The Informativeness of Retail and Institutional Trades: Evidence from the Finnish Stock Market

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Abstract

This paper examines the informativeness of retail and institutional trades in the Finnish Stock Market. We extend the structural model of Madhavan et al. (1997) to a framework that allows us to assess the degree of private information held by different trader types. We document that trades by financial institutions have a significantly greater price impact than trades by retail investors. A decomposition of the bid-ask spread shows that about 9% of the spread is a compensation for trading against better informed retail traders, while 45% of the spread is a compensation for trading against better informed institutions. Intraday, we observe significant variation in the proportions in which institutions and retail traders trade, and document that the informativeness of both type of trades diminishes throughout the trading day. A decomposition of the daily variance of price changes shows that about 19% of the daily variance is due to informed institutional trade, while only 3% of daily price change variance is due to retail trades.

JEL Codes: C22; G14.

Keywords: Private Information, Trader Types, Market Microstructure.

1 Introduction

This paper investigates the informativeness retail and institutional trades, making use of a unique Finnish data set that identifies the type of trader behind each trade. In contrast, to previous studies that make use of proprietary data that identify retail trades (e.g. (Kaniel et al.; 2008); (Kelley and Tetlock; 2013)) or broker types to identify retail trades (e.g. (Fong et al.; 2014)) to demonstrate that retail trade has an impact on future stock returns, we assess the the question of trade informativeness directly by estimating a structural model that captures the price impact of retail and institutional trades. Although we find that institutional trades have a greater price impact than retail trades, the price impact of retail trade is not negligible. Our structural model shows that 45% of the spread reflects a compensation for trading against better informed institutions. This is only 9% for trading against retail traders. When we decompose the variance of daily price changes, we observe that informed institutional trades contribute about 19% to this, while trades initiated by individuals contribute about 3%.

The question of why security prices change has been on the forefront of market microstructure research for several decades. Market microstructure theory suggests that prices change either due to the arrival of public or private news, where private news reveals itself through the trading activity of informed trades. Models aimed at capturing the degree of private information in the market, therefore often look at the price impact of trades (Lin et al.; 1995; Madhavan et al.; 1997; Huang and Stoll; 1997) or the daily order imbalance (Easley et al.; 1996).

A separate strand of literature has focused on the question of how the trade activity of different groups of traders affects the cross-section of stock returns. For instance, Barber et al. (2008) evaluate retail trades in the US market and document that retail trades are positively correlated with contemporaneous returns, and returns over the next two weeks. This correlation turns negative over longer horizons. Rather than attributing the positive correlation to information, Barber et al. (2008) argue that their finding is in line with models of investors sentiment, where systematic buying and selling by retail investors, temporarily induces a price pressure, that mean-reverts over longer periods. Similar to Barber et al. (2008), Kaniel et al. (2008) also find that retail trades positively predict future stock returns. However, in contrast to Barber et al. (2008), they do not observe a reversal in this predictability. Rather than attributing this positive relation to investor sentiment, Kaniel et al. (2008) state that their findings are best explained by retail investors acting as liquidity providers to institutions, who must offer price concessions to retail traders. Hvidkjaer (2008) use small signed trade turnover (SSTT) as a measure for retail trade, and evaluates the performance of stocks that that have high or low SSTT in the past. He finds that stocks with high past SSTT underperform those with low SSTT over a period of several years. Hvidkjaer (2008) argues that his results suggest that favored by retail investors are overvalued and subsequently underperform stocks that are not favored by retail investors. Kelley and Tetlock (2013) use a proprietary database that contains virtually all retail trades conducted on main US stock markets, and show that daily order imbalances positively predict future cross-sectional returns. In addition, retail investors are also able to predict news about firm cash flow. These findings suggest that retail trades are not mere "noise" traders, but trade on novel information they possess. Overall, this literature demonstrates that retail trades affect prices, however, whether this is due to private information, investor sentiment or temporary price pressure is still not clear.

The aim of this paper is to determine the degree of information asymmetry of retail versus institutional traders. Doing so, we make three important contributions to the literature. First, we contribute to the market microstructure literature by extending the framework of Madhavan et al. (1997) by allowing for different trader types, and assess the adverse selection costs induced by these different trader types. Based on this model we can compute the implied spread and its various components, and decompose the variance of price changes into different parts showing the variance induced by the trading of the different trader types. Second, we contribute to the literature on the informativeness of traders of different trader types. We document that while institutional trades are more informative than retail trades, retail trades, on average, are by no means uninformed.

We empirically implement our model using a unique Finnish data set that identifies traders as retail (henceforth household), institutional or other (non-financial corporations, government agencies and other minor investor type groups). We document for our sample of 22 stocks over the period 29 May 2007 to 13 November 2009, that the price impacts are higher for institutional trades than for household trades. Although this difference is statistically significant, the price impact of household trades themselves are also significant, suggesting that retail investors are not pure noise traders.

When we decompose the spread into its various components, we observe that about 9% of the spread represents a compensation of trading against a better informed retail investor, while about 45% of the spread is a compensation for trading against a better informed institution. Likewise, we observe that the contribution to the daily price change variance of retail traders is about 3%, on average, while that of institutional investors is about 19%. In line, with various market microstructure studies, we observe that the degree of information asymmetry for both trader types declines during the day, but we observe a considerable drop in this for retail traders in the late afternoon. We also document that trading activity of different trader types is not constant during the day, but observe that the proportion of household trades is considerably larger during the start of the trading day than at the end.

A study related to ours is that of Linnainmaa and Saar (2012), who examine the price impact of orders coming from different brokers on the Helsinki Stock Exchange. Their study addresses the questions of whether different types of traders trade more through specific brokers and whether market participants could learn whether they trade with an informed counter party from trade initiated by a specific broker. Linnainmaa and Saar (2012) document that broker identity provides a strong signal about trader type, and that the price impact of trades coming from brokers that mostly execute order submissions from institutions have a greater price impact than brokers that mostly execute trades coming from retail investors. Instead of considering broker ID, we directly address the question of whether different trader types have different levels of private information. Our finding, that institutional traders are more informed than retail traders, confirms the observation of

Linnainmaa and Saar (2012) that brokers who execute more institutional order are better informed.

The remainder of this paper is structured as follows. In Section 2, we develop a structural model along the lines of Madhavan et al. (1997), but which allows for the presence of different trader types. Section 3 discusses the Finnish data set we employ. Section 4, documents the empirical results for our model developed in Section 2, provides estimates for the various components of the bid-ask spread, and documents how the private information of different trader types contributes to the daily price change variance. Finally, Section 5 concludes.

2 Model

To assess the degree of private information held by different groups of traders, we develop a market microstructure model similar to Madhavan et al. (1997). According to this model, prices change either due to the arrival of public information, or due to the arrival of private information. Private information is held by so-called informed traders, who, through their trading activity reveal the private information they possess. In addition, there is a liquidity provider (either a market maker or a trader who submits limit orders). In our market, we distinguish between three different types of traders: households (H), institutions (I) or other (O). These groups can have private information to different degrees and we are interested in the degree of private information held by each group.

2.1 A Market Microstructure Model for Different Trader Types

In this section, we develop a market microstructure model that captures the degree of private information held by different trader types. This model extends the model of Madhavan et al. (1997), which is nested in our model.

