

Liquidity Dynamics in Limit Order Markets under Asymmetric Information

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Abstract

This paper provides evidence that informed traders dominate the dynamics of liquidity provision in a pure limit order market. In the market we study, uninformed traders are relatively insensitive to spreads, volatility, and momentum and they do not respond to depth. By contrast, informed traders are highly sensitive to all these market conditions and generally tend to be stabilizing. The dominance of the informed on liquidity dynamics is magnified by their use of aggressively-priced limit orders.

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Liquidity Dynamics in Limit Order Markets under Asymmetric Information

This paper undertakes an empirical investigation of liquidity provision by informed and uninformed traders in a pure limit order market. The main conclusion is that informed traders dominate the dynamics of liquidity provision. Order choice of uninformed traders responds very little, if at all, to changes in spreads, volatility, depth, and momentum. By contrast, informed traders are highly sensitive to all these market conditions and generally tend to stabilize them. A secondary finding is that the dominance of the informed over liquidity dynamics partly reflects a striking contrast between the informed and the uninformed in their treatment of limit orders priced within the spread.

Academic understanding of the influence of information on order choice has changed dramatically over the past decade. Initially, researchers assumed that all limit orders would be placed by uninformed traders, with informed traders impatiently placing market orders (e.g., Rock 1990, Glosten 1994, and Seppi 1997). This assumption has been challenged by empirical results as and by theory. The empirical analysis of Keim and Madhavan (1995) shows that institutionally-based fundamentalist traders, whom they interpret as informed, rely heavily on limit orders. Consistent with this, the theoretical analysis of Harris (1998) reveals that informed traders may rationally use limit orders when their information has low value. Chakravarty and Holden (1995) shows that informed traders may use combined limit and market orders to exploit their private information. Kaniel and Liu (2006) also shows that informed traders could rationally use limit orders; in their model this occurs when the information is long-lived.

More recent analysis indicates that the informed may actually provide more liquidity than the uninformed, on average. Bloomfield *et al.* (2005) find this to be true in an experimental asset

market in which subjects are exogenously given either information or a specific need for liquidity. They attribute the willingness of the informed to place limit orders to those agents' insulation from picking-off risk.¹

These results concern the static provision of liquidity. But the literature has moved on in recent years to consider the dynamics of liquidity provision (e.g., Parlour 1998, Foucault 1999, Goettler *et al.* 2005, 2007, Rosu 2006). The response of order choice to changes in spreads, depth, volatility, and other market conditions contributes to the ecological process that returns liquidity to its "natural balance" (Handa and Schwartz 1996, p. 1836). What differences are there between the contributions of the informed and uninformed to this process? This is the focus of our analysis.

As yet, theory provides only limited guidance on this issue, largely because models of dynamic limit order markets quickly become analytically intractable (Goettler *et al.* 2005, 2007, Rosu 2006): "An analytic model that incorporates the relevant frictions of limit order markets (such as discrete prices, staggered trader arrivals, and asymmetric information) is prohibitively difficult at best, and intractable at worst." To date, there are only two models of limit order markets with endogenous order-choice under asymmetric information, neither of which directly addresses the issue on which we focus. Back and Baruch (2007) compares the equilibrium properties of limit order and floor traded-markets, while Goettler *et al.* (2007) focuses on stationary, symmetric equilibria where strategies are independent of market conditions.

We therefore examine this issue empirically. We analyze comprehensive transactions data from the MICEX (Moscow Interbank Currency Exchange), an electronic interdealer market for rubles. Our data include identifying information for individual participants. This advantage, which may be unique among existing market-wide limit order datasets, permits us to distinguish between

¹ The informed also provide more liquidity on average in the theoretical model of Goettler *et al.* (2007). In this setting, however, information itself – which is costly to acquire – does not influence the placement of limit orders. Instead, both choices are the result of a third factor, private valuations.

those likely to be informed and uninformed. We base this identification on either the location of a trader or the level of his trading activity, both of which find justification in the existing finance literature. Our qualitative conclusions are sustained across both criteria.

We first characterize the market-wide response of order placement to changes in spreads, volatility, same-side depth, opposite-side depth, and momentum. We find that the average response of liquidity to these market conditions conforms closely to theoretical predictions (e.g., Handa and Schwartz 1996, Harris 1998, Parlour 1998, and Goettler *et al.* 2005). As predicted, there is a shift towards limit orders when spreads widen, when volatility rises, when depth increases on the same side of the market, and when depth decreases on the opposite side of the market. There is also an overall shift towards sell limit orders and buy market orders after upward price momentum, and vice versa. These results are sustained over robustness tests.

We then compare the dynamics of order choice among informed and uninformed traders. Our primary finding is that the response of aggregate market liquidity to changing market conditions is dominated by the informed. Order choice among informed agents responds to market conditions similarly to the overall market, but more intensely. By contrast, the uninformed have muted responses to changes in spreads, volatility, depth, and momentum. This finding appears to be new to the literature.

The stronger responses of the informed to spreads and volatility, like their greater average provision of liquidity, can be explained in terms of picking-off risk (or equivalently, bagging costs). Consider, for example, a rise in spreads. This could reflect a transitory rise in order flow, in which case the wider spread would encourage limit order placement for all agents. Alternatively, however, the rise in spreads could reflect higher underlying uncertainty about the asset's true value. In this case limit order placement for the uninformed – but not the informed – would be discouraged by the associated rise in picking-off risk (Foucault 1999). The influence of picking-off

risk on the uninformed could thus mute their average response to wider spreads relative to the average response of the informed.

We also identify a striking contrast between the informed and the uninformed in their use of “aggressive limit orders,” meaning orders priced within the spread. These orders are, of course, less aggressive than market orders and more aggressive than more “patient” limit orders (meaning those priced at or less attractively than the current best bid and offer). Agents could rationally treat aggressive limit orders as a substitute for market orders or as a substitute for patient limit orders. We find that the informed treat these as a substitute for market orders while the uninformed treat these as a substitute for patient limit orders.

These opposing tendencies intensify the effect of the informed, and further mute the effect of the uninformed, on the stability of liquidity and volatility. Consider a rise in volatility. This prompts both agent types to reduce their placement of market orders and increase their placement of patient limit orders, thus helping volatility return to normal levels (Handa and Schwartz 1996). However, the informed accompany this overall shift by placing more aggressive limit orders, which magnifies their contribution to price stability. The uninformed, by contrast, accompany this overall shift by placing fewer aggressive limit orders, which moderates their contribution to price stability. This contrasting treatment of aggressive limit orders has not, to our knowledge, been noted elsewhere in the literature.

To our knowledge, there are no other comprehensive empirical comparisons of the informed and the uninformed in limit order markets. Beber and Caglio (2005) examines the response of market-wide liquidity to a similarly wide range of market conditions, but does not distinguish informed from uninformed agents. Instead, that paper attempts to distinguish periods when informed trading is highly likely from other periods. Unfortunately, an analysis of market-wide patterns cannot identify differences between the informed and the uninformed. Anand *et al.*

(2005) does examine how order choice varies between informed and uninformed traders, but that paper focuses almost entirely on the influence of time *per se*. In that study of TORQ data from the NYSE, “institutional” traders are considered “informed” and others are considered uninformed. Anand *et al.* (2005) confirms Bloomfield *et al.*'s (2005) conclusion that the informed shift from market orders to limit orders over the course of the trading day, while the uninformed make the reverse shift.

Section I, which follows, describes the interdealer ruble market and presents our data. Section II explains our empirical methodology. Section III reports how overall market liquidity responds to market conditions and how it changes over the trading day. Section IV compares these same aspects of liquidity provision for the informed and the uninformed. Section V presents robustness tests and Section VI concludes.

I. Data and market structure

Our data represents the entire record of order placement and trading on the Moscow Interbank Currency Exchange, or MICEX.² The MICEX serves as the primary electronic interdealer market for the Russian ruble, which is otherwise traded by Russian banks on non-integrated regional exchanges.³ The market has pivotal importance for the ruble since it sets each day's official exchange rate and has a strong influence on the daily rates on each regional exchange. Our sample period spans the nine trading days from 11 through 21 March, 2002; during that time 26,859 orders were placed, of which 14,109 were market orders.

Our data include all orders, trades, and cancellations, regardless of size, an anonymous identifying tag for each individual trader, and that trader's location. The dataset's

² Goldberg and Tenorio (1997) analyze an earlier market structure of the MICEX.

