask quotes which can be revised only after a trade has been executed. This system allows the trader to know the execution price for each order before the trade is executed and hence results in no execution risk. The order driven system is characterised by dealers who engage in competition by submitting a 'set of price-quantity combinations such that the quantity demanded at each price is the desired order quantity conditional upon that particular price clearing in the market' (Madhavan, 1992).

Madhavan conjectures that price variability in the continuous auction mechanism is higher than in a dealership system. He argues that competition between market makers in a quote driven system should eliminate the difference between the transacted price and the expected security value. However, the competition in the price-quantity schedule that takes place in an order driven system allows for strategic behaviour between dealers and this distorts prices and makes the system more sensitive to information asymmetry.

Both the Paris Bourse and the IE resemble the order driven mechanism described by Madhavan whereas the IBIS trading system, because of the presence of market makers (*Kursmaklers, Freimaklers)* and bank traders that trade for their own account (constituting the major competing counterparties to investors willing to trade) is nearer to the quote-driven system as defined by Madhavan (1992). Hence, it is expected that the price generating process of securities on the CAC and the IE should be more sensitive, compared to IBIS, to the news of a block trade executed on SEAQ-I.

2.4 Data and Methodology

2.4.1 Data

The data for the LSE is provided through the Transaction Data Service of the LSE's Quality of Markets Group. The data consists of transaction records in relation to the first six months of 1996 and collected from the settlement system.[5]

Before conducting the analysis, the transactions data needs to be screened to extract records of transactions from the reporting records as explained by Hansch and Neuberger (1993, 1996), Board and Sutcliffe (1995), and Reiss and Werner (1996, 1997). The main three screening devices to achieve the proper data set are briefly explained here.

The original SEAQ-I data is constructed from the transcripts of transactions. For each transaction, there are two records: one submitted by the buyer, the other one submitted by the seller. Each transaction bears a unique transaction number and as such any transaction will be identified and one record per transaction should be extracted from the paired transactions data.

The trade direction needs to be inferred so as to divide the screened data

[5]The transactions data contains the quantity and price for each transaction executed and the classification of the 'capacity' of each trading parties. In particular, trading parties (which are named as 'firm' or 'counter party') are classified in five categories: brokers acting on behalf of clients (assigned class 'A'), market makers (assigned class 'M'), market makers' private clients (assigned class 'N'), inter dealer brokers (assigned class 'I') and non-market makers acting as principals (assigned class 'P').

in buy records and sell records. In line with Board and Sutcliffe (1995), a transaction is assigned a buy record if the transaction represents a purchase from the market maker while a transaction which involves a sale to a market maker is assigned a sell direction. For reasons which are explained below, only Agent to Market Maker trades (the so-called Customer trades) are extracted from the screened data.

Data for the Paris Bourse is extracted from the trade file of the Paris Bourse Data Base. Data contains the transaction date, transaction time, the record sequence number (used to rank trades which are recorded at the same time), the trade price, trade size and a cross-trade indicator. The latter indicates whether a member firm enters a pre-arranged trade. The put-through trade can be matched either between two customers or with a member firm when the latter is acting as a principal. All put-through trade records are removed from the data set since they are pre-arranged and do not fall within the scope of this study.

The trade direction could not be inferred directly from the trade file and quotes data, provided by the Paris Bourse, was used to classify trade directions. Transactions and quotes data were merged together and the best bid and best ask prices were obtained in continuous time. For transactions executed inside the spread, the Harris (1989) methodology was used, in which case trades are called buys if they are closer to the ask and classified as sells if they are closer to the bid price. This approach leaves trades executed at the mid-quote unclassified. In the sample used, there were 2.18% of all transactions carried out at the midquote and these records are removed from the sample.

The data for IBIS was provided by the Institut Für Entscheidungstheorie und Unternehmensforschung of the University of Karlsruhe. The database contains tick-by-tick price and volume for securities traded on IBIS from which the relevant data for the DAX30 securities was extracted. In addition, the date and time of the transaction is provided together with the flag that indicates whether a transaction is initiated by a Makler or by a Bank. If no flag is used, then the transaction is initiated by an IBIS member bank, if the flag is assigned a value of 'A' then the transaction was initiated by the Kursmakler and if the flag is assigned a value of 'F' then the transaction was initiated by a Freimakler. The time-stamp is accurate to the 100th second. There is one record for each transaction executed.

Data for the IE was provided by the "Servizio Studi Sviluppo e Dati" of the IE. The data contains the date, time, price and volume for each transaction, including those executed at the opening call. The data contains one record for each trade transacted. Data for transactions executed at the opening call auction is removed. The IE does not provide any information about put-through trades and no filtering of these trade records can be undertaken.

The data for both IBIS and the IE does not allow a direct inference of the trade direction of each transaction in these two markets. In this case, direction is decided by using a version of the tick test proposed by Lee and Ready (1991) under which trades are classified as buys if they occur on an uptick or zero-uptick and sells if they occur on a downtick or zero-downtick.

2.4.2 Methodology

The three most relevant event studies considered for this work are those employed by Holthausen *et al.* (1990), Board and Sutcliffe (1995) and Gemmill (1996). These three studies, in contrast with those produced by Kraus and Stoll (1972), Ryngaert (1983), Ball and Finn (1983), and Holtahusen *et al.* (1987), use transactions data rather than closing prices, which allows a more precise measurement of the price impacts produced by large trades. It must be noted, however, that the three studies cited deal with price impacts produced in the same equity market where large transactions are executed. This study is different in that it deals with inter-market price impacts produced by large trades.

However, in the light of documented behaviour of market makers in terms of pre- and post-positioning and given that this Chapter is set in an inter-market environment, a number of methodological changes in traditional event studies are introduced in this Chapter.

2.4.3 Changes From Established Techniques

The trading set-up utilised for this study, where the impact of a large trade in one market is analysed in different parallel markets rather than in the same market where the trade was executed, calls for a number of changes from the methodologies employed so far. The first major change has to do with the definition of the event. Holthausen *et al.* (1990) and Gemmill (1996) define the event as the largest trades, by number of shares traded, for each security in their sample. This definition within the context utilised here creates comparison problems because it does not use a common yardstick to define the size of a large trade across the securities.

The second major change applied deals with the definition of the benchmark period. In view of the Board and Sutcliffe (1995) results on pre- and post-positioning, it is argued that a benchmark period as used in the Gemmill (1996) analysis may be temporally too close to the event and as such could be affected by the pre-positioning behaviour of market makers. It should be recalled that a certain amount of positioning before a large trade (defined in this case as trade of a size at least 10 X NMS) was found when Board and Sutcliffe (1995) analyse the activities of London market makers. It is possible that using an estimation period as defined by Holthausen *et al.*

(1990) and Gemmill (1996) can produce bias caused by the market makers' pre-positioning. In this case, the pre-positioning which is directly caused by the event itself will interfere in the estimation of the mean trade-to-trade returns in the benchmark period and will influence the parameter estimates.

Another improvement proposed by this Chapter deals with the problem of handling event-induced increases in volatility. Mikkelson (1981), Penman (1982) and Rosenstein and Wyatt (1989) found that the event-period's standard deviation is about 1.2 to 1.5 higher than that experienced during the benchmark-period.

Although this is a central problem in event studies since it influences the ability of the t-statistics used by event-study methodologies to test for excess returns, it has only received sparse attention. Brown and Warner (1980, 1985) argue that the variance of returns will increase when an event produces different effects on securities.

They warn that under these circumstances, the traditional event-studies fail to produce correct results. More recently, Brown, Harlow and Tinic (1988, 1989) show that events cause a temporary increase in the variance of abnormal returns which accompany the shift in the mean. This increase in variance is caused by the temporary change in the securities' systematic risk. Hence, controlling for event-induced variance is a necessary step in order to conduct the appropriate test of the null hypothesis.

One way to deal with event-induced variance is provided by a number of event-studies (See Charest (1978), Dann (1981), Mikkelson (1981), Penman (1982) and Rosenstein and Wyatt (1990)) that use cross-sectional variance extracted from the event window rather than estimated from a benchmark period. Other methods include a generalised least squares technique to deal with event-date clustering (Collins and Dent (1984)), applying a Maximum

Likelihood estimation to stock return data (Ball and Torous (1988)) and non-parametric rank tests to capture asymmetry in cross-sectional excess returns (Corrado (1989)).

2.4.4 Trade Clustering and Filtering Rules

Large trades transacted in a quote-driven market can be executed in three possible ways: (a) the market maker is one of the parties to the trade as a buyer in which case its inventory is increased with the quantity bought; (b) the market maker is one of the parties in the capacity of a seller in which case its inventory is reduced; and (c) no market maker is involved in the trade which gives rise to an agency cross. Trades classified as (a) or (b) above can include protected trades[6], that are trades where the initiator agrees with the market maker for the trade to be deferred later on in the trading day possibly leading to a better price for the initiator.

A material number of trades are reported as having taken place after the home markets are closed. In particular, for all three types of cross-quoted securities, there is a surge of large trades executed between 16:00:00 hrs and 17:00:00 hrs (London time) which coincides with the hour following the home markets closure. In addition, a substantial number of these trades are reported as having been executed between 17:00:00 hrs and 20:00:00 hrs, although the number of trades in French and Italian cross-quoted securities is higher than that for German securities.

The large trades for every security were also sorted by the time interval between one large trade and the other (in the same security group) for each single trading day. The results are shown in Table 5 and demonstrates trade clustering for most securities, in that more than half of the number of trades

[6]Since the LSE is not informed that a particular trade was covered by the one day protection rule, these trades cannot be identified as such in the data provided by the LSE.

are executed within one hour of each other with very few large trades being executed within the two and three hours intervals. Trades executed in the four hours interval form a substantial group.

Only large Customer trades are investigated since the main objective is to analyse price impacts in home markets produced by total buying or selling pressures in London which is not due to inventory positioning; trades between market maker trades are expected to be executed for purely inventory management reasons and so are not considered. In addition, the Agent to Agent trades (the so-called agency crosses) are also ignored since in this case the trade direction cannot be identified. The classification of large trades into three categories is motivated by the need to analyse the impacts produced by large trades of different sizes.

For the event study methodology, four filtering rules are used to define the event under consideration. First, any large trade which occurred in the two hours following another large trade is removed from the sample. Secondly, any large trade which is followed in the following two-hour interval by other large trades is ignored. Thirdly, any large trade for which there was another large trade (in any size class) in the previous trading day is also removed from the sample. The fourth filtering rule removes those trades which are reported as having been executed before 09:00:00 hrs (London time) and those after 17:00:00 hrs (London time) in the case of French and Italian cross-quoted securities and trades executed before 07:30:00 hrs (London time) and those after 17:00:00 hrs (London time) in the case of German cross-quoted securities.

Following the identification of the large trade in London, a four hour event-window is opened in the home market and the trades which are executed in the home markets in the two hours before the event and two hours

Table 5: **Temporal aggregation of trades in French, German and Italian cross-quoted securities executed on SEAQ-I**

	French quoted	German quoted	Italian quoted
INTERVAL A			
Number of trades	22240	12302	14332
% of total trades	62.32	53.79	63.42
INTERVAL B			
Number of trades	3187	1242	1512
% of total trades	7.62	8.52	7.66
INTERVAL C			
Number of trades	927	524	704
% of total trades	2.95	4.47	3.74
INTERVAL D			
Number of trades	583	248	403
% of total trades	1.98	2.55	2.46
INTERVAL E			
Number of trades	6106	2596	3414
% of total trades	25.13	30.66	22.72

Large trades were extracted from the datasets and sorted by the date and time of execution. The exercise was implemented for every trading day in the period January-June 1996.

Large trades with an inter-trade interval of less than 1 hour are placed in Interval A; large trades with an inter-trade interval between 1 to 2 hours are placed in Interval B; large trades with an inter-trade interval between 2 to 3 hours are placed in Interval C; large trades with an inter-trade of 3 to 4 hours are placed in Interval D; while large trades with an inter-trade interval larger than 4 hours are placed in Interval E.

following the event are considered. Although it could be argued that the decision about the duration of the event-window is in itself arbitrary, it should be noted that the duration chosen is broadly in line with the findings of Board and Sutcliffe (1995) for SEAQ securities.[7]

In order to avoid the problems caused by the bid-ask bounce, the analysis is conducted in the Board and Sutcliffe (1995) vein whereby all *buy trades executed in the home markets* during the four-hour event-window are combined with the large *London buy* and all *sell trades executed in the home market* are combined with the *large London sale.*

The four hour window periods are then divided into five-minute intervals. The time at which the London-executed trade takes place is used to fix the initial time of interval 0. Since SEAQ-I dealers have up to 3 minutes to report a trade to the LSE, it is possible that trade time misreporting occurs and this means that the real trade execution time is not necessarily placed at interval 0 but could effectively be in close intervals. However, since we adopt a very wide event window period, this problem is not likely to pose serious problems. The 47 five-minute intervals before and after the large London-executed trade are identified with respect to time interval 0.

Two methodologies are utilised. The first one generally follows conventional literature where excess returns are computed and the null hypothesis is tested through the usual t-test, while the second one uses standardized returns and the standardized cross-sectional test.

Event time is denoted by t, with the reporting time of the execution of the large trade on SEAQ-I being $t = 0$. The benchmark period is defined as

[7]They essentially find that most of the pre-positioning that London market makers carry out takes some 185 minutes but 75% of the pre-positioning for very liquid securities takes just over 2 hours while that for low liquid securities take 108 minutes. The post-event window has been chosen to provide sufficient time for the price impact to materialise given that trades of different sizes are being considered.

the interval $t = T_o + 1$ to $t = T_1$, being followed by the event window which occupies the time period from $t = T_1 + 1$ to $t = T_2$.

This set-up implies that $Z_1 = T_1 - T_0$, being the benchmark period, and $Z_2 = T_2 - T_1$ being the event window. For the purpose of this Chapter, the event window starts at time interval -24 and ends at time interval +23. The LSE data is only utilised to identify the large trade (the time of transaction and the trade size) and define the four hour interval period. However, the event-window itself is exclusively populated by the trades executed in the respective home market. The one hour clock time difference between London and the home markets is taken into consideration and the necessary adjustments in the home markets' transaction reported time are implemented in the data.

For a number of large trades, the event-window opened does not fit in the same trading day. In particular, the trades reported as having been executed before 11:00:00 hrs will have an event-window that starts in the previous trading day while the large trades executed after 14:00:00 hrs will have an event-window that ends in the following trading day. The event-window for the trades that are reported between 16:00:00 hrs and 17:00:00 hrs is constituted by trades executed in the two last trading hours in that trading day and the first two trading hours of the following trading day in the home market.

The choice of this event-window is justified by the consideration that if London market makers do use the home markets to pre- and post-position large trades executed on SEAQ-I, then it is expected that trades which occur near the home markets' close should experience a pre- and post-positioning phases that stretch from one trading day to another. In such cases, the opening trade in the home markets is omitted so as to minimise the impact of the accumulation of information in the overnight period.

The Excess Returns (ER) on day d for each of the 48 five-minute intervals t over which transactions are executed in the home market m for security j and transacted before and after the large trade l is executed in London, are given by:

$$ER_{dtjlm} = R_{dtjlm} - BR_{(d-1)tm} \tag{1}$$

where ER_{dtjlm} represents the interval-to-interval return for trades executed in the home market (sell trades in the case of a sell large trade on SEAQ-I and buy trades in the case of a buy large trade on SEAQ-I) from interval -24 to interval +23.

The benchmark interval-to-interval returns, $BR_{(d-1)tm}$, are calculated using all trades transacted in the home market the day before the particular large trade in London is executed. In the case of trades that are executed before 11:00hrs and hence have part of the pre-event window starting in the previous trade, the benchmark returns are computed using all trades executed up to one hour before the start of the event-window.

Average excess returns (AER) are obtained by averaging across all securities and event-window intervals. In particular abnormal returns for Customer buy trades at time t are computed by averaging across all companies and blocks in the following way:

$$AER_{tb} = \sum_{j=1}^{J} \sum_{l=1}^{L_b} \frac{ER_{dtjlmb}}{L_b} \tag{2}$$

where L_b is the total number of large Customer buy trades for all companies.

The average excess returns (AER) from trading in the home markets are cumulated to produce the cumulative average abnormal return measure around the execution of the large trade on SEAQ-I, denoted as $CAR(t_1, t_2)$, in the following way (the following refers to buy trades)

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} \left(\sum_{j=1}^{J} \sum_{l=1}^{L_b} \frac{ER_{dtjlmb}}{L_b} \right) \tag{3}$$

where L is the number of large buy trades and $T_1 < t_1 \leq t_2 \leq T_2$.

The standard deviation of interval-to-interval returns was computed using the same trades used to obtain the benchmark returns. The $t - statistic$ was calculated by adjusting the excess returns obtained for each day, large trade, security and interval by $\sqrt{N_{(d-1)tm}}$, the number of intervals used for the computation of the standard deviation, and then divided by the standard deviation $SD_{(d-1)jm}$in the following way:

$$t_{dtjlm} = \frac{ER_{dtjlm} \times \sqrt{N_{(d-1)tm}}}{SD_{(d-1)tm}} \tag{4}$$

After conducting the analysis using the updated version of conventional methodologies, we address the problem of event-induced increases in volatility. It must be noted that if the variance induced by the event is underestimated, this leads to the serious problem of having a test statistic that rejects the null hypothesis of zero average abnormal returns more frequently than it should (Brown and Warner, 1980 and 1985). In order to solve this problem, the present work will make use of the standardized cross-sectional test developed by Boehmer, Musumeci and Poulsen (1991) in addition to the traditional method.

The standardized cross-sectional test is the result of combining together the standardized-residual technology developed by Patell (1976) and the ordinary cross-sectional methodology proposed by Charest (1978) and Penman (1982). The innovative aspect of this test is the combination of variance information extracted both from the benchmark period and the event-window period.

For the standardized cross-sectional residuals methodology, interval-to-interval standardized returns for each security j and large trade t is calculated in the following way:

$$SR_{dtjlm} = ER_{dtjlm}/SD_{(d-1)tm}\sqrt{1+\frac{1}{N_{(d-1)tm}}+\frac{(R_{dtjlm}-B\bar{R}_{(d-1)tm})^2}{\sum_{n=1}^{N}(BR_{(d-1)tm}-B\bar{R}_{(d-1)tm})^2}} \quad (5)$$

where $B\bar{R}_{(d-1)tm}$ is the average interval-to-interval returns obtained for the benchmark period.

The test-statistic is obtained in the following way:

$$\frac{1}{J}\sum_{i=1}^{F} SR_{dtjlm}/\sqrt{\frac{1}{J(J-1)}\sum_{i=1}^{J}(SR_{dtjlm}-\sum_{i=1}^{J}\frac{SR_{dtjlm}}{J})^2} \quad (6)$$

where J is the number of firms used in the computations.

As explained, this study makes use of interval-to-interval returns rather than trade-to-trade returns. Although this methodology is expected to standardize the time over which different series of excess returns (resulting from different large trades) are aggregated, it is not immune to the problems associated to nonsynchronous trading. Although many cross-quoted securities trade heavily in their respective home markets, a limited number of such securities present lower trading frequencies. Hence, the possible impact of the nonsynchronous trading presence must be explored.

The nonsynchronous trading effect takes place when asset prices are recorded at intervals of irregular lengths when in fact the computation assumes that they are recorded at intervals of equal lengths. The case which is of interest here is represented by those securities with unequal trading frequencies and are included in the same sample used for the event study. In particular, although the length of the intervals used is five minutes, different trading frequencies within and between intervals should create a situation where that interval-to-interval returns are not recorded with a five minute time span.

This is because the first trade in each interval does not necessarily take place on the first second of each interval and as such these trades are not evenly spaced. In addition, it is also possible that no trades are executed in a particular security for a number of intervals in which case the time interval between the first trade of one interval and the first trade for the next available interval is substantially higher than five minutes.

In view of this problem, the mean time of the interval-to-interval returns for different securities was computed. The cross-quoted securities were divided into two groups - first, those with less than 150 trades per trading day; the second group being formed by those securities for which there are more than 150 trades per trading day.

The mean time of the interval-to-interval return in the first group is 7.01 minutes while that for the second group is 6.14 minutes. The difference between the two mean times is not statistically significant and, hence, the problems caused from the presence of nonsynchronous trading are not considered to be severe.

Following the analysis of the large trades filtered from the presence of other large trades, the whole sample of large trades is then utilised in a regression model.

2.5 Results

2.5.1 Event Study Methodology

Results show that the excess returns in the home markets around the execution of the block trade on SEAQ-I are statistically significant whereas the excess returns in both tails of the event-window are not statistically significant. Tables 6-8 and Figures 1-4 shows the mean excess returns recorded over a smaller number of time intervals (from the larger four-hour interval) that spans from time interval -14 to time interval +14 (henceforth the 'statistically significant period').

Figures 5-8 provide the Cumulative Abnormal Returns on the home markets over the four hour interval period surrounding the large trade generated by the large buy and sell trades, using the Excess Returns as computed in (1). The mean interval-to-interval excess returns over a number of intervals that surround the time when the large trade is executed on SEAQ-I are significantly different than zero. In general, most of the excess returns recorded over the period that spans from interval -13 to interval +13 are statistically significant.

The $t-statistics$ for most of the mean excess returns within the statistically significant period reject the null hypothesis of zero excess returns at the 1% confidence level. The mean excess returns recorded from interval -12 to interval -1, and hence before the large trade is actually executed on SEAQ-I, are statistically different than zero which can be explained in two different ways. It is either because there is a leakage of information and prices start adjusting accordingly in view of the large trade due to be executed or the pre-positioning carried out by London market makers in the home markets leads to prices adjusting accordingly.

Interestingly, there are few intervals (especially at or around interval 0)

Table 6: **Excess Returns and Standardized Cross-Sectional Residuals around large trades (6 to 45 NMS) for French cross-quoted securities**

	LARGE BUY TRADES				LARGE SELL TRADES			
Inter.	Excess Return	t-test	SC-S Resid.	SCR-ts	Excess Return	t-test	SC-S Resid.	SCR-ts
-9	*0.0292*	2.83	*0.0213*	2.55	*-0.0480*	-3.70	*-0.0378*	-3.16
-8	*0.0311*	3.82	*0.0210*	2.14	*-0.0712*	-13.34	*-0.0254*	-5.39
-7	*0.0378*	3.91	*0.0422*	4.19	*-0.0251*	-3.72	*-0.0151*	-2.35
-6	*0.0639*	12.21	*0.0929*	7.92	*-0.0459*	-3.55	*-0.0359*	-2.12
-5	*0.0911*	14.61	*0.0390*	3.99	-0.0124	-1.68	*-0.0708*	-5.54
-4	*0.0467*	2.04	*0.0192*	3.15	*-0.0062*	-2.96	*-0.0215*	-3.15
-3	*0.0474*	2.58	*0.0124*	2.17	0.0211	1.23	*-0.0213*	-6.79
-2	*0.0705*	14.68	*0.0401*	4.70	*-0.0458*	-3.34	*-0.0419*	-4.24
-1	*0.0506*	3.75	*0.0486*	3.16	*-0.0832*	-13.01	*-0.0779*	-10.75
0	-0.0023	-0.81	-0.0001	-1.17	*-0.0505*	-3.02	*-0.0334*	-2.98
1	*0.0668*	16.23	*0.0433*	6.21	*-0.0596*	-4.26	*-0.0712*	-6.80
2	*0.0905*	10.06	*0.0145*	2.19	0.0214	1.95	*-0.0611*	-2.10
3	*0.0214*	3.18	*0.0188*	3.86	*-0.0642*	-4.27	*-0.0544*	-4.11
4	*0.0292*	2.52	*0.0218*	3.11	*-0.0568*	-11.80	*-0.0436*	-4.99
5	*0.0446*	14.98	*0.0229*	3.35	*-0.0466*	-11.13	*-0.0277*	-3.83
6	*0.0293*	4.37	*0.0295*	3.17	*-0.0265*	-2.77	*-0.0395*	-3.23
7	*0.0388*	2.30	*0.0212*	2.85	*-0.0484*	-3.06	*-0.0295*	-2.38
8	*0.0197*	2.32	*0.0130*	2.01	*-0.0417*	-2.92	-0.0050	-1.12
9	*0.0071*	2.24	*0.0193*	2.52	*-0.0034*	-2.01	-0.0024	-1.14

The Table shows the Excess Returns, with the corresponding t-test, together with the Standardised Cross-Sectional Residuals and the Standardised Cross-Sectional test for trades in the 6 NMS - 45 NMS trade size bracket. Excess returns are calculated as:

$$ER_{dtjlm} = R_{dtjlm} - BR_{(d-1)tm}$$

where R_{dijtm} represents the interval-to-interval return for trades executed in the home market over the interval period and $BR_{(d-1)tm}$ is benchmark interval-to-interval returns. Standardised Cross-Sectional Residuals are calculated as follows:

$$SR_{dtjlm} = ER_{dtjlm} / SD_{(d-1)tm} \sqrt{1 + \frac{1}{N_{(d-1)tm}} + \frac{(R_{dtjlm} - B\bar{R}_{(d-1)tm})^2}{\sum_{n=1}^{N}(BR_{(d-1)tm} - B\bar{R}_{(d-1)tm})^2}}$$

where $B\bar{R}_{(d-1)tm}$ is the average interval-to-interval returns obtained for the benchmark.

Table 7: **Excess Returns and Standardized Cross-Sectional Residuals around large trades (6 to 45 NMS) for German cross-quoted securities**

	LARGE BUY TRADES				LARGE SELL TRADES			
Inter.	Excess Return	t-test	SC-S Resid.	SCR-ts	Excess Return	t-test	SC-S Resid.	SCR-ts
-9	*0.0592*	6.23	*0.0620*	6.80	*-0.0436*	-5.38	*-0.0221*	-4.12
-8	*0.0117*	2.14	*0.0148*	2.54	*-0.0294*	-2.62	*-0.0433*	-5.40
-7	*0.0587*	6.34	*0.0499*	4.21	*-0.0689*	-6.98	*-0.0611*	-7.38
-6	*0.0633*	12.48	*0.0513*	9.48	*-0.0126*	-12.16	*-0.0412*	-4.11
-5	*0.0182*	2.56	*0.0205*	2.52	*0.0128*	11.97	*0.0183*	2.17
-4	*0.0597*	11.16	*0.0391*	8.95	*-0.0696*	-2.13	*-0.0487*	-4.11
-3	*0.0452*	2.43	*0.0221*	2.24	*-0.0565*	-7.87	*-0.0486*	-4.18
-2	*0.0714*	15.14	*0.0875*	11.42	*-0.0552*	-11.59	*-0.0341*	-6.94
-1	-0.0384	-0.55	-0.0124	-0.60	*-0.0205*	-2.85	*-0.0257*	-3.68
0	*0.0324*	4.29	*0.0321*	4.22	-0.0145	-0.44	*0.0058*	1.11
1	*0.0554*	7.65	*0.0627*	8.73	*-0.0244*	-2.95	*-0.0165*	-2.24
2	*0.0221*	2.40	*0.0206*	4.20	*0.0110*	2.48	*0.0186*	-2.90
3	*0.0162*	2.69	*0.0169*	3.47	*-0.0392*	-12.96	*-0.0228*	-10.69
4	*0.0134*	2.32	*0.0129*	2.17	*-0.0238*	-6.57	*-0.0241*	-4.91
5	*0.0204*	2.66	*0.0202*	2.20	*-0.0081*	-2.39	*-0.0115*	-2.50
6	*0.0495*	15.13	*0.0237*	4.16	*-0.0097*	-2.65	*-0.0142*	-2.15
7	*0.0374*	6.90	*0.0283*	5.70	*-0.0431*	-2.53	*-0.0227*	-4.11
8	*0.0051*	2.93	*0.0318*	3.91	*-0.0104*	-2.93	*-0.0286*	-4.98
9	*0.0097*	2.36	*0.0137*	2.82	*-0.0254*	-4.92	*-0.0198*	-3.11

The Table shows the Excess Returns, with the corresponding t-test, together with the Standardised Cross-Sectional Residuals and the Standardised Cross-Sectional test for trades in the 6 NMS - 45 NMS trade size bracket. Excess returns are calculated as:

$$ER_{dtjlm} = R_{dtjlm} - BR_{(d-1)tm}$$

where R_{dijtm} represents the interval-to-interval return for trades executed in the home market over the interval period and $BR_{(d-1)tm}$ is benchmark interval-to-interval returns. Standardised Cross-Sectional Residuals are calculated as follows:

$$SR_{dtjlm} = ER_{dtjlm}/SD_{(d-1)tm}\sqrt{1 + \frac{1}{N_{(d-1)tm}} + \frac{(R_{dtjlm} - B\bar{R}_{(d-1)tm})^2}{\sum_{n=1}^{N}(BR_{(d-1)tm} - B\bar{R}_{(d-1)tm})^2}}$$

where $B\bar{R}_{(d-1)tm}$ is the average interval-to-interval returns obtained for the benchmark.

Table 8: **Excess Returns and Standardized Cross-Sectional Residuals around large trades (6 to 45 NMS) for Italian cross-quoted securities**

	LARGE BUY TRADES				LARGE SELL TRADES			
Inter.	Excess Return	t-test	SC-S Resid.	SCR-ts	Excess Return	t-test	SC-S Resid.	SCR-ts
-9	*0.0497*	10.65	*0.0251*	3.11	*-0.0447*	-5.43	*-0.0344*	-3.21
-8	*0.0328*	4.47	*0.0218*	13.37	*-0.0471*	-5.65	*-0.0311*	-4.72
-7	*0.0662*	5.50	*0.0466*	5.26	*-0.0273*	-2.38	*-0.0271*	-2.79
-6	*0.0847*	12.97	*0.0631*	5.17	*-0.0315*	-4.52	*-0.0208*	-2.91
-5	*0.0965*	8.26	*0.0551*	5.10	*-0.0375*	-4.79	*-0.0121*	-2.21
-4	*0.0817*	13.11	*0.0788*	4.22	*-0.0761*	-10.16	*-0.0561*	-11.66
-3	*0.0799*	13.74	*0.0597*	8.73	*-0.0498*	-13.95	*-0.0351*	-8.90
-2	*0.0506*	5.03	*0.0517*	6.10	*-0.0815*	-4.39	*-0.0639*	-8.72
-1	*0.0210*	2.71	*0.0188*	3.18	*-0.0584*	-9.59	*-0.0641*	-9.95
0	-0.0111	-0.66	-0.0029	-1.28	*-0.0214*	-2.79	*-0.0124*	-3.93
1	*0.0711*	4.73	*0.0249*	2.20	0.0158	1.44	-0.0102	-1.91
2	*0.0433*	2.98	*0.0362*	4.41	*-0.0428*	-5.18	*-0.0311*	-3.63
3	*0.0221*	2.18	*0.0191*	2.64	*-0.0387*	-4.43	*-0.0231*	-2.49
4	*0.0285*	4.36	*0.0388*	4.10	*-0.0274*	-3.50	*-0.0166*	-2.14
5	*0.0121*	2.89	*0.0192*	2.97	*-0.0121*	-3.62	*-0.0112*	-2.13
6	*0.0312*	4.65	*0.0236*	4.91	0.0126	1.38	*-0.0107*	-2.48
7	*0.0265*	2.00	*0.0117*	2.12	*-0.0232*	-8.56	*-0.0176*	-3.15
8	*0.0134*	2.63	*0.0128*	2.62	*-0.0098*	-2.99	*-0.0118*	-3.53
9	*0.0067*	2.18	*0.0107*	2.30	*-0.0052*	-2.44	*-0.0019*	-2.12

The Table shows the Excess Returns, with the corresponding t-test, together with the Standardised Cross-Sectional Residuals and the Standardised Cross-Sectional test for trades in the 6 NMS - 45 NMS trade size bracket. Excess returns are calculated as:

$$ER_{dtjlm} = R_{dtjlm} - BR_{(d-1)tm}$$

where R_{dijtm} represents the interval-to-interval return for trades executed in the home market over the interval period and $BR_{(d-1)tm}$ is benchmark interval-to-interval returns. Standardised Cross-Sectional Residuals are calculated as follows:

$$SR_{dtjlm} = ER_{dtjlm} / SD_{(d-1)tm} \sqrt{1 + \frac{1}{N_{(d-1)tm}} + \frac{(R_{dtjlm} - B\bar{R}_{(d-1)tm})^2}{\sum_{n=1}^{N} (BR_{(d-1)tm} - B\bar{R}_{(d-1)tm})^2}}$$

where $B\bar{R}_{(d-1)tm}$ is the average interval-to-interval returns obtained for the benchmark.

where price reversals are detected. However, the individual abnormal returns in each interval are not statistically significant at the 5 % confidence level.

Additional tests were carried out to investigate whether the results obtained above are sensitive to the inclusion of large trades for which the event window period stretches over two consecutive trades. The results from dropping these large trades, in terms of both the abnormal returns for single intervals and for the CARs, are not statistically different from the results obtained above. In addition, another test was carried out to investigate whether the basic results are sensitive to the inclusion of the opening trade in the case of large trades for which the event window period stretches over two consecutive trades. The basic results are not influenced when the opening trade is included.

The pattern of the price impacts found is different than those found by Holthausen *et al.* (1990) and Gemmill (1996). The pattern found here shows that the price impact starts materialising some time before the trade is reported as having been executed but with an interval-to-interval mean returns that are relatively small.

Most of the mean excess returns which are statistically significant have the expected signs, i.e. positive for large purchase trades in London and negative for large sale trades and this is consistent with the view that large buy trades signal good news while large sales are signal for bad news. For a small number of intervals, the mean excess returns have the opposite expected sign and are not statistically significant. This occurs mainly after a number of intervals in which the mean excess returns are relatively high. This could imply that there is a price correction following periods characterised by price overreaction. The number of intervals with anomalous signs get smaller as the size bracket increases.

There is also a clear indication that the SEAQ-I's one-hour publication delay does not appear to be holding prices in the home markets from adjusting to their new equilibrium before the trade is actually published by the LSE. This result is consistent with similar results obtained by Board and Sutcliffe (1995) and Gemmill (1996). In particular, the publication delay is unnecessarily long, in that the price adjustment process is fully implemented by the time the large trade is published by the LSE.

The general pattern of price impacts does not materially change when the standardized returns and the standardized cross-sectional test are used. However, with the same level of abnormal performance but high event-induced variance, the standardized cross-sectional test appears to be rejecting the null hypothesis less frequently when compared to the traditional test. This would imply that the event-induced variance generated by a large trade is likely to be higher in Paris and the IE compared to IBIS.

2.5.2 Permanent Price Impacts

A number of studies (Kraus and Stoll 1972, Ball and Finn 1983, Holthausen *et al.* 1987, Holtahusen *et al.* 1990, Board and Sutcliffe 1995, and Gemmill 1996) document the temporary and permanent price effects produced by large trades executed in the same equity market. In general, defining P_{pr} as the pre-block price, P_b as the price at which the block trade is executed and P_{ps} as the post-block price, the temporary price effect is measured as $ln(P_b/P_{ps})$, the permanent price effect is given by $ln(P_{ps}/P_{pr})$ and the total price effect is measured as $ln(P_b/P_{pr})$.

The transactions data used in Section 2.4 is used to calculate the permanent price impacts produced by the large trades included in the sample. Since the large trade is not itself executed in the home market it is not possible to obtain P_b and hence both the temporary price effect and the total price effects cannot be reasonably inferred. However, the permanent price effects can be calculated by using prices over time intervals before and after the large trade's execution time which are free from the large trade's influences.

For each trade, the prices P_{pr} are calculated at time interval -20 and P_{ps} are calculated at time interval +20. The mean excess returns in these intervals are not statistically significant and they have adjacent time intervals with statistically insignificant mean excess returns. The permanent price impacts for large trades are matched with the permanent price impacts produced by trades smaller than 2 X NMS for the same security and transacted during the benchmark period employed in Section 2.4.

Table 9 shows the results with the mean difference between the price impacts produced by small trades and large trades in each size bracket. The t-statistics, which test whether the mean difference between small and large trades is significantly different than zero, show that the null hypothesis of zero mean difference can be rejected at the 1% confidence level, confirming that large trades do produce a permanent price impact. The sell large trades appear to be producing a slightly different price impact pattern for the three cross-quoted securities groups. The results also show that rebalancing on IBIS trading system produces the lowest price impact for each trade size when compared to the price impact obtained on CAC and IE.

In addition, the Kruskal-Wallis test to examine the permanent price impact differences across the different trade sizes was run. The p-values show that the price impact are not statistically significant different across trade sizes.

Table 9: **Permanent price impacts in home markets**

PANEL A: LARGE BUY TRADES

	Paris Bourse	**Deutsche Börse**	**Italian Exchange**
6 NMS - 15 NMS	0.5928*	0.4676*	0.5829*
16 NMS - 25 NMS	0.7007*	0.5845*	0.7869*
26 NMS - 35 NMS	0.8541*	0.7007*	0.9049*
36 NMS - 45 NMS	0.8891*	0.7161*	0.9411*
46 NMS - 55 NMS	0.8535*	0.7368*	0.9599*
56 NMS - 65 NMS	0.8109*	0.7221*	0.8736*
66 NMS - 75 NMS	0.7853*	0.6788*	0.8510*
$\geq$ 2NMS	0.0021	0.0015	0.0028
p-value of differences across NMS sizes	0.481	0.266	0.291

PANEL B: LARGE SELL TRADES

	Paris Bourse	**Deutsche Börse**	**Italian Exchange**
6 NMS - 15 NMS	-0.5326*	-0.4282*	-0.6128*
16 NMS - 25 NMS	-0.6288*	-0.4511*	-0.7661*
26 NMS - 35 NMS	-0.7897*	-0.5052*	-0.6664*
36 NMS - 45 NMS	-0.7996*	-0.5178*	0.6831*
46 NMS - 55 NMS	-0.7677*	-0.5251*	-0.6981*
56 NMS - 65 NMS	-0.7836*	-0.4936*	-0.6841*
66 NMS - 75 NMS	-0.7131*	-0.4294*	-0.6088*
$\geq$ 2NMS	-0.0032	-0.0024	-0.0041
p-value of differences across NMS sizes	0.411	0.564	0.122

Each large trade for cross-quoted securities is put into different size brackets in terms of NMS and the permanent price impact is calculated as $ln(P_{ps}/P_{pr})$ where the prices P_{pr} are calculated at time interval -20 and P_{ps} are calculated at time interval +20. The permanent price impacts for large trades are matched with the permanent price impacts produced by trades smaller than 2 X NMS for the same security and transacted during the benchmark period.

An (*) indicates that the mean difference between the permanent price impact of a large trade in the different size brackets and the price impact of a trade smaller than 2 NMS is statistically significantly different than zero.

The Kruskal-Wallis test is used to examine the mean permanent price impact difference across the different trade size groups.

Figure 1. Excess returns in the home markets before and after the SEAQ-I large buy trade (6-45 NMS)

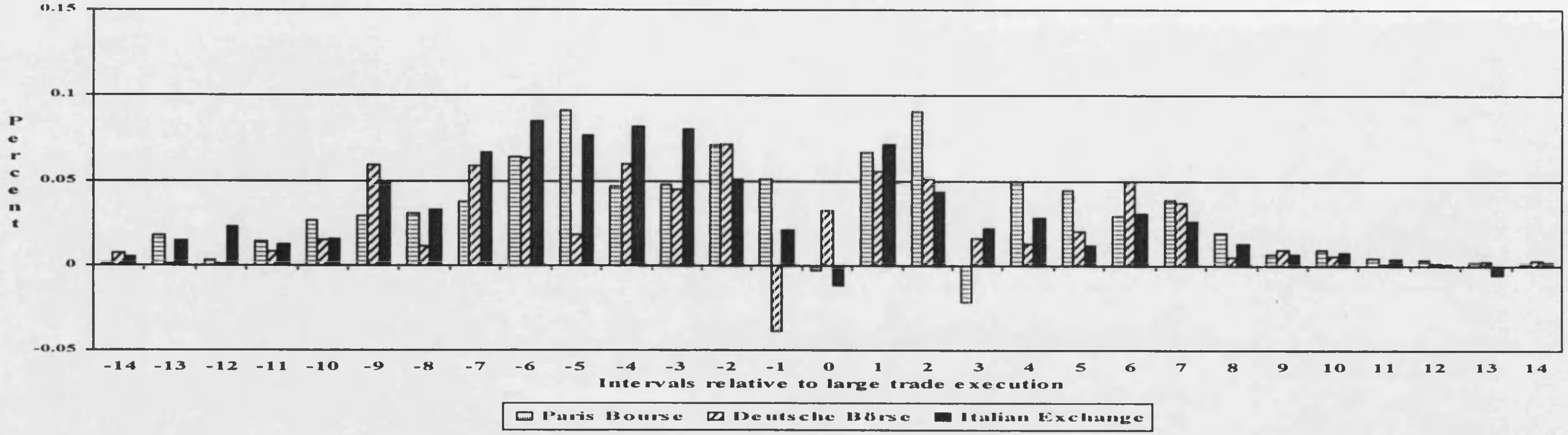


Figure 2. Excess returns in the home markets before and after the SEAQ-I large sell trade (6-45 NMS)

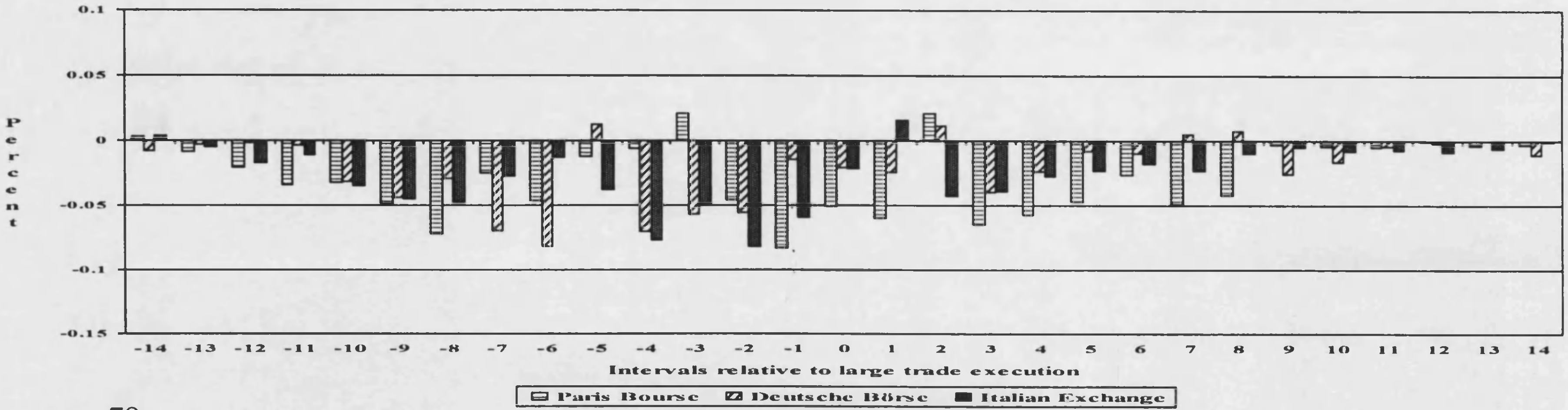


Figure 7. CARs in the home markets generated by the SEAQ-I large buy trade (46-75 NMS)

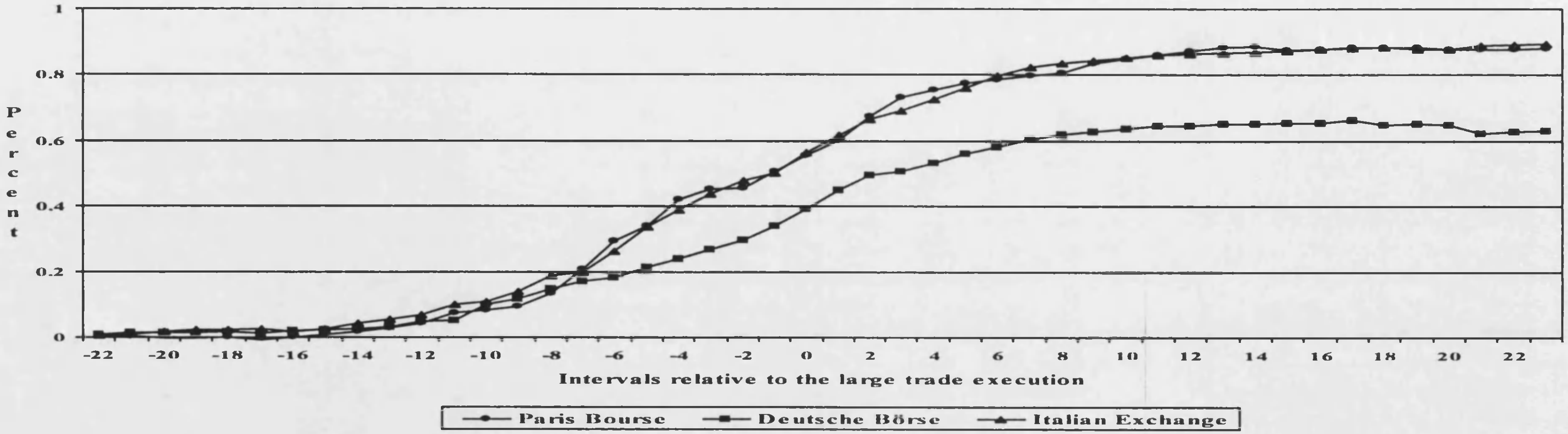
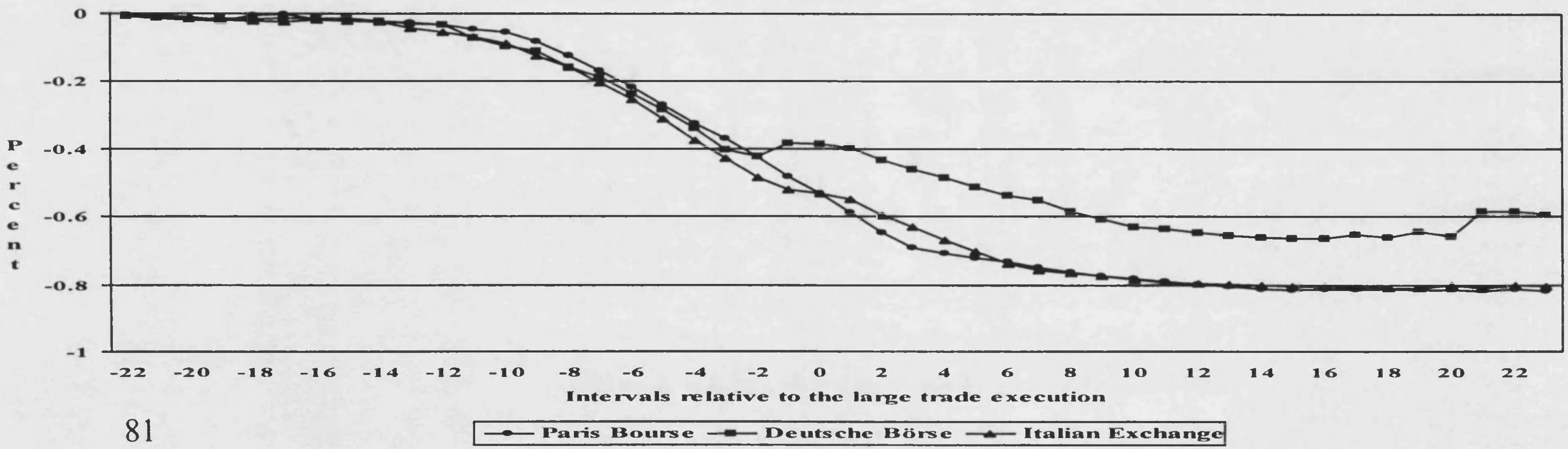


Figure 8. CARs in the home markets generated by the SEAQ-I large sell trade (46-75 NMS)



These results, together with the one obtained for the buy (large) trades, are in line with the Seppi (1990) conjecture regarding the type of trades executed in the upstairs market. It is quite possible that very large trades are actually liquidity-motivated, rather than information-motivated, and hence produce a price impact of the same level or lower than trades which are relatively smaller but contain trade information.

2.5.3 Regression Results

Following the results obtained from the event-study methodology, a regression model was run to analyse the simultaneous effects of various trading factors, where no filtering rules are employed and hence the entire sample of large trades is considered.

Excess returns are calculated in the same way as used for the event-study methodology. As in that case, the London-executed large trade is used to define the trade size class and the time of execution fixes the initial time of interval 0. The interval-to-interval excess returns are calculated over the interval period that starts from interval -25 until time interval +25.

The benchmark returns are calculated in a different way, than described above, to accommodate the high number of large trades and their distribution in the trading day which produces overlapping event-windows for different large trades. In the case that two clear hours between one large trade's event window and another large trade's event window exist, benchmark returns are calculated using the interval-to-interval returns over this two-hour period. If in one particular trading day this benchmark period is not available, the benchmark returns are provided by the most recent two hours which are clear of any effect produced by other large trades.

The dependent variable is the mean interval-to-interval excess returns in the home markets over the two hours before and two hours after the large trade in London.

The independent variables are chosen in the following way:

a. *Volumes on the home market:* If London market makers use the home markets to rebalance their trading positions on the LSE then a large order executed in London will generate higher volumes in the home markets as market makers re-establish the optimal inventory position. In this case, we use total volume transacted in the home markets from interval -25 until time interval +25. We use the logarithmic change in the volume from the benchmark period to each time interval.

b. *Volumes on the London market:* London market makers can also use SEAQ-I market, in conjunction with the home markets, to fetch liquidity for the rebalancing of their trading positions. This is expected generate higher volumes on SEAQ-I as market makers re-establish their optimal inventory position. In line with (a) above, we use total volume transacted on SEAQ-I from interval -25 until time interval +25 and employ the logarithmic change in the volume from the benchmark period to each time interval.

c. *Interval dummy:* The time interval to capture the price pattern seen in the event-study methodology above where the price impact is not a one-shot phenomenon but rather a protracted process over a long period, before and after the large trade is executed. In order to model the price impact over the interval period, a number of dummy variables are used to identify different intervals. Interval Dummy 1 takes a value of 1 for the excess returns in the interval period between interval -25 to interval -15 and 0 otherwise; Interval Dummy 2 takes a value of 1 for the excess returns in the interval period between interval -14 to interval 0 and 0 otherwise; Interval Dummy 3 takes a value of 1 for the excess returns in the interval period between interval 1 to interval +15 and 0 otherwise; and Interval Dummy 4 takes a value of 1 for the excess returns in the interval period between interval +16 to +25 and 0 otherwise.

d. *Trade size:* The size of the trade executed to investigate whether the price impact is increasing in size. Dummy variables are used to capture the trade size effects. In order to be consistent, different trades are grouped using the same classification criteria used for the event-study methodology, namely (i) trades between 6 NMS to 15 NMS; (ii) trades between 16 NMS to 35 NMS; and (iii) trades between 36 NMS to 75 NMS.

e. *Activity in the market:* Number of trades in the four hours immediately before the large trade's execution to control for the level of market activity and clustering of trades. Section 2.4.4 shows that large trades are mainly clustered within one hour of each other with very few trades taking place within two, three or four hours of each other. These patterns could cause a clustering problem that is likely to reflect in the price impacts produced by each individual large trade. If two or more large trades of the same trade direction are executed few minutes of each other, the price impact is expected to be larger than when one trade is executed.

f. *Time of the day:* Hour of the trading day is used to capture (i) the time of the day effects and (ii) the behaviour of SEAQ-I market makers who are likely to become more aggressive in rebalancing large trades executed in London as the available trading time decreases. In addition, the price impacts produced in the last trading hour are expected to be higher than for other trading hours due to the 'deadline effect'.[8] Dummy variables are used for every trading hour.

g. *Trade type:* The type of trade to control for the presence of put-

[8]This is in line with Roth *et al* (1988) who conducted a simulated experiment to test for patterns of bargaining across time and found that the most visible phenomenon was a very high percentage of agreements being reached just before the deadline for the negotiations.

throughs in the data set. The put-throughs' characteristics imply that these trades are not expected to generate any price impact which is directly attributable to the market makers' inventory management since immediate rebalancing takes place in two opposing directions and undertaken for the same volume. It is also possible that put-throughs do not touch in any way the home markets in that market makers find the counter-party for such trades directly in London. However, put-throughs' characteristics do not necessarily imply no price impact since these trades can generate information flows to the market makers involved in the trade. The dummy variable takes on a value of 1 if the trade is not a put-through and 0 if it is a put-through.

The following regression model is estimated:

$$AER_{tlm} = \alpha_0+\beta_1\Delta HVol_{tlm}+\beta_2\Delta FVol_{tl}+\beta_2 Dummy_l\ /\ Interval_t+\beta_3\,\mathrm{Si}\,ze_l+$$

$$\beta_4 Activity_m+\beta_5 Dummy_m\ /\ Time\ of\ day+\beta_6 Dummy_l\ /\ Trade\ Type+\epsilon_{tlm} \quad (7)$$

In order to avoid multicollinearity, four dummy variables (one each from the groups of dummies) are dropped from the estimation procedure. The interval dummy 1, the trade size dummy 1, the dummy variable for the 4^{th} trading hour and the dummy for the time gap 4 were dropped and their impact will be reflected in the intercept. Dummy variables in the model must be interpreted with respect to the dummies dropped in each group.

As suggested by results obtained by Hausman *et al.* (1992), true price innovations are heteroskedastic, one reason being the calendar time difference between one trade and another. It is suspected that, due to the mentioned reason and others, there is a time-varying conditional variance. While the coefficients are estimated by Ordinary Least Squares, the standard errors are adjusted for conditional heteroscedasticity and serial correlation using White's (1980) methodology.

Table 10: **Regression results of the price impacts**

	French securities		German securities		Italian securities	
	Buys	Sales	Buys	Sales	Buys	Sales
Intercept	*0.0511*	*-0.0497*	*0.0385*	*-0.0302*	*0.0455*	*-0.0404*
	(3.144)	(-2.981)	(2.415)	(-2.177)	(2.912)	(-2.889)
Volume (home)	*0.0047*	*-0.0041*	*0.0037*	*-0.0038*	*0.0055*	*-0.0061*
	(2.273)	(-2.216)	(2.061)	(-2.94)	(4.141)	(-4.716)
Volume (SEAQ-I)	*0.0028*	-0.0026	*0.0025*	*-0.0021*	*0.0035*	*-0.0039*
	(2.016)	(1.945)	(2.158)	(1.961)	(2.192)	(2.851)
Interval dummy 2	*0.0041*	*-0.0047*	*0.0027*	*-0.0112*	*0.0051*	*-0.0056*
	(2.294)	(-3.118)	(4.723)	(-3.868)	(6.375)	(-4.771)
Interval dummy 3	*0.0038*	*-0.0042*	*0.0021*	*-0.0019*	*0.0058*	*-0.0048*
	(2.133)	(-2.969)	(2.648)	(-2.768)	(5.341)	(-4.661)
Trade size dummy 2	*0.0109*	*-0.0167*	*0.0121*	*-0.0158*	*0.0301*	*-0.0314*
	(2.628)	(-4.128)	(2.814)	(-3.515)	(2.283)	(-2.114)
Trade size dummy 3	*0.0108*	*-0.0145*	*0.0109*	*-0.0122*	*0.0319*	*-0.0328*
	(2.039)	(-2.498)	(1.977)	(-1.992)	(2.681)	(-2.304)
Buy trades (interval)	*0.0036*	*0.0014*	*0.0023*	*0.0011*	*0.0013*	*0.0016*
	(4.345)	(2.796)	(2.818)	(1.983)	(2.054)	(2.108)
Sell trades (interval)	*-0.0024*	*-0.0015*	*-0.0022*	-0.0022	-0.0021	*-0.0034*
	(-2.673)	(-2.303)	(-2.373)	(-1.608)	(-1.444)	(-3.909)
R^2	10.92	9.12	9.51	10.96	12.72	13.82

For all large trades in cross-quoted securities, the following regression model is estimated:

$$AER_{tlm} = \alpha_0 + \beta_1 \Delta HVol_{tlm} + \beta_2 \Delta FVol_{tl} + \beta_3 Dummy_l \ / \ Interval_t + \beta_4 \, \mathrm{Si}\,ze_l$$
$$+\beta_5 Activity_m + \beta_6 Dummy_m \ / \ Time \ of \ day + \beta_7 Dummy_l \ / \ Trade \ Type + \epsilon_{tl}$$

where AER are the average excess returns calculated from interval -25 until interval +25, $\Delta HVol$ is the logarithmic change in the transacted volume in the home market from the benchmark period to each interval, $\Delta FVol_{tl}$ is the logarithmic change in the transacted volume on SEAQ-I from the benchmark period to each interval, $Dummy \ / \ Interval$ is a dummy variable to denote the intervals within the 4 hour period around the large trade, Si ze is the size of the trade on SEAQ-I, *Activity* is to the number of trades in the two hours before the large trade's execution, $Dummy \ / \ Time \ of \ day$ is a dummy variable capturing the time of the day effect, while $Dummy \ / \ Trade \ Type$ is a dummy variable to control for the type of trade (presence of put-through trades).
The t-statistics are calculated using White's (1980) standard errors.

The results from the regression model, shown in Table 10, lead to the following major conclusions:

a. As expected, transacted volume in the home market rises around the execution of the large trade on SEAQ-I market and this produces a substantial impact on the prices observed in the home markets. This result suggests that, indeed, rebalancing, or part of it, is taking place on the home markets and this accounts for the price impact observed above.

b. Transacted volume also increases on SEAQ-I around the execution of the large trade. This result implies that London market makers search for liquidity on the London market in conjunction with the pre- and post-positioning on the home markets. One major implication is that SEAQ-I is an "active market" that allows the re-balancing of part of the inventory positions through trading with counter-parties rather than just a place that has a limited role, mainly for the "book-keeping" of trades that are then entirely worked in the home markets.

c. In all three home markets, the price impact recorded over the interval period from interval -14 to interval +15 are statistically significant and this result shows that the price impact takes place slowly over these intervals and in the hypothesised direction. In some cases large buy trades carry higher impacts compared to the large sell trades but this is not a consistent phenomenon.

d. The type of trade dummy variable is statistically significant and holds the hypothesized sign implying that the price impact produced by non-paired trades is different than that of paired trades.

e. There is contrasting evidence on the trade size dummies' impact, although most of these dummy variables are statistically significant. In the case of the IE, the trade size seems to matter for both large purchase and sale trades with the price impact getting marginally bigger as the trade size gets larger. However, the difference between the price impacts does not seem to be economically significant. The same cannot be said for the French and German cross-quoted securities. Indeed the results show that the price impact for the trades included in the 36-75 NMS trade size group (the biggest trades in our sample) is slightly lower when compared to the price impact produced by the second trade size groups and this result holds for both buy and sell large trades.

f. Most of the coefficients for the time of the trading day are statistically significant and in the hypothesized direction. This implies that as the trading day's close nears, any rebalancing that takes place becomes more aggressive, causing larger price impacts towards the close. In particular, for most home markets the last trading time coefficients are larger than most of the results obtained for other trading times which could imply that pre- and post-positioning in the home markets becomes very aggressive in the final hour of trading.

g. In general, the number of large buy trades and large sell trades in the two hour interval prior to each trade seems to have an influence on the price impacts of large trades. The existence of large buy trades appear to lead to an increase in the price impact produced by a buy large trade while having a dampening effect on the price impact produced by sell large trades. The opposite effect is produced by the number of sell large trades.

