Learning from post-trade identity disclosure in electronic trading

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Abstract:

This paper shows how traders learn from post-trade identity disclosure in a currency limit order market. We establish that identity disclosure reveals information and show how traders react by reversing their order flow in line with the better informed. This result holds when controlling trading decisions for proxies of other private and public information. Moreover, we find that informed traders process information differently from the uninformed. The informed focus relatively more on public information, whereas uninformed amplify price discovery by learning from the informed.

JEL-Classification: G12, G15, D82, F31
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1 Introduction

Learning is an important characteristic of financial markets. The information to be learned is often private and spread among market participants. Therefore, prices have to be "discovered" via "the aggregation of heterogeneous private information (or heterogeneous interpretation of public information) through trading" (Brandt and Kavajecz, 2004, p.2624). The vehicle of this price discovery process is order flow (e.g. Lyons, 2001).[1] Accordingly, traders are eager to learn from order flow and an important signal in this learning process is the identity of a flow's initiator: can he reasonably be assumed to be informed or not?

While it is generally accepted that transparency and trade disclosure impact market quality and outcome (e.g Bloomfield and O'Hara, 1999, de Frutos and Manzano, 2005, Goldstein et al., 2007, Madhavan et al., 2005, Porter and Weaver, 1998, Reiss and Werner, 2004), there is little empirical evidence on how a common form of trade disclosure, namely *pre-trade* anonymity but *post-trade* identity disclosure, impacts the behavior and learning process of market participants in real-time. Due to an unusually detailed data set, we are the first – to the best of our knowledge – to comprehensively analyze this important issue empirically.[2]

We show that post-trade identity disclosure heavily affects trading decisions of market participants. A learning mechanism can be observed in the sense that traders react more strongly to order flow when their counterparty is larger and is thus likely to possess superior information. This effect is often so strong that traders reverse their previous trading direction. We also document considerable heterogeneity between large and small traders and explore the specific learning mechanism by which order flow information is incorporated into prices.

It is an interesting characteristic of modern limit order markets that information about trade counterparties is scarcer than in decentralized markets, such as the conventional foreign

[1] This understanding about the role of order flow is consistent with evidence from studies covering equity markets (Hasbrouck, 1991, 1991a; Odders-White and Ready, 2008), foreign exchange markets (Evans and Lyons, 2002, 2008), and bond markets (Brandt and Kavajecz, 2004).

[2] Porter and Weaver (1998) also analyze post-trade identity disclosure (for U.S. stock markets) and find that reporting sometimes is strategically delayed to hold back private information. This is consistent with our argument that traders learn from post-trade transparency. However, the authors do not analyze how market participants react to post-trade identity disclosure in real-time, the main object of interest in this study.

exchange market ten years ago, or in floor trading. Whereas in other market forms, informed trade may be anticipated due to knowing the counterparty before the trade, in limit order markets this information is missing. Counterparties are either revealed only for settlement purposes, i.e. *ex post* and to the counterparty only, or counterparties are never revealed due to the intermediary function of a central clearing party.[3] Moreover, informed traders do not seem to be identifiable by trade size, as assumed in traditional models (e.g. Kyle, 1985), since robust evidence in limit order markets demonstrates that most transactions are of standardized size and that traders split large volumes into several small trades. Therefore, publicly observable order flow cannot be distinguished into informed or uninformed on trade size alone (Bernhardt and Hughson, 1997, Chakravarty, 2000). Accordingly, the flow of information between traders is hampered in limit order markets.

Nevertheless, in our market there is identity disclosure about the counterparty *after* the trade, i.e. there is pre-trade but no post-trade anonymity. This identity disclosure can be used to identify a particular route of information flow, namely from the initiator of a trade to the counterparty. Different from all other traders in the market, the counterparty does not only see the trade direction and volume, but also the identity of the initiator. This piece of information is not available to other traders and only enters the counterparty's individual information set.

As the true identities of market participants are unknown to us, we have to proxy for whether a certain trader is likely to be informed or not. Fortunately, our data allows us to use a straightforward proxy of informed traders, i.e. their total trading volume (see Bjønnes et al., 2007). In their survey of US foreign exchange traders Cheung and Chinn (2001) explicitly show that this group regards large traders as better informed than small ones. There may be several ways in which volume generates information, such as capacity for research and more information from customers and their order flow. Reassuringly, trader size is a significant determinant of the permanent price impact of order flow in our data set (Menkhoff and Schmeling, 2008), so that larger traders do indeed seem to have superior information.

We apply this size proxy of informed trade and analyze in a fixed-effects dynamic panel approach whether it significantly affects traders' reactions to each other. The main finding is that traders react to the size of their last counterparty: if the counterparty is large – and necessarily has taken a position opposite to one's own – traders tend to reverse their trading direc-

[3] The *ex ante* knowledge of the counterparty was an important element in earlier models of trader interaction in foreign exchange, such as Perraudin and Vitale (1996), Chakrabarti (2000), and in the experiments of Flood et al. (1999).

tion and thus take positions in line with the better informed. Interestingly, this result holds when we control for the full set of trading determinants as predicted by Goodhart (1988): trades not only depend on the expected degree of information of the counterparty, but also depend positively on a trader's own former order flow (see Lyons, 2001) and former market-wide order flow (e.g. Evans and Lyons, 2002). These determinants represent trading motivation owing to original private information, i.e. either liquidity needs or information from own customer orders, and market-wide available information, respectively.

In a more in-depth analysis traders are grouped into large-, medium-, and small-sized traders. This yields a second finding, that large, and presumably informed, traders process information differently from small and less informed traders. While trading directions are strongly autocorrelated for all traders, large traders rely more heavily on market-wide order flow, whereas small traders are more likely to consider information obtained from the action of their last counterparty, i.e. from post-trade identity disclosure. This ascribes different roles to informed (large) and uninformed (small) traders: informed traders primarily incorporate their own private as well as public information into prices and the uninformed contribute to price discovery by adjusting their order flows in the direction of the more informed, i.e. they magnify the effect of informed traders.

Finally, the credibility of the above findings is underlined by distinguishing the analysis by order type. We find that traders stick more strongly to their own market orders than to their limit orders, indicating that market orders contain relatively more private information. Complementing this pattern, traders react more strongly on market orders of other traders relative to limit orders of other traders.

We believe that these findings are new for limit order markets. The related literature incorporates three strands. A first important strand follows Peiers (1997) in analyzing how – if at all – banks influence each other in their quoting behavior. These studies, including those of Dominguez (2003) and Chari (2007), consistently find dependencies in quoting pattern but they do not confirm a "permanent" leadership of one or a few institutions. However, in all studies the data refers to a small sample of (relatively homogeneous) large banks. A second strand analyzes individual currency traders, starting with Lyons (1995). These studies, including Bjønnes and Rime (2005), and Bjønnes et al. (2007), consistently confirm the relevance of asymmetric information for traders' decision-making. A last related strand shows that the identity of traders provides useful information to counterparties. In this respect, Foucault et al.

(2007) demonstrate that closing pre-trade trader identifiers at the Paris Bourse in 2001 significantly decreased the information content of quotes, indicating that traders' identities provide relevant information. As mentioned above, Porter and Weaver (1998) show that also post-trade transparency seems to be a valuable source of information that is worth being strategically delayed. Overall, these studies provide sufficient motivation to examine if and how traders with different degrees of information interact in real-time.

