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Using Time Series Methods to Assess Information and Inventory Effects in a Dealer Market in Less-Liquid Stocks

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Abstract

The purpose of this paper is to test for the existence of inventory control and asymmetric information in stock market price quotes, and then quantify these microstructure effects. The paper extends the time series work of Hasbrouck (1988, 1991) to the institutional setting of the London Stock Exchange. In contrast to the NYSE work our model and institutional framework enables us to 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 decompose price changes into a component due to the arrival of public and private news about fundamentals, and another 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 test the model on trade-by-trade observations for fifteen relatively illiquid stocks on the LSE. Our findings are that both asymmetric information and inventory control are a robust feature of our sample of less-liquid stocks. This result accords 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 stock's fundamental value. Further, those stocks in which in which we find microstructure effects are important, also display high quoted spreads, which is consistent with theoretical predictions.

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1. Introduction

In this paper we quantify and test for the existence of inventory control and asymmetric information in stock market price quotes, extending the time series work of Hasbrouck (1988, 1991) to the institutional setting of the London Stock Exchange (LSE). The LSE operates as a pure dealer system with competing market makers quoting firm prices whereas the NYSE is a hybrid system where a limit order book complements the monopoly specialist. The differences in these microstructures fundamentally effects the properties of the data and the methods that we may use to carry out tests. We argue that our data set is better suited to testing for information and inventory effects in price quotes than that of the NYSE, on which much previous empirical work has been carried out, and show that the techniques used previously would be inappropriate in the context of LSE data.

An important contribution of this paper is that we conduct our tests on a sample of less-liquid stocks outside of those in the FTSE100 index, which is in contrast to other empirical work on the LSE which has concentrated on liquid stocks.[1] As well as verifying whether asymmetric information and inventory control is found in the less liquid stocks, we are able to 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. As a result we can assess the relative importance of public information and private information revealed through trades, on the change in prices. We also measure how much of the volatility of prices is due to inventory effects unrelated to the arrival of news and quantify the costs of liquidating a position in a dealer market. A feature of our work is that we use an underlying theoretical structure to interpret time series regressions of the price-volume relationship, and this enables us to obtain estimates of important microstructure effects. In quantifying these microstructure effects this paper can contribute to the on-going debate in London over the appropriate trading mechanism for these less liquid stocks.[2]

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[1]A number of authors [Breedon (1993), Snell and Tonks (1995,1996), Hansch et.al., (1995)] have examined aspects of the trading process on the LSE in liquid stocks. Neuberger (1992) looks at the size of market maker profits in a sample of liquid and illiquid stocks.

[2] These estimates have implications for the way that stock markets are organised. The London Stock Exchange is undertaking a thorough review of its trading system, and issued a consultation document in January 1996 entitled *New Electronic Trading Services*, in which it questioned whether the optimal

Work in the area of market microstructure has developed at the theoretical and empirical levels. On the theoretical side, papers by Amihud and Mendelson (1980), Ho and Stoll (1983), Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Admati and Pfleiderer (1988,1989) and Foster and Viswanathan (1990) focus on different aspects of the response of market makers' quoted prices to disequilibrium in their inventories, to asymmetric information and to anticipated noise trades. In the empirical work using NYSE data, Hasbrouck (1988,1991a,1991b), Hasbrouck and Sofianos (1993), Petersen and Umlauf (1992) and Madhavan and Smidt (1991) have examined the factors that determine the setting of stock prices. These papers estimate time series models for price quotes, trades and market maker inventories, and then interpret the statistical properties of the estimated model in the light of simple theories of market maker (mm) behaviour. By contrast, Madhavan and Smidt (1993) and Snell and Tonks (1991) derive estimating equations from an explicitly theoretical intertemporal model of the market making function. Whilst both these papers test for inventory control within their respective models, the former tests for asymmetric information on the NYSE via the imposition of Bayesian learning whilst the latter uses the rational expectations assumption and data from the London Stock Exchange (LSE). [3]

In the current paper, we follow *inter alia* Hasbrouck (1991) and use time series methods to estimate and test for inventory control and asymmetric information effects. We then use these estimates to quantify the importance of various microstructure effects. There are several important aspects of our work that distinguish it from its predecessors which use NYSE data. Using LSE data, we are able to exploit the fact that on the LSE all trades pass through the dealer's inventory whereas on the NYSE public limit orders can be matched with outside trades, and large block trades are prearranged in the so-called upstairs market. This feature of the NYSE breaks a vital link between inventories and trades namely, the identity that

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microstructure for liquid stocks will also be optimal for less liquid and illiquid stocks. The current paper in quantifying the extent of microstructure effects in less liquid stocks is able to help answer this question.

[3] De Jong, Nijman and Roell (1996) estimate price effects of trading on the Paris Bourse, using both an explicit microstructure model (Glosten, 1994) and also a time series model.

says that the change in inventories over a given period of time are equal to the sum of the net trades over that period.. This has two implications. First the only method by which the dealer may alter her inventory level on the LSE is by changing price quotes to elicit buys or sells so that if inventory control exists it must be via the classic price control mechanism. 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 (1994)]. Second, the tight relationship between trades and inventories on the LSE enables us to undertake our analysis within a simple bivariate VAR for price quotes and inventories. This is more difficult on the NYSE where inventories, trades and prices all need to be modeled. For this reason it is not possible to test for inventory control on the NYSE, using only trades data whereas this *is* possible using data from the LSE. In fact the integrated approach for testing for inventory control and asymmetric information within a single system of estimated equations that we discuss below, is only possible on LSE data because of the existence of the identity linking inventories and trades.

