Price Discovery in London's Upstairs Equity Market

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Abstract

The paper presents new evidence on the contribution to price discovery of the upstairs market. The 'component share' and 'information share' measures are used, supplemented by the probability of informed trading (PIN) analysis. Most discovery arises downstairs, consistent with previous findings. But the upstairs market makes a non-negligible contribution, which approaches that of the downstairs market at the start and close of the day. The PIN estimates indicate that a higher proportion of upstairs than downstairs trades are informed. The upstairs has a larger role in price discovery than previous evidence suggests.

JEL classification: G12; G14

Keywords: upstairs market, downstairs market, price discovery, informed trading, London Stock Exchange

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1. Introduction

What is the role of an upstairs market on an exchange with a liquid electronic order book? The answer from the literature is that an upstairs market reduces the execution costs, including price-impact costs, of certain trades. This role is most prominent for large trades in less liquid stocks, where the trades are perceived to be executed for liquidity reasons. However, in recent years stock markets have changed enormously. Since the early 2000s there has been a huge growth in trading volume, and huge reductions in transaction costs and in the size of trades (see for example, Chordia et al., 2011). The reason for these changes appears to be the rapid growth of algorithmic trading. On the face of it, the changes would be expected to undermine the rationale for upstairs markets. We would expect algorithmic trading to benefit the order book more than the upstairs market. In particular, it should have become easier and cheaper to trade a block of shares by splitting the block into many smaller trades, and executing the trades on the order book by means of an algorithm.

In view of the fundamental changes in the nature and technology of trading that have occurred in recent years, a re-examination of the role of the upstairs market is of interest. This paper compares trading activity and price discovery on the upstairs and downstairs markets of the London Stock Exchange (LSE), using a large dataset from 2012-13.

The key characteristic of an upstairs market is that trades are facilitated by the efforts of dealers who negotiate directly with potential counterparties, using their information about the wishes of counterparties to trade. Seppi (1990) argues that the lack of anonymity upstairs benefits investors who can credibly claim to be trading for liquidity or portfolio reasons, as opposed to trading to exploit private information. Similarly, Madhavan and Cheng (1997) argue that upstairs dealers screen out orders motivated private information, and that without this screening function, investors would be less willing to provide liquidity. Grossman (1992) emphasises a different potential benefit, the knowledge of dealers about the unexpressed or latent demand to trade on the part of investors. Burdett and O'Hara (1987) and Keim and Madhavan (1996) present models of upstairs block trading in which the value added by the process is that the dealer for a given block is able to find several counterparties, which enables a better overall price for the block to be secured.

The empirical evidence to date is largely consistent with the above ideas. Smith et al. (2001) study the Toronto Stock Exchange. They find that upstairs trades have a much lower permanent price impact on average than downstairs trades. This finding is corroborated to varying degrees by Booth et al. (2002) for Helsinki, Jain et al. (2003) for the UK, and Bessembinder and Venkataraman (2004) for Paris. These authors interpret the results from price impact as evidence that upstairs dealers screen out information-based trades. Booth et al. (2002) also measure price discovery by means of alternative techniques based on a vector error correction model. They find that for most stocks price discovery occurs via the order book. Smith et al. (2001) present evidence that the upstairs market facilitates large trades especially in less liquid stocks. For example, the cost of trading upstairs is lower for large trades, and the proportion of upstairs trades is positively related to the bid-ask spread of the stock. Bessembinder and Venkataraman (2004) compare the actual execution costs in the upstairs market in Paris with the costs that would have been incurred if the same trades had been routed to the order book. They find that upstairs execution costs are on average 35% of what would have been paid downstairs, and the upstairs market has a greater role for smaller stocks. They argue that this is direct evidence supporting the Grossman (1992) view that dealers exploit unexpressed sources of liquidity. Finally, Gajewski and Gresse (2007) compare the Paris and London electronic order books, using data from 2001. They note that trading on the Paris stock exchange is much more concentrated on its limit order book (Euronext) than is trading on the LSE. Matching firms across the two exchanges by trading volume, they find that the Paris order book is cheaper than the London order book, and has smaller trade sizes. This is consistent with the view that upstairs dealers in London skim off the least informed trades.

All the above research uses data from before the time that the rapid growth in volume and algorithmic trading had got going. Our paper adds to previous research by presenting evidence which is much more recent. It therefore reflects market conditions in the era of algorithmic trading. The paper is also based on a much larger sample than is used in any of the previous papers. Our dataset consists of 95 million trades along with corresponding bid and ask quotes, in 259 of the most frequently traded stocks in Europe. We are interested especially in the role of the upstairs market in price discovery. The question is, in which market do innovations in prices tend to arise? Price discovery is central to our enquiry because it pertains to the key distinction between upstairs and downstairs markets. As noted above, existing research indicates that the comparative advantage of upstairs markets is in facilitating trades which are not driven by information. We examine whether this remains the case in the algorithmic era, by measuring the extent to which upstairs dealers execute trades which move prices, and which are more likely to be driven by information. We use techniques which are explicitly designed to measure price discovery. Our main results are from a vector error correction model, and they enable us to estimate, for each market of the LSE, the 'component share' (CS) measure of price discovery of Gonzalo and Granger (1995), and the 'information share' (IS) measure of Hasbrouck (1995). For further evidence on informed trading upstairs, we use the probability of informed trading (PIN) model of Easley et al. (1996, 1997). A new feature of our study is that we examine whether there are changes in trading and price discovery during the trading day.

We find that, despite the rise in algorithmic trading, the upstairs market remains a substantial part of the LSE, with about one third of total volume by value (in our sample, which consists of most of the largest 350 stocks). Our results on price discovery suggest that the role of upstairs markets might have changed in recent years. The majority of price discovery occurs on the downstairs market of the LSE, the Stock Exchange Electronic Trading System (SETS). But around one fifth of discovery occurs upstairs. This is the case for the most liquid stocks, as well as for less liquid stocks. The findings on price discovery from the component share and information share measures are supported by the PIN results. The latter indicate that the proportion of trades which are informed is actually higher upstairs than downstairs. The investigation of trading during the day reveals the existence of clear intraday variation. The proportion of price discovery upstairs, and the incidence of informed trading upstairs, are much higher during the first hour and, especially, during the last half hour. The proportion of price discovery upstairs in the last half hour is close to the proportion of discovery downstairs. A possible explanation is that dealers accumulate information about potential counterparties during the trading day, and exploit this information by facilitating a higher proportion of informed trades near the close of the day, and into early trading next day.

We cannot be definitive about how much the role of the upstairs market has changed in recent years. Most of the existing evidence on price discovery upstairs is inference from the price impact of trades, and the inference made is that there is little or no discovery upstairs. The only study, which uses the same methods we use, is Booth et al. (2002). They find more evidence of discovery upstairs from these methods than from price impact. However, their data are from a much smaller and less liquid stock market than the LSE. The large gaps between trades in their data calls into question the reliability of their estimates of the CS and IS measures. In fact they view their evidence from the CS and IS measures as consistent with small price discovery upstairs. Whatever the extent of discovery upstairs in the era before algorithmic trading, our recent evidence suggests that upstairs dealing towards the end of the day encompasses all trades, and not only trades that dealers judge likely to be for liquidity purposes. Thus, the nature of contemporary upstairs trading is not entirely consistent with the models of Seppi (1990) and Madhavan and Cheng (1997), which predict that dealers screen out information-driven trades.

