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LIQUIDITY, PRICE IMPACT AND TRADE INFORMATIVENESS – EVIDENCE FROM THE LONDON STOCK EXCHANGE

ABSTRACT: *The rapid development of electronic trading has significantly changed stock exchange markets. Electronic systems providing trading processes have defined a new stock market environment. Such a new environment requires trading process redefinition (generally defined as algorithmic trading), as well as redefinition of well known microstructure hypotheses. This paper conducts standard Hasbrouck's (1991a, 1991b) market microstructure time series analysis to examine adverse selection and information asymmetry issues on diverse liquidity levelled stocks listed on the London Stock Exchange, which is a market with a significant algorithmic trading share. Based on the results obtained from the considered sample, this paper suggests that the contribution of unexpected trade in the volatility of the efficient price is larger for intensively traded stocks, arguing that Hasbrouck's (1991a, 1991b) model recognizes algorithmic trading as an unexpected trade, i.e. as a trade caused by superior information.*

KEY WORDS: *liquidity measures, price impact, trade informativeness, algorithmic trading*

JEL CLASSIFICATION: C02, C10, C32, C60, D80, D82

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1. INTRODUCTION

The rapid development of electronic trading in recent years has significantly improved the process of transferring securities from one market participant to another. Electronic trading enables a large number of participants to interact in the market, decreases transaction costs, improves the speed of trade execution, and also requires participants' fast reaction to any new information. Such powerful technological improvements have led to more sophisticated trading - algorithmic trading. Algorithmic trading usually refers to the use of computer algorithms to break up a large order into a sequence of smaller orders, and the engagement of automated trading strategies for their execution with respect to numerous user-defined parameters, such as time horizon, liquidity constraints, depth of market, volatility, etc. The overwhelming trend in recent years has been to create unique trading algorithms that need to be tested and applied in the market as quickly as possible, due to fast market changes.

Such a new financial environment requires the reinvestigation of market microstructure hypotheses. The market microstructure concept has been defined in various ways, by focusing on diverse aspects of it. It follows the definition given by O'Hara (1995), "market microstructure is a study of the process and outcomes of exchanging assets under a specific set of rules. Microstructure theory focuses on how specific trading mechanisms affect the price formation process." The main objective in this paper is the information aspect of market microstructure.

Market microstructure hypotheses are typically empirically tested by vector autoregressive (VAR) models (Hasbrouck (2007), Kunst (2007), Lütkepohl (1993)). In the empirical market microstructure literature two approaches are predominant when studying the impact of trades on price formation. The first one is the approach for investigating the effects of trade informativeness on price formation, based on the vector autoregression of return and trade equation. The second one is the extension of Hasbrouck's (1991a) model by incorporating the waiting time (duration) between successive transactions given by Engle et al. (2000). This model was used to empirically test the role of duration in the process of price formation in the sample of stocks traded on the

New York Stock Exchange (NYSE). The time between trades is modelled by the autoregressive conditional duration (ACD) model (Engle (1998)). To model duration, volume, and returns simultaneously, Manganelli (2005) introduced the model which provides a link between Hasbrouck (1991a) and Engle et al. (2000), by incorporating the trade sign into the specification of mean of return and adding an extra equation for the trade sign. The model is tested on the sample of NYSE stocks.

The theoretical background of the approaches of Hasbrouck (1991a, 1991b), Engle et al. (2000), and Manganelli (2005) to the effects of trades to price formation is the theory of the asymmetrically informed market, which basically criticizes the efficient market hypothesis. The efficient market hypothesis assumes that a market is anonymous and all the participants in the market are equally informed about the traded instrument. Therefore, no participant can make economic profit by trading such information, and information contained in trades is immediately reflected in stock prices. However, these assumptions would hardly hold in practice. In reality, all information is not available to all participants at the same time; hence some market participants have a definite advantage over the others. Moreover, although information is public, there is still a difference in the speed of processing them by various participants, which produces a lag effect between the news announcement and trade realization.

Traders may be classified into informed traders - traders with superior information - and uninformed or liquidity traders - traders with public information only. Informed traders may possess information on the true value of securities, fundamentals, or quantities. They tend to trade the specific stock on which they have private information. Liquidity traders trade to decrease costs or to adjust the risk return profiles of their portfolios. They buy stocks if they have excess cash or become more risk tolerant, and they sell stocks if they need cash or become less risk tolerant. The presence of informed and uninformed traders causes an asymmetric distribution of information among market participants. Bagheot (1971) was the first to consider a market with heterogeneously informed traders. This problem was then analyzed by Copeland et al. (1983) and formulated and developed by Kyle (1985), Glosten et al. (1985), Easely et al. (1987), Admati et al. (1988), and Foster et al. (1990), among others.

Hasbrouck (1991a, 1991b) analyzed the influence of an asymmetric distribution of information among market participants on future price formation. In a market with asymmetrically informed participants the market environment is measured by bid-ask spread and the trade is described by its direction - positive if the trade is buyer-initiated and negative if the trade is seller-initiated. The concept of an asymmetrically informed market implies that market makers possessing only public information interact with other market participants who have superior private information. The informed and uninformed traders are undistinguishable to market makers. Hence they compensate for the loss that appears from trading with informed traders by fixing a spread. The main idea of the model is that the trade conveys information and that market makers post bid and ask prices after the realized transaction and with respect to that information. The model is represented by the vector autoregression system of the return and trade equation based on both price and order flow history. Taking into consideration such a system the effect of public and private information on price formation is analyzed, and the transitory and permanent price impact is identified. Hasbrouck's (1991a, 1991b) empirical findings from the sample of NYSE stocks indicate that the effect of permanent price impact is not instantaneous and that it takes several transactions before it is fully realized. By using the impulse response technique (Hasbrouck (2007), Kunst (2007), Lütkepohl(1993), Hasbrouck constructed the permanent price impact as a cumulative response of return to a shock in the innovation of trade equation, where private information must arise if such exists. Also, by the variance decomposition technique (Hasbrouck (2007), Kunst (2007), Lütkepohl(1993)) he calculated the contribution of private information, i.e. unexpected trade to variation in efficient price.

Information asymmetry influences the bid-ask spread in the market and hence the liquidity. Before the information is publicly available the spread tends to be wider, producing a lot of market volatility. The informed traders, knowing that the spread will narrow once the information becomes public, tend to take the liquidity from the market by executing trades at the available price.

The described concept of the asymmetrically informed market basically coincides with the classical market, or the so-called quote-driven market. In such a market, market makers have an obligation to continuously quote two-way prices at which they are prepared to buy and sell a security. In this way they fill gaps arising from imperfect synchronization between the arrival of buyers and sellers. They are the counterpart in all transactions at the quoted prices: the bid price, at which they are willing to buy securities, and the ask price, at which they are willing to sell. They are the only providers of liquidity in the quote-driven market.

The development of electronic trading technology in recent years has led to a rapid spread of so-called order-driven trading. In an order-driven market there are no designated market makers. Any trader can choose to execute trade via a limit[1] or a market[2] order. They input buy and sell orders for a security into a central computer system where they are automatically executed whenever they can be matched in terms of price and amount.

In this paper we were interested in the informational aspect of price formation across diverse liquidity levelled stocks traded on the London Stock Exchange (LSE), which is predominately an order-driven market. We chose the sample of 18 LSE stocks with different liquidity levels from the FTSE 100 index - the share index of the 100 largest publicly quoted UK companies. The trading process of FTSE 100 stocks is provided by the stock electronic order driven system, called the Stock Exchange Trading System, or SETS. The SETS is an order-matching system based on the concept of priority trading, where orders are ranked in priority of price, then in time within the price. The order book is conveyed publicly in real time. As a result the market benefits from pre-trade transparency, which means that participants have access to the whole order book, and post-trade transparency, which means that participants can immediately observe the last trades recorded by the system. On the other hand, orders and trades are mostly anonymous. Regarding liquidity and price settings, the order-driven market is significantly different from the classical quote-driven

1 A limit bid or ask stock price at which the transaction has to be executed.

2 A buy or sell order of a certain number of stocks at the current standing (bid or ask) price.

market. Limit orders allow a trader to set a limit price at which the order can be filled, but there is a risk the order will not be executed. Therefore liquidity and price (bid, ask) settings in an order-driven market rely only on limit orders. Interaction between market participants in the electronic stock-driven system environment becomes much more complex, requiring the development of dynamic trading strategies or algorithms that consider everything that can affect price formation. At the London Stock Exchange there is a significant proportion of algorithmic trading. According to the International Banking Systems Journal (June 2007), in 2006 over 40% of all orders were entered by algorithmic traders, with 60% predicted for 2007. Algorithmic trading influence on market microstructure has recently been investigated by Hasbrouck et al. (2007), Bloomfield et al. (2005), and Payne (2003), among others.

