Measuring Microstructure Effects
in a Dealer Market for Less-Liquid Stocks

by

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September 17, 2007

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We would like to thanks Ron Anderson, John Board, Narayan Naik, Pradeep Yadav for comments. In addition this paper has benefited from seminar presentations at FMG Conference on Market Microstructure, May 1998; European Econometric Society Meetings, Santiago, September 1999; Lancaster University, Louvain-la-Neuf, University of Bristol, and Stockholm School of Economics.
Abstract

This paper tests for the existence of inventory control and asymmetric information in stock market price quotes in the dealer market setting of the London Stock Exchange. We deduce exact restrictions on the effects of public and liquidity-plus-private information shocks, within a simple bivariate VAR for price quotes and inventories. We show that the existence of asymmetric information or inventory control rests on the significance of precise functions of parameters in a single estimating system. We test the model on trade-by-trade observations for fifteen relatively illiquid stocks on the LSE, and find that both microstructure effects are a robust feature of our sample of less-liquid stocks. We decompose price changes into a component due to the arrival of news about fundamentals, and a second component due to dealers desire to exploit noise trades and control inventories. We are able to assess the relative importance of public information and private information revealed through trades, on the change in prices. We find that on average 46% of the change in the fundamental price is revealed by trades and that approximately 40% of the variance of the change in prices is accounted for by market microstructure effects. Further we compute the standard error of mispricing as a measure of market quality, and estimate its average value as 2% of stock value. Finally those stocks in which we find private information is important also display high quoted spreads, which is consistent with asymmetric information theories of market microstructure. These estimates are important since they provide an input into the current debate on whether to extend the SETS order book system to less liquid FTSE 250 stocks.

JEL Classification G10, G15, G19

Keywords: Market Microstructure, Dealer Market, London Stock Exchange
1. Introduction

This paper provides estimates of trading frictions on the London Stock Exchange (LSE) which provide an important input into the current debate about the best way for the LSE to organise its trading system.\(^1\) In an efficient market, stocks should trade at their fundamental values, but market microstructure frictions generated by the trading mechanism will cause stock prices to diverge from their efficient market levels. In this paper we test for the existence of these frictions and measure the microstructure effects implied by the movements in dealers' price quotes for a sample of less-liquid stocks listed on the LSE. We establish the existence of asymmetric information and inventory control for most of our stocks and go on to estimate measures of trade informativeness and market quality analogous to those derived in Hasbrouck (1991b, 1993). We find that on average 46% of the change in the fundamental price is revealed by trades and that approximately 40% of the variance of the change in prices is accounted for by market microstructure effects. The standard error of mispricing (the difference between fundamental and actual prices), is estimated for each stock and on average is found to be 2% of stock value, which is substantially higher than that given in Hasbrouck (1993) for liquid NYSE stocks. These estimates provide a quantitative input to the on-going debate in London over the appropriate trading mechanism.

The LSE for less-liquid stocks is organised as a dealer system. Dealers may set prices away from fundamental values to accommodate microstructure frictions. These frictions arise from the market maker’s response to inventory shocks [Amihud and Mendelson (1980), Ho and Stoll (1983)], the existence of private information [Glosten and Milgrom (1985), Kyle (1985), Easley and O’Hara (1987)], and to predictable noise trades [Admati and Pfleiderer (1988, 1989), Foster and Viswanathan (1990)]. Stock Exchanges around the world operate different trading systems, and by examining the time series properties of stock prices on a specific exchange we may gauge the importance of trading frictions for that particular type of microstructure. The original time series work of Hasbrouck (1988, 1991a) and Madhavan and Smidt (1991) found that adverse selection rather than inventory control is the important feature of trading on the NYSE. Subsequent work by Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) uncovered evidence of mean reversion in inventories consistent with inventory control. The latter estimate the average half life of inventories across stocks as being 49 days, falling to 7.3 days after controlling for shifts in desired inventories. In contrast for a sample of liquid stocks on the LSE, Snell
and Tonks (1995, 1998) find strong evidence of inventory control, and calculate average inventory half lives of 1.5 days. From data on the trades of individual market makers Hansch, Naik and Viswanathan (1998) and Reiss and Werner (1998) also found inventory control is important on the LSE.

Hasbrouck (1991b, 1993) proposed a new methodology to characterise properties of trading systems, by decomposing stock prices into random walk and transitory components, identifying the former as an efficient price, and the latter as a residual due to market microstructure effects. In Hasbrouck (1991b) the coefficient of determination between the change in the efficient price and the long run effect of a trade innovation on price quotes, measures the informativeness of trades. This measure is inversely related to a company’s market capitalisation, and trades are found to be more informative at the start of the day. He estimated that on average 34 percent of the variance in the change in efficient prices is explained by trades. Hasbrouck (1993) used an estimate of the variance of the deviation of actual from efficient prices to measure market quality, and calculated its value for a sample of NYSE stocks as 0.33 percent of the stock price. De Jong, Nijman and Roell (1996) use trade and price data from the Paris Bourse and obtain similar results with respect to these informativeness and market quality measures. Using a VAR approach Hamao and Hasbrouck (1995) investigate impulse response functions of trade shocks on the Tokyo Stock Exchange.

In the current paper, we build on the earlier work in Snell and Tonks (1995, 1998), but rather than test a structural model, we apply time series methods to identify microstructure effects on the London Stock Exchange. A distinctive feature of our work is the close link between the time series estimates and the underlying theoretical model. We conduct our analysis on a new sample of fifteen "less-liquid" LSE stocks, whose prices are not in the FTSE100 index, in contrast to other empirical work on the LSE which has concentrated on liquid stocks. In our paper tests for the existence of inventory control and asymmetric information and estimates of the relative magnitudes of these and other microstructure effects on prices arise naturally from a single structural model of the market making process on the LSE. In the next section, we develop a bivariate VAR based on an underlying structural model which we believe captures the salient features of market maker and trader behaviour on the LSE. Section 3 describes the data used in the study, and in Section 4 we explain how the existence of asymmetric information or inventory control
depends on the significance of precise functions of parameters in a single estimating
system. Importantly we show that the test for asymmetric information depends on the
time-series properties of inventories. Section 5 gives the results of the asymmetric
information and inventory control tests. A dominant feature of these results is that, after
allowing for a shift in the mean level of inventories in four of the stocks, inventory control
is very strong. Further, in contrast to the findings in Snell and Tonks (1995, 1998) with
respect to liquid stocks, we find that nearly all our

In Section 6 we decompose trade-by-trade quote changes into components due to the
arrival of public and private news about fundamentals, the dealers ability to exploit noise
trades and her desire to control inventories. This decomposition is derived from our
theoretical model and is analogous to the permanent-plus-transitory time series
formulation of Hasbrouck (1991b, 1993). less-liquid stocks display “informational
feedback” from trades to quote revisions. Further results in Section 7 provide estimates of
the microstructure frictions on price volatility, in particular the relative importance of
public versus private information, and the contribution due to inventory and noise trader
effects unrelated to the arrival of news. The final section provides a summary and

Any modelling of a specific trading system should take account of the institutional
structure and features of the data it generates. Using LSE data, we are able to exploit the
fact that on the LSE all trades pass through the dealer’s inventory. Therefore, the only
method by which the dealers in a particular stock may alter their collective aggregate
inventory level on the LSE is by the classical mechanism of changing price quotes to elicit
buys or sells. This contrasts with the NYSE where there is a limit order book and the
specialist may control inventories by satisfying these limit orders rather than by changing
price quotes [see for example, Madhavan and Sofianos (1998)].

In keeping with previous empirical work on quoted prices and trades, our study identifies
two shocks from the VAR, namely a public information shock and a liquidity-plus-private-
information shock or “trade shock”. On the LSE current price quotes fully reflect current
public information but because firm prices are posted before the current trade arrives,
current quotes cannot depend on the trade shock. This institutional characteristic gives us
the exclusion restriction that current trade shocks do not affect prices, which we may use to uniquely identify the public information and trade shocks from the VAR. By contrast, the institutional structure of the NYSE implies that price quotes are predetermined which necessitates a behavioral assumption to identify these public and trade shocks.\(^4\)

The absence of a limit order book which on certain exchanges yields information to the market maker and the fact that all but a small number of large trades are made public when they occur, simplifies the analysis of information flows on the LSE. The LSE is well characterised by the classic case of a dealer facing informed traders. Gemmill (1996) and Board and Sutcliffe (1995) find that even though large trades on the LSE are reported with a delay, part of their price effects are incorporated within the next trade and are fully incorporated before the public disclosure time. This rapid response may be due to the IDB (Inter-Dealer Broker) network to which market makers have exclusive access, and disseminates information on block trades.