The paper proceeds as follows. The next section describes the data and presents descriptive evidence. Section 3 summarises the component share and information share measures. Section 4 presents the results for these measures, and for the PIN estimates. Section 5 concludes.

2. Institutional Background, Data, and Descriptive Evidence

The LSE introduced an electronic order-matching system, SETS, on 20 October 1997, initially for stocks in the Financial Times – Stock Exchange (FTSE) 100 Index. Since then SETS has grown to become one of the most liquid electronic order books in the world. It now covers all the largest 350 UK stocks, and many smaller stocks. Trading on the LSE also occurs via a parallel dealer or upstairs market. Dealers operating in the upstairs market compete with SETS for order flow. Participants in the upstairs market are under no obligation to provide liquidity or post quotes, whereas market makers on SETS are required to provide liquidity and post binding quotes. There are two main rules under which dealers execute orders off SETS. The first is 'best execution': orders with sizes not exceeding the visible order quantities on SETS are required to be executed at prices at least as favourable as those on SETS. Second, all upstairs trades must be reported to the Exchange within three minutes of execution.

We obtain trade-by-trade data from the Thomson Reuters Tick History (TRTH) database. The sample period is the 12 months from 1 October 2012 to 30 September 2013 (251 trading days). The data for each transaction include a Reuters Identification Code (RIC) which identifies the stock in which the trade occurs, an indicator for whether the trade is executed on SETS,[1] date and time, transaction price, number of shares in the trade, and the prevailing bid (ask) prices and the volumes of buy (sell) orders. We clean the data of errors using standard criteria (see as examples, Chordia et al., 2001; Ibikunle, 2015). We exclude shares which are not in the relevant index for the whole sample period, and which have non-negligible amounts of missing or anomalous data (e.g. the bid price exceeds the offer price). The final sample contains 71,990,640 transactions for 70 FTSE 100 stocks, and 23,421,690 transactions for 189

[1] Our data consist of trades which are executed on the LSE, either on SETS or the upstairs market. Trades executed on trading platforms that are not part of the LSE are not included.

FTSE 250 stocks. The FTSE 100 (250) stocks in our sample account for 91% (86%) of the FTSE 100 (250) market capitalisation as at 30 September 2013.

INSERT TABLES 1, 2 AND 3 ABOUT HERE

Tables 1 and 2 present data on the average number of transactions, trading volume (in pounds), and trade size (in pounds) per day, for FTSE 100 and 250 stocks. The two subsamples are divided into quintiles according to the average daily trading volume per stock. We divide the sample by volume because of the negative association between volume and upstairs participation found in previous studies. We also divide the trading day into three periods, 8.00 to 9.00 am, 9.00 am to 4.00 pm, and 4.00 to 4.30 pm, as there is clear intraday variation in the results. Table 1 shows the data for SETS trades, Table 2 for upstairs trades.

Comparison between Tables 1 and 2 reveals that there are more than ten times more trades on SETS, while the average trade size is more than five times larger upstairs. These findings are consistent with previous research. The average trade size is especially large upstairs for the most liquid stocks, the top quintile of the FTSE 100: the average trade upstairs is nearly ten times larger than the average trade on SETS for these stocks. In addition, the decline in trade size with trading volume is less pronounced upstairs than it is on SETS. In fact the average trade size upstairs is nearly as large for the least liquid stocks in the sample as it is for the most liquid, if we leave aside the top quintile of the FTSE 100.

The total daily volume traded on SETS by value is around twice that traded upstairs. Jain et al. (2003), using data from 2000 on 149 FTSE 100 and 250 stocks, report that the upstairs market was slightly larger than SETS in that year. So SETS has gained substantial market share since then. However, SETS was only two years old in 2000. Most computer-driven trades, which have grown rapidly in number, are presumably executed via the limit order book. Despite this, the upstairs market remains an important part of the LSE.

Tables 1 and 2 also show how trading activity is concentrated in the most liquid stocks, in both subsamples. In the FTSE 100 subsample, the top-quintile stocks trade on average 7,014 times per day on SETS and account for 44% of SETS volume in this sample, compared with 1,242 times and 3% of volume for the bottom quintile. In the FTSE 250, the top-quintile stocks trade 1,245 times a day on SETS and account for 55% of SETS volume, compared with 61 times and 2% of volume for the bottom quintile. In the upstairs market, the concentration of trading activity in the most liquid stocks is even more pronounced. The top quintile of the FTSE 100 accounts for 67% of the upstairs volume in this subsample. Trading upstairs is more evenly distributed below the top quintile of the FTSE 100.

Table 3 shows the proportions by market of transactions and volume traded upstairs. There are certain striking findings. The overall proportions of transactions and volume upstairs are similar for both subsamples, at around 8% and 33% respectively. The proportion of volume upstairs is highest for both the most liquid stocks (42%), i.e. the top quintile of the FTSE 100, and the least liquid, i.e. the bottom three quintiles of the FTSE 250 (62% for the bottom quintile). Thus, we do not find a clear negative relationship between the liquidity of a stock and upstairs participation. The upstairs market is important for very liquid stocks. This contrasts with previous studies, which find a negative relationship between liquidity and trading upstairs (Madhavan and Sofianos, 1998).

Turning to the intraday pattern of trading, volume per minute rises in both markets as the trading day draws to a close, implying increased urgency to execute trades before the end of trading. The volume of trading in the last half hour increases more among less liquid stocks. In the upstairs market, this is because of a marked increase in average trade size towards the close across all quintiles except the top quintile of the FTSE 100. Among the FTSE 250, for example, the average trade size upstairs is about three times larger in the last half hour than during the rest of the day. The proportion of volume traded upstairs is highest in the middle of the day for FTSE 100 stocks (36%), and highest at the end of the day for FTSE 250 stocks (44%). The end-of-day rise in the average size of trades upstairs suggests that there might be an intraday difference in price discovery across the two markets. Previous research indicates that there is a positive relation between size of trade and permanent price impact (see for example, Keim and Madhavan, 1996), though this might no longer hold given the growth in algorithmic trading and increased splitting up of blocks.

3. Methodology

Our objective is to measure the distribution of price discovery between the two LSE markets. We employ two complementary measures, the component share (CS) or permanent-transitory method of Gonzalo and Granger (1995), and the information share (IS) measure of Hasbrouck (1995). We use these measures because they are the most precise available for measuring which out of two (or more) markets incorporates information first into an asset's price. They provide a direct answer because they produce estimates of the proportion of price discovery for which each market is responsible. We summarise the methods below. Readers are referred to Booth et al. (2002), Baillie et al. (2002), and the two source papers, for more detail.[2]

The concept of price discovery in the CS and IS methods is that discovery occurs in the market in which the price tends to change independently of changes in the price in the other market. And correspondingly, the price in the second, non-discovery, market tends to respond to changes in the first market. This idea is captured in the CS and IS methods by the notion of error correction, where the error in this case is $z_t = p_{1t} - p_{2t}$, the difference in the prevailing prices of a given share in market 1 and market 2. The extent to which errors, as defined, are corrected in each market is measured by error-correction parameters, α_1 and α_2. In a simple model with one lag, the specification is

$$p_{1t} = \alpha_1(1 - z_{t-1}) + e_{1t} \tag{1}$$

$$p_{2t} = \alpha_2 z_{t-1} + e_{2,t} \tag{2}$$

More price discovery occurs in the market with the lower estimated α. In this market, the price tends to move independently of the difference in price between the markets. In the second market, the price tends to move in a way that reduces the difference, or corrects the error, by moving towards the price in the first market. Price changes in the market with discovery tend to have a 'permanent' impact on the price. Permanent here means changes which do not result from correction of the error. The differences in the