In the chosen sample we considered different liquidity dimensions according to several liquidity measures - volume, trade size in pounds, duration, and flow ratio. Following Hasbrouck (1991a, 1991b)} and Payne (2003), the total permanent price impact and contribution of unexpected trade in volatility of the efficient price are calculated for all 18 stocks. To enable the comparison of estimated permanent price impact across different stocks, a slight modification of the return variable in Hasbrouck's (1991a) model is applied. Applying the Spearman rank correlation test, the obtained results are compared with results on liquidity across different stocks.

Results obtained from the considered sample of 18 LSE stocks suggest that the contribution of unexpected trade in the volatility of the efficient price is larger for intensively traded stocks, where trade intensity is measured by duration and flow ratio. Also, we did not find any significant correlation between these liquidity measures and permanent price impact. We suggest that such results can be explained by algorithmic trading. It is expected that the proportion of algorithmic trading is larger for intensively traded stocks. Therefore in this paper we suggest that algorithmic trading behaves as an unexpected trade in Hasbrouck’s model (1991a, 1991b).

The paper is organized as follows. Section 2 presents Hasbrouck's model of permanent price impact and contribution of unexpected trade in efficient price volatility. Section 3 describes the data we used in our analysis as well as the cleaning procedure. Section 4 describes variables for liquidity and Hasbrouck's analysis. The estimation procedure is also described. The results are given in Section 5. Finally, Section 6 summarizes and concludes.

2. THE MODEL

We followed Hasbrouck's (1991a) basic vector autoregression model to examine different information components in price changes. For a sample of NYSE stocks Hasbrouck considered the following trading mechanism. The transaction x_t is realized at time t and at price p_t After the transaction and announcement of trade x_t the market makers post bids and ask quotes denoted by p_t^b and p_t^a. In this notation the transaction realized at time t is realized at the bid or ask price prevailing before that transaction, denoted by p_{t-1}^b and p_{t-1}^a. Midquote

$$m_t = \frac{p_t^a + p_t^b}{2}$$

is taken as an unbiased proxy of the efficient price. The change in the natural logarithm of the midquote that follows the current trade at time t

$$r_t = \ln(m_{t-1}) - \ln(m_t)$$

is considered as a return variable. For the trade variable Hasbrouck suggested a trade indicator variable which takes value 1 if the trade is buyer initiated, and value -1 if the trade is seller initiated. The return and trade dynamic is modelled as a non-standard bivariate vector autoregression VAR

$$r_t = a_1 r_{t-1} + a_2 r_{t-2} ... + b_0 x_t + b_1 x_{t-1} + ... + v_{1,t} \tag{1}$$

$$x_t = c_1 r_{t-1} + c_2 r_{t-2} ... + d_1 x_{t-1} + .d_2 x_{t-2} .. + v_{2,t} \tag{2}$$

Theoretically, this model can be of infinite order, but for practical purposes it is truncated at some lag.

Coefficient b_0 in the return equation represents the immediate impact of contemporaneous trade x_t . Coefficients b_i, i=1, 2,… in the same equation capture transitory trade and effect prices. The innovation term $v_{1,t}$ represents the effect of non-trade public information. The innovation in the trade equation $v_{2,t}$ captures an unexpected transaction activity where the private information resides, if such exists. The model assumes predetermined regressors, i.e. that the innovations $v_{1,t}$ and $v_{2,t}$ are uncorrelated with regressors. Also, it is assumed that they have zero mean, i.e. that $E(v_{1,t}) = E(v_{2,t}) = 0$.

In addition, it is assumed that they are jointly and serially uncorrelated

$$E(v_{1,t}v_{1,s}) = E(v_{2,t}v_{2,s}) = E(v_{1,t}v_{2,s}) = 0, \textit{ for all } t \neq s$$

The described VAR model is not entirely standard since it assumes that a market maker has information on all lagged returns and lagged trades, as well as information on contemporaneous trades available at time t. That means that return r_t contains all publicly available information at time t, and that market makers act primarily on this information set. This model permits Granger's causality (1963) running from trade to return both contemporaneously and with lags. The model also permits Granger's causality running from the lagged returns to trades, but it does not permit contemporaneous causality running from returns to trades. The presence of contemporaneous trade x_t, and the assumption of predetermined regressors implies that errors are contemporaneously orthogonal, i.e. $E(v_{1,t}) = E(v_{2,t}) = 0$, which does not hold for the standard VAR model in general. Under assumptions of predetermined regressors and contemporaneous orthogonality of errors $v_{1,t}$ and $v_{2,t}$, the least squares estimation of the described VAR model is consistent and efficient.

Hasbrouck formally defined the informational impact of the trade as the ultimate impact on the stock price resulting from an unexpected component of the trade, i.e. the persistent price impact of the trade innovation. This impact will probably not be instantaneous, but rather occurs over a long period of time and will be permanently impounded in the stock prices. Hasbrouck (1991a) obtained the permanent price impact by calculating the impulse responses from the moving average representation as in Hasbrouck (2007), Kunst (2007), Lütkepohl (1993) of the system (1), (2).

Under a weak stationarity assumption of time series system (1), (2), by Wold's (1938) theorem the VAR is invertible and it has the vector moving average representation of an infinite order given by

$$r_t = v_{1,t} + a_1^* v_{1,t-1} + \ldots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + \ldots \qquad (3)$$

$$x_t = c_1^* v_{1,t-1} + \ldots + v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} \ldots \qquad (4)$$

The impulse response coefficients b_i^*, i=1, 2,... give the effect of a unit trade innovation on the return at an i period horizon. The sum $\sum_{i=0}^{l} b_i^*$ represents the impact of an unexpected trade on returns after l transactions. The cumulative sum of impulse responses creates the price impact function. Since the model operates with the data indexed in tick time, the price impact is measured in units of transactions. Hasbrouck's (1991a) estimates for a sample of NYSE stocks suggest that the price impact takes many periods before it is fully realized, and that the price impact function is concave with positive horizontal asymptote. The asymptote of price impact function represents the total price impact of the trade.

To measure a proportion of the unexpected trade in the future price formation, Hasbrouck (1991b) assumed that the midquote may be divided into two unobservable components $m_t = e_t + s_t$

The term e_t is the efficient price that is the expected value of the asset conditional on all currently available public information modelled as a random walk process

$$e_t = e_{e-1} + \omega_t$$

Efficient price is the permanent component of the midquote. The white noise innovation $\omega_t \sim WN(0, \sigma_\omega^2)$ reflects updates to the public information set. The second component s_t is a zero mean stochastic process jointly covariance stationary with ω_t. It is a transitory component of the midquote. It represents the disturbance term that incorporates inventory control, price discreteness, and other market imperfections that drive the midquote away from the efficient price. Since the random walk decomposition is unobservable, Hasbrouck(1991a) proved that the variance decomposition coefficient R^2_ω - the part of variance in the efficient price attributable to the trade innovation - can be calculated from the trade/return VMA representation (3), (4)

$$R^2_\omega = \frac{(1+\sum_{i=1}^{\infty} a_i^*)^2\sigma_1^2 + (\sum_{i=1}^{\infty} b_i^*)^2\Lambda}{(\sum_{i=1}^{\infty} b_i^*)^2\Lambda}\ ,\ Var(\nu_{1,t}) = \sigma_1^2 \text{ i } Var(\nu_{2,t}) = \Lambda \tag{5}$$

The final result needs to be understood as follows. Public information events are incorporated into return via the innovation $\nu_{1,t}$. The permanent effect on midquotes of a unit return innovation is given as the sum of one (the contemporaneous impact) and $\sum_{i=1}^{\infty} a_i^*$. Hence, the variation in efficient price implied by public information is given by the first term in the numerator of equation (5). The variation in efficient price implied by private information is the second term in the numerator of equation (5). The variation in efficient price caused by both public and private information is then a sum of variations in the efficient price caused by public and private information separately.