The paper is organized in the following steps: Section 2 describes the data, Section 3 outlines the econometric approach, and Section 4 provides and interprets the main results. Robustness tests confirm the main findings, as shown in Section 5, and Section 6 concludes.

2 Data

The study covers a period in the year 2002 in the Russian interbank spot market for Russian roubles versus US dollars. At that time the MICEX bourse in Moscow had introduced countrywide electronic trading in foreign exchange in which 722 traders participated. The trading platform has very similar characteristics to the main foreign exchange markets as it was designed in cooperation with Reuters. Participants see the best bid and ask prices with corresponding volumes. They also see information about the size of the last trade and cumulative trading volume on both sides of the market (cumulated over the current trading session). However, as in many electronic markets, trading is anonymous and identification is only revealed after completing a trade, i.e. there is post-trade but no pre-trade identity disclosure. Disclosure takes place by an e-mail messaging system similar to the Reuters FX dealing systems as mentioned above. Immediately after completion of a trade, both traders obtain information about the counterparty's identity for settlement purposes.

Since the trading system we analyze is similar to other existing limit order markets, we believe that our findings are instructive for other markets with a similar structure, such as the main foreign exchange markets and many stock markets organized around a limit order book (Porter and Weaver, 1998, Parlour and Seppi, 2008). Moreover, the working of post-trade disclosure is also of interest for limit order markets in general as it captures an intermediate form between the more common market form with pre- and post-trade *disclosure* and the increasingly important market form with both pre- and post-trade *anonymity*.

The importance of the currency market analyzed here stems from the fact that it provides more liquidity than the earlier established regional electronic exchanges in Russia and that Russia's official exchange rate is fixed in this market. Trading at this platform only reflects domestic trading, as there are controls on foreign exchange trading. Foreigners trade Russian roubles offshore in the form of non-deliverable forward contracts. The only participants in the domestic market are banks, but we understand that the orders put into the trading system also reflect customer orders that banks have received.

During the nine sample days between March 11 and March 22, 2002, trading occurred only during one hour per day. In total, 14,109 market orders were observed, which roughly translates, on average, into 26 market orders per minute. As this is the domestic market the median transaction size is only about 50,000 USD – compared to about 1 million USD in major markets. At the time the total Russian economy only had three percent of the US gross national product. Despite its smaller size, in comparison to the largest markets in the world, the Russian market appears to be quite efficient as indicated by its percentage spread of 0.0071, which is even slightly narrower than the EUR/USD market (Payne, 2003). The Russian market is also conventional with respect to market statistics (Table 1): a notable U-shaped pattern in spreads, as well as mean zero spot returns with heavy fat tails and negative first order midquote return autocorrelation (for more detail see Menkhoff and Schmeling, 2008).

Thus the data comes from a market whose characteristics match other foreign exchange markets. A particularly exciting feature of the data is the availability of coded trader identities. This allows the total trading volume of each trader during the sample period to be added up, which we use as a proxy for overall trader size and the likely degree of a trader's information. Based on these statistics, each trader is allocated to one of three groups depending on their size, i.e. large, medium, and small traders. The large trader group consists of the largest individual traders and accounts for 25% of total trading volume, the small trader group consists of the smallest individual traders and also accounts for 25% of total trading volume, with the medium-sized traders taking the remaining share.

Accordingly, the following statistics about these three groups show a significant degree of variation in our sample (Table 2). Although the large trader group consists of only 21 traders it naturally has the largest trading volume per trader (5.5 million USD) – about twice as much as for medium traders and larger by a factor of 22 compared to small traders. Similar relations hold for the submitted volume of limit orders per trader in the three groups. We are, therefore, confident that there is enough spread between these three groups to make them an interesting focus for the cross-sectional perspective below.

Notably, it can be seen that large traders, on average, do not necessarily submit the largest orders. More specifically, the large trader group employs an average market order size of only 58,000 USD whereas medium-sized traders, on average, submit market orders of about 64,000 USD. This is a first indication that trade size may be a poor indicator to identify informed traders which is shown for our sample in detail in Menkhoff and Schmeling (2008) (see also Chakravarty, 2000).

Overall, this provides a reasonable basis for the goal to examine information flows between heterogeneous traders, characterized by different levels of information.

3 The econometric approach

This section motivates the empirical set-up in capturing learning from order flow at trader level. We use a panel fixed-effects regression approach basically because of the individual trader data available.

In order to explore how a trader might learn from counterparties' order flow, we analyze the effect in a framework explaining the trading decision, i.e. order flow volume, of trader *i* at a given point in time.[4] We expect that a trader's order flow rationally reflects the information available to them, and it is updated in a Bayesian manner (see e.g. Glosten and Milgrom, 1985, Kyle, 1985). The information set of a trader will contain private as well as public information. Private information can stem from own research as well as customer order flow and can be recognized from the trader's last own order flow, i.e. prior trading decisions of a market participant. Public information to traders (although not to anyone outside of this market) can be derived from order flow in the market with respect to direction, volume, and return change. In addition to these sources of information, which have been studied before, the private information a trader receives from trade disclosure was added and tested as to whether the information has value. These determinants are captured by the following variables in our regression approach.

[4] We focus on order flow volume rather than an order flow indicator (see e.g. Bjønnes and Rime, 2005) to capture both trading direction and volume effects. A trader might well adjust his trading volume without changing the direction of his trades. Therefore, using order flow volumes seems more general than just focusing on trading directions with an order flow indicator.

We include a trader-specific intercept (α^i) as a means to capture trader-specific buying and selling behavior. For example, a trader or bank with an end-user customer base mainly consisting of export firms will more than likely be a seller of foreign currency, on average, while banks or traders from regions with many importers will tend to buy. Therefore, the individual constant is an approximate way of capturing such effects.

The first explanatory variable, the trader's last own order flow (denoted below as $x^i_{[k-1]}$), serves to capture persistence effects induced by (unobserved) prior information as described above. Therefore, it is not unlikely that traders will trade in the same direction over longer periods of time (this could, for example reflect a persistent unwinding of inventory or repeated trades with end-customers in the same direction). The second explanatory variable (denoted as $x^i_{[k-1]} \cdot \lambda^{i,C}_{[k-1]}$) serves to capture the information obtained from trade disclosure by the interaction of previous own order flow with the size of the counterparty. If signals from large – and presumably informed traders – are more informative than trades from small traders, the interaction variable should capture this effect of identity disclosure. The third explanatory variable ($x^A_{k-1;t}$) measures aggregate and publicly observed order flow, a key microstructure variable which earlier studies have made extensive use of (e.g. Evans and Lyons, 2002, Payne, 2003). If there is learning from public order flow in general, it will be reflected in this variable. The fourth explanatory variable included are lagged returns (r_{k-1}) to control for possible bandwagon effects and to control for possible learning about fundamental asset values from publicly available past returns.