[2] We employ the same methods as Booth et al. (2002). Other papers comparing upstairs and downstairs markets rely on comparing the price impacts of trades in the two markets. Booth et al. (2002) also estimate price impacts and find that the results from price impact and from the CS and IS methods are broadly consistent with each other, though their IS results imply more price discovery upstairs than do their price-impact or CS results.

two prices are temporary and are corrected primarily in the non-discovery market. The economic interpretation is that there is a common factor, new information that affects the value of the company that drives price changes in both markets. The new information tends to be reflected first in the market with more discovery, which therefore has a larger share of the trades in both markets motivated by new information. To estimate an error-correction model, the price data need to imply that the two price series do not tend to diverge, in which case the errors are in fact being corrected. Formally, the two series should be $I(1)$ cointegrated.

The price-setting process in each market can be modelled with more structure than is contained in equations (1) and (2). The process can include serial correlation of price changes within each market, and also relations between the price changes in one market and changes in the other market, i.e. cross-correlations between the price changes. Such a vector autoregression model, combined with an error correction term, is a vector error correction model (VECM). The VECM common to the CS and IS methods is, in matrix notation,

$$\Delta P = \alpha\beta' P_{t-1} + \sum_i^{\tau} A_i \Delta P_{t-i} + e_t \quad (3)$$

where $P_t = (P_{1t}, P_{2t})'$, $\alpha = (\alpha_1, \alpha_2)'$ is the error-correction vector, $\beta' = (1, -1)'$, known as the cointegrating vector, A_i is a vector of parameters that quantify the serial correlation and cross-correlation relations, and the error vector e_t has a mean of zero, zero serial correlation, and covariance matrix Ω:

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}. \quad (4)$$

σ_1^2 (σ_2^2) is the variance of e_{1t} (e_{2t}) and ρ is the correlation coefficient for e_{1t} and e_{2t}.[3] The interval over which price changes are measured is not specified as yet. The first term on the right hand side in equation (3) is the error-correction term. The second term captures the short-term dynamics caused by market imperfections.

The empirical model we use to estimate equation (3) is as follows:

$$\Delta P_t^{SETS} = \alpha_0^{SETS} + \alpha_1^{SETS}(1 - \hat{z}_{t-1}) + \sum_{i=1}^{\tau} \gamma_i \Delta P_{t-i}^{SETS} + \sum_{i=1}^{\tau} \eta_i \Delta P_{t-i}^{SETS} + \varepsilon_t^{SETS} \quad (5)$$

$$\Delta P_t^{DEAL} = \alpha_0^{DEAL} + \alpha_1^{DEAL} \hat{z}_{t-1} + \sum_{i=1}^{\tau} \gamma_i \Delta P_{t-i}^{DEAL} + \sum_{i=1}^{\tau} \eta_i \Delta P_{t-i}^{DEAL} + \varepsilon_t^{DEAL} \quad (6)$$

where α_0^{SETS} and α_0^{DEAL} are constants, α_1^{SETS} and α_1^{DEAL} are the estimated error correction coefficients, $z_{t-1} = P_{t-1}^{SETS} - P_{t-1}^{DEAL}$ and the γ_i and η_i variables are estimated coefficients. We use the Schwarz Information Criterion to determine the optimum number of lags for each stock in the third and fourth terms on the right of the equations. The optimum is between one and three lags for most stocks.

The difference between the CS and IS measures lies in how they use the results from the estimation of equations (5) and (6). This in turn reflects a difference in their conception of what price discovery is. The CS measure for a given share only uses the estimated error-correction coefficients:

$$CS^{SETS} = \frac{\alpha_1^{DEAL}}{\alpha_1^{SETS} + \alpha_1^{DEAL}} \quad (7)$$

and

[3] The errors have no serial correlation because any serial correlation in the price process is represented in the second term on the right of equation (3).

$$CS^{DEAL} = \frac{\alpha_1^{SETS}}{\alpha_1^{SETS}+\alpha_1^{DEAL}} \tag{8}$$

where the denominator ensures that the two measures sum to one. They can be interpreted as the proportions of price discovery in each market. It can be seen from equations (7) and (8) that price discovery according to the CS measure is the extent to which the price in the first market moves independently of the price in the second market, or equivalently, discovery in the first market is the proportion of error correction in the second market.

Turning to Hasbrouck's IS measure, the share of price discovery in a given market is the proportion of the common factor price innovations that arise in the market. The common factor is the flow of new information which drives changes in the price, abstracting from price differences between the markets. For notational convenience, let SETS be market *S* and the upstairs market be *D*, and let the variance of the error term in equations (5) and (6) be σ_S^2 and σ_D^2, respectively. Baillie et al. (2002) show that, if there is zero cross-correlation between the error terms, the IS measure can be expressed as

$$IS_s = \frac{CS_S^2\sigma_S^2}{CS_S^2\sigma_S^2+CS_D^2\sigma_D^2} \tag{8}$$

and

$$IS_D = \frac{CS_D^2\sigma_D^2}{CS_S^2\sigma_S^2+CS_D^2\sigma_D^2} \tag{9}$$

where the measures sum to one and are proportions of price discovery in each market, as for the CS measure. Thus, according to the IS measure, price discovery in a given market not only includes the CS measure, the tendency for price changes to occur that are independent of the difference in price between the markets, but also the variance of the price in the relevant market due to changes that are not captured by the effect of lagged price changes in both markets, as modelled by the VECM. The underlying reason for this conception is that Hasbrouck (1995) views *any* change in the price which is 'permanent' as an instance of price discovery. Permanent now means any change which does not tend systematically to be reversed, either by error correction or by the serial processes modelled by the third and fourth terms on the right of equations (5) and (6). The price changes that arise in a random walk are permanent in this sense.

If the error terms are cross-correlated, the variance of the common factor price innovations cannot be split unambiguously between the two markets in the manner of equations (8) and (9). To achieve an unambiguous split, it is necessary in effect to assign the cross-correlation to one of the two markets. Applying Cholesky factorisation results in:

$$IS_S = \frac{(CS_S\sigma_S + CS_D\sigma_D\rho)^2}{(CS_S\sigma_S + CS_D\sigma_D\rho)^2 + CS_D^2\rho_D^2(1-\rho)^2} \tag{10}$$

and

$$IS_D = \frac{CS_D^2\rho_D^2(1-\rho)^2}{(CS_S\sigma_S + CS_D\sigma_D\rho)^2 + CS_D^2\rho_D^2(1-\rho)^2} \tag{11}$$

where ρ is the coefficient of correlation between ε_t^{SETS} and ε_t^{DEAL}. It can be seen that the factorisation results in an upward bias of the IS measure for the market which is factorised first, SETS in the above case. To avoid this bias, we report the average of the IS scores from two factorisations in which the order of factorisation differs.[4]

4. Results

[4] Yan and Zivot (2010) also propose a price-leadership measure based on estimating the CS and IS measures. According to Yan and Zivot, CS measures the level of noise in one market in relation to the other, and IS measures the combined effect of noise and relative price leadership. The metric they propose combines the CS and IS estimates, to attempt an elimination of the relative avoidance of noise. But their approach is most suitable with sampling at a much higher frequency than we can use.