³ The domestic market was segmented from foreign participation by trading restrictions. Foreigners could only trade rubles offshore as non-deliverable forwards.

comprehensiveness distinguishes it from other datasets examined in the literature. Most importantly, limit order-market datasets rarely include trader-specific identifying information.⁴ Many datasets truncate the limit order book (e.g., Hamao and Hasbrouck 1995, Biais *et al.* 1995) or exclude large orders (e.g., Griffiths *et al.* 2000), and many datasets do not identify the initiator of a trade. Because our data are so comprehensive, we can reconstruct the limit order book precisely, unlike most other studies.

The structure of the MICEX's electronic trading platform, known as SELT (System of Electronic Lot Trading) is fairly straightforward.⁵ Strict price-time priority applies; there are no hidden orders; limit orders can be placed at any level and can be canceled at will; trading is anonymous until after the transaction; all orders are automatically cancelled at the end of the trading day. Traders are informed of the best bid and best offer together with corresponding depth, as well as the price and quantity of the most recent trade.

Like some other markets, including the Stock Exchange of Hong Kong (Ahn *et al.* 2001) and Island (Hasbrouck and Saar 2004), the MICEX only permits limit orders. The absence of formal market orders is unlikely to have practical implications for liquidity provision, since traders can always place a marketable limit order – meaning, for example, a buy order with limit price above the prevailing ask. Since such orders will be immediately executed against the best ask quotes, they are functionally equivalent to market orders, at least for small orders. Accordingly, we follow Payne (2003) and Hasbrouck and Saar (2004) and use the term “market order” interchangeably with “marketable limit order”.⁶ The share of marketable limit orders on the

⁴ To our knowledge, only Keim and Madhavan (1995) has identifying information for individual traders.

⁵ SELT was developed in cooperation with Reuters, which also runs Reuters Matching, one of the dominant electronic interbank limit order markets for major currency pairs. The two markets are structured very similarly.

⁶ Market and marketable limit orders are equivalent for orders no bigger than the depth at the quote. For larger quantities, marketable limit orders limit the execution price at the cost of introducing uncertainty

MICEX, 47 percent, is roughly the same as the share of formal market orders in other markets, such as 44 percent in the TORQ data on NYSE trading (Bae *et al.* 2003).⁷

The MICEX displays many of the intraday patterns we now associate with limit order markets with fixed opening and closing times. For example, spreads and volatility follow a U-shaped pattern across the trading day, as shown in [Figure 1](#), and the U-shape for spreads is asymmetric, with spreads higher at the open than the close. Order placement on the MICEX is very high when the market opens, as shown in [Figure 2](#), as it is on the Paris Bourse (Biais *et al.* 1995), the NYSE (Bae *et al.* 2003), and the Saudi Stock Market (Al-Suhaibani and Kryzanowski 2000). On markets like the MICEX, which has no pre-opening session in which to place orders before trading begins, this is required for the market to function. [Figure 2](#) also shows that the size of the order book rises sharply at first, crests, and then declines slowly over the course of the day, an inverse U-shaped pattern similar to those documented for the interbank market in dollar-yen (Ito and Hashimoto 2004), and for active stocks on the NYSE (Lee 1993, Chung *et al.* 1999), the Paris Bourse (Biais *et al.* 1995), and the Stock Exchange of Hong Kong (Ahn *et al.* 2001).⁸

The mean transactions size in this market, \$50,000, is similar to the mean transaction size in other equity markets studied in the literature: the mean transaction size in the NYSE sample of Jones and Lipson (2003) is \$39,000. The average number of ruble trades per day on the MICEX, 1,568, exceeds the average number of trades for most assets traded on limit order markets. The average NYSE stock examined in Jones and Lipson (2003), for example, traded 1,465 times per day. The high level of ruble trading is especially notable since, during our sample period, the

about the quantity actually executed (Peterson and Sirri 2002). The use of market orders and marketable limit orders responds similarly to market conditions when both types are available (Ellul *et al.* 2005).

⁷ The share of market and/or marketable limit orders among all orders is 47 percent on the MICEX, 48 percent on the Stockholm Stock Exchange (Hollifield *et al.* 2004), 50 percent on the Paris Bourse (Biais *et al.* 1995), 50 percent on the Toronto Stock Exchange (Griffiths *et al.* 2000) and 46 percent in the SuperDOT data (Harris and Hasbrouck 1996).

⁸ We aggregate buy and sell orders because their placement patterns did not differ much, in contrast to placement patterns on for the Swiss Stock Exchange reported in Ranaldo (2004).

MICEX was open only one hour per day.⁹ It is also worth noting that, though the insights of Bloomfield *et al.* (2005) serve as critical benchmarks for our analysis, daily trading activity on the MICEX far exceeds the 55 trades per security observed in the experiments reported there.

II. Methodology

This section first describes our estimating strategy. It then explains how we distinguish the informed from the uninformed and how we measure market conditions.

A. Estimating strategy

To identify how order choice responds to market conditions we estimate an ordered logit model of order (price) aggressiveness. Ordered logit models provide more efficient parameter estimates than those provided by multinomial logit models because they exploit a natural ordering in the dependent variable (Griffiths *et al.* 2000 also employs ordered choice models). We use this approach since we focus on choice among orders at three increasing levels of price aggressiveness. These levels are:

- Level 1: “Patient limit orders”: Limit orders priced at the quotes or worse.
- Level 2: “Aggressive limit orders”: Limit orders priced within the quotes.
- Level 3: “Market orders”: Limit orders priced better than the opposite-side quote.

Our decision to disaggregate order choice into three categories seems sensible. Many studies of order choice focus only on the broad choice between market and limit orders (e.g., Handa and Schwartz 1996, Parlour 1998, Bae *et al.* 2003, Bloomfield *et al.* 2005). This is an important first step but it is fairly limiting. For example, it does not permit one to examine how

⁹ Though this is fewer hours than most well-studied markets stay open, it is far more hours than were observed for the experimental markets of Bloomfield *et al.* (2005). The market has since extended its trading hours.

spreads are determined over time. We join other researchers, including Biais *et al.* (1995), Griffiths *et al.* (2000), Goettler *et al.* (2005), and Ellul *et al.* (2005), in distinguishing aggressive limit orders, meaning those priced within the spread, from patient limit orders, meaning those priced at or behind the quotes.¹⁰ Aggressive limit orders represent 21 percent of all limit orders on the MICEX. This fraction varies widely across markets, though it is always below 50 percent: such orders represent only 6 percent of all limit orders on the NYSE (Beber and Caglio 2005), 29 percent Toronto Stock Exchange (Griffiths *et al.* 2000) and 42 percent on the Paris Bourse (Biais *et al.* 1995).

The ordered logit model is well-known (see Hausman *et al.* (1992) for an early application of ordered choice models to finance), so we briefly summarize the main building blocks. Each order placed represents one observation, which means we use transactions time rather than clock time. The dependent variable, Y_k , is an ordinal measure of order k 's aggressiveness: $Y_k \in \{1,2,3\}$.

We assume that the categories of Y_k represent segments of the continuous latent variable Y_k^* :

$$Y_k = \begin{cases} 1 & \text{if } Y_k^* \leq \gamma_1 \\ 2 & \text{if } \gamma_1 < Y_k^* \leq \gamma_2 \\ 3 & \text{if } \gamma_2 < Y_k^* \end{cases} \quad (1)$$

where γ_1 and γ_2 are scalar constants. We also assume that Y_k^* depends linearly on a vector of explanatory variables X_k : $Y_k^* = X_k' \beta + \varepsilon_k$. The individual elements of X_k are discussed below.

Assuming a logistic cumulative distribution function for ε_k , $L(\varepsilon_k) = \exp(\varepsilon_k) / (1 + \exp(\varepsilon_k))$, the

¹⁰ Biais *et al.* (1995), Griffiths *et al.* (2000), and Ellul *et al.* (2005) use finer disaggregations than our own. Since the ordinal ranking on the left-hand-side should continue to work if some adjacent categories are combined to form broader categories it seems unsurprising that our qualitative results for the entire sample line up closely with those of these other studies.

probability of observing an observed level of price aggressiveness will depend on two parameters, γ_1 and γ_2 , plus the β coefficients:

$$\begin{aligned}
 P(Y_k = 1 | \mathbf{X}, \boldsymbol{\gamma}, \boldsymbol{\beta}) &= L(\gamma_1 - \mathbf{X}'_k \boldsymbol{\beta}) \\
 P(Y_k = 2 | \mathbf{X}, \boldsymbol{\gamma}, \boldsymbol{\beta}) &= L(\gamma_2 - \mathbf{X}'_k \boldsymbol{\beta}) - L(\gamma_1 - \mathbf{X}'_k \boldsymbol{\beta}) \\
 P(Y_k = 3 | \mathbf{X}, \boldsymbol{\gamma}, \boldsymbol{\beta}) &= 1 - L(\gamma_2 - \mathbf{X}'_k \boldsymbol{\beta})
 \end{aligned} \tag{2}$$

We estimate γ_1 , γ_2 , and β via Maximum Likelihood (see Campbell *et al.* 1997 for details), employing bootstrapped t -values throughout.

