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, Richardson and Roomans (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 48% 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 investors trade, and document that the informativeness of both types of trades diminishes throughout the trading day. A decomposition of the daily variance of price changes shows that about 13.5% of the daily variance is due to informed institutional trades, while only 2.5% of daily price change variance is due to retail trades.

JEL Codes: C22; G14.

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1 Introduction

Financial institutions are generally believed to possess more information about a stock's fundamentals than individual investors. This hypothesis is based on the notion that financial institutions, being professional traders, often have close connections with the management of the firm, and employ their own security analysts (Edelen et al., 2016). Individual investors, on the other hand, are diverse in their background; most of them are not professional investors and generally considered noise traders.[1] Despite this common conjecture, empirical research on the informativeness of individual and institutional investors has often yielded mixed findings. For example, Daniel, Grinblatt, Titman and Wermers (1997) examine the quarterly holdings of mutual funds in the U.S. and find that many funds exhibit superior performance. Chen, Jegadeesh and Wermers (2000) find that stocks that mutual funds actively buy outperform those they sell by 2% per year. Recently, Hendershott, Livdan and Schürhoff (2015) find that institutions are informed about future firm-specific news. In contrast, Carhart (1997) shows that the performance of mutual funds can be explained by well known risk factors such as size, book-to-market, and momentum factors, and find no evidence of persistent skill in US mutual funds. This finding is corroborated by Fama and French (2010), who show that the performance mutual funds could be attributable to luck, rather than skills. On the trading of individual investors, the evidence seems to be equally mixed. For instance, Odean (1999) and Barber and Odean (2000) analyze the trading records of retail investors at a large brokerage house and find that those investors underperform the market and that more active investors earn significantly worse returns than those following a passive buy-and-hold strategy. On the other hand, Kaniel, Saar, and Titman (2008) employ a proprietary dataset of individual investors' trading activity in

[1]Barber and Odean (2013) provide an excellent review of the literature on the behavior of individual investors and institutional investors.

the New York Stock Exchange (NYSE) and show that the top decile of stocks bought by those investors in their dataset earn a market-adjusted return of 16bps in the next month. Kelley and Tetlock (2012) analyze the trades of individual investors via two market centers in the NYSE and find that those investors are informed about future news and that their trades can positively predict future returns. These studies suggest that the trading of individual investors is informative, rather than pure noise.

A common feature in prior studies is that they employ a subset of trades by either individual investors or institutions, which are obtained from proprietary sources. A few studies are able to jointly examine the interaction between institutions and individual investors. For example, Grinblatt and Keloharju (2000) analyze a unique dataset of two years of trading for 16 largest stocks by various categories of investors in Finland and find that individual investors tend to pursue contrarian strategies while institutions are momentum traders. Griffin, Harris and Topaloglu (2003) also document similar findings for investors in the Nasdaq 100 stocks over the period from May 1, 2000 to February 28, 2001. Moreover, Griffin et al. (2003) find that although institutions trade on past returns, the magnitude is not significant enough to cause subsequent return reversals. These findings indicate that the price impact of these investors in their dataset is small. Barber, Lee, Liu and Odean (2009a) construct portfolios that mimic the trading of Taiwanese individual and institutional investors and find that the long-short portfolio of institutions earns significantly positive abnormal returns while a similar portfolio of individual investors yields a negative return before costs.

Perhaps due to the fact that most prior studies only consider parts of the market, the question of whether institutional trading is more informative than retail trading is still not resolved. Most studies rely on daily trading data at best, and therefore there is a lack of evidence on the intraday interaction between various categories of investors. Investigating which investor type has a larger price impact is important because it helps us to understand why security prices change – a fundamental issue in asset pricing and market microstructure research. Particularly, market microstructure theory suggests two reasons why stock prices change: either due to the arrival of public news or private information, which reveals itself through the trading activity of informed traders. As a result, models aimed at capturing the degree of private information in the market examine either the price impact of trades (e.g., Lin et al., 1995; Madhavan et al., 1997; and Huang and Stoll, 1997) or the daily order imbalance (Easley et al., 1996). There is thus a need for a market microstructure study on how the time variation in the trading of various investor types might impact stock prices, information asymmetry, and volatility.

Our study aims to fill this gap by investigating a unique dataset of intraday trading records of all investors of 22 largest stocks in the Finnish market between May 29, 2007 and November 13, 2009. By employing this comprehensive dataset, we provide a novel market microstructure perspective on the informativeness of each investor type as well as their contributions to the bid-ask spread and volatility. We also offer a methodological contribution to the market microstructure literature by extending the framework of Madhavan, Richardson and Roomans (1997) (hereafter MRR) to explicitly model the trade impact of different investor types as well as the adverse selection costs induced by various traders. Based on this model, we can compute the implied spread and decompose the variance of price changes into various components attributable to each investor type. A unique result of our study is that spreads and price volatility are not only a function of the degree of information asymmetry in the market, but also a function of who is active in the market (retail or institutional traders). Furthermore, we find that while institutional trades are more informative than retail trades, individual investors are by no means uninformed.

When we decompose the spread into its various components, we observe that about

9% of the spread represents a compensation for trading against better informed retail investors, while about 48% of the spread is a compensation for trading against better informed institutions. This finding is consistent with the notion that institutions are more sophisticated investors, but at the same time suggests that retail investors are not pure noise traders. Further, we observe that the contribution to the daily price change variance of retail traders is on average about 2.5% while that of institutional investors is approximately 13.5%. In line with prior market microstructure studies, we find that the degree of information asymmetry in the market caused by both trader types declines during the trading day, but we point out a considerable drop in information asymmetry for retail traders in the late afternoon. We document that the trading activity of different trader types is not constant during the day, and that the proportion of household trades is considerably larger during the start of the trading day than at the end. Overall, our results provide new insights into how different types of traders affect information asymmetry, spreads and volatility.