3. DATA AND CLEANING

Over a period of 62 days, from March 1, 2006 to May 31, 2006, the trading attributes of interest for our analysis were observed trade-by-trade for a group of 18 LSE stocks listed on the FTSE 100 index. The 62-day trading sample is long enough to allow reasonably precise estimations (Easley et al. (1993, 1996), Engle et al. (2000)). The trading attributes of interest for our analysis were time, price and volume of the executed trade, and pre-trade bid and ask prices with their related volumes. All data that occur outside the normal trading hours, i.e. before 8:00 a.m. and after 4:30 p.m., were deleted from the sample. We matched the executed trades with their related pre-trade bid and ask prices and bid and ask sizes. After that we excluded all rows in the order book for which column "is a trade"[3] was zero. We then eliminated all anomalous data obviously caused by human and system errors, such as negative spreads, zero bid prices, and spreads larger than 10% of actual stock prices. Since there might be several transactions reported at the same time executed at different price levels, we applied an aggregation procedure which was consistent with liquidity analysis and Hasbrouck's VAR model. The trades that occurred at the same time with the same price and in the same direction were treated as one trade. The volume of such trade was then simply a sum of the volume corresponding to individual trades. After this aggregation procedure the number of observations for each stock decreased on average more than two times. The information about the number of transactions after the aggregation procedure and average midquote for each stock are given in Table 1.

Table 1. Basic stock information after the aggregation procedure.

symbol	company name	number of transactions	average midquote
ABF	Associated British Foods	27384	800.68
AZN	Astra Zenaca	88232	2878.9
BARC	Barclays	75709	655.28
CPI	Capita Group	33198	462.61
GSK	Glaxosmithkline	86972	1515.4
HBOS	Hbos	71450	961.46
HSBA	Hsbc Hldgs-Uk	87085	963.23
IAP	Icap	22854	493.3
KAZ	Kazakhmys	29439	1107.6
LLOY	Lloyds Tsb	66833	533.46
PRU	Prudential	63535	642.6
RB	Reckit Bencksr	54738	2008
RIO	Rio Tinto	125383	2943.3
SHP	Shile	41806	862.57
SLOU	Slough Estates	23189	625.65
VOD	Vodafone	85138	124.63
WPP	Wpp Group	40899	677.89
XTA	Xstata	85921	1994.2

[3] The column "is a trade" in an order book takes value 1 if the trade was executed, and 0 if the trade was not executed.

4. VARIABLES AND ESTIMATION

For the purpose of our analysis we considered the following four liquidity measures at the trade execution time *t*. Compared to the known definition of these measures in the literature, some of them are slightly modified so they can be calculated trade-by-trade as well as compared across different stocks.

1. Volume per trade, V_t . Higher volume per trade indicates higher liquidity.
2. Trade size in pounds

$$TS_t = p_t V_t$$

where p_t is the executed price. Higher trade size in pounds indicates higher liquidity.

3. Duration between two successive trades

$$Dur_i = t_{i+1} - t_i$$

where t_i is the execution time of trade *i*, and t_{i+1} is the execution time of the subsequent trade. Lower duration between two successive trades indicates higher liquidity.

4. Flow ratio between two successive trades

$$FR_t = \frac{TS_{t-1}}{Dur_t}$$

where Dur_t is time between a transaction at the time point *t* and a transaction prior to that, and TS_{t-1} is the size in pounds of the last transaction realized prior to time point *t*. Higher flow ratio indicates higher liquidity.

The variables of interest for Hasbrouck's VAR model are the trade x_t^0 and return r_t . The trade variable can be determined by the Lee and Ready rule (1991): 1 - buyer initiated, 0 -undetermined, -1 – seller initiated, i.e.

$$x_t^0 = \begin{cases} 1, & p_t > m_{t-1} \\ 0, & p_t = m_{t-1} \\ -1, & p_t < m_{t-1} \end{cases} \tag{6}$$

To see the real effect of the price impact of the trade on price formation it is natural to observe its pressure on the spread. By slight modification of return variable

$$r_t = \frac{\ln(m_{t+1}) - \ln(m_t)}{\bar{S}^{prop}} \tag{7}$$

where $\bar{S}^{prop}$ is the average of proportional spread

$$\bar{S}^{prop} = \frac{p_a^t - p_b^t}{m_t}$$

obtained price impacts of the trade will be expressed as part of the average proportional spread. In such a way it is possible to compare total price impact across stocks.

Following Hasbrouck (1991a, 1991b) and Engle et al. (2000), we assumed that the model given by equations (1), (2) can be truncated at five lags, i.e.

$$r_t = \sum_{i=1}^{5} a_i r_{t-i} + \sum_{i=0}^{5} b_i x_{t-i} + v_{1,t} \tag{8}$$

$$x_t = \sum_{i=1}^{5} c_i r_{t-i} + \sum_{i=1}^{5} d_i x_{t-i} + v_{2,t} \tag{9}$$

The trade variable is a limited dependent variable and it is quite unusual to have such a variable in vector autoregression. The limited dependent variable presents no econometric difficulties when it is an explanatory variable, which is the case for the return equation, but in the case of the trade equation the linear specification is potentially inappropriate. The least squares estimation yields to an inefficient estimation of the trade coefficients and the standard errors are biased. Following Engle et al. (2000) we avoided this problem by correcting the standard errors after using White's heteroskedasticity consistent covariance estimator (White (1980)) to correct the Wald and t-statistics.

For each day of the sample of 62 observation days we calculated the return vector given by (7) and the trade vector given by the Lee and Ready rule (6). The return and trade prior to the first observation of each day was set to zero. Adding the return vector of day i+1 at the end of the return vector of day i, i=1,..., 61, we obtained the $n\times 1$ return vector r, where n is the size of the 62 days' sample. In the same way, the $n\times 1$ trade vector x^0 is obtained from the trade vectors of each day. For estimating Hasbrouck's VAR (5) given by (8), (9) we made vectors r_t and x_t^0 by cutting the first five entries of the return vector r and trade vector x^0. The lagged vectors r_{t-k} and x_{t-k}^0, k=1, 2,..., 5 were obtained by cutting the first 5-k, and the last k entries of the return and trade vector by order. Further, to obtain the least squares coefficients of the return equation we regressed vector r_t on the matrix

$$[\, r_{t-1}, r_{t-2}, r_{t-3}, r_{t-4}\ r_{t-5}, x_t^0, x_{t-1}^0, x_{t-2}^0, x_{t-3}^0, x_{t-4}^0, x_{t-5}^0\,].$$

To obtain the least squares coefficients of the trade equation, we regressed vector x_t^0 on the matrix

$$[\, r_{t-1}, r_{t-2}, r_{t-3}, r_{t-4}\ r_{t-5}, x_{t-1}^0, x_{t-2}^0, x_{t-3}^0, x_{t-4}^0, x_{t-5}^0\,].$$

All calculations were performed using Matlab software.

5. RESULTS

The average liquidity measures are provided in Table 2. The estimated least squares coefficients for the return and trade equation, together with the corresponding *t*-statistics for all 18 stocks, is given in Table 3 and Table 4. The *t*-statistics in the trade equation are corrected by using White's heteroskedasticity consistent covariance estimator.

Table 2. Average liquidity measures.

