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THE EFFECT OF THE MARKET ON STOCK'S SPREAD: THE CASE OF THE ATHENS STOCK EXCHANGE

By

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Abstract

This paper presents a portfolio trading model which attempts to explain changes in market spread due to general market conditions. For 18 large and 13 medium capitalization stocks in the Athens Stock Exchange (ASE), we estimate the adverse selection and the order handling component of the bid-ask spread as well as the probability of a same side trade continuation based on a portfolio model of price formation which combines the work of Madhavan et al. (1997) and Huang and Stoll (1997). We find that, information coming out of the movements of the general ASE index does not affect significantly the low cap stocks, while there are indications this is not the case for high capitalization shares.

Keywords: Bid-Ask Spread, Asymmetric Information (JEL Nos: D4, C1).

Introduction

In an influential paper, Huang and Stoll (1997) developed a structural model of price formation in order to decompose the spread into components due to three factors: (1) order processing, (2) inventory, and (3) adverse information. Their empirical results supported the presence of a *large* order processing component and a *smaller* adverse selection and inventory ones. They also argued that changes in prices arise not only from order flow innovations, but also from

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changes in related stocks or indexes. In order to accommodate these effects into their model, they postulate that a market maker (or anyone supplying liquidity) will not only alter the bid-ask prices of the traded stock but also of other correlated securities in the attempt to hedge his/her initial position.

In an independent work, Madhavan et al. (1997) (MRR) showed that security prices change due to: (1) new arrival of public information, and (2) the trading process itself. They pointed out that information asymmetry stemming out of the first factor declines during the day, while transaction costs increase. Chan (2000) substantiated this decrease (increase) of the adverse selection component at the New York Stock Exchange, since average trading volume decreased (increased). He then used data from the Hong Kong Stock Exchange and concluded that, in the latter market, 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 smaller cap, high tech NASDAQ stocks and concluded that the inventory cost component dominated the adverse selection one. Finally, Declerck (2000) studied the spread components of the French CAC 40 index stocks and found out that order processing explains 82% of the spread.

In this paper, we present a price formation model, like the one in Huang and Stoll (1997), but for portfolio trading since anecdotal evidence suggests investors trade shares of one company only because other shares in the same industrial sector or index trade at the same time period as well. Using that model for stocks in the Athens Stock Exchange (ASE), we find indications that (a) the general market information component is statistically important *only* in high capitalization stocks and, (b) adverse selection is the most important factor affecting the bid-ask spread.

The remainder of the paper is organized as follows. The next section briefly describes the trading process of the ASE and presents the data, while section 3 demonstrates the portfolio-trading model. The final section concludes the paper.

Dataset

The Athens Stock Exchange (ASE) is the unique official stock market in Greece. At the end of year 2002, approximately 375 companies were listed in it, with a total capitalization approaching € 85.5 billion. Only ASE Members (i.e., security brokerage houses, credit institutions,etc.) can execute purchase and sale orders for shares through the Integrated Automatic Electronic Trading System (OASIS) of the market.

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. Liquidity is therefore practically provided only through the entry of different types of orders without the intermediation of market makers, while orders are ranked first by price priority and then by arrival time stamp. The tick size allowed equals 1 cent for securities with a price up to € 2.99, 2 cents for securities up to € 59.99 and 5 cents for the rest.

Transaction data used in this study were drawn from intraday transaction data files of the ASE for the period from February 4, to December 30, 2002. It contained, for all securities traded in that period, the time-stamped price to the nearest second, volumes, and the highest bid and the lowest offer with their corresponding sizes just before a transaction occured. Our stock sample was picked first out of the two major equity indexes, the FTASE-20 and FTASE-40, representing the large and medium capitalization companies respectively.[1] For each index, we classiffied stocks in two independent groups: the first one included those with an average price greater than (or equal to) € 10 and the second those with an average sample price less than € 10.[2] Members of each group and their average price for the chosen time period are presented in Table 1.