4.1 Common Information in Parallel Market Prices

We first investigate the extent to which there are common implicit prices in the two markets. We experiment with three sampling intervals: one minute, five minutes, and ten minutes, similar to Korczak and Phylaktis (2010). The results reported use the five-minute interval: the prices we use for a given stock are the most recent prices in the data, every five minutes during the trading day. The one-minute interval is problematic given that upstairs trades can be reported up to three minutes after execution, and the ten-minute interval is more likely to be influenced by stale quotes. But we calculate results for all three intervals, and find that the results are similar.[5]

To begin, we confirm that both series of market prices (P_t^{SETS}, P_t^{DEAL}) are $I(1)$ processes. This is done by conducting the augmented Dickey and Fuller (1981) (ADF) test to determine whether each of the pair of price processes for each share is non-stationary. We find that the null of a unit root is rejected for only three of the stocks at the 0.05 level of statistical significance. The next step is to check that all the (P_t^{SETS}, P_t^{DEAL}) series are cointegrated of the first order, by applying the Engle and Granger (1987) test. We run the following regression:

$$P_t^{SETS} = \beta_0 + \beta_1 P_t^{DEAL} + u_t \tag{12}$$

The two series are cointegrated if the error term is stationary. The Engle and Granger (1987) test uses a parametric ADF approach to test for the null that the u_t series is unit

[5] Booth et al. (2002) proceed by forming matched pairs of downstairs and upstairs markets. A problem with their data is the time between trades: the mean time between the two trades in a pair is 14.4 minutes, and the mean time between each matched pair is 49.9 minutes. The time between the matched pairs results in large cross-correlations in the error terms of the pair of VECMs for each share, which make the IS scores uncomfortably sensitive to the order in which the Cholesky factorisation is applied. Our approach of using a five-minute sampling interval is a high enough frequency to result in much lower cross-correlations than in Booth et al, but also a low enough frequency to avoid distortion due to transitory frictions (see Yan and Zivot, 2010).

root non-stationary. The *p*-values for the test statistics are computed from MacKinnon (1996) response surface simulation results. The test results confirm that all the pairs of price processes are cointegrated at the 0.01 level of significance. What these results show is that for all the 259 stocks in our sample, the prices in the upstairs and downstairs markets are inextricably linked. Thus, the fragmentation of the LSE into two parallel markets does not appear to have impaired the important task of price discovery.

4.2 Price Discovery

INSERT TABLES 4 AND 5 ABOUT HERE

4.2.1 CS and IS Estimates

Tables 4 and 5 show the CS and IS estimates, respectively. The results from the two methods are fairly similar, and lead to the same qualitative conclusions, with one important exception: price discovery upstairs for FTSE 100 stocks is much greater from the IS estimates than from the CS estimates. In the majority of cells (by index, volume quintile, and intraday period) the IS estimates across stocks display less variation than do the CS estimates. Since there are clear intraday differences in the mean CS and IS scores, the lower dispersion in the IS scores within most intraday periods suggests that the IS estimates are more reliable.

SETS trades account for the greater proportion of price discovery during most of the trading day. For the full day the proportion of price discovery is 10% CS (26% IS) for the FTSE 100 and 24% (14%) for the FTSE 250. A striking finding is the larger impact of upstairs trades on pricing during early and late trading. The average proportion of price discovery upstairs for FTSE 100 stocks is 17% CS (42% IS) during the first hour, 7% (22%) during the middle period, and 42% (48%) during the last half hour. The equivalent figures for FTSE 250 stocks are 43% CS (27% IS), 20% (10%), and 44% (38%). The pattern applies to stocks across the full range of liquidity. Intraday shifts in price discovery across two parallel markets have not previously been examined in the literature.

One possible reason for the late-afternoon rise in price discovery upstairs is the use by dealers of information about unexpressed liquidity accumulated during the day. The hypothesis is that dealers know more about who potential counterparties might be as the day goes on, and seek to take advantage of this knowledge before the market closes, by executing information trades as well as liquidity-driven trades. The longer a dealer sits on private information, the more likely it is that the information will become public before it can be put to use (see Foster and Viswanathan, 1993). Possibly the early-morning price discovery upstairs is due to a spillover of the process from the previous day. We note that the average trade size upstairs is larger for the third trading period, especially for FTSE 250 stocks. The late increase in average trade size is consistent with more aggressive informed trading in the upstairs market. In addition, a smaller proportion of dealer orders will be bound by the 'best execution' condition (because they exceed the value of orders on the order book), implying that the larger orders are executed at prices decided in the upstairs market.

It is also likely that the increased price discovery by the upstairs market is connected to a preferential trading arrangement for institutional investors, who are more likely to trade via the upstairs market as a result. Investors are allowed to submit volume weighted average price (VWAP) orders to the LSE upstairs market, which can be executed at the close. VWAP orders do not include price, only the quantity to buy or sell, since the price is based on the weighted average price generated by the day's trading volume upstairs. Our sample does not include VWAP orders or trades, but it is possible that the increased trade sizes are a result of large orders aimed at influencing the VWAP.[6] Given the lateness of the trading day, a few sufficiently large trades could achieve a shift in the VWAP.

In contrast to the pattern of intraday changes in price discovery across the two markets, which is clear in both Tables 4 and 5, the results show no clear relationship between the distribution of price discovery and trading volume. There is a discrepancy here between the CS and IS estimates. The CS estimates suggest that price discovery upstairs is less dominant for FTSE 100 stocks than for the FTSE 250, whereas the IS suggest the reverse. The CS estimates show a negative relation between volume traded and the proportion of discovery upstairs. The proportion ranges from 4% for quintile 1 of the FTSE 100 to 33% for quintile 5 of the FTSE 250. However, CS estimates for the last half hour show no clear relation between volume and discovery upstairs. The relation between IS price discovery upstairs and volume is negative for the FTSE 100 (but all the proportions are higher than the equivalent CS proportions). The IS results for the FTSE 250 show a *positive* relation between the proportion of price discovery upstairs and trading volume.

[6] The exclusion of VWAP trades is deliberate: they are trades dependent on price discovery during the trading day and thus do not contribute to price discovery. In addition, VWAP trades apply only to the upstairs market and can be executed after SETS closes at 16:30. We wish to compare trading when both markets are open.

Our results suggest that upstairs dealers do execute some information-motivated trades, in both liquid and less liquid stocks. This role is not prominent in previous studies. Most measure the scale of price discovery by the average permanent price impact of trades (see Smith et al., 2001; Booth et al., 2002; Jain et al., 2003; Bessembinder and Venkataraman, 2004 who measure price discovery by price impact). The permanent impact is interpreted as the effect on the price of new information implied by a trade. The studies find that the average permanent price impact is approximately zero upstairs (Jain et al., 2003, for the LSE), or if non-zero, the impact downstairs is several times larger. The inference in these studies is that upstairs dealers filter out information-motivated trades. Booth et al. (2002) report an average CS (IS) estimate of 18% (44%) of discovery upstairs, across their 20 Finnish stocks. But they downplay their IS results: 'Our findings suggest that... the upstairs price has little effect on the pricing of downstairs trades' (p. 1112). We find the IS proportion is higher for the FTSE 100 stocks, consistent with Booth et al. (2002), but lower for the FTSE 250. It is possible that the measures based on a VECM imply a larger role in price discovery for upstairs markets than do price impact models.