2.5.4 Volatility Levels

If SEAQ-I large trades generate uncertainty in the home markets around the time when these trades are executed, then it is expected that market participants in the home markets will increase the bid-ask spreads to cover themselves from the increased risk. This behaviour is expected to be captured by the volatility tests computed for each home market.

The first investigation of the impact of large trades on home markets' volatility levels is conducted through the conventional variance ratios. We consider a sample with the same large trades employed in Section 2.4, and applying the same filter rules used before. The unconditional volatility of the interval-to-interval returns (in the home markets) during the benchmark period is obtained. Following this, the unconditional volatility of the interval-to-interval returns (in the home markets) in the one hour before and one hour after the reporting of the large trade on SEAQ-I are calculated. The two variance ratios are measured as follows:

$$Variance\ Ratio_{(\text{pre- large trade})} = \frac{\sigma^2(R_{djxl})}{\sigma^2(BR_{(d-1)ji})} \qquad (8)$$

$$Variance\ Ratio_{(\text{post- large trade})} = \frac{\sigma^2(R_{djyl})}{\sigma^2(BR_{(d-1)ji})} \qquad (9)$$

For each security j and each large trade l, the interval-to-interval returns in the hour before (denoted as period x) and the hour after (denoted as period y) the execution of the large trade on SEAQ-I are computed and the variance of these returns, $\sigma^2(R_{djxl})$ and $\sigma^2(R_{djyl})$, is then derived. This level of variance is then compared with the variance obtained for the same security j in the benchmark period, $\sigma^2(BR_{(d-1)ji})$, which is given by the corresponding four hours of trading for that security in the day previous the large London trade's execution.

Tables 11-13 show that, in general, the large trade on SEAQ-I increases the returns volatility in the hour before and after the execution of the large trades. The results also show that volatility is lower on the IBIS system which combines dealership and auction characteristics, suggesting that the *maklers* trading on the system provide a higher level of price stabilisation compared to the order book used by the Paris Bourse and the IE.

Table 11: **Variance Ratios for French cross-quoted securities around the execution of large trade**

	HOUR BEFORE	HOUR AFTER
Alcatel Alsthom	2.48*	2.36*
	(15.83)	(22.89)
AXA	1.92*	2.28*
	(9.79)	(18.42)
BNP	2.31*	2.52*
	(14.84)	(16.67)
Elf Aquitaine	2.35*	1.78*
	(16.67)	(11.72)
Paribas	3.29*	2.81*
	(23.44)	(17.22)
Peugeot	3.99*	2.25*
	(25.96)	(18.61)
Rhone-Poul.	3.40*	2.32*
	(22.85)	(16.63)
Schneider	3.24*	3.15*
	(22.85)	(26.29)
Societe General	2.81*	2.09*
	(18.79)	(18.55)
UAP	2.06*	2.18*
	(18.51)	(19.77)
ALL FRENCH	3.15*	2.68*
	(24.91)	(16.59)

The Table shows the Variance Ratio for interval-to-interval returns volatility one hour before and one hour after the large trade is reported on SEAQ-I over the interval-to-interval returns volatility during the benchmark period. The Variance Ratio for the hour before the SEAQ-I trade is calculated as:

$$Variance\ Ratio = \frac{\sigma^2(R_{djxl})}{\sigma^2(BR_{(d-1)ji})}$$

For each security j and each large trade l, interval-to-interval returns in period x (1 hour before the SEAQ-I trade) are computed and the variance of these returns, $\sigma^2(R_{jit})$, is then derived.
This variance is compared with the variance obtained for the same security j in the benchmark period.

The null hypothesis for individual securities is tested employing Lagrange Multiplier test; whereas for the whole sample the Wald Statistic is utilised. An asterisk denotes significance at the 1 % level.

Table 12: **Variance Ratios for Italian cross-quoted securities around execution of large trade**

	HOUR BEFORE	HOUR AFTER
Assicurazioni Generali	2.58*	3.54*
	(18.17)	(32.11)
BCI	3.38*	2.96*
	(22.72)	(27.38)
Benetton Group	3.78*	2.02*
	(29.98)	(21.33)
Credito Italiano	3.15*	2.67*
	(29.22)	(24.58)
FIAT	2.83*	1.91*
	(15.34)	(9.68)
Istituto San Paolo	4.49*	3.53*
	(26.18)	(28.71)
Mediobanca	3.54*	2.65*
	(28.22)	(28.08)
Olivetti	3.86*	2.77*
	(23.79)	(15.47)
STET	2.94*	1.39
	(21.47)	(9.18)
Telecom Italia	2.63*	3.82*
	(17.48)	(31.16)
ALL ITALIAN	3.68*	2.97*
	(29.86)	(25.36)

The Table shows the Variance Ratio for interval-to-interval returns volatility one hour before and one hour after the large trade is reported on SEAQ-I over the interval-to-interval returns volatility during the benchmark period. The Variance Ratio for the hour before the SEAQ-I trade is calculated as:

$$Variance\ Ratio = \frac{\sigma^2(R_{djxl})}{\sigma^2(BR_{(d-1)ji})}$$

For each security j and each large trade l, interval-to-interval returns in period x (1 hour before the SEAQ-I trade) are computed and the variance of these returns, $\sigma^2(R_{djxl})$,is then derived.
This variance is compared with the variance obtained for the same security j in the benchmark period.

The null hypothesis for individual securities is tested employing Lagrange Multiplier test; whereas for the whole sample the Wald Statistic is utilised. An asterisk denotes significance at the 1 % level.

Following the first test, we augment the sample of large trades considered in the first test in order to test whether the result holds when a larger sample of large trades is considered. For this second test, the third and fourth filter rules which were used in the event study methodology in Section 2.4.2 were applied. However, the first and second filter rules were changed so that only those large trade which occurred within less than one hour from each other are removed from the sample. In this way, a larger number of trades is captured and, thus, volatility impacts could be measured for a larger sample of trades.

The event window is found using the same technique explained in Section 2.4. However, instead of using the interval-to-interval returns, the volatility tests will use the trade-to-trade returns for the group of trades within each interval in both the event window period and the benchmark period. As is the case for the event study methodology, the volatility tests use only the trades that take place in the home markets within the event period. For each security j and each large trade l, the trade-to-trade returns in interval i placed in the event window are computed and the variance of these returns, $\sigma^2(R_{jil})$, is then derived.

The volatility level is then compared with the volatility obtained for the same security j in each interval i in the benchmark period, which is given by the corresponding four hours of trading for that security in the day previous to the large London trade execution. The trade-to-trade returns within each interval i in the benchmark period are obtained for each security j and each London large trade l and the variance of these benchmark returns, $\sigma^2(BR_{ji})$, are then obtained.

Following this, an F-test was computed in the following way:

Figure 9. Price volatility in the home markets before and after the SEAQ-I large buy trade (6-45 NMS)

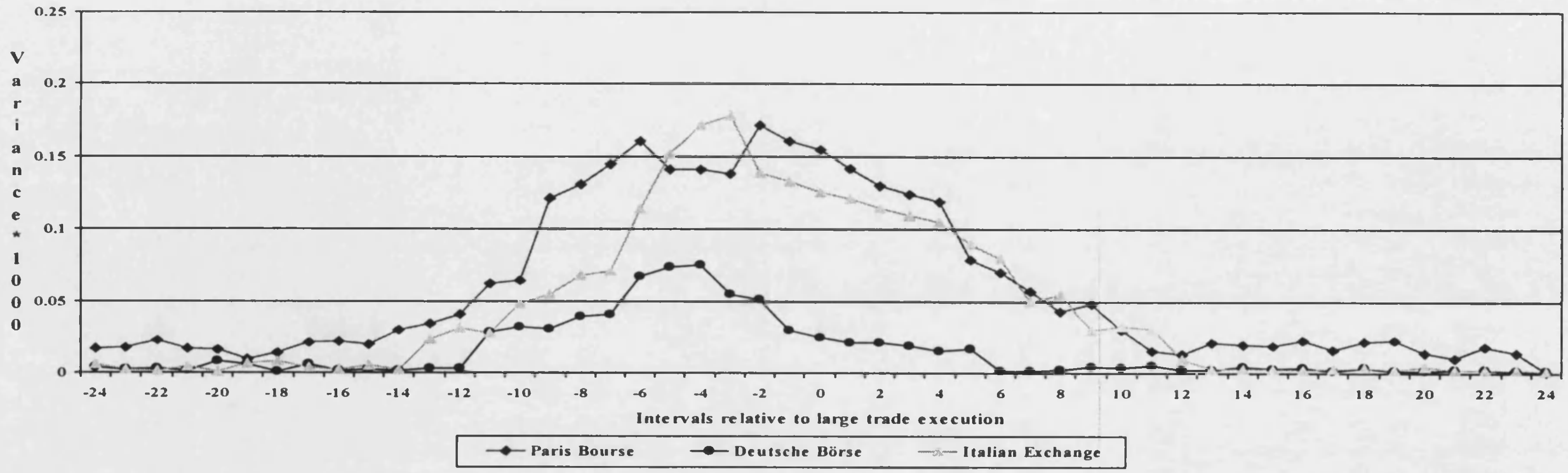


Figure 10. Price volatility in the home markets before and after the SEAQ-I large sell trade (6-45 NMS)

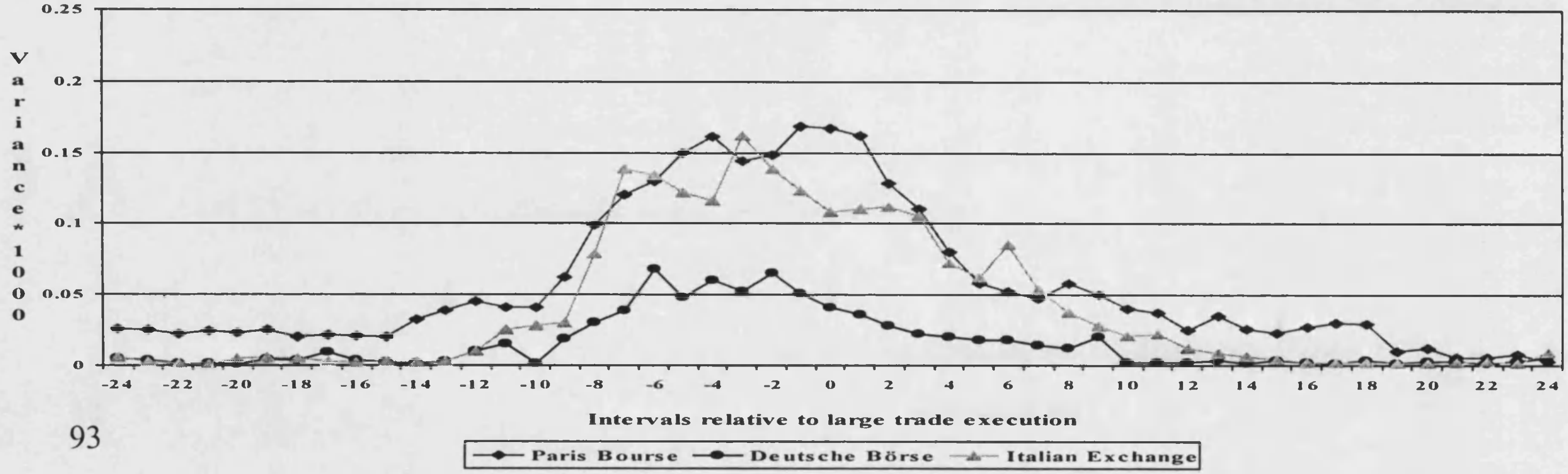


Figure 11. Price volatility in the home markets before and after the SEAQ-I large buy trade (46-75 NMS)

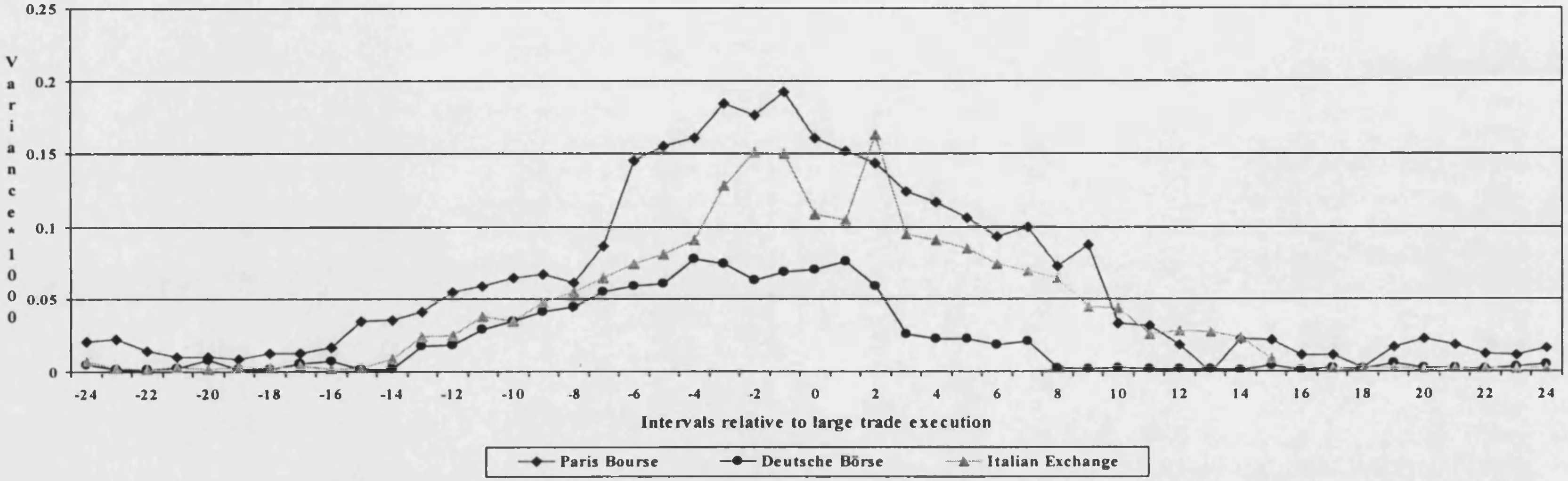
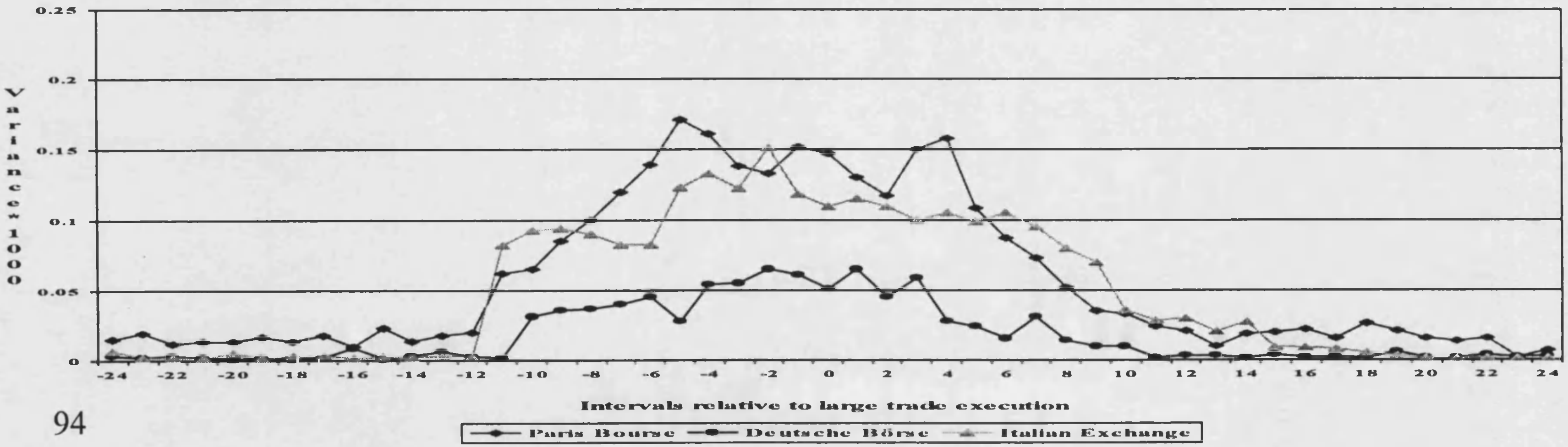


Figure 12. Price volatility in the home markets before and after the SEAQ-I large sell trade (46-75 NMS)



$$F_{jil} = \sigma^2(R_{jil})/\sigma^2(BR_{ji}) \quad (10)$$

for $i = -24..... + 23$

Figures 8-12 show that volatility is highest in the case of large trades executed for French cross-quoted securities. For both buy and sell trades within the three trade size groups, the London-executed large trades appear to induce high returns volatility for the trades within the event period executed in the same security on the Paris Bourse. Volatility is protracted over a number of intervals before and after the trade is reported as having been executed on SEAQ-I. The same pattern is noticed for the large trades for the Italian cross-quoted securities.

The volatility levels induced by London large trades on IBIS appear to be generally limited to few intervals before the large trade is actually executed on SEAQ-I. In addition, the volatility levels appear to be materially smaller than those obtained for the Paris Bourse and the IE.

The $F - test$ analysis shows that the increase in the returns volatility levels for the cross-quoted securities traded on both the Paris Bourse and the IE around the execution of the large trades on SEAQ-I is statistically significant and spans a number of time intervals. The F-test also indicates that the increase in returns volatility for the cross-quoted securities traded on the IBIS system is limited to few time intervals, generally to the time intervals before the trade is reported as executed.

To test hypothesis 5, volatility in auction markets is compared with volatility in the hybrid market using the following model:

$$Volat_{ji} = \alpha_0 + \beta_1 \cdot Mar_{ji} + \beta_2 MCap_j + \beta_3 BE/ME_{ji} + \beta_4 Vol_{ji-1} + \sum_{k=1}^{N} \beta_5 DT_{j,t} + \varepsilon_{ji} \quad (11)$$

Table 13: **Variance Ratios around the execution of large trades of French cross-quoted securities**

	LARGE BUY TRADES		LARGE SELL TRADES	
Interval	Trade Size 1	TradeSize 2	Trade Size 1	Trade Size 2
-9	1.86*	2.02*	2.01*	2.35*
-8	2.04*	2.26*	2.16*	2.75*
-7	2.28*	2.41*	2.26*	2.73*
-6	2.56*	2.62*	2.83*	2.82*
-5	2.68*	2.86*	2.97*	3.04*
-4	2.76*	2.98*	3.07*	3.14*
-3	2.82*	3.02*	3.14*	3.21*
-2	2.88*	3.04*	3.30*	3.38*
-1	3.01*	3.28*	3.57*	3.66*
0	3.08*	3.24*	3.52*	3.61*
1	3.15*	3.37*	3.68*	3.77*
2	3.36*	3.45*	3.77*	3.87*
3	3.42*	3.52*	3.84*	3.94*
4	3.44*	3.54*	3.86*	3.97*
5	3.39*	3.49*	3.81*	3.91*
6	3.36*	3.45*	3.77*	3.87*
7	3.38*	3.48*	3.79*	3.89*
8	3.16*	3.25*	3.53*	3.63*
9	3.06*	3.14*	3.42*	3.51*

The Table shows the Variance Ratio for trade-to-trade returns volatility around the time when the large trade is reported as executed on SEAQ-I over the trade returns volatility during the benchmark period. The Variance Ratio, calculated in the home markets, is measured as:

$$F_{jil} = \sigma^2(R_{jil})/\sigma^2(BR_{ji})$$

For each security j and each large trade l, trade-to-trade returns in interval i is obtained and the variance of these returns, $\sigma^2(R_{jil})$, is then derived. This variance is compared with the variance obtained for the same security j in the benchmark period.
Large trades are classified in (a) Size 1 (trade sizes of 6-45 NMS), and (b) Size 2 (trade sizes of 46-75 NMS).
An asterisk denotes significance at the 1 % level.

Table 14: **Variance Ratios around the execution of large trades of German cross-quoted securities**

	LARGE BUY TRADES		LARGE SELL TRADES	
Interval	Trade Size 1	Trade Size 2	Trade Size 1	Trade Size 2
-9	1.61	1.68	1.62	1.62
-8	1.62	1.61	1.66	1.63
-7	1.74*	1.76*	1.74*	1.92*
-6	1.89*	1.92*	1.96*	2.04*
-5	1.96*	2.12*	2.05*	2.21*
-4	2.04*	2.14*	2.15*	2.36*
-3	2.14*	2.32*	2.26*	2.41*
-2	2.25*	2.46*	2.37*	2.37*
-1	2.36*	2.51*	2.42*	2.59*
0	2.42*	2.56*	2.47*	2.64*
1	2.66*	2.69*	2.59*	2.72*
2	2.68*	2.72*	2.69*	2.68*
3	2.59*	2.75*	2.72*	2.74*
4	2.29*	2.67*	2.71*	2.72*
5	2.16*	2.43*	2.52*	2.66*
6	2.02*	2.28*	2.48*	2.54*
7	1.91*	2.02*	2.29*	2.26*
8	1.73*	1.83*	2.07*	2.09*
9	1.65	1.75*	1.78*	1.96*

The Table shows the Variance Ratio for trade-to-trade returns volatility around the time when the large trade is reported as executed on SEAQ-I over the trade returns volatility during the benchmark period. The Variance Ratio, calculated in the home markets, is measured as:

$$F_{jil} = \sigma^2(R_{jil})/\sigma^2(BR_{ji})$$

For each security j and each large trade l, trade-to-trade returns in interval i is obtained and the variance of these returns, $\sigma^2(R_{jil})$, is then derived. This variance is compared with the variance obtained for the same security j in the benchmark period.

Large trades are classified in (a) Size 1 (trade sizes of 6-45 NMS), and (b) Size 2 (trade sizes of 46-75 NMS).

An asterisk denotes significance at the 1 % level.

Table 15: **Variance Ratios around the execution of large trades of Italian cross-quoted securities**

	LARGE BUY TRADES		LARGE SELL TRADES	
Interval	Trade Size 1	Trade Size 2	Trade Size 1	Trade Size 2
-9	2.49*	2.52*	2.92*	2.97*
-8	2.58*	2.61*	3.03*	3.09*
-7	2.56*	2.59*	3.01*	3.06*
-6	2.71*	2.75*	3.21*	3.26*
-5	2.84*	2.88*	3.37*	3.43*
-4	2.93*	2.97*	3.48*	3.55*
-3	2.98*	3.04*	3.57*	3.64*
-2	3.15*	3.21*	3.77*	3.84*
-1	3.41*	3.45*	4.09*	4.17*
0	3.36*	3.41*	4.03*	4.12*
1	3.52*	3.55*	4.22*	4.31*
2	3.59*	3.64*	4.33*	4.42*
3	3.66*	3.71*	4.42*	4.51*
4	3.68*	3.73*	4.44*	4.54*
5	3.62*	3.68*	4.37*	4.46*
6	3.59*	3.64*	4.32*	4.42*
7	3.61*	3.67*	4.36*	4.45*
8	3.37*	3.42*	4.05*	4.13*
9	3.26*	3.31*	3.91*	3.98*

The Table shows the Variance Ratio for trade-to-trade returns volatility around the time when the large trade is reported as executed on SEAQ-I over the trade returns volatility during the benchmark period. The Variance Ratio, calculated in the home markets, is measured as:

$$F_{jil} = \sigma^2(R_{jil})/\sigma^2(BR_{ji})$$

For each security j and each large trade l, trade-to-trade returns in interval i is obtained and the variance of these returns, $\sigma^2(R_{jil})$, is then derived. This variance is compared with the variance obtained for the same security j in the benchmark period.

Large trades are classified in (a) Size 1 (trade sizes of 6-45 NMS), and (b) Size 2 (trade sizes of 46-75 NMS).

An asterisk denotes significance at the 1 % level.

for $i = -24.....+24$ and where Mar_{ji} is a dummy variable which takes the value of 1 if the trade takes place on IBIS and 0 if the trade is executed on either the Paris Bourse or the IE; $MCap$ is the log of the firm's capitalisation (in £ to create a common measure through the different markets) in January 1996; BE/ME is the ratio of the book to market for each firm measured in January 1996; Vol is the log of the volume (in number of shares) in interval $i-1$; and DT is the time of the day dummy variable. This regression model is chosen in order to test whether the market design has any impact on the price volatility generated by large trade while controlling for (a) firm characteristics; (b) trading activity in the market; and (c) time of the day effects that have been found in empirical literature to influence volatility measures during the trading day.

It is expected that if returns volatility is lower on IBIS, β_1 should have a negative sign. The estimation results show that β_1 = -0.0716 with a t-statistic of 2.88 implying that volatility is significantly lower on IBIS compared to the Paris Bourse and the IE. Hence, hypothesis 5 cannot be accepted.

These results have important implications in relation to the optimal design of markets. It is found that a trading platform that allows a substantial intervention of market makers produces a more orderly market when a large order is placed in the marketplace. The potential impact and the uncertainty associated with such orders could be quite high and this could damage the market's quality, generating more inefficient prices and can decrease traders' participation in the market, leading to lower volumes transacted.

2.6 Conclusions

This Chapter investigated the impacts produced by block trades in cross-quoted securities in an inter-market set-up, with different trading systems in operation in the home and foreign markets.

The large trades executed on SEAQ-I produce a permanent impact on the price levels obtained in the home markets with the impact being larger in the case of continuous auction systems (the Paris Bourse and IE) and lower in a trading system that combines auction and dealership characteristics (IBIS).

The results obtained from both the event-study methodology and the regression model show that the price impact in each home market takes place in a protracted fashion rather than as a one-shot phenomenon. Moreover, the price impact starts manifesting itself in the home markets some time before the trade is actually reported as executed on the foreign market. This implies that there are information leakages that occur before the trade is executed, possibly due to market makers' pre-positioning strategies in the home markets.

Another result worth noticing is that there is sufficient time after the trade's execution over which trading profits (before charging transaction costs) can be made by market participants who are aware of the existence of the large trade before the trade information is published. Hence, hypotheses 1 and 2 are both rejected.

The permanent price impacts show that such impacts are not increasing in trade size. This implies either that the information contained in the very large trades is actually lower than that contained in (large) trades of relatively smaller size (possibly implying that very large trades are generally executed by liquidity traders who can credibly signal their true trading motivation) or that pre- and post-trade positioning for the very large trades is not as aggressive as for block trades of smaller sizes. This means that hypothesis 3 cannot be rejected.

The price impact is implemented by the time the LSE publishes the trade information, indicating that any asymmetric information that arises from a large trade is fully utilised by market participants, at least those aware of the large trade, before the relevant trade information is published. This evidence could be interpreted in a slightly different way - market participants aware of the large trade take advantage of the 1 hour publication delay on the LSE and trade on this information either for inventory or for profit motives. This leads us not to reject hypothesis 4.

Finally, volatility tests computed for the three home markets demonstrate that the returns volatility around the time when a block trade is executed is higher in home markets that use continuous auction trading systems compared to the returns volatility found in a hybrid system that contains substantial dealership characteristics. Hence, hypothesis 5 is not accepted.

This result implies that, as hypothesized by Madhavan (1992), the strategic behaviour of market participants, mainly limit order traders, present in the continuous auction markets produce higher levels of returns volatility, following a trading shock such as a large order, compared to the volatility actually generated in a trading system that provides dealership liquidity. From a policy-making point of view, this is an important issue because it sheds light on the optimal design of markets and the impact that trading mechanisms have on orderly markets.

Chapter 3. Spreads and Their Components

3.1 Introduction

In the recent past we have witnessed a wide-ranging debate among market practitioners, regulators and academics regarding the benefits of screen-based trading systems and automated order execution systems together with the appropriate role of mandatory (or voluntary) dealers in such markets. While major markets have introduced or enhanced screen-based trading, there has been a re-appraisal of dealers' contributions towards improving liquidity provision and market quality.

A very important issue related to this debate is the level and evolution of trading costs in different market microstructures. The spread paid by traders is important to the entire gamut of investors: small traders' costs have come under close scrutiny from regulators while they can also impact on the profitability of portfolio managers' positions. Furthermore, these trading costs directly reflect the level of frictions in financial markets and it is important to investigate the sources of these frictions.

Some of the most important reforms undertaken by Exchanges have focused on decreasing trading costs. But the success of these reforms depends heavily to our ability to understand the different sources of these frictions.

The major purpose of this Chapter is exploring the possible links between the mark-up charged by the suppliers of liquidity in different markets - the bid-ask spread - and market structures. This analysis is carried out through an empirical investigation of the trading costs (both quoted and effective spreads) in a multiple dealer market set-up (London Stock Exchange's SEAQ system), a pure limit order book market set-up (Paris Bourse's CAC system) and a screen-based hybrid trading system (Deutsche Börse's IBIS platform). These three systems differ in terms of information dissemination (pre- and post-trade transparency), level of competition, cost structures and institutional design.

But should different market microstructures influence the levels and formation of the spreads? Existing literature, making use of the differences between the "traditional" dealership versus auction systems, provides a positive answer. It is because of this reason that hybrid trading systems are getting more attention and their attributes, in terms of liquidity provision, price formation and spread levels are being investigated.

Viswanathan and Wang (1998) provide a theoretical background for the comparison between the different trading systems ((i) dealership, (ii) limit order book, and (iii) hybrid) through a welfare comparison of the different market structures. They make use of the trade-off between the bid reduction effect (that takes place in both the auction and the dealership markets but in opposing directions as the trade size increases) and the zero-quantity spread to show that a risk-neutral customer would choose an auction system when the number of market makers is low and the variability of the trade size is low. The dealership system is chosen by a risk-averse customer when the number of market makers is large and the variability of the trade size is high.

They show that a hybrid structure, an environment where trades smaller than an exogenously fixed level are channelled to the limit order book while bigger sizes are submitted to a dealership mechanism, dominates the pure dealership system wherever this type of architecture is found to improve on the auction system. The main conclusion is that "when the cutoff point (in terms of trade size) is chosen appropriately, the hybrid limit-order book/dealership market generates higher trading profits for the customer than the pure dealership market" (Viswanathan and Wang, 1998).

The issue relating to the level of execution costs is receiving substantial attention both from academics and regulators. NASDAQ has undergone through a number of reforms, aimed at increasing competition and reducing transaction costs. Barclay *et al.* (1997) find that trading costs on NASDAQ fell after the reforms. The same appears to have happened for the execution of small orders on the LSE since the introduction of the limit order book in October 1997, although spreads at the open have widened (Naik and Yadav, 1999).

In view of these developments, this Chapter analyses the absolute levels and the components of the bid-ask spread developing in different systems, considering, for the first time, two screen-based systems that differ in terms of the interaction between public traders and designated dealers. Another interesting issue considered here is whether the level of dealers competition and their market power can contribute towards our understanding of trading costs.

In order to carry out a meaningful analysis, comparable orders must be found across the three different trading systems. Due to different institutional designs, it is likely that orders submitted to the different systems would have different sizes. This complicates our analysis since a comparison of trading costs can only be carried out while keeping order size constant. In view of this, we use the Normal Market Size (defined as 2.5 % of average daily volume transacted in the previous three months on each market) measure to standardise order sizes. The comparisons will be drawn on order within the same NMS size brackets.

This Chapter is structured as follows. Section 2 reviews the theoretical and empirical literature on spread formation and spread components. Section 3 presents the data and the methodology used for the analysis. Sections 4 and 5 present the results for quoted and effective spreads on competing market microstructures with Section 6 providing the results for the decomposition of the spread.

3.2 Literature Review

3.2.1 Real Resources

Following Bagehot (1971), the bid-ask spread can be decomposed into two major segments. The first part is represented by the monopoly power, the order processing costs and inventory costs sustained by market makers in the course of their business. The second segment refers to the presence of asymmetric information in the market that leads market makers to set prices in a way to protect themselves from the presence of traders with superior information. Stoll (1978b), Amihud and Mendelson (1980), Ho and Stoll (1981), Ho and Macris (1985) and Laux (1995) have modelled the trading friction as being due to the real resources incurred in the process of executing orders. Copeland and Galai (1983) and Glosten and Milgrom (1985) have focused on the adverse information part.

Suppliers of immediacy require real economic resources to execute orders submitted to the marker and then to settle trades once executed. The expenses incurred - to get capital and labour - must be covered by the final customers. Besides these operational expenses, liquidity suppliers sometimes deviate from their optimal inventory policy so as to provide immediacy whenever it is required. This inventory risk must be compensated. Finally, the dealers' market power is one of the possible contributors to market frictions since such agents can use their power to widen the spread relative to their costs.

In particular, Ho and Macris (1985) use the dealers' collective ability to adjust inventory levels, arguing that market depth is increasing in the number of dealers present on the market. This benefit, however, is achieved at a cost represented by wider bid-ask spreads. A multiple dealer market set-up enhances the collective ability to absorb imbalances in inventory levels while competition limits the individual power of each dealer on the bid-ask quotes. In this set-up, transaction of large orders is facilitated but the community of dealers will pay higher costs for carrying more inventory.

Ho and Macris also argue that dealers' fixed costs, such as the opportunity costs of dealers' time, increase proportionately with the number of dealers on the market. These higher fixed and inventory costs are expected to translate into wider bid-ask spreads in dealership markets.

3.2.2 Information in the Market

Another view of the spread is based on trade information that exists in the market to explain why market makers set wide bid-ask spreads. This approach can be divided into two branches: (a) one based on the free trading option, and (b) the other based on the presence of asymmetric information. Copeland and Galai (1983) models the first approach while Easley and O'Hara (1987), Glosten and Milgrom (1985) and Glosten (1989, 1994) model the second approach.

Suppliers of immediacy provide free options to traders and their position becomes more difficult at times when the arrival of information is intense. Because posting and adjusting/removing quotes takes time, suppliers of immediacy can suffer at times when new information hits the market since informed traders can "pick off" these quotes. In such a scenario, if dealers (or limit order traders) are not fast enough in adjusting existing quotes they will lose out. In view of this, the spread exists to compensate suppliers of immediacy for the option they grant to the rest of the market.

The second branch is based on the presence of asymmetric information.

Dealers face the danger that their firm quotes will be accepted by traders with superior information. Market makers are aware that there are investors with superior information and they widen the spread in order to offset the losses they incur when trading with informed traders. In other words, the adverse selection component is the reward paid to market makers for providing liquidity when there is the risk of trading with superior informed traders. In equilibrium, the spread has to cover these possible losses.

Continuing in this vein, Glosten (1989) argues that, due to adverse selection, cross-subsidisation between different types of trades will occur. The market maker is expected to lose out to informed traders and tries to recover this lost revenue by earning excessive profits from liquidity-motivated traders. The question that arises relates to the type of market microstructure that is most likely to be effective in protecting traders against the presence of adverse selection.

One possible approach is to classify markets on the "centralised - fragmented" continuum, depending on whether orders submitted to the market are channelled to one location or whether they are submitted to different dealers who do not share trading information amongst themselves. Dealership markets, such as the telephone broking system in operation on the LSE, NASDAQ, the foreign exchange markets and the Treasury bond markets are classified as fragmented markets since trading occurs through bilateral negotiation, whereas the New York Stock Exchange (NYSE) in the USA and the Cotation Assistée en Continu (CAC) system used by the Paris Bourse are classified as centralised markets.

The underlying difference between the two market set-ups refers to market participants' ability to view the order flow and the price discovery process. In centralised markets, information about the (i) order flow, (ii) bidding by other market participants, and (iii) trades and volumes executed is readily available given that pre-trade transparency is higher in a centralised market.

In this sense, the dealers' information set in centralised markets is richer than the corresponding sets of market makers in fragmented dealership markets. Hence, centralised markets are expected to deal more effectively with private information. In view of this, the adverse selection component of the spread should be lower in centralised markets compared to fragmented systems.

Rock (1991) provides a further extension, using the specialist structure employed by the NYSE to show that the specialist has two alternatives for trading - either to take up the order himself or let it trade against the limit orders submitted to the market. This flexibility is expected to limit the specialist's losses due to adverse selection. On the other hand, Benveniste, Marcus and Wilhelm (1992) show how the specialist could have enough power to discipline informed traders leading to a reduction of the losses suffered by the market makers community from adverse selection.

However, Biais (1993), modelling the fragmented market similarly to a Dutch auction (sealed bid) and the centralised market along the vein of Ho and Stoll (1983), shows that the expected bid-ask spread in a fragmented market is expected to be the same as the spread generated by a centralised market, achieving the irrelevancy argument. What differs between the two markets is the volatility of the spread whereby volatility is expected to be higher in the centralised market.

3.2.3 Trading Practices

A useful extension to these arguments is provided by considering the trading practices, mainly the practice of preferencing, internalisation and collusion, existing in different markets. Preferencing is a trade practice whereby an order is directed to a market maker not posting the best quotes but, because of best execution arrangements, provides an assurance that the order will be executed at the best quoted price in the market.

Internalisation occurs when a broker routes his order flow to the market maker belonging to the same firm. Both the LSE and NASDAQ allow the practices of preferencing and best execution of the order flow. "Soft dollar" arrangements (which provide an incentive for internalisation) are not illegal. Such arrangements are less likely to take place in screen-based systems.

These arrangements are expected to have a material impact on how market makers deal with adverse selection. Preferencing and internalisation imply that a long-term business relationship is built between the trader (especially the institutional investor) and the market maker in a way that the latter should, adopting the Huang and Stoll (1996) terminology, "know their order flow". This means that market makers know their clients well enough that they can extract information from the order flow submitted to them, thus being able to effectively protect themselves from adverse selection.

According to Battalio and Holden (1996), Kandel and Marx (1996) and Dutta and Madhavan (1997), preferencing and arrangements of best execution go against Bertrand competition since the order flow is rendered insensitive to quote changes. Under these circumstances, there are low incentives to engage into aggressive quote revisions since posting better quotes will not necessarily increase the order flow to the market maker posting the best quotes. The expected outcomes are (a) wider bid-ask spreads, (b) worse execution quality, and (c) higher market maker profits being generated.

The possibility of collusion between market makers must also be investigated further, given the evidence of Christie and Schultz (1994) in relation to implicit collusion among NASDAQ market makers.

Preferenced order flow can only lead to better execution if trades occur within the best quotes; this is what normally happens when trade negotiation takes place. In turn, it is likely that negotiation occurs for larger trades, submitted by institutional investors, rather than for small orders. In line with Harris (1993) and Grossman *et al.* (1997), this feature of dealership markets can account for the differential treatment of small and larger orders, also found for SEAQ trades. However, negotiation within the spreads is not a costless activity since it normally involves searching costs for the dealer who is able to provide the best execution terms (Harris 1993 and Grossman *et al.* 1997). In view of this, a trader who wants immediacy but no searching costs will decide in favour of preferencing his order flow but the quality of execution is expected to be worse than that obtained by a patient trader who is willing to search for the best quotes submitted by dealers.

On their part, Rhodes-Kropf (1997) show that negotiation leads to wide spreads since dealers know that there will be an amount of negotiation taking place and prices will be improved from the wide spreads. It is expected that negotiation is more likely to take place for certain traders, especially larger ones. The model shows that wider spreads will obtain for those traders who cannot negotiate and a differential treatment of orders on the same market.

3.2.4 Empirical Evidence

Empirical research has provided useful insights how various trading behaviours and incentives influence the spread and its formation. Huang and Stoll (1996) use 175 paired securities on NASDAQ and NYSE and show that quoted spreads, effective half spreads and perfect foresight spreads are wider for the paired securities trading on NASDAQ compared to NYSE.

One possible explanation for such a result can be that the NASDAQ market does not protect effectively against the presence of adverse selection.

However, Huang and Stoll found that (a) realised half spreads are still higher on NASDAQ compared to NYSE; and (b) adverse selection component of the effective half spread is effectively bigger on NYSE than on NASDAQ. These results imply that adverse selection is not an appropriate explanation why bid-ask spreads are wider on NASDAQ compared to NYSE.

The reforms implemented in NASDAQ, in January 1997, were aimed at enforcing mandatory display of customer limit orders leading to more competitive quotes. According to the new rules (imposed by the Securities and Exchange Commission), when a NASDAQ dealer receives a customer limit order he has four alternative ways to transact the order: (a) use his inventory to accommodate the order; (b) send the order to another dealer for execution; (c) push the order through a proprietary trading system; or (d) post the order through the system by specifying the quote price and the quote size.

Barclay *et al.* (1997) find that the rule change, allowing wider scope for limit orders to be submitted to the market, narrowed the quoted and effective spreads by some 30% from the pre-reform trading. The biggest drop in transaction costs were actually registered for the widest spreads. The narrowing of the spread was not obtained at the cost of a lower liquidity; in fact, market depth was not materially affected after the rule change.

Naik and Yadav (1999) investigate the impact of the reforms carried out by the LSE after October 1997 when the FTSE-100 securities started trading on the order book system called SETS. They show that, although SETS had only attracted about 20%-30% of public trades, there was an appreciable impact on the spreads for these securities. When the first hour of trading is excluded (spreads in the opening hour widened appreciably after SETS's introduction), the average effective spread decreased significantly from the period when FTSE-100 securities were traded exclusively in a dealership system (1996 and 1994). These results confirm those obtained for NASDAQ after the reforms enacted in January 1997.

Besides the literature based on spread's behaviour following system changes, there is also some work based on preferencing's impact on execution terms. Hansch *et al.* (1998) provide empirical evidence of the profitability of trading practices practiced by market makers on SEAQ and their impact on the quality of execution. They found that preferenced trades face worse execution terms than non-preferenced trades without market makers executing the preferenced order flow realising higher trading profits.

Some branches of the literature have investigated the interactions between market orders and limit orders in centralised markets. One such study is by Biais, Hillion and Spatt (1995) on the Paris Bourse who found that (a) large market orders (by Paris Bourse levels; such orders are larger than the depth at the quotes submitted) are only partially executed; (b) the remaining part of the market order which is unexecuted is converted into a limit order; (c) following a market order coming on the market, there is a high probability that the next order will come in to provide liquidity to the market order; (d) the evidence shows that substantial monitoring from outside the book, on the state of affairs in the book, takes place with traders investigating and waiting for advantageous trading opportunities to submit their orders. Most of the order flow is placed at or inside the bid-ask quote, with a large part of the order placements improving upon the best quotes in the market. These improvements on each side of the market occur in quick succession, reflecting the competition in the supply of liquidity. The authors argue that this result is due to the tradeoff faced by traders in such cases: when the market is already deep, the only way for orders to execute is for traders to undercut the existing quotes, creating competition on that side of the market.

Biais *et al.* (1995) also find that "after large sales (purchases), which consume liquidity at the quote and thus induce a decrease in the bid (increase the ask), there is often a new sell (buy) order placed within the quotes, which generates a decrease in the best ask (increase the best bid) and reflects the adjustment in the market expectation to the information content of the trade." (Biais *et al.,* 1995)

3.3 Hypotheses

The hypotheses to be tested in this Chapter deal with, on one hand, the absolute level of the bid-ask spreads in the three different market systems and, on the other, the adverse selection components of the spread.

Hypothesis 1_O: By facilitating the matching of buy and sell orders without the need of the intervention from a market maker and allowing the submission of public orders that increase competition, both IBIS and CAC will produce lower bid-ask spreads compared to SEAQ.

Hypothesis 2_O: Since both IBIS and CAC allow public traders to submit competing orders to compete with designated dealers, the two systems should produce spreads that are not statistically different from one another.

Hypothesis 2_O draws on theoretical and empirical work, reviewed above, which shows that allowing different traders to compete with each other is expected to increase competition for the order flow and reducing the bid-ask spread on screen-based systems. As far as total operational costs are concerned, screen-based systems are perceived to be more cost-effective compared to dealership markets. The former leave investors (both the public and market members) the freedom to trade against each other without the presence of an intermediary, leading to a reduction of execution costs.

In addition, limit orders are intrinsically different than market orders (the only type submitted in a dealership market). Limit orders are price-contingent orders that have to be priced aggressively otherwise they become stale and run the risk of being 'picked off'. This outcome is particularly true when market conditions change fast.

The arguments used for Hypothesis 2_O are an extension of the arguments mentioned above. If, as it has emerged from previous studies, an auction system has the ability to reduce transaction costs mainly due to its trading architecture based on limit orders submitted to the order book, than IBIS should produce bid-ask spreads that are not statistically significantly different from those on CAC.

Hypothesis 3_O: Given that screen-based systems centrally collect all available information used by market participants, it is expected that such an arrangement will provide better protection to liquidity suppliers from traders who possess superior trade information. This should reduce the adverse selection component of the bid-ask spread in auction systems compared to dealership markets. Hence, the adverse selection component of SEAQ trades must be higher than for IBIS and CAC trades.

Hypothesis 3_A: The trading relationships between market makers and their customers together with the trading practices on dealership markets, such as preferencing and internalisation, allow market makers to extract information from their order flow. In this way, they can more easily separate liquidity-oriented from information-oriented traders. Hence, it is expected that the adverse selection component for IBIS and CAC trades will be bigger than for SEAQ trades.

3.4 Methodology and Data

3.4.1 Methodology

A natural sample for such a comparison would be the cross-quoted securities across European exchanges. De Jong *et al.* (1993) compare bid-ask spreads for French securities cross-quoted on the Paris Bourse and SEAQ-I. Their study uses data from 1991, at a time when quoted spreads on SEAQ-I were firm and London market makers were committing substantial capital to make markets in such securities.

These arrangements appear to have changed and spreads on SEAQ-I now only serve for advertising purposes with firm quotes available after contacting directly the market maker. This makes the publicly disseminated quotes data very unreliable. Other well-documented problems include trade reporting for securities listed on London's SEAQ-I (Jacquillat and Gresse 1995, Pagano and Steil 1995). In view of these problems, it was decided to ignore cross-quoted securities and match securities on the different Exchanges on a different basis.

There are a number of alternative pairing technologies which can be devised. For example, the one used by Booth *et al.* (1995) is based on pairing securities between IBIS, the Frankfurt Stock Exchange and NASDAQ was based on the level of transacted volume for individual securities. Although this pairing exercise provides some advantages, chief amongst them is the ease of devising the paired sample, it ignores the possible impact of individual firm characteristics, such as the sector, size, growth prospects etc., on the bid-ask spread which could damage the pairing process.

Considering these constraints, we must identify a number of proxies for securities' risk across different markets in order to pair securities in a meaningful way. The pairing exercise is considered to be fundamental for our purpose, in that securities with similar risk characteristics across different trading systems must be chosen to effectively control for the impact of a number of firm-specific characteristics together with institutional differences, on the bid-ask spreads.

One possible starting point is the application of the Fama-French (1992) framework, whereby securities are paired based on firm characteristics, such as book-to-market and market capitalisation. However, such a framework can be perceived as restrictive when applied in a cross-country and cross-system environment. In view of this, the Heston *et al.* (1998) framework for European securities must be closely considered.

Hence, the major objective here is to devise a paired sample based on similar risk characteristics leaving institutional differences to explain the differences between the bid-ask spreads registered for the different markets. We employ the Fama and French (1992) and the Heston *et al.* (1998) to pair securities across markets. Appendix B reviews the Fama and French (1992) and the Heston *et al.* (1998) methodologies.

The first pairing exercise is based on the Fama-French (1992) framework and takes into consideration three major factors. First, paired securities across markets must be in the same industrial sector. Secondly, the securities were paired so as to minimise the "book-to market" values (Book Equity/Market Equity) and "size" (Market Equity) premiums differences across the exchanges.

The statistics used are those obtained for December 1995. Pairs were deleted if

$$\left| \frac{BE/ME_{sk} - BE/ME_{tj}}{(BE/ME_{sk} + BE/ME_{tj})\ /\ 2} \right| \geq 0.40$$

or

$$\left| \frac{ME_{sk} - ME_{tj}}{(ME_{sk} + ME_{tj}) \ / \ 2} \right| \geq 0.40$$

where the subscripts sk and tj refers to security s trading on market k and security t trading on market j.

This deletion process is undertaken to avoid pairs with securities listed in the same industrial sector but having value and size premia far apart from each other, making the spread analysis very difficult.

Having carried out the first pairing exercise, the second one is implemented based on the Heston *et al.* (1998) framework. The first condition is that paired securities must be in the same industrial sector. Following this condition, pairing took place in terms of minimising the Beta and ME differences across securities trading on different systems. Pairs in the second exercise were deleted if

$$\left| \frac{Beta_{sk} - Beta_{tj}}{(Beta_{sk} + Beta_{tj}) \ / \ 2} \right| \geq 0.40$$

or

$$\left| \frac{ME_{sk} - ME_{tj}}{(ME_{sk} + ME_{tj}) \ / \ 2} \right| \geq 0.40$$

where the subscripts have the same meanings as in the first pairing exercise.

These pairing exercises are similar, but not identical, to the Huang and Stoll (1996) methodology used to pair securities from the NYSE and NASDAQ. The methodology used for this study does not merely attempt to minimise differences between different factors but imposes a ceiling for these differences. The two pairing exercises were run and there were no major differences neither in terms of the companies nor in the results obtained. In view of these similarities, we reproduce the results obtained from the second pairing exercise.

The pairing exercises are done at two different levels to capture different security samples. First, SEAQ securities were paired with CAC securities and IBIS securities. This pairing exercise produces the sample of securities used for the SEAQ-CAC and SEAQ-IBIS comparisons. Hence, we have the samples of securities for the "Dealership-Limit Order Book" (henceforth "D-B") and the "Dealership-Hybrid" (henceforth "D-H") comparisons.

Following this, the second pairing exercise was undertaken whereby IBIS securities were paired with CAC securities for the "Limit Order Book-Hybrid" (henceforth "B-H") comparison.

Tables 16 and 17 provide the characteristics of the D-B and D-H matched samples, dividing the samples according to firms' size. The whole list of matched securities is provided in Appendix C. Tables 16, 17 and 18 show that the matched securities have ME/BE and ME characteristics very similar to each other.

In general, the market capitalisation of SEAQ securities is larger than for CAC securities whereas the BE/ME magnitude of CAC securities is marginally higher than that of SEAQ securities. As regards the D-H matched sample, Table 17 shows that SEAQ securities, with the exception of the smaller firms, have a lower market capitalisation but a larger ME/BE ratio compared to IBIS securities. Beta for the matched samples are also similar.

The major difference between the matched samples that arises from Tables 16 and 18 is the share price level. The share prices of SEAQ securities are materially lower when compared to the share prices of CAC and IBIS securities (in £, using the share price in the respective currencies and the sterling exchange rate as at the end of 29 December 1995).

When this difference was investigated further, it was found that the number of outstanding shares is much higher for SEAQ securities compared to

Table 16: **Firms' characteristics of SEAQ-CAC paired securities**

PANEL A: SEAQ SECURITIES PAIRED WITH CAC SECURITIES

	Market Cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,162.04	2.207	0.71	2.95
Portfolio II	3,321.99	2.468	0.81	4.24
Portfolio III	12,062.87	1.988	0.86	5.15

PANEL B: CAC SECURITIES PAIRED WITH SEAQ SECURITIES

	Market Cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,026.57	2.485	0.80	36.17
Portfolio II	3,599.02	3.203	0.92	38.43
Portfolio III	9,515.36	2.192	0.96	56.76

The three firm capitalisation categories were obtained on the basis of the firm's market capitalisation as at the end of December 1995. Portfolio I contains firms with market capitalisation of less than £2,500m; Portfolio II contains firms with capitalisation larger than £2,500m but lower than £5,000m; while Portfolio III has firms with a capitalisation larger than £5,000m.

Market capitalisation, ME/BE, beta and price were extracted from Datastream and refer to values obtained at the end of December 1995. Reported statistics refer to mean values.

Table 17: **Firms' characteristics of SEAQ-IBIS paired securities**

PANEL A: SEAQ SECURITIES PAIRED WITH IBIS SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,918.67	1.987	0.85	2.56
Portfolio II	3,493.10	2.316	0.83	4.91
Portfolio III	12,711.94	2.932	0.96	6.72

PANEL B: IBIS SECURITIES PAIRED WITH SEAQ SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,495.26	2.011	0.94	83.74
Portfolio II	3,033.65	1.955	0.92	92.08
Portfolio III	15,228.97	2.606	1.05	149.51

The three firm capitalisation categories were obtained on the basis of the firm's market capitalisation as at the end of December 1995. Portfolio I contains firms with market capitalisation of less than £2,500m; Portfolio II contains firms with capitalisation larger than £2,500m but lower than £5,000m; while Portfolio III has firms with a capitalisation larger than £5,000m.

Market capitalisation, ME/BE, beta and price were extracted from Datastream and refer to values obtained at the end of December 1995. Reported statistics refer to mean values.

Table 18: **Firms' characteristics of CAC-IBIS paired securities**

PANEL A: CAC SECURITIES PAIRED WITH IBIS SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,426.52	2.682	0.96	42.81
Portfolio II	3,981.66	3.438	0.98	48.92
Portfolio III	15,291.22	2.894	1.06	62.29

PANEL B: IBIS SECURITIES PAIRED WITH CAC SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,581.21	2.251	0.98	85.81
Portfolio II	3,624.16	2.105	1.02	94.41
Portfolio III	16,181.02	2.511	1.10	152.81

The three firm capitalisation categories were obtained on the basis of the firm's market capitalisation as at the end of December 1995. Portfolio I contains firms with market capitalisation of less than £2,500m; Portfolio II contains firms with capitalisation larger than £2,500m but lower than £5,000m; while Portfolio III has firms with a capitalisation larger than £5,000m.

Market capitalisation, ME/BE, beta and price were extracted from Datastream and refer to values obtained at the end of December 1995. Reported statistics refer to mean values.

both IBIS and CAC securities. This confirms the conjecture that share prices differ across countries due to different share capital structures and corporate governance mechanisms adopted by firms in different countries.

The substantial difference in the outstanding shares is bound to generate differences in the volume of shares traded and, as a consequence, the mean trade sizes transacted on different markets. Tables 19 and 20 show that the mean daily volume and the mean trade size are much bigger for SEAQ securities compared to IBIS and CAC securities.

In such a scenario, when outstanding shares are very different across markets, a number of difficulties can arise when calculating transaction costs across different systems. To solve this problem, a common trade yardstick is devised to rank trades. Following the pairing exercise, the Normal Market Size (NMS) for each security was calculated using the same methodology adopted by the LSE.

The NMS statistics for the different samples are shown in Tables 19 and 20. Trades were ranked in the following classification: (a) "small trades" are smaller than 0.5 X NMS; (b) "medium trades" are those between 0.5 X NMS and smaller than 1 X NMS; and (c) "large trades" are those of at least 1 X NMS.

The quoted and effective spreads are calculated over the period of continuous trading on the CAC and IBIS systems and for the Mandatory Quote Period on SEAQ. The effective spreads on CAC and IBIS were also measured one second before trades are executed. This methodology has been undertaken since trades on order driven platforms can potentially alter the effective spread.

Table 19: **Trading characteristics of SEAQ-CAC paired securities**

PANEL A: SEAQ SECURITIES PAIRED WITH CAC SECURITIES

	Issued shares (in 000)	Daily volume (Mean)	Mean NMS	Mean trade size
Firm size				
Portfolio I	642,419	3,078,873	5,996	13,212
Portfolio II	1,584,064	3,212,327	18,931	16,828
Portfolio III	3,997,531	3,380,847	38,758	21,770

PANEL B: CAC SECURITIES PAIRED WITH SEAQ SECURITIES

	Issued shares (in 000)	Daily volume (Mean)	Mean NMS	Mean trade size
Firm size				
Portfolio I	151,409	347,843	1,050	651
Portfolio II	172,439	386,424	2,735	427
Portfolio III	309,011	428,722	6,722	389

The three firm capitalisation categories were obtained on the basis of the firm's market capitalisation as at the end of December 1995. Portfolio I contains firms with market capitalisation of less than £2,500m; Portfolio II contains firms with capitalisation larger than £2,500m but lower than £5,000m; while the remaining firms with a capitalisation larger than £5,000m are classified in Portfolio III.

Outstanding shares is the number of shares issued by each firm as of December 1995. Mean daily volume is the average volume in shares transacted during the period under consideration. NMS is the mean value of the Normal Market Size in December 1995. Mean volume per trade is the average trade size transacted over the period considered.

Table 20: **Trading characteristics for SEAQ-IBIS paired securities**

PANEL A: SEAQ SECURITIES PAIRED WITH IBIS SECURITIES

	Issued shares (in 000)	Daily volume (Mean)	Mean NMS	Mean trade size
Firm size				
Portfolio I	962,312	3,092,677	6,150	10,706
Portfolio II	1,449,424	3,526,483	18,357	16,641
Portfolio III	1,693,028	3,713,465	56,718	21,513

PANEL B: IBIS SECURITIES PAIRED WITH SEAQ SECURITIES

	Issued shares (in 000)	Daily volume (Mean)	Mean NMS	Mean trade size
Firm size				
Portfolio I	59,932	204,524	957	2,083
Portfolio II	121,913	254,618	1,497	1,455
Portfolio III	459,897	1,242,054	10,079	3,280

The three firm capitalisation categories were obtained on the basis of the firm's market capitalisation as at the end of December 1995. Portfolio I contains firms with marketcapitalisation of less than £2,500m; Portfolio II containsfirms with capitalisation larger than £2,500m but lower than £5,000m; while the remaining firms with capitalisation larger than £5,000m are classified in Portfolio III.

Outstanding shares is the number of shares issued by each firm as of December 1995. Mean daily volume is the average volume in shares transacted during the period under consideration. NMS is the mean value of the Normal Market Size for each firm in December 1995. Mean volume per trade is the average trade size transacted over the period considered.

3.4.2 Test Procedure

After obtaining the measure of spreads for different trade sizes, we test whether the mean spread for each trade size class differs across the three different trading platforms. The traditional $t - test$ is not deemed to be appropriate in our case since the mean spreads obtained for each market come from different distributions. A more appropriate methodology is the boostrapping technology based on permutation tests is applied to test for statistical significance.

The major application of permutation tests is to the two-sample problem. In our case, when we pair two different markets we obtain observations of the mean quoted and effective spreads $s_a = (s_{1a,} s_{2a}, ..., s_{na})$ and $s_b = (s_{1b,} y_{2b}, ..., y_{nb})$ where s_a is the mean spread from the first market and s_b is the spread from the second market being paired. It is assumed that these observations are drawn from different probability distributions F_a and G_b.

Having observed s_a and s_b, we want to examine whether the null hypothesis of no difference between the two population distributions, F_a and G_b is correct: i.e. there is no difference between the probabilistic behaviour of a random s_a or a random s_b.

In this Chapter we make use of the Fisher's permutation test to investigate the null hypothesis that the level of spreads across the different markets are the same (hence $F_a = G_b$). We combine all the spread observations from the two markets being paired at each time, in all $m + n$ observations from both groups together. Following this, a sample of size m without replacement is taken from the combined sample to represent the first group with the remaining n observations constituting the second group. We compute the difference between group means and then repeat this process 10,500 times.