Let p_t be the transaction price at which market participants trade at time t. Let x_t be a trade indicator that is equal to +1 if a trade is buyer initiated and -1 if a trade is seller initiated. In cases where trades occur within the spreads, $x_t = 0$. We define the unconditional probability of trades occurring within the spread as $\lambda \equiv P[x_t = 0]$. If we assume that, unconditionally, buys and sells are equally likely, then we can compute the probability of a crossing trade as $\lambda = 1 - Var[x_t]$. In line with market microstructure theory, the evolution of the efficient price is assumed to follow a random walk with respect to public information. Privately informed traders, trade on the basis of private information and their trades reveal some of the private information they hold. Hence their trade will have a permanent impact on the evolution of the efficient price. The efficient price process can thus be expressed as,

$$\mu_t = \mu_{t-1} + \theta(x_t - E[x_t|\Im_{t-1}]) + \varepsilon_t, \tag{1}$$

where μ_t is the efficient price of the asset, $(x_t - E[x_t|\Im_{t-1}])$, captures the surprise in order flow, θ measures the impact of a trade on the efficient price and thus captures the degree of private information in the market. It measures the permanent impact a trade will have on the efficient price. We measure the surprise in order flow as the difference between the actual buy/sell indicator observed at time t minus the expectation that a liquidity provider might have for the order flow $E[x_t|\Im_{t-1}]$, where $\Im_{t-1}$ is the information set the liquidity provider has at time $t-1$. This expectation can be different from zero if liquidity providers expect traders to split orders, or if they expect some patterns in liquidity for whatever reason. Finally, ε_t refers to the arrival of public information. Equation (1) thus shows that the efficient price of an asset is driven by public news shocks and private news which is revealed through the trading of informed traders.

Given that there are three different groups of traders active in the market, $i = H, I, O$, these groups can have different levels of private information and we would like to measure the degree of private information held by each group. Define the proportions in which these different traders types trade as π^i. These proportions are also the unconditional probabilities of a trade being initiated by a trader from group i. We assume that the liquidity provider knows what these unconditional probabilities are (or can infer this from trading activity). We define the trade indicators for each group of traders as $x_t^i = \mathbf{1}_t^i x_t$, where $\mathbf{1}_t^i$ is an indicator function, that is equal to one if a trade is initiated by a trader from group i and zero otherwise. We measure the unconditional probability of a trade being initiated by type i as $\pi^i = \frac{Var[x_t^i]}{(1-\lambda)}$. With these three different groups of traders, we can now extend the the evolution of the efficient price process in Equation (1) to

$$\begin{aligned} \mu_t = \quad & \mu_{t-1} + \theta^H(x_t^H - E[x_t^H|\Im_{t-1}]) + \theta^I(x_t^I - E[x_t^I|\Im_{t-1}]) \\ & + \theta^O(x_t^O - E[x_t^O|\Im_{t-1}]) + \varepsilon_t, \end{aligned} \tag{2}$$

where θ^H captures the degree of informed trading by households, θ^I the degree of informed trading by institutions, and θ^O the degree of informed trading by other traders. The expected trade direction for each trader type is given as $E[x_t^i|\Im_{t-1}] = \pi^i E[x_t|\Im_{t-1}]$.

The transaction price process can now be expressed as a function of the efficient price process, i.e.

$$p_t = \mu_t + \phi x_t + \xi_t, \tag{3}$$

where ϕ measures the transitory impact trades have on the price of the asset, and provides a measure for the costs of providing liquidity (e.g. order processing costs, etc.), ξ_t captures any remaining market microstructure noise due to, for instance price discreteness. Substituting Equation (2) into Equation (3) yields

$$\begin{aligned} p_t = \;& \mu_{t-1} + \theta^H(x_t^H - \pi^H E[x_t|\Im_{t-1}]) + \theta^I(x_t^I - \pi^I E[x_t|\Im_{t-1}]) \\ & + \theta^O(x_t^O - \pi^O E[x_t|\Im_{t-1}]) + \phi x_t + \varepsilon_t + \xi_t. \end{aligned} \tag{4}$$

Similar to Madhavan et al. (1997) we assume that the expected order flow can be gleaned from past order flow, i.e. $E[x_t|\Im_{t-1}] = \rho x_{t-1}$, where ρ captures the first order autocorrelation in order flow. Substituting this into Equation (4), we obtain

$$\begin{aligned} p_t = \;& \mu_{t-1} + \theta^H(x_t^H - \pi^H \rho x_{t-1}) + \theta^I(x_t^I - \pi^I \rho x_{t-1}) \\ & + \theta^O(x_t^O - \pi^O \rho x_{t-1}) + \phi x_t + \varepsilon_t + \xi_t. \end{aligned} \tag{5}$$

We can rewrite Equation(5) in first differences and solving for x_t^i and x_{t-1}, we obtain

$$\begin{aligned}\Delta p_t &= (\theta^H+\phi)x_t^H + (\theta^I+\phi)x_t^I + (\theta^O+\phi)x_t^O \\ &\quad -((\theta^H\pi^H + \theta^I\pi^I + \theta^O\pi^O)\rho + \phi)x_{t-1} + \eta_t,\end{aligned} \tag{6}$$

where $\eta_t = \varepsilon_t + \xi_t - \xi_{t-1}$.

Using the fact that $\pi^O = 1 - \pi^H - \pi^I$, we can estimate Equation (6) by GMM using the following orthogonality conditions,

$$E\begin{pmatrix} (\eta_t-\alpha) \\ (\eta_t-\alpha)x_t^H \\ (\eta_t-\alpha)x_t^I \\ (\eta_t-\alpha)x_t^O \\ (\eta_t-\alpha)x_{t-1} \\ x_t x_{t-1} - \rho x_t^2 \\ |x_t| - (1-\lambda) \\ |x_t^H| - \pi^H \\ |x_t^I| - \pi^I \end{pmatrix} = 0. \tag{7}$$

This model is exactly identified. We estimate the model by a two-step GMM using a Newey-West consistent weighting matrix. Similarly, we compute standard errors based on a Newey-West consistent covariance matrix.

2.2 Components of the bid-ask spread

Based on the model developed in the previous subsection, we can derive the implications for the bid-ask spread in the market. Liquidity providers post bid and ask spreads, which are prices conditional on a sell or buy order arriving to the market. In the case where we do not make a distinction between the different groups of traders, we would state the ask and bid price as,

$$\begin{cases} p_t^a = E[p_t|x_t = 1] = \mu_{t-1} + \theta(1 - E[x_t|\Im_{t-1}) + \phi + \varepsilon_t \\ p_t^b = E[p_t|x_t = -1] = \mu_{t-1} + \theta(-1 - E[x_t|\Im_{t-1}) - \phi + \varepsilon_t \end{cases} \tag{8}$$

The implied spread from this model is given as $p^a - p^b = 2(\theta + \phi)$.

In our specification, with the three different groups of traders, we can also decompose the spread and see what the contributions of the information asymmetry of the different trader types are. In this case the ask price is the probability-weighted average of trades from the different trader types, i.e.

$$\begin{cases} p_t^a = & \mu_{t-1} + \pi^H\theta^H(1 + E[x_t^H|\Im_{t-1}]) + \pi^I\theta^I(1 + E[x_t^I|\Im_{t-1}]) \\ & +\pi^O\theta^O(1 + E[x_t^O|\Im_{t-1}]) + \phi + \varepsilon_t \\ & \\ p_t^b = & \mu_{t-1} + \pi^H\theta^H(-1 + E[x_t^H|\Im_{t-1}]) + \pi^I\theta^I(-1 + E[x_t^I|\Im_{t-1}]) \\ & +\pi^O\theta^O(-1 + E[x_t^O|\Im_{t-1}]) - \phi + \varepsilon_t \end{cases} \tag{9}$$

This suggests that the implied spread from this model is equal to $p^a - p^b = 2(\pi^H\theta^H + \pi^I\theta^I + \pi^O\theta^O + \phi)$. Thus the spread reflects the cost of trading against a better informed counterparty from a specific trader group, multiplied by the probability of trading against a trader from that group.