We first estimate the parameters for the complete sample of orders, and then estimate them separately for orders placed by informed and uninformed traders. The seven conditioning variables are: the spread, volatility, depth on the same side, depth on the opposite side, momentum, trading volume, and time.¹¹ All variables are defined below.

B. Information

Our main proxy for the possession of information is a traders' location. The "informed" are taken to be the 461 traders from Russia's two financial centers: Moscow and St. Petersburg; the "uninformed" are taken to be the 261 traders from the exchange's six Periphery regions: Ekaterinburg, N. Novgorod, Novosibirsk, Rostov, Samara, and Vladivostock.

The use of location as a proxy for information is inspired by research showing that proximity to decision-makers has information value. The strongest evidence comes from equity markets. According to Hau (2001), equity traders from the financial center in Germany are more profitable than traders from peripheral cities in that country. Coval and Moskowitz (2001) shows that mutual funds earn abnormally high returns if they invest relatively heavily in firms located

¹¹ Keim and Madhavan (1995) include two other conditioning variables, order size and order direction, but neither is suggested by theory and neither is statistically significant.

near the funds' headquarters. Malloy (2005) reveals that equity analysts provide more accurate assessments if they are located near the firms they assess. Finally, Erenburg et al. (2005) find that local traders tend to react faster to macroeconomic announcements than others.

Evidence for the value of location in foreign exchange markets is less direct. Peiers (1997) shows that Deutsche Bank, the largest German bank, tended to lead the Deutsche mark around intervention episodes prior to the introduction of the euro, and Covrig and Melvin (2002) shows that Japanese traders tend to lead prices in the market for dollar-yen. More broadly, the best informed agents in foreign exchange markets appear to be large financial institutions and central banks (Lyons 2001, Marsh and O'Rourke 2005, Osler *et al.* 2006). In Russia, most such institutions are located in Moscow and St. Petersburg.

Taken as a whole, the evidence suggests that traders in Russia's financial centers might well be better informed than traders in the periphery. This idea gains direct support in a companion piece (Menkhoff and Schmeling 2007), which shows that trades carried out by MICEX dealers in the financial centers (henceforth "Center" traders) have a substantial permanent price impact while trades by those in the periphery cities (henceforth "Periphery" traders) have only a transitory price impact, even after controlling for trade size and trader size. This is true when Center traders provide liquidity through an aggressively priced limit order as well as when Center traders place market orders.

Since Center traders account for the bulk of trading on the MICEX, they might dominate market dynamics simply by virtue of their size. To test the reliability of our conclusions we also rely on a second proxy for information is trading activity, an approach motivated by the information structure of foreign exchange dealing. Research shows that customer order flow is a critical source of private information for foreign exchange dealers (this research is surveyed in Lyons 2001 and Osler 2006). Indeed, such information is so important that dealers seek to increase

their business with the customers that bring them the most information (Osler *et al.* 2006, Ramadorai 2006), and then exploit this private information when trading in the interdealer market (Bjønnes *et al.* 2007).

To construct this second proxy we rank traders by their total trading volume and then divide them into four groups that account for equal amounts of total trading. The 21 traders at the top of the ranking that together account for 25 percent of total trading volume comprise our second proxy for “informed” traders; the 546 traders at the bottom of the ranking that together account for 25 percent of total trading volume are used as our second proxy for “uninformed” traders.¹² Our qualitative conclusions are immune to whether we identify the informed by location or by trading activity.

The distribution of order submission activities for these groups of traders is provided in Table 1, Panel A. Traders in the financial centers of Moscow and St. Petersburg trade more frequently and submit larger quantities on average than traders in the periphery. Nonetheless, the two sets of proxies are quite different. The group of least active traders comprises 291 of the 461 Center traders and 255 of the 261 Periphery traders. The group of most active traders comprises 20 Center traders and one Periphery trader.

C. Market Conditions

Descriptive statistics for the market conditions on which we focus are provided in Table 2. Our variable definitions are consistent with standard practice in the literature (e.g., Hasbrouck and Saar 2004).

¹² We exclude the middle 50 percent so that these two sets of proxies are quite different: The group of smallest traders comprises 291 of the 461 Center traders and 255 of the 261 Periphery traders. The group of largest traders comprises 20 Center traders and one Periphery trader.

- *Spread* is measured as the absolute difference between the best bid and ask prices visible on the trading screen just prior to the submission of the order.
- *Volatility* is measured as the standard deviation of midquote changes over the 20 seconds prior to the submission of the order.¹³
- *Depth on the same side* is measured as the volume at the bid just prior to a buy order's submission and as the volume at the ask just prior to a sell order's submission, respectively.
- *Depth on the opposite side* is measured as the volume at the ask just prior to a buy order's submission and as the volume at the bid just prior to a sell order's submission, respectively. Note that depth on either side is, on average, over fifty percent larger than the average market order.
- *Momentum* is measured in terms of order flow. We cumulate signed transaction indicators over the 20 seconds just prior to the submission of an order, where positive (negative) transactions are triggered by market buy (sell) orders. We direction-adjust order flow by multiplying it by minus one if the current order is a sell order.
- *Trading volume* is measured as the cumulative trading volume – i.e. the total volume of market orders – over the 20 seconds just prior to the submission of an order.
- *Time* is measured as a linear trend of 60 trading minutes.

In Section III, which follows, we analyze order choice for the market as a whole by estimating equation (2) on our entire dataset. In Section IV we estimate equation (2) separately for the informed and the uninformed.

¹³ A similar measure is referred to as “transient volatility” in Ahn *et al.* (2001) and in Rinaldo (2004).

III. Market-wide dynamics of order-choice

In this section we investigate how market-wide liquidity on the MICEX responds to changing market conditions. Later we compare these results with those for informed and uninformed traders analyzed separately.

The results of estimating equation (2) on our entire dataset are presented in [Table 3](#), which reports estimated coefficients and marginal effects, measured as semi-elasticities, evaluated at sample means. Average trader responses to market conditions largely conform to predictions from theoretical models of order-choice dynamics and to existing empirical results.

Spread: A rise in spreads induces a modest shift towards limit orders (of any type) and away from market orders. This is consistent with behavior documented for other markets, including the Toronto Stock Exchange (Griffiths *et al.* 2000), the Vancouver Stock Exchange (Hollifield *et al.* 2004), the Swiss Stock Exchange (Rinaldo 2004), and the NYSE (Chung *et al.* 1999, Ellul *et al.* 2005). The response is also consistent with theoretical predictions in Handa and Schwartz (1996) and Goettler *et al.* (2005).¹⁴ Higher spreads make market orders more costly while increasing the potential gains from limit orders. The coefficient on spreads in our regression is not quite significant at the five percent level (p -value 0.067). We show later that the average effect mingles a strong response from the informed with a muted response from the uninformed.

Volatility: A rise in volatility, like a rise in spreads, induces MICEX traders to shift towards limit orders (of any type) and away from market orders. A similar response pattern has been identified for other markets including the NYSE (Bae *et al.* 2003, Chung *et al.* 1999), the Hong Kong Stock Market (Ahn *et al.* 2001), and the Swiss Stock Exchange (Rinaldo 2004).

¹⁴ The theoretical analysis of Foucault (1999) also finds a positive association between spreads and limit order trading, but that association applies to cross-sectional analysis rather than time-series analysis.

Theoretical predictions regarding the direction of this response vary according to the source of the volatility, the type of agents that dominate trading, and the specific model. In Handa and Schwartz (1996), a rise in volatility due to increased liquidity trading brings heavier reliance on limit orders among (patient) uninformed investors, due to the reduction in non-execution risk. A rise in volatility due to increased fundamentals-based trading, by contrast, induces this group to rely less on limit orders. Goettler *et al.* (2007) likewise finds a reduced reliance on limit orders in markets with higher fundamental volatility, as informed speculators use market orders to pick off stale limit orders. Foucault (1999), by contrast, finds a higher reliance on limit orders in markets with greater fundamental volatility. In his model anyone placing a limit order is effectively uninformed, and these agents insist on wider spreads to compensate for higher picking-off risk; this raises the cost of market orders, thereby leading those with information to rely more heavily on limit orders as well.