The Achieved Significance Level (henceforth the "ASL") is obtained after making 10,500 replications of the different measures of quoted and effective spread from each trading system. This number of replications allow us to obtain confidence levels lower than 0.025. Further background to the permutation tests is provided in Appendix D.

3.4.3 Data

Trades and quotes data for SEAQ stocks were obtained from the LSE's Quality of Markets Department, whereas the Paris Bourse provided data for CAC securities. Data for IBIS securities was obtained from two sources: trades data was provided by the Institut fur Entscheidungstheorie und Unternehmensforschung of the University of Karlsruhe whereas the Institut fur Geld- und Kapitalverkehr at the University of Hamburg provided the quotes data.

There are substantial differences in the type of data across the different Exchanges. For the Paris Bourse, trades and quotes data come together with the orders data, providing exact information as to the types of orders submitted on the limit order book, the quantity for each order and the time limit for each order.

On the other hand, data for IBIS contains the best bid and best ask quotes at each point in time (generated from the order book by an algorithm used by Institut fur Geld- und Kapitalverkehr). However, due to lack of sufficient order data (mainly the history of the order flow), the order book itself cannot be built for IBIS securities.

Data for the LSE contains the trades data together with the best bid and best ask prices (the so-called yellow strip) with the relevant information as to the counter-parties for each trade. No order book was in operation for SEAQ during the January-June 1996 period. Only Agent to Market Maker trades (the so-called Customer trades) are extracted from the data.

Trade classification for the different markets was carried out through three different methodologies. For SEAQ trades, the Board and Sutcliffe (1995) methodology was used. In this algorithm, a transaction is assigned a buy (sell) record if the transaction represents a purchase from (sale to) the market maker.

For CAC trades, the trade direction could not be inferred directly from the trade file. Hence, the best bid and best ask prices were obtained in continuous time and merged with the trades data to classify trade direction for each trade. For transactions executed inside the spread, the Harris (1989) methodology was used. Using this algorithm, trades are classified as buys if they are closer to the ask and as sells if they are closer to the bid price. This approach leaves trades executed at the mid-quote unclassified. In the sample used, there were 3.11% of all transactions carried out at the midquote and these records are removed from the sample.

For trades executed on IBIS, direction is decided by using a version of the tick test proposed by Lee and Ready (1991) under which trades are classified as buys if they occur on an uptick or zero-uptick and sells if they occur on a downtick or zero-downtick. As far as the quotes data for the three markets is concerned, bid-ask quotes are removed from the data if either the bid price or the ask price are reported as being 0.

It should be noted that the time accuracy of trades' reported execution varies across the different markets. Trades on CAC and IBIS are reported to the nearest second and the nearest hundredth of a second respectively. Trades on SEAQ are time-stamped to the nearest second but market makers had up to three minutes to report it to the LSE.

The delay on SEAQ is bound to increase the measurement error of the effective spread at the time of trade execution. Under certain circumstances, this lack of accuracy could lead to a downward bias in SEAQ's transaction costs. For example, Porter and Weaver (1995) found that NASDAQ dealers take advantage of the allowed window of 90 seconds to report trades to 'paint the tape' to their advantage. If similar practices occur on SEAQ then it is expected that measures of transaction costs will be downward biased. In order to attempt a solution to this problem, the analysis is run three times with SEAQ's reported transaction times anticipated by one, two and three minutes respectively.

3.5 Spreads on Different Trading Architectures

This Section analyses the execution costs for different trades on the three trading systems. Quotes submitted by market makers represent the costs of immediacy on SEAQ while the limit order book provides the cost of immediacy for trades executed on CAC and IBIS.

The quoted spread on SEAQ is the difference between the best bid and best ask prices submitted by the market makers (the so-called yellow strip). On both CAC and IBIS the quoted spreads are measured by the difference between the bid and ask prices submitted by limit orders for different trade sizes.

The spreads in this Section are all measured in percentage to normalise over the three markets, each using a different currency for the price, ask and bid quotes.

3.5.1 Quoted Spreads

The first methodology is based on a "crude" measurement of the difference between the best ask and bid prices at each point in time in the following way:

$$\% \; spread_t \;= 100 \cdot \frac{ask\ price_t - bid\ price_t}{midprice_t} \tag{12}$$

The second approximation for the average quoted spread was obtained through the calendar-time average of spreads for the different markets in the following way:

$\% \; spread_C \, (m) \;=$

$$100 \cdot \sum_{i=1}^{N} (t_{i+1} - t_i) \sum_{x=1}^{m} x^{-1} \left[\frac{ask\ price\,[t_i, x] - bid\ price\,[t_i, x]}{midprice\,[t_i, x]} \right] / \sum_{i=1}^{N} (t_{i+1} - t_i) \tag{13}$$

where t_i is the calendar time index of the i^{th} change in the best bid and best ask prices, $ask\ price\,[t_i, x]$ is the ask price at time t_i for order of size m, $bid\ price\,[t_i, x]$ is the bid price at time t_i for order of size m and N denotes the number of changes in the best prices. This measure of the calendar-time average provides the average quoted spread for a particular transaction size by averaging the spread for all smaller trades denoted by x.

The major drawback of the calendar-time average quoted spread is that equal weights are allocated to heavy-trading and low-trading periods. In line with de Jong *et al.* (1993), the transaction-time average is calculated conditional on the time that elapses between one trade and another in the following way:

$$\% \; spread_T \, (m) = 100 \cdot \frac{1}{N} \sum_{i=1}^{N} \sum_{x=1}^{m} \left[\frac{(ask\ price\,[t_i, x] - bid\ price\,[t_i, x])}{midprice\,[t_i, x]} \right] \; / \; m \tag{14}$$

where t_i still denotes the calendar time index of transaction i.

3.5.2 Effective Spreads

The quoted spread is neither the only methodology nor the optimal technique that can be used in order to measure trading costs. First, some transactions, especially those involving medium-sized and large orders, do not necessarily take place at the best bid or ask prices. The price for such orders could be negotiated, with the execution taking place within the spread.

This process takes place both on dealership and order book markets, albeit through a different mechanism. For example, SEAQ market makers who submit quotes appear to be willing to trade inside the spread and improve on the best prices quoted at the time when a larger order is submitted. In this case, best quotes can be perceived to be a starting point for negotiation.

On the other hand, the Paris Bourse allows crosses to be made and these are expected to be the product of negotiation between two counterparties and take place within the spread. Principal trades in the top 53 stocks which exceed the Normal Block Size (the 'NBS' is defined by the Paris Bourse and it is an order whose size is approximately 2.5% of average daily trading volume in the preceding three months) are not bound to satisfy orders in the central book. Such orders can be transacted within the weighted average CAC spread (the *fourchette moyenne ponderee* which, according to the Paris Bourse's rules, is 'based upon the average prices that are formed, after weighting of prices by number of shares, by the interaction of buy and sell orders that are posted on the central market') rather than the narrower *fourchette.* Furthermore, hidden orders are allowed to be placed on the limit order book without any visibility except when they are executed and are subsequently reported to the Bourse.

Furthermore, one has to consider that even on markets expected to execute trades at the best quotes, such as the screen-based system used by

CAC and IBIS, there is a transaction cost difference between patient trading and aggressive trading. It is expected that patient trading is carried out by traders willing to trade only when the market is deep enough and lower transaction costs are obtained.

In view of these reasons, the effective spread is a more reliable and indicative measure of the true execution costs and is calculated in the following way:

$\%\ spread_{eff} = (\underline{m}, \bar{m}) =$

$$100 \cdot 2 \sum_{i=1}^{N} S(\ \underline{m} < mi \leq \bar{m}\ ) \cdot \left[\frac{SB_{it}\left(p_t\left[i\right] - v_t\left[i\right]\right)}{v_t\left[i\right]} \right] \ / \ \sum_{i=1}^{N} S(\ \underline{m} < mi \leq\ \bar{m}\ ) \tag{15}$$

where $\%\ spread_{eff}$ is the percentage effective spread, trades are grouped into classes with $\underline{m}$ being the smallest trade size and $\bar{m}$ being the largest trade size within each group, $S(\cdot)$ is a binary variable that takes the value of 1 if the trade falls between $\underline{m}$ and $\bar{m}$, $p\left[i\right]$ is the transaction price for trade i and $v_t\left[i\right]$ is the mid price which existed at the time when the i^{th} transaction took place and SB_{it} is a binary value that takes on the value of +1 if the trade is a buy and -1 if it is a sell. In line with Biais *et al.* (1992) and de Jong *et al.* (1993), who suggest that large trades are clustered at times when the quoted spread is relatively low, the measurement of the effective spread is made conditional on the trade size.

The effective spread can be viewed as an implicit spread at which trades take place and is expected to be lower than the quoted spread. In setting the effective spread, market makers must cover the usual operating and inventory costs together with the adverse selection component.

One important issue involved with the estimation of the effective spread is the use of mid quotes, considered to be a proxy for the security's true economic value. However, there are issues regarding the amount of bias in the estimation of (15) using the mid quote that could occur under certain trade reporting practices. A formal exposition of this concept follows.

Transaction i takes place at time t at a transaction price P_t. From market efficiency, we know that before the trade is executed, P_t is a random variable, conditional on the information available to the market in such a way that

$$P_t = E\left(P_t \mid \phi_{t-1}\right) + v_t$$

$$= P_t^* + v_t$$

where ϕ_{t-1} is the information set before transaction i is executed at time t, v_t is a random term with mean zero and P_t^* is the unbiased estimate of P_t.

In order to use (15) an estimate for P_t^* must be found. Assuming that $P_t^{\sim}$ is an unbiased estimate of P_t^*, we have

$$P_t^{\sim} = P_t^* + \varepsilon_t$$

where ε_t is the disturbance term, with mean zero, uncorrelated with both P_t^* and v_t.

Blume and Goldstein (1992) produce two assumptions under which the effective spread measured in (4) is unbiased. First, when $\mid \varepsilon_t \mid$ is always less than the difference $\mid P_t - P_t^{\sim} \mid$ wherever the difference is positive and the conditional expectation of ε_t is zero and, secondly, when $\mid \varepsilon_t \mid$ is zero when the difference $\mid P_t - P_t^{\sim} \mid$ is zero then (4) will not result in any unbiasedeness. Using these two assumptions, it is possible to show that

$$2E\left(\mid P_t - P_t^{\sim} \mid\right) = 2E\left(\mid P_t - P_t^* \mid\right)$$

In essence, if $| \varepsilon_t |$ is small relative to $| \upsilon_t |$ (when $| \upsilon_t |$ is positive), we have the sign of $(\upsilon_t - \varepsilon_t)$ being determined by the sign of υ_t. Hence

$$E(| P_t - P_t^{\sim} |) = E(-\upsilon_t + \varepsilon_t \mid \upsilon_t < 0) + E(| \varepsilon_t || \ \upsilon_t = 0) + E(\upsilon_t - \varepsilon_t \mid \upsilon_t > 0)$$

The assumptions that the conditional expectation of $\varepsilon_t > 0$ when $\upsilon_t > 0$ and that $\varepsilon_t = 0$ when $\varepsilon_t = 0$ lead to the following

$$\begin{aligned} E(| P_t - P_t^{\sim} |) &= E(-\upsilon_t \mid \upsilon_t < 0) + E(\upsilon_t \mid \upsilon_t > 0) \\ &= E(| \upsilon_t |) \\ &= E(| P_t - P_t^{*} |) \end{aligned}$$

Whenever ε_t is correlated with either $(P_t - P_t^{\sim})$ or $(P_t - P_t^{*})$ there will be bias in the estimation of (15). One possible cause of the bias occurs when trades are reported with some delay but the adjustments to the quotes are reported immediately. This is the case of SEAQ where trades could be reported within three minutes from their execution. This is likely to cause bias in the estimation of the effective spread for SEAQ spreads and it is unlikely that the bias will be completely corrected by the methodology adopted.

Following the calculation of the effective spread, the natural extension for this analysis is to calculate how much a trader is expected to pay, on average, from the quoted spread submitted at each point in time on different markets. As such, the transaction price at which each trade takes place is compared to the quoted spread and the mid-quote at the trade's execution time in the following way

$$\%\ payable\ spread = 100 \cdot 2 \cdot \frac{| [trade\ price_t - (bid\ price_t + ask\ price_t)/2] |}{(ask\ price_t - bid\ price_t)} \tag{16}$$

Neal (1992) defines this measure as the percentage effective spread-2 (as against the effective spread-1 which is defined as max[trade $price_t$ - bid $price_t$, ask $price_t$ - trade $price_t$]). However, it is preferred to call this measure as the payable spread since it shows the proportion of the quoted spread, being quoted at the time of the trade execution, expected to be paid by the trader.

The payable spread assumes a value of 1 when the trade is executed at the touch, 0 if it takes place at the mid price. This type of spread measurement would reflect the trading difference between markets since the payable spread must be lower on SEAQ compared with IBIS and CAC given the amount of negotiation that takes place within the spread for larger orders.

3.5.3 Summary Statistics

Summary statistics for the quoted spread, effective spread and payable spread are reproduced in Table 21. The quoted spread shown in the Table is the calendar-time average quoted spread obtained at every point in time. The results indicate that, in general, the type of market microstructure appears to produce a direct impact on the absolute level of the spreads.

The mean and median values for both quoted and effective spreads generated on SEAQ are much higher than those generated on either CAC or IBIS. The mean value for the quoted spread of CAC-traded securities is 0.3491% for the sample which is SEAQ-matched and 0.2714% for the IBIS-matched sample. The corresponding values for SEAQ-traded securities are more than double these figures.

The pattern emerging from comparing the IBIS-traded and the CAC-traded samples demonstrates that, although CAC and IBIS use some similar trading practices, the quoted spread for CAC-traded securities is higher than for IBIS-traded securities. In so far as the two samples have been matched

Table 21: **Statistics for quoted, effective and payable spreads**

PANEL A (1). CAC SECURITIES PAIRED WITH SEAQ SECURITIES

	Mean	Median	Std. Dev.	Skewness	Kurtosis	90%	95%	99%
Quoted	0.3491	0.2203	0.3744	4.77	77.64	0.781	0.912	1.798
Effective	0.3004	0.1922	0.3262	4.02	32.02	0.684	0.838	1.594
Payable	0.8901	0.8321	0.1661	3.77	16.11	0.971	0.984	0.996

PANEL A (2). CAC SECURITIES PAIRED WITH IBIS SECURITIES

Quoted	0.2714	0.1974	0.2593	4.08	35.58	0.519	0.748	1.294
Effective	0.2361	0.1735	0.2143	4.26	40.93	0.456	0.599	1.055
Payable	0.9119	0.8715	0.1508	3.15	11.18	0.981	0.983	0.997

PANEL B (1). IBIS SECURITIES PAIRED WITH SEAQ

	Mean	Median	Std. Dev.	Skewness	Kurtosis	90%	95%	99%
Quoted	0.1708	0.1176	0.1963	7.87	170.61	0.388	0.541	0.896
Effective	0.1517	0.1059	0.1776	8.25	189.13	0.311	0.434	0.810
Payable	1	1	0	-	-	1	1	1

PANEL B (2). IBIS SECURITIES PAIRED WITH CAC

Quoted	0.1687	0.1168	0.1903	8.01	170.15	0.316	0.444	0.847
Effective	0.1506	0.1042	0.1825	8.39	188.92	0.309	0.436	0.829
Payable	1	1	0	-	-	1	1	1

PANEL C (1). SEAQ SECURITIES PAIRED WITH CAC

	Mean	Median	Std. Dev.	Skewness	Kurtosis	90%	95%	99%
Quoted	0.7248	0.5479	0.7243	6.12	64.92	1.210	1.524	2.175
Effective	0.4881	0.3631	1.2252	7.48	71.75	0.632	0.867	1.714
Payable	0.7518	0.7021	1.3611	4.24	51.42	0.899	0.952	0.982

PANEL C (2). SEAQ SECURITIES PAIRED WITH IBIS

Quoted	0.5973	0.5084	0.3583	1.57	56.76	1.061	1.432	1.770
Effective	0.3456	0.2347	1.2487	8.01	71.62	0.562	0.745	1.329
Payable	0.7419	0.6831	1.2711	6.22	59.14	0.888	0.942	0.971

The quoted spread is calculated as follows:

$$\%\ spread_t = 100 \cdot \frac{ask\ price_t - bid\ price_t}{midprice_t}$$

The effective spread is measured as follows:

$$100 \cdot 2 \sum_{i=1}^{N} S(\underline{m} < mi \leq \bar{m}) \cdot \left[\frac{SB_{it}(p_t[i] - v_t[i])}{v_t[i]} \right] \ / \ \sum_{i=1}^{N} S(\underline{m} < mi \leq \bar{m})$$

trades are grouped into classes with $\underline{m}$ being the smallest trade size and $\bar{m}$ being the largest trade size within each group. The payable spread is measured as follows:

$$100 \cdot 2 \cdot \frac{||trade\ price_t - (bid\ price_t + ask\ price_t)/2||}{(askprice_t - bidprice_t)}$$

together on the basis of securities' risk factors, this preliminary result cannot be explained as an artifact of sample design and needs further explanation.

Analysing the different samples, it can be noticed that quoted and effective spreads are generally lower for heavily traded stocks compared with low active securities. For example, the mean effective spread for CAC-traded securities paired with SEAQ-traded securities (which includes firms of heterogenous liquidity) is 0.3004% whereas the securities paired with IBIS-traded firms (larger securities and with higher liquidity), the mean effective spread on CAC is 0.2361%.

Table 21 also shows that the effective spread is lower than the quoted spread across the three markets. Trades, especially medium to large ones, can be transacted strategically to maximise the benefits from periods with liquidity surplus and avoid times of liquidity deficits. Secondly, the result suggests that trading costs associated with patient trading are generally lower than those obtained by aggressive trading. Thirdly, the difference between the mean quoted spread and the mean effective spread is greater on SEAQ, implying that negotiation between market makers and traders is generally heavier on such a market than on IBIS and CAC. This result is the product of pure trading microstuctures since negotiation is contemplated by SEAQ but can only take place on CAC for a small number of trades (crosses).

Similarly, the payable spread is clearly smaller on SEAQ than on IBIS or CAC. On the latter markets, traders are expected to pay the quoted spread submitted at the time when the trade is executed (both the mean and the median values are 1) whereas on SEAQ, on average, traders with medium to large orders should expect to negotiate their trade and pay 86.6% of the quoted spread.

3.6 Quoted and Effective Spreads

The calendar time average quoted spread, transaction time average quoted spread and the effective spread for the three trading systems are shown in Tables 22-30. For ease of comparison, while trades have been classified as follows: (a) small trades when the trade size is smaller than 0.5 X NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; and (c) large if the trade size is greater than 1 X NMS. The major problem encountered with such a classification is that auction-based systems are bound to have very small trades being executed, most of them being smaller than 1 X NMS. To address this problem, the Tables show the different measurement of the spread in different trade bands, each of 0.1 X NMS up to 1 X NMS. In addition, securities held in the different samples have been classified as small, medium and large depending on their market capitalisation as of December 1995.

The calendar time average quoted spread shows that limit order book-based systems produce very low spreads compared to the dealership system. For example, the average quoted spread for small trades in large firms transacted on CAC is 0.1863% at the ask and 0.1894% for a trade at the bid compared with spreads of 0.4947% at the ask and 0.4896% at the bid for SEAQ trades. In each single trade size and security class, the two systems that allow limit orders produce lower spreads compared to the dealership system, with the difference being statistically significant using the ASL test.

It is clear that the quoted spreads on both the auction and the hybrid systems increase with trade size. This is not the case with SEAQ whereby there appears to be a U-shaped transaction costs. Very small trades are executed at relatively high transactions costs which decrease for medium sized trades and goes up again for large trades.

Table 22: **Calendar-time quoted spread (percent) for CAC- and SEAQ-paired securities**

PANEL A. MEAN QUOTED SPREAD FOR CAC-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.4775	0.4853	< 0.1	0.3198
I	Medium	0.5001	0.5107	0.1 - 0.2	0.3103
I	Large	0.5664	0.5761	0.2 - 0.3	0.3185
				0.3 - 0.4	0.3176
II	Small	0.2878	0.2928	0.4 - 0.5	0.3188
II	Medium	0.3444	0.3418	0.5 - 0.6	0.3196
II	Large	0.3901	0.4019	0.6 - 0.7	0.3152
				0.7 - 0.8	0.3177
III	Small	0.1863	0.2051	0.8 - 0.9	0.3213
III	Medium	0.1947	0.1952	0.9 - 1.0	0.3361
III	Large	0.2259	0.2243		

PANEL B. MEAN QUOTED SPREAD FOR SEAQ-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.6753**	0.6862**	< 0.1	0.6102
I	Medium	0.6609*	0.6735*	0.1 - 0.2	0.5987
I	Large	0.6447*	0.6436*	0.2 - 0.3	0.5896
				0.3 - 0.4	0.5802
II	Small	0.6415**	0.6391**	0.4 - 0.5	0.5758
II	Medium	0.6118**	0.6088**	0.5 - 0.6	0.5696
II	Large	0.6315*	0.6284*	0.6 - 0.7	0.5601
				0.7 - 0.8	0.5598
III	Small	0.6215**	0.6301**	0.8 - 0.9	0.5370
III	Medium	0.6042**	0.6156**	0.9 - 1.0	0.5287
III	Large	0.6181*	0.6175*		

Trades were classified on their trade position - whether at the best ask or the best bid. The calendar time quoted spread is measured as:

$$100 \cdot \sum_{i=1}^{N}(t_{i+1} - t_i) \sum_{x=1}^{m} x^{-1} \left[\frac{ask\ price[t_i,x] - bid\ price[t_i,x]}{midprice[t_i,x]}\right] / \sum_{i=1}^{N}(t_{i+1} - t_i)$$

Trades have been classified as follows:- (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured $[SEAQ - CAC]$ spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Table 23: **Calendar-time quoted spread (percent) for CAC- and IBIS-paired securities**

PANEL A. MEAN QUOTED SPREAD FOR CAC-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.4014	0.3985	< 0.1	0.2308
I	Medium	0.4622*	0.4721*	0.1 - 0.2	0.2406
I	Large	0.5236*	0.5324*	0.2 - 0.3	0.2453
				0.3 - 0.4	0.2517
II	Small	0.2660*	0.2707*	0.4 - 0.5	0.2529
II	Medium	0.3182**	0.3160**	0.5 - 0.6	0.2489
II	Large	0.3606**	0.3715**	0.6 - 0.7	0.2511
				0.7 - 0.8	0.2538
III	Small	0.1522	0.1696	0.8 - 0.9	0.2659
III	Medium	0.1801*	0.1804*	0.9 - 1.0	0.2784
III	Large	0.2087*	0.2073*		

PANEL B. MEAN QUOTED SPREAD FOR IBIS-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.3306	0.3358	< 0.1	0.1389
I	Medium	0.3326	0.3226	0.1 - 0.2	0.1379
I	Large	0.3714	0.3658	0.2 - 0.3	0.1351
				0.3 - 0.4	0.1514
II	Small	0.1517	0.1571	0.4 - 0.5	0.1704
II	Medium	0.2213	0.2262	0.5 - 0.6	0.2047
II	Large	0.2819	0.2696	0.6 - 0.7	0.2287
				0.7 - 0.8	0.2305
III	Small	0.1316	0.1330	0.8 - 0.9	0.2369
III	Medium	0.1541	0.1498	0.9 - 1.0	0.2366
III	Large	0.1667	0.1608		

Trades were classified on their trade position - whether at the best ask or the best bid. The calendar time quoted spread is measured as:

$$100 \cdot \sum_{i=1}^{N}(t_{i+1} - t_i) \sum_{x=1}^{m} x^{-1} \left[\frac{ask\ price[t_i,x] - bid\ price[t_i,x]}{midprice[t_i,x]}\right] / \sum_{i=1}^{N}(t_{i+1} - t_i)$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured $[CAC - IBIS]$ spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Table 24: **Calendar-time quoted spread (percent) for IBIS- and SEAQ-paired securities**

PANEL A. MEAN QUOTED SPREAD FOR IBIS-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Firm	Trade	At Ask	At Bid	Trade size	Spread
Small	Small	0.3236	0.3287	< 0.1	0.1146
Small	Medium	0.3255	0.3157	0.1 - 0.2	0.1228
Small	Large	0.3635	0.3581	0.2 - 0.3	0.1291
				0.3 - 0.4	0.1641
Medium	Small	0.1485	0.1538	0.4 - 0.5	0.1954
Medium	Medium	0.2166	0.2214	0.5 - 0.6	0.2347
Medium	Large	0.2759	0.2639	0.6 - 0.7	0.2394
				0.7 - 0.8	0.2378
Large	Small	0.0995	0.1008	0.8 - 0.9	0.2433
Large	Medium	0.1508	0.1466	0.9 - 1.0	0.2401
Large	Large	0.1632	0.1574		

PANEL B. MEAN QUOTED SPREAD FOR SEAQ-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Firm	Trade	At Ask	At Bid	Trade size	Spread
Small	Small	0.5717**	0.5701**	< 0.1	0.5159
Small	Medium	0.5596**	0.5449**	0.1 - 0.2	0.4825
Small	Large	0.5458*	0.4852*	0.2 - 0.3	0.4815
				0.3 - 0.4	0.4846
Medium	Small	0.4822**	0.4738**	0.4 - 0.5	0.4783
Medium	Medium	0.4716**	0.4557**	0.5 - 0.6	0.4731
Medium	Large	0.4459*	0.4389*	0.6 - 0.7	0.4718
				0.7 - 0.8	0.4564
Large	Small	0.4177**	0.4219**	0.8 - 0.9	0.4371
Large	Medium	0.4059**	0.4148**	0.9 - 1.0	0.4469
Large	Large	0.3877*	0.3898*		

Trades were classified on their trade position - whether at the best ask or the best bid. The calendar time quoted spread is measured as:

$$100 \cdot \sum_{i=1}^{N}(t_{i+1} - t_i) \sum_{x=1}^{m} x^{-1} \left[\frac{ask\ price[t_i,x] - bid\ price[t_i,x]}{midprice[t_i,x]}\right] / \sum_{i=1}^{N}(t_{i+1} - t_i)$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured $[SEAQ - IBIS]$ spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

The other interesting feature arises when the pure limit order book and the hybrid system are compared. In this case, contrary to the null hypothesis $1B_O$, IBIS appears to generate lower quoted spreads compared with CAC. The spread differential in favour of IBIS is especially pronounced for small and medium trades. For most trade classes, the difference between IBIS and CAC is statistically significant. For example, for the trade sizes not exceeding 0.1 X NMS, the quoted spread on IBIS is 0.1389% while on CAC is 0.2408%.

In order to avoid the problems associated with the calendar time average, the second set of calculations use the transaction time average quoted spread. Tables 25-27 show that the two sets of spread measurements are similar, implying that trades are not, generally speaking, very sensitive to spread changes. The results obtained for CAC are similar to those obtained by de Jong *et al.* (1993) for French securities cross-quoted on SEAQ-I.

The market with the highest difference between the two measurements is IBIS. This could be due to the intraday patterns explained in the next Chapter. For both SEAQ and CAC, the number of trades and total volume transacted are relatively high during the opening phase when the bid-ask spreads are high compared to the levels reached during the day.

Table 25: **Transaction-time quoted spread (percent) for CAC- and SEAQ-paired securities**

PANEL A. MEAN QUOTED SPREAD FOR CAC-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.4917	0.5008	< 0.1	0.3015
I	Medium	0.5161	0.5242	0.1 - 0.2	0.3196
I	Large	0.5691	0.5741	0.2 - 0.3	0.3245
				0.3 - 0.4	0.3251
II	Small	0.2918	0.3021	0.4 - 0.5	0.3275
II	Medium	0.3512	0.3528	0.5 - 0.6	0.3301
II	Large	0.3921	0.4001	0.6 - 0.7	0.3376
				0.7 - 0.8	0.3412
III	Small	0.2171	0.2164	0.8 - 0.9	0.3425
III	Medium	0.2245	0.2210	0.9 - 1.0	0.3471
III	Large	0.2451	0.2384		

PANEL B. MEAN QUOTED SPREAD FOR SEAQ-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.6084*	0.5912*	< 0.1	0.6381
I	Medium	0.5819*	0.5793*	0.1 - 0.2	0.6269
I	Large	0.5924	0.6008	0.2 - 0.3	0.6178
				0.3 - 0.4	0.6098
II	Small	0.5987**	0.5963**	0.4 - 0.5	0.5988
II	Medium	0.5646**	0.5608**	0.5 - 0.6	0.5891
II	Large	0.5812*	0.5791*	0.6 - 0.7	0.5886
				0.7 - 0.8	0.5801
III	Small	0.5747**	0.5826**	0.8 - 0.9	0.5681
III	Medium	0.5568**	0.5674**	0.9 - 1.0	0.5621
III	Large	0.5706*	0.5689*		

Tr[illegible]he best bid.
$\% \ spread_T\ (m) = 100 \cdot \frac{1}{N} \sum_{i=1}^{N} \sum_{x=1}^{m} \left[\frac{(ask\ price[t_i,x] - bid\ price[t_i,x])}{midprice[t_i,x]} \right] \ / \ m$
The transaction time quoted spread is measured as:

$$\% \ spread_T\ (m) = 100 \cdot \frac{1}{N} \sum_{i=1}^{N} \sum_{x=1}^{m} \left[\frac{(ask\ price[t_i,x] - bid\ price[t_i,x])}{midprice[t_i,x]} \right] \ / \ m$$

Trades have been classified as follows:- (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured $[SEAQ - CAC]$ spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Table 26: **Transaction-time quoted spread (percent) for CAC- and IBIS-paired securities**

PANEL A. MEAN QUOTED SPREAD FOR CAC-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.4526*	0.4615*	< 0.1	0.2478
I	Medium	0.4731*	0.4842*	0.1 - 0.2	0.2519
I	Large	0.5299*	0.5361*	0.2 - 0.3	0.2508
				0.3 - 0.4	0.2581
II	Small	0.2788*	0.2801*	0.4 - 0.5	0.2594
II	Medium	0.3278*	0.3314*	0.5 - 0.6	0.2557
II	Large	0.3711*	0.3801*	0.6 - 0.7	0.2535
				0.7 - 0.8	0.2598
III	Small	0.1601	0.1664	0.8 - 0.9	0.2714
III	Medium	0.2045*	0.2151*	0.9 - 1.0	0.2801
III	Large	0.2241*	0.2312*		

PANEL B. MEAN QUOTED SPREAD FOR IBIS-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.3424	0.3478	< 0.1	0.1454
I	Medium	0.3455	0.3342	0.1 - 0.2	0.1459
I	Large	0.3847	0.3789	0.2 - 0.3	0.1535
				0.3 - 0.4	0.1721
II	Small	0.1571	0.1628	0.4 - 0.5	0.1829
II	Medium	0.2292	0.2343	0.5 - 0.6	0.1959
II	Large	0.2921	0.2793	0.6 - 0.7	0.2045
				0.7 - 0.8	0.2234
III	Small	0.1352	0.1367	0.8 - 0.9	0.2316
III	Medium	0.1596	0.1552	0.9 - 1.0	0.2475
III	Large	0.1727	0.1665		

Trades were classified on their trade position - whether at the best ask or the best bid. The transaction time quoted spread is measured as:

$$\%\ spread_T\ (m) = 100 \cdot \frac{1}{N} \sum_{i=1}^{N} \sum_{x=1}^{m} \left[\frac{(ask\ price[t_i,x] - bid\ price[t_i,x])}{midprice[t_i,x]} \right] \ /\ m$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured $[CAC - IBIS]$ spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Table 27: **Transaction-time quoted spread (percent) for IBIS- and SEAQ-paired securities**

PANEL A. MEAN QUOTED SPREAD FOR IBIS-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.3315	0.3409	< 0.1	0.1219
I	Medium	0.3376	0.3275	0.1 - 0.2	0.1301
I	Large	0.3771	0.3714	0.2 - 0.3	0.1373
				0.3 - 0.4	0.1742
II	Small	0.1540	0.1596	0.4 - 0.5	0.2037
II	Medium	0.2247	0.2297	0.5 - 0.6	0.2487
II	Large	0.2862	0.2737	0.6 - 0.7	0.2427
				0.7 - 0.8	0.2424
III	Small	0.1132	0.1145	0.8 - 0.9	0.2408
III	Medium	0.1565	0.1521	0.9 - 1.0	0.2373
III	Large	0.1694	0.1631		

PANEL B. MEAN QUOTED SPREAD FOR SEAQ-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.5605*	0.5681*	< 0.1	0.5514
I	Medium	0.5381*	0.5308*	0.1 - 0.2	0.5402
I	Large	0.5541*	0.5532*	0.2 - 0.3	0.5391
				0.3 - 0.4	0.5342
II	Small	0.5596**	0.5426**	0.4 - 0.5	0.5371
II	Medium	0.5288**	0.5311**	0.5 - 0.6	0.5308
II	Large	0.5627**	0.5601**	0.6 - 0.7	0.5272
				0.7 - 0.8	0.5281
III	Small	0.5441**	0.5484**	0.8 - 0.9	0.5255
III	Medium	0.5191**	0.5216**	0.9 - 1.0	0.5115
III	Large	0.5496**	0.5508**		

Trades were classified on their trade position - whether at the best ask or the best bid. The transaction time quoted spread is measured as:

$$\%\ spread_T\ (m) = 100 \cdot \frac{1}{N} \sum_{i=1}^{N} \sum_{x=1}^{m} \left[\frac{(ask\ price[t_i,x] - bid\ price[t_i,x])}{midprice[t_i,x]} \right] \ / \ m$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured $[SEAQ - IBIS]$ spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Figure 13. Intraday patterns of quoted spreads (in %) on IBIS

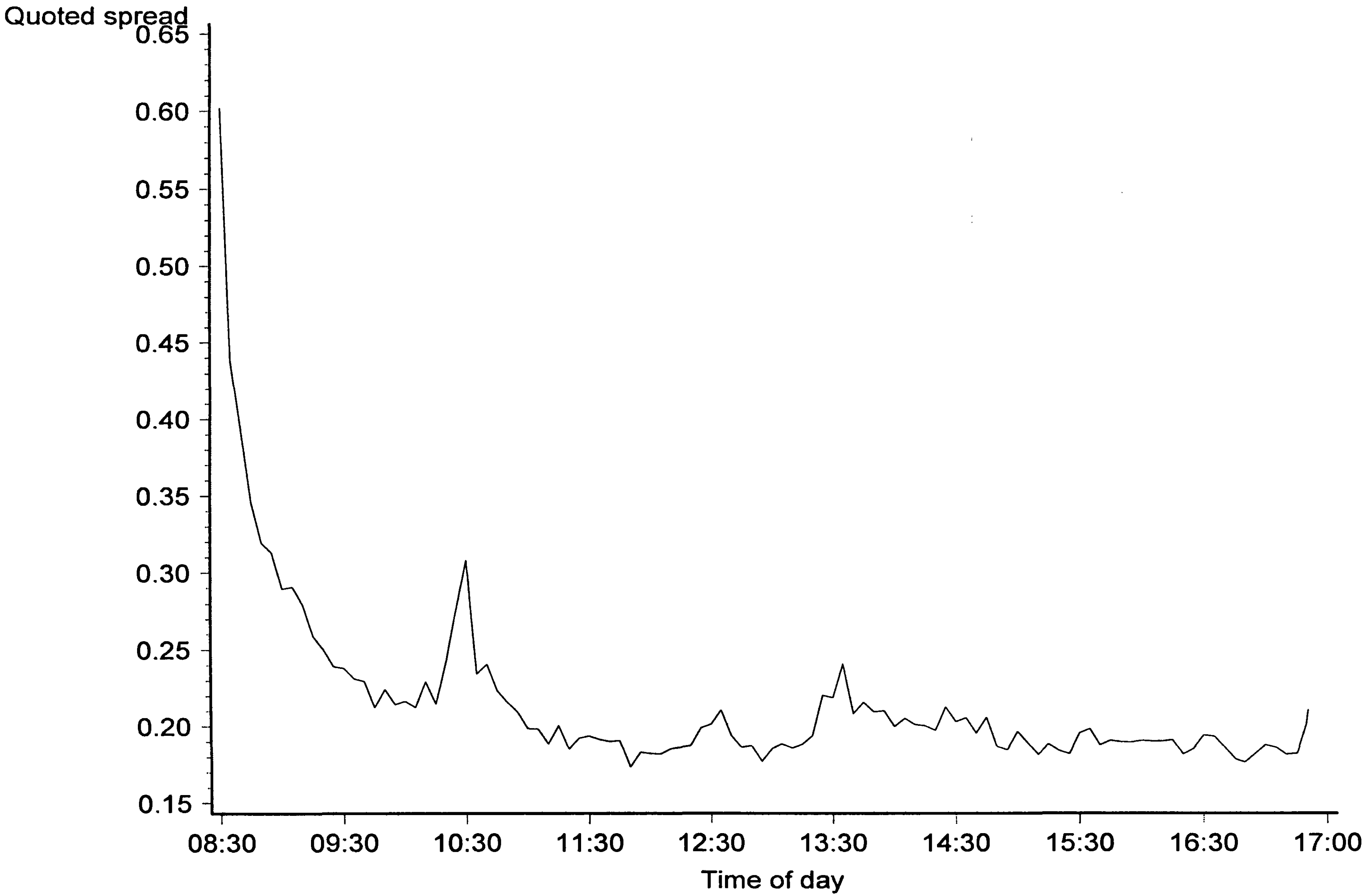


Figure 14. Intraday patterns of quoted spreads (in %) on CAC

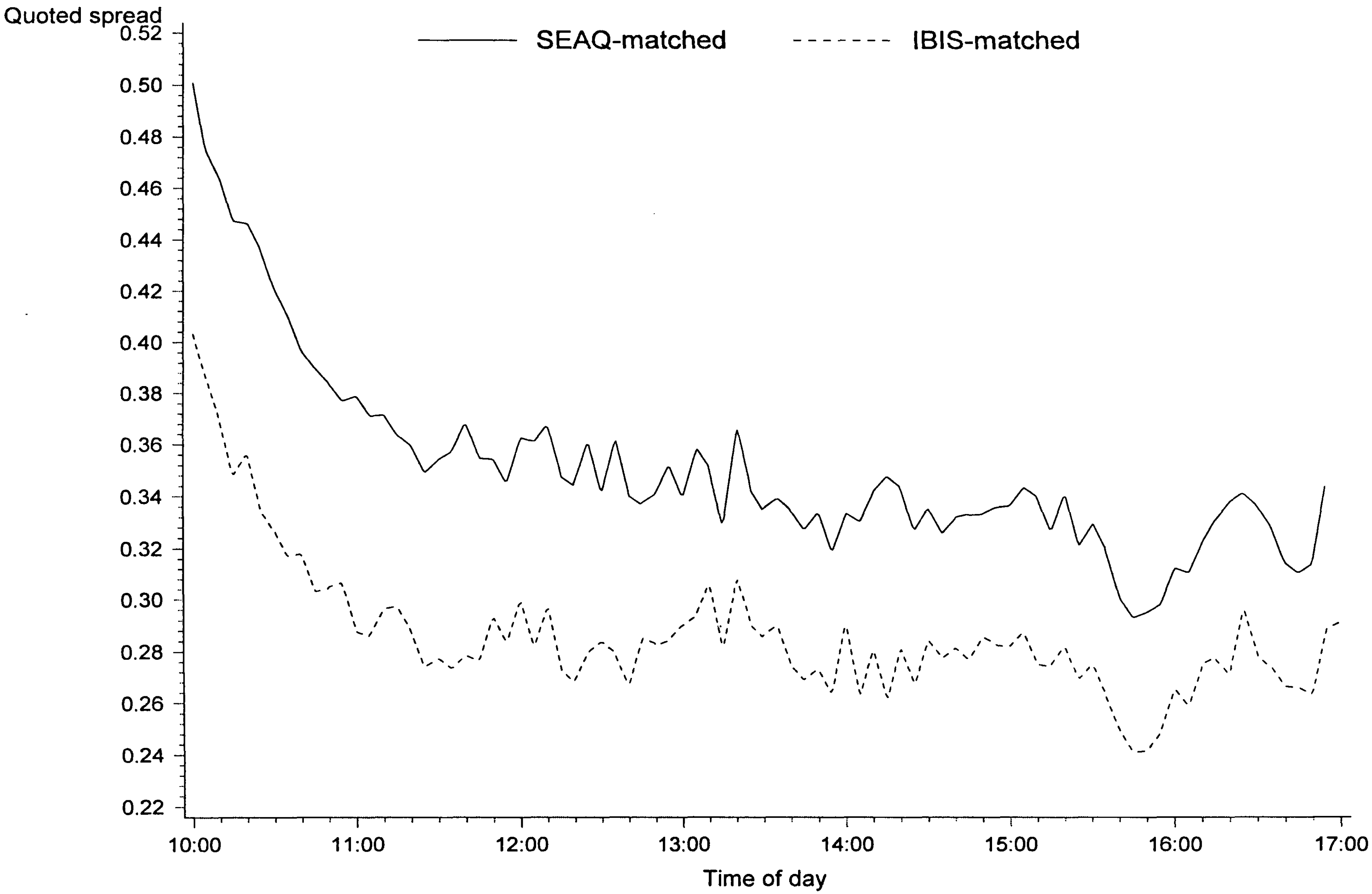


Figure 15. Intraday patterns of quoted spreads (in %) on SEAQ

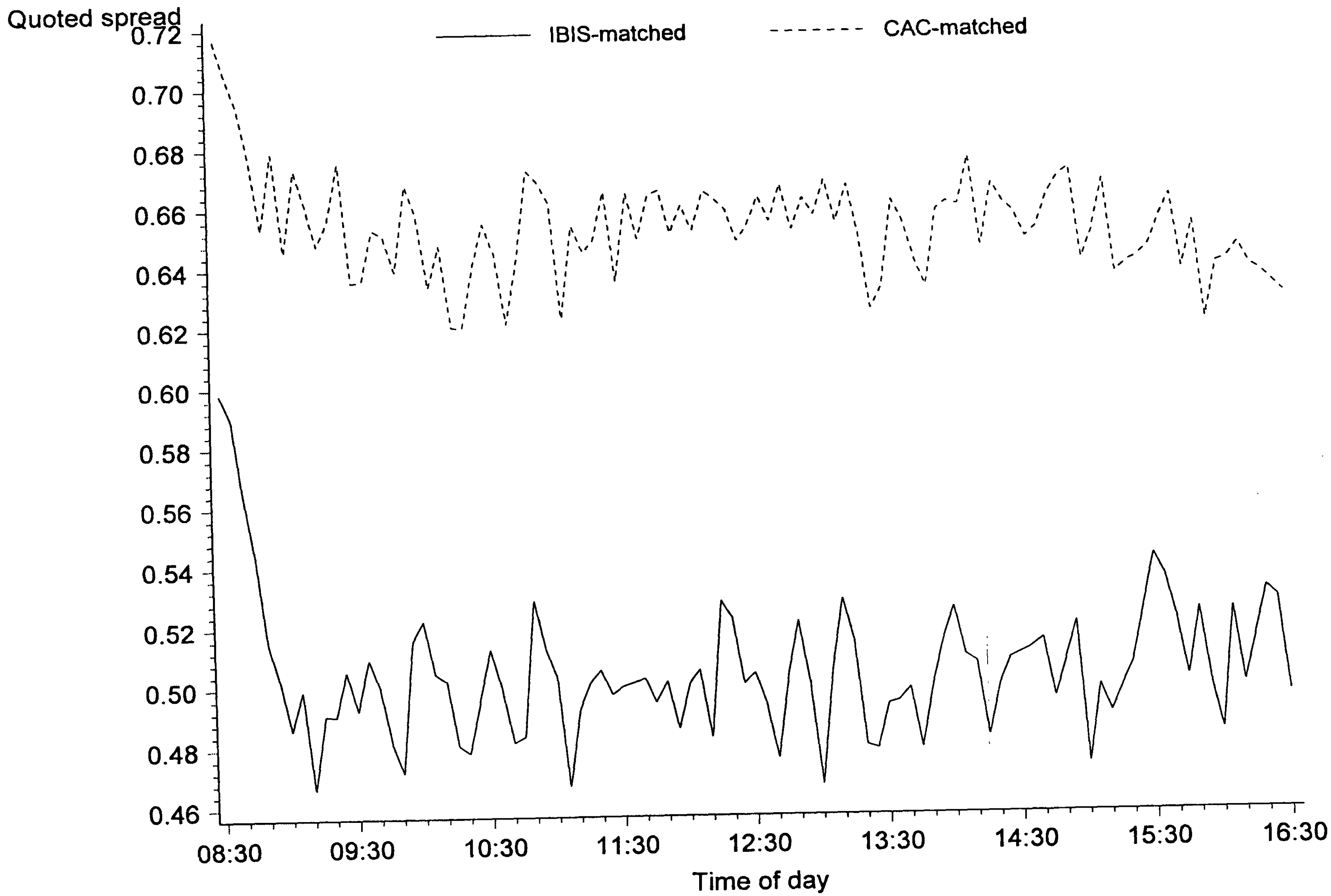


Figure 16. Effective spreads (in%) by trade size

Trade size censored at 1 NMS

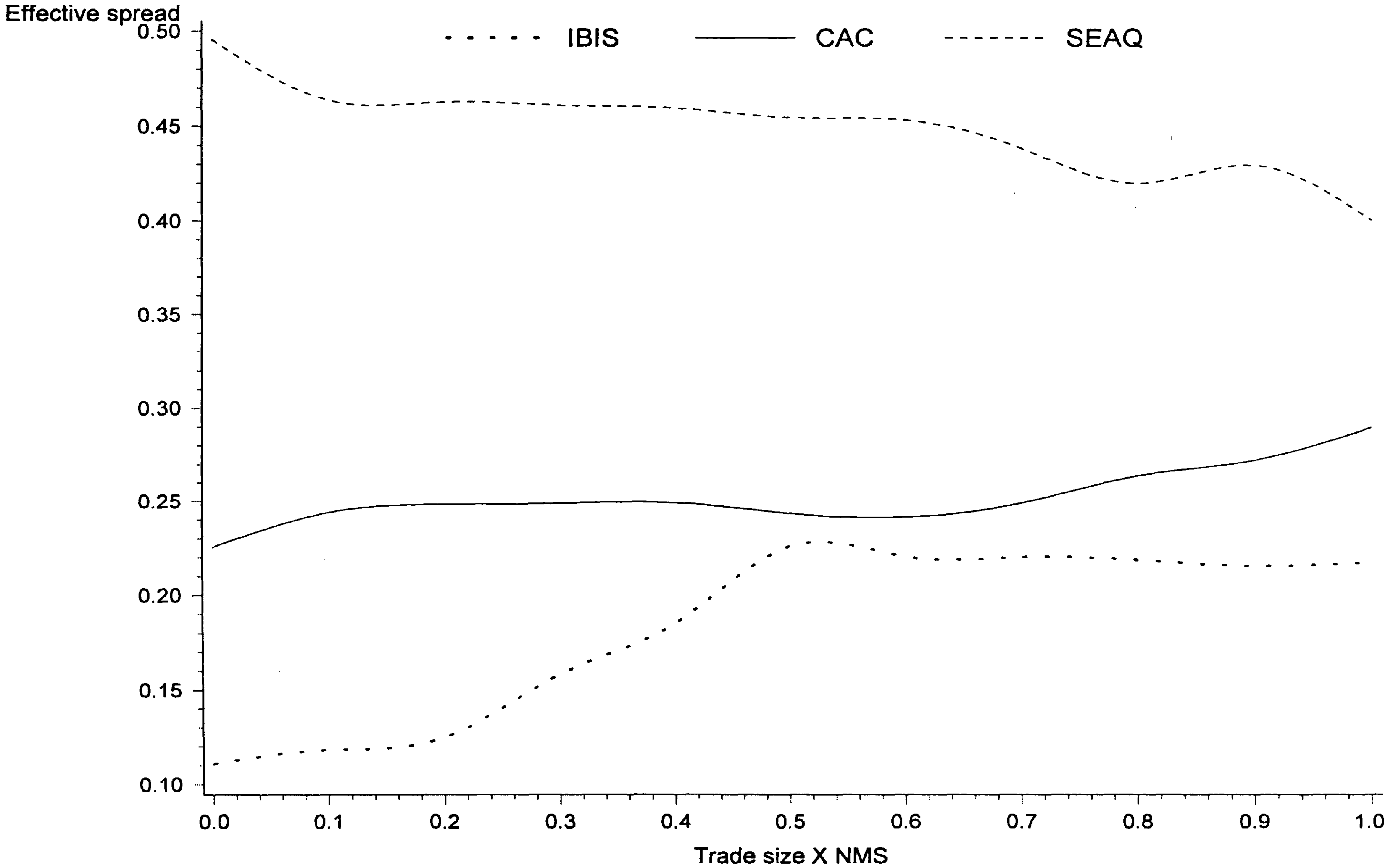
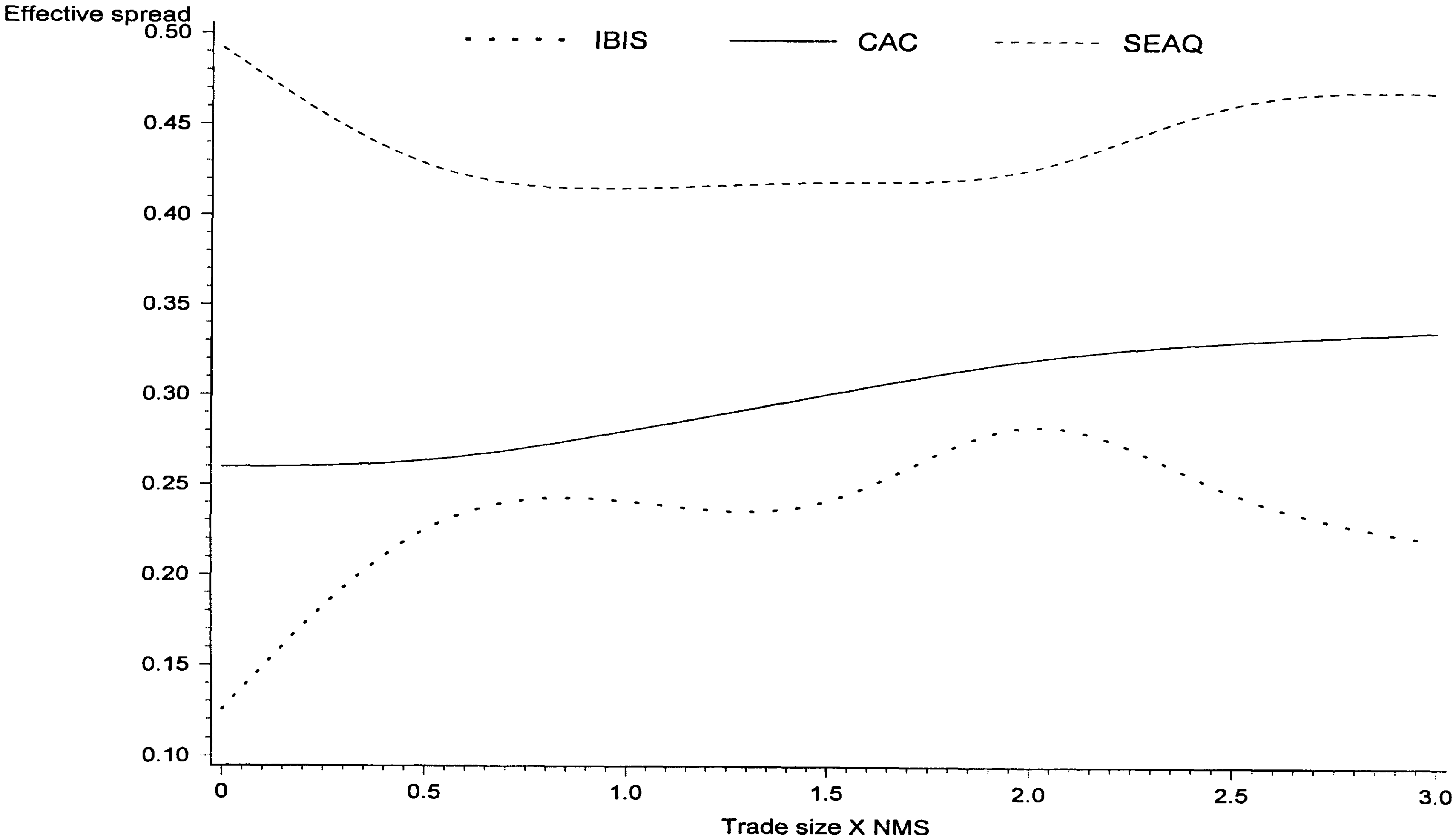


Figure 17. Effective spreads (in%) by trade size

Trade size censored at 3 NMS



Tables 28 to 30 show the effective spread for the three markets. For CAC and IBIS, it is expected that the costs sustained by a patient trader would be smaller compared to costs associated with aggressive trading. In addition, given the negative price impact generated by order book-based systems when a large order executes, large traders should submit their order when the market is deep. Hence, it is to be expected that effective spreads are smaller than quoted spreads, especially for larger trades.

For SEAQ, the argument is different reflecting the different microstructure in place. On SEAQ, it is expected that larger trades, in contrast to small trades, take place within the touch and are executed at prices that are negotiated between the market maker and the trader (London Stock Exchange, 1992).

The analysis is divided in two parts. First, all trades on all markets are considered and classified using the same methodology used for quoted spreads. Secondly, only trades up to 1 X NMS are considered on all the three markets in order to focus on the most common type of trades across the three systems. Following this, all trades are considered but the analysis is cut off at the 3 X NMS trade size since there is not much scope in analysing trades beyond this size when comparing these three markets.

The results are summarised in Figures 16 and 17 and in Tables 12-14.

When considering trades smaller than 1 X NMS, some definite patterns emerge. For the CAC, the effective spread seems largely stable for trade sizes up to 0.7 X NMS and then increases slightly over the 0.8-1 X NMS. Over this range, the effective spread does not increase with trade size, as was the case with the quoted spreads.

When the 0-3 X NMS size range is considered, some other interesting patterns emerge. The CAC spreads is stable up to 1 X NMS size, peaking

Table 28: **Mean effective spread (percent) for CAC- and SEAQ-paired securities**

PANEL A. EFFECTIVE SPREAD FOR CAC-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.4311	0.4381	< 0.1	0.2725
I	Medium	0.4515	0.4611	0.1 - 0.2	0.2916
I	Large	0.5115	0.5201	0.2 - 0.3	0.3055
				0.3 - 0.4	0.3047
II	Small	0.2599	0.2644	0.4 - 0.5	0.3059
II	Medium	0.3107	0.3087	0.5 - 0.6	0.3064
II	Large	0.3522	0.3629	0.6 - 0.7	0.3088
				0.7 - 0.8	0.3188
III	Small	0.1782	0.1802	0.8 - 0.9	0.3228
III	Medium	0.1858	0.1901	0.9 - 1.0	0.3317
III	Large	0.2039	0.2025		

PANEL B. EFFECTIVE SPREAD FOR SEAQ-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.6265**	0.6366**	<0.1	0.5699
I	Medium	0.6131**	0.6248**	0.1 - 0.2	0.5631
I	Large	0.5981*	0.5971*	0.2 - 0.3	0.5587
				0.3 - 0.4	0.5511
II	Small	0.4314**	0.4238**	0.4 - 0.5	0.5484
II	Medium	0.3807*	0.3915*	0.5 - 0.6	0.5426
II	Large	0.3483	0.3545	0.6 - 0.7	0.5383
				0.7 - 0.8	0.5244
III	Small	0.3497**	0.3468**	0.8 - 0.9	0.5268
III	Medium	0.3153*	0.3098*	0.9 - 1.0	0.5261
III	Large	0.3061*	0.3072*		

Trades were classified on their trade position - whether at the best ask or the best bid. The percentage effective spread is measured as:

$$100 \cdot 2 \sum_{i=1}^{N} S(\underline{m} < mi \leq \bar{m}) \cdot \left[\frac{SB_{it}(p_t[i] - v_t[i])}{v_t[i]}\right] \ / \ \sum_{i=1}^{N} S(\underline{m} < mi \leq \bar{m})$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured SEAQ-CAC spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Table 29: **Mean effective spread (percent) for CAC- and IBIS-paired securities**

PANEL A. EFFECTIVE SPREAD FOR CAC-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.3719	0.3732	< 0.1	0.2254
I	Medium	0.3913*	0.3878*	0.1 - 0.2	0.2438
I	Large	0.4152*	0.4201*	0.2 - 0.3	0.2484
				0.3 - 0.4	0.2488
II	Small	0.2822*	0.2892*	0.4 - 0.5	0.2490
II	Medium	0.3304**	0.3273**	0.5 - 0.6	0.2433
II	Large	0.3656**	0.3764**	0.6 - 0.7	0.2414
				0.7 - 0.8	0.2489
III	Small	0.1567	0.1564	0.8 - 0.9	0.2635
III	Medium	0.1831*	0.1791*	0.9 - 1.0	0.2719
III	Large	0.2170*	0.1882*		

PANEL B. EFFECTIVE SPREAD FOR IBIS-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.3292	0.3344	<0.1	0.1188
I	Medium	0.3312	0.3213	0.1 - 0.2	0.1201
I	Large	0.3699	0.3643	0.2 - 0.3	0.1455
				0.3 - 0.4	0.1654
II	Small	0.1511	0.1565	0.4 - 0.5	0.1975
II	Medium	0.2204	0.2253	0.5 - 0.6	0.2295
II	Large	0.2808	0.2685	0.6 - 0.7	0.2315
				0.7 - 0.8	0.2341
III	Small	0.1282	0.1306	0.8 - 0.9	0.2298
III	Medium	0.1535	0.1492	0.9 - 1.0	0.2306
III	Large	0.1661	0.1601		

Trades were classified on their trade position - whether at the best ask or the best bid. The percentage effective spread is measured as:

$$100 \cdot 2 \sum_{i=1}^{N} S(\underline{m}< mi \leq \bar{m}) \cdot \left[\frac{SB_{it}(p_t[i]-v_t[i])}{v_t[i]}\right] \ / \ \sum_{i=1}^{N} S(\underline{m}< mi \leq \bar{m})$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured CAC-IBIS spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

Table 30: **Mean effective spread (percent) for IBIS- and SEAQ-paired securities**

PANEL A. EFFECTIVE SPREAD FOR IBIS-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.3243	0.3294	< 0.1	0.1108
I	Medium	0.3262	0.3165	0.1 - 0.2	0.1183
I	Large	0.3644	0.3588	0.2 - 0.3	0.1248
				0.3 - 0.4	0.1584
II	Small	0.1488	0.1542	0.4 - 0.5	0.1852
II	Medium	0.2171	0.2219	0.5 - 0.6	0.2261
II	Large	0.2766	0.2645	0.6 - 0.7	0.2206
				0.7 - 0.8	0.2204
III	Small	0.1096	0.1106	0.8 - 0.9	0.2189
III	Medium	0.1412	0.1469	0.9 - 1.0	0.2157
III	Large	0.1536	0.1577		

PANEL B. EFFECTIVE SPREAD FOR SEAQ-PAIRED SECURITIES

		All trades		Trades censored at 1 X NMS	
Portfolio	Trade	At Ask	At Bid	Trade size	Spread
I	Small	0.5325*	0.3571*	< 0.1	0.4956
I	Medium	0.5212*	0.5311*	0.1 - 0.2	0.4635
I	Large	0.5083*	0.5075*	0.2 - 0.3	0.4626
				0.3 - 0.4	0.4655
II	Small	0.4492**	0.4519**	0.4 - 0.5	0.4595
II	Medium	0.4393**	0.4414**	0.5 - 0.6	0.4544
II	Large	0.4153**	0.4244**	0.6 - 0.7	0.4533
				0.7 - 0.8	0.4384
III	Small	0.3891**	0.3931**	0.8 - 0.9	0.4199
III	Medium	0.3781**	0.3863**	0.9 - 1.0	0.4294
III	Large	0.3611**	0.3622**		

Trades were classified on their trade position - whether at the best ask or the best bid. The percentage effective spread is measured as:

$$100 \cdot 2\sum_{i=1}^{N} S(\underline{m}< mi \leq \bar{m}) \cdot \left[\frac{SB_{it}(p_t[i]-v_t[i])}{v_t[i]}\right] \; / \; \sum_{i=1}^{N} S(\underline{m}< mi \leq \bar{m})$$

Trades have been classified as follows: (a) small when trade size is less than 0.5 NMS; (b) medium if trade size falls between 0.5 X NMS and 1 X NMS; (c) large if trade size is larger than 1 X NMS.

