The Components of the Bid-Ask Spread:
The case of the Athens Stock Exchange[*]

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Abstract

We analyze the components of the bid-ask spread in the Athens Stock Exchange (ASE), which was recently characterized as a developed market. For large and medium capitalization stocks, we estimate the adverse selection and the order handling component of the spreads as well as the probability of a trade continuation on the same side of either the bid or the ask price, using the Madhavan et al. (1997) model. We extend it by incorporating the traded volume and we find that the adverse selection component exhibits U-shape patterns, while the cost component pattern depends on the stock price. For high priced stocks, the usual U-shape applies, while for low-priced ones, it is an increasing function of time, mainly due to the order handling spread component. Furthermore, the expected price change and the liquidity adjustment to Value-at-Risk that is needed is higher in the low capitalization stocks, while the most liquid stocks are the high priced ones. Moreover, by estimating the Madhavan et al. (1997) model for two distinct periods we explain why there are differences in the components of the bid-ask spread.

Keywords: Bid-Ask Spread, Asymmetry Information, Transaction Costs, Price Impact.
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1 Introduction

In an influential paper, Madhavan et al. (1997) (MRR) showed that security prices change due (a) to new arrival of public information, and (b) to the trading process. They pointed out that information asymmetry declines during the day, while transaction costs increase. In an independent work, Huang and Stoll (1997) developed another structural model that incorporated all previous approaches. Their empirical results supported the presence of a large order processing component and a smaller adverse selection and inventory ones. Moreover, they argued that spreads are depending on trading volume, a similar conclusion reached by Ahn et al. (2002).

This remark offered the insight for the present paper, which goes on to provide an empirical application to a small electronic order book market. Many researchers have used transaction volume as an explicit variable to model spread components. Easley and O'Hara (1987), in an influential theoretical paper, predict that informed investors prefer to make large trades. Hausman et al. (1992) conducted a probit analysis to measure the effect of several variables in existing microstructure models. De Jong et al. (1995), showed that, for small trades, the Paris Bourse had lower transaction costs than that of the London Stock Exchange and the cost of trading was a decreasing function of trading volume. A year later, working on the Glosten (1994) model, they provided evidence (De Jong et al., 1996) that, in the Paris Bourse, expected price change increases with volume and accounts for 25% and 60% of the spread for small and large trades respectively. They also used Hasbrouck's (1991) VAR model and conclude that the permanent price impact effect was between 40% and 115% of the spread and hence the Glosten (1994) model underestimated the transaction costs. Dufour and Engle (2000) also used and expanded Hasbrouck's (1991) model by adding the time between consecutive transaction to the exciting variables and argued that high trading activity is positive associated with spread, volumes and price impacts, while Pascual et al. (2004) showed that trading frequency increases after a trade with high information content and therefore price discovery improves after such trades. Furthermore, Berkman et al. (2005) studied the effect of transaction volume on execution costs in the London International Financial Futures and Options Exchange. They substantiated that effective spreads are smaller in future markets compared to the underlying market, a result that confirms the main finding of Subrahmanyam (1991). Moreover, Chan (2000) studied the price formation process on the Hong Kong Stock Exchange and pointed out that the information component was more important than the inventory one. On the contrary, Bollen et al. (2004) developed and tested a model of market makers' bid-ask spread for NASDAQ stocks and concluded that the inventory cost component dominated the adverse selection one.

On the other hand, many researchers examined the effect of volume on spreads, execution costs and order flows. By studying the volatility-volume relationship, Chan and Fong (2000) demonstrated that, for NYSE and NASDAQ stocks, traded volume was a more significant variable for volatility than the number of trades, but remained rather unclear on the main factors affecting this significant variable. Ahn et al. (2002) and Huang and Stoll (1997) found that the order processing cost decreases with traded volume. Degryse (1999) showed that total trading costs in the Brussels CATS system, as compared to London's, are lower (higher) for small (large) trade

sizes and concluded that the relation between the effective spread and trade volume depends on the specific characteristics of the exchange. Easley et al. (1997) argued that large trades have almost twice as much information as small ones, with buys and sells differing only marginally. In contrast to all of these findings, Aitken and Frino (1996) analyzed institutional trades on the Australian Stock Exchange and pointed out that buy orders are associated with larger costs than sell orders, probably due to short selling restrictions. Similarly, Chan and Lakonishok (1993) argued that the higher permanent impacts that are observed after block purchases are result of the high cost of short selling and the reluctance of investors to short sell stocks. For the Helsinki Stock Exchange, Hedvall et al. (1997) reported that asymmetries in the order flow depend on the traded volume and pointed out that "there are more often information reasons behind large buy trades than large sell trades".

Several studies explore the behavior of the bid-ask spread components during the trading day. Ahn et al. (2002) found that both the adverse and the order handling components of the Tokyo Stock Exchange exhibit U-shape intraday patterns. Declerck (2000) studied the trading costs and the spread components for the CAC 40 index stocks and found out that the order processing explains 82% of the spread, while all its components are positively related to the traded volume. Menyah and Paudyal (2000) showed that the inventory cost component is smaller than that of the order processing one for the London Stock Exchange and the asymmetry of information cost accounts for about 47% of the quoted spread, a percentage almost equal to that reported for NYSE/AMEX stocks by Kim and Ogden (1996). The same authors also found that high Normal Market Size (NMS)[1] stocks exhibit higher asymmetric information than low NMS ones: market makers widen the spread in order to limit expected losses from trading with informed investors. Ke et al. (2004) examined the impact of tick size on spreads, volatility, autocorrelation and trading volume and demonstrated that these variables displayed a U-shape pattern, while they showed that a larger tick size is related to wider bid-ask spread. Chan (2000) and Brockman and Chung (1998) studied intraday price formation of the Hong Kong Stock Exchange and found that both price impacts and spreads display the familiar U-shape patterns. Silva and Chavez (2002) reported that the higher execution costs of the Mexican Stock Exchange can be attributed to a higher adverse selection cost and not to the specific characteristics of stocks. Kim et al. (2002) analyzed the SIMEX future contract on the Nikkei 225 index and reported an L-shaped intraday pattern for the information cost and an inverse U-shaped one for the inventory holding cost. Gwilym and Thomas (2002) used trades and quotes of the LIFFE FTSE100 futures contract and by examining several measures of spread, they concluded that the spreads widen at the open and narrow at the close of day, with transaction spreads being biased estimators of quoted ones. Last but not least, two other studies examined the bid-ask spreads in option markets: Nordén (2003) used data from the Swedish OM market and found that both in- and out-of-the money options are more asymmetric than at-the-money ones, with the theoretical option value closer to the bid than to the ask price. Pinder (2003) used data from the Australian Options Market to examine spread components both before and after a switch from a quote-driven floor-traded system to an order-driven screen-traded one. Among other things, he reported smaller spreads when market makers were providing bid-ask

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[1] The minimum mandatory quote size for which market makers are obligated to post prices.

prices continuously.

This paper applies well-known methodologies (Madhavan et al., 1997 and Glosten and Harris, 1988) to the estimation of the theoretical components of the bid-ask spread (adverse selection and order processing costs) of the Athens Stock Exchange. We try to achieve two objectives in the present paper: first, we incorporate the volume as a variable to the structural model of Madhavan et al. (1997) to examine the idea proposed by Ahn et al. (2002). The Athens Stock Exchange (ASE) lends itself to such an exercise because a lot of listed stocks trade very passively for long periods during the day, making the information asymmetry contained inside the sign traded volume a more important factor than either the trade or the volume individually. At first reading, we reach similar conclusions to those of other researchers, since the adverse selection component exhibits the familiar U-shape pattern. The cost component, however, displays a clear U-shape only for high priced stocks and is *monotonically increasing* for low priced ones. These differences may be explained in the volume-extended model, since the order handling cost effect in low priced stocks is smaller. Furthermore, the adverse selection component explains a significant part of the spread and is increasing with volume, while the cost component is decreasing in it. Therefore, looking only at the latter component, we observe economies of scale in trading. During a distinct time period, however, from June 1st to August 31, 1999, the cost component was the most significant part of the spread. At that time, it seems that there were mainly uninformed traders participating in the market and, hence, the adverse selection risk was demoted. Second, by studying price impacts caused by different factors, such as order-flow dependence, trade volume and market capitalization, we conclude that high priced - high capitalization stocks are less sensitive to anyone of these factors. Moreover, we show that the observed exception rates, in an out-of-sample study, of a liquidity adjusted Value-at-Risk (L-VaR) measure, which is based on the augment model, are closer to the expected ones than that of the MRR model. As it will be shown in the next sections, these estimates (price impacts and L-VaR) can be calculated only by incorporating the volume as a variable to the structural model of MRR.

The remainder of the paper is organized as follows. The next section briefly describes the trading process of the ASE. Section 3 presents the data, while section 4 demonstrates the two structural models, describes the estimation procedure and explains the results. Section 5 presents and estimates the price impact and the L-VaR functions. The final section concludes the paper.