Depth, same side: When same-side depth rises, traders on the MICEX tend to shift towards market orders and away from patient limit orders. That means, for example, that higher buy-side depth increases the likelihood of market buy orders and reduces the likelihood of limit buy orders. This is predicted in Parlour (1998), based on a model where limit order placement is critically influenced by non-execution risk. This risk is low when same-side depth is low, which explains the inverse relationship between limit order placement and same-side depth. Similar empirical results are reported in Griffiths *et al.* (2000), Rinaldo (2004), and Beber and Caglio (2005).¹⁵

Depth, opposite side: Our estimates indicate that traders on the MICEX tend to shift away from market orders and towards limit orders (of both types) when depth is high on the opposite side of the order book. This, too, is predicted in Parlour (1998), where the pattern is explained in

¹⁵ Hasbrouck and Saar find that lower depth on the same side increases both market orders and regular limit orders, while “fleeting” limit orders decline. They attribute this to “correlated trading.”

terms of non-execution risk. If depth is high at the bid, the next buy order is relatively likely to be a market order, as explained above; this, in turn encourages limit sell orders by reducing their non-execution risk. This prediction is consistent with behavior on the Stock Exchange of Hong Kong (Ahn *et al.* 2001), the Toronto Stock Exchange (Griffiths *et al.* 2000), and the Swiss Stock Exchange (Ranaldo 2004), though it is not consistent with behavior on Island (Hasbrouck and Saar 2004). The pattern on Island may reflect the inverse relationship between opposite-side depth and the price impact of large market orders.

Momentum: The coefficient on signed order flow is positive and significant. This implies that after a sequence of, say, market buy orders, the next buy order is relatively likely to be a market order as well, while the next sell order is relatively likely to be a limit order. Similar effects have been documented for the Stock Exchange of Hong Kong (Ahn *et al.* 2001), the NYSE (Beber and Caglio 2005), and for Island (Hasbrouck and Saar 2004).¹⁶ Existing theory suggests that order choice could be influenced by order flow (Evans and Lyons 2004) and/or past returns (Brown and Jennings 1989), both of which can provide information about future prices. The known tendency for large orders to be split into many smaller transactions could also explain this result. If order flow has been positive, meaning market buy orders have been dominant, dealers might infer a relatively high likelihood of further positive order flow and associated price momentum. Dealers intending to buy should therefore increase the frequency of market orders and dealers intending to sell should increase the frequency of limit orders.

Trading volume: Trading volume, the last market condition we consider, proved insignificant in all our regressions. We include this variable because it has been significant in a few

¹⁶ This property may also characterize the NYSE, according to results presented in Ellul *et al.* (2005, Table 3), though the effect's statistical significance is not evaluated in the paper. Ranaldo (2004) shows that submission probabilities are sensitive to the market's direction, though those results cannot be directly compared with ours.

other studies, notably Hasbrouck and Saar (2004) and Chung *et al.* (1999). Since there is no strong theoretical motivation for its inclusion, its insignificance neither contradicts nor confirms existing limit order models.

Time: The positive and significant coefficient for time implies an overall shift towards market orders over the trading day, other things equal. The implied shift is modest: over the course of the trading day the coefficient implies a seven percentage point increase in the likelihood that an order is a patient limit order and a comparable decrease in the likelihood that it is a market order. Bloomfield *et al.* (2005) finds, in an experimental market, that the informed tend to shift from market orders to limit orders over the course of a trading session, while the uninformed make the opposite shift. The market's overall change, which is the net of these two shifts, could theoretically be either positive or negative but is unlikely to be dramatic, consistent with our results. Beber and Caglio (2005) shows, using TORQ data from 1990-1991, that trading on the NYSE shifted modestly towards market orders over the day during their sample period, consistent with the pattern we find here. However, Ellul *et al.* (2005) finds that the reverse was true in 2001: during their sample period trading on the NYSE shifted modestly towards limit orders over the day.

IV. Order choice of informed and uninformed traders

In this section we present the paper's main result, which is that the informed dominate the dynamics of liquidity provision. We also show that the informed treat aggressive limit orders differently than the uninformed, a difference that magnifies the relative importance of the informed for liquidity dynamics. The next section shows that the results are robust to many alternative specifications.

Table 4 presents the results of our baseline regressions, in which the ordered logit analysis described in Section II is carried out separately for the informed and the uninformed and in which

information is proxied by location. Panel A, on the left, provides the results for informed traders while Panel B, on the right, provides the results for uninformed traders. For each set of traders we provide regression coefficients plus marginal effects (which are again measured as semi-elasticities and calculated with all variables at their sample means). [Table 5](#), which reports results from the same regressions with information proxied by trading activity, shows that our proxy for information does not influence our qualitative conclusions.

A. The informed dominate liquidity dynamics

Our results indicate that the informed respond to spread, volatility, depth, and market momentum the same way the market does overall. That is, they shift towards limit orders in response to higher spreads, higher volatility, lower depth on the same side, and higher depth on the opposite side. They also shift towards limit buy orders when the market is falling and towards limit sells when the market is rising. As shown in Section III, above, these responses are consistent with the predictions of theory.¹⁷

Our results suggest that the uninformed respond to market conditions far less vigorously than the informed. It is not clear whether the uninformed respond at all to spreads and volatility: these variables only reach standard significance levels in one of the two sets of regressions. It is clear, however, that the uninformed respond much less than the informed to spreads and volatility, since the associated marginal effects of both variables are well below those estimated for the informed. It appears that the uninformed do not respond at all to depth. Same-side depth and

¹⁷ Theory gives mixed predictions about the response of traders to volatility. It might seem that the shift of informed traders towards limit orders in response to higher price volatility supports Foucault's (1999) theoretical conclusion that higher fundamental volatility brings an increased reliance on limit orders by the informed. However, our finding could equally well be consistent with Goettler *et al.*'s (2007) very different theoretical conclusion, because our empirical tests do not distinguish the underlying source of volatility shifts. If microstructure noise is the primary source of volatility shifts in our sample, then informed MICEX traders might reduce their use of limit orders in response to higher fundamental volatility but those shifts would not dominate our estimated coefficients.

opposite-side depth are both insignificant regardless of how we identify the uninformed. It is clear that the uninformed respond to order-flow momentum: this is the only market condition that consistently has a significant effect on their order choice. Nonetheless, it is again clear from the marginal effects that the uninformed respond to momentum far more weakly than the informed.

The contrast between the informed and the uninformed can be well illustrated by looking closely at volatility. Suppose volatility increases by one standard deviation from its unconditional mean of 0.63. If we use location as our proxy for information (Table 4), this raises the probability that an informed trader places a limit order (either patient or aggressive), conditional on their placing any order, by 11 percentage points from its unconditional mean of 53. For the uninformed, by contrast, it raises the conditional probability of a limit order by only 3 percentage points, from the unconditional mean of 46 percent. If we use trading activity as our proxy for information (Table 5), the contrast is more extreme. A one standard deviation rise in volatility is estimated to increase the probability that an informed trader places a limit order by 20 percentage points. For the uninformed, by contrast, the coefficient point estimates indicates this probability rises a mere 2.5 percentage points – but the point estimate itself is not significant at standard significance levels.

Few empirical studies of limit order markets distinguish the informed from the uninformed, so we can be brief in comparing these results with other empirical findings. Consistent with our results, Jones and Lipson (2003) finds that institutional traders on the NYSE – who are considered relatively informed – are sensitive to spreads while retail traders, who are considered uninformed, are not sensitive. Rinaldo (2004) shows traders placing large market orders are more sensitive to market conditions than those placing small market orders. This is consistent with our finding if order size is positively related to information content as suggested in Easley and O’Hara (1987) and Glosten (1989). However, when order splitting is common, as recommended in theory by

Bertsimas and Lo (1998), the relation between order size and information need not be monotonic. Chakravarty (2000) finds that medium-sized stock trades carry more information than either large or small trades. Thus the sensitivity of large orders to market conditions may be unrelated to information.

Are these results consistent with theory? Theory shows that a surge in volatility should increase the frequency of limit orders relative to market orders for informed traders, since higher volatility reduces non-execution risk (Handa and Schwartz 1996). While existing models do not allow a direct comparison of how the informed and uninformed will respond, existing theory can be interpreted to suggest that the response of the uninformed should be either muted or perhaps even reversed relative to the informed. A rise in spreads or volatility sometimes reflects transitory, non-fundamental influences, in which case the placement of limit orders is encouraged for all agents. At other times, however, a rise in spreads and volatility reflects a change in the market's underlying information structure such that each new bit of information moves the asset's true value more dramatically than before (Foucault 1999). For the uninformed, but not the informed, this brings higher picking-off risk which discourages limit order placement. The overall influence of spreads and volatility on limit order placement, which should be a weighted average of the two effects just noted influence and the informed are likely to respond more strongly than the informed.