Our study is related to the literature examining the microstructure relation with trader identity. Chan and Lakonishok (1995) find that consecutive block trades (most likely by institutions) create significant price impact on stocks listed in the NYSE and Amex. Sias et al. (2001) employ quarterly institutional ownership and document that institutional trading can predict future stock returns because they create price pressure on those stocks. However, Cai, Kaul and Zheng (2000) find that institutional trades follow patterns in historical returns, but their trades do not forecast future returns. Similarly, Griffin et al. (2003) use daily and intraday data of all trades and quotes in Nasdaq 100 stocks from May 1, 2000 to February 28, 2001 and find that institutions are momentum traders while individual investors are contrarian. On the whole, Griffin et al. (2003) find little evidence of return predictability and price pressure from either institutions or individual investors.

Comerton-Forde, O'Brien and Westerholm (2007) study the intraday behavior of informed and uninformed traders in the Helsinki Stock Exchange for the period from April 12, 1999 to May 26, 2000. Rather than developing a model for information asymmetry as in our study, they differentiate between informed and uninfomed traders by comparing the profitability of their trades. The authors find that there is a noticeable concentration of informed and liquidity traders at the open and close of the trading day. Since our study explicitly models the interaction between various investor types, we do not need to measure the performance of individual investors – a thorny issue because researchers do not observe the time and original price at which an investor bought the stock.[2] Our study therefore extends Comerton-Forde, O'Brien and Westerholm (2007) by providing a methodological contribution with more recent data. Frino, Johnstone and Zheng (2010) examine a sample of transactions from the Australian equity market, where broker identify is transparent, and find that a sequence of buyer/seller-initiated trades by the same broker can cause permanent price impact. They further find that medium-sized trades are more informative than small-sized trades by the same broker. A more recent study that is somewhat related to ours is that of Linnainmaa and Saar (2012), who use a similar dataset to ours from the Helsinki Stock Exchange between July 10, 2000 and October 23, 2001 and examine the price impact of orders coming from different brokers. Their study addresses the questions of whether different types of investors trade more through specific brokers and whether investors could learn whether they trade with an informed counterparty through a trade initiated by a specific broker. Linnainmaa and Saar (2012) document that broker identity provides a strong signal about the 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. In this paper, instead

[2] Researchers also have to rely on a benchmark model to compute the risk-adjusted returns for investors.

of considering broker identity, 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, provides support for the observation of Linnainmaa and Saar (2012) that brokers who execute more institutional orders are better informed.

The remainder of this paper is structured as follows. In Section 2, we review the relevant literature related to our study. In Section 3, we develop a structural model similar to MRR, but allows for the presence of different trader types. Section 4 discusses the characteristics of the Finnish data set we employ. In Section 5 we document the empirical results for our model developed in Section 3, provide estimates for the various components of the bid-ask spread, and report how the private information of different trader types contributes to price change variance. Finally, Section 6 concludes.

2 Related literature

Our study joins a long-standing literature on the informativeness of trading by insititutions and individual investors on stock prices. Theoretical models of investor behavior posit that individual investors are uninformed noise traders while institutions are considered sophisticated investors (e.g., DeLong et al. (1990a,b)). Other models allow for the interaction between informed and uninformed traders in which informed traders observe similar information and therefore trade in the same direction, while uninformed traders infer information from the trading activity of others (e.g., Hong and Stein (1999)) and Bikhchandani et al. (1992)). Empirically, the question of whether individual investors are purely noise traders has not been completely answered.

Perhaps due to the nature of research that requires access to detailed trading records, the empirical literature evolves in accordance with the availability of such data. Historically, studies that examine institutional trading had to rely on quarterly institutional ownership from the 13F fillings, which cover holdings data for large financial institutions in the U.S. market. Using this ownership dataset, Lakonishok et al. (1992) document that pension funds in the U.S. do not pursue a quarterly momentum investing strategy. However, Grinblatt et al. (1995) and Badrinath and Wahal (2001) analyze mutual funds data and find strong evidence of momentum investing by institutions. Campbell et al. (2009) infer daily institutional trading activity by combining quarterly 13F ownership data with trade size data. Using this daily proxy for institutional trading, they find that daily trading activity negatively predicts near-term stock returns, but positively predicts longer-term stock returns. They interpret this finding as institutions being short-term liquidity demanders, while they are profitable traders in the long run. Furthermore, institutions tend to buy ahead of positive earnings surprises, and ahead of stocks that experience a positive earnings announcement drift. Recently, Edelen et al. (2016) examine institutional trading around twelve well-known market anomalies. They find that institutions predominantly trade in the wrong direction of the reported anomalies, e.g. buying when the observed anomaly suggests one should sell and vice versa. This evidence rejects the notion that institutional investors are sophisticated. Further testing reveals that institutional investors may actually contribute to the mispricing of the anomalies themselves.

Other studies make use of proprietary databases that contain more detailed trading activity at an (intra-)day frequency. One of the more popular databases is the ANcerno database which contains complete records of institutional trading for a subset of about 10% of the trading volume conducted by institutions. Irvine et al. (2007) use the ANcerno database to examine institutional trading around the release of analyst recommendations. They document a significant increase in institutional buying activity that starts about five days before the release of a positive recommendation. They conclude that their finding is most in line with institutional traders receiving tips from brokers regarding the content of the recommendation. Puckett and Yan (2011) use the ANcerno database and find strong evidence of institutions conducting profitable intraquarter trades, i.e. short-term trades by institutions, on average, are profitable. They further document that there is persistence in trading performance, i.e. those funds that are able to generate high trading profits in the previous quarters also generate high trading profits in the current quarter. Note that Puckett and Yan (2011) focus on trades that are conducted within a calendar quarter, i.e. those trades that would never show up in 13F filings. Chakrabarti et al. (forthcoming) conduct a similar study to Puckett and Yan (2011), focusing on short term trades regardless of whether the trades are within the quarter and show that those trades on average make losses, and that there is no persistent skill in winning short-term trades.