Thus, we start with panel fixed-effects regressions of individual traders' order flow on lagged order flows (both publicly and privately observed) and lagged returns. The equation to be estimated is:

$$x^i_k = \alpha^i + \beta_1 x^i_{[k-1]} + \beta_2 x^i_{[k-1]} \cdot \lambda^{i,C}_{[k-1]} + \gamma x^A_{k-1;t} + \delta r_{k-1} + \xi_k \qquad (1)$$

where x^i_k is the order flow of trader *i* at *k* (k measures event time), $x^i_{[k-1]}$ denotes order flow of the last trade of trader *i*, and $\lambda^{i,C}_{[k-1]}$ is a measure of the size of the last counterparty which equals one (zero) for the largest (smallest) trader in our sample.[5] As can be seen from the superscript *i*, the order flow and counterparty information is trader-specific so that only those past trades impact upon a trader's decision through the second term on the RHS in (1) where the trader actually participated in a transaction. In this first basic setting, $x^i_{[k-1]}$ comprises both past market orders of trader *i* as well as this trader's executed limit orders, i.e. market order of this trader's counterparties.[6] Executed limit and market orders enter $x^i_{[k-1]}$ as the positive (negative) volume of trade [k−1] when trader *i* was the buyer (seller). Finally, $x^A_{k-1;t}$ measures aggregate observed order flow of all trades over the last minute just prior to x^i_k and r_{k-1} is the midquote return over the last minute. As mentioned above, all order flows are measured in terms of volume (and not as an order flow indicator) and, for ease of interpretation, all variables are standardized.

In the following analysis, we will estimate the above equation on the sample of all traders and three sub-samples, covering large, medium, and small traders. Estimation is carried out using fixed-effects panel regressions so that each trader *i* has an individual intercept α^i but all slope coefficients are restricted to be equal across traders. More specifically, since we have lagged values of x^i_k on the RHS of the regression, we employ GMM estimator for dynamic panel data (Arellano and Bond, 1991, Arellano and Bover, 1995). Inference in the paper is based on robust standard errors from these GMM regressions.

Finally, it must be mentioned that the regressions below do not include all 14,109 market orders, as documented in Table 2, for two reasons. First, lagged order flows and returns were measured over intervals of one minute. Since all overnight observations were eliminated there is a loss of observations at the start of each day. Second, all trades of traders executed within ten seconds were excluded since the analysis seeks to investigate learning by traders from post-trade identity disclosure and, therefore, it is necessary to be certain that a trader has time to really find out about his counterparty from this market's e-mail messaging system. The time interval was arbitrarily set to 10 seconds as this seems an intuitively reasonable

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[5] The remaining traders are distributed between zero and one proportionally to their total trading volume.

[6] This paper only considers all orders that are immediately executed, i.e. market orders. Market and executed limit orders are split up later in the paper. We do not consider the placement of ordinary limit orders.

number; it should be noted that larger and somewhat shorter (e.g. 5 seconds) intervals do not change the qualitative findings below.

Owing to these two adjustments a sample of roughly 9,700 trades remains, which still yields sufficient degrees of freedom to carry out the analysis.

4 Results

The main results support the expectation of rational trading decisions as introduced in Section 3 (see Section 4.1). Further analyses of learning by different trader groups (Section 4.2), and learning through market and limit orders (Section 4.3) provide additional insights into the learning process at the trader level.

4.1 Learning by the average trader

This section reports test results on the three kinds of information potentially contained in order flow (see Section 3): it shows that the trader's decision depends on whether their last trading counterparty was informed, on their last trading decision (i.e. last own order flow), and on aggregate market order flow.

The starting point of the discussion is an isolated trader who trades only on the basis of own private information. This information may stem from either analysis of publicly available information or from information about the trader's own customers' trades. It is impossible to distinguish between these two sources since we do not know about research activities or possible customer orders. Nevertheless, own order flow of a trader is a measure which, among other determinants, reflects the trader's private information.

In order to distinguish this kind of private information from other trading determinants, we exploit a typical characteristic of limit order markets, i.e. their normalized trade size. Owing to this clustering of trade sizes around a "normal" amount, in this case 50,000 USD, informed trade is not easily revealed by the size of a trade as professionals traders hesitate to make their information obvious to all others via the trade size. Instead, it is common practice for informed traders to split the total amount into a sequence of many normalized trades. Due to the anonymity of trades the universe of traders can observe the total number and volume of trades but does not know who is trading and, in particular, does not know that the originator of a number of trades may be just one single trader. Therefore, it is more difficult for others to learn that there is, indeed, an informed trader in the market. This common practice of order splitting is important for our purpose because we can infer that there is a certain probability that any trading decision is partially determined by the last trade and that the direction of these two trades, i.e. the actual and the last one, will be the same.

Thus the "last own order flow" (LOOF) can be taken as a crude determinant of a trading decision partially revealing the private information of a trader. We recognize, of course, that there are also random influences on the last trade caused by liquidity traders, etc. but it is sufficient for our argument that private information of a trading decision is systematically revealed by the last own trade.

This simple measure is implemented in the above introduced panel regression framework and, indeed, it can be seen that the actual trade is determined by the direction and size of the last trade. The coefficient for this determinant is positive, as theoretically expected, and statistically highly significant (see column (i) in Table 3). The estimated coefficient of 0.21 seems economically significant as well, since it implies that a one standard deviation rise in the last own order flow leads to a 0.21 standard deviation higher order flow in the current trade.

The next determinant of a trading decision is derived from publicly available information. All traders can observe all trades so that a sequence of directed trades indicates that there may be a revelation of information occurring. Accordingly, one may expect that rational traders observe this revelation of information and consider it in their own decisions in that they go with the market.

This element of information incorporation is implemented by analyzing whether the lagged order flow in the market, i.e. the sum of order flows over the minute just prior to trade *k*, and whether the lagged returns (also over the last minute) determine actual order flow of individual traders. Column (ii) in Table 3 shows that both coefficients are positive as theoretically expected and that on lagged order flow is statistically significant. These effects of past aggregate order flow (or returns) on current order flow are not new to the literature (see e.g. Hasbrouck, 1991, or Payne, 2003) but we stress that we are – to the best of our knowledge – the first to conduct such an analysis in a panel setting with *all* individual traders acting in a complete limit order book.

Turning to the third information determinant of individual order flow, it can be seen that transactions may be informative. After any transaction, traders learn which other trader has taken the opposite position in the market. This newly gained knowledge may be relevant if the counterparty is expected to be informed, i.e. in this setting if the counterparty is a larger trader. Therefore, the larger the counterparty of the last trade the more traders tend to revert their trading direction.

This element of learning can be implemented by interacting the variable of the last own order flow, LOOF, multiplied by the size of the counterparty.[7] The empirical result of this variable, in addition to the LOOF from column (i), is shown in column (iii): the coefficient of the interaction variable is negative, as theoretically expected, and significant. This suggests that order flow directions and magnitudes spill over from past counterparties' trades as predicted by standard microstructure learning models. The estimated coefficient of −0.173 is about 70% the (absolute) size of the coefficient of the last own order flow (estimated to be 0.257). This result implies that the positive autocorrelation (as measured by LOOF) is reduced by about 70% when the last counterparty was a very large trader while it is increased by about 70% when the last counterparty was a very small, and presumably uninformed, market participant. This reliance on information gained by post-trade identity disclosure suggests an important role for individual learning from order flow and, in particular, that order flow of large traders is highly important for price discovery. We believe that this finding is an important contribution of our paper, since it illuminates and quantifies the way in which traders incorporate order flow information into prices in real-time.