2　The ASE Trading Process

The Athens Stock Exchange is the unique official stock market in Greece. At the end of 2002, approximately 375 companies were listed in it, with a total capitalization approaching €85.5 billion. ASE members include security brokerage houses, credit institutions and investment service companies that have been granted a license by the Bank of Greece or by the Capital Market Commission. Only ASE Members can execute purchase and sale orders for shares through the Integrated Automatic Electronic Trading System (OASIS) of the market. Members are under the obligation to (a) keep the ASE informed of their realized transactions on a daily basis, (b) keep the Capital Market Commission informed on the use of their own funds, loans and shares on a

weekly basis, (c) disclose to the same Commission their larger financial exposure and solvency ratio on a monthly basis, (d) issue transaction slips for all completed transactions and (e) follow the accounting and tax laws.

Five different market segments currently operate inside the ASE: (i) The Main Market, (ii) the Parallel Market, (iii) the New Market (NEHA), (iv) the Greek Market of Emerging Companies (EAGAK), and finally, (v) the Secondary Listings on the ASE from Stock Exchanges outside Greece. The main classification rule for any company to be listed in the first four segments is the amount of their own equity. For example, the minimum amount for the Main Market is €11.7 million, while, for the parallel market, it is only €2.9 million.

Three major stock indices are calculated on a daily basis:

1. The **ASE General**, a market cap-weighted index, represents the general trend of the Greek stock market and its composition criteria include capitalization, transactions value and shares marketability.

2. The **FTSE/ASE - 20** is the large Cap Index, featuring the 20 largest blue chip companies. Companies are included in it on the basis of their capitalization and their free float.

3. The **FTSE/ASE Mid 40** follows the performance of the next 40 larger companies.

The last two indices cover approximately 2/3 of the total market capitalization of the ASE Main Market.

Turning now to the discussion of the trading process, we can safely argue that the ASE is basically an order-driven market, where members may continuously enter bid and offer orders in the system from 11:00 a.m. to 4:00 p.m. (the main trading period of the day). In such a setup, liquidity is provided only through the entry of different types of orders without the intermediation of market makers. Orders are ranked first by price priority and then on time arrival. In this way, interests of buyers and sellers are served in the most efficient way, while only *after* trade execution, the member who entered the order can be informed about his counterparty's identity. The tick size allowed equals 1 cent of a euro for securities with a price up to €2.99, 2 cents for securities up to €59.99 and 5 cents for the rest.

Inside each market segment, there are two different trading mechanisms: the "instantaneous market" includes all securities under regulatory surveillance or having "low liquidity" as classified by the ASE authorities.[2] For these stocks, order execution is serviced through five consecutive call auctions during the trading day. For the rest of the listed stocks in that segment, orders are cleared continuously from 11:00 a.m. to 4:00 p.m. In both mechanisms, all orders in the pre-opening period (10:30 a.m.–11:00 p.m.) are cleared in an opening call auction.

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[2]Since June 2003, all securities that in the last six months had an average relative spread greater than 2%, were regarded as being rather illiquid. They cannot be a part of any official ASE index.

3 Data

Transaction data used were drawn from intraday files of the ASE for the period from February 4, to December 30, 2002 and contains the time-stamped prices to the nearest second, volumes, and bid and offer prices with corresponding sizes just before a transaction occurs, for all transactions. Our stock sample was based on the two major equity indexes, the FTASE-20 and FTASE-40, representing the large and medium capitalization companies respectively. For each index, we classified stocks in two independent groups: the first one included those with an average sample price greater than (or equal to) €10 and the second those with an average sample price less than €10[3].

For all stocks opening transactions have been eliminated from the dataset, since the opening period of the ASE is cleared as a call market.[4] We also eliminated all trades where the bid was greater than the corresponding ask, as well as those where the time stamp was clearly erroneous. We also grouped all trades conducted at the same time and price as a single trade (Chan, 2000). Lastly, given the fact all trades in this market involve a limit order stored on the limit order book (the passive side) and a market order (the active side), the distinction between buyer-initiated and seller-initiated trades is immediate.

3.1 Descriptive statistics

Table 1 presents summary statistics for the four subgroups. Stocks in Group 1 are the most active, based on trade intensity (180 transactions per day on average) and on average time between trades (99 seconds). Their mean spread is €0.0368 or 0.19% of the bid-ask midpoint. Members of group 2, high cap but low price stocks, are less liquid: there are fewer transactions per day and their average spread (in percentage) is twice than that of the first group. On the contrary, for midcap stocks, it is not clear which subgroup is more liquid: trade intensity and time between trades favour the low priced subgroup, while relative spread favours the high priced subgroup 3. Overall, stocks in the midcap index are less actively traded than the corresponding large cap index, as relative spread and time between trades are greater, while trade intensity is lower. We further address this important issue in section 5.

We observe other essential differences between the two share groups. For example, the number of transactions in the FTASE-20 stocks is almost twice as high as that for the FTASE-40 stocks, while the relative spread is twice as low. These differences were tested using the non-parametric Kruskal-Wallis test, a generalization of the Mann-Whitney test for more than two subgroups.[5] For both the absolute and the relative spread, the null hypothesis of all subgroups having the same median has clearly been rejected. Table 2 presents results in detail.

Finally, table 3 shows summary statistics during the trading day: we use a shorter half-hour interval after the opening and before the closing of the market and one-hour intervals in between.

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[3]The members of each group and their average price are available from the authors upon request.

[4]Amihud and Mendelson (1987) pointed out that prices produced by such a call auction are likely to be generated from a different distribution than that of the rest of the trading day.

[5]For more details see Sheskin (1997).

This divides the trading day in six intervals: 11:00-11:30, 11:30-12:30, 12:30-13:30, 13:30-14:30, 14:30-15:30, 15:30-16:00.[6] For all groups, the hypothesis that the average and the relative spread are equal during the trading day is rejected. Generally speaking, the mean and the standard deviation of the spread and the mean relative spread display the familiar U-shape pattern over the day, a result reported by several empirical studies. Especially for the ASE, Niarchos and Alexakis (2003) reported that stock returns follow a U-shape pattern during the trading session. For group 1 (shown in panel A of the table), the average spread is almost 5 cents at the opening, drops to 3 cents in the middle of the day and increases back to more than 4 cents towards the closing. The corresponding group of midcap stocks (panel C of the table) shows similar behavior, but with much larger values. The same occurs for groups 2 and 4 (low priced stocks), though spread differences throughout the day are not as large. Therefore, the highest trading costs in the ASE occur at the beginning and the end of the day and, therefore, smaller private investors should focus on trading periods in the middle of the day, as supported by the theoretical model of Admati and Pfleiderer (1988).

4 Two structural models for intraday price movements

4.1 The MRR model

There are many decomposition methods of the bid-ask, such as Stoll (1989), George et al. (1991), Hasbrouck (1991), Lin et al. (1995), de Jong et al. (1996), Huang and Stoll (1996), Huang and Stoll (1997) and MRR. A recent study by Winne and Majous (2003) compares alternative decomposition models on Euronext Brussels, an electronic order driven market too. All models assign a negligible weight to inventory-holding costs. Under the assumption of zero inventory-holding costs, all models report similar adverse selection costs estimates. They compare Huang and Stoll (1997), Madhavan et al. (1997) and Lin et al. (1995) estimations with different proxies of information asymmetries, but they do not succeed in finding a superior methodology. Therefore, we chose to work with MRR decomposition method among all the possibilities at hand, as it is widely applied and there are no significant differences between the various methods.

4.1.1 Description and estimation procedure

We first introduce the MRR model which will serve as a benchmark for our work. According to that seminal paper, the factors moving prices are twofold. First, prices change due to the arrival of new public information, which we assume to be a series of independent and identically distributed random shocks with zero mean and constant variance. Second, the "order of trade" indicator reveals informed traders' beliefs, since a buy (sell) order is associated with an upward (downward) price movement.

Let p_t denotes the transaction price of the security at time t and X_t be the "trade indicator" variable, equaling +1 if the trade is buy-oriented, and -1 if it is sell-oriented. The coefficient $\phi \geq 0$

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[6]We did not use a finer time partitioning since thin trading caused lack of observations for statistically significant estimates of structural models for individual stocks.

represents the cost per share of the market maker in supplying liquidity on demand, θ measures the degree of information asymmetry and μ_t is the expected value of the stock. We assume a standard cost model of market making, $p_t = \mu_t + \phi X_t$, and an information asymmetry model for fundamentals, $\mu_t = \mu_{t-1} + \theta(X_t - \rho X_{t-1})$. Combined, they produce the following intraday price change model:

$$p_t - p_{t-1} = (\phi + \theta)X_t - (\phi + \rho\theta)X_{t-1} + u_t, \tag{1}$$

where ρ is the first-order autocorrelation of X_t. The pure random walk is a special case of 1 if $\phi = \theta = 0$.