Huang et al. (2014) make use of ANcerno data to determine whether institutional trade can predict the news tone (measured by the fraction of negative relative to positive words in a news release). They document that institutions trade on the news tone only on the day of the news release and not on any other days. Trades based on news tone result in outperformance for the next 4 weeks. The authors conclude that institutional investors are not able to predict news, but their informational advantage is mainly due to their ability to process information quickly.

Jegadeesh and Tang (2010) examine institutional trading activity and profitability around takeover announcements. They document that institutional trades around these announcements, on average, are not profitable. However, for institutions where the main broker of the institution is also the advisor to the target firm in the takeover, they document a significant increase in buying activity in the target firm prior to the takeover announcement. This suggests that there is leakage of inside information.

More recently, Hendershott et al. (2015) use data from the NYSE Consolidated

Equity Audit Trail over the period 2003-2005 to examine daily buy and sell institutional trading volume around news announcement. They find that institutions are informed about both the occurrence of news events, and the content of the news (measured either by tone, stock market reaction or surprise in news). Overall, the studies on the informativeness of institutional trades presented above, provide mixed results, while some studies find that institutional trades are mainly noise trades, some suggest that institutions have the ability to process public information faster than other market participants, while others show that institutions may have access to private information.

The evidence on the informativeness of retail trades is equally mixed. For instance, Barber et al. (2009b) employ trade size as a proxy for trader types in the U.S. 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. (2009b) argue that their finding is in line with models of investor sentiment, where systematic buying and selling by retail investors, temporarily induces a price pressure, that mean-reverts over longer periods. Employing a unique Australian dataset of retail trades, Jackson (2003) shows that these trades positively forecast future short-term stock returns and while retail investors trade in a systematic fashion, their behavior may not be irrational. Kumar (2009) uses a similar dataset to Barber et al. (2009) and finds that individual investors shift their preferences across investment style portfolios (small vs. large and value vs. growth). These findings suggest that individual investors trade in a systematic fashion, but also exhibit variation in their trading preferences.

Similar to Barber et al. (2009b), Kaniel et al. (2008) also find that retail trades positively predict future stock returns. However, in contrast to Barber et al. (2009b), 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) uses small signed trade turnover (SSTT) as a measure for retail trade, and evaluates the performance of stocks 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 stocks favored by retail investors are overvalued and subsequently underperform those that are not favored by retail investors. Kelley and Tetlock (2013) use a proprietary dataset that contains retail trades conducted on two major market centers in the U.S. 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 traders are not mere "noise" traders, but trade on novel information they possess.

In short, similar to research on institutional trading, the literature on the trading behavior of individual investors is inconclusive. One potential reason for the equivocal evidence is that individual investors are a heterogenous group with differing trading skills. Consistent with this idea, Fong, Gallagher and Lee (2014) find that trades via full-service retail brokerage houses are more informative about future stock returns than those from online discount brokers. Thus, examining a subset of retail investors may capture one type of individual investors and miss out the critical heterogeneity among them. Our study employs all investors' accounts in the Finnish market, thereby providing a more complete picture on the impact of trading by various investor types on stock prices both at the daily and intraday levels.

3 Model

To assess the degree of private information held by different groups of traders, we develop a market microstructure model similar to MRR. 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.

3.1 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 MRR, 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 mid-point 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,

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

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 permanent impact of a trade on the efficient price and thus captures the degree of private information in the market. 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, $i = \{H, I, O\}$ for households, institutions, and others, 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 trader 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 evolution of the efficient price process in Equation (1) to

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

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 (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 MRR 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 expression 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,

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

In these conditions we include α as a constant in the model to ensure that the residuals of the model have a zero mean. We estimate the model by two-step GMM using a Newey-West consistent weighting matrix. Similarly, we compute standard errors based on a Newey-West consistent covariance matrix.

3.2 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 quotes, which are prices conditional on a sell or buy orders 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.

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

Equation (9) 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 $IA = \sum_i IA^i$.

4 Data

In this study, we make use of a unique intraday dataset from Euroclear, which is the clearinghouse for all stocks traded on the Helsinki Stock Exchange.[3] To trade on this exchange, investors must register with Euroclear and are given a unique account number, even when they trade through multiple brokers. Euroclear provides us with the unique trader's identifier and an indicator identifying the type of trader. The database classifies each trader into one of 37 categories and two main ownership types (either nominee account for foreign traders or individual account for traders domiciled in Finland). Following Grinblatt and Keloharju (2000), we separate investors into three main groups using the information from Euroclear: 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 similar to that of institutional traders. However, as Stoffman (2014) points out that 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 solely on the trades that occur on the OMX Helsinki.[4]

[3]This database is formerly known as the Finnish Central Share Depository (FCSD). Grinblatt and Keloharju (2000) provide a detailed description of the database.