TABLE 1

Sample stocks of the four subgroups and their average price

FTASE-20				FTASE-40			
Group 1		Group 2		Group 3		Group 4	
Reuter's Code	Price	Reuter's Code	Price	Reuter's Code	Price	Reuter's Code	Price
EFGr.AT	13.03	ETBr.AT	3.31	INLr.AT	17.44	VAL.AT	2.55
DEHr.AT	13.75	PANr.AT	5.77	FOLr.AT	18.06	DOLr.AT	2.85
HLBr.AT	15.41	HEPr.AT	6.07			EGNr.AT	3.22
ACBr.AT	17.02	HELr.AT	6.15			SINr.AT	3.49
OTEr.AT	17.45	VIO.AT	6.41			EPAr	3.56
NBGr.AT	22.55	BOPr.AT	6.99			OLYr.AT	3.59
CBGr.AT	23.2	INRr.AT	9.65			MYTr.AT	3.63
ALGr.AT	28.43	OPAr.AT	9.69			MTKr.AT	4.31
TTNr.AT	38.16	COSr.AT	9.87			EXCr.AT	4.43
						EYDr.AT	5.00
						AKTr.AT	6.01

Table 1: Stocks studied for the period 02/02 to 12/02. "Price" means here the average daily closing price in that time period. Groups 1 and 3 include stocks with average price over € 10 that belong to the FTASE-20 and the FTASE-40 indexes respectively. Groups 2 and 4 include stocks, belonging to the same indexes, with average price less than € 10.

We have eliminated open quotes for all stocks from the dataset, since the mechanism governing the opening period of the ASE is a Walrasian call market, clearly different from the continuous call auction used throughout the day.[3] We also eliminated all trades where the bid was greater than the corresponding ask, for it was clearly due to noise in the data, as well as all those trades where the time stamp was evidently erroneous. We also grouped all trades conducted at the same time and at the same price as a single trade (following Chan (2000)). Last, we classified all trades as either buy-or sell-oriented using a slightly different criterion than the simple "tick" rule, namely that a transaction is considered to be buy-side (sell-side) generated if its execution price is higher (lower) than the mean of the prevailing bid-ask quotes.[4]

Table 2 presents summary statistics for the four subgroups. Stocks in Group 1 are the most active, irrespective on whether we look at trade intensity (180 transactions per day on average) or 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 i.e., high cap but low price stocks, are less liquid: there are fewer transactions per day and their average percentage spread is twice that of the first group. On the contrary, for medium capitalization stocks, a liquidity ranking is not that clear: trade intensity and time between trades favor the low priced subgroup 4, while relative spread favors the high priced subgroup 3. Overall, stocks in the FTASE-40 index are less actively traded than the corresponding large cap FTASE-20 index, as both relative spread and time between trades are greater while trade intensity is lower.

TABLE 2

Descriptive Statistics

Grp	Avg Spread	Spread SD	Intensity	% Spread	Avg Size	Time Between 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 2: Descriptive statistics for the 4 stock subgroups for the period February to December 2002.

Portfolio model of price formation

Madhavan et al. (1997) argued that the factors moving prices are (a) the arrival of new public information, and (b) the "order of trade" indicator which 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-generated, and -1 if it is sell-generated. The coefficient $\varphi > 0$ represents the cost per share of the liquidity supplier, θ measures the degree of information asymmetry and μ_t is the expected value of the stock. We assume a standard inventory cost model of market making, modelled as $p_t = \mu_t + \varphi X_t$, and an information asymmetry model for the stock's fundamentals: $\mu_t = \mu_{t-1} + \theta(X_t - \varrho X_{t-1})$. Combined, they produce the following intraday price change model:

$$p_t - p_{t-1} = (\varphi + \theta)X_t - (\varphi + \varrho\theta)X_{t-1} + ut \tag{1}$$

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

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

$$aX_t{=}1 = \mu_{t-1} + \theta[1 - \mathrm{E}(X_t \mid X_{t-1})] + \varphi$$

$$bX_t = -1 = \mu_{t-1} - \theta[1 + \mathrm{E}(X_t \mid X_{t-1})] - \varphi$$

$$aX_t{=}1 - b_{X_t} = -1 = 2[\theta + \varphi]$$

Changes in prices arise, however, not only from order flow innovations, but also from changes in the price of related stocks or indices. In particular, selling or buying pressures in the market will produce quote changes in specific stocks, because liquidity suppliers attempt to keep their overall portfolios in balance. We, hence, extend the MRR model by posing that:

$$p_t = \mu_t + \varphi X_t$$

$$\mu_t = \mu_{t-1} + \theta(X_t - \varrho X_{t-1}) + \eta Y_t,$$

The intraday model of price movements then becomes:

$$p_t - p_{t-1} = \theta(X_t - \varrho X_{t-1}) + \varphi(X_t - X_{t-1}) + \eta Y_t + u_t, \quad (2)$$

where Y_t is the aggregate buy-sell indicator variable based on the General Index of the ASE and η is the degree of asymmetric information produced by general market conditions. It should be noted that the ASE General Index is a market cap weighted index that includes all listed stocks and is the most widely media-followed index in the country, despite its weaknesses. Equation (1) is a special case of equation (2) when there are no spillover effects from other stocks ($\eta = 0$)