We estimate 1 by using the generalized method of moments (GMM) methodology, because it does not require as strong distributional assumptions as the maximum likelihood methods. It can also easily accommodate conditional heteroskedasticity of any form. The GMM method is based on a moment condition, $E(f(\chi_t, \vartheta_0)) = 0$, where $f(\chi_t, \vartheta_0)$ is a $q \times 1$ vector function and ϑ_0 is a p-dimensional parameter vector. The estimated GMM parameters ($\hat{\vartheta}_T = argmin_\vartheta Q_T(\vartheta)$) are weakly consistent and asymptotically normally distributed and are calculated by minimizing the function $Q_T(\vartheta) = f_T(\chi_t, \vartheta)' A_T f_T(\chi_t, \vartheta)$, where $f_T(\chi_t, \vartheta)$ is the sample mean vector and A_T is the sample symmetric weighting matrix. For equation 1, we set the following moments conditions:

$$E \left\{ \begin{array}{c} X_t X_{t-1} - \rho X_{t-1}^2 \\ u_t - \alpha \\ (u_t - \alpha)X_t \\ (u_t - \alpha)X_{t-1} \end{array} \right\} = 0, \tag{2}$$

with α a constant. The first condition defines the autocorrelation of the trade variable and the last three are the normal OLS equations. We use the lagged trade indicator and a constant as instrumental variables.[7]

4.1.2 Empirical results

Panel A of table 4 presents the GMM estimates of the MRR model and the corresponding standard errors for each subgroup.[8] We also report the p-value of a Wald within-index subgroup equality test. Moreover, we calculate the implied spread, $2(\theta + \phi)$, and the proportion of it explained by asymmetric information, $\gamma \equiv \theta/(\theta + \phi)$. This ratio is expected to be quite large, due to anonymous trading, until trade execution at least. Anonymity is considered to increase information asymmetry, as Foster and George (1992) showed: if traders are not fully anonymous and make their motivations widely known, the bid-ask spread and the expected price change are expected to be

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[7]Although, Madhavan et al. (1997) introduced one more conditional moment in order to estimate the probability (λ) of a trade to occur between the bid and the ask price, this is not necessary in our dataset because all trades were executed at either endpoint.

[8]The time series of the different stocks in the same portfolio were stacked together. Panel B of table 4 presents summary statistics on the parameters across the sample stocks. In all cases the average values are too close to the reported one in panel A of table 4 and therefore, since our main findings do not alter significantly, our analysis will based on those of panel A.

lower relative to a fully anonymous market.[9] This conclusion is also supported by the work of Admati and Pfleiderer (1991), where liquidity traders who preannounce the size of their orders enjoy lower transactions costs.

We reach the same conclusion as Easley et al. (1996), who pointed out that, in less frequently traded stocks, it is more common to observe more information-based traded risk. The percentage of the spread attributed to the information component (i.e., parameter γ) is higher in the smaller cap stocks (subgroups 3 and 4), as lower trading activity and, consequently, lower liquidity increase the probability of dealing with an informed investor. Furthermore, as with Ahn et al. (2002), this component is more important in high-priced stocks (γ is higher for subgroups 1 and 3). A possible explanation is that, during 2002, only institutional investors were active in the Exchange, dealing with high-priced stocks in a "bear" environment. Given that such investors are rather more informed than private ones, spreads were increasing to take care of such cases. On the contrary, since it is generally assumed that institutional investors are not interested in penny stocks as much, the cost component received a higher weight for subgroups 2 and 4. We compute Wald statistics to test for parameter equality in the subgroups of each index: in all cases, they are significantly different at all usual confidence levels, revealing the importance of such partitioning.

Many researchers (cf. Ahn et al., 2002, Madhavan et al., 1997, Huang and Stoll, 1997) argued that spread components and especially the adverse selection one, tend to be underestimated since the elevated percentage of midpoint trades in US markets biases downwards the estimation of the implicit spread. We calculate such bias to be between 21% and 30% of the quoted spread.[10] One explanation of this bias may be the breaking up of large trades into smaller ones. As trading takes place continuously at the one side of the spread, pointing possibly to the fact that this side is more liquid (exhibits larger depth), the spread, as a percentage of the midquote, seems to be smaller, since the midquote converges to the trade price. Given that the implied spread is calculated conditional to actual trades, trade asymmetry will cause the underestimation of the implied spread. This is further supported by the probability of a trade reversal – from a trade at the bid (ask) to a trade at the ask (bid) – being quite low.[11] For example, the reversal probability for stocks in group 1 is 35,34% and for group 3 is only 28,62%, a result reinforcing our belief that investors prefer to execute a series of continuous trades at one side of the quotes.

Table 5 summarizes intraday estimations of spread components, calculates the implied spread and presents the percentage of it explained by the asymmetry information for the six intraday time intervals.[12] We also report the p-value of a Wald test for differences between subgroups for estimated parameters, showing all are significant at all usual levels.

The autocorrelation coefficient does not show any clear pattern during the day. We observe, however, that its maximum value occurs in the last half hour, producing the lowest value for the probability of a trade reversal at that same period. Positive autocorrelation has been reported by

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[9]Also Bryant and Haigh (2004) reported that on commodity future markets spreads widen after the trading was made anonymous.

[10]The bias is defined as $1 -$ (implied spread/absolute quoted spread).

[11]This probability, in the MRR structural model, is defined as $\pi = \frac{1-\rho}{2}$.

[12]We have also estimated equation (1) by using ten time intervals instead, but results were similar.

several authors (see Hasbrouck (1988, 1991), Madhavan et al. (1997), Biais et al.(1995) and Ahn et al. (2002) among others) but the feature of the last half-hour is, to the best of our knowledge, unique to the ASE and probably due to the increase in trading activity. As more investors are coming late into the market and, simultaneously, the traded volume increases, the procedure of splitting the trades increases the trade autocorrelation. For example, if an informed investor is attempting to hide a large buy order at the last half-hour, he will choose to split it to smaller bits in order to better conceal his motivation. Dufour and Engle (2000) reached a similar conclusion, when they found out that higher trading activity is positively associated with trade autocorrelation, volumes and spreads.

The adverse selection component, θ, for all groups, drops sharply after the first 30 minutes, as the trading process adds valuable information to all investors, pushing more uninformed traders into the market. It then remains steady or declines slightly during the rest of the day, and increases sharply again in the last 30 minutes. Informed investors come in to close up their intraday positions just before the close, since by so doing, (a) they minimize risk, and (b) they profit more easily from superior information. Similar to Chan (2000), the increase of traded volume in the last time period, would also lead to a larger adverse selection problem and, hence, widen spreads. Using this argument, Chan (2000) explained the decrease (increase) of the adverse selection component at the NYSE, as average volume decreased (increased).

An other possible explanation of the adverse selection component decrease after the first 30 minutes may be the effect of the opening of the US market on European stock exchanges. The literature documents that the highest degree of information asymmetries in the US markets occurs right after the opening (Madhavan et al, 1997). The opening of the US market coincides with the afternoon trading in European markets. Since trading sessions overlap, the price discovery after the US opening remarkably affects the European afternoon patterns (e.g., Hupperets and Menkveld, 2002, Pascual et al., 2005). In the particular case of the ASX, the overlapping occurs during the last half-hour of trading (15:30-16:00). Even if the close of ASE does not coincides exactly with the opening of US markets, it might be affected by the expectation of US or European investors that are being revealed through the future markets.

On the other hand, the cost component ϕ does not behave uniformly but shows two different time patterns according to the average stock price. For high priced stocks (groups 1 and 3), it exhibits a clear U-shape, while, for groups 2 and 4, it monotonically increases with time. This is a striking result, since, under the MRR framework, there is no apparent reason behind these differences. We will, however, see shortly that such differences may be explained in the extended model.

4.1.3   Do these relations change over time?

The entire preceding analysis was done on the latest available intraday dataset from February 4 to December 30, 2002. We found that the adverse selection component (θ) had greater effect on the spread than the cost component (ϕ). It is interesting, however, to examine if this relation holds also during a much different historical period for the ASE. The new dataset covers the period from June

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1 to August 31, 1999 and contains exactly the same variables: time-stamped prices to the nearest second, volumes, bids and offers with the corresponding sizes just before a transaction occurs. We limited, however, our analysis only to the large capitalization stocks included in FTASE-20 index.[13] The ASE authorities themselves, as do most of the Greek economic press and researchers, consider, that the year 2002 was a very distinct period from the 1999 specific summer months for three main reasons: (a) The level of the FTASE-20 index increased by 13% during this 3-month period, while during the eleven months in 2002, it decreased by 38%; (b) more than 1 million small investors were actively trading in the Athens Stock Exchange at that time, as opposed to a much lower number for the latter period; and (c) the average, reported *increase* in pre-tax profits of listed companies in 1999 was 43%, compared to a 32% *decline* in 2002.