A further advantage of our data set is that the LSE tape unambiguously classifies trades as buys from or sales to the market maker, which is not the case for the NYSE transaction records. The convention when dealing with NYSE data [Lee and Ready (1991)] has been to presume that trades that occur below midpoint quoted prices are buys by the market maker 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]

Our study combines a theoretical model with the institutional structure of the LSE's trading system to identify two fundamental economic shocks from the VAR. The first of these is public information and the second is a liquidity-plus-private-information shock or "trade shock" which is revealed to market maker's through the current trade. The market microstructure on the LSE enables us to deduce *exact* restrictions on the

[4] One final difference of the LSE to the NYSE, is that there is a two week settlement period such that all trades during the period must be settled in cash at the end of the two weeks. This institutional

effects of these shocks on price quotes and inventories that are implied by the existence of inventory control and asymmetric information respectively. By contrast, in the NYSE studies there is a much weaker link between the theory and the restrictions on the VAR which are tested.[5] The institutional structure of the NYSE implies that price quotes are predetermined, and this creates difficulties in the NYSE studies because it necessitates a behavioral assumption to identify public and trade shocks.[6] On the LSE however, price quotes fully reflect public information but because firm prices are posted before the current trade arrives, current quotes cannot depend on the trade shock.[7] This institutional characteristic gives us the exclusion restriction that current trade shocks do not affect prices, which we may use to identify public information and trade shocks from the VAR. Finally, the absence of a limit order book 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. In particular, the classic case of a dealer facing informed traders is far more tenable than on the NYSE, where the specialist has some informational advantage in that they observe the limit order book. Gemmill (1994) 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 network to which market makers have exclusive access, and disseminates information on block trades. [8]

In Section 2, we develop a bivariate VAR based on the theoretical models of Madhavan and Smidt (1993) and Snell and Tonks (1996) which, we believe, captures the salient features of market maker and trader behaviour on the LSE. In Section 3 we

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feature is likely to make any inventory control features more pronounced, since short positions within the settlement period are costless but need to be financed after this.

[5]Madhavan and Smidt (1993) test their theoretical model of the trading process *directly* on NYSE data rather than use the model to analyse time series properties of the data.

[6]Predetermined prices require that current trades be modeled jointly with the next period's revision in quotes rather than the current revision. Next period's revision may depend on both public information and trade shocks so that an exclusion restriction is required. The restriction invoked by Hasbrouck (1991) and Hasbrouck and Sofianos (1993) is that trades are independent of current public information which is a behavioral assumption.

[7]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".

explain how the existence of asymmetric information or inventory control depends on the significance of precise functions of parameters in a single estimating system, and outline a method of computing various microstructure effects. Section 4 describes the data used in the study, and Section 5 gives the results of the tests for fifteen less-liquid stocks traded on the LSE. A dominant feature of the results is that, after allowing for a shift in the mean level of inventories in four of the stocks, inventory control is very strong. In addition, nearly all stocks display "informational feedback" from trades to quote revisions. Section 6 provides a summary and conclusions.

At this point, we should make clear the scope of our paper and indicate what it does not attempt to do. First, we only explain movements in the mid-point of quoted bid and ask prices and we do not address the issue of the size of the spread. Theoretical papers by Glosten and Milgrom (1985) and the empirical work of Glosten and Harris (1988), Choi, Salandro and Shastri (1988), Stoll (1989), George, Kaul and Nimalendran (1991) view movements in the spread as a response to changes in the level of uncertainty facing market-makers with the spread widening as the variance of private information increases. By contrast, movements in mid-point quoted prices are a result of the perpetual arrival of public and (possibly trade-revealed) private information. Broadly speaking, the spread responds to movements in the second moment of information whereas mid-point prices reflect changes in its mean. We believe, therefore, that although the study of spreads is interesting, changes in the spread are quantitatively far less important than variations in mid-point quoted prices.[9]

Second, Hasbrouck (1991) and Hasbrouck and Sofianos (1993) allow for nonlinearities in the feedback from trades to quotes. Whilst these effects are undoubtedly present in the data, we consider them to be of second order importance. Rather than attempt to model all the features of the data, we focus on only those features that are of first order importance for identifying inventory control and asymmetric information effects.

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[8]Trades in excess of three times NMS are not disclosed for ninety minutes. All other trades are disclosed immediately.

2. Methodology.

Previous time series work quantifying and testing for the existence of inventory control and asymmetric information has been founded on two propositions.

First, if inventory control exists, inventories will be stationary and trades that involve the market maker will (by virtue of the fact that they are the first difference of inventories) have a unit root in their moving average representation. Hasbrouck (1988) estimates a moving average model for trades using maximum likelihood methods and imposing a lag polynomial scheme for the parameters. Despite allowing a lag length of up to 200 (trades), he finds weak reversal of trades effects. This surprising result can be explained by the institutional structure and the nature of trades outlined in the previous section. Leaving aside the noise generated by having to infer the signs of trades, only a minority of recorded trades actually pass through the market maker's inventory on the NYSE [see Madhavan and Sofianos (1994)]. Under inventory control on the NYSE, therefore, trades will be the sum of two components. The first pass through the market makers inventory and have a unit root in their MA representation whilst the second do not involve the market maker and are unlikely to have a unit root. Hence, looking at trades on the NYSE is not likely to be very informative about inventory control.

The data sets used by Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993), on the other hand, include end of day inventory levels themselves. This does enable a direct test of inventory control to be executed by means of unit root methodology. If there is inventory control, Dickey-Fuller type tests on inventory levels should reject the unit root hypothesis. Around one half of Madhavan and Smidt's stocks exhibit mean reversion whereas Hasbrouck and Sofianos find the proportion of their stocks that are stationary to lie between one-third and seven-eighths, depending on the lag length adopted. As all these authors note, univariate

[9] Reiss and Werner (1994) and Abhyanka, et.al. (1995) have examined the size of spreads on the LSE.

unit root tests on persistent high frequency data may not have much power.[10] There are two advantages to testing for inventory control based on a bivariate time series representation of trades and quote revisions. First, the validity of the estimated system for the asymmetric information test does not depend on correct inference being made about the stationarity of inventories. Second, adopting a bivariate approach improves the efficiency of the estimates of the inventory control effects and may lead to better inference concerning their existence.

The second proposition concerns asymmetric information. It states that if there is asymmetric information revealed by trades, then shocks emanating from trades will have a persistent effect on price quotes. This proposition has great intuitive appeal but to execute empirically needs an estimate of the trade shocks. Hasbrouck (1991) and Hasbrouck and Sofianos (1993) use a VAR methodology to identify reduced form errors. They then require identification restrictions on these errors so that they can label the resulting (uncorrelated) innovations as "trade shocks" and "price-quote shocks", respectively.[11] However these identification restrictions are imposed as an additional theoretical restriction, and therefore the accuracy of the simulated cumulative response of price quotes to trade shocks depends on the validity of this assumption. In this paper using LSE data the necessary identifying restrictions arise naturally from the market microstructure itself.

Hasbrouck (1991) uses a bivariate VAR of trades and price-quote revisions which is motivated by a simple illustrative theoretical model. Hasbrouck and Sofianos (1993) extend this to include inventory levels and two other variates that are nonlinear transformations of trades. The latter identifies five fundamental shocks but it is not clear what the economic interpretation of these shocks are. In this paper, we focus purely on a two variate system which is motivated by an economic model so that the interpretation of the shocks in our system is unambiguous.