	Vx10^7	TS	Dur	S^{prop}	FRx10^{10}
ABF	14796	1.17	0.0163	15681	0.850
AZN	16200	4.67	0.0054	16590	4.60
BARC	44944	2.93	0.0063	12566	2.61
CPI	25979	1.20	0.0137	18365	0. 913
GSK	24601	3.72	0.0055	12328	3.44
HBOS	28901	2.77	0.0066	14055	2.37
HSBA	49354	4.75	0.0055	11445	4.22
IAP	20612	1.01	0.0188	31079	0.646
KAZ	14499	1.60	0.0153	43141	0.888
LLOY	52383	2.78	0.0071	21893	2.14
PRU	36226	2.34	0.0074	15139	2.08
RB	9682.2	1.95	0.0086	16563	1.66
RIO	11696	3.44	0.0038	20959	3.78
SHP	17363	1.50	0.0110	17268	1.20
SLOU	14980	0.939	0.0190	17135	0.606
VOD	448310	5.58	0.0056	10397	5.60
WPP	31490	2.13	0.0114	13985	2.43
XTA	12856	2.56	0.0055	24304	2.43

Note: V_t -volume per trade; TS_t - trade size in pounds; Dur_i - duration between two successive trades; S^{prop} - proportional spread in tick size FR_t - flow ratio between two successive trades.

Table 3. The coefficient estimations and *t*-statistics for the return equation (8)

	a_1	a_2	a_3	a_4	a_5	b_0	b_1	b_2	b_3	b_4	b_5	R_r^2
ABF	-0.08	-0.01	-0.01	0.02	-0.04	0.24	0.03	0.01	0.001	-0.02	-0.003	17.90
	-12.9*	-1.26	-1.76	3.39*	-6.85*	68.32*	8.59*	3.13*	0.22	-4.34*	-0.72	
AZN	-0.08	-0.01	0.02	0.023	0.01	0.3	0.03	0.01	-0.01	-0.01	-0.01	27.28
	-23.22*	-2.31*	4.83*	6.55*	3.51*	166.6*	13.01*	3.93*	-2.30*	-4.61*	-3.97*	
BARC	-0.091	-0.01	0.008	0.014	0.014	0.222	0.031	0.007	-0.003	-0.006	-0.011	24.64
	-24.21*	-1.94	2.00*	3.78*	3.61*	139.4*	16.55*	4.02*	-1.76*	-3.35*	-5.90*	
CPI	-0.086	0.003	0.020	-0.020	-0.001	0.269	0.041	0.009	-0.009	-0.002	-0.003	20.76
	-5.40*	0.50	3.58*	-3.61*	-0.24	83.32*	11.14*	2.42*	-2.52*	-0.53	-0.89	
GSK	-0.097	0.006	0.024	0.012	0.011	0.205	0.034	0.008	-0.003	-0.004	-0.006	22.89
	-27.70*	1.67	6.82*	3.53*	3.22*	140.70*	0.26*	4.70*	-1.68	-2.67*	-3.97*	
HBOS	-0.067	0.016	0.024	0.013	0.006	0.263	0.029	0.005	-0.003	-0.007	-0.007	26.50
	-17.32*	4.23*	6.23*	3.43*	1.50	146.2*	13.54*	2.54*	-1.67	-3.20*	-3.37*	
HSBA	-0.121	-0.022	0.005	0.004	0.003	0.184	0.029	0.010	-0.005	-0.005	-0.010	20.92
	-34.21*	-6.09*	1.48	1.13	0.78	128.6*	18.09*	6.31*	-3.18*	-3.19*	-6.32*	
IAP	-0.060	0.001	0.004	0.015	-0.002	0.275	0.037	0.011	0.006	-0.015	-0.007	15.92
	-8.91*	0.19	0.54	2.20*	-0.37	59.34*	7.28*	2.08*	1.14	-3.02*	-1.47	
KAZ	-0.268	-0.01	-0.047	-0.014	0.011	0.271	0.088	0.031	0.006	0.013	-0.016	17.16
	-45.20*	-16.24*	7.60*	-2.32*	1.86	52.53*	15.95*	5.69*	1.13	2.37*	-2.87*	
LLOY	-0.097	-0.006	-0.002	0.009	0.004	0.200	0.033	0.007	0.002	-0.007	-0.003	22.02
	-24.05*	-1.56	-0.52	2.35*	0.98	120.0*	17.65*	3.56*	0.96	-3.68*	-1.78	
PRU	-0.132	-0.051	0.009	0.049	-0.030	0.246	0.033	0.018	0.003	-0.023	0.001	21.71
	-32.39*	-12.37*	2.09*	11.89*	-7.42*	114.4*	13.62*	7.22*	1.30	-9.47*	0.52	
RB	-0.049	0.026	0.01	0.004	0.007	0.270	0.033	0.007	-0.001	-0.007	-0.008	24.72
	-11.27*	5.89*	2.22*	1.03	1.50	123.53*	13.02*	2.57*	-0.32	-2.85*	-3.13*	
RIO	-0.095	-0.004	0.018	0.023	0.015	0.292	0.034	0.013	0.005	-0.003	-0.003	26.48
	-32.80*	-1.55	6.32*	8.01*	5.11*	193.6*	19.60*	7.31*	2.67*	-1.70	-1.67	
SHP	-0.114	-0.074	-0.005	-0.02	-0.001	0.265	0.034	0.024	0.009	0.006	-0.003	18.56
	-22.89*	-14.87*	-0.97	-3.95*	-0.10	86.18*	10.17*	7.18*	2.77 *	1.67	-0.97	
SLOU	-0.129	-0.092	-0.047	-0.018	-0.029	0.238	0.039	0.021	0.016	-0.002	0.002	15.19
	-19.36*	-13.63*	-6.98*	-2.69*	-4.36*	53.85*	8.09*	4.48*	3.38*	-0.31	0.38	
VOD	-0.13	-0.06	-0.037	-0.003	-0.005	0.078	0.031	0.012	0.007	-0.001	-0.006	11.69
	-36.26*	-16.48*	-10.12*	-0.94	-1.35	71.33*	27.03*	10.46*	6.09*	-0.84	-5.01*	
WPP	-0.07	0.001	0.021	0.015	0.002	0.223	0.024	0.011	-0.008	-0.004	-0.01	22.98
	-13.68*	0.18	4.18*	2.99*	0.40	99.64*	9.51*	4.09*	-2.94*	-1.50	-3.75*	
XTA	-0.101	-0.007	0.013	0.001	0.009	0.289	0.039	0.014	0.004	-0.003	-0.004	25.66
	-28.96*	-2.14*	3.76*	0.39	2.46*	154.7*	18.28*	6.26*	1.79	-1.16	-1.70	

Note: r_t is the return variable viewed as a part of the proportional spread. x_t^0 is the trade indicator variable which takes value +1 for buy order, -1 for sell order, and 0 for indeterminate. The sample covers 18 stocks listed on the London Stock Exchange from the FTSE 100 index over a period from March 1, 2006 to May 31, 2006.

Table 4. The coefficient estimations and *t*-statistics for trade equation (9)