Based on Equation (9), we can determine the part of the spread that the liquidity provider charges for trading against a better informed counterparty from a specific group. We label this as the information asymmetry component due to a specific trading group, i.e.

$$IA^i = \frac{\pi^i\theta^i}{(\pi^H\theta^H + \pi^I\theta^I + \pi^O\theta^O + \phi)}, \tag{10}$$

while the total information asymmetry component is $IA = \sum_i IA^i$.

3 Data

In this study, we make use of intraday data from Euroclear. Euroclear is the clearing house for all stocks traded on the Helsinki stock exchange, and provides us with trade records on all trades in stocks that are listed on the Helsinki Stock Exchange (HSE). Each trader has a unique identifier, and an indicator identifying the type of trader. Traders are classified into various groups: households, financial institutions, non-financial corporations, government agencies, and foreign investors. From these classifications we construct three groups: Households (H); Institutions (I) consisting of domestic and foreign institutions; and Other (O) consisting of non-financial and government agencies. As pointed out by Grinblatt and Keloharju (2000) and Leung et al. (2013) the behavior of foreign investors is typical to that of institutional traders. However, as Stoffman (2014) points out, although the group of foreign investors mainly consists of foreign institutions, it may also contain some foreign retail trades through ADRs. We exclude trades in ADRs by focusing only on the trades that occur on the OMX Helsinki.

Although Euroclear provides us with a full record of all trades that occur in Finish stocks, it does not provide us with the intraday timing of the trades.

To obtain this timing we merge the Euroclear data with the intraday data on trades at the OMX Helsinki which we obtain from Thomson Reuters Tick History (TRTH). We obtain intraday data on all trades by trader type for the period 29 May 2007 to 13 November 2009. As many stocks trade very infrequently on the OMX Helsinki, we focus on the most liquid stocks in the market. We obtain intraday data for 22 of the largest stocks traded on the OMX Helsinki. Regular trading hours on the HSE are from 10:00 to 18:30, with a pre-opening call from 9:45 to 10.00 and a closing call from 18:20 to 18:30. Hence to stay clear of the open and close of the market we focus on the intraday period from 10:05 to 18:20.

We follow a standard approach to classify trades as buyer or seller initiated. Trades executed at or above the ask are classified as buyer initiated ($x_t = +1$), trades executed at or below the bid are classified as seller initiated ($x_t = -1$), and trades that occur within the spread are left unclassified ($x_t = 0$). Trades that occur within the same second, are in the same direction (buyer or seller initiated), and are from the same trader type are treated as a single trade.[1] We further clean our data by removing outliers. Specifically, we remove observation where the intraday transaction-to-transaction return is greater than 5%, and we remove observations where the percentage spread is greater than 15% of the quoted midpoint or negative. Finally, for the estimation of the model we remove the overnight return.

INSERT TABLE 1 HERE

[1] Note that a single market order can execute against several limit orders. In our database, we observe all these executions as separate data points. Hence it often occurs that a single market order is recorded as multiple data entries in the same second.

Table 1 reports the company name, its industry, the number of trading days of the stock in the sample (note that for some stocks we do not have data covering the full sample period), and various summary statistics. As we can see, there is quite some variation in the trading activity of the different stocks in the sample. Nokia is by far the most heavily traded stock in the OMX Helsinki, with on average over 5,000 trades per day. This is in stark contrast to the least actively traded stock in the sample (Fiskars), which trades only 28 times a day, on average. There is also quite some variation in the average price at which the assets trade, ranging from 2.38 Euro to 32.81 Euro. The next column report the average Euro spread of the different stocks, which ranges from 0.011 to 0.0617 Euro. Generally, we observe that there is a positive relation between the average price and the Euro spread. The average % spread (defined as the ask price minus the bid price divided by the midpoint of bid and ask price), which can be seen as a measure of trading costs, shows that there substantial variation across the different assets. These trading costs can be as high as 0.85% (Metsa Board) and as low as 0.09% (Fortum and Nokia). These statistics show that the frictions defined in Section 2 that affect the spread, clearly differ across the stocks in our sample. The last column report the volatility of trade-by-trade price changes. As we will demonstrate later, these volatilities are largely affected by the frictions defined in Section2. We again observe substantial variation in the volatility of price changes, with price change volatility ranging from 0.731% to 5.527%.

4 Results

4.1 Original Model

We start by presenting the estimation results for the model developed in Section 2. We first document the results for the original Madhavan et al. (1997) model, where we do not make a distinction between the different trader types. We present parameter estimates together with standard errors, which are based on a Newey-West correction in parentheses in Table 2. In the first column of Table 2, we report the estimates for θ (multiplied by 100), which captures the per-trade permanent price impact of trades, and so provides a measure for private information. On average, we observe that θ is about 0.69, but note that there is quite some variation for the different stocks, with Stockman (1.50) and Fiskars (1.41) having the highest degree of price impact on a per trade basis. The lowest impacts are for Metsa Board (0.15) and Nokia (0.18). The informativeness of a single trade is negatively related to the liquidity of the stock, and has a correlation of -0.44 with the average number of trades per day.

The order processing costs, ϕ (multiplied by 100), are reported in the next column. On average, the per-trade processing costs are 0.46, but again there is substantial variation among the different stocks with the highest degree of order processing costs for Fiskars (1.15) and Stockmann (0.73), and the lowest degree of order processing costs for Huhtamaki (0.26) and Stora Enso (0.31). Order processing costs show little correlation with liquidity, having a correlation of -0.05 with trades per day.

The next column reports the implied spread ($2(\theta+\phi)$) based on the model (recall that the model only uses transaction prices and estimates spread measures based on these). We observe that the implied spread is close to the spread computed from bid and ask quotes and reported in Table 1, which is reassuring and implies that the model can describe the patterns observed in the actual data. We observe that in all cases the implied spread is slightly smaller than the observed spread, which is due to the fact that some transactions take place at prices within the quoted spreads.

INSERT TABLE 2 HERE

The next column shows the degree of autocorrelation in order flow, which on average is close to 20%, all these correlations are distributed relatively closely around 20%, except for Nokia, where the autocorrelation in order flow is lower at about 2%. With regards to the probability of trades within the spread, λ, we find that this probability is low and in all cases less than 5%. The average probability of a trade within the quoted spreads is close to 1.15%.

The estimates of the model allow us to draw some conclusions about the degree of informational asymmetry in the market. In the last column of Table 2, we report the information asymmetry component of the spread, which is computed as $IA = \frac{\theta}{(\theta+\phi)}$. We can compute the standard errors of this estimate from the covariance matrix of the original parameter estimates, i.e. $SE(IA) = \frac{\partial IA}{\partial \beta}' V_\beta \frac{\partial IA}{\partial \beta}$, where β is the vector of parameters estimated by Equation (7). We find that the average IA is about 58% indicating that more than half of the spread is a compensation to the market maker for trading against a better informed counterparty. There is again considerable variation in the information asymmetry component of the spread, with the highest degrees of information asymmetry observed for Amer Sport Corp. (72.65%) and Konecranes (71.12%) and the lowest degree of information asymmetry observed for Nokia (25.85%) and Metsa Board (30.69%). As expected this degree of information asymmetry is strongly negatively correlated with liquidity, the correlation between the information asymmetry measure and average number of trades per day is -0.62.