We find that substantial proportions of discovery upstairs arise near the start and close of the trading day. Our results for the middle period support Seppi's (1990) prediction that uninformed traders prefer to trade in the upstairs market, and Pagano and Röell (1992) argument that information can be impounded more rapidly into an asset's prices in a centralized order book than in a non-centralised upstairs market. The results for the middle period are also in line with the evidence from price impact, mentioned above.

4.2.2. Estimates of Informed Trading

The evidence from the CS and IS estimates of price discovery indicates that some price discovery does occur in the upstairs market, especially at each end of the trading day. We now use a measure of informed trading to investigate the intensity of informed trading upstairs, and whether the intraday variation in informed trading matches the intraday variation in price discovery which we have uncovered. Specifically, we measure the probability that a trade occurring in a given market is based on news not previously available on either market, and therefore leads to a permanent innovation in the price. We employ the probability of informed trading (PIN) model first developed by Easley et al. (1996). The PIN model assumes that trading by informed traders and liquidity traders occurs with the same respective probabilities in each period. The model is explained in Figure 1. At the start of each period, informed (but not liquidity) traders are assumed either to acquire, with probability α, a private signal regarding the value of the stock, or not to acquire a private signal with probability $1 - \alpha$. If there is a private signal, it is bad news with probability δ and good news with probability $1 - \delta$. Informed traders buy in the event of good news, and sell on bad news. Information events are independent across periods. The probability per period of an informed trade, conditional on an information event having occurred, is μ. The trading of liquidity traders is not affected by what informed traders do, and the probability per period that there is a liquidity buy = the probability of a liquidity sell = ε. Higher numbers of trades imply that there has been an information event, as informed traders only trade after there has been such an event. The PIN model enables us to draw inferences about the unobservable distribution of trades by informed and uninformed traders simply from data on the number of buy and sell trades.[7]

[7] We infer buys and sells by using the Lee and Ready (1991) trade-classification algorithm.

In our case we divide the trading day into the same three periods as for the price-discovery analysis, i.e. the first hour, middle seven hours, last half hour. As the periods differ in length, the four probabilities α, δ, μ, and ε are multiplied by the relevant fraction T of the trading day. We calculate separate PIN estimates for each of these intraday periods. In common with much preceding research, we assume that the various types of trade arise as draws from a Poisson distribution, governed by the relevant parameter. For example, the probability of b number of buys by uninformed traders in the first hour of the day is $e^{-\varepsilon T}\varepsilon T^{b}/b!$, where T = 1.0/8.5. The mean number of uninformed buys per period from this process is εT. The four probabilities are estimated via maximum likelihood from the total number of buy trades, B, and sell trades, S, during each trading period in a day.

The likelihood function for the PIN model over a given period is:

$$L((B,S)|\theta) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!} \quad (13)$$

where $\theta = (\alpha, \delta, \mu, \varepsilon)$. The specification of the above likelihood function represents how buys and sell arise, assuming the trading process and the roles of the four probabilities are as outlined, and assuming the four probabilities result in numbers buys and sells per period via draws from a Poisson distribution. Given the assumed processes, the estimation finds the values of the four probabilities that maximise the likelihood that the processes produce the sample of B and S values that we observe. The specification is such that an unusually large number of trades for a given period implies that there has been an information event. PIN is calculated as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \quad (14)$$

and the resulting estimate is the proportion of trades which are informed, in the relevant period and market. Note that the PIN estimates for each market are not constructed to sum to one, unlike the CS and IS estimates. The number of maximum likelihood estimations computed is 1,554, being for three intraday periods × two markets × 259 stocks.

INSERT TABLE 6 ABOUT HERE

Table 6 presents the cross-sectional mean, median and standard deviation of the PIN estimates by volume quintile. For the FTSE 100 stocks, the PIN estimates for the upstairs market are generally higher than those for the downstairs market, across all three periods. This means that the proportion of informed trades is estimated to be higher upstairs. This result is not necessarily inconsistent with the evidence presented above of greater price discovery downstairs, because there are many more trades downstairs. The evidence from the PIN estimates for the FTSE 100 is nonetheless surprising, considering the prevailing view that upstairs dealers screen out information-motivated trades. However, Jain et al. (2003) also report higher PIN estimates for the upstairs market for just over half of their FTSE 100 and 250 stocks.

We find that the intraday pattern of the PIN results for the FTSE 100 matches the pattern of higher price discovery upstairs at the start and close of the trading day. The mean PIN estimates for the upstairs market as a proportion of the PIN estimate for SETS are 135%, 113%, and 144% for the start, middle, and close of the day, respectively. These estimates therefore support the idea that there is greater informed trading during early and late trading in the upstairs market.

The constancy of informed trading downstairs for the FTSE 100 is possibly connected to the market depth downstairs in liquid stocks, which allows for rapid filling of orders. When orders are executed, the probability decreases of a rise in order imbalance in the order flow. Order imbalances creates opportunities for placing informed market orders, to take advantage of deviations in stock price from fundamental value. When orders are frequently filled, such quasi-arbitrage opportunities, and the influence of arbitrageurs/informed traders, are reduced, leading to less informed trading activity (see Chordia et al., 2008).

Panel B of Table 6 shows the PIN estimates for FTSE 250 stocks. There are much higher proportions of informed trades for the less liquid stocks, especially in the downstairs market. The mean PIN estimate for SETS is 0.54 for the FTSE 250, compared with 0.20 for the FTSE 100. We find for the FTSE 250 stocks that there is no clear difference in the proportion of informed trades across the two markets. Also, there is a clear intraday pattern in both markets, not only upstairs, of a greater proportion of informed trading at the start and close, and the percentage intraday changes in the PIN estimates are similar for both markets. The PIN results for the FTSE 250 are consistent with greater price discovery downstairs, given the much larger number of trades downstairs. But the PIN results for the FTSE 250 do not help explain the substantial intraday changes in the upstairs proportion of price discovery upstairs, revealed by both the CS and IS methods.

5. Conclusion

This paper studies the role of the upstairs market on the London Stock Exchange, using recent data for 2012-13. The study is motivated by the fundamental changes arising from the rapid growth of algorithmic trading in the 2000s, changes which include vastly increased volumes of trading, and much lower trade sizes. Our evidence suggests that the role of the upstairs might indeed have evolved. Previous studies, using datasets from before the era of algorithmic trading, find that price discovery occurs almost exclusively in the downstairs market, suggesting that information-driven trades tend to be routed to the order book. The role of upstairs dealers appears to be, or have been, to facilitate liquidity-driven trades, particularly large trades in less liquid stocks. Consistent with this picture, we find that the average trade size is several times larger on the upstairs market than on SETS, and that there is more price discovery on SETS than upstairs. But there are a number of new findings.