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[10] Madhavan and Smidt pool their stocks to do a joint test. In this case there is a joint null that *all* stocks are I(1) versus an alternative that *all* are I(0).

[11] The identifying restrictions used in both cases are that trades are prior to price quotes and that trades do not depend on current public information.

A simple theoretical model.

Unlike the NYSE the LSE does not have a monopoly specialist, but in the less liquid stocks has a small number of market makers quoting prices in each stock. Reiss and Werner (1994) document that trades between market makers through an anonymous IDB (Inter-Dealer Broker) network takes place at prices close to the mid-point spread, which implies that the adverse selection costs is 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 pricing rule taken by a representative market maker. 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. If z_t is a buy order, it takes a negative sign but if it represents a sale to the market maker it is positive. All orders pass through the pool of market makers so the aggregate inventory level, I_t, obeys the identity

$$I_t \;=\; I_{t-1} + z_t \qquad (1)$$

As noted above, the identity in (1) is crucial for our time series representation for trades and prices. Equation (1) is *not* satisfied by trades and inventories from the NYSE.

The stock is assumed to have an intrinsic value, v_t, which we could think of as an efficient price, although its exact definition is not central to the analysis. We assume that v_t, which henceforth we refer to as the fundamental price, follows the random walk process

$$v_t = v_{t-1} + \xi_{1t} + \xi_{2t} \qquad (2)$$

where ξ_{1t} and ξ_{2t} are mutually uncorrelated white noise errors. The errors in (2) represent "information increments" with ξ_{2t} being public information (such as changes in the market index or public announcements about firm-specific events) whilst the other component, ξ_{1t}, is necessarily private information and is *never* observed by market makers. At time t then, the market maker's information set consists of lagged trades, current and lagged market maker prices and current and lagged public information.

The assumption that fundamental prices follow a random walk is a familiar feature of the theoretical and empirical literature. The decomposition of the innovation into private and public components is more controversial. 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. There are market events such as takeovers, profit announcements, etc where the information structure may be of this form. However, there are also informational increments which are naturally heterogeneous such as that generated by private research into a company by analysts. It is not clear what the implications of heterogeneous information sets are for a data set such as ours where the (non market maker) participants are not identified. 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.

In making the identification restriction, we assume that trades may be affected by *both* public and private information whereas quotes may only respond to the former. These assumptions are a direct consequence of the trading mechanism on the LSE where prices may be adjusted to reflect current public information up to the time of an order but where they cannot be changed when an order is received and where, as we argued above, market makers only receive a signal containing the private information from the order flow. This contrasts with the *behavioral* assumptions made by Hasbrouck (1991) and Hasbrouck and Sofianos (1993), who take market maker prices to be predetermined and trades to be unaffected by current public information. This assumption is made necessary by the trading rules on the NYSE which only allow price adjustments immediately after a trade.

We assume that there are two motives for trading by investors following Seppi (1990). The trader may possess private information about the fundamental price v_t and wish to trade speculatively on the basis of this information. This private information means that the trader knows more about the fundamental price than the market maker who must form an expectation based on public information and on previous order flows. According to this motive the trader will buy (sell) when the quoted price is below (above) its fundamental value. We call this the speculative motive for trade. The second motive for trading is a liquidity or noise consideration, and we discuss the generation of this component in more detail below. Total trades are the sum of the speculative and liquidity components and are given by

$$z_t = \alpha(p_t - v_t) + x_t \tag{3}$$

where the term α is positive and bounded. 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, we follow Madhavan and Smidt (1993) and Snell and Tonks (1996) in describing the representative market maker's pricing policy as setting quotes equal to the expected value of the fundamental price, plus adjustments for inventory holdings and anticipated noise trades

$$p_t = E_t v_t + k(I_{t-1} - I^*) + \gamma E_t x_t \tag{4}$$

where I^* is the desired inventory level which is assumed to be constant, and γ and k are negative parameters, and we adopt the notation that $E_t(.)$ denotes the conditional expectation of (.) given the information set at time t. The specification of the market maker's information set is crucial to our analysis, and consistent with the institutional setting of the LSE, we assume that at time t, when they set current prices, the representative market maker knows all current and past public information ξ_{2t-i} ($i \geq 0$), and lagged aggregate trades z_{t-i} ($i > 0$). Having observed current trades the market maker can update her price quotes in the next period before the next trade. Henceforth, and without loss of generality, we take I^* to be zero. The term $E_t v_t$ in (4) is the expectation of v_t conditioned on the market maker's information set at time t. We follow Snell and Tonks (1995,1996) and adopt the rational expectations assumption which, given the informational assumptions implicit in (2), implies that

$$E_t v_t = E_t v_{t-1} + \xi_{2t} \qquad (5)$$

Equations (4) and (5) state that 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. The coefficient k plays a crucial role in the analysis. If k is negative (zero), then inventories are stationary (non-stationary) so that market makers are (are not) setting prices in such a way as to induce their inventory level to return to its mean after a shock. It follows that if inventories are to affect stationary variates in the model, they must enter the system with coefficients that are a multiple of k. In this way, k acts as a dummy variable, switching inventories out of the model when they are non-stationary (k=0) but allowing them to enter when they are stationary (k<0).

Equations (1) to (4), which constitute the model minus informational assumptions, is as we have already noted, that given in Snell and Tonks (1996) and similar to that given in Madhavan and Smidt (1993). One important difference between these models is that in the latter case, desired inventories explicitly enter the market maker's objective whereas in the former, market maker's are assumed to care about the variance of inventory value around its mean rather than the quantity of inventory around some desired level. The key similarity is that both papers solve an intertemporal optimisation problem to derive a form describing market maker's price setting behaviour.