[4]Unlike investors based in Finland, foreign investors are not required to register with Euroclear and are allowed to trade via a financial institution (nominee). As pointed out by Grinblatt and Keloharju (2000), there is no perfect method to identify foreign household traders trading via a nominee. We attempt to identity accounts that are likely to be nominee or ADR accounts by using the information from Thomson Reuters Tick History to identify only trades that occur on the OMX Helsinki. Further,

Although Euroclear provides us with the record of all transactions (e.g., price, timestamp, and traders' details) that occur in Finnish stocks for the period from 29 May 2007 to 13 November 2009, it does not provide us with the intraday bid and ask quotes of the trades.[5] To sign the trade initiation, we merge the Euroclear data with the intraday data on trades at the OMX Helsinki from Thomson Reuters Tick History (TRTH).[6] Since many stocks trade infrequently on the Finnish market, we focus on the most liquid stocks in the market by obtaining the intraday data for 22 of the largest stocks by market capitalization at the beginning of the sample period. For similar liquidity reasons, Grinblatt and Keloharju (2000) focus their investigation of Finnish traders' behavior for 19 largest stocks at the daily frequency. Regular trading hours on the OMX Helsinki 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. Thus, 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.[7] Trades executed at or above the ask are classified as buyer initiated ($x_t = +1$) while trades executed at or below the bid are classified as seller initiated ($x_t = -1$). For trades executed within the bid and ask prices, we follow the advice of Ellis, Michaely and O'Hara (2000) and classify as buyer initiated if the trade price is above the last executed

we employ the procedure outlined in Stoffman (2014) to screen out nominee accounts as follows. First, using the detailed holdings data from Euroclear, we require an institution to hold at least ten percent of the total shares outstanding to be considered acting as a nominee. We then calculate the fraction of trading volume by that institution for each stock on a day over the total market trading volume for that stock/day. Finally, we count the number of days in a month in which the institution accounts for more than ten percent of the quantity of shares traded. If the number of days is greater than ten in a month, we determine that the institution acts as nominee. Consistent with Stoffman (2014), this procedure identifies only a few accounts that act as nominees for each stock, which is expected.

[5]Even though our data is recorded at a one second granularity, a preferable feature of our Finnish data is that trades executed in the same second are not netted (i.e., they are shown as separate trades in the same second with trader's identity on both sides). With the help of Thomson Reuters Tick History's millisecond data, we are able to sign those same second trades as well.

[6]Lai, Ng and Zhang (2014) test the quality of TRTH and find that trades from TRTH and TAQ for NYSE stocks are identical, suggesting the high reliability of the former database.

[7]See for example, Lee and Ready (1991), Barber et al. (2009b), and Ellis, Michaely and O'Hara (2000).

trade price and seller initiated if the trade price is below the last executed trade price. 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. We further mitigate the impact of outliers by removing observation where the intraday transaction-to-transaction return is greater than 5%, and where the percentage spread is greater than 15% of the quoted midpoint or negative. For the estimation of the model, we also remove the overnight return.

INSERT TABLE 1 HERE

Table 1 reports the company name, its industry, the number of trading days of each stock in the sample (note that for some stocks we do not have data covering the full sample period), and various summary statistics. There is considerable variation in the trading activity of the different stocks in the sample. Nokia is the most heavily traded stock on the OMX Helsinki, with on average about 1,800 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 some variation in the average price at which the assets trade, ranging from 2.40 Euro to 34.39 Euro. The next column reports the average Euro spread of the different stocks, which ranges from 0.0108 to 0.0612 Euro. Generally, we observe that there is a positive relation between the average price and the Euro spread. The average percentage 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 is substantial variation across the different assets. These trading costs can be as high as 0.83% (Metsa Board) and as low as 0.07% (Nokia). These statistics show that the frictions defined in Section 3 that affect the spread clearly differ across the stocks in our sample. The last column reports the volatility of trade-by-trade price changes. As we will demonstrate later, these volatilities are largely affected by the frictions defined in Section 3. We again observe substantial variation in the volatility of price changes, with price change volatility ranging from 0.719% to 5.505%.

5 Results

5.1 Original Model

We start by presenting the estimation results for the model developed in Section 3. We first document the results for the original MRR model, where we do not make a distinction between 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 0.71, but there is quite some variation for the different stocks, with Stockman (1.49) and Fiskars (1.42) having the highest degree of price impact on a per trade basis. The lowest impacts are for Metsa Board (0.15) and Nokia (0.22). 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 order processing costs are 0.41, but again there is substantial variation among the different stocks with the highest degree of order processing costs for Fiskars (1.15) and Stockmann (0.72), and the lowest degree of order processing costs for Huhtamaki (0.24) and Stora Enso (0.27). 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 24%, all these correlations are distributed relatively closely around this average. 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 0.96%.

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 62% 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. (74.96%) and Konecranes (74.09%) and the lowest degree of information asymmetry observed for Metsa Board (31.51%) and Nokia (39.66%). 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.

5.2 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 has an impact of about 0.71, while households (θ^H) have a price impact of 0.67. 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 difference in means 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 probabilities in which the different trader types are active. On average, around 16% of trades are conducted by households while the majority of all trades is conducted by financial 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 54.79% and 27.90% of trades conducted by households, respectively. Logically, these are also the stocks for which the proportions of trades by institutions are lowest. The stocks least actively traded by households are Stora Enso (5.87%) and Tieto (7.34%), 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 0.485. This is followed by households (0.09) and other trader types (0.03). The sum of these three components equals 0.6091, 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 39.09% as a compensation for order processing and inventory imbalance costs, 48.42% as a compensation for trading against a better informed institutional trader, 9.09% as a compensation of trading against a better informed individual trader and 3.40% as as a compensation for trading against a better informed other types of traders. 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).

In short, 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 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, in which we report the cross-sectional average of the coefficients and their 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 entire trading day. This finding is in line with prior studies (e.g., Hasbrouck (1991) and MRR) 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. 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, except the early afternoon, we observe that institutions are more privately informed than individuals. These differences are largest at the start and end of the trading day.

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 74% at the start of the trading day to a high of 82% at the end of the trading day.