In less liquid stocks on the LSE there are a small number of market makers quoting prices. Reiss and Werner (1994) document that trades between market makers through the anonymous IDB network takes place at prices close to the mid-point spread, which implies that the adverse selection costs are relatively unimportant for inter-market maker trades. Therefore we adopt a model in which competing market makers adopt symmetric equilibrium strategies, and we analyse the behaviour of a price quote set by a representative market maker and the level of aggregate inventories arising as a consequence of this pricing behaviour: we may therefore disregard inter-market maker trades. The representative market maker in each stock sets a mid-point price \(p_t\) immediately prior to receiving a buy or sell order \(z_t/n\), where there are \(n\) identical market makers quoting prices, and \(z_t\) is negative for buys, and positive for sell orders. Given our assumption of a symmetric equilibrium the distinction between aggregate and individual dealer inventories/trades is redundant. Apart from affecting the numerical values of coefficients, the number of traders \(n\), is irrelevant to the model and has been suppressed in the subsequent notation. Henceforth we refer solely to aggregate inventories and aggregate trades. The equations of the structural model are presented in Table A below.

[TABLE A ABOUT HERE]
All orders pass through the pool of market makers so the aggregate inventory level, $I_t$, obeys the identity given in (1). The stock has a fundamental value $v_t$, and as (2) shows, follows a random walk with white noise “information increments” $\xi_{1t}$ and $\xi_{2t}$. The latter is public information observed by the market maker at time $t$ (such as changes in the market index or public announcements about firm-specific events) whilst the former is current private information and is never observed by market makers. Hence, the market maker’s information set $\Omega_t$ is given in Table A as lagged trades and inventories, current and lagged quoted prices and current and lagged public information.

Our characterisation of the information shocks deserves some comment. First it is obvious that fundamentals have public and private components but it is less obvious that private information consists of a single signal that is commonly known by a sub-group of traders. Although some market events such as takeovers and profit announcements, may have this information structure, other informational increments, such as private research generated by analysts, are naturally heterogeneous. The implications of heterogeneous information sets for a dataset such as ours where the (non-market maker) participants are not identified, is unclear. As a result, the usefulness of our empirical results may be limited by the degree to which private information possessed by the traders in our sample was homogenous. Second it is questionable whether private information is never subsequently revealed. This drawback is not as serious as it seems, since it is likely that between the time the privately observed information is acted on by informed traders and the time of its subsequent public release, the intervening trades will have revealed most of the private signal to the market makers. If this is so, then our procedure will be approximately correct.

Following Seppi (1992), equation (3) splits trades into speculative and liquidity components. The trader speculates on the basis of his private information and will buy (sell) when the quoted price is below (above) its fundamental value. This gives rise to the first term on the right of (3). The second term, $x_t$, is trading arising from liquidity motives and is discussed below. Equation (3) is also part of the theoretical model in Madhavan and Smidt (1993). It captures the idea that, although traders are prepared to buy or sell at favourable prices, they dislike risk and, for any given positive (negative) discrepancy $(p_t - v_t)$, will take on (sell) only a limited amount of stock per period. Finally, (4) follows Madhavan and Smidt (1993) and Snell and Tonks (1998) in describing the representative
market maker’s pricing policy. Both papers solve an intertemporal optimisation problem to derive the market maker’s price setting behaviour. Prices will be set above (below) the market maker’s best guess of fundamental prices only if the latest inventory level lies below (above) the target level or if they expect noise traders to sell (buy) to (from) them.\(^5\) Without loss of generality, we set the target inventory level \(I^*\) to zero. The market maker may only infer the trader’s private information subsequently through her observation of lagged trades. In contrast to Madhavan and Smidt (1993) who adopt a Bayesian learning approach, we assume that the market maker forms rational expectations (RE) of the fundamental price and of the current noise trade.

To derive a time series representation for trades and quote revisions we shall require an assumption about noise trades. In general, noise trades are usually thought of as arising from trading to satisfy exogenously determined liquidity needs, and Hasbrouck (1991a) and Hasbrouck and Sofianos (1993) treat noise trades as an exogenous shock. However, Keim and Madhavan (1995) provide evidence to suggest that some traders trade on the market index. In this paper the only assumption we make about noise trades is that they are stationary and this assumption is stated in (5). It follows from this that the market maker’s (rational) expectation of noise trades will in general be a linear function of the stationary variables in her information set and we shall give an explicit definition of this function below.

\[\text{TABLE B ABOUT HERE}\]

Table B shows that our structural model implies a bivariate VAR in price quote revisions and volumes of trade with trade and public information shocks as the innovations. Equation (7) decomposes trades into expected trades \(E_t z_t\) and the RE error \(\eta_t\) which by definition is uncorrelated with all terms in the information set, including \(\xi_{2t}\). Substituting for \(z_t\) in (7) using (3) gives (8). Using (4) for \(p_t\) in (8) gives (9), which may be re-written in terms of inventories using the identity in (1) to give (10). Equation (10) combined with (7) shows that inventories are stationary only if \(k<0\). If \(k=0\), then inventories have a unit root and will be non-stationary. Note that the variables \(kI_{t-i}\) are always stationary a fact that we use below when constructing a general form for the RE of a stationary variable. The price quote \(p_t\) is always non-stationary because it depend on the expected value of a random walk as equation (4) shows. The list of stationary variables in the information set
at time $t$ can be summarised as: $\xi_{2t-i}, \eta_{t-1-i}, z_{t-1-i}, \Delta p_{t-i}$ and $kI_{t-1}$ ($i=0,1,2...$) where the last of these is either zero (when $k=0$ and inventories are non stationary) or stationary (when $k<0$ and inventories are stationary).

Equation (11) decomposes noise trades into a rational expectation $E\xi_t$ and an RE error $\xi_{3t}$. The latter forms a part of $\eta_t$ and is not separately identified by our econometric analysis. By definition the RE of noise trades $E\xi_t$ is a general linear function of the stationary variables in the information set and this is stated formally in (12). Note that a single lagged inventory term $kI_{t-1}$ on the RHS of (12) is sufficient because of the identity linking lagged trades and lagged inventories. We should re-emphasize that equation (12) does not constitute an assumed model for noise trades but is a direct consequence of their stationarity, RE and the definition of the market maker’s information set.

Differencing (4) gives (13). Equation (14) is proved in the Appendix (Lemma 2), and says that the revision the market makers’ beliefs about the fundamental $\Delta E\nu_{t}$, is made up of the public innovation $\xi_{2t}$ and the market makers’ revision in the expectation of $\nu_{t-1}$. This latter term is linear in the trade shock coming to light between time $t$ and $t-1$, namely $\eta_{t-1}$. The new public information $\xi_{2t}$ is orthogonal to $\nu_{t-1}$ and so is irrelevant to the revision in its expected value. In the Appendix (Lemma 3ii) we show that $a_{1}$ in (15) equals $\text{var}(\xi_{2})/\text{var}(\eta)$ and measures the liquidity shock component of $\eta$. Substituting (14) into (13) gives (15). Lagging (9) one period, rearranging for $\eta_{t-1}$ and using (1) to write $I_{t-2}$ as $I_{t-1}-z_{t-1}$ gives (16), which may be used on the RHS of (15) to get (17). Equations (9) and (17) explain trades and quote revisions respectively in terms of their lags, current and lagged expected noise trades, lagged inventories and the white noise innovations $\eta_t$ and $\xi_{2t}$. We may use (12) to substitute for $E\xi_t$ and $E\nu_{t-1}$ on the RHS of (9) and (17) to get the bivariate VAR

$$\Delta p_t = \theta_1(L) \Delta p_{t-1} + \theta_2(L) z_{t-1} + \psi_1 I_{t-1} + \xi_{2t}^* \quad (18)$$

$$z_t = \theta_3(L) \Delta p_t + \theta_4(L) z_{t-1} + \psi_2 I_{t-1} + \eta_t \quad (19)$$

where $\xi_{2t}^* = \xi_{2t}/(1-\gamma \phi_{2t})$, $\theta_i(L) = 1+\theta_{i1}L+\theta_{i2}L^2+... \ (i=1,2,3,4)$, $\psi_1 = (\gamma \delta + 1-\alpha \gamma)k/(1-\gamma \phi_{2t})$, $\psi_2 = \alpha k+(1+\alpha \gamma)\delta k$.
Although (18) and (19) do not explicitly define the coefficients in \( \theta_i(L) \) \( i=1,\ldots,4 \), they may be lined up with the parameters in (12) and the theoretical model in (9) and (17). We are able to obtain estimates of the deep parameters \( \alpha, \gamma \) and \( k \) in the theoretical model as follows. We show in the Appendix (Lemma 4) that an alternative representation for trades implied by the model is

\[
\Delta z_t = (\alpha + (1-L)\phi_2(L))\Delta p_t + [(1-L)\phi_1(L) + \delta k]z_t - a_1 \eta_{t-1} - \alpha \xi_{2t} + \eta_t \quad (20)
\]

If we use the residuals \( \xi_{2t} \) and lagged residuals \( \eta_{t-1} \) from the VAR in place of \( \xi_{2t} \) and \( \eta_{t-1} \) respectively then (20) is a regression equation that will give consistent parameter estimates. We can now compute consistent estimates of the deep parameters by taking certain estimated quantities from equation (20) plus the VAR, equating them with their theoretical values and solving these equations for \( \alpha, \gamma \) and \( k \). From equation (20) we use

- the coefficient on \( \eta_{t-1} \) and the sum of the coefficients on lagged trades to directly estimate \( a_1 \) and \( \delta k \) respectively.
- From the VAR we use: (a) the long run effect of \( \xi_{2t} \) on prices which we denote by \( \omega \); (b) the long run effect of \( \eta \) on prices which we denote by \( \tau \); (c) the coefficient on lagged inventories in the trades equation (19), \( \psi_2 \); (d) the coefficient on the current price quote change in the same equation, \( \theta_{31} \).