We now show that these four equations can be expressed as a bivariate VAR, in terms of price quote revisions and volumes of trade with one fundamental shock in each equation. To derive the price revision equation, substitute the market maker's expectations of fundamental prices from (5) into the price setting equation (4), and subtracting p_{t-1} from both sides yields

$$\Delta p_t = (E_t v_{t-1} - p_{t-1}) + kI_{t-1} + \gamma E_t x_t + \xi_{2t} \tag{6}$$

To obtain an expression for the deviation between the market maker's price quote last period and her expectation of last period's fundamental price (the first term in equation (6)), lag equation (3) by one period, take expectations at time t, and invert. Substituting the resulting expression into (6) we may write an expression for price quote revisions which depends linearly on observables (z_{t-1}, I_{t-1}), a public shock ξ_{2t}, and the as-yet-unspecified process for noise trades

$$\Delta p_t = (E_t x_{t-1} - z_{t-1})/\alpha + kI_{t-1} + \gamma E_t x_t + \xi_{2t} \tag{7}$$

Turning to the volumes equation in the VAR, we define the forecast error between realised trading volumes and expected trading volumes as η_t which from equation (3) can be decomposed into two shocks

$$\eta_t = z_t - E_t z_t = \alpha(E_t v_t - v_t) + (x_t - E_t x_t) \tag{8}$$

The shock, η_t, represents the new information flowing to the market maker after observing the current trade z_t. It consists of an informational increment about the fundamental price and a noise trade shock. Taking expectations of (3) and combining with (8) we may rewrite the trades equation as

$$z_t = \alpha(p_t - E_t v_t) + E_t x_t + \eta_t \tag{9}$$

Then substituting the price setting equation (4) into (9) gives an expression for trades which depends linearly on the observables I_{t-1}, a fundamental shock η_t, and the still-unspecified process for noise trades

$$z_t = (1+ \alpha\gamma)E_t x_t + \alpha kI_{t-1} + \eta_t \tag{10}$$

The time series representation for trades and quote revisions implied by the model, will depend on the process for noise trades. In Snell and Tonks (1995, 1996), noise trades are taken to be an exogenous autoregressive process and in general, they are usually thought of as arising from trading to satisfy exogenously determined liquidity needs. However, there is also some evidence to suggest that some traders trade on the market index[12]. Other authors, notably Hasbrouck (1991) and Hasbrouck and Sofianos (1993) treat noise trades as an exogenous shock. To make the VAR explicit without being specific about the process generating noise trades we simply invoke the rational expectations hypothesis which determines $E_t x_t$ as a linear function of the variables in the information set. As a result we may write

$$x_t\ [\equiv E_t x_t + \xi_{3t}] = \phi_1(L)z_t + \phi_2(L)\Delta p_t + \delta k I_{t-1} + \xi_{3t} \qquad (11)$$

where ξ_{3t} is a rational expectations error, uncorrelated with ξ_{1t} , ξ_{2t}, the past history of z and Δp and I_{t-1}. The coefficients $\phi_1(L)$ and $\phi_2(L)$ are invertible (possibly infinite order) lag polynomials with leading terms of $\phi_{11}L$ and ϕ_{21}, respectively reflecting the fact that while current price quotes are available to the market maker to forecast noise trades at time t, current total trades are not. The inventories term enters (11) with a coefficient of δk, because in the absence of inventory control (when $k = 0$) inventories will be non-stationary and will not be useful in forecasting noise trades.

To demonstrate that equations (7) and (10) imply that a VAR exists, note that $E_t x_t$ and $E_t x_{t-1}$ are both linear in the information $\{\Delta p_{t-i}\ (i \geq 0),\ z_{t-i}\ (i > 0)$ and $kI_{t-1}\}$, and from equation (1) trades are just the first difference in inventories. Therefore, substituting for these terms in (7) and (10) would give a system that looked like a bivariate VAR[13] in inventories and the change in market maker's prices. If k=0, the system reduces to one that would appear to be a VAR in trades and price changes. To show that the system *is* a genuine VAR we need to examine the innovations, ξ_{2t} and η_t. These are both independent of past values of x and Δp. The first is, by definition,

[12]See for example, Keim and Madhavan(1995).

[13]The appearance of Δp_t on the right of the equation for z_t is non-standard for a VAR. However, the system is easily converted to the familiar VAR by substituting out for Δp_t using the second equation in the system. This augments the error in the z_t equation by a term in ξ_{2t}.

non auto-correlated and as is evident from (8), the second is a one-step-ahead rational expectations error. It follows that (7) and (10) *do* actually constitute a bivariate VAR in inventories (note from equation (1) that $\Delta I_t = z_t$) and price changes.

A more parsimonious and informative form for the price equation (7) would be obtained by substituting for the $E_t x_{t-1}$ term, which represents the market maker's updated view at time t of liquidity trades at time t-1. Given the linearity of the noise trade projections we show in the Appendix (Lemma 1), that the market maker will update her view of the unobserved noise trades x_{t-1} moving from period t-1 to t as follows

$$E_t x_{t-1} - E_{t-1} x_{t-1} = a_1 \eta_{t-1} \tag{12}$$

In the Appendix we show that the innovations ξ_{2t} and η_{t-1} represent the new information flowing to the market makers at time t. Lagged noise trades x_{t-1} cannot be correlated with this first innovation because the innovation is only realised after the noise trade realisation. On the other hand the second innovation η_{t-1} is important in revising the market maker's view of lagged noise trades, so that given the linearity of the model, the revision in the market maker's expectation takes the form given in equation (12).

Subtract $E_{t-1}x_{t-1}$ from both sides of equation (7), and use equation (12) and the lag operator to substitute for $E_t x_{t-1}$ in the quote revision equation (7). Then substitute for η_{t-1} using (10) lagged one period to obtain

$$\Delta p_t = (a_1-1+a_1\alpha k)z_{t-1}/\alpha + [(\alpha\gamma+L)-a_1(1+\alpha\gamma)L]E_t x_t /\alpha + k(1-a_1)I_{t-1} + \xi_{2t} \tag{13}$$

Equations (10) and (13) now express trades and quote revisions in terms of lagged trades, lagged inventories and anticipated liquidity trades. With the RE assumption for forecasted noise trades from (11) we may estimate the following bivariate VAR

$$\Delta p_t = \theta_1(L)\,\Delta p_{t-1} + \theta_2(L)\,z_{t-1} + \psi_1 I_{t-1} + \xi_{2t}^{*} \tag{14}$$

$$z_t = \theta_3(L)\,\Delta p_t + \theta_4(L)\,z_{t-1} + \psi_2 I_{t-1} + \eta_t \qquad (15)$$

where $\xi_{2t}^* = \xi_{2t}/(1-\gamma\phi_{21})$, and $\theta_i(L)$ (i=1,4) are lag polynomials with leading coefficients of unity.[14] Note that (15) explains trades in terms of lagged trades and inventories, and can therefore be rewritten to explain inventories in terms of lagged inventories.

In the results section, we report the results of estimating (14) and (15) free of constraints and use the estimated parameters to assess the strength and significance of inventory control and information effects. We view the time series representation in (14) and (15) through the "eyes" of the parallel economic model (10) and (13) considering the implications for the significance of certain VAR parameters of the existence of inventory control and asymmetric information in the underlying economic model.