An * or ** symbol signifies that the difference in the measured SEAQ-IBIS spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

for trades within the 1-1.5 X NMS trade size and then declining marginally and staying stable over the remaining trade range. It must be stated that the data for trades above 1 X NMS is generally sparse.

For IBIS, different patterns than those experienced on CAC are observed. The effective spread increases steadily from 0.11% obtained for trades smaller than 0.1 X NMS to reach 0.221% for trades between 0.4-0.5 X NMS. After which, the effective spread remains largely stable, declining marginally for trades classified in the 0.8-1 X NMS trade size class. However, Figures 16 and 17 and Table 29 show that effective spreads on CAC are consistently bigger than those on IBIS, confirming the result obtained for quoted spreads. The biggest absolute difference is obtained for the smallest trades where spreads for the smallest sample (less than 0.1 X NMS) are almost double on CAC than they are on IBIS.

The effective spread for SEAQ follows a declining trend up to 1 X NMS and this is particularly clear for the larger SEAQ securities (the most active securities). For example, this particular sample produces spreads that start off at 0.4956% for the smallest trades and then settling at 0.454% for the 0.5-0.6 X NMS trades. Trades that are about 1 X NMS are transacted with a spread of 0.429%. When the trade size range is expanded to consider trades up to 3 X NMS, a U-shaped curve appears. Smallest trades attract 0.492%; 1 X NMS trades attract 0.415%; while 3 X NMS attract spreads in the magnitude of 0.462%.

Similar patterns for SEAQ were observed by Breedon (1992), Tonks and Snell (1992) and Röell (1992). Medium-sized trades have the lowest bid-ask spreads on SEAQ. This could be directly related to the stealth trading hypothesis advanced by Barclay and Warner (1993). They suggest that informative trading does not take place through large trades but rather via medium-sized trades employed by informed traders to camouflage themselves and hide their information.

Another important aspect resulting from the SEAQ results is that effective spreads are substantially lower than quoted spreads. There are a number of plausible explanations for such a result. First, it could be due to timing misreporting (market makers executing trades on SEAQ are allowed up to three minutes to report the trade to the LSE). This reporting lag could induce a bias since quote changes are entered in the system faster than trades' execution, leading to the bias explained above.

In view of this, transaction times in the LSE data set were randomly anticipated by 30, 60, 90, 120, 150 and 180 seconds to investigate the robustness of the results obtained directly from the market makers' trade reports. The new results obtained from these exercises were not statistically different from the results shown before, leaving scope to search for different causes.

Secondly, this result implies that spreads are submitted by market makers as the basis to start a negotiation with the traders submitting certain types of trades. SEAQ market makers do not seem to update their quotes as often compared to what happens on CAC and IBIS. If submitting quotes to the market is tantamount to writing a free option to traders and noting that negotiation is expected in a dealership market, then it is clear that quote updates on SEAQ are bound to be less frequent than on CAC and IBIS.

As stated above, the ASL test is employed in order to investigate whether the spreads' absolute levels are statistically different across the various market microstructures. This test was employed since it was deemed to be better suited for our case where spreads drawn from different populations were employed. However, it must be stated that the same conclusion was obtained when a more traditional $t - test$, based on two normal distributions with unequal variances, was employed.

One possible explanation for the tight IBIS spreads can also be given by the fact that floor trading on the FSE takes place over a number of IBIS trading hours, hence increasing the level of competition in the German trading system. Figure 13 indicates that IBIS quoted spreads do not widen after 13:30:00 hrs when the floor trading on FSE closes, indicating that IBIS quoted spreads are relatively high in the 08:30:00 hrs-10:30:00 hrs, before floor trading starts. This evidence, however, is consistent with the view that spreads are higher at the open on any system under consideration.

To investigate further whether competition from the FSE has a significant impact on IBIS spreads and explaining the lower trading costs, the IBIS sample was divided into two samples: (a) Sample 1 with trades that take place between 08:30:00 hrs and 10:29:59 hrs and trades between 13:31:00 hrs and 17:00:00 hrs; and (b) Sample 2 with trades taking place between 10:30:00 hrs and 13:30:00 hrs. The first sample has trades taking place when the FSE is closed while the second sample containing trades when the FSE is closed.

If the suggestion that spreads on IBIS are low because of FSE trading is correct, then we should expect to have spreads in Sample 2 to be significantly lower than spreads in Sample 1. Table 31 shows that the low spreads on IBIS cannot be explained by trading on FSE since most of the quoted and effective spreads are not statistically significantly different across the two samples. Indeed, it appears that trades and volume cluster when quotes are low, not just in the morning, when FSE is open, but also in the afternoon when the FSE is closed. Furthermore, the B-H spread differential over the period when the FSE is closed is not significantly different from when the FSE is open.

The general result obtained from the analysis of the different impacts generated by various factors, such as inventory costs and adverse selection, on

Table 31: **Impact of floor trading on IBIS effective spreads**

PANEL A. IBIS SPREAD WHEN FSE IS CLOSED

		All Trades (1)		All Trades (2)	
Portfolio	Trade	At Ask	At Bid	At Ask	At Bid
I	Small	0.3511*	0.3603*	0.3237*	0.3311*
I	Medium	0.3385	0.3368	0.3006	0.3058
I	Large	0.3582	0.3741	0.3282	0.3293
II	Small	0.1653*	0.1608*	0.1447	0.1404
II	Medium	0.2179	0.2217	0.2123	0.2107
II	Large	0.2705	0.2597	0.2475	0.2427
III	Small	0.1073	0.1086	0.0983	0.0996
III	Medium	0.1637*	0.1602	0.1451	0.1414
III	Large	0.1659	0.1652	0.1518	0.1562

PANEL B. IBIS SPREAD WHEN FSE IS OPEN

		All trades	
Portfolio	Trade	At Ask	At Bid
I	Small	0.2802	0.2781
I	Medium	0.3221	0.3198
I	Large	0.3829	0.3851
II	Small	0.1288	0.1311
II	Medium	0.2097	0.2147
II	Large	0.2944	0.2815
III	Small	0.0926	0.929
III	Medium	0.1389	0.1307
III	Large	0.1538	0.1386

Trades were classified on their trade position - whether at the best ask or best bid. Trades executed within the touch were not considered in order to obtain a common measure for both the two sub-periods. All trades (1) consider trades in two periods 08:30:00 hrs - 10:29:00 hrs and 13:31:00 hrs - 17:00:00 hrs. All trades (2) consider trades transacted in the period 13:31:00 hrs - 17:00:00 hrs.

An * or ** symbol signifies that the difference in the spread is statistically significant at the 5% and 1% levels of confidence respectively using ASL.

effective spreads appear to be mixed. Generally speaking, effective spreads on IBIS do increase with size, especially if trades smaller than 1 X NMS are considered, implying that dealers take into consideration the fact that inventory costs and adverse selection increase with size when setting quotes. The same cannot be said for the CAC system whereby effective quotes are not very sensitive to changes in trade size for trades lower than 1 X NMS. SEAQ results provide mixed evidence whereby small and large trades attract relatively higher trades, with medium trades attracting lower spreads.

In terms of the first set of hypothesis tested, hypothesis 1_O is not rejected in that spreads on the dealership system are higher than spreads generated in both the pure order book system and the hybrid platform. On the other hand, hypothesis 2_O is not accepted given the number of instances where IBIS quoted and effective spreads are lower than those generated by CAC.

3.7 Adverse Selection Component

Another important issue is the identification of the components forming the spread and how they change, if at all, from one market to another. If market microstructure does matter, then we should find that not only does the level of the spread change from one market to another, but also its components differ. The most intriguing question, and the one that has received most attention, is what percentage of the spread accounts for adverse selection and whether it is affected by different trading architectures.

Addressing the spread's components issue is necessary for two reasons. Firstly, to assess whether the spread differentials between the trading systems, found above, can be explained by the presence of informed traders. The preceding Section has shown that spreads on SEAQ are wider than those on CAC and IBIS. These wider spreads could be the result of higher adverse selection on SEAQ or due to market makers' inability in dealing effectively with private information.

Secondly, we need to shed light on the sources of the spread and investigate the impact of different market designs on how trade information is impounded into prices. The latter analysis will indicate whether one particular trading system is more effective than others in dealing with asymmetric information.

To investigate the spreads' component due to adverse selection, different methodologies will be used. The Huang and Stoll (1996) technique is applied in the first place. Secondly, we apply the George *et al.* (1991), Booth *et al.* (1995), Madhavan *et al.* (1997) and the Huang and Stoll (1997) methodologies to analyse the robustness of the results obtained.

Following Huang and Stoll (1996) and Bessembinder and Kaufman (1997), the spread's component due to adverse selection is found by measuring the dealers' (market makers or limit order traders) profits net of adverse selection. Due to price movements caused by the presence of adverse selection, the effective spread is not the best measure of the actual dealers' profits. Prices have been found to adjust, often in a direction against the dealer, after the execution of a large trade mainly due to the information contained in such trades.[9] This implies that dealers' revenue is the difference between the initial transaction price for a particular trade and the liquidation value of the stock some time after the original trade, when information is assumed to have been impounded in the price.

The first step is to calculate the price impact generated by each trade, defined as the change of the underlying value of the security following the

[9] Holtahusen *et al.* (1990) together with Hasbrouck (1988) and Huang and Stoll (1994) have found such price movements on NYSE. Gemmill (1996) and Board and Sutcliffe (1995) found similar price movements on the LSE.

execution of a trade.The mid price is assumed to be a good proxy for the security's economic value. If v_t is the stock's economic value at the time of trade execution, then v_{t+1} represents the stock's economic value some time after the trade when the information has been impounded in the price.

Hence, while the percentage effective half spread is given by:

$$\%\ half\ spread_{eff} = 100 \cdot \left[\frac{SB_{it}\left(p_t\left[i\right] - v_t\left[i\right]\right)}{v_t\left[i\right]}\right] \tag{17}$$

with the same notations used for (15) above, the permanent price impact is measured as:

$$\%\ price\ impact_{it} = 100 \cdot \left[\frac{SB_{it}\left(v_{t+n}\left[i\right] - v_t\left[i\right]\right)}{v_t\left[i\right]}\right] \tag{18}$$

where SB_{it} is the usual binary variable that equals to +1 in the case of a customer buy and -1 in case of a customer sell.

Dealers' gross revenue is measured as the effective spread less the price impact generated by the trade. Following Huang and Stoll (1996) and Bessembinder and Kaufman (1997) the gross revenue is given as:

$$\%\ gross\ revenue = 100 \cdot \left[\frac{SB_{it}\left(p_t\left[i\right] - v_{t+n}\left[i\right]\right)}{v_t\left[i\right]}\right] \tag{19}$$

This measure uses the correction of the mid quote following the execution of the trade, v_{t+n}, to reflect any possible information contained in the original trade. It represents the dealers' revenue net of losses incurred due to adverse selection but before other costs, such as inventory and operating costs, are taken into account.

A number of explanations and caveats must be used at this stage. No prior empirical evidence can be used to correctly identify the time over which the information contained in a trade is impounded into prices. The period chosen is the product of an arbitrary decision. Too short a period will not capture the total effect of price reversal. On the other hand, taking a long period of time would allow for substantial variability in the price discovery process not directly attributable to one particular trade. Huang and Stoll (1996) use two time intervals after the trade's execution; they analyse the price level (a) around 5 minutes after the trade; and (b) around 30 minutes after the trade. On the other hand, Bessembinder and Kaufman (1997) use a 24 hour gap for their analysis.[10]

In view of the uncertainty for the duration of price impact across markets, three time horizons have been used for this analysis, namely (a) 5 minutes after the trade; (b) 30 minutes after the trade; and (c) 45 minutes after the trade. Our suspicion is that the last time interval is excessively protracted for CAC and IBIS trades and thus the results obtained should reflect additional variability induced by other factors.[11]

There are two additional issues that must be considered. First, a proxy for the security's true economic value after the trade execution must be found to measure correctly the actual dealers' profits. There appear to be two alternatives, namely the actual trade price for trades being executed after the specified time horizon has elapsed or using the mid quote over the same time horizon. The mid quote is used as the proxy for the security's true economic value.

Secondly, following Huang and Stoll (1996), the average price impact

[10] Board and Sutcliffe (1995), using large trades executed on SEAQ and considering clock time rather than transaction time, found that the price impact takes some 50 minutes to fully materialise.

[11] De Jong *et al.* (1995) studying trades on the Bourse de Paris through a VAR methodology found that for large transactions the price impact is slightly increasing over 20 transactions from the original trade but the biggest part takes place within 5 transactions. For SEAQ, the situation is slightly different and, following Board and Sutcliffe (1995), it is expected that some additional price impact is found using the last two time intervals.

generated by all trades is close to zero. This means that in order to measure the gross revenue, only trades executed at the best bid and ask quotes are considered. While this measurement will not bias the results obtained for CAC and IBIS, it will overestimate the net revenue earned by SEAQ market makers (in so far as a substantial number of trades take place within the touch).

Tables 32-34 show the gross revenues earned by market makers on SEAQ and limit order traders on CAC and IBIS. The price impact generated five minutes after a small and medium trade is not substantial resulting in gross revenues that are quite similar to the effective spread. However, large trades do appear to cause a price impact resulting in gross revenues equivalent to 25.6% of effective spreads on CAC, 19.17% on IBIS and 13.44% for SEAQ transactions.

The most important results arise from gross revenues obtained over a 30-minutes time horizon. For small trades, gross revenues still show no sign of a price impact. In fact, gross revenues are of the same magnitude of effective spreads for all markets, implying that small trades do not contain information. For medium-sized trades, the picture is different. First, CAC appears to experience a material price impact. In fact, the gross revenues for medium-sized trades on CAC are only 12.15% of effective spreads, with the difference explained by the price impact. On IBIS, medium-sized trades do produce a price impact but it is lower than on CAC (only 62.02% against the 84.19% on CAC).

The dealers' gross revenues show a number of interesting features. First, the price impact on CAC is very high, with gross revenues amounting to 13.64% of total effective spreads. This implies that the price impact generated by large trades on CAC is substantially higher than the impact gener-

Table 32: **Liquidity providers' gross revenue on the CAC system**

PANEL A. MEAN GROSS REVENUE (IN %) ON CAC

		5 minute		30 minute		45 minute	
Portfolio	Trade	At Ask	At Bid	At Ask	At Bid	At Ask	At Bid
I	Small	0.4225	0.4294	0.3794	0.3855	0.3707	0.3768
I	Medium	0.3612	0.3781	0.1084	0.1014	0.1084	0.1014
I	Large	0.3785	0.3744	0.0665	0.0624	0.0691	0.0624
II	Small	0.2559	0.2604	0.2339	0.2379	0.2287	0.2326
II	Medium	0.2517	0.2531	0.0932	0.0864	0.0746	0.0803
II	Large	0.2642	0.2612	0.0598	0.0581	0.0528	0.0472
III	Small	0.1665	0.1834	0.1514	0.1667	0.1481	0.1629
III	Medium	0.1442	0.1481	0.0509	0.0511	0.0475	0.0476
III	Large	0.1570	0.1569	0.0265	0.0263	0.0306	0.0243

Dealers' gross revenue is measured as the effective spread less the price impact generated by the trade as follows:

$$\%\ gross\ revenue = 100 \cdot \left[\frac{SB_{it}(p_t[i] - v_{t+n}[i])}{v_t[i]}\right]$$

where SB_{it} is a binary variable that equals to +1 in the case of a customer buy and -1 in case of a customer sell.

This measure uses a correction of the mid quote following the execution of the trade, v_{t+n}, to reflect any possible information contained in the original trade.

In view of the uncertainty in the exact duration for price impacts across markets, three time horizons have been used for this analysis: (a) 5 minutes after the trade; (b) 30 minutes after the trade; and (c) 45 minutes after the trade.

Table 33: **Liquidity providers' gross revenue on the IBIS platform**

PANEL A. MEAN GROSS REVENUE (IN %) ON IBIS

		5 minute		30 minute		45 minute	
Portfolio	Trade	At Ask	At Bid	At Ask	At Bid	At Ask	At Bid
I	Small	0.3226	0.3277	0.3095	0.3177	0.3160	0.3177
I	Medium	0.2848	0.2698	0.1491	0.1253	0.1524	0.1317
I	Large	0.3244	0.3124	0.1506	0.1521	0.1487	0.1495
II	Small	0.1488	0.1542	0.1420	0.1471	0.1435	0.1471
II	Medium	0.1807	0.1915	0.0859	0.0946	0.0760	0.0971
II	Large	0.2345	0.2329	0.1093	0.1098	0.1167	0.1134
III	Small	0.1018	0.1016	0.0921	0.0934	0.0931	0.0975
III	Medium	0.1289	0.1269	0.0599	0.0627	0.0629	0.0619
III	Large	0.1398	0.1381	0.0797	0.0717	0.0689	0.0652

Dealers' gross revenue is measured as the effective spread less the price impact generated by the trade as follows:

$$\% \; gross \; revenue = 100 \cdot \left[\frac{SB_{it}(p_t[i] - v_{t+n}[i])}{v_t[i]} \right]$$

where SB_{it} is a binary variable that equals to +1 in the case of a customer buy and -1 in case of a customer sell.

This measure uses a correction of the mid quote following the execution of the trade, v_{t+n}, to reflect any possible information contained in the original trade.

In view of the uncertainty in the exact duration for price impacts across markets, three time horizons have been used for this analysis: (a) 5 minutes after the trade; (b) 30 minutes after trade; and (c) 45 minutes after the trade.

Table 34: **Dealers' gross revenue on SEAQ system**

PANEL A. MEAN GROSS REVENUE (IN %) ON SEAQ

		5 minute		30 minute		45 minute	
Portfolio	Trade	At Ask	At Bid	At Ask	At Bid	At Ask	At Bid
I	Small	0.6140	0.6239	0.6014	0.6112	0.5889	0.5984
I	Medium	0.5383	0.5314	0.4187	0.3902	0.4068	0.3883
I	Large	0.5457	0.5498	0.3672	0.3923	0.3549	0.3798
II	Small	0.4249	0.4174	0.4185	0.4111	0.4098	0.4026
II	Medium	0.3274	0.3327	0.2508	0.2492	0.2532	0.2314
II	Large	0.3065	0.3119	0.2634	0.2711	0.2564	0.2539
III	Small	0.3462	0.3433	0.3392	0.3259	0.3322	0.3191
III	Medium	0.2712	0.2633	0.2191	0.2066	0.2128	0.1904
III	Large	0.2571	0.2704	0.2221	0.2205	0.2159	0.2043

Dealers' gross revenue is measured as the effective spread less the price impact generated by the trade as follows:

$$\%\ gross\ revenue = 100 \cdot \left[\frac{SB_{it}(p_t[i] - v_{t+n}[i])}{v_t[i]}\right]$$

where SB_{it} is a binary variable that equals to +1 in the case of a customer buy and -1 in case of a customer sell.

This measure uses a correction of the mid quote following the execution of the trade, v_{t+n}, to reflect any possible information contained in the original trade.

In view of the uncertainty in the exact duration for price impacts across markets, three time horizons have been used for this analysis: (a) 5 minutes after the trade; (b) 30 minutes after trade; and (c) 45 minutes after the trade.

ated by medium sized trades. On IBIS, the same tendency obtains but the magnitude is smaller. Price impact for large trades on IBIS is not materially higher than that for medium sized trades, accounting for 67.02% of effective spreads. However, the results obtained for SEAQ trades are different.

In terms of classifying the magnitude of the adverse selection component, it is found that the costs associated with private information are highest on CAC, with the price impact wiping some 85% of the effective spread. This result can be compared to those obtained by de Jong *et al.* (1995) for the Paris Bourse. Using the Glosten (1994) model, they found that the adverse selection cost component of small trades amounts for 30% of the effective spread whereas it reaches 45% for large trades. When they used a VAR methodology to make the Hasbrouck (1991a, 1991b, 1993) model operational, they found that the mean permanent price impact generated by large trades (defined as 1 X NMS) is in the region of 115% of the estimated effective bid-ask spread. The results obtained here would place the adverse selection cost component somewhere in between the two different estimates made by de Jong *et al.* (1995).

After the first round of results obtained from the Huang and Stoll (1996) methodology, the algorithms proposed by George *et al.* (1991), Booth *et al.* (1995), Madhavan *et al.* (1997) and the Huang and Stoll (1997). Appendix E provides an extensive description of the different methodologies proposed by the latter set of models. These theoretical models are made operational through a trade-by-trade analysis. At this stage, one could ask whether a trade-by-trade approach is likely to impact the results. George, Kaul, and Nimalendran (1991) indicate that the differencing interval should not affect estimates of the order-processing cost and adverse selection components of the quoted spread. They suggest that the "use of high frequency data is more appropriate" because of potential small-sample bias. The intraday quote and transaction returns is used to calculate autocovariances and estimate these models using daily time-series observations.

The results obtained from the various metrics confirm those obtained from the Huang and Stoll (1996) methodology and show that the adverse selection component of the spreads are lowest on the dealership system. This suggest that although SEAQ produces the widest bid-ask spreads, these cannot be explained in terms of the adverse selection component. SEAQ market makers deal effectively with informed traders, possibly because of the relationships that are built. Hence different reasons should be found to explain wider spreads on dealership markets.

In view of the above results, Hypothesis 3_O cannot be accepted since for most trades the adverse selection component of the effective spread is significantly lower on SEAQ.

It is pertinent to remember that the measure of the spread used in each of these methodologies to calculate the adverse selection component differs across the different algorithms. The George, Kaul and Nimalendran (1991) and the Booth, Lin and Sanger (1995) methodologies use the effective spread, the Madhavan, Richardson and Roomans (1997) algorithm uses the implied spread whereas the adverse selection component measured on the lines of Huang and Stoll (1997) uses the spread as derived by the same authors. In view of these differences in terms of the spread used to calculate the adverse selection component, it is useful to analyse the correlation between the different measures. Table 38 reports the Pearson correlation coefficients which shows that the different measures are highly correlated within the same Exchange.

Table 35: **Adverse selection component (CAC and SEAQ)**

PANEL A. ADVERSE SELECTION COMPONENT ON CAC

Portfolio	Trade	HS (96)	GKN	BLS	MRR	HS (97)
I	Small	4.91	3.11	3.82	4.42	4.48
I	Medium	79.12	49.69	58.22	61.28	61.04
I	Large	84.56	50.12	59.10	64.12	63.61
II	Small	5.21	4.54	4.01	5.72	4.95
II	Medium	81.22	51.28	59.43	62.49	62.88
II	Large	85.62	52.18	61.29	65.21	64.91
III	Small	6.01	5.01	5.21	5.86	4.89
III	Medium	82.41	52.11	60.01	65.88	64.81
III	Large	86.98	53.02	62.46	68.14	66.21

PANEL B. ADVERSE SELECTION COMPONENT ON SEAQ

Portfolio	Trade					
I	Small	4.82	5.18	4.92	4.86	5.28
I	Medium	50.89**	32.81**	36.70**	41.60**	44.17**
I	Large	53.14**	34.58**	39.09**	43.15**	46.42**
II	Small	6.02	5.96	4.51	5.46	5.81
II	Medium	54.26**	34.61**	39.91**	42.82**	45.33**
II	Large	55.81**	35.87**	42.21**	45.78**	49.82**
III	Small	6.51	5.02	6.68	5.19	5.44
III	Medium	56.11**	35.51**	40.97**	44.39**	47.87**
III	Large	58.22**	36.89**	43.86**	47.96**	51.13**

The Table provides estimates of the adverse selection component of the spreads on CAC and SEAQ (in percentage terms).
The HS (96) estimates are measured using the Huang and Stoll (1996) approach on the effective spread. GKN estimate is calculated using the George, Kaul and Nimalendran (1991) measure and expressed on the quoted spreads; BLS refers to the measure proposed by Booth, Sangpx and Lin (1995) and expressed in terms of the effective spread; MRR is the Madhavan, Richardson and Roomans (1997) methodology using the implied spread; while the HS (97) refers to the Huang and Stoll (1997) methodology.
An * or ** signify that the difference in the spread's adverse selection component is significant at the 5% and 1% levels of confidence respectively using ASL.

Table 36: **Adverse selection component (IBIS and SEAQ)**

Portfolio	Trade	HS (96)	GKN	BLS	MRR	HS (97)
PANEL A. ADVERSE SELECTION COMPONENT ON IBIS						
I	Small	4.48	4.69	5.01	4.66	4.79
I	Medium	65.01	39.31	46.72	49.18	51.96
I	Large	67.82	40.82	48.81	51.69	53.15
II	Small	4.98	4.81	5.09	4.81	5.01
II	Medium	68.86	43.44	49.25	52.81	55.14
II	Large	70.21	45.62	51.88	54.21	57.81
III	Small	6.02	5.21	5.66	5.81	4.98
III	Medium	69.98	45.39	51.21	54.48	56.09
III	Large	71.22	47.42	53.67	56.58	59.98
PANEL B. ADVERSE SELECTION COMPONENT ON SEAQ						
Portfolio	Trade					
I	Small	4.18	4.01	3.58	3.86	4.01
I	Medium	49.18*	31.76*	35.17*	39.29*	43.02*
I	Large	51.21*	32.18*	38.11*	41.88*	45.08*
II	Small	5.11	4.51	4.22	4.01	4.06
II	Medium	52.12*	33.26*	39.22*	41.04*	44.28*
II	Large	53.02*	34.18*	41.02*	43.97*	46.64*
III	Small	5.68	4.48	4.46	4.28	4.20
III	Medium	54.18*	33.85*	39.22*	43.14*	45.29*
III	Large	56.26*	34.82*	41.84*	45.19*	49.94*

The Table provides estimates of the adverse selection component of the spreads on IBIS and SEAQ (in percentage terms).
The HS (96) estimates are measured using the Huang and Stoll (1996) approach on the effective spread. GKN estimate is calculated using the George, Kaul and Nimalendran (1991) measure and expressed on the quoted spreads; BLS refers to the measure proposed by Booth, Sanger and Lin (1995) and expressed in terms of the effective spread; MRR is the Madhavan, Richardson and Roomans (1997) methodology using the implied spread; while the HS (97) refers to the Huang and Stoll (1997) methodology.
An * or ** signify that the difference in the spread's adverse selection component is significant at the 5% and 1% levels of confidence respectively using ASL.

Table 37: **Adverse selection component (CAC and IBIS)**

PANEL A. ADVERSE SELECTION COMPONENT ON CAC

Portfolio	Trade	HS (96)	GKN	BLS	MRR	HS (97)
I	Small	4.22	4.18	4.62	4.81	4.01
I	Medium	77.42	47.19	56.26	60.19	60.92
I	Large	82.14	51.62	57.46	62.05	62.14
II	Small	4.62	4.18	4.29	4.45	4.52
II	Medium	80.44	50.28	57.51	62.82	63.18
II	Large	82.54	52.11	60.62	64.14	64.11
III	Small	5.12	4.88	4.26	4.56	4.68
III	Medium	81.11	51.22	60.81	64.71	63.92
III	Large	84.09	52.14	62.02	68.42	65.18

PANEL B. ADVERSE SELECTION COMPONENT ON IBIS

Portfolio	Trade					
I	Small	4.85	4.02	4.18	4.29	4.15
I	Medium	63.22	39.21*	44.12	49.91	50.86*
I	Large	64.18*	38.18**	45.29*	51.28*	52.66*
II	Small	5.06	4.29	4.41	4.56	4.18
II	Medium	67.91	41.28	49.25*	51.08	54.08
II	Large	68.09*	42.02*	50.28*	52.22*	55.61*
III	Small	5.21	4.46	4.66	4.61	4.41
III	Medium	69.12	43.08	51.81*	54.82	56.19
III	Large	70.21**	42.84*	52.26*	55.22*	58.22*

The Table provides estimates of the adverse selection component of the spreads on CAC and IBIS (in percentage terms).
The HS (96) estimates are measured using the Huang and Stoll (1996) approach on the effective spread. GKN estimate is calculated using the George, Kaul and Nimalendran (1991) measure and expressed on the quoted spreads; BLS refers to the measure proposed by Booth, Sanger and Lin (1995) and expressed in terms of the effective spread; MRR is the Madhavan, Richardson and Roomans (1997) methodology using the implied spread; while the HS (97) refers to the Huang and Stoll (1997) methodology.
An * or ** signify that the difference in the spread's adverse selection component is significant at the 5% and 1% levels of confidence respectively using ASL.

Table 38: **Correlation among the estimates of adverse selection**

PANEL A. CORRELATION ON CAC

	HS(96)	GKN	BLS	MRR	HS(97)
HS (96)	1.00	0.52	0.66	0.72	0.89
		(0.00)	(0.00)	(0.00)	(0.00)
GKN		1.00	0.71	0.49	0.56
			(0.00)	(0.00)	(0.00)
BLS			1.00	0.51	0.76
				(0.00)	(0.00)
MRR				1.00	0.82
					(0.00)
HS (97)					1.00

PANEL B. CORRELATION ON IBIS

	HS(96)	GKN	BLS	MRR	HS(97)
HS (96)	1.00	0.66	0.71	0.74	0.86
		(0.00)	(0.00)	(0.00)	(0.00)
GKN		1.00	0.79	0.52	0.61
			(0.00)	(0.00)	(0.00)
BLS			1.00	0.48	0.81
				(0.00)	(0.00)
MRR				1.00	0.86
					(0.00)
HS (97)					1.00

PANEL C. CORRELATION ON SEAQ

	HS(96)	GKN	BLS	MRR	HS(97)
HS (96)	1.00	0.71	0.75	0.76	0.85
		(0.00)	(0.00)	(0.00)	(0.00)
GKN		1.00	0.82	0.50	0.72
			(0.00)	(0.00)	(0.00)
BLS			1.00	0.56	0.79
				(0.00)	(0.00)
MRR				1.00	0.89
					(0.00)
HS (97)					1.00

The Table reports the Pearson correlation coefficients between the various measures of the adverse selection component
The HS (96) refers to the Huang and Stoll (1996) approach; GKN refers to the George, Kaul and Nimalendran (1991) measure; BLS refers to the Booth, Sanger and Lin (1995) methodology; MRR is the Madhavan, Richardson and Roomans (1997) approach; while the HS (97) is the Huang and Stoll (1997) methodology.

3.8 Motivations for the Results

To recapitulate, the results show that (a) quoted and effective spreads are higher on a dealership system, compared to both the pure order book system and the hybrid platform; (b) quoted and effective spreads on the hybrid system is significantly lower compared to the pure limit order book; and (c) the higher dealership spreads are not due to the adverse selection present in the market.

3.8.1 Higher Dealership Spreads

The possible explanations for the wider SEAQ spreads are higher (a) adverse selection, (b) inventory carrying, (c) processing costs, (d) higher realised profits earned by SEAQ market makers, or (e) institutional factors and trading behaviour that influence liquidity provision and spreads.

The results obtained for the adverse selection component are consistent with those obtained by Huang and Stoll (1996) for the NYSE and NASDAQ. Our results show that limit order traders on CAC and IBIS tend to suffer from private information more than SEAQ market makers.

As stated earlier, the reason for lower adverse election component on dealership markets can be attributed to trading practices, such as preferencing and internalisation, that give rise to long-term business relationships between traders and market makers. This relationship can best be explained in terms of a repeated game where reputation is of importance. In such a relationship, it is quite difficult for informed traders to hide their private information from the market maker because there is a repeated use of the market makers' services.

When investigating LSE market makers' profits, Hansch *et al.* (1998) found that they made profits on small trades, broke even on large trades but lost money on medium-sized trades. This finding implies that market makers do not cover completely themselves against adverse selection when they accept to execute medium-sized orders. In doing so, they provide narrower spreads (for medium sized trades) when they should widen them to protect themselves from informed traders.

Inventory management on SEAQ has been analysed, in particular the pre-positioning and post-positioning of market makers, by Board and Sutcliffe (1995). The implication from such results is that dealership markets are flexible in terms of accommodating different types of trades, using inventory levels to accommodate the order flow. Applying the Ho and Macris (1985) argument, one can conclude that continuous deviation from the optimal inventory level produces a cost to the market makers that has to be covered by wider bid-ask spreads.

However, the impact of inventory holding costs cannot be overestimated. Although inventory management is undoubtedly an essential part of a market maker's operations, SEAQ market makers could hedge the inventory risk by either taking positions in the derivative markets; and/or make use of the Inter Dealer Broker system that provides market makers with a market where to adjust and properly manage inventory positions.

After having investigated adverse selection and inventory holding costs, we need to consider the level of competition in each system as a possible explanation for the differences in the spreads. Existing literature shows that the monopoly power of dealers can contribute in a significant way to the formation of spreads.

Firstly, both CAC and IBIS systems allow public traders to submit limit orders, increasing competition in these systems. In the case of IBIS, these public traders will compete with the quotes submitted by the designated dealers (the kursmakler). On SEAQ, before the market reforms in 1997, public traders were not allowed to compete with the designated market makers.

Secondly, limit orders which were allowed on CAC and IBIS are intrinsically different from the market orders submitted on a dealership system and as such induce different trading behaviour. An impatient trader using limit orders must price such orders very aggressively for them to be executed. Moreover, using the free option hypotheses proposed by Copeland and Galai (1983) suggests that rapid changes in market conditions can make limit orders to go stale and fast quote revisions must be entered; otherwise such orders will be picked off. This can explain why quote revisions on CAC and IBIS are much more frequent than on SEAQ, reflecting limit orders traders' attempt to avoid staleness.

A related approach is based on the free options hypothesis, which could be at work on dealership markets in two contrasting ways. On one hand, if a market maker gains operational savings by not writing free options he should be in a position to share some of these savings with public traders by guaranteeing at least best execution. This result, however, depends on the market makers' power. On the other hand, analysing the issue from a market-wide perspective, the market makers' unwillingness to submit frequent quote revisions and avoid giving free options to public traders, leads to less competition in quote revisions, resulting in wider bid-ask spreads.

Thirdly, the levels of commissions charged across the different markets should also be investigated. Indeed, if the commission levels are lower on SEAQ compared to both CAC and IBIS, this could partly explain the higher spread levels; in that case, market makers would be charging their clients less on commissions and charging them more in terms of spreads.

Although such an analysis could lead to some interesting results, this is hampered by lack of appropriate data that can produce a meaningful comparison across the different systems. In fact, after the so-called Big Bang in 1986, the commissions charged by market makers were liberalised and each single market maker could charge his own commissions without any reference to any official commissions schedule. This state of affairs makes it difficult to compare commissions across the different trading systems since no general result could be obtained.

A more fruitful avenue is to consider the trading practices on dealership markets (such as preferencing and internalisation) can produce an important impact on spreads' formation since they could be restricting competition in a number of ways. Such practices are possible on SEAQ but are of difficult implementation on CAC and IBIS.

Market concentration on SEAQ appears to be materially different from what obtains on CAC and IBIS. Data for the different market concentration indices is not homogenous over the three systems. SEAQ data is collected for the period January-February 1996, the Paris Bourse and the Deutsche Börse provided data for January 1996.

The largest three market makers on SEAQ are involved in over 50% of the total £-denominated volume. The market is even more concentrated when the number of trades is considered. An interesting feature is the fact that small orders appear to be mostly channelled to the biggest three market makers.

Figure 20 shows the concentration ratio for the first five dealers/market makers on the three markets. While the biggest five SEAQ market markets transact over 70% of the £-denominated volume, the biggest five CAC dealers transact 41% of the market (the Ffr-denominated volume) and the respective biggest five IBIS dealers transact almost 30.5% of the DM-denominated volume. SEAQ is more concentrated than either CAC or IBIS and this level of concentration is expected to produce a direct impact on how the different market makers use quotes to compete for business.

To complement this analysis, an adjusted Herfindahl Index was implemented to assess market concentration. Following McInish and Wood (1992), the Herfindahl Index is calculated in the following way:

$$concentration = \left(1 - \sum P_i^2\right) / \left[(n-1)\sum P_i^2\right]$$

where P_i is the market share of each market maker or dealer and n is the number of market maker or dealers trading on the market. The Herfindahl Index for SEAQ is 0.532358 whereas the Index for IBIS reaches just 0.267629.

These results appear to show that, after controlling for variables that have been previously found to influence spreads, the lack of competition in the market for liquidity provision is one of the major reason influencing the level of trading costs on different trading systems.

3.8.2 Order Book vs. Hybrid Spread Differential

The results show that the hybrid system has consistently generated lower spreads compared to the continuous auction system. In view of this, institutional and structural differences between the two systems, such as cost of access, the market position and the market concentration in the two systems were analysed to search for possible explanations.

One major factor that could explain the spread differential is the level of market concentration on the two markets both in terms of the number of registered dealers trading on the two systems and the market share of the biggest dealers. The number of *societe de bourse* trading on CAC was over 60 as of January 1996 whereas there were 118 dealers trading on IBIS in the period January-November 1996. The data for IBIS dealers shows that out of these 118 dealers, some 92 dealers had a market share of less than 1% in the period January-November 1996. These figures show that IBIS has managed to attract a higher number of dealers, possibly because the cost of access, in this case the fixed costs components, are lower on IBIS compared to those for CAC.

In addition, and perhaps more importantly, the market share data shows that concentration on IBIS is materially lower than on CAC. The Herfindahl Index, calculated in the same fashion as above, shows a value of 0.2514 for IBIS whereas the value for CAC reaches 0.35621, indicating that concentration is higher on CAC compared to IBIS. Figure 20 shows that the biggest three dealers on CAC have a market share of almost 30% whereas the biggest three on IBIS command 22% of the market share. These results imply that competition for the order flow is higher between IBIS dealers than CAC dealers. This higher level of competition is expected to translate itself into more aggressive quoting strategies so as to attract order flow to the individual dealer.

From information provided by the Paris Bourse and the Deutsche Börse it appears that the cost of access to the CAC system is somewhat larger than that for IBIS. The Paris Bourse defines two types of traders: (a) traders who will only trade for customers in the capacity as brokers; and (b) traders who may act as dual-capacity brokers-dealers, generally called as *societe de bourse.* The fixed costs incurred by a broker to access the CAC is Ffr400,500 per year; a *societe de bourse* incurs Ffr400,000 per year to become a member of the Paris Bourse and then pay Ffr150,000 for every broker it employs with another Ffr200,000 being paid to cover the clearing of transactions. The fixed costs for an IBIS trader are, in absolute terms, lower than those on CAC; each IBIS trader pays an annual fixed cost of DM2,500 in order to access the system.

The structure of variable access costs is different in the two systems and appears to be more expensive on CAC. Trades on CAC carry the following trading charges: (a) trades smaller than 10,000 shares pay Ffr13; (b) trades involving 10,000 to 20,000 shares pay Ffr11; (c) trade sizes between 20,000 to 30,000 shares pay Ffr9; (d) trade sizes between 30,000 and 40,000 shares pay Ffr7; (e) trade sizes between 40,000 and 50,000 shares pay Ffr5; (f) trade sizes bigger than 50,000 shares pay Ffr3. In addition to the trade charges, the CAC traders have to pay Ffr2 for every order submitted on the book. On the other hand, the IBIS cost structure was based on a flat charge of DM3.5 for every trade transacted and there were no charges for submitting any order on the book.

Since most of the trades on CAC fall within the trade size band of 1-10,000 shares, the cost of an average CAC trade of Ffr13 (together with the additional Ff2 for each order submitted) must be compared with the total transaction cost of DM3.5. The variable costs of access to the system tend to be marginally lower on IBIS compared to CAC, implying that suppliers of liquidity are expected to pay less on the IBIS system compared to the CAC system. In addition, the dual-responsibility dealers, who trade on behalf of customers and for their own account, face lower variable costs when using IBIS. In this sense, IBIS can be seen as a hit-and-take system, cheap in terms of processing costs.

Figure 18. Market makers' market share of total trades transacted

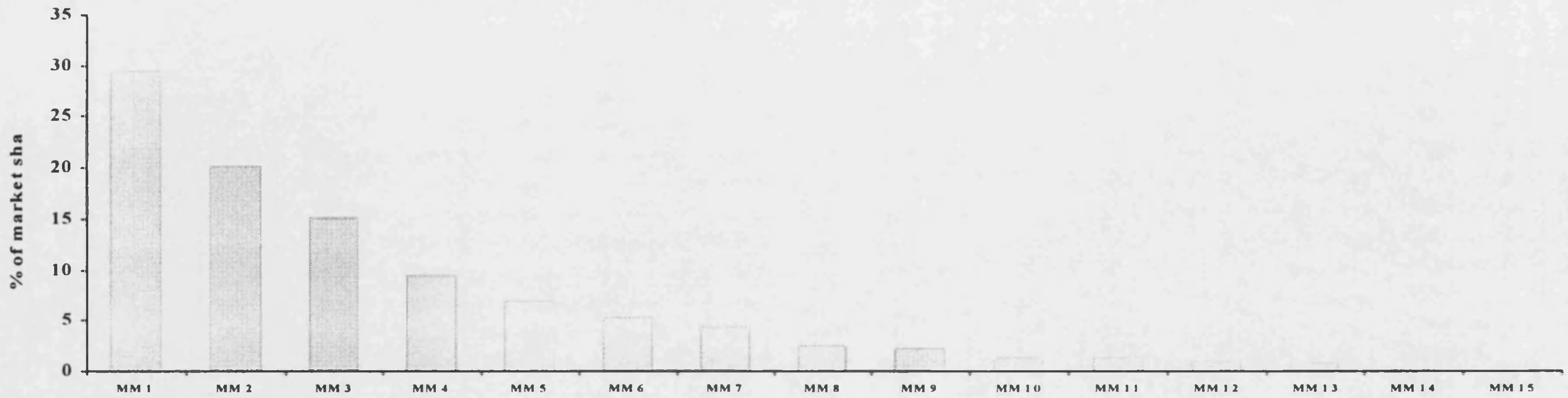


Figure 19. Individual and cumulative market shares in volume transacted

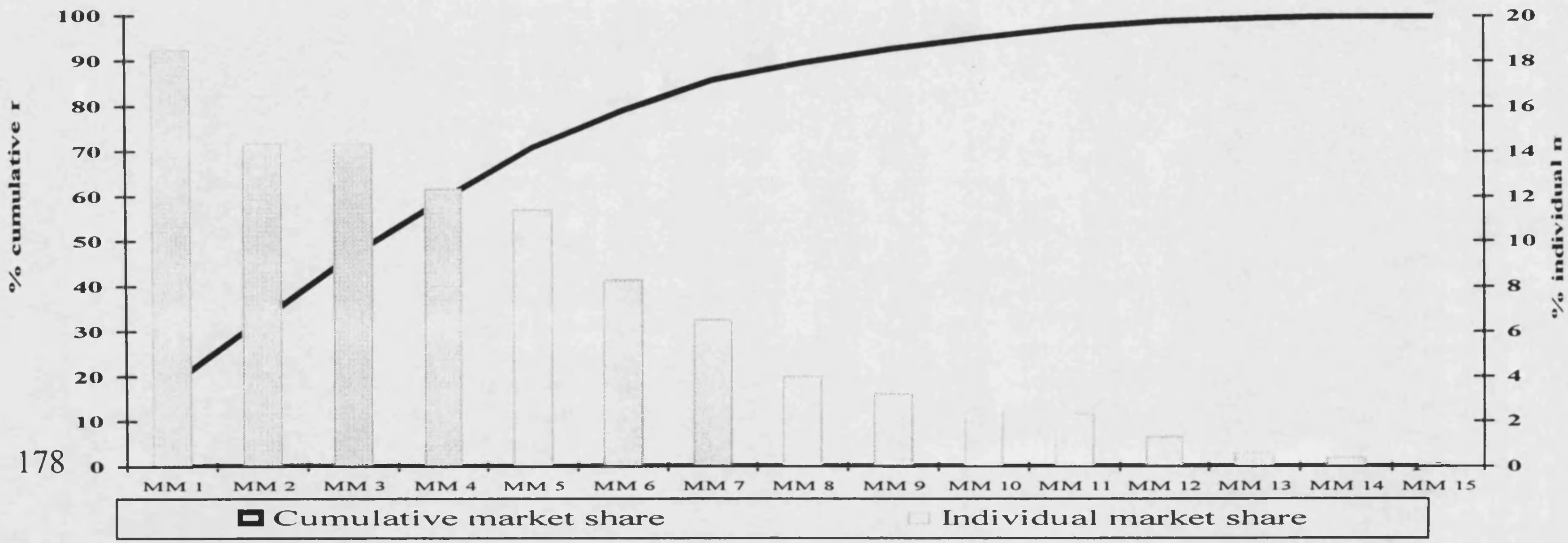
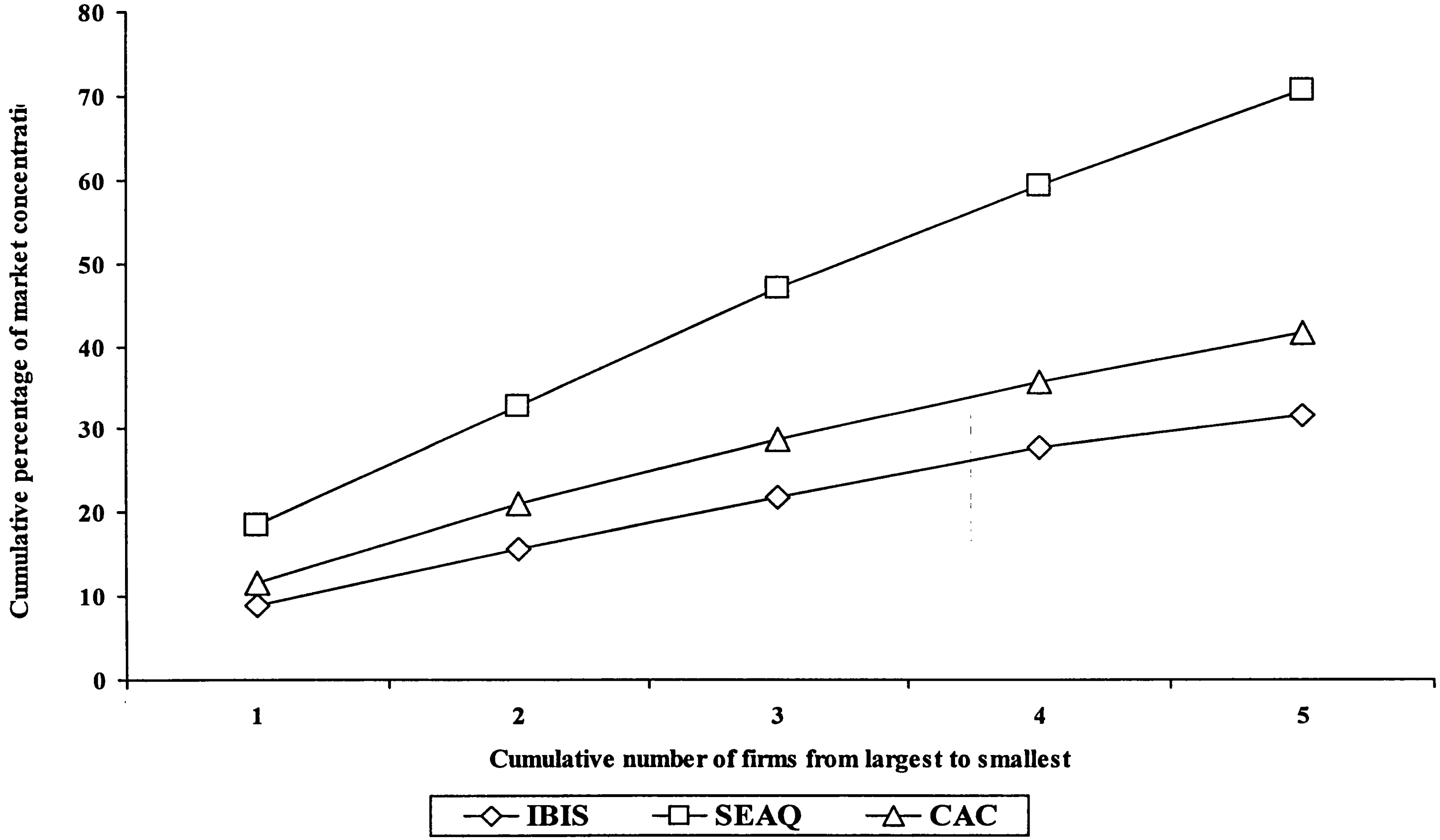


Figure 20. Market concentration on CAC, IBIS and SEAQ



3.9 Conclusions

This Chapter analysed trading frictions and their sources in three different market microstructures: (a) a pure dealership system; (b) a pure order book driven platform; and (c) a hybrid trading system. Liquidity provision in these three systems is undertaken by different market participants. In addition, the institutional set-up (in terms of transparency, entry in the market, etc.) varies across these three systems.

The analysis employs comparable orders (by size) across the different trading systems and the conclusions that are drawn are based, exclusively, on these types of orders. The results obtained in this Chapter show that SEAQ market makers post spreads that are much wider than those posted by CAC and IBIS dealers. When effective spreads are investigated, we find that these are also wider on SEAQ compared with the other two markets. In addition, both the quoted spreads and the effective spreads on IBIS, for most trade locations, are the tightest when compared to all the other systems, implying that a hybrid system produces spreads that are narrower than both a dealership and an auction system. A closer analysis of trading shows that competition between different liquidity providers is highest on the hybrid system.

The evidence shows that, after controlling for variables that have been previously found to influence spreads, market-microstructure explains the absolute level of spreads generated on different market architectures. It is found that the order book-based and the hybrid systems generate lower bid-ask spreads than the dealership market.

The empirical results provide a confirmation of the Viswanathan and Wang (1998) hypotheses that a well-calibrated hybrid trading system dominates both dealership and order book systems.

The surprising result from this Chapter is that the hybrid system adopted for some time by the German Börse, IBIS, generated spreads which are generally lower than those on the order book-based system.

This result is important for policy makers and regulators because it shows that interacting the order book with designated dealers can actually improve liquidity and markets' quality. The issue then becomes finding the right balance between the order book and the role of dealers and fine-tuning this balance is likely to be an arduous task.

The Chapter also shows that trade information is "digested" differently in different market microstructures and the strategic behaviour that results impact trading frictions in various ways. Mandatory market makers in a pure dealership system are likely to identify private information better than limit order trades on the order book or on a hybrid system. In fact, the adverse selection component is highest on the order book and lowest in the dealership system.

Mandatory market makers contribute to the price discovery process through their screening function for which they must be compensated through a higher spread. On the other hand, order book-based systems generate lower trading frictions but the risk of trading with informed traders is higher. These results indicate that, once more, there are different trade-offs in market designs that should be fully addressed.

Chapter 4. Spreads Dynamics

4.1 Introduction

In the previous Chapter we have analysed the absolute levels of quoted and effective spreads in three different market microstructures, producing also an investigation of the adverse selection component in each market. A natural question that arises is how bid-ask spreads are formed in each trading system and which are the major factors driving the formation of spreads. For example, are there any market microstructure-specific effects or are spreads in different markets responding to common factors? How do liquidity providers react to volatility in the market? Do market makers behave differently than limit order traders when volatility increases? How do they react when the arrival of information intensifies? Can concentration in the market for liquidity provision account for the different spread levels?

In order to answer these questions, we start from the analysis undertaken in Chapter 3 and build on it so as to analyse the spread dynamics. In line with the previous Chapter, we use Paris Bourse's CAC system to represent a pure limit order book, Deutsche Börse's IBIS platform to capture the dynamics of a hybrid system and the LSE's SEAQ market to represent a dealership market. Our aim is not only to investigate whether microstructure effects hold when controlling for the level of competition in each market, but also to understand how liquidity providers behave under different market conditions.

There are many institutional and market microstructure differences between automated screen-based trading systems on one hand and dealership systems (or floor-based trading) on the other. It is important to investigate whether these institutional designs can impact transaction costs; such an issue is becoming central to traders and portfolio managers who transact across different markets in their bid to reach international diversification. In this

Chapter, we shall focus the discussion on the impact that such differences may have on the spread, its intra-daily evolution and its components.

The emergence of screen-based systems, which is now being used by many Exchanges in some form or another, has led to a substantial body of theoretical and empirical work analysing, in some instances, the main characteristics of screen-based systems and, in other instances, comparing it with dealership-based trading. Most of these studies (for example, Glosten, 1994, Domowitz and Wang, 1994, Bollerslev, Domowitz and Wang, 1997) demonstrate that, under normal conditions and when information arrival is not too intense, the market quality characteristics of electronic trading is not any worse when compared to dealership systems (and floor trading systems). It has also been established that trading costs and market depth for small to medium sized traders are, on the whole, better when carried out on screen-based systems. For example, some empirical work shows that automated systems appear to incorporate trade information more rapidly than floor trading (designed as a dealership system). At the same time, there is evidence indicating that at times of intense information arrival, dealership-based systems are able to generate more efficient prices.

Market designs affect the way in which traders' information is impounded in prices. When a liquidity provider, whether a limit order trader or a market maker, announces or posts quotes she is effectively providing a short option position. The time to expiration of such a position is equal to the time required to make revisions to the same quote. Such time differs across different trading systems.

In a dealership system, the quote can be seen as remaining valid only as long as the market maker decides to change it. Sometimes such action does not involve going through official channels, such as removing the quotes from the screen; in such systems, quotes are valid as long as "the breath is warm".

This is not the case in screen-based trading where the limit order trader has to withdraw her quote, creating *de facto* an environment where quotes can be exposed for a longer period compared to a dealership system, increasing the value of the short option position.

There are various channels through which the difference in quote setting behaviour can impact spread dynamics. Firstly, the mechanics of screen-based trading render quote revision costly and time consuming operations (relative to dealership systems). Secondly, limit order traders have to leave their quotes on the screen for a longer period, making them more vulnerable to traders with superior trade information. There is a higher probability of their quotes being "picked off", effectively providing an incentive to liquidity providers to set higher spreads to compensate for potential losses they could incur by trading with traders holding superior information.

The dynamics driving the quote submission is not the only major difference across the different trading systems. The way information flows and the channels employed by traders to impound such information in prices are also different. Market makers are expected to have good information on the prevailing market conditions since they enter into direct contact with traders, getting to know their identity and their trading styles and learning about their previous transactions. Market makers can learn from this process and the signals they receive through the bilateral negotiation with large traders will help them to adjust their inventory, and more importantly, the spread in anticipation of large orders. They may also anticipate a particular traders' behaviour by estimating her inventory position.

Arguably, since dealership systems are, in general, not centralised but rather fragmented, these advantages can be toned down by the fact that information collection and dissemination is not centralised, reducing the market makers' feel of the market.

In comparison, screen-based trading is built on the notion of centralised markets where trade information is pooled at one place. For example, limit order traders generally have better access to real time fundamental information given by price movements across several markets. Post trade transparency is generally higher in screen-based systems compared to dealership platforms. For example, most screen-based trading systems publish market depth at different prices. However, limit order traders are isolated from each other and full information about traders' identity and their previous trading is not known. In effect, these limitations could hinder their feel of the market, making limit order traders more concerned with asymmetric information.

In addition, given the nature of the interaction between liquidity providers and traders on both systems, the effect of asymmetric information is likely to be different. Traders recognise that the presence of information-based trading is likely to increase the bid-ask spread and reduce the volume and revenue from liquidity trading, making the provision of liquidity more problematic. This position has been argued by Benveniste *et al.* (1992) who show that dealership-based trading can reduce the effects of asymmetric information on the trading process.

To a large extent, the long-standing professional relationships that exist between market makers and traders in a dealership system are expected to induce cooperation among the two counter-parties, giving the market maker the added advantage of improved learning from trading and the extraction of better signals from successive orders.

These relationships, which cannot exist in an order book-driven system, are likely to act as a deterrent, limiting the traders' ability to exploit their own superior information in a systematic way. Traders who are perceived to make substantial benefits at the expense of market makers are likely to get some form of sanction from the market making community.

In conclusion, a market maker is able to receive a higher level of information and hence can form a better view of the trading motivation, style and strategies of traders in the market. This implies that, everything else remaining constant, the quotes submitted by the market maker are likely to be more competitive and stable over the trading day.

This Chapter investigates (a) the impact exercised by market microstructures on the formation of the spread; (b) whether competition in the market for the provision of liquidity also matters to explain spreads levels, and (c) liquidity providers' quote setting behaviour under different market conditions. To reach the objective of disentangling the effects of market microstructures from other effects, that are presumed to impact the spread, we must employ a methodology that clearly separates the various effects.

We proceed as follows. First we investigate the intraday patterns of spread formation together with the evolution of trading over the day. We analyse how total volumes, number of trades and trade sizes vary across the three markets under consideration. Following this preliminary analysis, an investigation of the effective spread's drivers is carried out, taking into consideration both the arrival of news on the market and the concentration levels in the market for liquidity provision. We find that the hybrid type of trading appears to generate the lowest effective spreads and such result holds even after controlling for (public) news arrival and market competition. This means that market microstructure effects do matter in terms of explaining the levels of the effective spreads generated by the different markets.

This Chapter is organised as follows. Section 2 goes through the literature review and Section 3 provides the data and methodology. Section 4 presents the results obtained for the various models tested together with a discussion and Section 5 concludes.