4.2 Asymmetric Information of Different Trader Types

In Table 3, we report the results for the extended model, where we estimate the degree of informational asymmetry for each of the different trader types: Households (H), Institutions (I) and Other (O). In the first three columns, we report the estimates for the permanent price impact due to each different trader type. When we first consider the averages, we note that θ^I and θ^O have impacts of similar magnitudes of about 0.69 each. Households (θ^H) have a price impact of 0.65. This suggests that institutions are more informed than individual traders, as the price impact of institutions is larger than that of individual traders. We note that for 17 out of the 22 stocks, $\theta^I > \theta^H$. In addition, a test on ($\theta^I - \theta^H$) produces a t-statistic of 4.77, showing that the difference in the price impacts is significant at the 1% level. The estimate for the liquidity friction component ϕ is not much affected by the inclusion of the different trader types and estimated values are close to what they were in the basic model.

INSERT TABLE 3 HERE

The next three columns show the unconditional proportions in which the different trader types are active. On average, around 17% of trades are conducted by individual traders. However, the majority of all trades is conducted by institutions. The other group of traders represent less than 6% of all trades. We note that there is quite some variation in the proportions across the different stocks. The most heavily traded stocks by household investors are Fiskars and Metsa Board with 55.10% and 28.51% of trades conducted by households, respectively. Logically, these are also the stock for which the proportions of trade by institutions are lowest. The stocks least actively traded by households are Stora Enso (6.13%) and Tieto (7.47%), which are the most actively traded stocks by institutions.

The last columns of Table 3 show the information asymmetry components of the spread, IA^i, as defined in Equation (10). From these results, we can observe that, on average, the majority of the information asymmetry component of the spread comes from institutional traders, with an average information asymmetry component of about 0.45. This is followed by households (0.09) and other trader types (0.03). The sum of these three components equals 0.5723, close to the total information asymmetry component reported in Table 2. Thus, we can conclude that the total spread for these stocks, on average, consists of 42.77% as a compensation for order processing and inventory imbalance costs, 45.13% as a compensation for trading against a better informed institutional trader, 8.89% as a compensation of trading against a better informed individual trader and 3.21% as as a compensation for trading against a better informed other type of trader. For households, the information asymmetry component ranges from 0.29 (Fiskars) to 0.02

(Nokia). For institutional traders, the information asymmetry component ranges from 0.63 (Amer Sports) to 0.20 (Fiskars).

Table 3 revealed that there is substantial variation in the proportion of trade conducted and the degree of information asymmetry by the different trader types. In Table 4, we assess whether there is not only variation across stocks, but whether there is also variation during the trading day. we thus re-estimate the model for the different trader types over different period of the day, focusing on the early morning (10:05am - 11:00am), morning (11:00am - 1:00pm), midday (1:00pm - 3:30pm), afternoon (3:30pm - 5:30pm), and late afternoon (5:30pm - 6:20pm) periods.

INSERT TABLE 4 HERE

In Table 4, we present the results for the different times of the day, where we report the cross-sectional average and the cross-sectional average of the standard errors. If we first consider the patterns over the trading day, we observe that the measures of informed trading by households and institutions (θ^H and θ^I) decline monotonically over the trading day. This finding is in line with e.g. Hasbrouck (1991), Madhavan et al. (1997), and shows the resolution of private information during the trading day. For households, we observe a big decline in private information after the opening period, and another sharp decline in private information going from the afternoon to the late afternoon session. For institutional traders, we observe a large drop in private information at the start of the trading day, but not at the end of the trading day. This suggests that the decline in private information at the start of the trading day is mostly related to the revelation of news that arrived in the overnight period, while the decline in private information at the end of the trading day (which is only observed for households) may reflect households trading more for liquidity purposes. In all periods, we observe that institutions are more privately informed than individuals. These differences are largest at the start and end of the trading day. Around the midday period, our results suggest that the private information held by institutions and individuals is similar.

The liquidity friction costs (ϕ) are highest at the end of the trading day, an observation that is again in line with Madhavan et al. (1997), and increases sharply going from the afternoon to the late afternoon period. This may reflect an increase in inventory costs as liquidity providers may be less willing to take on any unwanted inventory positions before the market closes.

When we consider the proportions in which the different trader types trade, we observe that the proportion of trades by individuals decreases during the trading day, suggesting that individual trades are more concentrated in the early hours of the trading day. In contrast, the proportion of trade by institutions increases over the trading, from a low of 72% at the start of the trading day to a high of 81% at the end of the trading day.

Finally, we document the information asymmetry components for the different trader types over the different times of the day, i.e. the percentage of the spread attributable to the information asymmetry coming from a specific trader type. We observe that the information asymmetry component due to household trades decreases sharply over the trading day, from a high of 13.36% at the start of the trading day to a low of 5.64% at the end of the trading day. The information asymmetry component of the spread due to institutions displays virtually no pattern over the trading day and sits between 44% to 46%. These result suggest that perhaps the trading by individual traders may become more predictable during the trading day, while that of institutional traders remains at the same level.

4.3 Contribution to Transaction Price Change Volatility

Similar to Madhavan et al. (1997), we can decompose the variance of the returns into different components, such as the variance due to innovation in public information, the variance due to asymmetric information of the different trader types and the variance due to frictions. We can obtain these different components by taking the variance of Equation (6), and using the fact that $Cov[x_t^i, x_t^j] = 0 \, \forall \, i \neq j$ and $Cov[\mathbf{1}_t^i, x_{t-1}] = 0 \, \forall \, i$. We obtain

$$\begin{aligned} Var[\Delta p_t] = \; & \sigma_\varepsilon^2 + 2\sigma_\xi^2 \\ & +(1-\lambda)\left\{(\theta^H+\phi)^2\pi^H + (\theta^I+\phi)^2\pi^I + (\theta^O+\phi)^2\pi^O \right. \\ & +[(\theta^H\pi^H + \theta^I\pi^I + \theta^O\pi^O)\rho + \phi]^2 \\ & -2(\theta^H+\phi)[(\theta^H\pi^H + \theta^I\pi^I + \theta^O\pi^O)\rho + \phi]\pi^H\rho \\ & -2(\theta^I+\phi)[(\theta^H\pi^H + \theta^I\pi^I + \theta^O\pi^O)\rho + \phi]\pi^I\rho \\ & \left. -2(\theta^O+\phi)[(\theta^H\pi^H + \theta^I\pi^I + \theta^O\pi^O)\rho + \phi]\pi^O\rho\right\}, \end{aligned} \tag{11}$$

where $\sigma_\varepsilon^2 = Var[\varepsilon_t]$, the variance of the innovation in public news and $\sigma_\xi^2 = Var[\xi_t]$, the variance of the frictions due to price discreteness.

