Issues in pricing, liquidity, information efficiency, asymmetric information and trading sysyems

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ISSUES IN ASSET PRICING, LIQUIDITY, INFORMATIONAL EFFICIENCY, ASYMMETRIC INFORMATION AND TRADING SYSTEMS

A thesis submitted for the degree of Doctor of Philosophy

By

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ABSTRACT

Market microstructure is a relatively new area in finance which emerged as a result of inconsistency between actual and expected prices due to a variety of frictions (mainly trading frictions and asymmetric information) and the realisation that the trading process through which investors' demand is ultimately translated into orders and volumes is of greater importance in price formation than it was originally thought. Despite increased research in the area of liquidity, asset pricing, asymmetric information and trading systems, all subfields in the area of market microstructure, there are a number of questions that remain unanswered such as the effect of different trading systems on systematic liquidity, informational efficiency or components of the spread. This thesis aims at shedding light on those questions by providing a detailed empirical investigation of the effect of trading systems on systematic liquidity, pricing, informational efficiency, volatility and bid-ask spread decomposition mainly with respect to the UK market (FTSE100 and FTSE250) and to a less extent with respect to the Greek market. Those two markets are at different levels of development/sophistication and are negatively correlated.

The aims of this thesis are outlined in chapter one with chapter two providing a detailed review of the theoretical literature relevant to this study. Chapter three is the first empirical chapter and tests for the presence of a common underlying liquidity factor (systematic liquidity) and its effect on pricing for FTSE100 and FTSE250 stocks under different trading regimes. Results show the presence of commonality for FTSE100 and FTSE250 stocks although commonality is weaker for FTSE250 stocks and its role on pricing is reduced. Chapter four investigates the same issues with respect to the Greek market and we find that commonality appears to be stronger in some periods while it is reduced to zero for other periods.

Chapter five focuses on the effect that changes in the trading systems can have on informational efficiency and volatility primarily with respect to FTSE100 and FTSE250. Different methodologies and data are employed for this purpose and produce similar results. We find that order driven markets are more responsive to incoming information when compared to quote driven markets. Volatility has a greater impact on the spread when the market is quote driven. We also examined if automated trading increased informational efficiency with respect to the Greek market. The results obtained indicated that the effect of automation was positive.

Finally the last chapter focused on the effect of different trading systems on the components of the spread and their determinants. Our main finding is that the asymmetric component of the spread is higher under a quote driven market. Also stock volatility appears to affect the asymmetric component to a greater extent when the market is quote driven. We believe that the main justification for those findings is affirmative quotation.

CHAPTER ONE: INTRODUCTION

Contemporary empirical work in finance has concentrated on understanding financial markets and providing explanations for the observed behaviour. The most important concept in the finance literature is that of the efficient market hypothesis (EMH). The efficient market hypothesis postulates that asset prices reflect all available information quickly and accurately. The last two decades a new strand has developed in the finance literature, which is known as market microstructure. Market microstructure studies the process by which investors' demands are translated into prices and volumes. The central idea, which characterises this area of finance, is that asset prices do not necessarily reflect full information expectations of value because of a variety of frictions such as departures from symmetric information, different trading protocols etc. This study will concentrate on examining how those frictions affect full information expectations of value.

Market microstructure literature has expanded tremendously the last few years into a versatile body of knowledge however it can be grouped in three generic areas namely:

- Price formation and price discovery which looks into the determinants of trading costs and the process by which prices come to impound information over time
- Market structure and design issues which looks into how different market rules affect trading, liquidity and therefore pricing and

- Information and disclosure which focuses on the extent to which investors have access on information regarding the trading process.

This study will concentrate on the first two areas of market microstructure and examine how different trading regimes/protocols can affect liquidity with special reference to systematic liquidity, pricing, the speed at which new information is incorporated into prices and the different components of the bid-ask spread (asymmetric and order processing component).

All theoretical work in the area concentrates on the market maker that assumes a prominent role given the inability of traders to engage in transactions between themselves. This inability of traders to transact by themselves due to different time preferences was originally introduced by Demsetz (1968) who argued that demand does not necessarily equal supply at each time period (t), therefore there cannot be a single market-clearing price, a fact that necessitates the existence of market makers.

Market makers aim at providing immediacy at a cost dictated by inventory risks and asymmetric information. Two different 'schools of thought' have emerged as a result of the reasons for the existence of costs in providing immediacy. The first school postulates that immediacy costs arise as a result of inventory risks present due to lack of diversification. Stoll (1978), Amihud & Mendelson (1980), Ho & Stoll (1981) and O'Hara & Oldfield (1986), main advocates of this particular school of thought postulate that market makers have a desired inventory level and there are certain costs involved when they are forced to deviate from this optimal level as a result of providing immediacy. The second school represented mainly by Bagehot (1971), Glosten & Milgrom (1985), Kyle (1985) and Easley & O'Hara (1992) view the existence of costs in providing immediacy as a result of asymmetric information and the inability of market makers to distinguish between informed and uninformed traders. To cover for costs and avoid losing money consistently, market makers buy stocks at a lower price than they are willing to sell them, hence the spread. However on average market makers lose money when trading with the informed and make money when trading with the uninformed.

All the work presented above is clearly theoretical. Empirical work with reference to price formation and liquidity has concentrated on examining the relation of liquidity and asset returns. Amihud & Mendelson (1986) document the existence of a positive relation between liquidity and returns during 1961-1980 proxying liquidity as quoted bid-ask spread. Eleswarapu & Reinganum (1993) looking into a similar time period (1961-1990) proxying liquidity as quoted bid-ask spread find that the positive relation documented in A&M is restricted only in January. Brennan & Subrahmanyam (1996) take an innovative approach and decompose transaction costs into variable and fixed components and find only weak evidence in favour of A&M (1986). Datar et al.(1998) look into the same relation proxying liquidity as turnover rate(number of shares/number of shares outstanding) find positive evidence. Generally speaking there are a number of studies looking into the relation of liquidity and returns proxied in different ways but none of those looks into common factors in liquidity (commonality) and returns. All the studies mentioned above aim at providing an overview of the literature in the area of market microstructure & asset pricing and highlight the absence of research in commonality and returns, which is one of the areas this study concentrates on. It is well known that each security has its own liquidity dictated by a number of factors such as order flow, number of trades, trading volume, returns, volatility etc. The nature of the factors identified above is clearly idiosyncratic and we would expect each security to have its own liquidity. Alternatively we would expect to find correlation in liquidity across securities if there is a common component to the cost of providing liquidity or if securities are substitutes. In this study we wish to test the prospect that liquidity has common underlying determinants, which are not captured by the factors mentioned above and the extent to which this common factor affect stock returns over time.

Three papers have appeared up to the moment looking into common underlying determinants such as returns, returns volatility, trading volume, and other macroeconomic factors for the US market namely i) Chordia et al (2000), ii) Huberman & Halka (2001) and iii) Hasbrouck & Seppi (2001). The first two papers come up with strong evidence supporting the existence of common underlying factors yet unidentified while the third finds only weak evidence of common underlying factors. Apart for the controversy mentioned above, the literature suffers from gaps as well. For example although there is some evidence regarding common underlying factors with reference to the US market, there is no other single study for developed or developing countries. This provides us with an excellent opportunity to investigate the existence of this phenomenon in other markets.

With reference to the second generic area of market microstructure namely market structure and design, most empirical literature has concentrated on i) comparing execution costs between continuous auctions and dealerships (Huang & Stoll, 1996; Lee, 1993; Pagano & Roell, 1990; Stoll, 1993) finding higher execution costs in dealer markets when compared to continuous trading markets even though Affleck-Graves, Hedge & Miller (1994) find that quoted spreads are the same for a matched sample of NASDAQ and NYSE/ASE stocks in 1985 ii) trading mechanisms and price behaviour emphasizing the introduction of call auctions within continuous trading mechanisms (Ko, Lee & Chung, 1995; Amihud & Mendelson, 1987,1989,1991) with special reference to the Korean, Japanese and US stock market respectively iii) the value effects gained by changing from single call auctions to continuous trading (Amihud, Mendelson & Lauterbach, 1997) iv) the effects of full automation on trading (Naidu & Rozeff, 1994) with special reference to the Singapore Stock Exchange and v) a comparison between dealerships and continuous action with respect to informational efficiency (Greene & Watts, 1996).

Summarizing the empirical results, one could say that dealer markets appear to have higher execution costs in comparison to continuous markets although there is no unanimity. However little can be said about how informational efficiency/price discovery changes under the two primary exchanging regimes: dealerships and order driven markets. There is only a limited number of studies looking into informational efficiency under different trading regimes. The first study that investigates the value effects from changes in market microstructure and explicitly looks into price discovery and assesses the degree of informational efficiency achieved each time is that of Amihud, Mendelson & Lauterbach (1997). However the above study is confined to changes from single call auctions to continuous trading mechanisms with reference to the Tel Aviv stock Exchange. Stocks under the call auction regime used to trade once a day but after the introduction of continuous trading, trading frequency increased tremendously. As it was expected changes in informational efficiency/price discovery and liquidity were dramatic. Based on their approach and their findings we thought that it would be a wonderful idea to examine how the transition from one trading system to another (e.g. from quote-driven to order-driven or from public outcry to automated trading) affected the degree of informational efficiency. The second study (Greene & Watts, 1996) examines market response to quarterly earnings announcements made during trading and non-trading hours on the NYSE and the NASDAQ. They find that NASDAQ is more efficient in impounding information into prices. Given the limited number of studies on market design/trading protocols and informational efficiency we think that it is worth examining this issue with reference to a highly developed (UK) and less developed market (Greek market). Naidu & Rozeff (1994) look into the effects of automation on volume, volatility and liquidity, which is relevant to our study with reference to the Athens Stock Exchange however, they do not investigate the effect of automation on informational efficiency, which is exactly the area we concentrate on. Despite this, Naidu & Roseff (1994) motivated us to look into smaller markets such as the Athens Stock Exchange which introduced full automation of the trading process. In addition we are not aware of any studies concentrating on spread sensitivity to volatility under a dealership and an order driven market. In perspective, we explore price discovery/informational efficiency and spread sensitivity to volatility between competing trading mechanisms: dealerships, order driven markets and hybrid markets for FTSE 100 & FTSE250 stocks. We also examine the effect of computerisation on informational efficiency for the Greek market.

The last chapter of the thesis is concerned with examining the components of the bid-ask spread under different trading protocols. Stoll (1989), George, Kaul & Nimaledran (1991) and Kim & Ogden (1996) have concentrated on estimating the components of the bid-ask spread employing different techniques.

The London Stock exchange has gone through a number of changes the last few years as far the trading regime is concerned. In particular the

London stock exchange has changed from a quote driven market to an order driven market. The main attributes of quote driven markets are the market makers who are obliged to post bid and ask quotes along with the number of shares (depth) they are willing to trade at each price (affirmative quotation). In an order driven market makers are not obliged to post bid-ask quotes therefore the whole trading process depends on limit-order submission. As a consequence of the changes in the trading process described above, we conjecture that the different cost components of the spread and in particular the asymmetric information cost component must have been affected. We believe that this is an exploitable opportunity to expand the literature and examine the components of the bid-ask spread under different trading regimes given that all previous work in this area has merely concentrated on decomposing the bid-ask spread to its components. We also examine how each of the components of the bid-ask spread is affected by volatility, trading volume etc under different trading regimes.

To summarise, this thesis aims i) to investigate the existence of common underlying factors in liquidity and how those factors affect returns, ii) explore informational efficiency and spread sensitivity to volatility between different trading regimes and iii) investigate how the components of the bid-ask spread change between different trading regimes and how volatility, trading volume etc affects those components. In the process of doing so, the following questions are also raised:

- Is commonality in liquidity present in other markets as well or does it constitute a stylized fact pertinent to the US market only?
- Is commonality priced?
- How do changes in the trading regime affect the relationship between commonality and expected returns?
- How does the degree of informational efficiency and spread sensitivity to volatility change in response to different trading regimes/closing price formation algorithms?
- How are the components of the spread affected as a result of changes in the trading regime?

The main focus of the thesis is the UK market and in particular FTSE100 and FTSE250 socks. We employ those stocks for our research because these are the only stocks for which the trading protocol changed. In addition those stocks are frequently traded which helped us avoid problems of non-synchronous/thin trading. We undertake the same research for the Greek market, a newly developed market which is quite different from the UK market in terms of sophistication even though data restrictions do not allow us to achieve this to the extent we would like to. Therefore direct comparisons are not always possible.

The thesis contributes to the literature in several ways; the main contributions could be presented as follows:

- It shows that systematic liquidity is not pertinent only to the US market but also other markets. It also shows for the first time that commonality in liquidity does affect excess returns and that the trading regime plays an important role on the extent to which commonality is priced. In particular we find that the effect of commonality on excess returns appears to be considerably reduced after the change from quote-driven to order-driven trading. Results obtained for FTSE250 show that commonality is not equally strong while results for the Greek market show that commonality per se is quite reduced.

- It shows that the extent to which new information is incorporated into prices is affected by the trading regime using different methodologies. In particular we find that order driven markets respond faster to information in comparison to dealerships (FTSE100). With reference to the Greek market we find that the computerization of the trading process has increased informational efficiency.
- It shows that spread sensitivity to volatility depends on the trading regime and provides explanations for it. We find that the spread is more sensitive to volatility in a dealership than in an order driven market. Spread sensitivity to volatility remains the same between quote driven and hybrid regimes.
- It estimates the components of the bid ask spread under different trading regimes enriching previous work in the area and provides explanation for the changes observed for the very first time. In particular we find that the asymmetric information component reduces when the market changes from quote driven to order driven (FTSE100). The reason for this is that market makers do not have to provide liquidity any more. However when the market changes from

quote driven to hybrid (FTSE250), there is no change in the asymmetric information component. We also found that the effect of volatility on the asymmetric information component of the spread reduces when the market is order driven.

The structure of the thesis is as follows. In chapter two the established theoretical literature which is relevant to the economics of market making, trading, asymmetric information, liquidity and order processing is thoroughly reviewed. The purpose of this literature survey is to provide the theoretical foundations for the empirical studies that will follow as well as to highlight issues investigated or under investigation and pinpoint any possible gaps. At this point it is worth mentioning that literature presented in chapter two is mainly theoretical in nature. Empirical literature specific to each of the issues examined in this thesis is presented at the beginning of each empirical chapter.

Chapter three which is the first empirical of this thesis concentrates on systematic liquidity and excess returns under different trading regimes and algorithms. The key objective of the chapter is to examine if there are common components affecting stock liquidity and the extent to which those components can affect pricing. We find that liquidity has a common component unidentified yet which remains quite strong even after accounting for a number of factors which we know that affect stock liquidity (expected trading volume, unexpected trading volume, volatility, macro economic variables etc). These findings are valid regardless of trading regime. At a later stage we examine if the common underlying component affects excess returns. It appears that the common underlying liquidity component is quite strong when the market is quote driven but reduces once the market changes to order driven (FTSE100 stocks). We are able to identify a common underlying component for FTSE250 stocks however it does not seem to affect FTSE250 stock pricing as in the case observed for FTSE100 stocks.

The fourth chapter is a replication of the previous chapter for the Greek market. The Greek stock market has recently gone through troughs and peaks, achieving record growth by any standards but returning to lower levels than it started in the first place. The reason we decided to present the case for the Greek market in a different chapter is because we were afraid that we might cause confusion to the reader since we capture liquidity using a different variable to the ones used in the UK market due to lack of data but also because the reasons we examine liquidity in the Greek market are different from the reasons we examine liquidity in the UK market. There has been no change in the trading regime in the Greek market so as to examine how different regimes might affect liquidity however each of the periods examined represent a different era for the Greek market in terms of trading activity and profits.

The fifth chapter examines how informational efficiency and spread sensitivity to volatility changes as a result of changes in the trading regimes for FTSE100 and FTSE250 stocks. We also look into the effects that the computerization of the trading process can have on informational efficiency for the Athens stock Exchange. With reference to the UK market we find that an order driven market is more responsive to new information when compared to a quote driven market. Secondly we find that the spread formed in a quote driven market is more sensitive to volatility than in an order driven market because of affirmative quotation. Finally we find that computerization has a positive impact on informational efficiency with reference to the Greek market.

The sixth chapter looks into the components of the bid-ask spread and their determinants and how they might change over time as a result of changes in the trading regime. We find that the asymmetric component of the spread is higher under a quote driven regime. This can be explained by the fact that market makers are obliged to quote bid and ask prices therefore they bear all the risk of a transaction especially if they trade with a trader who is in possession of superior information. However under an order driven regime market makers are not obliged to provide any liquidity therefore the asymmetric information component reduces significantly. There are no changes in the asymmetric information component of the bid ask spread between a quote driven and a hybrid market because market makers are obliged to provide quotes under any circumstances. Finally we examine how different variables such as number of trades, trading volume and volatility affects the asymmetric information and order processing component of the spread.

Finally in chapter seven the main results in the thesis are summarized and concluding remarks are drawn.

CHAPTER 2: LITERATURE REVIEW

2.1. THE EMERGENCE OF MARKET MICROSTRUCTURE

Market microstructure is a relatively old area in finance, which has recently attracted a lot of attention. Of course some readers might wonder why it remained obscure and it did not attract attention before. Well I believe that the answer to this question is two-fold. Most importantly a growing number of traders, practitioners and academics have realised that asset prizes do not reflect expected prices based on all available information because of a variety of frictions. Secondly the trading processes through which investors' aggregate demand is translated into transactions are of greater importance in price formation than it was originally thought and therefore worth of further examination. In the words of Madhavan (2000)

> "Interest in market microstructure is most obviously driven by the rapid structural, technological and regulatory changes affecting the securities industry worldwide. The causes of these structural shifts are complex. In the US, they include the substantial increase in trading volume, competition between exchanges and Electronic Communications Networks (ECNs), changes in the regulatory environment, new technological innovations, the growth of the Internet and the proliferation of financial instruments. In other countries, globalisation and

> intermarket competition are more important in forcing change. For example European economic integration means the almost certain demise of certain national stock exchanges, perhaps to be replaced eventually with a single market for the European time zone. These factors are transforming the landscape of the industry, spurring interest in the relative merits of different trading protocols and designs." (Madhavan, 2000, page 1)

2.2.MARKET MICROSTRUCTURE: DEFINITIONS AND TENETS

Market microstructure can be defined as the area of finance that studies the process by which investors' latent demands are ultimately translated into prices and volumes (Madhavan, 2000). It can also be defined as the study of the process and outcomes of exchanging assets under explicit trading rules (O'Hara, 1994). Having provided the readers of this review with two short definitions of market microstructure, I think that it would be helpful to discuss the sub-domains that market microstructure literature expands. Market microstructure theory is a versatile body of knowledge and incorporates many sub-domains such as

- price formation and price discovery; this section looks into the determinants of trading costs and the process by which prices come to impound information over time

- market structure and design issues; this section concentrates on the relation between price formation and trading protocols. More specifically it focuses on how different market rules can affect trading, liquidity and therefore prices.
- Information and disclosure; this section focuses on the extent to which investors have access on information regarding the trading process.

We shall be concerned with price formation & price discovery and market structure & design issues.

2.3.PRICE FORMATION

A basic tenet of the theory of market microstructure is that asset prices need not equal full information expectations of value because of a variety of frictions. Market microstructure theory is concerned with how various frictions such as departures from symmetric information affect the trading process and how prices are ultimately defined. A simple mathematical model of price formation and frictions is developed below.

It is assumed that in efficient markets i) all agents posses symmetric information and ii) frictions are negligible resulting in prices reflecting expected values conditional upon the set of public information available at time t. Symbolically this is expressed as $p_t=\mu_t$ where p_t denotes the price of the risky asset at time t and $\mu_t=E[v_t/H_t]$ is the conditional expectation of a fundamental value (v_t) of a risky asset based on all available information at time t (H_t). Taking into consideration that returns are given by changes in prices between two different time periods, then

$$r_t=p_t-p_{t-1} \Rightarrow r_t=\mu_t-\mu_{t-1} \Rightarrow r_t=E[v_t/H_t]-E[v_{t-1}/H_{t-1}] \quad (2.1)$$

where $E[v_t/H_t]-E[v_{t-1}/H_{t-1}]$ is the innovation in beliefs. Since μ_t follows a martingale process, applying the Law of Iterated Expectations, returns are serially uncorrelated. Markets are efficient in the sense that prices at all points in time reflect expected values.

2.3.1 TRADING FRICTIONS

Having introduced a frictionless market model, the next step is to construct a model that will incorporate frictions and will take into consideration the fact that market agents have different information. The new model is given by the following formula $p_t=\mu_t+s_t$ where p_t is price, $\mu_t= E[v_t/H_t]$ and s_t is an error term with mean zero that reflects the effects of frictions. At this point it should be made clear that s_t is modelled as $s_t= sx_t$ where s_t is a positive constant (representing one half the bid ask spread) and x_t represents signed order flow.

2.3.2 PRIVATE INFORMATION

Having considered frictions, the next step is to incorporate private information into the model. Madhavan (2000) postulates that if some market agents possess private information, then revision in beliefs about asset values from t-1 to t given by

$\varepsilon_t = E[v_{t-1}/H_{t-1}]$ need not reflect new information arrivals. Revision in beliefs will depend on signed order flow denoted by x_t since informed traders will buy when prices are below true value and will sell if prices are above true value. Thus revision in beliefs is given by $\varepsilon_t = \lambda x_t + u_t$ where x_t is order flow, u_t is pure noise and $\lambda > 0$.

Price formation and price discovery may be viewed as synonymous to liquidity, which may be defined as the bid and ask prices at which market makers (liquidity providers) buy and sell assets for themselves or their clients. In the rest of this review we seek to answer the question of how prices are formed.

The answer to price formation is given by the standard demand & supply framework. In particular the intersection of the demand and supply curves provide the equilibrium price at which buyers and sellers are willing to transact. Nevertheless this simplistic procedure provides absolutely no information on how this equilibrium price is attained.

There appear to be two approaches to the mechanics of price formation. The first approach, which can be, described as completely agnostic postulates that the procedure followed in attaining equilibrium is of no importance because the equilibrium price achieved is independent of any procedure. Even if there were several procedures, the same equilibrium would arise. Clearly this approach is limited to analysing the properties of the equilibrium rather than the procedure of equilibrium attainment. The second approach, which actually looks into the mechanics of price formation, is the Walrasian auctioneer.

2.3.3 TRADITIONAL VIEW

The Walrasian auctioneer is perceived as the traditional view of price formation. The formation process could be easily captured by the general representation of an auctioneer who aggregates traders' demands and supplies to find a market-clearing price. Specifically the procedure followed is like the one described below. Each trader submits his demand schedule to the auctioneer and then he comes up with a potential trading price. At this point, traders determine their optimal demand sets and submit them to the auctioneer. If no equality is achieved between quantity demanded and quantity supplied, then the auctioneer announces a new trading price. This procedure will be repeated until supply equals demand, achieving an equilibrium price. The procedure described above constitutes a very simple way of explaining equilibrium attainment. However as we are all aware the above frictionless representation is nowhere close to reality at least as far as financial markets are concerned.

2.3.4 THE COST OF TRANSACTING: BID-ASK PRICES

An alternative view to the archaic Walrasian auctioneer model briefly described above is that of Demsetz (1968). Demsetz introduces the notion of 'time dimension' in supply and demand analysis and literally sets the stage for the development of market microstructure theory.

Demsetz based his analysis on the notion that trade may involve some kind of cost either explicit or implicit. Explicit costs could be charges levied by a particular market while implicit costs would be costs reflecting the price of immediate trading. Demsetz argued that demand does not necessarily equal supply at each time period, t, therefore there cannot be a single market-clearing price. Demsetz postulates that there are two sources of supply and demand at each point in time. On both sides there are traders who wish to trade immediately and some others who wish to put off trading for the time being. If there is an imbalance between demand and supply those who wish to trade now must pay a higher price to induce the other side to trade at the same time. If some traders wish to buy now they must increase their bid to attract sellers who otherwise would not have traded. On the other side if some traders wish to sell now they must lower their ask price to attract buyers. Thus two prices emerge a bid and an ask price. Today the difference between bid and ask prices is known as the spread and this is exactly where the notion of liquidity is based. In the words of Demsetz (1968)

"...Thus, a specialist who buys at $98 and sells at $100 substitutes two transactions for what would be one transaction if the outside traders could count on their orders arriving simultaneously and at the same price, say $99."
(Demsetz, 1968, page 37)

Of course Demsetz did not merely provide a theoretical framework in an attempt to explain the cost of transacting. Demsetz went even further to investigate the relationship between spread and volume in the NYSE. For this reason Demsetz runs a couple of regressions in order to formally establish the relationship between spread and volume employing a random sample of 192 securities. At this point it should be noted that Demsetz employs two different variables in order to identify the precise relationship between spread and volume namely i) number of transactions per day based on data for two non-adjacent days of trading and ii) the number of shareholders being in possession of the securities under consideration. Demsetz comments on the results:

"Both regressions give highly similar fits; although (IA) gives a slightly better fit, the use of number of shareholders does surprisingly well. All coefficients take on the expected algebraic signs and all except the M coefficient are highly significant. The coefficients of lnT and lnN yield the expected second derivatives. The coefficient of M cannot be judged to differ significantly from zero in the light of the evidence presented here. The reader will note that the significance of the M coefficient increases slightly when lnN is used in place of lnT. The reason for this is that M is associated slightly with differences in transaction rates that are not explained by differences in N". (Demsetz, 1968, page 49)

Demsetz's results show that the greater the activity in the stock (as measured by the number of trades or the number of shareholders) the lower the spread, clearly indicating that the cost of non-synchronization between demand and supply for similar assets is a function of the rate at which buying and selling orders arrive.

2.4. DETERMINANTS OF LIQUIDITY

All financial literature previous to the seminal work of Demsetz (1968) perceived security price formation as a macroeconomic phenomenon. Demsetz changed this view by diverting attention away from the macroeconomic foundations of security price formation towards the micro foundations of security markets. In doing so, he showed that security price formation depends on economic agents' optimising behaviour meaning that prices in particular the bid-ask spread is set by a specific person(s), institution(s) or mechanism worthy of further study. Having indicated the 'turn' in financial literature from the macro aspect to the micro aspect of the bid-ask spread formation initiated by Demsetz the next step will be to look into how the spread is determined. In order to answer this question we should delve into the behaviour of market makers and the incentives or the disincentives they have to increase or reduce the spread. Inventory risk and the presence of asymmetric information determine their behaviour. More specifically we shall be concerned with inventory models and adverse selection (asymmetric information) models.

2.4.1 INVENTORY MODELS

Inventory models are concerned with changes in inventory risk level and how this might affect the setting of bid and ask prices. If one delves into the inventory models literature, one can clearly distinguish three research paradigms. The first paradigm known as order-based analysis is represented by Garman (1976) and Amihud & Mendelson (1980) who focus on the nature of order flows in determining security-trading prices. Portfolio risk analysis that constitutes the second paradigm is typified by the works of Stoll (1978), Ho & Stoll (1981) and O'Hara & Oldfield (1986). Portfolio risk analysis examines bid-ask spread formation in relation to the liquidity providers' optimisation problem while the third approach 'competitive trade order submission' analyses the effects of multiple liquidity providers on spread behaviour. It is represented mainly by Cohen, Maier, Schwartz & Whitcomb (1981).

2.4.1.1 ORDER-BASED ANALYSIS

2.4.1.1.1 GARMAN'S MODEL

The equilibrium price derived from the intersection of the standard demand and supply schedules combined in a single diagram constitutes a first approximation to a fully balanced market, however this simple intuitively appealing approach appears to be severely limited when it comes to studying equilibrium attainment at financial markets. The main reason for the limitation observed is the complete lack of consideration for the empirically observed non synchronization of buy and sell order arrival and subsequent price change as a response to the temporary order flow imbalance. All those issues are considered in Garman's model.

Garman (1976) introduces a model that assumes a stochastic buy and sell order arrival process that is a function of the dealer's bid and ask prices. In Garman's model there is a single, monopolistic market maker that sets prices, receives all orders and clears trades. The dealer's objective is to maximise expected profit per unit of time, subject to the avoidance of bankruptcy or failure i.e. running out of inventory or running out of cash. The dealer has an infinite horizon but selects bid and ask prices only once at the beginning of his trading horizon. The market maker's only decision is to set an ask price p_a at which he will fill orders wishing to buy the stock and a bid price p_b at which he will fill orders wishing to sell the stock.

Garman's model is constructed in such a way so that the market maker is faced as it was stated at the beginning with stochastic order arrival processes. Buy and sell orders are assumed to follow a Poisson process with stationary arrival rate functions $\lambda_a(p)$ and $\lambda_b(p)$. In that way the stochastic nature of the buy/sell orders can be observed and followed in a consistent way. Nevertheless even if the order arrival process is modelled in such a consistent way, this does not ensure synchronicity between buy and sell order arrival making inventory and cash reserve balance a very delicate issue. This problem emerges and is aggravated by one of the assumptions of the model, primarily the inability of the market maker to change prices after the initial prices have been set in an attempt to avoid failure and secondly the restrictive condition of stock/money borrowing.

Having explained the objectives of Garman's market maker as well as the restrictions imposed on him by assumption, the next step is to view the model in a more rigorous way. Garman's market maker is supposed to maintain a level of cash and stock inventory to allow him transacting while maximizing profits per unit of time. The market maker's cash $I_c(t)$ and stock $I_s(t)$ inventory are given by

$$I_c(t)=I_c(0)+p_aN_a(t)-p_bN_b(t) \text{ and } I_s(t)=I_s(0)+N_b(t)-N_a(t) \quad (2.2)$$

where $N_a(t)$ is the cumulative number of shares that have been bought from traders up to time (t), $N_b(t)$ is the cumulative number of shares that have been sold to traders up to time (t), p_a is the ask price and p_b is the bid price.

The two functions above describe cash and stock inventory behaviour. However as you can see the level of cash and stock at each time depends on the arrival of buy and sell orders governed by a Poisson process that does not ensure buy/sell order arrival synchronicity. Therefore we are interested in estimating the time at which failure will occur. Nonetheless calculating a 'ruin probability' is unattainable due to the existence of multiple stochastic processes.

Garman goes around the problem identified above in the following way. Assume that the variable $Q_k(t)$ is the probability that $I_c(t)=k$ meaning that at time (t) the market maker's inventory of cash is equal to k units and $R_k(t)$ is the probability that

$I_s(t)=k$ meaning that at time (t) the market maker's stock inventory is equal to k units. The position of having exactly k units of cash at time (t) can be achieved in the following ways:

1. the market maker held exactly k-1 units of cash at time $t-\Delta t$ and in the next instant an order to sell one unit to him arrives.

2. the market maker held exactly k+1 units of cash at time $t-\Delta t$ and in the next instant an order to buy from him arrives.

3. the market maker is holding K units at time $t-\Delta t$ and in the next instant nothing happens.

Before calculating the probability that the market maker has exactly k units of cash Garman assumes that a unit of cash arrives with rate $\lambda_a(p_a)$ and departs at rate $\lambda_b(p_b)$. Therefore the probabilities are given by

1. the probability the dealer had k-1 units of cash and in the interval $t-\Delta t$ receives a cash flow is $Q_{k-1}(t-\Delta t)[\lambda_a(p_a)p_a\Delta t][1-\lambda_b(p_b)p_b\Delta t]$ (2.3)

2. the probability the dealer had k+1 units of cash and in the interval $t-\Delta t$ receives a cash flow is $Q_{k+1}(t-\Delta t)[\lambda_b(p_b)p_b\Delta t][1-\lambda_a(p_a)p_a\Delta t]$ (2.4)

3. the probability that the dealer is holding k units of cash at time $t-\Delta t$ and in the next instant nothing happens is $Q_k(t-\Delta t)[1-\lambda_b(p_b)p_b\Delta t][1-\lambda_a(p_a)p_a\Delta t]$ (2.5)

The probability that the dealer has exactly k units of cash at time t is the sum of these probabilities. To calculate the time derivative of the probability $Q_k(t)$, we take the limit as $\Delta t \rightarrow 0$ of $[Q_k(t)-Q_k(t-\Delta t)]/\Delta t$. As it was stated at the beginning of the model the market maker cannot ameliorate his cash position if he wishes to do so by either borrowing cash or changing prices because of the restrictive assumptions imposed by the model. Changes in his/her cash position can only be a result of trading.

Based on the standard solution to 'ruin' problems, Garman shows that the failure probability for running out of cash yields:

$$\lim_{t\to\infty} Q_0(t) \approx \left(\frac{\lambda_b(p_b)p_b}{\lambda_a(p_a)p_a}\right)^{Ic(0)\,\bar{p}} \text{ if } \lambda_a(p_\alpha)p_\alpha > \lambda_b(p_b)p_b \quad (2.6)$$

where $\bar{p}$ is defined to be the average price, $I_c(0)$ is cash level, $\lambda_b(p_b)$ is the rate at which cash departs and $\lambda_a(p_\alpha)$ is the rate at which cash arrives. Similarly the stock failure probability is given by

$$\lim_{t\to\infty} R_0(t) \approx \left(\frac{\lambda_a(p_a)}{\lambda_b(p_b)}\right)^{Is(0)} \text{ if } \lambda_a(p_\alpha) < \lambda_b(p_b) \quad (2.7)$$

The failure probabilities above imply that if the market maker wishes to avoid certain failure then he must set p_α and p_b so that $p_\alpha\lambda_a(p_\alpha) > p_b\lambda_b(p_b)$ and $\lambda_b(p_b).> \lambda_a(p_\alpha)$. In other words he must set a higher price when he sells and a lower price when he buys which results in the development of a spread. Having explained the necessity for the existence of the bid-ask spread, the next step is to discuss how this spread is determined. Garman modifies the assumptions and analyses two different cases.

As it is clear from Garman's model, there will be a positive drift on the market maker's inventory and cash positions that will inevitably complicate price behaviour. For that reason Garman assumes that the market maker pursues a zero drift inventory policy. As a result of the previous assumption prices are set so as to maximize the dealer's expected profit. By setting two prices the market maker extracts larger rents while still maintain the zero drift inventory requirement. In the second case Garman assumes zero price spread. However such an assumption leads to imminent failure as it was explained above.

Garman's model is simple and intuitively appealing since it manages to clearly demonstrate the problems that the market maker faces when setting prices. Nonetheless the model introduced above is highly abstract out of contact with reality and therefore implausible. However this first model spurred further research in the area of market microstructure.

2.4.1.1.2 AMIHUD AND MENDELSON'S MODEL

A more realistic approach to that of Garman is the one introduced by Amihud & Mendelson (1980). They consider the problem of a price-setting monopolistic market maker in a dealership market where the stochastic demand and supply are depicted by price dependent Poisson processes based on Garman's analysis (1976).

The new feature that differentiates this particular model is the dependence of the bid-ask spread prices on the market maker's inventory position. In this new model the market maker has the ability to change quoted prices to influence stochastic buy/sell order arrivals in order to maintain his desired inventory position. This new feature was not incorporated in Garman's model discussed previously even though Garman was well aware of its importance. In the words of Garman (1976)

"The specialists must pursue a policy of relating their prices to the inventories in order to avoid failure". (Garman, 1976, page 32)

Amihud & Mendelson (1980) derive the optimal policy of the market maker based on Garman's dealership market subject to upward and downward inventory constraints. They show that the bid-ask prices are monotone decreasing functions of the stock at hand and that the resulting bid-ask spread is always positive while stress the existence of a preferred inventory position.

Having briefly described the innovations as well as the direction of this new study as suggested by Amihud & Mendelson, the next step is to obtain a more rigorous view of the model. Amihud & Mendelson based on Garman make a number of assumptions on which they base their model. We will look into those assumptions and then we will derive the optimality conditions. They assume

A) All exchanges are made through a single central market maker, who possesses a monopoly on all trading. No direct exchanges between buyers and sellers are permitted.

B) The market maker is a price setter. He sets an ask price, P_a at which he will fill a buy order for one unit and a bid price P_b for an one unit sell order.

C) For a given pair of prices P_a and P_b the next incoming order will be a buy order with probability $D(P_a)/[D(P_a)+S(P_b)]$ or a sell order with probability $S(P_b)/[D(P_a)+S(P_b)]$. The time until the next arriving order has an exceptional distribution with mean $1/[D(P_a)+S(P_b)]$.

D) The objective of the market maker is to maximize his expected average profit per unit-time. Profit is defined as net cash inflow.

E) The permissible stock inventory level are {-K, -K+1, -K+2, L-2, L-1, L}. For convenience of exposition, we re-number the states as {0,1,2,...M-1, M}, where M=L+K. We assume M>=3. We also adopt the conventional terminology of birth and death processes and let λ_K denote the birth rate in state k and μ_K the corresponding death rate. We also define $\mu_0=\lambda_M=0$. Since $\lambda_K=S(P_{bk})$ is a monotone increasing function of P_{bk}, there is a one to one correspondence between λ_K and P_{bk}. Similarly, μ_K is a monotone decreasing function of P_{ak} with a one to one correspondence. Thus, the transition rates λ_K and μ_K will be used as the decision variables in state k.

F) The revenue and cost functions are equal to:

$$R(\mu)=\mu P_{\alpha}(\mu)=\mu D^{-1}(\mu) \text{ and } C(\lambda)=\lambda P_{b}(\lambda)=\lambda S^{-1}(\lambda) \quad (2.8)$$

and the following regularity assumptions hold

i) R(.) is strictly concave

ii) C(.) is strictly convex

iii) R'(0)>C'(0), R'()<C'()

G) there are no transaction costs to the market maker

Based on the above assumptions and in particular on the assumption D that the objective of the market maker is to maximize his expected average profit per unit time we introduce the following function

$$g(\lambda,\mu)=\sum_{k=0}^{M} \varphi_k q_k \quad (2.9)$$

where $\lambda=(\lambda_0,\ldots\lambda_{M-1})$ and $\mu=(\mu_1,\ldots\ \mu_M)$, q_k is the earning rate for a transition from state k and it is mathematically expressed as $q_k= R(\mu_k)-C(\lambda_k)$.

Let

$$\bar{\lambda}=\sum_{k=0}^{M}\lambda_\kappa\phi_\kappa \text{ and } \quad \bar{\mu}=\sum_{k=0}^{M}\mu_k\phi_\kappa \quad (2.10)$$

be the mean rates of incoming sell and buy orders. Then $\lambda_k\varphi_k=\mu_{k+1}\varphi_{k+1}$ implies $\lambda=\mu$, that is, the expected flows in both directions are equal. Relations $\lambda_k \varphi_k=\mu_{k+1}\varphi_{k+1}$ and $\varphi_k=\varphi_0(\lambda_0\lambda_1\ldots\lambda_{k-1}/\mu_1\mu_2\ldots\mu_k)$ are valid only when $\lambda_k>0$ for k=0,1,...M-1 and $\mu_k>0$ for k=1,2,...,M.

Having discussed the assumptions and explained the components of the objective function, the next step is to derive the optimality conditions and then study their implications on the behaviour of the market maker. The necessary conditions for optimality are:

$$\lambda_k: \sum_{j=k+1}^{M} \varphi_j[R(\mu_j)-C(\lambda_j)]-\lambda_k\varphi_k C'(\lambda_k)=g(\lambda,\mu)\sum_{j=k+1}^{M} \varphi_j \quad (2.11)$$

$$\mu_k: \sum_{j=k}^{M} \varphi_j[R(\mu_j)-C(\lambda_j)]-\mu_k\varphi_k R'(\mu_k)=g(\lambda,\mu)\sum_{j=k}^{M} \varphi_j \quad (2.12)$$

By subtracting the (k+1)st equation of the second equation above from the kth equation from the first equation and using $\lambda_k\varphi_k=\mu_{k+1}\varphi_{k+1}$ we obtain

$$R'(\mu_{k+1})=C'(\lambda_k) \quad k=0,1,\ M-1 \quad (2.13)$$

which reminds of the ordinary optimality condition of a monopoly, except that here it relates to each pair of neighbouring states. Note that since

$$P_a(\mu_{k+1})> R'(\mu_{k+1})=C'(\lambda_k)>P_b(\lambda_k) \quad (2.14)$$

a purchase of one unit at state k and its sale at state k+1 always yields a profit. It follows that a loop of transitions starting from any state k, traversing other states and returning to state k yields a positive profit with probability one. Thus, when the market maker's initial resources exceed $\sum_{k=0}^{M-1} P_{bk}$, the probability of cash failure is zero, even in the worst possible case. Since the probability of default by the market maker is zero, initial credit should be available. Subtraction of the first condition of optimality from the second give the basic relation between λ_k and μ_K and thus the relation between the bid and ask prices for each inventory position k.

Having provided readers with a rigorous overview of Amihud & Mendelson's model, we should stress those points that make it different from Garman's model. The first important difference is that the bid-ask spread in Garman's model arose because of the need to reduce failure probabilities given that in Garman's model bid-ask prices are set only once at the beginning of the trading period. In Amihud & Mendelson model the bid-ask spread is viewed as an element of the monopolistic power of the market maker whose efforts concentrate on profit maximization. The second difference lies on the dealer's preferred inventory position, which is a function of the order arrival process. The value of the shares comprising the inventory is not important in determining the preferred inventory position. In other words the preferred inventory position is not a function of its value but rather of the order arrival process. Those two models constitute the order-based approach to price setting and dealer behaviour. The next approach we will look into assumes a completely different perspective, which shall be discussed later on.

2.4.2 PORTFOLIO RISK ANALYSIS

2.4.2.1 STOLL'S MODEL

The next model described below assumes a different perspective from that of Garman (1976) and Amihud & Mendelson (1980). In particular Stoll's (1978) analysis departs from order-based analysis models and focuses on portfolio risk. The market maker in Stoll's model is perceived as a market participant who alters his portfolio holdings in order to accommodate the desires of other traders. In other words the market maker is perceived as a 'financial needs server' rather than a monopolist whose prices reflect largely his market power. In that way the bid-ask spread is viewed as compensation for the services provided (immediacy following Demsetz's terminology) and the risk undertaken when moving away from desired portfolio positions. The market maker's compensation for immediacy incorporates a number of costs such as holding costs, which arise from holding a sub-optimal portfolio; order processing costs such as exchange fees, transfer taxes etc and asymmetric information costs which refer to the existence of private information and how this piece of information can be manipulated towards profit making. Nevertheless at this point it must be stressed that it is holding costs that matter mainly because of the dealer's inability to hedge his inventory exposure. Obviously Stoll's analysis can be classified as 'risk aversion based spread model' coming into sharp contrast with Garman's 'defence against bankruptcy/failure' model or Amihud & Mendelsons 'market power' model.

Stoll introduces a two period model and a risk averse maker who aims at maximizing the expected utility of his terminal wealth which is a function of his initial level of wealth (W_0) and the market making positions he will assume over the two date trading period which is actually restricted to one date period only because at t=2, assets are liquidated.

Stoll's model is based on the following assumptions: i) the market maker buys/sells the asset at time t and liquidates it at time t+1. ii) the market maker finances his inventory by borrowing at the risk free rate R_f and lends excess funds at the same rate R_f again. iii) The market maker's probability of going bankrupt is virtually limited to zero given that the model under consideration is a two-period model. iv) the market maker has some exogenous beliefs about the 'true' value of the assets he trades as well as about the 'true' rate of return of those assets. v) These values are stable and do not change over time and vi) the market maker will only trade if his utility after the trade remains the same or is increased.

As it was mentioned in the very first paragraph, the market maker aims at maximizing the expected utility of his terminal wealth which is equal to the initial wealth (W_0) times the rate of return ($\widetilde{R}^*$) on that portfolio plus the rate of return ($\widetilde{R}_i$) on the true value of a transaction in stock (i), (Q_i), minus the costs of carrying the inventory $(1+R_f)(Q_i-C_i)$. In other words, the terminal wealth is equal to the initial portfolio position plus any returns from transactions minus the costs of getting involved in those transactions.

Based on assumption (vi) with respect to changes in the market maker's utility function, one obtains the following mathematical expression:

$$E\{U[Wo(1+\widetilde{R}^{*})]\}=E[U(\widetilde{W})] \quad (2.15)$$

which simply states that the expected utility of his initial wealth times returns must be equal to the expected utility of his terminal wealth. In other words the market maker will not trade if he is not guaranteed his initial level of utility. If one elaborates on the above expression, expands both sides in a Taylor series expansion, drops terms of order higher than two and sets $R_f=0$ then one obtains

$$Ci/Qi = \frac{z}{W_0}(\sigma_{ip}Q_p)+1/2\frac{z}{W_0}(\sigma_i^2 Q_i) \quad (2.16)$$

where Ci/Qi is the percentage cost that is necessary for the dealer to be willing to take that position Q in stock (i), z is the dealer's coefficient of relative risk aversion, Wo is the initial wealth/portfolio, σ_{ip} is the correlation between the rate of return on stock (i) and the rate of return on the optimal efficient portfolio, Q_p is the true value of stocks held in the dealer's portfolio, σ_i^2 is the variance of stock (i)'s return and Q_i is the true value of a transaction in stock (i).

The function derived above shows clearly that the cost of immediacy for every stock (i) depends on a number of different factors. As you can see the dealer's initial wealth (Wo) enters the function directly as well as the degree of risk aversion (z). Greater initial wealth reduces the cost of immediacy while a risk averse attitude increases the cost. Q_p, which is the value of stock, held in the market maker's inventory is also important. It appears that a larger stock position will increase costs since it will make it more difficult for the market maker to absorb more inventory. Costs are also affected by Q_i which represents the 'true' value of stock (i) which a function of the size of every transaction given that the value of each asset is exogenously fixed . Therefore the size of each transaction is important in determining final costs. Finally the acquisition of new stocks and their correlation to the optimal efficient portfolio in terms of rate of return (σ_{ip}) as well as the variance of the rate of return (σ_i^2) for each newly acquired stock also appear to affect the market maker's costs. The resultant spread is equal to

$$P_a\text{-}P_b/P_i^* = C_i(Q_i^b)\text{-}C_i(Q_i^a)=(z/Wo)\sigma_i^2|Q| \text{ where } |Q_i^a|=|Q_i^b|=Q \quad (2.17)$$

and clearly indicates that the spread is not a function of the inventory as one would normally expect since it does not appear in the spread function. However it seems that the spread depends on trades size due to the linearity between percentage costs (C_i) and trade size. At this point it should be made clear that the dealer's inventory affects the bid and ask price but not the difference, which constitutes the spread. A large inventory increases new inventory absorption costs therefore the market maker sets lower bid and ask prices. A depleted inventory will force the market maker to charge higher prices.