Furthermore, putting the determinants introduced above into a single regression the variables are seen to keep their signs and significance levels, indicating that the approach is robust to some variation (column (iv) in Table 3).

Finally, the table also shows the fraction of variance of the dependent variable due to individual fixed-effects (labeled τ in the table). This fraction is sizeable and ranges from 20 to 35 percent, indicating that individual trader heterogeneity is important. Also, the correlation of fixed-effects and conditional means ($\rho(u,\mu)$) tends to be large which indicates the usefulness of our fixed-effects specification.

Next, we extend the above analysis and analyze learning over time. The previous results dealt with direct effects of order flow on trading decisions, i.e. the impact of the last trade on the current decision to trade. We now investigate the persistence of effects, or learning over

[7] The size of a trader is calculated by computing their total trading volume over all days in our sample. We then compute a trader's share of total trading volume and rescale the size to the unit interval so that the largest (smallest) trader has a size of one (zero).

time, and show that order flow from informed traders dominates trading decisions over short to medium horizons.

To tackle this question, sequences of equations which differ only by the timing of the dependent variable are estimated:

$$x^{i}_{k+j-1} = \alpha^{i}_{j} + \beta_{1,j} x^{i}_{[k-1]} + \beta_{2,j} x^{i}_{[k-1]} \cdot \lambda^{i,C}_{[k-1]} + \gamma_{j} x^{A}_{k-1;t} + \delta_{j} r_{k-1} + \xi_{k,j} \qquad (2)$$

i.e. we estimate equation (1) for subsequent trading decisions j=1,2,…,6, in event time. This approach projects future order decisions on current measures of information and allows us to study how long it takes until information from the most frequent order flow is fully incorporated into individual trading decisions. The sequence of coefficient estimates $\beta_{1,j}$, $\beta_{2,j}$ can be used to construct impulse responses in the spirit of Jordá (2005).

Results from these local projections can be found in Figure 1. Panel A shows results for a scenario where the last trade occurred with a completely uninformed trader, i.e. $\lambda^{C} = 0$, and Panel B shows a scenario where the last counterparty is highly informed, i.e. $\lambda^{C} = 1$.[8] As can be seen, the last own order flow is a significant and positive driver of future trading decisions when the last counterparty was small and thus little can be learned from counterparty order flow. There is significant autocorrelation in individual trading decisions for two periods.

Contrary to this, Panel B shows, that large and presumably informed counterparties significantly impact traders' order decisions. While the direct impact on the next trade seems dominated by own past trading decisions, it is obvious from this figure, that information gained from past counterparties is fairly persistent and leads to a significant reversal of trading directions after only about three trades.

Summarizing the evidence so far, it appears that traders learn a great deal from large counterparties' order flow. This learned information is important enough to even outweigh own past actions and to dominate future trading directions.

4.2 Learning by large, medium-, and small-sized traders

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[8] Numbers underlying Figure 1 are calculated as $\hat{\beta}_{1,j}$ for the case of an uninformed last counterparty and as $\hat{\beta}_{1,j} + \hat{\beta}_{2,j}$ for the informed last counterparty with j=1, 2, … ,6. All other explanatory variables are set to their mean value (which is zero due to the standardization of explanatory variables).

This section shows that traders with different levels of information rely to a specific degree on the three kinds of information introduced above. The pattern that emerges appears to be compatible with rational behavior.

Basically, the analysis from Section 4.1 is rerun, but for different groups of traders. The group was split into large-, medium-, and small-sized traders as documented in Section 3 above (see Table 2). The results in Table 4 show that coefficient signs are the same as in Table 3 for all traders taken together. However, with regard to several key features, large and small traders exhibit a different behavior. Large traders' behavior seems to be best understood by relying on all three measures of information introduced. These determinants have the expected coefficient signs and are statistically significant. The relatively weakest determinant – with regard to coefficient size and level of significance – seems to be the interactive term which indicates that large traders learn less from other traders' order flow than the average market participant (see Table 3).

Turning to the smallest traders, they react strongly on their last counterparty, indicating that they learn much from others. Compared to large traders they do not react strongly on lagged order flow and returns in the market, i.e. publicly available information. In this respect, coefficient signs are small and significance is only borderline. This may be a rational stance for those market participants who are less active in the market and thus generally care less about the incorporation of market developments into prices.

Finally, looking at the medium-sized traders, they behave in a way that lies somewhere in between large and small traders. Regarding their own order flow and the market-wide lagged order flow they are closer to the large traders, but regarding the interactive term they seem to be closer to the small traders.[9]

Thus the three groups demonstrate continuous behavior with respect to the four variables of interest. This is principally a desired result as it indicates that the formation of groups according to trader size is a useful way of disaggregating the market. Moreover, results are interesting since they imply that information is aggregated into prices in a different way by different subgroups of heterogeneous agents. In particular, large vs. small traders seem to perform different roles in the price discovery process: large traders are responsible for incorporating public information whereas small traders rely relatively more on private infor-

[9] The standard errors of coefficient estimates generally do not imply a statistically significant difference between the three groups. The groups are, however, clearly different in economic terms.

mation gained during the trading process and, thereby, augment the information learned from larger and presumably more informed traders.

Learning effects over time are shown in Figure 2. This figure is analogous to Figure 1 above, but displays results for the three different trader groups separately. As can be seen from Panel A of Figure 2, trading decisions are most heavily autocorrelated for small- and medium-sized traders when the last counterparty was small, i.e. uninformed. Large traders show less autocorrelated trading behavior. Panel B shows results for the case when the last trade occurred with an informed counterparty. In that case, large traders do not adjust their trading behavior over time, whereas small- and medium-sized traders strongly adjust, or rather reverse, their previously taken trading directions. Therefore, effects over time are consistent with the one period of results shown in Table 4.

Overall, this section on the role of differently informed traders in the price discovery process suggests that all traders use private information but that certain groups have specific roles: large traders are key in incorporating public information but small traders are important because they amplify this process. These findings again highlight the specific process of how order flow information becomes embedded into prices through real-time learning of heterogeneous traders.

4.3 Learning through market and limit orders

This section further extends our understanding of the price discovery process by also considering limit orders in addition to the market orders analyzed so far. We recognize that basic insights extend from market to limit orders but that market orders are more informative.

This analysis appears relevant, since it allows us to infer whether traders learn more from executed limit orders (i.e. the counterparty used a market order) or from market orders (i.e. the counterparty originally submitted a limit order). The literature usually assumes that private information is revealed by market orders, thus a natural hypothesis would be that order flow from own limit orders (i.e. counterparty's market orders) should have a stronger impact than own market orders (i.e. the counterparty originally submitted a limit order).

Table 5 shows that this is, indeed, the case. Looking first at results for all traders jointly, it can be seen that the effect of the last counterparty's trade impacts a trader's order flow decision more heavily when the last counterparty used a market order relative to a counterparty originally submitting a limit order. Nevertheless, it should be noted that there is a significant effect for both limit and market order flow from the last counterparty. This result strongly suggests that traders learn from market and limit orders of their counterparties and it rejects the view that information is conveyed by market orders only. This finding complements earlier results by Kaniel and Liu (2006) and Bloomfield et al. (2005) who also found that limit orders are informative for future price movements and that informed traders use limit orders, respectively.