Rearranging the terms on the right-hand side of Equation (11), we can obtain the contribution of asymmetric information of trades from group i, δ^i

as

$$\delta^i = \frac{(1-\lambda)\theta^{i^2}\pi^i(1-\pi^i\rho^2)}{Var[\Delta p_t]}. \tag{12}$$

The contribution of order processing costs is the same as in Madhavan et al. (1995), i.e.

$$\delta^\phi = \frac{2(1-\lambda)\phi^2(1-\rho)}{Var[\Delta p_t]}. \tag{13}$$

To identify the different contributions to return volatility and to estimate the values for σ_ε and σ_ξ, we need to add two more moments, that we can identify in the GMM. We add the following two conditions to Equation (7),

$$E\begin{pmatrix} (\eta_t-\alpha)^2-(\sigma_\varepsilon^2+2\sigma_\xi^2) \\ (\eta_t-\alpha)(\eta_{t-1}-\alpha)+\sigma_\xi^2 \end{pmatrix} = 0. \tag{14}$$

We report the results for the transaction price change variance and the contributions of the different components to this variance in Table 5. In the first column we report the variance of transaction price changes as implied by the model. Comparing these results with the volatility of transaction price changes computed from the data (see last column of Table 1), we observe that our estimates are in line with the data, again giving confidence that the model describes the data well.

When we consider the contribution to transaction price change volatility of public news shocks, δ^ε, we observe that, on average, it contributes about 28% to the price change variance. There is wide variation across the stocks in terms of the contribution of public news. Amer Sports has the highest contribution of public information at about 42%, whereas Nokia has the lowest contribution at 0%. The largest contribution to the transaction price variance, however, comes from price discreteness, δ^{ξ}, contributing about 49%, which could be expected when considering the variance of trade-by-trade price changes. We observe some variation across stocks in terms of the contribution of price discreteness, with Metsa Board having the lowest level of price discreteness (24%), and Nokia having the highest level of price discreteness (79%).

INSERT TABLE 5 HERE

The next three columns report the contributions of that the different trader groups make to the price change variance. For household trades, the contribution to the price change variance, δ^{H}, on average, is close to 1%, with some variation ranging from 3.52% (Fiskars) to 0.04% (Nokia). For institutional trades, the contribution, δ^{I}, on average is close to 5% and ranges from 8.74% (Amer Sports) to 0.77% (Nokia). Overall, we observe that frictions due to information asymmetry of institutions have a greater impact on price change volatility than frictions due to information asymmetry of households.

The last column reports the contribution to price change volatility due to liquidity frictions, δ^{ϕ}. On average the contribution due to frictions is close to 7%, but there is substantial variation in these frictions across stocks. This contribution is highest for Metsa Board (31.62%) and lowest for Konecranes (2.27%).

Overall, the results demonstrate that the price change variance at the transaction level is mostly due to frictions (either due to price discreteness, liquidity or information), and only for a small part driven by public information. At the transaction level, this may be expected, as microstructure noise should be most prominent at this frequency.

4.4 Contribution to Daily Price Change Variance

The previous section demonstrated how each part contributes to the variance of transaction price changes, and we observed that frictions make up the majority of the contributions to this variance. In this section, we consider how the different parts contribute to the variance of daily price changes, $Var[\Delta p_T]$, where Δp_T refers to the change in the price from the start of day T to the end of day T. At the daily level, we would expect that some of the frictions would diminish, such as the frictions due to price discreteness and due to liquidity frictions. At the daily level, we would also expect that the importance of public and private news increases in terms of contribution to price change variance.

Since the know that $Var[\Delta p_T] = Var[\sum_T \Delta p_t]$, it follows that the daily variance can be written as,

$$\begin{aligned} Var[\Delta p_T] = \quad & N_T \sigma_\varepsilon^2 + 2\sigma_\xi^2 \\ & + Var[(\theta^H + \phi) \textstyle\sum_T x_t^H + (\theta^I + \phi) \sum_T x_t^I + (\theta^O + \phi) \sum_T x_t^O \\ & - ((\theta^H \pi^H + \theta^I \pi^I + \theta^O \pi^O)\rho + \phi) \textstyle\sum_T x_{t-1}], \end{aligned} \tag{15}$$

where N_T is the number of transactions on day T. From Equation (15) we can immediately see that the contribution of price discreteness to the total daily volatility will decrease as N_T increases. From Equation (15), we can again evaluate the contributions due to news and the various frictions.[2]

INSERT TABLE 6 HERE

In Table 6, we report the contributions to the daily price change variance of the various components. As Equation (15) demonstrates, these contributions are a function of the number of trades N_T in a given day. Hence, in Table 6 we report the various contributions for an average trading day, using the average number of trades per day for N_T.

In the first column of Table 6, we report the contribution to the daily price change variance due to public news, DV^{ε}. We can see that, on average, over 77% of daily price change variance is due to public information, with a high of 87.15% for Finnair and a low of 76.22% for Tieto. Hence, we can clearly see that at the daily level most of the price change variance is due to the arrival of public information.

At the daily level, we observe that the contribution due to price discreteness, DV^{ξ}, is very small, on average 0.42%. However, the most illiquid stocks in the sample (Fiskars and Finnair) have a price change variance that is still affected by price discreteness even at the daily level.

When we consider the contributions to daily price change variance of households (DV^{H}), we observe that the private information held by households contributes about 3% to daily price change variance. Private information of households has the greatest impact on Fiskars where it contributes

[2]Note that these measures bear some similarities to the measure of trade informativeness of Hasbrouck (1991), who measures trade informativeness by looking at the contribution of trades to the variance of the efficient price. Our measure differs in two ways as 1. it looks at the contribution of various component to the variance of transaction price changes, as opposed to efficient price changes, and 2. it measures the contribution to daily price changes as opposed to hourly price changes.

over 6% to daily price change variance, and the smallest impact on Stora Enso at 0.72%. For institutions, the contribution, DV^I, is considerably higher at 18.58% on average. This shows that the private information held by institutions has a considerable effect on daily price change variance. Variation across stocks is again substantial ranging from 4.88% (Fiskars) to 21.41% (Tieto).

The last column of Table 6 reports the contribution of liquidity frictions to the daily price change variance. We observe that at a daily frequency these contributions negligible.

5 Conclusion

This paper examines the informativeness of trades by retail and institutional traders. We develop a structural market microstructure model that extends the work of Madhavan et al. (1997) by allowing for different trader types. Based on this model, we can estimate the price impact of trades by retail and institutional investors, compute the components of the spread that are due to the informed trading of the different trader types, and determine contribution of informed trade to the price change variance. Overall, our results show that institutional trades are more informed than trades by retail investors, although the price impact of retail trades is significant as well, suggesting that retail traders are not purely noise traders.

Our results have important implications for people who find this information useful.

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Table 1: Summary Statistics

Stock	Industry	Number of Days	Av. Daily Trades	Av. Price	Av. Spread	Av. %Spread	Volatility of Δp
Amer Sports Corp.	Personal & Household Goods	595	249.17	12.751	0.0271	0.2543%	2.602%
Elisa Corp.	Telecommunications	622	803.92	15.756	0.0191	0.1267%	1.829%
Finnair	Travel & Leisure	622	66.61	7.032	0.0317	0.5004%	2.979%
Fiskars	Personal & Household Goods	478	28.18	11.593	0.0617	0.5566%	5.228%
Fortum	Utilities	622	1803.70	22.151	0.0192	0.0912%	1.982%
Huhtamaki	Industrial Goods & Services	622	265.28	7.753	0.0164	0.2264%	1.454%
Konecranes	Industrial Goods & Services	622	745.71	21.478	0.0304	0.1485%	3.370%
Kesko	Retail	622	690.29	28.362	0.0329	0.1270%	3.767%
Kemira	Chemicals	622	319.52	10.431	0.0195	0.2096%	1.990%
Metso	Industrial Goods & Services	622	1434.50	25.851	0.0260	0.1190%	2.986%
Metsa Board	Basic Resources	622	248.33	2.377	0.0110	0.8514%	0.731%
Nokia	Technology	622	5264.00	16.405	0.0134	0.0942%	1.888%
Nokian Renkaat	Automobiles & Parts	622	980.40	20.224	0.0262	0.1419%	2.810%
Pohjola Bank	Financials	579	521.37	10.179	0.0185	0.1934%	1.742%
Outokumpo	Basic Resources	622	1468.00	18.540	0.0214	0.1318%	2.239%
Rautaruukki	Industrial Goods & Services	622	1085.40	24.781	0.0280	0.1288%	3.202%
Sampo	Insurance	622	1293.70	16.495	0.0185	0.1178%	1.801%
Stockmann	Retail	622	151.64	23.268	0.0530	0.2521%	5.527%
Stora Enso	Basic Resources	596	1147.40	8.012	0.0129	0.1893%	1.044%
Tieto	Technology	622	546.51	13.987	0.0204	0.1588%	2.014%
UPM-Kymmene	Basic Resources	622	1359.70	11.157	0.0138	0.1358%	1.237%
Wartsila	Industrial Goods & Services	563	950.10	32.809	0.0373	0.1206%	4.198%