Up to the moment we have considered only holding costs, however Stoll extends his analysis to incorporate order-processing costs, which are assumed to be a fixed fee for each transaction. Therefore he concludes that the market maker's total cost function must assume a U shape due to the decreasing nature of processing costs as a function of order/trade size and the increasing nature of holding costs as a function of order/trade size. This of course implies an optimal level of trade size/transactions at which the total cost function assumes its lowest value.

Stoll's model assumes a different perspective and it appears to be more realistic in comparison to the other two models. Nonetheless it suffers from a great drawback, the complete absence of intertemporal characteristics. As it was clearly explained at the beginning this model was designed as a two period model, in which at t=2 the stock is liquidated; therefore uncertainty is virtually non-existent when it comes to deciding for how long the market maker will hold the stock, let alone showing consideration for the order flow process which may constitute a very important parameter when setting prices. In addition to those simplifications the exogenous nature of the stock's true price and the portfolio's return further enhance the feeling of safety for the market rendering the mode too unrealistic. Of course Stoll considers order-processing costs, which are also important and were not considered in any of the models above. The model that follows below incorporates all those 'missing' attributes.

2.4.2.2 MULTIPERIOD PORTFOLIO RISK ANALYSIS: HO & STOLL

Having introduced Stoll's model (1978), the next step is to discuss a more elaborate model in particular that of Ho & Stoll (1981) which extends the intuition of the Stoll analysis to a multiperiod framework in which both order flow and portfolio returns are stochastic. Stoll's initial model was an one trade-one period model. The dealer faces no uncertainty as to the time extent he has to hold his inventory position since stock is liquidated at time t+1.

This new model can be described as a multiperiod finite horizon (T period) dynamic programming approach to characterise the dealer's optimal pricing policy. Ho & Stoll demonstrate a number of important properties of the dealer's optimal pricing behaviour. First the spread depends on the time horizon of the dealer. As the dealer nears the end of trading, the spread reduces because the inventory/portfolio risk involved is less pronounced. As the time horizon lengthens however portfolio risk increases and the spread increases as well. Another property of the model under consideration is that transaction uncertainty per se does not affect the spread. Ho & Stoll argue that transactions variability has no direct effect on the dealer but rather works indirectly through its effect on his overall portfolio position. The third property of this optimal pricing policy is that the spread is independent of the inventory level. Of course bid and ask prices are affected but the spread itself remains unaffected.

Having provided a brief description of the Ho & Stoll model the next step is to have a more inquisitive look concentrating on the technical aspect of the model and how the authors reach all those conclusions briefly mentioned above. First we will concentrate on the assumptions of that particular model as we did for all previous models and then we will concern ourselves with the computational and derivational aspect of the model.

Firstly transactions are assumed to evolve as a stationary continuous time stochastic jump process as in Garman (1976) where Q is the jump size (number of trades in a transaction) λ_α and λ_β represent the average number of public purchase/sale transactions respectively per unit time and $\lambda_\alpha dt$ and $\lambda_\beta dt$ are interpreted as the probabilities of a dealer sale/purchase over the next instant.

Secondly Ho & Stoll assume that he 'true' value of the stock is fixed at some value p, similar to the assumptions made in Stoll (1978). The bid and ask prices that the market maker sets have an effect on the arrival of the buy/sell orders influencing the probability of the next transaction being either a buy or a sell order. Unfortunately however bid and ask prices cannot guarantee the existence of a buy or sell order introducing uncertainty over the order flow and the time length that the market maker under consideration will have to carry the same inventory position.

In addition to the order flow uncertainty introduced above, there is also uncertainty about the return on the market maker's existing portfolio. In the absence of a transaction, portfolio growth (dX) is represented by a stochastic differential equation of the following form

$$dX=r_xXdr+XdZ_x \quad (2.18)$$

where r_x is the mean return per unit time, dZ_x is a non-standard Wiener process with mean zero and instantaneous variance σ_x^2. Of course Ho & Stoll's market maker is assumed to have some wealth that is made up of three different components namely cash, inventory and base wealth. Each of those components is described below:

Cash

Cash is accumulated when the dealer sells securities and paid out when the dealer buys securities. Any balance in the cash account earns or pays the risk free rate of interest, r. The change in the value of the cash account, F, is

$$dF=rFdt-(p-b)dq_b+(p+\alpha)dq_\alpha \quad (2.19)$$

Uncertainty in the cash account is due to uncertainty about transactions and not to any uncertainty about the interest to be earned.

Inventory

The dealer's inventory consists of shares of the one stock in which he makes a market. The change in the value of the inventory account, I is

$$dI=r_IIdt+pdq_b-pdq_\alpha+IdZ_I \quad (2.20)$$

where r_I is return on inventory, dq_a and dq_b are transactions at the bid/ask prices, dZ_I is the Wiener process and p is exogenous share price. Uncertainty arises both from transactions uncertainty reflected in dq_a and dq_b and from uncertainty about return on the stock which is reflected in the instantaneous variance σ_I^2 of the Wiener process, dZ_I.

Base wealth

The dealer has base wealth Y. On the day he starts as a dealer $F_0=0$ and $I_0=0$ and base wealth is his wealth. The change in base wealth is given by

$$dY=r_Y Y dt+Y dZ_Y \quad (2.21)$$

where r_Y is mean return and dZ_Y is a Wiener process.

Having described the assumption on which Ho & Stoll construct their model as well as the components of the dealer's wealth, the next step is to discuss the objectives of the dealer. The objective of the dealer is to maximize the expected utility of his total wealth, $E[U(W_T)]$, at time T, where

$$W_T=F_T+I_T+Y_T \quad (2.22)$$

The optimal strategy is complicated by the multiperiod framework which permits the dealer to adjust α and b as he moves through time usually in response to inventory changes. Although these inventory changes may be stochastic, they are in turn influenced by bid and ask prices. This is known as a closed loop control problem because the optimal values of α and b depend on the observed state variables (F,I,Y) as well as on time, t. In other words the optimal dealer strategy we seek is a function that specifies the choice of α and b for any position (described by t, F, I, Y) in which the dealer finds himself. The appropriate procedure for such a problem is dynamic programming. Mathematically this can be expressed as

$$J(t,F,I,Y)=\max\{E[U(W_T)]|t,F,I,Y\} \quad (2.23)$$

The solution to the market maker's wealth can be found by maximizing function J(.) for an optimal bid and ask strategy spanning from T_0 to T which is the end of the trading period. Based on the assumption that there is no consumption prior to T, the fundamental recurrence relation implied by the principle of optimality of dynamic programming is simply that

$$\max_{a,b} dJ(t,F,I,Y)=0 \text{ and } J(T,F,I,Y)=U(W_T) \quad (2.24)$$

In other words J must meet the condition that the maximized increments to J are always zero; for if they were not, one could increase derived utility by an alternative bid-ask strategy. Also at time T, J must give the same level of utility as the elementary utility function, U. More important to the dealer and to our problem is

$$\max_{a,b} \{\lambda_\alpha[J(F+pQ+\alpha Q,I-pQ,Y)-J(F,I,Y)]+\lambda_\beta[J(F-pQ+bQ,I-pQ,Y)-J(F,I,Y)\}=0 \quad (2.25)$$

which represents the maximized increments to J( ) resulting from transactions, the value of which are pQ and which occur with probability $\lambda_\alpha dt$ in the case of dealer sales or $\lambda_b dt$ in the case of the dealer purchase. The dealer also adds his fee αQ or bQ, to his cash account. These increments do depend on α and b. The independence of the processes, dq_α and dq_b, allows us to write effect as the sum of the two increments.

While the two equations above determine the solution, finding the actual solution requires solving explicitly for the J( ) function. This is not straightforward and Ho & Stoll do not solve the general problem. Instead they introduce some transformations and simplifications into the problem in order to solve it. First they consider the problem only at endpoint. Thus when t=0, it follows that J(0,F,I,Y)=U(W). Second, since it would be useful if the cash and inventory effects on utility could be handled explicitly, Ho & Stoll take a first order approximation of the Taylor's series expansion of the max term $J(t,F,I,Y)=\max\{E[U(W_T)]|t,F,I,Y\}$. Also, Ho & Stoll now assume symmetric linear demand and supply to the dealer, so that

$$\lambda_a=\lambda(a)=\alpha-\beta a \quad (2.26)$$

$$\lambda_b=\lambda(b)=\alpha-\beta b \quad (2.27)$$

Finally they define the sell operator, S, as

$$SJ=S[J(F,I,Y)]+J(F+Q,I-Q,Y) \quad (2.28)$$

and the buy operator, B, as

$$BJ=B[J(F,I,Y)]=J(F-Q,I+Q,Y) \quad (2.29)$$

The sell operator acting on J describes the dealer's derived utility after a sale by the dealer but before including the selling fee. Utility will decrease if the sale drives the dealer further away from his desired portfolio by increasing a short inventory position. Utility will increase if the sale reduces a long inventory position. With these simplifications and substitutions and suppressing the time argument, the dealer's problem can be restated as follows. The change with respect to time remaining of derived utility depends on the return and risk of the dealer's current wealth (LJ) over which he has no direct control and the maximized value of two terms that reflect the net contribution to the dealer's derived utility from dealer sales and purchases respectively over which he has no control. The first order conditions to this problem can be solved for the dealer's optimal prices, which in the case of the bid is simply

$$b^{*}=\frac{\alpha}{2\beta}+\frac{J(.)-BJ(.)}{2BQJ_{F}} \quad (2.30)$$

The ask is given by

$$\alpha^{*}=\frac{\alpha}{2\beta}+\frac{J(.)-SJ(.)}{2SQJ_{F}} \quad (2.31)$$

where α and β are parameters of the linear supply and demand functions. From the bid and ask equations derived above one ca obtain the spread which is equal to

$$s=\alpha/\beta+\frac{J(.)-SJ(.)}{2SQJ_{F}}+\frac{J(.)-BJ(.)}{2BQJ_{F}} \quad (2.32)$$

the first term is the spread which maximizes expected revenues per share from sale and purchase transactions from the symmetric linear demand functions. The remaining terms are 'risk premiums' for a sale and purchase transaction, which assume optimal dealer behaviour in the future. the optimal dealer spread is given by:

$$s=\alpha/\beta-\tfrac{1}{2}Z(Q/W)\sigma_{I}^{2}t+\tfrac{1}{2}Z(Q/W)\sigma_{I}^{2}[(r_{I}-r+G_{I})+Z(r_{w}+2\Pi/W)]t^{2} \quad (2.33)$$

where $Z = U''W/U'$ is the coefficient of relative risk aversion and $G_I = r_I + 1/2\,\sigma_I^2$ is the instantaneous growth in the variance of I, $(r_I - r)$ is the risk premium, r_w is the expected return on total portfolio and $2\Pi/W$ is expected dealer profits expressed as a function of his wealth. The spread equation actually omits certain small second order terms.

Having obtained the spread function above, it is high time we had a better look at the factors that affect the spread. However before doing so, the time horizon of the dealer must be taken into consideration. When t=0 and the dealer is just about to liquidate all his assets, he is only interested in the fee he can collect from a last purchase or a last sale, therefore the relevant term is α/β. If however the time horizon of the market maker is elongated then the first order risk adjustment becomes relevant. Observing closely this term, one can clearly see that the spread does not depend on the market maker's inventory as one would expect but on a number of factors which are considered to be relatively stable over time such as the market maker's attitude towards risk reflected by Z, the relative value of the transaction given by Q and finally the risk of the stock as measured by its instantaneous variance reflected in σ_I^2. Extending the market maker's horizon even further makes the second term relevant. Again the market maker's spread depends on the factors mentioned above as well as on i) the risk premium which is equal to $(r_I - r)$, ii) the growth in the variance of I given by G_I, iii) the relative risk aversion given by Z, iv) expected returns on the market maker's total portfolio (r_w)

and v) expected dealer profits as a fraction of his wealth (2Π/W). Since the expected returns and growth in variance of I are likely to be small relative to the market maker's horizon, the principal effect comes from (2Π/W). The larger the monopoly profits today the more the dealer stands to lose tomorrow and therefore the larger the second-order risk adjustment. The findings of Ho & Stoll render support to the one period model of Stoll (1978). The dealer's inventory position will not affect the spread itself, however it can have a significant effect on bid and ask prices. The market maker will increase both bid and ask prices if his inventory is depleted and vice versa.

Despite the interesting findings of Ho & Stoll model, there are a number of underlying restrictions in the model that need to be considered. The model just described employs just a finite horizon, implying that inventory is liquidated at time T introducing deterministic patterns in the dealer's prices. Spreads are bigger if horizon is infinite and shorter if horizon is predetermined. Indeed traders would be worse off dealing with a specialist who had a long time horizon as opposed to a market maker with shorter horizon. A second restriction is that the model assumes a fixed true price for the stock, which can be realistic, if there is a short horizon only. Thirdly the model assumes that the order flow follows a Poisson process effectively precluding informed trading. All those restrictions allow only for market orders to be considered. The model that follows incorporates limit orders as well.

2.4.2.3 OHARA & OLDFIELD' MODEL

The restrictions described above are incorporated as features of the O'Hara & Oldfield (1986) model. In their model the market maker is described as risk averse, receives both limit and market orders and faces order flow and inventory value uncertainty. The trading period is assumed to contain n trading intervals and the dealer's utility s maximised over an infinite number of trading days. In addition to the above characteristics, it is also presumed that the dealer operates with an infinite horizon implying that there is no pre-determined date at which inventory is liquidated and therefore no deterministic trading patterns can emerge. Also the value of the stock may vary in contrast to the previous model where value is fixed dictating that the value of the dealer's inventory is also not fixed. The market maker sets bid and ask prices at the beginning of every period at which all market orders and any limit orders must be cleared. However the above model presents a drawback and this is that limit orders are implicitly assumed to last only for a period.

The dealer trade models considered in this section illustrate the complexities of the pricing problem faced by the dealer. In each model inventory introduces risk for the trader and his pricing strategy reflects at least partially his efforts to minimise those risks.

Having provided an overview of the characteristics of the model, the next step is to further elaborate on it.

The dealer's problem is to set bid and ask prices, b_t and a_t to solve

$$\max E[\sum_{j=0}^{\infty} \varphi^{j} U(\sum_{t=1}^{n} \pi_{jt})] \quad (2.34)$$

where φ is the discount rate, j is the index for trading days, U is a strictly concave utility function, t is the index of trading periods in each day and π_{jt} is the trading profit in period t of day j. In other words the dealer is trying to maximise expected utility that is based on the total profit he makes over the trading period.

The market maker's order flow in any period is potentially composed of buy/sell limit orders and buy/sell market orders. The limit orders are assumed to be linear functions of the price and they are represented by cumulative order functions defined as integrals of the incremental orders.

The limit orders to buy from the dealer in period t, denoted A^L are given by

$$A_t^L = \alpha^L - \alpha_t \gamma^L = \int_{at}^{a} q_a(\alpha_t)\, d\alpha_t \quad (2.35)$$

and the limit orders to sell to the dealer b^l are given by

$$B_t^L = \beta^L - \alpha_T \varphi^L = \int_0^{bt} Q_B(B_T)\, DB_T \quad (2.36)$$

where the l superscripted variables refer to the limit order book, α, β, γ, φ are parameters of the limit order flow, the q functions are the incremental orders at each price and the limits of integration α and β are the highest ask and lowest bid price, respectively at which traders will submit orders.

A period's market maker order flow is composed of both price-dependent and liquidity-based orders. The market maker uses the information from his limit orders to form his expectation about the market order flow. Thus the market order flow is represented as functions

$$A_t^m = \alpha^m - \alpha_t \gamma^m + \omega_t \quad (2.37)$$

$$B_t^m = \beta^m - b_t \varphi^m + \varepsilon_t \quad (2.38)$$

where the ω_t and ε_t are random variables incorporating both deviations from the market maker's expected price- dependent orders and the liquidity-based orders.

A characteristic particular in this model which was not explicitly mentioned above is that of the overnight market where the market maker under consideration has the ability to borrow or lend according to this wish but most importantly according to this portfolio position. If the market maker is short inventory then he will borrow in the overnight market so as to assume his desired position if on the other hand he is long then he will lend to other traders. These borrowing and lending activities overnight will contribute towards the emergence of a price (p) at which shares are bought and sold and an interest rate (r). If the dealer is short, he pays rpI_n and if he is long he receives the same amount.

These overnight activities described above attribute a special meaning to inventory since it appears to have a major effect on current cash flow and the dealer's future operations. As a result of that inventory is treated as the state variable of the system and the market maker's dynamic program for any trading day can be expressed as

$$\max E[U\sum_{t=1}^{n} \pi_t + V(I_n)] \quad (2.39)$$

where V is the market maker's derived value function which depends on inventory and incorporates the effect of current actions on future expected utility given that future actions are chosen optimally. As a consequence of that the dealer's expectation of the future value of the inventory affects his optimal strategy. The dealer's profit in period n, π_n is captured by

$$[\alpha_n(\alpha-\alpha_n\gamma+\omega_n)-b_n(\beta-b_n\varphi+\varepsilon_n)+rp(I_{n-1}+\beta+b_n\varphi-\varepsilon_n-\alpha+\alpha_n\gamma-\omega_n)] \quad (2.40)$$

where $\alpha_n(\alpha-\alpha_n\gamma+\omega_n)$ and $b_n(\beta-b_n\varphi+\varepsilon_n)$ are direct cash flow effects and

$rp(I_{n-1}+\beta+b_n\varphi-\varepsilon_n-\alpha+\alpha_n\gamma-\omega_n)$ gives the cash flow cost of financing or lending the resulting inventory. The problem is a constrained maximisation problem because the limit orders must be positive.

The first order conditions can be solved for the optimal bid and ask prices for period n. Assuming interior solutions, these are given by

$$\alpha_n=\alpha/2\gamma+E(U'\omega_n)/E(U')2\gamma+rE(U'p)/2E(U')+E(V')/2E(U') \quad (2.41)$$

$$b_n=-\beta/2\varphi-E(U'\varepsilon_n)/E(U')2\varphi+rE(U'p)/2E(U')+E(V')/2E(U') \quad (2.42)$$

These expressions are not explicit solutions for α_n and b_n because they contain U' and V', both of which depend on α_n and b_n however they provide us with useful information with respect to the determinants of the bid and ask spread. The first terms on both expressions reflect the slope of the order flow, the second terms reflect market order flow while the third and fourth terms reflect inventory effects. In particular the third term captures the overnight effects of borrowing or lending at rp while the fourth term captures the value of carrying the market maker's current position into the future. An interesting point to be made at this stage is that the third and fourth terms that capture the inventory effects on the bid and ask prices appear to affect those prices in exactly the same way in accordance to all previous models. Therefore increases or decreases in inventory will shift both bid and ask prices in the same direction leaving the actual spread unaffected. These trading prices can be solved for the spread given by

$$\alpha_n\text{-}b_n=(\alpha\phi+\beta\gamma)/2\phi\gamma+[\phi E(\omega_n)+\gamma E(\varepsilon_n)]/2\phi\gamma+[\phi\mathrm{cov}(U',\omega_n)+\gamma(U',\varepsilon_n)]/2\phi\gamma E(U') \quad (2.43)$$

The mathematical expression just presented clearly indicates that the spread depends on the market maker's expected order flow as it becomes apparent from the first two terms while the third term indicates that market order uncertainty also plays an important role in spread determination. The last term, which is related to market order uncertainty, may assume different values. If the market maker is risk neutral this term equals zero however if the market maker is risk averse then this term may assume both positive and negative values depending on the covariance. As it appears from the mathematical expression above, inventory and the value function have absolutely no role in determining the spread rendering full support to the Ho & Stoll arguments with respect to the inventory-spread independence. Nonetheless closer observation of the mathematical expression above will reveal that the spread depends on the marginal utility term (U'), which incorporates the inventory variables, therefore inventory enters the bid-ask spread function implicitly.

Having shown that inventory affects the bid-ask spread through marginal utility, the next step is to look into the degree to which this happens. This can be achieved by assuming that the dealer is risk averse, which can be represented by a negative exponential utility function. However if this assumption is made, there arises a problem with respect to the value function that does not appear to be negatively exponential. Nevertheless this kind of problem is overcome by taking into account Hakasson's work (1970) who has shown that under some fairly general conditions, exponential preferences lead to an indirect utility function that is exponential in wealth. Taking into account the work of Hakasson, O'Hara & Oldfield show that the spread is equal to

$$(\alpha\phi+\beta\gamma)/2\phi\gamma+[\phi E(\omega_n)+\gamma E(\varepsilon_n)]/2\phi\gamma+[\phi \mathrm{cov}(U',\omega_n)+\gamma(U',\varepsilon_n)]/2\phi\gamma E(U') \quad (2.44)$$

if only order variability is taken into consideration incorporating a risk adjustment term (the last term) while the level of inventory does not seem to be an argument in the whole expression at least explicitly. Based on the above results one can safely conclude that faced with either order uncertainty or price uncertainty alone, the market maker moves his prices symmetrically and his spread remains invariant with respect to his inventory.

It is very well known that at each time (t) the market maker faces both order and inventory value variability and therefore any conclusions drawn from this model must take into consideration this dual complexity. When both order and value variability is considered it appears that the spread is inventory dependent. These results relate to the dealer's period n problem. Given these optimal prices, the dealer's n-1 period problem can be solved. Moreover solving for earlier problems rapidly becomes intractable, illustrating the practical difficulties with applying a discrete time multiperiod model to analyse the dealer's problem. Interestingly the same difficulty arose in the continuous time framework of Ho & Stoll (1981) described above.

As it is customary, after having provided readers with a technical treatment of the issue, the next step is to look into the drawbacks and identify the limitations of the model. Despite the innovative characteristics of overnight trading and the introduction of limit orders, the trading process is modelled as a series of call markets rather than a continuous trading process, which characterises most markets. Nevertheless this kind of problem can be overcome by shortening the time period of each trading session. A second drawback is identified on the duration of limit orders, which are assumed to last only for a period. After the passing of that time period, limit orders are cancelled.

2.4.3 COMPETITIVE TRADE ORDER SUBMISSION

In the models considered thus far, the main activity of the specialist is the provision of immediacy to traders. In the model considered below, the presence of a specialist is not essential. Cohen, Maier, Schwartz & Whitcomb (1981) examine the order strategies of traders who can choose between submitting a market order for immediate execution or a limit order that specifies a specific price for execution. In this model market prices evolve as a result of orders crossing between traders. What is an important feature of this model, however, is the existence of exogenous transaction costs. These transaction costs influence the order decisions of traders and hence determine the trading process of the underlying asset. CMSW assume a particular cost structure such that the trader pays a cost for submitting a limit order and an additional one if the order executes. Alternatively if the trader submits a market order then he faces a single transaction cost. The trader's optimal order strategy is shown to depend on factors such as transaction costs, the parameters of his utility function and the existing market spread.

Having provided readers with an overview of the new model, we should concentrate on the investor's maximization problem. As in all models the investor under consideration is supposed to maximize the expected utility of his terminal wealth by allocating funds between a risky asset and a risk free asset. Nevertheless the existence of transaction costs as it was stated above hinders the continuous change of the investor's portfolio. Actually the investor can trade only at discrete points in time and these time points are exogenously dictated. However if the investor decides to trade can choose between a market order and a limit order.

Given the alternatives available the investor will make a decision on whether to submit a limit order or a market according to the properties that those two kind of orders exhibit. CMSW assume that the market ask/bid price depends only on the last previous market ask/bid and hence is a Markov process. Assume an investor submits a bid limit order close to a counterpart ask limit order in an attempt to achieve a better trading price what is the probability that this limit order will execute? One would expect that the closer he submits his bid/ask limit order to the counterpart bid/ask limit order the more likely it is that his order will execute. Nevertheless CMSW show that the probability of the limit order executing is always less than one. This is because there will be a jump in the probability of a limit order executing since a market order always executes. This 'jump' attribute however depends heavily on the existence of transaction costs. CMSW show that without transaction costs the underlying process becomes a Wiener process and the 'jump' property disappears. This probability jump can also be explained by the 'gravitational pull' that market orders exercise. Intuitively stated, as a trader contemplates placing a bid limit closer and closer to an ask order already established on the market, he is increasingly attracted by this counterpart offer. There will be a point that the 'gravitational pull' exerted by the established ask will dominate. Eventually the investor will choose to 'jump' his price and execute with certainty via a market order.

Having described the attributes peculiar to each kind of order, the next step is to look into the strategy that each investor will follow. For this reason CMSW introduce a number of assumptions. Firstly all orders are for the same quantity and secondly limit orders are assumed to last only for one trading period and are cancelled in the next trading period if they are not executed. If the spread pertinent in the market is quite wide, investors will opt to submit limit orders. In case those limit orders execute, those traders will have achieved better trading prices in comparison to the other traders and this will bring about a shift from market orders to limit orders, decreasing the spread. A narrower spread will induce a surge of market orders, which are absolutely certain to execute in comparison to limit orders. Any limit orders outstanding will be immediately filled and the spread will start widening again.

There are two important properties that should be noted as a result of the process just described. The gravitational pull described above is one of the main reasons for the existence of the spread. The existence of transaction costs and in particular the double charge peculiar to the submission of limit orders as well as execution uncertainty constitutes constant trading non optimal. In that way investors will submit market orders rather than limit orders. Increased submission of market orders implies reduced liquidity and if this occurs in a neighbourhood of market prices then the spread does not collapse to zero. Second the size of the spread depends on the movement of traders between limit orders and market orders and this in turn partially depends on the execution probability of the limit order. In the absence of transaction costs, all orders would be limit orders because the continuity of the price process would guarantee execution but with transaction costs this probability falls with trading intensity. In thin markets, limit order execution is low and hence even with a large spread traders may prefer to enter marker orders rather than limit orders. This trading strategy dictates that larger spreads will be an equilibrium property of thinner markets.

In this model, inventory does not play an explicit role in determining the bid-ask spread and this is because the model is designed to concentrate on competitive traders essentially endeavouring to minimize transaction costs in meeting their own needs. If those competitive traders acted as dealers then inventory would play an important role.

The models examined in this chapter present a varied view of the behaviour of market prices and spreads. However despite the differences between the different models discussed, there is an underlying similarity to the inventory based approach to market making and this is the balancing problem that the specialist or market maker faces when it comes to equilibrating deviations in outflows and inflows. Those deviations of course are irrelevant in determining the long run future value of the stocks but quite relevant in determining the short run value of those shares. The dealer's effect on prices is temporary with prices ultimately revering to 'true' levels that prevail when order flows are balanced.

2.5 ADVERSE SELECTION MODELS

2.5.1 INTRODUCTION TO ADVERSE SELECTION MODELS

All previous models were concerned with examining the impact of inventory on price formation. In this part we will analyse major information based models in an attempt to understand how those models explain price behaviour. Information based models allow for examination of market dynamics and hence provide insights into the adjustment process of prices.

2.5.2 THE EMERGENCE OF INFORMATION MODELS

The origin of information models can be traced back to Bagehot (1971) who suggested that liquidity providers are confronted with the potential of trading with counter parties that have informational advantage. The market maker knows that when he is trading with an informed trader he always losses. To remain in business, the market maker must offset those losses by making gains from uninformed traders. These gains arise from the bid-ask spread. Therefore in the rest of this paper we will attempt to explain bid-ask spreads without relying on exogenous technological specifications of transaction costs.

Bagehot (1971) based his paper on the distribution between 'market agents' and 'trading gains'. The term 'market gains' refers to gains achieved as a result of a general increase in the price of stocks. In that way all investors make money without engaging in any kind of sophisticated trading strategy. Of course it is equally likely that stocks prices go down and every single trader incurs losses. Assuming an equal number of general price increases and general price decreases, all investors achieve a neutral market rate of return. On the other hand, the term 'trading gains' incorporates the notion of information costs. These costs arise as a result of information asymmetry between traders. As a result of this information asymmetry, investors who are at an informational disadvantage make losses in relation to the normal market rate return while investors who are in possession of superior information achieve a higher rate of return in relation to the normal market rate. Distinction between those two groups of traders from the point of view of the market maker is almost impossible and the market maker will end up incurring losses when engaging into trading with informed traders. As a consequence of that, the setting of bid and ask prices (quotes) are deemed necessary. Information asymmetry and the costs that arise for the market maker give rise to the spread, which is perceived as compensation for the losses incurred mentioned above at the expense of the uninformed (liquidity) traders who engage in trading just to satisfy their current financial needs.

2.5.3 FORMALIZATION OF INFORMATION COSTS: COPELAND & GALAI (1983)

The first attempt to formalize the notion of information costs, as a factor besides inventory costs capable of having an effect on the bid-ask spread was made by Copeland & Galai, hereafter C&G. They constructed a one period model with a single monopolistic neutral dealer along with a number of informed and uninformed traders. C&G approach the problem of price setting in two different ways: the first approach assumes the existence of a risk neutral dealer who sets bid & ask prices to maximize expected profit while the second approach views the bid & ask prices as call & put options provided by the dealer under consideration to the traders.

C&G construct a model with a single monopolistic neutral dealer and a number of traders who are indistinguishable information wise from the market maker's point of view. The stock price (P) is drawn from some known density f(P) which is exogenous to the market, however there are some traders who are aware of that density f(P) and the actual value of the stock. In addition traders arrive at the market according to some exogenous probabilistic framework independent of prices and are allowed to have price elastic demand functions so that they can choose whether to trade or not. At this point, it must be made clear that the above assumption is of particular convenience profit wise to liquidity traders who are given the possibility to defer trading if they perceive themselves at an exceptional information disadvantage. C&G also assume that all trades are of the same fixed size, an assumption not quite realistic since trade size has the ability to signal information content i.e. degree of importance attached to every single piece of information. Another assumption considered to be quite important is the recognition that the dealer's order flow may include information based trades. In particular while individuals traders are anonymous to the dealer, the market maker knows that any given trade comes from an informed trader with probability Π_I and from an uninformed trader with probability $1-\Pi_I$. This probabilistic structure is an important contribution of the model. C&G also assume that a liquidity trader will buy with probability (Π_{BL}), sell with probability (Π_{SL}) and engage in no trading with probability (Π_{NL}). The informed trader is assumed to buy or sell so as to achieve profit maximisation.

In the instantaneous quote framework assumed in the model under consideration, the market maker sets his quotes and trading occurs with no intervening time passing. In this way the market maker can calculate his gain or loss. If the market maker trades with an informed trader then he knows he is going to incur a loss. On the contrary if the market maker trades with a liquidity trader then he knows he will make profits. The dealer's objective function is given by

$$\{\Pi_I[\int_{PA}^{\infty}(P - P_A)f(P)dP + \int_{0}^{PA}(P_B - P)f(P)dP] + (1-\Pi_I)[\Pi_{BL}(P_A-P) + \Pi_{SL}(P-P_B) + \Pi_{NL}(0)]\} \quad 2.45)$$

The optimal bid and ask prices emerge as the solutions to the dealer's maximization problem, provided these prices are positive.

Having described the model and shown how the market maker will set his bid and ask prices, the next step is to evaluate hoe the model under consideration contributed to the general literature. Specifically the model showed that the bid-ask spread depends on the calculation of the market maker's expected gains and losses which makes it a similar model to the inventory control models discussed in the previous section. However this model showed that the market spread will exist without either risk aversion or market power on behalf of the market maker since the market maker in this model is risk neutral and by imposing a zero profit restriction the market maker under consideration turns from a monopolistic one to a competitive one without any alteration to the predictions of the model described already. The only disadvantage of the model is identified on the static one-trade framework. The models to follow take this point into consideration and assume a more sophisticated structure.

2.5.4 SEQUENTIAL TRADING MODELS

2.5.4.1 GLOSTEN & MILGROM (1985): A DICHOTOMIZATION OF INFORMATION & INVENTORY EFFECTS

In the one period-one trade model of Copeland & Galai considered previously market spread emerged as a result of the need to balance the various risks from trading indistinctively with both informed and uninformed trades. The bid-ask spread depended on a number of factors such as: i) the probability of trade by the informed ii) the stochastic process of the stock and iii) the elasticities of demand. It follows that if those factors remained unchanged, then the bid-ask spread would remain unchanged. In a world of multiple trading the market maker's total loss would equal constant loss (loss for a single trade) times the number of trades since the bid-ask spread would remain unaffected as a consequence of zero changes on the factors mentioned above which is not true because frequency and volume of trading has the ability to convey information, therefore the above mode is rendered obsolete.

In a multiple trading world, the market maker observes trading activity and then sets prices. If he observes traders selling a specific stock then he suspects that thee is bad news for the stock under consideration and he adjusts prices accordingly. However it may very well be the case that the traders observed by the market maker are just liquidity traders and their trading decisions do not incorporate any kind of information. Nevertheless if further selling occurs then the market maker will adjust prices downwards showing that the has received their 'hidden message' of bad news. In other words the market maker conditions his beliefs about the unobserved value of each stock on the trades he observes for the stock under consideration. Over time the imbalance observed between buys and sales for a specific stock will lead the market maker to learn all information and his prices will converge to the expected value of the asset given this information.

Similar to the spirit described above Glosten & Milgrom (1985) introduce a sequential trade model similar to that of Copeland & Galai. Specifically they assume that all participants are risk neutral and act competitively, the asset value is given by random variable V, market maker's capital is unlimited and bankruptcy is non existent but most important of all there are no transaction or holding inventory costs which preclude the consideration of any inventory effects bringing about an absolute dichotomization between inventory and information effects.

As it was explained above, informed traders use the information they possess to make money at the expense of the uninformed and the market maker. Any piece of information available to the informed traders would lead to increased trading activity on their behalf inducing imminent readjustment of prices. In order to avoid a situation like that which may pose a problem to the development of rational expectations models, the assumption made is that investors trade probabilistically and if they are chosen to trade, they are allowed to trade only one unit of the asset (stock) under consideration. If any trader wishes to engage in further training because he believed that the quotes provided by the market maker do not reflect the actual value of the asset (stock) as it is implied by the information available to him then he must 'join the queue' and wait to be selected again.

Having explained the rationale behind this kind of models as well as discussed the assumptions, the next step is to concentrate on price formation. In the model under consideration, the specialist sets prices such that the expected profit on any trade is zero. This is because of the assumptions of risk neutrality and competition made above. In other words each market maker sets his prices by considering the trading strategy to be followed by other market participants. In effect each market maker selects an expected profit maximising supply and demand schedule given his competitor's supply and demand schedules, playing a kind of game against each other. Considering the fact that each one of them has the same prior belief regarding the value of an asset and observing the same kind of trading activity, then it s natural for then to quote the same bid and ask prices. If any of them quoted different prices, competition would completely eliminate any deviations.

The mechanism implied by the model works in the following way. Each market maker has a perception about the value of an asset. This can be either $\underline{V}$ or $\overline{V}$. Based on this preconception he estimates $P[V=\underline{V}/B_1]$ & $P[V=\overline{V}/B_1]$ if he observes a buy order or $P[V=\underline{V}/S_1]$ & $P[V=\overline{V}/S_1]$ if he observes a sale. Having done that he estimates the expected value of the asset under consideration depending on the trade observed i.e. $E[V/B_1]$ and $E[V/S_1]$. Of course every time another trade, he revises his expectations with his posterior belief becoming his prior.

Having explained the workings of the model, the next step is to evaluate its contribution. In this model the spread arises as a result of the revisions in the asset's value conditioned on observed trades while in the model of Copeland & Galai the spread arises as a result of balancing expected gains and losses. Undoubtedly the incorporation of asymmetric information combined with learning on behalf of the market maker represent an important advancement in the market microstructure literature. In addition to this, the transaction prices obtained from this model form a Martingale meaning that an observer cannot do better in predicting the future price than by simply using the current price. Finally this model predicts that a high degree of asymmetric information can lead to market failure since the spread can get so wide precluding any trading. Although this model will be employed as the basis for studying the impact of asymmetric information on prices and looking into the usefulness of trading halts or circuit breakers, it suffers from order size restrictions since only one unit of each asset ca be traded each time completely disregarding the effect of block trading on prices. The models to be considered incorporate this new characteristic.

2.5.4.2 EASLEY & O'HARA: INFORMATION UNCERTAINTY AND THE IMPACT OF TRADE SIZE ON PRICES.

Another sequential model similar to the one described right above is that of Easley & O'Hara, hereafter E&O. Although the model under examination is similar in nature in the following points i) investors trade an asset with competitive, risk neutral market makers ii) inventory effects do not matter allowing full examination of information effects iii) trading takes place sequentially according to a probabilistic structure and iv) bid & ask prices are conditioned on the trades observed, there are two characteristics that make this model unique. Those innovative characteristics are primarily the ability of investors to transact at different sizes in sharp contrast to the Glosten & Milgrom model where trading is restricted only to one unit per trade allowing us to address the effect of different trade sizes on security prices. The second innovative characteristic is information uncertainty, which means that the market maker must decide about the existence of new information and then evaluate its content and possible effects on prices.

Those two innovative characteristics affect the way the market maker sets bid and ask prices. This process of price setting will be explained right below.

Informed traders as in previous models always make money at the expense of the uninformed or the market makers. However the trading behaviour of the informed in this model assumes a completely different dimension and this is a direct result of the characteristics of the mode, which allows variable trade sizes. In this model the informed trader will increase the amount of shares traded per single trade so as to take advantage of the superior information he possesses. Of course this kind of behaviour is peculiar to the informed trader only. This increased share dealing per single trade induces some kind of adverse selection problem and the market maker will perceive this behaviour as a sign of superior information upon which the market maker will condition his beliefs to set bid and ask prices. It becomes evident that the bid & ask prices obtained in the Copeland & Galai (1983) or Glosten & Milgrom (1985) are irrelevant when variable trade size is taken into consideration.

In the Easley & O'Hara model, the equilibrium achieved depends on the choices of the informed traders regarding their preferable trading size. If the informed traders choose to trade only large quantities then they will be separated from the uninformed traders who will trade small quantities and a 'separating' equilibrium will be relevant. If on the other hand the informed traders choose to trade both large and small quantities then a 'pooling' equilibrium will be relevant. In order for the market maker to decide which equilibrium will be relevant, it is necessary that we determine which of the two alternatives is more profitable to the trader, therefore both equilibria must be obtained. At this point it must be stressed that trying to obtain either of the two equilibria involves the same general approach to Bayesian learning as it was shown in the previous model with the specific trade probabilities adjusted to reflect the market maker's conjecture as to where the informed are trading. The equilibrium prices are given by the following formulae:

$$b^{*}=V^{*}-\frac{\sigma_v^2}{\overline{V}-\underline{V}}\left(\frac{\alpha\mu}{X_s^2(1-\alpha\mu)+\delta\alpha\mu}\right) \quad (2.46)$$

$$\alpha^{*}=V^{*}+\frac{\sigma_v^2}{\overline{V}-\underline{V}}\left(\frac{\alpha\mu}{X_B^2(1-\alpha\mu)+\alpha\mu(1-\delta)}\right) \quad (2.47)$$

where V^{*} is the expected value of V with $V\in[\underline{V},\overline{V}]$, X is the fraction of uninformed traders who trade the large quantity, δ is the probability that V is equal to $\underline{V}$, σ_v^2 is the variance of V and αμ is the probability of informed trading.

If the informed traders are trading large quantities only then the market maker sets bid and ask prices for large quantities only and forgoes setting a spread by equalizing bid and ask prices for the small trades since informed investors trade only large quantities. Given the above decision of the market maker regarding spreads, the informed traders must decide whether it is in their interests to keep trading large quantities. Obviously there is a trade off involved between large quantities-worse prices due to the existence of the spread and smaller quantities-better prices due to the non-existence of a spread. In order for the informed traders to keep trading large quantities the following conditions must hold

$$S^2/S^1<1+\alpha\mu(1-\delta)/X_s^2(1-\alpha\mu) \quad (2.48)$$

$$B^2/B^1<1+\alpha\mu(1-\delta)/X_B^2(1-\alpha\mu) \quad (2.49)$$

If this is not the case the market must be in a separating equilibrium.

Two important implications arise as a result of the two separate equilibria. First there is no such thing as a single market price. The price will be a direct result of trade size and the type of equilibrium prevailing each time. Secondly spreads do not constitute an appropriate measure of 'market goodness' simply because the spreads employed to measure 'market goodness' are usually small trade spreads which do not constitute good proxies of the presence of asymmetric information or of the costs of trading.

This revolutionary concept of the two separate equilibria has also provided an explanation for the severe drop observed when block trades occur and the subsequent weird price behaviour of prices of small trades. However before we provide an explanation for this kind of behaviour I strongly believe that it would be wise to remind readers of one of the innovative assumptions of this model namely the uncertainty regarding the existence of new information, which plays a crucial role in explaining the puzzling behaviour, mentioned above.

It is well known that block trades transact at worst prices than small trades and any subsequent small trades occur at improved prices. This can be explained according to the following rationale. If the market is in a separating equilibrium which means that informed investors trade only large quantities then two subsequent block sales will make the market maker think that those trades incorporate bad news and as a consequence will revise prices downwards for all subsequent buys or sales. However as it was explained above there is no spread in a separating for small trades implying the complete lack of asymmetric information, therefore small trades carried out by any type of investor implies that there is no new information in the market. If there was any kind of information then the market maker would observe a block trade. Since this is not the case given the occurrence of a small trade, the market maker will revise his expectations setting a higher price. Obviously the 'information uncertainty' characteristic of this model has ensured the market of the non-existence of any type of information and thus he chose to revise his prices. If on the other hand this 'information uncertainty' characteristic is not present then a small size sale following a block sale will appear as incorporating bad information and the price will remain at the block sale level in contrast to the previous case where some kind of recovery is present. This is because the market maker is always certain that even small trades contain some kind of bad information. The above rationale has been found to be consistent with observed empirical behaviour. Kraus & Stoll (1972), Dann, Myers & Raab (1977).

This 'information uncertainty' characteristic has introduced a new dimension on the analysis of asymmetric information simply because it appears that price formation does not depend solely on the previous period trade but it extends backwards many periods (small trade, block trade, small trade). In other words prices are Martingales but do not follow a Markov process.

2.5.5 ADVANTAGES AND DISADVANTAGES OF SEQUENTIAL TRADE MODELS

Having described and explained the peculiarities of each of the two models, the next step is to delve into the advantages and disadvantages of sequential models.

Sequential trade models allow the learning problem of the market maker and the uninformed trader to be analysed explicitly employing the Bayesian learning rule while at the same time look into the dynamic linkages between trades and price formation.

There are two main advantages, which must be outlined as far as the nature of those models is concerned. Sequential model are the first models in the asymmetric information category, which allow the full characterization of the bid-ask spread. Specifically the Easley & O'Hara model (1987) allows us to view price formation as i) a function of the trade size and ii) the ratio of large to small trades. This is considered to be a novelty in the market microstructure literature since we all know that trade size and direction can convey important information about the true value of an asset. In addition the Bayesian learning technique on which those models are based upon have the ability to demonstrate that prices converge to full time information values in the limit even though the specific time period required for this outcome to be achieved is not clear. This specific characteristic of those models is of tremendous importance to the notion of market efficiency and market organisation & design issues. Those models therefore can be considered as the basis for a number of different areas in market microstructure (such as institutional market design) worth of further investigation.

Even though the models presented above appear to have a number of virtues over older models, they however suffer from a number of structural problems with particular emphasis on the mechanics of the trading process. Both models Glosten & Milgrom (1985) and Easley & O'Hara (1987) assume that traders are chosen from a pool of traders according to the population probabilities. This means that if there are x percent informed traders in the population then the probability that a market maker is trading with an informed trader is x percent again. Each trader in those models is supposed to be able to train only once if he is picked in the first place of course and then after he completes his trading, he must return to the queue and wait to be chosen again. Of course this particular process of trading does not appear to be very realistic since an informed trader would prefer to trade constantly so as to take full advantage of the information he possesses leading to an immediate price change on behalf of the market maker who realises that the trading activity observed contains important information. A second assumption, which is rendered obsolete, by the most fundamental tenets of both models i.e. the sheer existence of asymmetric information and competition is that the percentage of both informed and uninformed traders remains constant. If uninformed traders observed increased trading behaviour then they would decide to forego trading for a certain period of time because it is almost certain that if they kept trading they would incur significant losses. The uninformed traders reaction is believed to be entirely rational considering the observed trading activity.

Another point that was criticized in both models is the sheer lack of informed traders' strategic behaviour, which can be considered a direct result of the assumptions on which both models were built. One would normally expect that informed traders would collude in a way so as to hide their trading intentions perhaps by splitting big orders to smaller ones taking advantage of their superior information for a longer period of time. However the assumption of competition and full-information price convergence does not allow any of the behaviour described above. In addition actual profits cannot be readily estimated because the price path depends on a number of variables, therefore an estimate of the profits achieved as a result of possession of superior information is impossible. This particular shortcoming inherent in sequential models is overcome in the next category of models to be reviewed namely batch models. However because of the nature of batch models that allow trades to be cleared at a single price we cannot clearly see the effects of trading on price formation as in this model. Obviously no single model can combine peculiar characteristics inherent in the two different groups of models. Nevertheless the models to be reviewed next provide an excellent treatment of the issue of strategic behaviour.

2.5.6 STRATEGIC TRADING MODELS

2.5.6.1 INTRODUCTION TO STRATEGIC TRADING MODELS

The previous chapter was concerned with sequential models and the effect of particular trades on prices. Although the previous models vividly illustrated the effects that trade size and trade direction can have on prices, they exhibited a complete disregard for the strategic use of asymmetric information and how informed traders who are in possession of such information can employ it for their own benefit. Obviously such a disregard appears to be the result of the fundamentals of the model and in particular of the trading process, which disallows the use of superior information, unless it is extremely long lived. In this type of models our attention concentrates on the strategic use of superior information to the benefit of the informed trader.

Strategic trading models are very closely linked t rational expectation models. In rational expectation models all agents make conjectures about the information that any other agents may have and thus decide on their actions. In a market microstructure context the following analogy would be relevant. Informed traders condition their trading policy on the pricing policy of the market maker and the market maker in his turn observes trades before deciding on the prices. Obviously pricing and trading are inter-related and it is on this basis that we will consider how a single informed trader could best exploit his informational advantage to maximise his profits. The model to be considered soon, is a batch trading model meaning that all trades clear at a single price disallowing idiosyncratic effects of single trades but allowing profit estimation made on superior information.