	c_1	c_2	c_3	c_4	c_5	d_1	d_2	d_3	d_4	d_5	R_r^2
ABF	-0.328	-0.020	-0.019	-0.021	-0.0119	0.2618	0.101	0.074	0.044	0.0386	10.57
	-8.79*	-0.92	-1.35	-2.03*	-0.93	23.67*	12.15*	10.31*	6.47*	5.55*	
AZN	-0.4847	-0.0379	-0.0040	-0.0027	-0.0081	0.2609	0.0754	0.0415	0.027	0.0268	8.64
	-55.23*	-5.12*	-0.55	-0.40	-1.21	59.95*	18.72*	10.25*	6.91*	6.86*	
BARC	-0.6537	-0.0400	-0.0236	-0.0222	-0.0083	0.2914	0.0667	0.0494	0.038	0.0265	10.84
	-75.09*	-4.55*	-2.67*	-2.55*	-0.96	69.26*	15.71*	11.56*	8.95*	6.40*	
CPI	-0.3585	-0.0052	-0.0223	-0.0236	-0.0237	0.2611	0.0800	0.0637	0.044	0.0283	9.17
	-28.95*	-0.49	-2.26*	-2.39*	-2.42*	40.92*	12.64*	10.17*	6.95*	4.60*	
GSK	-0.6173	-0.0347	0.0058	0.0111	0.0198	0.2860	0.0689	0.0552	0.033	0.0255	10.49
	-74.42*	-4.18*	0.69	1.35	2.41*	74.03*	17.56*	14.04*	8.46*	6.65*	
HBOS	-0.4957	0.0138	0.0074	0.0042	-0.0043	0.2992	0.0645	0.0448	0.031	0.0276	9.65
	-57.14*	1.62	0.90	0.51	-0.53	67.63*	14.35*	9.97*	7.01*	6.36*	
HSBA	-0.6958	-0.1113	-0.0543	-0.0217	-0.0135	0.2852	0.0797	0.0688	0.035	0.0378	12.23
	-70.95*	-12.49*	-6.27*	-2.57*	-1.57	72.57*	20.41*	17.71*	9.10*	10.03*	
IAP	-0.3031	-0.0348	-0.0262	-0.0051	-0.0068	0.2380	0.0837	0.0661	0.034	0.0427	09.04
	-19.99*	-3.44*	-2.51*	-0.47	-0.72	31.04*	11.28*	8.91*	4.61*	5.97*	
KAZ	-0.2031	-0.0596	-0.0322	-0.0196	-0.0084	0.1992	0.1060	0.0700	0.0465	0.0368	8.00
	-5.45*	-2.32*	-2.93*	-2.47*	-1.07	14.68*	11.30*	10.43*	7.10*	5.78*	
LLOY	-0.6585	-0.0414	-0.0409	-0.0241	-0.0013	0.2814	0.0538	0.0514	0.0432	0.0233	10.55
	-72.17*	-4.40*	-4.34*	-2.56*	-0.14	64.23*	12.12*	11.53*	9.73*	5.37*	
PRU	-0.4363	-0.0372	-0.0256	0.0095	0.0225	0.2531	0.0661	0.0535	0.0334	0.0241	8.75
	-10.93*	-2.72*	-1.93	0.66	1.80	21.63*	13.30*	9.49*	5.76*	4.83*	
RB	-0.4174	0.0050	0.0113	-0.0045	-0.0139	0.2589	0.0835	0.0388	0.0344	0.0294	8.13
	-37.00*	0.54	1.27	-0.46	-1.56	49.46*	16.56*	7.70*	6.67*	5.95*	
RIO	-0.430	-0.018	0.021	0.0226	0.0189	0.2187	0.0706	0.038	0.031	0.022	6.86
	-64.09*	-3.13*	3.60*	3.93*	3.38*	62.49*	21.11*	11.52*	9.44*	6.60*	
SHP	-0.2823	-0.0364	-0.0363	-0.0194	-0.0332	0.2004	0.0846	0.0617	0.0365	0.0370	6.43
	-8.01*	-3.39*	-1.59	-2.17*	-4.14*	19.22*	13.70*	7.92*	6.55*	6.80*	
SLOU	-0.2831	-0.0450	-0.0370	-0.0336	-0.0076	0.2086	0.0662	0.0535	0.0295	0.0246	6.65
	-12.05*	-3.47*	-2.33*	-3.08*	-0.71	24.28*	8.76*	6.92*	4.09*	3.46*	
VOD	-0.9751	-0.3274	-0.1958	-0.1168	-0.0640	0.2816	0.0863	0.0772	0.0532	0.0574	16.22
	-65.47*	-26.85*	-16.80*	-9.52*	-4.71*	74.40*	22.54*	20.29*	14.02*	15.39*	
WPP	-0.5630	-0.0267	0.0102	0.0177	-0.0055	0.2835	0.0799	0.0446	0.0298	0.0232	10.08
	-33.22*	-2.01*	0.79	1.54	-0.49	43.10*	13.65*	7.56*	5.19*	4.15*	
XTA	-0.4282	-0.0326	0.0030	-0.0052	-0.0051	0.2521	0.0796	0.0457	0.0301	0.0262	8.06
	-56.08*	-4.78*	0.44	-0.79	-0.77	61.18*	19.78*	11.39*	7.54*	6.63*	

Note: r_t is the return variable viewed as a part of the proportional spread. x_t^0 is the trade indicator variable which takes value +1 for buy order, -1 for sell order, and 0 for indeterminate. The *t*-statistics are computed using White's heteroskedasticity consistent covariance estimator. The sample covers 18 stocks listed on the London Stock Exchange from the FTSE 100 index over a period from March 1, 2006 to May 31, 2006.

The asterisks above *t*-statistics denote the significance at the 5% level. For each equation the coefficient of multiple determination R_ω^2 is given. We proceed with the Wald test of hypothesis of estimated coefficients. The results are provided in

Table 5. The Wald statistics of trade equation coefficients is computed by using White's heteroskedasticity consistent covariance estimator. The most important coefficients are coefficients of trade variables in the return equation and trade equation. The coefficient b_0 in the return equation for each of the 18 stocks represents the immediate impact of contemporaneous trade x_t^0 . It measures an average rise of return with respect to average proportional spread immediately after the buy order. The coefficients b_i, i=1, 2, ..., 5 in the return equation for all 18 stocks tend to be positive, meaning that the buys tend to increase and sells tend to decrease the return. According to the Wald test, the null hypothesis that the coefficients b_i, i=1, 2, ..., 5 are jointly equal to zero is rejected. The sum of them is positive, and according to the Wald test, significantly different from zero at the 1% level, indicating that the order flow has a positive influence on the return. Positive autocorrelation in trades is visible in positive coefficients on the lagged trade variable, indicating that a purchase tends to follow a purchase, and a sell tends to follow a sell. These coefficients are significantly different from zero, even at the 1% level. Negative autocorrelations in returns are visible in negative coefficients on lagged return variables in the trade equation, which is predominant for stocks with the symbols ABF, CPI, KAZ, SHP, SLOU, and VOD. For other stocks this behaviour is weaker. The Wald test of the hypothesis that the coefficients of return variables in the trade equation are jointly zero is rejected at the 1% level, indicating Granger's causality running from returns to trades.

Table 5. The Wald test of three hypotheses of estimated coefficients.

ABF	5670.3	1808.8	83.8
AZN	31065	6911.2	3171
BARC	22984	6139.4	5660.8
CPI	8243.5	2395.3	860.5
GSK	23947	7276.6	5545.9
HBOS	24744	5828.9	3273.4
HSBA	20286	7338.8	5037.9
IAP	4143	1153.1	405.3
KAZ	3856.5	2366	43.9
LLOY	17364	5392.1	5243.9
PRU	15388	5105.3	446.7
RB	17482	4114.3	1422.1
RIO	41816	10600	4152.7
SHP	8682.8	3170.9	99.8
SLOU	3483.8	1555.3	169.1
VOD	89148	10432	4578.9
WPP	11576	2971.3	1238.7
XTA	27776	7597.9	3190.6

Note: The Wald statistics of trade equation coefficients is computed using White's heteroskedasticity consistent covariance estimator.

We calculated the return/trade moving-average representation (3), (4) truncated at 40 lags. The algorithm for calculating VMA(q) representation of the Hasbrouck VAR(p) in Matlab is given in Appendix 1. The price impact function is calculated as a cumulative impulse response of return to the innovation in the trade equation. The graphs of price impact functions for each stock are provided in Appendix 2. The total price impact PI is calculated as well as the number of transactions k needed for its realization. Notice that the obtained impulse response coefficients $b_i^*, i = 1,2,...,40$ from (3), as well as the obtained total price impact, are expressed as a part of the average proportional spread. The variance σ_1^2 of innovation in the return equation and the variance Λ of innovation in the trade equation are calculated. At the end the variance decomposition coefficient R_ω^2 given by (5) is calculated. These results are provided in Table 6. For this test all measures are ranked as in Table 7, i.e. from the highest to the lowest liquidity.

This means that, for example, stocks are ranked from the lowest to the highest duration and from the highest to the lowest trade volume. Therefore, stocks are ranked from the lowest to the highest total price impact. We ranked stocks from the highest to the lowest variance decomposition coefficient. From all calculated correlations we are most interested in correlations between total price impact *PI* and considered liquidity measures, and between the variance decomposition coefficient R^2_{ω} and considered liquidity measures.