Note: This table reports summary statistics for the stocks in our sample. We report the company's name and its industry. We also report the number of days that we have the specific firm in the sample, the average number of daily trades, the average price in Euro, the average bid-ask spread in euro, the percentage spread defined as $\frac{(ask_t - bid_t)}{(bid_t + ask_t)/2}$, and the volatility of price changes.

Table 2: Parameter Estimates Basic Model

Company	$\theta\,(\times 100)$	$\phi\,(\times 100)$	Impl. Spr.	ρ	λ	IA
Amer Sports Corp.	0.8533 (0.0096)	0.3213 (0.0167)	0.0235	0.2287 (0.0160)	0.0067 (0.00048)	0.7265 (0.0085)
Elisa Corp.	0.5402 (0.0038)	0.3424 (0.0070)	0.0177	0.1996 (0.0044)	0.0131 (0.00038)	0.6121 (0.0034)
Finnair	0.8373 (0.0197)	0.5174 (0.0342)	0.0271	0.2653 (0.0328)	0.0042 (0.00062)	0.6181 (0.0112)
Fiskars	1.4069 (0.0568)	1.1524 (0.1056)	0.0512	0.2662 (0.1660)	0.0004 (0.00021)	0.5497 (0.0146)
Fortum	0.4557 (0.0032)	0.4533 (0.0062)	0.0182	0.1566 (0.0032)	0.0193 (0.00036)	0.5013 (0.0018)
Huhtamaki	0.4830 (0.0052)	0.2607 (0.0095)	0.0149	0.2226 (0.0057)	0.0083 (0.00049)	0.6494 (0.0063)
Konecranes	1.0119 (0.0076)	0.4109 (0.0139)	0.0285	0.2293 (0.0157)	0.0072 (0.00029)	0.7112 (0.0056)
Kesko	1.1184 (0.0086)	0.4722 (0.0159)	0.0318	0.1898 (0.0194)	0.0086 (0.00032)	0.7031 (0.0056)
Kemira	0.5499 (0.0055)	0.3386 (0.0099)	0.0178	0.2330 (0.0066)	0.0060 (0.00039)	0.6189 (0.0050)
Metso	0.7162 (0.0050)	0.5050 (0.0093)	0.0244	0.1824 (0.0073)	0.0136 (0.00033)	0.5865 (0.0029)
Metsa Board	0.1493 (0.0018)	0.3372 (0.0035)	0.0097	0.2505 (0.0037)	0.0105 (0.00057)	0.3069 (0.0015)
Nokia	0.1827 (0.0036)	0.5240 (0.0072)	0.0141	0.0229 (0.0016)	0.0187 (0.00028)	0.2585 (0.0012)
Nokian Renkaat	0.7588 (0.0051)	0.4429 (0.0094)	0.0240	0.2054 (0.0079)	0.0119 (0.00035)	0.6315 (0.0036)
Pohjola Bank	0.5019 (0.0055)	0.3511 (0.0105)	0.0171	0.2064 (0.0060)	0.0102 (0.00041)	0.5884 (0.0049)
Outokumpo	0.5645 (0.0036)	0.4488 (0.0069)	0.0203	0.1897 (0.0043)	0.0138 (0.00032)	0.5571 (0.0024)
Rautaruukki	0.8616 (0.0057)	0.4700 (0.0103)	0.0266	0.1909 (0.0098)	0.0102 (0.00029)	0.6471 (0.0037)
Sampo	0.4579 (0.0034)	0.3886 (0.0066)	0.0169	0.1776 (0.0034)	0.0179 (0.00038)	0.5409 (0.0025)
Stockmann	1.5043 (0.0243)	0.7322 (0.0428)	0.0447	0.2123 (0.0711)	0.0024 (0.00028)	0.6726 (0.0100)
Stora Enso	0.2667 (0.0017)	0.3052 (0.0032)	0.0114	0.1750 (0.0019)	0.0251 (0.00051)	0.4663 (0.0013)
Tieto	0.6140 (0.0055)	0.3573 (0.0105)	0.0194	0.1741 (0.0070)	0.0138 (0.00053)	0.6321 (0.0050)
UPM-Kymmene	0.3067 (0.0018)	0.3197 (0.0033)	0.0125	0.1796 (0.0019)	0.0209 (0.00040)	0.4897 (0.0014)
Wartsila	1.1085 (0.0084)	0.6147 (0.0158)	0.0345	0.1991 (0.0192)	0.0099 (0.00033)	0.6433 (0.0043)
Average	0.6932	0.4575	0.0230	0.1981	0.0115	0.5778
Av. SE	(0.0089)	(0.0163)		(0.0189)	(0.00039)	(0.00485)

Note: This table reports point estimates and standard errors for the model that does not distinguish between different trader types. We report the information asymmetry component (θ), the liquidity provision component (ϕ), the implied spread ($2(\theta + \phi)$), the autocorrelation in order flow (ρ), the probability of a crossing trade (λ), and the proportion of the spread due to information asymmetry ($\frac{\theta}{\theta+\phi}$). Standard errors are based on a heteroskedasticity and autocorrelation robust covariance matrix and are reported in parentheses. The last lines in the table report the average coefficients and the average standard errors (in parentheses).