2.5.6.2 THE STRATEGIC BEHAVIOUR OF AN INFORMED TRADER

2.5.6.2.1 ONE-SHOT TRADING MODEL

In the previous models discussed any informed trader would just submit order(s) at any trading opportunity that might arise until prices would converge to their information value. However the stance of strategic trading models is entirely different. The informed trader is perceived as an information monopolist who aims at taking full advantage of the information he possesses. Kyle (1985) adopting the above stance introduces a model with a single risk neutral informed trader along with a number of uninformed traders who submit orders to a risk neutral market maker.

Kyle's (1985) informed trader receives exclusive information about the liquidation value (v) of an asset, which is assumed to be normally distributed with mean p_0 and variance Σ_0. In addition there are liquidity traders who submit their orders and their aggregate trade quantity (μ) is normally distributed with mean zero and variance σ_{μ}^2. This random variable (μ) is assumed to be independent of the distribution of the asset value (v). The market maker in the model under consideration observes the aggregate order flow i.e. the order flow from both informed and uniformed traders but can not distinguish between the two flows. As a consequence of this inability to distinguish order flow, the learning process differs in the sense that it is the aggregate trade quantity that affects price behaviour rather than informed trading only. The informed trader faces a similar problem to that of the market maker. In particular the informed trader cannot conjecture the uninformed traders' actual demands so as to hide his trades even though he is aware of the distribution of the uninformed traders' order flow.

Having explained the positions of the three agents involved in this model, the next step is to look into the trading process. The trading process in the model under consideration evolves in two different stages. In he first stage the informed trader obtains exclusive information about the liquidation value of the asset (v), learns about the distribution of the uninformed traders' order quantity (μ) and decides about his trade quantity (X). In the second stage, the market maker observes the aggregate net order quantity ($x+\mu$) and decides on a single clearing price, (p). At this point it must be stressed that the single clearing price, (p) set by the market maker is 'regret free' and the market maker earns zero expected profit.

If the market maker's pricing strategy is represented by a function $p=P(x+\mu)$, then the following condition must hold $P(x+\mu)=E[v/x+\mu]$ which means that the price the market maker sets is equal to the expected value of the asset conditioned on the aggregate order flow.

As we explained above the informed trader's order strategy depends on the pricing rule illustrated above and the order flow of the uninformed traders. However as it was explained before the informed trader is not aware of the actual order flow but is familiar only with the parameters of the distribution. The strategy of the informed trader is: $X(v)=B(v-p_0)$ where $B=(\sigma_\mu^2/\Sigma_0)^{1/2}$ and the strategy of the market maker $P(x+\mu)=p_0+\lambda(x+\mu)$ where $\lambda=1/2(\sigma_\mu^2/\Sigma_0)^{-1/2}$. Observing the informed trader's optimal trading policy, one ca clearly see that his optimal order quantity depends directly on the variance of the uninformed traders' order flow. As it was stressed above the informed trader is unaware of the uninformed traders' actual order flow but is familiar with parameters of the distribution $\mu \sim N(0,\sigma_{\mu}^{2})$ and he decides to hide his trades. Now as far as the market maker's trading price is concerned, it appears that it is linearly connected to the aggregate order flow $(x+\mu)$. However since informed and uninformed trades are indistinguishable to the eyes of the market maker, he decides to adjust prices according to the ratio of the amount of noise trading σ_{μ}^{2} to the amount of private information Σ_0. O'Hara comments on the above equilibrium conditions:

> "What makes this equilibrium so easy to characterize is its linear structure. This linearity in order strategy is important because it means that the informed trader will not pursue a more complex mixed strategy or submit orders that are linked to the underlying signal value in a non-linear manner. Consequently, given this strategic behaviour by the informed trader, the market maker knows that the relationship between the aggregate order flow and the underlying signal value must also be linear. Since in equilibrium the market efficiency condition requires the market maker to set prices equal to the conditional expected value, this, in turn means that market prices will also be linear in volume". (O'Hara, 1995, page 96)

2.5.6.2.2 MULTIPLE TRADING PERIOD

Up to the moment, we concentrated on one-shot trading models. Now we will look into a multi-period trading model. Specifically we will delve into the nature of a sequential auction model in which N rounds of trade occur in a trading day. Of course the same model ca be expanded to approximate a continuous auction as the number of periods becomes large.

In the previous model described the market maker had to consider the impact of trading only on that period. Now however he will have to consider the impact of his trading on other periods as well. This is because his trading decisions in each period are linked because of their effect on the informativeness of prices. Thus if the informed trader decides to trade heavily in the early periods then he will be penalised at later periods with worst prices. Obviously his trading strategy is much more complex than it was in a single trading period and a number of factors must be considered.

Kyle assumes that as the number of periods becomes large, the uninformed trades $\bar{u}(t)$ follow a Brownian motion so that $\Delta \bar{u}_n$ is normally distributed with mean zero and variance $\sigma_{\mu}^2 \Delta t_n$, implying that the quantity traded at one auction is independent of the uninformed quantity traded at the other auctions. Nevertheless this not true for the informed trader.

The informed investor's trading strategy and the market maker's trading clearing price are given by the following formulae

$$\begin{aligned} \Delta X_n(\overline{v}) &= B_n(\bar{v} - P_{n-1})\Delta t_n \\ P_n &= \lambda_n(\Delta X_n + \Delta \mu_n) \end{aligned} \quad (2.50)$$

And as it becomes apparent the market-clearing price is linearly related to the total order flow and optimal order strategy is also linearly related to the true asset value, similar to the one-shot trading model. In addition the informed trader's expected profit is given by

$$\mathrm{E}\{\Pi_n / P_1....P_{n-1}, v\} = \alpha_{n-1}(v - P_{n-1})^2 + \delta_{n-1} \quad (2.51)$$

Obviously the sequential auction equilibrium is much more complex than the sequential auction equilibrium described previously. A key property of this model that should be stressed is that information is gradually incorporated into prices across time. In the long run prices will reflect all superior information implying efficiency. Statistically speaking prices follow a martingale meaning that an uninformed observer's expectation of the future price is today's price.

Kyle's model (1985) and its extension (sequential batch trading) have provided an excellent treatment of the issue of asymmetric information and strategic trading. However as all models considered up to now, it is liable to certain shortcomings. In particular there is no consideration for price contingent order submission and informed trading is restricted simply to a single trader. Since this single informed trader makes positive profits, then it is quite natural that this will induce other traders to obtain superior information and trade in a similar way in pursuit of positive profits. Such behaviour is examined below. Another issue that is worth looking into is the possibility that superior information is disseminated not through private channels but rather through public channels. In other words looking into a situation where the informed trader described above ceases to be a monopolist and enters a competitive mode as described below.

2.5.6.2.3. MULTIPLE INFORMED TRADERS: KYLE (1984)

The previous model was concerned with a single informed trader who traded in a sequential auction model. This model will be concerned with multiple informed traders and market makers trading over a finite period of time. In particular Kyle (1984) introduces a three-date framework involving N speculators (informed traders) and M market makers. The model under consideration (Kyle, 1984) shares a number of similar characteristics to Kyle (1985). Specifically both models assume the same batch trading approach and informed traders must submit their orders without being aware of the price they will trade at. However the model to be discussed differs in a very important way to Kyle (1985) and this is to be found in the trading structure since all assets are assumed to liquidate at the end of time 2. As a consequence of this trading peculiarity price adjustment cannot be observed. In order to be more revealing regarding the peculiarities of this model I should say that price behaviour in this model is viewed in relation to the following triptych namely multiple informed traders, information revelation and increased noise trading.

Starting with 'multiple informed traders', one can easily conjecture that informed trader endogeneity (i.e. the number of informed traders is determined within the model) could have a number of effects as far as individual trader profits and individual trading behaviour are concerned. Needless to say the above changes will induce a kind of 'chain reaction' with stock prices being the ultimate recipient of all those changes.

An increase in the number of informed traders is expected to have a decrease in individual profits since a certain amount of profits generated by making use of superior information needs now to be shared with more informed traders. Besides individual profit shrinkage, informed trader endogeneity is also expected to affect individual trading behaviour. This is because each informed trader will have to consider his fellow traders behaviour before making any decision regarding trading size.

Having indicated that there will be changes in optimal trading size and individual profits as a consequence of informed trader endogeneity, the next step is to delve into those changes in relation to increased noise trading and increases in the amount of publicly available information.

The first stimulus (change) employed in studying the effects of informed traders endogeneity on prices is an increase in the amount of noise trading σ_{μ}^{2}. If the number of informed traders is exogenously determined (X is fixed), then an increase in noise trading will induce current informed traders to increase their individual trading orders so as to keep aggregate relative trading in the same level as before given the increase in noise trading. Of course no change is expected in the price level. If however the number of informed traders is determined endogenously then an increase in noise trading will bring about an increase in potential profits to be made by current informed traders. However given the possibility of increased profit potentiality, more informed traders will enter. Increased informed trading will have as a consequence prices to impound superior information much faster than before. At the same time this increased informed trading activity will reduce the total amount of rents to be shared.

The second stimulus employed in studying the effects of informed traders endogeneity-exogeneity on prices is an increase in the amount of publicly available information. Again if the number of informed traders is given endogenously then an increase in the amount of publicly available information will result in an immediate decrease in future profits since their corporate advantage (superior information) has now been dissipated. Needless to say, the market under consideration is much more efficient now. If on the other hand the number of informed traders is endogenous then some of them will leave the market since they believe that it is not worth trading any more, leading to a kind of market inefficiency since their information is no longer impounded on prices. Of course Kyle shows that the market will appear more efficient since the increased public information inflow will offset any private information not impounded in current prices due to the informed traders' reluctance to transact.

The model just described was developed under the assumption that all market makers are risk neutral, which greatly simplified the whole process. If the risk neutrality is dropped, then the results obtained may be entirely different.

This last chapter concluded the description of Kyle models and their extensions. As it was stressed at the introduction of batch trading models, these models are not concerned with how specific trades will affect prices as it was the case with previous models but rather they are concerned with strategic behaviour of informed traders. I hope that the analysis above provided readers of this dissertation a good insight in strategic trading.

CHAPTER 3: SYSTEMATIC LIQUIDITY AND EXCESS RETURNS: EVIDENCE FROM THE LONDON STOCK EXCHANGE

3.1. INTRODUCTION

Market microstructure has traditionally concentrated on the characteristics of single assets exhibiting absolute disregard for attribute(s) that can have an effect on multiple assets simultaneously. 'Transaction costs' studies and in particular 'liquidity' studies concentrate on the repeated trading of a single homogenous asset or assets and any patterns that may emerge during trading. No research has been undertaken in 'transaction costs' or 'liquidity' concentrating on systematic variations and how this affects stocks. This study aspires to enhance the limited research in the area of systematic liquidity for the UK market employing FTSE100 and FTSE250 as its sample.

The purpose of this study is two-fold. First we look for evidence of commonality (common underlying factors) in liquidity and secondly we examine the effect of systematic liquidity on asset pricing in a market that changes form quote-driven trading to order-driven trading for FTSE100 stocks and from quote driven to hybrid for FTSE250. Commonality refers to the proposition that an individual firm's liquidity is determined by market-wide factors (unidentified yet) besides well-documented idiosyncratic factors such as volatility, trading volume, number of trades etc. Research has also shown that predictable differences in liquidity lead to cross-sectional differences in excess returns. Traditionally empirical work in the area of market microstructure has concentrated exclusively on trading patterns of individual assets, seasonal patterns and market crashes. The very first studies to look into the relation of liquidity and asset returns were those of Amihud & Mendelson (1986), Eleswarapu & Reinganum (1993), Brennan & Subrahmanyam (1996) and Datar et al. (1998). Quite recently research interest has shifted to the common components of liquidity (Chordia et al. 2000; Huberman & Halka 2001; Hasbrouck & Seppi 2001). Generally speaking there are a number of studies that have investigated the relation of liquidity and returns and documented the presence of commonality in liquidity but no study has looked into common factors in liquidity (commonality) and returns. *This study combines those two lines of research and examines if and to what extent commonality(common underlying factors) affects excess returns when the trading regime changes from quote driven to order driven for FTSE100 stocks and from quote driven to hybrid for FTSE250 stocks.*

It is well known that each security has its own liquidity dictated by a number of factors such as order flow, number of trades, trading volume, volatility, number of institutional investors holding the stock, the number of market makers assigned to each stock and the number of different markets a specific stock is traded etc as discussed in Tinic (1972) and Menyal & Paudyal (1996). The nature of the factors identified above is clearly idiosyncratic and we would expect each security to have its own liquidity. Alternatively we would expect to find correlation in liquidity across securities if there is a common component to the cost of providing liquidity or if securities are substitutes as Huberman & Halka (2001) postulate. Plausible reasons for the existence of common factors affecting liquidity are increased trading activity/order flow taking the form of either increased buying or selling which may signify the existence of superior information making market makers to re-evaluate the optimal level of their inventory, inducing a co-movement of spread. Covariation in liquidity can have interesting implications for markets. With reference to equity markets Chordia et al (2000) note that a higher return would surely be required for stocks with higher average liquidity costs. In other words if a stock is illiquid, then investors would require higher returns for this stock. In addition there might be extra compensation demanded of stocks with higher sensitivities to broad liquidity shocks. For example if a market becomes highly illiquid due to a shock then investors would demand an even higher return for stocks with low liquidity following he market wide shock. Roll (1988) commenting on the international market crash of October 1987 identifies no noteworthy event that would be capable of bringing about such turbulence. However he stresses the existence of a temporary severe reduction in liquidity and puts forward as the most prevalent reason for the crash, mistaken expectations regarding the current level of liquidity. Therefore the real question that arises is whether liquidity shocks constitute a source of non-diversifiable priced risk. We test for the effect of market wide unidentified factors controlling for well known spread determining variables on excess returns over different trading regimes namely when the market is quote driven/order driven for FTSE100 stocks and when the market is quote driven/hybrid for FTSE250 stocks. However for FTSE100 when the market is order-driven, closing prices are estimated under different protocols therefore we need to make a further distinction. Under order-driven trading closing prices are estimated based on i) the last automated transaction ii) average volume weighting and iii) closing auction.

The last few years a shift in trading regimes has been observed from quote driven to order-driven and the London stock exchange has followed this trend (for FTSE100 stocks only). In a quote-driven regime, market makers are obliged to provide liquidity under any circumstances. In a hybrid market and with special reference to FTSE250 market makers are obliged to provide liquidity as well but in an order-driven regime market makers are not obliged to do so. Brockman & Chung (2002) term this the 'free-exit' aspect of order-driven trading. We wish to test how those two different trading regimes respond to market-wide liquidity changes (commonality) and what is the effect on asset pricing. There is a high chance that in an order-driven regime the common component of liquidity affecting all stocks indistinguishably will be less pronounced because of the non-mandatory nature of market making (free-exit aspect). Market makers even if present do not have to provide liquidity. Alternatively there is also a high chance that higher spreads will invite more investors to provide liquidity given the higher profit margins. Brockman & Chung term this the 'free-entry' aspect of order-driven-trading. We do not know which effect is going to dominate; therefore the common component of liquidity and its subsequent effect on asset pricing under different trading regimes is an open issue. In other words we seek to address the following questions:

- Q1) Is commonality in liquidity present in the UK market as well or it constitutes a stylized fact pertinent to the US market only?
- Q2) Is commonality priced?
- Q3) How do changes in the trading regime affect the relationship between commonality and excess returns?

The results obtained in this study contribute to the commonality literature in the following ways. First we show that commonality in liquidity is not just a US characteristic but it is also pertinent in other markets namely the UK market, secondly we find that commonality does affect excess returns and thirdly the trading regime plays an important role on the extent to which commonality is priced for FTSE100 stocks only. In particular the effect of commonality on excess returns appears to be considerably reduced after the change of the trading regime from quote-driven to order-driven. Results obtained for FTSE250 show that commonality is not equally strong and it is not priced.

3.2.EXPERIMENTAL DESIGN[1]

Huberman & Halka (2001) postulate that liquidity can be defined as the ability of an investor or market maker to trade any quantity of shares after

[1]The first part of the experimental design pertinent to the identification of commonality presented here has been adopted from Huberman & Halka (2001)

the desire to trade arises at a price, which is close to price and depth quoted prior to the specific trade and after it. Liquidity for the i^{th} stock is comprised of an idiosyncratic and a systematic component. This is similar to the total risk of a stock, which includes both idiosyncratic relating to firm specific factors, and systematic i.e affected by market-wide factors. Symbolically this is expressed as:

$$L_{it}=\alpha_i+b_i f_t+\varepsilon_{it}+\eta_{it} \quad (3.1)$$

Where L_{it} represents total liquidity for the i^{th} stock, α_i is a constant, f_t is a common liquidity shock, ε_{it} is an idiosyncratic shock and η_{it} is a rounding error designed to equate the stock specific liquidity measure to the nearest acceptable integer multiple. These three random variables are assumed to be independent of each other. Moreover the ε's and the η's are cross-sectionally independent.

We assume that both the common liquidity shock (f_t) and the idiosyncratic term (ε_{it}) follow AR(1) processes[2]. Symbolically this is expressed as[3]:

$$f_t = \rho f_{t-1} + u_t = \sum_{\tau=0}^{\infty} \rho^{\tau} u_{t-\tau} \quad (3.2)$$

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[2] We could have assumed any other AR process but an AR(1) process greatly simplifies mathematical operations

[3] The final form of both equations (2) and (3) is obtained in the following way:

$$\left.\begin{array}{l}
f_t = \rho f_{t-1} + u_t = \sum_{\mathrm{T}=0}^{\infty} \rho^{\tau} u_{t-\mathrm{T}} \\
f_{t+1} = \rho f_t + u_{t+1} \Rightarrow f_{t+1} = \rho(\rho f_{t-1} + u_t) + u_{t+1} = \rho^2 f_{t-1} + \rho u_t + u_{t+1} \\
f_{t+2} = \rho f_{t+1} + u_{t+2} \Rightarrow f_{t+2} = \rho(\rho^2 f_{t-1} + \rho u_t + u_{t+1}) + u_{t+2} = \rho^3 f_{t-1} + \rho^2 u_t + \rho u_{t+1} + u_{t+2} \\
f_{t+3} = \rho f_{t+2} + u_{t+3} \Rightarrow f_{t+3} = \rho(\rho^3 f_{t-1} + \rho^2 u_t + \rho u_{t+1} + u_{t+2}) = \rho^4 f_{t-1} + \rho^3 u_t + \rho^2 u_{t+1} + \rho u_{t+2} + u_{t+3} \\
. \\
.
\end{array}\right\}$$

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$$f_t = \rho^{\mathrm{T}} f_{t-1} + \sum_{\mathrm{T}=0}^{\infty} \rho^{\mathrm{T}} u_{t-\mathrm{T}}$$

Since $|\rho|<1$, as $\mathrm{T} \to \infty$, it reduces to $f_t = \sum_{\mathrm{T}=0}^{\infty} \rho^{\mathrm{T}} u_{t-\mathrm{T}}$, because $\lim_{\mathrm{T}\to\infty} \rho^{\mathrm{T}} f_{t-1} = 0$.

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + \nu_{it} = \sum_{\tau=0}^{\infty} \rho_i^{\tau} \nu_{it-\tau} \quad (3.3)$$

Next consider L_{It}, the average liquidity of a subset of stocks, I, which has L members

$$L_{It} = \overline{\alpha}_I + \overline{b}_I f_t + [\sum_{i \in I} (\sum_{\tau=0}^{\infty} \rho_i^{\tau} \nu_{it-\tau}) + \eta_{it}] / |I| \quad (3.4)$$

where $\overline{a_I}$ is the average α_i and $\overline{b}_I$ is the average b_i. The term $\overline{b}_I f_t$ represents the common liquidity shock while the term inside the square brackets represents idiosyncratic liquidity shocks. The variance of the term in the square brackets converges to zero as $|I|$ approaches infinity[4], which by Chebychev's inequality[5] implies this term converges to zero in probability as $|I|$ approaches infinity. Therefore if indeed the common liquidity shock is present, it will dominate fluctuations in the average liquidity and render approximately AR(1) processes. Moreover the residuals from the approximately AR(1) processes describing the average liquidity fluctuations of mutually exclusive sets of stocks will be correlated. To see this note that

$$L_{It} = \overline{\alpha}_I + \overline{b}_I \sum_{\tau=0}^{\infty} \rho^{\tau} u_{t-\tau} + [\sum_{i \in I} (\sum_{\tau=0}^{\infty} \rho_i^{\tau} \nu_{it-\tau}) + \eta_{it}] / |I| \quad (3.5)$$

$$L_{It} = \overline{\alpha}_I + \overline{b}_I \sum_{\tau=0}^{\infty} \rho^{\tau} u_{t-\tau} + \xi_t \quad (3.6)$$

Now if we re-write equation (3.6) at time (t-1), multiply by ρ and add to itself we obtain:

$$L_{It} = \overline{\alpha}_I (1-\rho) + \rho L_{It-1} + \overline{b}_I u_t + \xi_{It} + \rho \xi_{It-1} \quad (3.7)$$

[4] An analogy is that of a portfolio. Idiosyncratic risk cancels out as the number of stocks increases.
[5] Chebychev's inequality states that if x_n is a random variable and c_n and ε are constants then $\mathrm{Prob}(|x_n - c_n| > \varepsilon) \leq E[(x_n - c_n)^2]/\varepsilon^2$.

where the last two terms are small and shows that average liquidity for a subset of stocks I is dominated by the systematic component. However our focus is on the residuals from the approximately autoregressive process (eq.3.7) namely

$$u_{It}=L_{It}-\rho L_{It-1} \quad (3.8)$$

In particular note that if the sets I and J are mutually exclusive then

$$CORR(u_{It}u_{Jt}) \approx \frac{\bar{b}_I\bar{b}_J VAR(u_t)}{\sqrt{VAR(\bar{b}_I u_t + \xi_{It} - \rho\xi_{It-1})VAR(\bar{b}_J u_t + \xi_{Jt} - \rho\xi_{Jt-1})}} \quad (3.9)$$

the correlation is positive if there is a common liquidity component and the stocks' average exposures to it $\bar{b}_I$ and $\bar{b}_J$ are positive.

In order to show the presence of common components in liquidity we are going to make use of equations (3.7), (3.8) and (3.9). For this reason equation (3.7) needs to be written in a regression form for different portfolios (I,J,K) to facilitate understanding of this study:

$$\text{Spread}_{I,J,Kt}=c+\lambda_1\text{spread}_{I,J,Kt-1}+\lambda_2\text{spread}_{I,J,Kt-2}+..+\lambda_v\text{spread}_{I,J,Kt-v}+\phi_1\text{idiosynctatic}_{I,J,Kt}+..+\phi_v\text{idiosynctatic}_{I,J,Kt}+u_{I,J,Kt} \quad (3.10)$$

Where spread represents daily absolute spread and daily proportional spread. It is used as a proxy for average liquidity ($L_{I,J,Kt}$) and is regressed on past values of itself. The AR process used each time depends on the stock group under consideration. The subscript (I,J,K) refers to the particular group of stocks under examination. Equation (3.10) also incorporates terms for idiosyncratic variables pertinent to groups (I,J,K). Remember that we are interested in the residuals (u_{It}), (u_{Jt}), (u_{Kt}), obtained from regression (3.10) and the correlations between them. Correlations are examined by making use of formula (3.9). If correlations turn out to be positive we proceed with the extraction of the common component from the residuals obtained from eq (3.10) for mutually exclusive portfolios (I,J,K) which is achieved by principal component analysis/principal axis factoring. Singular value decomposition (SVD) operations on the correlation matrices provide the relevant eigenvalues and component scores, which are then used to explain excess returns. The regressions estimated to test the effect of common component of liquidity on excess returns are of the following form:

$$\text{EXCESS RETURNS}_{I,J,Kt}=CF_{I,J,Kt}+CF_{I,J,Kt-1}+CF_{I,J,Kt-2}+CF_{I,J,Kt-3}+CF_{I,J,Kt-4}+e_t \quad (3.11)$$

Where excess returns are estimated as the difference between returns and the risk free rate, CF stands for common factor and is estimated by principal component analysis/principal axis factoring and the subscript (I,J,K) represents different portfolios.

SVD is an operation according to which any matrix M is expressed as the product of three matrices: M=PΔU. If we performed such an operation on X, so that $X = P\Delta U'$ then P would be equal to the matrix of eigenvectors of XX' and U would be equal to the matrix of eigenvectors of $X'X$. Matrix Δ contains the square roots of the eigenvalues of XX'. Other simplifications can be made. We know that $X'X/(n-1)$ is equal to the correlation matrix R. Hence we might as well examine the eigenstructure of R, for the eigenvalues of R are simply the eigenvalues of $X'X$ divided by n-1. Moreover R is a square symmetric matrix. In such a case the SVD operation is greatly simplified because in the product $P\Delta U'$ it holds for symmetric matrices that P=U. It follows that $R = UDU'$ in which U is the matrix of eigenvectors of R, D is the matrix of eigenvalues of R or the matrix of eigenvalues of $X'X/(n-1)$ or the matrix of squares of eigenvalues of X divided by (n-1). It becomes clear that finding the eigenstructure of X amounts to the same as finding the eigenstructure of R. Standardised values are used for all of the above operations.

In order to investigate whether common liquidity components are present in the UK market and the extent to which they affect excess returns under different trading regimes we formulate the following hypotheses:

- H1) the residuals obtained by modelling innovations in spread and also controlling for idiosyncratic factors for mutually exclusive group of stocks are significantly positively correlated which indicates the presence of a common component.

If average liquidity proxies for mutually exclusive group of stocks are modelled as shown above and the residuals (u_{It}, u_{Jt}, u_{Kt}) obtained from these regressions are significantly positively correlated, then this indicates the presence of a common liquidity component.

- H2) the common component extracted from the residuals obtained by modelling innovations in spread and also controlling for idiosyncratic factors for mutually exclusive groups of stocks explains excess returns for that combined group.

The rationale for this particular hypothesis is explained in the following way. Assume that a particular group namely GROUPI is split in two mutually exclusive sub groups namely IA and IB. If a common component is extracted from the residuals u_{IA} and u_{IB} for those two groups and explains excess returns for GROUPI, then it means that the common liquidity factor is priced

- H3) changes in the trading regime (from quote driven to order driven or from quote driven to hybrid) reduce the extent to which commonality impacts excess returns.

In an order driven regime, provision of liquidity is not dependent on market makers but every single investor, therefore commonality will be less pronounced and it will not be priced as much. In addition investors by placing limit orders have the ability to achieve better execution prices, dampening the effect of commonality on excess returns. In a hybrid market where market makers still have to provide liquidity, there should not be any changes on the degree to which commonality is priced if it is priced at all.

3.3.DATASET AND DESCRIPTIVE STATISTICS

Daily price data for the FTSE100 companies was obtained from DATASTREAM. The data set under consideration ranges from 18/10/1996 to 18/5/2001. The choice of the data set reflects a quote-driven trading regime and an order-driven trading regime, which is further sub-divided into three different periods. This allows us to test if commonality is present under different trading regimes, which relates to the first research question and the extent to which it is priced under those regimes which relates to the second and third research questions. Each subset represents a different price reporting period/trading regime and incorporates the following time period: the first subset ranges from 18/10/1996 to 17/10/1997 and reflects a dealership, the second subset ranges from 20/10/1997 to 13/12/1998 during which period the closing prices were based on the last automated transaction (order book), the third subset ranges from 14/12/1998 to 26/05/00 during which period the closing prices were based on weighted trading volume (order book) and finally the fourth subset ranges from 30/05/2000 to 18/05/2001 during which period the closing prices were formed by a closing auction. Daily price data for FTSE250 was obtained from DATASTREAM. It ranges from 01/01/2003 to 12/08/2004 and it is split in two subsets. The first subset represents a quote driven regime and the second subset represents a hybrid market. The data obtained includes the following variables: closing bid price, closing ask price, closing price and closing trading volume for each stock. These variables were further processed to obtain other variables such as: absolute spread, proportional spread, returns, returns volatility using GARCH(1,1), excess and unexpected trading volume employing the Box-Jenkins methodology. We use two liquidity proxies namely: i) absolute spread which is the difference between bid and ask prices and ii) proportional spread, which is estimated as: absolute spread/mid-quote where mid-quote is equal to (bid-price+ask-price)/2.

Descriptive statistics (TABLE3.1: Panel A and B) with reference to the whole sample over the four periods examined show that absolute spread has increased from 2.67 up to 6.48 and proportional spread from 0.18% up to 0.9%. When testing for mean (in)equality, the ANOVA F statistic obtained for absolute spread is equal to 329.70 with (3,984)df and p=0.00 rejecting H_0:mean equality while the value for proportional spread is equal to 593.5413 with (3,888)df and p=0.00 rejecting H_0 again. Cross sectional correlations between the lowest and the highest market capitalization groups show that there is some difference for the first, second and third period. There appear to be no differences between the two extremes for the fourth period. Panel C presents results for FTSE250 which show that the spread has changed between the two periods. The ANOVA F statistic obtained is equal to 7.47 and p=0.00. Proportional spread for FTSE250 is non-stationary and is excluded from the analysis altogether.

TABLE 3.1

DESCRIPTIVE STATISTICS OF THE TWO LIQUIDITY PROXIES FOR EQUALLY WEIGHTED PORTFOLIOS OF THE WHOLE SAMPLE AND THREE SIZE-BASED GROUPS FOR ALL PERIODS

PANEL A: FTSE100 DAILY ABSOLUTE SPREAD

		WHOLE SAMPLE	MRKT CAPIT1 £665.85-£3920.82	MRKT CAPIT2 £3954.96-£9228.13	MRKT CAPIT3 £9236-£140684.3
MEAN	PERIOD1	2.67	3.32	2.48	2.21
	PERIOD2	4.15	5.61	3.73	3.46
	PERIOD3	4.28	5.29	4.06	3.49
	PERIOD4	6.48	7.13	5.00	7.31
MEDIAN	PERIOD1	2.66	3.34	2.49	2.19
	PERIOD2	4.04	5.34	3.52	3.24
	PERIOD3	3.98	5.02	3.57	3.21
	PERIOD4	5.75	6.20	4.24	6.67
MAX	PERIOD1	4.17	5.07	3.56	4.19
	PERIOD2	15.7	17.8	16.5	17.4
	PERIOD3	22.3	30.8	16.9	19.6
	PERIOD4	18.9	24.1	16.6	19.1
MIN	PERIOD1	1.79	2.23	1.69	1.19
	PERIOD2	1.68	2.37	1.42	1.06
	PERIOD3	2.06	2.40	1.13	1.57
	PERIOD4	3.14	2.65	2.01	3.94
SE	PERIOD1	0.32	0.39	0.32	0.41
	PERIOD2	1.18	1.70	1.61	1.54
	PERIOD3	1.68	2.24	1.96	1.53
	PERIOD4	2.38	3.36	2.60	2.35

PANEL B:FTSE100 DAILY PROPORTIONAL SPREAD (% OF MID-PRICE)

		WHOLE SAMPLE	MRKT CAPIT1 £665.85-£3920.82	MRKT CAPIT2 £3954.96-£9228.13	MRKT CAPIT3 £9236-£140684.3
MEAN	PERIOD1	0.18%	0.26%	0.15%	0.13%
	PERIOD2	N/S	N/S	N/S	N/S
	PERIOD3	0.7%	1%	0.7%	0.42%
	PERIOD4	0.9%	1%	0.8%	0.9%
MEDIAN	PERIOD1	0.18%	0.26%	0.15%	0.13%
	PERIOD2	N/S	N/S	N/S	N/S
	PERIOD3	0.7%	1%	0.6%	0.3%
	PERIOD4	0.8%	1%	0.7%	0.8%
MAX	PERIOD1	0.23%	0.35%	0.19%	0.23%
	PERIOD2	N/S	N/S	N/S	N/S
	PERIOD3	3.6%	5.1%	3%	3%
	PERIOD4	2%	4%	2%	2%
MIN	PERIOD1	0.13%	0.18%	0.10%	0.73%
	PERIOD2	N/S	N/S	N/S	N/S
	PERIOD3	0.3%	0.5%	0.1%	0.1%
	PERIOD4	0.4%	0.4%	0.3%	0.6%
SE	PERIOD1	0.01%	0.03%	0.01%	0.01%
	PERIOD2	N/S	N/S	N/S	N/S
	PERIOD3	0.2%	0.3%	0.2%	0.4%
	PERIOD4	0.3%	0.5%	0.3%	0.2%

PANEL C:FTSE250 DAILY ABSOLUTE SPREAD

		WHOLE SAMPLE	MRKT CAPIT1	MRKT CAPIT2	MRKT CAPIT3
MEAN	SEAQ	6.85	8.43	6.33	5.90
	SETSMM	6.14	7.33	5.65	5.42
MEDIAN	SEAQ	6.54	7.46	6.30	5.82
	SETSMM	6.09	7.42	5.51	5.16
MAX	SEAQ	10.2	17.1	8.68	10
	SETSMM	10.7	10.8	12.9	17.6
MIN	SEAQ	5.4	5.7	4.75	4.36
	SETSMM	3.9	4.13	3.40	2.94
SE	SEAQ	0.95	2.68	0.53	0.57
	SETSMM	0.98	1.24	1.26	1.71

3.4.METHODOLOGICAL ISSUES

In order to examine the above hypotheses and with special reference to the first hypothesis we need to i) describe the splitting technique ii) determine the optimal lag structure for each group of stocks (remember that in the experimental design we assume an AR(1) process just for convenience), iii) decide on the idiosyncratic variables to include in our regressions and iv) test if the residuals obtained for mutually exclusive groups of stocks are significantly positively correlated[6].

With reference to the second hypothesis we need to i) extract the common factor between mutually exclusive groups of stocks employing principal axis factoring/singular value decomposition and ii) regress the common factor (commonality) on excess returns for that group.

For the third hypothesis we need to test for the (in)significance of coefficients of the common factor over the different trading regimes.

H1.1.SAMPLE SPLITTING TECHNIQUE

[6] The significance of the correlation coefficients is evaluated by the t statistic given in parenthesis. If the true ρ=0, the sampling distribution of r is symmetric:

$$r \sim N(0, \sigma_r = \sqrt{(1-r^2)} / \sqrt{(n-2)})$$

and we can apply the Student's t test for establishing the significance or non-significance of the sample estimate r. The value of the t statistic is estimated from the sample correlation coefficient r, by the expression

$$t^* = r/\sigma_r = r\sqrt{n-2} / \sqrt{1-r^2}$$

and is compared with the theoretical value of $t_{0.025}$ (for a two tailed test at the 5% level of significance) with n-2 degrees of freedom. The critical value at 5% is equal to 1.960.

Initially we obtain the bid-ask spread for each stock in our sample and then we split the original sample into three size-based groups namely: MK1, MK2 and MK3[7]. We further split the three size-based groups each into smaller subgroups (A & B). At this point we ensure that random splitting occurs so that group A (GA) does not end up with the lowest market capitalization stocks in its category and group B (GB) with the highest market capitalization stocks. Then all type A subgroups are placed in a single portfolio and all type B subgroups in another portfolio, forming two randomly constructed, equally weighted portfolios.[8] Finally we obtain average values for all subgroups and the two portfolios. All testing to follow uses these portfolios and subgroups as the basis for drawing conclusions.

H1.2.OPTIMAL LAG STRUCTURE DETERMINATION AND PRELIMINARY RESIDUAL CORRELATIONS

In this part we will define the optimal lag structure for each of the two-liquidity proxies namely daily average absolute spread (DABSP) and daily average proportional spread (DPRSP) by running the following regressions:

$$DABSP^i_t=C+DABSP^i_{t-1}+DABSP^i_{t-2}+DABSP^i_{t-v}+\ldots+e^i_t \quad (3.12)$$

$$DPRSP^i_t=C+DPRSP^i_{t-1}+DPRSP^i_{t-v}+\ldots+ e^i_t \quad (3.13)$$

for a different number of lags each time. We run those regressions for all portfolios and all subgroups and decide on the optimal lag structure based

[7] MK stands for market capitalization. MK1 consists of the lowest MK stocks in the sample.
[8] In that way portfolio 1 is made up of: P1MK1GA, P1MK2GA and P1MK3GA while portfolio 2 is made up of: P2MK1GB, P2MK2GB and P2MK3GB.

on both the Box-Jenkins methodology and the Akaike and Schwarz information criteria. TABLE3.2 (PANELS A AND B) summarise the results obtained for each of the four periods at subgroup level and whole sample level. In the case under examination absolute and proportional spread for the third and the fourth period are best modelled as AR(5) while for the first and the second period are best modelled as AR(4) and AR(3) respectively. PANEL C presents results for FTSE250. Those results were reached by obtaining the autocorrelations functions and graphs for each of the groups and portfolios under consideration. The optimal autoregressive structure for FTSE250 portfolios and subgroups varies considerably when compared to FTSE100. FTSE250 portfolios 1 and 2 are modeled as AR(6) and AR(7) while there is greater variation for MK2 and MK3 over the two periods. If residuals between the two portfolios constructed randomly or between market capitalisation subgroups are positively correlated, then we have a first indication of the existence of a common factor[9].

H1.3.IDIOSYNCRATIC VARIABLES

A number of studies over the years have shown that the competitiveness of the environment in which stocks are traded, trading characteristics, risk and share price are important in determining spreads. In particular Tinic (1972) identifies a number of 'classic spread-determining factors' such as: stock price, average number of shares traded daily (trading volume),

[9] In order to claim the presence of a common factor, it is necessary that spread determining factors alsobe included in the regressions estimated here to obtain residuals. Of course this will be done at a later stage.

average number of transactions per day (number of trades), trading continuity (number of days a stock is traded/number of days sampled) and standard deviation of price while he goes even further to test whether i) the number of different markets a specific stock is traded, ii) the number of institutional investors holding the stock iii) the total number of stocks carried by the market agent registered in the ith stock and iv) the purchasing capacity of the market agent under consideration are significant spread-determining factors. Tinic (1972) finds that all of the above are significant except the standard deviation of price and total purchasing capacity of the unit market agent.

TABLE 3.2
OPTIMAL LAG STRUCTURE DETERMINATION

PANEL A: FTSE100 LAG DETERMINATION FOR ABSOLUTE SPREAD

	WHOLE SAMPLE		MK1		MK2		MK3	
	PORTFOLIO1	PORTFOLIO2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
PERIOD1	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)
PERIOD2	AR(3)	AR(3)	AR(3)	AR(3)	AR(3)	AR(3)	AR(3)	AR(3)
PERIOD3	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)
PERIOD4	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)

PANEL B: FTSE100 LAG DETERMINATION FOR PROPORTIONAL SPREAD

	WHOLE SAMPLE		MK1		MK2		MK3	
	PORTFOLIO1	PORTFOLIO2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
PERIOD1	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)	AR(4)
PERIOD2	N/S	N/S	N/S	N/S	N/S	N/S	N/S	N/S
PERIOD3	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)
PERIOD4	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)	AR(5)

PANEL C: FTSE250 LAG DETERMINATION FOR ABSOLUTE SPREAD

	WHOLE SAMPLE		MK1		MK2		MK3	
	PORTFOLIO1	PORTFOLIO2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
SEAQ	AR(7)	AR(6)	AR(6)	AR(6)	AR(5)	AR(2)	AR(4)	AR(4)
SETSmm	AR(6)	AR(7)	AR(6)	AR(7)	AR(10)	AR(9)	AR(10)	AR(2)

The insignificance of the standard deviation of price is a very strange finding given that all studies to follow find that the standard deviation of price, which measures risk, is a very important factor.

Menyah & Paudyal (1996) test for the significance of all the 'classic spread-determining factors' mentioned above and they also include a new factor (number of market makers) representing the competitiveness of the environment each stock is traded. Menyah & Paudyal (1996) perceive 'risk' to be quite important in determining spreads. For this reason they use three variables to approach 'risk' in a wholistic way namely: i) standard deviation of returns to capture total risk, ii) standard market model betas to capture systematic risk and iii) residual errors to capture unsystematic risk. They find that the bid-ask spread is affected by the unit price of the security, variability in security returns (risk), trading volume and competition among market makers.

Another study concentrating on common factors in liquidity by Chordia, Roll & Subrahmanyam (2000) employs i) average dollar size of a transaction in stock j, ii) aggregate dollar trading volume for the entire market excluding the stock j and iii) dollar volume in stock j's industry besides the 'classic spread-determining factors' mentioned above. Chordia, Roll & Subrahmanyam (2000) find evidence of commonality even after considering all those factors.

Finally Huberman & Halka (2001) testing for common factors in liquidity, use dummy variables for daily returns to assess the effect of positive and negative returns on the spread, decompose daily trading volume into its expected and unexpected components while they also incorporate i) two day volatility of yields on the one year treasury note ii) daily spread changes between the Baa corporate bond yield & the one year treasury note yield and iii) daily spread changes between yields on ten year & one year treasury bonds. In addition they estimate volatility by fitting returns into GARCH(1,1). Most variables appear to be significant in explaining spreads except daily spread changes between the Baa corporate bond yield & the one-year treasury note yield, expected and unexpected volume. They find evidence of co-movement even after incorporating all those spread-determining variables in their regressions.

Having considered all of the above studies and subject to data availability constraints, we decided to include the following variables namely: i) daily return on the portfolio or group when that return is positive and zero otherwise, ii) daily return on the portfolio or group when that return is negative or zero and zero otherwise, iii) returns volatility modelled as GARCH(1,1), iv) expected volume which is obtained by subtracting unexpected volume from actual volume v) unexpected volume which is obtained by modelling actual trading volume and obtaining innovations, vi) default premium which is estimated as the change in the spread between the corporate bond yield and the two year government bond yield and vii) term structure which is estimated as the change in the spread between the ten-year government bond yield and the three month treasury bill yield. The first two variables are included in the regression because we wish to examine how the spread is affected by positive and negative returns, volatility and trading volumes are included in order to capture risk while default premium and term structure are included in order to capture the macroeconomic environment and alternative opportunities of investment for market makers/investors but are not always used together due to the presence of high correlations with other variables. Most of the time they are used interchangeably to avoid inducing multicollinearity. Omission of those variables in the final regressions did not change the residuals correlation in any way. All variables are stationary[10].

H1.4 FINAL RESIDUALS CORRELATION

Residuals obtained from modelling innovations in the spread controlling for other well known spread determining variables for mutually exclusive group of stocks are devoid of any idiosyncratic or macroeconomics factors. Therefore they should be uncorrelated. If it turns out that they are significantly positively correlated then it means that there is a common factor that drives liquidity for all stocks.

H2.1 COMMON FACTOR AND EXCESS RETURNS

Extraction takes place at i) the portfolio level where a single factor is extracted from the two portfolios that together make up

[10]All variables to be included in the regressions are tested for stationarity using the Dickey-Fuller and Phillips-Perron tests.

FTSE100/FTSE250 and regressed on returns for the whole sample (FTSE100/FTSE250) and ii) at the market capitalisation groups level where a single factor is extracted from each sub-group (group A and group B) comprising the relevant market capitalisation group (MK1, MK2 and MK3) and regressed on returns for that particular market capitalisation group. In other words, a single factor is extracted from MK1GA and MK1GB and regressed on returns for MK1. According to the Kaiser criterion only common factors with eigen-values higher than 1.00 are retained for analysis as it is usually the practice.

3.5.EMPIRICAL FINDINGS

The statistical analysis aims at i) detecting the presence of a common component ii) extracting a common factor from the two sub-groups within each market capitalisation group or the two portfolios that comprise the whole sample and regress it on returns for those groups or the whole sample respectively over the periods examined and iii) observing the extent to which commonality is priced under different trading regimes. The sections that follow present results for each of those objectives.

3.5.1 MODELLING LIQUIDITY: PRELIMINARY CORRELATION TESTS

In order to detect the presence of a common factor, we need to model liquidity and obtain innovations. TABLE3.3 (PANELS A and B) and

TABLE3.4 present results for absolute and proportional spread for all portfolios and subgroups. Having run those regressions, the next step is to obtain residuals and test the extent to which they are correlated. Results are represented in TABLE3.5 and TABLE3.6. The null hypothesis states that correlations between portfolios and subgroups should have an arbitrary sign and be insignificant. Results obtained in TABLE3.5 (PANELS A and B) and TABLE3.6 (PANELS A and B) indicate towards the existence of a common component given that most correlations are positive and significant. At this point it is worth mentioning that correlations are stronger for FTSE100 stocks. Correlations for FTSE250 stocks appear to be weak in most cases and insignificant for both periods (SEAQ/SETSmm) under consideration. Nevertheless it is still too early to draw conclusions for FTSE100 stocks bearing in mind that a number of spread determining factors have not been considered yet. After all, such positive correlations may be capturing those 'missing' variables. This possibility is considered next.