Estimates for the three different groups of traders, also presented in Table 5, again show that large traders react least to information gained by observing the identity of counterparties, irrespective of whether the last counterparty used a market order or limit order. Also, all trader groups learn more from their last counterparty's trade when the counterparty used a market order compared to a limit order. The only difference between the three groups seems to be the relative size of their reaction coefficients. The general finding that large traders react least to information gained from trade disclosure and most to publicly observable order flow is not sensitive to splitting into limit and market orders.

5 Robustness tests

This section undertakes several tests to check robustness of the results. We show that the results do not depend (a) on certain states of the market, e.g. high versus low trading volume or bid–ask spreads, (b) on other measures of privately and publicly observed order flow, and (c) on estimating the main regression on two different sub-samples.

The first robustness test is in respect to the impact of market conditions, such as trading volume, bid–ask spreads, and return volatility. In the microstructure literature it is well known that these conditions impact trading behavior or market outcomes (e.g. Evans and Lyons, 2002a, Hasbrouck and Saar, 2007). We are interested in seeing whether our results remain stable when factoring in these sorts of market conditions. Therefore, the sample is split into times of high and low (lagged) trading volume, bid–ask spreads, and return volatility. To do this, we calculated the three statistics over periods of one minute, deseasonalized the series, and split the total sample along the median value of each of the three measures.[10] Then, equation (1) is estimated for these sub-samples.

[10] More specifically, at each observation k, the three measures were computed over an interval of one minute prior to k (and excluding observation k). The resulting series of trading volumes, spreads, and volatilities are then regressed on 12 five-minute dummies for the time of the trading session to net out

Results of this procedure can be found in Table 6. For *trading volume*, results suggest that LOOF has a larger impact when lagged trading volume is high, meaning that the autocorrelation of individual traders' orders are larger when the market has been very active. In contrast to this, there is less reaction to trades of the counterparty in times of high volume compared to low volume periods. This result suggests that the information contained in other traders' trades is less valuable when the market is active. This is in line with early theoretical models where high trading volume suggests the presence of noise trading that is rather uninformative for fundamental asset values (e.g. Admati and Pfleiderer, 1988, or Campbell, Grossman, and Wang, 1993).

Results for lagged *bid–ask spreads* suggest that traders pay particular attention to other traders' trades and publicly observable order flow when the spread is high. This result corroborates theoretical conjectures that a high spread signals a high likelihood of informed trade (e.g. Easley and O'Hara, 1987). Earlier empirical evidence (e.g. Payne, 2003) has, indeed, shown that the price impact of order flow is higher in times of high spreads and vice versa. Our result suggests that this higher price impact may stem from greater willingness to revert the trading direction in response to larger traders.

Finally, results for lagged midquote *return volatility* are similar to the results for spreads, although the differences between periods of high and low volatility are less pronounced than they are for spreads. The similarity to the results for spreads seems natural since spreads and volatility are correlated and as high volatility is also taken to be a sign of information processing and thus a signal of informed trade.

Turning to the measure of order flow, we have up to now used information from the last trade of a given trader. While this seems a natural starting point, it is also interesting to extend the information set of traders beyond the last trade. For this reason, a measure of cumulated, trader-specific order flows which cumulates all trades of a given day is also computed. The base regression (1) now reads:

$$x_k^i = \alpha^i + \beta_1 \tilde{x}_{[k-1]}^i + \beta_2 \delta_{[k-1]}^i + \gamma x_{k-1;t}^A + \delta r_{k-1} + \xi_k \tag{3}$$

where $\tilde{x}_{[k-1]}^i$ denotes the cumulated order flow of trader *i* just prior to the actual trade *k*. Order flow is cumulated on a day-by-day basis so that $\tilde{x}_{[k-1]}^i$ starts with a value of zero each day

intraday seasonalities. The residuals of these regressions are then used to split the sample along the respective medians.

when the trading session opens. The interaction term is denoted by $\delta^{i,C}_{[k-1]} = \sum_{h=1}^{k-1} x^{i}_{[h]} \cdot \lambda^{i,C}_{[h]}$ so that every single order flow of a given day is weighted by that counterparty's size and summed up over the day.

Results for this specification are shown in Table 7 where estimates for all traders jointly are provided, as well as individual results for large, medium, and small traders. As the results for all traders show, the findings above are robust to this modification of the order flow measure. Traders still significantly tend to follow their previous trading direction, and they still tend to switch their trading direction when their last counterparty was a large trader. Also, results for the three trader groups are qualitatively very similar to the findings reported above. Large traders tend to rely less on their earlier trading decisions and less on the information contained in privately observed trades, but tend to follow aggregate order flow movements more strongly. In contrast to this, small traders adhere to their own information and the information gained by trade disclosure more heavily than large traders.

Moreover, we run regressions, where we split up total past cumulated own order flow into two components by separating the last own order flow from the remaining cumulated own order flow, i.e. we include $\tilde{x}^{i}_{[k-2]}$ and $x^{i}_{[k-1]}$ (and interactions with counterparty size thereof) separately as explanatory variables. Results are not qualitatively different from our earlier analyses and we therefore do not report them here. We mention, however, that the most recent own order flow (i.e. $x^{i}_{[k-1]}$) has a stronger effect on current trading decisions than cumulated past flows.

Similarly, changing our proxy for publicly available information, i.e. aggregate market order flow over the last minute prior to a trade, to cumulated aggregate market order flow over the whole trading session does not change our qualitative conclusions. Short-term trends in aggregate order flow (e.g. our measure of one minute), however, seem to have more explanatory power than longer-run trends of market-wide order flow measures.

Finally, the base regression (1) on two sub-samples is also estimated, namely on data ranging from March 11 to March 15 only and on data ranging from March 18 to 21. Results shown in Table 8 suggest that the qualitative results are not sensitive to a certain time period since coefficient signs and significance levels do not change in any economically important way between the two sub-periods.

Apart from the robustness checks documented here, we also performed a number of additional tests (which are not reported in the interests of space). These additional tests include methodological and economic robustness tests. With regard to the former, pooled regressions were used instead of fixed effects and we also experimented with regressions where equation (1) was estimated separately for each trader in the sample so that intercepts and slope coefficients were allowed to vary. However, the results are robust to these variations. With regard to additional economic robustness tests, order flows were replaced with order flow indicators and different trader group classifications used instead of the 25/50/25 scheme. Again, results are similar to those reported in the paper.

6 Conclusions

Our study examines how individual traders learn from their counterparties by analyzing individual traders' direction and size of order flow after post-trade identity disclosure. This work thus complements earlier studies looking at pre-trade disclosure (e.g. Foucault et al., 2007) and it shows how traders incorporate information from identity disclosure into their trading decisions in real-time.