3. Empirical Implications

(I) Implications for inventory control

In the economic model, inventory control hinges on the parameter k. If k is zero then inventories are non-stationary. If k<0 then prices are set to induce trades that will stabilise the level of inventories. Equations (10), (11) and (13) show that when k=0, lagged inventories wash out of the model completely. In the time series model, therefore, the existence of inventory control rests on the significance of a lagged inventory term in the VAR trades equation. Under the null of k=0 (no inventory control), the OLS estimate of ψ_2 has the unit root distribution. It is easy to show that under the alternative of inventory control, ψ_2 will be negative so that the usual one-tailed test is appropriate.

Note, the economic model (13) shows that k=0 implies that inventories also disappear from the price equation so that ψ_1 in (14) is zero. However we cannot base a test for inventory control on the significance of ψ_1 because this parameter is also zero when there is no asymmetric information as we show below.

(ii) Implications for asymmetric information

Equation (8) shows that new information on fundamental prices is contained in the trade shock η_t. We have assumed that market makers never observe the private shock ξ_1 so that η_t is their only "window" on this private information. There are two cases to consider, either private information exists (the asymmetric case) and var(ξ_1)>0 or there is no private information (the symmetric case) and here the variance of private information, var(ξ_1) is zero.

In the symmetric information case, ξ_1 disappears from the system making η_t equal to the pure liquidity shock, ξ_{3t}.[15] In the Appendix (Lemma 2, and Corollary), we show that in the symmetric case, a_1 is equal to unity. To analyse the implications of this condition for the VAR estimates under symmetric information we need to distinguish between the two further subcases of $k<0$ and $k=0$. In the first of these subcases ($k<0$ and $a_1=1$) equation (13) can be written as

$$\Delta p_t = kz_{t-1} + \gamma(1-L)E_t x_t + \xi_{2t} = kz_{t-1} + \gamma(1-L)\phi_1(L)z_t + \gamma(1-L)\phi_2(L)\Delta p_t + \xi_{2t} \qquad (16)$$

Equation (16) shows that if there is both symmetric information and inventory control then the lagged inventory term disappears from the price equation. Note that under an alternative hypothesis of asymmetric information but still with inventory control lagged inventories term should be significant in this equation. Therefore the t-ratio on the coefficient ψ_1 is our asymmetric information test under inventory control.

Turning to the second of these subcases ($k=0$ and $a_1=1$), there is no inventory control and since inventories are nonstationary and disappear from the system altogether, equation (13) reduces to

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[14]Since expected noise trades depend on the current quote revision, and the quote revision depends on expected noise trades, substituting (11) into (13) will give a form for Δp_t which depends on Δp_t. Therefore in writing (14) we have written an explicit form for Δp_t.

[15] Under rational expectations, market makers know the value of all the data moments so that they will appreciate that the variance of ξ_1 is zero.

$$\Delta p_t = \gamma(1\text{-}L)E_t x_t + \xi_{2t} = \gamma(1\text{-}L)\phi_1(L)z_t + \gamma(1\text{-}L)\phi_2(L)\Delta p_t + \xi_{2t} \qquad (17)$$

Equation (17) shows that if there is both symmetric information and no inventory control then the long run effect of trades on price quote revisions is zero. Therefore the significance of the t-ratio of the sum of the coefficients on lagged trades in the price equation is our test of the null hypothesis of symmetric information when k=0.

The intuition behind these tests lies in the way in which information is gleaned by the market maker on the unobserved private signal ξ_{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 *inventories,* which are non-stationary, that is indicative of an information flow through to prices.

(iii) Empirical implementation

In the light of the preceding analysis, we adopt the following empirical procedure to test for inventory control and asymmetric information. We estimate (14) and (15) free of constraints and compute the quantities $\theta_i(1)$ (i=1,2,3,.4), ψ_1 and ψ_2 together with their respective standard errors. The significance of ψ_2 is then examined by comparing its t-ratio with the unit root distribution. If ψ_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 ψ_1. If ψ_2 is insignificant, then we may deduce that inventory control is absent and that the existence of asymmetric information rests on the significance of $\theta_2(1)$.

The system in (14) and (15) also allows us to test for the existence[16] of anticipated noise trades.[17] If $E_t x_t$ is zero, then neither lagged trades nor lagged price changes enter

[16]Many authors (Kyle, 1985 and Glosten and Milgrom, 1985) have noted that noise traders are necessary for the existence of a market because otherwise, market makers will make negative profits with probability one. However, even if unanticipatable, noise trades may still exist as a random, mean

(15). A test for the joint significance of $\theta_3(L)$ and $\theta_4(L)$ from zero is therefore, a test of the existence of predictable noise trades.

We should note that our informational assumption is restrictive in the sense that private information is *never* subsequently revealed by way of public announcement. In general, this will not be the case. For example, if we consider information about a takeover bid or about earnings, then pure private information of the type modeled above may exist for a time, but will certainly become public at a future date. This drawback is not as serious as it seems for our analysis. It is quite likely that, between the time the privately observed information is discovered by informed traders and the time of its subsequent announcement, 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.[18] If it is not so, then three shocks would enter our system (ξ_1, ξ_2 and ξ_3) not two. Unfortunately, it is not possible to identify three shocks from a bivariate system.

In addition to the above tests which result from analysing the VAR in (14) and (15), we are also able to obtain estimates of the deep parameters α, γ and k in the theoretical model. We show in the Appendix (Lemma 3) that an alternative representation for trades implied by the model can be written as

$$\Delta z_t = \{\alpha+(1-L)\phi_2(L)]\Delta p_t + [(1-L)\phi_1(L)+\delta kL]z_t - a_1\eta_{t-1} - \alpha\xi_{2t} + \eta_t \qquad (18)$$

If we use the VAR residuals ξ_{2t}* and lagged residuals η_{t-1} from equations (14) and (15) in place of ξ_{2t} and η_{t-1} respectively in (18), then we may treat the equation as an

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zero shock. In this case, the existence of a bid-ask spread allows market makers to make non-negative profits.

[17] Of course if anticipated noise trades were constant, then this would show up in the intercept along with desired inventories. Our test does would not detect this.