TABLE 3.3

AUTOREGRESSIVE ESTIMATES FOR ABSOLUTE SPREAD (p value in parentheses)

PANEL A: FTSE100 UNDER FOUR DIFFERENT PERIODS

	WHOLE SAMPLE		MRKT CAPIT1		MRKT CAPIT2		MRKT CAPIT3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	1.89(0.03)	0.64(0.57)	1.13(0.00)	0.52(0.27)	0.17(0.66)	0.74(0.02)	0.16(0.79)	0.31(0.22)
	6.05(0.00)	3.04(0.04)	4.02(0.00)	1.51(0.00)	1.55(0.01)	2.01(0.00)	1.93(0.00)	1.56(0.00)
	7.04(0.00)	2.65(0.00)	5.12(0.00)	0.94(0.00)	1.76(0.00)	1.33(0.00)	1.45(0.00)	1.26(0.00)
	2.02(0.00)	1.60(0.00)	3.94(0.00)	1.63(0.00)	1.31(0.00)	0.24(0.00)	3.38(0.00)	2.30(0.00)
-1	0.44(0.00)	0.38(0.00)	0.42(0.00)	0.32(0.00)	0.37(0.00)	0.35(0.00)	0.49(0.00)	0.31(0.00)
	0.08(0.00)	0.15(0.00)	0.23(0.00)	0.23(0.00)	0.19(0.00)	0.10(0.00)	0.06(0.10)	0.12(0.01)
	0.21(0.00)	0.17(0.07)	0.27(0.00)	0.23(0.00)	0.12(0.07)	0.14(0.09)	0.11(0.03)	0.06(0.31)
	0.29(0.000	0.20(0.00)	0.33(0.00)	0.07(0.30)	0.10(0.18)	0.17(0.02)	0.05(0.23)	0.26(0.00)
-2	0.09(0.25)	0.08(0.27)	0.21(0.00)	0.21(0.04)	0.22(0.01)	0.03(0.65)	0.08(0.35)	0.08(0.27)
	0.23(0.15)	0.17(0.37)	0.21(0.07)	0.14(0.29)	0.23(0.20)	0.12(0.45)	0.16(0.02)	0.13(0.29)
	0.19(0.05)	0.31(0.00)	0.03(0.67)	0.28(0.00)	0.20(0.05)	0.17(0.01)	0.19(0.00)	0.23(0.00)
	0.11(0.01)	0.24(0.00)	0.13(0.05)	0.25(0.00)	0.18(0.07)	0.05(0.51)	0.01(0.76)	0.10(0.00)
-3	0.11(0.06)	0.25(005)	-0.05(0.39)	0.09(0.25)	0.20(0.00)	0.15(0.01)	0.23(0.09)	0.21(0.10)
	0.19(0.05)	0.38(0.03)	0.06(0.37)	0.15(0.21)	0.17(0.24)	0.21(0.00)	0.24(0.08)	0.26(0.08)
	0.08(0.40)	0.13(0.20)	0.00(0.98)	0.04(0.61)	0.09(0.29)	0.15(0.04)	0.22(0.13)	0.10(0.10)
	0.00(0.97)	0.09(0.30)	0.01(0.87)	0.19(0.00)	0.28(0.06)	0.05(0.42)	0.01(0.73)	0.07(0.15)
-4	0.13(0.04)	0.18(0.02)	0.18(0.02)	0.15(0.01)	0.12(0.10)	0.15(0.02)	0.27(0.03)	0.24(0.00)
	------------	------------	------------	------------	------------	------------	------------	------------
	0.06(0.15)	0.06(0.27)	0.08(0.01)	0.06(0.26)	0.05(0.44)	0.02(0.59)	0.00(0.93)	0.18(0.01)
	0.18(0.02)	0.06(0.38)	0.00(0.98)	0.05(0.25)	0.09(0.05)	0.04(0.53)	0.09(0.03)	0.16(0.07)
-5	------------	------------	------------	------------	------------	------------	------------	------------
	------------	------------	------------	------------	------------	------------	------------	------------
	-0.00(0.9)	0.04(0.30)	-0.08(0.06	0.16(0.06)	0.16(0.00)	0.12(0.04)	0.05(0.37)	0.02(0.63)
	0.07(0.26)	0.11(0.11)	0.09(0.11)	0.04(0.44)	0.06(0.37)	0.10(0.10)	0.09(0.01)	0.13(0.01)

The estimated model is

$DABSP^{i}t=C+DABSP^{i}_{t-1}+DABSP^{i}_{t-2}+DABSP^{i}_{t-v}+\ldots+e^{i}_{t}$

$DPRSP^{i}_{t}=C+DPRSP^{i}_{t-1}+DPRSP^{i}_{t-v}+\ldots+e^{i}_{t}$

where S_t^i is the spread of portfolio (i) or each of the subgroups on day t. Portfolios 1 & 2 are mutually exclusive and make up the whole sample while subgroups make up the whole market capitalization group. The number in parenthesis is the probability of a t-statistic being at least as extreme as the observed p value under H_0:p=0

PANEL B: FTSE250 UNDER SEAQ AND HYBRID/SETSMM

	WHOLE SAMPLE		MARKET CAPITALIZATION 1		MARKET CAPITALISATION 2		MARKEY CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	8.07(0.00)	0.56(0.00)	10.4(0.00)	6.14(0.00)	7.45(0.00)	4.91(0.00)	6.21(0.00)	5.63(0.00)
	5.99(0.00)	6.40(0.00)	10.1(0.00)	7.79(0.00)	3.37(0.00)	5.35(0.00)	5.64(0.00)	5.88(0.00)
-1	0.16(0.01)	0.25(0.00)	0.11(0.10)	0.10(0.20)	0.39(0.00)	0.36(0.00)	0.28(0.01)	0.19(0.02)
	0.15(0.09)	0.33(0.02)	0.23(0.00)	0.25(0.00)	-0.01(0.6)	0.07(0.25)	0.17(0.01)	0.32(0.03)
-2	0.12(0.10)	0.07(0.11)	0.11(0.12)	0.12(0.03)	0.20(0.00)	------------	0.04(0.40)	0.04(0.28)
	0.18(0.00)	-0.08(0.5)	0.34(0.00)	0.14(0.01)	0.08(0.03)	0.13(0.04)	-0.03(0.6)	------------
-3	0.10(0.12)	-0.00(0.9)	0.12(0.08)	0.08(0.05)	0.04(0.61)	------------	-0.11(0.06)	-0.11(0.10)
	0.07(0.22)	0.12(0.02)	0.09(0.15)	0.07(0.20)	0.00(0.79)	0.22(0.00)	-0.04(0.5)	------------
-4	0.02(0.72)	0.06(0.17)	0.01(0.89)	0.07(0.09)	0.10(0.25)	------------	------------	
	0.16(0.02)	-0.04(0.3)	0.07(0.24)	-0.09(0.2)	0.01(0.78)	-0.00(0.9)	0.09(0.21)	
-5	0.08(0.36)	0.03(0.56)	0.09(0.34)	0.06(0.21)	0.11(0.08)	------------	------------	
	0.07(0.17)	-0.01(0.8)	0.00(0.99)	0.14(0.00)	0.10(0.24)	-0.00(0.9)	0.09(0.20)	
-6	-0.15(0.07)	0.10(0.03)	-0.14(0.07)	0.12(0.03)	------------	------------	------------	
	0.15(0.02)	0.12(0.15)	0.19(0.04)	0.08(0.29)	0.00(0.65)	-0.03(0.5)	0.03(0.56)	
-7	0.15(0.04)	------------		------------	------------	------------	------------	
	------------	0.18(0.06)		0.12(0.07)	0.01(0.58)	0.00(0.96)	0.08(0.34)	
-8					------------	------------	------------	
					-0.01(0.6)	0.03(0.66)	0.07(0.23)	
-9					------------	------------	------------	
					0.09(0.03)	0.14(0.04)	-0.06(0.4)	
-10					------------		------------	
					0.0.8(0.00)		0.20(0.02)	
R^2	0.13	0.12	0.08	0.10	0.53	0.13	0.09	0.05
ADJ	0.29	0.15	0.54	0.28	0.04	0.11	0.14	0.10

The estimated model is
$DABSP^{i}t=C+DABSP^{i}_{t-1}+DABSP^{i}_{t-2}+DABSP^{i}_{t-v}+\ldots+e^{i}_{t}$

where S_t^i is the spread of portfolio (i) or each of the subgroups on day t. Portfolios 1 & 2 are mutually exclusive and make up the whole sample while subgroups make up the whole market capitalization group. The number in parenthesis is the probability of a t-statistic being at least as extreme as the observed p value under H_0:p=0

TABLE 3.4
AUTOREGRESSIVE ESTIMATES FOR PROPORTIONAL SPREAD (p values in parentheses)

	WHOLE SAMPLE		MRKT CAPIT1		MRKT CAPIT2		MRKT CAPIT3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00(0.00) ------------[11] 0.08(0.00) 0.00(0.00)	0.00(0.05) ------------ 0.00(0.00) 0.00(0.00)	0.00(0.00) ------------ 0.00(0.00) 0.00(0.00)	0.00(0.00) ------------ 0.00(0.00) 0.05(0.00)	0.00(0.00) ------------ 0.00(0.00) 0.00(0.01)	0.00(0.00) ------------ 0.00(0.00) 0.00(0.00)	0.00(0.14) ------------ 0.06(0.00) 0.00(0.00)	0.00(0.00) ------------ 0.00(0.00) 0.00(0.00)
-1	0.46(0.00) ------------ -0.02(0.6) 0.29(0.00)	0.31(0.00) ------------ 0.21(0.00) 0.14(0.02)	0.51(0.00) ------------ 0.24(0.00) 0.33(0.00)	0.26(0.00) ------------ 0.23(0.00) 0.01(0.78)	0.23(0.00) ------------ 0.18(0.00) 0.19(0.02)	0.23(0.00) ------------ 0.20(0.02) 0.27(0.00)	0.33(0.00) ------------ -0.01(0.6) 0.03(0.57)	0.26(0.01) ------------ 0.06(0.17) 0.25(0.00)
-2	0.07(0.30) ------------ 0.01(0.64) 0.11(0.01)	0.04(0.56) ------------ 0.27(0.00) 0.26(0.00)	0.14(0.01) ------------ 003(0.68) 0.12(0.09)	0.19(0.01) ------------ 0.20(0.00) 0.19(0.00)	-0.04(0.50) ------------ 0.23(0.04) 0.12(0.21)	-0.04(0.50) ------------ 0.21(0.00) 0.02(0.75)	0.17(0.20) ------------ 0.01(0.63) 0.05(0.27)	-0.01(0.81) ------------ 0.18(0.00) 0.09(0.03)
-3	0.07(0.30) ------------ 0.00(0.98) -0.01(0.8)	0.15(0.12) ------------ 0.04(0.65) 0.14(0.03)	-0.03(0.58) ------------ -0.03(0.5) 0.00(0.92)	0.12(0.07) ------------ -0.02(0.6) 0.15(0.01)	0.15(0.00) ------------ 0.02(0.79) 0.12(0.34)	0.15(0.00) ------------ 0.13(0.15) 0.16(0.02)	0.16(0.04) ------------ 0.00(0.95) 0.07(0.24)	0.05(0.57) ------------ 0.06(0.25) 0.00(0.87)
-4	0.12(0.12) ------------ 0.06(0.10) 0.22(0.01)	0.11(0.14) ------------ 0.02(0.52) 0.04(0.50)	0.14(0.03) ------------ 0.06(0.10) 0.05(0.39)	0.15(0.01) ------------ 0.05(0.21) 0.05(0.20)	0.08(0.27) ------------ 0.02(0.70) 0.16(0.00)	0.08(0.27) ------------ -0.02(0.6) -0.01(0.8)	0.02(0.77) ------------ 0.06(0.08) 0.11(0.01)	0.10(0.17) ------------ 0.10(0.10) 0.11(0.10)
-5	------------ ------------ 0.04(0.41) 0.05(0.37)	------------ ------------ 0.09(0.03) 0.05(0.34)	------------ ------------ -0.08(0.06 0.09(0.03)	------------ ------------ 0.07(0.11) 0.01(0.73)	------------ ------------ 0.11(0.02) 0.02(0.73)	------------ ------------ 0.16(0.01) 0.19(0.02)	------------ ------------ 0.05(0.31) 0.14(0.00)	------------ ------------ 0.01(0.79) 0.09(0.17)

The estimated model is
$DABSP^{i}t = C + DABSP^{i}_{t-1} + DABSP^{i}_{t-2} + DABSP^{i}_{t-v} + \ldots + e^{i}_{t}$
$DPRSP^{i}_{t} = C + DPRSP^{i}_{t-1} + DPRSP^{i}_{t-v} + \ldots + e^{i}_{t}$
where S_t^i is the spread of portfolio (i) or each of the subgroups on day t. Portfolios 1 & 2 are mutually exclusive and make up the whole sample while subgroups make up the whole market capitalization group. The number in parenthesis is the probability of a t-statistic being at least as extreme as the observed p value under H_0:p=0

[11] proportional spread for the second period is not stationary therefore it is excluded from the study.

TABLE 3.5
RESIDUALS CORRELATION MATRIX BETWEEN PORTFOLIOS EXCLUDING SPREAD DETERMINING VARIABLES

PANEL A: FTSE100 (all correlations above 0.10 are significant)

		PORTFOLIO 1	
		ABSOLUTE SPREAD	PROPORTIONAL SPREAD
PORTFOLIO 2	ABSOLUTE SPREAD	0.71 0.73 0.60 0.47	
	PROPORTIONAL SPREAD		0.45 non stationary insignificant 0.47

PANEL B: FTSE250 (all correlations above 0.13 are significant)

	PORTFOLIO1
	ABSOLUTE SPREAD
PORTFOLIO2	0.20 0.23

TABLE 3.6

RESIDUALS CORRELATION MATRIX EXCLUDING SPREAD-DETERMINING VARIABLES BETWEEN SUBGROUPS

PANEL A: FTSE100 UNDER FOUR DIFFERENT PERIODS (all correlations above 0.10 are significant)

		ABSOLUTE SPREAD					
		MK1GA	MK1GB	MK2GA	MK2GB	MK3GA	MK3GB
PROPORTIONAL SPREAD	MK1GA	1	0.14	0.19	0.04	0.15	0.19
		1	0.51	0.48	0.34	0.41	0.46
		1	0.49	0.34	0.37	0.54	0.24
		1	0.22	0.13	0.23	0.22	0.29
	MK1GB	0.04	1	0.47	0.42	0.45	0.40
		------------	1	0.70	0.43	0.61	0.56
		0.50	1	0.40	0.50	0.59	0.32
		0.18	1	0.15	0.16	0.16	0.35
	MK2GA	0.14	0.34	1	0.36	0.46	0.48
		------------	------------	1	0.50	0.65	0.61
		0.43	0.45	1	0.23	0.39	0.20
		0.20	0.21	1	0.16	0.23	0.30
	MK2GB	-0.02	0.26	0.25	1	0.32	0.32
		------------	------------	------------	1	0.48	0.53
		0.41	0.54	0.41	1	0.50	0.27
		0.34	0.24	0.31	1	0.16	0.24
	MK3GA	0.15	0.40	0.41	0.28	1	0.52
		------------	------------	------------	------------	1	0.60
		0.03	-0.0	-0.05	0.01	1	0.39
		0.29	0.20	0.39	0.30	1	0.38
	MK3GB	0.12	0.28	0.38	0.28	0.43	1
		------------	------------	------------	------------	------------	1
		0.37	0.46	0.36	0.43	-0.01	1
		0.32	0.26	0.33	0.36	0.50	1

PANEL B:FTSE250 UNDER SEAQ AND SETSMM (all correlations above 0.13 are significant)

	ABSOLUTE SPREAD					
	MK1GA	MK1GB	MK2GA	MK2GB	MK3GA	MK3GB
MK1GA	1	0.11	0.02	-0.00	0.03	0.04
	1	0.15	0.28	0.05	0.02	0.04
MK1GB		1	0.08	0.05	0.20	0.15
		1	0.16	0.07	0.17	0.10
MK2GA			1	0.14	0.31	0.34
			1	0.13	0.17	0.11
MK2GB				1	0.22	0.17
				1	0.28	0.04
MK3GA					1	0.55
					1	0.13
MK3GB						1
						1

3.5.2.MODELLING LIQUIDITY: FINAL CORRELATION TESTS

In order to detect the presence of a common component we need to model the time series properties of the average liquidity proxies controlling for serial correlation and incorporating well-known liquidity determining variables. For this reason regressions of the following type are estimated:

$$DABSP^{I}_{t}=C+DABSP^{I}_{t-1}+DABSP^{I}_{t-2}+DABSP^{I}_{t-3}+DABSP^{I}_{t-4}+DABSP^{I}_{t-V}+NEGATIVERETURNS^{I}_{t}+POSITIVERETURNS^{I}_{t}+VOLATILITY^{I}_{t}+EXPECTEDVOLUME^{I}_{t}+UNEXPECTEDVOLUME^{I}_{t}+DEFAULT\ YIELD^{I}_{t}+TERM\ PREMIUM^{I}_{t}+e_{t} \quad (3.14)$$

Where $DABSP^{I}_{t}$ represents daily average absolute spread, POSITIVE RETURNS represent daily return on the portfolio or group when that return is positive and zero otherwise, NEGATIVE RETURNS represent daily return on the portfolio or group when that return is negative or zero and zero otherwise, volatility is modelled as GARCH(1,1), expected trading volume is obtained by subtracting unexpected volume from actual volume, unexpected trading volume is obtained by modelling actual trading volume and obtaining innovations, default premium is estimated as the change in the spread between the corporate bond yield and the two year government bond yield and term structure is estimated as the change in the spread between the ten-year government bond yield and the three month treasury bill yield. The above regression is pertinent to daily average absolute spread however similar regressions are estimated for both liquidity proxies, all portfolios and subgroups over different trading periods. Results are presented in TABLE3.7 (PANELS A, B AND C) and TABLE3.8 for absolute and proportional spread respectively. Each line within each box in the table represents results for a specific time period. When a variable is missing either because it is non-stationary or it is highly correlated with some other variable it is substituted by a line of dashes(-).

Now as far as the significance of the variables is concerned, it seems that that the first and the second lags are almost always significant for both absolute and proportional spread. The significance of higher order lags appears reduced. The sign of negative returns is positive which means that negative returns increase the spread even though its significance is considerably reduced for FTSE250 stocks and in the proportional spread table for FTSE100 stocks. The positive returns variable bears a negative sign, which means that spread is reduced if a stock performs well even though its significance is considerably reduced in the proportional spread table (FTSE100) and for FTSE250 stocks.

Returns volatility appears to have a positive effect on spreads, which means that more volatile stocks have higher spreads. This finding is consistent with Huberman & Halka (2001) but inconsistent with Tinic (1972) who finds that the standard deviation of returns in insignificant. Expected and unexpected volume variables appear to play some role in explaining absolute spread but their importance is diminished when it comes to explaining proportional spread or FTSE250 stocks spread. Some would anticipate unexpected volume to play a very important role in explaining spread since this variable is supposed to capture asymmetric information effects. Of course trading volume would play a significant role if depth variables were examined. Finally macroeconomic variables do not appear to have a significant explanatory power bearing mixed signs. Residuals correlations for FTSE100 stocks between portfolio 1 and portfolio 2 which are equally weighted range from 0.47 to 0.59 for absolute spread and from 0.37 to 0.47 for proportional spread respectively. All correlations are highly significant with the exception of residuals obtained from proportional spread regressions for the third period. Residual correlations for FTSE250 portfolios 1 and 2 are equal to 0.19 and 0.22 for SEAQ and SETSmm respectively. Results are presented in TABLE3.9 (PANELS A and B). Correlations between subgroups for FTSE100 are presented in TABLE3.10 (PANEL A) and all of them are significant with the exception of two or three cases meaning that there is a common liquidity component present not captured by any of the know classic spread determining variables. Correlations between subgroups for FTSE250 are presented in TABLE3.10 (PANEL B) and most of them are insignificant.

TABLE 3.7

REGRESSION RESULTS FOR ABSOLUTE SPREAD INCORPORATING SPREAD DETERMING VARIABLES (p values in brackets)

PANEL A: FTSE100 UNDER FOUR DIFFERENT PERIODS

	WHOLE SAMPLE		MARKET CAPITALIZATION 1		MARKET CAPITALIZATION 2		MARKET CAPITALIZATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	2.82(0.00)	0.00(0.99)	1.01(0.00)	0.77(0.10)	0.61(0.08)	0.95(0.01)	0.34(0.48)	0.56(0.07)
	9.99(0.00)	6.25(0.00)	5.66(0.00)	2.83(0.00)	6.77(0.00)	3.30(0.00)	2.94(0.00)	2.88(0.02)
	6.09(0.00)	1.17(0.45)	5.15(0.00)	0.41(0.56)	1.01(0.40)	2.19(0.02)	1.66(0.00)	0.26(0.54)
	11.47(0.00)	14.03(0.00)	3.04(0.20)	5.71(0.00)	1.90(0.09)	4.35(0.00)	4.75(0.00)	7.28(0.00)
-1	0.42(0.00)	0.35(0.00)	0.42(0.00)	0.32(0.00)	0.37(0.00)	0.30(0.00)	0.39(0.00)	0.25(0.00)
	0.17(0.06)	0.09(0.09)	0.21(0.00)	0.16(0.00)	0.06(0.40)	0.06(0.22)	0.03(0.36)	0.12(0.04)
	0.20(0.00)	0.14(0.17)	0.26(0.00)	0.16(0.05)	0.11(0.09)	0.09(0.31)	0.09(0.04)	0.03(0.71)
	0.26(0.00)	0.19(0.00)	0.31(0.00)	0.03(0.63)	0.09(0.23)	0.15(0.01)	0.03(0.44)	0.23(0.00)
-2	0.05(0.47)	0.06(0.37)	0.22(0.00)	0.20(0.06)	0.22(0.01)	0.03(0.69)	0.07(0.46)	0.02(0.78)
	0.25(0.19)	0.12(0.46)	0.20(0.13)	0.11(0.38)	0.16(0.25)	0.06(0.64)	0.12(0.02)	0.11(0.34)
	0.18(0.09)	0.29(0.00)	0.01(0.88)	0.21(0.00)	0.17(0.09)	0.12(0.09)	0.17(0.01)	0.19(0.00)
	0.09(0.05)	0.20(0.00)	0.15(0.03)	0.22(0.00)	0.18(0.07)	0.04(0.55)	-0.00(0.98)	0.05(0.22)
-3	0.09(0.12)	0.23(0.06)	-0.06(0.30	0.07(0.36)	0.19(0.01)	0.13(0.02)	0.21(0.03)	0.13(0.32)
	0.30(0.16)	0.38(0.02)	0.05(0.49)	0.13(0.26)	0.14(0.25)	0.16(0.00)	0.21(0.12)	0.24(0.09)
	0.07(0.42)	0.12(0.16)	-0.01(0.80	0.00(0.98)	0.08(0.27)	0.12(0.07)	0.20(0.16)	0.07(0.19)
	-0.01(0.77)	0.08(0.36)	0.00(0.93)	0.20(0.00)	0.27(0.07)	0.04(0.53)	0.00(0.96)	0.05(0.31)
-4	0.10(0.12)	0.16(0.05)	0.13(0.04)	0.14(0.04)	0.10(0.18)	0.12(0.05)	0.06(0.33)	0.18(0.04)
	------------	------------	------------	------------	------------	------------	------------	------------
	0.05(0.20)	0.05(0.29)	0.07(0.07)	0.01(0.78)	0.05(0.40)	0.00(0.91)	-0.00(0.92)	0.15(0.03)
	0.17(0.03)	0.05(0.44)	-0.01(0.84	0.01(0.73)	0.09(0.06)	0.02(0.64)	0.07(0.09)	0.14(0.11)
-5	------------	------------	------------	------------	------------	------------	------------	------------
	------------	------------	------------	------------	------------	------------	------------	------------
	-0.01(0.75)	0.01(0.78)	-0.10(0.02)	0.04(0.40)	0.16(0.00)	0.09(0.08)	0.04(0.48)	-0.01(0.77)
	0.06(0.32)	0.08(0.23)	0.09(0.14)	0.00(0.99)	0.05(0.40)	0.10(0.11)	0.09(0.01)	0.12(0.04)
R(-)	-0.03(0.47)	-0.14(0.19)	0.12(0.31)	-0.08(0.35)	-0.10(0.29)	-0.01(0.87)	0.12(0.15)	-0.00(0.98)
	1.46(0.08)	-0.21(0.57)	0.67(0.08)	-0.09(0.50)	-0.08(0.67)	0.13(0.52)	0.28(0.15)	-0.27(0.14)
	-0.11(0.90)	-0.27(0.52)	-0.05(0.88)	-0.06(0.77)	-0.50(0.42)	-0.02(0.91)	-0.24(0.25)	0.10(0.58)
	0.61(0.55)	1.07(0.25)	-0.05(0.94)	0.93(0.04)	0.03(0.92)	-0.18(0.60)	0.20(0.53)	-0.30(0.37)
R(+)	0.00(0.99)	0.43(0.15)	0.02(0.61)	-0.03(0.57)	-0.05(0.33)	-0.07(0.14)	-0.04(0.53)	-0.02(0.64)
	-0.37(0.66)	-1.48(0.01)	-0.25(0.43)	-0.38(0.01)	-0.60(0.01)	-0.50(0.02)	-0.18(0.34)	-0.55(0.01)
	0.09(0.93)	-0.36(0.45)	-0.49(0.23)	0.18(0.20)	0.21(0.44)	-0.09(0.63)	-0.03(0.84)	0.00(0.97)
	-0.79(0.44)	-0.04(0.96)	0.09(0.91)	0.13(0.75)	-0.27(0.35)	-0.73(0.09)	0.09(0.78)	-0.24(0.44)
RVOL	0.11(0.01)	0.15(0.03)	0.35(0.09)	0.23(0.13)	0.04(0.57)	1.39(0.00)	0.28(0.06)	0.40(0.00)
	-0.32(0.93)	0.11(0.78)	0.14(0.35)	0.62(0.52)	0.55(0.71)	0.25(0.17)	0.84(0.46)	0.35(0.69)
	0.71(0.45)	0.93(0.03)	0.57(0.04)	0.51(0.01)	0.55(0.12)	0.36(0.01)	0.28(0.88)	0.31(0.04)
	0.40(0.89)	0.38(0.43)	0.42(0.09)	0.11(0.50)	0.67(0.52)	0.95(0.21)	0.19(0.23)	0.27(0.01)
VEXP	0.00(0.40)	0.00(0.17)	-0.0(0.50)	-0.0(0.35)	-0.0(0.25)	-0.00(0.00	-0.0(0.64)	-0.0(0.95)
	-0.00(0.03)	-0.00(0.13)	-0.00(0.20)	-0.00(0.20	-0.0(0.01)	-0.00(0.10)	-0.00(0.13)	-0.0(0.47)
	0.00(0.23)	0.00(0.38)	-0.0(0.84)	0.00(0.53)	0.00(0.74)	-0.00(0.39)	0.0(0.17)	0.0(0.10)
	-0.00(0.02)	-0.00(0.01)	0.00(0.38)	-0.0(0.00)	-0.0(0.83)	-0.00(0.01	-0.0(0.01)	-0.00(0.00)
VUNX	0.0(0.28)	-0.0(0.24)	-0.0(0.19)	-0.0(0.11)	-0.0(0.40)	-0.0(0.26)	-0.0(0.25)	-0.0(0.20)
	-0.00(0.16)	0.00(0.04)	-0.00(0.20)	0.00(0.09)	0.00(0.01)	-0.00(0.11)	-0.0(0.14)	-0.0(0.98)
	-0.0(0.71)	-0.0(0.58)	-0.0(0.78)	-0.0(0.60)	-0.00(0.10)	-0.0(0.30)	0.0(0.73)	0.0(0.73)
	-0.0(0.20)	0.0(0.26)	0.00(0.05)	0.0(0.55)	-0.0(0.57)	-0.0(0.60)	-0.0(0.54)	0.0(0.12)
DEF	------------	------------	------------	------------	------------	------------	------------	------------
	1.40(0.14)	1.37(0.11)	-0.13(0.80)	0.27(0.24)	0.85(0.02)	0.57(0.05)	0.47(0.03)	0.23(0.36)
	-0.68(0.40)	-0.65(0.12)	0.21(0.63)	-0.28(0.18)	-0.59(0.08)	-0.27(0.21)	-0.35(0.08)	-0.30(0.07)
	------------	------------	------------	------------	------------	------------	------------	------------
TERM	------------	------------	------------	------------	------------	------------	------------	------------
	-1.79(0.09)	-0.86(0.17)	-0.44(0.49)	-0.02(0.91)	-1.01(0.03)	-0.42(0.11)	-0.31(0.27)	-0.14(0.57)
	------------	------------	------------	------------	------------	------------	------------	------------
	-0.98(0.65)	1.24(0.48)	-1.11(0.36)	0.67(0.37)	-0.12(0.80)	0.05(0.94)	0.44(0.77)	0.66(0.36)
R^2ADJ	0.36	0.39	0.35	0.23	0.35	0.24	0.34	0.33
	0.25	0.24	0.15	0.14	0.25	0.12	0.10	0.11
	0.16	0.33	0.08	0.32	0.14	0.18	0.16	0.18
	0.33	0.35	0.25	0.22	0.30	0.07	0.01	0.35

PANEL B: FTSE250 UNDER SEAQ

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	5.39 (0.00)	6.46 (0.00)	INSIGNIFICANT CORRELATIONS	8.92 (0.00)	6.22 (0.00)	5.60 (0.00)	6.69 (0.00)	4.76 (0.00)
-1	0.15 (0.03)	0.22 (0.02)		0.05 (0.48)	0.39 (0.00)	0.34 (0.00)	0.27 (0.00)	0.14 (0.05)
-2	0.09 (0.21)	0.13 (0.49)		0.05 (0.34)	0.18 (0.01)		0.04 (0.40)	0.01 (0.70)
-3	0.09 (0.23)	-0.05 (0.30)		0.01 (0.62)	0.05 (0.52)		-0.10 (0.06)	-0.12 (0.80)
-4	0.02 (0.73)	0.03 (0.50)		0.01 (0.69)	0.08 (0.38)			
-5	0.06 (0.48)	-0.01 (0.80)		-0.00 (0.9)	0.10 (0.09)			
-6	-0.17 (0.00)	0.07 (0.11)		0.00 (0.25)				
R(+)	0.61 (0.86)	0.32 (0.63)		-0.37 (0.90)	-0.11 (0.10)	-0.43 (0.50)	0.85 (0.90)	1.32 (0.85)
R(-)	0.21 (0.57)	0.30 (0.18)		0.23 (0.95)	0.24 (0.89)	0.33 (0.53)	0.20 (0.94)	1.15 (0.85)
VOL	0.35 (0.8)	0.26 (0.20)		0.20 (0.00)	0.15 (0.07)	0.32 (0.00)	0.74 (0.60)	0.21 (0.14)
EXP	0.00 (0.57)	-0.00 (0.50)			-0.00 (0.80)	0.00 (0.50)	-0.00 (0.17)	0.00 (0.01)
UN	-0.00 (0.30)	-0.00 (0.50)		0.00 (0.48)	-0.00 (0.60)	-0.00 (0.40)	0.00 (0.31)	0.00 (0.70)
DEF	0.23 (0.00)	-0.79 (0.00)		-0.17 (0.00)	0.13 (0.00)	-0.50 (0.10)	0.53 (0.80)	0.50 (0.92)
R^2ADJ	0.16	0.16		0.15	0.54	0.16	0.10	0.07

PANEL C:FTSE250:HYBRID/SETSMM

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	6.83	4.23	11.1	1.29	-0.25	INSIGNIFICANT INITIAL CORRELATION	3.14	11.1
	(0.01)	(0.18)	(0.00)	(0.46)	(0.83)		(0.01)	(0.08)
-1	0.13	0.31	0.19	0.18	-0.04		0.13	0.30
	(0.19)	(0.04)	(0.01)	(0.00)	(0.26)		(0.07)	(0.03)
-2	0.18	-0.07	0.33	0.11	0.06		-0.05	
	(0.00)	(0.60)	(0.00)	(0.07)	(0.08)		(0.52)	
-3	0.07	0.09	0.14	-0.00	-0.03		-0.05	
	(0.26)	(0.08)	(0.04)	(0.91)	(0.38)		(0.45)	
-4	0.15	-0.03	0.07	-0.09	-0.03		0.05	
	(0.04)	(0.46)	(0.30)	(0.26)	(0.29)		(0.43)	
-5	0.10	-0.02	-0.01	0.09	0.05		0.10	
	(0.09)	(0.73)	(0.87)	(0.13)	(0.45)		(0.17)	
-6	0.15	0.08	0.16	-0.02	-0.02		0.03	
	(0.01)	(0.43)	(0.06)	(0.82)	(0.34)		(0.58)	
-7		0.10		0.07	-0.01		0.07	
		(0.06)		(0.41)	(0.60)		(0.42)	
-8					-0.03		0.06	
					(0.18)		(0.30)	
-9					0.06		-0.06	
					(0.17)		(0.36)	
-10					0.02		0.20	
					(0.45)		(0.02)	
R(+)	-0.14	0.30	-0.18	-0.45	-0.11		0.19	0.60
	(0.28)	(0.50)	(0.32)	(0.08)	(0.35)		(0.29)	(0.56)
R(-)	0.72	0.10	0.16	0.39	0.50		0.78	0.28
	(0.15)	(0.56)	(0.28)	(0.11)	(0.35)		(0.29)	(0.56)
VOL	-0.30	0.15	0.49	0.99	0.62		0.13	0.20
	(0.93)	(0.47)	(0.84)	(0.20)	(0.53)		(0.69)	(0.60)
EXP	-0.00	-0.00	-0.00	0.00	0.00		-0.00	-0.00
	(0.46)	(0.73)	(0.13)	(0.60)	(0.08)		(0.64)	(0.11)
UN	-0.00	0.00	0.00	0.00	0.00		-0.00	0.00
	(0.32)	(0.64)	(0.92)	(0.78)	(0.86)		(0.16)	(0.86)
DEF	-0.98	0.33	-0.35	0.10	0.44		0.46	-0.82
	(0.77)	(0.57)	(0.27)	(0.00)	(0.00)		(0.03)	(0.45)
R^2ADJ	0.25	0.10	0.53	0.28	0.08		0.10	0.12

TABLE 3.8

REGRESSION RESULTS FOR PROPORTIONAL SPREAD[12] INCORPORATING SPREAD DETERMING VARIABLES (p values in brackets)

	WHOLE SAMPLE		MARKET CAPITALIZATION 1		MARKET CAPITALIZATION 2		MARKET CAPITALIZATION 3	
	PORTF1[13]	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00(0.00)	0.00(0.04)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.17)	0.00(0.01)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	0.01(0.00)	0.00(0.01)	0.00(0.38)	0.00(0.03)	0.10(0.00)	0.00(0.00)
	0.01(0.00)	0.02(0.00)	0.00(0.27)	0.01(0.00)	0.00(0.04)	0.00(0.00)	0.00(0.00)	0.00(0.00)
-1	0.44(0.00)	0.27(0.00)	0.50(0.00)	0.25(0.00)	0.29(0.00)	0.20(0.00)	0.29(0.00)	0.27(0.01)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-0.00(0.61)	0.17(0.01)	0.16(0.00)	0.14(0.11)	-0.03(0.46	-0.00(0.50)
	0.27(0.00)	0.13(0.13)	0.32(0.00)	-0.01(0.85)	0.19(0.02)	0.25(0.00)	0.01(0.73)	0.25(0.00)
-2	0.02(0.66)	0.02(0.78)	0.15(0.01)	0.16(0.04)	0.19(0.04)	-0.04(0.54)	0.15(0.25)	-0.01(0.82)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-0.03(0.17)	0.14(0.04)	0.21(0.07)	0.17(0.01)	0.00(0.95)	-0.00(0.34)
	0.10(0.03)	0.23(0.00)	0.13(0.07)	0.16(0.02)	0.12(0.23)	0.00(0.88)	0.04(0.39)	0.06(0.20)
-3	0.03(0.55)	0.13(0.14)	-0.04(0.52)	0.09(0.18)	0.10(0.12)	0.15(0.00)	0.17(0.03)	0.05(0.59)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	0.01(0.43)	-0.06(0.34	0.01(0.84)	0.10(0.23)	-0.01(0.76)	0.01(0.14)
	-0.02(0.73)	0.13(0.05)	0.00(0.97)	0.15(0.00)	0.11(0.38)	0.16(0.02)	0.07(0.29)	-0.00(0.89)
-4	0.08(0.29)	0.08(0.31)	0.14(0.02)	0.13(0.06)	0.11(0.05)	0.06(0.35)	0.03(0.69)	0.12(0.15)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-0.04(0.21)	0.00(0.92)	0.01(0.74)	-0.04(0.32)	0.05(0.17)	-0.00(0.90)
	0.21(0.02)	0.04(0.37)	0.04(0.46)	0.03(0.27)	0.15(0.00)	-0.02(0.65)	0.10(0.02)	0.10(0.14)
-5	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	0.023(0.22)	0.02(0.64)	0.10(0.05)	0.13(0.04)	0.03(0.45)	-0.00(0.63)
	0.04(0.44)	0.03(0.56)	0.09(0.04)	-0.02(0.65)	0.01(0.81)	0.20(0.02)	0.13(0.00)	0.09(0.20)
R(-)	-0.00(0.92)	-0.00(0.14)	0.00(0.20)	-0.00(0.70)	-2.6E5(0.6)	1.6E5(0.13)	8.6E5(0.04)	5.2E5(0.2)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	0.00(0.91)	-0.00(0.84)	-0.00(0.79)	0.00(0.74)	-0.00(0.48)	-5E5(0.81)
	0.00(0.47)	0.00(0.02)	0.00(0.86)	0.00(0.05)	0.00(0.60)	-0.00(0.22)	0.00(0.55)	-0.00(0.64)
R(+)	-0.00(0.92)	0.00(0.17)	-0.00(0.56)	-0.00(0.90)	-5.6E5(0.09)	-4.1E5(0.13)	-3E5(0.38)	-4E5(0.22)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-0.00(0.10)	0.00(0.30)	-2.3E5(0.94)	-0.00(0.66)	-0.00(0.31)	-0.00(0.47)
	-0.00(0.25)	-0.00(0.44)	-0.00(0.93)	0.00(0.45)	-0.00(0.11)	-0.00(0.00)	3.9E5(0.89)	-0.06(0.21)
RVOL	0.00(0.00)	0.00(0.00)	0.00(0.02)	0.00(0.03)	8.7E5(0.16)	0.00(0.48)	8.4E8(0.18)	4E5(0.50)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	9.20(0.04)	10.75(0.03)	11.47(0.03)	7.43(0.00)	-54.5(0.36)	8.83(0.00)
	1.04(0.76)	0.71(0.91)	-3.03(0.28)	3.81(0.38)	1.08(0.39)	0.76(0.32)	0.95(0.50)	-1.52(0.09)
VEXP	-0.00(0.48)	0.00(0.81)	-0.00(0.34)	0.00(0.94)	-2.1E9(0.32)	-8.6E8(0.00)	-1E8(0.40)	-3.9E8(0.7)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-0.00(0.16)	0.00(0.67)	4.9E8(0.82)	-1.4E7(0.58)	-2E7(0.47)	7.6E8(0.12)
	-0.00(0.07)	-0.00(0.19)	0.00(0.34)	-0.00(0.01)	-1.2E7(0.34	-2.8E7(0.05)	-3.6E8(0.04)	-1E7(0.04)
VUNX	-0.00(0.48)	-0.00(0.18)	-0.00(0.24)	-0.00(0.03)	-7.8E9(0.38)	-1.3E8(0.22)	-7E9(0.18)	-3.6E9(0.3)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-0.00(0.20)	-0.00(0.52)	-2.9E7(0.1)	-1.5E7(0.37)	1.4E8(0.95)	-8E10(0.98)
	-0.00(0.25)	0.00(0.19)	-0.00(0.17)	1.9E7(0.38)	-6.7E8(0.24	-6.7E8(0.24)	-1E8(0.28)	5.9E8(0.11)
DEF	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	0.00(0.71)	0.00(0.82)	-0.00(0.09)	-0.00(0.06)	0.01(0.11)	-0.00(0.00)
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
TERM	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-0.00(0.54)	0.00(0.68)	-0.00(0.31)	0.00(0.49)	-0.00(0.76)	0.00(0.70)	-9.9E5(0.92)	0.00(0.89)
R^2ADJ	0.31	0.18	0.44	0.25	0.25	0.10	0.22	0.07
	-------------	-------------	-------------	-------------	-------------	-------------	-------------	-------------
	-------------	-------------	0.02	0.17	0.15	0.27	0.02	0.04
	0.39	0.27	0.25	0.09	0.27	0.29	0.10	0.10

[12] Proportional spread is not stationary in the second period therefore it is excluded.

[13] Portfolios 1 & 2 are not significantly correlated in the third period and as a consequence there is no reason to run regressions for those two portfolios incorporating well-known spread determining variables. Correlation results for proportional spread between portfolios 1 & 2 were presented back in table 5.

TABLE 3.9
RESIDUALS CORRELATION MATRIX BETWEEN PORTFOLIOS INCLUDING SPREAD DETERMINING VARIABLES (all correlations above 0.10 are significant)

PANEL A:FTSE100

		PORTFOLIO 1	
		ABSOLUTE	PROPORTIONAL
PORTFOLIO 2	ABSOLUTE SPREAD	0.55 0.59 0.59 0.47	
	PROPORTIONAL SPREAD		0.37 non stationary insignificant 0.47

PANEL B: FTSE250

	PORTFOLIO1
	ABSOLUTE SPREAD
PORTFOLIO2	0.19 0.22

TABLE 3.10

RESIDUALS CORRELATION MATRIX BETWEEN SUBGROUPS INCLUDING SPREAD-DETERMINING VARIABLES

PANEL A:FTSE100(all correlations above 0.10 are significant)

		ABSOLUTE SPREAD					
		MK1GA	MK1GB	MK2GA	MK2GB	MK3GA	MK3GB
PROPORTIONAL SPREAD	MK1GA	1	*0.12*	*0.19*	*0.04*	*0.14*	*0.15*
		1	*0.49*	*0.43*	*0.31*	*0.37*	*0.42*
		1	*0.49*	*0.33*	*0.36*	*0.53*	*0.24*
		1	*0.22*	*0.11*	*0.22*	*0.22*	*0.29*
	MK1GB	0.02	1	*0.47*	*0.41*	*0.45*	*0.38*
		----------	1	*0.62*	*0.39*	*0.58*	*0.50*
		0.50	1	*0.40*	*0.48*	*0.58*	*0.31*
		0.16	1	*0.14*	*0.16*	*0.13*	*0.30*
	MK2GA	0.14	0.33	1	*0.34*	*0.45*	*0.47*
		----------	----------	1	*0.44*	*0.59*	*0.52*
		0.40	0.45	1	*0.21*	*0.37*	*0.18*
		0.18	0.18	1	*0.15*	*0.23*	*0.30*
	MK2GB	-0.01	0.27	0.24	1	*0.30*	*0.29*
		----------	----------	----------	1	*0.45*	*0.49*
		0.34	0.52	0.40	1	*0.48*	*0.26*
		0.32	0.18	0.29	1	*0.16*	*0.23*
	MK3GA	0.14	0.38	0.40	0.27	1	*0.52*
		----------	----------	----------	----------	1	*0.56*
		0.03	-0.00	-0.04	0.01	1	*0.39*
		0.28	0.17	0.38	0.29	1	*0.38*
	MK3GB	0.10	0.28	0.38	0.27	0.43	1
		----------	----------	----------	----------	----------	1
		0.40	0.46	0.36	0.43	-0.00	1
		0.31	0.20	0.32	0.35	0.49	1

PANEL B: FTSE250 UNDER SEAQ AND SETSMM (all correlations above 0.13 are significant)

	ABSOLUTE SPREAD					
	MK1GA	MK1GB	MK2GA	MK2GB	MK3GA	MK3GB
MK1GA	1	0.11	0.02	-0.00	0.03	0.04
	1	0.12	0.28	0.05	0.02	0.04
MK1GB		1	0.08	0.05	0.20	0.15
		1	0.13	0.07	0.17	0.10
MK2GA			1	0.14	0.31	0.32
			1	0.13	0.11	0.11
MK2GB				1	0.22	0.15
				1	0.22	0.04
MK3GA					1	0.55
					1	0.13
MK3GB						1
						1

3.5.3.EXTRACTION OF COMMON FACTORS AND PRICING OF COMMONALITY

Having established the presence of commonality in liquidity, the next step is to extract that factor. Extraction takes place at i) the portfolio level and ii) at the market capitalisation groups level. The decision on how many factors to include was based on the Kaiser criterion[14]. The variance captured each time by the common factor is presented in TABLE3.11 (PANELS A and B) and TABLE3.12 along with the relevant eigenvalues for absolute and proportional spread respectively. The lowest variance extracted for FTSE100 stocks by the first factor is 50% and the highest 83% further fortifying the results obtained previously regarding the presence of commonality. The variance extracted for FTSE250 is much lower. In some cases there is no commonality and this is indicated by a dashed line At this point we must stress once again that common factors are extracted from residuals obtained from spread regressions after having considered all known variables, which can have an effect on spread formation. Such high commonality between stocks with different characteristics is very unusual and unaccounted by market microstructure theory however it provides us with an excellent opportunity to test the effect of commonality on asset pricing under different trading regimes. The form of the regression employed is presented right below:

$$\text{EXCESS RETURNS}_t = CF_t + CF_{t-1} + CF_{t-2} + CF_{t-3} + CF_{t-4} + e_t \quad (3.15)$$

where CF stands for common factor. Four lags are used so as to capture the activity of a whole week. Regression results of returns against

[14] only common factors with eigen-values higher than 1.00 should be retained for analysis

common factors are presented in TABLE3.13 (PANELS A and B) and TABLE3.14 for absolute and proportional spread respectively. Goodness of fit (R^2) for FTSE100 stocks ranges from 0.01 to 0.14, which shows that common factors explain a very small percentage of asset prices. At this point we must stress once again that the explanatory variables (common factors) are devoid of any spread determining effects and R^2 should have been absolutely zero if commonality is supposed to play no role is asset pricing. Results presented in TABLE3.13 (PANEL A) and TABLE3.14 clearly indicate that the effect of systematic liquidity is quite pronounced in the quote-driven trading period for FTSE100 (R^2=0.13) and reduces after the introduction of SETS (order-driven stock exchange electronic trading service) but it still appears to play some role in asset pricing. The role of systematic liquidity has proven to be exceptionally important in turbulent periods and misconceptions of its level can lead even to market crashes according to Roll (1988). The reduction observed in the pricing of commonality right after the introduction of SETS (order-driven trading) may be attributed to the 'free entry' and 'free exit' aspect of order-driven trading employing the terminology used by Brockman & Chung (2002). Higher liquidity costs, which assume the form of wider spreads and provide the opportunity for higher profit margin per trade, invite more investors in to the market that act as liquidity providers. Thus commonality becomes less pervasive and is priced to a lesser extent. On the contrary in a quote driven market, specialists are obliged to provide liquidity under any circumstances. A negative liquidity shock leading to subsequent inventory imbalances is born by the specialists themselves exclusively, can accentuate the extent to which commonality is priced. Results obtained for FTSE250 show that commonality is very weak and it is not priced. As it is shown in TABLE3.13 (PANEL B), R^2 is not higher than 0.03 for those cases where a common factor can be extracted.