The database for this research comprises a short but completely documented sample period in the Russian rouble vs. US dollar limit order market during March 2002, covering the whole order book. The main advantage of this data is the availability of anonymous trader identities. This allows analysis of the determinants of several hundred individual traders' buying and selling decisions in an unusually detailed approach. In addition, the trading statistic provides information about the total transaction volume of each trader, and this is used as a proxy for the expected degree of information that a trader possesses.

Our main finding is that traders significantly learn from post-trade disclosure, in that they tend to reverse their trading direction – i.e. buying or selling – if their last counterparty was a larger and thus better informed trader. This finding holds when controlling for other trading determinants, whose identification may be interesting in themselves: traders' direction and volume of trading is positively autocorrelated, indicating their reliance on private information; moreover, traders' trading is positively related to lagged trends in market momentum, indicating the use of public information.

Interestingly, the effect from informed counterparty order flow is so strong that it leads to a statistically significant reversal of the former own trading direction. In our sample, this is estimated to occur after about two further trades.

Further disaggregated regressions provide a second finding about the price discovery process. In particular, large and small traders diverge in their use of information: all traders rely on their private information, but whereas large traders react strongly to and thus process public information, small traders react more strongly on the trades of their larger counterparties. These findings are essentially confirmed when we complement the earlier analyses of market orders by also considering limit orders. The intuition also holds when further robustness checks, such as splitting the sample and using other methods than the fixed-effects panel specification are performed.

Overall, this research presents an unusually detailed picture of the price discovery process in a modern limit order market. It also cautiously indicates a policy implication in the sense that the revelation of counterparties especially benefits uninformed traders, since these traders seem to learn most heavily from counterparty identities. Identity disclosure may also contribute to market efficiency as this learning amplifies the impact of informed traders and thus leads to a faster dissemination of order flow information. However, there may be a balancing effect when informed traders adjust their trading behavior in order to avoid these revelation “costs”.

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Table 1. Descriptive statistics

This table shows descriptive statistics for RUR/USD spot returns (in percent) for the whole sample period (row "All") and for non-overlapping five minute subsamples (rows "5" to "60"), where "5" denotes the first five minutes of the trading sessions, "10" denotes minutes five to ten of the trading sessions and so on. Columns two to five show moments of the return distribution and first order midquote return autocorrelation coefficients (ρ_{-1}). "Trade size" denotes the average size of a market order in USD and "Number of trades" shows the number of market orders for a given sample. The last column shows the quoted percentage spread in a given interval.

	Mean ($\times 10^4$)	St. dev. ($\times 10^3$)	Kurtosis	ρ_{-1}	Trade size	Number of trades	quoted pct. spread
All	0.02	0.301	18.70	-0.0961	49,396	14,109	0.0071
5	-0.01	0.276	24.65	-0.1318	55,795	3,140	0.0115
10	0.01	0.294	18.80	-0.1070	52,236	2,404	0.0045
15	0.13	0.289	16.32	-0.1361	49,009	1,907	0.0043
20	-0.03	0.290	18.82	-0.0600	47,362	1,242	0.0049
25	-0.09	0.299	19.03	-0.0447	46,821	1,024	0.0049
30	-0.11	0.308	17.02	-0.0132	39,200	832	0.0046
35	0.04	0.321	15.96	-0.1488	44,903	585	0.0050
40	0.05	0.287	18.89	-0.5050	50,000	760	0.0049
45	0.04	0.352	14.09	-0.0895	51,427	597	0.0045
50	0.18	0.345	16.26	-0.2230	42,732	541	0.0045
55	0.18	0.358	13.32	-0.0459	39,900	581	0.0059
60	-0.02	0.324	18.35	-0.1420	44,429	496	0.0120

Table 2. Descriptive statistics for order submissions and trader groups

This table presents descriptive statistics for traders in our sample. The upper part of the table shows aggregate volume (in million USD) and the number of market and limit orders. The middle part shows statistics for market orders per trader and per order (in million USD for volume figures) while the lower part shows the same for limit orders. Numbers are for all traders jointly, or for large, medium-sized, and small traders.

	All traders	Large traders	Medium-sized traders	Small traders
Market order vol.	697	116	438	138
Market order obs.	14,109	1,993	6,826	5,290
Limit order vol.	1,633	265	973	395
Limit order obs.	15,959	882	5,831	9,246
Market orders (vol. per trader)	0.97	5.52	2.86	0.25
Market orders (obs. per trader)	19.54	94.9	44.04	9.69
Market orders (vol. per order)	0.049	0.058	0.064	0.026
Limit orders (vol. per trader)	2.26	12.62	6.28	0.72
Limit orders (obs. per trader)	22.10	42.00	37.62	16.93
Limit orders (vol. per order)	0.102	0.300	0.167	0.043
No. of traders	722	21	155	546

Table 3. Private and public order flow

This table shows results for fixed-effects panel regressions of market order flow by trader *i* on his own last order flow (LOOF), on his last own order flow interacted with the size of the counterparty (LOOF x size), on lagged, aggregate market order flow (Lagged oflow), and on lagged midquote returns (Lagged returns). τ denotes the fraction of variance due to individual fixed-effects , ρ(u,μ) denotes correlation of the fixed-effects and conditional means. Stars refer to the level of significance: ***: ≤0.01, **: ≤0.05, *: ≤0.10.

	(i)	(ii)	(iii)	(iv)
LOOF	0.211		0.288	0.257
	***[2.99]		***[3.67]	***[4.51]
LOOF ×size			-0.191	-0.173
			***[-5.29]	***[-5.75]
Lagged oflow		0.101		0.039
		***[3.13]		***[2.76]
Lagged returns		0.024		0.011
		[0.55]		[1.12]
Const.	0.074	0.079	0.080	0.069
	**[2.22]	***[5.01]	**[2.12]	**[1.96]
R^2	0.11	0.09	0.16	0.16
τ	0.30	0.35	0.32	0.21
ρ(u,μ)	0.25	0.09	0.18	0.28
Obs	9,688	9,688	9,688	9,688

Figure 1. Learning over time

This figure shows responses of future order flows (in event time) to earlier order flows. Panel A shows the evolution of a trader's order flow following an own buy order with an uninformed trader as last counterparty. Panel B shows the same for a buy order with an informed trader as last counterparty. The horizontal axis measures the number of trades after the initial transaction, whereas the vertical axis shows order flow decisions (volumes, divided by 100,000 USD). A positive value means that a trader is buying and vice versa.