Similar reasoning might also help explain why the response of the uninformed to order flow momentum is more muted than the response of the informed. A string of market buy orders and/or a sharp upward price movement could reflect transitory factors, in which case all sellers would be wise to place limit orders. Alternatively, these developments could reflect a change in the fundamental value of the asset, in which case the use of limit sell orders by the uninformed would

be discouraged by higher picking-off risk. This possibility could moderate the response of the uninformed, relative to the informed, to market momentum, consistent with our results.

B. The use of aggressive limit orders

The dominance of the informed in liquidity dynamics is reinforced by a striking difference between the informed and the uninformed in their use of aggressive limit orders. As revealed by the pattern of marginal effects, the informed treat aggressive limit orders as an alternative to market orders. By contrast, the uninformed treat such limit orders as an alternative to patient limit orders. This pattern holds consistently for every variable that is significant in both sets of regressions.

To illustrate this difference between the informed and the uninformed, [Figure 3](#) shows how the probability of submitting an aggressive limit order responds to volatility for a series of regressions that rolls through our sample of traders. Traders were ranked by trading activity, so the first regression includes only the largest traders and the last regression includes only the smallest traders. The traders in each regression sample account for twenty percent of total trading activity. The marginal effects are strongly positive for the large traders, decline fairly steadily as the firms' average trading activity declines, and are clearly negative for the small traders.

Existing theory says relatively little about the placement of aggressive limit orders and how it might differ between the informed and the uninformed. To our knowledge, the only theory to anticipate any part of this result comes from Harris (1998). That paper shows that if uninformed traders face a trading deadline they should place more aggressive limit orders as their deadline nears. The end of the day serves as a trading deadline for most interbank FX dealers, since they generally prefer not to carry inventory overnight (Bjønnes and Rime 2005). Combining Harris' insight with the shift by uninformed traders towards market orders documented in the experiments

of Bloomfield *et al.* (2005), one infers that we should also see an increase in the placement of aggressive limit orders over the day. Harris' work does not address the treatment of aggressive limit orders by informed traders.

The dominance of the informed over liquidity dynamics is magnified by this contrasting treatment of aggressive limit orders. To see why, consider how liquidity provision responds to a rise in spreads. When the informed provide more liquidity in the form of patient limit orders they also place more aggressive limit orders, which helps return the spread to its normal level. By contrast, when the uninformed place more patient limit orders they simultaneously place fewer aggressive limit orders, which mitigates their already-muted contribution to liquidity.¹⁸ Our results thus indicate that the informed stabilize spreads by shifting towards aggressively priced limit orders when spreads widen, while there is little or no change in the way the uninformed place aggressive limit orders. Ellul *et al.* (2005) find that the placement of aggressive limit orders on the NYSE increases after spreads widen: our results suggest that this could be due exclusively to the informed.

Handa and Schwartz (1996) discuss an “ecological” process, analyzed further in Bae *et al.* (2003), whereby volatility shocks induce endogenous shifts in order choice that help return volatility to normal levels. Our results suggest that this endogenous stabilizing response is dominated by the informed. A rise in volatility induces the informed to shift strongly towards limit orders, including aggressive orders, while the uninformed show a modest increase in their likelihood of placing patient limit orders but a reduced likelihood of placing aggressive limit orders.

¹⁸ Both of these outcomes are entirely reasonable, since aggressive orders represent an intermediate level of aggressiveness between two extremes.

Overall, these results extend our understanding of how informed traders contribute to liquidity by highlighting other dimensions of liquidity. Depth, the focus in both Bloomfield *et al.* (2005) and Goettler *et al.* (2007), is just one of three critical dimensions of liquidity. The other two are spreads and resiliency. Our results suggest that the informed dominate the dynamics of the second dimension, spreads. As discussed above, when spreads widen the informed switch from market orders to aggressive limit orders, thus bringing spreads back to normal levels. In our baseline analysis, a one standard deviation increase of the spread from its unconditional mean increases the conditional likelihood that an informed trader places an aggressive limit order by almost three percentage points – a large change relative to the unconditional likelihood of eleven percent. By contrast, the uninformed do not change their placement of aggressive limit orders at all.

It is tempting to interpret this result, which concerns spreads, in terms of resiliency, or the speed with which prices return to their efficient level after a liquidity shock. Indeed, resiliency is sometimes redefined as the speed with which spreads revert to normal after a series of market orders or alternatively “the probability that enough limit orders will arrive to return the book to the minimum bid-ask spread before the next transaction” (Parlour and Seppi 2007, p. 14). According to this definition, our result does imply that the informed contribute most to resiliency.¹⁹ We do not stress this interpretation, however, because it assumes a fixed efficient price. In reality spreads could conceivably revert quickly to normal after a shock while the mid-quote remains away from its fundamental value.

¹⁹ Foucault *et al.* (2005) shows that resiliency increases with the share of patient traders. Ideally, there would be a clear mapping between their patient traders and our informed traders, but we have not yet found one.

V. Robustness

This section shows that our results are robust to modifications of our empirical methodology. First we first define some of the variables differently, to enhance comparability with a few earlier studies. Then we consider whether our results are sustained when we permit autocorrelation of order type in the regressions. Finally, we report results from two additional sensitivity analyses: one uses multinomial logit regressions rather than ordered logit regressions; the other uses one regression with interaction terms rather than separate regressions for the informed and uninformed.

Three of our variables could arguably be defined differently, so we examined whether the results were sensitive to these definitions. In specification (I), volatility is measured as the high-low range over the preceding 20 seconds (Bae *et al.* 2003 also uses this measure). In specification (II), signed order-flow momentum is replaced by signed price momentum, following Hasbrouck and Saar (2004), measured here as the cumulative (direction-adjusted) log midquote change over the 20 seconds just prior to the submission of an order. In specification (III), time enters as a set of dummy variables for the six ten-minute intervals of the trading hour, rather than as a linear trend. [Table 6](#) shows the results when these definitions are applied to all traders together. [Table 7](#) shows the results when the definitions are applied to informed and uninformed traders separately, with information proxied by the Center-Periphery distinction.²⁰ These alternative variable definitions do not suggest any changes in our qualitative conclusions.²¹

The empirical analysis of Biais *et al.* (1995) suggests that our overall specification might be improved by including a lagged dependent variable, as in Griffiths *et al.* (2000) or Ellul *et al.*

²⁰ In unreported regressions we apply these redefinitions with information proxied by trading activity, as in Table 5. The results are not qualitatively changed.

²¹ In unreported regressions we (i) measure volatility as the sum of absolute midquote returns over the preceding 20 seconds and (ii and iii) measure the conditioning variables over the 40 or 60 seconds prior to an order's submission. These regressions have no relevant effect on our qualitative conclusions. Results of these robustness tests are available from the authors on request.

(2005). We use the Biais approach, in which the lagged variable is coded one if the last order was a market order of the same direction as the present order, all other cases are coded as zero. The intuition is thus related to the idea of a market momentum, however, we include the lagged variable in addition to momentum. Results in Table 8 show the lagged variable has the expected effect and is highly significant. Nonetheless, our main qualitative conclusions are again essentially unchanged.

For comparison with Griffiths *et al.* (2000) and Hasbrouck and Saar (2004), we carried out regressions using multinomial logit rather than the ordered logit. In those cases there is no natural ordering, due to the inclusion of cancellations or fleeting orders, so the multinomial logit is necessary. In our case the natural ordering is readily apparent and there is a loss of efficiency if it is ignored. The multinomial approach does not produce different results, except for reduced explanatory power due to the loss of information (results available upon request).

For completeness we conducted the analysis for both information proxies using a single regression in which differences across trader types were identified via interaction terms. The results, available upon request, are quite similar to those reported in the text, both qualitatively and numerically. This consistency is notable for the trading activity proxy, since the single-regression approach involves all trades while the multiple-regression approach involved only trades by the most active and least active traders.

VI. Conclusion

Research on limit order markets has shown that it was too simplistic to assume, as researchers did initially, that informed traders place only market orders and uninformed place only limit orders. Indeed, it now appears that the informed may place more limit orders, on average, than the uninformed (Bloomfield *et al.* 2005). Our paper moves beyond this static analysis to consider the

dynamics of liquidity provision by informed and uninformed agents, analysis of which has been impeded at the theoretical level by the inherent complexity of limit order markets. We therefore provide a purely empirical analysis, focusing on the interdealer market for rubles. Unlike most earlier studies of limit order markets, our data include trader identifying information that permits us to determine which traders are likely to be informed.