TABLE 3.11
PERCENTAGE OF VARIANCE EXPLAINED BY PRINCIPAL FACTOR AND EIGEN VALUES FOR ABSOLUTE SPREAD

PANEL A:FTSE100

	PORTFOLIO 1		MK1GB		MK2GB		MK3GB	
	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES
PORT2	57.48 74.70 74.90 61.00	1.48 1.67 1.59 1.47						
MK1GA			57.48 74.70 74.92 61.02	1.14 1.49 1.49 1.22				
MK2GA					69.34 72.05 60.5 57.92	1.38 1.44 1.21 1.15		
MK3GB							75.87 78.43 69.62 69.47	1.51 1.56 1.39 1.39

PANEL B FTSE250

	PORTFOLIO 1		MK1GB		MK2GB		MK3GB	
	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES
P2	25.22 24.18	1.01 1.01						
MK1 GA			-------- --------	-------- -------				
MK2 GA					20.66 ----------	1.04 ----------		
MK3 GA							19.89 -----------	1.00 ---------

TABLE 3.12
PERCENTAGE OF VARIANCE EXPLAINED BY PRINCIPAL FACTOR AND EIGEN VALUES FOR PROPORTIONAL SPREAD FOR ALL FOUR PERIODS

	PORTFOLIO 2		MK1GB		MK2GB		MK3GB	
	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES
PORT2	63.04 ----------- ----------- 73.92	1.26 ---------- ---------- 1.47						
MK1GA			53.75 ----------- 75.04 58.14	1.07 ------- 1.50 1.16				
MK2GA					64.08 ----------- 70.03 64.52	1.28 ------- 1.40 1.29		
MK3GA							70.75 ----------- 50.20 74.84	1.41 ------- 1.00 1.49

TABLE 3.13

REGRESSION RESULTS OF COMMON COMPONENT ON EXCESS RETURNS FOR THE WHOLE SAMPLE AND MARKET CAPITALISATION SUBGROUPS (p values in parentheses)

PANEL A: FTSE100

		QUOTE DRIVEN EXCESS RETURNS				LAST AUTOMATED ORDER EXCESS RETURNS				VOLUME WEIGHTED EXCESS RETURNS				CLOSING AUCTION EXCESS RETURNS			
		WS	MK1	MK2	MK3	WS	MK1	MK2	MK3	WS	MK1	MK2	MK3	WS	MK1	MK2	KM3
	CONS	-0.08	-0.08	0.05	0.12	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.01	0.03	0.02	0.03	0.03
		(0.55)	(0.54)	(0.64)	(0.48)	(0.99)	(0.98)	(0.96)	(0.95)	(0.88)	(0.85)	(0.86)	(0.87)	(0.77)	(0.87)	(0.79)	(0.80)
COMMON FACTOR	T	-0.18	-0.08	-0.11	-0.17	-0.01	0.02	0.06	0.01	-0.10	-0.04	-0.09	-0.14	-0.05	-0.13	-0.10	-0.06
		(0.10)	(0.31)	(0.21)	(0.38)	(0.91)	(0.83)	(0.55)	(0.90)	(0.17)	(0.44)	(0.15)	(0.03)	(0.41)	(0.10)	(0.25)	(0.53)
	T-1	-0.18	-0.19	-0.14	0.00	0.05	0.05	0.11	0.04	-0.11	0.02	-0.17	-0.10	-0.05	-0.12	-0.05	0.10
		(0.02)	(0.04)	(0.13)	(0.96)	(0.66)	(0.65)	(0.27)	(0.71)	(0.07)	(0.75)	(0.00)	(0.02)	(0.42)	(0.12)	(0.47)	(0.45)
	T-2	-0.32	-0.19	-0.23	-0.11	-0.01	0.00	0.03	0.05	-0.04	-0.03	-0.06	-0.02	-0.03	-0.05	-0.04	0.04
		(0.00)	(0.08)	(0.01)	(0.36)	(0.92)	(0.93)	(0.68)	(0.60)	(0.44)	(0.51)	(0.29)	(0.71)	(0.53)	(0.54)	(0.52)	(0.73)
	T-3	-0.20	-0.10	-0.19	-0.14	-0.14	-0.08	-0.07	-0.03	-0.15	-0.04	-0.11	-0.19	-0.02	-0.08	-0.21	-0.03
		(0.01)	(0.28)	(0.01)	(0.31)	(0.15)	(0.37)	(0.40)	(0.62)	(0.00)	(0.51)	(0.06)	(0.00)	(0.73)	(0.24)	(0.00)	(0.80)
	T-4	-0.25	-0.15	-0.20	-0.05	-0.04	-0.08	-0.03	0.02	-0.15	-0.15	-0.08	-0.16	-0.01	-0.18	-0.13	0.08
		(0.00)	(0.10)	(0.03)	(0.63)	(0.51)	(0.22)	(0.66)	(0.72)	(0.01)	(0.04)	(0.28)	(0.02)	(0.81)	(0.00)	(0.08)	(0.53)
	R^2	0.13	0.06	0.05	0.03	0.01	0.00	0.00	0.00	0.04	0.01	0.04	0.06	0.01	0.04	0.04	0.01

WS stands for whole sample(FTSE100)
CONS stands for constant
T,T-1 represents current and lag values of the common factor.

PANEL B: FTSE250

		SEAQ				SETSmm			
		EXCESS RETURNS				EXCESS RETURNS			
		WS	MK1	MK2	MK3	WS	MK1	MK2	MK3
	CONS	-0.00 (0.00)	NO COMMON FACTOR	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	NO COMMON FACTOR	NO COMMON FACTOR	NO COMMON FACTOR
COMMON FACTOR	T	0.00 (0.31)		-0.00 (0.56)	0.00 (0.27)	-0.00 (0.13)			
	T-1	0.00 (0.86)		-0.00 (0.45)	0.00 (0.81)	-0.00 (0.06)			
	T-2	0.00 (0.74)		-0.00 (0.33)	0.00 (0.04)	0.00 (0.20)			
	T-3	-0.00 (0.53)		-0.00 (0.87)	0.00 (0.70)	-0.00 (0.63)			
	T-4	-0.00 (0.67)		-0.00 (0.62)	0.00 (0.89)	-0.00 (0.18)			
	R^2	0.00		0.00	0.01	0.03			

WS stands for whole sample(FTSE250)
CONS stands for constant
T,T-1 represents current and lag values of the common factor.

TABLE 3.14

REGRESSION RESULTS OF COMMON COMPONENT ON EXCESS RETURNS FOR THE WHOLE SAMPLE AND MARKET CAPITALISATION SUBGROUPS OVER THREE DIFFERENT TIME PERIODS (p values in parentheses)

		QUOTE DRIVEN RETURNS				VOLUME WEIGHTED RETURNS				CLOSING AUCTION RETURNS			
		WS	MK1	MK2	MK3	WS	MK1	MK2	MK3	WS	MK1	MK2	MK3
	CONS	-0.06 (0.64)	-0.07 (0.61)	0.08 (0.50)	0.13 (0.43)	NON STATIONARY	0.02 (0.84)	0.02 (0.85)	0.02 (0.87)	0.03 (0.77)	0.02 (0.87)	0.03 (0.78)	0.03 (0.80)
COMMON FACTOR	T	-0.06 (0.57)	-0.07 (0.36)	0.01 (0.62)	-0.20 (0.28)		-0.04 (0.48)	-0.12 (0.14)	0.15 (0.03)	-0.03 (0.57)	-0.13 (0.08)	-0.18 (0.06)	-0.07 (0.46)
	T-1	-0.08 (0.37)	-0.09 (0.21)	0.06 (0.43)	0.01 (0.90)		0.09 (0.23)	-0.12 (0.01)	0.10 (0.08)	-0.03 (0.52)	-0.09 (0.24)	-0.04 (0.58)	0.12 (0.34)
	T-2	-0.20 (0.07)	-0.12 (0.31)	-0.01 (0.91)	-0.13 (0.39)		-0.00 (0.96)	-0.06 (0.21)	0.01 (0.80)	-0.02 (0.68)	-0.00 (0.96)	-0.02 (0.69)	0.03 (0.73)
	T-3	-0.14 (0.10)	-0.05 (0.57)	0.03 (0.68)	-0.13 (0.26)		-0.02 (0.70)	-0.10 (0.10)	0.16 (0.02)	-0.00 (0.90)	-0.02 (0.68)	-0.14 (0.06)	-0.02 (0.86)
	T-4	-0.12 (0.13)	-0.15 (0.11)	-0.00 (0.95)	-0.00 (0.98)		-0.12 (0.14)	-0.07 (0.25)	0.09 (0.16)	-0.00 (0.92)	-0.14 (0.05)	-0.13 (0.09)	0.03 (0.76)
	R^2	0.04	0.03	0.00	0.04		0.01	0.03	0.05	0.00	0.03	0.04	0.01

Only three time periods/regimes are presented in this table and this is because proportional spread is not stationary in the second period/trading regime.
WS stands for whole sample(FTSE100)
CONS stands for constant
T,T-1 represents current and lag values of the common factor.

3.6.ROBUSTNESS

After having reached the above conclusions, we decided to perform robustness tests as is usually done in studies of this kind to see if our results are sample specific. We did so by extending the sample in each period (45 daily observations) so as to ensure that news about changes in the trading/reporting regime known before the actual change and any consequent changes in the trading behaviour of investors and market makers are fully considered. Our results remain unchanged for all subgroups and portfolios over the periods considered.

3.7.CONCLUSION

Amihud & Mendelson (1986), Eleswarapu & Reinganum (1993), Brennan & Subrahmanyam (1996), Datar et al (1998) and Amihud(2002) have argued that predictable differences in liquidity lead to cross-sectional differences in excess returns. We instead concentrate on systematic liquidity, a new phenomenon in market microstructure. This study tested for i) the presence of a common liquidity factor in FTSE100 stocks under four different trading/reporting regimes and FTSE250 stocks under two regimes, ii) the effect of commonality on asset pricing and iii) the extent to which it is priced. The results obtained from this study clearly show that i) there is a common factor affecting FTSE100 stocks simultaneously as it is captured by high subgroup residuals correlations and the variance explained each time by common factors ii) commonality in liquidity appears to play an important role in asset pricing before the introduction of the order driven trading but appears reduced for the rest of the periods examined with reference to FTSE100 stocks and iii) commonality is reduced for FTSE250 stocks and it is not priced. Based on the discussion above, the policy implications of our findings and implications for market makers and investors, are self explanatory and relate to the presence of liquidity commonality under different trading provisions and spread effects among other things. We conclude that order driven regimes have the ability to dampen the effect of commonality; hence policy makers should consider this when deciding on trading systems. For market participants, the evidence show that it may be more desirable to trade under an order driven market due to the dampened commonality and hence the possible negative effects of severe illiquidity.

CHAPTER 4: SYSTEMATIC LIQUIDITY AND EXCESS RETURNS: EVIDENCE FROM THE ATHENS STOCK EXCHANGE

4.1. INTRODUCTION

As it was discussed in the literature review and in the introductory parts of the previous chapters market microstructure has traditionally concentrated on the characteristics of single assets exhibiting absolute disregard for attribute(s) that can have an effect on multiple assets simultaneously. Limited research has been undertaken in 'transaction costs' or 'liquidity' concentrating on systematic variations and how this affects stocks. The only published research undertaken in the area concentrates on developed markets such as the US market. In the previous chapters we discussed the effect of systematic liquidity on asset pricing for the London stock exchange. In this chapter we will look into the effect of systematic (il)liquidity on asset pricing by concentrating on less developed markets such as the Athens Stock Exchange.

The Greek capital market and in particular the Athens stock exchange has attracted a lot of investment since the establishment of the economic and monetary union. During this period the Greek capital market has contributed significantly to the development of the Greek economy and provided investors with alternative methods of investment, which was received with unprecedented enthusiasm. The Athens stock exchange also served as the primary mechanism for privatizing public law companies which further increased the interest of both Greek and international investors.

On the basis of the above facts, the Athens stock exchange has embarked on creating an economic and investing environment, which would be comparable to that of international capital markets. In order to achieve that it has introduced a number of changes concentrating on restructuring the legal and regulatory framework, modernizing the trading process and introducing new financial products. In other words the Greek market has gone through a number of development stages within a very short period of time before it achieved recognition as a developed market (31 May, 2001). For this reason I believe that it is worth examining the effect of systematic liquidity on asset pricing for a market that has developed exceptionally fast to go from 'boom to bust' within two years.

Besides the exceptionally fast development, briefly described above, a study undertaken by the department of research and development of the Athens Stock Exchange (ASE) has revealed that the general index of the ASE exhibits a very low correlation with the indices of other European stock exchanges namely: United Kingdom, Germany, Italy and France. In particular the ASE exhibits the highest correlation with the German market index and this is a mere 0.3. Correlations between indices for the United Kingdom, Germany, Italy and France excluding Greece are quite high ranging from 0.61 to 0.81. On the contrary the Greek stock exchange does not follow the course of the exchanges mentioned above, providing the necessary differentiation that the optimum portfolio must have according to financial theory, therefore if an international investor wishes to invest in European stocks, he will definitively invest in Greek stocks as well given the low correlation with the market indices mentioned above so as to achieve as balanced a portfolio as possible. For this reason I believe that it is important to examine systematic liquidity in the Greek market and its effect on asset pricing since liquidity is an important component of the trading process.

The purpose of this study is to investigate for the presence of commonality in liquidity in the Greek market and secondly examine the effect of systematic liquidity on asset pricing. Commonality refers to the proposition that an individual firm's liquidity is determined by market-wide factors (unidentified yet) besides well-documented idiosyncratic factors such as volatility, trading volume, number of trades etc. Research has also shown that predictable differences in liquidity lead to cross-sectional differences in excess returns. A natural extension of this argument is that if liquidity is random and co-varies across stocks then a stock's sensitivity to systematic liquidity randomness could play the role of a priced risk factor. This possibility is examined here. Traditionally empirical work in the area of market microstructure has concentrated exclusively on trading patterns of individual assets, seasonal patterns and market crashes. The very first studies to look into the relation of liquidity and asset returns were those of Amihud & Mendelson (1986), Eleswarapu & Reinganum (1993), Brennan & Subrahmanyam (1996) and Datar et al.

(1998). Quite recently research interest has shifted to the common components of liquidity (Chordia et al. 2000; Huberman & Halka 2001; Hasbrouck & Seppi 2001). Generally speaking there are a number of studies that have investigated the relation of liquidity and returns and documented the presence of commonality in liquidity but no study has looked into common factors in liquidity (commonality) and returns. *This study combines those two lines of research and examines if and the extent to which commonality affects excess returns.* In other words we seek to address the following questions:

- Q1) Is commonality in liquidity present in less developed markets such as the Greek market or it constitutes a stylized fact pertinent to major markets such as the US market and the UK market?
- Q2) Is commonality priced?
- Q3) Does commonality come in waves?
- Q4) Is commonality a phenomenon pertinent to low or high market capitalization companies?

The results obtained in this study contribute to the commonality literature in the following ways. First we show that commonality is not just a US or a UK characteristic but it is also pertinent in less developed markets namely the Greek market, secondly we find that the presence of commonality in the Greek capital market is not as strong as it appears to be in the US market and the UK market and that appears to be pertinent in high capitalization companies, thirdly commonality in the Greek market appears to come in waves and fourthly it is not priced.

4.2 OVERVIEW OF SHARES TRADING IN THE ASE

Trading hours are set between 11:00 and 16:00 with a half an hour pre-opening period and fifteen minutes after the end of the trading session until 16:15 where only 'at the close' trades are realized. ASE members - namely brokerage firms and credit institutions - which have obtained approval from the Board of Directors of the ASE, are allowed to trade in the exchange. All transactions are realized either in cash, or through margin account.

Trades are conducted electronically through the Automated Exchange Trading System (OASIS). Orders are entered into the system by stock exchange representatives, who are supplied with a code number for that purpose. Orders are entered from Members' offices by means of remote broker operations. Each ASE member is permitted up to eight terminals, four of which are free. The use of all terminals is restricted to the trading hours of the Stock Exchange. All orders introduced into the system before the beginning of the main trading session on 11:00 may participate in the formation of the opening price. Orders receive a time stamp upon their entry into the system. At the pre-opening period, the system accepts limit and market orders. Limit orders determine the day's opening price. Market orders get time priority and are executed upon the opening of the market. If no limit orders exist, the opening price will be the same as the previous closing price. The criterion used for the determination of the opening price is the maximization of transactions' volume. When two prices produce the same maximum volume, the price closest to the previous closing price is selected. If their differential from the previous close coincides, the system will select the highest price of the two. Closing price is considered the weighted average as regards the number of shares, of the prices of the 10% of the trading realized during the session, at two decimal points. The calculation of the closing price is realized by starting from the last trading before the end of the session moving towards the beginning until the cardinal number of the trading that corresponds to 10% of the total number of trading of the session is completed. If no trading has been realized as regard the share, the 'start price' of the share is taken as closing prices. The closing prices of the shares that belong to trading category B or C (auction) are considered the price of the last call auction. If no trading has been realized during the session, then the start price is considered as closing price. The closing price of the indices is calculated on the basis of the closing price of the shares.

During the main trading session, orders are matched by price (the buy order at the highest price is matched with the sell order at the lowest price) and time. The orders, which are inserted in the OASIS before the beginning of the main trading session, participated in the definition of the opening price. The criterion for the definition of the opening price is the maximization of the trading volume, which also determines the best point of equilibrium between demand and supply.

Members can change or reverse their orders during the main trading session if they feel that their orders cannot be executed at the given price. In case of reversing, one minute at least must have elapsed since the time the initial order was entered. During the trading session, the trading system forms a central book of pending round lot orders at any given moment of time. Orders are distinguished between buy and sell orders and are ranked by price and time. Furthermore, the trading system forms a secondary book of pending odd lot orders. All new orders, depending on the share quantity, are automatically checked against the orders listed in the Main Board and the odd lot book.

4.3.EXPERIMENTAL DESIGN[1]

The experimental design is similar to the one presented in the previous chapter therefore it is not repeated again.

4.4.DATASET AND DESCRIPTIVE STATISTICS

Daily price data for the FTSE/ASE 20 Index, FTSE/ASE Mid 40 Index and FTSE 80 Index companies was obtained from DATASTREAM. The data set under consideration ranges from 01/01/1998 to 31/12/2003. The choice of the data set reflects a different period in terms of trading activity for the Athens Stock Exchange. The first year of the sample, 1998, was an inactive year however during the two following years, the ASE reached a record volume of transactions. After the end of 2000, the ASE returned

[1]The first part of the experimental design pertinent to the identification of commonality presented here has been adopted from Huberman & Halka (2001)

to modest levels of activity. Actually during the last year in our sample (2003), trading activity in the ASE was even lower than 1998 signifying the end of an unprecedented three-year rally since the establishment of the ASE. The choice of dataset allows us to test if commonality is present under different levels of trading activity and investor psychology. During 1999 and 2000, every single stock's price rose reflecting unprecedented investor confidence regarding the future prospects of the stocks they were investing. However this feeling of confidence did not last for long and the market went into a falling trajectory at the beginning of 2001. The actual figures are given in TABLE4.1. The relevant variables are total value of transactions, volume of transactions and number of trades. The data obtained from DATASTREAM includes the following variables: closing price and closing trading volume for each stock. These variables were further processed to obtain other variables such as: returns, returns volatility using GARCH(1,1) and expected and unexpected trading volume employing the Box-Jenkins methodology. We use only one (il)liquidity proxy due to data unavailability which is calculated as absolute stock return/euro trading volume. The very same variable was used by Amihud (2002) in order to assess the cross section relationship between illiquidity and returns. This variable was selected because it captures the very essence of (il)liquidity and it is the only variable that can be calculated given bid and ask price unavailability on behalf of DATASTREAM and the ASE.

Liquidity is a very elusive concept and unfortunately has a number of aspects that cannot be captured in a simple measure. However all academics and practitioners agree that (il)liquidity reflects the impact of order flow/trading volume on price. In other words the market maker will sell at a higher price than he will buy because of adverse selection and inventory costs. Market makers cannot distinguish between informed and liquidity/noise traders therefore any imbalance in the observed order flow will be considered to incorporate asymmetric information and will bring about price changes. Kyle (1985) shows that market makers set prices, which is an increasing function of the order flow observed in the market.

Academics and market microstructure researchers have used a number of illiquidity measures depending on data availability. Chalmers and Kaldec (1998) used amortised affective spread, which is estimated as effective spread divided by the stock's holding period. Brennan and Subrahmanyam (1996) measure stock illiquidity as the price response to signed order flow and by the fixed cost of trading. As you can see those measures of illiquidity require a lot of market microstructure data, which unfortunately are not available for many advanced markets around the world let alone the Greek market. Therefore as it was stated at the very beginning we will have to revert to simpler illiquidity measures, which however do capture the effect of trading/order flow on prices which constitutes the main definition of (il)liquidity.

Amihud (2002) employs daily absolute return to dollar trading volume as an (il)liquidity measure in his study and postulates that this particular (il)liquidity measure follows Kyle's (1985) concept of illiquidity which is defined as the response of price to order flow and Silber's (1975) measure of thinness which is defined as the ratio of absolute price change to absolute excess demand for trading. Amihud (2002) also argues that the (il)liquidity measure under consideration can also be interpreted as the level of consensus between investors/traders regarding the nature of incoming information. If investors/traders agree about the content of incoming information prices will change without much trading occurring however if investors/traders disagree about the content of incoming information then there will be some trading before consensus is reached. Amihud (2002) also empirically tests the extent to which the proposed variable captures (il)lliquidity by regressing the variable under consideration against Kyle's λ (price impact measure) and ψ (fixed cost component related to the bid-ask spread) and finds that the ratio of absolute price change to dollar trading volume is significantly positively correlated to the two illiquidity regressors mentioned above.

TABLE 4.1
TOTAL VALUE OF TRANSACTIONS AND NUMBER OF TRADES

Year	Total value of transactions	Total number of trades
1998	41,331,148,094	7,480,176
1999	172,865,880,833	24,051,742
2000	101,423,125,768	22,134,712
2001	42,345,164,601	12,147,407
2002	24,771,040,059	9,130,476
2003	34,887,159,150	11,401,653

4.5.METHODOLOGICAL ISSUES

In order to examine if commonality is present in the Greek market as well we need to i) describe the splitting technique ii) determine the optimal lag structure for each group of stocks (remember that in the experimental design we assume an AR(1) process just for convenience), iii) decide on the idiosyncratic variables and iv) test if the residuals obtained for mutually exclusive groups of stocks are significantly positively correlated[2].

Now in order to find the extent to which commonality is priced we need to i) extract the common factor between mutually exclusive groups of stocks employing principal axis factoring/singular value decomposition and ii) regress the common factor (commonality) on excess returns for that group.

For the third empirical question we need to examine if commonality remains present for all the years under consideration while for the fourth empirical question we need to examine if residuals correlations are significant for the highest market capitalization groups and not the lower market capitalization groups.

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[2] The significance of the correlation coefficients is evaluated by the t statistic given in parenthesis. If the true p=0, the sampling distribution of r is symmetric:

$$r \sim N(0, \sigma_r = \sqrt{(1-r^2)} / \sqrt{(n-2)})$$

and we can apply the Student's t test for establishing the significance or non-significance of the sample estimate r. The value of the t statistic is estimated from the sample correlation coefficient r, by the expression

$$t^* = r/\sigma_r = r\sqrt{n-2} / \sqrt{1-r^2}$$

and is compared with the theoretical value of $t_{0.025}$ (for a two tailed test at the 5% level of significance) with n-2 degrees of freedom. The critical value at 5% is equal to 1.960.

4.5.1.SAMPLE SPLITTING TECHNIQUE

Initially we obtain absolute return over euro trading volume (|return|/trading volume) for each stock in our sample and then we split the original sample into three size-based groups namely: MK1, MK2 and MK3[3]. We further split the three size-based groups consisting of 76 up to 102 stocks[4] each into smaller subgroups (A & B). At this point we ensure that random splitting occurs so that group A (GA) does not end up with the lowest market capitalization stocks in its category and group B (GB) with the highest market capitalization stocks. Then all type A subgroups are placed in a single portfolio and all type B subgroups in another portfolio, forming two randomly constructed, equally weighted portfolios.[5] Finally we obtain average values for all subgroups and the two portfolios. All testing to follow uses those portfolios and subgroups as the basis for drawing conclusions

4.5.2.OPTIMAL LAG STRUCTURE DETERMINATION AND PRELIMINARY RESIDUAL CORRELATIONS

In this part we will define the optimal lag structure for |return|/trading volume by running the following regressions:

$$|\text{return}|/\text{trading volume}^{i}_{t}=C+|\text{return}|/\text{trading volume}^{i}_{t-1}+|\text{return}|/\text{trading volume}^{i}_{t-2}+|\text{return}|/\text{trading volume}^{i}_{t-v}+\ldots+e^{i}_{t} \quad (4.1)$$

[3] MK stands for market capitalization. MK1 consists of the lowest MK stocks in the sample.
[4] The sample size varies according to the year under consideration. The data available increases as we approach the current date
[5] In that way portfolio 1 is made up of: P1MK1GA, P1MK2GA and P1MK3GA while portfolio 2 is made up of: P2MK1GB, P2MK2GB and P2MK3GB.

for a different number of lags each time. We run those regressions for all portfolios and all subgroups and decide on the optimal lag structure based on both the Box-Jenkins methodology and the Akaike and Schwarz information criteria. TABLE4.2 summarizes the results obtained for each of the six periods at subgroup level and whole sample level. In most cases within each year, portfolios and subgroups follow similar autoregressive structures however autoregressive structures vary considerably for portfolios and subgroups over the years.

TABLE 4.2
OPTIMAL LAG STRUCTURE DETERMINATION

	WHOLE SAMPLE		MK1		MK2		MK3	
	PORTFOLIO1	PORTFOLIO2	GROUPA	GROUPA	GROUPA	GROUPA	GROUPA	GROUPA
98	AR(3)	AR(4)	AR(3)	AR(4)	AR(5)	AR(4)	AR(3)	AR(3)
99	AR(8)	AR(7)	AR(6)	AR(7)	N/S	AR(5)	AR(6)	AR(5)
00	AR(4)	AR(3)	AR(9)	AR(9)	AR(5)	AR(3)	AR(4)	AR(4)
01	AR(5)	AR(8)	AR(4)	AR(6)	AR(4)	AR(5)	AR(4)	AR(4)
02	AR(2)	AR(2)	AR(2)	AR(4)	AR(4)	N/S	AR(2)	AR(5)
03	AR(5)	AR(3)	AR(5)	AR(3)	AR(5)	AR(3)	N/S	AR(5)

4.6.EMPIRICAL FINDINGS

The statistical analysis aims at i) detecting the presence of a common component ii) extracting a common factor from the two sub-groups within each market capitalisation group or the two portfolios that comprise the whole sample and regress it on returns for those groups or the whole sample respectively over the periods examined and iii) observing the extent to which commonality is priced under different trading regimes. The sections that follow present results for each of those objectives.

4.6.1 MODELLING LIQUIDITY: PRELIMINARY CORRELATION TESTS

In order to detect the presence of a common factor, we need to model (il)liquidity and obtain innovations. TABLE4.3 (PANELS A,B,C,D,E & F) presents autoregressive estimates for |return|/trading volume for all portfolios and subgroups for each year separately. R^2ADJ for most portfolios and sub-groups appears to be quite high however for some sub-groups modelling was not possible because the data was not stationary. Having run those regressions, the next step is to obtain residuals and test the extent to which they are correlated. Results are shown in TABLE4.4 and TABLE4.5. The null hypothesis states that correlations between portfolios and subgroups should have an arbitrary sign and be insignificant. TABLE4.4 shows that correlations between portfolios are particularly strong for 2001 only. For the rest of the years under examination correlations between portfolios are insignificant. TABLE4.5 shows that correlations between subgroups are significant for 2000 and 2001 only. Another point that it is worth mentioning is that correlations between subgroups for 2001 become stronger between higher market capitalization groups. Correlations between subgroups and portfolios are zero for 1998, 1999, 2002 and 2003.

TABLE 4.3

AUTOREGRESSIVE ESTIMATES FOR |return|/trading volume (p value in parentheses)

PANEL A: GREEK MARKET (1998)

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00 (0.00)	1.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
AR(1)	0.31 (0.00)	0.12 (0.06)	0.32 (0.00)	0.11 (0.07)	0.08(0.04)	0.26 (0.00)	0.09 (0.09)	0.23 (0.00)
AR(2)	0.16 (0.00)	0.01 (0.65)	0.16 (0.00)	0.02 (0.65)	0.08 (0.22)	0.17 (0.00)	0.46 (0.00)	0.16 0.04)
AR(3)	0.23 (0.00)	0.01 (0.70)	0.22 (0.00)	0.01 (0.74)	0.03 (0.39)	0.07 (0.09)	0.16 (0.01)	0.11 (0.04)
AR(4)		0.23 (0.03)		0.22 (0.04)	0.01 (0.65)	0.12 (0.03)		
AR(5)					0.27 (0.01)			
R^2 ADJ	0.33	0.07	0.33	0.07	0.10	0.23	0.48	0.14

PANEL B GREEK MARKET (1999)

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUP A	GROUP B	GROUP A	GROUP B	GROUP A	GROUP B
C	0.00 (0.07)	0.00 (0.13)	0.00 (0.16)	0.00 (0.09)		0.00 (0.02)	0.00 (0.00)	0.00 (0.00)
AR(1)	0.08 (0.33)	0.01 (0.76)	0.09 (0.34)	0.03 (0.58)		0.03 (0.62)	0.25 (0.00)	0.29 (0.00)
AR(2)	0.25 (0.15)	0.17 (0.04)	0.19 (0.35)	0.14 (0.05)		0.16 (0.30)	0.14 (0.03)	0.15 (0.02)
AR(3)	-0.01 (0.87)	0.02 (0.77)	-0.02 (0.79)	0.10 (0.16)		0.04 (0.46)	0.08 (0.49)	0.06 (0.41)
AR(4)	0.16 (0.21)	0.08 (0.40)	0.13 (0.33)	-0.00 (0.90)		0.13 (0.25)	-0.04 (0.68)	0.07 (0.41)
AR(5)	0.04 (0.75)	0.06 (0.56)	0.06 (0.63)	-0.07 (0.03)		0.15 (0.23)	0.10 (0.24)	0.18 (0.12)
AR(6)	0.31 (0.05)	0.06 (0.38)	0.26 (0.07)	0.03 (0.26)			0.22 (0.03)	
AR(7)	0.06 (0.39)	0.28 (0.14)		0.39 (0.12)				
AR(8)	-0.23 (0.03)							
R^2 ADJ	0.29	0.22	0.24	0.20		0.11	0.24	0.32

PANEL C GREEK MARKET (2000)

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
AR(1)	0.02 (0.08)	0.17 (0.03)	0.01 (0.07)	0.07 (0.22)	0.20 (0.00)	0.17 (0.00)	0.24 (0.00)	0.23 (0.00)
AR(2)	0.00 (0.45)	0.14 (0.00)	-0.00 (0.97)	0.03 (0.53)	0.23 (0.00)	0.21 (0.00)	0.21 (0.00)	0.12 (0.01)
AR(3)	0.00 (0.55)	0.30 (0.00)	0.00 (0.75)	0.21 (0.00)	0.11 (0.20)	0.30 (0.00)	0.15 (0.03)	0.04 (0.52)
AR(4)	0.02 (0.03)		0.00 (0.18)	0.06 (0.51)	0.10 (0.06)		0.14 (0.02)	0.22 (0.03)
AR(5)			0.00 (0.93)	0.11 (0.43)	0.17 (0.01)			
AR(6)			0.00 (0.51)	0.01 (0.81)				
AR(7)			-0.00 (0.26)	0.01 (0.76)				
AR(8)			-0.00 (0.63)	0.33 (0.63)				
AR(9)			0.01 (0.04)	0.28 (0.00)				
R^2 ADJ	0.00	0.20	0.00	0.22	0.44	0.27	0.35	0.19

PANEL D GREEK MARKET (2001)

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
AR(1)	0.06 (0.11)	0.11 (0.24)	0.05 (0.17)	0.11 (0.25)	0.11 (0.12)	0.04 (0.53)	0.17 (0.00)	0.20 (0.00)
AR(2)	0.13 (0.01)	0.18 (0.06)	0.09 (0.10)	0.15 (0.22)	0.11 (0.16)	0.19 (0.00)	0.09 (0.18)	0.02 (0.70)
AR(3)	0.06 (0.25)	0.02 (0.78)	0.05 (0.26)	0.00 (0.93)	0.12 (0.04)	0.08 (0.15)	0.16 (0.08)	0.06 (0.28)
AR(4)	0.12 (0.00)	0.14 (0.05)	0.10 (0.04)	0.10 (0.22)	0.18 (0.00)	0.21 (0.02)	0.17 (0.02)	0.11 (0.15)
AR(5)	0.13 (0.03)	0.00 (0.94)		0.03 (0.71)		0.15 (0.03)		
AR(6)		0.19 (0.21)		0.23 (0.06)				
AR(7)		0.10 (0.26)						
AR(8)		-0.12 (0.08)						
R^2 ADJ	0.10	0.18	0.03	0.17	0.12	0.21	0.17	0.07

PANEL E GREEK MARKET (2002)

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00	0.00	0.00	0.00	0.00		0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
AR(1)	0.04	0.03	0.04	0.02	0.02		0.10	-0.02
	(0.22)	(0.55)	(0.24)	(0.57)	(0.03)		(0.14)	(0.65)
AR(2)	0.37	0.05	0.47	0.04	0.01		0.11	0.00
	(0.02)	(0.02)	(0.00)	(0.02)	(0.25)		(0.10)	(0.94)
AR(3)				0.01	0.14			0.03
				(0.47)	(0.35)			(0.22)
AR(4)				0.04	0.02			-0.00
				(0.03)	(0.00)			(0.68)
AR(5)								0.06
								(0.02)
R^2 ADJ	0.14	0.00	0.22	0.00	0.02		0.02	0.00

PANEL F GREEK MARKET (2003)

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00	0.00	0.00	0.00	0.00	0.00		0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
AR(1)	0.04	0.21	0.03	0.29	0.22	0.11		0.34
	(0.14)	(0.01)	(0.17)	(0.00)	(0.00)	(0.12)		(0.00)
AR(2)	0.01	0.18	0.00	0.06	0.28	0.17		0.17
	(0.51)	(0.00)	(0.85)	(0.27)	(0.00)	(0.00)		(0.01)
AR(3)	0.18	0.18	0.17	0.28	0.05	0.04		0.02
	(0.21)	(0.00)	(0.26)	(0.00)	(0.42)	(0.07)		(0.77)
AR(4)	-0.00		-0.02		0.10			0.07
	(0.79)		(0.30)		(0.20)			(0.38)
AR(5)	0.08		0.06		0.13			0.22
	(0.01)		(0.08)		(0.01)			(0.00)
R^2 ADJ	0.04	0.19	0.03	0.26	0.43	0.05		0.52

TABLE 4.4
RESIDUALS CORRELATION MATRIX BETWEEN PORTFOLIOS EXCLUDING SPREAD-DETERMINING VARIABLES

		Portfolio2
		|return| /trading volume
1998	Portfolio1	0.12
1999		0.06
2000		0.05
2001		0.16
2002		0.00
2003		0.13

TABLE 4.5
RESIDUALS CORRELATION MATRIX BETWEEN SUBGROUPS EXCLUDING LIQUIDITY-DETERMINING VARIABLES

PRELIMINARY CORRELATIONS: GREEK MARKET

	MK1GA	MK1GB	MK2GA	MK2GB	MK3GA	MK3GB
MK1GA	1	0.10	-0.04	0.09	0.03	0.09
	1	0.04	N/A	0.02	0.04	0.06
	1	0.04	-0.01	0.04	0.05	-0.01
	1	-0.01	0.36	0.38	0.21	0.20
	1	0.00	0.00	N/A	0.00	-0.02
	1	0.14	0.00	0.02	N/A	0.12
MK1GB		1	0.00	0.06	0.02	0.04
		1	N/A	0.20	0.01	0.20
		1	0.35	0.37	0.30	0.28
		1	-0.01	0.03	-0.02	0.01
		1	0.00	N/A	0.09	0.01
		1	0.23	0.09	N/A	0.25
MK2GA			1	0.06	0.06	-0.04
			1	N/A	N/A	N/A
			1	0.61	0.54	0.49
			1	0.46	0.46	0.37
			1	N/A	0.08	0.03
			1	0.22	N/A	0.48
MK2GB				1	0.16	0.22
				1	-0.07	0.08
				1	0.55	0.44
				1	0.51	0.46
				1	N/A	N/A
				1	N/A	-0.08
MK3GA					1	0.25
					1	0.44
					1	0.46
					1	0.34
					1	0.09
					1	N/A
MK3GB						1
						1
						1
						1
						1
						1

4.6.2.MODELLING LIQUIDITY: FINAL CORRELATION TESTS

In order to detect the presence of a common component we need to model the time series properties of the average (il)liquidity proxies controlling for serial correlation and incorporating well-known (il)liquidity determining variables. For this reason regressions of the following type are estimated:

$$|\text{return}|/\text{trading volume}^{I}_{t}=C+|\text{return}|/\text{trading volume}^{I}_{t-1}+|\text{return}|/\text{trading volume}^{I}_{t-2}+|\text{return}|/\text{trading volume}^{I}_{t-3}+|\text{return}|/\text{trading volume}^{I}_{t-4}+|\text{return}|/\text{trading volume}^{I}_{t-v}+\text{NEGATIVERETURNS}^{I}_{t}+\text{POSITIVERETURNS}^{I}_{t}+\text{VOLATILITY}^{I}_{t}+\text{EXPECTEDVOLUME}^{I}_{t}+\text{UNEXPECTEDVOLUME}^{I}_{t}+\text{TERM PREMIUM}^{I}_{t}+e_t \quad (4.2)$$

Where $|\text{return}|/\text{trading volume}^{I}_{t}$ represents absolute returns over euro trading volume, POSITIVE RETURNS represent daily return on the portfolio or group when that return is positive and zero otherwise, NEGATIVE RETURNS represent daily return on the portfolio or group when that return is negative or zero and zero otherwise, volatility is modelled as GARCH(1,1), expected trading volume is obtained by subtracting unexpected volume from actual volume, unexpected trading volume is obtained by modelling actual trading volume and obtaining innovations and interest rate term structure is estimated as the change in the spread between the ten-year government bond yield and the three month treasury bill yield. Results are presented in TABLE4.6 (PANELS A,B,C,D and E) for each year with exception 2002 for which correlations between portfolios and sub-groups are insignificant. At this point it is also worth reminding readers that correlations between portfolios for all years are insignificant with exception 2001. In addition correlations for a number of subgroups for different years are also insignificant, therefore there is no point for running any regressions. Results presented in TABLE4.6 show that higher order lags remain significant for most of the years under consideration while results in the previous chapters indicated that only the first two lags remained significant after the introduction of other well known (il)liquidity determining variables. The sign of negative returns is positive which means that negative returns increase illiquidity. The positive returns variable bears a negative sign, which means that illiquidity is reduced if a stock performs well. Returns volatility appears to have a positive effect on illiquidity. This finding is consistent with Huberman & Halka (2001) but inconsistent with Tinic (1972) who finds that the standard deviation of returns in insignificant. Expected and unexpected volume variables appear to play some role in explaining illiquidity especially unexpected trading volume that always bears a positive sign if it significant even though in absolute terms the value obtained is very small. Some would anticipate unexpected trading volume to play a very important role in explaining illiquidity since this variable is supposed to capture asymmetric information effects. Expected trading volume bears a negative sign when it is significant. Of course trading volume would play a more significant role if depth variables were examined. Finally term structure does not appear to have a significant explanatory power bearing mixed signs. The term structure of interest rates in not included in regressions for 1998 because of lack of data. Residuals correlations for portfolios and subgroups are presented in TABLE4.7 and TABLE4.8. TABLE4.7 shows that the correlation between portfolios for 2001 is insignificant after inclusion of (il)liquidity determining variables. Correlations for the remaining years (although insignificant) are taken from TABLE4.4 and are marked with (P). Correlations between subgroups for 2000 and 2001 remain significant even after the inclusion of (il)liquidity determining variables. Correlations for the remaining years (although insignificant) are taken from TABLE4.5 and are marked with (P). In other words commonality in liquidity in the Greek market comes in waves and is present during 2000-2001.