Table 3: Parameter Estimates Types Model

Company	θ^H (×100)	θ^I (×100)	θ^O (×100)	ϕ (×100)	π^H	π^I	π^O	IA^H	IA^I	IA^O
Amer Sports Corp.	0.7618 (0.0103)	0.8499 (0.0083)	0.9336 (0.0018)	0.3214 (0.0006)	0.0925 (0.0022)	0.8624 (0.0374)	0.0451 (0.0373)	0.0604 (0.0014)	0.6281 (0.0286)	0.0361 (0.0298)
Elisa Corp.	0.5464 (0.0028)	0.5240 (0.0034)	0.5693 (0.0009)	0.3425 (0.0005)	0.1160 (0.0009)	0.8393 (0.0175)	0.0446 (0.0172)	0.0728 (0.0006)	0.5049 (0.0106)	0.0292 (0.0112)
Finnair	0.7504 (0.0186)	0.8484 (0.0177)	0.8897 (0.0041)	0.5218 (0.0012)	0.2363 (0.0073)	0.7173 (0.0279)	0.0465 (0.0283)	0.1315 (0.0041)	0.4511 (0.0183)	0.0306 (0.0187)
Fiskars	1.3491 (0.0587)	1.4681 (0.0527)	1.4466 (0.0073)	1.1572 (0.0063)	0.5510 (0.0347)	0.3403 (0.0219)	0.1087 (0.0396)	0.2907 (0.0186)	0.1954 (0.0134)	0.0615 (0.0226)
Fortum	0.3786 (0.0020)	0.4507 (0.0028)	0.3877 (0.0007)	0.4521 (0.0005)	0.1270 (0.0006)	0.8104 (0.0124)	0.0626 (0.0124)	0.0540 (0.0004)	0.4106 (0.0058)	0.0273 (0.0054)
Huhtamaki	0.4874 (0.0038)	0.4692 (0.0048)	0.6436 (0.0016)	0.2601 (0.0006)	0.1437 (0.0013)	0.8190 (0.0228)	0.0373 (0.0226)	0.0948 (0.0013)	0.5204 (0.0170)	0.0325 (0.0195)
Konecranes	0.9429 (0.0086)	1.0195 (0.0067)	0.9585 (0.0011)	0.4098 (0.0005)	0.1860 (0.0023)	0.7541 (0.0108)	0.0599 (0.0110)	0.1243 (0.0016)	0.5447 (0.0075)	0.0407 (0.0076)
Kesko	1.1015 (0.0110)	1.1020 (0.0075)	1.1651 (0.0009)	0.4721 (0.0004)	0.1187 (0.0021)	0.8362 (0.0180)	0.0451 (0.0180)	0.0829 (0.0015)	0.5844 (0.0128)	0.0333 (0.0133)
Kemira	0.5364 (0.0041)	0.5351 (0.0051)	0.7444 (0.0018)	0.3386 (0.0005)	0.1810 (0.0018)	0.7701 (0.0166)	0.0489 (0.0164)	0.1098 (0.0013)	0.4661 (0.0117)	0.0412 (0.0137)
Metso	0.6397 (0.0041)	0.7132 (0.0044)	0.7031 (0.0009)	0.5045 (0.0005)	0.1813 (0.0014)	0.7549 (0.0091)	0.0638 (0.0091)	0.0964 (0.0008)	0.4473 (0.0053)	0.0372 (0.0054)
Metsa Board	0.1120 (0.0010)	0.1590 (0.0020)	0.1186 (0.0026)	0.3366 (0.0010)	0.2851 (0.0006)	0.6668 (0.0132)	0.0481 (0.0132)	0.0665 (0.0006)	0.2208 (0.0042)	0.0119 (0.0033)
Nokia	0.1153 (0.0008)	0.1789 (0.0036)	0.1643 (0.0004)	0.5222 (0.0004)	0.1039 (0.0005)	0.8423 (0.0118)	0.0538 (0.0118)	0.0173 (0.0002)	0.2172 (0.0042)	0.0127 (0.0028)
Nokian Renkaat	0.7515 (0.0047)	0.7394 (0.0044)	0.7887 (0.0009)	0.4436 (0.0005)	0.1358 (0.0012)	0.8116 (0.0138)	0.0525 (0.0138)	0.0860 (0.0009)	0.5055 (0.0087)	0.0349 (0.0091)
Pohjola Bank	0.4373 (0.0038)	0.5120 (0.0046)	0.3550 (0.0018)	0.3511 (0.0005)	0.1245 (0.0010)	0.8021 (0.0205)	0.0734 (0.0206)	0.0647 (0.0008)	0.4876 (0.0104)	0.0309 (0.0088)
Outokumpo	0.5362 (0.0027)	0.5593 (0.0032)	0.4795 (0.0008)	0.4480 (0.0005)	0.1623 (0.0009)	0.7635 (0.0100)	0.0743 (0.0100)	0.0872 (0.0006)	0.4280 (0.0052)	0.0357 (0.0049)
Rautaruukki	0.8550 (0.0056)	0.8480 (0.0048)	0.8033 (0.0009)	0.4699 (0.0004)	0.1770 (0.0016)	0.7667 (0.0100)	0.0563 (0.0100)	0.1150 (0.0011)	0.4938 (0.0062)	0.0344 (0.0061)
Sampo	0.4533 (0.0021)	0.4414 (0.0031)	0.4301 (0.0008)	0.3890 (0.0005)	0.1160 (0.0008)	0.8156 (0.0148)	0.0684 (0.0148)	0.0633 (0.0005)	0.4332 (0.0076)	0.0354 (0.0077)
Stockmann	1.4256 (0.0387)	1.5028 (0.0230)	1.7039 (0.0030)	0.7346 (0.0007)	0.1995 (0.0088)	0.7531 (0.0220)	0.0474 (0.0228)	0.1275 (0.0056)	0.5071 (0.0156)	0.0362 (0.0174)
Stora Enso	0.1985 (0.0009)	0.2562 (0.0015)	0.2413 (0.0006)	0.3049 (0.0006)	0.0613 (0.0003)	0.9001 (0.0297)	0.0386 (0.0297)	0.0218 (0.0001)	0.4140 (0.0130)	0.0167 (0.0129)
Tieto	0.5359 (0.0049)	0.6068 (0.0049)	0.5710 (0.0009)	0.3570 (0.0006)	0.0747 (0.0008)	0.8845 (0.0334)	0.0408 (0.0334)	0.0418 (0.0006)	0.5608 (0.0201)	0.0244 (0.0200)
UPM-Kymmene	0.2593 (0.0010)	0.2969 (0.0016)	0.3262 (0.0007)	0.3200 (0.0005)	0.1182 (0.0004)	0.8321 (0.0139)	0.0497 (0.0139)	0.0499 (0.0003)	0.4025 (0.0068)	0.0264 (0.0074)
Wartsila	1.0706 (0.0102)	1.1181 (0.0071)	0.8338 (0.0011)	0.6121 (0.0005)	0.1558 (0.0021)	0.7703 (0.0128)	0.0740 (0.0130)	0.0980 (0.0016)	0.5061 (0.0073)	0.0362 (0.0065)
Average	0.6475	0.6909	0.6935	0.4577	0.1658	0.7779	0.0564	0.0889	0.4513	0.0321
Av. SE	(0.0091)	(0.0081)	(0.0016)	(0.0008)	(0.0033)	(0.0182)	(0.0190)	(0.0020)	(0.0109)	(0.0116)

Note: This table reports point estimates and standard errors for the parameters in Equation(4). We report the information asymmetry components for Households (θ^H), Institutions (θ^I), and Other (θ^O), the liquidity provision component (ϕ), the proportions in which Households (π^H), Institutions (π^I), and Other (π^O) trade, and the proportions of the spread due to information asymmetry coming from each of the trader types (IA^H, IA^I, and IA^O, respectively). Standard errors are based on a heteroskedasticity and autocorrelation robust covariance matrix and are reported in parentheses. The last lines in the table report the average coefficients and the average standard errors (in parentheses).