Our main conclusion is that informed traders dominate the market's overall response to changing market conditions. The uninformed are either insensitive to certain market conditions and respond in a more muted fashion than the informed to other market conditions. A secondary conclusion is that the informed and uninformed treat aggressive limit orders quite differently, and this difference magnifies the dominance of the informed over liquidity dynamics.

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Figure 1. Intraday patterns in spreads and volatility

The bars show average percentage spreads, the line shows average volatility, for the twelve successive time intervals that jointly comprise each daily trading session for the MICEX, Moscow Interbank Currency Exchange, which serves as the Russia-wide electronic order book for interdealer trading in rubles. Data cover the nine trading days from 11 through 21 March, 2002, a period with 26,859 orders and 14,109 trades and include all orders placed and all trades. Volatility is measured as the standard deviation of midquote changes.

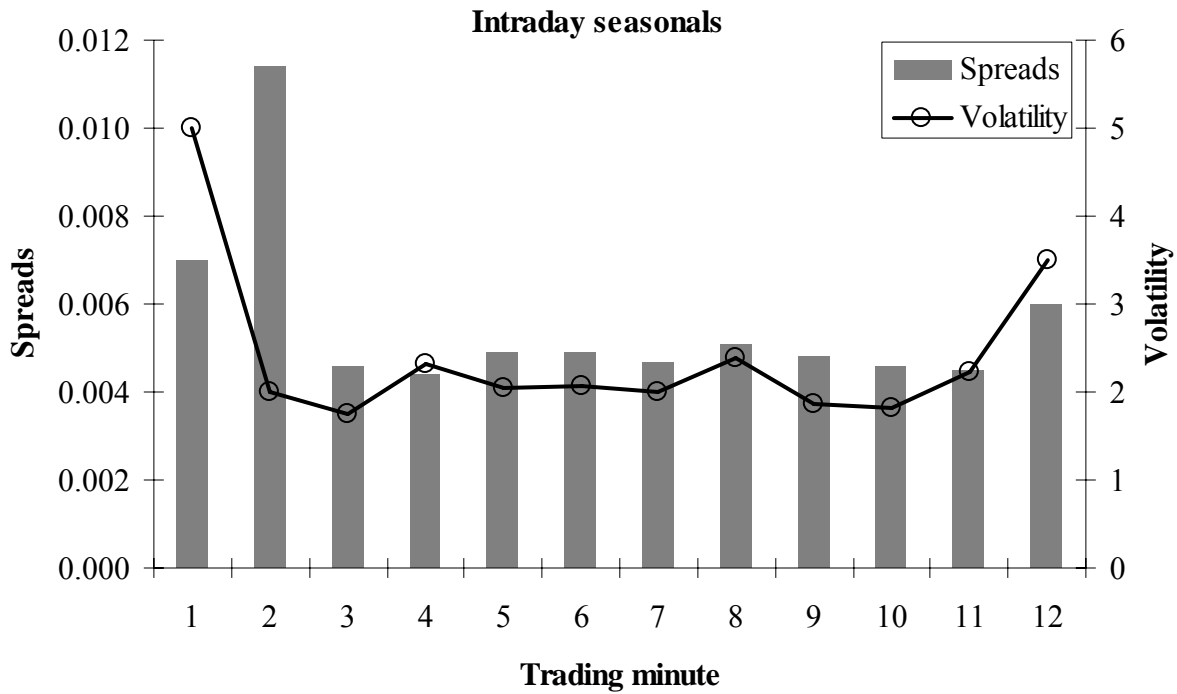


Figure 2. Intraday inflow of orders and order-book size

The smooth line shows the number of orders outstanding (right axis) and the marked line shows the share of limit order placement (left axis) across the twelve successive time intervals that jointly comprise each daily trading session for the MICEX, Moscow Interbank Currency Exchange. This is the Russia-wide electronic order book for interdealer trading in rubles. Data cover the nine trading days from 11 through 21 March, 2002, a period with 26,859 orders and 14,109 trades and include all orders placed and all trades. The pattern is unchanged if the value of orders is used rather than their number.

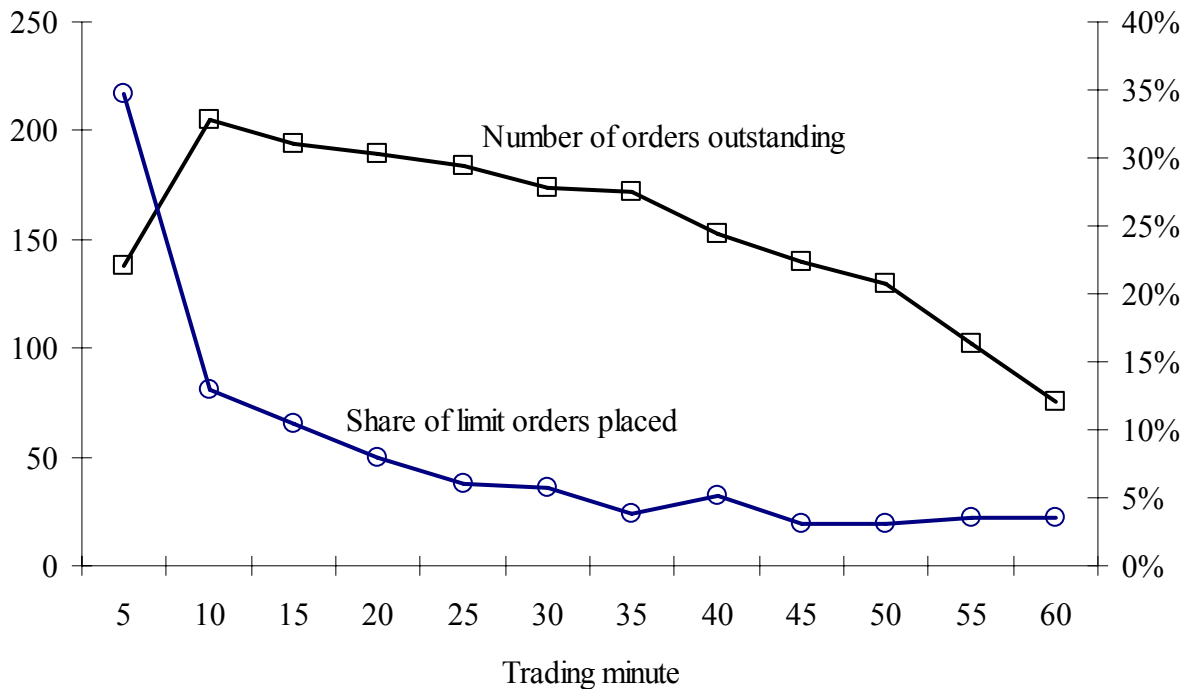


Figure 3. Effects of volatility on aggressive limit order submission

The chart shows the estimated marginal effect of volatility, with 90 percent confidence intervals, on the submission of aggressive limit orders for groups of traders representing twenty percent of total trading volume. Traders are ranked from largest to smallest.

Effects on the left side correspond to the largest traders; effects on the right side correspond to the smallest traders.