First, we find that around one fifth of price discovery occurs upstairs. This is a higher proportion than would be expected from previous evidence, most of which consists of estimates of the price impact of trades. The evidence on price discovery, from component share and information share measures, is supported by evidence from the PIN analysis, which is designed to measure the proportion of trades that are informed on a given market. The PIN results indicate that the proportion of informed trades is actually higher upstairs than on SETS.

Second, there is no clear relation in our results between stock liquidity, measured by volume of trading, and the participation of the upstairs market. This is the case for the proportion of trading upstairs, of price discovery, and of informed trading. On price discovery, there is a discrepancy in the results from the CS and IS measures. The CS measure shows a negative relation between liquidity and price discovery upstairs. This is consistent with previous findings, based mainly on the price impact of trades. But the

IS measure shows, if anything, a positive relation between liquidity and price discovery upstairs. The large role of the upstairs market for liquid stocks is unexpected, given previous findings.

Third, we find that the proportion of price discovery upstairs is higher in the first half hour of the trading day, and, especially, in the last half hour. For example, the average proportion of price discovery upstairs for FTSE 100 stocks, according to the IS method, is 42%, 22%, and 48%, during the first half hour, middle seven hours, and last half hour, respectively. The PIN results also suggest that there is a higher proportion of informed trading upstairs at the start and close of the day. This intraday evidence is new; there is no previous intraday evidence.

Taken together, the findings point to an evolution in the role of upstairs markets in recent years. This conclusion is based on a comparison of our results from recent data from the LSE with the results for the LSE and other stock exchanges in the past. The upstairs market could be more important in facilitating informed trades than it used to be, and upstairs trades have more effect on prices, independently of downstairs prices. A possible explanation for the intraday pattern we observe is that during the day dealers build up knowledge of potential counterparties willing to trade, and that they seek to exploit this knowledge by executing trades before the market closes, or failing that, at the start of the next day. The increased contribution of the upstairs market to price discovery during the closing period is of wider significance, because large volumes of derivatives and other instruments are settled each day at the closing price.

It would be worthwhile to investigate the extent to which our findings for the LSE generalise to other stock exchanges. On the LSE, upstairs dealers are in competition for order flow with the order book. This competitive setting might help explain the wider intermediary role that dealers seem to have adopted in recent years. It would also be worthwhile to investigate the reasons why the growth of algorithmic trading has led to a wider role for the upstairs market, if indeed the changes implied by our results are due to increased algorithmic trading. The wide role of upstairs trading also invites comparison with the recent growth of trading via ‘dark pools’. Both are characterised by lack of pre-trade transparency, and knowledge by dealers of sources of liquidity.

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Figure 1: Tree Diagram for the Easley, Kiefer and O'Hara (1996, 1997)

A corresponds to the probability of an information event, δ represents the probability that a low signal ensues, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders. The nodes to the left of the thick vertical line occur only once a day.

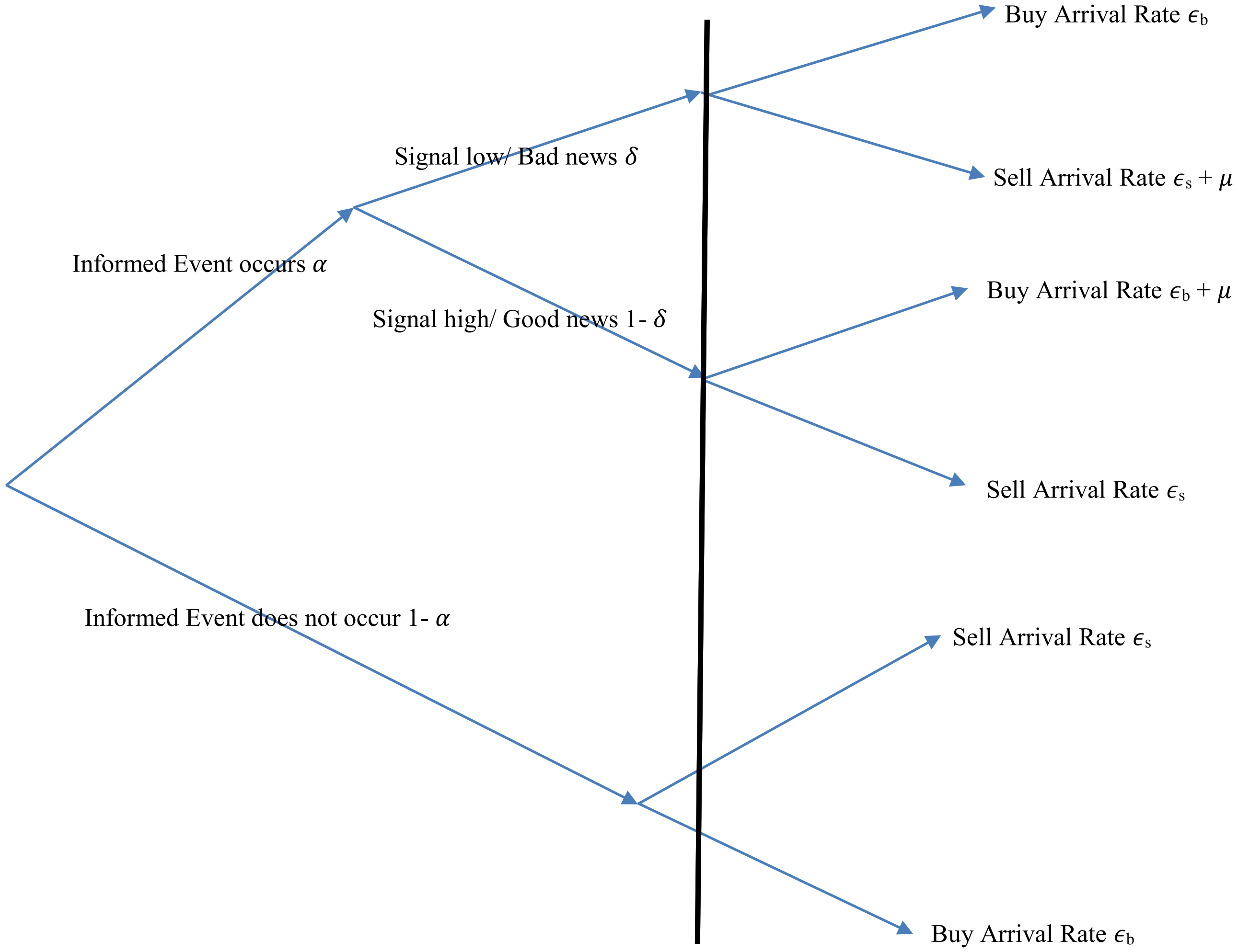

Table 1: Trading Statistics of FTSE 100 and FTSE 250 Stocks on SETS (Downstairs Market)

The table shows mean daily trading activity for 70 FTSE 100 and 189 FTSE 250 stocks on the London Stock Exchange's Electronic Trading System (SETS), by volume quintile, for three intraday time periods. The sample period 1 October 2012 to 30 September 2013. The quintiles are based on mean daily volume of trading on SETS by value. The sample, quintiles and intraday periods are the same in all subsequent tables. Source of data for all tables: Thomson Reuters Tick History.