[18] A counter argument might point to the fact that earnings announcements, etc. always result in discrete movements in market makers prices so that the market makers cannot be fully informed about such events at the time of their announcement. However, it is not obvious that the informed traders are fully informed at the announcement time either. In terms of our model, if the announcement is at time t but private information is discovered n periods earlier, then the former effect would be a ξ_{2t} shock whereas the latter would be a ξ_{1t-n} shock. The ξ_{1t-n} shock, may be revealed to market makers between t-n and t via the trades $x_{t-n}, x_{t-n+1}..x_t$.

ordinary regression and obtain from it a consistent estimate of a_1, as the coefficient on η_{t-1}. Inspection of (18) shows that the equation will also yield a consistent estimate of δk (the parameter on lagged inventories in the anticipated noise trade equation (11))as the sum of the coefficients on lagged trades. We now compute consistent estimates of the deep parameters by taking certain estimated quantities from the VAR in (14) and (15), using the theoretical model to write these estimates as functions of the deep parameters, and then solving these relationships for α, γ and k. The estimated quantities from the VAR are the long run effect of ξ_{2t}* (the residual in (15)) on prices which we denote by ω, the long run effect of η on prices which we denote by τ, the coefficient on lagged inventories in the trades equation (15), ψ_2, and the coefficient on the current price quote change in the same equation (15), θ_{31}.[19] We show in the Appendix (Lemmas 6, 7 and 8) that the theoretical model implies the following relationships between these estimated quantities and the parameters of the theory

$$\omega = 1 - \gamma\phi_{21} \tag{19a}$$

$$\tau = (a_1 - 1)/\alpha \tag{19b}$$

$$\psi_2 = (1+\alpha\gamma)\delta k + \alpha k \tag{19c}$$

$$\theta_{31} = (1+\alpha\gamma)\phi_{21} \tag{19d}$$

where ϕ_{21} is the coefficient on current price quotes in the anticipated noise trades equation (11). Given the estimates of a_1 and δk from (18) and of ω, τ, ϕ_{21} and θ_{31} from the VAR, equation (19) solves uniquely for α, γ 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.

(iv) Quantifying Market Microstructure Effects

[19]The estimates of α, γ 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 α, γ and k using ω, τ, ψ_2 and θ_{31} 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 α, γ, and k produced qualitatively similar results to those given in section 5 below.

In an efficient market, stocks would trade at their fundamental values v_t. Equation (4) shows that the existence of asymmetric information, inventory control and anticipated noise trades, the so-called market microstructure effects, cause market makers to set prices away from their fundamental values. Therefore, prices vary not only as a result of public information arrival but also because of these market microstructure effects. These effects have formed the focus of the microstructure literature and we show below that using our VAR estimates from (14) and (15) we can quantify them, identify their components and assess their impact on price volatility for the LSE.

The microstructure effects may be categorised as a pure asymmetric information component and components due to inventory control and anticipated noise trades. The first of these discrepancies between actual price quotes and the stock's fundamental value arises from a mistake on the part of the market maker whose only source of information on the private signal is lagged trades. The other two discrepancies are deliberately generated by the market maker and arise from a desire to manage inventory holding costs and to exploit anticipated noise trades. As a result, we refer to discrepancies between prices and fundamentals arising from inventory control and anticipated noise trades as being "actively induced" by the market maker, and the price volatility that these effects produce as "induced volatility". The price volatility which results from the arrival of public information and "trade revealed" private information on the other hand, represents a passive response by the market maker to news about the fundamental.

We show in the Appendix (Lemma 9) that we can decompose the change in price quotes as

$$\Delta p_t = \xi_{2t} + \left(\frac{a_1 - 1}{\alpha}\right)\eta_{t-1} + kz_{t-1} + \gamma\Delta E_t x_t \qquad (20)$$

Equation (20) identifies the three components of the price change: the public information effect (first term) and the two components of the microstructure effects [trade-revealed private information (second term) and actively induced effects (third and fourth terms)]. 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 variance ratio

$$P1 = \frac{\text{var}(\Delta p_t - \xi_{2t})}{\text{var}(\xi_{2t})} \tag{21}$$

By noting that the residual from (14), ξ_{2t}*, is just ξ_{2t}/ω where ω is defined in (19b) and that ω may be estimated directly from the VAR, we can see that P1 may be computed using data on prices and using residuals and coefficient estimates from the VAR.

To assess the relative importance of induced volatility versus that arising from public and trade revealed information we may compute the variance ratio

$$P2 = \frac{\text{var}\left[\Delta p_t - \xi_{2t} - \left(\frac{a_1 - 1}{\alpha}\right)\eta_{t-1}\right]}{\text{var}\left[\xi_{2t} + \left(\frac{a_1 - 1}{\alpha}\right)\eta_{t-1}\right]} \tag{22}$$

The quantity $(a_1\text{-}1)/\alpha$, the long run effect of trade shocks on prices [τ in equation (19)] is estimated from the VAR and the lagged trade residual from equation (15) of the VAR may be used in place of η_{t-1} to compute this variance ratio.

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

$$P3 = \frac{\text{var}\left[\left(\frac{a_1 - 1}{\alpha}\right)\eta_{t-1}\right]}{\text{var}\left[\xi_{2t} + \left(\frac{a_1 - 1}{\alpha}\right)\eta_{t-1}\right]} \tag{23}$$

Equation (23) 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. As before the quantities in (23) are estimated directly from the VAR, and do not depend on the structural parameter estimates.

4. Data

The trading mechanism on the LSE is different to that on the NYSE. The LSE is a quote driven market, as opposed to the NYSE which is an order driven exchange. Trading in shares at the LSE takes place by telephone through a small number of registered market makers.[20] 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.

The 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.[21] 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) 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 group of market makers’ inventory level.

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

[20] Hansch et.al. (1995) have specifically examined the interactions of market makers on the LSE
[21] 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).

turnover (£3.5m) with stock 15 having the lowest (£0.15m). The mean price changes were all positive, indicating a general upward trend in prices over the period. On the other hand, inventories, which we computed as the sum of trades, generally show little to no trend. Figure 1, which plots inventories and prices in "transaction time", confirms the general absence of trend in the former series, with the possible exceptions of stocks 14 and 8. Of course, this does not imply widespread inventory control because untrended series may still be I(1) processes with zero drifts. One feature that stands out from the plots is the clear breaks in mean inventory of stocks 3, 7, 10 and 15 at around the (transaction) times 1450, 4000, 1500 and 1250 respectively. These breaks in mean and any others that exist but are not so clearly visible to the naked eye, constitute permanent shocks to the series. If the inventory series were genuinely I(0), the existence of these breaks would seriously undermine the power of our tests for inventory control [see Perron (1989)]. Below, we allow for mean shifts and test for their importance. A further feature of the data is the abnormally large "spikes" in the inventory series for stocks 4, 11 and 13. All three of these are initiated by one or two extraordinarily large sells to the market maker. Trades of this size are well outside the range for which quoted prices are firm so that their actual transactions prices will be the subject of bilateral negotiations between the market maker and the seller. It is also possible that the market maker made prior arrangements for their subsequent sale, and this certainly seems to be the case for stock 4 where the "spike" is reversed within two trades. Though for stocks 11 and 13 the excess inventory appears to have been dispersed over 50 to 100 subsequent buy-transactions following a 2-3% reduction in prices. We are careful to examine the sensitivity of our results for these stocks to the omission of these large outliers.