Table 6 displays GMM estimates (and corresponding standard errors) of the MRR model for the 2 subgroups of FTASE-20 stocks, for the 1999 dataset. As expected, estimated parameters differ between subgroups. The adverse selection component, θ, is close to zero for both subgroups, but statistically insignificant for the second one. The cost component, ϕ, on the contrary, is significant at all usual confidence levels and is more important than θ in defining the spread, since γ is near to zero. We believe these results come into contrast with those of the 2002 dataset, for two reasons: (a) the overconfidence of the uninformed investors about the future positive direction of the market which turned out to be unsubstantiated, and (b) the optimistic fundamentals of listed companies in 1999 fostered a bullish movement in prices, as opposed to their serious deterioration that appeared in the following years.

A value of θ close to zero indicates a possible lack of information-based risk. Given that the majority of investors participating in the stock rally of the summer of 1999 were uninformed, they put much more weight on the cost component of the spread rather than on the adverse selection one. They most probably presumed that none had more information than them, a belief grounded on the effortless increase of their wealth during this same period: The price of most small stocks at least doubled during that period. Under this point of view, differences in the significance of θ can be attributed to the large number of uninformed traders with no previous experience in share investments. On the contrary, during 2002, there were mainly institutional investors participating in the same market, more naturally considered as informed traders, consequently upgrading the role of the asymmetric information component, θ.

Moreover, the decline of pre-tax profits can decrease uninformed trading, since possible financial distress increases the risk that private investors face, pushing them out of the market. Agrawal et al. (2004) argued that market makers increase the spread of firms that encounter financial problems, in order to protect themselves in case they trade against an informed trader. In such companies, it is common to observe a higher proportion of informed traders, as Hotchkiss and Mooradian (1997) showed, due to the fact that they are more able to use sophisticated methods, not available to small investors, in order to value the companies with greater accuracy. Since, during the 2002 fiscal year, reported pre-tax profits declined by 32%, a larger presence of informed traders was expected and, hence, the adverse selection component became more significant than during the 1999 period.

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[13]The mid-cap FTASE-40 index was created at the end of this period and, precisely on December 8, 1999.

4.2 The volume dependent model

We now turn to an extension of the MRR model, where we explicitly incorporate trade volume as a factor affecting price change. In particular, we assume that there are two cost components that must be decomposed. The first one (ϕ) does not depend on the traded volume, while the second one (κ) depends on the sign traded volume. Similar, we pose that also the adverse selection component is related to the size of a trade. Following the idea of MRR, we postulate that:

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\begin{aligned}
p_t &= \mu_t + \phi X_t + \kappa(X_t V_t) \\
\mu_t &= \mu_{t-1} + \theta V_t(X_t - \rho X_{t-1}),
\end{aligned}
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where V_t is the number of traded shares. Given this setup, equation 1 now becomes:

$$
p_t - p_{t-1} = \theta V_t(X_t - \rho X_{t-1}) + \phi(X_t - X_{t-1}) + \kappa(X_t V_t - X_{t-1}V_{t-1}) + u_t, \tag{3}
$$

If κ turns out to be negative, the total cost ($\phi X_t + \kappa(X_t V_t)$) decreases with the increase of the traded volume, since the $\kappa(X_t V_t)$ component is a function of the signed volume.

Now, let $a_{X_t=1}$ and $b_{X_t=-1}$ be the ask and bid quotes for trade indicator X_t. Then the implied spread can be modelled as:

$$
\begin{aligned}
a_{X_t=1} &= \mu_{t-1} + \theta V_t[1 - \mathbb{E}(X_t|X_{t-1})] + (\phi + \kappa V_t) \\
b_{X_t=-1} &= \mu_{t-1} - \theta V_t[1 + \mathbb{E}(X_t|X_{t-1})] - (\phi + \kappa V_t) \\
a_{X_t=1} - b_{X_t=-1} &= 2[V_t(\theta + \kappa) + \phi]
\end{aligned}
$$

The implied spread is an increasing function of the absolute volume V_t, the adverse selection θ and the ϕ parameter, while its relation with κ depends on the sign of it.[14] If $\kappa < 0$, then economies of scale in trading are produced, as cost decreases with increasing volume.

We chose to model transaction prices as functions of the signed traded volume for obvious reasons. The investor in an electronic market, required to implicitly supply liquidity through his orders, will not only consider the direction of the coming trade (a buy or a sell), but also its size. It is normal to adjust the spread accordingly, narrowing it for small sizes and widening it for large ones. Although theoretical models suggest expressing the cost component as a linear function of volume, we adopt a concave (square root) function, since several empirical studies have shown its advantages. Barra (1997), in the Market Impact Model[TM] handbook, argues that, in order to achieve the best fit between midquote returns and volume, they had to use the one-half power law. Almgren (2001) postulated that price impact functions were not linear in volume and chose the power law family, which includes the square root function. Lastly, Hisata and Yamai (2000) also formulated the market impact as a square root function, when they proposed a methodology for Liquidity Adjusted Value-at-Risk.

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[14]If $V_t=1$ and $\kappa=0$, this specification simplifies to the MRR model.

We estimate model 3 based on the following implied moment conditions:

$$E\left\{\begin{array}{c} X_t X_{t-1} - \rho X_{t-1}^2 \\ u_t - \alpha \\ (u_t - \alpha) X_t \sqrt{V_t} \\ (u_t - \alpha) X_{t-1} \sqrt{V_{t-1}} \\ (u_t - \alpha) \sqrt{V_t} \\ (u_t - \alpha) \sqrt{V_{t-1}} \end{array}\right\} = 0. \tag{4}$$

To eliminate outlier effects, we discarded trades with size greater than the 99.5% percentile of their empirical distribution.[15]

For robustness, we also estimated the well known Glosten and Harris (1988) specification of intraday price changes, which, in our notation, can be set out as follows:

$$\begin{aligned} p_t &= \mu_t + \phi_t X_t \\ \mu_t &= \mu_{t-1} + \theta_t X_t + U_t \\ \phi_t &= c_0 + c_1 V_t \\ \theta_t &= z_0 + z_1 V_t, \end{aligned}$$

The U_t variable captures both public information and other factors affecting prices. Using the above equations, the price change can then be estimated as:

$$p_t - p_{t-1} = \alpha + c_0 \Delta X_t + c_1 \Delta X_t V_t + z_0 X_t + z_1 X_t V_t + U_t, \tag{5}$$

where α is a constant. Like the MRR model, the implied spread is equal to $2(c_0 + c_1 V_t + z_0 + z_1 V_t)$, which equals to twice the sum of the order processing and the adverse selection components. Both models (3 and 5) describe in a similar fashion the order processing component, since c_0 and ϕ measure fixed costs, while c_1 and κ express the relation between cost and volume. On the other hand, Glosten and Harris's equation writes the asymmetric information component by using two different coefficients: (a) z_0 measures the part of adverse selection **not** affected by volume, and (b) z_1 describes the relation with traded volume. In our specification (3), we assume $z_0 = 0$. Lastly, in 5, Glosten and Harris (1988) set $\rho = 0$, implying that the order flow does not provide information about the future value of the asset.

4.2.1 Estimation results

Panel A of table 7 presents the GMM estimates of the extended model[16], the corresponding standard errors for each stock subgroup, the p-value of the Wald test, calculated implied spreads and the coefficient γ, which, in this framework, equals to:

$$\gamma = \frac{\theta \sqrt{V}}{\theta \sqrt{V} + \kappa \sqrt{V} + \phi}.$$

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[15]See Hausman et al. (1992), De Jong et al. (1995, 1996) among others, for similar transaction filtering.

[16]Panel B of table 7 is similar to Panel B of table 4 and presents summary statistics on the parameters across the sample stocks. In all cases the average values are too close to the reported one in panel A of table 7 and therefore, since our main findings do not alter significantly, our analysis will based on those of panel A.

The last two parameters are calculated for two values of volume: the officially minimum allowed trade size and the average number of shares traded during the sample period.

All parameters are statistically significant and differ between the four subgroups. In most cases, the estimates of model 3 are similar to those of the standard MRR one[17]. Using the average period volume, implied spreads are slightly smaller. We must not forget, however, that we can generate the true implied spread by inputting explicitly the number of shares in the model 3. For subgroups 1, 2 and 3, the average γ is lower than 50%, showing that, here, the cost component of the spread $(\phi + \kappa\sqrt{\overline{V}})$ is more important than the adverse selection one $(\theta\sqrt{\overline{V}})$. As volume increases, however, γ rises and, hence, the importance of the cost component decreases, similarly to Chan (2000). For a small size trade, the market will most probably believe that it has a relatively low information content and, consequently, it will place more weight on the order processing cost. On the other hand, if an investor is willing to trade a large quantity of shares, then the adverse selection risk facing the counterparty will take over, pushing spreads upwards. We calculate the minimum number of shares causing such a switch to be equal to 602, 1081, 274 and 785 for groups 1, 2, 3 and 4, respectively. For these sizes, γ equals to $1/2$.