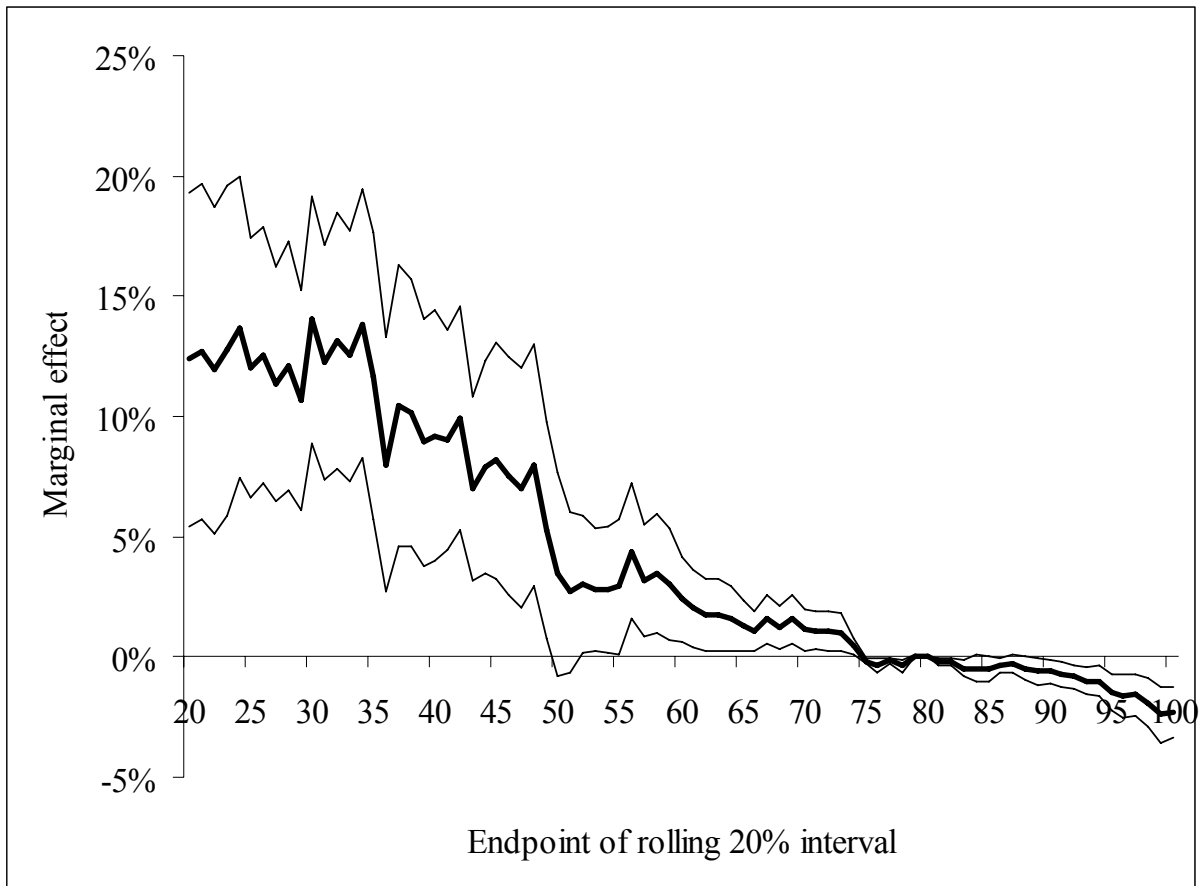


Table 1. Descriptive statistics of order submissions

This table shows descriptive statistics for the distribution of market orders, aggressive orders and patient orders on the Moscow Interbank Currency Exchange (MICEX). This is the Russia-wide electronic order book for interdealer trading in rubles. Data cover the nine trading days from 11 through 21 March, 2002, a period with 26,859 orders and 14,109 trades and include all orders placed and all trades. All figures are calculated on a per trader basis. Value is measured in millions of US dollars.

	All traders	Center	Periphery	Largest	Smallest
Number of traders	722	461	261	21	546
<i>Order Value</i>					
Market Orders	697	568	129	116	138
Aggressive Orders	256	202	54	32	72
Patient Orders	1377	1120	257	233	323
<i>Order Number</i>					
Market Orders	14,109	10,476	3,633	1,993	5,290
Aggressive Orders	3,397	2,072	1,325	256	1,957
Patient Orders	12,562	7,611	4,951	626	7,289

Table 2. Descriptive statistics for conditioning variables

Data represent all orders and trades on the Moscow Interbank Currency Exchange (MICEX), the Russia-wide electronic order book for interdealer trading in rubles, over the nine trading days from 11 through 21 March, 2002. Data cover a period with 26,859 orders and 14,109 trades.

	Mean	5	25	Percentiles			Std. dev.	Skewness	Kurtosis
				50	75	95			
Spread (percentage)	0.0057	0.0016	0.0019	0.0052	0.0068	0.0113	0.0074%	7.853	112.328
Volatility	0.633	0.000	0.184	0.363	0.634	1.263	1.258	8.664	105.220
Depth same side	127,802	1,000	3,000	25,000	95,000	385,000	248,289	2.623	9.080
Depth opposite side	124,020	1,000	4,000	25,000	100,000	385,000	238,432	2.704	9.726
Momentum	1.271	-13.000	-3.000	1.000	6.000	12.000	9.964	0.068	6.119
Trading volume	66.036	0.000	0.500	9.040	80.680	197.854	113.381	2.619	11.016
Time (trading minute)	19.526	2.000	7.000	15.000	31.000	47.000	16.575	0.840	2.546

Table 3. Order choice

Table presents ordered logit estimates of the determinants of market-wide order choice. Dependent variable is an index of order aggressiveness, with 1 corresponding to patient limit orders, 2 corresponding to aggressive limit orders, and 3 corresponding to market orders. Spread and depth variables are measured immediately prior to an order's placement. Volatility, trading volume, and momentum are measured over the twenty seconds prior to an order's placement. Data represent all orders and trades on the Moscow Interbank Currency Exchange (MICEX), the Russia-wide electronic order book for interdealer trading in rubles. Data, which cover the nine trading days from 11 through 21 March, 2002, include 26,859 orders and 14,109 trades. (Figures in square brackets are *t*-statistics; * indicates significance at the 10 percent level; ** indicates significance at the 5 percent level; *** indicates significance at the 1 percent level.)

	Coefficient	Marginal Effects (semi-elasticity)		
		Patient	Aggressive	Market
Spread	-0.001 *[-1.81]	0.43%	0.01%	-0.44%
Volatility	-0.102 ***[-6.74]	1.56%	0.05%	-1.61%
Depth, Same Side	0.154 ***[3.13]	-0.48%	-0.02%	0.49%
Depth, Other Side	-0.124 ***[-2.42]	0.37%	0.01%	-0.39%
Momentum	0.040 ***[30.67]	-1.31%	-0.05%	1.36%
Trading Volume	-0.088 [0.76]	0.13%	0.00%	-0.13%
Time	0.002 ***[3.27]	-1.21%	-0.04%	1.25%
LR χ^2	1255.81 ***(0.00)	Unconditional Probabilities		
Pseudo R ²	0.024	47.61%	11.79%	40.60%
Obs.	26,859			

Table 4. Order choice, informed and uninformed traders, information proxied by location

Table presents ordered logit estimates of the determinants of market-wide order choice. Dependent variable is an index of order aggressiveness, with 1 corresponding to patient limit orders, 2 corresponding to aggressive limit orders, and 3 corresponding to market orders. Spread and depth variables are measured immediately prior to an order's placement. Volatility, trading volume, and momentum are measured over the twenty seconds prior to an order's placement. Data represent all orders and trades on the Moscow Interbank Currency Exchange (MICEX), the Russia-wide electronic order book for interdealer trading in rubles. Data, which cover the nine trading days from 11 through 21 March, 2002, include 26,859 orders and 14,109 trades. Information is proxied by the traders' location: Traders located in the financial centers of Moscow and St. Petersburg are assumed to be informed, others are assumed to be uninformed. (Figures in square brackets are *t*-statistics; * indicates significance at the 10 percent level; ** indicates significance at the 5 percent level; *** indicates significance at the 1 percent level.)

	A: Informed/Financial Center				B: Uninformed/Periphery			
	Coefficient	Marginal Effects			Coefficient	Marginal Effects		
		Patient	Aggress.	Market		Patient	Aggress.	Market
Spread	-0.003 **[-2.96]	0.85	0.07	-0.91	0.001 [0.17]	-0.07	0.00	0.07
Volatility	-0.120 **[-6.10]	1.69	0.14	-1.83	-0.057 **[-2.48]	0.96	-0.07	-0.89
Depth, Same Side	0.140 **[2.29]	-0.42	-0.03	0.45	0.151 *[1.75]	-0.46	0.03	0.43
Depth, Other Side	-0.141 **[-2.15]	0.39	0.03	-0.43	0.009 [0.11]	-0.03	0.00	0.03
Momentum	0.048 **[29.19]	-2.02	-0.16	2.18	0.019 **[8.49]	-0.19	0.01	0.18
Trading Volume	-0.102 [-0.72]	0.15	0.01	-0.16	0.020 [0.10]	-0.03	0.00	0.03
Time	-0.001 **[-2.56]	0.40	0.03	-0.43	0.010 **[7.54]	-5.00	0.36	4.64
LR χ^2	1158.14 *** (0.00)	Unconditional Probabilities			156.59 *** (0.00)	Unconditional Probabilities		
Pseudo R ²	0.034	35.95	10.81%	53.24%	0.010	49.65%	13.71%	36.64%
Obs.	18,026				8,833			

Table 5. Order choice, informed and uninformed traders, information proxied by trading activity

Table presents ordered logit estimates of the determinants of market-wide order choice. Dependent variable is an index of order aggressiveness, with 1 corresponding to patient limit orders, 2 corresponding to aggressive limit orders, and 3 corresponding to market orders. Spread and depth variables are measured immediately prior to an order's placement. Volatility, trading volume, and momentum are measured over the twenty seconds prior to an order's placement. Data represent all orders and trades on the Moscow Interbank Currency Exchange (MICEX), the Russia-wide electronic order book for interdealer trading in rubles. Data, which cover the nine trading days from 11 through 21 March, 2002, include 26,859 orders and 14,109 trades. Information is proxied by trading activity: Traders are ranked by trading activity. Those with the most activity who are jointly responsible for one quarter of trading activity are taken to be informed; those with the least trading activity who are jointly responsible for one quarter of trading activity are taken to be uninformed. (Figures in square brackets are *t*-statistics; * indicates significance at the 10 percent level; ** indicates significance at the 5 percent level; *** indicates significance at the 1 percent level.)