The declines in θ^H and θ^I, as well as in the proportion of household trades, have an interesting implication to the original model of MRR, who find that the general information asymmetry in the market decreases toward the end of the trading day. MRR acknowledge that this decline has two competing interpretations: (1) it could reflect the fact that price discovery is enhanced as trading continues or (2) it could be driven by the large percentage of liquidity traders (less information asymmetry) at the end of the day. Our study offers direct evidence to distinghuish between the two competing explanations. We observe that information asymmetry declines over the trading day is consistent with the monotonic drop in both θ^H and θ^I, suggesting that individual and institutional investors contribute to this effect (rather than other investor types since the pattern of θ^O does not exhibit such a clear decrease). More importantly, the decline in information asymmetry is also in line with the lower proportion of household traders toward the end of the trading day – a finding that does not support the second explanation. Rather, our results point to the first interpretation that price discovery is improved as trading continues and prices better reflect fundamental values toward the end of the day.

We also find that the liquidity friction costs (ϕ) are highest at the end of the trading day, an observation that is again in line with MRR, 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.

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 13.88% at the start of the trading day to a low of 6.08% 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 48% to 51%. These results suggest that trading by individual traders may become more predictable during the trading day, while that of institutional traders remains at the same level.

5.3 Contribution to transaction price change volatility

Similar to MRR, 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 MRR, 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, 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 33% 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 48%, whereas Nokia has the lowest contribution at 14%. The largest contribution to the transaction price variance, however, comes from price discreteness, δ^{ξ}, contributing about 45%, 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 (23%), and Nokia having the highest level of price discreteness (66%).

INSERT TABLE 5 HERE

The next three columns report the contributions 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 3.49% (Fiskars) to 0.12% (Nokia). For institutional trades, the contribution, δ^{I}, on average is close to 6% and ranges from 9.36% (Tieto) to 2.08% (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 6%, but there is substantial variation in these frictions across stocks. This contribution is highest for Metsa Board (30.25%) and lowest for Konecranes (1.71%).

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.

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

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

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.[8]

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 83% of daily price change variance is due to public information, with a high of 88.71% for Metsa Board and a low of 79.51% for Kesko. 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 0.35%. However, the most illiquid stocks in the sample (Fiskars

[8]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.

and Finnair) have a price change variance that is still affected by price discreteness even at the daily level.

Considering the contributions to daily price change variance of households (DV^H), we observe that the private information held by households contributes about 2.5% to daily price change variance. Private information of households has the greatest impact on Fiskars where it contributes over 6.50% to daily price change variance, and the smallest impact on Nokia at 0.73%. For institutions, the contribution, DV^I, is considerably higher at 13.53%, 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 5.01% (Fiskars) to 18.32% (Tieto). The last column of Table 6 reports the contribution of liquidity frictions to the daily price change variance, where we observe that at a daily frequency these contributions negligible.

6 Conclusion

This paper examines the informativeness of trades by retail and institutional traders. We contribute to the literature by developing a structural market microstructure model that is similar in spirit to MRR, but allows for the interaction between various trader types. Based on this model, we 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. Our results show that institutional trades are more informed than trades by retail investors, but the price impact of retail trades is non-negligible, suggesting that individual investors are a heterogenous group and that some investors are not purely noise traders. Equally important, our results extend the current understanding of the price formation process by showing that price impacts, spreads and price volatility are not only functions of the degree of information asymmetry in the market, but also of the time-variation in the activeness of different trader types.

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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	234.78	12.76	0.0264	0.2490%	2.537%
Elisa Corp.	Telecommunications	622	669.39	15.93	0.0187	0.1229%	1.826%
Finnair	Travel & Leisure	622	65.41	7.01	0.0313	0.4972%	2.957%
Fiskars	Personal & Household Goods	478	28.39	11.57	0.0612	0.5525%	5.251%
Fortum	Utilities	622	1,057.20	22.82	0.0182	0.0832%	1.925%
Huhtamaki	Industrial Goods & Services	622	253.20	7.78	0.0161	0.2213%	1.423%
Konecranes	Industrial Goods & Services	622	589.99	21.79	0.0299	0.1432%	3.395%
Kesko	Retail	622	594.30	28.36	0.0322	0.1240%	3.724%
Kemira	Chemicals	622	291.76	10.51	0.0191	0.2042%	1.988%
Metso	Industrial Goods & Services	621	896.42	27.48	0.0252	0.1086%	3.037%
Metsa Board	Basic Resources	622	228.82	2.40	0.0108	0.8324%	0.719%
Nokia	Technology	622	1,785.30	18.06	0.0117	0.0729%	1.342%
Nokian Renkaat	Automobiles & Parts	622	726.97	20.59	0.0253	0.1351%	2.825%
Pohjola Bank	Financials	579	464.47	10.32	0.0183	0.1878%	1.694%
Outokumpo	Basic Resources	622	827.84	18.46	0.0204	0.1277%	2.179%
Rautaruukki	Industrial Goods & Services	622	751.21	25.87	0.0282	0.1240%	3.294%
Sampo	Insurance	622	850.15	17.15	0.0176	0.1072%	1.704%
Stockmann	Retail	622	145.59	23.25	0.0522	0.2491%	5.505%
Stora Enso	Basic Resources	596	1,005.30	8.17	0.0126	0.1815%	1.028%
Tieto	Technology	622	481.05	13.98	0.0198	0.1544%	1.912%
UPM-Kymmene	Basic Resources	622	1,063.60	11.43	0.0134	0.1286%	1.233%
Wartsila	Industrial Goods & Services	563	690.33	34.39	0.0375	0.1152%	4.329%