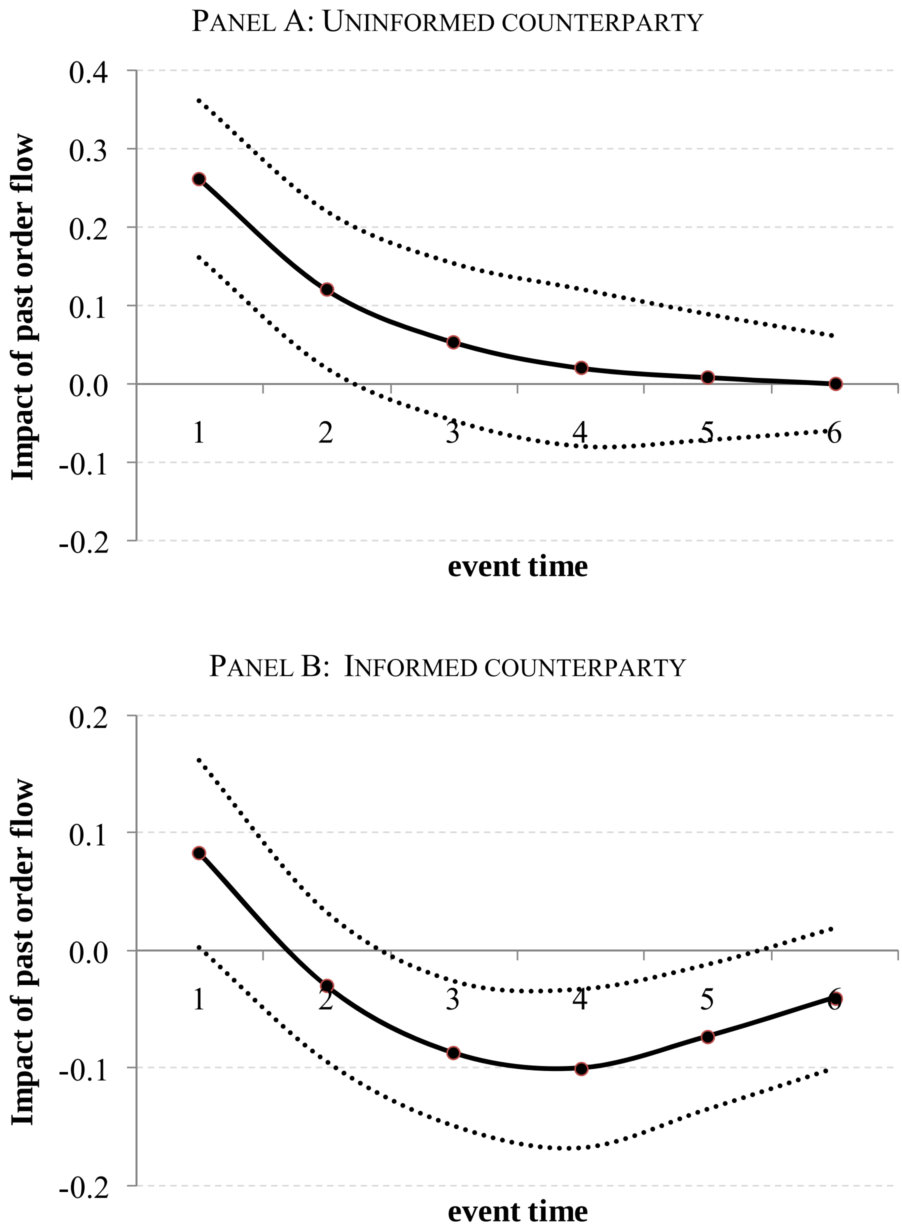


Table 4. Different trader groups

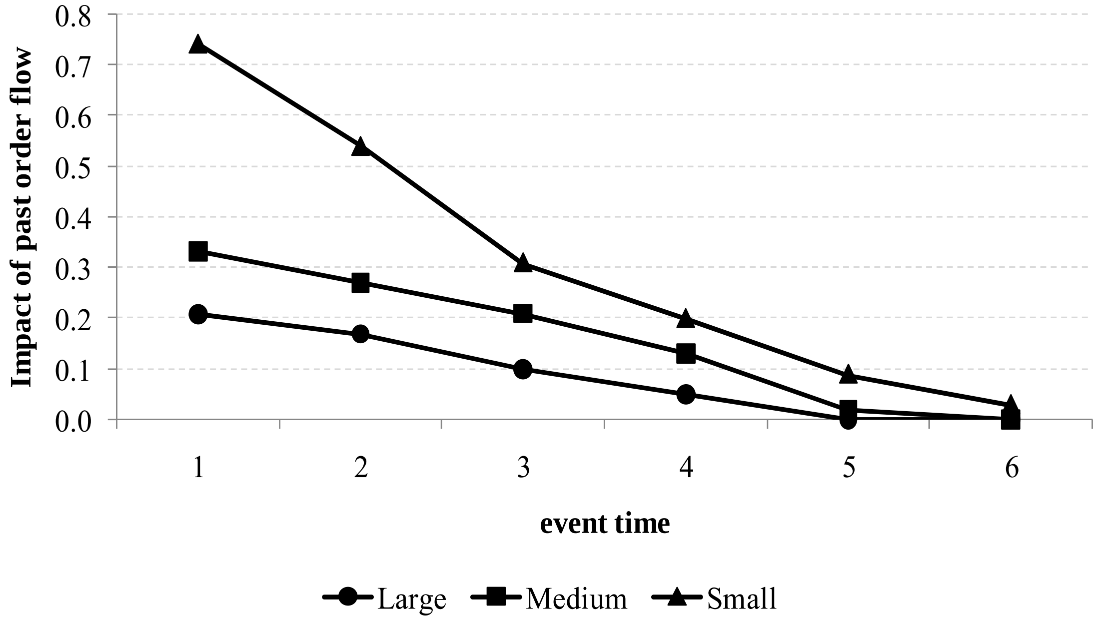
This table shows results from the same regression underlying Table 3 but for three different groups of traders. Traders are grouped by size, where size is proxied for by total trading volume. τ denotes the fraction of variance due to individual fixed-effects, ρ(u,μ) denotes correlation of the fixed-effects and conditional means. Stars refer to the level of significance: ***: ≤0.01, **: ≤0.05, *: ≤0.10.

	Large traders	Medium-sized traders	Small traders
LOOF	0.210	0.333	0.742
	***[3.61]	***[4.23]	***[7.35]
LOOF×size	-0.101	-0.545	-0.698
	*[-1.89]	***[-2.71]	***[-3.76]
Lagged oflow	0.449	0.401	0.079
	***[6.12]	***[3.12]	*[1.74]
Lagged returns	0.431	0.124	0.011
	**[2.11]	*[1.89]	[0.78]
Const.	0.342	0.181	-0.050
	*[1.74]	[1.65]	[-1.19]
R^2	0.16	0.15	0.15
τ	0.36	0.35	0.46
ρ(u,μ)	0.32	0.30	0.39
Obs	1,798	4,321	3,569

Figure 2. Learning over time by different trader groups

This figure shows responses of future order flows (in event time) to earlier order flows for different trader groups (large, medium, and small traders). Panel A shows the evolution of a trader group's order flow following an own buy order with an uninformed trader as last counterparty. Panel B shows the same for a buy order with an informed trader as last counterparty. The horizontal axis measures the number of trades after the initial transaction, whereas the vertical axis shows order flow decisions (volumes, divided by 100,000 USD). A positive value means that a trader is buying and vice versa.