The negative sign of κ also has a clear implication: the order processing component decreases with volume, while fixed cost component remain unaltered, resulting in economies of scale in trading. This was somehow expected because, in an order-driven market like the ASE, without any explicit market makers, fixed costs cannot be regarded as significant by the large number of anonymous order suppliers, who play the role of liquidity suppliers here. Hausman et al. (1992) reported, on the contrary, diseconomies of scale for their dataset, with an upward sloping price response function, although at a decreasing rate. Ahn et al. (2002) also observed economies of scale in their study, with the order handling part dominating the inventory component. We also find that there is a certain amount of shares that makes the cost component disappear that equals to 2928, 11216, 2759 and 6112 for each subgroup respectively. For larger sizes, the spread is due solely to asymmetric information, as $\phi + \kappa\sqrt{V}$ becomes negative!

Table 8 displays the OLS estimates of the Glosten and Harris equation 5 for all four stock subgroups, as well as the corresponding standard errors, adjusted using the Newey and West (1987) procedure.[18] We also report the Wald test results and calculate the implied spread and the γ coefficient, which is here defined as:

$$\gamma = \frac{z_0 + z_1\sqrt{V}}{z_0 + z_1\sqrt{V} + c_0 + c_1\sqrt{V}}.$$

Estimated implied spreads and gammas for both models (3 and 5) are quite similar. As the volume, however, increases, implied spreads become larger in our specification than the Glosten et al. one. Like De Jong (1996), the order processing component is more important than the

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[17]We also compute the Adjusted R-squared for both models (equations 1 and 3) in order to evaluate their in-sample fit. The values of the Adjusted R-squared measure are quite similar and therefore the usefulness of the augment specification will be supported by the ability to calculate the price impact functions in section 5.1 and in an out-of-sample study of adjusting Value-at-Risk to liquidity in section 5.2.

[18]For subgroup 1, we have slightly altered the specification of 5, assuming that $z_0 = 0$, in order to produce statistically significant parameters.

adverse selection one, for average traded volumes, with γ ranging from 33% to 43%. Moreover, the negative sign of c_1 – which can be compared to the parameter κ of our model – indicates that order handling dominates fixed costs, with total costs falling with the number of traded shares. For subgroups 2, 3 and 4, coefficient c_1 is at least four times larger than κ, resulting in a comparative weakening of the effect of order handling costs.

Table 9 presents the two components of the spread and the proportion of the information effect for the three specifications. While the two models that explicitly incorporate volume as a spread-affecting variable, generate similar estimations, they both differ significantly with the standard MRR model, since they underestimate the adverse selection part and overestimate the cost part (cf. a similar result by Ahn et al., 2002). In most cases, estimated parameters of model 3 are closer to those of MRR, yielding smaller biases. We should of course remember that MRR results are *treated* as benchmarks, without them *being* necessarily so.

Table 10 presents the estimated parameters of model 3 using six time intervals. All measures exhibit the familiar U-shape time pattern throughout the day, except for κ which seems to follow an inverse U-shape. This may be mean that, as the trading day unfolds, order handling becomes less important than fixed costs. Generally speaking, all time patterns mentioned in our previous analysis, are replicated in table 10. For example, in most cases, the average implied spread and the adverse selection component are smaller than those of the classical MRR model, while costs are greater. The differences in the pattern of the cost component $(\phi + \kappa\sqrt{V_t})$ between the subgroups of high and low priced stocks is mainly due to the new coefficient κ. For the two subgroups with low priced shares, the increase in the cost component during the day can be attributed to the smaller effect of order handling, as κ is getting closer to zero, although it remains always negative. This dominates the decrease of coefficient ϕ. This pattern reverses in the last 30 minutes of trading, since the increase in ϕ, the part of the cost component that does **not** depend on volume, causes the overall cost to increase. This may be associated to the risk of maintaining a position overnight. For high priced stocks (subgroups 1 and 3), this coefficient is more important than $\kappa\sqrt{V}$, because the total cost follows the same pattern as ϕ. For such expensive stocks, the order handling component is more important than for cheap stocks (subgroups 2 and 4), as the absolute value of κ is always greater in the former than in the latter group.

5   The usefulness of the augment model

A perfectly liquid market gives the opportunity to investors to buy or sell any amount of stock without causing any price change. Consequently, in an illiquid market, the main objective of a trader should be to measure and minimize the transaction costs. Aitken and Comerton-Forde (2003) stated that here are two kinds of transaction costs in a stock market: *explicit* ones include general commissions and fees, and *implicit* ones, linked to the trading procedure per se and including bid-ask spreads and price impact. In this paper, we will limit our analysis to implicit execution costs and order-based measures of liquidity, since the augment model(3) can directly estimate them for different traded volumes, while it can be used in order to construct a Liquidity Adjusted Value-at-Risk (L-VaR) measure, as Angelidis and Benos (2006) did, in the attempt to investigate

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its out-of-sample forecasting performance.

5.1 Price impact functions

We define the price impact function as the percentage of the median price explained by the cost component:

$$\frac{\phi + \kappa\sqrt{\overline{V}}}{MedianPrice}.$$

Such a definition translates the natural interpretation of "effect of volume on price": how much will the transaction price change for large trade sizes? In table 11, we present such a price impact function for the four stock subgroups and for chosen trade sizes. While in a perfectly liquid market, we would expect the impact of volume to be nil i.e., such a function to be flat, this is not the case here. It may even show whether there are any economies or diseconomies of scale in trading. In our dataset and for all stock subgroups, the downward-sloping curves reveal the presence of economies of scale, as the percentage of price due to order handling costs decreases with the traded size. Moreover, according to this criterion, high priced stocks (subgroups 1 and 3) are the most liquid, since it is in these groups that we observe the minimum price impact for a fixed trade size. This result is similar to that of Brennan and Subrahmanyam (1995), who observed that transactions costs are negatively related to share price. Hausman et al. (1992) also reported that low priced stocks were less liquid than high priced ones, since the percentage price impact for a given traded value was considerably higher.

In order to measure more accurately the "depth" of each stock subgroup, we calculate the percentage price change for different sequences of traded volumes. In table 12, we present how the price changes when we switch from a buy transaction at time $t-1$ (row) to a sell transaction at time t (column) for a range from 1 to 3000 shares. Generally speaking, we find that the price effect is bigger if the first trade is small, because the $\kappa(X_t V_t - X_{t-1} V_{t-1})$ part of the impact decreases the total price change (negative κ). By comparing the stock subgroups according to their capitalization, we observe that, in most of cases, expected price change is higher in mid cap stocks (subgroups 3 and 4), as Hasbrouck (1991a, b) reported. An interesting point here is that, for small trade volumes, the percentage change in high priced, middle capitalization stocks is smaller than that in low priced, high capitalization stocks. This is not, however, the case for large traded volumes.

5.2 Liquidity adjusted Value-at-Risk

Value-at-Risk[19], which refers to a portfolio's worst outcome likely to occur over a predetermined period and a given confidence level, does not take into account the risk of liquidating a large position. However, according to Bangia et al. (1999), VaR can be adjusted to liquidity risk (L_1) as follows:

$$L - VaR = VaR + L_1$$

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[19]For more information on Value-at-Risk, see Dowd (2002).

Angelidis and Benos (2006) proposed a L-VaR measure by adjusting VaR to liquidity effects, as follows:

$$L - VaR = VaR + [(\theta + \kappa)\sqrt{V_t^{\alpha'}} + \phi], \tag{6}$$

where $V_t^{\alpha'}$ is the α' quantile of the traded volume. Under this framework, the computation of the L-VaR number is simple and intuitive, as it splits the total risk into a "market" component:

$$VaR = P_t(1 - e^{-\alpha'\sigma_t}) \tag{7}$$

and an "liquidity" one $((\theta + \kappa)\sqrt{V_t^{\alpha'}} + \phi)$, where P_t is the stock price, α' is the standardized normal distribution ordinate that corresponds to the chosen VaR confidence level and σ_t is the standard deviation of the underlying distribution. Similarly, the L-VaR forecast for the MRR model (equation: 1) is calculated as:

$$L - VaR = VaR + (\theta + \phi) \tag{8}$$

By comparing the measures (equations 6 and 8), the main drawback of 8 is being revealed: irrespectively of the chosen VaR confidence level, liquidation factor $(\theta + \phi)$ remains constant, while in case of the augment model (6), it changes according to the traded volume quantile $(V_t^{\alpha'})$.