To test the null hypothesis

H_0: *There is no relationship between diverse liquidity measures, total price impact PI, and variance decomposition coefficient* R^2_{ω} *,*

against the alternative hypothesis

H_1: *There is a relationship between the diverse liquidity measures, total price impact PI, and variance decomposition coefficient* R^2_{ω} *,*

we use the Spearman rank correlation test, whose results, with related *P*-values in brackets, are provided in Table 6.

Table 6. VMA representation (3), (4) of VAR (8), (9) truncated at 40 lags.

	b_0	PI	k	σ_1^2	Λ	R_ω^2(%)
ABF	0.2423	0.4175	27	0.2876	0.8354	47.72
AZN	0.2961	0.4092	18	0.2391	0.8572	51.48
BARC	0.2222	0.3240	18	0.1562	0.8115	51.79
CPI	0.2695	0.4355	23	0.2946	0.8485	49.42
GSK	0.2051	0.3339	21	0.1544	0.8357	50.99
HBOS	0.2631	0.4181	20	0.1934	0.8358	54.40
HSBA	0.1838	0.2743	20	0.1475	0.8293	48.75
IAP	0.2748	0.4541	23	0.4286	0.8744	39.95
KAZ	0.2713	0.4406	22	0.7062	0.8994	40.30
LLOY	0.1999	0.2991	19	0.1523	0.8210	49.17
PRU	0.2465	0.3531	20	0.2474	0.8392	44.75
RB	0.2705	0.4327	20	0.2241	0.8540	51.71
RIO	0.2921	0.4355	20	0.2507	0.8780	51.09
SHP	0.2649	0.3995	23	0.3437	0.8703	45.91
SLOU	0.2376	0.3341	20	0.3995	0.8857	36.44
VOD	0.0775	0.1613	21	0.0821	0.8155	42.60
WPP	0.2230	0.3438	19	0.1677	0.8189	48.60
XTA	0.2888	0.4389	19	0.2631	0.8790	54.58

Note: b_0 - immediate price impact with respect to the average proportional spread; PI - total price impact with respect to the average proportional spread; k - number of transactions needed for full realization of total price impact; σ_1^2 - variance of innovation in return equation; Λ - variance of innovation in trade equation; R_ω^2 - variance in decomposition coefficient.

Table 7. Stocks ranked from the highest to the lowest liquidity according to diverse liquidity measures, and from the highest to the lowest variance decomposition coefficient R^2_ω.

	V	*TS*	*Dur*	*FR*	*PI*	R^2_ω
ABF	14	16	16	16	11	12
AZN	12	3	2	2	10	5
BARC	4	6	7	6	4	3
CPI	8	15	14	14	14	8
GSK	9	4	4	5	5	7
HBOS	7	8	8	8	12	2
HSBA	3	2	3	3	2	10
IAP	10	17	17	17	18	17
KAZ	15	13	15	15	17	16
LLOY	2	7	9	9	3	9
PRU	5	10	10	10	8	14
RB	18	12	11	12	13	4
RIO	17	5	1	4	15	6
SHP	11	14	12	13	9	13
SLOU	13	18	18	18	6	18
VOD	1	1	6	1	1	15
WPP	6	11	13	11	7	11
XTA	16	9	5	7	16	1

Table 8. Spearman rank correlation test for diverse liquidity measures, total price impact *PI*, and variance decomposition coefficient R^2_ω.

	V	*TS*	*Dur*	*FR*	*PI*
V					
TS	0.4262				
	(0.0789)				
Dur	0.1496	0.9195			
	(0.5372)	(0.0001)			
FR	0.3560	0.9814	0.9525		
	(0.1421)	(0.0001)	(0.0001)		
PI	0.7399	0.5170	0.2817	0.4489	
	(0.0023)	(0.0330)	(0.2454)	(0.0642)	
R^2_ω	-0.1393	0.4407	0.6244	0.5088	-0.0980
	(0.5657)	(0.0692)	(0.0100)	(0.0359)	(0.6860)

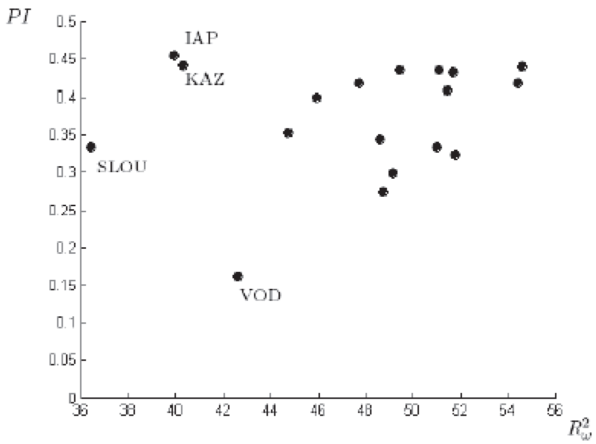
Note: Stocks are ranked from the highest to the lowest liquidity, from the lowest to the highest total price impact, and from the highest to the lowest variance decomposition coefficient R^2_ω.

Correlations between total price impact and volume (trade size in pounds) are positive and significant at the 1% level, indicating that higher liquidity measured by these measures means lower total price impact. The duration is positively but not significantly correlated with total price impact. The flow ratio is positively correlated to total price impact at the 10% level. On the other hand, correlations between the variance decomposition coefficient R_{ω}^{2} and diverse liquidity measures are mostly insignificant. The duration and the flow ratios are the only two measures that are significantly correlated to R_{ω}^{2} at the 5% level. These correlations are positive, implying that intensively traded stocks present a larger contribution of unexpected trade in the variation of efficient price. Also, the trade size in pounds is positively correlated to the variance decomposition coefficient at the 10% level. It is interesting that there is no significant correlation between total price impact and variance decomposition coefficient. Figure 1 shows the variance decomposition coefficient versus total price impact across the 18 analyzed stocks. Certain kind of stock clustering can be noticed. The most isolated stocks are the three most illiquid stocks according to Table 7, IAP, KAZ and SLOU, and they have the lowest R_{ω}^{2}. The other more liquid stocks have higher R_{ω}^{2}. The Vodafone stock is quite separate from this group, showing its own behaviour. Our findings present that the variance decomposition coefficient R_{ω}^{2} strongly depends on the return and trade equation's predictability. According to the coefficients of multiple determination R_{r}^{2} and R_{x}^{2}, the return equation presents higher predictability than the trade equation for each stock, except for Vodafone. Such results are reasonable, since in the trade equation the trade variable x_{t}^{0} as a limited dependent variable takes only three values, -1, 0, 1. It can be observed from Table 3 and Table 4 that the stocks with higher predictability of the return equation compared to predictability of the trade equation have higher R_{ω}^{2}. The predictability of the return equation strongly depends on the return volatility. The proportion of positive returns, zero returns, and negative returns for each of the 18 analyzed stocks are given in Table 9.

Table 9. The proportion of positive returns, zero returns, and negative returns for each stock.

	Positive return (%)	Zero return (%)	Negative return (%)
ABF	25,34	49,99	24,67
AZN	28,95	41,84	29,21
BARC	21,31	56,87	21,82
CPI	27,51	44,73	27,77
GSK	19,44	61,08	19,48
HBOS	25,16	49,49	25,35
HSBA	16,33	67,45	16,22
IAP	30,72	38,02	31,26
KAZ	33,39	32,73	33,87
LLOY	20,48	58,83	20,69
PRU	25,35	48,56	26,09
RB	27,77	44,14	28,09
RIO	32,75	34,43	32,81
SHP	27,7	43,58	28,72
SLOU	24,9	49,8	25,3
VOD	6,81	86,25	6,94
WPP	23,24	53,59	23,17
XTA	32,91	33,87	33,22

Figure 1. Variance decomposition $R^2_\omega(\%)$ coefficient vs. total price impact *PI*, with respect to average proportional spread.