4.2 Extant Literature

One simple approach to investigate the formation of spreads is to assume that traders submit orders for purely exogenous reasons. In this way, the model can focus exclusively on dealers' behaviour during the process of suppling immediacy to (liquidity motivated) traders. The seminal work in this branch of the literature was proposed by Demsetz (1968), and Tinic (1968). Such models do not contemplate competition between dealers, in the sense that there is a single dealer providing liquidity to traders who submit their orders in an asynchronous fashion dictated by a pre-determined statistical processes.

In such a trading set-up, the dealer stands ready to accommodate the order flow arriving on the market. The major influence that the dealer is allowed to have in this strand of literature is limited to his quote setting behaviour: quotes are set in a way as to enable the dealer to equilibrate the stream of buy and sell orders. The main point here is an optimal behaviour adopted by dealers in order not to deviate from their preferred inventory level. These models consider only the inventory-effect (rather than the presence of superior information in the market). As a result, the spread exists in order to compensate the dealer for standing in the market as a permanent counterparty for orders hitting the market. In this sense, the major contribution of the market maker is the reduction of search costs incurred by the trading community.

The issue of competition was neither considered by Amihud and Mendelson (1980, 1982) who make use of a monopolistic price-setter (market maker) to show the optimal price setting policy under the assumption of profit maximisation. The main features of this behaviour are the following: (a) the bid and ask quotes are set in a way that will balance the volumes submitted by buy and sell traders; (b) the spread between the two sides will reach its minimum and this leads to a maximisation of combined volume transacted in the market; (c) the market maker will keep in mind her preferred inventory position, with deviations being materially costly; and (d) the securities' volatility is not taken into consideration in determining quotes and their submission.

All these models leave out one major characteristic of the trading process: competition for the order flow. In a market microstructure context, competition can be introduced from two main sources: (a) competition coming from other market makers (or dealers) present in the market; or (b) limit order traders who submit orders that compete with the market maker for the order flow. One way to model competition in the market place is to consider a game theoretic set-up in order to allow for strategic positions that dealers can adopt vis-a-vis (a) other dealers, and (b) limit order traders in the market.

Cohen, Maier, Schwartz and Whitcomb (1981 and 1986) and Ho and Stoll (1983) were the first proponents of models where competition is analysed; the major focus being on the dealers' optimal bidding policy and how this influence market equilibria. In the former model, there is an analysis of the trader's choice between limit orders and market orders where a trader has to balance expected price with order execution and faces a choice between submitting a limit order, that has no execution certainty, and a market order that gives the trader certainty of execution. Cohen, Maier, Schwartz and Whitcomb (1981 and 1986) show that traders will not place limit orders close to the best spread but will submit a market order at a close price (worse that the best spread) which gives them execution certainty. In equilibrium, the optimal spread is the product of two opposite forces: (a) the incentive to place limit orders below the market ask or above the bid that will only execute with some probability, and (b) the incentive to submit orders at the market price which guarantee execution.

In Ho and Stoll (1983) there is an investigation of the choice of the optimal bid and ask quotes with the major concern being competition in a centralised market. The approach adopted by this model tries to simplify the competition process by treating limit orders as equivalent to the posted quotes of dealers. The same approach was adopted by Biais (1993) who argues that a centralised market is characterised by firm orders that are visible to all traders and where information about the orders flow is complete. On the other hand, a market where the posted quotes are effectively visible to only one trader (or a sub-set of traders) and information is incomplete can be modelled as a fragmented market. Biais models the former as an English, or progressive, auction while the latter is modelled as a sealed bid, or Dutch, auction.

The bidders' strategic actions in the progressive and sealed bid auctions were first analysed by Vickrey (1961). Bidders in the English auction hold different reservation values (the price at which the bidder would be indifferent between trading and not trading), and each bidder will go on increasing her bids as the auction progresses until her reservation value is reached. The bidder will drop out of the auction when this reservation value is obtained and the last bidder standing in the auction will win. In this type of auction, the selling price is effectively set by the second best reservation value.

In the sealed bid auction, the price is lowered in successive rounds until a bid is received from one of the bidders, producing the winning bid. Hence, in the Dutch auction, each bidder has to base her bidding strategy on her (subjective) conjecture of the strategies of competing participants. As the price is lowered, a larger pool of bidders will participate in the auction and each bidder must weigh the benefit of allowing the price to fall further against the increasing probability that a bid will be submitted by another participant. The major result generated by Vickrey (1961) is the equivalence of the selling price in both forms of auctions: the well-known result of the Revenue Equivalence Theorem. However, the price variance is higher in the English auction than in the Dutch auction.

Biais employs the Revenue Equivalence Theorem to show that the spread obtained in the two different market set-ups - whether centralised or fragmented - is the same in equilibrium; only the variance of the spread will be different. This result holds even if participants are risk-averse. Indeed, one of the model's main assumptions is that all participants have different degrees of risk aversion, implying that traders' private valuation of the security differ.

This model can be easily applied to the three markets being investigated here and this can help us in generating hypotheses about spread behaviour. Trading on CAC and IBIS is conducted via a screen based system that display the best quotes (the best five in the case of CAC and the best ten in the case of IBIS) and sizes on the two sides of the market. On IBIS, these prices are firm. All information is available from the screen to all market participants, with high pre- and post-trade transparency, making these systems examples of centralised markets. On the other hand, we can consider SEAQ as a fragmented market even though market makers submit their quotes on the screen. Notwithstanding this feature, we consider SEAQ to be a fragmented market because (a) these quotes were posted to show indicative prices, with traders having to solicit firm quotes by telephone from market makers, and (b) of the opaqueness of the post-trade transparency, especially for large trades. Given that not all traders shared the same information, SEAQ is best described as a fragmented market.

On the other hand, Viswanathan and Wang (1998) focus on the choice of market architectures that the customer takes in order to decide where to trade, with the decision being taken before the trader observes the order size (the model considers orders that vary from a minimum to a maximum size). The trading location decision is between a trading set-up that can take the form of (a) dealership, (b) order book, or (c) hybrid system. In the hybrid system, limit orders are only accepted for quantities that are smaller than some exogenously fixed level. The model makes extensive use of the "bid reduction" which is present in both the dealership market and the limit-order book but operates differently across these two market structures. The amount of bid reduction is increasing in the quantity obtained in the dealership market and is decreasing in the order book. This results in demand functions that are flatter in the book.

In the dealership system, there is a finite number of risk averse market makers that compete for the order flow. In equilibrium, the market makers' trading strategies account for the pre-trading inventory positions, the pricing and order routing rules adopted by the Exchange. However, due to the flatter demand curve in the order book, price competition is fiercer in this system but this is partially offset by the presence of a zero-quantity price discount (or "zero-quantity spread"), not present in the dealership market. The model's major results are the product of the trade-off between the bid reduction effect and the zero-quantity spread that work in different ways in the different trading platforms.

The main results can be described as follows: (a) for very small order size variation, a trader would always choose the limit-order market over a dealership market; (b) when the trader must make the choice on the trading location before the order size is observed, the limit-order book becomes the preferred location by all risk neutral customers; (c) when suppliers of order flow are risk averse, there is no dominance of the limit-order book over dealership market; (d) the dealership market becomes the preferred trading location when the variability in order sizes (i) is significant, and (ii) when there is a large number of market makers present in the market; and (e) when the dealership market is found to dominate the order book, a hybrid structure can further improve traders' welfare on the exclusively dealer market.

The first result is obtained from the fact that the zero-quantity spread is relatively unimportant when the variation in the order sizes is low and, hence, a flat demand curve makes the book a better choice for this trader. For orders that can vary a lot in size, there is a greater amount of price variation associated with the multiple prices at which the orders are filled in a limit-order book. The added source of uncertainty tends to cause the risk averse customer to favour a dealership market. As the number of market makers increases, the demand function in a limit-order book becomes steeper while the demand function in a dealership market becomes flatter.

The model employs a trade size cutoff level (exogenously chosen) and orders greater than this size cannot be executed in the book and must be routed to the dealership market. When the cutoff point is chosen appropriately, the hybrid limit-order book/dealership market generates higher trading profits for the customer than the pure dealership market.

The empirical work that has investigated the impact of market microstructure on spreads have considered the impacts generated by reforms in market systems. Two major market reforms carried out in the last few years and which have provided natural experiments for this type of literature were the reforms on NASDAQ and LSE. Barclay *et al.* (1997) find that the rule change, allowing wider scope for limit orders to be submitted to the market, narrowed the quoted and effective spreads by some 30% from the pre-reform trading. The biggest drop in transaction costs were actually registered for the widest spreads. The narrowing of the spread was not obtained at the cost of a lower liquidity; in fact, market depth was not materially affected after the rule change.

Naik and Yadav (1999) investigate the effects of the LSE reforms on (i) levels of the spread; and (b) intra-day patterns of the spread. The first result they obtain is that effective half spread of public investors has narrowed after the reforms and this improvement in trading costs has been much more marked than the corresponding change on NASDAQ and documented by Barclay *et al.* (1998). In addition, the change from obligatory to voluntary market making has produced another significant result: an increase in the "positioning revenue" earned by voluntary dealers from a change in the price of a stock while they carry the stock in their inventory. This implies that the overall gain of public investors in terms of the realised half-spread is not significantly different from zero.

The cross-subsidisation across trade sizes which characterised the dealership system before the reforms has disappeared with the result that the average execution costs of small public trades has decreased whereas those for large public trades have increased. Finally, the inside half-spread has increased very sharply in the first hour of trading, implying that market makers in a dealership system contributed significantly to price stabilisation during the market's opening.

4.3 Data and Methodology

The data used in this Chapter for the analysis of spread formation is identical to the data used in Chapter 3. More information about the data, the sources and data type, is provided in that Chapter.

The pairing methodology used is also identical to the one used in Chapter 3. In fact, we pair securities across the three different markets using a similar methodology to the one used in the previous Chapter. Table 39 shows descriptive statistics for the firm characteristics in relation to the CAC-listed, IBIS-listed and SEAQ-listed securities.

The major objective is to devise a paired sample based on similar risk characteristics leaving institutional differences to explain the differences in the evolution of the spreads in the different trading platforms. We employ the Fama and French (1992) and the Heston *et al.* (1998) to pair securities across markets. Appendix B reviews both the Fama and French (1992) and the Heston *et al.* (1998) methodologies.

The first pairing exercise is based on the Fama-French (1992) framework and takes into consideration three major factors. First, paired securities across markets must be in the same industrial sector. Secondly, the securities were paired so as to minimise the "book-to market" values (Book Equity/Market Equity) and "size" (Market Equity) premia differences across the exchanges.

Having carried out the first pairing exercise, the second one is implemented based on the Heston *et al.* (1998) framework. The first condition is that paired securities must be in the same industrial sector and then pairing took place in terms of minimising the Beta and ME differences across securities trading on different systems.

One of the most important issues that must be addressed in studies such

Table 39: **Firms' characteristics of CAC-, IBIS- and SEAQ-listed securities**

PANEL A: CAC-LISTED SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,528.62	2.81	0.98	41.92
Portfolio II	3,816.52	3.58	0.97	49.28
Portfolio III	15,701.06	3.02	1.08	63.58

PANEL B: IBIS-LISTED SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	1,601.78	2.18	1.02	86.92
Portfolio II	3,782.95	2.41	1.04	96.21
Portfolio III	16,519.56	2.67	1.08	150.02

PANEL C: SEAQ-LISTED SECURITIES

	Market cap (in £m)	ME/BE	Beta	Mean Price (£)
Firm size				
Portfolio I	2,162.18	2.08	0.89	2.61
Portfolio II	3,528.96	2.51	0.98	5.08
Portfolio III	13,061.71	2.86	1.02	6.98

The three firm capitalisation categories were obtained on the basis of the firm's market capitalisation as at the end of December 1995. Portfolio I contains firms with a market capitalisation of less than £2,500m; Portfolio II contains firms with capitalisation larger than £2,500m but lower than £5,000m; while Portfolio III has firms with a capitalisation larger than £5,000m.

Market capitalisation, ME/BE, beta and price were extracted from Datastream and refer to values obtained at the end of December 1995. Reported statistics refer to mean values.

as this one, when different trading environments are being compared, is to devise a proper methodology that can separate the effect of the market microstructure from the effects generated by the general market environment, mainly the presence of private information, news arrival (which is related to the level of asymmetric information), and market concentration for liquidity provision. In each model tested, we shall take into consideration the effect of these variables and we shall try to control for them. Data for market concentration was provided by the various Exchanges whereas news announcements, which in our case are earnings and dividend announcements, major changes in board composition and mergers and takeovers announcements, are obtained from the *Financial Times.*

4.4 Intraday Patterns

A starting point for this analysis is an investigation of intraday patterns in order to document some preliminary evidence on how spreads and volume, orders, order size, etc. evolve during the trading day. The intraday patterns of the evolution of quoted spreads, the size of orders executed, the number of trades and total volume transacted are all factors that must be considered in order to have a more comprehensive analysis of transaction costs.

Intraday patterns are important because they indicate which are the periods with liquidity surpluses and and those characterised by liquidity deficits. The ability to obtain "good" prices from trading is a function of liquidity in the market and this is, in turn, related to the number of traders that congregate on the market to deal. There is ample evidence that traders are not present on the market all the time; rather markets experience substantial variations in terms of trading activity over the day.

A number of theories try to explain the reasons behind these patterns and how these intra day variations can arise endogenously. Some of the theories emphasise differences in the type of traders present in the market, building on the nature of the demand submitted by traders who are informed versus demand submitted by liquidity-motivated traders. The implicit idea behind such models is that superior information is time-sensitive, creating liquidity patterns over the trading day.

Other theories assume that traders act out of exogenously-determined factors. This is the case of Admati and Pfleiderer (1989) and Foster and Viswanathan (1990). The idea behind such models is based on the notion that trade concentration is beneficial to both liquidity-motivated traders - because they can get the best prices when liquidity is high - and to informed traders - because these can camouflage their activity and obtain better prices than when they trade in periods of low liquidity. It all depends on whether both sets of traders are allowed to choose the time at which they can trade. If these traders are allowed this freedom, then all traders will desire to trade when all other market participants are also active. Since this process produces some beneficial results - transactions are at their cheapest - trade concentration takes place. These models predict that more traders will come to the market as volume increases and this lowers the spreads on markets.

But trade concentration is not always seen as beneficial in terms of reducing trading costs. One such model, proposed by Brock and Kleidon (1992), make the opposite prediction. In this model, there is no distinction between informed and liquidity traders but it assumes that the motivation for trading depends on the traders' need to adjust their optimal portfolio. The need for portfolio adjustments arise from the arrival of information and this will determine the intraday patterns in trading activity in that information is being released continuously.

The most important adjustments are likely to occur in two different periods: (a) when the market opens, and (b) when the market closes. In the case of the open, traders have to adjust their optimal portfolio to reflect the information they received in the overnight period when the market for trading was closed but the market of information was not. In terms of the market closure, market participants are assumed to correctly predict the market's closing period and they have to adjust their portfolio in view of the period over which they cannot trade. These considerations led Brock and Kleidon (1992) to argue that opening and closing volumes will be higher than those over the rest of the trading days and by implication the spread will also be highest in these periods.

In terms of intraday patterns in volume, orders, etc. on the Paris Bourse, Biais *et al.* (1995) document that new orders tend to be submitted in the morning, near the market's open. Likewise, small trades also tend to execute in the morning. These two results are important because they show which type of orders are being used by traders to establish the security's price when the market opens. Indeed, given the overnight period, in which trading does not occur, traders would need to establish a price conditional on all the price-sensitive information that has been generated during the overnight period. The Biais *et al.* (1995) results imply that this takes place through small orders and not through institutional investors' orders. In fact, large orders (and order cancellations) tend to aggregate later on in the trading day, when the most substantial part of the price discovery process would have already taken place.

4.4.1 Hybrid System

IBIS presents some peculiar intra-day patterns, mainly due to the parallel trading for the same securities traded on IBIS and the Frankfurt Stock Exchange (FSE). The 08:30:00 hrs to 17:00:00 hrs (local time) trading period over which IBIS is open could be sub-divided into three intervals, depending on whether the FSE is open or closed. The first period spans from 08:30:00 hrs to 10:29:59 hrs; the second period from 10:30:00 hrs to 13:30:00 hrs; and the third period from 13:31:00 hrs to 17:00:00 hrs. The FSE is closed in the first and third time intervals while it is open during the second interval.

As shown in Figure 1 in Chapter 3, the quoted spread follows a U-shape in all the three time intervals but it is much more pronounced during the first and second periods. The mean quoted spread is very high at the open, touching a mean value of 0.6%, but decreases to 0.23% at around 09:45:00 hrs, staying in that region for about 45 minutes. Then it shoots up to above 0.30% in the period around 10:30:00 hrs when the FSE opens. Following the FSE's open, the quoted spread decreases to, approximately, 0.20% increasing slightly around the time when the FSE closes and returning back to the 0.20% territory afterwards. Towards the end of the trading day, the spread increases again to touch 0.35%.

Figures 21(a) and (b) provide some additional light on patterns of trading behaviour. The number of shares traded together with the total volume executed follow, albeit in an opposite direction, very closely the intraday patterns of the quoted spread (Figures 21(c) and (d)). The number of trades executed and the mean volume increase and remain stable when the quoted spread is low during the day, except for the peak at the end of the trading day. The mean volume (in shares) transacted is particularly low immediately after IBIS opens and when FSE opens and at the time when floor trading is closing.

Figures 21(a) and (b) indicate that the mean size of the trades (in shares) and the mean trade size is fairly constant during the trading day. However, a closer look at the mean trade size indicates that it is relatively low between 08:30:00 hrs and 10:30:00 hrs, when the FSE opens. This indicates that smaller trades are normally executed during this period, with medium and larger trades avoiding this time window when quoted spreads are relatively large compared to the spreads obtainable during the trading day.

4.4.2 Order Book

Figure 14 in Chapter 3 shows the intraday patterns of the quoted spreads for the CAC-traded securities for the sample matched with SEAQ securities and the sample matched with IBIS securities.

In terms of a general intraday pattern, CAC does not show the U-shape patterns seen for IBIS. The quoted spread for both samples is high at the time of opening reaching above the 0.50% region for the SEAQ-paired sample and 0.40% for the IBIS-paired sample. The spread diminishes constantly and one hour after the open it reaches a stabilising point which is largely maintained till the close.

Figures 22(c) and (d) show that both the number of trades executed and the volume transacted follow a U-shaped pattern, which is much more pronounced for the number of trades. The number of trades when the system opens is substantially high with the mean volume (in shares) being relatively higher than at other times during the trading day, except for the close. The two U-shaped patterns touch the bottom during the 13:00:00 hrs to 14:00:00 hrs. The mean volume transacted is much higher at the close than at the open while the number of trades executed at the close is very similar to that transacted at the open.

Figure 21. Trading characteristics on IBIS

Exhibit a. Mean size (in shares) of trades executed during the day

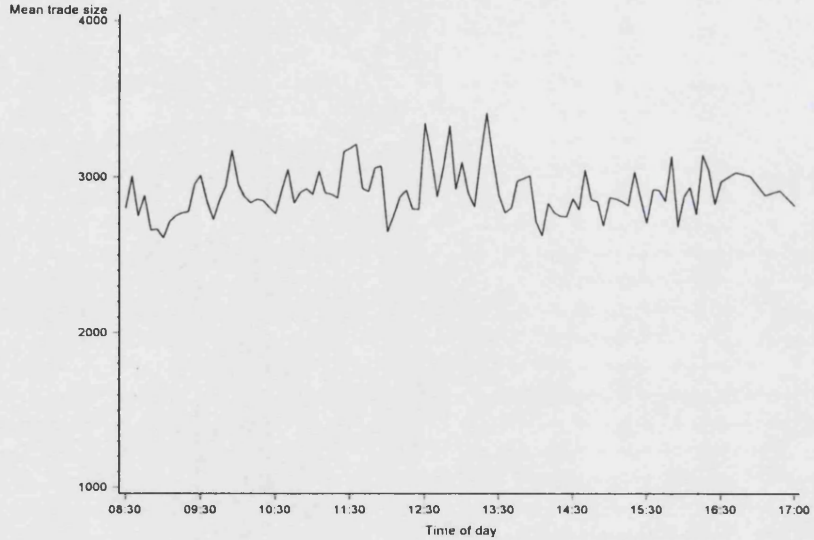


Exhibit b. Mean X NMS size of trades executed during the day

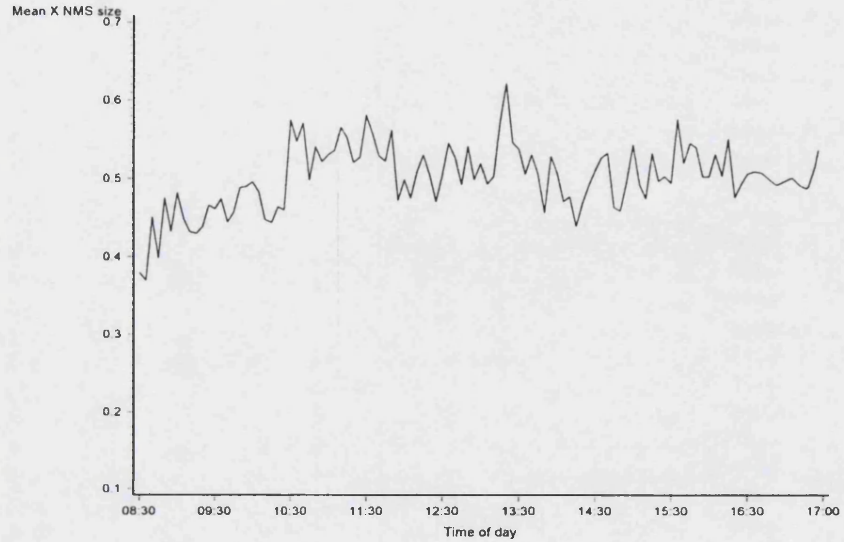


Exhibit c. Number of trades executed during the day

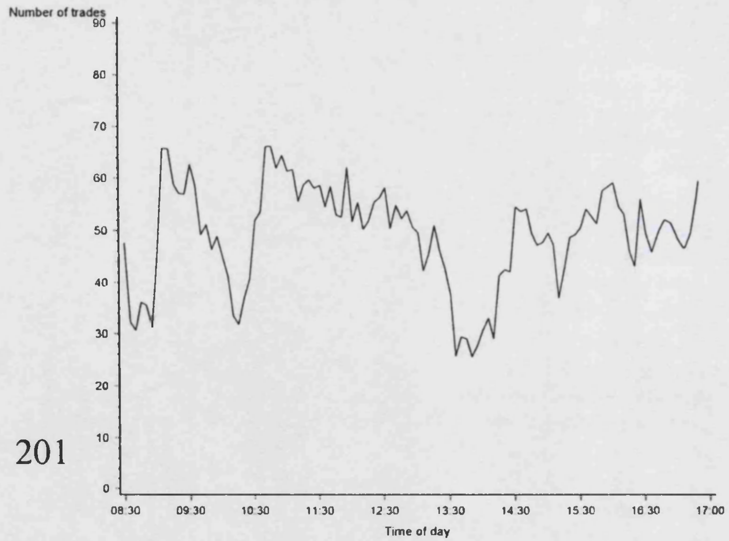


Exhibit d. Mean volume (in shares) executed during the day

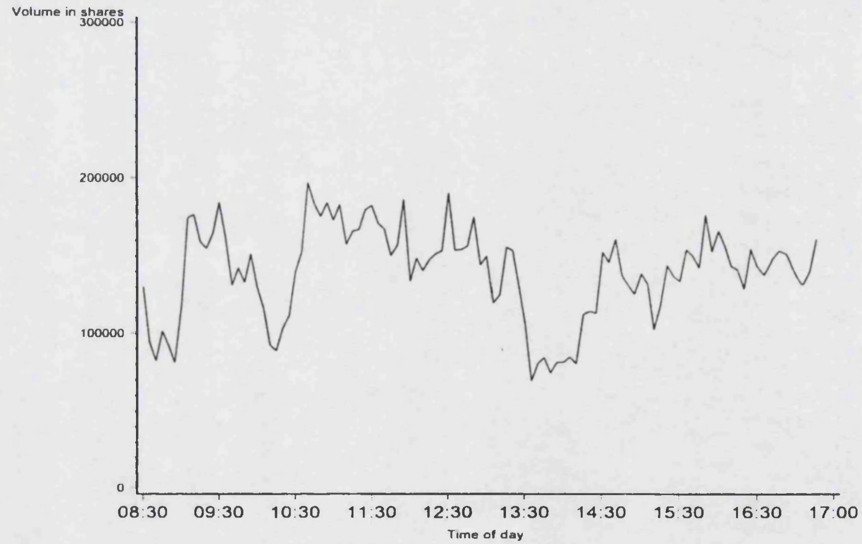


Figure 22. Trading characteristics on CAC

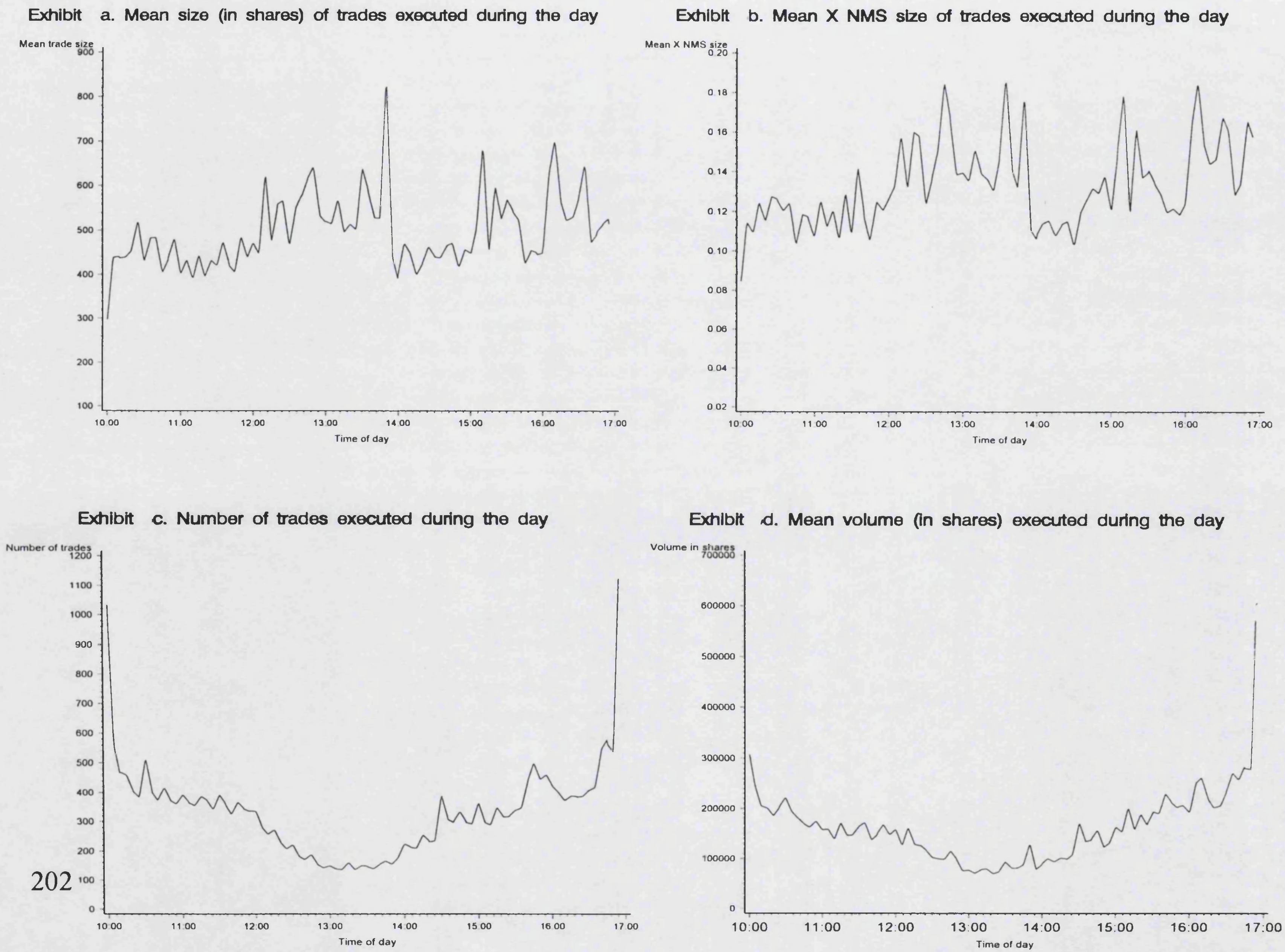


Figure 23. Trading characteristics on SEAQ

Exhibit a. Mean size (in shares) of trades executed during the day

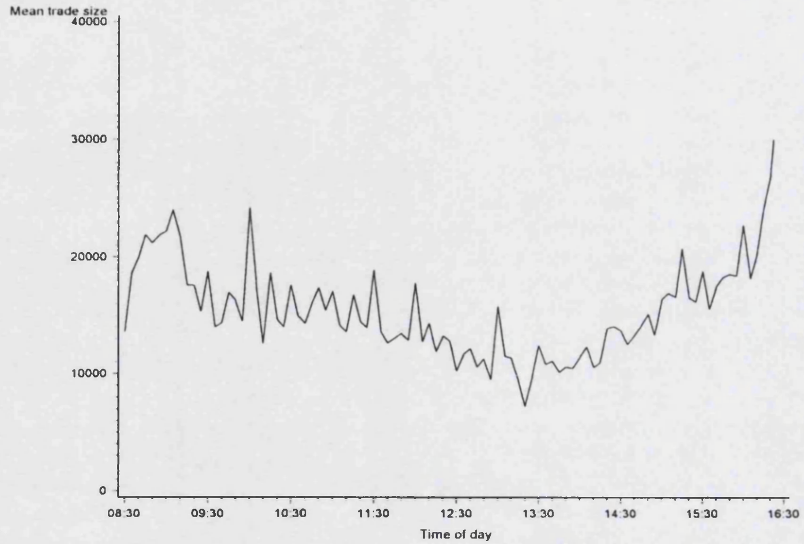


Exhibit b. Mean X NMS size of trades executed during the day

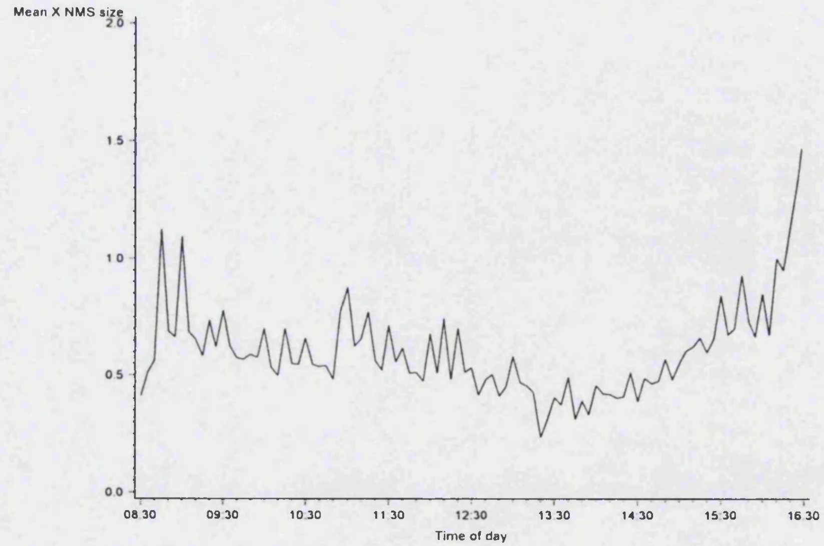


Exhibit c. Number of trades executed during the day

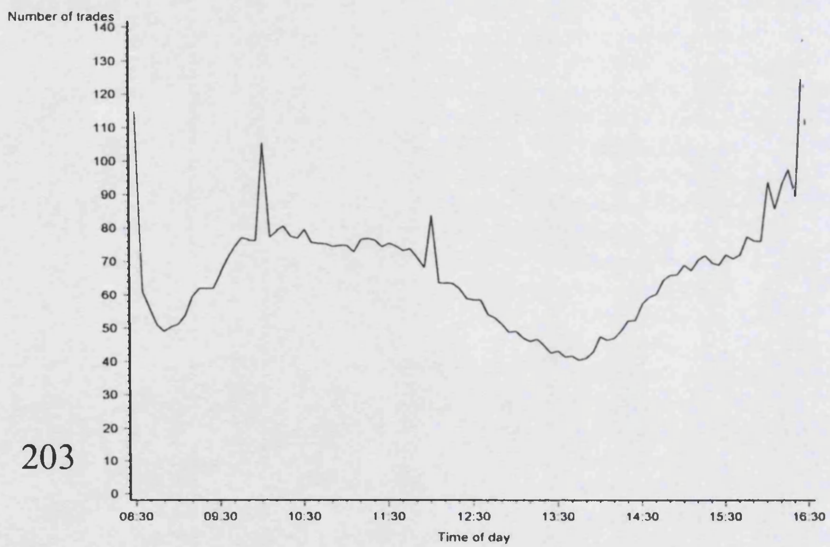
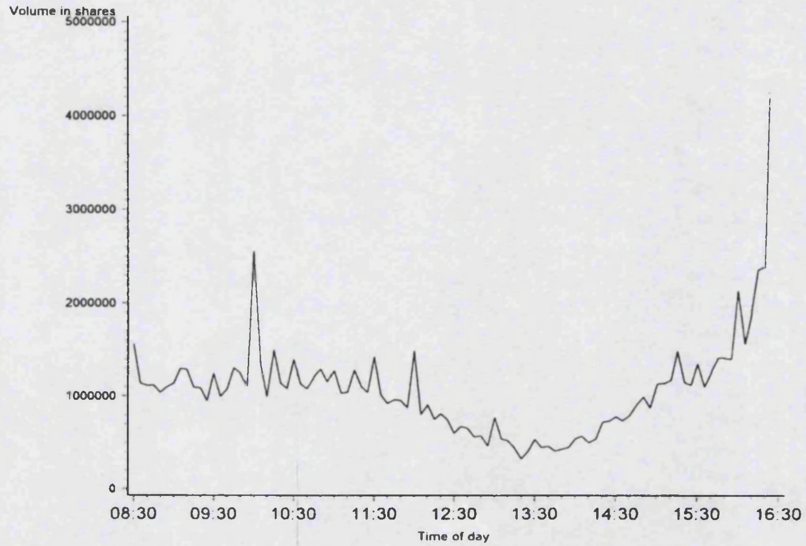


Exhibit d. Mean volume (in shares) executed during the day



Analysing Figures 22(c) and (d) together indicate that the mean size must be lower in the opening compared to the close. In fact, Figure 22(b) confirms this intuition since at mean trade size at the open is around 0.08 X NMS whereas just before closing the mean size reaches above the 0.16 X NMS. The mean (X NMS) size remains low until around 12:00:00 hrs and rises afterwards. This period coincides with the intraday pattern with the highest quoted spreads during the day (refer to Figure 14 in Chapter 3) and implies that larger orders tend to avoid times when spreads are wider during the day.

The very small size of trades executed at the beginning could be due, partially, to the opening algorithm used by the CAC whereby a call auction is implemented, after which trading is carried out as a continuous auction. These patterns, however, confirm the findings of Biais *et al.* (1995).

4.4.3 Dealership System

The quoted spread on the dealership system, SEAQ, does not follow any particular pattern except falling from the relatively high levels experienced in the initial period of the Mandatory Quote Period (the "MQP") (See Figure 15 in Chapter 3).

In contrast to what happens on the order book and the hybrid system, both the mean size of trades executed and the mean trade size are not particularly small in the initial stages of transactions. Figure 23(b) shows that, although the trade size at the very beginning is low, it recovers and within the first 30 minutes the mean size goes beyond the 1 X NMS size, a level which is reached only subsequently towards the end of the MQP. The same pattern is encountered in Figure 23(a) where the trade size in shares reaches a high level within a few minutes from the start, retreats during the day and increases again towards the end of the MQP.

Compared to the trade sizes transacted on the order book and the hybrid system, trades executed on SEAQ are substantially higher, confirming the stylised fact that dealership systems attract larger trades than do continuous auction systems (Pagano and Steil 1995, and Schwartz and Steil, 1995).

In addition, the intraday quoted spread patterns for the three markets shows that using longer time intervals (for example when considering 30 minutes) the quote changes appear to be smoother on CAC and IBIS than on SEAQ. A closer investigation of the data shows that best quote revisions occur with much more intensity on IBIS and CAC, especially on the former, than on SEAQ.

4.5 Empirical Results

This Section's objective is to investigate the Exchange-specific and the various generic factors that are expected to influence the bid-ask spread in the three markets being considered. Following Benston (1978), Stoll (1978a, 1978b) and Neal (1992), the bid-ask spread in a competitive market is modelled to depend on common factors, namely inventory holding cost, adverse selection, order processing cost and trading activity, together with institutional differences between the three markets in the following way:

$$\begin{aligned}\%\ spread^{eff}_{sjt} = {} & \alpha_0+\alpha_1 M_A + \alpha_2 M_B + \alpha_3 P_{sj}+(\beta_0+\beta_1 M_A + \beta_2 M_b) Vol_{sjd}+ \\ & (\lambda_0 + \lambda_1 M_A + \lambda_2 M_B)\sigma^2_{sjt-1} + (\varphi_0 + \varphi_1 M_A + \varphi_2 M_B) TS_{sjt}+ \\ & (\gamma_0+\gamma_1 M_A+\gamma_2 M_B) AdS_{sjt-1}+(\delta_0+\delta_1 M_A+\delta_2 M_B) SyNT_{sjt-1}+ \\ & (\xi_0 + \xi_1 M_A + \xi_2 M_B) USyNT_{sjt-1} + \alpha_4 TIME_{jt} + \varepsilon_{sjt} \qquad (20)\end{aligned}$$

The $spread^{eff}_{sjt}$ is the mean effective spread calculated for each security s on market j at time interval t as follows:

$$100 \cdot 2 \sum_{i=1}^{N} \left[\frac{SB_{it} \left(p_t [i] - v_t [i] \right)}{v_t [i]} \right]$$

where $p[i]$ is the transaction price for trade i and $v_t[i]$ is the mid price which existed at the time when the i^{th} transaction took place and SB_{it} is a binary value that takes on the value of +1 if the trade is a buy and -1 if it is a sell.

In (20) above, M_A, M_B and M_C are intercept dummy variables to capture the market on which the order is executed ((a) $Market_A$ takes a value of 1 if trading occurs on CAC and 0 everywhere else; (b) $Market_B$ takes a value of 1 if trading occurs on IBIS and 0 everywhere else; and (c) $Market_C$ takes a value of 1 if trading occurs on SEAQ and 0 everywhere else); P_{sj} is the transaction price for each security at the beginning of the period under consideration (January 1996); TS_{sjt} is the trade size expressed as a fraction of the NMS calculated for each market; σ^2_{sjt-1} is the security's return volatility calculated using the mid-quote in each market; Vol_{sjd} is the total £-denominated volume transacted in the security in each trading day; AdS_{sjt-1} refers to the adverse selection component of the effective spread; $SyNT_{sjt-1}$ is the systematic number of trades executed for each security (explained below); $USyNT_{sjt-1}$ is the unsystematic number of trades (explained below); while $TIME_{jt}$ is a dummy variable to account for the time of the day effect.

In order to decompose the total number of trades, Tr_{sjt}, into the systematic part (the expected component of the number of trades) and the unsystematic part (the surprise component of the order flow), we use the following model:

$$Tr_{sjt} = \alpha + \beta_1 \sigma^2_{sjt-1} + \beta_2 Tr_{sjt-1} + \beta_3 Asy_{sjt-1} + \beta_4 AdS_{sjt-1} + \sum_{k=1}^{N} \beta_5 T_{k,t} + \varepsilon_t \qquad (21)$$

where σ^2_{ijt-1} is the return volatility in interval $t-1$; Tr_{sjt-1} and Asy_{sjt-1} are the number of trades and trade imbalances, respectively, in the previous interval; while AdS_{sjt-1} is the adverse selection component of the effective spread (measured as explained below) and $T_{k,t}$ is a dummy variable to control for the time of the day effect.

After obtaining the expected number of trades, conditional on the trading activity in the previous interval (each interval is of ten minutes each, as explained below), we compare the figure with the actual number of trades to obtain the surprise component of the trading variable.

The period under consideration is January to February 1996, allowing a common time framework for the securities across the three different markets. The trading day in each market is divided into sub-periods of 10 minutes each; the effective spread and the independent variables under consideration are calculated (as averages in each interval) over these sub-periods.

The percentage effective spread, rather than the quoted spread, is used to obtain a common measure of transaction costs across markets. Given the different trading architecture and the subsequent negotiation that takes place on SEAQ, using the quoted spread would not capture the real differences in expected transaction costs across markets.

Processing costs and adverse selection costs are variables that, while expected to influence the bid ask spread, are not directly observable. The proxy which is normally employed to capture processing costs is the security's price since the average processing cost is a function of transacted price. Total processing cost is considered to be a fixed cost, with average costs per transaction falling with the level of transacted price. A negative sign is expected.

Adverse selection costs are expected to exert a substantial impact on the total spread. Since asymmetric information costs are not directly observed, a proxy is employed in the form of the adverse selection component obtained in Chapter 3. For every trade, the George *et al.* (1991), Booth *et al.* (1995), Huang and Stoll (1996), Madhavan *et al.* (1997) and the Huang and Stoll (1997) methodologies were employed. As was demonstrated in Chapter 3, the different measures of the adverse selection are heavily correlated and hence the choice of the final measure to be employed in the model is not too difficult. In the final analysis, it was decided that the Booth *et al.* (1995) was the most appropriate since the component is measured using the effective spreads. However, the other measures were also run in turns to investigate the robustness of the results obtained using the Booth *et al.* (1995) methodology. A positive sign is expected.

The other cost component that must be considered is related to inventory which liquidity providers (especially if these are mandatory dealers) must carry in order to meet traders' orders. Inventory cost is directly related to the holding period of inventory and inventory costs are expected to increase as the holding period increases. This means that having a security for which the holding period is long implies that position cannot be reversed easily and this is bound to increase inventory costs. Information about the mean holding period can be obtained for SEAQ market makers but this type of information is not available for CAC and IBIS trading. Hence, the proxy to be used is the daily £-value of trading volume and it is computed for each day included in the sample period. It is expected that positions taken in securities with high £-value volume are not difficult to reverse, even within one particular day, resulting in a reduction of total inventory costs. As such, a negative sign is expected.

The proxy used for the dealers' risk aversion is captured by the security's price volatility; in this way, a dealer trading in a high volatile stock is expected to post wider spreads and lower spreads in low volatile securities. The problem lies in identifying the proper measurement for the security's volatility in the presence of a bid-ask spread. A number of studies, most notably those of Stoll (1978) and Neal (1992), use stock returns and option returns respectively. In view of the recent evidence of negative serial correlation, and spurious variance, this measurement is better avoided.

The analysis covered by Niederhoffer and Osborne (1966), Cohen, Maier, Schwartz and Whitcomb (1979, 1981) and Roll (1984) indicate that the bid-ask spread induces negative serial correlation in returns measured from stock prices. According to French and Roll (1986), the existence of the spread produces spurious variance, while sometimes it causes an overestimation of the true mean returns.

Furthermore, Glosten (1987) demonstrates that the problems of negative serial correlation, spurious variance and excessive mean returns are caused by the relative magnitudes of the two components of the spread (the gross profit component and the adverse selection component) and the spread's width. Glosten (1987) shows that the gross profit component leads to transacted price's volatility around the true price while the adverse selection component (which reflects new information) causes the volatility in the true price. Hence, it is the gross profit component that induces problems of spurious volatility, bias in the mean return and causes negative serial covariance. In view of this analysis, the proxy used is the volatility of the mid quote calculated in each sub-period over the entire trading day. A positive sign is expected.

The different institutional characteristics across the three markets are taken into account through a set of dummy variables in line with Grossman and Miller (1988) in the following way: (a) $Market_A$ takes a value of 1 if trading occurs on CAC and 0 everywhere else; (b) $Market_B$ takes a value of 1 if trading occurs on IBIS and 0 everywhere else; and (c) $Market_C$ takes a value of 1 if trading occurs on SEAQ and 0 everywhere else. To avoid multicollinearity, $Market_C$ is dropped leaving its impact to materialise through the intercept. In addition to the intercept dummy variable, slope dummy variables are introduced to capture the major difference between the typology of trading on (a) pure order book system and (b) hybrid systems on one hand and dealership systems on the other.

There is no theoretical basis to form any *a priori* functional form for the model. A number of studies (Benston and Hagerman, 1974, Stoll, 1978) use a log linear functional form that would appear to eliminate the skewness in a number of independent variables. Given the difficulty in deriving an acceptable a priori functional form, a Box-Cox transformation is used so as to leave the data determines the optimal functional form.

4.5.1 General Results

Results for the model estimated in (20) are provided in Table 40. The Box-Cox parameters were first obtained from a nonlinear least squares procedure. The parameters are all less than 1 and they carry statistically significant $t-statistics$, implying that there is an effective departure from linearity. After the Box-Cox coefficients were found and the data transformed accordingly, Ordinary Least Squares estimates were obtained.

Following Hausman, Lo and Mackinlay (1992), it is expected that the results contain time-varying variance with one major reason being the difference in the calendar time between transactions. Under these circumstances, OLS estimates are consistent but standard errors must be computed taking into account autocorrelation and heteroscedasticity. In view of this, the standard errors were adjusted in order to obtain the Heteroscedastic and

Autocorrelated Consistent errors following the methodology of White (1980) and Hansen (1982).

The results show that, in line with the findings of Chapter 3, market microstructure appears to have an impact on the formation of the spreads. The $Market$ dummy variables carry negative signs, confirming that the bid-ask spreads are lower on both the order book and the hybrid system when compared to a dealership system. Furthermore, the IBIS's dummy variable has a larger negative value compared to the CAC dummy variable, confirming the earlier conclusion reached in the previous Chapter. Furthermore, the Wald test rejects the hypothesis $\alpha_1^{IBIS} = \alpha_1^{CAC}$, showing that a hybrid trading mechanism does bear an impact on the level of transaction costs. This means that even after controlling for a number of different factors, indicated by the literature to bear an influence on transaction costs, we still find that the hybrid trading system produces lower spreads than both the dealership platform and the pure limit order book.

Furthermore, we find that the coefficients of the return volatility for the dealership system is approximately 20% of the size of the coefficients for the order book $(\lambda_0 + \lambda_1)$ and about 30% of the adjustment that takes place on the hybrid system $(\lambda_0 + \lambda_2)$. The estimated coefficient for the dealership system has very low significance, implying that market makers do respond to changes in market volatility by updating their quotes but such a result is not very strong.

On the other hand, liquidity providers on order book-based systems adjust the quotes much more aggressively when return volatility intensifies. This result supports the view that mandatory market makers, by virtue of the direct contact they maintain with traders, are better able to decompose market volatility into (a) volatility due to the arrival of private information

Table 40: **Relationship between market structures and intraday spreads**

	Entire sample		CAC sample		IBIS sample		SEAQ sample	
	Effective spread	HAC t-stat	Effective spread	HAC t-stat	Effective spread	HAC t-stat	Effective spread	HAC t-stat
Intercept	0.2265	11.13	0.2312	8.65	0.1275	9.20	0.3216	4.36
α_1^{CAC}	-0.0891	-5.70						
α_2^{IBIS}	-0.1076	-4.96						
λ_0	0.0181	1.82	0.0914	4.21	0.0461	5.83	0.01781	1.89
λ_1	0.0865	4.46						
λ_2	0.0415	2.85						
φ_0	-0.0097	-2.07	0.0815	6.09	0.0364	7.98	-0.0058	2.26
φ_1	0.0889	7.98						
φ_2	0.0382	4.24						
γ_0	0.0161	1.62	0.0481	7.12	0.0219	2.85	0.0189	1.95
γ_1	0.0528	8.25						
γ_2	0.0316	5.26						
δ_0	-0.0358	-4.02	0.0218	4.52	0.0122	2.02	-0.0218	2.91
δ_1	0.0301	6.49						
δ_2	0.0224	2.08						
ξ_0	0.0156	1.96	0.0628	7.61	0.0491	6.65	0.0192	2.06
ξ_1	0.0382	4.98						
ξ_2	0.0211	2.91						
R^2	42.58		36.42		41.51		34.17	

The Table shows empirical results for the model tested as follows:

$$\begin{gathered}\%\ spread^{eff}_{sjt} = \alpha_0 + \alpha_1 M_A + \alpha_2 M_B + \alpha_3 P_{sj} + (\beta_0 + \beta_i M_X) Vol_{sjd} + \\ (\lambda_0 + \lambda_i M_X)\sigma^2_{sjt-1} + (\varphi_0 + \varphi_i M_X) TS_{sjt} + (\gamma_0 + \gamma_i M_X) AdS_{sjt-1} \\ +(\delta_0 + \delta_i M_X) SyNT_{sjt-1} + (\xi_0 + \xi_i M_X) USyNT_{sjt-1} + \alpha_4 TIME_{jt} + \varepsilon_{ijt}\end{gathered}$$

where sp^{eff}_{sjt} is the effective spread, M_A, M_B and M_C are intercept dummy variables to capture the different markets (CAC, IBIS and SEAQ); P_{sj} is transaction price; TS_{sjt} is trade size expressed in NMS multiples; σ^2_{sjt-1} is the security's return volatility; Vol_{sjd} is the total £-denominated volume transacted in each trading day; AdS_{sjt-1} refers to the adverse selection component; $SyNT_{sjt-1}$ refers to the systematic number of trades; $USyNT_{sjt-1}$ refers to the unsystematic order flow; while $TIME_{jt}$ is a dummy variable to account for the time of the day effect.

which is likely to have a long term impact, and (b) volatility driven by noise trading which is expected to have a short term impact. The evidence obtained here confirms that spreads posted by mandatory market makers are less sensitive to return volatility implying that these dealers do contribute towards the stabilisation of prices on markets.

The variable used to capture adverse selection have positive signs but the statistical significance varies substantially. On the dealership system, an increase in the level of adverse selection does not automatically lead the community of market makers to widen the spread. This result, however, does not obtain on the order book-based systems. In fact, in both the pure limit order book and the hybrid trading system, an increase in the level of asymmetric information leads to an immediate response in terms of spread updating to provide better "defences" against the presence of informed traders.

Similarly, we find some interesting results when considering the trade size which, as previous literature indicates, can also serve as a proxy for the information content of each trade. The results show that on the dealership system, effective spreads narrow as trade size increase whereas the opposite takes place on both CAC and IBIS. This result implies that the average liquidity provider in these two markets is not entirely efficient in separating larger orders that effectively carry information from those that are submitted for liquidity reasons.

Of particular interest is the response of the spreads to the level of trading activity in the market, measured by the number of trades executed. It appears that an increase in the systematic component of the order flow decreases the spreads on the dealership market but increases spreads on screen based trading platforms. On the other hand, an increase in the unsystematic part of the order flow leads to a material widening of the spread in both the pure limit order book and the hybrid trading system. The first result - dealing with the effect of systematic order flow - seems to confirm, for the dealership market, the results obtained in a number of price formation models that hypothesize the reduction of the level of asymmetric information present in the market. Such a result is obtained because trading reveals private information. Some other models achieve the same result but the channel is different: a higher level of activity assure traders of the non-existence of superior trading information.

The result obtained here, in terms of the unsystematic part of the order flow, goes contrary to these models implying that as trading increases, generating an update in the beliefs about the presence of private information, liquidity providers across markets widens their spreads. However, mandatory market makers do not update their spreads as aggressively as limit order traders do on order book based systems. As argued above, market makers are in a better position to identify whether a surge in activity is due to liquidity reasons or whether it is driven by the arrival of information.

Finally, and as was expected, the price level has a negative sign while the activity variable which proxies for the holding period, £-denominated volume, also carries a negative sign (as expected). The latter result implies that average processing costs and inventory-related costs tend to be lower for higher priced securities.

4.5.2 Market Concentration

Following the first round of results, we augment the regression model in order to take into consideration the impact of (a) market concentration, and (b) news arrival on the market in order to identify better whether market microstructures will still bear an influence on the level of the spread after controlling for these factors.

The main difficulty in this type of work lies in the fact that liquidity characteristics, such as depth and breadth, are not only influenced by the trading mechanisms adopted by single Exchanges. One has also to consider (a) the level of competition between dealers and other liquidity providers allowed in the market place, and (b) traders' self-reinforcing beliefs where liquidity begets more liquidity.

The level of competition in the market for the provision of liquidity is influenced by a number of factors which are largely determined directly by each single Exchange, rather than a direct and immediate consequence of a certain market microstructure model. For example, Madhavan (1992) shows that with free entry and equal access to the market, a dealership system will produce an identical outcome to the one obtained in an auction platform.

The main issue is, therefore, the access to information and the entry costs imposed by every single Exchange.

Restricting access to the trading floor, or the screen, is a decision that must be taken by each Exchange (or better, the stakeholders of the Exchange) largely independently of the type of trading platform adopted. One of the main policy-oriented questions made in the past few years, and which has led to major reforms, is whether there will be an appreciably positive effect on competition by allowing public traders to the market to compete with designated market makers.

The technology used, the amount of pre- and post-trade transparency, the entry fees, order submission and cancellation fees, etc., are all factors that determine the amount of competition allowed in the market. As such, these factors must be fully considered, in conjunction with the trading mechanism, in order to determine the impact on the level of trading costs.

Having said this, one major issue that must be considered is the endogenity in the measure of the level of competition in the market. There are two main problems with this type of analysis: (a) obtaining useful data on market concentration has proved to be historically difficult, and (b) the issue of endogenity will always "threaten" the validity of the results obtained.

However, in view of the issues raised above it seems reasonable to investigate whether the market microstructure effect remains robust when controlling for the level of competition in the market. We obtain data from the three Exchanges being considered that allows us to construct the Herfindahl Index as explained in Chapter 3 to provide us with an estimate of the level of concentration in the market for liquidity provision.

The model being investigated is given by:

$$\begin{aligned}\%\ sp_{ijd}^{eff} = {} & \alpha_0+\alpha_1 M_A + \alpha_2 M_B + \alpha_3 P_{sj}+(\beta_0+\beta_1 M_A + \beta_2 M_b) Vol_{sjd}+ \\ & (\lambda_0 + \lambda_1 M_A + \lambda_2 M_B)\sigma^2_{sjd} + (\delta_0+\delta_1 M_A+\delta_2 M_B) Tr_{sjd}+ \\ & (\zeta_0 + \zeta_1 M_A + \zeta_2 M_B) HI_{sjd} + \alpha_4 NEWS_{sjd}+\alpha_5 DAY_{jd}+\varepsilon_{sjt} \qquad (22)\end{aligned}$$

In (22) above, $spread_{sjd}^{eff}$ is the mean effective spread calculated for each security s on market j for every trading day d; M_A, M_B and M_C are intercept dummy variables to capture the market on which the order is executed in the fashion of model (20) above; P_{sj} is the transaction price for each security at the beginning of the period under consideration (January 1996); Vol_{sjd} is the total £-denominated volume transacted in the security in each trading day; σ^2_{sjd} is the security's return volatility calculated using the mid-quote for each trading day in each market; Tr_{sjd} is the number of trades executed for each security on each trading day; HI_{sjd} refers to the Herfindahl Index (explained below) which is calculated for every security and for every trading day; $NEWS_{sjd}$ is a dummy variable to capture the days when any major news (earnings and dividend announcements, takeovers, change in boards, etc.) has been announced; while DAY_{jd} is a dummy variable to account for the day-of-the-week effect.

The variable that is assumed to capture the level of competition in the market is the Herfindahl Index. Following McInish and Wood (1992), the Index is calculated in the following way:

$$concentration = \left(1 - \sum P_i^2\right) / \left[(n-1) \sum P_i^2\right]$$

where P_i is the market share of each market maker or dealer (for every security included in our sample) in each trading day and n is the number of market maker (or dealers) present on the market.

While we can calculate the Herfindahl Index for trading on LSE for the entire month of January 1996, we can only estimate the Index for the CAC-listed and IBIS-listed securities using selective days in the month of January 1996. In particular, we have obtained data with daily levels of concentration for the period (a) 10 January to 24 January 1996 (11 trading days) for CAC-listed securities, and (b) 16 January to 31 January 1996 (12 trading days) for IBIS-listed securities.

Table 41 shows estimates for the model in (22). The major result we are mostly interested in is the market microstructure variable; in particular, whether there is still any such effect on the spread differentials after controlling for the level of market concentration. The results obtained here indicate that the microstructure effect on spreads is robust to the introduction of the variable to capture competition in the market. In fact, the intercept dummy variables for both order book-based systems remain negative (a reduction of the spreads from the dealership level) and retain their statistical significance.

In addition, the Wald test rejects the hypothesis that $\alpha_1^{CAC} = \alpha_2^{IBIS}$ implying that, even when the level of competition in the market is explicitly taken into consideration, the hybrid trading system still emerges as the

Table 41: **Relationship between market structures and daily spreads**

	Entire sample		CAC sample		IBIS sample		SEAQ sample	
	Effective spread	HAC t-stat	Effective spread	HAC t-stat	Effective spread	HAC t-stat	Effective spread	HAC t-stat
Intercept	0.1415	9.51	0.2608	8.12	0.1418	7.25	0.3528	5.13
α_1^{CAC}	-0.0606	-4.58						
α_2^{IBIS}	-0.0752	-6.52						
α_3	-0.0164	-4.41	-0.0057	-2.57	-0.0018	-2.72	-0.0072	-2.07
β_0	-0.0391	-6.51	-0.0251	-2.15	-0.0296	-5.14	-0.0356	-6.38
β_1	0.0168	4.49						
β_2	0.0112	4.06						
λ_0	0.0211	1.82	0.0456	4.82	0.0392	2.85	0.0218	1.76
λ_1	0.0350	5.12						
λ_2	0.0215	4.52						
δ_0	-0.0119	2.28	0.0181	4.85	0.0115	2.18	-0.0211	2.21
δ_1	0.0302	4.26						
δ_2	0.0218	3.16						
ζ_0	0.0118	1.87	0.0218	2.06	0.0296	2.51	0.0125	1.86
ζ_1	0.0154	2.16						
ζ_1	0.0226	2.66						
R^2	46.98		42.81		46.22		41.56	

The Table shows empirical results for the model tested as follows:

$$\begin{aligned} \%\ sp_{ijd}^{eff} &= \alpha_0 + \alpha_1 M_A + \alpha_2 M_B + \alpha_3 P_{sj} + (\beta_0 + \beta_1 M_A + \beta_2 M_b) Vol_{sjd} \\ &+ (\lambda_0 + \lambda_1 M_A + \lambda_2 M_B)\sigma_{sjd}^2 + (\delta_0 + \delta_1 M_A + \delta_2 M_B) Tr_{sjd} \\ &+ (\zeta_0 + \zeta_1 M_A + \zeta_2 M_B) HI_{sjd} + \alpha_4 NEWS_{sjd} + \alpha_5 DAY_{jd} + \varepsilon_{sjt} \end{aligned}$$

where sp_{sjd}^{eff} is the effective spread, M_A, M_B and M_C are the intercept dummy variables to capture the different markets (CAC, IBIS and SEAQ); P_{sj} is the transaction price; Vol_{sjd} is the total £-denominated volume; σ_{sjd}^2 is the security's return volatility for each trading day; Tr_{sjd} is the number of trades executed on each trading day; HI_{sjd} is the Herfindahl Index for every trading day; $NEWS_{sjd}$ is a dummy variable to capture days with major company-specific news; while DAY_{jd} is a dummy variable to account for the day-of-the-week effect.