This approach will not only distinguish the adverse selection (θ) and the cost compone (φ) of the spread, but will also reveal the importance, if any, of buying and selling pressures in the process of the bid/ask adjustment. Specifically, our model (2) assumes that the adverse selection component is not only produced by the order flow for the *stock,* but also depends on the sign of trades in the *entire* market. The implied spread falls into one of the following four cases:

$$\left.\begin{cases} a_t(X_t = 1, Y_t = 1) = \mu_{t-1} + \theta + \eta + \varphi \\ b_t(X_t = -1, Y_t = -1) = \mu_{t-1} - \theta - \eta + \varphi \end{cases}\right\} \Rightarrow \text{Spread} = 2(\theta+\eta+\varphi)$$

$$\left.\begin{cases} a_t(X_t = 1, Y_t = -1) = \mu_{t-1} + \theta - \eta + \varphi \\ b_t(X_t = -1, Y_t = 1) = \mu_{t-1} - \theta + \eta - \varphi \end{cases}\right\} \Rightarrow \text{Spread} = 2(\theta-\eta+\varphi)$$

$$\left.\begin{cases} a_t(X_t = 1, Y_t = 1) = \mu_{t-1} + \theta + \eta + \varphi \\ b_t(X_t = -1, Y_t = 1) = \mu_{t-1} - \theta + \eta - \varphi \end{cases}\right\} \Rightarrow \text{Spread} = 2(\theta+\varphi)$$

$$\left.\begin{cases} a_t(X_t = 1, Y_t = -1) = \mu_{t-1} + \theta - \eta + \varphi \\ b_t(X_t = -1, Y_t = -1) = \mu_{t-1} - \theta - \eta - \varphi \end{cases}\right\} \Rightarrow \text{Spread} = 2(\theta+\varphi)$$

An investor who is willing to buy a stock from a "market maker" at the ask price, is expected to execute his trade at midquote$+\theta + \varphi$, based on the MRR model. In the case of buying pressures, however, the seller of the stock must adjust his ask price upwards by η, because of the positive correlation between the general index and the stock. If he does not do so, he loses the opportunity of a higher price sale, fostered by optimistic market conditions. On the other hand, if there are selling pressures in the market, he must lower his bid price by η, as he expects to buy if back later at a still lower price due to the general price decline. Based on these relations, the mean value of the implied spread is now defined as $2(\theta + \eta + \varphi)$. The other three cases lead to the respective implied spreads shown above.

We estimate equation (2) by using the Generalized Method of Moments (GMM) methodology, which 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's fundamental moment condition is $E(f(\chi_t, \theta_0)) = 0$, where $f(\chi_t, \theta_0)$ is a q X 1 vector function and θ_0 is a p-dimensional parameter vector. The estimated GMM parameters ($\hat{\theta}_T = argmin_\theta Q_T(\theta)$) are calculated by minimizing the function $Q_T(\theta) = f_T(\chi t, \theta)' A_T f_T(\chi_t, \theta)$, where $f_T(\chi t, \theta)$ is the sample mean vector and AT is the sample symmetric weighting matrix. They are weakly consistent and asymptotically normally distributed. For our specific equation (2), we set the following moment conditions:

$$E\begin{Bmatrix} X_t X_{t-1} - \varrho X_{t-1}^2 \\ u_t - a \\ (u_t - a)X_t \\ (u_t - a)X_{t-1} \\ (u_t - a)Y_t \\ (u_t - a)Y_{t-1} \end{Bmatrix} = \theta, \tag{3}$$

with α a constant. The first condition defines the autocorrelation of the trade variable and the last five are the standard OLS equations with a lagged trade indicator and a constant used as instrumental variables.

3.1 Empirical Results

Our method divides the trading day in 15-minute time intervals for all trades of all four stock subgroups, in order to align the trading time for stocks.[5] The trade indicator variables X_t and Y_t were set equal to either +1 or -1, if the transaction price was higher or lower than the previous one, and to zero if the price of the security did not change during the 15-minutes time interval.