TABLE 4.6

REGRESSION RESULTS FOR |return|/trading volume INCORPORATING LIQUIDITY DETERMINING VARIABLES (p values in brackets)

PANEL A: GREEK FINAL 98

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C			0.00 (0.00)	0.00 (0.00)		0.00 (0.00)	0.00 (0.00)	0.00 (0..00)
AR(1)			0.31 (0.00)	0.09 (0.25)		0.24 (0.01)	0.11 (0.07)	0.21 (0.00)
AR(2)			0.16 (0.20)	-0.01 (0.80)		0.18 (0.00)	0.38 (0.00)	0.17 (0.05)
AR(3)			0.22 (0.00)	-0.02 (0.65)		0.08 (0.05)	0.17 (0.02)	0.09 (0.09)
AR(4)				0.22 (0.06)		0.11 (0.08)		
R(+)			-0.09 (0.05)	0.02 (0.59)		0.00 (0.57)	0.00 (0.38)	0.00 (0.23)
R(-)			-0.04 (0.57)	-0.02 (0.67)		-0.00 (0.21)	0.01 (0.01)	-0.00 (0.42)
VOL			-0.44 (0.91)	-2.70 (0.45)		-0.08 (0.23)	0.03 (0.00)	-0.00 (0.53)
EXP			-0.00 (0.29)	-0.00 (0.00)		-0.00 (0.09)	-0.00 (0.01)	0.00 (0.28)
UNX			0.00 (0.07)	-0.00 (0.52)		-0.00 (0.18)	-0.00 (0.38)	0.00 (0.36)
TERM			0.00 (0.35)	-0.00 (0.22)		0.00 (0.18)	0.00 (0.22)	0.00 (0.33)
R^2 ADJ			0.35	0.09		0.22	0.38	0.15

PANEL B: GREEK FINAL 99

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C				0.00 (0.72)			0.00 (0.32)	0.00 (0.45)
AR(1)				-0.09 (0.00)			0.35 (0.00)	0.29 (0.00)
AR(2)				0.29 (0.00)			0.21 (0.07)	0.08 (0.34)
AR(3)				0.14 (0.00)			0.01 (0.92)	-0.13 (0.05)
AR(4)				-0.12 (0.00)			-0.00 (0.97)	0.15 (0.17)
AR(5)				-0.17 (0.07)			0.10 (0.35)	0.25 (0.07)
AR(6)				0.09 (0.02)			0.13 (0.19)	
AR(7)				0.50 (0.07)				
R(+)				0.00 (0.85)			-0.00 (0.06)	-0.00 (0.00)
R(-)				0.00 (0.28)			0.00 (0.64)	0.00 (0.00)
VOL				0.16 (0.27)			-0.00 (0.39)	-0.00 (0.13)
EXP				0.00 (0.34)			0.00 (0.50)	0.00 (0.30)
UNX				0.00 (0.71)			0.00 (0.01)	0.00 (0.12)
TERM				-0.00 (0.53)			0.00 (0.80)	0.00 (0.59)
R^2 ADJ				0.63			0.26	0.39

PANEL C: GREEK FINAL 00

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C				0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
AR(1)				-0.00 (0.94)	0.23 (0.01)	0.19 (0.00)	0.27 (0.00)	0.29 (0.00)
AR(2)				-0.00 (0.96)	0.22 (0.03)	0.18 (0.00)	0.22 (0.00)	0.07 (0.15)
AR(3)				0.21 (0.01)	0.10 (0.25)	0.27 (0.00)	0.14 (0.08)	0.01 (0.87)
AR(4)				0.01 (0.86)	0.08 (0.18)		0.08 (0.28)	0.21 (0.04)
AR(5)				0.05 (0.65)	0.16 (0.03)			
AR(6)				-0.04 (0.44)				
AR(7)				-0.02 (0.65)				
AR(8)				-0.00 (0.96)				
AR(9)				0.26 (0.02)				
R(+)				0.00 (0.79)	0.00 (0.76)	-0.00 (0.77)	0.00 (0.42)	-0.00 (0.06)
R(-)				-0.00 (0.44)	-0.00 (0.77)	-0.00 (0.86)	0.00 (0.47)	0.00 (0.20)
VOL				-0.01 (0.23)	-0.01 (0.10)	0.01 (0.07)	0.01 (0.01)	-0.00 (0.72)
EXP				-0.00 (0.01)	0.00 (0.93)	-0.00 (0.56)	0.00 (0.69)	-0.00 (0.18)
UNX				-0.00 (0.35)	-0.00 (0.51)	0.00 (0.00)	-0.00 (0.23)	-0.00 (0.63)
TERM				0.00 (0.00)	0.00 (0.59)	0.00 (0.07)	0.00 (0.19)	0.00 (0.44)
R^2 ADJ				0.29	0.45	0.31	0.38	0.23

PANEL D: GREEK FINAL 01

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C	0.00 (0.00)	0.00 (0.02)	0.00 (0.00)		0.00 (0.03)	0.00 (0.02)	0.00 (0.01)	0.00 (0.00)
AR(1)	0.10 (0.13)	0.19 (0.13)	0.03 (0.42)		0.28 (0.00)	0.13 (0.13)	0.14 (0.05)	0.19 (0.00)
AR(2)	0.15 (0.00)	0.05 (0.40)	0.04 (0.23)		0.04 (0.51)	0.17 (0.03)	0.12 (0.13)	0.03 (0.46)
AR(3)	0.06 (0.28)	0.06 (0.47)	0.02 (0.58)		0.12 (0.07)	0.08 (0.18)	0.16 (0.10)	0.02 (0.69)
AR(4)	0.08 (0.06)	0.19 (0.04)	0.05 (0.05)		0.13 (0.01)	0.15 (0.09)	0.17 (0.02)	0.08 (0.30)
AR(5)	0.06 (0.13)	-0.04 (0.69)				0.09 (0.16)		
AR(6)		0.22 (0.13)						
AR(7)		0.07 (0.44)						
AR(8)		-0.12 (0.09)						
R(+)	-0.00 (0.03)	-0.00 (0.86)	-0.00 (0.05)		-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
R(-)	0.00 (0.26)	-0.00 (0.38)	0.00 (0.12)		0.00 (0.03)	0.00 (0.10)	-0.00 (0.20)	0.00 (0.27)
VOL	0.02 (0.64)	-0.02 (0.37)	0.12 (0.03)		0.02 (0.66)	0.00 (0.68)	-0.03 (0.23)	0.05 (0.00)
EXP	-0.00 (0.03)	-0.00 (0.54)	-0.00 (0.00)		-0.11 (0.76)	-0.00 (0.05)	-0.00 (0.24)	-0.00 (0.00)
UNX	0.00 (0.33)	-0.00 (0.15)	0.00 (0.97)		-0.00 (0.47)	-0.00 (0.15)	0.00 (0.00)	0.00 (0.03)
TERM	0.00 (0.30)	-0.00 (0.99)	0.00 (0.24)		0.00 (0.27)	0.00 (0.05)	0.00 (0.20)	-0.00 (0.85)
R^2 ADJ	0.15	0.21	0.07		0.21	0.26	0.21	0.12

PANEL E: GREEK FINAL 03

	WHOLE SAMPLE		MARKET CAPITALISATION 1		MARKET CAPITALISATION 2		MARKET CAPITALISATION 3	
	PORTF1	PORTF2	GROUPA	GROUPB	GROUPA	GROUPB	GROUPA	GROUPB
C			-0.00 (0.47)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)		0.00 (0.00)
AR(1)			0.03 (0.43)	0.21 (0.02)	0.14 (0.06)	0.06 (0.31)		0.35 (0.00)
AR(2)			0.00 (0.48)	-0.03 (0.35)	0.21 (0.00)	0.12 (0.00)		0.16 (0.06)
AR(3)			0.11 (0.40)	0.19 (0.04)	0.04 (0.50)	-0.00 (0.79)		0.00 (0.96)
AR(4)			-0.01 (0.51)		0.04 (0.60)			0.01 (0.87)
AR(5)			0.10 (0.00)		0.09 (0.48)			0.17 (0.01)
R(+)			0.00 (0.24)	-0.00 (0.06)	-0.00 (0.08)	0.00 (0.77)		0.00 (0.83)
R(-)			0.02 (0.01)	0.00 (0.42)	0.00 (0.00)	0.01 (0.38)		0.00 (0.16)
VOL			0.78 (0.41)	0.51 (0.01)	0.25 (0.00)	-0.89 (0.32)		0.13 (0.04)
EXP			-0.00 (0.81)	-0.00 (0.07)	-0.00 (0.00)	-0.00 (0.16)		-0.00 (0.76)
UNX			0.00 (0.01)	0.00 (0.02)	-0.00 (0.15)	-0.00 (0.15)		0.00 (0.01)
TERM			0.00 (0.39)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)		-0.00 (0.00)
R^2 ADJ			0.07	0.32	0.48	0.11		0.52

TABLE 4.7
RESIDUALS CORRELATION MATRIX BETWEEN PORTFOLIOS INCLUDING SPREAD DETERMINING VARIABLES

		Portfolio2
		|return| /trading volume
1998	Portfolio1	0.12(P)
1999		0.06(P)
2000		0.05(P)
2001		0.13
2002		0.00(P)
2003		0.13(P)

TABLE 4.8

RESIDUALS CORRELATION MATRIX BETWEEN SUBGROUPS INCLUDING LIQUIDITY-DETERMINING VARIABLES

FINAL CORRELATIONS: GREEK MARKET

	MK1GA	MK1GB	MK2GA	MK2GB	MK3GA	MK3GB
MK1GA	1	0.10(P)	-0.04(P)	0.09(P)	0.03(P)	0.09(P)
	1	0.04(P)	N/A	0.02(P)	0.04(P)	0.06(P)
	1	0.04(P)	-0.01(P)	0.04(P)	0.05(P)	-0.01(P)
	1	-0.01(P)	0.28	0.34	0.15	0.18
	1	0.00(P)	0.00(P)	N/A	0.00(P)	-0.02(P)
	1	0.11	0.00(P)	0.02(P)	N/A	0.12(P)
MK1GB		1	0.00(P)	0.06(P)	0.02(P)	0.04(P)
		1	N/A	0.20	0.01(P)	-0.13
		1	-0.10	0.35	0.13	0.28
		1	-0.01(P)	0.03(P)	-0.02(P)	0.01(P)
		1	0.00(P)	N/A(P)	0.09(P)	0.01(P)
		1	0.19	0.09(P)	N/A	0.21
MK2GA			1	0.06(P)	0.06(P)	-0.04(P)
			1	N/A	N/A	N/A
			1	-0.03	0.07	0.00
			1	0.44	0.43	0.34
			1	N/A	0.08(P)	0.03(P)
			1	0.20	N/A	0.46
MK2GB				1	0.16	0.22
				1	-0.07(P)	0.08(P)
				1	0.27	0.44
				1	0.46	0.46
				1	N/A	N/A
				1	N/A	-0.08
MK3GA					1	0.25
					1	0.38
					1	0.22
					1	0.34
					1	0.09(P)
					1	N/A
MK3GB						1
						1
						1
						1
						1
						1

4.6.3.EXTRACTION OF COMMON FACTORS AND PRICING OF COMMONALITY

Having established the presence of commonality in liquidity for a number of sub-groups over different periods, the next step is to extract that factor. Extraction takes place at market capitalisation groups level only since correlations between portfolios are not significant. The decision on how many factors to include was based on the Kaiser criterion[6]. The variance captured each time by the common factor is presented in TABLE4.9 along with the relevant eigenvalues. The lowest variance explained is 19.9% for 1998 between subgroups MK1GA and MK1GB and the highest 27.18% between subgroups MK2GA and MK2GB for 2001. In most cases there is no commonality and this is indicated by a dashed line At this point I must stress once again that common factors are extracted from residuals obtained from the final regressions after having considered all known variables, which can have an effect on (il)liquidity. The commonality observed between stocks with different characteristics is very unusual even though it is not as high as it was shown for other markets and unaccounted by market microstructure theory however it provides us with an excellent opportunity to test the effect of commonality on asset pricing for different periods. The form of the regression employed is presented right below:

$$\text{EXCESS RETURNS}_t = CF_t + CF_{t-1} + CF_{t-2} + CF_{t-3} + CF_{t-4} + e_t \quad (4.2)$$

[6] only common factors with eigen-values higher than 1.00 should be retained for analysis

where CF stands for common factor. Four lags are used so as to capture the activity of a whole week. Regression results of returns against common factors are presented in TABLE4.10. Goodness of fit (R^2) ranges from 0.01 to 0.07, which shows that common factors explain a very small percentage of asset prices. At this point I must stress once again that the explanatory variables (common factors) are devoid of any spread determining effects and R^2 should have been absolutely zero if commonality is supposed to play no role is asset pricing. Generally speaking commonality appears to come in waves and it appears to be more pronounced between 2000-2001. The degree to which it is priced for those years is left for the individual to decide.

4.7.CONCLUSION

Research on the Greek market for common underlying factors shows that commonality is considerably reduced when considering the level of commonality observed in other markets. Commonality appears to be stronger in certain years and less intense in others. In particular common underlying factors and their effect on pricing appear to be considerably stronger for 2000 and 2001 considering the explanatory power of the common underlying factor on excess returns.

TABLE 4.9
PERCENTAGE OF VARIANCE EXPLAINED BY PRINCIPAL FACTOR AND EIGEN VALUES FOR ILLIQUIDITY

	MK1GB		MK2GB		MK3GB	
	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES	% OF VARIANCE EXPLAINED	EIGEN VALUES
MK1GA	19.9 -------- --------- -------- -------- 20.04	1.01 ------- ------- ------- ------- 1.01				
MK2GA			-------- --------- 24.01 27.18 -------- 22.01	------- ------- 1.05 1.14 ------- 1.07		
MK3GA					-------- 20.08 23.15 26.05 ------- --------	------- 1.03 1.23 1.11 ------- -------

TABLE 4.10

REGRESSION RESULTS OF COMMON COMPONENT ON EXCESS RETURNS FOR THE WHOLE SAMPLE AND MARKET CAPITALISATION SUBGROUPS (p values in parentheses)

		EXC.RET 98		EXC.RE 99	EXC.RET 00		EXC.RET 01		EXC.RET 03	
		MK1	MK3	MK3	MK2	MK3	MK2	MK3	MK1	MK2
	CONS	0.00 (0.02)	0.00 (0.05)	0.00 (0.02)	-0.00 (0.10)	-0.00 (0.34)	-0.00 (0.78)	0.00 (0.88)	0.00 (0.25)	0.00 (0.11)
COMMON FACTOR	T	-0.00 (0.20)	-0.00 (0.68)	0.00 (0.54)	-0.00 (0.01)	-0.00 (0.03)	-0.01 (0.00)	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)
	T-1	0.00 (0.33)	-0.00 (0.18)	0.00 (0.35)	-0.00 (0.01)	-0.00 (0.05)	-0.00 (0.81)	0.00 (0.91)	0.00 (0.48)	-0.00 (0.43)
	T-2	0.00 (0.62)	-0.00 (0.60)	-0.00 (0.89)	-0.00 (0.82)	-0.00 (0.98)	0.00 (0.94)	0.00 (0.85)	0.00 (0.59)	0.00 (0.72)
	T-3	-0.00 (0.87)	0.00 (0.14)	-0.00 (0.17)	0.00 (0.36)	0.00 (0.51)	0.00 (0.76)	0.00 (0.08)	-0.00 (0.43)	0.00 (0.81)
	T-4	0.00 (0.90)	0.00 (0.48)	-0.00 (0.60)	-0.00 (0.57)	-0.00 (0.08)	-0.00 (0.50)	0.00 (0.89)	0.00 (0.56)	-0.00 (0.06)
	R^2	0.01	0.02	0.02	0.05	0.04	0.05	0.07	0.02	0.02

CHAPTER 5: TRADING MECHANISMS AND VALUE EFFECTS: EVIDENCE FROM THE LONDON AND ATHENS STOCK EXCHANGES

5.1. INTRODUCTION

In today's increasingly competitive environment for stock exchanges there is a great payoff to those exchanges that manage to improve their performance by reducing execution costs and providing improved services for both institutions and retail clients.

In the last few years, there has been observed a race between stock exchange markets all around the world to modernize their trading processes. This came as a response to growing competition among stock exchange markets to attract more and more customers and of course the need to introduce modern technology in trading. Modernization usually assumes the form of full computerization of the trading process and at the same time poses a question as to what form of trading mechanism should be used. Three basic models of trading mechanisms are applied in today's exchanges, continuous quote driven systems where dealers post bid quotes and ask quotes before order submission, order driven systems where traders submit orders before prices are determined and single call auctions where orders are batched and executed at discrete points in time. This study will concentrate on comparing the value effects achieved with respect to informational efficiency and spread sensitivity to volatility by i) changing from one primary trading mechanism to the other, employing different closing price formations algorithms each time with reference to FTSE100 and FTSE250 and ii) by computerising the trading process with reference to the Athens Stock Exchange

The number of changes that have occurred around the world do not indicate that a consensus has been reached as to which trading mechanism is the best or at least the most popular. Actually the issue of the best trading mechanism with respect to informational efficiency and spread sensitivity to volatility is far form being resolved. On the one hand the London Stock Exchange replaced SEAQ (dealer market) with SETS (order-driven) for FTSE100 stocks and SEAQ (dealer market) with SETSmm (hybrid) for FTSE250 stocks. NASDAQ has introduced public limit orders competing with market makers' quotes following allegations of market markers' collusion to maintain high bid-ask spreads (Christie & Schultz, 1994; Christie et al, 1994). Obviously those three examples indicate a change from quote driven markets (dealerships) to pure order driven markets or hybrids. On the other hand in France (NSC) and Germany (XETRA), market makers were introduced to provide additional liquidity to already electronic continuous auction markets indicating a change from order driven systems to hybrids. In addition continuous trading for less liquid stocks in the French CAC system and in German XETRA was replaced with call auctions. At the same time stocks listed on the French Nouveau Marche were transferred form a call market to an electronic continuous auction system. The last two incidents indicate movements in completely different directions (Theissen, 2000). Obviously a consensus as to which is the best trading mechanism or which of the available trading mechanisms matches stocks with specific characteristics is far from clear. Call auctions are usually employed at the beginning or the end of the trading process to provide more efficient opening/closing prices since they allow order flow consolidation however call auctions are randomly used for the whole trading process since they restrict information flow and trading frequency. Most stock exchanges that used single call auctions as their main trading system have now changed to continuous trading achieving tremendous gains in terms of liquidity and informational efficiency, (Amihud, Mendelson & Lauterbach, 1997).

All those examples of stock exchange markets changing their trading systems suggest that more empirical research may be needed into identifying the value effects gained from changing from one trading mechanism to the other. The existing empirical literature has concentrated on comparing the liquidity of continuous auction and dealer markets (Huang & Stoll, 1996; Christie & Huang, 1994; Pagano & Roell, 1990), to the value gained by changing from single call auctions to continuous trading (Amihud, Mendelson & Lauterbach, 1997); the effects of computerization of the trading process (Naidu & Rozeff, 1994) or on market microstructure and returns volatility (Amihud, Mendelson & Murgia, 1990; Amihud & Mendelson, 1991; Gerety & Mullherin, 1994; Ko & Chung, 1995). *In this study we wish to examine the degree to* *which informational efficiency changes as a result of i) computerisation of the trading process with reference to the Greek market, ii) changes in trading regime/closing price formation algorithms employed each time with reference to FTSE100 & FTSE250 and iii) spread sensitivity to volatility under different trading regimes with reference to the UK market.* We believe that there is a very good reason to focus on informational efficiency and spread sensitivity to volatility under different trading regimes because these characteristics of stock trading are linked to the expected rate of return on a traded financial asset.

The London Stock Exchange (LSE) had always been a pure dealership (quote driven market) but in October 1997 the LSE introduced an order driven system for FTSE100 stocks. This decision was made i) as a response to fear of losing market share to other European exchange houses and electronic networks such as Tradepoint, ii) recent UK regulation allowing market makers to quote better prices on electronic networks than those that they were quoting on the LSE and iii) EU regulation allowing European markets to enrol remote members in other EU countries without securing permission from the regulatory authorities in that country. In addition research (Christie & Schultz, 1994; Christie et al, 1994) indicating that NASDAQ market makers were colluding to maintain artificially higher spreads necessitated a change from quote driven to order driven since the LSE was a pure dealership market itself.

Changes in FTSE250 were introduced in 3/11/2003. The trading system changed from pure dealership (SEAQ) to a hybrid system (SETSmm), which combines the benefits of SETS with LSE market making. Those changes were introduced as a result of i) growth in alternative trading systems covering FTSE250 and the immediate threat of shifting liquidity away from the central market, ii) soundings from market participants that SEAQ (the system that FTSE250 was trading) could eventually become fragmented, iii) new regulation that requires to display customer limit orders to the wider market, iv) requests from technical traders to be able to access prices on screens so as to respond to intraday price movements and increase liquidity.

Changes in the Greek stock exchange market were introduced back in 17/08/92. Those changes were necessitated because of the increased need to modernise the market. Even though the changes introduced had a major impact in the trading process, those changes did not change the nature of trading. The Athens stock exchange market remained an order driven market. The only difference in the new trading system is that orders are submitted electronically. The trading method changed from 'public outcry' to ASIS (automatic system of electronic trading).

Dealer markets appear to exhibit higher execution costs as compared to order driven markets (Huang & Stoll, 1996; Christie & Huang, 1994; Pagano & Roell, 1990) even though there is no unanimity on this issue. In particular Affleck-Graves, Hedge & Miller (1994) find that quoted spreads are the same for a matched sample of NASDAQ and NYSE/ASE stocks in 1985. In addition Kothare & Laux (1995) report a dramatic increase in quoted spread for NASDAQ between Oct 1984-1992 while Huang and Stoll (1994) report a decline in execution costs for NYSE between 1989-1991, an indication that spreads can change rapidly over time. Another important issue relating to market architecture is the degree of informational efficiency achieved by computerising the trading process, changing from quote driven to order driven or a combination of both (hybrid) and the issue of spread sensitivity to volatility under different trading regimes, which has not been examined at all. Informational efficiency and price discovery are quite important since they relate to the expected return of a stock. We believe that it is crucial to shed some light on those issues with reference to one of the most important exchange markets in the world (LSE) as well as developing markets (Greek market).

One would expect several changes to occur once a market changes from quote driven to order driven. From the individual investor's point of view access to trading is much easier which may increase the frequency and the actual numbers of investors trading. Now orders enter the computer straight away and they are matched instantly provided of course that there are orders with similar characteristics pending. It is obvious that the bargaining power of individual investors is increased given their ability to place limit orders achieving better deals. By placing limit orders individual investors avoid the cost of immediacy i.e. the spread. From the market maker's point of view handling costs are lower because of automated order execution and bid-ask quote manipulation to maintain optimal inventory is no longer necessary since they are no longer obliged to act as liquidity providers. Of course changes in market microstructure (from quote driven to order driven) can have disadvantages as well. The limit order book can make every single investor more vulnerable to asymmetric information and thus reduce the incentive to trade, which may lead to reductions in liquidity. Pagano & Roell (1992) state that 'an electronic auction market does not provide a means for communicating the trading motives or identity of traders to the market at large beyond displaying brokers' codes alongside limit orders'.

The degree of informational efficiency is an issue worth examining as well. Every single participant in the market has access to the electronic limit order book and can decide more easily on the value of the asset based on the limit orders shown in the order book. However one might argue that given the easier access to trading, there will be more noise in the market distorting the real value of the asset and decreasing informational efficiency. Market makers are supposed to have a better 'feel' of the market at any point in time in comparison to individual investors who trade based on what they see on their screens. Wang (1999) with reference to the Sydney Futures Exchange has shown that floor traders can better assess the presence of adverse information i.e. they get a better feel of the market compared to screen traders who are isolated from each other. Experimental research (Thiessen, 2000) has shown that dealer markets can convey information of high quality once the bid-ask spread is eliminated. In addition Greene & Watts (1996) with reference to the NASDAQ/NYSE markets show that NASDAQ is faster in impounding information into prices. Nevertheless no research has been undertaken with reference to the LSE and we do not know if the alleged enhanced ability of the market makers to get a better feel of the market will dominate over the electronic limit order book. In addition we would like to extend this line of research to smaller European Markets such as the Athens Stock Exchange.

Another issue, which has not been examined at all, is the spread sensitivity to volatility under different trading regimes for both FTSE100 and FTSE250. Spread is supposedly less sensitive to volatility under an order driven regime for three main reasons: i) market makers do not have to manipulate bid-ask quotes to maintain optimal inventory therefore volatility is not more of a concern to them than it is to the rest of the investors, ii) inventory imbalances are diffused among a greater number of market participants since any investor can act conceivably as liquidity provider and iii) in case higher spreads occur because of increased volatility, this will invite more liquidity providers due to the opportunity of making increased profits. Of course it may also be the case that increased volatility will discourage investors to trade and since there are no liquidity providers of last resort as there are in a quote driven market, this will further increase the spread causing severe illiquidity.

In addition closing price formation algorithms could potentially affect price discovery/informational efficiency. The LSE has changed closing price formation algorithms three times ever since it has become an order driven market to accommodate investors' demands for more representative closing prices. Closing prices need to be representative of the trading activity each day since they are used in portfolio valuation and for trading after the exchange has closed. Following the introduction of SETS for FTSE100 (order-driven), closing prices were initially based on the last automated transaction (20/10/97-13/12/98), then closing price calculation was based on the ten minutes trading volume weighted average (14/12/98-26/05/00) and quite recently price formation is based on a closing call auction (30/05/00 onwards). We believe that the last two closing price formation algorithms provide more efficient closing prices and this should be apparent in the price discovery process because order flow is consolidated. Closing prices have always been formed in the same way for FTSE250 and in the Athens Stock Exchange. As it has been stated above informational efficiency and spread sensitivity under different trading regimes and closing price algorithms are important issues relating to the expected return of a common stock worthy of further examination under real trading conditions, therefore we seek to answer the following questions:

Q1) How does the degree of informational efficiency change in response to different trading regimes/closing price formation algorithms for FTSE100 and FTSE250?

Q2) How does spread sensitivity to volatility change in response to different trading regimes?

Q3) How did the computerization of the trading process affect informational efficiency in the Athens Stock Exchange?

The results obtained in this study contribute to the trading mechanisms comparison literature with reference to the London Stock Exchange and the Greek market in the following ways. First we show that the pace with which information is incorporated into prices is much faster in order driven markets when compared to quote driven markets (FTSE100). Secondly we show that spread is more sensitive to volatility in dealer markets because of their obligation to post affirmative quotes with respect to FTSE100 stocks. There appear to be no significant improvements in informational efficiency for FTSE250 when changing from quote driven to hybrid. In general terms the degree of informational efficiency remains the same. In addition spread sensitivity to volatility is the same since dealers are obliged to post affirmative quotes (committed principal orders) under both trading regimes. As far as spread sensitivity to volatility is concerned findings with respect to FTSE250 provide extra support for the findings with respect to FTSE100. Now as far the Greek market is concerned, results show that the computerisation of the trading process has increased informational efficiency (the speed at which new information is incorporated into prices). To summarize we have learnt that the computerisation of the trading process increases informational efficiency, order-driven markets respond faster to new information (FTSE100) and that spread sensitivity is higher in dealerships because of their affirmative obligation to quote bid and ask prices.

5.2.PREVIOUS RESEARCH

In a call auction, market and limit orders are batched and executed at discrete points in time. Very few exchanges around the world use this sort of mechanism as their main trading mechanism simply because it is considered to be obsolete and it does not make full use of existing technology. Call auctions have been found to be in serious disadvantage with respect to continuous trading markets (Amihud, Mendelson & Lauterbach, 1997). However call auctions are used by a great number of stock exchange houses around the world to start or finish the trading process. Batching which is the main characteristic of call auctions allows for simultaneous execution of a large number of orders, which is believed to lead to better price discovery and reduce the effect of asymmetric information. Thus it is used to determine the opening and closing prices. The LSE has introduced call auctions in the middle of the trading process in order to achieve order flow consolidation and more representative prices for FTSE250 stocks and closing call auctions for FTSE100 stocks. Another advantage of call auctions is that the effect of large orders on liquidity and consequently on prices is considerably reduced. Of course one of the main disadvantages of call auctions is that there is no immediacy and the fact that no information is conveyed between the calls may lead to severe informational inefficiency.

In an order driven market, participants submit or accept limit orders/market orders of other participants at any point in time. All limit orders are displayed in the electronic order book, so participants get a feeling of the market. Trades may occur between individual investors or between an investor and a market maker. In order driven regimes, market makers (if they exist) are not obliged to provide liquidity therefore immediate execution of market orders is not guaranteed. Of course those who provide liquidity are compensated by the bid-ask spread. In a quote driven regime or dealership, market makers are the only suppliers of liquidity. They are obliged to quote bid and ask prices at any point in time in order to accommodate liquidity demand.

The majority of theoretical work in the area of trading regimes concentrates on modelling a single trading mechanism. Mendelson (1982), Ho et al (1985), Sattertwaite & Williams (1993) and Rustichini et al (1994) concentrate on call auctions. Friedman (1984, 1991), Wilson (1987), Easley & Ledyard (1993) and Glosten (1994) concentrate on continuous auction markets while O'Hara (1995) presents a survey of dealership models. Deciding on the best trading mechanism based on the above models is simply impossible and this is because each model is built on a different set of assumptions making the results obtained each time difficult to compare however some general statements can be made. Call auctions are quite robust in information processing especially in cases of high information asymmetry however immediacy is a major problem since trading occurs at discrete points in time. Order driven markets offer unsurpassed immediacy but the chances of trading with an informed trader and making losses is quite high. Of course some theoretical work has been undertaken in comparing different trading mechanisms on a common basis. In particular Kyle (1985) compares single call auction and continuous trading equilibria and finds that noise trader losses in continuous trading are twice as large as in call auctions. Pagano & Roell (1992) show that trading costs are lower in call markets and higher in dealer markets. The only study to compare all three trading mechanisms (call, continuous and dealership) is that of Madhavan (1992) who shows that call markets are more robust in the presence of information asymmetries. The results obtained from all those studies were expected since order batching which is the main characteristic of call auctions consolidates order flow and all orders are executed at a single price, therefore informed traders cannot take advantage of the information they possess.

Most empirical literature in the area of trading mechanisms has concentrated on i) comparing execution costs between continuous auctions and dealerships (Huang & Stoll, 1996; Lee, 1993; Pagano & Roell, 1990; Stoll, 1993) finding higher execution costs in dealer markets when compared to continuous trading markets even though Affleck-Graves, Hedge & Miller (1994) find that quoted spreads are the same for a matched sample of NASDAQ and NYSE/ASE stocks in 1985 ii) trading mechanisms and price behaviour emphasizing the introduction of call auctions within continuous trading mechanisms (Ko, Lee & Chung, 1995;

Amihud & Mendelson, 1987,1989,1991) with special reference to the Korean, Japanese and US stock market respectively iii) the value effects gained by changing from single call auctions to continuous trading (Amihud, Mendelson & Lauterbach, 1997) iv) the effects of full automation on trading (Naidu & Rozeff, 1994) with special reference to the Singapore Stock Exchange and v) a comparison between dealerships and continuous action with respect to informational efficiency (Greene & Watts, 1996).

Summarizing the empirical results, one could say that dealer markets appear to have higher execution costs in comparison to continuous markets although there is no unanimity. However little can be said about how informational efficiency/price discovery changes under the two primary exchanging regimes: dealerships and order driven markets. There are only two studies looking into informational efficiency under different trading regimes. The first study that investigates the value effects from changes in market microstructure and explicitly looks into price discovery and assesses the degree of informational efficiency achieved each time is that of Amihud, Mendelson & Lauterbach (1997). However the above study is confined to changes from single call auctions to continuous trading mechanisms with reference to the Tel Aviv stock Exchange. Stocks under the call auction regime used to trade once a day but after the introduction of continuous trading, trading frequency increased tremendously. As it was expected changes in informational efficiency/price discovery and liquidity were dramatic. The second study

(Greene & Watts, 1996) examines market response to quarterly earnings announcements made during trading and non-trading hours on the NYSE and the NASDAQ. They find that NASDAQ is more efficient in impounding information into prices. We are not aware of any studies concentrating on spread sensitivity to volatility under a dealership and an order driven market. We explore price discovery/informational efficiency and spread sensitivity to volatility between competing trading mechanisms: dealerships, order driven markets and hybrid markets for FTSE 100 & FTSE250 stocks. We also examine the effect of computerisation on informational efficiency for the Greek market.

5.3.METHODOLOGY

In order to answer how the degree of informational efficiency and spread sensitivity to volatility changes in response to different trading mechanisms and closing price formation algorithms we need to formulate six hypotheses:

H1) Closing auctions achieve a higher degree of informational efficiency when compared to trading volume weighted average pricing or closing prices based on the last automated transaction (with reference to FTSE100).

The main characteristic of closing auctions is order batching. In that way order flow consolidation and information consolidation is achieved and the possibility of obtaining a price incorporating as much information as possible increases. In addition the ability of block trading to distort prices is minimised due to the batching nature of single call auctions as well as the risk of trading under asymmetric information.

H2) Order driven markets achieve a higher degree of informational efficiency when compared to quote driven markets (with reference to FTSE100).

One the one hand one could argue that that market makers have the ability to get a better 'feel' of the market and respond faster to general market conditions when compared to individual investors who trade mainly on information conveyed by limit orders posted in the electronic limit order book. Market makers have good information on market condition because they can observe buyers and sellers and their transactions. Market makers may have information on the clients of a broker and may be able to draw conclusions about any sort of information that he may possess from his buying and selling behaviour. They may also anticipate the behaviour of particular traders by estimating their inventory position. On the other hand, one could argue that market makers cannot always evaluate correctly the information they are presented with and the only information they may get is from the outstanding limit orders on their screens. In addition the ability to post limit could potentially increase participation from individual investors increasing information flow or noise. According to Pagano & Roell (1992) an electronic auction does not provide a means for communicating the trading motives or identity of traders to the market at large. Thus individual traders and market makers are not aware of the trading motives of their counterparts and can not assess their quantity and quality of information. Generally speaking the degree of informational efficiency between different trading regimes is an empirical issue.

H3) Hybrid markets achieve a similar degree of informational efficiency compared to dealerships (with reference to FTSE250).

The degree of informational efficiency achieved in those two markets is an empirical issue. We are not aware of any previous studies looking into quote driven and hybrid markets. On the one hand some might argue that the ability to post limit orders will improve information flow. On the other hand others might argue that the posting of limit orders will not necessarily improve order flow since limit orders may provide mixed signals, reducing informational efficiency. As you can see the degree of informational efficiency for quote driven and hybrid is an important empirical issue examined for the very first time.

H4) Spread sensitivity to volatility is higher in dealer markets (with reference to FTSE100).

In a dealership, market makers are obliged to maintain an orderly market under any circumstances (volatile or non-volatile). Therefore the bid and ask quotes they post must incorporate some sort of compensation for volatility. In times of high volatility investors may wish to sell volatile stocks and buy less volatile stocks. If this is the case since markets makers have to accommodate liquidity demand under any circumstances, this will induce inventory imbalances accompanied by severe fluctuations in the value of their inventory. Obviously the spread will be more sensitive to volatility in dealerships in order to compensate for higher risk. Nevertheless in order driven markets, liquidity demand is diffused among a greater number of market participants since any investor can act as liquidity provider and in case higher spreads occur because of increased volatility, this will invite more liquidity providers due to the opportunity of making increased profits. Therefore if the market is order driven, the spread will be less sensitive to volatility.

H5) Spread sensitivity to volatility is similar in dealer markets compared to hybrid markets (with reference to FTSE250).

In both trading regimes, market makers are present therefore we expect that spread sensitivity to volatility will be similar.

H6) Computerization of the trading process increases informational efficiency (with reference to the Greek market only)

Computerization of the trading process allows faster dissemination of information and imminent reaction to posted prices on the trading screens, therefore the degree to which new information is incorporated into prices must increase.

The methodology that follows was initially introduced by Amihud, Mendelson & Lauterbach (1997) to examine the degree of informational efficiency for different trading mechanisms. It was employed to test the efficiency of single call auctions and continuous trading in the Tel Aviv Stock exchange market. Variations of it were employed to test the efficiency of call auctions within the framework of continuous trading in the Tokyo Stock Exchange in two separate occasions. We use this methodology to examine the degree of informational efficiency between a dealership, an order driven market, a hybrid market, different closing price formation algorithms and the effects of computerisation. This methodology is known as 'relative return dispersion' (RRD) and is based on the variance of returns across securities. In the first instance we need to regress individual stock returns on market index returns and obtain the residuals. Then we square the residuals obtained from the market model and average over the stocks included in our sample over different trading regimes and different closing price formation algorithms. Symbolically this is given by:

$$R_{it}=c+\beta MR_t+e_t \quad (5.1)$$

$$RRD_t=\frac{1}{N}\sum_{1}^{N} e_{it}^2 \quad (5.2)$$

The dispersion of values at every single point in time due to firm specific information should be independent of the trading mechanism used each time, therefore any systematic differences observed between the different trading mechanisms and the different algorithms can be attributed solely to the trading mechanism. Lower relative return dispersion indicates smaller pricing errors relative to contemporaneous market index returns, which means that information is incorporated faster into prices. This may be due to faster adjustment to changes in the market index and smaller firm specific errors. Higher relative return dispersion indicates underreaction and may be due to lagged adjustment to market returns and high firm specific noise. The extent to which each of those factors (adjustment to market returns and firm specific noise) affects the degree of efficiency of each trading regime and closing price formation algorithms is examined by estimating a lagged market regression model for each stock in the sample:

$$R_{it}=c+\beta MR_t+L\beta MR_{t-1}+e_t \quad (5.3)$$

Where R_{it} is returns for each individual stock and MR_t and MR_{t-1} are contemporaneous and lagged index returns. Examination of the (in)significance of the coefficients obtained will allow us to determine if the degree of efficiency observed is due to lagged adjustment to the index. Controlling for lagged adjustment will also allow us to examine the variance of the residuals obtained from the lagged market model for each stock and see how fast firm specific information is incorporated in prices. Changes in the trading system should not have changed any fundamental information about the stocks traded, therefore any systematic differences in the variance of the residuals will reflect how fast firm specific information is incorporated in prices. If it turns out that the variance increases then firm specific information is not incorporated fast enough into prices and this can be attributed to the trading mechanism.

We modify the methodology described above (Amihud et al, 1997) by adding the Fama & French factors. Therefore equations (1) and (3) are re-written as:

$$R_{it}=c+\beta MR_{it}+SMB_t+HML_t+e_{it} \quad (5.4)$$

$$R_{it}=c+\beta MR_{it}+L\beta MR_{it-1}+SMB_t+HML_t+e_{it} \quad (5.5)$$

We also employ a second methodology to examine informational efficiency, which can only be used with high frequency data. The issue of over reaction or under reaction has attracted a lot of attention recently (Barberis et al,1998; Daniel et al, 1998 and Odean, 1998) and we believe that it is worth examining how informational efficiency changes with respect to the trading regime. In order to examine this we regress changes in transaction prices on changes in the real value of the asset (mid-quotes) and on past pricing errors. Symbolically this is expressed as:

$$(p_t-p_{t-1})=\alpha+\beta(v_t-v_{t-1})+\gamma(p_{t-1}-v_{t-1})+\varepsilon_t \quad (5.6)$$

where p_t is the transaction price as formed under the different trading regimes and v_t is the real value of the asset as captured by the mid-quote. In all empirical market microstructure studies, the mid-quote is generally accepted to be the real value of the asset. Kim & Ogden (1996) consider the mid-quote following a transaction as the real value of the asset and they use it to estimate the components of the bid-ask spread. In an efficient market the real value of the asset as captured by the mid quote should be reflected imminently in prices, therefore β should assume the value of one. If β assumes a value lower than one then it means that the market underreacts to incoming information while if it assumes a value higher than one then it means that it overeacts to incoming information. Restrictions on β are tested by Wald tests. γ provides estimates of the effects of past pricing errors on changes in prices and the extent to which they are corrected. In an efficient market γ should assume negative values meaning that past pricing errors are corrected, therefore the more negative the value is the faster past pricing errors are corrected. We strongly believe that the above methodology is the ultimate way to examine informational efficiency and provides first class evidence since it allows us to consider every single trade during the day. Our sample is in excess of one million trades.

In order to examine the effect of volatility on spread sensitivity under different regimes we need to introduce two separate measures of volatility. The first one will be used as a descriptive measure to provide us with an idea of the level of market volatility under different trading regimes while the second one will be used as a regressor on the sensitivity model. The volatility descriptive measure is estimated as:

$$\mathrm{VOLATILITY1}_{it} = \frac{H_{it} - L_{it}}{0.5(H_{it} + L_{it})} \quad (5.7)$$

Where H_{it} is the highest price recorded within the day and L_{it} is the lowest price recorded within the day. The difference between high price and low price divided by the average of those two prices can provide us with an indication of volatility under different regimes. However we believe that this is a crude measure of volatility to include as regressor in the sensitivity model because it fails to distinguish the effect of the trading mechanism from that of the general market environment (e.g news, events, liquidity and asymmetric information). For that reason we estimate a GARCH(1,1) model for each stock in our sample and incorporate in the variance equation changes in the real value of the asset as captured by the bid-ask midquote. The mean equation is given by:

$$R_t=c+e_t \quad (5.8)$$

Where R_t is returns and e_t is the error term. This equation is estimated separately for each stock in the sample. The variance equation is given by:

$$\sigma_t^2 = c + \delta\varepsilon_{t-1}^2 + \zeta\sigma_{t-1}^2 + \eta\left[\left(\frac{bid_t + ask_t}{2}\right) - \left(\frac{bid_{t-1} + ask_{t-1}}{2}\right)\right] \quad (5.9)$$

where σ_t^2 is the conditional variance, ε_{t-1}^2 is the lagged squared residual from the mean equation or news about volatility from the previous period, σ_{t-1}^2 is the last period's forecast variance and the term in squared brackets represents changes in the real value of the asset. We believe that by including changes in the real value of the asset we manage to separate the effect of the trading mechanism from the market environment. Any news, trading activity, liquidity or asymmetric information pertinent to each stock in the sample should be reflected in changes in the real value, captured by changes in the mid quote allowing full investigation of spread sensitivity to volatility. Wang (1999) comparing different trading systems in the Sydney Futures Exchange uses 'daily average transaction size' and 'number of trades' to separate the effect of the trading mechanism from that of the market environment. We believe that by incorporating changes in the real value of the stock we capture every change in the external environment. Spread sensitivity to volatility will be estimated by the following pool regression:

$$\text{spread}_{it}=c+\mu_{it}\sigma_{it}^2+e_{it} \quad (5.10)$$

where spread is the daily closing bid-ask spread for each stock in our sample and μ_{it} is the coefficient of the conditional variance for each individual stock obtained by running a GARCH (1,1). If μ_{it} turns out to be significant then it means that volatility affects the spread set either by market makers or individual traders.

The above exercise is undertaken by employing high frequency data for FTSE100 and FTSE250 stocks. The only difference is that returns this time are based on transaction prices rather than daily closing prices.

5.4.DATASET AND DESCRIPTIVE STATISTICS

Daily price data for FTSE100 companies was obtained from DATASTREAM and transactions data from Securities industry Research Centre of Asia Pacific (SIRCA). The data set under consideration ranges from 18/10/1996 to 30/04/2003. The choice of the data set reflects a quote-driven trading regime and an order-driven trading regime, which is further sub-divided into three different closing price formation periods. This allows us to test the degree of informational efficiency under different trading regimes, which relates to the first and second research hypotheses and the extent to which spread is sensitive to volatility under those regimes which relates to the fourth research hypothesis. Each subset represents a different trading regime/closing price formation algorithm and incorporates the following time period: the first subset ranges from 18/10/1996 to 17/10/1997 and reflects a dealership where closing prices are based on the bid-ask midquote, the second subset ranges from 20/10/1997 to 13/12/1998 during which period the market is order driven and the closing prices were based on the last automated transaction (order book), the third subset ranges from 14/12/1998 to 26/05/00 during which period the closing prices were based on the last ten minutes of trading volume (VWAP: volume weighted average price) and finally the fourth subset ranges from 30/05/2000 to 30/04/2003 during which period the closing prices were formed by a closing auction. Unfortunately the transactions data sample does not extend over all those periods. We use trade data for two months following changes in the trading regime.

Daily price data for FTSE250 companies was obtained from DATASTREAM and transactions data from securities industry Research Centre Asia Pacific (SIRCA). The data set under consideration ranges from 01/01/2003 to 12/08/2004. The choice of the data set reflects a quote-driven trading regime (SEAQ) where liquidity is provided solely by market makers and a hybrid market (SETSmm) where individual traders can choose to trade between themselves if they wish to do so or trade with market makers who are obliged to provide liquidity through 'committed principal orders'. The change from one system to the other occurred in 03/11/03. This allows us to test the degree of informational efficiency under different trading regimes, which relates to the third research hypothesis and the extent to which spread is sensitive to volatility under those regimes, which relates to the fifth research hypothesis.

Daily price data for the Greek stocks was obtained from DATASTREAM. The data set under consideration ranges from 19/08/1991 to 17/08/1993. The choice of the data set reflects a public outcry trading regime and a fully computerized electronic trading system (ASIS). This allows us to test the degree of informational efficiency under different trading processes, which relates to the sixth research hypothesis. Unfortunately we cannot test spread sensitivity to volatility because neither The Athens Stock Exchange nor DATASTREAM nor SIRCA have data on bid and ask prices.

The daily data obtained includes the following variables: closing bid price, closing ask price, daily closing price, highest daily price, lowest daily price and closing trading volume. These variables were further processed to obtain other variables such as: bid-ask spread, bid-ask mid quote which is equal to (bid-price+ask-price)/2 and is used as a proxy for the real value of the asset, returns, returns volatility modeled as GARCH(1,1), 'volatiltity1' estimated as the difference between daily high and daily low prices divided by the average of those two prices and another liquidity measure 'LR1' which is estimated as the ratio of volume turnover to volatility1. The intuition behind this liquidity measure is that if the £ amount of stocks traded is high while price movement is small then the market is very liquid. However if the £ amount of stocks traded is relatively constant but price fluctuation is high then this particular market is not liquid. The transactions data incorporates all trades, transaction prices, bid-ask quotes and volume.

Descriptive statistics for FTSE100 (TABLE 5.1) with reference to the two liquidity measures employed here (bid-ask spread and LR1) show that liquidity decreased once the market changed from quote driven (dealership) to order driven. In particular absolute spread appears to have increased from 2.66 to 4.18 following the change in the trading regime while it remains relatively stable for the rest of the periods examined. In order to decide on the (in)significance of changes in the mean values we undertake ANOVA tests. The increase in absolute spread following the change form quote driven to order driven is significant while changes in the spread for the rest of the periods are insignificant. The p values obtained for the estimated ANOVA statistic are much higher than 0.05. This result was somewhat expected since for the rest of the periods, the trading mechanism has remained the same; the only difference is in the closing price formation algorithm. The results obtained for absolute spread are further confirmed by LR1, which captures liquidity in terms of £s of stocks traded controlling for price fluctuations. Higher (lower) values of LR1 indicate that liquidity increases (decreases). When testing for mean (in)equality, the ANOVA tests show that the decrease in LR1 is significant when the trading mechanism changes but changes in the mean values of LR1 for the rest of the periods are insignificant at 0.05. Finally we calculate descriptive statistics for volatility1 (TABLE5.1) estimated as the difference between high price and low price divided by the average of those two prices over all four periods examined and we find that volatility increases through time, reaches an all time high and remains at the same level for the period following. The first two ANOVA tests reject mean equality between the first, second and third period but they fail to reject mean equality between the third and the fourth period during which volatility is stabilized.

Descriptive statistics for FTSE250 (TABLE5.2) show that absolute spread decreased over the period examined which indicates an improvement in liquidity however ANOVA tests show that this improvement is not significant. The p value obtained is equal to 0.49. LR1, which is an alternative measure of liquidity, shows that liquidity had actually decreased however ANOVA tests indicate that the decrease is insignificant. In other words the change from dealership (SEAQ) to a hybrid system (SETSmm) does not seem to have brought about any changes in liquidity. Finally 'volatility1' shows that volatility has increased. The p value obtained is equal to 0.07.

Results for the Greek market (TABLE5.3) show that the introduction of electronic trading (ASIS) increased liquidity slightly however this increase is not considered to be significant based on ANOVA tests. The p value obtained is equal to 0.88. Normally we would expect a major increase in liquidity given the introduction of electronic trading. Unfortunately we do have data on bid and ask prices for the Greek market, therefore the results obtained for LR1 can not contrasted against another variable such as the spread. Volatility as captured by 'volatilitty1' appears to decrease; however this decrease is insignificant.

Computerization of the trading process is supposed to increase both liquidity and volatility however this does not appear to be the case for the Greek market.

TABLE5.1: LIQUIDITY AND VOLATILITY MEASURES: FTSE100 (p values in brackets)

	LIQUIDITY MEASURES								VOLATILITY1			
	ABSOLUTE SPREAD				£ VALUE OF SHARES TRADED/STDEV							
TRADING REGIME	SEAQ	SETS	SETS:VWAP	CLOSING AUCTION	SEAQ	SETS	SETS:VWAP	CLOSING AUCTION	SEAQ	SETS	SETS:VWAP	CLOSING AUCTION
MEAN	2.66	4.18	4.20	3.72	538.5	226.3	148.6	387.7	1539.2	41081	73809	54789
ANOVA H_0: mean equality		10.62 (0.00)	0.00 (0.96)	0.93 (0.33)		2.12 (0.03)	0.46 (0.64)	1.86 (0.06)		4.98 (0.00)	2.96 (0.00)	1.46 (0.14)
MEDIAN	2.49	3.40	3.15	2.93	196.8	89.5	64.7	136.4	9173	27757	41609	33317
S.D	1.73	3.73	3.28	3.10	1217.3	470.8	190.5	916.7	14683	41642	86555	57605

TABLE5.2: LIQUIDITY AND VOLATILITY MEASURES: FTSE250 (p values in brackets)

	LIQUIDITY MEASURES				VOLATILITY1	
	ABSOLUTE SPREAD		£ VALUE OF SHARES TRADED/STDEV			
TRADING REGIME	SEAQ	SETSmm	SEAQ	SETSmm	SEAQ	SETSmm
MEAN	6.84	6.14	178.3745	143.98	10059.28	15931.37
ANOVA H_0: mean equality		0.68(0.49)		0.66 (0.50)		1.80(0.07)
MEDIAN	4.68	4.03	51.56	40.36	3467.952	6226.750
S.D	9.47	7.47	478.96	397.69	25573.10	29072.65

TABLE5.3: LIQUIDITY AND VOLATILITY MEASURES: GREEK MARKET (p values in brackets)

	LIQUIDITY MEASURES				VOLATILITY1	
	ABSOLUTE SPREAD		£ VALUE OF SHARES TRADED/STDEV			
TRADING REGIME	PUBLIC OUTCRY	ELECTRONIC CONTINUOUS TRADING	PUBLIC OUTCRY	ELECTRONIC CONTINUOUS TRADING	PUBLIC OUTCRY	ELECTRONIC CONTINUOUS TRADING
MEAN	N/A	N/A	234.47	247.57	2.87	2.37
ANOVA H_0: mean equality	N/A	N/A		0.14(0.88)		0.20(0.83)
MEDIAN	N/A	N/A	67.81	71.69	0.22	0.36
S.D	N/A	N/A	396.4	502.8	15.5	7.88

5.5.EMPIRICAL FINDINGS

The statistical analysis aims at i) investigating how fast information is incorporated into prices and the degree to which individual stocks under/over react to incoming information and ii) examine if and the extent to which bid-ask spread is sensitive to volatility under different trading regimes. Examination occurs under different trading regimes namely a dealership (SEAQ), a quote drive- market (SETS) and a combination of both (SETSmm) for the UK market and between a public outcry and fully computerized system (ASIS) for the Greek market.

5.5.1 RELATIVE RETURN DISPERSION

The methodology employed here allows comparisons between different trading regimes: quote-driven (SEAQ), hybrid (SETSmm), order-driven (SETS) and different closing price formation algorithms. Relative return dispersion has been successfully employed in the past by Amihud & Mendelson (1997) to test informational efficiency. This methodology concentrates on the squared residuals obtained from regressing individual stock returns against the index to which stocks belong to and of course against the index for which changes were introduced. It would not be possible to regress individual FTSE100/FTSE250 stock returns against FTSE ALL SHARE simply because stocks that comprise FTSE ALL SHARE trade in at least three different trading regimes.