In order to evaluate the two L-VaR models, we generate out-of-sample forecasts for each stock of the four subgroups for a period, ranging from January 2nd, 2003 to March 31st, 2003 (308 trading days). Table 13 presents the average number of violations[20] for each group, for the 99% confidence level and for three models: a conventional VaR model (equation 7), a MRR L-VaR(equation 8) and a Volume L-VaR (equation 6) one. In all cases the augment model produces exception rates closer to the expected number (3.08) than both the other two techniques. Gains from applying the proposed model are substantial for the low capitalization stocks (Groups 3 and 4), as not even the MRR adustment is not enough to cover future losses, while based on the volume dependent specification the observed number of violations is close to the theoretical one.

6   Conclusions

This research investigates the bid-ask spread behaviour of the Athens order-driven stock market. For the 11-month period from February to December 2002, we analyze high frequency transaction level data for four stock groups, sorted by their average transaction prices and their capitalization. Although information asymmetry is expected to decrease over the day due to "learning by trading" process, we report a U-shape pattern for all stocks. Furthermore, the cost component exhibits the same U-shape pattern only for high-priced stocks, while, for low-priced ones, it is monotonically increasing during the day. We think this is due to the order handling part of this component, which is more significant in high-priced stocks. This difference is further analyzed in a volume dependent structural model, a natural extension of the MRR specification. Based on it, we have strong indications that the adverse selection increases with trade size while the cost component

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[20]A violation occurs if the predicted VaR is smaller than actual, realized losses.

decreases, a result similar to those of Ahn et al. (2002). For robustness purposes, we also estimate the Glosten and Harris (1988) model, reaching once again to similar conclusions.

We also test the robustness of such results for another time period from June to August 1999 and provide evidence that the cost component accounted then for more than 98% of the implied spread. At that time, most investors participating in the market had no information of any kind of stocks and trading was generated mostly from a herd behaviour. It is natural that, given such an environment, the importance of adverse selection risk was downgraded by market participants. The differences between the two periods are clearly due to the above mass participation of uninformed traders but also to a rather significantly different fundamental background of listed companies.

Furthermore, we form two different price impact functions in order to investigate the behaviour of each stock subgroup to large orders. We find that, in such an order-driven market, seems to exist economies of scale in trading, with the fixed cost component being less important than the order processing cost. High-priced, high-capitalization stocks are the most liquid for both price impact measures. Generally speaking, there are indications that the price changes of high-capitalization stocks are less sensitive to trade sizes and transaction sequence. Finally the superiority of the extended model is demonstrated in an out-of-sample study by calculating a Liquidity Adjusted Value-at-Risk measure.

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	Table 1. Descriptive Statistics.					
Group	Aver. Spr.	Spr. SD	Trade Intens.	% Spread	Aver. Size/Trade	Time Bet. Trades
FTASE-20						
1	0.0368	0.0431	180	0.19	379	99
2	0.0256	0.0159	138	0.38	634	130
FTASE-40						
3	0.0720	0.1289	76	0.41	373	236
4	0.0216	0.0140	98	0.63	607	183

Table 1: Descriptive statistics for the 4 stock subgroups for the period February to December 2002. Specifically, presents the average spread (Aver. Spr), the standard deviation of the spread (Spr. SD), the transaction per day on average (Trade Intens.), the mean spread in terms of bid-ask midpoint (% Spread), the average size of a trade (Aver. Size/Trade) and the time between trades (Time Bet. Trades).

Table 2. Non-parametric tests.			
Absolute Spread			
	Observations	Median	Number above the Overall Median
FTASE-20 Group 1	275,199	0.02	127,272
FTASE-20 Group 2	211,229	0.02	97,518
FTASE-40 Group 3	25,726	0.04	18,162
FTASE-40 Group 4	232,153	0.02	66,888
Whole Sample	744,307	0.02	309,840
Kruskal-Wallis p_value:0			
Relative Spread			
	Size	Median	Number above the Overall Median
FTASE-20 Group 1	275,199	0.14	30,340
FTASE-20 Group 2	211,229	0.32	105,118
FTASE-40 Group 3	25,726	0.25	10,592
FTASE-40 Group 4	232,153	0.53	225,706
All	744,307	0.32	371,756
Kruskal-Wallis p_value:0			

Table 2: Non-parametric test for the absolute and the relative spread. (Sample period from February to December 2002.

Table 3. Intraday descriptive statistics.

Statistics	Time Intervals						P-Value of F-stat.
	11-11.30	11.30-12.30	12.30-13.30	13.30-14.30	14.30-15.30	15.30-16.00	
Panel A. FTASE-20 stocks with average price over €10							
Average Spread	0.0487	0.0361	0.0324	0.0323	0.0327	0.0438	0
Spread SD	0.0706	0.0404	0.0313	0.0306	0.0302	0.0535	
Trade Intensity	18	35	31	30	32	33	
% Spread	0.26	0.19	0.17	0.17	0.17	0.22	0
Average Trade Size	308	318	354	394	415	486	
Time Between Trades	70	199	217	234	219	55	
Panel B. FTASE-20 stocks with average price below €10							
Average Spread	0.029	0.025	0.024	0.024	0.024	0.029	0
Spread SD	0.022	0.013	0.011	0.012	0.015	0.021	
Trade Intensity	13	28	24	23	25	26	
% Spread	0.42	0.36	0.35	0.36	0.36	0.43	0
Average Trade Size	496	558	591	681	699	781	
Time Between Trades	86	249	280	300	280	71	
Panel C. FTASE-40 stocks with average price over €10							
Average Spread	0.118	0.074	0.059	0.065	0.056	0.085	0
Spread SD	0.131	0.078	0.057	0.258	0.052	0.094	
Trade Intensity	4	12	12	13	15	21	
% Spread	0.67	0.42	0.34	0.37	0.32	0.49	0
Average Trade Size	292	358	390	431	430	338	
Time Between Trades	109	464	547	588	525	112	
Panel D. FTASE-40 stocks with average price below €10							
Average Spread	0.024	0.021	0.020	0.020	0.021	0.024	0
Spread SD	0.018	0.013	0.011	0.012	0.012	0.018	
Trade Intensity	8	19	17	16	18	19	
% Spread	0.70	0.62	0.59	0.60	0.60	0.69	0
Average Trade Size	550	571	584	622	634	681	
Time Between Trades	109	345	435	446	414	113	

Table 3: Intraday descriptive statistics for the 4 stock subgroups (Sample period from February to December 2002). The description of the variables is given in table 1. The last column presents the p-values of the hypothesis that the average and the relative spread are equal during the trading day.

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Table 4. Panel A. Estimation results of the MRR model.						
	FTASE-20		Chi-square	FTASE-40		Chi-square
Components	Group 1	Group 2	p-value	Group 3	Group 4	p-value
ρ	0.2932	0.2818	0	0.4276	0.2580	0
SE	2.33E-03	2.53E-03		7.12E-03	2.27E-03	
θ	0.0075	0.0048	0	0.0176	0.0047	0
SE	6.49E-05	4.27E-05		5.14E-04	3.30E-05	
ϕ	0.0066	0.0052	0	0.0074	0.0038	0
SE	6.07E-05	4.11E-05		5.22E-04	2.99E-05	
Implied Spread	0.0282	0.0200		0.0500	0.0169	
γ	53,04%	48,48%		70,54%	54,92%	
Panel B. Summary statistics of the MRR model estimates of the parameters for the group members.						
Components	Group 1			Group 2		
	Average	Maximum	Minimum	Average	Maximum	Minimum
ρ	0.2995	0.4143	0.2067	0.2820	0.3338	0.2238
θ	0.0077	0.0199	0.0043	0.0054	0.0102	0.0027
ϕ	0.0064	0.0110	0.0054	0.0051	0.0060	0.0040
	Group 3			Group 4		
ρ	0.4200	0.4242	0.4159	0.2522	0.3022	0.0961
θ	0.0176	0.0191	0.0161	0.0057	0.0090	0.0023
ϕ	0.0077	0.0095	0.0059	0.0036	0.0074	0.0014

Table 4: Panel A presents the estimation results of the MRR model for the 4 stock subgroups (sample period from February 4 to December 30, 2002) and reports the p-value of a Wald within-index subgroup equality test. Panel B presents summary statistics of the MRR model estimates of the parameters for the four group members.

Table 5. Estimation results for the 6 intraday time intervals.