We show in the Appendix (Lemmas 5, 6, and 7) that the theoretical model implies the following relationships between these estimated quantities and the parameters of the theory

\[
\omega = 1 - \gamma \phi_{21} \quad (21a)
\]

\[
\tau = (a_1 - 1)/\alpha \quad (21b)
\]

\[
\psi_2 = (1 + \alpha \gamma) \delta k + \alpha k \quad (21c)
\]

\[
\theta_{31} = (1 + \alpha \gamma) \phi_{21} \quad (21d)
\]

Given the estimates of \( a_1 \) and \( \delta k \) from (23) and of \( \omega \), \( \tau \), \( \phi_{21} \) and \( \theta_{31} \) from the VAR, equation (21) solves uniquely for \( \alpha, \gamma \) and \( k \). We may then examine the signs and relative magnitudes of these deep parameter estimates to support the relevance and accuracy of our theoretical model with respect to the empirical VAR estimates.
3. Data

The LSE is a quote driven market. Trading in shares at the LSE takes place by telephone through a small number of registered market makers. Market makers announce firm prices at which they are willing to buy (bid) and sell (ask) on SEAQ screens for quantities of stock up to a preset maximum size. From among the prices quoted on the screens, the lowest ask price and highest bid price, which represents the best prices from the point of view of the customer, are highlighted on the SEAQ screens and are called the “yellow strip” prices or the “touch”. Finally, there is an obligation for customer generated business that the transactions price be no worse than the best price on the screens. Up to the time of the trade, market makers are free to revise their price quotes in the light of any new information, but once an order is placed, market makers are obliged to honour their quotes.

Our data consists of a continuous record of all transactions in fifteen less-liquid stocks on the LSE that occurred between April 1st 1992 and March 11th 1994. This period constitutes 491 trading days during 50 settlement periods over two years. The stocks were chosen as a random selection from the FTSE 250-Midi index, which is an index of 250 relatively illiquid stocks on the LSE. Midpoint quote prices \( p \), signed trade \( x \) and inventory level (computed as the cumulated sum of \( x \), initialised at zero) are available from the tape. The quoted prices from which the midpoints are computed are firm quotes up to a maximum transaction size. The transactions price may be different from the quoted for two reasons. First, if the trade was larger than the maximum for the quotes then the price would be negotiated. Second, the market maker is free to offer a more competitive quote than the touch if she so desires. She may not, of course, offer a less competitive price. Trades that pass between market makers, including those executed through the IDB network, are excluded from the sample as they have no implications for the aggregate inventory level for the group of market makers trading in a stock.

Summary statistics on (midpoint) market maker prices and trades in these stocks, are given in Table 1. As the table shows, all stocks were traded throughout the whole period except for stock 11, which was first floated in July 1992. We see that in terms of daily volume, there is a good deal of heterogeneity. Stock 2 has the largest daily turnover (£3.5m) with stock 15 having the lowest (£0.15m). Mean price changes were all positive, indicating a general upward trend in prices over the period. On the other hand inventories, computed
as the sum of trades, generally show little to no trend, though this does not imply widespread inventory control because untrended series may still be I(1) processes with zero drifts. Figure 1 plots inventories and prices in “transaction time”, for two stocks in our sample which illustrates some interesting features of the data. In stock 3 there is a clear breaks in mean inventory at around the (transaction) time 1450, and breaks in inventories are also apparent in stocks 7, 10 and 15. A further feature of the data is the abnormally large “spike” in the inventory series for stock 13 (also present in stocks 4 and 11). These are all initiated by one or two extraordinarily large sells to the market maker, and since trades of this size are well outside the range for which quoted prices are firm, their actual transactions prices will be the subject of bilateral negotiations between the market maker and the seller. We are careful to examine the sensitivity of our results for these stocks to the omission of these large outliers.

Finally, we note that the LSE tape unambiguously classifies trades as buys from or sales to the market maker, which is not always the case for order driven transaction records. Studies of order driven systems have had to adopt the convention [Lee and Ready (1991)] that trades that occur below midpoint quoted prices are market maker buys and those at prices above are her sales. It is not obviously true that this classification will be correct in all cases, particularly where trades take place very close to the mid-point of quoted prices.

4. Testing for the existence of market microstructure effects.

Inventory Control

In the economic model, inventory control hinges on the parameter \( k \). When there is no inventory control, \( k=0 \), inventories are non-stationary and wash out of the VAR completely. In this case both \( \psi_1 \) and \( \psi_2 \) are zero, so that (18) and (19) constitute a VAR in trades and price quote revisions only. As we show below, because \( \psi_1 \) is also zero under symmetric information regardless of the existence of inventory control our test for inventory control rests solely on the significance of \( \psi_2 \). Under the null of non stationary inventories, the OLS estimate of \( \psi_2 \) has the unit root distribution. When there is inventory control, \( k<0 \), and we can rearrange (18) and (19) using the inventory/trade identity (1) to show that the system constitutes a VAR in inventories and price quote revisions only. Under the alternative hypothesis of inventory control, \( \psi_2 \) will be negative and the usual one-tailed test is appropriate. We should note that in contrast to the test in Hasbrouck and
Sofianos (1993) which is based on estimates from a univariate autoregression of inventories, our test is from a bivariate system. If price quote changes are relevant in explaining inventories, then our test based on the bivariate model should be more powerful than that arising from a univariate analysis.

Asymmetric information

We test a null of symmetric information where \( \text{var}(\xi_1) = 0 \) against an alternative of asymmetric information where \( \text{var}(\xi_1) > 0 \). We show in the Appendix (Corollary) that \( a_t = 1 \) under symmetric information, so that under the null and irrespective of inventory control we may re-write (17) as

\[
\Delta p_t = k z_{t-1} + \gamma (1-L) E_t x_t + \xi_{2t} = k z_{t-1} + \gamma (1-L) \phi_1(L) z_t + \gamma (1-L) \phi_2(L) \Delta p_t + \xi_{2t} \quad (22)
\]

The test for asymmetric information is based on estimates from the price quote equation (8) in the VAR, but the actual form of the test depends on whether or not inventory control exists.

If there is inventory control, a null of symmetric information implies that inventories wash out of (18) and the relevant price equation is (22). Under the alternative, lagged inventories remain and the relevant price equation is (18). Therefore the t-ratio on the lagged inventory term in (18) is our test for asymmetric information under inventory control.

On the other hand if there is no inventory control, then \( k = 0 \), and a null of symmetric information means that (18) simplifies to

\[
\Delta p_t = \gamma (1-L) E_t x_t + \xi_{2t} = \gamma (1-L) \phi_1(L) z_t + \gamma (1-L) \phi_2(L) \Delta p_t + \xi_{2t} \quad (23)
\]

and the long run effect of trades on price quote revisions is zero. Under the alternative, this long run effect is non-zero. Therefore the t-ratio of the sum of the coefficients on lagged trades in (18) is our test for asymmetric information under no inventory control.
The intuition behind these tests lies in the way in which information is gleaned by the market maker on the unobserved private signal $\xi_{1t}$. When there is inventory control, inventories are stationary whilst trades are an over-difference stationary series. Long run information about fundamental prices is therefore contained in inventories rather than trades and the significance of the inventory term in the price equation indicates the transmission of news into prices. When there is no inventory control it is trades which carry information to the market maker and so it is the significance of the long run effect of trades rather than non-stationary inventories that indicates an information flow from trades to prices.

Implementation of the tests
We estimate (18) and (19) free of constraints and compute the quantities $\theta_i(1) \ (i=1,2,3,4)$, $\psi_1$ and $\psi_2$ together with their respective standard errors. The significance of $\psi_2$ is then examined by comparing its t-ratio with the unit root distribution. If $\psi_2$ is significant, then we may conclude that there is inventory control and test for the existence of asymmetric information by examining the significance of $\psi_1$. If $\psi_2$ is insignificant, then we may deduce that inventory control is absent and the existence of asymmetric information rests on the significance of $\theta_2(1)$.

The VAR also allows us to test for the existence of anticipated noise trades. From (12) if $E_t x_t$ is zero i.e. if noise trades are white noise then as (9) shows the VAR equation for trades (19), becomes

$$z_t = \alpha_k I_{r,1} + \eta_t$$  \hspace{1cm} (24)

Comparing (24) with (19) shows that a joint test for the joint significance of $\theta_3(L)$ and $\theta_4(L)$ from zero is a test of the existence of predictable noise trades.

5. Results for the tests and estimates of the structural model’s parameters
We estimated the VAR in (18) and (19) with a lag order of 20. Although no formal tests are given, lags beyond 15 were generally not very significant. Further, whilst increasing
the order to 30 reduced the significance of the test statistics for asymmetric information and inventory control, it did not qualitatively alter the conclusions.