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.	0.8592 (0.0092)	0.2870 (0.0154)	0.0229	0.2552 (0.0152)	0.0112 (0.0006)	0.7496 (0.0085)
Elisa Corp.	0.5620 (0.0038)	0.3002 (0.0068)	0.0172	0.2374 (0.0045)	0.0177 (0.0005)	0.6518 (0.0039)
Finnair	0.8336 (0.0197)	0.5114 (0.0344)	0.0269	0.2751 (0.0329)	0.0020 (0.0003)	0.6198 (0.0115)
Fiskars	1.4160 (0.0568)	1.1519 (0.1048)	0.0514	0.2663 (0.1662)	0.0020 (0.0005)	0.5514 (0.0145)
Fortum	0.4813 (0.0034)	0.3768 (0.0061)	0.0172	0.2282 (0.0035)	0.0182 (0.0005)	0.5609 (0.0025)
Huhtamaki	0.4847 (0.0044)	0.2380 (0.0076)	0.0145	0.2448 (0.0050)	0.0045 (0.0002)	0.6707 (0.0055)
Konecranes	1.0419 (0.0079)	0.3645 (0.0139)	0.0281	0.2575 (0.0164)	0.0112 (0.0005)	0.7409 (0.0061)
Kesko	1.1593 (0.0084)	0.4081 (0.0150)	0.0313	0.2297 (0.0193)	0.0103 (0.0004)	0.7396 (0.0059)
Kemira	0.5562 (0.0057)	0.3255 (0.0103)	0.0176	0.2505 (0.0070)	0.0103 (0.0005)	0.6308 (0.0055)
Metso	0.7683 (0.0056)	0.4211 (0.0102)	0.0238	0.2366 (0.0089)	0.0059 (0.0001)	0.6460 (0.0041)
Metsa Board	0.1511 (0.0017)	0.3284 (0.0033)	0.0096	0.2729 (0.0036)	0.0164 (0.0008)	0.3151 (0.0017)
Nokia	0.2181 (0.0014)	0.3318 (0.0027)	0.0110	0.1682 (0.0013)	0.0152 (0.0004)	0.3966 (0.0008)
Nokian Renkaat	0.7936 (0.0056)	0.3908 (0.0102)	0.0237	0.2472 (0.0092)	0.0178 (0.0005)	0.6700 (0.0045)
Pohjola Bank	0.5180 (0.0045)	0.3124 (0.0075)	0.0166	0.2385 (0.0049)	0.0055 (0.0002)	0.6237 (0.0040)
Outokumpo	0.5746 (0.0040)	0.3813 (0.0075)	0.0191	0.2392 (0.0050)	0.0062 (0.0001)	0.6011 (0.0033)
Rautaruukki	0.9135 (0.0065)	0.4188 (0.0115)	0.0266	0.2317 (0.0119)	0.0048 (0.0001)	0.6857 (0.0046)
Sampo	0.4695 (0.0028)	0.3201 (0.0052)	0.0158	0.2259 (0.0032)	0.0081 (0.0002)	0.5946 (0.0028)
Stockmann	1.4949 (0.0245)	0.7213 (0.0434)	0.0443	0.2318 (0.0722)	0.0015 (0.0002)	0.6745 (0.0103)
Stora Enso	0.2791 (0.0015)	0.2683 (0.0027)	0.0109	0.2274 (0.0018)	0.0112 (0.0002)	0.5098 (0.0016)
Tieto	0.6407 (0.0044)	0.2766 (0.0077)	0.0183	0.2266 (0.0059)	0.0060 (0.0002)	0.6985 (0.0048)
UPM-Kymmene	0.3253 (0.0018)	0.2845 (0.0033)	0.0122	0.2261 (0.0019)	0.0208 (0.0005)	0.5335 (0.0018)
Wartsila	1.1479 (0.0100)	0.5680 (0.0197)	0.0343	0.2425 (0.0251)	0.0048 (0.0001)	0.6690 (0.0060)
Average	0.7131	0.4085	0.0224	0.2391	0.0096	0.6152
Av. SE	(0.0088)	(0.0159)		(0.0193)	(0.0003)	(0.0052)