5. The empirical results.

We estimated the VAR in (14) and (15) 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.

As we outlined in the earlier section on empirical implementation, we deal with the inventory control tests first. The results for the t-test on ψ_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. The third column gives the half life of inventories implied by the estimated value of ψ_2. This is the time taken for inventories to recover one-half of their initial value after they have suffered a shock.[22] The Table shows 9 of our 15 stocks display significant inventory control and half lives vary from below 2 to over 573 trading days. The absence of strong inventory effects for nearly half of these less-liquid stocks is surprising. Snell and Tonks (1995,1996) and Hansch et al (1995) find inventory control to be prominent in their samples of alpha-rated stocks on the LSE so we would have expected such effects to be even more important in these less liquid stocks. Stocks 3 and 15 display the smallest $t(\psi_2)$ values and have half lives of a completely different order of magnitude to the other stocks. A look at the inventory series in figure 1 shows that both these stocks experience large permanent jumps in their inventory levels. These 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) approach using Tsay's (1986) method, identifies breaks through a sequential search, but there are two reasons why their approach is not adopted. The first is that their procedure is impractical when the number of data points is as large as ours (they deal with daily closing inventories whilst we have inventories for every single transaction). Second, and more important, is the effect such "snooping" procedures would have on could be computed. We therefore adopt a pragmatic approach similar to Perron (1989), and allow a single break in mean under both the null hypothesis of non-stationary inventories and under the alternative of stationarity. Unless the break t_b is obvious from inspection of the time series, we impose that it occurs 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.

We enter two dummy terms in each of the VAR equations, an impulse dummy and a once and for all switch dummy. We denote them Dum_1 and Dum_2 and they enter the z_t and Δp_t equations with coefficients d_{z1},d_{z2} and $d_{\Delta p1}$ and $d_{\Delta p2}$ respectively. They are defined explicitly as

$$\textbf{(24)} \quad \begin{array}{lll} Dum_{1t} = 1 & \text{if } t = t_b, & Dum_{1t} = 0, \text{ otherwise} \\ Dum_{2t} = 0 & \text{if } t < t_b+1 & Dum_{2t} = 0, \text{ otherwise} \end{array}$$

Under the null of no inventory control and a switching (unconditional) mean, d_{i1} (i = z,Δp) should be significant and d_{i2} (i = z, Δp) should be insignificant.[23] Under a null of no inventory control only, it is easy to show that the t-ratios on the d's and on ψ_2 follow non-standard distributions that depend only on t_b/T, the proportion of the sample occurring before the break.[24] Note that the distributions of d_{i1} and d_{i2} are independent because the regressors Dum_1 and Dum_2 are orthogonal. Under the alternative hypothesis of inventory control, of course, the usual $\sqrt{T}$ asymptotics apply and all distributions are standard. The break points t_b were set at transaction time 1450, 4000, 1500 and 1250 for stocks 3, 7, 10 and 15 respectively but for the remaining stocks, it was fixed half-way through the sample. For the former stocks, this choice was guided by the graphs in Figure 1 but for the latter, there was no strong

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of trades as the average in the sample.

[23]We assume no drift, and hence, no change in drift under this null. Drifting inventories would be very hard to rationalise by economic reasoning.

[24]Proof of this result is a trivial extension of Perron(1989) and is available on request from the authors. The critical values for these statistics were estimated by simulation and are given in the notes to Table 3.

case for any particular value of t_b so we set it to T/2. Critical values for the t-ratios on ψ_2, d_{z2} and $d_{\Delta p2}$ for the five break points were computed by Monte Carlo simulation and are reported at the foot of Table 2.

The results for the t-ratios of d_{i2} ($i=z,\Delta p$) and ψ_2 are given in columns four to six in Table 2.[25] Whilst the t-ratios on the dummy in the Δp_t 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 χ^2_2 statistic.[26] 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. Besides showing more significant inventory control after allowing for a break, the stocks' half lives, reported in column 7, are now substantially lower than before. Interestingly, the average half life after including the break in mean, has now fallen to around 5.5 days which is only slightly lower than 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.[27]

The asymmetric information tests are displayed in the third and fourth columns of Table 3 for the stationary and non-stationary inventory cases respectively. Strictly speaking, only one of these statistics is relevant for each stock, but it is interesting to see that there are few cases where a false inference with regards to the stationarity of inventories matters for the asymmetric information test. 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

[25]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.
[26]This follows because the errors are independent across equations by construction.
[27] These estimates are crucially important for the LSE, since on 24/06/96 the Chancellor of the Exchequer announced that "financial intermediaries" will be exempt from a "stamp duty" transactions tax, where the definition of an intermediary is in terms of the length of time that stocks are held.

information. 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 (χ^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 spikes that have been removed strongly reinforced any mean reversion that was already present. Despite this, the t-ratios on ψ_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, on the whole, become more significant in the absence of the outliers. In particular, stock 11 now shows significant asymmetric information effects whereas before it did not. At the technical level, this is not surprising, since outliers increase standard errors so that removing them is likely to increase the significance of test statistics. Also, if these huge trades were uninformative, then removing them will have sharpened up the response of prices to informative trades.

As a check on our time series results, we report estimates of the deep parameters α, γ and k for each of the stocks in table 5. These were computed using the methods outlined in equation (19), 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.

Table 6 gives the results for the variance ratios given in equations (21) to (23). Importantly, these estimates do not depend on the values of the structural parameters, but are estimated directly from the VAR. The first column, P1, 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 P2 measures the contribution to price volatility of the induced price effects relative to the contribution of information effects as a whole. As with P1 it is the high turnover stocks that have the highest ratios, however unlike P1, the dispersion across stocks of the ratio P2 is much lower. The distinction between these two ratios is that P1 has the trade-revealed component in the numerator, whereas P2 has it in the denominator. 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 P3, 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.