Examining the inventory control tests first, the results for the t-test on $\psi_2$ are given in the second column of Table 2. We only report t-values, since it is the significance of the coefficient which determines the presence or not of inventory control. The economic importance of the coefficient value is that it determines the size of the inventory half-life. This is the time taken for inventories to recover one-half of their initial value after they have suffered a shock. The third column gives the half life of inventories implied by the estimated value of $\psi_2$.

The Table shows that 9 of our 15 stocks display significant inventory control and that half lives vary from below 2 to over 573 trading days. The absence of stronger inventory effects in a larger proportion of these stocks is somewhat surprising. Snell and Tonks (1995, 1998) and Hansch et al (1995) find inventory control to be prominent in their samples of alpha-rated stocks on the LSE so we might have anticipated such effects to be even more important in less liquid stocks. However inventory series in some stocks, such as stock 3 illustrated in figure 1, experience large permanent jumps in their inventory levels, which must be allowed for if proper inference is to be conducted.

Identifying potentially several breaks in large data series such as ours is difficult when one has no prior view where the breaks are. Madhavan and Smidt’s (1993) suggest identifying breaks through a sequential search, but we prefer to adopt a pragmatic approach similar to Perron (1989), and allow a single break in mean $t_b$ under both the null hypothesis of non-stationary inventories and under the alternative of stationarity. We enter two dummy terms in each of the VAR equations, an impulse dummy and a once and for all switch dummy, and they enter the $z_t$ and $\Delta p_t$ equations with coefficients $d_z, d_{z2}$ and $d_{\Delta p1}$ and $d_{\Delta p2}$ respectively:

$$Dum_{zt} = \begin{cases} 1 & \text{if } t = t_b \\ 0 & \text{otherwise} \end{cases} \quad Dum_{zt} = \begin{cases} 1 & \text{if } t < t_b + 1 \\ 0 & \text{otherwise} \end{cases}$$
Under the null of no inventory control and a switching (unconditional) mean, \( d_{i1} (i = z, \Delta p) \) should be significant and \( d_{i2} (i = z, \Delta p) \) should be insignificant. Under a null of no inventory control only, it follows from Perron (1989) that the t-ratios on the d’s and on \( \psi_2 \) follow non-standard distributions that depend only on \( t_b/T \), the proportion of the sample occurring before the break. Under the alternative hypothesis of inventory control, the usual \( \sqrt{T} \) asymptotics apply and all distributions are standard. The choice of break points \( t_b \) was guided by plots of inventories and were set at transaction time 1450, 4000, 1500 and 1250 for stocks 3, 7, 10 and 15 respectively. For the remaining stocks, there was no strong case for any particular value of \( t_b \) so it was fixed half-way through the sample. This runs the risk of missing mean-shifts that do not fit into the two subperiods but we would expect that if there was one or more significant mean shift over the sample, the test on a mid-sample break dummy would be significant.

The results for the t-ratios of \( d_{i2} (i=z,\Delta p) \) and \( \psi_2 \) are given in columns four to six in Table 2. Whilst the t-ratios on the dummy in the \( \Delta p \) equation were not very significant, many of those in the \( z_t \) equation were. To get an overall view of their joint significance in both equations, they may be squared and added to get a \( \chi^2 \) statistic. Doing this, we see that stocks 1, 3, 7, 8, 9, 10 and 15 have significant mean shifts and display significant inventory control. Of the remainder, all but stocks 2 and 14 show significant inventory control. Clearly, mean-shifts are important for many stocks. The resilience of the non-stationarity of stocks 2 and 14 is not too surprising. They have the third and first highest daily turnovers respectively so that mean reversion for these relatively liquid stocks may well be less marked. Half lives for all stocks, after including the break in mean, reported in column 7, are substantially lower than before. The average half life has fallen to around 5.5 days which is only slightly below the average of 7 days found by Madhavan and Smidt (1993) in their analysis of NYSE stocks, but above the average of 1.5 days found by Snell and Tonks (1995) for liquid stocks on the LSE.

The asymmetric information tests are displayed in the third and fourth columns of Table 3 for the stationary and non-stationary inventory cases respectively. All but one of the statistics have the right sign, with the perverse coefficient being insignificant. The statistics are very large with all but stocks 7, 8 and 11 displaying significant asymmetric
information. We can see that for stocks 2 and 14 which have non-stationary inventories, had we applied the asymmetric information test relevant to the stationary we would have failed to reject the null of symmetric information. This result illustrates the importance of testing for inventory control and asymmetric information in a single estimating system. We should note that the results for asymmetric information were qualitatively unchanged when we dropped the mean-shift dummies. With regard to the tests for predictability of noise trades, the relevant ($\chi^2_{40}$) statistics are given in the final column of Table 4, and all are significant, supporting the idea that there are predictable patterns in trades throughout the day.

We also examine the sensitivity of the results to the huge outliers in stocks 4, 11 and 13. Those data points corresponding to each respective “spike” plus twenty further observations on the right of the end of the spike (to allow for lagged effects) were dropped from the sample and the test results were re-computed. The results are given in Table 4. Not surprisingly, the half lives in all three cases have increased from below 3 to around 3, 6 and 7 days respectively. The t-ratios on $\psi_2$ are still significant although for stocks 11 and 13, the p-values have increased considerably. The tests for asymmetric information and for the predictability of noise trades have become more significant, and stock 11 in particular now shows significant asymmetric information effects.

As a check on our time series results, we report estimates of the deep parameters $\alpha$, $\gamma$ and $k$ for each of the stocks in table 5. These were computed using the methods outlined in equation (21), and it can be seen that all the estimates have the correct signs, and this gives us considerable confidence that the theoretical model is a valid description of the data.

6. Quantifying the Relative Importance of the Market Microstructure Effects

In a world with microstructure frictions, stock prices vary not only as a result of public information arrival but also because of the market microstructure effects. We now show how these microstructure frictions can be identified using estimates from the VAR, and how we may assess their impact on price volatility.

The components of quote revisions
We show in the Appendix (Lemma 9) that our theoretical model allows us to decompose the total change in price quotes into

\[
\Delta p_t = \xi_{2t} + \left(\frac{a_1 - 1}{\alpha}\right) \eta_{t-1} + k z_{t-1} + \gamma \Delta E_t x_t,
\]  

(25)

Equation (25) identifies four components of the price change: a public information effect (first term), and three microstructure frictions: trade-revealed private information (second term), inventory control (third term) and the change in anticipated noise trades (fourth term). In an analogous decomposition Hasbrouck (1991b) splits price changes into permanent and transitory components. Similarly, in the decomposition in (25) the first two terms are permanent effects on prices whilst the last two are temporary.

To assess the relative importance of the total microstructure versus the public information effects on the volatility of price changes, we may estimate the following ratio

\[
P_1 = \frac{\text{var}(\Delta p_t - \xi_{2t})}{\text{var}(\xi_{2t})},
\]  

(26)

By noting that the residual from (18), \(\xi_{2t}^*\), is just \(\xi_{2t}/\omega\) and that \(\omega\) may be estimated directly from the VAR, we can see that \(P_1\) may be computed using data on prices and using residuals and coefficient estimates from the VAR.

To assess the relative importance of temporary versus permanent effects we may compute the variance ratio

\[
P_2 = \frac{\text{var}[kz_{t-1} + \gamma \Delta E_t x_{t-1}]}{\text{var}\left[\xi_{2t} + \left(\frac{a_1 - 1}{\alpha}\right) \eta_{t-1}\right] + \text{var}[kz_{t-1} + \gamma \Delta E_t x_{t-1}]}.
\]  

(27)

The quantity \((a_1 - 1)/\alpha\), the long run effect of trade shocks on prices (\(\tau\) in (21b)) is estimated from the VAR and the lagged trade residual from (19) may be used in place of \(\eta_{t-1}\) to compute a consistent estimate of this variance ratio. When \(P_2\) is zero then all price volatility is due to information effects. If \(P_2\) is unity then all price volatility is due to
induced microstructure effects. If the two components in the denominator were uncorrelated then \( P2 \) could be interpreted as the proportion of the variance of price changes arising from induced effects. To the extent that the two components are correlated, such an interpretation may only be considered only as an approximation.

We also wish to quantify the relative importance for price volatility of trade-induced versus public information. To this end, we compute the variance ratio

\[
P3 = \frac{\text{var}\left[\frac{(a_1-1)}{\alpha} \eta_{t-1}\right]}{\text{var}\left[\varepsilon_{2t} + \frac{(a_1-1)}{\alpha} \eta_{t-1}\right]}
\]  

(28)

Equation (28) is a measure of the impact on volatility of price quote changes attributable to trade revealed information as a proportion of that induced by information as a whole. In an efficient market \( P3 \) is zero and rises to one with the increasing prevalence of private information. Hasbrouck (1991b) estimates an analogous ratio for NYSE stocks which he terms the relative informativeness of trades, and we compare our results to his.