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 ($\times100$)	θ^I ($\times100$)	θ^O ($\times100$)	ϕ ($\times100$)	π^H	π^I	π^O	IA^H	IA^I	IA^O
Amer Sport Corp.	0.7463 (0.0096)	0.8455 (0.0073)	0.7241 (0.0023)	0.2893 (0.0008)	0.0881 (0.0021)	0.8380 (0.0363)	0.0740 (0.0365)	0.0588 (0.0015)	0.6343 (0.0247)	0.0480 (0.0239)
Elisa Corp.	0.5463 (0.0029)	0.5386 (0.0032)	0.6119 (0.0009)	0.3013 (0.0007)	0.1124 (0.0009)	0.8407 (0.0168)	0.0470 (0.0168)	0.0727 (0.0007)	0.5364 (0.0113)	0.0340 (0.0121)
Finnair	0.7527 (0.0186)	0.8491 (0.0178)	0.8624 (0.0041)	0.5159 (0.0009)	0.2379 (0.0072)	0.7181 (0.0273)	0.0441 (0.0279)	0.1333 (0.0042)	0.4541 (0.0178)	0.0283 (0.0180)
Fiskars	1.3533 (0.0590)	1.4742 (0.0524)	1.4210 (0.0072)	1.1611 (0.0067)	0.5479 (0.0350)	0.3424 (0.0218)	0.1097 (0.0398)	0.2893 (0.0188)	0.1969 (0.0133)	0.0608 (0.0223)
Fortum	0.4090 (0.0021)	0.4688 (0.0027)	0.4640 (0.0008)	0.3779 (0.0006)	0.1190 (0.0007)	0.8243 (0.0130)	0.0567 (0.0130)	0.0580 (0.0004)	0.4604 (0.0072)	0.0314 (0.0072)
Huhtamaki	0.5034 (0.0033)	0.4716 (0.0040)	0.6569 (0.0016)	0.2373 (0.0003)	0.1439 (0.0013)	0.8229 (0.0220)	0.0332 (0.0218)	0.1007 (0.0012)	0.5393 (0.0172)	0.0303 (0.0197)
Konecranes	0.9625 (0.0094)	1.0367 (0.0063)	1.0031 (0.0012)	0.3659 (0.0007)	0.1823 (0.0022)	0.7553 (0.0110)	0.0624 (0.0112)	0.1265 (0.0018)	0.5646 (0.0079)	0.0451 (0.0081)
Kesko	1.1212 (0.0112)	1.1359 (0.0070)	1.2461 (0.0010)	0.4097 (0.0005)	0.1159 (0.0021)	0.8389 (0.0173)	0.0452 (0.0173)	0.0839 (0.0015)	0.6152 (0.0132)	0.0364 (0.0139)
Kemira	0.5384 (0.0043)	0.5322 (0.0053)	0.7707 (0.0018)	0.3262 (0.0007)	0.1723 (0.0019)	0.7760 (0.0170)	0.0518 (0.0168)	0.1064 (0.0013)	0.4737 (0.0124)	0.0458 (0.0146)
Metso	0.6958 (0.0051)	0.7684 (0.0047)	0.8431 (0.0011)	0.4225 (0.0003)	0.1690 (0.0014)	0.7795 (0.0098)	0.0515 (0.0098)	0.0994 (0.0010)	0.5065 (0.0066)	0.0367 (0.0070)
Metsa Board	0.1107 (0.0010)	0.1546 (0.0019)	0.1212 (0.0026)	0.3291 (0.0012)	0.2790 (0.0006)	0.6673 (0.0127)	0.0537 (0.0127)	0.0658 (0.0005)	0.2196 (0.0042)	0.0139 (0.0034)
Nokia	0.1682 (0.0006)	0.2101 (0.0013)	0.2873 (0.0005)	0.3323 (0.0005)	0.0766 (0.0003)	0.8829 (0.0150)	0.0405 (0.0150)	0.0238 (0.0001)	0.3421 (0.0066)	0.0215 (0.0079)
Nokian Renkaat	0.7617 (0.0053)	0.7621 (0.0047)	0.8370 (0.0010)	0.3934 (0.0007)	0.1291 (0.0014)	0.8170 (0.0139)	0.0539 (0.0139)	0.0848 (0.0010)	0.5371 (0.0095)	0.0389 (0.0100)
Pohjola Bank	0.4730 (0.0033)	0.5297 (0.0034)	0.3715 (0.0020)	0.3130 (0.0003)	0.1213 (0.0010)	0.8090 (0.0198)	0.0697 (0.0200)	0.0696 (0.0007)	0.5195 (0.0107)	0.0314 (0.0091)
Outokumpo	0.5532 (0.0030)	0.5709 (0.0034)	0.5607 (0.0010)	0.3823 (0.0003)	0.1609 (0.0010)	0.7767 (0.0110)	0.0624 (0.0111)	0.0937 (0.0007)	0.4669 (0.0065)	0.0368 (0.0065)
Rautaruukki	0.9098 (0.0067)	0.9013 (0.0054)	0.9606 (0.0010)	0.4202 (0.0002)	0.1687 (0.0018)	0.7834 (0.0106)	0.0479 (0.0107)	0.1158 (0.0013)	0.5326 (0.0074)	0.0347 (0.0077)
Sampo	0.4927 (0.0019)	0.4570 (0.0026)	0.4764 (0.0009)	0.3210 (0.0002)	0.1095 (0.0007)	0.8360 (0.0156)	0.0545 (0.0155)	0.0689 (0.0005)	0.4880 (0.0092)	0.0332 (0.0095)
Stockmann	1.4422 (0.0390)	1.4892 (0.0232)	1.7138 (0.0031)	0.7236 (0.0007)	0.2009 (0.0091)	0.7536 (0.0211)	0.0455 (0.0220)	0.1309 (0.0058)	0.5070 (0.0151)	0.0352 (0.0171)
Stora Enso	0.2332 (0.0009)	0.2738 (0.0013)	0.2081 (0.0012)	0.2693 (0.0002)	0.0587 (0.0002)	0.8888 (0.0272)	0.0525 (0.0273)	0.0255 (0.0001)	0.4530 (0.0123)	0.0203 (0.0106)
Tieto	0.6165 (0.0038)	0.6348 (0.0038)	0.6533 (0.0009)	0.2773 (0.0002)	0.0734 (0.0009)	0.8942 (0.0304)	0.0325 (0.0304)	0.0496 (0.0006)	0.6229 (0.0214)	0.0233 (0.0218)
UPM-Kymmene	0.2744 (0.0011)	0.3126 (0.0016)	0.3607 (0.0008)	0.2857 (0.0006)	0.1108 (0.0004)	0.8421 (0.0137)	0.0471 (0.0137)	0.0510 (0.0003)	0.4414 (0.0076)	0.0285 (0.0083)
Wartsila	1.0819 (0.0128)	1.1652 (0.0086)	0.9223 (0.0012)	0.5678 (0.0003)	0.1455 (0.0023)	0.7919 (0.0137)	0.0626 (0.0140)	0.0923 (0.0018)	0.5410 (0.0083)	0.0339 (0.0076)
Average	0.6703	0.7083	0.7307	0.4101	0.1601	0.7854	0.0545	0.0909	0.4842	0.0340
Av. SE	(0.0093)	(0.0078)	(0.0017)	(0.0008)	(0.0034)	(0.0180)	(0.0189)	(0.0021)	(0.0114)	(0.0121)