Statistics	Time Intervals						P-Value
	11-11.30	11.30-12.30	12.30-13.30	13.30-14.30	14.30-15.30	15.30-16.00	
Panel A. FTASE-20 stocks with price over €10							
ρ	0.2926	0.2772	0.2748	0.2789	0.2856	0.3334	0.00
SE	0.0062	0.0048	0.0049	0.0052	0.0051	0.0050	
θ	0.0106	0.0074	0.0069	0.0067	0.0068	0.0100	0.00
SE	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	
ϕ	0.0073	0.0063	0.0057	0.0063	0.0063	0.0068	0.00
SE	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	
Implied Spread	0.0360	0.0274	0.0253	0.0260	0.0262	0.0335	
γ	59.21%	54.15%	54.72%	51.80%	52.23%	59.36%	
Panel B. FTASE-20 stocks with price below €10							
ρ	0.2420	0.2637	0.2666	0.2780	0.2796	0.3220	0.00
SE	0.0068	0.0051	0.0054	0.0054	0.0054	0.0053	
θ	0.0068	0.0050	0.0044	0.0046	0.0045	0.0059	0.00
SE	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	
ϕ	0.0044	0.0048	0.0047	0.0048	0.0051	0.0053	0.00
SE	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
Implied Spread	0.0224	0.0196	0.0183	0.0187	0.0192	0.0224	
γ	60.48%	51.32%	48.67%	48.63%	47.15%	52.79%	

Table 5. Estimation results for the 6 intraday time intervals. (cont'd)

Statistics	Time Intervals						P-Value
	11-11.30	11.30-12.30	12.30-13.30	13.30-14.30	14.30-15.30	15.30-16.00	
Panel C. FTASE-40 stocks with price over €10							
ρ	0.4077	0.3901	0.3801	0.3656	0.3947	0.5299	0.00
SE	0.0245	0.0149	0.0153	0.0141	0.0141	0.0122	
θ	0.0333	0.0186	0.0158	0.0160	0.0147	0.0233	0.00
SE	0.0030	0.0010	0.0008	0.0009	0.0007	0.0012	
ϕ	0.0060	0.0050	0.0048	0.0051	0.0047	0.0053	0.86
SE	0.0026	0.0010	0.0008	0.0009	0.0008	0.0011	
Implied Spread	0.0787	0.0472	0.0411	0.0423	0.0387	0.0571	
γ	84.72%	78.69%	76.80%	75.76%	75.94%	81.54%	
Panel D. FTASE-40 stocks with price below €10							
ρ	0.2063	0.2200	0.2281	0.2375	0.2465	0.3562	0.00
SE	0.0061	0.0048	0.0049	0.0049	0.0047	0.0050	
θ	0.0063	0.0052	0.0046	0.0045	0.0046	0.0057	0.00
SE	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
ϕ	0.0030	0.0033	0.0035	0.0037	0.0036	0.0038	0.00
SE	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	
Implied Spread	0.0187	0.0170	0.0162	0.0163	0.0164	0.0189	
γ	67.59%	60.75%	57.04%	55.23%	56.36%	59.88%	

Table 5: Intraday estimation of MRR model for the 4 subgroups of stocks (sample period from February 4 to December 30, 2002). The p-value of a Wald test for differences between subgroups for estimated parameters is also reported.

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Table 6. Estimation results of the MRR model for the 1999 dataset.			
	FTASE-20		Chi-square
Components	Group 1	Group 2	p-value
ρ	0.3214	0.2155	0
SE	0.0028	0.0039	
θ	0.00059	0.00001	0.0133
SE	0.0002	0.00015	
ϕ	0.07165	0.04741	0
SE	0.0005	0.00040	
Implied Spread	0.144	0.095	
γ	0.82%	0.01%	

Table 6: Estimation results of the MRR model for the 2 subgroups of large cap stocks (sample period from June 1st to August 31st, 1999). The p-value of a Wald within-index subgroup equality test is also reported.

Table 7. Panel A. Estimation results of the volume dependent model.						
	FTASE-20		Chi-square	FTASE-40		Chi-square
Components	Group 1	Group 2	p-value	Group 3	Group 4	p-value
ρ	0.2906	0.2801	0.0018	0.4279	0.2557	0
SE	2.29E-03	2.50E-03		7.00E-03	2.23E-03	
θ	0.0003	0.0002	0	0.0007	0.0002	0
SE	2.68E-06	1.61E-06		2.37E-05	1.25E-06	
κ	-0.0002	-0.0001	0	-0.0003	-0.0001	0
SE	3.55E-06	1.91E-06		2.87E-05	1.42E-06	
ϕ	0.0124	0.0077	0	0.0175	0.0066	0
SE	9.13E-05	5.33E-05		6.14E-04	4.27E-05	
Minimum Trade Size	10	10		10	10	
Average Trade Size	379	634		373	607	
Implied Spread with min size	0.0252	0.0159		0.0376	0.0136	
Implied Spread with ave size	0.0267	0.0198		0.0502	0.0165	
γ with min size	6.96%	6.40%		12.21%	7.01%	
γ with ave size	40.36%	40.92%		55.80%	45.15%	

Panel B. Summary statistics of the augment model estimates of the parameters for the group members.						
Components	Group 1			Group 2		
	Average	Maximum	Minimum	Average	Maximum	Minimum
ρ	0.2918	0.4061	0.1977	0.2757	0.3293	0.2195
θ	0.0003	0.0017	0.0001	0.0002	0.0005	0.0001
κ	-0.0003	-0.0001	-0.0006	-0.0001	0.0000	-0.0002
ϕ	0.0124	0.0212	0.0086	0.0074	0.0098	0.0059
	Group 3			Group 4		
ρ	0.4141	0.4185	0.4097	0.2471	0.2949	0.1075
θ	0.0007	0.0008	0.0007	0.0002	0.0004	0.0001
κ	-0.0004	-0.0003	-0.0005	-0.0001	0.0000	-0.0003
ϕ	0.0163	0.0195	0.0131	0.0059	0.0133	0.0029

Table 7: Panel A presents the estimation results of extended model for the 4 stock subgroups (sample period from February 4 to December 30, 2002). The p-value of a Wald test for differences between subgroups for estimated parameters is also reported. Panel B demonstrates summary statistics of the augment model estimates of the parameters for the group members

Table 8. Estimation results for the Glosten and Harris specification.						
	FTASE-20		Chi-square	FTASE-40		Chi-square
Components	Group 1	Group 2	p-value	Group 3	Group 4	p-value
c_0	0.0139	0.0071	0	0.01613	0.00608	0
SE	6.94E-05	8.79E-05		1.98E-04	6.46E-05	
c_1	-0.00023	-0.00002	0	-0.00007	-0.00004	0
SE	3.87E-06	3.41E-06		1.01E-05	2.56E-06	
z_0	-	0.00256		0.00871	0.00280	0
SE	-	1.14E-04		2.44E-04	8.58E-05	
z_1	0.00024	0.00005	0	0.00010	0.00004	0
SE	3.40E-06	4.47E-06		1.30E-05	3.41E-06	
Minimum Trade Size	10	10		10	10	
Average Trade Size	379	634		373	607	
Implied Spread with min size	0.0279	0.0195		0.0499	0.0178	
Implied Spread with aver. size	0.0282	0.0208		0.0508	0.0180	
$\gamma$with min size	5.45%	27.86%		36.17%	32.97%	
$\gamma$with aver. size	33.15%	36.67%		41.67%	42.68%	

Table 8: Estimation results for the Glosten and Harris specification for the 4 stock subgroups (sample period from February 4 to December 30, 2002). The p-value of a Wald test for differences between subgroups for estimated parameters is also reported.

Table 9. Comparative results.				
	FTASE-20		FTASE-40	
	Group 1	Group 2	Group 3	Group 4
Information component				
MRR	0.0075	0.0048	0.0176	0.0047
Trade dependent MRR	0.0054	0.0041	0.0140	0.0037
Glosten-Harris	0.0047	0.0038	0.0106	0.0038
Cost component				
MRR	0.0066	0.0052	0.0074	0.0038
Trade dependent MRR	0.0080	0.0059	0.0111	0.0045
Glosten-Harris	0.0094	0.0066	0.0148	0.0052
Relative Proportion				
MRR	53.19%	48%	70.40%	55.29%
Trade dependent MRR	40.36%	40.92%	55.80%	45.15%
Glosten-Harris	33.15%	36.67%	41.67%	42.68%

Table 9: Comparative results for the three models (sample period from February 4 2002 to December 30, 2002.

Table 10. Intraday estimated parameters of the extended model.