To examine further the pattern of these variance ratios across stocks, we execute simple cross-stock regressions of bid-ask spreads on our estimated quantities. 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 an interesting and stringent test of our model to see whether our estimated microstructure quantities can explain the variation in the size of spreads across stocks.

Table 7 reports the results of some simple 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. This suggests that the two components of the microstructure reinforce each other in that they both tend to be associated with higher spreads. Regression 3 assesses the effect of trade revealed private information on spreads by using P3 as a measure of the relative variance of trade-revealed private information. The effect of P3 is significantly positive and this again is in keeping with prior expectations.

6. 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 has been to extend the time series framework of Hasbrouck to the institutional setting of a quote driven market microstructure. The institutional setting is important for two reasons. First, in a pure dealer market such as the LSE, all trades must pass through the market maker's inventory, so that inventory levels are the sum of all past trades. As a result, market makers can only control inventories by altering price quotes, as opposed to the NYSE where specialists can choose whether to participate in a trade or not. Second, in a dealer market the current quoted prices are firm so that price quotes may depend on current public information but may not depend upon current trades, and hence, current private information. Current trades, on the other hand, 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 two fundamental uncorrelated innovations that have a unique economic interpretation as, respectively, trade shocks containing private information and quote revision shocks containing only public information. Estimation of the pure time series VAR allowed us to identify and 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 pervasive feature of dealer trading in less liquid stocks. We quantified the extent of microstructure effects directly from the time series model, and found that the measures of private information and inventory control 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.

The London Stock Exchange is proposing to introduce a limit order book for very liquid FTSE100 stocks, and replace market makers with "financial intermediaries", who may act as principal or agent when dealing with a client. The strong implication of our work is that in the more illiquid stocks the market microstructure effects are dominated by the public information effects and that in these cases the current dealer structure appears to function effectively. Further it is intended that the intermediaries in the new structure will be exempt from the stamp duty transactions tax, where the classification of an intermediary is defined in terms of holding the securities for a short period of time. Our estimates of inventory half-lives can be used for the definition of these proposed intermediaries.

Finally, it should be re-emphasised that the *only*

Appendix

Lemma 1: Revision in lagged noise trader beliefs is given in (12) Note that the existence of the VAR implies that the market maker's information set at time t may be written as$\{\eta_{t-1}, \eta_{t-2}, \eta_{t-3}, \eta_{t-4},...\xi_{2t}, \xi_{2t-1}, \xi_{2t-2}, \xi_{2t-3},....\}$. Because of the linearity of the system the rational expectations forecasts formed at time t of any variable can be written as a linear functions of these VAR innovations. We may write that

$$E_t x_{t-1} = \sum_{i=1}^{\infty} a_i \eta_{t-i} + \sum_{i=0}^{\infty} b_i \xi_{2t-i} \qquad \text{(A1)}$$

It is safe to assume that noise traders have no prior knowledge of ξ_{2t} when deciding on their trades at t-1. Thus x_{t-1} will be independent of ξ_{2t}, so that the coefficient b_0 in (A1) will be equal to zero. Taking expectations of both sides of (A1) conditional on information at t-1, and applying the law of iterative expectations gives:

$$E_{t-1} x_{t-1} = \sum_{i=2}^{\infty} a_i \eta_{t-i} + \sum_{i=1}^{\infty} b_i \xi_{2t-i} \qquad \text{(A2)}$$

Subtracting (A1) from (A2) gives equation (12). QED

Lemma 2: Revision in beliefs about fundamentals From equation (5), revisions in beliefs about fundamentals can be written as

$E_t v_t - E_{t-1} v_{t-1} = E_t v_{t-1} - E_{t-1} v_{t-1} + \xi_{2t}$. Lag (8) one period and note that $\eta_{t-1} = E_t z_{t-1} - E_{t-1} z_{t-1}$;

so we may write: $\eta_{t-1} = (E_t x_{t-1} - E_{t-1} x_{t-1}) - \alpha(E_t v_{t-1} - E_{t-1} v_{t-1})$ (A3)

Substituting from (12) into (A3) and rearranging gives: $E_t v_{t-1} - E_{t-1} v_{t-1} = \eta_{t-1}(a_1-1)/\alpha$

so $E_t v_t - E_{t-1} v_{t-1} = \xi_{2t} + \eta_{t-1}(a_1-1)/\alpha$ 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

$\eta_{t-1} = (E_t x_{t-1} - E_{t-1} x_{t-1})$, so from (12) $a_1=1$. QED

Lemma 3: Derivation of equation (18) Difference equation (9) 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 the expectation of (11), and for $\Delta E_t v_t$ from Lemma 2, to obtain

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

Simplifying the error term gives equation (18). QED

Lemma 4: $\eta_t = a_1 \eta_{t-1} + \Delta \xi_{3t} - \alpha \xi_{1t}$ Difference equation (8) 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: $\Delta \eta_{t-1} = -\alpha \xi_{1t} - \alpha \xi_{2t} + (a_1 - 1)\eta_{t-1} + \alpha \xi_{2t} + \Delta \xi_{3t}$ QED

Lemma 5: Long-run effects of ξ_2 and ξ_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 ξ_1 on η is obtained from Lemma 4, 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 ξ_2* on p is $(1-\gamma\phi_{21})$ From equation (14) and Lemma 5, we may write $\Delta p = \xi_1+\xi_2^*(1-\gamma\phi_{21})$ QED

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

Lemma 8: Derivation of equation (19) Equations (19a) and (19b) are established from Lemmas 6 and 7 above. To establish the other parts substitute for $p_t-E_tv_t$ from equation (4) into (9), to obtain: $z_t = (1+\alpha\gamma)E_tx_t + \alpha kI_{t-1} + \eta_t$

Now substitute for the E_tx_t from equation (11) to give

$$z_t = (1+\alpha\gamma)[\phi_1(L)z_t + \phi_2(L)\Delta p_t + \delta kI_{t-1}] + \alpha kI_{t-1} + \eta_t$$

Collecting the coefficients on Δp_t and I_{t-1} respectively and noting that the leading coefficient on $\phi_2(L)$ is ϕ_{21}, gives equations (19c) and (19d)

Lemma 9: Decomposition of Δp_t is given in (20) From (4) the change in prices is:

$$\Delta p_t = E_tv_t - E_{t-1}v_{t-1} + kz_{t-1} + \gamma\Delta E_tx_t$$

Using Lemma 2, this becomes equation (20). QED

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