The Pearson correlation coefficient between R_r^2 / R_x^2 and the proportion of zero returns is -0.7211 with the *P*-value of 0.0007, indicating significance at the 1% level. Vodafone has an extremely large proportion of zero returns, considering all 18 stocks. This can explain the low predictability of its return equation compared to the predictability of the trade equation, and its specific behaviour is shown in Figure 1.

Hasbrouck (1991b) formally suggested that the variance decomposition coefficient R_ω^2 indicates the proportion of volatility in the efficient price caused by the presence of informed traders represented in the unexpected component of the trade. According to Table 5, stocks with the symbols IAP, KAZ, and SLOU take 17th, 15th, and 18th rank by order according to duration, and their flow ratio has the lowest coefficient R_ω^2. Excluding these three stocks, Vodafone has the smallest R_ω^2. According to the Spearman rank correlation test, it seems that for intensively traded stocks (stocks with lower duration), and stocks with ability to absorb large trades in a short time interval (stocks with higher flow ratio), the coefficient R_ω^2 is highly overestimated.

6. CONCLUSIONS

We have examined the empirical test of Hasbrouck's (1991a, 1991b) VAR - VMA model on diverse liquidity levelled stocks listed on the London Stock Exchange from the FTSE 100 index. The results on coefficients of return/trade equations (8) and (9) are consistent with Hasbrouck (1991a). The total price impact in this model is calculated as a response of the return scaled by the average proportional spread to the trade innovation. Our results suggest that for more liquid stocks, where liquidity is measured by volume per trade and trade size in pounds, this impact is lower. However, according to the Spearman rank correlation test, duration is positively but not significantly correlated to total price impact. The flow ratio is positively correlated to total price impact at the 10% level.

Considering the contribution of unexpected trade in the variation of the efficient price, our results suggest that for intensively traded stocks (small duration) and stocks with ability to absorb large trades in a short time interval (large flow ratio), this contribution is higher. We have found that duration and flow ratios are positively and significantly correlated to the contribution of unexpected trade in variation of the efficient price at the 5% level. The contribution of unexpected trade in variation of the efficient price is positively correlated to trade size in pounds at the 10% level.

Hasbrouck's model assumes a rather simplified trading mechanism between market participants. It assumes the presence of market makers who post bid and ask quotes after the realized transaction at time *t* and according to information contained in the recent order flow. Every trade this model cannot predict is taken as an unexpected trading activity caused by the presence of traders with private information. In an order-driven market interaction between market participants this is rather complicated. First, there are no classical market makers. Transactions are realized by complementing the price and the amount of various orders placed in the central computer system by diverse participants. A large number of transactions can be realized in a short time interval, or even more in the same time period. Trading on such a market becomes complex and multidimensional, requiring the development of dynamic trading strategies, i.e. the implementation of diverse algorithms. As discussed in Parlour and Seppi (2008), "when choosing limit prices and quantities for (potentially multiple) limit orders and choosing quantities for market orders, a trader needs to condition on everything that can affect the future evolution of the trading process. This potentially includes a complete description of the existing limit order book - namely, all quantities for multiple orders at multiple prices from multiple past investors at multiple points in time - as well as the histories of all past trades and orders. Dynamic trading strategies also involve decisions about how frequently to monitor changing market conditions and when and how to modify or cancel unexecuted limit orders." Following the previous discussion, trades realized by algorithms will behave as an unexpected trade, i.e. as a trade caused by the superior information in Hasbrouck's VAR model. Since for intensively traded stocks significant employment of algorithmic trading is expected, this could explain the obtained results on the contribution of unexpected trade to variation of the efficient price.

Results obtained in this paper suggest that algorithmic trading behaves as informed trading, i.e. trading with superior or private information. Furthermore, there is a weaker indication that algorithmic trading increases the total money value of transactions (trade size in pounds), which is quite consistent with expectations.

This research was limited by the relatively small stock sample. A larger set of observations would provide more robust results. However, even based on such a small sample, these results still indicate a significant relationship between liquidity and information asymmetry on the LSE. More sensitive analysis of the liquidity / information asymmetry relationship would consider the proportion of trades realized by different types of order – market or limit. Copeland and Galai (1983) emphasize that limit orders, giving options to other traders to trade at the quoted price, can be picked off by later traders who possess updated public information or private information. Parlour and Seppi (2008) state that the "limit order book should impound forward-looking information about future price volatility, the intensity of future adverse selection, and future order flow". Therefore, "limit orders are not just susceptible to being picked off by informed traders; they are also potentially a vehicle for informed trading themselves."

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APPENDIX 1

THE ALGORITHM FOR CALCULATING THE HASBROUCK'S VAR(P).

Step 1. Use the obtained least squares coefficients of equations (8) and (9) to form matrices

$$A_i = \begin{bmatrix} a_i + b_0 c_i & b_i + b_0 d_i \\ c_i & d_i \end{bmatrix}, \; i=1,2,...,p.$$

Step 2. Construct the $2q \times 2$ matrix given by

$$\varphi = \begin{bmatrix} A_1 & A_2 & A_3 & A_4 & A_5 & Z \end{bmatrix}^T$$

where Z is the $2(q-p)\times 2$ zero matrix.

Step 4. Construct the $2 \times 2q$ matrix

$$\Psi = \begin{bmatrix} I & Z \end{bmatrix}^T$$

where *I* is the 2×2 identity matrix, and *Z* is the $2(q-1)\times 2$ zero matrix.

Step 3. For $I = 1,..., q$ c

1. Calculate

   $$\Psi'' = \Psi_i \cdot \varphi$$

2. Construct a matrix Ψ'' by putting matrix Ψ' at begin of the matrix Ψ and by cutting the

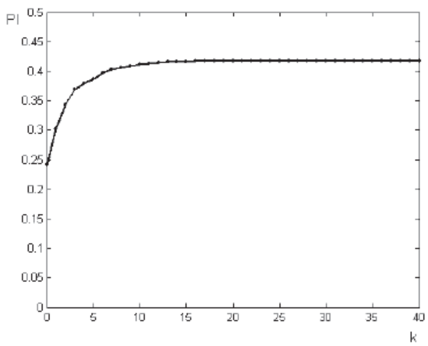
   2×2 zero matrix at the end of Ψ.

3. Put $\Psi' = \Psi''$

APPENDIX 2

The price impact function obtained from the representation of VAR (8) and (9) across 18 analyzed LSE stocks listed on the FTSE 100 index.

ABF



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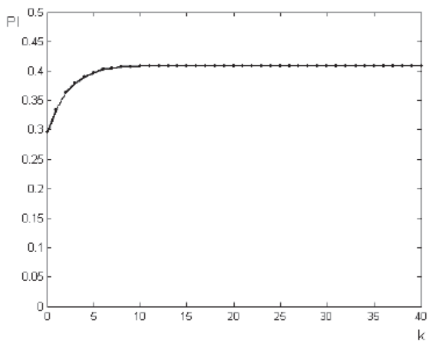

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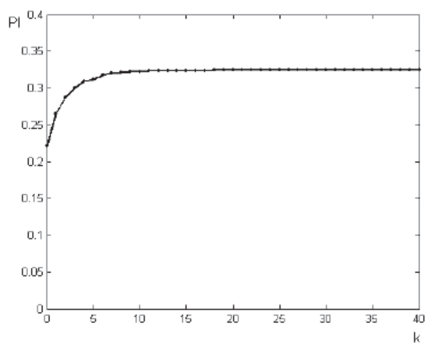

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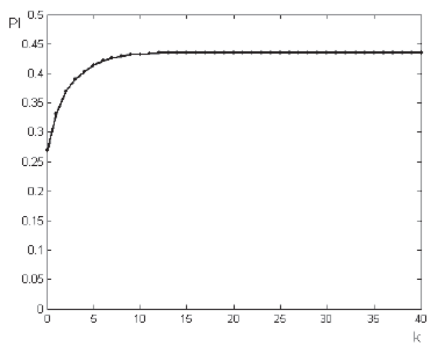