Table 4: Informed Trading during the Day

Parameter	10:05am - 11:00am	11:00am - 1:00pm	1:00pm - 3:30pm	3:30pm - 5:30pm	5:30pm - 6:20pm
θ^H ($\times$100)	0.8354 (0.0469)	0.7043 (0.0188)	0.6676 (0.0146)	0.6259 (0.0163)	0.4777 (0.0229)
θ^I ($\times$100)	0.9163 (0.0265)	0.7487 (0.0166)	0.6723 (0.0115)	0.6681 (0.0136)	0.6535 (0.0198)
θ^O ($\times$100)	0.7651 (0.0080)	0.6749 (0.0031)	0.6785 (0.0030)	0.6988 (0.0028)	0.7301 (0.0041)
ϕ ($\times$100)	0.4518 (0.0131)	0.4403 (0.0019)	0.4694 (0.0034)	0.4192 (0.0016)	0.4758 (0.0018)
π^H	0.2169 (0.0121)	0.1886 (0.0076)	0.1702 (0.0042)	0.1510 (0.0053)	0.1348 (0.0067)
π^I	0.7213 (0.0549)	0.7527 (0.0325)	0.7732 (0.0336)	0.7926 (0.0364)	0.8136 (0.0515)
π^O	0.0619 (0.0581)	0.0587 (0.0347)	0.0567 (0.0338)	0.0564 (0.0374)	0.0516 (0.0531)
IA^H	0.1336 (0.0093)	0.1070 (0.0046)	0.0942 (0.0029)	0.0825 (0.0035)	0.0564 (0.0038)
IA^I	0.4613 (0.0341)	0.4585 (0.0198)	0.4401 (0.0196)	0.4691 (0.0226)	0.4458 (0.0312)
IA^O	0.0332 (0.0335)	0.0316 (0.0202)	0.0319 (0.0199)	0.0342 (0.0243)	0.0310 (0.0341)

Note: This table reports average coefficients and average standard errors for Equation(4) over different periods of the trading day. We report the information asymmetry components for Households (θ^H), Institutions (θ^I), and Other (θ^O), the liquidity provision component (ϕ), the proportions in which Households (π^H), Institutions (π^I), and Other (π^O) trade, and the proportions of the spread due to information asymmetry coming from each of the trader types (IA^H, IA^I, and IA^O, respectively).

Table 5: Decomposition of Variance of Transaction Price Changes

Company	Var(Δp) ($\times 10,000$)	δ^{ε}	δ^{ξ}	δ^{H}	δ^{I}	δ^{O}	δ^{ϕ}
Amer Sport Corp.	6.763	41.89%	38.24%	0.78%	8.74%	0.58%	2.34%
Elisa Corp.	3.336	29.61%	46.61%	1.02%	6.59%	0.43%	5.56%
Finnair	8.870	47.49%	31.84%	1.47%	5.50%	0.41%	4.49%
Fiskars	27.349	44.19%	30.95%	3.52%	2.62%	0.82%	7.18%
Fortum	3.910	17.01%	59.95%	0.46%	4.05%	0.24%	8.65%
Huhtamaki	2.111	36.55%	37.13%	1.59%	8.13%	0.73%	4.94%
Konecranes	11.338	31.96%	50.63%	1.43%	6.59%	0.48%	2.27%
Kesko	14.167	27.59%	54.61%	1.00%	6.89%	0.43%	2.53%
Kemira	3.958	32.36%	47.33%	1.29%	5.31%	0.68%	4.42%
Metso	8.892	20.44%	62.12%	0.82%	4.15%	0.35%	4.62%
Metsa Board	0.531	23.46%	24.36%	0.65%	3.01%	0.13%	31.62%
Nokia	3.511	0.00%	79.35%	0.04%	0.77%	0.04%	14.70%
Nokian Renkaat	7.880	26.17%	55.34%	0.96%	5.37%	0.41%	3.92%
Pohjola Bank	3.023	30.01%	45.14%	0.78%	6.65%	0.30%	6.41%
Outokumpo	4.998	19.40%	59.06%	0.92%	4.58%	0.34%	6.42%
Rautaruukki	10.23	23.10%	59.34%	1.24%	5.18%	0.35%	3.46%
Sampo	3.230	18.88%	57.68%	0.72%	4.71%	0.38%	7.57%
Stockmann	30.547	42.59%	40.78%	1.31%	5.37%	0.45%	2.78%
Stora Enso	1.082	24.56%	42.63%	0.22%	5.17%	0.20%	13.82%
Tieto	4.041	26.29%	49.91%	0.52%	7.73%	0.32%	5.14%
UPM-Kymmene	1.523	22.38%	49.73%	0.51%	4.59%	0.34%	10.80%
Wartsila	17.585	24.26%	58.70%	1.00%	5.26%	0.29%	3.38%
Average	8.131	27.74%	49.16%	1.01%	5.32%	0.40%	7.14%

Note: This table reports a decomposition of the variance of transaction price changes. The first column shows the trade-by-trade variance of transaction price changes. The other columns report the percentages that each component contributes to this transaction price change variance. The components we consider are the contribution due to public news (δ^{ε}), the contribution due to price discreteness (δ^{ξ}), the contributions due to average information asymmetry due to households (δ^{H}), Institutions (δ^{I}), and other (δ^{O}), and the contribution due to liquidity frictions (δ^{ϕ}). The last row of the table reports the average for all stocks.

Table 6: Decomposition of Variance of Daily Price Changes

Company	DV^{ε}	DV^{ξ}	DV^{H}	DV^{I}	DV^{O}	DV^{ϕ}
Amer Sports	81.82%	0.30%	1.52%	15.83%	1.13%	0.01%
Elisa Corp.	79.81%	0.16%	2.73%	16.78%	1.15%	0.01%
Finnair	87.15%	0.87%	2.63%	9.32%	0.75%	0.04%
Fiskars	85.48%	2.14%	6.42%	4.88%	1.57%	0.16%
Fortum	78.91%	0.15%	2.10%	18.13%	1.08%	0.01%
Huhtamaki	79.14%	0.30%	3.41%	16.45%	1.58%	0.01%
Konecranes	80.59%	0.17%	3.56%	15.56%	1.20%	0.00%
Kesko	77.90%	0.22%	2.81%	18.48%	1.21%	0.00%
Kemira	82.89%	0.38%	3.27%	12.69%	1.76%	0.01%
Metso	80.33%	0.17%	3.18%	15.63%	1.36%	0.00%
Metsa Board	86.91%	0.36%	2.36%	10.42%	0.45%	0.16%
Nokia	0.00%	1.70%	4.54%	88.61%	4.92%	0.15%
Nokian Renkaat	80.74%	0.17%	2.92%	15.64%	1.26%	0.00%
Pohjola Bank	80.64%	0.23%	2.07%	16.86%	0.77%	0.01%
Outokumpo	78.05%	0.16%	3.65%	17.59%	1.33%	0.01%
Rautaruukki	78.47%	0.19%	4.18%	16.79%	1.18%	0.00%
Sampo	77.44%	0.18%	2.94%	18.47%	1.57%	0.01%
Stockmann	86.23%	0.54%	2.62%	10.27%	0.91%	0.01%
Stora Enso	82.17%	0.12%	0.72%	16.50%	0.67%	0.02%
Tieto	76.22%	0.26%	1.51%	21.41%	0.94%	0.01%
UPM-Kymmene	81.32%	0.13%	1.84%	15.92%	1.24%	0.01%
Wartsila	79.91%	0.20%	3.26%	16.44%	0.92%	0.00%
Average	77.37%	0.42%	2.92%	18.58%	1.32%	0.03%

Note: This table reports a decomposition of the variance of daily price changes. We report the percentages that each component contributes to this daily price change variance. The components we consider are the contribution due to public news (DV^{ε}), the contribution due to price discreteness (DV^{ξ}), the contributions due to average information asymmetry due to households (DV^{H}), Institutions (DV^{I}), and other (DV^{O}), and the contribution due to liquidity frictions (DV^{ϕ}). The last row of the table reports the average for all stocks.