Table 42: **Tests for the coefficient estimates of spreads determinants**

PANEL A: INTRA-DAY SPREADS

Wald Test		χ^2 *Test*	
$\alpha_1^{CAC} = \alpha_2^{IBIS}$	49.22*	$\lambda_{0+}\lambda_1 = 0$	20.18*
$\lambda_1 = \lambda_2$	21.26*	$\lambda_{0+}\lambda_2 = 0$	18.19*
$\gamma_1 = \gamma_2$	28.94*	$\gamma_0 + \gamma_1 = 0$	25.14*
$\delta_1 = \delta_2$	1.62	$\gamma_0 + \gamma_2 = 0$	22.01*
$\xi_1 = \xi_2$	25.72*	$\delta_0 + \delta_1 = 0$	21.26*
		$\delta_0 + \delta_2 = 0$	19.86*

PANEL B: MEAN DAILY SPREADS

Wald Test		χ^2 *Test*	
$\alpha_1^{CAC} = \alpha_2^{IBIS}$	8.21*	$\lambda_{0+}\lambda_1 = 0$	16.56*
$\lambda_1 = \lambda_2$	9.26*	$\lambda_{0+}\lambda_2 = 0$	14.25*
$\delta_1 = \delta_2$	1.52	$\gamma_0 + \gamma_1 = 0$	19.22*
$\zeta_1 = \zeta_2$	10.86*	$\gamma_0 + \gamma_2 = 0$	16.15*
		$\delta_0 + \delta_1 = 0$	18.26*
		$\delta_0 + \delta_2 = 0$	19.21*

The Table shows the results for the Wald Test and the χ^2 Test for a number of hypotheses from the two models estimated.

An * indicates significance at the 1% levels.

platform that generates the lowest transaction costs.

4.6 Conclusions

This study investigated (a) whether market microstructure really matters in terms of transaction costs when competition in the market for the provision of liquidity is directly taken into consideration, and (b) liquidity providers' quote setting behaviour under different market conditions.

The major result is that market microstructure effects can explain the absolute levels of transaction costs paid by traders. Traders on a hybrid mechanism face the lowest costs and this result holds even when we control for (a) the level of market concentration in liquidity provision, and (b) company-specific news. These results provide a preliminary confirmation of the Viswanathan and Wang (1998) hypothesis that a hybrid structure dominates both a pure dealership system and order book-based system.

In addition, some other results were obtained that can shed some light on liquidity providers' quote setting behaviour. First, spreads on a dealership system are less sensitive to market volatility than both the order book and the hybrid systems. This result can be interpreted in the light of the market maker's position, allowing them to decompose better volatility into (a) volatility due to the arrival of private information, likely to have a long term impact, and (b) volatility driven by noise trading, which is expected to have a short term impact.

It is also relevant to point out that spreads on both the order book and the hybrid system are more sensitive than those on a dealership system to the level of trading activity in the market, and particularly to the systematic component of the order flow. Indeed, a market maker is able to receive higher levels of price-sensitive information by entering in contact directly with traders and hence can form a better view of traders' motivation, strategies and styles. This implies that, everything else remaining constant, the quotes submitted by a market maker are likely to be more stable over the trading day.

Chapter 5. Price Efficiency and Order Flow Dynamics in a Hybrid Market

5.1 Introduction

The provision of liquidity in different market microstructures is carried out by different dealers - limit order traders in order book-based systems and market makers (mandatory or voluntary) in dealership-based systems. Which type of liquidity provision set-up generates the most efficient prices, taking into consideration market depth and breadth, is an empirical question of substantial importance. The issue of price efficiency, understood as the deviations of transaction prices from the security's true value, is strictly related to excessive short-term price volatilities which, in turn, is related to trading mechanisms. It is evident that investigating price efficiency and volatility is important since risk averse traders are assumed to care about price and execution uncertainty.

It is expected that strategic behaviour between traders differ across different market microstructures which would, in turn, generate different volatilities in the systems. Recent developments in market microstructure have analysed the interaction of different traders in the market, such as informed traders and liquidity traders (Admati and Pfleiderer, 1988, Easley and O'Hara, 1992, Lyons, 1995), traders with heterogeneous beliefs (Morris, 1994), and traders that herd on specific types of information (Froot *et al.*, 1992). Such considerations are important for the analysis of the order flow, its size, frequency and direction and impact on price stability.[12]

If the presence of a market maker is found to dampen excessive price

[12]The analysis of intradaily volatilities has already received a substantial level of attention through theoretical and empirical research (Cohen, Maier, Schwartz and Whitcomb, 1978, Goldman and Beja, 1979, Roll, 1984, Kyle, 1985, Hasbrouck, 1988, Hasbrouck and Ho, 1987, Admati and Pfleiderer, 1988, Foster and Viswanathan, 1988, Stoll, 1978).

volatility, then this will improve the market's quality (generating less inefficient prices) and will, in turn, increase traders' participation in the market, leading to higher volumes transacted.

Furthermore, the issue of price discovery process and order flow dynamics in parallel markets (operated by the same Exchange) has already attracted extensive theoretical attention. For example, Pagano (1989) investigates trading across multiple markets and shows that traders select the most suitable market to submit their order to on the sole basis of the maximum expected utility *ex ante*. One major result obtained by Pagano is based on the idea of self-fulfilling aspect of trading: agents will trade when they expect the market to be deeper. Furthermore, when transactions costs across the two markets on which the security trades are not equal, Pagano shows that larger trades may migrate to the market with the highest fixed costs, provided such a market appears to be deeper. This result is rooted in the impact of transaction costs on the trading positions of large and small traders. For the large traders, going to the most expensive but deeper market, means that they will incur a loss from transaction costs but this loss is outweighed by market depth which minimises the price impact due to a higher liquidity value.

Another model is by Seppi (1990) where a trader is given the choice between trading in the "upstairs" or going to the "downstairs" market. In this model, a liquidity trader may use the "upstairs" market if he can credibly signal to the market maker that his trade is not information-based.

Grossman (1992) explores a similar trading set-up, where the "downstairs" market is an open-order trading environment whereas in the "upstairs" prices are negotiated bilaterally. Going to the "upstairs" market entails additional search cost but these are offset by decreased volatility resulting from the fact that market makers on the "upstairs" market are better informed and are therefore in a better position to intermediate between the different traders. Due to the different costs in these two markets, in equilibrium trading may take place on both the "upstairs" and "downstairs" markets.

In this Chapter we are also interested in analysing order flow dynamics in parallel markets. One major study investigating several aspects of order flow dynamics was carried out by Biais, Hillion and Spatt (1995) when they analyse order flows on the Paris Bourse. Although this work is not directly related to the issue of parallel markets, the evidence presented in this work provides a good background on how limit orders and market orders interact together.

Biais *et al.* (1995) find that in a pure limit order book environment, the conditional probability that traders submit limit orders, instead of hitting the quotes (with a market order), is larger when (i) the spread is wide, or (ii) the order book is not very deep. On the other hand, liquidity is consumed through traders who tend to hit the prevailing quote when the spread is very narrow. From this evidence, the authors conclude that traders provide liquidity at times of liquidity shortages (when such an exercise is really valuable) and consume liquidity at times when liquidity is in surplus. Furthermore, at times of liquidity deficits, and to obtain time priority in these adverse market conditions, traders on the Paris Bourse place limit orders very quickly.

We investigate the various issues using the experience of the LSE which, in October 1997, changed its trading environment, for the most liquid securities (the FTSE 100 securities), from a pure dealership mechanism to a hybrid trading system based on an order book and voluntary dealers providing liquidity off the book. The trading regime change was expected to improve transparency in the market and enhance the bargaining power of investors vis-a-vis dealers, leading to lower trading costs of public investors. One major consequence resulting from these changes was that the obligations of mandatory market makers, enforced prior to the reform, ceased to exist. Today, dealers for the FTSE 100 index securities are entirely voluntary in terms of liquidity provision.

In some Exchanges, dealers are under a specific obligation to provide price stabilisation. The New York Stock Exchange, for example, defines one of the specialist's "affirmative obligations" as the "maintenance of a fair and orderly market". Hence, the specialist must contribute towards price stabilisation through his quotes and trading behaviour. On the other hand, dealers on the LSE are under no such obligation, prompting the question whether dealers provide price stabilisation even if they are not obliged to do so.

In view of these changes, this Chapter investigates (a) which type of liquidity provision set-up, in a hybrid trading system, generates the highest price efficiency, taking into consideration market depth and breadth, (b) the strategic interactions between the limit order book and the dealers, and (c) how the order flow behaves at times of price uncertainty.

Such analysis has been hampered by the fact that most Exchanges have, until recently, adopted one trading system and hence the price discovery process for a particular security could not be compared across different trading mechanisms. To investigate these issues,we use the FTSE 100 index's securities listed on the LSE, which are now traded on two parallel trading systems - an order driven system and a dealership system. This environment provides an ideal place for the analysis of transaction price efficiency, trading behaviour on the two systems and the strategic interaction between them.

The Chapter finds that prices on the dealership system track the security's true price more efficiently. The results provide a useful insight into the contribution made by dealers towards price stabilisation. The results should lead to a re-evaluation of the dealers' role in promoting orderly markets. The Chapter also provides a dynamic analysis of market making, in the sense that the role of dealers is investigated under various market conditions, mainly adverse conditions, for example when price volatility increases.

The rest of the Chapter is organised as follows. Section 2 presents some institutional characteristics of the LSE and of trading for the FTSE 100 securities taking place on the dealership system and SETS. Section 3 provides the literature review and attempts to capture the price discovery processes taking place on competing market microstructures. Section 4 investigates price efficiency through a model that takes into consideration the order flow, time between trades and trade sizes while Section 5 analyses trading behaviour on order book and dealership systems. Section 6 summarises and concludes.

5.2 Institutional Design

As from 20 October 1997, the constituents of the FTSE 100 index trading on the LSE started trading on two parallel systems - the new order book system, the Stock Exchange Electronic Trading Service (the "SETS") system, and an off-book, dealership-based system which succeeded the old telephone dealing system (the old SEAQ system). The dealership mechanism is based on "voluntary market makers" that stand ready for bilateral trades but are no longer obliged to provide quotes through the publicly available quote-display system.

Hence, the new trading environment provides traders with a choice where to trade: traders can either submit/hit limit orders electronically or they can trade directly with dealers supplying liquidity off-book. In such a system, price formation and liquidity dynamics are decided by market forces rather than through any regulatory requirements imposed on market makers.

Before the introduction of SETS, market makers were bound to provide firm quotes in the Mandatory Quote Period (MQP) which covered the trading period from 08:30:00 hrs to 16:30:00 hrs. This arrangement changed for trading in the FTSE 100 securities when SETS was introduced and the MQP for these securities now tracks the trading period over which trading can be executed on SETS.

Different types of orders can be submitted to SETS system, such as (a) "limit orders" which specify the size, price and expiry time; (b) "execute and eliminate" which are similar to the "at best" order, but with a limit price specified; (here the order will execute, in full or in part, at no worse than the specified price); (c) "fill or kill" where orders only execute in full immediately, or are totally rejected and may include a limit price; and (d) "at best" where participants are allowed to enter orders that will be executed immediately at the best possible price. No limit price is specified on the "at best" type of order while a "limit order" will either be executed in full or in part immediately, or will sit on the order book (until the expiry date/time, or until they are deleted) waiting for an order to match.

At present, the minimum order size which can be entered in the order book is 1 share. The arrangement for the minimum order size was changed in June 1998. Up to that date, the minimum order size was 1000 shares for stocks with price below £5 and 500 shares for all others. The maximum order size is 20 times Normal Market Size (NMS).

Securities traded on SETS are categorised for the purposes of certain rules according to a system based on NMS.[13] NMSs are reviewed quarterly by the LSE. The tick size in SETS is set in bands depending on securities' prices in the following way - (a) a price below 500 pence will have a tick size of 0.25 pence; (b) prices from 500 pence to 1000 pence will have a tick size of 0.5 pence; (c) prices over 1000 pence will have a corresponding tick size of 1.0 pence.

The opening algorithm on SETS is by means of a call auction, which is one major difference compared to the dealership system. In the period covered, the SETS system started accepting orders from 08:30:00 hrs up to 08:50:00 hrs with orders having the possibility of deletion. At exactly 09:00:00 hrs all order on the book are frozen temporarily while the uncrossing algorithm is run. No additional orders may be added or deleted until the uncrossing process for that security is complete. This algorithm calculates the price at which the maximum volume of shares in each security can be traded.

Any remaining unexecuted orders are left on the book for execution during the normal trading period. It normally takes about three minutes to complete uncrossing for all SETS securities. Once the uncrossing process for each security is complete, continuous automated execution in that security begins and orders can be entered and deleted as before.

In the continuous trading session, orders are submitted to the order book with the identity of the trader held anonymous. As soon as the order is executed, the trade is automatically reported to the LSE and the market is informed immediately that the trade has taken place. Only member firms involved in the trade discover the traders' identity once their orders match. The rest of the market is not informed which member firms were involved.

[13]Each security's NMS is equivalent to the average institutional trade size in that particular security and is calculated in accordance with a formula which takes into account the value of customer turnover over the previous 12 months and the closing price of the security at the end of the latest calendar quarter.

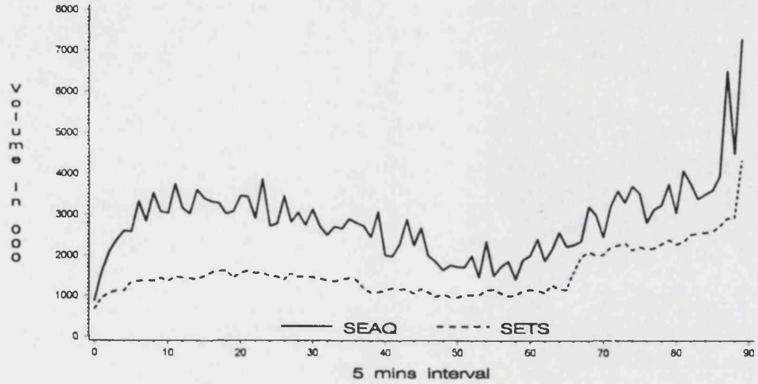


Figure 24. Daily aggregate volume for the FTSE 100 securities

Figures 24-26 and Table 44 provide some insights as to the different trades which are being channelled to SETS and the dealership system. The Figures show how aggregate volume flow mainly to the dealership system during the opening period. In addition, the number of trades transmitted to the dealership system is also much higher than those sent to the order book.

The preliminary statistics refer to the transacted volume in the period June-October 1998. In this period, the SETS system transacted approximately 36% of the total order flow for the FTSE 100 components.

Table 44 shows that the dealership system dominates the auction system for the small order size and for the large order size, whereas medium sized trades are being channelled to the SETS system. This is, to a certain extent, a curious result in so far as the dominance for the smaller sizes is concerned. Given that dealers provide substantial depth and breadth to the market, using their inventory to accommodate large orders, the fact that trades bigger than 50,000 shares are transacted through the market making system comes as no surprise.

However, the order book-driven system is assumed to provide a com-

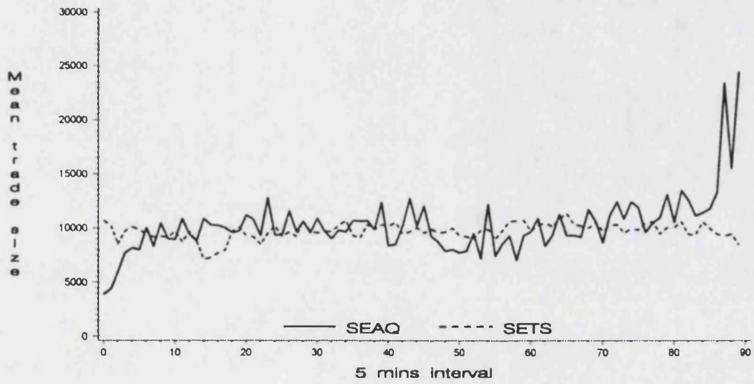


Figure 25. The mean trade size for FTSE 100 securities

Table 43: **A sample of securities from the FTSE 100 index used for analysis**

Top 10 securities by volume		**Bottom 10 securities by volume**	
Security	Name	Security	Name
1	AstraZeneca	11	Associated British Food
2	Barclays Bank	12	Alliance & Leicester
3	British Telecom	13	Hays
4	BP Amoco	14	Kingfisher
5	HSBC Bank	15	Land Securities
6	Glaxo Wellcome	16	Misys
7	Lloyds TSB Bank	17	Reckitt & Colman
8	Rentokil Initial	18	RMC
9	Shell Transport	19	Schroders
10	Unilever	20	Severn Trent

Table 44: **Typology of trades being executed on SETS and SEAQ (July - October 1998)**

Trade size	TRADING ON DS Volume on DS	% of Total Order Flow	TRADING ON SETS Volume on SETS	% of Total Order Flow
0-499	1198260	27.50	109182	2.54
500-999	562819	12.92	105681	2.43
1000-1999	407766	9.36	234059	5.37
2000-4999	240643	5.52	379898	8.72
5000-9999	103841	2.39	259376	5.95
10000-19999	91473	2.10	224902	5.16
20000-49999	92459	2.12	171684	3.94
50000-99999	51910	1.19	41781	0.96
=>100000	73300	1.68	8661	0.20
Total		64.78		35.22

The Table shows the total volume in each trade size group transacted on the order book and on the dealership system during 1 June - 31 October 1998.

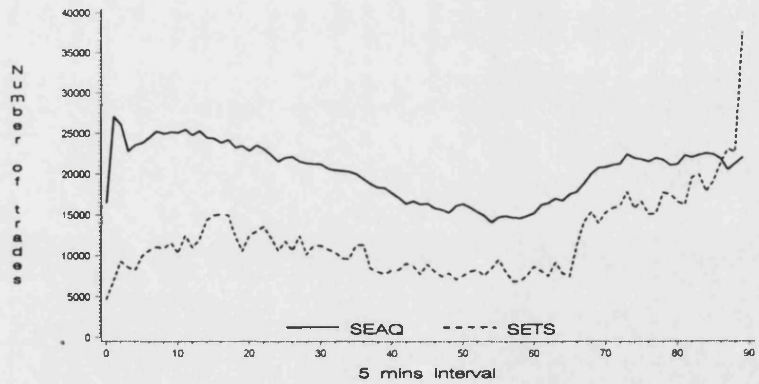


Figure 26. Number of trades for FTSE 100 securities

Table 45: **Descriptive statistics for a sample of FTSE 100 securities used for the analysis**

	Market Capital. £ millions	Mean Price (pence)	Mean Number of daily trades SETS	DS
TOP 10 BY VOLUME				
AstraZeneca	24,914	2170	208	245
Barclays Bank	19,583	1209	260	548
British Telecom	41,673	783	345	1555
BP Amoco	86,905	831	394	551
HSBC Bank	41,997	1248	267	565
Glaxo Wellcome	74,979	1761	359	607
Lloyds TSB Bank	46,478	712	370	1144
Rentokil Initial	12,978	345	173	103
Shell Transport	36,716	351	338	647
Unilever	46,255	550	228	368
BOTTOM 10 BY VOLUME				
Associated British Food	4,561	592	102	146
Alliance & Leicester	5,165	848	97	450
Hays	4,302	831	93	119
Kingfisher	6,478	516	167	187
Land Securities	5,806	874	112	164
Misys	4,148	404	113	128
Reckitt & Colman	3,245	956	93	121
RMC	2,146	752	62	46
Schroders	3,120	981	105	142
Severn Trent	3,558	1046	88	91

The Table provides descriptive statistics for a sample of FTSE 100 index securities. "Market Capital." is the market capitalisation on 30 June 1998; "Mean Price" is the average security price over the period from June to October 1998.

petitive advantage over the dealership system for smaller trades (at least in terms of execution costs) and hence it was expected that these trades would go through the limit order system.

It is suspected that this result, where small, retail-oriented orders are directed to the dealership system rather than the order book, is due to the specific institutional design introduced by the LSE and which remained in place up to June 1998 whereby the Minimum Order Size on SETS was fixed at 500 shares for some securities and 1000 shares for other, effectively excluding smaller orders (presumably made by retail investors) to be directed on SETS.

In addition, the presence of the so-called Retail Service Providers (the "RSPs") who receive orders from retail investors could also provide an explanation for this result. In fact, most of these RSPs, in many cases, form part of financial institutions that also have dealers (the previous market making firms) within the same organistion. This could give rise to a situation where, for orders that do not explicitly state that execution should be carried through the order book, RSPs sent these orders to their in-house dealers for execution there. Given that dealers are bound by the best-execution rules, investors will be give the same prices by the dealer as they would have obtained had these orders been executed in the order book.

Having said this, the evidence produced here may be consistent with the results obtained by Hansch *et al.* (1998) who found that pre-1997 market makers made profits on small trades, broke even on large trades but lost money on medium-sized trades.

5.3 Extant Literature and Hypotheses

This Section attempts to capture the basic characteristics of the order book and dealership markets used by the LSE, taking into consideration (a) the information available in each system when the price of a transaction is set; (b) the type of orders submitted in each market mechanism; and (c) the strategic behaviour between different traders in the market.

The objective is to go through the theoretical literature that is most relevant in order to understand the major characteristics of the price discovery process in the two systems and the trading behaviour so as to produce hypothesis to be tested in the following Section.

As stated above, the continuous auction system provides information of the order flow arriving in the order book except that the identity of the trader submitting the order is withheld. It is expected that prices aggregate information about the entire order flow arriving on the order book system.

On the other hand, the dealership system is based on bilateral negotiations between the trader and the market-maker and this is private information. Each market maker does not know the order flow being directed to other dealers operating on the dealership system. On the other hand, the market maker receives two pieces of information: (a) the identity of the trader willing to enter into a transaction, hence providing invaluable information to disentangle liquidity-motivated from information-motivated trades; and (b) the order flow and the prices being formed on the SETS system.

On top of this, the SEAQ dealers are bound by the "best execution" arrangements which state that the best prices for transactions smaller than 1 X NMS are dictated by the best ask and bid prices generated by the SETS system. Trades larger than such a size are subject to negotiation.

The model we consider here is based on the familiar framework used in the rational expectations literature. There are two assets, cash and a single risky asset which has a stochastic liquidation value. There are two types of agents - the "traders" who arrive on the market through an exogenous stochastic process and the "dealers" (who are called "market makers" on the dealership system) who provide liquidity.

Traders are assumed to have a negative exponential utility function of the form:

$$u(W_i) = -e^{-\rho W_i} \tag{23}$$

where W_i is the final period wealth of trader i and $\rho > 0$ denotes the coefficient for the absolute risk aversion. It is expected that traders maximise the expected utility of the final period wealth.

It is assumed that the risky asset traded has a true value of V which may be high V_H or low V_L, each with a probability of 0.5.

The realisation of V_H and V_L are known exclusively to a risk-neutral informed trader, who is present on the market with probability Φ and who places a market order to buy or sell an amount that maximises his expected profit.

With probability Θ a liquidity-motivated trader arrives on the market and places a market order to buy or sell one unit of the risky asset, each with a probability of 0.5. Denote p as the price at which the trade takes place, e_i as the investor's initial share endowment, c_i as the investor's initial cash position and Δ_i as the number of shares purchased.

Suppose that the prior distribution of the unknown asset value, V, is normal with mean μ and precision ρ. Assume also that informed traders are price takers and they have information set denoted by Ω.

They receive a signal, ϱ, drawn from the normal distribution with mean V and precision π. In this case, trader i views V as normally distributed with mean $V_0 = E[V \mid \Omega_i] = \mu\tau + \varrho(1-\tau)$ where $\tau = \rho/(\rho+\pi)$ and variance $(\rho+\pi)^{-1}$.

The informed trader will submit an order to trade that is a linear function of the price in the following way:

$$\Delta_i(p) = \xi_i - \psi_i p \tag{24}$$

where $\xi_i = \frac{V_0}{\rho(\rho+\pi)^{-1}}$ and $\psi_i = \frac{1}{\rho(\rho+\pi)^{-1}}$. The latter reflects the trader's risk aversion and the uncertainty regarding the private information he obtains. In addition to the informed traders, the $\Upsilon \geq 0$ uninformed traders will trade for liquidity-related reasons with uninformed trader d submitting ς_d to the market.

The aggregate excess demand from the traders will be a function of the price as follows:

$$\Xi(p) = \Sigma^N \Delta_i(p) + \Sigma^\Upsilon \varsigma_d \tag{25}$$

Denote p^* as the market-clearing price in such a set-up (this must be identical to the Walrasian price) and we have:

$$p^* = V_0 + \zeta \tag{26}$$

where

$$\zeta = \frac{\Sigma^\Upsilon \varsigma_d - \Sigma^N e_i}{\Sigma^N \psi_i}$$

which is equivalent to the noise term capturing the impact of the uninformed trading and the hedging of endowment risk.

5.3.1 Dealership Market

We consider a model for the quote driven mechanism where prices are set by M risk-neutral and competitive market makers who stand by to satisfy the order flow and provide liquidity by acting as a counter-party to traders.

The market makers will provide the bid and ask prices, which are regret-free prices, at which they will execute the order flow. As in Madhavan (1992), these quotes are assumed to be firm, meaning that they can only be changed after the individual order is transacted.

However, in order to capture the linkages that exist in hybrid markets between the order book and the dealership system, we consider the market maker as behaving in a way that conditions his prices not only on the information he obtains from his own order flow but also on the information emerging from the order book (publicly available). This is consistent with the view that observing the evolution of the order book will generate signals about the asset value and will be used by the market maker in setting his own quotes for bilateral trades.

This mechanism is represented as a two-stage game, on the lines of Madhavan and Panchapagesan (2000), where in the first stage market makers determine the firm quotes and in the second stage the trader chooses whether to submit the order given the quotes provided by the market maker. We also assume that the market maker trades for his own account in order to (a) hedge the risk of his inventory, and (b) to maintain an optimal inventory level. We denote his trade by q where $q > 0$ represents market maker purchases and $q < 0$ denotes market maker sales. By observing the order flow on the order book, the market maker can generate the statistic $\digamma$ which provides an additional noisy signal about the informed trader's private signal. The statistic $\digamma$ is represented by $\frac{\xi_i \psi_i^{-1} - \mu\tau}{1-\tau}$.

The market clearing condition implies that $\Xi(p) + q = 0$ and hence the prices, $\mathbf{p}_i^{cd}$, formed in the continuous dealership (cd) that will clear the market will be as follows:

$$\mathbf{p}_i^{cd} = p^* + \kappa q \tag{27}$$

where $\kappa = \frac{1}{(\Sigma_i \psi_i)}$.

The unconditional variance of p_i^{cd} around the true value of the asset is given by (28):

$$Var\left[\mathbf{p}_i^{cd} - V_0\right] = Var[\zeta] + 2\kappa_i Cov(\zeta, q_i) + \kappa_i^2 Var\left[\mathbf{q}_i\right] \tag{28}$$

5.3.2 Order Book System

As in Madhavan (1992), the order driven system is characterised by dealers who engage in competition by submitting a set of price-quantity combinations such that the quantity demanded at each price is the desired order quantity conditional upon that particular price clearing in the market. Hence, in the order driven system the execution price is only known after the trade has been executed and the price depends on liquidity in the market at any point in time.

Consider the limit order placed on an auction market. This type of order will be executed with a probability ϕ in which case the trader i will get the share, paying price p_i, and pay the cost of transmitting the order c_i^T and the cost involved with settlements, etc., denoted by c_i^A.

In the case that the limit order does not get executed, the trader will not get the share but will have to pay the cost of transmitting the limit order book, c_i^T.

Hence the trader's payoff structure is:

$$\phi\left(p_i - c_i^T - c_i^A\right) + (1 - \phi)\left(-c_i^T\right) \tag{29}$$

Empirical evidence shows that the probability, ϕ, of a trade executing depends on the trade size since market depth decreases with trade size.

The market depth is unknown at any point in time (depending on the limit orders submitted) and is assumed to be a random variable, which is distributed uniformly on {0,1,...Z}. Each trader makes a decision as to the optimal size for the order to be submitted, knowing that each order executed leads to a payoff of w_i ($w_i = p_i - c_i^T - c_i^A$) and each order not transacted leads to a loss of $\left(-c_i^T\right)$.

The decision as to the optimal size to be transmitted is found in the following way. Suppose that a trade size j is transacted. Then the total payoff is given as:

$$\Psi_j = \begin{cases} wj; & if\ D > j \\ wD - c^T (j - D) & if\ j > D \end{cases} \tag{30}$$

The expected payoff would be:

$$\begin{aligned} \mathbf{E}(\Psi_j) &= wj\mathbf{P}(D \geqslant j) + w\sum_{D=1}^{j-1} \frac{d}{Z+1} - c^T \sum_{=0}^{j-1} \frac{j-d}{Z+1} \\ &= \frac{j}{Z+1}\left[w\left(Z+\frac{1}{2}\right) - \frac{1}{2}c^T - \frac{1}{2}j\left(w+c^T\right)\right] \end{aligned} \tag{31}$$

Now

$$2(Z+1)\left(\mathbf{E}(\Psi_{j+1}) - \mathbf{E}(\Psi_j)\right) = (2Z+1)\,w - c^T - (2j+1)\left(w+c^T\right)$$

and the expected payoff is largest when $j = \tilde{j}$, where:

$$\tilde{j} = \max\left\{0, \frac{Zw - c^T}{w + c^T}\right\} \tag{32}$$

In this model, the quantity traded in the continuous auction system is different from the quantity transacted in a dealership market, with the difference being due to market liquidity at the time when the order is transmitted to the market. This suggests that in an auction market, market depth is a fundamental statistic and the trader will have to monitor closely the depth of the order book before submitting any order.

Following Kyle (1989), we define depth (the liquidity parameter) in the continuous auction market, φ, as:

$$\varphi = \frac{1}{\mathrm{M}\gamma_i}$$

where γ refers to the behaviour of dealers with $\gamma > 0$ meaning that dealers sell when prices rise and buy when prices fall.

The derivation for the prices on the auction system is based on the construction of the Bayes-Nash equilibrium by solving for each trader's best response given the strategies adopted by other traders submitting the orders in the order book.

As in Madhavan (1992), we assume that trader i arriving at time t_i believes that the limit order traders adopt the following strategy:

$$d_j^i(p_i) = \gamma_i(\mu_i - p_i) \tag{33}$$

In equilibrium, we have:

$$\mathrm{M}\gamma_i(\mu_i - p_i) + j_i = 0 \tag{34}$$

It follows that in such a mechanism, the price, $\mathbf{p}_i^{ca}$ that will clear the market will be formed as follows:

$$\mathbf{p}_i^{ca} = \mathbf{p}^* + \varphi_i \mathbf{j}_i \tag{35}$$

The unconditional variance of p_i^{ca} around the true value of the asset is given by:

$$Var\left[\mathbf{p}_i^{ca} - V_0\right] = Var[\zeta] + 2\varphi_i Cov(\zeta, j_i) + \varphi_i^2 Var\left[\mathbf{j}_i\right] \tag{36}$$

5.3.3 Hypothesis Tested

To recapitulate, we have that the unconditional price volatility on the dealership is given by:

$$Var\left[\mathbf{p}_i^{cd} - V_0\right] = Var[\zeta] + 2\kappa_i Cov(\zeta, q_i) + \kappa_i^2 Var\left[\mathbf{q}_i\right]$$

whereas the unconditional variance on the order book is provided by:

$$Var\left[\mathbf{p}_i^{ca} - V_0\right] = Var[\zeta] + 2\varphi_i Cov(\zeta, j_i) + \varphi_i^2 Var\left[\mathbf{j}_i\right]$$

The variance relative to the asset's true value (price efficiency) in each trading system is the product of (a) the noise, produced by trading, around the Walrasian price, (b) the variance of the trades generated by liquidity providers, and (c) the covariance between the liquidity providers' trades and those submitted by liquidity traders. The question as to whether price volatility (around the true value) is higher on an order book or a dealership system becomes an empirical one since we need to investigate the strategic behaviour of dealers on the dealership system and the limit order traders on the order book.

The issue of price efficiency, as used in this Chapter, is strictly related to short term price volatilities. As Stoll and Whaley (1990) argue, volatility in a market microstructure set-up is generated from three major sources - (a) the trading behaviour of investors, especially the strategic interaction between informed and liquidity investors, bound to produce trading pressures; (b) the arrival of public information on the market; and (c) the channels used by market participants to provide immediacy to the market.

Strategic behaviour that takes place in the submission of limit orders to the order book, between limit order traders and liquidity traders, can exacerbate short term price volatility in such a trading platform. Order submission strategies are expected to influence short term price volatility. For example, an over-reliance of market orders in an order driven system will produce different price impacts than a strategy based on strategic limit orders that continuously hit the best prices on the other side of the book.

On the other hand, a dealer on the market have a better view of the evolution of the price discovery process since she does not only have the public order book to look at, but has also her own order flow from which information can be extracted. In addition, such a dealer can build long-standing professional relationships with traders, contributing towards extracting clearer signals from the trading process.

If dealers, in the process of maintaining an optimal inventory position, post quotes that are asymmetric (buying when the stock price is low and selling when the price is high) relative to the perceived true economic price of the security, then the covariance between the dealers' trades and the noise produced by liquidity traders will be negative.

On the other hand, Handa and Schwarz (1996) argue that liquidity shocks transmitted to the system will attract more limit orders to the system and hence liquidity will be supplied when it is mostly needed. They argue that under these circumstances, the net gain obtained from supplying liquidity is greater than the risk of being picked off by the informed traders present in the system. This influx of limit orders in the system will cause short-term volatility to decline.

Even within the subset of limit orders, aggressively priced limit orders are likely to produce different impacts than similar orders submitted by patient traders. In this sense, the depth, breadth and resilience of the order book are fundamental features that must be analysed.

Hypothesis 1_O: The competition in the price-quantity schedule that takes place in an order driven system allows for strategic behaviour between liquidity providers, distorting short term prices. On the other hand, voluntary dealers' trading pattern leads to quotes that are asymmetric relative to the perceived true economic price of the security resulting in a negative covariance between dealers' trades and the noise produced by liquidity traders. Hence, price efficiency will be higher in a dealership system.

Hypothesis 1_A: When there are short-term price fluctuations, limit order traders will find it more profitable to submit limit orders to the order book, supplying liquidity when it is mostly needed. This influx of limit orders will enhance market liquidity, causing short-term price volatility to decline. This process will generate higher price efficiency in the order driven system.

5.4 Price Efficiency

In this Section we empirically investigate the efficiency of prices generated by the order book and dealership trading and attempt to answer the question which competing microstructure, in a hybrid set-up, leads to highest efficiency.

The investigation will be divided into two parts. In the first place, given the hybrid nature of the LSE's trading environment, we assume that SETS and the dealership systems are closely linked with each other in a way that prices in the two systems cannot diverge for a long period of time. Any pricing divergences are short-lived and are mainly due to market microstructure reasons, such as lack of transparency, lack of liquidity, pricing errors, etc.

We obtain the true "system-wide" price that would emerge from a combined order flow. The true "system-wide" price, which is unobservable due to the splitting of the order flow over the two systems, is obtained via a Kalman smoothing technique.

In the second stage, we investigate price volatility in the dealership and the auction systems around the "system-wide" true price, making use of variance ratios, to test price efficiency on the two competing market microstructures.

The transaction prices on SETS and the dealership system (henceforth "DS") systems can be modelled in the following way

$$p_t^{DS} = m_t + \xi_t \qquad \xi_t \sim N(0, \sigma_\xi^2) \tag{37}$$

$$p_t^{SETS} = m_t + \omega_t \qquad \omega_t \sim N(0, \sigma_\omega^2) \tag{38}$$

where m_t is the true "system-wide" price that is expected to emerge if the two trading systems where perfectly linked and complete pre- and post-trade transparency obtains, ξ_t is the pricing error occurring on DS while ω_t is the pricing error occurring on SETS. For the purpose of this Chapter, testing for price efficiency in the two systems can be obtained by testing whether the variance of the pricing error ξ_t is larger than that of ω_t.

5.4.1 Methodology

Existing Empirical Models Various methodologies could be adopted to analyse the case when a financial asset trades in parallel markets. One such technique is employing a "benchmark price", such as the price at a relatively quiet trading period in the day (such as the price obtained at 13:00:00 hrs) or the price at the close which is the period when it is assumed that all relevant information, realeased during the trading day, would have been impounded in the price. The researcher can then compare the price volatility on SETS and DS around this benchmark price.

Another approach would be employing mid-quotes but such a technique, although presenting the benefit of simplicity, poses a number of problems. First, there are substantial doubts on the validity of the mid-quote as a proxy for the true price (see Hansch *et al.*, 1999, and Reiss and Werner, 1996). Secondly, it is very difficult to obtain a valid mid-quote for a security trading on two different trading mechanisms, using completely different trading rules. Any such mid-quote would have to take into consideration aspects of depth and breadth of the market so as to make the statistic significant across the two trading systems. Thirdly, since dealers do not disseminate their quotes in a central location it is very difficult to obtain their quotes. In fact, the LSE data set only provides quotes from the order book.

Besides these *ad hoc* models, there are other, more robust, methodologies that have been used to investigate the price discovery process aimed at measuring the contribution made by each market to the security's price discovery process. On the econometric level, the major models employed have been the so-called common factor models, where the price series of the same securities on the different markets share a common factor, perceived to be the true value of the security.

It is assumed that each trading location goes through a process of collecting, interpreting and analysing price-sensitive news; in this way each market contributes to the security's price discovery. Intermarket arbitrage is expected to keep the prices in the different locations from deviating from each other in the long term, allowing deviations to exist for only very brief periods. The main source of these deviations is mainly market frictions. In fact, disequilibria in these models occur because traders in different markets can process news at different rates. In econometric terms, the transaction prices in each of the different locations are cointegrated $I(1)$, meaning that these price series share one common stochastic factor which is typically referred to as the efficient price. It is this common component which is the source of any permanent movement in the transacted prices obtained on the different markets.

The two major empirical methodologies applied in this field are the Hasbrouck (1995) model, known also as the Information Sharing Model, and the Gonzalo and Granger (1995) model, known as the Permanent-Transitory Model. Although these two models differ in the way they capture the price discovery process taking place in the different trading locations, they can be considered as complimentary, rather than substitute models. In fact, they can provide similar results when certain conditions hold. The two models employ the vector error correction model (VECM) of price discovery as their basis. While the Information Sharing model of Hasbrouck (1995) considers the contribution of each trading location to the variance of the innovations of the efficient price, the Gonzalo and Granger (1995) model captures the components of the efficient price and the error correction process.

When the residuals in the price series generated by the different markets are uncorrelated then the two models will produce similar results; but if a significant level of correlation exists then results will differ. In fact, Hasbrouck (1995) incorporates contemporaneous correlation in the model (through the Cholesky factorisation), but Gonzalo and Granger (1995) not contemplating such a measure. However, the benefit of the Hasbrouck's model to deal with contemporaneous correlation comes at a cost: prices must be ordered. This can be a problem if the high frequency data at the disposal of the researcher is not temporally ordered which is the case with a number of fragmented markets.

One major difference between the Hasbrouck (1995) and the Gonzalo and

Granger (1995) models is the way in which price discovery is defined. The former defines price discovery as the variance of the innovations to the efficient price (common factor) while the latter perceives the process in terms of an error correction process, generating permanent shocks leading to disequilibrium. Whereas each market's contribution to the price discovery process is defined by Hasbrouck as the market's contribution to the variance of the common factor, in Gonzalo and Granger is defined as a function of the markets' error correction coefficients.

5.4.2 Cointegration and common factors

Both the Information Sharing and the Permanent-Transitoy models consider two integrated $I(1)$ price series, $P_t = (p_{1t}, p_{2t})'$ with the differential being the error correction term, i.e., $z_t = \beta P_t = p_{1t} - p_{2t}$, with $\beta = (1, -1)'$ representing the cointegration vector. The following VECM represents the starting point of the two models:

$$\Delta Y_t = \alpha\beta Y_{t-1} + \sum_{j=1}^{k} A_j \Delta Y_{t-j} + \varepsilon_t \tag{39}$$

which can be decomposed into the long run relationship between the price series on the different locations - $\alpha\beta Y_{t-1}$ - and a short run dynamics factor - $\sum_{j=1}^{k} A_j \Delta Y_{t-j}$ - driven by market frictions and other imperfections. In the VECM model, α is error correction vector and ε_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix Ω such that

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$$

σ_1^2 (σ_2^2) is the variance of ε_{1t} (ε_{2t}) and ρ is the correlation between ε_{1t} and ε_{2t}.

Hasbrouck (1995) transforms (39) into a vector moving average (VMA):

$$\Delta Y_t = \Psi(L)\varepsilon_t \tag{40}$$

and its integrated form:

$$Y_t = \Psi(1)\sum_{s=1}^{t}\varepsilon_s + \Psi^*(L)\varepsilon_t \tag{41}$$

where $\Psi(L)$ and $\Psi^*(L)$ are matrix polynomials. The long run impact of innovations, due to news, on each of the price series in the different trading locations is represented by $\Psi(1)\varepsilon_t$. Denoting $\Upsilon = (\Upsilon_1, \Upsilon_2)$ as the common row vector in $\Upsilon(1)$, then equation (41) becomes

$$Y_t = \iota\Upsilon(\sum_{s=1}^{t}\varepsilon_s) + \Psi^*(L)\varepsilon_t \tag{42}$$

where $\iota = (1,1)'$ is a column vector of ones.

Hasbrouck (1995) suggests that the increment $\Upsilon\varepsilon_t$ in equation (42) is being driven by news arriving on the market and represents the change that is permanently impounded into the price. Transitory effects, such as bid-ask bounces and inventory adjustments, are not considered.

If market innovations are uncorrelated across markets, then in the Hasbrouck (1995) model the matrix Ω will be diagonal and $\Upsilon\Omega\Upsilon'$ will have two terms: the first (second) represents the contribution to the common factor innovation from the first (second) market. The information share of market j is defined as:

$$S_j = \frac{\Upsilon_j^2\sigma_j^2}{\Upsilon\Omega\Upsilon'}$$

The relative information share of market j is the square of its common factor component weighted by its variance.

In Gonzalo and Granger (1995), the common factor is modelled as a combination of the variables P_t, such that $f_t = \Gamma P_t$, where Γ is the common factor coefficient vector and orthogonal to the error correction coefficient vector α. In this sense, f_t may be expressed in terms of either price, i.e. p_{1t} and p_{2t} and the error correction term, z_t with f_t being $I(1)$. In this sense, the Gonzalo and Granger model decomposes the common factor into a combination of two prices. Moreover, because the size of z_t is almost surely small relative to p_{it}, f_t's evolutionary process is dominated by p_{it}.

When we have informationally linked markets, it is expected that σ_1^2 and σ_2^2 have similar values and this scenario the results obtained by Hasbrouck (1995) and Gonzalo and Granger (1995) are similar. However, if price innovations across the different markets are significantly correlated, then the two models generate different results. The way Hasbrouck (1995) model deals with this problem is to use the Cholesky factorisation in order to eliminate the contemporaneous correlation.

Hasbrouck (1995), using one-second interval sampling of the quotes, reports that the upper and lower bounds in his study of price discovery between NYSE and off-NYSE quotes are almost the same. For this type of high frequency data, problem posed by contemporaneous correlation is not significant. However, it is expected that for lower frequency datasets the contemporaneous correlation between innovations across markets is likely to pose a problem. Studies using lower frequency data sets report significant differences between the upper and lower bounds. Mentioning one example, Huang (2000), employing one-minute intervals for Yahoo Inc. to investigate the price discovery between ECNs and various NASDAQ dealers finds that the lower and upper bounds are 80% and 31% respectively.

Kalman Smoothing As mentioned above, one major requirement of the Hasbrouck methodology is ordered data which means that trades must have strict sequentiality. As we shall see, this is one major problem in the dataset provided by the LSE and is mainly due to (a) the competitive dealership nature of the DS, and (b) the trade reporting regime. As such, the only source of the lack of sequentiality comes from the off book trades but becomes a major issue for our purpose.

We can refer to two notions of data sequentiality: (a) the first one refers to the microstructure adopted by the Exchange; while (b) the second has to do with the reporting regime adopted by the Exchange which will, in turn, influence the data sets available to the researcher. In markets where (a) securities trade through the presence of a single market maker, as is the case of the NYSE, and (b) liquidity is provided through a screen-based system based on the public order book, produce one single price at each point in time (given that only one order is executed at each point in time) and hence data sequentiality is obtained automatically. This is the case with the SETS system.

However, in a competitive dealership market where a number of dealers complete for the order flow and negotiate trades simultaneously in a fragmented market there is likely to be different prices for the same security at each point in time. This is the case with the DS on the LSE. On this system we could have a situation where several orders for the same security are transacted at different prices at the same point in time because information is not centralised and negotiation takes place in a bilateral fashion between each dealer and trader. Furthermore, the LSE allows dealers to report their trades within three minutes from the order's execution which means that data collected by the LSE could be intrinsically non-sequential.

Given these problems, it is unlikely that the Hasbrouck (1995) model will produce a good estimate of the common factor - the security's true price - which is an important aspect of our analysis. We need an econometric model that preserves the time series properties of the price series without the need to have data sequentiality as a necessary condition. One such model was proposed by Lai and Koopman (1999) where the time series properties are modelled explicitly without the need of data sequentiality.

In view of such constraints, we attempt to calculate the "system-wide" true price at each point in time and compare the price volatility on SETS around this true price with the dealership's price volatility around the same price.

In line with Madhavan *et al.* (1997) we write the transaction price discovery process, for every security, as follows:

$$p_{t,i} = m_t + s_{t,i} + \varepsilon_{t,i} \qquad \varepsilon_{t,i} \sim N(0, \sigma_\varepsilon^2) \qquad i = 1, ..., N_t \tag{43}$$

$$m_t = m_{t-1} + v_t + \varsigma_t \qquad \varsigma_t \sim N(0, \sigma_\varsigma^2) \qquad t = 1, ..., n \tag{44}$$

where $p_{t,i}$ is the transaction price at time t for trade i, $s_{t,i}$ is the half-spread and $\varepsilon_{t,i}$ is the pricing error in the transaction price. On the other hand, m_t is the fundamental (true) price, v_t is the price-relevant information released by the order flow while ς_t refers to the disturbances generated by the information coming from other sources besides the volume transacted.

The transaction price discovery process is given by the evolution of the true price, m_t, and the factors that impact on the half-spread. In turn, the true price at period t is the lagged value of the fundamental price adjusted for information from the order flow and from other sources. The disturbances $\varepsilon_{t,i}$ and ς_t are normally distributed and independent of each other.

In the model used (explained below), there is the implicit assumption that spreads have one component - adverse selection - while the inventory component and the order processing component are not modelled. As explained above, Amihud and Mendelson (1980) and Ho and Stoll (1981, 1983) suggest that the rebalancing of the inventory held by the dealers is a cost that must be covered by the bid-ask spread. However, Hansch *et al.* (1999) and Reiss and Werner (1997) show that this component is not of particular importance to London dealers who can rebalance using the inter-dealer market resulting in low risk from inventory holdings.

Additional structure is needed to calculate the "system-wide" price in that (i) the information impounded from the order flow, and (ii) the factors affecting the spreads must be specifically modelled. In line with Koopman and Lai (1999), we specify the half-spread at time t on the i-th trade to follow the following process:

$$s_{t,i} = d_{t,i}(\tau_t'\Pi + \varkappa_x'\Omega) \qquad x = x_{t,i}$$

where

$$d_{t,i} = \begin{cases} 1 & \text{if trade is buyer-initiated} \\ -1 & \text{if trade is seller-initiated} \end{cases}$$

while $(\tau_t\Pi + \varkappa_x\Omega)$ represents a cubic spline regression with parameter vectors Π and Ω.

The explanatory variables τ_t and $\varkappa_x$ are vectors based on the time-of-day effect τ and the trade size $x_{t,i}$ respectively.

Following the literature introduced by Copeland (1976) and Easley and O'Hara (1987 and 1992) we assume that the order flow, the trade size, the order persistency and the time interval between successive trades are factors that signal information about the true value of the security. In addition, we follow Hasbrouck (1991) in that the order flow is assumed to be serially correlated because of order fragmentation and price stickiness.

In particular, if we allow the vector $q_t = (q_{1,t}, ..., q_{S,t})$ to contain the lagged trade volumes multiplied by the binary variable $d_{t,i}$, we allow for serial correlation in the following fashion

$$q_{j,t} - E(q_{j,t} \mid q_{j-1,t}, q_{j-2,t}, q_{j-3,t} \ldots) = q_{j,t} - \theta_1 q_{j-1,t} - \theta_2 q_{j-2,t} - \theta_3 q_{j-3,t} \ldots \quad (45)$$

With this structure, we model the information contained in the order flow as follows

$$v_t = q_t \lambda = \sum_{j=1}^{S} \lambda_j q_{j,t} \quad (46)$$

where, as explained above, $q_{j,t} = \sum_{i=1}^{N_{t-j}} d_{t-j,i}\, x_{t-j}$ and $\lambda = (\lambda_1, ..., \lambda_S)$ is a fixed unknown vector of coefficients.

We write the model in (43) and (44) in a state space framework with the following transition and measurement equations:

$$\alpha_t = \Omega_t \alpha_{t-1} + \Pi_t \gamma_\varkappa + \beta_t \eta_t \qquad \eta_t \sim N(0, \sigma_\eta^2) \qquad t = 1, ..., n \quad (47)$$

$$p_{t,i} = \Phi_{t,i} \alpha_t + X_{t,i} \gamma_x + \varepsilon_{t,i} \qquad \varepsilon_{t,i} \sim N(0, \sigma_\varepsilon^2) \qquad i = 1, ..., N_t \quad (48)$$

where the α_t is the $m \times 1$ state vector which follows a vector autoregressive process with transition matrix Ω_t, explanatory matrix Π_t and selection matrix Ω_t for the disturbance term η_t. The parameter vectors $\gamma_\varkappa$ and γ_x allow the inclusion of the fixed effects in the model. The matrices Ω_t, Π_t, β_t and the vectors $\Phi_{t,i}$, $X_{t,i}$ are assumed to be deterministic and known.

The time-of-day effect in the spread and the trade size effect are modelled as regression spline functions with a number of knots which can be determined using the Akaike Information Criterion (AIC) to obtain fit and parsimony in the model, with the lowest AIC value being chosen as the most appropriate one.

Following the Lai and Koopman (1999) technology, the model used has four knots for the time spline and three knots for the size spline to take into account the maximum trade sizes observed in both the order book and the dealership systems.

In this state space model, the volume effect v_t is modelled through $\Pi_t \gamma_x$ while the regression effect $X_{t,i}\gamma_x$ is used to model the spread. The state vector is the scalar m_t and it is modelled as a nonstationary process with the initial state requiring a diffuse prior condition, that is

$$\alpha_1 \sim N\{0, \kappa\} \tag{49}$$

where κ is assumed to have a value of 10^6.

The Kalman filter uses the past vector observations of $p_{1,\ldots}p_t$ to evaluate the minimum mean squared linear estimator of the state vector $\alpha_{t+1}$with $\alpha_{t+1} = E(\alpha_{t+1} \mid p_{1,\ldots}p_t)$ and variance matrix by $Y_{t+1} = var(\alpha_{t+1} \mid p_{1,\ldots}p_t)$. In this way, the Kalman filter runs to evaluate one-step and multi-step predictions of the state vector. It will also obtain one-step ahead prediction errors together with their variances.

Lai and Koopman (1999) use the following technology, which is also applied in this work. Define $a_{t,1} = E(\alpha_{t+1} \mid P_{t-1})$ and $a_{t,i} = E(\alpha_{t+1} \mid P_{t-1}, p_{t,1,\ldots}p_{t,i-1})$ with $Y_{t,1} = var(\alpha_{t+1} \mid P_{t-1})$ and $Y_{t,i} = var(\alpha_{t+1} \mid P_{t-1}, p_{t,1,\ldots}p_{t,i-1})$ for $i = 2, \ldots, N_t$, where $P_t = \{p_{1,1}, \ldots, p_{1,N_1}, p_{2,1}, \ldots, p_{t,N_t}\}$. The filtering equations are then given by

$$a_{t,i+1} = a_{t,i} + N_{t,i} Z_{t,i}^{-1} j_{t,i}$$

$$Y_{t,i+1} = Y_{t,i} - N_{t,i} Z_{t,i}^{-1} N_{t,i}'$$

where

$$j_{t,i} = p_{t,i} - K_{t,i} a_{t,i}$$

$$Z_{t,i} = K_{t,i} Y_{t,i} K_{t,i}^{-1} + \sigma_{t,i}^2$$

$$N_{t,i} = Y_{t,i}K'_{t,i}$$

for $i = 1, ..., y_t$ and $t = 1, ..., n$.

Minimum mean squared linear estimators using all observations P_n are evaluated by a smoothing algorithm which require output of the Kalman filter.

Following Harvey (1993), Koopman and Durbin (1998) and Koopman and Lai (1999), we know that some of the elements of these matrices and vectors may be unknown and these elements are collected in the vector ϖ and estimated by maximum likelihood

$$LogL(\varpi) = constant - \frac{1}{2}\sum_{t=t_o}^{n}\sum_{i=1}^{y_t}\log Z_{t,i} + \frac{j_{t,i}^2}{Z_{t,i}} \tag{50}$$

The disturbances in the model are normally distributed while the variance of η_t can be expressed as a ratio of the variance of ε_t which is referred to as the signal-to-noise ratio, given as

$$\psi = \sigma_\eta^2/\sigma_\varepsilon^2 \tag{51}$$

and ψ is estimated by numerically optimising the likelihood function.

5.4.3 Variance Ratios

Following the calculation of the true "system-wide" price, we proceed to measure the price volatility on DS and the order book system (SETS) around the fundamental price calculated from the state space model.

Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on DS and SETS respectively, we can calculate $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$.

The conventional variance ratio, given by $\sigma_\omega^2/\sigma_\xi^2$ is defined as:

$$\Lambda = \frac{Var[\ln(m_t) - \ln(p_t^{SETS})]}{Var[\ln(m_t) - \ln(p_t^{DS})]} \tag{52}$$

Ronen (1997) indicates a number of econometric problems that could severely impact the validity of these conventional variance ratios and which are of interest for this work. Mainly (a) over-lapping observations, (b) cross stock correlations, and (c) serial correlation and heteroscedasticity in the return series are likely to induce biases in variance ratios and a Generalised Method of Moments (GMM) technology has been found to deal effectively with these problems. This methodology has been used by Madhavan and Panchapagesan (2000) in another context.

Specifically, given N stocks, the $2N \times 1$ vector could be formed in the following way:

$$v(\Lambda) = \frac{1}{T}\sum_{t=1}^{T}\begin{bmatrix} \psi_{1,\xi}^2 - \Lambda_1\vartheta_{1,sy} \\ \vdots \\ \psi_{N,\xi}^2 - \Lambda_N\vartheta_{N,sy} \\ \Xi_{1,\omega}^2 - \vartheta_{1,sy} \\ \vdots \\ \Xi_{N,\omega}^2 - \vartheta_{N,sy} \end{bmatrix} \tag{53}$$

where $\psi_{1,\xi}$ is the DS system pricing error, $\Xi_{1,\omega}$ denotes the SETS system pricing error, $\vartheta_{1,sy}$ denotes the true variance of the "system-wide" price and Λ_1 is the variance ratio of the pricing errors $(\frac{\sigma_\xi^2}{\sigma_\omega^2})$ for stocks $i = 1, ..., N$.

We use the Lagrange Multiplier to test the null hypothesis of unity variance ratios for *individual securities* while we employ the Wald statistic $T(\hat{\Lambda} -1)'\sum_{\hat{\Lambda}}^{-1}(\hat{\Lambda} -1) \sim \chi^2(N)$ to test the null hypothesis that the variance ratios are *jointly* equal to unity.

The variance ratios are run for the whole trading period except for the opening 15 minutes and the closing 15 minutes. Empirical and theoretical research (Amihud and Mendelson, 1987, Stoll and Whaley, 1990) indicate that these trading periods are qualitatively different from the rest of the trading day and would merit a separate analysis which is beyond the scope of this Chapter. Hence, in order not to bias our results, we opted to remove the impact of the opening and closing periods.

5.4.4 Results From Variance Ratios

The results from the variance ratios technique are shown in Tables 46-51. The ratios for the most-heavily traded securities (top 20 securities by volume) are shown separately from those in respect of the least-traded securities (bottom 20 securities by volume).

When the 20 top and bottom securities by volume are considered as a group, we find that the price efficiency on the order book system around the true "system-wide" price is lower than that observed in the dealership market. This result is confirmed when the entire FTSE 100 securities are analysed. In addition, the result finds confirmation when (a) trading sub-periods, and (b) different trade sizes are considered.

All trades on both the order book and the dealership system, except the trades flagged as being part of a "Worked Principal Agreements", have been used for (a) the calculation of the "system-wide" price, and (b) the transaction prices used to calculate the variance ratios. As described in Appendix F, trades from the dealership system could be reported to the LSE within three minutes from their execution. In view of this, the time of trades from the dealership system were randomly changed by 20, 60, 90, 120, 150 and 180 seconds.