Panel A: FTSE 100 Stocks

Quintile by Volume	Number of Transactions				Volume (£'000)				Average Trade Size (£)			
	08:00:01 - 09:00:00hrs	09:00:01- 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All
Highest	966	5,227	821	7,014	9,166	39,827	6,328	55,321	9,490	7,619	7,709	7,887
2	729	4,116	672	5,516	5,850	28,930	4,792	39,572	8,027	7,029	7,136	7,174
3	357	2,177	375	2,909	2,282	12,660	2,244	17,186	6,387	5,815	5,989	5,908
3	243	1,510	273	2,026	1,278	7,107	1,363	9,748	5,267	4,705	4,998	4,812
Lowest	135	930	177	1,242	489	3,062	607	4,157	3,623	3,293	3,421	3,347
All	486	2,792	463	3,741	3,813	18,317	3,067	25,197	7,847	6,560	6,617	6,734

Panel B: FTSE 250 Stocks

Quintile by Volume	Number of Transactions				Volume (£'000)				Average Trade Size (£)			
	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All
Highest	133	1,041	71	1,245	310	2,503	169	2,982	2,339	2,403	2,372	2,395
2	61	560	42	663	122	1,190	81	1,393	2,002	2,124	1,923	2,100
3	26	255	21	302	52	533	37	622	2,031	2,088	1,746	2,059
4	14	141	11	166	25	258	16	298	1,816	1,828	1,439	1,801
Lowest	4	53	5	61	7	94	7	108	1,652	1,797	1,405	1,757
All	48	412	30	490	104	920	62	1,086	2,177	2,233	2,060	2,217

Table 2: Trading Statistics for FTSE 100 and FTSE 250 Stocks in the Dealer (Upstairs) Market

The table shows equivalent information to Table 1 for the upstairs market of the London Stock Exchange. The quintiles are based on mean daily volume of trading upstairs by value.

Panel A: FTSE 100 Stocks

Quintile by Volume	Number of Transactions				Volume (£'000)				Average Trade Size (£)			
	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All
Highest	79	405	44	527	1,814	35,279	2,405	39,498	23,068	87,160	54,784	74,908
2	75	394	39	508	1,253	8,440	1,373	11,065	16,766	21,404	35,006	21,772
3	46	244	23	313	534	3,969	531	5,034	11,638	16,250	22,820	16,063
4	26	146	15	187	283	1,991	389	2,663	11,000	13,598	26,328	14,248
Lowest	9	57	6	72	92	865	113	1,071	10,633	15,076	18,856	14,855
All	47	249	25	322	795	10,100	962	11,866	17,018	40,528	37,833	36,900

Panel B: FTSE 250

Quintile by Volume	Number of Transactions				Volume (£'000)				Average Trade Size (£)			
	08:00:01hrs-09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All
Highest	12	67	3	82	119	837	69	1,025	10,001	12,582	21,040	12,544
2	6	35	2	43	58	469	66	592	10,217	13,249	43,866	13,933
3	4	30	1	36	57	433	59	550	12,815	14,540	46,233	15,468
4	3	20	1	24	46	288	32	366	15,317	14,624	38,163	15,542
Lowest	1	12	1	14	13	149	15	176	8,623	12,768	29,472	12,939
All	5	33	1	40	59	437	48	544	11,049	13,346	32,573	13,759

Table 3: Proportion of Trading Activity Upstairs

The table shows the mean proportions of trading activity upstairs. The proportions of trading on SETS are 1 minus the proportions shown.

Panel A: FTSE 100 Stocks

Quintile by Volume	Proportion of Transactions (%)				Proportion of Volume by Value (%)			
	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All
Highest	7.5	7.2	5.1	7.0	16.5	47.0	27.5	41.7
2	9.3	8.7	5.5	8.4	17.6	22.6	22.3	21.8
3	11.4	10.1	5.8	9.7	18.9	23.9	19.1	22.7
4	9.6	8.8	5.1	8.4	18.1	21.9	22.2	21.5
Lowest	6.0	5.8	3.3	5.5	15.9	22.0	15.7	20.5
All	8.8	8.2	5.2	7.9	17.2	35.6	23.9	32.0

Panel B: FTSE 250 Stocks

Quintile by Volume	Proportion of Transactions (%)				Proportion of Volume by Value (%)			
	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	All	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01hrs- 16:30:00hrs	All
Highest	8.3	6.0	4.4	6.2	27.8	25.1	29.0	25.6
2	8.5	5.9	3.5	6.0	32.1	28.3	44.9	29.8
3	14.8	10.5	5.7	10.5	52.4	44.8	61.7	46.9
4	18.1	12.3	7.1	12.4	65.1	52.8	66.9	55.1
Lowest	25.5	18.1	9.7	18.1	64.1	61.1	69.3	62.0
All	10.0	7.4	4.7	7.5	36.1	32.2	43.8	33.4

Table 4. Price Discovery: Component Shares Estimation

The table presents the proportions of price discovery computed using the component shares (CS) method (equations (8) and (9)). The mean, median and standard deviation of the proportions are presented for the stocks in each volume quintile. ***, ** and * denote that the median proportion is different from the proportion for the downstairs market at the 0.001, 0.01 and 0.05 level of statistical significance, respectively, using the Wilcoxon/Mann-Whitney test.

Panel A: FTSE 100 Stocks

Quintile by Volume	% Price Discovery	Upstairs Market			
		08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	08:00:01 – 16:30:00hrs
Highest	Mean	6.3	1.4	34.2	3.9
	Median	3.0***	0.8***	27.7***	2.6***
	Std. Dev.	5.7	1.61	18.7	3.1
2	Mean	10.4	2.0	37.9	5.1
	Median	3.7***	1.1***	33.3***	3.3***
	Std. Dev.	10.3	2.2	8.9	3.6
3	Mean	10.5	8.7	41.0	10.8
	Median	7.6***	8.4***	38.5***	10.1***
	Std. Dev.	7.5	4.8	12.3	5.6
4	Mean	22.7	6.3	54.1	11.0
	Median	18.5***	4.7***	56.5**	9.4***
	Std. Dev.	9.3	5.5	8.9	6.1
Lowest	Mean	33.7	20.9	55.2	24.4
	Median	22.1***	17.1***	56.7**	20.00***
	Std. Dev.	23.3	12.2	2.3	12.9
All	Mean	16.8	7.2	41.8	10.4
	Median	15.3***	4.7***	39.0**	8.0***
	Std. Dev.	16.8	8.9	15.2	10.2

Table 4 cont. Price Discovery: Component Shares Estimation

Panel B: FTSE 250 Stocks

Volume by Quintile	**% Price Discovery**	**Upstairs Market**			
		08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	08:00:01 – 16:30:00hrs
Highest	Mean	37.0	10.9	51.7	16.3
	Median	34.0***	8.7***	50.7***	14.1***
	Std. Dev.	11.1	9.1	2.3	9.0
2	Mean	37.1	15.0	43.5	19.3
	Median	36.3***	13.6***	43.5***	18.1***
	Std. Dev.	11.5	9.6	3.5	9.5
3	Mean	44.9	20.7	43.1	24.8
	Median	44.0***	18.0***	37.7***	22.2***
	Std. Dev.	15.2	12.9	15.2	13.3
4	Mean	46.2	21.0	40.4	25.1
	Median	44.7***	17.6***	37.9***	22.0***
	Std. Dev.	15.2	12.7	11.8	12.9
Lowest	Mean	49.6	29.2	45.2	32.6
	Median	50.00	29.7***	44.4***	32.9***
	Std. Dev.	16.8	12.3	13.1	12.9
All	Mean	43.41	19.8	43.5	24.0
	Median	42.7***	17.3***	42.3***	21.8***
	Std. Dev.	15.1	13.0	12.7	13.3

Table 5: Price Discovery: Information Shares Estimation

The table presents the proportions of price discovery computed using the information shares (IS) method (equations (10) and (11)), and using Cholesky factorisation. Since Cholesky factorisation is order-dependent, the price series are ordered first and second over two sets of estimations, and the average of the upper and lower bounds of the information shares is obtained for each stock in each of the three trading periods. The mean, median and standard deviation of the proportions are presented for the stocks in each volume quintile. ***, ** and * denote that the median proportion is different from the proportion for the downstairs market at the 0.001, 0.01 and 0.05 level of statistical significance, respectively, using the Wilcoxon/Mann-Whitney test.