PANEL A: UNINFORMED COUNTERPARTY



PANEL B: INFORMED COUNTERPARTY

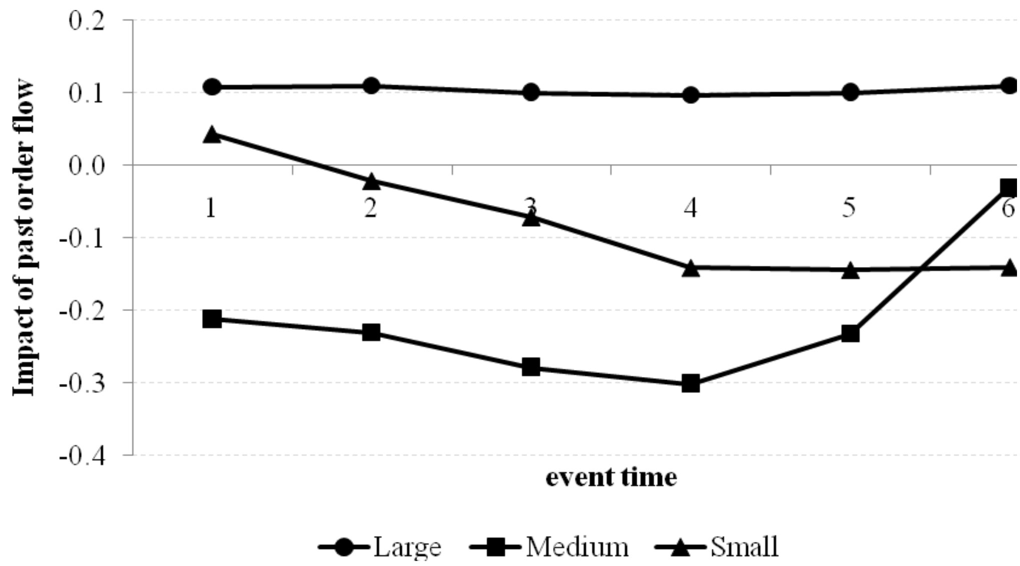


Table 5. Order flow sources

This table reports regression results of traders' market order flow on their last own order flow executed by market and limit orders (LOOF, market and LOOF, limit), the same variables interacted with the size of the respective last counterparty, lagged aggregate market order flow and lagged returns. τ denotes the fraction of variance due to individual fixed-effects, ρ(u,μ) denotes correlation of the fixed-effects and conditional means. Stars refer to the level of significance: ***: ≤0.01, **: ≤0.05, *: ≤0.10.

	All traders	Large traders	Medium-sized traders	Small traders
LOOF, market	0.391	0.217	0.378	0.643
	***[5.99]	***[3.44]	***[4.23]	***[4.09]
LOOF, limit	0.195	0.132	0.201	0.232
	**[2.52]	**[2.12]	**[2.31]	**[2.44]
LOOF, market × size	-0.139	-0.093	-0.145	-0.164
	**[-2.14]	**[-1.99]	**[-2.03]	**[-2.50]
LOOF, limit × size	-0.181	-0.110	-0.164	-0.276
	***[-4.56]	**[-2.32]	**[-2.49]	***[-3.08]
Lagged oflow	0.050	0.402	0.371	0.042
	***[3.01]	***[3.76]	**[2.05]	[0.87]
Lagged returns	0.019	0.387	0.109	0.009
	*[1.79]	**[2.15]	*[1.97]	[0.54]
Const.	0.054	0.341	0.092	-0.067
	*[1.72]	**[2.43]	*[1.96]	[-0.98]
R^2	0.15	0.17	0.14	0.16
τ	0.31	0.34	0.32	0.33
ρ(u,μ)	0.27	0.30	0.28	0.38
Obs.	9,688	1,798	4,321	3,569

Table 6. Market states

This table provides results for the base regression in (1) but for different market states, namely times of high and low trading volume, bid-ask spreads, and return volatility. τ denotes the fraction of variance due to individual fixed-effects, ρ(u,μ) denotes correlation of the fixed-effects and conditional means. Stars refer to the level of significance: ***: ≤0.01, **: ≤0.05, *: ≤0.10.

	Trading volume		Bid-ask spread		Return volatility	
	High	Low	High	Low	High	Low
Loof	0.326	0.167	0.101	0.323	0.212	0.301
	***[2.98]	**[2.31]	**[2.03]	**[2.18]	**[2.14]	**[2.03]
Loof ×size	-0.099	-0.269	-0.314	-0.065	-0.199	-0.154
	**[-1.96]	***[-3.56]	***[-3.68]	*[1.89]	**[2.47]	**[2.04]
Lagged oflow	0.032	0.043	0.046	0.022	0.040	0.035
	**[2.07]	**[2.15]	**[2.09]	*[1.91]	**[2.13]	**[1.98]
Lagged returns	0.007	0.016	0.019	0.008	0.014	0.010
	[0.56]	[1.44]	[1.57]	[0.83]	[1.39]	[1.07]
Const.	0.067	0.075	0.065	0.070	0.066	0.071
	**[1.97]	**[1.99]	*[1.91]	**[2.03]	*[1.92]	**[2.00]
R^2	0.13	0.17	0.19	0.14	0.16	0.16
τ	0.23	0.20	0.17	0.24	0.20	0.21
ρ(u,μ)	0.30	0.23	0.24	0.32	0.26	0.28
Obs	4,844	4,844	4,844	4,844	4,844	4,844

Table 7. Cumulated order flows

This table shows results for fixed-effects panel regressions of market order flow by trader *i* on his own order flow cumulated over the day (Loof cum), on his last own order flow interacted with the size of the counterparty cumulated over the day, on lagged, aggregate market order flow, and on lagged midquote returns. τ denotes the fraction of variance due to individual fixed-effects, ρ(u,μ) denotes correlation of the fixed-effects and conditional means. Stars refer to the level of significance: ***: ≤0.01, **: ≤0.05, *: ≤0.10.

	All traders	Large traders	Medium-sized traders	Small Traders
Loof cum	0.231	0.187	0.289	0.305
	**[2.07]	**[1.97]	**[2.37]	**[2.54]
Loof cum ×size	-0.174	-0.132	-0.191	-0.287
	***[-3.37]	**[2.30]	**[-2.18]	***[-3.48]
Lagged oflow	0.043	0.301	0.121	0.051
	***[2.78]	**[2.61]	*[1.87]	[1.25]
Lagged returns	0.014	0.214	0.083	0.007
	[1.12]	**[1.98]	[1.61]	[0.83]
Const.	0.058	0.212	0.104	-0.081
	*[1.69]	**[2.01]	[1.34]	[-1.41]
R^2	0.16	0.18	0.16	0.17
τ	0.32	0.30	0.34	0.31
ρ(u,μ)	0.29	0.28	0.30	0.33
Obs.	9,688	1,798	4,321	3,569

Table 8. Sub-sample analysis

This table shows results for the analysis in Table 3 when we split the sample into two sub-samples of five and four days, respectively. τ denotes the fraction of variance due to individual fixed-effects, ρ(u,μ) denotes correlation of the fixed-effects and conditional means. Stars refer to the level of significance: ***: ≤0.01, **: ≤0.05, *: ≤0.10.

	March 11th to 15th	March 18th to 21st
Loof	0.201	0.344
	***[3.43]	***[4.10]
Loof×size	-0.152	-0.189
	***[-4.22]	***[-5.17]
Lagged oflow	0.041	0.036
	**[2.15]	**[2.21]
Lagged returns	0.004	0.014
	[0.71]	[1.39]
Const.	0.043	0.074
	[1.56]	**[2.02]
R^2	0.14	0.17
τ	0.20	0.23
ρ(u,μ)	0.25	0.30
Obs.	5,293	4,495