**Market Quality**

Following Hasbrouck (1993) we refer to the gap between current prices \( p_t \) and the fundamental \( v_t \) as mispricing. Under this terminology, the numerator in \( P2 \) is the variance of the expected change in mispricing conditional on current public information. We now derive a measure of the variance of the expected level of mispricing. In Lemma 10 of the Appendix we show that

\[
E_t v_t = \frac{(a_1-1)/\alpha}{\text{var}(\eta)} \sum_i \eta_{t-1-i} + \sum_i \xi_{2t-i}
\]

(29)

The estimated VAR implies a unique Wold form for \( \Delta p_t \). Summing the Wold form for \( \Delta p_t \) back to time zero (taking \( p_0=0 \)) and subtracting (29) gives \( p_t-E_t v_t \) in terms of \( \eta_{t-1-i} \) and \( \xi_{2t-i} \) (\( i=0,1..t-1 \)). The variance of \( p_t-E_t v_t \) is then readily computed in terms of \( (a_1-1)/\alpha \), \( \text{var}(\eta) \), \( \text{var}(\xi_2) \), and the coefficients in the Wold form for \( \Delta p_t \). Unique estimates of all of these quantities may be obtained from the VAR. We compute \( P4 \) the normalised standard error.
of expected mispricing, analogous to Hasbrouck’s “quality of markets” index for NYSE stocks

$$P_4 = \frac{S.E.(p_e - E_{1,v})}{p}$$  \hspace{1cm} (30)

where $S.E.$ denotes empirical standard error and $p$ is the mean quoted price.

7. Results for the estimation of the market microstructure effects

The first three columns of Table 6 give the results for the variance ratios given in equations (26) to (28). These estimates do not depend on the values of the structural parameters, but are estimated directly from the VAR. The first column, $P_1$, displays the contribution to price volatility of the market microstructure effects relative to the contribution of public information. Stocks 2, 4, 8, 11 and 14 stand out as having a ratios much larger than the other stocks. Interestingly apart from stock 8 these are the most liquid stocks in our sample, having the highest average daily turnover. The second column $P_2$ measures the contribution to price volatility of the temporary versus permanent effects. As with $P_1$ it is the high turnover stocks that have the highest ratios, however unlike $P_1$, the dispersion across stocks of the ratio $P_2$ is much lower. The distinction between these two ratios is that $P_1$ has the trade-revealed component in the numerator, whereas $P_2$ has it in the denominator. Averaging the estimates of $P_2$ across stocks we calculate that 40% of the variance of the change in prices is accounted for by temporary effects. These results reinforce the asymmetric information tests reported in table 3, in that they show trade revealed information is a pervasive feature of our sample of stocks.

In the third column of table 6 we report $P_3$, the contribution to volatility of trade revealed information relative to total information. We find that in stocks 1, 2, 4, 5, 8 and 9 trade revealed information dominates public information as a source of price volatility. Averaging the numbers across stocks we estimate that trade revealed information accounts for 46% of the variance of the change in fundamental prices of the stocks as a whole. This is higher than the 34% reported by Hasbrouck (1991) for NYSE stocks. Hasbrouck finds that trades in smaller stocks are more informative than those in larger stocks. If this were also true for the LSE the higher informativeness shown by our sample is to be expected because our stocks are typically smaller than those dealt with by Hasbrouck.
The final column of Table 6 gives our estimates of $P4$ in (30) the standard error of mispricing as a percentage of the stock price. With the exception of stocks 1, 2 and 9, the figures are narrowly dispersed around the 1% level. Stock 2 is a clear outlier with a figure of over 10.5%. This was the stock for which inventory control was least important and one of the two which yielded insignificant inventory test statistics even after allowing for shifts in desired inventories. Given that the market quality computations were made under the assumption of inventory control, the mispricing estimate may not be reliable for this stock. On average, the standard error of mispricing was 1.97% of stock price but if the outlier of stock 2 is excluded this figure falls to 1.30%. This figure is substantially higher than the 0.33% found by Hasbrouck (1993) for NYSE stocks. Again the fact that the stocks in our sample are smaller and less liquid than those in Hasbrouck’s may contribute to some of the difference.\footnote{12}

Although not the focus of our paper, the size of the spread has been a dominant aspect of much market microstructure research. Because our results make no use of spread data, it is interesting to see whether our estimated microstructure quantities can explain the variation in the size of spreads across stocks. To this end we executed simple cross-stock regressions of bid-ask spreads on the log of turnover and each of $P1$ to $P4$.

Table 7 reports the results of the OLS cross-stock regressions. The dependent variable is the average bid-ask spread as a proportion of price given in Table 1. In each regression we include the log of daily turnover to proxy for the effects on spreads of liquidity and the coefficients on this term are always negative as expected. Regression 1 shows that our measure of total microstructure effects $P1$ is positive and very significant, so we may infer that stocks with large microstructure effects are associated with wider spreads. Regression 2 focuses on the separate effects of the microstructure components (trade-revealed information and market-maker induced price effects) by including $P2$ and $P3$ in the regression. Both coefficients are positive as expected although they are only significant at the 10% level. Dropping $P3$ (regression 4) gives a positive and significant coefficient on $P2$. Dropping $P2$ (regression 5) gives a positive and significant coefficient on $P3$. This suggests that the two components of the microstructure reinforce each other in that they both tend to be associated with higher spreads.
Regression 4 explains the extent to which mispricing variance and spreads are related. Although positive, the coefficient on $P4$ is small and insignificant, which suggests that spread and our mispricing measure are different measures of market quality. Indeed our theory predicts that they should differ because of the opposite response of spreads and mispricing volatility to expected noise trades. If market makers are able to exploit expected noise trades then this has a positive effect on profits and if the market is competitive this should translate into smaller spreads. However, exploitation of noise trades unambiguously increases volatility. This conflicting influence contrasts with the effect of inventory costs and asymmetric information on spreads and mispricing volatility which is uniformly positive in both cases.

8. Conclusions
This paper has examined the importance of inventory control and asymmetric information in price quotes set by market makers in a sample of less-liquid stocks on the London Stock Exchange. Our approach built on the earlier work of Snell and Tonks (1995, 1998) and has applied time series methods to the institutional setting of a quote driven market microstructure. In a dealer market since the current quoted prices are firm, they may not depend upon current private information. In contrast current trades may depend on both current private and public information. These identification restrictions allow us to express quote revisions and trades as a bivariate VAR with errors that can be written in terms of trade shocks containing private information and quote revision shocks containing only public information.

Estimation of the time series VAR allowed us to jointly assess the significance and extent of inventory control and asymmetric information, independently of the estimates of the structural parameters. Our findings are that both asymmetric information and inventory control are a robust feature of less liquid stocks traded on the LSE. The results accord with previous findings concerning NYSE stocks, particularly with regard to the speed of adjustment of inventories, the existence of a shift in their desired levels and the pervasive influence of trades on the long run level of prices through their role in revealing information on the stocks’ fundamental values. We also found that in contrast to earlier work on liquid stocks on the LSE, the adverse selection problem is a significant feature of dealer trading in less liquid stocks.
We further estimated measures of trade informativeness and market quality directly from the time series model, and found that on average 46% of the variance of the change in the fundamental price is due to trade-revealed components and that approximately 40% of the variance of the change in quoted prices is accounted for by market microstructure effects as a whole. The standard error of mispricing (the difference between fundamental and actual prices), was found to be 2% on average of stock value, which is substantially higher than that given in Hasbrouck (1993) for liquid NYSE stocks. We also found that our measures of the microstructure effects are positively correlated with bid-ask spreads across stocks, which supports the theoretical argument that spreads are a necessary compensation for the risks of adverse selection and price movements. These estimates are important since they provide an input into the current debate in London on whether to extend the SETS order book system to less liquid FTSE 250 stocks.
Table A: The Structural Form of the Model

| Aggregate Inventories: | $I_t \equiv I_{t-1} + z_t$  
| Fundamental Price: | $v_t = v_{t-1} + \xi_{1t} + \xi_{2t}$  
| Trades: | $z_t = \alpha(p_t - v_t) + x_t$  
| Price Quotes: | $p_t = E_t v_t + k(I_{t-1} - I^*) + \gamma E_t x_t$  
| Noise Trades: | $x_t$ is a covariance stationary process independent of $\xi_{1t}, \xi_{2t}$  
| Market Maker’s Information Set: | $\Omega = \{ \xi_{2t}, \xi_{2t-1}, .., \eta_{t-1}, \eta_{t-2}, .., z_{t-1}, z_{t-2}, .. \}$  
| Notation: | $I_t$ = aggregate inventories; $z_t$ = aggregate trades; $v_t$ = fundamental price; $\xi_{1t}, \xi_{2t}$ = private (public) information; $x_t$ = liquidity trades; $\eta_t$ = unanticipated trades