Panel A: FTSE 100 Stocks

Volume by Quintile	% Price Discovery	Upstairs Market			
		08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	08:00:01 – 16:30:00hrs
Highest	Mean	43.6	16.6	47.3	21.6
	Median	44.6**	21.2***	47.9**	25.5***
	Std. Dev.	2.8	13.0	2.1	11.2
4	Mean	42.6	19.4	47.1	23.8
	Median	44.3**	23.2***	47.0**	27.1***
	Std. Dev.	5.0	12.8	1.6	11.2
3	Mean	39.8	23.0	48.6	26.5
	Median	43.9**	26.5***	48.9**	29.9***
	Std. Dev.	10.7	12.8	1.0	11.8
2	Mean	41.3	23.2	48.2	26.8
	Median	43.0**	21.9***	48.5**	26.0***
	Std. Dev.	5.7	11.3	1.2	10.1
Lowest	Mean	41.6	27.4	50.1	30.4
	Median	43.3**	29.8***	49.2*	33.0***
	Std. Dev.	5.8	10.0	4.1	9.15
Overall	Mean	41.8	21.7	48.2	25.7
	Median	43.6**	24.6***	48.6**	28.3***
	Std. Dev.	6.5	12.6	2.5	11.3

Table 5 cont. Price Discovery: Information Shares Estimation

Panel B: FTSE 250 Stocks

Volume by Quintile	% Price Discovery	Upstairs Market			
		08:00:01 - 09:00:00hrs	09:00:00 - 16:00:00hrs	16:00:01 - 16:30:00hrs	08:00:01 – 16:30:00hrs
Highest	Mean	40.7	15.6	52.6†	20.7
	Median	40.9***	15.2***	51.8***	20.4***
	Std. Dev.	5.5	11.4	1.3	10.1
4	Mean	34.2	14.2	44.1	18.3
	Median	35.0***	14.3***	44.1***	18.5***
	Std. Dev.	6.0	6.1	0.8	5.8
3	Mean	26.9	11.1	41.2	14.7
	Median	29.2***	10.7***	40.4***	14.6***
	Std. Dev.	9.2	6.1	3.7	6.3
2	Mean	20.8	7.1	34.7	10.4
	Median	21.9***	6.3***	38.7***	10.0***
	Std. Dev.	9.8	4.02	8.7	5.0
Lowest	Mean	12.9	5.0	35.1	7.7
	Median	8.1***	4.9***	37.3***	7.2***
	Std. Dev.	11.2	2.84	5.8	4.0
Overall	Mean	26.7	10.4	38.2	13.9
	Median	29.2***	9.4***	39.4***	13.4***
	Std. Dev.	12.9	7.5	8.1	8.2

Table 6: Probability of Informed Trading Analysis

The table presents probability of informed trading (PIN) estimates (equation (14)). The mean, median and standard deviation of the proportions are presented for the stocks in each volume quintile. † denotes that the PIN estimate for a given period for one market's differs from the estimate for the same period for the other market at the 0.01 level of significance, using the Wilcoxon/Mann-Whitney test.

Panel A: FTSE 100 Stocks

Quintile by Volume	PIN	Downstairs Market			Upstairs Market		
		08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs
Highest	Mean	0.217	0.190	0.220	0.285	0.256	0.292
	Median	0.147†	0.143	0.142†	0.231†	0.190	0.249†
	Std. Dev.	0.131	0.112	0.142	0.121	0.175	0.106
2	Mean	0.195	0.225	0.216	0.237	0.215	0.288
	Median	0.145	0.164	0.147†	0.232	0.183	0.250†
	Std. Dev.	0.102	0.119	0.111	0.061	0.084	0.104
3	Mean	0.151	0.157	0.160	0.235‡	0.189	0.367
	Median	0.149†	0.148	0.157†	0.239	0.160	0.252†
	Std. Dev.	0.016	0.024	0.014	0.025	0.122	0.269
4	Mean	0.168	0.206	0.203	0.251	0.225	0.229
	Median	0.149	0.151	0.155†	0.217	0.191	0.226†
	Std. Dev.	0.100	0.116	0.116	0.126	0.119	0.027
Lowest	Mean	0.155	0.172	0.148	0.226	0.195	0.283
	Median	0.178†	0.180	0.139†	0.223†	0.198	0.314†
	Std. Dev.	0.034	0.012	0.026	0.031	0.015	0.051
All	Mean	0.188	0.198	0.201	0.253	0.223	0.290
	Median	0.149†	0.153	0.155†	0.231†	0.185	0.248†
	Std. Dev.	0.104	0.105	0.114	0.094	0.128	0.136

Panel B: FTSE 250 Stocks

Quintile by Volume	PIN	Downstairs Market			Upstairs Market		
		08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs	08:00:01 - 09:00:00hrs	09:00:01 - 16:00:00hrs	16:00:01 - 16:30:00hrs
Highest	Mean	0.211	0.210	0.485	0.251	0.221	0.454
	Median	0.206†	0.163†	0.487†	0.247†	0.218†	0.464†
	Std. Dev.	0.027	0.142	0.019	0.051	0.038	0.062
2	Mean	0.278	0.227	0.514	0.258	0.228	0.438
	Median	0.248	0.167†	0.510†	0.234	0.226†	0.438†
	Std. Dev.	0.117	0.146	0.033	0.071	0.055	0.096
3	Mean	0.349	0.224	0.548	0.293	0.246	0.476
	Median	0.323†	0.213	0.531†	0.274†	0.231	0.487†
	Std. Dev.	0.084	0.061	0.041	0.104	0.092	0.069
4	Mean	0.376	0.246	0.551	0.298	0.267	0.472
	Median	0.365†	0.221	0.537†	0.295†	0.241	0.460†
	Std. Dev.	0.077	0.072	0.044	0.118	0.109	0.090
Lowest	Mean	0.502	0.306	0.590	0.424	0.298	0.497
	Median	0.505†	0.312	0.580†	0.397†	0.280	0.493†
	Std. Dev.	0.092	0.065	0.057	0.166	0.098	0.102
All	Mean	0.342	0.243	0.537	0.304	0.252	0.466
	Median	0.311†	0.218	0.523†	0.276†	0.232	0.462†
	Std. Dev.	0.129	0.110	0.054	0.125	0.088	0.087