Results and corresponding p-values of the Wald test are displayed in Table 3. Estimated parameters from the portfolio model indicate the following findings:

1. For all stock subgroups, the probability of a trade reversal - from a trade at the bid (ask) to a trade at the ask (bid) - is larger than 50%. Note that this

probability, in the MRR structural model, is defined equal to $\pi = \frac{1-\varrho}{2}$. This means traders prefer *not* to execute their trades in sequential time intervals. It also points that the well-known practice of institutional traders to break up large trades to smaller ones, in order to limit their price impact, does not seem to last for more than 15 minutes. Huang and Stoll (1997) and Kim et al. (2002) report similar trade reversal probabilities from 58% to 97%, after bunching related data.

2. The spread proportion explained by asymmetric information, defined as $\gamma = \theta/(\theta + \varphi)$ is reported in Table 3. It is expected to be quite large, due to anonymous trading, until at least the final trade execution. As Foster and George (1992) showed, anonymity is thought to increase information asymmetry: if traders are not fully anonymous and instead make their trading motivations widely known, the bid-ask spread and the price impact are expected to be lower than a fully anonymous market. This conclusion is also supported by the work of Admati and Pfleiderer (1991). In our case, this proportion is close to 87%, meaning investors rather neglect the cost component implicit in the spread and put higher weight in the adverse selection ingredient.

TABLE 3

Estimation results of the portfolio trading model

	FTASE-20		Chi-square	FTASE-40		Chi-square
Components	**Group 1**	**Group 2**	**p-value**	**Group 3**	**Group 4**	**p-value**
ρ	-0.0893	-0.1540	0	-0.0659	-0.1332	0
SE	0.0061	0.0058		0.0046	0.0129	
θ	0.0549	0.0310	0	0.0936	0.0306	0
SE	0.0009	0.0004		0.0037	0.0003	
η	0.0032	0.0042	0.0086	0.0011	0.0001	0.59
SE	0.0004	0.0002		0.0018	0.0001	
φ	0.0018	0.0008	0.0020	0.0088	0.0046	0.14
SE	0.0003	0.0001		0.0028	0.0001	
γ	0.96	0.97		0.91	0.87	

Table 3: Estimation results for the portfolio trading model (sample period from February 4 to December 30, 2002. ρ is the first-order autocorrelation of X_t (X_t is the "trade indicator" variable, equaling +1 if the trade is buy-oriented, and -1 if it is sell-oriented), θ measures the degree of information asymmetry, η is the degree of asymmetry information that is generated by the general conditions of the market. $\varphi \geq 0$ represents the cost per share of the market maker in supplying liquidity on demand. ($\gamma = \theta/(\theta + \varphi)$ describes the proportion of spread that is explained by asymmetric information.

3. The information asymmetry parameter (η) describing general market conditions is positive and statistically significant at all usual confidence levels, but differs between the two high capitalization stock subgroups 1 and 2. Given our previous discussion, we find a liquidity supplier must increase (decrease) the ask (bid) price by € 0.0032 and € 0.0042 for subgroups 1 and 2 respectively, if there are buying (selling) pressures in the ASE. On the other hand, for the two medium capitalization stock subgroups, (η) is statistically insignificant (and equal for the two subgroups). Therefore, it seems that no "market pressure adjustment" is necessary: the spread mechanism for midcap stocks is not affected by market movements.

Conclusions

We investigate the bid-ask spread behavior of the Athenian order-driven Stock Exchange. For the 11-month period from February to December 2002, we analyze high frequency transaction level data for four independent stock groups, sorted by their average transaction prices and their capitalization. We then build a portfolio model that tries to explain spread adjustment due to changes in general market conditions. The effect on one stock's spread of trading pressures in other stocks is statistically significant only for high - capitalization stocks. This may due to the fact that, despite its inclusion of all stocks listed with the ASE, the ASE General Index impacts much more blue chips than medium cap stocks. On the other hand, asymmetric information on the given stock affects predominantly its bid-ask spread for lower-capitalization shares in such an anonymous market.

Notes

1. FTSE-20 is the Large Cap Index, featuring the 20 largest blue chip companies. FTSE-40 follows the performance of the next 40 larger capitalization companies.

2. Though a tick size classification rule would have been more appropriate, this was not possible as there were not enough stocks in each category.

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

4. Aitken and Frino (1996) also reported that the "tick" rule accuracy was not as high as Lee and Ready (1991) had previously stated.

5. We did not use a 5-or a 10-minute trading interval due to thin trading for some stocks.

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