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$100)	0.9051 (0.0545)	0.7475 (0.0203)	0.7135 (0.0153)	0.6663 (0.0163)	0.5077 (0.0230)
θ^I ($\times$100)	0.9781 (0.0289)	0.7833 (0.0171)	0.6984 (0.0111)	0.6897 (0.0133)	0.6710 (0.0194)
θ^O ($\times$100)	0.8086 (0.0084)	0.7432 (0.0035)	0.7250 (0.0032)	0.7381 (0.0028)	0.7751 (0.0042)
ϕ ($\times$100)	0.3980 (0.0125)	0.3911 (0.0014)	0.4095 (0.0030)	0.3730 (0.0012)	0.4367 (0.0012)
π^H	0.2096 (0.0135)	0.1829 (0.0079)	0.1657 (0.0043)	0.1485 (0.0054)	0.1345 (0.0067)
π^I	0.7376 (0.0624)	0.7686 (0.0350)	0.7868 (0.0345)	0.8032 (0.0352)	0.8217 (0.0479)
π^O	0.0528 (0.0661)	0.0486 (0.0372)	0.0476 (0.0348)	0.0483 (0.0364)	0.0439 (0.0495)
IA^H	0.1388 (0.0109)	0.1113 (0.0050)	0.0999 (0.0030)	0.0878 (0.0036)	0.0608 (0.0038)
IA^I	0.5088 (0.0401)	0.5009 (0.0227)	0.4812 (0.0214)	0.5072 (0.0234)	0.4764 (0.0315)
IA^O	0.0309 (0.0394)	0.0295 (0.0236)	0.0298 (0.0222)	0.0324 (0.0252)	0.0293 (0.0346)

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 Sports Corp.	6.426	48.42%	32.49%	0.77%	8.96%	0.61%	1.92%
Elisa Corp.	3.323	36.22%	42.33%	0.98%	6.87%	0.52%	4.09%
Finnair	8.745	48.19%	31.19%	1.51%	5.59%	0.38%	4.39%
Fiskars	27.587	43.12%	32.15%	3.49%	2.63%	0.79%	7.16%
Fortum	3.692	27.64%	52.35%	0.53%	4.61%	0.31%	5.86%
Huhtamaki	2.018	41.53%	32.84%	1.78%	8.58%	0.70%	4.19%
Konecranes	11.504	36.36%	47.56%	1.43%	6.63%	0.54%	1.71%
Kesko	13.845	31.57%	51.47%	1.04%	7.40%	0.50%	1.85%
Kemira	3.935	34.55%	45.98%	1.24%	5.26%	0.76%	4.01%
Metso	9.194	25.73%	58.86%	0.88%	4.76%	0.39%	2.94%
Metsa Board	0.512	26.60%	23.12%	0.64%	2.91%	0.15%	30.25%
Nokia	1.799	13.85%	66.30%	0.12%	2.08%	0.18%	10.05%
Nokian Renkaat	7.963	30.61%	52.73%	0.92%	5.56%	0.46%	2.87%
Pohjola Bank	2.863	40.21%	35.48%	0.93%	7.52%	0.33%	5.18%
Outokumpo	4.744	25.19%	55.23%	1.02%	5.07%	0.41%	4.66%
Rautaruukki	10.845	27.71%	56.07%	1.27%	5.59%	0.40%	2.49%
Sampo	2.898	28.17%	49.81%	0.90%	5.72%	0.41%	5.46%
Stockmann	30.307	44.22%	39.48%	1.36%	5.28%	0.44%	2.65%
Stora Enso	1.054	29.23%	40.67%	0.31%	6.16%	0.20%	10.46%
Tieto	3.652	37.67%	39.64%	0.76%	9.36%	0.38%	3.24%
UPM-Kymmene	1.514	27.66%	47.34%	0.54%	5.09%	0.39%	8.18%
Wartsila	18.720	27.24%	57.20%	0.90%	5.45%	0.28%	2.60%
Average	8.052	33.26%	45.01%	1.06%	5.78%	0.43%	5.74%

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 Corp.	83.90%	0.2 %	1.33%	14.16%	1.05%	0.00%
Elisa Corp.	82.73%	0.14%	2.23%	14.50%	1.19%	0.00%
Finnair	87.28%	0.87%	2.66%	9.29%	0.69%	0.04%
Fiskars	85.18%	2.27%	6.50%	5.01%	1.54%	0.16%
Fortum	84.76%	0.15%	1.60%	13.16%	0.95%	0.01%
Huhtamaki	80.63%	0.25%	3.42%	15.35%	1.36%	0.01%
Konecranes	82.74%	0.18%	3.20%	13.91%	1.21%	0.00%
Kesko	79.51%	0.22%	2.58%	17.30%	1.26%	0.00%
Kemira	84.04%	0.38%	2.97%	11.81%	1.88%	0.01%
Metso	82.53%	0.21%	2.77%	14.21%	1.26%	0.00%
Metsa Board	88.71%	0.34%	2.08%	8.97%	0.49%	0.14%
Nokia	85.78%	0.23%	0.73%	12.33%	1.15%	0.01%
Nokian Renkaat	83.12%	0.20%	2.46%	13.91%	1.26%	0.00%
Pohjola Bank	83.49%	0.16%	1.92%	14.46%	0.66%	0.01%
Outokumpo	81.16%	0.21%	3.25%	15.17%	1.30%	0.01%
Rautaruukki	80.80%	0.22%	3.65%	15.21%	1.18%	0.00%
Sampo	81.43%	0.17%	2.59%	15.40%	1.20%	0.01%
Stockmann	86.92%	0.53%	2.63%	9.72%	0.87%	0.01%
Stora Enso	82.69%	0.11%	0.87%	16.10%	0.56%	0.01%
Tieto	79.67%	0.17%	1.59%	18.32%	0.79%	0.01%
UPM-Kymmene	83.43%	0.13%	1.60%	14.29%	1.17%	0.01%
Wartsila	82.00%	0.25%	2.67%	15.19%	0.82%	0.00%
Average	83.29%	0.35%	2.51%	13.53%	1.08%	0.02%

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.