5.5.1.1 RELATIVE RETURN DISPERSION: FTSE100 STOCKS

The average value of squared residuals obtained by regressing individual FTSE100 stocks returns against the index appears to decrease slightly over time (SUMMARY TABLE 5.7, this table is at the end of the relative return dispersion section). The highest value is achieved when the market is quote-driven (dealership) implying that market makers fail to assess information as fast as they should. Once the market regime changes from quote driven (dealership) to order driven the mean squared value of residuals reduces by 0.01. ANOVA tests reject mean equality between the first two periods but fail to reject mean equality between the third and the fourth periods. This means that the introduction of a closing auction did not bring about the desired result of increasing the degree of informational efficiency achieved up to that moment implying that a closing auction is not much superior to that of VWAP (volume weighted average pricing). Actually a closing auction and VWAP appear to achieve the same degree of informational efficiency (H1 is rejected). The observed decrease in relative return dispersion between the first and the second period as captured by the mean values of the squared residuals can be attributed either to increased adjustments to changes in the relevant index or/and low firm specific noise. The extent to which each of these factors has contributed to the observed increase in RRD is examined by running the following regressions:

$$R_{it}=c+\beta MR_t+L\beta MR_{t-1}+e_t. \quad (5.11)$$

$$R_{it}=c+\beta MR_{it}+L\beta MR_{it-1}+SMB_t+HML_t+e_{it} \quad (5.12)$$

Which were discussed above and are given new numbers here.

The results presented in TABLE5.4 (PANEL A AND PANEL B) indicate that the degree of informational efficiency increases slightly following changes in the trading regime. PANEL A presents results for regression (11) and PANEL B presents results for regression (12). We will start by commenting on results in PANEL A and then we will proceed to PANEL B. When the market is quote driven (dealership) the coefficient for contemporaneous market returns assumes a highly significant positive value (0.73) implying that individual stocks respond to FTSE100 returns and the general market condition as captured by the index. Of course if individual stocks responded to a full extent the value obtained should be equal to 1. The R^2 adj obtained in this case is equal to 0.17. When we add lagged market returns we find that the coefficient of contemporaneous market returns remains the same and the coefficient of lagged market returns assumes a value of 0.11 which is significant indicating that individual stocks respond with a small lag to the index. R^2 adjusted increases slightly to 0.18. When the market regime changes from quote driven (dealership) to order-driven the coefficient of current index returns increases to 0.78 and R^2 ADJ becomes 0.20, indicating that the explanatory power of current FTSE100 returns has increased. When we add lagged index returns, the coefficient of contemporaneous index returns gets quite small. From 0.11 (quote driven market) reduces to 0.02 (order driven market). In this case R^2 adjusted increases indicating that FTSE100 stocks respond faster. This pattern remains valid for the rest of the periods examined. We would expect to see some changes for the second, third and fourth period given the change in the closing price formation algorithm however it appears that it is only changes in the trading regime itself (from quote driven to order driven) that can affect informational efficiency. PANEL B presents results for FTSE100 stocks incorporating the FF factors: SMB (equally weighted) and HML (equally weighted). The results are similar to the ones obtained from the simple regressions. The coefficient of contemporaneous index returns is equal to 0.69(0.00) for the first period (quote driven) and then increases to 0.72(0.00) for the second period (order driven). The coefficient of lagged index returns is equal to 0.10(0.00) for the first period (quote driven) and then reduces to 0.02(0.00) for the second period (order driven) indicating that the degree of informational efficiency increases in the second period (order driven). At this point it is worth mentioning that R^2 ADJ increases from 0.18 to 0.20. The FF factors are significant for both periods under consideration and their inclusion in the regressions does not appear to alter the results in any way. Results are qualitatively the same for the rest of the periods.

<u>Size-based analysis</u>: Results obtained for small and big companies indicate that it takes longer for smaller companies to adjust to incoming information. The coefficient of lagged market returns is slightly higher for smaller companies for most of the periods under consideration. In particular in the

first period under examination (quote driven) the coefficient of lagged index returns for big companies is 0.11 and for small companies is 0.14. Of course it is not a sizeable difference but you need to keep in mind that the stocks are under examination are FTSE100 stocks. Perhaps the results would be more pronounced if we employed stocks with major differences in market capitalisation. When the trading regime changes the coefficient of lagged market returns for small companies reduces from 0.14 to 0.04 and for big companies from 0.11 to 0.01, which is evidence of improvement in informational efficiency. Results remain similar even when we add the FF factors.

Amihud, Mendelson & Lauterbach (1997) state that any increases/ decreases in RRD can very well be attributed to either lagged/increased adjustments to changes in the relevant index or/and high/low firm specific noise. The above exercise was undertaken to control for the effect of lagged adjustment and test the extent to which firm specific noise contributes to decreased RRD. The variance of the residuals obtained from the lagged index regression and FF factors as shown in SUMMARY TABLE 5.8 (all 'residuals variance' is summarised in TABLE 5.8 which is presented at the end of the relative return dispersion section) appears to decrease between the first two periods. ANOVA tests reject mean equality for the first two periods but fail to reject mean equality between VWAP and the closing auction, indicating that the closing auction is not superior to VWAP. Generally speaking while the change in market microstructure should not have changed any fundamental information about the stocks, it had an favourable effect on the precision with which new firm specific information is incorporated into prices. In conclusion the decrease in RRD can be attributed both to increased response to the index and reduced firm specific noise.

TABLE5.4: FTSE100 INFORMATIONAL EFFICIENCY OVER FOUR DIFFERENT PERIODS (p values in brackets)

PANEL A

QUOTE DRIVEN MARKET/DEALERSHIP:SEAQ								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00 (0.15)	0.00 (0.18)	0.00(0.18)	0.00(0.19)	0.00(0.20)	0.00(0.20)	0.00(0.12)	0.00(0.25)
MR_t	0.73 (0.00)	0.73 (0.00)	0.68(0.00)	0.66(0.00)	0.69(0.00)	0.68(0.00)	0.75(0.00)	0.75(0.00)
MR_{t-1}		0.11 (0.00)		0.14(0.00)		0.14(0.00)		0.11(0.00)
R^2ADJ	0.17	0.18	0.18	0.19	0.17	0.18	0.20	0.21

ORDER DRIVEN MARKET:SETS-LAST AUTOMATED TRANSACTION								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00 (0.68)	0.00 (0.69)	0.00(0.67)	0.00(0.65)	0.00(0.69)	0.00(0.12)	0.00(0.75)	0.00(0.79)
MR_t	0.78 (0.00)	0.77 (0.00)	0.69(0.00)	0.67(0.00)	0.71(0.00)	0.70(0.00)	0.78(0.00)	0.77(0.00)
MR_{t-1}		0.02 (0.02)		0.04(0.00)		0.05(0.00)		0.01(0.00)
R^2ADJ	0.20	0.20	0.20	0.21	0.21	0.21	0.19	0.20

VOLUME-WEIGHTED AVERAGE PRICE								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00 (0.00)	0.00 (0.00)	0.00(0.10)	0.00(0.12)	0.00(0.13)	0.00(0.15)	0.00(0.22)	0.00(0.28)
MR_t	0.76 (0.02)	0.75 (0.00)	0.68(0.00)	0.67(0.00)	0.73(0.00)	0.72(0.00)	0.78(0.00)	0.77(0.00)
MR_{t-1}		0.03 (0.00)		0.09(0.00)		0.08(0.00)		0.02(0.00)
R^2ADJ	0.19	0.19	0.19	0.20	0.18	0.19	0.19	0.19

CLOSING AUCTION								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	-0.00 (0.45)	0.00 (0.00)	0.00(0.45)	0.00(0.80)	0.00(0.20)	0.00(0.34)	0.00(0.42)	0.00(0.40)
MR_t	0.70 (0.00)	0.69 (0.00)	0.65(0.00)	0.66(0.00)	0.68(0.00)	0.66(0.00)	0.73(0.00)	0.72(0.00)
MR_{t-1}		0.03 (0.00)		0.05(0.00)		0.05(0.00)		0.02(0.00)
R^2ADJ	0.18	0.19	0.18	0.19	0.19	0.19	0.18	0.19

PANEL B

QUOTE DRIVEN MARKET/DEALERSHIP								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00 (0.08)	0.00 (0.06)	0.00(0.08)	0.00(0.09)	0.00(0.09)	0.00(0.10)	0.00(0.10)	0.00(0.11)
MR_t	0.69 (0.00)	0.69 (0.00)	0.62(0.00)	0.63(0.00)	0.64(0.00)	0.68(0.00)	0.73(0.00)	0.74(0.00)
SMBEW	-0.002(0.00)	-0.00(0.00)	0.01(0.00)	0.01(0.00)	0.00(0.00)	0.00(0.00)	-0.001(0.00)	-0.001(0.00)
HMLEW	-0.001(0.01)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)
MR_{t-1}	0.10(0.00)		0.13(0.00)		0.09(0.00)		0.08(0.00)	
R^2ADJ	0.18	0.17	0.17	0.16	0.17	0.17	0.20	0.19

ORDER DRIVEN MARKET:SETS-LAST AUTOMATED TRANSACTION								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00(0.49)	0.00(0.49)	0.00(0.50)	0.00(0.49)	0.00(0.80)	0.00(0.76)	0.00(0.42)	0.00(0.33)
MR_t	0.72(0.00)	0.72(0.00)	0.68(0.00)	0.70(0.00)	0.71(0.00)	0.73(0.00)	0.76(0.00)	0.77(0.00)
SMBEW	-0.002(0.00)	-0.002(0.00)	0.00(0.00)	0.02(0.00)	0.00(0.00)	0.00(0.00)	-0.001(0.00)	-0.001(0.00)
HMLEW	-0.001(0.10)	-0.001(0.10)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)
MR_{t-1}	0.02(0.02)		0.07(0.00)		0.05(0.00)		0.01(0.00)	
R^2ADJ	0.20	0.20	0.20	0.19	0.20	0.18	0.21	0.19

VOLUME-WEIGHTED AVERAGE PRICE								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00(0.06)	0.00(0.06)	0.00(0.09)	0.00(0.10)	0.00(0.12)	0.00(0.15)	0.00(0.10)	0.00(0.15)
MR_t	0.72(0.00)	0.72(0.00)	0.65(0.00)	0.67(0.00)	0.70(0.00)	0.73(0.00)	0.72(0.00)	0.75(0.00)
SMBEW	-0.001(0.05)	-0.001(0.05)	0.01(0.00)	0.01(0.00)	0.00(0.00)	0.00(0.00)	-0.001(0.00)	-0.001(0.00)
HMLEW	-0.001(0.05)	-0.01(0.05)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)
MR_{t-1}	0.02(0.00)		0.07(0.00)		0.06(0.00)		0.02(0.00)	
R^2ADJ	0.21	0.20	0.20	0.19	0.19	0.17	0.22	0.21

CLOSING AUCTION								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
MR_t	0.67(0.00)	0.68(0.00)	0.60(0.00)	0.63(0.00)	0.67(0.00)	0.70(0.00)	0.73(0.00)	0.74(0.00)
SMBEW	-0.003(0.00)	-0.003(0.00)	0.01(0.00)	0.01(0.00)	0.00(0.00)	0.00(0.00)	-0.001(0.00)	-0.001(0.00)
HMLEW	-0.001(0.00)	-0.001(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)	-0.00(0.00)
MR_{t-1}	0.03(0.00)		0.08(0.00)		0.05(0.00)		0.04(0.00)	
R^2ADJ	0.19	0.18	0.17	0.16	0.19	0.18	0.19	0.18

5.5.1.2 RELATIVE RETURN DISPERSION: FTSE250 STOCKS

Results obtained for FTSE250 stocks are presented in TABLE5.5, PANEL A and PANEL B. PANEL A presents results for the two trading regimes without the FF factors while PANEL B presents results for the same trading regimes incorporating the FF factors. The average value of squared residuals obtained by regressing individual FTSE250 stocks returns against the index and the FF factors appears to decrease over time (SUMMARY TABLE 5.7) however ANOVA tests do not reject the null hypothesis of mean equality. In other words there appears to be no change in the degree of informational efficiency between a dealership and a hybrid market, which implies that the third hypothesis is not rejected. The main characteristic of both trading systems (SEAQ and SETSmm) is the presence of market makers even though SETSmm allows trading through the electronic book. The ability to engage in individual trading (without employing the services of market makers) did not bring about an increase in informational efficiency.

In order to be consistent with the methodology described above, we need to present results for FTSE250 stocks response to current and lagged index returns following changes in the trading regime (TABLE 5.5). By examining closely the results presented for all stocks in FTSE250, one might argue that there is an improvement in informational efficiency given the increases in the coefficients observed for current market returns and reductions observed for lagged market returns. In particular the coefficient of current market returns increases from 0.60 to 0.74 while the coefficient for lagged market returns decreases from 0.11 to –0.05 following the introduction of the order book, however we can talk about 'real' increases in informational efficiency when the coefficient for lagged market returns is insignificant. In addition the mean value of squared residuals discussed above remains unchanged between the two regimes, which means that the degree of informational efficiency has remained unchanged. At this point one should notice that the sum of current and lagged returns coefficients remains almost the same, 0.71 before the introduction of SETSmm against 0.69 after the introduction of SETSmm. The fundamental relation between returns on individual stocks and the market was unaffected by the change even though the coefficient of lagged market returns appears reduced. However this reduction is not significant to affect RRD. PANEL B presents results for FTSE250 stocks incorporating the FF factors. When the market is quite driven (SEAQ) the coefficient of current market returns is equal to 0.59 and the coefficient of lagged market returns is equal to 0.06. When the trading regime changes both coefficients increase. The increase in the coefficient of current market returns is offset by an increase in the coefficient of lagged market returns indicating that there is not any improvement in informational efficiency. Thus the insignificant reduction in RRD (SUMMARY TABLE 5.7). Residuals variance obtained by running the same regression ($R_{it}=c+\beta MR_{it}+L\beta MR_{it-1}+SMB_t+HML_t+e_{it}$) remains the same (SUMMARY TABLE 5.8) which means that the degree to which firm specific information is incorporated into prices has remained unchanged.

Size-based analysis: the number of stocks in FTSE250 compared to FTSE100 allows us to vary the number of stocks included in the small and big groups so we run regressions for two different sub-samples in each category. Results obtained for the smaller groups show that the coefficient of current returns increases more when compared to the bigger groups. In particular the coefficient of current returns for the 20 smallest companies in the sample (TABLE 5.5, PANEL B) increases from 0.49 to 0.71 while the coefficient of current returns for the 20 biggest companies in the sample increases from 0.69 to 0.77. Unfortunately however this increase in the coefficient of current returns for small companies, which might imply an increase in informational efficiency, is offset by an increase in the coefficient of lagged index returns from 0.04 to 0.21 following the change in the trading regime. The coefficient of lagged index returns for big companies is insignificant under both trading regimes (TABLE 5.5, PANEL B), implying that the change in the trading regime did not have much impact on the biggest companies even though it did increase the coefficient of current returns.

TABLE 5.5: FTSE250 INFORMATIONAL EFFICIENCY OVER SEAQ AND SETSmm (p values in brackets)

PANEL A: FTSE250 INFORMATIONAL EFFICIENCY OVER SEAQ AND SETSmm WITHOUT FF FACTORS

FTSE250: SEAQ/DEALERSHIP										
	ALL STOCKS		SMALL20		SMALL30		BIG20		BIG30	
C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.70)	(0.78)	(0.26)	(0.35)
MR_t	0.61	0.60	0.46	0.44	0.52	0.50	0.72	0.72	0.70	0.70
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MR_{t-1}		0.11		0.11		0.00		0.11		0.11
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
R^2ADJ	0.12	0.13	0.04	0.05	0.06	0.07	0.21	0.22	0.18	0.19

FTSE250:HYBRID/SETSmm										
	ALL STOCKS		SMALL20		SMALL30		BIG20		BIG30	
C	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.29)	(0.85)	(0.82)
MR_t	0.75	0.74	0.84	0.84	0.75	0.75	0.77	0.76	0.77	0.76
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MR_{t-1}		-0.05		0.04		0.00		-0.07		-0.07
		(0.00)		(0.04)		(0.79)		(0.00)		(0.00)
R^2ADJ	0.10	0.11	0.03	0.04	0.05	0.05	0.17	0.17	0.14	0.15

PANEL B: FTSE250 INFORMATIONAL EFFICIENCY OVER SEAQ AND SETSmm WITH FF FACTORS

FTSE250: SEAQ/DEALERSHIP FF FACTORS EQUALLY WEIGHTED										
	ALL STOCKS		SMALL20		SMALL30		BIG20		BIG30	
C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.70)	(0.64)	(0.23)	(0.28)
MR_t	0.61	0.59	0.56	0.49	0.57	0.55	0.69	0.69	0.67	0.67
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MR_{t-1}		0.06		0.04		0.04		-0.01		0.00
		(0.00)		(0.00)		(0.00)		(0.29)		(0.76)
SMB(EW)	-0.00	-0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.51)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HML(EW)	0.00	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	0.00	0.00
	(0.09)	(0.13)	(0.95)	(0.78)	(0.91)	(0.80)	(0.28)	(0.31)	(0.60)	(0.68)
R^2ADJ	0.12	0.12	0.04	0.04	0.06	0.06	0.22	0.22	0.18	0.18

FTSE250:HYBRID/SETSmm FF FACTORS EQUALLY WEIGHTED										
	ALL STOCKS		SMALL20		SMALL30		BIG20		BIG30	
C	0.00	0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00
	(0.03)	(0.04)	(0.00)	(0.00)	(0.67)	(0.58)	(0.16)	(0.16)	(0.08)	(0.08)
MR_t	0.64	0.65	0.69	0.71	0.54	0.56	0.76	0.77	0.70	0.71
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MR_{t-1}		0.10		0.21		0.21		0.07		0.10
		(0.00)		(0.03)		(0.00)		(0.13)		(0.02)
SMB(EW)	0.00	0.00	-0.00	0.00	-0.00	0.00	0.00	0.00	0.00	0.00
	(0.71)	(0.00)	(0.15)	(0.75)	(0.45)	(0.07)	(0.17)	(0.05)	(0.72)	(0.10)
HML(EW)	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.69)	(0.74)	(0.21)	(0.29)	(0.04)	(0.05)	(0.23)	(0.25)
R^2ADJ	0.08	0.08	0.03	0.04	0.03	0.04	0.16	0.17	0.12	0.12

5.5.1.3 RELATIVE RETURN DISPERSION: THE GREEK MARKET

The average value of squared residuals obtained by regressing individual stocks returns against the market index appears to decrease over time (SUMMARY TABLE 5.7). ANOVA tests reject the null hypothesis of mean equality, which means that informational efficiency has improved. This is a direct result of computerising the trading process. Computerisation of the trading process allows more orders to be processed per unit of time and any information circulating in the market is incorporated into prices almost imminently. Results presented in TABLE 5.6 (PANEL A) show that when the market was a public outcry the coefficient of current returns was equal to 0.73(0.00) and the coefficient for lagged returns was equal to –0.01(0.04). Following the computerisation of the trading process, the coefficient of current returns increased to 0.89(0.00) while the coefficient for lagged returns became insignificant, which indicates that the degree of informational efficiency improved tremendously and individual stocks respond fully to the market. Results remain the same once we introduce the FF factors. In TABLE 5.6 (PANEL B) the coefficient of current returns increases from 0.72 to 0.87 following the computerization of the trading process while the coefficient of lagged index returns becomes insignificant. The variance of residuals (TABLE5.8) obtained by running similar regressions (R_{it}=c+βMR_{it}+LβMR_{it-1}+SMB_t+HML_t+e_{it}) indicate that there is a decrease in the mean value of the variance of residuals however this is not significant which means that the degree to which stock specific information is incorporated into prices has not changed however individual stock response to the market has improved tremendously. The results obtained for the Greek market are similar to the results obtained for the Tel Aviv market by Amihud, Mendelson & Lauterbach (1997)

Size-based analysis: Results obtained for small companies are a bit out of the ordinary. Even though the response to current market returns appears to increase following the computerization of the trading process, the coefficient of lagged index returns gets significant. Results for big companies are more or less as expected. The coefficient of lagged index returns is insignificant under both trading regimes implying that there is no lagged adjustment however the coefficient of current market returns decreases but still remains quite high.

TABLE 5.6: ATHENS STOCK EXCHANGE INFORMATIONAL EFFICIENCY OVER PUBLIC OUTCRY AND ASIS (p values in brackets)

PANEL A

GREEK MARKET: PUBLIC OUTCRY						
	ALL COMPANIES		SMALL COMPANIES		BIG COMPANIES	
C	0.00 (0.00)	0.02 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MR_t	0.73 (0.00)	0.73 (0.00)	0.41 (0.00)	0.41 (0.00)	0.91 (0.00)	0.91 (0.00)
MR_{t-1}		-0.01 (0.04)		-0.00 (0.49)		-0.00 (0.22)
R^2ADJ	0.18	0.18	0.04	0.04	0.35	0.35

GREEK MARKET:ASIS						
	ALL COMPANIES		SMALL COMPANIES		BIG COMPANIES	
C	0.00 (0.00)	0.02 (0.00)	0.00 (0.01)	0.00 (0.02)	0.00 (0.15)	0.00 (0.15)
MR_t	0.89 (0.00)	0.89 (0.00)	0.78 (0.00)	0.77 (0.00)	0.84 (0.00)	0.84 (0.00)
MR_{t-1}		-0.00 (0.96)		0.08 (0.00)		-0.00 (0.75)
R^2ADJ	0.25	0.25	0.16	0.16	0.31	0.31

PANEL B

GREEK MARKET: PUBLIC OUTCRY						
	ALL COMPANIES		SMALL COMPANIES		BIG COMPANIES	
C	0.00 (0.00)	0.02 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
MR_t	0.72 (0.00)	0.72 (0.00)	0.39 (0.00)	0.38 (0.00)	0.89 (0.00)	0.89 (0.00)
MR_{t-1}		-0.00 (0.00)		-0.00 (0.36)		-0.00 (0.30)
SMB(EW)	0.09(0.00)	0.10(0.00)	0.15(0.00)	0.15(0.00)	0.01(0.00)	0.01(0.00)
HML(EW)	-0.05(0.01)	-0.05(0.02)	-0.05(0.03)	-0.06(0.04)	-0.03(0.06)	-0.04(0.06)
R^2ADJ	0.19	0.19	0.05	0.06	0.33	0.35

GREEK MARKET:ASIS						
	ALL COMPANIES		SMALL COMPANIES		BIG COMPANIES	
C	0.00 (0.00)	0.02 (0.00)	0.00 (0.01)	0.00 (0.02)	0.00 (0.15)	0.00 (0.15)
MR_t	0.88 (0.00)	0.87 (0.00)	0.76 (0.00)	0.75 (0.00)	0.82 (0.00)	0.81 (0.00)
MR_{t-1}		-0.00 (0.99)		0.06 (0.00)		-0.00 (0.75)
SMB(EW)	0.13(0.03)	0.12(0.02)	0.19(0.05)	0.17(0.03)	0.01(0.05)	0.01(0.06)
HML(EW)	-0.08(0.02)	-0.06(0.02)	-0.07(0.02)	-0.04(0.02)	-0.01(0.05)	-0.03(0.05)
R^2ADJ	0.25	0.27	0.16	0.18	0.31	0.33

SUMMARY TABLE 5.7: RELATIVE RETURN DISPERSION: SQUARED RESIDUALS
FOR FTSE100, FTSE250 AND THE GREEK MARKET (p values in brackets)

	RELATIVE RETURN DISPERSION: SQUARED RESIDUALS WITH FF FACTORS							
	FTSE100				FTSE250		GREEK MARKET	
TRADING REGIME	SEAQ:DEALERSHIP	SETS:LAST TRANSACTION	SETS:VWAP	CLOSING AUCTION	SEAQ	HYBRID (SETSmm)	PUBLIC OUTCRY	ASIS
MEAN	0.0296	0.0121	0.0185	0.0189	$0.57*10^{-3}$	$0.44*10^{-3}$	$0.5*10^{-2}$	$0.9*10^{-3}$
ANOVA		12.7(0.00)	1.15(0.27)	1.11(0.26)		1.02(0.30)		6.63(0.00)
MEDIAN	0.0247	0.0108	0.0170	0.0177	$0.29*10^{-3}$	$0.24*10^{-3}$	$0.6*10^{-3}$	$0.6*10^{-3}$

SUMMARY TABLE 5.8 RESIDUALS VARIANCE
FOR FTSE100, FTSE250 AND THE GREEK MARKET (p values in brackets)

	RESIDUALS VARIANCE WITH FF FACTORS							
	FTSE100				FTSE250		GREEK MARKET	
TRADING REGIME	SEAQ:DEALERSHIP	SETS:LAST TRANSACTION	SETS:VWAP	CLOSING AUCTION	SEAQ	HYBRID (SETSmm)	PUBLIC OUTCRY	ASIS
MEAN	$0.5*10^{-3}$	$0.2*10^{-3}$	$0.2*10^{-3}$	$0.2*10^{-3}$	0.02	0.01	0.005	$0.7*10^{-3}$
ANOVA		8.75 (0.00)	0.39(0.69)	0.39(0.69)		1.58(0.11)		1.27(0.20)
MEDIAN	$0.4*10^{-3}$	$0.1*10^{-3}$	$0.7*10^{-3}$	$0.4*10^{-3}$	0.017	0.015	$0.7*10^{-3}$	0.0005

5.5.2 INFORMATIONAL EFFICIENCY: AN ALTERNATIVE METHODOLOGY

In this section we regress the transaction price of each trade on the real value of the asset as captured by the mid-quote and past pricing errors. Results presented in TABLE 5.9 (PANEL A, all companies) show that β increases from 0.06 to 0.68 following the change from quote driven to order driven indicating that individual stocks react much faster to incoming information however do not react as fast as one would expect. This would be the case if β was equal to 1. Actually β gets equal to 1 only if we omit past pricing errors. Despite the fact that the inclusion of past pricing errors produces a β of 0.68, the improvement is dramatic. γ which provides an estimate of the past pricing error remains almost the same indicating that the degree to which pricing errors are corrected has not changed. In other words the informational efficiency of FTSE has improved dramatically following changes in the trading regime. This could be a direct result of increased trading capability. The results presented for FTSE100 following this specific methodology are conducive to the results obtained by RRD. Unfortunately the Results obtained for FTSE250 are not as intriguing as those for FTS100 however they are conducive to the results obtained by using the RRD methodology. In particular β increases from 0.40 to 0.42 following the change from SEAQ to SETSmm while γ changes from -0.64 to –0.63. In other words there are no significant changes in the market. We undertake the same exercise concentrating on company size. Again the results obtained are not particularly intriguing. Big companies appear to react faster than smaller companies maybe because there is bigger coverage by analysts. The change in the trading regime does not seem to bring about any changes in the degree of informational efficiency as far FTSE250 stocks are concerned.

TABLE 5.9:INFORMATIONAL EFFICIENCY USING HIGH FREQUENCY DATA

PANEL A:FTSE100

QUOTE DRIVEN MARKET/DEALERSHIP:SEAQ								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00(0.00)	-0.35(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
β	0.07(0.00)	0.06(0.00)	0.06(0.00)	0.05(0.00)	0.11(0.00)	0.08(0.00)	0.15(0.00)	0.13(0.00)
γ		-0.89(0.00)		-0.80(0.00)		-0.87(0.00)		-0.93(0.00)

ORDER DRIVEN MARKET:SETS-LAST AUTOMATED TRANSACTION								
	ALL COMPANIES		SMALL COMPANIES		MEDIUM COMPANIES		BIG COMPANIES	
C	0.00(0.12)	-0.09(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
β	1.00(0.00)	0.68(0.00)	0.77(0.00)	0.72(0.00)	0.90(0.00)	0.83(0.00)	1.01(0.00)	0.91(0.00)
γ		-0.87(0.00)		-0.60(0.00)		-0.89(0.00)		-0.91(0.00)

PANEL B:FTSE250

FTSE250: SEAQ/DEALERSHIP										
	ALL STOCKS		SMALL20		SMALL30		BIG20		BIG30	
C	0.00(0.00)	-0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
β	0.42(0.00)	0.40(0.00)	0.30(0.00)	0.28(0.00)	0.32(0.00)	0.31(0.00)	0.67(0.00)	0.62(0.00)	0.60(0.00)	0.53(0.00)
γ		-0.64(0.00)		-0.54(0.00)		-0.56(0.0)		-0.82(0.0)		-0.77(0.00)

FTSE250:HYBRID/SETSmm										
	ALL STOCKS		SMALL20		SMALL30		BIG20		BIG30	
C	0.00(0.05)	0.00(0.09)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)	0.00(0.00)
β	0.44(0.00)	0.42(0.00)	0.35(0.00)	0.30(0.00)	0.36(0.00)	0.32(0.00)	0.68(0.00)	0.61(0.00)	0.66(0.00)	0.55(0.00)
γ		-0.63(0.00)		-0.58(0.00)		-0.58(0.0)		-0.85(0.0)		-0.79(0.00)

5.5.3 SPREAD SENSITIVITY TO VOLATILITY: FTSE100 & FTSE250

The results presented in TABLE5.10 show that volatility appears to be significant when market makers set the spread. The coefficient obtained is positive and significant at 0.01. The results obtained are absolutely normal since when volatility increases the spread increases as well. However when trading occurs by submission of limit orders and the spread is regressed against volatility, it appears to be insignificant at 0.05 or 0.10. The p value obtained is equal to 0.36. We believe that this is the case because inventory imbalances are distributed among all traders rather than a specific group of people namely the market makers, therefore volatility to market makers is not more of a concern than it is to every single investor. The results obtained indicate that the spread is more sensitive to volatility under a dealership than in an order driven market. This is further supported by the fact that volatility is at its lowest point during the first period when the spread is set by the market makers and increases afterwards. Despite that it has the ability to affect the spread however when it increases for the rest of the periods its ability to affect the spread is reduced. When the effect of volatility on spread is tested for FTSE250 stocks (TABLE5.11) before and after the introduction of SETSmm, we find that volatility is significant for both periods and this is explained from the fact that under both trading regimes markets makers are present. Volatility does affect their inventories and as a consequence of that the spread must incorporate some sort of compensation for the extra risk that they face. The above findings provide support for the fourth and fifth hypothesis.

TABLE 5.10: FTSE100 SPREAD SENSITIVITY TO VOLATILITY OVER A QUOTE DRIVEN MARKET (DEALERSHIP) AND AN ORDER DRIVEN MARKET (p values in brackets)

QUOTE DRIVEN MARKET:SEAQ			
	ALL STOCKS	SMALL	BIG
C	1.44 (0.00)	2.39 (0.00)	1.09 (0.00)
GARCH	0.43 (0.00)	0.74 (0.00)	0.16 (0.00)

ORDER DRIVEN MARKET			
	ALL STOCKS	SMALL	BIG
C	2.09 (0.00)	2.72 (0.00)	0.93 (0.00)
GARCH	0.71 (0.36)	0.80 (0.11)	0.49 (0.38)

TABLE 5.11: FTSE250 SPREAD SENSITIVITY TO VOLATILITY OVER A QUOTE DRIVEN MARKET (DEALERSHIP) AND A HYBRID MARKET (p values in brackets)

QUOTE DRIVEN MARKET:SEAQ			
	ALL STOCKS	SMALL	BIG
C	3.23(0.00)	1.33 (0.00)	2.64 (0.00)
GARCH	0.39 (0.00)	0.49 (0.00)	0.23 (0.00)

HYBRID MARKET			
	ALL STOCKS	SMALL	BIG
C	2.26 (0.00)	2.19 (0.00)	3.10 (0.00)
GARCH	0.42 (0.00)	0.40 (0.00)	0.32 (0.00)

5.6.CONCLUSION

The last years exchange markets around the world have embarked on a race to improve their services in an attempt to attract more and more investors. We investigate the value effects achieved by changing from an electronic quote driven market (dealership) to an order driven market and the efficiency of the various closing price formation algorithms employed each time in terms of price discovery/informational efficiency and spread sensitivity to volatility for FTSE100 stocks. We also undertake a similar exercise for FTSE250 and the Greek market. We find that there is no difference as far as informational efficiency is concerned between different closing price formation algorithms since the introduction of SETS (order driven market). However we find that order driven markets respond faster to information in comparison to dealerships. We also find that the spread is more sensitive to volatility in a dealership than in an order driven market. We are not familiar with any other study examining spread sensitive to volatility therefore we can not compare the results obtained here. Stocks in FTSE250 were initially traded in a quote driven market (SEAQ) but then they changed to a hybrid system (SETSmm), which combines both market making and an order book. The degree of informational efficiency as well as spread sensitivity to volatility remains the same. Research for the Greek market shows that the computerisation of the trading process has increased informational efficiency.

CHAPTER 6: DETERMINANTS OF THE COMPONENTS OF THE BID-ASK SPREADS ON THE LONDON STOCK EXCHANGE

6.1. INTRODUCTION

In the last few years there have been major changes in the way stock trading is conducted. Trading systems have changed from 'floor trading' to 'electronic trading', from 'batch trading' occurring at discrete points in time to 'continuous trading' and from 'quote driven' to 'order driven' or 'hybrid' for already electronic trading continuous markets. As one can understand all those innovations in trading mechanisms and protocols can bring about significant changes to the information structure and in particular to the way information is disseminated between market makers and investors. A consequence of all those changes is that the cost components of the bid-ask spread will be affected. Naturally research in the area of spread cost components is split in two parts namely the theoretical and the empirical part. The theoretical part has concentrated on explaining the existence of spreads based on 'inventory management' and 'asymmetric information'. In particular Demsetz (1968) and Tinic (1972) postulate that the spread exists to compensate market makers for maintaining and managing inventories in order to accommodate investors' demand when it arises. Based on this proposition Stoll (1978) and Amihud & Mendelson (1980) model the inventory component of the spread. However Bagehot (1971) approaches the existence of the spread in an entirely different way and proposes that the spread is the result of the existence of asymmetric information. In this case the market maker sustains losses on trades with informed traders but makes money on trades with liquidity traders. This proposition gave rise to the formal modelling of the asymmetric information cost component of the spread by Copeland & Galai (1983) and Glosten & Milgrom (1985). Empirical research, as was expected has concentrated simply on estimating the cost components of the spread. In particular Glosten & Harris (1988), Hasbrouck (1988), George, T.J., Kaul, G & Nimalendran, M (1991) hereafter GKN estimate transitory costs, which comprise a combination of inventory and order processing costs and of course asymmetric information costs. Stoll (1989) explicitly estimates the three cost components of the spread namely order processing costs, inventory holding costs and asymmetric information costs and finds that asymmetric information costs account for 43% of the spread for NASDAQ stocks. Although Stoll's model is intuitively appealing, it appears to have certain drawbacks. In particular GKN (1991) criticize the Stoll model by saying that the spread components are biased as a result of the existence of positive autocorrelation in expected returns as shown by Conrad & Kaul (1988, 1989) and Conrad et al.(1991) which leads to a downwards bias in the estimation of the realised spread. GKN correct for this drawback in Stoll's model by estimating returns based on the difference of transaction returns and bid to bid quotes which are unaffected by positive autocorrelation and find that asymmetric information accounts only for 10% of the spread for NASDAQ stocks. In other words the GKN model improves over the Stoll model in the sense that it relaxes Stoll's first assumption, which states that the market is informationally efficient so that the expected price change in a security is independent of current and past information. Despite the improvements over the Stoll model, GKN adopt the rest of Stoll's assumptions, firstly that the bid-ask spread is constant over time and all transactions occur at the highest bid or lowest ask and secondly that the proportions of the bid-ask components are the same for all securities. Kim & Ogden (1996) improve over GKN's methodology by using the bid-ask mid quote as the unobservable true price of the security rather than the bid price as GKN did. In addition Kim & Ogden improve over the assumption of equal proportion of the bid-ask components for all securities by employing a new estimator $\sqrt{\bar{S}_{Qt}^{2}}$ known as the Kim & Ogden estimator and find that asymmetric information costs account for 50% of the bid ask spread which comes into contrast with GKN's estimate of 21% for NYSE/AMEX stocks. All the studies mentioned above concentrate on US stocks. There is only a limited number of studies that look into this area of market microstructure with reference to the UK. In particular Snell & Tonks (1995, 1998), Hansch et al. (1998, 1999) and Reiss & Werner (1998), investigate the significance of inventory control and/or asymmetric information in dealer quote behaviour however the do not decompose spread into its cost components. The only study we are aware of which decomposes the spread into its components for the UK market is that of Menyah & Paudyal (2000). We advance the literature in this area by investigating the cost components of the spread under different trading regimes for FTSE100 and FTS250 stocks and also examine the effect of variables such as number of trades, trading volume and volatility on the asymmetric information and order processing costs of the bid-ask spread.. We use GKN's (1991) and Kim & Ogden's (1996) methodologies rather than Stoll's (1989) methodology, which imposes some unrealistic assumptions. We use high frequency intraday data covering a period of two months before and after the introduction of SETS (order driven) for FTSE100 stocks and two months before and after the introduction of SETSMM for FTSE250 stocks rather than transactions data towards the end of day, which fails to capture intraday activity, as is the case in some other studies.

Market microstructure theory has always been concerned with determining the bid-ask spread set by market makers. There are two theoretical approaches and each one views the existence of the spread from a completely different point of view.

The first group of theorists postulate that the spread emanates from the risk that arises when market makers process orders and hold inventories to accommodate liquidity demand as it arises. Even though early papers perceive the market maker merely as a liquidity provider, Demsetz (1968) views the market maker both as a liquidity provider and as a trader engaging in transactions with other traders/individuals for his own account. Amihud & Mendelson (1980) and Ho & Stoll(1981) postulate that the market maker sets bid and ask prices as a function of incoming orders and the discrepancies that those orders create between the optimal and current level of inventory. In other words the bid ask spread is related to the market maker's inventory position.

The second group of theorists postulate that the spread arises as a result of asymmetric information and is mainly represented by Bagehot (1971). In this particular case the market maker is incapable of distinguishing between informed traders, liquidity traders and noise traders therefore he sets a wide spread so as to reduce losses when trading with informed traders. However the wider the spread gets the lower the probability of transacting with liquidity traders, therefore there is an optimal level of spread. Copeland & Galai (1983) postulate that the market maker will set his spread to achieve profit maximasation.

6.2.TRADING MECHANISMS IN THE LONDON STOCK EXCHANGE AND SPREAD COST COMPONENTS.

The London Stock exchange has gone through a number of changes the last few years as far the trading regime is concerned. In particular the London stock exchange has changed from a quote driven market to an order driven market. The main characteristic of a quote driven market is the market makers who are obliged to post bid and ask quotes along with the number of shares (depth) they are willing to trade at each price (affirmative quotation). In an order driven market makers are not obliged to post bid-ask quotes therefore the whole trading process depends on limit order submission. As a consequence of the changes in the trading process described above, we believe that the different cost components of the spread and in particular the asymmetric information cost component must have been affected. Nevertheless we believe that we should elaborate on how different characteristics of the two trading processes briefly described above could affect the cost components of the spread.

When trading in a quote driven system, market makers must post 'firm' or 'affirmative' bid and ask quotes for a minimum quantity of shares (depth) which is also known as normal market size (NMS) and is calculated as 2.5% of the daily average turnover in the preceding quarter. Although this percentage seems to be a very small figure and some readers will think that it has no effect on the quotes of market makers, this impression can be erroneous especially when it comes to such highly traded stocks as FTSE100 stocks. Single trades for FTSE100 stocks may run in the range of hundreds of thousands of pounds. At this point it is worth noting that the NMS for stocks traded in the LSE is much higher than for stocks traded in other markets such as NASDAQ, which is also a quote driven market (Menyah & Paudyal, 2000). As one can understand, the affirmative obligation of market makers to post bid and ask quotes in combination with the high NMS mandated by the LSE 'forces' market makers to post wide spreads so as to finance inventory carrying cost, imbalances that may arise during intense trading as well as protect themselves against traders with superior information. Obviously the high NMS implies that market makers will incur enormous losses when they transact with investors with superior information, therefore they will widen the spread so as to cover themselves against this possibility and make their profits from the liquidity traders. Of course one might argue that high NMS stocks do not pose such a big problem for market makers when it comes to rebalancing their inventory to reach their optimal level because they can unwind their positions really fast as a result of the high NMS. In addition if market makers feel exceptionally pressured by unwanted inventory they can always make use of the inter dealer brokerage system which allows them to trade anonymously with other market makers and revert to their desired inventory positions. Menyah & Paudyal (2000) also discuss 'preferencing' and 'internalization' as two practices that can affect spread cost components in opposite directions. 'Preferencing' means the ability of a broker to direct an order to a market maker not posting the best quote but who has agreed to transact at the best quote while 'internalisation' is used to describe the ability of the broker to direct an order to a market maker working for the same company. On the one hand, this means that the market maker may have to buy (sell) when his actual inventory position implies that he should sell (buy) even when he suspects that the transaction under consideration involves superior information and he might incur losses in order to satisfy the 'preference' that the broker has shown towards him. On the other hand preferenced market makers get a higher proportion of buy and sell orders and thus it is easier for them to manipulate their inventory to reach their optimal level or compensate for any losses that they might have incurred by trading with other investors/traders who are in possession of superior information. Of course the same arguments can apply for the practice of 'internalisation'. Hansch et al (1999) find that for the top 102 LSE stocks effective spreads on preferenced trades are higher than those on non-preferenced trades and that internalised trades receive better execution than non-internalised trades which implies that preferencing leads to higher inventory costs and dealers compensate for it by higher effective spreads.

The effects of 'preferencing', 'internalisaton' and high NMS on spreads described above should be dampened once the trading regime changes form quote driven to order driven. In an order driven market there is no obligation on behalf of any market maker to act as a 'liquidity supplier of last resort' therefore the effect of asymmetric information on spreads should be reduced considerably. Brockman & Chung (2002) call this the 'free-exit' aspect of order-driven trading. Of course, if the spread gets very wide and some traders see opportunities to go into the market and make money by providing liquidity then they are free to do so. This is called the 'free-entry' aspect of order-driven trading (Brockman & Chung, 2002). In other words changes in the trading regime and the effect that such changes can have on the cost components of the spreads and in particular on the asymmetric component of the spread is an empirical question. We propose the following research hypotheses:

H1: the asymmetric component of the spread is higher under a quote-driven trading regime as a result of the 'affirmative obligation' on behalf of market makers to constantly post 'firm' bid and ask quotes and lower under an order-driven trading regime as a result of the 'free entry and exit' aspect of order-driven trading.

H2: the asymmetric information component of the spread does not change between quote driven and hybrid markets.

H3: volatility appears to have a stronger impact on both cost components under a quote driven regime but reduces significantly under an order driven regime (FTSE100).

H4: volatility appears to have the same impact on the cost components of the spread under a quote driven and a hybrid market.

6.3.METHODOLOGY

A number of models have been developed over the years to decompose bid-ask spreads into their cost components, the first one being that of Stoll (1989) which was later modified by GKN (1991). The last empirical approach correcting for all shortcomings in the previous models is that of Kim & Ogden (1996).

Stoll (1989) decomposes the spread into three cost components namely: asymmetric information/adverse selection, inventory holding cost and order processing cost based on three assumptions:

- The market is informationally efficient so that expected price changes are independent of current and past information.
- The bid-ask spread is constant over time and all transactions occur at the highest bid or the lowest ask

- The proportions of bid-ask spread components are the same for all securities

Stoll postulates that the realised spread earned by a market maker is less than the quoted spread. The reason for this is that the market maker will lower bid and ask prices after a sell order and raise bid and ask prices after a buy order to reflect the information content of those orders. However when a trade is reversed the size of a price reversal is not the quoted spread S_{Qi} but rather $(1-\delta)S_{Qi}$ where $0 \leq \delta \leq 1$ because of inventory and asymmetric information costs. The probability of a trade reversal is given by θ. As in all models that will follow the adverse selection component is measured as the difference between quoted spread and realised spread. The realised spread is further decomposed into inventory cost and order processing cost. The various cost components are given by: adverse selection cost = $1-2(\theta-\delta)$, inventory cost = $2(\theta-0.5)$, order processing cost = $1-2\delta$.

GKN (1991) propose a new model to decompose the bid-ask spread to its cost components as they postulate that the Stoll estimators are biased because of the existence of positive autocorrelation in expected returns as documented by Conrad & Kaul (1988, 1989) and Conrad et al. (1991). In particular the estimated spread S_i for each security is given by:

$$S_i=2[-\text{cov}(RD_{i,t},RD_{i,t-1})]^{1/2} \quad (6.1)$$

Where $RD_{i,t}$ is defined as the difference between transaction returns $R_{Ti,t}$ and returns based on unobservable true prices $R_{Bi,t}$ which in this case is captured by subsequent bid quotes following a transaction for each security i at time t (subscript t in returns always refers to transaction prices while subscript b always refers to bid prices). Then they run a cross section regression of estimated spread S_i on quoted spread S_{Qi}. Symbolically this is expressed as:

$$S_i=\beta_0+\beta_1 S_{Qi}+\varepsilon_t \quad (6.2)$$

Where β_1 provides an unbiased estimator of the proportion of order processing cost π under the assumption of zero inventory cost and $1-\beta_1$ becomes the unbiased estimator of the adverse selection cost component. Even though the approach adopted by GKN relaxes Stoll's first assumption by calculating estimated spread S_i as the difference between transaction returns and subsequent bid quote returns, they still assume that Stoll's second and third assumptions still hold.

Kim & Ogden improve GKN methodology by relaxing the second assumption of constant spreads for each security introducing a new way to capture unobservable true prices. In particular they use the bid-ask midquote as a proxy for the true price of an asset because the bid –ask prices change over time and have a systematic time series structure. In market microstructure literature, it is considered that the mid-quote captures the real price of a financial asset. They also relax the third assumption of equal proportions of components of the bid-ask spread between securities by regressing estimated spread on the Kim & Ogden estimator ($\sqrt{\bar{S}^2_{Qi}}$).