	A: Informed/Most Active Quartile				B: Uninformed/Least Active Quartile			
	Coefficient	Marginal Effects			Coefficient	Marginal Effects		
		Patient	Aggress.	Market		Patient	Aggress.	Market
Spread	-1.150 ***[-3.47]	2.34	0.52	-2.86	-0.003 ***[-2.59]	1.05	-0.00	-1.05
Volatility	-0.183 ***[-2.65]	1.90	0.42	-2.32	-0.042 *[-1.75]	0.68	-0.01	-0.67
Depth, Same Side	0.500 ***[3.15]	-1.58	-0.35	1.93	0.114 [1.31]	-0.34	0.01	0.35
Depth, Other Side	-0.635 ***[-3.44]	1.45	0.32	-1.77	-0.108 [-1.22]	0.34	-0.01	-0.33
Momentum	0.066 ***[13.52]	-4.05	-0.90	4.95	0.019 ***[8.39]	-0.14	0.01	0.15
Trading Volume	-0.258 [-0.67]	0.30	0.07	-0.37	-0.085 [-0.43]	0.14	-0.00	-0.14
Time	-0.007 ***[-2.20]	2.30	0.51	-2.81	0.003 **[1.97]	-1.31	0.01	1.30
LR χ^2	336.94 ***(0.00)	Unconditional Probabilities			117.58 ***(0.00)	Unconditional Probabilities		
Pseudo R ²	0.08	24.56%	10.30%	65.14%	0.01	45.07%	11.16%	43.77%
Obs.	2,725				12,817			

Table 6. Robustness tests for all traders

This table shows ordered logit estimation results for all traders as in Table 3 where some explanatory variables are replaced, one at a time. The “high-low range” is measured over the preceding 20 seconds just prior to an order; “price momentum” is the cumulative change in midquote returns over the preceding 20 seconds; the “time” rows represent time dummies that are equal to one, when an order falls in the respective interval. All other variables and notations are the same as in table 3.

	(I)	(II)	(III)
Spread	-0.002 ***[-2.90]	-0.000 [-0.55]	-0.002 **[-2.02]
Volatility		-0.116 ***[7.15]	-0.101 ***[-6.68]
High-Low Range	-0.111 ***[5.66]		
Depth, Same Side	0.154 ***[3.12]	0.157 ***[3.23]	0.159 ***[3.20]
Depth, Other Side	-0.125 **[2.44]	-0.097 *[-1.96]	-0.118 **[-2.28]
Momentum	0.040 ***[30.81]		0.041 ***[30.80]
Price Momentum		0.143 ***[8.05]	
Trading Volume	-0.108 [-0.94]	-0.100 [-0.75]	-0.094 [-0.61]
Time	0.002 **[2.45]	0.003 ***[3.34]	
Time 1-10			-0.238 ***[-4.78]
Time 11-20			-0.130 **[-2.53]
Time 21-30			-0.260 ***[-4.72]
Time 31-40			-0.137 **[-2.34]
Time 41-50			-0.211 ***[-3.46]
LR χ^2	1240.41 ***(0.00)	292.36 ***(0.00)	1281.44 ***(0.00)
Pseudo R ²	0.02	0.01	0.02
Obs.	26,859	26,859	26,859

Table 7. Robustness tests for center and periphery traders

This table shows ordered logit estimation results for traders from financial centers and the periphery as in Table 4 where some explanatory variables are replaced, one at a time. The “high-low range” is measured over the preceding 20 seconds just prior to an order, “price momentum” is the cumulative change in midquote returns over the preceding 20 seconds and the “time” rows represent time dummies that are equal to one, when an order falls in the respective interval. All other variables and notations are the same as in Table 4.

	Informed / Financial Center			Uninformed / Periphery		
	(I)	(II)	(III)	(I)	(II)	(III)
Spread	-0.04 ***[4.14]	-0.001 **[1.97]	-0.003 ***[-2.66]	-0.000 [-0.02]	0.000 [0.14]	-0.001 [-0.74]
Volatility		-0.151 ***[6.97]	-0.113 ***[-5.83]		-0.051 **[-2.19]	-0.061 ***[-2.61]
High-Low range	-0.120 ***[4.84]			-0.073 *[-2.31]		
Depth, Same Side	0.139 *[2.28]	0.143 **[2.39]	0.129 **[2.10]	0.151 [1.75]	0.152 *[1.77]	0.170 **[1.97]
Depth, Other Side	-0.141 **[-2.15]	-0.122 **[1.98]	-0.143 **[-2.18]	0.008 [0.10]	0.039 [0.46]	0.030 [0.35]
Momentum	0.048 ***[29.36]		0.048 ***[29.17]	0.019 **[8.51]		0.020 ***[8.90]
Price Momentum		0.188 ***[7.85]			0.057 **[2.13]	
Trading Volume	-0.129 [-0.91]	-0.097 [-1.01]	-0.087 [-0.36]	0.054 [0.07]	0.052 [0.33]	-0.041 [-0.06]
Time	-0.002 *[-1.99]	-0.001 [-0.86]		0.009 **[7.09]	0.10 ***[7.73]	
Time 1-10			-0.001 [-0.02]			-0.738 ***[-8.80]
Time 11-20			0.111 *[1.73]			-0.624 ***[-7.25]
Time 21-30			0.069 [1.00]			-0.974 ***[-10.32]
Time 31-40			0.081 *[1.74]			-0.632 ***[-6.30]
Time 41-50			-0.099 *[-1.91]			-0.420 ***[-4.17]
LR χ^2	1142.64 ***(0.00)	260.21 ***(0.00)	1173.91 ***(0.00)	166.73 **(0.00)	97.36 ***(0.00)	234.98 ***(0.00)
Pseudo R ²	0.03	0.02	0.04	0.01	0.01	0.01
Obs.	18,035	18,026	18,035	8,840	8,833	8,833

Table 8. Lagged aggressiveness

This table shows results from ordered logit estimates for all traders, financial center traders, periphery traders, the quartile of most active traders and the quartile of least active traders. All explanatory variables and notations are identical to those used in Tables 3 through 5, except for an additional explanatory variable “Last Aggressive”. This dummy variable equals one when the last order just was a market order with the same direction as the current order.

	All traders	Informed/ Center	Uninformed/ Periphery	Informed/ Most active	Uninformed/ Least active
Last	2.132	2.210	1.821	2.486	1.63
Aggressive	***[67.33]	***[56.03]	***[33.49]	***[24.56]	***[35.29]
Spread	-0.003	-0.005	-0.001	-0.003	-0.003
	***[-4.05]	***[-4.74]	[-0.62]	**[2.10]	**[-2.20]
Volatility	-0.056	-0.069	-0.032	-0.117	-0.059
	***[-3.62]	***[-3.42]	[-1.39]	**[-2.19]	*[-1.81]
Depth, Same	0.083	0.051	0.122	0.393	-0.125
Side	[1.56]	[0.77]	[1.34]	**[0.023]	[-1.58]
Depth, Other	-0.046	-0.105	0.104	-0.392	0.153
Side	[-0.83]	*[-1.89]	[1.17]	**[-2.08]	*[1.83]
Momentum	0.024	0.029	0.013	0.046	0.014
	***[17.64]	***[16.39]	***[5.54]	***[10.07]	***[6.90]
Trading	-0.031	-0.049	-0.044	-0.071	-0.321
Volume	[-0.20]	[-0.08]	[-0.04]	[-0.40]	**[-1.99]
Time	0.004	-0.002	0.008	-0.005	0.005
	***[4.27]	*[-1.91]	***[5.88]	**[-2.32]	***[4.34]
LR χ^2	6768.83	5060.02	1430.65	1194.81	1599.72
	***(0.00)	***(0.00)	***(0.00)	***(0.00)	***(0.00)
Pseudo R ²	0.13	0.15	0.08	0.21	0.07
Obs.	26,859	18,026	8,833	2,725	12,817