Table B: Deriving the VAR from the Model’s Structural Form

| Trades/Inventories: | $z_t = E_t z_t + (z_t - E_t z_t) = E_t z_t + \eta_t$  
| | $z_t = \alpha(p_t - E_t v_t) + E_t x_t + \eta_t$  
| | $z_t = (1+\alpha)E_t x_t + \alpha k I_{t-1} + \eta_t$  
| | $I_t = (1+\alpha)E_t x_t + (1+\alpha k) I_{t-1} + \eta_t$  
| Expected Noise Trades: | $x_t \equiv E_t x_t + (x_t - E_t x_t) \equiv E_t x_t + \xi_{3t}$  
| | $E_t x_t = \phi_1(L) z_t + \phi_2(L) \Delta p_t + \delta k I_{t-1}$  
| where $\phi_1(L) = \phi_{11} L + \phi_{12} L^2 + ...$ and $\phi_2(L) = \phi_{21} + \phi_{22} L + \phi_{23} L^2 + ...$.  
| Derivation of Quote Revisions: | $\Delta p_t = E_t v_t - E_t v_{t-1} + k z_{t-1} + \gamma \Delta E_t x_t$  
| | $E_t v_t - E_t v_{t-1} = \xi_{2t} + [(a_1-1)/\alpha] \eta_{t-1}$  
| | $\Delta p_t = [(a_1-1)/\alpha] \eta_{t-1} + k z_{t-1} + \gamma \Delta E_t x_t + \xi_{2t}$  
| | $\eta_{t-1} = (1+\alpha k) z_{t-1} - (1+\alpha \gamma E_{t-1} x_{t-1} - \alpha k I_{t-1}$  
| | $\Delta p_t = \gamma E_t x_t + [(1-a_1-a_1 \gamma)/\alpha] E_{t-1} x_{t-1} + k(1-a_1) I_{t-1} + [(a_1+\alpha k a_1-1)/\alpha] z_{t-1} + \xi_{2t}$  


Appendix

Lemma 1: Revision in expected noise trades: \( E_t x_{t-1} - E_{t-1} x_{t-1} = a_1 \eta_{t-1} \)

The existence of the VAR implies that we may rewrite \( \Omega_t \) as \( \{ \eta_{t-1}, \eta_{t-2}, \eta_{t-3}, \eta_{t-4}, \ldots, \xi_{2t}, \xi_{2t-1}, \xi_{2t-2}, \xi_{2t-3}, \ldots \} \). Rational expectations forecasts at time \( t \) of any variable can be written as a linear functions of these VAR innovations: \( E_t x_{t-1} = \sum_{i=0}^{\infty} a_i \eta_{t-i} + \sum_{i=0}^{\infty} b_i \xi_{2t-i} \) (A1)

Noise trades \( x_{t-1} \) is independent of \( \xi_{2t} \), so that the coefficient \( b_0 \) in (A1) is zero. Taking expectations of both sides of (A1) conditional on information at \( t-1 \), and applying the law of iterative expectations gives:

\[
E_t x_{t-1} = \sum_{i=2}^{\infty} a_i \eta_{t-i} + \sum_{i=1}^{\infty} b_i \xi_{2t-i} \] (A2)

Subtracting (A1) from (A2) gives Lemma 1. QED

Lemma 2: Revision in expected fundamental price: \( E_t v_t - E_{t-1} v_{t-1} = \xi_{2t} + \eta_{t-1}(a_1-1)/\alpha \)

From equation (2), and the information set in (6) the market makers’ revisions in beliefs about fundamentals can be written as

\[
E_t v_t - E_{t-1} v_{t-1} = E_t v_{t-1} - E_{t-1} v_{t-1} + \xi_{2t} \] (A3)

Substitute in (8) for \( z_t \) from (3), and rearrange in terms of \( \eta_t \)

\[
\eta_t = \alpha(E_t v_t - v_t) + (x_t - E_t x_t) \] (A4)

Lag (A4) one period, and take expectations at time \( t \)

\[
\eta_{t-1} = (E_{t-1} x_{t-1} - E_{t-1} x_{t-1}) - \alpha(E_{t-1} v_{t-1} - E_{t-1} v_{t-1}) \] (A5)

Using Lemma 1 in (A5) and rearranging gives: \( E_t v_t - E_{t-1} v_{t-1} = \eta_{t-1}(a_1-1)/\alpha \) which may be substituted into (A3) to obtain Lemma 2. QED

Lemma 3: i) \( \eta_t = a_1 \eta_{t-1} + \Delta \xi_{3t} - \alpha \xi_{2t} \) and ii) \( a_1 = \text{var}(\xi_3)/\text{var}(\eta) \)

Difference equation (A4) and use (11) to obtain:

\[
\Delta \eta_t = -\alpha(\Delta v_t - \Delta E_t v_t) + \Delta \xi_{3t} \]

Use Lemma 2 and equation (2) to write: \( \Delta \eta_t = -\alpha \xi_{2t} - \alpha \xi_{2t} + (a_1 - 1) \eta_{t-1} + \alpha \xi_{2t} + \Delta \xi_{3t} \). Rearranging gives i). To prove ii) multiply both sides of i) by \( \eta_{t-1} \) and take expectations to get

\[
0 = a_1 \text{var}(\eta) - E(\xi_{3t-1} \eta_{t-1}) = a_1 \text{var}(\eta) - \text{var}(\xi_3) \]

where we have used \( E(\xi_{3t-1} \eta_{t-1}) = E(\xi_{3t} \eta_t) = \text{var}(\xi_3) \) which is a consequence of stationarity and i). The above expression may be rearranged to give ii). QED

Corollary: With no private information \( a_1 = 1 \)
Note that if there is no private information \( E_t v_{t-1} = E_{t-1} v_{t-1} = v_{t-1} \), hence (A3) becomes
\[
\eta_{t-1} = (E_t x_{t-1} - E_{t-1} x_{t-1}), \text{ so from (12) } a_1 = 1.
\]

**Lemma 4: Derivation of equation (20)** Difference equation (8) to obtain:
\[
\Delta z_t = \alpha(\Delta p_t - \Delta E_t v_t) + \Delta E_t x_t + \Delta \eta_t
\]
Then substitute, for \( \Delta E_t x_t \) by Differencing (12), and for \( \Delta E_t v_t \) by using Lemma 2, to obtain
\[
\Delta z_t = [(a_1 - 1)/\alpha] \eta_{t-1} - \alpha \xi_2 t + \Delta \eta_t
\]
Simplifying the error term gives equation (20). QED

**Lemma 5: Long-run effects of \( \xi_2 \) and \( \xi_1 \) on p are unity** In equation (13), if \( k=0 \), long run equation is
\[
\Delta p = \xi_2 + \eta(a_1-1)/\alpha.
\]
If \( k \neq 0 \), \( z_{t-1} \) contains an MA unit root and long run equation is the same (because \( z = 0 \)). Now long run effect of \( \xi_1 \) on \( \eta \) is obtained from Lemma 3, as \( \eta = -\alpha \xi_1/(1-a_1) \). So the long run effects on price are \( \Delta p = \xi_1 + \xi_2 \). QED

**Lemma 6: Long-run effects of \( \xi_2^* \) on p is \( (1-\gamma \phi_2) \) From equation (14) and Lemma 5, we may write \( \Delta p = \xi_1 + \xi_2^* (1-\gamma \phi_2) \) QED

**Lemma 7: Long-run effect of \( \eta \) on p is \( (a_1-1)/\alpha \) Follows from Lemma 5. QED

**Lemma 8: Derivation of equation (21)** Equations (21a) and (21b) are established from Lemmas 6 and 7 above. Substitute for the \( E_t x_t \) from equation (8) in equation (12) to give
\[
z_t = (1 + \alpha \gamma) [\phi_1(L)z_t + \phi_2(L) \Delta p_t + \delta k I_{t-1}] + \alpha k I_{t-1} + \eta_t
\]
Collecting the coefficients on \( \Delta p_t \) and \( I_{t-1} \) respectively and noting that the leading coefficient on \( \phi_2(L) \) is \( \phi_2 \), gives equations (21c) and (21d) QED

**Lemma 9: Decomposition of \( \Delta p_t \) as given in (25)** From (4) the change in prices is:
\[
\Delta p_t = E_t v_t - E_{t-1} v_{t-1} + k z_{t-1} + \gamma \Delta E_t x_t
\]
Using Lemma 2, this becomes equation (25). QED

**Lemma 10: Derivation of equation (29)** Add \( \xi_2 t \) to both sides of Lemma 3(i), sum the equation backwards \( t \) periods and rearrange to get
\[
\sum_{i=0}^{t} \xi_{1r-i} + \sum_{i=0}^{t} \xi_{2r-i} = -\eta_t + \frac{(a_1 - 1)}{\alpha} \sum_{i=0}^{t} \xi_{1r-1-i} + \sum_{i=0}^{t} \xi_{2r-1-i} + \xi_3 t
\]
(A6)
where we have set \( \xi_{30} = 0 \). The left hand side is just \( v_t v_0 \). Using this fact, setting the initial value of \( v \) (\( v_0 \)) to zero and taking expectations of both sides of (A6) gives (29) in the text.
QED
Table 1: Summary Statistics