The main result emerging from the sample of the 40 securities considered is that price efficiency is higher on the dealership-based system, although there are individual securities for which this result does not hold. Only

Table 46: **Variance ratios for different trading periods for the top FTSE 10 securities (by volume) for all trades up to 2 NMS (See Appendix F)**

Security	Trading Period				
	9:15 - 10:00	10:01 - 11:01	13:00 - 14:00	14:01-15:00	15:15 -16:15
1	1.311*	1.345*	1.302*	1.298	1.358*
	(4.761)	(5.122)	(4.552)	(4.436)	(5.276)
2	1.296*	1.291*	1.219	1.315*	1.3014*
	(4.868)	(4.674)	(3.189)	(4.918)	(4.722)
3	1.474*	1.291*	1.315*	1.285*	1.308*
	(6.895)	(5.608)	(5.652)	(5.116)	(4.955)
4	1.002	1.021	0.963	0.958	1.025
	(1.959)	(2.148)	(1.822)	(1.741)	(1.832)
5	1.351*	1.327*	1.298*	1.351*	1.382*
	(5.108)	(4.613)	(4.687)	(5.201)	(5.571)
6	1.391*	1.318*	1.284*	1.116	1.351*
	(5.215)	(5.527)	(5.211)	(4.201)	(5.691)
7	0.942	0.963	1.003	1.024	1.046
	(1.827)	(1.858)	(1.976)	(1.981)	(2.151)
8	1.3282*	1.364*	1.023	1.371*	1.316*
	(5.225)	(5.351)	(2.248)	(5.721)	(5.162)
9	1.376*	1.339*	1.297*	1.496*	1.383*
	(5.277)	(6.131)	(4.877)	(6.551)	(5.139)
10	0.979	0.982	1.013	1.026	1.048
	(1.759)	(1.727)	(2.118)	(2.258)	(2.488)
Top 20	1.365*	1.345*	1.292*	1.396*	1.411*
	(5.61)	(4.84)	(4.18)	(5.91)	(6.18)

Following the calculation of the true "system-wide" price, volatility on SEAQ and SETS around the fundamental price. Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on SEAQ and SETS systems respectively, we have $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$ as the variance of the pricing errors on the two systems, where m_t is the true "system-wide" price and p_t^{DS} and p_t^{SETS} are given by:

$$p_t^{DS} = m_t + \xi_t \quad \xi_t\,\tilde{}\,N(0, \sigma_\xi^2)$$
$$p_t^{SETS} = m_t + \omega_t \quad \omega_t\,\tilde{}\,N(0, \sigma_\omega^2)$$

We employ a Generalised Method of Moment to estimate $\Lambda = \frac{Var[\ln(m_t) - \ln(p_t^{SETS})]}{Var[\ln(m_t) - \ln(p_t^{DS})]}$

The Lagrange Multiplier test (in parantheses) the null hypothesis of unity variance ratios for individual securities while we employ the Wald statistic (in brackets) to test the null hypothesis that the variance ratios are jointly equal to unity.

Table 47: **Variance ratios for different trading periods for the bottom FTSE 10 securities (by volume) for all trades up to 2 NMS (See Appendix F)**

Security	TRADING PERIOD				
	9:15 - 10:00	10:01 - 11:01	13:00 - 14:00	14:01-15:00	15:15 -16:15
11	*1.492**	*1.458**	*1.297**	*1.498**	*1.475**
	(4.481)	(4.706)	(4.044)	(5.465)	(5.173)
12	*1.4415**	1.215	1.024	*1.311**	*1.358**
	(4.786)	(2.812)	(2.495)	(5.634)	(5.941)
13	*1.458**	*1.348**	*1.297**	*1.505**	*1.486**
	(5.631)	(5.831)	(4.658)	(6.957)	(4.993)
14	1.012	*1.422**	*1.375**	*1.571**	*1.475**
	(2.154)	(5.996)	(5.531)	(4.841)	(4.771)
15	*1.395**	*1.485**	*1.316**	*1.428**	*1.291**
	(4.131)	(4.115)	(5.312)	(4.767)	(5.207)
16	*1.505**	*1.524**	*1.412**	*1.458**	*1.368**
	(5.224)	(5.275)	(4.496)	(4.299)	(5.203)
17	*1.533**	*1.569**	*1.405**	*1.512**	*1.598**
	(4.526)	(4.978)	(4.124)	(5.170)	(5.610)
18	*1.548**	*1.509**	*1.412**	*1.514**	*1.478**
	(5.142)	(4.102)	(5.775)	(3.959)	(4.904)
19	1.0119	1.023	1.011	1.1674	1.126
	(2.157)	(2.173)	(1.998)	(2.183)	(1.967)
20	*1.486**	*1.391**	*1.363**	*1.414**	*1.514**
	(5.117)	(4.567)	(4.761)	(2.245)	(5.732)
Bottom 20	*1.425**	*1.392**	*1.326**	*1.406**	*1.469**
	(6.01)	(5.66)	(4.95)	(5.76)	(5.81)

Following the calculation of the true "system-wide" price, volatility on SEAQ and SETS around the fundamental price. Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on SEAQ and SETS systems respectively, we have $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$ as the variance of the pricing errors on the two systems, where m_t is the true "system-wide" price and p_t^{DS} and p_t^{SETS} are given by:

$$p_t^{DS} = m_t + \xi_t \quad \xi_t \tilde{} N(0, \sigma_\xi^2)$$
$$p_t^{SETS} = m_t + \omega_t \quad \omega_t \tilde{} N(0, \sigma_\omega^2)$$

We employ a Generalised Method of Moment to estimate $\Lambda = \frac{Var[\ln(m_t) - \ln(p_t^{SETS})]}{Var[\ln(m_t) - \ln(p_t^{DS})]}$

The Lagrange Multiplier test (in parantheses) the null hypothesis of unity variance ratios for individual securities while we employ the Wald statistic (in brackets) to test the null hypothesis that the variance ratios are jointly equal to unity.

Table 48: **Variance ratios for different trading periods for the top 10 securities (by volume) for "Customer" trades up to 2 NMS (See Appendix F)**

Security	Trading Period				
	9:15 - 10:00	10:01 - 11:01	13:00 - 14:00	14:01-15:00	15:15 -16:15
1	*1.342**	*1.362**	*1.298**	*1.311**	*1.414**
	(4.741)	(4.822)	(4.572)	(4.619)	(4.916)
2	*1.342**	*1.348**	1.272	*1.327**	*1.366**
	(4.862)	(4.913)	(3.891)	(4.715)	(4.954)
3	*1.495**	*1.379**	*1.341**	*1.325**	*1.414**
	(6.343)	(5.972)	(5.419)	(4.948)	(5.277)
4	1.162	1.178	1.102	1.108	1.168
	(2.086)	(2.287)	(1.940)	(1.854)	(1.951)
5	*1.371**	*1.365**	*1.312**	*1.328**	*1.412**
	(5.446)	(5.029)	(4.618)	(5.392)	(5.468)
6	*1.499**	*1.358**	*1.325**	*1.284**	*1.466**
	(5.553)	(4.608)	(4.149)	(3.474)	(5.461)
7	*1.383**	1.107	1.163	1.296	*1.419**
	(4.145)	(1.978)	(2.104)	(2.109)	(4.491)
8	*1.574**	*1.476**	*1.294**	*1.486**	*1.465**
	(5.625)	(4.698)	(2.394)	(5.092)	(4.641)
9	*1.582**	*1.549**	*1.391**	*1.418**	*1.446**
	(5.621)	(5.529)	(4.694)	(4.976)	(5.173)
10	*1.326*	1.156	1.098	1.289	1.315
	(4.173)	(1.831)	(2.256)	(2.404)	(3.649)
Top 20	*1.519**	*1.462**	*1.385**	*1.416**	*1.482**
	(6.174)	(5.154)	(4.451)	(4.982)	(5.281)

Following the calculation of the true "system-wide" price, volatility on SEAQ and SETS around the fundamental price. Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on SEAQ and SETS systems respectively, we have $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$ as the variance of the pricing errors on the two systems, where m_t is the true "system-wide" price and p_t^{DS} and p_t^{SETS} are given by:

$$\begin{aligned} p_t^{DS} &= m_t + \xi_t \quad && \xi_t \tilde{} N(0, \sigma_\xi^2) \\ p_t^{SETS} &= m_t + \omega_t \quad && \omega_t \tilde{} N(0, \sigma_\omega^2) \end{aligned}$$

We employ a Generalised Method of Moment to estimate $\Lambda = \frac{Var[\ln(m_t)-\ln(p_t^{SETS})]}{Var[\ln(m_t)-\ln(p_t^{DS})]}$

The Lagrange Multiplier test (in parantheses) the null hypothesis of unity variance ratios for individual securities while we employ the Wald statistic (in brackets) to test the null hypothesis that the variance ratios are jointly equal to unity.

Table 49: **Variance ratios for different trading periods for the bottom 10 securities (by volume) for "Customer" trades up to 2 NMS (See Appendix F)**

Security	TRADING PERIOD				
	9:15 - 10:00	10:01 - 11:01	13:00 - 14:00	14:01-15:00	15:15 -16:15
11	*1.615**	*1.564**	*1.416**	*1.452**	*1.489**
	(5.431)	(5.013)	(4.359)	(4.891)	(4.976)
12	*1.448**	*1.371**	1.329	*1.416**	*1.461**
	(5.159)	(3.031)	(3.689)	(4.983)	(5.404)
13	*1.564**	*1.483**	*1.396**	*1.415**	*1.464**
	(6.570)	(5.685)	(5.021)	(5.391)	(5.581)
14	1.264	*1.326*	1.266	*1.398**	*1.384**
	(2.322)	(4.161)	(2.962)	(4.518)	(4.424)
15	*1.387**	*1.396**	*1.312**	*1.367**	*1.382**
	(4.453)	(4.436)	(4.136)	(4.338)	(4.613)
16	*1.421**	*1.414**	*1.308**	*1.364**	*1.395**
	(5.831)	(5.687)	(4.246)	(4.634)	(5.208)
17	*1.584**	*1.519**	*1.464**	*1.529**	*1.613**
	(5.679)	(5.366)	(4.445)	(5.173)	(6.047)
18	*1.613**	*1.595**	*1.518**	*1.591**	*1.608**
	(5.923)	(5.221)	(5.125)	(5.267)	(5.986)
19	*1.424**	*1.386**	1.223	*1.412**	*1.362**
	(4.412)	(4.342)	(2.154)	(4.353)	(4.121)
20	*1.518**	*1.503**	*1.419**	*1.461**	*1.491**
	(6.179)	(4.923)	(5.132)	(4.421)	(5.516)
Bottom 20	*1.541**	*1.524**	*1.454**	*1.482**	*1.516**
	(6.478)	(6.105)	(5.336)	(5.909)	(6.063)

Following the calculation of the true "system-wide" price, volatility on SEAQ and SETS around the fundamental price. Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on SEAQ and SETS systems respectively, we have $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$ as the variance of the pricing errors on the two systems, where m_t is the true "system-wide" price and p_t^{DS} and p_t^{SETS} are given by:

$$\begin{array}{ll} p_t^{DS} = m_t + \xi_t & \xi_t\tilde{\ }N(0,\sigma_\xi^2) \\ p_t^{SETS} = m_t + \omega_t & \omega_t\tilde{\ }N(0,\sigma_\omega^2) \end{array}$$

We employ a Generalised Method of Moment to estimate $\Lambda = \frac{Var[\ln(m_t)-\ln(p_t^{SETS})]}{Var[\ln(m_t)-\ln(p_t^{DS})]}$

The Lagrange Multiplier test (in parantheses) the null hypothesis of unity variance ratios for individual securities while we employ the Wald statistic (in brackets) to test the null hypothesis that the variance ratios are jointly equal to unity.

Table 50: **Variance ratios for different trade size groups for the top 10 securities (by volume) using "Customer" trades up to 2 NMS (See Appendix F)**

Security	TRADE SIZE			
	< 0.25 NMS	0.25 NMS - 0.5 NMS	0.50 NMS - 1 NMS	1 NMS - 2 NMS
1	0.961	*1.387**	*1.392**	*1.411**
	(2.259)	(4.827)	(5.262)	(5.816)
2	0.978	*1.361**	*1.374**	*1.392**
	(2.908)	(4.718)	(4.861)	(5.137)
3	0.989	*1.478**	*1.486**	*1.413**
	(2.061)	(5.742)	(5.787)	(5.238)
4	0.885	1.251	1.185	1.165
	(2.016)	(2.199)	(1.865)	(1.783)
5	0.978	*1.354**	*1.361**	*1.425**
	(2.526)	(4.916)	(4.988)	(5.214)
6	0.984	*1.426**	*1.448**	*1.489**
	(2.341)	(4.431)	(5.136)	(4.301)
7	0.964	1.061	1.084	1.122
	(2.871)	(1.903)	(2.024)	(2.028)
8	0.982	*1.417**	*1.366**	*1.497**
	(2.736)	(4.479)	(4.102)	(5.458)
9	1.018	*1.344**	*1.466**	*1.547**
	(2.403)	(3.278)	(4.994)	(5.708)
10	0.965	1.074	1.271	1.247
	(2.802)	(1.768)	(2.168)	(2.312)
Top 20	1.016	*1.368**	*1.412**	*1.518**
	(2.744)	(4.956)	(4.281)	(5.051)

Following the calculation of the true "system-wide" price, volatility on SEAQ and SETS around the fundamental price. Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on SEAQ and SETS systems respectively, we have $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$ as the variance of the pricing errors on the two systems, where m_t is the true "system-wide" price and p_t^{DS} and p_t^{SETS} are given by:

$$p_t^{DS} = m_t + \xi_t \quad \xi_t\tilde{}N(0,\sigma_\xi^2)$$
$$p_t^{SETS} = m_t + \omega_t \quad \omega_t\tilde{}N(0,\sigma_\omega^2)$$

We employ a Generalised Method of Moment to estimate $\Lambda = \frac{Var[\ln(m_t)-\ln(p_t^{SETS})]}{Var[\ln(m_t)-\ln(p_t^{DS})]}$

The Lagrange Multiplier test (in parantheses) the null hypothesis of unity variance ratios for individual securities while we employ the Wald statistic (in brackets) to test the null hypothesis that the variance ratios are jointly equal to unity.

Table 51: **Variance ratios for different trade size groups for the bottom 10 securities (by volume) using "Customer" trades up to 2 NMS (See Appendix F)**

Security	TRADE SIZE			
	< 0.25 NMS	0.25 NMS - 0.5 NMS	0.50 NMS - 1 NMS	1 NMS - 2 NMS
11	1.106	*1.405**	*1.467**	*1.597**
	(2.581)	(4.829)	(4.141)	(5.596)
12	0.997	1.142	1.225	*1.434**
	(2.901)	(2.879)	(2.554)	(4.778)
13	1.052	*1.348**	*1.471**	*1.607**
	(2.761)	(4.971)	(4.769)	(6.124)
14	0.982	*1.426**	*1.546**	*1.637**
	(2.205)	(5.139)	(5.661)	(4.957)
15	1.021	*1.448**	*1.441**	*1.461**
	(2.231)	(4.237)	(5.448)	(4.881)
16	1.081	*1.497**	*1.506**	*1.518**
	(2.349)	(4.402)	(4.604)	(4.701)
17	1.163	*1.517**	*1.531**	*1.672**
	(2.634)	(4.197)	(4.221)	(5.294)
18	1.146	*1.489**	*1.536**	*1.608**
	(2.246)	(4.201)	(4.914)	(5.051)
19	0.961	1.057	1.243	1.311
	(2.208)	(2.225)	(2.445)	(3.235)
20	1.068	*1.405**	*1.467**	*1.574**
	(2.181)	(4.476)	(4.875)	(5.129)
Bottom 20	1.068	*1.386**	*1.446**	*1.545**
	(2.154)	(4.795)	(5.068)	(5.989)

Following the calculation of the true "system-wide" price, volatility on SEAQ and SETS around the fundamental price. Denoting σ_ξ^2 and σ_ω^2 as the variance of the price discovery process on SEAQ and SETS systems respectively, we have $Var[\ln(m_t) - \ln(p_t^{DS})]$ and $Var[\ln(m_t) - \ln(p_t^{SETS})]$ as the variance of the pricing errors on the two systems, where m_t is the true "system-wide" price and p_t^{DS} and p_t^{SETS} are given by:

$$p_t^{DS} = m_t + \xi_t \qquad \xi_t\,\tilde{}\,N(0,\sigma_\xi^2)$$
$$p_t^{SETS} = m_t + \omega_t \qquad \omega_t\,\tilde{}\,N(0,\sigma_\omega^2)$$

We employ a Generalised Method of Moment to estimate $\Lambda = \frac{Var[\ln(m_t)-\ln(p_t^{SETS})]}{Var[\ln(m_t)-\ln(p_t^{DS})]}$

The Lagrange Multiplier test (in parantheses) the null hypothesis of unity variance ratios for individual securities while we employ the Wald statistic (in brackets) to test the null hypothesis that the variance ratios are jointly equal to unity.

one security (Schroders) from the group of the lowest-traded segment shows that price volatility on the order book system is not statistically significantly higher than the dealership system. However, when the top 10 securities by volume are considered, we find that the order book trading for three securities (BP Amoco, Lloyds TSB Bank and Unilever) does not cause higher volatilities when compared to trading via the dealership mode. It should be noted that these results do not change when the variance ratios are run using the sample of dealership trades with time stamps randomly changed as explained above.

The number of securities for which price volatility is not statistically significantly higher on the order book decreases with the trading activity (by volume). For securities with high volume transacted (for example, the securities listed in the top 20 by volume), it is expected that the order book is "thicker" compared to less traded securities and hence market and limit orders can be executed at reasonable prices. For the less traded securities, the risk of a "thin" book increases and orders can produce substantial impacts. In terms of price stabilisation, market making appears to be more useful for the latter group than the former.

These results provide evidence that dealers are indeed providing the necessary liquidity that can stabilise prices during the trading process. The provision of liquidity through limit order traders, who submit orders to the book, does not seem to be achieving the same outcome in terms of price stabilisation.

These results acquire more importance when considering that the dealership system is, in fact, attracting a higher number of trades and a bigger volume for execution. Existing literature has shown that volatility is positively related to number of trades executed and volume transacted. Given that the dealership system attracts the biggest number of orders and volume, it was expected that higher volatility would result on such system.

In the case considered here, however, the dealership system appears to be more robust in that it can transact higher volumes with lower price volatility than the order book and this evidence shows that dealers do indeed provide a useful service in terms of the stabilisation of short-period price fluctuations.

Having said this, our results do not indicate whether dealers are providing the socially optimum amount of price stabilisation. Arguably, competitive dealers, as is the case on the LSE, will not provide the socially optimal level of price stabilisation - price stability is an externality and as such dealers can free ride on each other's efforts with each market maker taking into consideration only her own private benefits.

Robustness Check The validity of the results obtained in this Section depends on the ability of the Kalman filtering methodology in finding the correct estimates of the security's implicit efficient price. The Kalman methodology has been presented in this Chapter as a possible improvement over the Hasbrouck (1995) model given that part of the data (the trades data on the DS) suffers from lack of sequentiality and this is likely to impact the estimates of the efficient price. One way to compare the methodology proposed in this Chapter and the Hasbrouck (1995) model is an analysis of the residuals of the two price series - the one on the order book and the other on the dealership system - with respect to the estimates of the common factor.

Tables 52-55 reproduce descriptive statistics for the residuals calculated through the two models. In general, the mean of the absolute value of the residuals together with the variance of the residuals is smaller when the common factor is calculated by the Kalman filtering technology than when the Hasbrouck (1995) methodology is used. Thus we can conclude that, at least for the data sample used in this work, the residuals obtained from the former model behaves better than those generated by the Hasbrouck (1995) model.

5.5 Trading Behaviour in a Hybrid Market

After investigating price volatility on the two trading systems, the next question that needs to be addressed is how the order flow behaves at times of price uncertainty - will higher levels of volatility induce a higher number of limit order traders to come in the book or will the order flow migrate to the dealers?

To a large extent, the choice between the trading systems is not an exogenous factor for our underlying analysis of price volatility. These behavioural patterns could well be relevant in terms of inducing a certain level and pattern of price volatility mainly because a trader has a choice of either going on the auction system or the dealership system.

The final choice between the two systems depends on the terms of trade offered at that particular point in time. Hence, it is assumed that liquidity, transaction costs, immediacy and market resilience are all important aspects that influence the trader's decision of where to trade. Hence, the attractiveness of each market architecture for the different traders must be ascertained to get evidence about the types of trades being transacted in the two systems.

5.5.1 Choosing the Trading Venue

As in Easley and O'Hara (1987) and Madhavan and Cheng (1997) we assume that the price impact of a trade in an auction market is increasing in the trade size. The trading costs on SETS are captured as

Table 52: **Mean residuals on DS using the Hasbrouck (1995) and Kalman filtering methodologies**

	Mean of $\|\varepsilon_{t,i}\|$	Variance	Skewness	Kurtosis
ASTRAZENECA				
(1)	0.5573	0.5309	-0.1979	5.8131
(2)	0.4916	0.4288	0.0868	3.9779
BARCLAYS BANK				
(1)	0.5951	0.5874	-0.2077	6.1037
(2)	0.5535	0.5166	-0.0924	4.2364
BRITISH TELECOM				
(1)	0.5350	0.4096	0.1899	6.1805
(2)	0.4719	0.4116	-0.1833	4.2887
BP AMOCO				
(1)	0.6018	0.5733	-0.2137	6.2781
(2)	0.5269	0.4596	0.0930	4.2643
HSBC BANK				
(1)	0.5637	0.5175	0.1972	5.7758
(2)	0.5080	0.4643	-0.0879	4.0297
GLAXO WELLCOME				
(1)	0.5748	0.4657	-0.2108	6.1944
(2)	0.5109	0.4931	0.0937	4.296
LLOYDS TSB				
(1)	0.6241	0.6198	-0.2273	6.6776
(2)	0.5887	0.7447	-0.1021	4.6827
RENTOKIL INITIAL				
(1)	0.6608	0.6795	-0.2346	5.8934
(2)	0.5928	0.6271	0.1046	5.7974
SHELL TRANSPORT				
(1)	0.6620	0.6307	-0.2351	6.9059
(2)	0.6034	0.5263	0.1065	4.8826
UNILEVER				
(1)	0.7812	0.7142	-0.2774	8.1490
(2)	0.7301	0.6368	-0.0289	5.9079

The Table reports summary statistics for the residuals of the price series on the dealership system with respect to the security's efficient price. Two different methodologies have been used: (a) the Hasbrouck (1995) model denoted by (1) in the Table, and (b) the Kalman filtering model denoted by (2).

Table 53: **Mean residuals on SETS using the Hasbrouck (1995) and Kalman filtering methodologies**

	Mean of $\lvert\varepsilon_{t,i}\rvert$	Variance	Skewness	Kurtosis
ASTRAZENECA				
(1)	0.5128	0.4098	0.1892	5.2641
(2)	0.4822	0.4425	-0.1962	5.6828
BARCLAYS BANK				
(1)	0.5384	0.5152	0.1986	5.5272
(2)	0.5135	0.4712	0.3154	4.4538
BRITISH TELECOM				
(1)	0.4922	0.4894	0.1816	4.0534
(2)	0.4629	0.4248	0.2843	4.6147
BP AMOCO				
(1)	0.5538	0.4505	-0.2043	5.6851
(2)	0.5169	0.4143	0.3175	5.4831
HSBC BANK				
(1)	0.5295	0.5165	0.1879	3.2303
(2)	0.4984	0.4682	-0.3024	2.2365
GLAXO WELLCOME				
(1)	0.5364	0.5432	0.2016	4.6093
(2)	0.5207	0.5279	0.3198	5.5165
LLOYDS TSB				
(1)	0.6290	0.5856	0.2173	5.0468
(2)	0.6076	0.5509	0.2486	5.9230
RENTOKIL INITIAL				
(1)	0.6080	0.6045	-0.1243	6.2422
(2)	0.5815	0.6136	0.3572	5.0434
SHELL TRANSPORT				
(1)	0.6192	0.6156	0.2247	6.2536
(2)	0.5918	0.5831	-0.0635	5.1331
UNILEVER				
(1)	0.7088	0.7246	0.2652	7.3792
(2)	0.7161	0.6472	0.0499	6.2111

The Table reports summary statistics for the residuals of the price series on the order book system with respect to the security's efficient price. Two different methodologies have been used: (a) the Hasbrouck (1995) model denoted by (1) in the Table, and (b) the Kalman filtering model denoted by (2).

Table 54: **Mean residuals on DS using the Hasbrouck (1995) and Kalman filtering methodologies**

	Mean of $|\varepsilon_{t,i}|$	Variance	Skewness	Kurtosis
ABF				
(1)	0.6174	0.5686	-0.2157	6.3362
(2)	0.5558	0.4873	0.0946	4.3359
ALLIANCE & LEICESTER				
(1)	0.6478	0.6176	-0.2264	6.6530
(2)	0.5906	0.5277	0.1007	4.6177
HAYS				
(1)	0.5715	0.5851	-0.2070	6.0828
(2)	0.5144	0.4486	0.0908	4.1624
KINGFISHER				
(1)	0.6560	0.6249	-0.2329	6.8431
(2)	0.5744	0.5010	0.1014	4.6480
LAND SECURITIES				
(1)	0.6035	0.5749	-0.2143	6.2957
(2)	0.5428	0.4734	0.0958	4.3924
MISYS				
(1)	0.6473	0.6166	-0.2298	6.7519
(2)	0.5787	0.5047	0.1021	4.6821
RECKITT & COLEMAN				
(1)	0.6977	0.6647	-0.2477	7.2785
(2)	0.6307	0.5502	0.1113	5.1042
RMC				
(1)	0.7203	0.6862	-0.2557	7.5138
(2)	0.6462	0.5636	0.1141	5.2291
SCHRODERS				
(1)	0.7216	0.6874	-0.2562	7.5274
(2)	0.6577	0.5736	0.1161	5.3220
SEVERN TRENT				
(1)	0.8515	0.8112	-0.3023	8.8824
(2)	0.7958	0.6941	0.1405	6.4397

The Table reports summary statistics for the residuals of the price series on the dealership system with respect to the security's efficient price. Two different methodologies have been used: (a) the Hasbrouck (1995) model denoted by (1) in the Table, and (b) the Kalman filtering model denoted by (2).

Table 55: **Mean residuals on DS using the Hasbrouck (1995) and Kalman filtering methodologies**

	Mean of $\lvert\varepsilon_{t,i}\rvert$	Variance	Skewness	Kurtosis
ABF				
(1)	0.5512	0.5480	0.2033	5.6588
(2)	0.5183	0.4756	0.3184	4.4956
ALLIANCE & LEICESTER				
(1)	0.5788	0.5754	0.2136	5.9417
(2)	0.5521	0.5066	0.3391	4.7879
HAYS				
(1)	0.5292	0.5261	0.1953	5.4324
(2)	0.4976	0.4567	0.3057	4.3158
KINGFISHER				
(1)	0.5954	0.5919	0.2197	6.1115
(2)	0.5557	0.5099	0.3413	4.8193
LAND SECURITIES				
(1)	0.5477	0.5445	0.2021	5.6226
(2)	0.5251	0.4819	0.3226	4.5543
MISYS				
(1)	0.5874	0.5840	0.2167	6.0300
(2)	0.5598	0.5137	0.3439	4.8553
RECKITT & COLEMAN				
(1)	0.6332	0.6295	0.2336	6.5004
(2)	0.6102	0.5600	0.3748	5.2923
RMC				
(1)	0.6537	0.6499	0.2412	6.7104
(2)	0.6251	0.5737	0.3840	5.4218
SCHRODERS				
(1)	0.6549	0.6511	0.2416	6.7227
(2)	0.6363	0.5839	0.3908	5.5181
SEVERN TRENT				
(1)	0.7728	0.7683	0.2851	7.9327
(2)	0.7699	0.7065	0.4729	6.6770

The Table reports summary statistics for the residuals of the price series on the dealership system with respect to the security's efficient price. Two different methodologies have been used: (a) the Hasbrouck (1995) model denoted by (1) in the Table, and (b) the Kalman filtering model denoted by (2).

$$\eta_i^{SETS} = \alpha^{SETS} X_i + \epsilon_i^{SETS} \tag{54}$$

where the price impact is given by η_i^{SETS}, X_i is a vector of variables while ϵ_i^{SETS} is the disturbance term.

On the other hand, the price impact on the dealership system will, especially for larger trades, reflect the negotiation process that is expected to take place between the trader and the dealer. In such a process the trader's reputational capital (built through repeated business with the same dealer) will be one major factor in the determination of the price.

In essence, if the trader, in the course of the negotiation, credibly signal that he is liquidity motivated, then he is expected to obtain a better deal from the dealer. This argument is similar to the Seppi (1990) model in which the price impact of a trade decreases with the probability that the trade is liquidity motivated. A similar argument can made based on the business relationships that are built in a dealership market between dealers and traders. These relationships are likely to act as a screening device used by dealers to disentangle liquidity-motivated from information-motivated traders.

For the dealership system, we capture these ideas by the following relationship

$$\eta_i^{DS} = \alpha^{DS} X_i - \Upsilon_i + \epsilon_i^{DS} \tag{55}$$

where Υ_i captures the dealers's information about the trader's identity and trading strategy.

The major econometric problem in analysing the choice of trading venue is given by the fact that while trader i knows his own reputational capital, Υ_i, this variable is not known by the econometrician. Given this lack of knowledge, 55above is reduced to

$$\eta_i^{DS} = \alpha^{DS} X_i + \Psi_i^{DS} \tag{56}$$

where Ψ_i^{DS} is given by $-\Upsilon_i + \epsilon_i^{DS}$.

Having stated the different price impacts generated by a trade on the two systems, we need to analyse the trading location decision made by the trader. Surely, the trader will trade on the system that provides the best execution given the size of the trade he wants to trade.

Denoting the information set available to trader i as Φ_i and Γ_i as the cost differential between trading on SETS and DS, given as

$$\Gamma_i = E\left[\eta_i^{SETS} - \eta_i^{DS} \mid \Phi_i\right] \tag{57}$$

and substituting equations 54 and 55 into 57 we can write the cost differential between the two systems as

$$\Gamma_i = \left[\alpha^{SETS} - \alpha^{DS}\right] X_i + \Upsilon_i \tag{58}$$

Equation 58 is the criterion function used by trader i to decide where to trade. It can be written as

$$\Gamma_i = \beta Z_i + \Upsilon_i \tag{59}$$

where $Z_i = (X_i)$ and β is a vector of coefficients.

Hence, if the price impact of a trade pushed through the auction system is higher than the respective price impact generated by a trade on the dealership system, then the trader would opt to trade on DS rather than SETS. Hence, if we denote the choice of trading venue as $\Gamma_i^{\bullet}$ we can obtain the trader's decision rule as

$$\Gamma_i^{\bullet} = \begin{cases} 1 & if\ \Gamma_i > 0 \\ 0 & if\ \Gamma_i \leq 0 \end{cases}$$

To analyse the trading behaviour on the two systems we need to specify the variables the trader uses in choosing between the two systems. These are captured by the criterion function in equation 60.

In this Chapter, the criterion function is measured as follows

$$\Gamma_{zit} = \beta_0 + \beta_1 q_{zit} + \beta_2 l_{zit-1} + \beta_3 s_{zit-1} + \beta_4 b_{zit-1} + \beta_5 \sigma^2_{zit-1} \tag{60}$$

where, for every security z, q_i is the trade size in terms of NMS multiples, l_i is the imbalance in the order book on SETS immediately before a trade takes place, s_i is the "best" spread on the order book immediately before each trade, b_i is the breadth of the order book before each trade and σ^2_{it-1} refers to the volatility calculated as the variance of the mid quotes formed on SETS in the interval before a trade is executed.

The imbalance measure on the order book in SETS, l_i, is calculated every 1 minute in the following way

$$\frac{\sum_{i=1}^{N_b} V_i^b - \sum_{j=1}^{N_s} V_j^s}{\sum_{i=1}^{N_b} V_i^b + \sum_{j=1}^{N_s} V_j^s} \tag{61}$$

where V_i^b and V_j^s are the Black-Scholes option values of the buy limit orders and the sell limit orders respectively, entered into the order book before the trade is executed. This statistic measures the level of asymmetry in the order book.

The order imbalance is measured through a revised technology employed by Harris and Panchapagesan (1999). The underlying idea for such a measure, and the reason why the Black-Scholes formula is used in such a case, is given by the intuition that a limit buy order entered into SETS provides the market with a free put option while a limit sell order constitutes a free call option.

In measuring the imbalance, we only take into account limit orders that are placed on the book within 10 ticks away from the best prices available on the book. All "execute and eliminate", "fill or kill" and "at best" trades are removed from the system.

One central problem in the calculation of the order book asymmetry is attaching a time to maturity to each limit order. A limit order placed on the book could follow different execution paths and this is expected to complicate matters.[14]

Also, the time to maturity is influenced by the trading strategy followed by the trader: a limit order priced far away from the best prices is likely to remain on the book much more than a limit order which is aggressively priced. Jarnecic and McInish (1997) use random maturities (for example, 5 minutes and 30 minutes) and disregard the type and size of the order placed. Lo, Mackinlay and Zhang (1997) employ a survival technology to estimate the time to expiration for each limit order.

In this Chapter, we follow a revised version of the linear approach used by Harris and Panchapagesan (1999) to calculate the expected time to removal (time to maturity) of the limit order in the following way:

$$MT_{iz} = \alpha_i + \beta_1 * \text{System Time}_z + \beta_2 * \text{Order Size}_z + \beta_3 * \text{Queue Length}_z$$

$$+\beta_4 * \text{Time to Close}_z + \beta_5 * \text{Order Arrival Rate}_z + \beta_6 * \text{Price Position}_z \quad (62)$$

where the subscript z defines the security z.

System time is the time (in minutes) already spent by the limit order in the SETS's order book. Order Size is in NMS multiples and the Queue

[14] The order could (a) be entirely filled and removed from the system; (b) partially filled and the unfilled part remains in the system; (c) cancelled by the trader who submitted it; or (d) its position changed by the system as other, more aggressively priced, limit orders are introduced.

Length refers to the size, always in NMS multiples, of other limit orders preceding the particular limit order. Price Position is the position of the limit order with respect to the market and the Order Arrival Rate captures the relative market order flow in the 30 minutes preceding the sampling time. Time to Close is the length of time until the end of the trading day.

For the calculation of the Black-Scholes valuation, we take the risk-free rate as the annualised rate of the 3-month government bonds; the strike price is the limit price of the order; and the annual volatility is computed by multiplying the daily return volatility in the day preceding the order's submission.

The spread, s, on the order book is calculated in the usual way -

$$s_{it} = \frac{pa_{it} - pb_{it}}{[pa_{it} + pb_{it}]/2} \tag{63}$$

where pa_{it} and pb_{it} are the best ask and bid prices at time t respectively. On the other hand, the breadth of the order book, b_i, is calculated as

$$b_i^{Ask} = pa_i * Qa_i \tag{64}$$

$$b_i^{Bid} = pb_i * Qb_i \tag{65}$$

where Qa_i is the quantity of shares being asked at the best ask and Qb_i is the quantity of shares offered at the best bid.

The methodology followed is as follows. All orders submitted to the SETS system are employed taking the time when such orders have been placed in the order book. On the other hand, all trades on the dealership system, except those flagged as being "Worked Principal Agreements" are utilised, again using the time of their execution for this analysis. The asymmetry in the order book, best spread, market breadth and volatility are calculated over the ten minutes preceding (a) the order submission to the order book, or (b) the trade's execution on the dealership system. Finally, in view of the possible problems in time stamps for the dealership system, trades' times were randomly changed by 20, 60, 90, 120, 150 and 180 seconds.

The coefficient estimates obtained from the probit model are shown in Table 56. The trade size coefficient estimate is significant at the 1% level using the Wald chi-square test and is positive, providing a confirmation that as the trade size gets larger, trades are channelled to the dealership system rather than facing the limit order book on the auction system. Coupled with this, we have the important result that the probability of a trade being directed to the dealership system increases as the volatility in the trading system increases.

These two results, when analysed together, provide a very important message related to the concept of immediacy in the market. Immediacy refers not only to the ability to trade promptly, but also to the ability to trade at prices that are reasonable under current market conditions. This leads us to another important concept, that is the supply of liquidity in depth, which is the ability of traders to execute their orders quickly, possibly also in large sizes. These characteristics are important for large traders and during adverse market conditions, such as the case when price volatility increases.

On the other hand, we find that the tighter the spread on the book the more likely it is for traders to direct their orders to the order book for execution there. This evidence is consistent with similar results obtained so far in the literature.

More importantly, we find that the (signed) imbalance of the order book is informative and it appears to be influencing the trader's decision as to where to transmit the order. This is contrary to most theoretical models that suggest that limit order imbalances are uninformative. In this case, we find that the asymmetries in the limit order book have some predictive power as to where the trader will direct his order.

These asymmetries may well reflect market sentiment or the presence of informed traders. The results show that traders appear to be trading in front of the heavy side of the market. An example of such traders are the quote matchers discussed in Amihud and Mendelson (1990) and Harris (1990). The results here are very much in the same spirit of Harris and Panchapagesan (1999) but they analyse whether order book asymmetries can indicate the likely direction of future price changes.

5.5.2 Order Book Depth and Volatility

Biais, Hillion and Spatt (1995) empirically analyse the order flow dynamics on the Paris Bourse and find (a) different ways in which liquidity is supplied and consumed by traders, and (b) how the two sides of the market interact. For example, in such a pure limit order book environment, the conditional probability that traders submit limit orders, instead of market orders, is larger when (i) the spread is wide, or (ii) the order book is not very deep. On the other hand, liquidity is consumed through traders who tend to hit the prevailing quote when the spread is very narrow. From this evidence, Biais (1995) conclude that traders provide liquidity at times of liquidity shortages (when such an exercise is really valuable) and consume liquidity at times when liquidity is in surplus. Furthermore, at times of liquidity deficits traders on the Paris Bourse adopt a very aggressive behaviour in submitting limit orders, partly to obtain time priority in such adverse market conditions.

It is of interest the way market orders interact with limit orders in such a centralised market. Generally speaking, these orders manage to obtain liquidity at relatively low cost. The main results stemming from the analysis

Table 56: **Estimates of the probit model**

PANEL A: BUY TRADES

Coefficient	Estimate	χ^2	P value	Log likelihood
				-5662.25
β_1	0.71 (0.076)	16.55	0.001	
β_2	-0.32 (0.055)	5.56	0.005	
β_3	-0.15 (0.032)	3.01	0.032	
β_4	0.12 (0.074)	1.81	0.219	
β_5	0.39 (0.027)	9.22	0.001	
				$R^2 = 14.68$
PANEL A: SELL TRADES				
				-5981.22
β_1	0.79 (0.058)	15.82	0.001	
β_2	-0.30 (0.061)	5.82	0.001	
β_3	-0.24 (0.044)	4.91	0.005	
β_4	-0.14 (0.091)	1.52	0.294	
β_5	0.34 (0.024)	7.85	0.001	
				$R^2 = 15.86$

The Table reports the coefficient estimates of the probit model with asymptotic standard errors in the parentheses. In Panel A, we provide the results for the buy orders while in Panel B we have the results for sell orders. The probit model estimated is the following:

$$Pr\left[\Gamma_i^\bullet = 1 \mid Z_i\right] = \Omega\left(\beta Z_i\right)$$

where Ω is the cumulative standard normal distribution, $\Gamma_i^\bullet$ is the indicator variable taking the value of 1 if the trade takes place on the dealership system and 0 if the trade is executed on SETS. Z_i is a vector of independent variables, while β is the vector of unknown coefficients. The linear combination of βZ_i is given by

$$\Gamma_{it} = \beta_0 + \beta_1 q_{it} + \beta_2 l_{it-1} + \beta_3 s_{it-1} + \beta_4 b_{it-1} + \beta_5 \sigma_{it-1}^2$$

where q_i refers to the trade size in terms of NMS multiples, l_i is the imbalance in the order book on SETS immediately before each trade, s_i is the "best" spread on the order book immediately before each trade, b_i is the breadth of the order book and σ_{it-1}^2refers to the volatility calculated as the variance of the prices formed on SETS.

are: (a) large market orders (larger than the depth at the quotes submitted) are only partially executed; (b) the remaining part of the market order which is unexecuted is converted into a limit order; (c) following a market order coming on the market, there is a high probability that the next order will come in to provide liquidity to the market order; (d) the evidence shows that substantial monitoring from outside the book, on the state of affairs in the book, takes place with traders investigating and waiting for advantageous trading opportunities to submit their orders.

A related question of interest for the purpose of this Chapter is how depth on the order book responds when price volatility increases. There are competing arguments regarding the relationship between price volatility and market depth. Ahn *et al.* (1999), for example, find that market depth rises subsequent to an increase in transitory volatility while transitory volatility declines subsequent to an increase in market depth.

These results appear to be consistent with the Handa and Schwartz (1996) model. Ahn *et al.* (1999) also find that when transitory volatility arises from the ask (bid) side, investors will submit more limit sell (buy) orders than market sell (buy) orders and conclude that this result is consistent with the presence of limit order traders placing orders that will supply liquidity.

However, the Biais, Hillion and Spatt (1995), Handa and Schwartz (1996) and Ahn *et al.* (1999) results are obtained in stand-alone trading systems where limit orders and market orders can only be placed in one system. But what will happen to market depth on the order book and the mix of limit orders and market orders when two systems compete with each other for the order flow? For example, at times when price volatility increases, will liquidity move to the order book where limit order traders will provide the necessary liquidity or will they "take refuge" in the dealership system, where voluntary market makers will provide the liquidity demanded by traders?

To investigate this question, we analyse whether intraday volatility has an impact on the depth in the order book. For the purpose of this Chapter, depth is defined both (i) as the number of orders at pre-specified ask and bid quotes and (ii) as the size of the orders at pre-specified ask and bid quotes. The trading day is divided into 90 5-minute intervals to cover the entire trading day and we estimate the following relationship for each security in the sample using GMM:

$$Depth_{zt}= \alpha + \beta_1 Depth_{zt-1}+\beta_2\sigma^2_{zt-1}+\beta_3 Tr_{zt-1}+\beta_4 Asym_{zt-1}+\sum_{k=1}^{89}\beta_5 DT_{k,t}+\varepsilon_t \tag{66}$$

where $Depth_{zt}$ is the depth on the order book (using both (i) as the number of orders at pre-specified ask and bid quotes and (ii) as the size of the orders at pre-specified ask and bid quotes) at time interval t, σ^2_{zt-1} is calculated as the volatility of the mid quotes formed on the SETS system, Tr_{zt} is the number of trades executed on the SETS system during interval t, $Asym_{zt-1}$ is the asymmetry in the order book in interval $t-1$, while $DT_{k,t}$ is a dummy variable to control for the time of the day effect.

The above relationship is estimated using GMM for each security in the sample and heteroskedastic and autocorrelated consistent t-statistics are obtained. Tables 57-58 report the cross-sectional means of the estimates and the $t-statistics$, together with the number of securities from the FTSE 100 index that have statistically significant coefficients.

The results show that, after controlling for the time of the day effect, an increase in mid quote volatility in the order book system leads to a decrease in the depth of the order book. The decrease seems to be more substantial when the depth up to 2 NMS is considered. This result is consistent with

Table 57: **Estimates for the relationship between (buy) depth on the order book and return volatility**

DEPTH	β_1	β_2	β_3	β_4
PANEL A: NUMBER OF LIMIT ORDERS				
Best ask	0.751	-0.032	-0.24	0.192
	(10.14)	(-3.21)	(-5.88)	(4.29)
	[81]	[82]	[78]	[84]
Up to 2 X NMS	0.919	-0.038	-0.28	0.252
	(8.21)	(-4.15)	(-7.52)	(4.86)
	[79]	[79]	[80]	[86]
PANEL B: SIZE OF LIMIT ORDERS				
Best ask	0.701	-0.041	-0.32	0.4101
	(12.78)	(-5.81)	(-9.61)	(6.52)
	[82]	[81]	[84]	[85]
Up to 2 X NMS	0.882	-0.045	-0.36	0.4671
	(11.41)	(-5.68)	(-7.81)	(6.56)
	[83]	[86]	[85]	[86]

The Table reports coefficient estimates for the following model:

$$D_{zt} = \alpha + \beta_1 D_{zt-1} + \beta_2 \sigma^2_{zt-1} + \beta_3 Tr_{zt} + \beta_4 A_{zt-1} + \sum_{k=1}^{89} \beta_5 T_{k,t} + \varepsilon_t$$

where D_{zt} is the depth on the order book at time interval t, σ^2_{zt-1} is the volatility calculated as the mid quote variance formed on SETS, Tr_{zt} is the number of trades executed on SETS during interval t, A_{zt-1} is the level of asymmetry in the order book during interval $t-1$ while $T_{k,t}$ is a dummy variable to control for the time of the day effect.
The coefficients are cross-sectional averages for the 100 stocks included in the FTSE 100 index.
Average $t-statistics$ are in parantheses; the number of firms with statistically significant coefficients are shown in brackets.

Table 58: **Estimates for the relationship between (sell) depth on the order book and return volatility**

DEPTH	β_1	β_2	β_3	β_4
PANEL A: NUMBER OF LIMIT ORDERS				
Best bid	0.722	-0.026	-0.35	0.211
	(9.75)	(-3.18)	(-4.22)	(3.74)
	[79]	[86]	[78]	[80]
Up to 2 X NMS	0.821	-0.042	-0.42	0.422
	(10.41)	(-5.25)	(-7.76)	(5.86)
	[81]	[85]	[82]	[86]
PANEL B: SIZE OF LIMIT ORDERS				
Best bid	0.811	-0.041	-0.39	0.422
	(12.56)	(-6.28)	(-7.72)	(4.52)
	[78]	[80]	[86]	[84]
Up to 2 X NMS	0.898	-0.054	-0.48	0.557
	(12.88)	(-6.61)	(-8.75)	(6.61)
	[79]	[86]	[82]	[85]

The Table reports coefficient estimates for the following model:

$$D_{zt} = \alpha + \beta_1 D_{zt-1} + \beta_2 \sigma^2_{zt-1} + \beta_3 Tr_{zt} + \beta_4 A_{zt-1} + \sum_{k=1}^{89} \beta_5 T_{k,t} + \varepsilon_t$$

where D_{zt} is the depth on the order book at time interval t, σ^2_{zt-1} is the volatility calculated as the mid quote variance formed on SETS, Tr_{zt} is the number of trades executed on SETS during interval t, A_{zt-1} is the level of asymmetry in the order book during interval $t-1$, while $T_{k,t}$ is a dummy variable to control to control for the of the day effect.
The coefficients are cross-sectional averages for the 100 stocks included in the FTSE 100 index.
Average $t-statistics$ are in parantheses; the number of firms with statistically significant coefficients are shown in brackets.

the view that as volatility increases traders submit less limit orders on the SETS system, and is contrary to the one found by Ahn *et al.* (1999).

After estimating the impact of price volatility on the market depth in the order book, we proceed to analyse whether at times when price volatility is high, traders converge to the dealership system. It has already been found that an increase in volatility reduces the depth in the order book, but does this mean that trading activity increases on the dealership system?

In order to analyse this question, we estimate the following relationship for each security in the FTSE 100 index using GMM:

$$DTrades^*_{zt} = \alpha + \beta_1 \sigma^2_{zt-1} + \beta_2 Depth_{zt-1} + \beta_3 A_{zt-1} + \sum_{k=1}^{89} \beta_4 T_{k,t} + \varepsilon_t \qquad (67)$$

where $DTrades^*_{zt}$ is the difference between the normalised number of trades transacted on the dealership system and on the order book system at time interval t, σ^2_{zt-1} is the return volatility of the prices formed on the SETS system, $Depth_{zt-1}$ is the depth on the order book at time interval $t-1$, A_{zt-1} is the asymmetry in the order book in interval $t-1$, while $T_{k,t}$ is a dummy variable to control for the time of the day effect.

The results, shown in Tables 59-60, provide evidence in favour of the argument that as volatility increases more traders converge to the dealership system for the market maker to execute their orders. In an Exchange that provides trading choices to different traders and as uncertainty in the trading process increases, a higher number of traders choose to migrate towards the dealership system.

The results shown in Tables 57-60 put together show that in these adverse market conditions, traders are not encouraged to provide liquidity on the order book through limit orders, with the order flow migrating to the dealership system for execution there. This also means that voluntary mar-

Table 59: **Estimates for the relationship between the order flow (buy side) on DS and SETS systems and return volatility**

LEVEL OF MARKET ACTIVITY	β_1	β_2	β_3
PANEL A: ALL SECURITIES IN FTSE 100 INDEX			
Number of trades	0.066	-0.691	-0.254
	(6.96)	(-7.12)	(-3.81)
	[87]	[80]	[84]
PANEL B: TOP 20 SECURITIES IN FTSE 100 INDEX			
Number of trades	0.051	-0.442	-0.122
	(5.24)	(-9.61)	(-3.66)
	[18]	[18]	[17]
PANEL C: BOTTOM 20 SECURITIES IN FTSE 100 INDEX			
Number of trades	0.079	-0.862	-0.229
	(6.42)	(-9.82)	(-2.96)
	[19]	[19]	[18]

The Table reports coefficient estimates for the following relationship:

$$DT^*_{zt} = \alpha + \beta_1\sigma^2_{zt-1} + \beta_2 D_{zt-1} + \beta_3 A_{zt-1} + \sum_{k=1}^{89} \beta_4 T_{k,t} + \varepsilon_t$$

where DT^*_{zt} is the difference between the normalised number of trades transacted on the dealership system and on the order book system at time interval t, σ^2_{zt-1} is the volatility of mid quotes formed on the order book; D_{zt-1} is the depth on the order book at time interval $t-1$, while A_{zt-1} is the asymmetry in the order book during interval $t-1$ and $T_{k,t}$ is a dummy variable to control for the time of the day effect.

The coefficients are cross-sectional averages for the 100 stocks included in the FTSE 100 index.

Average t-statistics are in parantheses; the number of securities with statistically significant coefficients are shown in brackets.

Table 60: **Estimates for the relationship between the order flow (sell side) on DS and SETS systems and return volatility**

LEVEL OF MARKET ACTIVITY	β_1	β_2	β_3
PANEL A: ALL SECURITIES IN FTSE 100 INDEX			
Number of trades	0.0741	-0.754	-0.298
	(6.44)	(-9.22)	(-6.82)
	[87]	[82]	[85]
PANEL B: TOP 20 SECURITIES IN FTSE 100 INDEX			
Number of trades	0.052	-0.582	-0.185
	(5.92)	(-9.06)	(-4.12)
	[17]	[18]	[18]
PANEL C: BOTTOM 20 SECURITIES IN FTSE 100 INDEX			
Number of trades	0.082	-0.881	-0.289
	(6.62)	(-7.98)	(-3.89)
	[18]	[19]	[18]

The Table reports coefficient estimates for the following relationship:

$$DT^*_{zt} = \alpha + \beta_1\sigma^2_{zt-1} + \beta_2 D_{zt-1} + \beta_3 A_{zt-1} + \sum_{k=1}^{89} \beta_4 T_{k,t} + \varepsilon_t$$

where DT^*_{zt} is the difference between the normalised number of trades transacted on the dealership system and on the order book system at time interval t, σ^2_{zt-1} is the volatility of mid quotes formed on the order book; D_{zt-1} is the depth on the order book at time interval $t-1$, while A_{zt-1} is the asymmetry in the order book during interval $t-1$ and $T_{k,t}$ is a dummy variable to control for the time of the day effect.

The coefficients are cross-sectional averages for the 100 stocks included in the FTSE 100 index.

Average t-statistics are in parantheses; the number of securities with statistically significant coefficients are shown in brackets.

ket makers are contributing to the trading process in a different way: they are providing liquidity when liquidity is really needed in the market, in this case when high price volatility leads to a shortage of liquidity provision.[15] This result appears to be stronger for the bottom decile of the securities included in the FTSE 100 index.

5.6 Conclusions

This Chapter investigates price efficiency and order flow dynamics generated in a hybrid trading system where trading fragments between two systems: (i) an order book based system that opens with a call auction and continues through a continuous trading mode; and (ii) a dealership system where voluntary market makers stand by to accommodate the order flow.

There are three major questions asked: (a) which trading system produces prices that track the true asset's value more efficiently; (b) are dealers making any contribution to price stabilisation; and (c) what are the major order flow dynamics when traders can choose to trade in two different trading platforms. We use high frequency data from the LSE, a marketplace where the most liquid securities (the FTSE 100 index securities) are now traded on two different market microstructures.

Price efficiency in the two systems is measured as the deviation of the price on the order book and the dealership system from the true "system-wide" price that is calculated using a state-space model using the information content in the order flow and the past values of the price.

The major result shows that the dealership system generates the highest price efficiency and this result is stronger for securities in the bottom decile

[15]The evidence presented here ties in with empirical evidence on how the order flow behaves in Bund contracts traded on two parallel trading systems, namely the LIFFE system and the the DTB system. Indeed, Franke and Hess (1995), Pirrong (1996) and Shyy and Lee (1995) find similar results for trading in futures trading.

of the FTSE 100 index, implying that the presence of dealers produces a positive impact on price stabilisation. The dealership system appears to be more robust in that it can transact higher volumes with higher price efficiency. The results indicate the dealers' ability in finding a more accurate price discovery, contributing to the short-term stabilisation of prices.

In order to investigate further the issue of price efficiency, we also analysed market depth and order flow dynamics in the two systems under adverse market conditions, namely when price volatility is high. This is done to analyse how the order flow behaves during uncertain times and to investigate whether it is dealers or limit order traders that provide liquidity when it is mostly required.

The results find that, in a hybrid market microstructure, market depth on the order book decreases when return volatility increases leading to a higher proportion of the order flow to migrate towards the dealership system. This contrasts with existing literature that has found that periods of high volatility attract limit orders to the order book.

This Chapter's objective is not to suggest that one market design is necessarily superior to another under all circumstances. It is clear that, given the existence of different traders' types, with heterogenous motivations and different sizes, no one system will fit all the requirements. This explains the emergence of hybrid trading systems in many Exchanges. The main objective for future research remains the analysis of the different trade-offs that exist between the different trading systems and which are central to traders' strategies.

References

Admati, Anat and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Admati, Anat, and Paul Pfleiderer, 1988, Divide and conquer: A theory of intraday and day-of-the-week mean effects, *The Review of Financial Studies* 2, 189-223.

Affleck-Groves, John, Shantaram P. Hegde, and Robert E. Miller, 1994, Trading mechanisms and the components of the bid-ask spread, *Journal of Finance* 49, 1471-1488.

Ahn, Hee-Joon, Kalok Hong Bae, and Kalok Chan, 1999, Limit orders, depth and volatility, Working Paper, Hong Kong University of Science and Technology.

Alford, A. and P. Jones, 1998, A simultaneous equations analsis of forecast accuracy, analyst following and trading volume, Working Paper, University of Pennslyvania.

Allen, Franklin, and Gary Gorton, 1992, Stock price manipulation, market microstructure and asymmetric information, *European Economic Review* 36, 624-630.

Amihud, Yakov, Thomas Ho, and Robert A. Schwartz, 1985, Overview of the changing securities markets, in Amihud, Y., T.S.Y. Ho, and R.A. Schwartz, eds.: *Market Making and the Changing Structure of the Securities Industries* (Lexington Books, Massachusetts), pp. 1-15.

Amihud, Yakov, and Haim Mendelson, 1980, Dealership market, *Journal of Financial Economics* 8, 31-53.

Amihud, Yakov, and Mendelson Haim, 1982, Asset price behaviour in a dealership market, *Financial Analyst Journal*, May-June, 50-59.

Amihud, Yakov, and Mendelson Haim, 1986,Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Amihud, Yakov, and Haim Mendelson, 1987, Trading mechanisms and stock returns: an empirical investigation, *Journal of Finance* 42, 533-53.

Amihud, Yakov, and Haim Mendelson, 1990, Option market integration: An evaluation, Working Paper, New York University.

Amihud, Yakov, and Haim Mendelson, 1991, Volatility, efficiency and trading: Evidence from the Japanese stock market, *Journal of Finance* 46, 1765-1789.

Andersen, T.G., and Tim Bollerslev, 1997, Intraday periodicity and volatility persistence in financial markets, *Journal of Empirical Finance* 4, 115-158.

Bagehot, W., 1971, The only game in town, *Financial Analysts Journal* 22, 12-14.

Ball, Clifford and Walter Torous, 1988, Investigating security price performance in the presence of event-date uncertainty, *Journal of Financial Economics* 22, 123-154.

Ball, Ray, and Frank J. Finn, 1989, The effect of block transactions on share prices: Australian evidence, *Journal of Banking and Finance* 13, 397-419.

Barclay, Michael J., and J.B. Warner, 1993, Stealth trading and volatility: Which trades move prices?, *Journal of Financial Economics* 34, 281-306.

Barclay, Michael J., William G. Christie, Jeffrey H. Harris, Eugene Kandel and Paul H. Schultz, 1997, The effects of market reform on the trading costs and depths of NASDAQ stocks, Vanderbilt University, Working Paper 97-10.

Benston, George.J., and Robert L. Hagerman, 1974, Determinants of bid-ask spreads in the over-the-counter market, *Journal of Financial Economics* 1, 353-363.

Benveniste, Lawrence M., Alan J. Marcus, and William J. Wilhelm, 1992, What's special about the specialist?, *Journal of Financial Economics* 32, 61-86.

Bessembinder, Hendrik, and Herbert M. Kaufman, 1997, A cross-exchange comparison of execution costs and information flow for NYSE-listed stocks, *Journal of Financial Economics* 46, 293-319.

Biais, Bruno, 1993, Price formation and equilibrium liquidity in fragmented and centralized markets, *Journal of Finance* 48, 157-185.

Biais, Bruno, Pierre Hillion, and Chester Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *Journal of Finance* 50, 1655-1689.

Biais, Bruno, Pierre Hillion and Chester Spatt, 1997, Price discovery and learning during the pre-opening period in the Paris Bourse, Working Paper, Carnegie Mellon University.

Blume, Marshall, and Michael A. Goldstein, 1992, Displayed and effective spreads by markets, Rodney L. White Centre for Financial Research, working Paper 27-92.

Board, John, and Charles Sutcliffe, 1995, The effects of trade transparency in the London stock Exchange, London International Financial Futures and Options Exchange and London Stock Exchange.

Boehmer, Ekkehart, Jim Musumeci and Annette Poulsen, 1991, Event-study methodology under conditions of event-induced variance, *Journal of Financial Economics* 30, 253-272.

Bollerslev, Tim, 1986, Generalised autoregressive conditional heteroscedasticity, *Journal of Econometrics* 31, 307-27.

Bollerslev, Tim, Ian Domowitz, and Jianxin Wang, 1997, Order flow and the bid-ask spread: An empirical probability model of screen-based trading, *Journal of Economic Dynamics and Control* 21, 1471-1492.

Bollerslev, Tim, 1987, A conditionally heteroscedastic time series model for speculative prices and rates of return, *Review of Economics and Statistics* 69, 542-547.

Booth, Geoffrey G., Peter Iversen, Salil Sarkar, Hartmut Schmidt, and Allan Young, 1995, Market structure and bid-ask spreads: NASDAQ vs. the German stock market, Working paper, University of Hamburg.

Booth, Geoffrey, J.C. Lin, and G.C. Sanger, 1995, Trade size and components of the bid-ask spread, *The Review of Financial Studies* 8, 1153-1183.

Booth, Geoffrey, Lin, Ji-Chair, Martikainen, Teppo, and Tse, Yiuman, 1999, Trading and pricing in upstairs and downstairs markets, Working Paper, Michigan State University.

Breedon, Francis, 1993, Intraday price formation on the London Stock Exchange, Discussion Paper No. 158, Financial Markets Group, London School of Economics.

Brown, Keith, William Harlow, and Seha Tinic, 1988, Risk aversion, uncertain information, and market efficiency, *Journal of Financial Economics* 22, 355-385.

Brown, Keith, William Harlow, and Seha Tinic, 1989, The effect of unanticipated events on the risk and return of common stock, Working Paper, University of Texas.

Brown, Nicholas, 1994, Information links and liquidity effects in parallel German and London equity markets, unpublished PhD dissertation, London Business School.

Brown, Stephen, and Jerold Warner, 1980, Measuring security price performance, *Journal of Financial Economics* 8, 205-258.