In our analyses in order to estimate π (order processing cost) we run the following regressions:

$$S_i=\beta_0+\beta_1 D_i+\beta_2 SQ_i+\beta_3(D_i SQ_i)+\varepsilon_t \text{ (GKN regression) (6.3)}$$

Where S_i is the estimated difference between transactions prices and subsequent bid quotes as in GKN, β_0 is the intercept, β_1 is the differential intercept coefficient, β_2 estimates the order processing cost, β_3 is the differential slope coefficient and D_i is a dummy assuming the value of zero for SEAQ and 1 for SETS.

$$S_i=\beta_0+\beta_1 D_i+\beta_2 SQ_i+\beta_3(D_i SQ_i)+\varepsilon_t \text{ (K\&O regression) (6.4)}$$

Where S_i is estimated as the difference between transactions prices and midquotes as in Kim & Ogden relaxing the second assumption of Stoll. The rest of the variables are as above.

$$S_i=\beta_0+\beta_1 D_i+\beta_2 SQ_i+\beta_3(D_i\sqrt{\bar{S}^2_{Qi}})+\varepsilon_t \text{ (K\&O regression with K\&O estimator) (6.5)}$$

Where S_i is estimated as the difference between transactions prices and midquotes quotes as in Kim & Ogden and the independent variable is given by $\sqrt{\bar{S}^2_{Qi}}$, the Kim & Ogden estimator. The rest of the variables are as above. By running these regressions we expect the order processing cost for security (i) to be smaller when the estimated spread is estimated as the difference between transaction returns and mid quotes and even smaller when the estimated spread is calculated as the difference between transaction returns and mid quotes and regressed on $\sqrt{\bar{S}^2_{Qi}}$. We also examine the extent to which volatility, number of trades and trading volume affect the asymmetric information cost component, order processing cost component and the spread based on all available trades to us by running the following panel regressions:

$$\text{closing spread}_{it} = \alpha_0 + \alpha_1 D_i + \beta_0 NT_{it} + \beta_1(D_i NT_{it}) + \gamma_0 TV_{it} + \gamma_1(D_i TV_{it}) + \delta_0 VOL_{it} + \delta_1(D_i VOL_{it}) + \varepsilon_{it} \quad (6.6)$$

$$\text{spread(every trade)}_{it} = \alpha_0 + \alpha_1 D_i + \gamma_0 TV_{it} + \gamma_1(D_i TV_{it}) + \delta_0 VOL_{it} + \delta_1(D_i VOL_{it}) + \varepsilon_{it} \quad (6.7)$$

$$\text{asymmetric information}_{it} = \alpha_0 + \alpha_1 D_i + \beta_0 NT_{it} + \beta_1(D_i NT_{it}) + \gamma_0 TV_{it} + \gamma_1(D_i TV_{it}) + \delta_0 VOL_{it} + \delta_1(D_i VOL_{it}) + \varepsilon_{it} \quad (6.8)$$

$$\text{order processing}_{it} = \alpha_0 + \alpha_1 D_i + \beta_0 NT_{it} + \beta_1(D_i NT_{it}) + \gamma_0 TV_{it} + \gamma_1(D_i TV_{it}) + \delta_0 VOL_{it} + \delta_1(D_i VOL_{it}) + \varepsilon_{it} \quad (6.9)$$

Where VOL stands for volatility and is estimated as the absolute value of the return at day t calculated from mid points of bid-ask quotes, $|\{(P_{A,t}+P_{B,t})-(P_{A,t-1}+P_{B,t-1})]/(P_{A,t-1}+P_{B,t-1})\}|$, TV stands for trading volume, NT stands for number of trades and ε is the error term. The asymmetric information component is estimated according to K&O as $[1-(\hat{S}_i/\sqrt{\bar{S}^2_{Qt}})]$ (6.10)

and according to GKN as $[1-(\hat{S}_{Bi}/\frac{1}{T}\sum_{t=1}^{T} S_{Qi,t})]$ (6.11).

The order-processing component is estimated according to K&O as $(\hat{S}_i/\sqrt{\bar{S}^2_{Qt}})$ (6.12)

and according to GKN as $(\hat{S}_{Bi}/\frac{1}{T}\sum_{t=1}^{T} S_{Qi,t})$ (6.13) where $\hat{S}_i = 2[-\frac{1}{T}\sum_{t=1}^{T}(RD_{it} - \frac{1}{T}\sum_{t=1}^{T}RD_{it})(RD_{it-1} - \frac{1}{T}\sum_{t=1}^{T}RD_{it})]^{1/2}$

(6.14)

and $\hat{S}_{Bi} = 2[-\mathrm{cov}(RD_{Bi,t},RD_{Bi,t-1})]^{1/2}$ (6.15).

6.4.DATA

The data used in this study covers a period of two months for FTSE100 stocks and for FTSE250 stocks. The reason we use FTSE100 and FTSE250 stocks is that changes in the trading regime were introduced only for those stocks. The data was obtained from SIRCA (Securities Industry Research Centre of Asia Pacific) and contains transaction prices, number of shares traded, volume of trades in monetary terms, quoted bid, quoted ask and mid quotes for every single second. In other words our files contain all trades that have occurred during that period.

6.5.RESULTS

6.5.1 BID-ASK SPREAD DECOMPOSITION

Results are presented in TABLE6.1. Panel A presents results for the GKN regression, K&O regression and K&O regression with K&O estimator. The order processing cost for SEAQ is given by β_2 and by $\beta_2+\beta_3$ under SETS. β_3 is known as the differential slope coefficient. The order-processing component (β_2) when stocks are traded in SEAQ is equal to 0.33 and increases to 0.76 after the introduction of SETS. The asymmetric information cost component is estimated as 1-β_2 and is equal to 0.67 when stocks are traded in SEAQ and reduces to 0.24 when stocks are traded in SETS. This is a first indication that the non-obligatory nature of trading reduces the effect of asymmetric information. The results obtained from the GKN regression are further reinforced when we employ the K&O regression. In this regression S_i is estimated as the difference between transactions prices and midquotes, which relaxes the second assumption of constant spread of each security. The processing component (β_2) is equal to 0.23 and the asymmetric information component is equal to 0.77 under the SEAQ trading regime. Once the change occurs from SEAQ to SETS the processing component increases to 0.73 and the asymmetric information component reduces to 0.27, a second indication that the non-obligatory nature of trading or the free entry and exit aspects of trading as discussed by Brockman & Chung (2002) can reduce the effect of asymmetric information. Finally we employ the K&O regression with the K&O estimator. In this case the dependent variable is estimated as the difference between transactions prices and midquotes as above but now the independent variable is equal to $\sqrt{\bar{S}^2_{Qi}}$. The results obtained from this final regression are consistent with results obtained above. The order-processing component is equal to 0.20 (β_2) under SEAQ and increases to 0.68 (β_2+β_3) under SETS. The asymmetric information component reduces from 0.80 to 0.32 with the change in the trading regime. Results for FTE250 are presented in

TABLE6.2 and are less intriguing than those obtained for FTSE100 however they are as expected. The difference in the asymmetric information component between regimes is very small and statistically insignificant. The reason for this is that under both trading regimes, market makers are obliged to provide liquidity and trade with every single investor/trader, therefore there is no change in their level of risk as captured by the asymmetric information cost component of the spread. Unfortunately the results obtained from our study can not be directly compared to results from other studies such as GKN(1991), K&O(1996) or Stoll(1989). The reason is that we undertake a comparative study between different trading regimes and how this can affect cost components and we employ only FTSE100 stocks and FTSE250 stocks, the only stocks for which there were a change in the trading regime while all the other studies mentioned above look into spread cost components for the same trading regime. The results of this study are in line with general findings regarding spread components in the LSE. The asymmetric information cost component dominates the order processing component which is consistent with Menyal & Paudyal (2000) and Hansch et al.(1999). The reason we obtain such high asymmetric information cost components is that a single informed trade in a high NMS stock as FTSE100 stocks is so much more expensive than an informed trade in a low NMS stock, therefore the market maker will charge a relatively high asymmetric information cost for high NMS stocks (Menyah & Paudyal, 2000). Of course this reverses once market makers are not obliged to provide liquidity and can choose with whom to trade if they believe that somebody is trading on superior information. At this stage one should notice that the asymmetric information cost component of the spread for FTSE250 stocks under SEAQ is much lower that than of FTSE100 stocks under SEAQ reinforcing the explanation provided above. Once the trading regime changes the FTSE100 asymmetric component reduces while the FTES250 asymmetric component remains stable.

TABLE 6.1: COST COMPONENTS OF THE BID-ASK SPREAD FOR FTSE100

PANEL A

	GKN REGRESSION	K&O REGRESSION	K&O REGRESSION WITH K&O ESTIMATOR
B_0	0.00(0.00)	0.00(0.00)	0.00(0.00)
B_1	0.00(0.22)	0.10(0.17)	0.17(0.13)
B_2	0.33(0.00)	0.23(0.00)	0.20(0.00)
B_3	0.43(0.00)	0.50(0.00)	0.48(0.00)
R^2 ADJ	0.13	0.12	0.13

PANEL B

	ORDER PROCESSING		ASYMMETRIC	
	SEAQ(B_2)	SETS(B_2+B_3)	SEAQ(1-B_2)	SETS 1-(B_2+B_3)
GKN REGRESSION	0.33	0.76	0.67	0.24
K&O REGRESSION	0.23	0.73	0.77	0.27
K&O REGRESSION WITH K&O ESTIMATOR	0.20	0.68	0.80	0.32

TABLE 6.2: COST COMPONENTS OF THE BID-ASK SPREAD FOR FTSE250

PANEL A

	GKN REGRESSION	K&O REGRESSION	K&O REGRESSION WITH K&O ESTIMATOR
B_0	0.00(0.09)	0.00(0.05)	0.00(0.09)
B_1	0.00(0.15)	0.00(0.85)	0.00(0.44)
B_2	0.41(0.00)	0.36(0.02)	0.34(0.01)
B_3	-0.02(0.12)	-0.06(0.14)	-0.01(0.13)
R^2 ADJ	0.10	0.10	0.11

PANEL B

	ORDER PROCESSING		ASYMMETRIC	
	SEAQ(B_2)	SETSmm(B_2+B_3)	SEAQ(1-B_2)	SETSmm 1-(B_2+B_3)
GKN REGRESSION	0.41	0.39	0.59	0.61
K&O REGRESSION	0.36	0.30	0.64	0.70
K&O REGRESSION WITH K&O ESTIMATOR	0.34	0.33	0.66	0.67

6.5.2.DETERMINANTS OF THE COMPONENTS OF THE BID-ASK SPREAD

Having discussed the changes in the asymmetric information and order processing components of the two groups of stocks, we now concentrate to the extent to which the spread itself and its components are affected by volatility, trading volume, and frequency of trades. Results for FTSE100 (all stocks) are presented in TABLE6.3 for both trading regimes. Again possible differences between trading regimes are estimated by differential slope coefficients. The number of trades is insignificant under both trading regimes. β_0 and β_1 are always insignificant but bear the right sign. The reason for this is that FTSE100 stocks are very highly traded stocks, therefore the number of times a FTSE100 stock is traded every day does not seem to be of great concern to market makers since they do not believe that any trader/investor is acting on superior information and even if this was the case market makers would be able to get rid of any unwanted FTSE100 stocks really fast because of the high trading frequency. We expect the effect of number of trades to be significant for smaller stocks (non FTSE100 stocks). The results obtained here are in line with K&O (1996) who find that the number of trades is significant and negatively related to bid-ask spread in a univariate regression however when they control for size the number of trades becomes insignificant. Trading volume has a positive effect on the spread and its both components under SEAQ however the sign changes when the trading regime changes from SEAQ to SETS, reducing the effect of trading volume since $\gamma_0+\gamma_1$ is lower than γ_0. This can be easily explained by the free exit and entry explanation attributed to Brockman & Chung (2002). The positive effect of trading volume on the bid-ask spread and its cost components under SEAQ is explained by the fact that big trades are thought to be initiated by individuals who might be in possession of superior information however when market makers are not obliged to provide liquidity the actual effect of TV declines. Notice that the trading volume coefficients for the highest capitalisation FTSE100 stocks (TABLE6.4) under SEAQ are slightly higher than the trading volume coefficients of FTSE100 ALL STOCKS under SEAQ (TABLE6.3) but not always higher than the trading volume coefficients of the lowest market capitalisation FTSE100 stocks (TABLE6.5), therefore there is no clear pattern emerging here. Despite the fact that there is no clear pattern emerging here our results are consistent with Menyah & Paudyal who postulate that high NMS stocks have a higher asymmetric component. Volatility appears to have a significant positive effect on spread and its components under SEAQ (TABLE 6.3, 6.4 AND 6.5) however this effect reduces significantly (all δ_1 differential coefficients are negative and significant) under SETS providing support to the third research hypothesis even though their explanatory power appears to be quite reduced for the order-processing component. Generally speaking the effect of volatility on the bid-ask spread is positive. Another issue worth concentrating on at this point is that the coefficients of volatility for almost all independent variables for the highest capitalisation FTS100 stocks (TABLE6.4) are higher than the coefficients of volatility for the same independent variables for the lowest FTSE100 stocks (TABLE6.5) and FTSE100 all stocks (TABLE6.3) under SEAQ. Notice also that reductions in δ_1 are higher for FTSE100 BIG STOCKS (TABLE6.4) following changes in the trading regime. We believe that this is explained by the fact that the highest market capitalisation stocks have a higher NMS and therefore sudden changes in prices especially if they are not supported by any news or increased trading activity affect the bid-ask spread and its components to a higher extent.

TABLE6. 3: REGRESSION OF FTSE100 ALL STOCKS ON NUMBER OF TRADES (NT), TRADING VOLUME (TV) AND VOLATILITY (VOL) UNDER SEAQ AND SETS

	Bid-ask closing	Bid-ask every trade	Assymetric-K&O	Assymetric-GKN	Processing-K&O	Processing-GKN
α_0	0.00 (0.22)	0.00 (0.10)	0.01 (0.03)	0.01 (0.03)	0.00 (0.01)	0.00 (0.05)
α_1	0.00 (0.30)	0.00 (0.46)	0.00 (0.00)	0.00 (0.12)	0.00 (0.00)	0.00 (0.00)
β_0	-0.01 (0.12)		-0.01 (0.37)	-0.00 (0.76)	-0.00 (0.53)	-0.00 (0.70)
β_1	0.00 (0.16)		0.02 (0.64)	-0.00 (0.88)	-0.00 (0.22)	-0.00 (0.34)
γ_0	0.02 (0.01)	0.04 (0.03)	0.09 (0.02)	0.07 (0.06)	0.15 (0.06)	0.13 (0.05)
γ_1	-0.01 (0.08)	-0.02 (0.01)	-0.04 (0.02)	-0.02 (0.02)	-0.04 (0.08)	-0.05 (0.06)
δ_0	0.10 (0.04)	0.14 (0.05)	0.14 (0.00)	0.12 (0.06)	0.04 (0.03)	0.00 (0.02)
δ_1	-0.01 (0.09)	-0.10 (0.08)	-0.06 (0.05)	-0.05 (0.06)	0.06 (0.11)	0.02 (0.35)
R^2 ADJ	0.09	0.08	0.09	0.09	0.09	0.08

TABLE6. 4: REGRESSION OF FTSE100 BIG STOCKS ON NUMBER OF TRADES (NT), TRADING VOLUME (TV) AND VOLATILITY (VOL) UNDER SEAQ AND SETS

	Bid-ask closing	Bid-ask every trade	Assymetric-K&O	Assymetric-GKN	Processing-K&O	Processing-GKN
α_0	0.01 (0.06)	0.00 (0.08)	0.00 (0.09)	0.00 (0.02)	0.00 (0.05)	0.00 (0.02)
α_1	-0.01 (0.02)	0.00 (0.10)	0.00 (0.11)	0.00 (0.10)	0.00 (0.00)	0.00 (0.19)
β_0	-0.03 (0.19)		-0.02 (0.12)	-0.05 (0.14)	-0.03 (0.18)	-0.03 (0.22)
β_1	-0.00 (0.56)		-0.03 (0.65)	-0.01 (0.13)	-0.02 (0.20)	-0.04 (0.33)
γ_0	0.05 (0.05)	0.08 (0.06)	0.14 (0.03)	0.09 (0.06)	0.17 (0.02)	0.15 (0.06)
γ_1	-0.02 (0.09)	-002 (0.09)	-0.05 (0.02)	-0.05 (0.00)	-0.07 (0.09)	-0.06 (0.01)
δ_0	0.14 (0.02)	0.20 (0.03)	0.22 (0.05)	0.18 (0.04)	0.09 (0.02)	0.07 (0.03)
δ_1	-0.07 (0.09)	-0.09 (0.08)	-0.10 (0.04)	-0.12 (0.00)	-0.01 (0.14)	0.01 (0.09)
R^2 ADJ	0.09	0.08	0.07	0.08	0.09	0.09

TABLE 6.5: REGRESSION OF FTSE100 SMALL STOCKS ON NUMBER OF TRADES (NT), TRADING VOLUME (TV) AND VOLATILITY (VOL) UNDER SEAQ AND SETS

	Bid-ask closing	Bid-ask every trade	Assymetric-K&O	Assymetric-GKN	Processing-K&O	Processing-GKN
α_0	0.00 (0.00)	0.00 (0.00)	0.00 (0.04)	0.00 (0.00)	0.00 (0.08)	0.00 (0.01)
α_1	0.00 (0.10)	0.00 (0.12)	0.00 (0.12)	0.00 (0.82)	0.00 (0.64)	0.00 (0.10)
β_0	-0.00 (0.11)		-0.03 (0.13)	-0.01 (0.14)	-0.10 (0.20)	-0.12 (0.33)
β_1	-0.00 (0.19)		-0.14 (0.17)	-0.09 (0.77)	-0.07 (0.12)	-0.17 (0.39)
γ_0	0.00 (0.03)	0.00 (0.04)	0.10 (0.06)	0.12 (0.03)	0.10 (0.02)	0.09 (0.00)
γ_1	0.00 (0.06)	-0.00 (0.00)	-0.02 (0.09)	-0.01 (0.09)	-0.03 (0.07)	-0.04 (0.01)
δ_0	0.02 (0.08)	0.01 (0.03)	0.17 (0.04)	0.14 (0.02)	0.11 (0.08)	0.10 (0.00)
δ_1	-0.01 (0.00)	-0.00 (0.00)	-0.09 (0.01)	-0.05 (0.08)	-0.02 (0.09)	-0.04 (0.08)
R^2 ADJ	0.08	0.09	0.08	0.08	0.08	0.09

The results obtained for FTSE250 ALL STOCKS and NT (number of trades) are quite interesting. The number of trades appears to have some explanatory power over the bid-ask spread, the asymmetric information component and the order processing cost component however the coefficients obtained are very small. notice that the differential coefficients for NT are insignificant implying that changes in the trading regime did not have any effect. If a stock is relatively small but it is traded relatively frequently, then market makers do not worry too much if they trade with somebody with superior information and left with unwanted inventory because they know that they will be able to dispose of this unwanted inventory relatively fast, thus the significant negative effect of the number of trades on the spread and its components. Trading volume has a significant positive effect on the bid-ask spread and its components for all FTSE250 stocks. There is also a pattern emerging, trading volume appears to have a stronger effect on FTSE250 20 SMALL than it appears to have on FTSE250 20 BIG. The reason for this is that market makers believe that high volume trades on small stocks are motivated by superior information, thus the positive effect on the bid-ask spread and it s components. Volatility appears to have similar effects on FTSE250 stocks under both trading regimes, providing support for the fourth research hypothesis. However volatility appears to have a stronger positive effect on FTSE250 20 SMALL than it has on FTS250 20 BIG or FTS250 ALL STOCKS. The reason for this is that FTSE250 20 SMALL are likely to be stocks which are not highly traded therefore any volatility observed is not due to increased trading but changes in prices which are not supported by trading activity which increases the level of risk as perceived by market makers which in turn increases the spread and its components. The differential slope coefficients for volatility are insignificant which means that changes in the trading regime had no effect on volatility and how it affects the components of the spread.

To summarise we find that a change in the trading regime from quote driven to order driven with direct reference to FTS100 stocks can lead to a reduction on the asymmetric information cost component of the spread. This is due to the non-obligatory nature of trading. This is not the case when the trading regime changes from quote driven to hybrid with reference to FTSE250 stocks because markets makers are still obliged to provide liquidity. Then we examine the effect of a number of variables such as number of trades, trading volume and volatility on the bid-ask spread, the asymmetric information cost component and order processing cost component. We find that volatility has a significant positive effect on both components when market makers are obliged to provide liquidity. We also find that the number of trades has a significant negative effect on the bid-ask spread and its components. Trading frequency has absolutely no effect on high capitalisation stocks such as FTSE100, which are highly traded by definition. These finding are similar to the findings of K&O (1996). Trading volume appears to have a significant positive effect on the bid ask spread and its components especially for small stocks. This is because market makers believe that high volumes for small stocks are motivated by superior information.

TABLE6. 6: REGRESSION OF FTSE250 ALL STOCKS ON NUMBER OF TRADES (NT), TRADING VOLUME (TV) AND VOLATILITY (VOL) UNDER SEAQ AND SETSMM

	Bid-ask closing	Bid-ask every trade	Assymetric-K&O	Assymetric-GKN	Processing-K&O	Processing-GKN
α_0	0.00 (0.09)	0.00 (0.00)	0.00 (0.06)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
α_1	0.20 (0.12)	0.18 (0.14)	0.03 (0.15)	0.00 (0.00)	0.00 (0.00)	0.00 (0.33)
β_0	-0.02 (0.04)		-0.01 (0.09)	-0.02 (0.10)	-0.04 (0.06)	-0.07 (0.06)
β_1	-0.00 (0.09)		-0.00 (0.22)	-0.01 (0.12)	-0.00 (0.47)	-0.00 (0.87)
γ_0	0.03 (0.04)	0.03 (0.09)	0.12 (0.03)	0.14 (0.05)	0.10 (0.03)	0.14 (0.02)
γ_1	0.00 (0.07)	0.09 (0.11)	0.01 (0.10)	0.01 (0.14)	0.04 (0.17)	0.03 (0.51)
δ_0	0.13 (0.01)	0.13 (0.00)	0.16 (0.02)	0.13 (0.04)	0.10 (0.02)	0.15 (0.06)
δ_1	0.01 (0.14)	0.02 (0.12)	0.02 (0.14)	0.01 (0.09)	0.03 (0.10)	0.04 (0.12)
R^2 ADJ	0.09	0.08	0.08	0.09	0.09	0.09

TABLE 6.7: REGRESSION OF FTSE250 20SMALL STOCKS ON NUMBER OF TRADES (NT), TRADING VOLUME (TV) AND VOLATILITY (VOL) UNDER SEAQ AND SETSMM

	Bid-ask closing	Bid-ask every trade	Assymetric-K&O	Assymetric-GKN	Processing-K&O	Processing-GKN
α_0	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
α_1	0.22 (0.12)	0.00 (0.50)	0.00 (0.00)	0.00 (0.80)	0.00 (0.24)	0.00 (0.00)
β_0	-0.08 (0.02)		-0.09 (0.04)	-0.10 (0.02)	-0.07 (0.06)	-0.05 (0.03)
β_1	-0.01 (0.18)		-0.02 (0.30)	-0.01 (0.13)	-0.03 (0.25)	-0.10 (0.46)
γ_0	0.10 (0.04)	0.01 (0.05)	0.20 (0.09)	0.19 (0.04)	0.17 (0.00)	0.12 (0.00)
γ_1	0.12 (0.16)	0.00 (0.00)	-0.02 (0.17)	0.01 (0.19)	-0.04 (0.61)	0.00 (0.00)
δ_0	0.16 (0.06)	0.21 (0.00)	0.30 (0.00)	0.22 (0.00)	0.16 (0.03)	0.14 (0.00)
δ_1	0.24 (0.17)	0.07 (0.33)	0.10 (0.16)	0.24 (0.31)	0.19 (0.23)	0.19 (0.28)
R^2 ADJ	0.08	0.09	0.08	0.08	0.08	0.08

TABLE6. 8: REGRESSION OF FTSE250 20BIG STOCKS ON NUMBER OF TRADES (NT), TRADING VOLUME (TV) AND VOLATILITY (VOL) UNDER SEAQ AND SETSMM

	Bid-ask closing	Bid-ask every trade	Assymetric-K&O	Assymetric-GKN	Processing-K&O	Processing-GKN
α_0	0.00 (0.07)	0.00 (0.09)	0.00 (0.01)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)
α_1	0.00 (0.01)	0.38 (0.22)	0.00 (0.11)	0.00 (0.00)	0.16 (0.74)	0.00 (0.17)
β_0	-0.02 (0.10)		-0.00 (0.11)	-0.01 (0.22)	-0.03 (0.24)	-0.02 (0.23)
β_1	-0.01 (0.14)		-0.02 (0.15)	-0.04 (0.12)	-0.00 (0.13)	-0.00 (0.25)
γ_0	0.07 (0.00)	0.00 (0.00)	0.10 (0.00)	0.08 (0.00)	0.09 (0.00)	0.12 (0.00)
γ_1	0.01 (0.03)	0.09 (0.12)	0.16 (0.22)	0.09 (0.21)	0.01 (0.04)	0.14 (0.11)
δ_0	0.10 (0.00)	0.17 (0.00)	0.15 (0.02)	0.13 (0.00)	0.16 (0.02)	0.17 (0.01)
δ_1	0.01 (0.05)	0.01 (0.00)	0.17 (0.14)	0.01 (0.01)	0.15 (0.20)	0.17 (0.19)
R^2 ADJ	0.08	0.09	0.08	0.08	0.09	0.09

6.6.CONCLUSION

This study used all transaction data and quotes for FTSE100 and FTSE250 stocks before and after the introduction of SETS and SETSmm respectively. The introduction of SETS (order-driven trading) for FTSE100 stocks and SETSmm (hybrid market combining order driven trading with market making) provided us with a constructive opportunity to look into spread cost components and in particular into the asymmetric information component of the spread over different trading regimes. The results we obtained clearly indicate that the components of the spread change as a result of changes in the trading regime and the asymmetric information component reduces when the market makers are not obliged to provide liquidity (FTSE100 stocks). The asymmetric information component of the spread does not reduce when the market changes from quote driven to hybrid because market makers are still obliged to provide liquidity. In order to show this we used the GKN(1991) and K&O (1996) methodologies. We also examined the effect of number of trades, trading volume and volatility under different trading regimes. We found that the effect of volatility on the asymmetric information component of the spread reduces when the trading regime changes from quote driven to order driven. We also found that trading frequency affects mainly small stocks and tends to reduce the spread and its components. The effect of trading volume appears to be positive for almost all stocks under examination irrespective of trading regime. Trading volume appears to have a strong positive effect on the bid ask spread and its cost components for small stocks.

Unfortunately the findings of this study are not directly comparable to those of the studies mentioned above because of its comparative nature and sample however they are in line with the general findings of those studies.

CHAPTER 7: CONCLUSION

At the beginning of this research thesis we argued that while research in the area of market microstructure and in particular in the area of systematic liquidity, trading systems, informational efficiency and spread decomposition was progressing steadily in the US, research for the UK and other smaller, less developed markets was quite limited.

Academic research into those areas has been motivated by the following considerations. Firstly a gap was identified in financial theory with respect to systematic liquidity. Systematic liquidity, which is defined as co-movement of liquidity for stocks with different characteristics, was observed for the very first time in the US. Financial theory offers no explanation for this and states that liquidity for each stock is determined by idiosyncratic factors such as own stock volatility, trading frequency, trading volume, accounting indicators etc. However what was being observed in the US was a co-movement in liquidity for stocks sharing no common characteristics. Obviously this newly observed phenomenon had to be further investigated so as to test if it was present in other markets as well. This provided us with an unprecedented opportunity to test for the presence of systematic liquidity in European markets at different stages of sophistication/development namely the UK and the Greek market. We also took this line of research a stage further by investigating how systematic liquidity could affect pricing under different trading regimes. Secondly research on the effect that changes in the trading systems can have on the degree of informational efficiency as well as on the spread and its components was quite limited despite the fact that those changes were introduced a number of years ago for both markets under consideration. While the issues investigated are not exhaustive in coverage, they address what are perceived to be the most important aspects of liquidity, trading, asset pricing and informational efficiency. We believe that the findings are of particular interest to market participants and academics alike.

After outlining the justification for the thesis in chapter one and reviewing the literature in chapter two, chapter three concentrated on examining the presence of systematic liquidity for FTSE100 and FTSE250 stocks. Then this line of research was further expanded to test if and the extent to which the common underlying factor identified (systematic liquidity) affected the pricing of stocks. In doing so we also considered how changes in the trading system (e.g. from quote driven to order driven) could affect the common underlying liquidity factor and consequently stock pricing. We found that the common underlying factor can affect stock pricing especially FTSE100 stocks when the market is quote driven but reduces after the introduction of SETS (order-driven). We also identified a common underlying factor for FTSE250 stocks even though it is not as strong as the factor identified for FTSE100 stocks and does not seem to affect pricing.

The fourth chapter follows the same line of research however we now concentrate on a less sophisticated market (Athens Stock Exchange), which managed to achieve unprecedented growth and eventually crash within a year or so. We believe that this provided us with an unprecedented opportunity to test for the presence of systematic liquidity under a number of different market conditions, shareholder sophistication, market maturity etc. We found that the common underlying liquidity factor appears to be stronger in certain periods while its presence appears to be reduced in other periods. In particular the common underlying factor appears to be considerably stronger for 2000 and 2001 and seems to be playing some role on stock pricing than it is for the rest of the periods.

The fifth chapter concentrated on examining how informational efficiency and spread sensitivity to volatility is affected by changes in the trading systems for FTSE100 and FTSE250 stocks. We also examined how informational efficiency is affected by automated trading with reference to the Greek market. We made use of two different methodologies and different data when testing the effect of different trading systems on informational efficiency for the UK market and found that an order driven market is more responsive to new information when compared to a quote driven market. We also found that the spread formed in a quote driven market is more sensitive to volatility than in an order driven market because of affirmative quotation. The results obtained for the Greek market show that informational efficiency has increased as a result of automation and are generally in line with the literature.

The sixth chapter, which is the last chapter of the thesis, focuses on bid-ask spread decomposition and the underlying determinants of the spread under different trading regimes. We find that the asymmetric component of the spread is higher under a quote driven regime most likely because of affirmative quotation as far as FTSE100 stocks are concerned. There appear to be no changes in spread decomposition for FTSE250 stocks under different trading regimes. Another important finding of this study is that the effect of volatility on the asymmetric information component of the spread reduces when the trading regime changes from quote driven to order driven as far as FTSE100 stocks are concerned. We are not aware of any research that looks into how the components of the spread as well as the underlying determinants of the spread are affected by changes in the trading regimes for the UK market therefore the results obtained are not directly comparable with any other studies however they are in line with other studies in the area for different markets around the world.

In conclusion this study examined the effect of different trading systems on common underlying liquidity factors, pricing, informational efficiency, volatility, the components of the spread as well as their determinants primarily with respect to the UK market and secondarily to the Greek market. We selected the UK market because of the changes in the trading system for FTSE100 besides the fact that it is a sophisticated market and the Greek market because of the tremendous growth it achieved within a limited period of time and its spectacular crash. This provided us with a number of different environments/conditions to test our hypotheses even though the data we had was quite limited.

WORKS CITED

Affleck- Graves et al. (1994) Trading Mechanisms And The Components Of The Bid-Ask Spread *Journal Of Finance* 49, 1471-1488

Amihud, Y (2002) Illiquidity & Stock Returns: Cross Section And Time Series Effects, *Journal Of Financial Markets* 5, 31-56

Amihud, Y & Mendelson, H (1980) Dealership Market: Market Making With Inventory *Journal Of Financial Economics*, 8, 31-53

Amihud, Y & Mendelson, H (1986) Asset Pricing And The Bid-Ask Spread. *Journal Of Financial Economics*, 17, 223-249

Amihud, Y & Mendelson, H (1987) Trading Mechanisms And Stock Returns: An Empirical Investigation, *Journal Of Finance* 42, 533-553

Amihud. Y, Mendelson, H & Wood, R.A (1990) Liquidity And The 1987 Stock Market Crash. *Journal Of Portfolio Management*, 16, 65-69

Amihud, Y, & Mendelson, H (1991) Volatility, Efficiency And Trading: Evidence From The Japanese Stock Market *Journal Of Finance*, 46, 1765-1789

Amihud, Y, Mendelson, H & Lauterbach, B (1997) Market Microstructure And Securities Values: Evidence Form The Tel Aviv Stock Exchange *Journal Of Financial Economics*, 45, 365-390

Amihud, Y, Mendelson, H & Murgia (1990) Stock Market Microstructure And Return Volatility: Evidence From Italy *Journal Of Banking And Finance*, 423-440

Bagehot, W (1971) The Only Game In Town. *Financial Analysts Journal*, March April, 12-15

Benston, G.J & Hagerman, R.L (1974) Determinants Of Bid-Ask Spreads In The Over-The-Counter Market. *Journal Of Financial Economics*, 1, 353-364

Branch B & Freed W (1977) Bid-Ask Spreads On The AMEX And The Big Board. *Journal Of Finance*, 32, 159-163

Brennan, M & Subrahmanyam, A (1996) Market Microstructure And Asset Pricing: On The Compensation For Illiquidity In Stock Returns. *Journal Of Financial Economics*, 1, 353-364

Brockman, P & Chung, D (2002) Commonality In Liquidity: Evidence from an order-driven market strucuture.*The Journal Of Financial Research,* 24:4, 521-539

Chalmers, J & Kadlec, G. (1998) An Empirical Examination Of The Amortized Spread *Journal Of Financial Economics* 48, 159-188

Chordia et al (2000) Commonality In Liquidity. *Journal Of Financial Economics,* 56, 3-28

Christie, G.W & Huang, R.D (1994) Market Structures & Liquidity: A Transactions Data Study Of Exchange Listings, *Journal Of Financial Intermediation* 3, 300-326

Christie, G.W & Schultz, P (1994) Why Do NASDAQ Market Makers Avoid Odd-Eighth Quotes? *Journal Of Finance*; 49, 1813-1840

Christie, G.W, Harris, J.H, Schultz, P (1994) Why Do NASDAQ Market Makers Stop Avoiding Odd-Eighth Quotes? *Journal Of Finance*; 49, 1841-1860

Clark, R.A, McConnell, J.J, Singh, M (1992) Seasonalities In Bid-Ask Spreads And Stock Returns In January *Journal Of Finance*, 47, 1999-2014

Cohen, K., Maier, S., Schwartz, R., Whitcomb, D. (1981) Transaction Costs, Order Placement Strategy And Existence Of The Bid-Ask Spread, *Journal Of Political Economy, 89, 287-305*

Conrad, J & Kaul, G (1988) Time Variation In Expected Returns, *Journal Of Business*, 61, 409-425

Conrad, J & Kaul, G (1989) Mean Reversion In Short Horizon Expected Returns, *Review Of Financial Studies*, 2, 225-240

Conrad et al (1991) Components Of Short-Horizon Individual Security returns, *Journal Of Financial Economics*, 29, 365-384

Copeland, T. & Galai, D., (1983) Information Effects And The Bid Ask Spread, *Journal Of Finance*, 38, 1457-1469

Dann, L et al. (1977) Trading Rules, Large Blocks And The Speed Of Price Adjustment, *Journal Of Financial Economics* 4, 3-22

Datar, V, Naik, N, Radcliffe, R (1998) Liquidity and Stock Returns *Journal Of Financial Markets*, 1, 203-219

Demsetz, H (1968) The Cost Of Transacting *Quarterly Journal Of Economics*, LXXXII (1), 33-53

Easley, D & Ledyard, J (1993) Theories Of Price Formation And Exchange In Double Oral Auctions. In: Friedman, D & Rust, J *The Double Auction Market.* Addison-Wesley, Reading, MA pp. 63-97

Easley, D & O'Hara, M (1987) Price Trade Size And Information In Securities Markets *Journal Of Financial Economics*, 19, 69-90

Easley, D & O'Hara, M (1991) Order Form And Information In Securities Markets *Journal Of Finance*, 47, 905-927

Easley, D & O'Hara, M (1992) Time And The Process Of Security Process Adjustment, *Journal Of Finance*, 47, 577-606

Easley, D & O'Hara, M (1992) Adverse Selection And Large Trade Volume: The Implications For Market Efficiency, *Journal Of Financial And Quantitative Analysis*, 27, 185-208

Eleswarapu, V, Reinganum, M (1993) The Seasonal Behavior Of Liquidity Premium In Asset Pricing *Journal Of Financial Economics,* 34, 373-386

Fortin, R.D, Grube, R.C & Joy, O.M (1992) Seasonality In NASDAQ Dealer Spreads. *Journal Of Financial And Quantitative Analysis*, 24, 395-407

Foster, F.D & Viswanathan, S (1990) A Theory Of Interday Variations In Volumes, Variances And Trading Costs In Securities Markets. *The Review Of Financial Studies*, 3, 593-624

Foster, F.D & Viswanathan, S (1993) Variations In Trading Volume, Return Volatility And Trading Costs: Evidence On Recent Price Formation Models. *Journal Of Finance*, XLVIII, 1 187-211

Friedman, D (1984) On The Efficiency Of Experimental Double Auction Markets *American Economic Review* 74, 60-72

Friedman, D (1991) A Simple Testable Model Of Double Auction Markets *Journal Of Economic Behaviour And Organization* 15, 47-70

Garman, M. (1976) Market Microstructure, *Journal Of Financial Economics*, 3, 257-275

George, T, Kaul, G & Nimalendran, M (1991) Estimation Of The Bid-Ask Spread And Its Components: A New Approach, *Review Of Financial Studies* 4, 623-656

Gerety, M & Mulherin, J.H (1994) Price Formation On Stock Exchanges: The Evolution Of Trading Within The Day *The Review Of Financial Studies*, 7:3, 609-629

Glosten, L (1989) Insider Trading And The Role Of The Monopolist Specialist, *Journal Of Business* 62, 211-236

Glosten, L (1994) Is The Electronic Open Limit Order Book Inevitable? *Journal Of Finance* 49, 1127-1161

Glosten, L.R & Harris, L.E (1988) Estimating The Components Of The Bid-Ask Spread. *Journal Of Financial Economics*, 21, 123-142

Glosten, L.R & Milgrom, P (1985) Bid, Ask And Transaction Prices In A Specialist Market With Heterogeneously Informed Traders *Journal Of Financial Economics*, 14, 71-100

Greene, J.S & Watts, G.S (1996) Price Discovery On The NYSE And The NASDAQ: The Case Of Overnight And Daytime News Releases *Financial Management*, 25:1, 19-42

Hakansson, N.H (1970) Optimal Investment And Consumption Strategies Under Risk For A Class Of Utility Functions, *Econometrica* 38, 587-607

Hansch, O, Naik, N.Y and Viswanathan, S (1998) Do Inventories Matter In Dealership Markets? Evidence From The London Stock Exchange, *Journal Of Finance*, 53, 1623-1656

Hansch, O, Naik, N.Y and Viswanathan, S (1999) Preferencing, Internalization Best Execution And Dealer Profits, *Journal Of Finance*, 54, 1799-1828

Harris, L (1986) Estimation Of True Price Variances And Bid-Ask Spreads From Discrete Observations. *Working paper. University Of Southern California*, LA, CA

Hasbrouck, J (1988) Trades, Quotes, Inventories And Information, *Journal Of Finance*, 4, 571-594

Hasbrouck, J & Seppi, J (2001) Common Factor In Prices, Order Flows And Liquidity. Journal Of Financial Economics, 59, 383-411

Hausman, J.A., Lo, A.W & MacKinley, A.C (1992) An Ordered Probit Analysis Of Transaction Stock Prices; *Journal Of Financial Economics* 31, 319-330

Ho, T.S.Y & Macris, R.G (1984) Dealer Bid-Ask Quotes And Transaction Prices: An Empirical Study Of Some AMEX Options. *Journal Of Finance*, 39, 23-45

Ho, T., Schwartz, R & Whitcomb, D (1985) The Trading Decision And Market Clearing Under Transaction Price Uncertainty *Journal Of Finance* 40, 21-42

Ho, T & Stoll, H.R (1981) Optimal Dealer Pricing Under Transactions And Return Uncertainty. *Journal Of Financial Economics*, 9, 47-73

Holthausen R, Leftwich R & Mayers D. (1987) The Effect Of Large Block Transactions On Security Prices: A Cross Sectional Analysis. *Journal Of Financial Economics,* 19, 237-267

Huang, R.D, & Stoll, H.R (1996) Dealer Versus Auction Markets: A Paired Comparison Of Execution Costs On NASDAQ And The NYSE *Journal Of Financial Economics*, 41, 313-357

Huberman, G & Halka, D (2001) Systematic Liquidity. *The Journal Of Financial Research*, XXIV (2), 161-178

Huberman, G & Kandel, S (1987) Value Line Rank And Firm Size. *Journal Of Business*, 60, 577-589

Huberman, G & Kandel, S (1990) Market Efficiency And Value Line's Record. *Journal Of Business*, 63, 187-216

Karpoff, J (1987) The Relation Between Price Change And Trading Volume: A Survey, *Journal Of Financial And Quantitative Analysis* 22, 109-126

Karpoff, J (1988) Short Sales And The Correlations Of Returns With Volume, *Journal Of Financial Research* 11, 178-188

Kim, S & Ogden, J (1996) Determinants Of The Components Of Bid-Ask Spreads On Stocks, *European Financial Management,* 1:1, 127-145

Kim, O & Verrecchia, R. E (1991) Market Reactions To Anticipated Announcements, *Journal Of Financial Economics* 30, 273-310

Ko, K, Lee, S & Chung, J (1995) Volatility, Efficiency And Trading: Further Evidence *Journal Of International Financial Management And Accounting*, 6:1, 26-42

Kothare, M & Laux, P (1995) Trading Costs And The Trading System For NASDAQ Stocks *Financial Analysts Journal* 51, 42-53

Kraus, A & Stoll, H (1972) Price Impacts Of Block Trading On The NYSE, *Journal Of Finance* 27, 569-588

Kyle, A (1984) Market Structure Formation, Futures Markets And Price Formation In International Agriculture Trade: Advanced Readings In Price Formation, Market Structure And Price Instability, ed by G.Story, A. Schmitz & Sarris, A (Westview Press)

Kyle, A (1985) Continuous Auctions And Insider Trading. *Econometrica*, 53, 1315-1335

Lee, C, Mucklow, B & Ready, M (1993) Spreads, Depths, And The Impact Of Earnings Information: An Intraday Analysis, *Review Of Financial Studies* 6, 345-374

Lo, A.W & MacKinley, A.C (1988) Stock Prices Do Not Follow Random Walks: Evidence From A Simple Specification Test, *Review Of Financial Studies* 1, 3-40

Madhavan, A (2000) Market Microstructure, Unpublished Paper (www.ssrn.com)

Mendelson, H (1982) Market Behaviour In A Clearing House *Econometrica* 50, 1505-1524

Menyah, K & Paudyal, K (1996) The Determinants And Dynamics Of Bid-Ask Spreads On The London Stock Exchange. *The Journal Of Financial Research*, XIX, 3, 377-394

Menyah, K & Paudyal, K (2000) The Components Of Bid-Ask Spreads On The London Stock Exchange. *The Journal Of Banking & Finance*, 24:3, 1767-1785

McInish, T.H & Wood, R.A (1992) An Analysis Of Intraday Patterns In Bid/Ask Spreads For NYSE Stocks. *Journal Of Finance*, 47, 753-764

Naidu, G.N & Rozeff, M.S (1994) Volume, Volatility, Liquidity And Efficiency On The Singapore Stock Exchange Before And After Automation *Pacific-Basin Finance Journal*, 2, 23-42

O'Hara, M (1995) Market Microstructure Theory. *Basil Blackwell*, Oxford

O'Hara, M & Oldfield, G (1986) The Microeconomics Of Market Making, *Journal Of Financial And Quantitative Analysis* 21, 361-376

Pagano, M & Roell, A (1990) Trading Systems In European Stock Exchanges: Current Performance And Policy Options, *Economic Policy*, 10, 65-115

Pagano, M & Roell, A (1992) Auction And Dealership Markets: What Is The Difference? *European Economic Review*, 36, 613-623

Reiss, R & Werner, M (1998) Does Risk Sharing Motivate Inter Dealer Trading? *Journal Of Finance*, 53, 1657-1703

Roll, R (1988) The International Crash Of October 1987. *Financial Analysts Journal*, 19-35

Rustichini, A et al. (1994) Convergence To Efficiency In A Simple Market With Incomplete Information *Econometrica* 62, 1041-1063

Silber, W (1975) Thinness In Capital Markets: The Case Of The Tel Aviv Stock Exchange, *Journal Of Financial And Quantitative Analysis* 10, 129-142

Sattertwaite, M & Williams, St (1993) The Bayesian Theory Of The K Double Auction. In: Friedman, D & Rust, J *The Double Auction Market.* Addison-Wesley, Reading, MA pp. 99-123

Snell, A & Tonks, A (1995) Determinants Of Price Quote Revisions On The London Stock Exchange *The Economics Journal*, 105, 77-94

Snell, A & Tonks, A (1998) Testing For Asymmetric Information And Inventory Control Effects In Market Maker Behavior On The London Stock Exchange, *Journal Of Empirical Finance*, 5, 1-25

Stoll, H (1978) The Supply Of Dealer Services In Securities Markets *Journal Of Finance*, 33, 1133-1151

Stoll, H.R (1978) The Pricing Of Security Services: An Empirical Study Of NASDAQ Stocks. *Journal Of Finance*, 33, 1153-1172

Stoll, H (1989) Inferring The Components Of The Bid-Ask Spread: Theory And Empirical Tests *Journal Of Finance*, 44, 753-776

Theissen, E (2000) Market Structure, Informational Efficiency And Liquidity: An Experimental Comparison Of Auction And Dealer Markets, *Journal Of Financial Markets*, 3, 333-363

Tinic, S.M (1972) The Economics Of Liquidity Services. *Quarterly Journal Of Economics* LXXXVI(1), 79-93

Tripathy, N & Peterson, L (1991) Portfolio Risk, Adjustment Costs And Security Dealers' Bid-Ask Spreads. *Journal Of Financial Services Research*, 5, 131-142

Wang, J (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

Wilson, R (1987) On Equilibria Of Bid-Ask Markets. In Feiwel, G Arrow And The Ascent Of Economic Theory, Essays In Honour Of Kenneth G Arrow Macmillan Press, Basingstoke

Wood R, McInish, T & Ord, J (1985) An Investigation Of Transactions Data For NYSE Stocks. *Journal Of Finance*, 40, 723-739