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<th>Stock</th>
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<th>Mean Quoted Spread (%)</th>
<th>Average mid-point quoted price</th>
<th>Average quoted price change</th>
<th>Standard deviation of quoted price change</th>
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<tr>
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<td>4.504</td>
<td>.0448</td>
<td>0.868</td>
</tr>
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<td>Textiles</td>
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<td>1.177</td>
<td>.0001</td>
<td>0.438</td>
</tr>
<tr>
<td>Scapa</td>
<td>Chemicals</td>
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<td>2.162</td>
<td>.0192</td>
<td>0.578</td>
</tr>
<tr>
<td>Spir.Sparco</td>
<td>Engineering</td>
<td>1.112</td>
<td>3.311</td>
<td>.0795</td>
<td>1.167</td>
</tr>
<tr>
<td>S.W.Elect.</td>
<td>Electrical Eng.</td>
<td>.892</td>
<td>5.839</td>
<td>.0194</td>
<td>1.095</td>
</tr>
<tr>
<td>Telegraph</td>
<td>Media</td>
<td>1.014</td>
<td>3.849</td>
<td>.0879</td>
<td>0.953</td>
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<td>Trans. DG</td>
<td>Transport</td>
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<td>2.663</td>
<td>.0088</td>
<td>0.889</td>
</tr>
<tr>
<td>Welsh Water</td>
<td>Water Supply</td>
<td>.952</td>
<td>5.545</td>
<td>.0176</td>
<td>1.033</td>
</tr>
<tr>
<td>Yule Catto</td>
<td>Chemicals</td>
<td>1.265</td>
<td>2.660</td>
<td>.0469</td>
<td>1.203</td>
</tr>
</tbody>
</table>

Table 1 shows various descriptive statistics for each of 15 less-liquid stocks in our sample over the period April 1992-March 1994. Prices, price changes and trades are measured in pounds, pence and 1000 stocks, respectively. Daily turnover is measured in £ million.
<table>
<thead>
<tr>
<th>Stock</th>
<th>$t(\psi_2)$</th>
<th>$H.Life_1$</th>
<th>$t(d_{z2})$</th>
<th>$t(d_{z2})$</th>
<th>$t(\psi_2)$</th>
<th>$H.Life_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-4.06</td>
<td>4.90</td>
<td>-2.62</td>
<td>-2.16</td>
<td>-5.03</td>
<td>3.04</td>
</tr>
<tr>
<td>2</td>
<td>-1.63</td>
<td>40.84</td>
<td>.97</td>
<td>1.19</td>
<td>-1.84</td>
<td>25.00</td>
</tr>
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<td>3</td>
<td>-4.44</td>
<td>364.57</td>
<td>4.33</td>
<td>2.77</td>
<td>-7.10</td>
<td>5.08</td>
</tr>
<tr>
<td>4</td>
<td>-6.19</td>
<td>2.50</td>
<td>1.01</td>
<td>1.80</td>
<td>-6.34</td>
<td>2.38</td>
</tr>
<tr>
<td>5</td>
<td>-5.14</td>
<td>4.64</td>
<td>.01</td>
<td>-.89</td>
<td>-5.14</td>
<td>4.64</td>
</tr>
<tr>
<td>6</td>
<td>-4.78</td>
<td>4.30</td>
<td>-1.88</td>
<td>.60</td>
<td>-5.23</td>
<td>3.61</td>
</tr>
<tr>
<td>7</td>
<td>-2.37</td>
<td>13.88</td>
<td>-2.97</td>
<td>.70</td>
<td>-3.44</td>
<td>5.55</td>
</tr>
<tr>
<td>8</td>
<td>-3.33</td>
<td>6.79</td>
<td>-5.46</td>
<td>-.62</td>
<td>-5.46</td>
<td>2.61</td>
</tr>
<tr>
<td>9</td>
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<td>5.81</td>
<td>-3.73</td>
<td>.48</td>
<td>-3.73</td>
<td>5.79</td>
</tr>
<tr>
<td>10</td>
<td>-2.25</td>
<td>11.18</td>
<td>-2.52</td>
<td>-1.65</td>
<td>-4.09</td>
<td>3.46</td>
</tr>
<tr>
<td>11</td>
<td>-7.13</td>
<td>1.57</td>
<td>.11</td>
<td>-.39</td>
<td>-7.14</td>
<td>1.57</td>
</tr>
<tr>
<td>12</td>
<td>-4.30</td>
<td>3.99</td>
<td>1.93</td>
<td>-.58</td>
<td>-4.58</td>
<td>3.47</td>
</tr>
<tr>
<td>13</td>
<td>-8.14</td>
<td>2.81</td>
<td>.74</td>
<td>.17</td>
<td>-8.16</td>
<td>2.79</td>
</tr>
<tr>
<td>14</td>
<td>-2.10</td>
<td>33.25</td>
<td>-1.97</td>
<td>.60</td>
<td>-2.84</td>
<td>19.36</td>
</tr>
<tr>
<td>15</td>
<td>-.19</td>
<td>573.05</td>
<td>5.81</td>
<td>.64</td>
<td>-6.30</td>
<td>5.81</td>
</tr>
</tbody>
</table>

Table 2 reports tests for inventory control outlined in section 3 by stock. The second column in the table gives the value of t-test on the coefficient $\psi_2$ in equation (19). The third column gives the half life of inventories implied by the estimated value of $\psi_2$. The half lives are in units of trading days, each of which are assumed to experience the same number of trades as the average in the sample. Columns 4 and 5 report t-ratios on the structural break dummies. Critical values for these dummies are +/-2.50 for stocks 3, 12 and 15, +/-2.36 for stock 9 and +/-3.00 for the other stocks. Columns 6 and 7 report t-test on $\psi_2$ and half lives after allowing for break dummies. Superscript '*' denotes significance at 5% level, $t(\psi_2)$ follows the Dickey-Fuller distribution with 95% critical value -2.99. The 95% critical values for $t(\psi_2)$ are -3.23 for stocks 12 and 15, -3.15 for stock 9 and -3.48 for the others.
Table 3: Tests for asymmetric information and anticipated noise trades

<table>
<thead>
<tr>
<th>Stock</th>
<th>Info(S)</th>
<th>Info(N)</th>
<th>Noise trades</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1.89*</td>
<td>-3.86*</td>
<td>72.40</td>
</tr>
<tr>
<td>2</td>
<td>-1.71*</td>
<td>-6.48*</td>
<td>66.26</td>
</tr>
<tr>
<td>3</td>
<td>-2.30*</td>
<td>-2.60*</td>
<td>81.28</td>
</tr>
<tr>
<td>4</td>
<td>-4.16*</td>
<td>-5.21*</td>
<td>57.64</td>
</tr>
<tr>
<td>5</td>
<td>-2.73*</td>
<td>-4.31*</td>
<td>54.41</td>
</tr>
<tr>
<td>6</td>
<td>-1.67*</td>
<td>-1.59</td>
<td>46.13</td>
</tr>
<tr>
<td>7</td>
<td>-0.50</td>
<td>0.78</td>
<td>49.23</td>
</tr>
<tr>
<td>8</td>
<td>-1.35</td>
<td>-2.21*</td>
<td>41.23</td>
</tr>
<tr>
<td>9</td>
<td>-3.65*</td>
<td>-3.41*</td>
<td>80.06</td>
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<tr>
<td>10</td>
<td>-2.17</td>
<td>-1.82*</td>
<td>60.97</td>
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<tr>
<td>11</td>
<td>-1.31</td>
<td>-2.49*</td>
<td>41.65</td>
</tr>
<tr>
<td>12</td>
<td>-2.81*</td>
<td>-2.13*</td>
<td>109.13</td>
</tr>
<tr>
<td>13</td>
<td>-2.70*</td>
<td>-1.65*</td>
<td>56.15</td>
</tr>
<tr>
<td>14</td>
<td>-0.75</td>
<td>-6.75*</td>
<td>44.42</td>
</tr>
<tr>
<td>15</td>
<td>-2.13*</td>
<td>-0.75</td>
<td>72.66</td>
</tr>
</tbody>
</table>

Table 3 reports tests for asymmetric information outlined in section 3 by stock. Info(S) and Info(N) are the t-ratios for asymmetric information for the stationary ($\psi_1$ in (18)) and non-stationary cases ($\theta_2(1)$ in (18)), respectively. Given the results from table 2, the appropriate t-ratios are highlighted in bold. The Info tests are one-tailed and follow a standard normal distribution. The standard errors for the tests were corrected for heteroscedasticity. Noise trades is the test for anticipated noise trades (joint significance of $\theta_3(L)$ and $\theta_4(L)$ from zero in (19)) and is distributed as a chi-squared statistic with 40 dof.

Table 4: Sensitivity of results for stocks 4, 11 and 13 to the removal of outliers

<table>
<thead>
<tr>
<th>Stock</th>
<th>$t(\alpha')$</th>
<th>Half Life</th>
<th>Info(S)</th>
<th>Info(N)</th>
<th>Noise Trades</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>-6.12*</td>
<td>3.20</td>
<td>-7.01*</td>
<td>-4.67*</td>
<td>101.29</td>
</tr>
<tr>
<td>11</td>
<td>-4.51*</td>
<td>6.09</td>
<td>-5.28*</td>
<td>-1.67*</td>
<td>46.45</td>
</tr>
<tr>
<td>13</td>
<td>-3.64*</td>
<td>6.90</td>
<td>-3.09*</td>
<td>-2.76*</td>
<td>47.58</td>
</tr>
</tbody>
</table>

All items are as in Tables 2 and 3.