Brown, Stephen, and Jerold Warner, 1985, Using daily stock returns: The case of event studies, *Journal of Financial Economics* 14, 3-31.

Burdett, Kenneth, and Maureen O'Hara, 1987, Building blocks: An introduction to block trading, *Journal of Banking and Finance* 11, 193-212.

Campbell, John, Andrew Lo, and Craig MacKinlay, 1996, The Econometrics of Financial Markets, Princeton University Press.

Charest, Guy, 1978, Dividend information, stock returns and market efficiency - II, *Journal of Financial Economics* 14, 3-32.

Chowdry, B., and Nanda, Vikram, 1991, Multimarket trading and market liquidity, *The Review of Financial Studies* 4 (3), 483-511.

Christie, Andrew, 1983, On information arrival and hypothesis testing in event studies, Working paper, University of Rochester.

Christie, William and Paul H. Schultz, 1994, Why do NASDAQ market makers avoid the odd-eight quotes?, *Journal of Finance* 49, 1813-1840.

Cohen, Kalman J., Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1979, On the existence of serial correlation in an efficient securities markets, in E.J. Elton and M.J. Gruber, *Portfolio Theory, 25 years after: Essays in Honour of Harry Markowitz*, New York:Elsevier North-Holland, 151-168.

Cohen, Kalman J., Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb,1979, Market makers and the market spread: A review of recent literature, *Journal of Financial and Quantitative Analysis* Volume XIV (4), 813-835.

Cohen, Kalman J., Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1981, Transaction costs, order placement strategy and existence of the bid-ask spread, *Journal of Political Economy* 89, 287-305.

Cohen, Kalman J., Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1986, *The Microstructure of Securities Markets* (Prentice-Hall, New Jersey).

Collins, and Dent, 1984, A comparison of alternative testing models used in capital market research, *Journal of Accounting Research* 22, 48-84.

Corrado, Charles, 1989, A nonparametric test for abnormal security price performance in event studies, *Journal of Financial Economics* 23, 385-395.

Copeland, Thomas, and Dan Galai, 1983, Information effects and the bid-ask spread, *Journal of Finance* 38, 1457-1469.

Copeland, Thomas, 1976, A model of asset trading under the assumption of sequential information arrival, *Journal of Finance* 31, 1149-1168.

Dann, Larry, 1981, Common stock repurchase: An analysis of returns to bondholders and stockholders, *Journal of Financial Economics* 23, 385-395.

Davis, Ruth, 1993, London trading in German equities, Stock Exchange Quarterly with Quality of Markets Review, Winter.

Davis, Ruth, 1993, London trading in German equities, *Stock Exchange Quarterly with Quality of Markets Review*, 11-16.

Davis, J, Eugene F. Fama, and Kenneth R. French, 1998, Characteristics, covariances and the average returns: 1929-1997, Working Paper, University of Chicago.

de Jong, Frank, Theo Nijman, and Ailsa Röell , 1995, A comparison of the cost of trading French shares on the Paris Bourse and on SEAQ International, *European Economic Review* 39, 1277-1301.

de Jong Frank, Theo Nijman, and Ailsa Röell , 1995, Price effects of trading and components of the bid-ask spread on the Paris Bourse, Financial Markets Group, Working Paper No. 207.

Demsetz, Harold, 1968, The cost of transacting, *Quarterly Journal of Economics* 82, 33-53.

Domowitz, Ian and Jianxin Wang, 1994, Auctions as algorithms: Computerised trade execution and price discovery, *Journal of Economic Dynamics and Control* 18, 29-60.

Domowitz, Ian, 1990, The mechanics of automated trade execution systems, *Journal of Financial Intermediation* 1, 167-194.

Domowitz, Ian, 1993, A taxonomy of automated trade execution systems, *Journal of International Money and Finance* 12, 607-631.

Domowitz, Ian, and Ananth Madhavan, 1998, Open sesame: Alternative opening algorithms in securities markets, Working Paper, University of Southern California.

Dufour, Alfonso, and Robert F. Engle, 1998, Time and the price impact of a trade, Working Paper, University of California, San Diego.

Easley, David, and Maureen O'Hara, 1987, Price, quantity, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance* 47, 577-605.

Efron, Bradley, and Robert Tibshirani, 1993, *An Introduction to the Boostrap*, Chapman & Hall, New York.

Engle, Robert F., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation, *Econometrica* 50, 987-1008.

Engle, Robert F., and Victor Ng, 1993, Measuring and testing the impact of news on volatility, *Journal of Finance* 48, 1749-78.

Franke, Gunther, and D. Hess, 1995, Anonymous electronic trading versus floor trading, working paper, University of Konstantz.

Freedman, Roert, 1989, A theory of the impact of international cross listing, Working Paper, Graduate School of Business, Stanford University.

French, Kenneth R., and Richard Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Eco-*

nomics 17, 5-26.

French, Kenneth R., and Richard Roll, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Foucault, Thierry, 1997, Order flow composition and trading costs in a dynamic limit order market, Working Paper, Carnegie-Mellon University.

Froot, Kenneth, David Scharfstein, and K.J.C. Stein, 1992, Herd on the street: Informational inefficiencies in a market with short term speculation, *Journal of Finance* 47, 1461-1484.

Garbade, Kenneth, and William L. Silber, 1979a, Structural organisation of secondary markets: Clearing frequency, dealer activity and liquidity risk, *Journal of Finance* 36, 577-593.

Garbade, Kenneth, and William Silber, 1979b, Dominant and satellite markets: A study of dually-traded securities, *Review of Economics and Statistics* 61, 455-460.

Gemmill, Gordon, 1996, Transparency and liquidity: a study of block trades on the London Stock Exchange under different publications rules, *Journal of Finance* 50, No.5, 1765-1790.

George, T.J., Gautam Kaul, and M. Nimalendran, 1991, Estimation of the bid-ask spread and its components: A new approach, *Review of Financial Studies* 4, 623-656.

Gerety, Mason, and Harold Mulherin, 1994, Price formation on stock exchanges: The evolution of trading within the day, *Review of Financial Studies* 3, 609-629.

Glosten, Lawrence, 1989, Insider trading, liquidity, and the role of the monopolist specialist, *Journal of Business* 62, 211-235.

Glosten, Lawrence, and Lawrence Harris, 1988, Estimating the components of the bid-ask spread, *Journal of Financial Economics* 21, 123-142.

Glosten, Lawrence, and P. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.

Gonzalo, J., and C.W.J. Granger, 1995, Estimation of common long-memory components in cointegrated systems, *Journal of Business and Economic Statistics* 13, 27-36.

Glosten, Lawrence, 1987, Components of the bid-ask spread and the statistical properties of transaction prices, *Journal of Finance* 42, 1293-1307.

Glosten, Lawrence, 1989, Insider trading, liquidity, and the role of the monopolist specialist, *Journal of Business* 62, 211-236.

Glosten, Lawrence, 1994, Is the electronic open limit order book inevitable, *Journal of Finance* 49, 1127-1161.

Glosten Lawrence, and P.R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.

Godek, Paul, 1996, Why NASDAQ market makers avoid odd eights quotes, *Journal of Financial Economics* 41, 465-474.

Goldman, Barry M., and Avraham Beja, 1979, Market prices and equilibrium prices: returns variance, serial correlation, and the role of the specialists, *Journal of Finance* 34, 595-607.

Grossman, Sandy, 1976, On the efficiency of competitive stock markets where traders have diverse information, *Journal of Finance* 31, 573-585.

Grossman, Sandy, 1992, The informational role of upstairs and downnstairs trading, *Journal of Business* 65 509-529.

Grossman, Sandy, Merton Miller, Daniel Fischel, Kenneth Cone, and David Ross, 1997, Clustering and competition in asset markets, *Journal of Law and Economics*, April issue, 23-60.

Haller, Andreas, and Hans Stoll, 1989, Market structure and transaction costs: Implied spreads in the German stock market, *Journal of Banking and Finance* 13, 697-708.

Handa, Puneet, and Robert Schwartz, 1996, Limit order trading, *Journal of Finance* 51, 1835-1861.

Hansch, Olivier, and Anthony Neuberger, 1993, Block trading on the London Stock Exchange, Institute of Finance and Accounting, London Business School, Working Paper 182

Hansch, Olivier, Narayan Naik, and S. Viswanathan, 1993, Market making on the London Stock Exchange: An empirical investigation, Working paper, London Business School.

Hansch, Oliver, Narayan Naik, and S. Viswanathan, 1999, Preferencing, internalisation, best execution and dealer profits, forthcoming in *Journal of Finance.*

Harris, Frederick H. deB., Thomas H. McInish, Gary L. Shoesmith and Robert A. Wood, 1995, Cointegration, error correction and price discovery on informationally linked security markets, *Journal of Financial and Quantitative Analysis* 30, 563-580.

Harris, Lawrence, 1989, A day-end transaction price anomaly, *Journal of Financial and Quantitative Analysis* 24, 29-14.

Harris, Lawrence, 1990, Liquidity, trading rules, and electronic trading systems, Working Paper, University of Southern California.

Harris, Lawrence, 1993, Consolidation, fragmentation, segmentation and regulation, *Financial Markets, Institutions and Instruments* 2, 1-27.

Harris, Lawrence, and V. Panchapagesan, 1999, The information-content of the limit order book: Evidence from NYSE specialist actions, Working Paper, Marshall School of Business, University of Southern California.

Harvey, Andrew, 1993, *Time Series Models* (2nd ed.), London: Harvester Wheatsheaf.

Hausman, Jerry, Andrew Lo, and Craig MacKinlay, 1992, An ordered probit analysis of transaction stock prices, *Journal of Financial Economics* 31, 319-379.

Hasbrouck, Joel, 1988, Trades, quotes, inventories and information, *Journal of Financial Economics* 22, 229-252.

Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, *Journal of Finance* 46, 179-207.

Hasbrouck, Joel, 1991b, The summary informativeness of stock trades: An econometric analysis, *Review of Financial Studies* 4, 571-595.

Hasbrouck, Joel, 1993, Assessing the quality of a security market: A new approach to transaction cost measurement, *Review of Financial Studies* 6, 191-212.

Hasbrouck, Joel, 1995,One security, many markets: Determining the contributions to price discovery, *Journal of Finance*, 50 (4), 1175-1199.

Hasbrouck, Joel, and T. Ho, 1987, Order arrival, quote behaviour, and the return generating process, *Journal of Finance* 42, 1035-1048.

Hausman, Jerry, Andrew Lo, and A. Craig MacKinlay, 1992, An ordered probit analysis of transaction stock prices, *Journal of Financial Economics* 31, 319-379.

Heston, Steven L., Geert K. Rouwenhorst, and Roberto E. Wessels, 1998, The role of beta and size in the cross-section of European stock returns, Working Paper, Yale School of Business.

Ho, Thomas, and Richard G. Macris, 1985, Dealer market structure and performance, in Amihud, Y., T.S.Y. Ho, and R.A. Schwartz, eds.: *Market Making and the Changing Structure of the Securities Industries* (Lexington

Books, Massachusetts).

Ho, Thomas, and Hans R. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.

Ho, Thomas, and Hand R. Stoll, 1983, The dynamics of dealer markets under competition, *Journal of Finance* 38 1053-1074.

Holthausen, Robert W., Richard W. Leftwich, and David Mayers, 1987, The effect of large block transactions on security prices: A cross sectional analysis, *Journal of Financial Economics* 21, 237-268.

Holthausen, Robert W., Richard W. Leftwich, and David Mayers, 1990, Large block transactions, speed of response, and temporary and permanent stock price effects, *Journal of Financial Economics* 26, 71-95.

Holthausen, Robert W., Richard W. Leftwich, and David Mayers, 1990, Large block transactions, speed of response, and temporary and permanent stock price effects, *Journal of Financial Economics* 26, 71-95.

Huang, Roger D., and Hans R. Stoll, 1994, Market microstructure and stock returns predictions, *Review of Financial Studies* 7, 179-213.

Huang, Roger D., and Hans R. Stoll, 1996, Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE, *Journal of Financial Economics* 41, 313-357.

Huang, Roger D., and Hans R. Stoll, 1997, The components of the bid-ask spread: A general approach, *Review of Financial Studies* 10, 995-1034.

Huang, Roger, and Hans R. Stoll, 1997, The components of the bid-ask spread: A general approach, *Review of Financial Studies* 10, 995-1034.

Huang, Roger, 2000, Price discovery by ECNs and NASDAQ market makers, Working Paper, University of Notre Dame.

Jacquillat, Bertrand, and Carole Gresse, 1995, The diversification of order flow in French shares from the CAC market to the SEAQ International:

An exercise in transactions accounting, Working Paper, University Paris Dauphine.

Kandel, Eugene and Leslie Marx, 1997, NASDAQ market structure and spread patterns, *Journal of Financial Economics* 35, 61-90.

Keim, Donald B., and Ananth Madhavan, 1995, Anatomy of the trading process: Empirical evidence on the behaviour of institutional traders, *Journal of Financial Economics* 37, 371-398.

Koopman, Siem Jan, 1993, Disturbance smoother for state space models, *Biometrika* 80, 117-126.

Koopman, Siem Jan, and Durbin, J., 1998, Fast filtering and smoothing for multivariate state space models, working paper, Tilburg University.

Koopman, Siem Jan, and Hung Neng Lai, 1999, Modelling bid-ask spreads in competitive dealership markets, Discussion Paper 324, Financial Markets Group.

Kraus, Alan, and Hans R. Stoll, 1972, Price impacts of block trading on the New York Stock Exchange, *Journal of Finance* 27, 569-588.

Kyle, Albert, 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Kyle, Albert, 1989, Informed speculation with imperfect competition, *Review of Economic Studies* 56, 317-356.

Laux, Paul, 1995, Dealer market structure, outside competition, and the bid-ask spread, *Journal of Economic Dynamics and Control* 19, 683-710.

Lee, Charles, and Mark Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-746.

Lee, Charles, B Mucklow, and Mark Ready, 1993, Spreads, depths and the impact of earnings information: An intraday analysis, *Review of Financial Services* 6, 345-374.

Lo, Andrew, and Craig MacKinlay, 1990, An econometric analysis of nonsynchronous trading, *Journal of Econometrics* 45, 181-212.

Lo, Andrew, A. MacKinlay, and J. Zhang, 1997, Econometric models of limit-order executions, Working Paper, MIT Laboratory for Financial Engineering.

London Stock Exchange, 1992, Price improvement and best execution, *Stock Exchange Quarterly*, spring edition, 25-31.

Lyons, Richard, 1995, Test of microstructural hypotheses in the foreign exchange market, *Journal of Financial Economics* 39, 321-351.

Lüdecke, Torsten, 1997, The Karlsruher Kapitalmarktdaten-bank (KKMDB): The IBIS data, Discussion Paper No. 190, University of Karlsruhe.

Madhavan, Ananth, 1992, Trading mechanisms in securities markets, *Journal of Finance* 47, 607-641.

Madhavan, Ananth, 1995, Consolidation, fragmentation, and the disclosure of trading information, *Review of Financial Studies* 8, 579-603.

Madhavan, Ananth, and Minder Cheng, 1997, In search of liquidity: Block trades in the upstairs and downstairs markets, *Review of Financial Studies* 10, 175-203.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies* 10, 99-134.

Madhavan, Ananth, and Venkatesh Panchapagesan, 2000, Price discovery in auction markets: A look inside the black box, *Review of Financial Studies* 13, 627-658.

McInish, Thomas, and Robert Wood, 1992, Competition, dispersion of trading and market performance, Working Paper, University of Memphis.

Mikkelson, Wayne, 1981, Convertible security calls and security returns, *Journal of Financial Economics* 9, 237-264.

Naidu, G.N., and Rozeff, M., 1994, Volume, volatility, liquidity and efficiency of the Singapore stock exchange before and after automation, *Pacific-Basin Finance Journal* 2, 23-42.

Naik, Narayan, and Pradeep Yadav, 1999, The effects of market reform on trading costs of public investors: Evidence from the London Stock Exchange, Working Paper, London Business School.

Neal, Robert, 1992, A comparison of transaction costs between competitive market maker and specialist market structures, *Journal of Business* 65,317-334.

Niederhoffer, Victor, and M.F.M. Osborne, 1966, Market making and reversals on the stock exchange, *Journal of the American Statistical Association* 61, 897-916.

Oesterhelweg, Olaf, Hartmut Schmidt, and Kai Treske, 1996, Competition among German trading mechanisms: Electronic trading on IBIS vs. trading on the floor based BOSS-CUBE system, 1996, paper presented during the conference "European Financial Markets", January 1996, organised by the Financial Markets Group (LSE).

Pagano, Marco, 1989, Trading volume and asset liquidity, *Quarterly Journal of Economics* 104, 255-276.

Pagano, Marco, and Benn Steil, 1995, Equity Trading I: the evolution of European trading systems, in *The European Equity Markets*, The Royal Institute of International Affairs.

Pagano, Marco, and Ailsa Röell, 1990a, Trading systems in European stock exchanges: Current performance and policy options, *Economic Policy* 5, 63-115.

Pagano, Marco, and Ailsa Röell, 1990b, Auction markets, dealership markets and execution risk, Discussion Paper No. 102, Financial Markets Group, London School of Economics.

Pagano, Marco, and Ailsa Röell, 1990c, Shifting gears: An economic evaluation of the reform of the Paris Bourse, Discussion Paper No. 103, Financial Markets Group, London School of Economics.

Pagano, Marco, and Ailsa Röell, 1991, Dually-traded Italian equities: London vs. Milan, Discussion Paper No. 116, Financial Markets Group, London School of Economics.

Pagano, Marco, and Ailsa Röell, 1992, Auction and dealership markets: What is the difference?, *European Economic Review* 36, 613-623.

Patell, James, 1976, Corporate forecasts of earnings per share and stock price behaviour: Empirical tests, *Journal of Accounting Research*, 246-276.

Penman, Stephen, 1982, Insider trading and the dissemination of firms' forecast information, *Journal of Business* 55, 479-503.

Pirrong, C., 1996, Market liquidity and depth in computerised and open outcry trading systems: a comparison of DTB and LIFFE Bund contracts, Journal of Futures Markets 16, 519-543.

Porter, David C., and Daniel G. Weaver, 1995, Do NASDAQ market makers 'paint the tape'?, Working Paper, Marquette University.

Reiss, Peter and Ingrid Werner, 1996, Transaction costs in dealer markets: Evidence from the London Stock Exchange, in A. Lo (ed) *The Industrial Organisation and Regulation of the Securities Industries*, University of Chicago Press.

Rhodes-Kropf, M, 1997, On price improvement in dealership markets, Working paper, Duke University.

Rock, Kevin, 1991, The specialist's order book, Working Paper, Harvard Business School, Cambridge, MA.

Röell , Ailsa, 1992, Comparing the performance of stock exchange trading systems, in Fingleton and Schoenmaker (eds.), *The Internalisation of Capital Markets and the Regulatory Response,* Graham and Trotman, London.

Röell , Ailsa, 1992, Comparing the performance of stock exchange trading systems, in Fingleton and Schoemaker (eds), The Internationalization of Capital Markets and the Regulatory Response, Graham and Trotman, London.

Roll, Richard, 1984, A simple measure of the effective bid-ask spread in an efficient market, *Journal of Finance* 39, 1127-39.

Ronen, Tavy, 1997, Tests and properties of variance ratios in microstructure studies, *Journal of Financial and Quantitative Analysis* 32, 183-204.

Rosenstein, Jeffrey, and Stuart Wyatt, 1990, Outside directors, board independence and shareholder wealth, *Journal of Financial Economics* 26, 175-192.

Roth, Alvin, Keith Murnigham, and Francoise Schoumaker, 1988, The deadline effect in bargaining: Some experimental evidence, *American Economic Review* 78, 806-823.

Schmidt, Hartmut, and Peter Iversen, 1992, Automating German equity trading on competing systems, *Journal of Financial Services Research* 6, 373-397.

Schmidt, Hartmut, Olaf Oesterhelweg, and Kai Treske, 1996, Competition among German trading mechanisms: Electronic trading on IBIS vs trading on the floor based BOSS-CUBE system, Working Paper, University of Hamburg.

Schwartz, Robert A., 1988, *Equity Markets: Structure, Trading and Performance* (Harper and Row, New York).

Schwartz, Robert A., and Benn Steil, 1995, Equity trading III: Institutional investor trading practices and preferences, in *The European Equity Markets*, The Royal Institute of International Affairs.

Schwert, William G., 1989, Why does stock market volatility change over time?, *Journal of Finance* 44, 1115-1153.

Seppi, Duane, 1990, Equilibrium block trading and asymmetric information, *Journal of Finance*, 45, 73-94.

Shyy, G., and J.H. Lee, 1995, Price transmission and information asymmetry in Bund futures markets: LIFFE vs. DTB, Journal of Futures Markets 15, 87-99.

Stoll, Hans, 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Stoll, Hans, 1989, Inferring the components of the bid-ask spread: Theory and empirical tests, *Journal of Finance* 44, 115-134.

Stoll, Hans, 1992, Principles of trading market structure, *Journal of Financial Services Research* 6, 75-107.

Stoll, Hans, and Robert Whaley, 1990, Stock market structure and volatility, *Review of Financial Studies* 3, 37-71.

Stoll, Hans, 1978a, The pricing of security dealer services: An empirical study of NASDAQ stocks, *Journal of Finance* 33, 1153-1172.

Stoll, Hans, 1978b, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Stoll, Hans, 1978c, Inferring the components of the bid-ask spread: Theory and empirical tests, *Journal of Finance* 44, 115-134.

Stoll, Hans, 2000, Presidential address: Friction, *Journal of Finance* 55, 1479-1516.

Seppi, Duane, 1990, Equilibrium block trading and asymmetric information, *Journal of Finance* 45, 73-94.

Seppi, Duane, 1992, Block trading and information revelation around quarterly earning announcements, *Review of Financial Studies* 5, 281-306.

Tinic, Seha M., 1968, The economics of liquidity services, *Quarterly Journal of Economics* 82, 79-93.

Tirole, Jean, 1988, *The theory of industrial organization*, Cambridge, Mass.; London: MIT Press.

Tonks, Ian, 1996, The equivalence of screen based continuous auction and dealer markets, Special Paper No. 92, Financial Markets Group.

Tonks, Ian and Andy Snell, 1992, Trading volumes and stock market prices, Discussion Paper No. 130, Financial Markets Group.

Van Ravenswaaij, Maarten, 1997, Intraday patterns and the bid-ask spread on the Paris Bourse, Working paper, Tilburg University.

Vickrey, William, 1961, Counterspeculation, auctions, and competitive sealed tenders, *Journal of Finance* 16 (1), 8-37.

Vijh, Anand M., 1988, Potential biases from using only trade prices of related securities on different exchanges: A comment, *Journal of Finance* 43, 1049-1055.

Vijh, Anand M., 1990, Liquidity of the CBOE equity options, *Journal of Finance* 45, 1157-1179.

Viswanathan S., and James D. Wang, 1998, Market architecture: Limit-order books versus dealership markets, Working Paper, Fuqua School of Business, Duke University.

Wang, Jianxin, 1999, Asymmetric information and the bid-ask spread: An empirical comparison between automated order execution and open outcry auction, *Journal of International Financial Markets, Institutions and Money* 9, 115-128.

Wells, Stephen, 1993, Transparency in the equity market - the publication of last trades, *Stock Exchange Quarterly*, January-March 1993.

White, H., 1980, A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, *Econometrica* 48, 817-838.

Appendix A: Institutional design of European equity markets

This Appendix provides the institutional design used by the four markets analysed in this paper *over the period from January to June 1996.* In many cases, there have been a number of significant reforms in these markets which were carried out after June 1996 which are not considered in this study.

7.1 SEAQ-I

SEAQ-I was launched by the LSE in 1986. Its trading architecture resembles the one used by SEAQ for UK securities in that it is based on the competing market makers system and as such was classified as a dealership market. There is no official mechanism by which international securities are listed on SEAQ-I since securities do not make a formal request for an official listing and are quoted only if one or several London market makers agree to make a market in such securities. Transactions may be carried out 24 hours a day and trades are normally executed within the best limit price range.

The 'Guide to International Equity Markets' (1994) published by the LSE states that market makers for securities listed on SEAQ-I are under a contractual obligation to display continuous two-way firm prices for the same securities. Each security is allocated a minimum marketable quantity (MMQ), which represents the smallest size for which firm prices must be provided.

The LSE also established the Mandatory Quote Period (MQP) which refers to the period over which two-way prices for the MMQ must be displayed. The MQP for French and Italian cross-quoted securities is established between 09:00:00 hrs and 16:00:00 hrs which is the period over which the Paris Bourse and the IE are opened for business.

10:00:00 hrs to 17:00:00 hrs (local time). Orders were accepted between 08:30:00 hrs and 10:00:00 hrs but they were only executed at the opening through a call auction, after which continuous trading starts. Orders were posted in the CAC by the *societes de bourse*, the corporate dual-capacity intermediaries operating on the Paris Bourse. However, these intermediaries have no obligation to provide liquidity.

The *societes de bourse* have access to the entire limit order book during the pre-opening period including the codes identifying the member firms placing orders while non-members see the five best limit prices on their screens. During the pre-opening period a theoretical price is computed and displayed continuously on the screens.[16]

Orders were executed according to the price and time priority rules. During the continuous trading period, limit orders are executed before market orders and any new order gives rise to a new transaction price if there is a compatible opposite order on the order book. This matching of orders produces an environment where most of the orders are excuted at either the best ask or the best bid quotes.

Market orders, on the other hand, are executed after limit orders have been transacted and their execution takes place on the limits of the order book. Unsatisfied market orders are entered in the book at the price at which the market orders were partially executed.

One characteristic of the Paris Bourse which has been often referred to is the level of pre-trade transparency it offers. During the continuous auction period, all Bourse members have a full breakdown of the central order book

[16] Jacquillat and Gresse (1995) appear to suggest that providing a full breakdown of the limit order at the pre-opening period to the *societes de bourse* is expected to produce equilibrium prices at the open. The opening price is usually the result of using all limit orders placed on the order book at 10:00hrs in order to maximize the number of shares exchanged.

while non-members have access only to the five best limit prices.

In reality, however, the actual order book could be deeper due to the presence of hidden orders which are normally used by investors willing to transact a large trade without experiencing the price impact which is normally produced by a block trade executed in an auction market.

A hidden order contains both a disclosed quantity (at least equal to 10 times the security's trading lot) and a hidden quantity which loses the time priority. The hidden part becomes visible only when it is executed, partially or fully. The Paris Bourse believes that these trades represent 20% to 40% of the disclosed quantity for active securities.

In addition, block trading has been facilitated in other ways. Out-of-CAC trades are allowed by the Paris Bourse.

Post-trade transparency has been reduced significantly over the last few years to protect the large *societes de bourse* when trading as a principal. The member codes of the parties involved in a transaction are suppressed when trade information is published. Trade reporting to the Bourse, including block reporting, is immediate. If two member firms are involved, both must file a declaration. Trade publication has also been delayed in the following way: (a) trades between 1 and 5 times the NBS have a two hour publication delay; and (b) trades exceeding 5 times the NBS are only published the following morning.

Principal trades in the top 53 stocks which exceed the Normal Block Size (the 'NBS' which is around 2.5% of average daily trading volume in the preceding three months) are not bound to satisfy orders in the central book and can be transacted within the weighted average CAC spread (the *fourchette moyenne ponderee* which, according to the Paris Bourse's rules, is 'based upon the average prices that are formed, after weighting of prices by number of shares, by the interaction of buy and sell orders that are posted on the central market') rather than the narrower *fourchette.*

The presence of hidden orders severely limit pre-trade transparency on the Paris Bourse while the post-trade transparency is additionally constrained by the two hour delay for trades in the 1 X NBS - 5 X NBS trade size bracket. It should be pointed out that publication of trades executed on SEAQ-I of similar sizes is immediate. For larger trades in the 6 X NMS - 75 X NMS trade size bracket executed on SEAQ-I there is a one hour delay while the Paris Bourse only publishes these trades in the following morning. Under these transparency regimes, the SEAQ-I has certainly achieved a higher post-trade transparency than the Paris Bourse.

7.3 Italian Exchange

Like the Paris Bourse, the IE utilises an automated order-driven and screen-based system with no designated market makers. From 08:00 hrs to 09:30 hrs (local time), the Exchange allows market participants to submit and cancel orders but no trades are executed. During this period, the system continuously calculates a theoretical price based on the orders which have been submitted. This price is made visible to the authorised market participants and its calculation is based on a set of four hierachical requirements with the second, third and fourth requirements being resorted to when there is more than one theoretical price.

The theoretical price is normally the one that maximizes the number of orders matched at the opening; if the same quantity is matched with different prices then the system calculates the theoretical price which minimizes the difference between the amount demanded and the amount supplied. If no single price is yet determined, the system will produce the price nearest to the 'reference price' that is a weighted average of the price at which the final 10% of the traded volume in the previous trading session was executed. Finally, if there are still two or more possible prices, the system will choose the highest price.

The validation of orders takes place between 09:30:00 hrs and 09:40:00 hrs. During these ten minutes, no new orders can be placed and existing orders cannot be adjusted or cancelled. From 09:40:00 hrs to 09:55:00 hrs, a call auction takes place for each security at the theoretical price established by the system. Following the opening call auction, trading resumes as a continuous auction from 10:00:00 hrs to 17:15:00 hrs.

The *societa' di intermediazione mobiliare* (SIM), most of which are dual-capacity intermediaries with the possibility of trading for their own account, have full access to the limit order book, including the identity of the traders submitting the orders, both before the continuous auction starts and during continuous trading. Data providers have access to the five best limit prices which are displayed on the screen. In this sense, the pre-trade transparency regime used by the Exchange is identical to the one used by the Paris Bourse.

Market orders are always executed after limit orders and the price priority and time priority rules are applied. The IE also allows hidden orders but it imposes no condition as to how much is to be disclosed and how much can remain hidden. This decision is entirely in the hands of the party submitting the order. The only obligation which existed during the period under consideration was for the disclosed segment of the order to be identified as forming part of a hidden order. This obligation has ceased on 1 January 1998.

The major difference between the IE and the Paris Bourse is how block trading is executed. All block trades, which are defined as trades larger than 20% of the average daily volume executed over the previous 3 months, are transacted off-the-floor with no obligation to satisfy the central limit order book. In addition, these block trades are not obliged to be executed within the weighted average spread and can be executed at any price. The block trade (and any other off-floor transaction) must be reported to the IE within 90 seconds of its execution with the trade price published separately from the other prices formed on the IE.

Trade publication is immediate for non-block trades and delayed by one hour in the case of block trades. In view of this publication regime, the IE can be said to possess a higher level of post-trade transparency compared to the Paris Bourse.

7.4 Deutsche Börse

Trading on the Deutsche Börse is fragmented between floor trading (with the Frankfurt Stock Exchange being the major player in terms of floor trading) and the Integriertes Börsenhandels- und Informations-System (IBIS), the electronic trading system which has now been replaced by the XETRA system. Launched in 1991, IBIS became a major player in German trading. In fact, some 60% of the volume transacted for the DAX 30 securities used to be transacted on IBIS (Pagano and Steil, 1995). IBIS had 234 bank and non-bank members at the end of 1994 (Oesterhelweg, Schmidt and Treske, 1996). There were three types of traders on IBIS: (a) the *Kursmaklers*, specialist brokers-dealers who could carry out proprietary trading; (b) the *Freimaklers,* independent brokers who could carry proprietary trading; and (c) bank traders, that could also do proprietary trading.

Trading took place between 08:30:00 hrs and 17:00:00 hrs and the system allowed dealers to quote indicative prices before trading starts. Entries were in round lots of 500 shares for the most active securities and 100 shares for the less active ones. Most of the entries were quotes, implying that most market participants act as market makers even if there is no obligation for them to provide two-way quotes throughout the trading day.

Up to six quotes on each side were allowed and, based on these entries, the system maintained an open book. The system, unlike the screen-based systems used by the Paris Bourse and the IE, was not able to automatically execute matched orders.A transaction is executed when the highest ranking bid or ask price displayed on the screen is electronically accepted by a market participant.

In principle, the transaction occured at the best bid or best ask. The system provides for trades bigger than the size of the best bid or ask to be executed by electronically accepting lower ranking bids or offers. Given this trading architecture, execution risk was minimised since there is limited uncertainty regarding the transaction price, the volume or the execution time.Trading was anonymous, with the identity of the parties to the trade becoming public at 15:30 hrs when the system provided confirmation of the transactions executed in the previous 24 hours.

The *Kursmakler* or *Freimakler* charged a transaction fee (called Courtage) in the case of a transaction which is makler-initiated. The fee amounted to 0.04 % of the market value in the case of DAX stocks and 0.08% in the case of non-DAX securities.

Appendix B: Pairing Methodology

Fama-French (1992) analysed all nonfinancial securities on NYSE, AMEX and NASDAQ over the period 1963-1990 and tried to find the variables that influence average returns.

They found that the univariate relation between Beta and average returns was weak, whereas the univariate relations between average returns and four variables - size (ME), Earnings-Price ratio (E/P), Book Equity to Market Equity ratio (BE/ME) and leverage - were strong. The findings from the multivariate tests which are of interest to this Chapter are two; namely, (a) Beta is flat and does not explain the cross-sectional average returns; and (b) combining together ME and the BE/ME absorbs the role of both leverage and E/P. Fama and French's results show that securities' risk is multidimensional, with one dimension being provided by ME while the other dimension is provided by the BE/ME ratio.

In addition, Davis *et al.* (1998), using securities listed on the NYSE between 1929 and 1997, reinforced the findings of Fama-French (1992) and ranked the proxies for risk with the value premium (BE/ME) being more robust and stronger than the size premium.

It could be argued that the Fama and French (1992) and the Davis *et al.* (1998) results are not necessarily relevant when European securities are considered. Such a sample contains cross-country observations and, hence, is bound to have cross-country and institutional differences of interest and these two factors could diminish the role of both ME and BE/ME as proxies for securities' risk. Hence, in terms of this study, the pervasive risk factors have to explain average returns not only within but also across different countries.

This suspicion finds some confirmation in the results obtained by Heston *et al.* (1998) when they tested the Capital Asset Pricing Model within the European contest. The authors study 2100 securities in 12 European countries, a mixture of stocks included in the Morgan Stanley Capital International (MSCI) and some additional small stocks, during the period 1980-1995. The major result from their work suggests that, contrary to the Fama-French evidence for US securities, both ME and Beta have distinct roles in explaining average returns in these European markets.

They show that for European securities, beta has no cross-sectional relationship with size and as such portfolios that vary independently in beta and size could be formed. The relation between average returns and Beta is based on intra-country and inter-country considerations. It is found that high Beta countries outperformed low Beta countries in addition to the expected relation between Beta and returns within countries. The size premium is largely due to intra-country differences in size.

Appendix C: Paired Securities

Table 61: **SEAQ securities paired with CAC securities**

Abbey National	First Choice	Racal Electronic
Airtours	FKI	Readicut International
Allied Domecq	General Electric	Reckitt & Colman
Allied Textile	GKN	RMC Group
Antofagasta Holdings	Great Portland Estates	Royal & Sun Alliance
ASDA Group	Guardian Royal Exc.	Royal Bank of Scotland
Assd. British Foods	Hambros	Royal Doulton
Barclays Bank	Hanson	Rutland Trust
Berkeley	HSBC	Safeway
Blue Circle Industries	ICI	Schroders
BPB	Independent Insurance Gr.	Scottish Media
British Petroleum	Kwik-Fit	Shell Transport
British Steel	Ladbroke Group	Smith & Nephew
BTP	Laporte	Smith Industries
BTR	Logica	SmithKline Beecham
Burmah Castrol	Manganese Bronze	South Stf. Water
Caledonia Investments	Marks & Spencer	Standard Chartered
Capita Group	Mayflower	Staveley Industries
Carlisle	Metalrax Group	Tesco
Carlton Communications	Misys	Thames Water
CGU	National Express	TI Group
Cobham	Next	Trafford Park
Courtalds Textile	Pearson	Unilever (UK)
Daejan Holdings	Peel	Verity Group
Derwent Valley	Pentland Group	Whitbread
Dewhirst Group	Pilkington	Wolsley
Dolphin Pack	Pillar Properties	WPP Group
EIS	Powell Duffryn	Zeneca
Electrocomponents	Provident Financial	
Field Group	Prudential Corporation	

The Table presents the securities listed on the London Stock Exchange, and whose trading takes place on SEAQ in the period under consideration, which are paired with securities listed on the Paris Bourse.

Table 62: **CAC securities paired with SEAQ securities**

Accor	Eridania Beghin Say	Pinault Printemps
AGF	Essilor	Poliet
Air Liquide	Eurodisney	Primagaz
Alcatel Asthom	Eurotunnel	Promodes
AXA	Finextel	Rexel
Bancaire	GAN	Rhone Poulenc "A"
Bertrand Faure	Groupe Andre	Rochette
BIC	Groupe Zannier	Saint Gobain
BIS	GTM	Sanofi
BNP	Guilbert	Schneider
Bouygues	Havas	Scor
Canal Plus	Havas Advertising	Sefimeg
Cap Gemini	Imetal	Sidel
Carrefour	Immeubles de France	Simco
Casino Guichard	Immob. Hoteliere	Sligos
Castorama Dubois	Lafarge	Societe Genereale
CCF	Lagardere Groupe	Sodexho Alliance
Cerus	Lapeyre	Sophia
Cetelem	Lectra Systems	Suez (Compagnie)
CGIP	Legrand	Suez Lyonnaise des Eaux
Chargeurs	Legris Industries	Sylea
Club Mediterranee	LVMH	Synthelabo
Coflexip	Marine Wendel	Technip
CFF	Metaleurop	TF1
Credit Locale France	Michelin	Total
Danone	Moulinex	UAP
DMC	Nord-Est	Usinor
Dynaction	Paribas	Vallourec
Eaux (Gle Eaux)	Pechiney	
Elf Aquitaine	Pechiney International	

The Table presents the securities listed on the Paris Bourse, and whose trading takes place on CAC in the period under consideration, which were paired with securities listed on the London Stock Exchange.

Table 63: **IBIS and SEAQ securities paired**

PANEL A. IBIS SECURITIES

IBIS FIRMS PAIRED WITH SEAQ FIRMS	IBIS FIRMS PAIRED WITH CAC FIRMS
Allianz	Allianz
BASF	BASF
BHW Bank	Bayer
Bayerische Vereisbank	BHW Bank
Commerzbank	Bayerische Vereisbank
Continental	Commerzbank
Degussa	Continental
Deutsche Bank	Daimler Benz
Deutsche Lufthansa	Degussa
Dresdner Bank	Deutsche Bank
Henkel	Dresdner Bank
Hoechst	Henkel
Karstadt	Hoechst
Kaufhof	Karstadt
Linde	Kaufhof
MAN	Linde
Mannesmann	MAN
Metallgesellschaft	Metallgesellschaft
Preussag	SAP
SAP	Schering
Schering	Siemens
Siemens	Thyssen
Thyssen	Volkswagen
VEBA	
VIAG	

PANEL B. SEAQ FIRMS PAIRED WITH IBIS FIRMS

Barclays Bank	Courtalds	Rentokil
BBA Group	Dixons	Rolls-Royce
BOC Group	General Electric	Royal Bank of Scotland
Boots	GKN	Scottish Power
British Aerospace	HSBC	Standard Chartered
British Airways	ICI	Tomkins
British Steel	National Power	Zeneca
BTR	Nat. West. Bank	
Cookson Group	Prudential	

Appendix D: Permutation Tests

This Appendix provides the background for the Fisher permutation tests and the Achieved Significance Level technique. It draws heavily from Chapter 15 of *An Introduction to the Boostrap* by Efron and Tibshirani (1993).

The main application of permutation tests is to the two-sample problem. In such as set-up there are two independent random samples $z = (z_1, z_2, ..., z_n)$ and $y = (y_1, y_2, ..., y_n)$ drawn from different probability distributions F and G. Having observed the values for z and y, the null hypothesis of no difference between F and G is tested. If the null hypothesis is true, then there should be no difference between the probabilistic behaviour of random variable z or random variable y.

The Achieved Significance Level (the "ASL") of a test generates the probability of observing at least a that large a value when the null hypothesis is true:

$$ASL = PROB_{Ho}\left\{\widehat{\theta^*} \geq \widehat{\theta}\right\}$$

The smaller the value of ASL, the stronger the evidence against the null hypothesis. We first fix the quantity $\widehat{\theta}$ at the observed value while the random variable $\widehat{\theta^*}$ is assumed to have the null hypothesis distribution (i.e. the distribution of $\widehat{\theta}$ if the null hypothesis were true).

The hypothesis test of the null hypothesis consists of computing ASL, then we have to take a view if it is acceptable (i.e. too small) according to established statistical thresholds. The main practical difficulty with this type of hypothesis test is given by the methodologies needed to calculate the ASL.

We have written $PROB_{Ho}\left\{\widehat{\theta^*} \geq \widehat{\theta}\right\}$ as if the null hypothesis specifies a single distribution, from which we can calculate the probability of $\widehat{\theta^*} \geq \widehat{\theta}$.

In many cases, we do not have one distribution for the null hypothesis but rather a family of possible null hypothesis distributions (in the normal case, the null hypothesis family includes all normal distributions with expectation zero). In order to actually calculate the ASL, we had to either approximate the null hypothesis variance. As an alternative, one can use Student's method which has the benefit of generating a simple solution for the problem but its application is confined only to the normal situation.

Fisher's permutation test is one established way to calculate the ASL for the general null hypothesis $F = G$. The description of such a permutation test is easy to provide. Let us assume that we have two sample of observations, where one sample consists of traders trading on Market A and the other sample consists of traders participating in Market B and we would like to test whether spreads are different across these two markets. If the null hypothesis is correct, any level of spread in Market A should be equal to that in Market B, and hence the spreads for any of the markets could have come equally well from either of these two markets being considered. So we combine all the $m + n$ observations from both markets together, then take a sample of size m without replacement to represent the first group of traders trading in Market A. The remaining n observations constitute the second group of traders on Market B. The difference between group means is calculated and then repeat this process a large number of times. If the original difference in sample means falls outside the middle 95% of the distribution of differences, the two-sided permutation test rejects the null hypothesis at a 5% level.

Following Efron and Tibshirani (1993), the permutation steps are undertaken in the following fashion:

"Step 1. Choose B independent vectors $g^*(1), g^*(2), ..., g^*(B)$, each consisting of n z's and m y's and each being randomly selected from the set of all $\binom{N}{n}$ possible such vectors.

Step 2. Evaluate the permutation replication of $\widehat{\theta}$ corresponding to each permutation vector,

$$\widehat{\theta}^*(b) = S(g^*(b), v)$$

Step 3. Approximate the ASL_{perm} by the following:

$$\widehat{ASL_{perm}} = \# \left\{ \widehat{\theta}^*(b) \geq \widehat{\theta} \right\} / B$$

The permutation ASL is close to the t-test ASL, even though there are no normality assumptions underlining ASL_{perm}." (Efron and Tibshirani, 1993)

An important question that must be addressed is the number of permutation replications we require in order to achieve a suitable level of appropriate testing. The following part will go through this central question by providing some background concepts that are useful in providing the necessary insight in this issue.

Let $A = ASL_{perm}$ and $\widehat{A} = \widehat{ASL_{perm}}$. Then $B \cdot \widehat{A}$ equals the number of $\widehat{\theta}^*(b)$ values exceeding the observed value $\widehat{\theta}$, with $E(\widehat{A}) = A$ and $var(\widehat{A}) = \frac{A(1-A)}{B}$.

The coefficient of variation is given by

$$cv_B(\widehat{A}) = \left[\frac{(1-A)/A}{B} \right]^{1/2}$$

Suppose we require $cv_B(\widehat{A})$ to be .10, meaning that Monte Carlo simulations should not generate an error that affect the estimate of ASL_{perm} by more than 10%. This means that for this level of significance, there is a need for something like 900 permutations. The number of permutations goes to 1901 and 3894 in case we require $cv_B(\widehat{A})$ to be .05 and .025 respectively.

Efron and Tibshirani (1993) provide more a whole range of permutations needed to obtain conventional confidence levels.

One of the most important advantages in using the permutation testing technology is the accuracy levels it achieves. If the null hypothesis $F = G$ is true, there is almost exactly a 5% chance that ASL_{perm} will be less than 0.5. In general,

$$PROB_{Ho}\{ASL_{perm} < \alpha\} = \alpha$$

for any value of α between 0 and 1.

Appendix E: Estimating the Adverse Selection Component

In this Appendix, we discuss in some detail our estimation procedures for microstructure-based measures of information asymmetry. The theoretical models reviewed in this Appendix are made operational in Chapter 3 through a trade-by-trade analysis. It is pertinent to ask whether this approach is likely to impact the results obtained from the methodology employed. George, Kaul, and Nimalendran (1991) indicate that the differencing interval should not affect estimates of the order-processing cost and adverse selection components of the quoted spread. They use daily closing price and quotes to calculate autocovariances of quote and transaction returns. GKN suggest that the "use of high frequency data is more appropriate" because of potential small-sample bias. In Chapter 3 we make use of intraday quote and transaction returns to calculate autocovariances and estimate these models using daily time-series observations.

11.0.1 Method 1

11.0.2 George, Kaul, and Nimalendran (1991)

The George, Kaul, and Nimalendran ("GKN") methodology decomposes the *quoted* spread into (a) the adverse selection component, and (b) the order processing component. The inventory cost component is assumed to be insignificant and hence not modelled. The methodology proposed by GKN is based on an estimator that uses the time series properties of the difference between the bid price and the transaction price to eliminate this bias. The GKN technique assumes a probability of 0.5 of a trade reversal.

In their model, GKN provide evidence that positively autocorrelated time-varying expected returns result in substantial biases in the estimation of the spread and the components making up the spread and their objective is to correct these biases. GKN argue that covariance-based spread estimators that ignore the fact that expected returns exhibit positive autocorrelation are expected to be biased downwards.

In the first place, transaction prices can be represented as follows:

$$P_t = M_t + \pi(s_q/2)Q_t$$

$$M_t = E_t + M_{t-1} + (1-\pi)(s_q/2)Q_t + U_t$$

where P_t is the observed price of transaction t, Q_t is the unobservable indicator for the bid-ask classification, M_t is the unobservable true price that reflects all publicly available information immediately following transaction t, E_t is the unobservable expected return for the period between transaction $t-1$ and t, U_t is the unobservable innovation in true prices due to the arrival of public information between transaction $t-1$ and t, s_q is the quoted spread of the market maker, π is the unobservable proportion of the quoted spread due to order processing costs, and $(1-\pi)$ is the unobservable proprtion of the quoted spread due to adverse selection.

The approach used measures the spread by considering the serial covariance of the difference between transaction returns and returns calculated using bid prices leading to a metric which, according to GKN, does not suffer from positive autocorrelation due to time-varying expected returns.

The GKN spread component corrects the downward bias in estimated order processing costs which are induced by time variation in expected returns. The difference between trade-by-trade return, $R_{T,i}$ and the subsequent quote (bid) return $R_{B,i}$ is used to construct a spread measure

$$\widehat{S}_t = 2\sqrt{-Cov(RD_i, RD_{i-1})}$$

11.0.3 Method 2

11.0.4 Booth, Lin and Sanger (1995)

Booth, Lin and Sanger ("BLS") develop a regression method to estimate the proportion of the *effective* spread that can be attributed to adverse selection. BLS assume that the specialist's inventory cost is zero.

The intuition behind the model is that changes in transaction prices will reflect order processing costs and the bid-ask bounce, while quote revisions will reflect the adverse selection component of the spread. This methodology allows for a persistence parameter that measures the probability of trade reversals.

In this model, the probability of order persistence is δ, and the probability of order reversal is $1-\delta$. That is, starting with a market sell order, that is executed at the market maker's bid price B_t at time t, we have that the probability of next trade occurring at the bid B_{t+1} is δ and $1-\delta$ that it will occur at the market maker's ask A_{t+1}. With this structure, the market maker's expected gross profit at time $t+1$ is

$$\delta(B_{t+1}-B_t)+(1-\delta)(A_{t+1}-B_t)=E_t(P_{t+1})-P_t$$

where $E_t(P_{t+1})=\delta B_{t+1}+(1-\delta)A_{t+1}$ is the expected market price conditional on the trade at time t.

Quote revisions are assumed to take the following form:

$$B_{t+1}=B_t+\lambda z_t$$

and

$$A_{t+1}=A_t+\lambda z_t$$

where z_t is the signed half effective spread and $1>\lambda>0$ is the component of the spread due to adverse selection.

Then the effective market maker profit, given a sell order, is the following:

$$E_t(P_{t+1}) - P_t = -(1 - \lambda - \theta)z_t$$

where $\theta = 2\delta - 1$ with $\delta = 0.5$ meaning that order types (buys or sells) arrive randomly on the market.

Given the equations above, the adverse selection and order persistence parameters are estimated from the following equations:

$$M_{t+1} - M_t = \lambda Z_t + \varepsilon_{t+1}$$

$$Z_{t+1} = \theta Z_t + \eta_{t+1}$$

where P_t is the transaction price at time t, M_t is the quote midpoint $Z_t = P_t - M_t$, $\delta = (\theta + 1)/2$ is the order persistence parameter and ε_{t+1} and η_{t+1} are random error terms.

11.0.5 Method 3

11.0.6 Madhavan, Richardson and Roomans (1997)

Madhavan, Richardson and Roomans ("MRR") develop a model that aims at understanding the effects generated by information flows on prices. As such, their model is related to other technologies which focus on the predictability of (very) short run returns, while controlling fully for market microstructure effects. The prices changes are assumed to be a linear function of contemporaneous and past order flows arriving on the market.

The MRR model is based on a methodology that relates price changes to the contemporaneous and past order flow. The MRR model allows for the estimated values to be affected by the surprise in the trade flow to the Exchange. Their model assumes that the updates in beliefs come from two sources: "(i) new public information announcements which are not associated with trading, and (ii) order flow, which may provide a noisy signal about future asset values" (Madhavan, Richardson and Roomans, 1997).In addition, it provides an estimate of the conditional probability of a trade occurring within the quoted spread.

In the model, p_t denotes the transaction price at time t while X_t is the trade indicator to determine trade initiation (with the familiar $X_t = +1$ for a buy-initiated trade and -1 for a seller-initiated trade. Let γ to denote the unconditional probability that a transaction takes place within the quoted spread. Allowing ν_t to represent the innovations in beliefs between successive trades (updates generated by new public information) and assuming that market makers want to defend themselves from traders who possess superior information, we would have a situation where a buy (sell) order will generate an upward (downward) revision in the market's beliefs. The change in beliefs, arising from the order flow hitting the market, can be denoted as $\lambda(X_t - E[x_t \mid x_{t-1}])$, where the component $(X_t - E[x_t \mid x_{t-1}])$ is the unexpected or unsystematic part of the order flow. In such a set-up, $\lambda \geq 0$ is the amount of adverse selection in the market.

Let φ_t be the post-trade (expected) value conditional upon (a) public information arriving on the market, and (b) the trade initiation. The updates in beliefs occurs in the following fashion:

$$\varphi_t = \varphi_{t-1} + \lambda(X_t - E[x_t \mid x_{t-1}]) + \varepsilon_t$$

Letting p_t^a and p_t^b as the bid price being the pre-trade ask quote at time t and allowing $\phi \geq 0$ as a compensation to market makers for incurring transaction costs, inventory costs, risk bearing, etc., we have an ask price of:

$$p_t^a = \varphi_{t-1} + \lambda(X_t - E[x_t \mid x_{t-1}]) + \phi + \varepsilon_t$$

and a bid price of:

$$p_t^b = \varphi_{t-1} - \lambda(X_t - E[x_t \mid x_{t-1}]) - \phi + \varepsilon_t$$

The transaction price could then be expressed as:

$$p_t = \varphi_t + \phi X_t + \xi_t$$

where ξ_t is an independent and identically distributed random variable with mean zero.

Using the equations above MRR get:

$$p_t^b = \varphi_{t-1} + \lambda(X_t - E[x_t \mid x_{t-1}]) - \phi X_t + \varepsilon_t + \xi_t$$

A general Markov process is assumed for the trade initiation variable.

In addition, we have:

$$\Delta p_t = (\phi + \lambda)X_t - (\phi + \rho\lambda)X_{t-1} + \varepsilon_t$$

where X_t is the trade indicator variable, ϕ is the order processing component, λ is the adverse selection component, ρ is the autocorrelation of the order flow, and γ is the probability a transaction takes place inside the spread.

The vector of price and quote parameters $(\phi, \lambda, \rho, \gamma)$ is estimated using a GMM methodology to decide the parameter values for the above vector that minimise a criterion function based on the moment conditions.

The following moments implied by the model exactly identify the vector $(\phi, \lambda, \rho, \gamma)$ and a constant drift term α:

$$E\begin{pmatrix} Q_t Q_{t-1} - Q_t^2 \rho \\ |Q_t| - (1-\gamma) \\ u_t - \alpha \\ (u_t - \alpha)Q_t \\ (u_t - \alpha)Q_{t-1} \end{pmatrix} = 0$$

The first equation is the definition of the autocorrelation in trade initiation. The second equation defines the crossing probability and the third equation defines the drift term.

The estimated implied bid-ask spread is equal to $2(\widehat{\phi}+\widehat{\lambda})$ and the proportion of the implied spread due to asymmetric information is equal to $\left(\frac{\widehat{\lambda}}{\widehat{\phi}+\widehat{\lambda}}\right)$.

11.0.7 Method 4

11.0.8 Huang and Stoll (1997)

Huang and Stoll (1997) develop a trade indicator model that yields a two-way decomposition of the spread. The Huang and Stoll (1997) model encompasses a number of other models, namely the GKN and MRR methodologies. They further extend this basic model to allow for serial correlation in trade flows. This extended model yields separate inventory and adverse selection components.

In this model, the unobserved fundamental value of the security, V_t, is modelled as:

$$V_t = V_{t-1} + \alpha\frac{S}{2}Q_{t-1} + \varepsilon_t$$

where Q_t is the trade indicator variable, α is the component of the half-spread directly attributable to adverse selection and ε_t is the public information shock.

In this model, the fundamental value is decomposed into two parts: (a) the private information observed from the last trade, $\alpha\frac{S}{2}Q_{t-1}$, and (b) the public information shock, ε_t.

As usual, the fundamental value is unobserved and the mid price is taken to be a proxy for such a value. The model assumes that, under the condition that past trades are of a normal size of one, the mid price is related to the fundamental value in the following way:

$$M_t = V_t + \beta \frac{S}{2} \sum_{i=1}^{t-1} Q_i$$

where M_t is the mid price, β is the component due to inventory costs $\sum_{i=1}^{t-1} Q_i$ and is the total inventory from the market open till the last trade.

Hence we have

$$\Delta M_t = (\alpha + \beta) \frac{S}{2} Q_{t-1} + \varepsilon_t$$

The model assumes the constant spread assumption in the following way:

$$P_t = M_t + \frac{S}{2} Q_t + \eta_t$$

with the error term η_t capturing the deviation of the observed half spread from the constant half spread.

Given the relationships above, the basic regression model is:

$$\Delta P_t = \frac{S}{2}(Q_t - Q_{t-1}) + \lambda \frac{S}{2} Q_{t-1} + \varepsilon_t$$

where S is the traded spread and $\lambda = (\alpha + \beta)$ is the sum of the adverse selection (α) and inventory holding (β) components of the half-spread, $(1-\lambda)$ is the proportion attributable to order processing. The model is estimated using GMM.

The approach then requires estimating the following two equations simultaneously:

$$\Delta M_t = (\alpha + \beta) \frac{S_{t-1}}{2} Q_{t-1} - \alpha(1 - 2\pi) \frac{S_{t-2}}{2} Q_{t-2} + \varepsilon_t$$

$$E(Q_{t-1} \mid Q_{t-2}) = (1 - 2\pi) Q_{t-2}$$

where π is the probability of a trade reversal.

Appendix F: LSE Data

The data was provided by the London Stock Exchange's "Transaction Data Service". The data set, covering the period from June 1998 to October 1998 contains trades data (for all trades taking place on both the order book and on the dealership system) together with the quotes data containing the best ask and best bid prices obtained from the SETS system. Moreover, order history data (date and time when the order is submitted, order type, quantity and limit prices) for the orders submitted on SETS is also provided. Although the entire order book, at each point in time, is not provided by the LSE, there is sufficient information to construct the book through an algorithm that takes into consideration the date and time when an order was submitted and when it was executed. The algorithm was kindly provided by Stephen Wells.

Trades data from the SETS system contains the transaction date, transaction time (to the nearest second), the trade price, trade size and trade direction. In addition, there is also a code for the trade counterparties (whether member firm or not).[17] However, there is no information as to the final identity of the counterparty.

Trades data from the dealership system contains the same information as that extracted from the order book with trades time-stamped to the nearest second. The rules require that these "non order book trades" are reported within three minutes of the trade being executed, the only exception for order book securities are Worked Principal Agreements (WPA). The trade times for these trades come from the brokers systems. In most cases they are reported automatically from trading systems.

[17]The LSE gives each counterparty a code for each particular security for each month with codes changing every month.

The quotes data provide the best ask and best bid quotes on the order book (there is no quotes data from the dealership system) time-stamped to the nearest second.

The trades data identifies the trader whose order has been executed (on both trading systems) as either a "Principal" (understood as a member firm registered with the LSE) or "Customer" (understood as a public trader) depending on the trader's status. In terms of trade reporting, the Regulatory Guide states that when there are trades "(a) between a member firm acting as principal and a member firm acting as agent, the principal shall trade report; (b) between two member firms both acting as principals, the seller shall trade report; (c) between two member firms both acting as agents, the seller shall trade report" (London Stock Exchange, 1999).

The distinction between "Principal to Principal" trades and "Customer" trades (where there is a "Customer" at least on one side of the trade) is not difficult for trades on the dealership system. This distinction, however, becomes complex when trades on the order book are considered. This difficulty is due to the choice provided to traders when submitting orders to the order book; traders can either submit orders directly to SETS or route them to an LSE member firm that will then submit the customer's order to the order book.

In the latter case, the resulting trade through the order book will, possibly, be registered with a flag of "P", meaning a trade from a member firm. Hence, there is no formal way of distinguishing between trades logged in with a flag of "P" in which the member firm was acting as a "Principal" and those trades in which the member firm was acting on behalf of a "Customer".

In our dataset, about 15.8% of all trades on the order book had a "Customer" at least on one side of the trade. The remaining trades where formally logged in as "Principal to Principal" trades. Anecdotal evidence, gathered from the LSE, indicates that a very high proportion of these trades are actually coming from "Customers" that place their orders with member firms. The LSE's "Secondary Market Fact Sheet", appears to provide additional evidence consistent with this view.

For the sake of clarity and results' robustness, Variance Ratios presented in Chapter 5 have been computed using two different methodologies: (a) one in which all trades on SETS up to 2 NMS are used; and (b) another where only SETS trades formally registered as originating from "Customers" are used.