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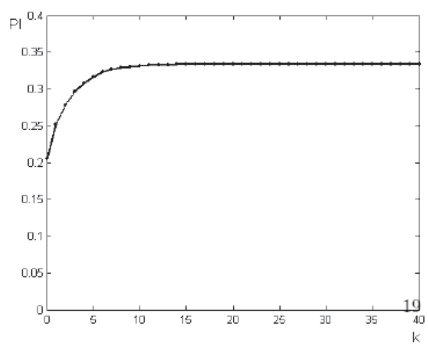
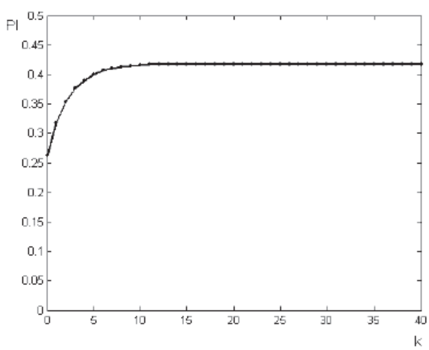
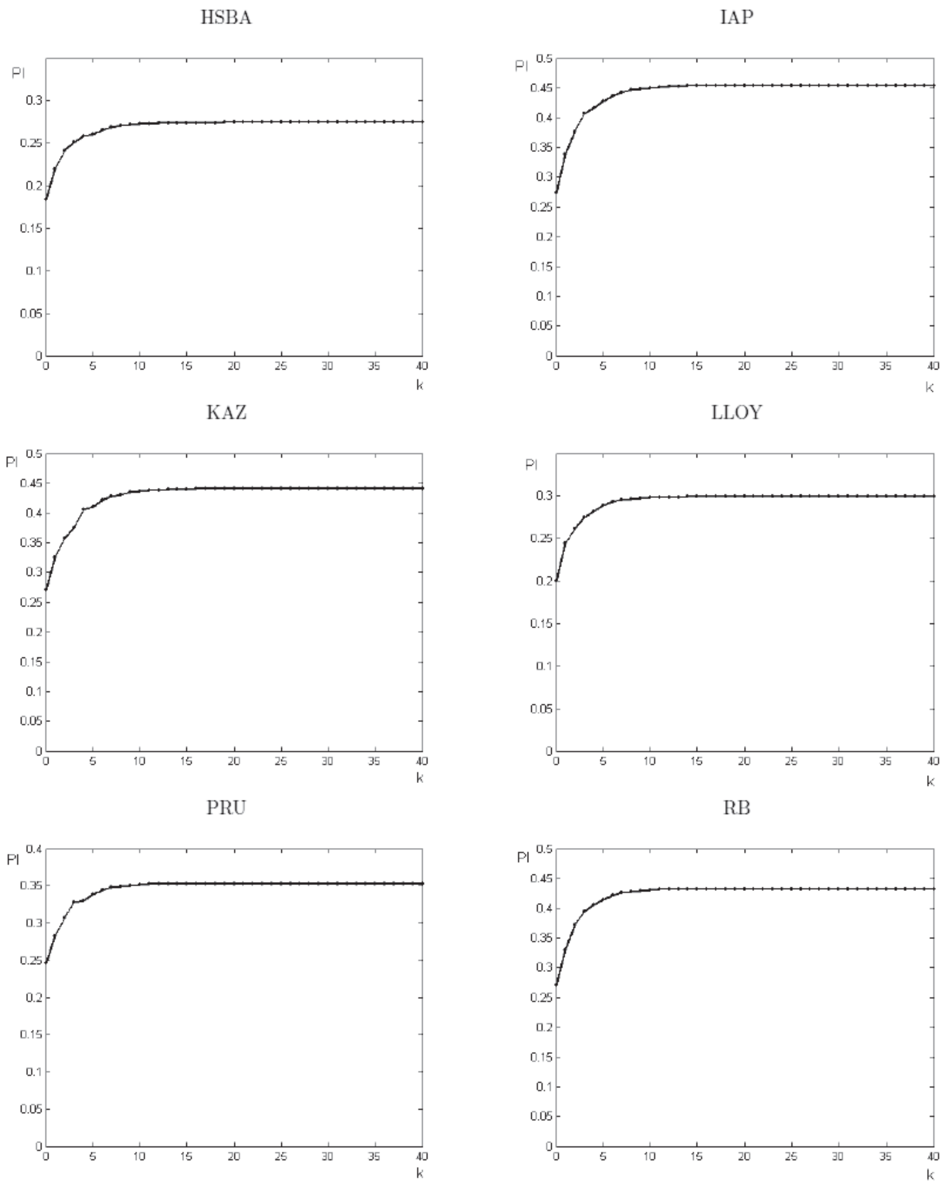


HBOS

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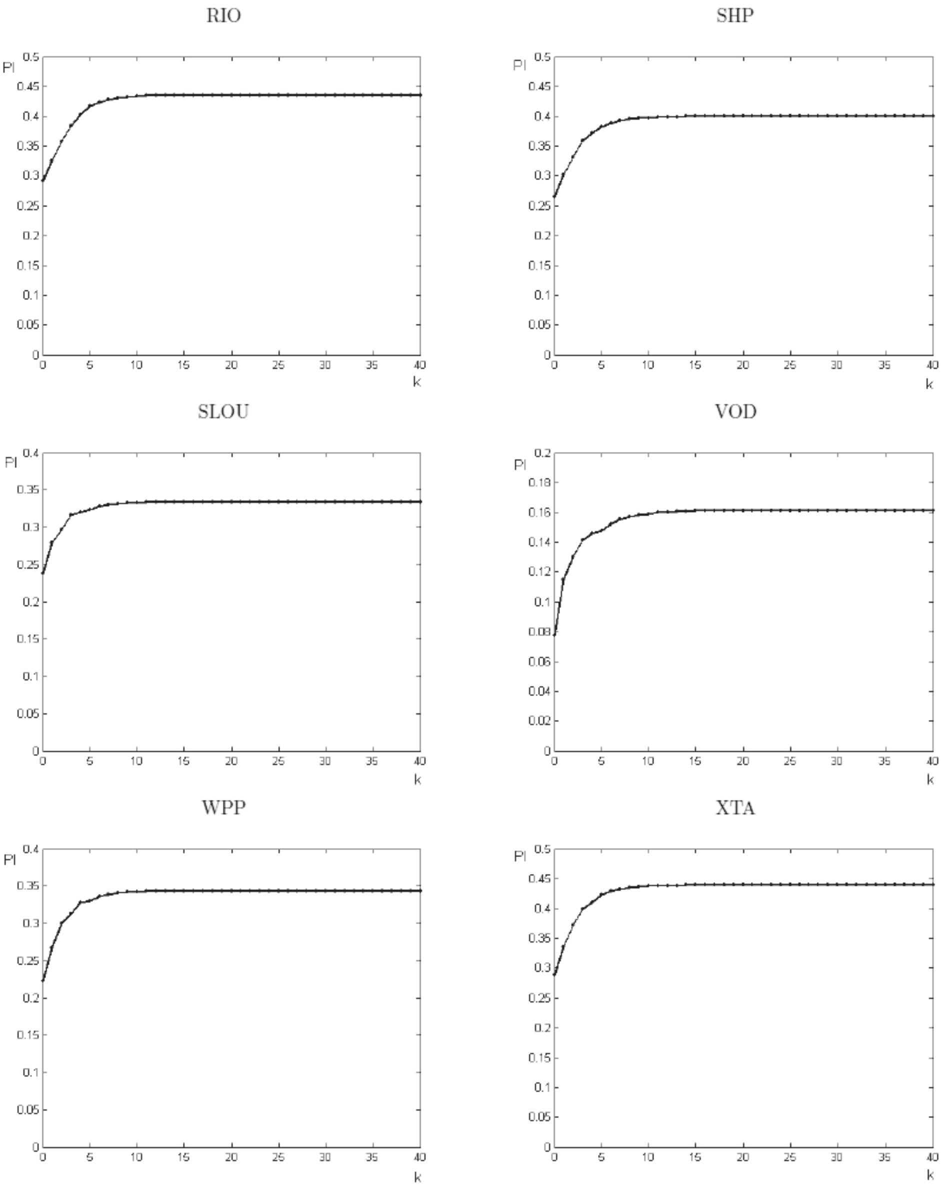

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