Statistics	Time Intervals					
	11-11.30	11.30-12.30	12.30-13.30	13.30-14.30	14.30-15.30	15.30-16.00
Panel A. Large cap stocks with price > €10						
ρ	0.2899	0.2753	0.2718	0.2784	0.2805	0.3316
SE	0.0056	0.0045	0.0047	0.0048	0.0048	0.0047
θ	0.00040	0.00029	0.00027	0.00023	0.00022	0.00030
SE	1.08E-05	5.36E-06	4.78E-06	4.55E-06	4.47E-06	5.42E-06
κ	-0.00043	-0.00025	-0.00021	-0.00017	-0.00018	-0.00022
SE	1.48E-05	6.40E-06	5.87E-06	5.24E-06	5.61E-06	6.25E-06
ϕ	0.0168	0.0122	0.0108	0.0111	0.0114	0.0138
SE	3.25E-04	1.44E-04	1.48E-04	1.29E-04	1.39E-04	1.76E-04
Size	307	318	354	394	415	486
$\theta\sqrt{Size}$	0.00707	0.00523	0.00506	0.00454	0.00457	0.00665
$\phi+\kappa\sqrt{Size}$	0.00929	0.00768	0.00691	0.00768	0.00778	0.00897
Implied Spread	0.0327	0.0258	0.0240	0.0244	0.0247	0.0312
γ	43.21%	40.52%	42.26%	37.13%	37.00%	42.56%
Panel B. Large cap stocks with price < €10						
ρ	0.2398	0.2639	0.2654	0.2775	0.2775	0.3208
SE	0.0062	0.0047	0.0051	0.0050	0.0049	0.0048
θ	0.00024	0.00018	0.00015	0.00014	0.00014	0.00018
SE	5.67E-06	3.27E-06	2.98E-06	2.85E-06	2.65E-06	3.22E-06
κ	-0.00012	-0.00008	-0.00006	-0.00006	-0.00006	-0.00010
SE	7.25E-06	3.69E-06	3.52E-06	3.26E-06	3.07E-06	3.73E-06
ϕ	0.0081	0.0073	0.0068	0.0072	0.0074	0.0087
SE	1.82E-04	9.04E-05	9.04E-05	9.41E-05	9.10E-05	1.13E-04
Size	496	558	591	681	699	781
$\theta\sqrt{Size}$	0.00540	0.00415	0.00374	0.00374	0.00361	0.00502
$\phi+\kappa\sqrt{Size}$	0.00549	0.00549	0.00533	0.00558	0.00579	0.00600
Implied Spread	0.0218	0.0193	0.0181	0.0187	0.0188	0.0220
γ	49.57%	43.06%	41.19%	40.14%	38.41%	45.56%

Table 10. Intraday estimated parameters of the extended model. (cont'd)

	11-11.30	11.30-12.30	12.30-13.30	13.30-14.30	14.30-15.30	15.30-16.00
Panel C. Mid cap stocks with price > €10						
ρ	0.3997	0.3903	0.3766	0.3658	0.3935	0.5262
SE	0.0207	0.0138	0.0139	0.0127	0.0126	0.0112
θ	0.00128	0.00074	0.00057	0.00057	0.00053	0.00103
SE	1.36E-04	4.48E-05	3.15E-05	3.28E-05	3.01E-05	5.05E-05
κ	-0.00082	-0.00041	-0.00019	-0.00021	-0.00018	-0.00040
SE	1.38E-04	4.79E-05	3.91E-05	3.69E-05	3.58E-05	4.89E-05
ϕ	0.0297	0.0164	0.0123	0.0139	0.0118	0.0176
SE	2.53E-03	1.03E-03	7.91E-04	7.95E-04	7.46E-04	1.03E-03
Size	292	358	390	431	430	338
$\theta\sqrt{Size}$	0.02182	0.01397	0.01124	0.01176	0.01094	0.01894
$\phi + \kappa\sqrt{Size}$	0.01560	0.00857	0.00853	0.00959	0.00820	0.01027
Implied Spread	0.0749	0.0451	0.0396	0.0427	0.0383	0.0584
γ	58.32%	62.00%	56.86%	55.10%	57.17%	64.84%
Panel D. Mid cap stocks with price < €10						
ρ	0.2033	0.2176	0.2254	0.2343	0.2445	0.3564
SE	0.0056	0.0045	0.0045	0.0046	0.0043	0.0046
θ	0.00020	0.00017	0.00015	0.00014	0.00014	0.00018
SE	3.93E-06	2.40E-06	2.25E-06	2.32E-06	2.10E-06	2.69E-06
κ	-0.00012	-0.00010	-0.00008	-0.00008	-0.00008	-0.00010
SE	3.97E-06	2.85E-06	2.71E-06	2.67E-06	2.54E-06	2.96E-06
ϕ	0.0071	0.0064	0.0061	0.0064	0.0065	0.0072
SE	1.04E-04	7.94E-05	7.48E-05	7.94E-05	7.45E-05	8.50E-05
Size	550	571	584	622	634	681
$\theta\sqrt{Size}$	0.00462	0.00402	0.00364	0.00353	0.00361	0.00470
$\phi + \kappa\sqrt{Size}$	0.00420	0.00415	0.00424	0.00444	0.00436	0.00457
Implied Spread	0.0176	0.0163	0.0158	0.0160	0.0159	0.0185
γ	52.33%	49.18%	46.20%	44.31%	45.29%	50.71%

Table 10: Intraday estimation of our trade size extension model (sample period from February 4 to December 30, 2002).

Table 11. Cost impact function.				
	Groups			
Trade Size	1	2	3	4
1	0.058%	0.107%	0.097%	0.178%
10	0.056%	0.105%	0.093%	0.173%
100	0.048%	0.098%	0.080%	0.157%
500	0.035%	0.085%	0.057%	0.129%
1000	0.025%	0.076%	0.039%	0.107%

Table 11: Percentage of the median price explained by the cost component (sample period from February 4 to December 30, 2002) calculated as $\frac{\phi + \kappa\sqrt{V}}{MedianPrice}$.

Table 12. Order flow price impact function.						
Group 1. Large cap stocks with price > € 10						
		V_t					
		-1	-10	-100	-1000	-2000	-3000
V_{t-1}	1	-0.1180%	-0.1193%	-0.1235%	-0.1366%	-0.1446%	-0.1507%
	10	-0.1157%	-0.1170%	-0.1211%	-0.1343%	-0.1422%	-0.1483%
	100	-0.1082%	-0.1095%	-0.1136%	-0.1268%	-0.1347%	-0.1408%
	1000	-0.0845%	-0.0858%	-0.0900%	-0.1031%	-0.1110%	-0.1171%
	2000	-0.0702%	-0.0715%	-0.0756%	-0.0887%	-0.0967%	-0.1028%
	3000	-0.0591%	-0.0605%	-0.0646%	-0.0777%	-0.0857%	-0.0918%
Group 2. Large cap stocks with price < € 10						
		V_t					
		-1	-10	-100	-1000	-2000	-3000
V_{t-1}	1	-0.2171%	-0.2212%	-0.2341%	-0.2748%	-0.2994%	-0.3183%
	10	-0.2149%	-0.2190%	-0.2319%	-0.2726%	0.2972%	-0.3161%
	100	-0.2080%	-0.2120%	-0.2249%	-0.2656%	-0.2902%	-0.3091%
	1000	-0.1859%	-0.1899%	-0.2028%	-0.2435%	-0.2681%	-0.2871%
	2000	-0.1725%	-0.1766%	-0.1894%	-0.2301%	-0.2548%	-0.2737%
	3000	-0.1622%	-0.1663%	-0.1792%	-0.2199%	-0.2445%	-0.2634%
Group 3. Mid cap stocks with price > € 10						
		V_t					
		-1	-10	-100	-1000	-2000	-3000
V_{t-1}	1	-0.1997%	-0.2083%	-0.2353%	-0.3207%	-0.3725%	-0.4122%
	10	-0.1957%	-0.2042%	-0.2312%	-0.3166%	-0.3684%	-0.4081%
	100	-0.1828%	-0.1913%	-0.2184%	-0.3038%	-0.3555%	-0.3952%
	1000	-0.1421%	-0.1507%	-0.1777%	-0.2631%	-0.3148%	-0.3546%
	2000	-0.1175%	-0.1260%	-0.1530%	-0.2384%	-0.2902%	-0.3299%
	3000	-0.0986%	-0.1071%	-0.1341%	-0.2195%	-0.2713%	-0.3110%
Group 4. Mid cap stocks with price < € 10						
		V_t					
		-1	-10	-100	-1000	-2000	-3000
V_{t-1}	1	-0.3611%	-0.3673%	-0.3870%	-0.4491%	-0.4868%	-0.5157%
	10	-0.3561%	-0.3623%	-0.3820%	-0.4442%	-0.4818%	-0.5107%
	100	-0.3404%	-0.3466%	-0.3662%	-0.4284%	-0.4660%	-0.4949%
	1000	-0.2905%	-0.2967%	-0.3164%	-0.3785%	-0.4162%	-0.4451%
	2000	-0.2603%	-0.2665%	-0.2862%	-0.3483%	-0.3860%	-0.4149%
	3000	-0.2371%	-0.2433%	-0.2630%	-0.3251%	-0.3628%	-0.3917%

Table 12: Percentage price changes from trade reversals of different sizes (sample period from February 4 to December 30, 2002.

Table 13. Average number of violations for the four subgroups.		
VaR	L-VaR (MRR)	L-VaR (Volume)
Group 1		
5.89	5.44	5.33
Group 2		
5.22	4.56	4.33
Group 3		
10.00	7.50	6.00
Group 4		
7.45	6.27	5.27

Table 13: Out-of-sample average number of violations for each group and for the 99% confidence level of the three risk models: VaR (equation 7), MRR L-VaR (equation 8) and a Volume L-VaR (equation 6). The out-of-sample period is from January 2nd, 2003 to March 31th, 2004.