Table 5: Structural Parameter Estimates

<table>
<thead>
<tr>
<th>Stock</th>
<th>$\alpha$</th>
<th>$k$</th>
<th>$\gamma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.30</td>
<td>-0.176</td>
<td>-0.924</td>
</tr>
<tr>
<td>2</td>
<td>9.87</td>
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<td>-0.142</td>
</tr>
<tr>
<td>3</td>
<td>4.98</td>
<td>-0.012</td>
<td>-0.214</td>
</tr>
<tr>
<td>4</td>
<td>5.79</td>
<td>-0.026</td>
<td>-0.197</td>
</tr>
<tr>
<td>5</td>
<td>3.98</td>
<td>-0.024</td>
<td>-0.271</td>
</tr>
<tr>
<td>6</td>
<td>7.65</td>
<td>-0.006</td>
<td>-0.140</td>
</tr>
<tr>
<td>7</td>
<td>7.77</td>
<td>-0.003</td>
<td>-0.130</td>
</tr>
<tr>
<td>8</td>
<td>5.90</td>
<td>-0.020</td>
<td>-0.215</td>
</tr>
<tr>
<td>9</td>
<td>4.70</td>
<td>-0.036</td>
<td>-0.261</td>
</tr>
<tr>
<td>10</td>
<td>3.70</td>
<td>-0.024</td>
<td>-0.278</td>
</tr>
<tr>
<td>11</td>
<td>19.75</td>
<td>-0.001</td>
<td>-0.051</td>
</tr>
<tr>
<td>12</td>
<td>1.97</td>
<td>-0.056</td>
<td>-0.595</td>
</tr>
<tr>
<td>13</td>
<td>7.38</td>
<td>-0.004</td>
<td>-0.135</td>
</tr>
<tr>
<td>14</td>
<td>4.73</td>
<td>-0.003</td>
<td>-0.219</td>
</tr>
<tr>
<td>15</td>
<td>6.90</td>
<td>-0.007</td>
<td>-0.150</td>
</tr>
</tbody>
</table>

Table 5 reports estimated values of the structural parameters identified in the price equation (4) by stock. The computation of these structural parameters is derived in equation (21).
Table 6: Market Microstructure Effects

<table>
<thead>
<tr>
<th>Stock</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Microstructure versus public information effects</td>
<td>Temporary versus permanent effects</td>
<td>Trade-revealed versus public information effects</td>
<td>Normalised standard error of expected mispricing (%)</td>
</tr>
<tr>
<td>1</td>
<td>0.11</td>
<td>0.42</td>
<td>0.75</td>
<td>3.04</td>
</tr>
<tr>
<td>2</td>
<td>4.90</td>
<td>0.53</td>
<td>0.95</td>
<td>10.55</td>
</tr>
<tr>
<td>3</td>
<td>0.94</td>
<td>0.46</td>
<td>0.44</td>
<td>1.09</td>
</tr>
<tr>
<td>4</td>
<td>1.37</td>
<td>0.50</td>
<td>0.81</td>
<td>1.25</td>
</tr>
<tr>
<td>5</td>
<td>0.08</td>
<td>0.35</td>
<td>0.57</td>
<td>1.65</td>
</tr>
<tr>
<td>6</td>
<td>0.42</td>
<td>0.33</td>
<td>0.22</td>
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</tr>
<tr>
<td>7</td>
<td>0.16</td>
<td>0.24</td>
<td>0.17</td>
<td>0.75</td>
</tr>
<tr>
<td>8</td>
<td>8.70</td>
<td>0.71</td>
<td>0.79</td>
<td>1.12</td>
</tr>
<tr>
<td>9</td>
<td>0.07</td>
<td>0.42</td>
<td>0.76</td>
<td>3.73</td>
</tr>
<tr>
<td>10</td>
<td>0.05</td>
<td>0.23</td>
<td>0.32</td>
<td>1.44</td>
</tr>
<tr>
<td>11</td>
<td>3.91</td>
<td>0.74</td>
<td>0.35</td>
<td>0.28</td>
</tr>
<tr>
<td>12</td>
<td>0.04</td>
<td>0.28</td>
<td>0.40</td>
<td>1.41</td>
</tr>
<tr>
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<td>0.13</td>
<td>0.11</td>
<td>0.86</td>
</tr>
<tr>
<td>14</td>
<td>1.99</td>
<td>0.64</td>
<td>0.16</td>
<td>0.65</td>
</tr>
<tr>
<td>15</td>
<td>0.09</td>
<td>0.08</td>
<td>0.04</td>
<td>0.95</td>
</tr>
</tbody>
</table>

Table 6 reports estimates of the market microstructure measures outlined in section 4 by stock. These market microstructure effects are computed in equations (26)-(28), and (30).

Table 7: Regressions to explain the bid-ask spread

<table>
<thead>
<tr>
<th>Regression no.</th>
<th>Log(Turnover)</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.23**</td>
<td>0.15**</td>
<td>1.02*</td>
<td>0.61*</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.20)</td>
<td>(4.27)</td>
<td>(1.46)</td>
<td>(1.35)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.35**</td>
<td>1.42**</td>
<td>0.89**</td>
<td>0.07</td>
<td>0.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.21)</td>
<td>(2.10)</td>
<td>(1.98)</td>
<td>(1.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-0.30*</td>
<td>1.40**</td>
<td>0.89*</td>
<td>0.07</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.89)</td>
<td>(2.10)</td>
<td>(1.98)</td>
<td>(1.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.27*</td>
<td>0.89**</td>
<td>0.89**</td>
<td>0.07</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.75)</td>
<td>(1.98)</td>
<td>(1.98)</td>
<td>(1.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-0.23</td>
<td>0.89**</td>
<td>0.89**</td>
<td>0.07</td>
<td>0.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.33)</td>
<td>(1.98)</td>
<td>(1.98)</td>
<td>(1.10)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7 reports the results of the cross-section regressions of bid-ask spreads against the various market microstructure measures estimated in Table 6. Number of observations is 15, and these cross-section regressions include a constant which is not reported; t-statistics are given in brackets, and * (**) denotes significance at 5% (10%) using a one tailed test.
References


1 The LSE produced consultation document “SETS Review & Consultation” (March 1998) which suggested that the SETS order book system introduced in October 1997 for liquid FTSE 100 stocks be extended to the less-liquid stocks that make up the FTSE 250 index. In addition the announcement in May 2000 of a merger between the London and Frankfurt Stock Exchanges, has been accompanied by a debate over the appropriate trading platform.

2 Neuberger (1992) examines the size of market maker profits in a sample of liquid and illiquid stocks.

3 Explicitly, Rule 4.5a from the LSE rule book states that “during the mandatory quote period, a normal size market maker shall display on SEAQ firm two-way prices in not less than the minimum quote size in each SEAQ security in which it is registered, and actively offer to buy and sell to an inquiring member at the price in up to the size in a security displayed by it on SEAQ”.

4 The usual identifying assumption is that current public information does not affect current trades.

5 In reality market makers deal in more than one stock, and may adopt a portfolio approach in setting prices. To the extent that stocks in the portfolio are correlated, market makers may be less concerned about inventory control in any single stock.

6 The estimates of $\alpha$, $\gamma$ and $k$ that we derive are consistent but not unique because the VAR from which we solve these estimates does not impose the model’s theoretical restrictions. We chose to solve for $\alpha$, $\gamma$ and $k$ using $\omega$, $\tau$, $\psi_2$ and $\theta_3$ because the latter were the best determined coefficients in terms of the t-ratios in the VAR. A sensitivity analysis using different estimated quantities from the VAR to solve for $\alpha$, $\gamma$, and $k$ produced qualitatively similar results to those given in section 5 below.

7 This data set was given to us by the LSE’s Quality of Markets Unit, via John Board. Further descriptive details of this dataset can be found in Board and Sutcliffe (1995).

8 Reiss and Werner (1996) suggest that breaks in inventory could be due to an offsetting trade in another market. Our sample of less-liquid stocks are only quoted on the LSE, and so there cannot be offsetting trades on other exchanges; though there could be offsetting trades in correlated securities.

9 We assume no drift, and hence, no change in drift under this null. Drifting inventories would be very hard to rationalise by economic reasoning. Note that the distributions of $d_{11}$ and $d_{12}$ are independent because the regressors Dum1 and Dum2 are orthogonal.

10 Critical values for the t-ratios on $\psi_2$, $d_{22}$ and $d_{3p2}$ for the five break points were computed by Monte Carlo simulation and are reported at the foot of Table 2.

11 We should note that the inclusion of mean shift dummies did not significantly alter the results with regard to previously well determined parameters in the VAR.

12 The average number of transactions per stock are roughly three times greater in Hasbrouck’s sample of NYSE stocks.