Informed Trading in Limit Order Markets: Evidence on Trinary Order Choice

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Abstract:

This study employs a unique data set from a pure limit order currency market which shows typical microstructural patterns. We distinguish between two types of limit orders. Screen orders are priced to show up on every dealers trading screen immediately, whereas ordinary limit orders are priced to line up invisibly in the order book. This decomposition allows us to identify different roots of endogenous liquidity provision: informed traders supply liquidity by means of speculative trading via screen orders and by spread trading via ordinary limit orders. The former turn out to have significant price impact similar to that of market orders. This suggests an extension of qualitative order choice to a trinary choice. Due to their informational advantage, informed traders also help to maintain liquidity in times of higher volatility. Thus limit orders and in particular screen orders are a pivotal point in understanding information processing and liquidity provision in currency markets.

JEL-Classification: G12, G15, D82, F31
Keywords: Market microstructure, limit orders, market orders, informed traders

August 18, 2005

We would like to thank the German Research Foundation (Deutsche Forschungsgemeinschaft DFG) for financial support. We gratefully acknowledge research assistance by Leila Gadijeva.

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1 Introduction

Limit order markets have become more important over time, an issue being addressed at an early juncture by Glosten (1994). In the case of some financial markets, their structure has completely changed during the last ten years or so. Take for example the largest financial market by volume – the US dollar-euro-market: here the dominance of direct interbank trades and (voice) brokered trades has faded and electronic limit order markets have gained the biggest market share.[1] As we know that market structure can determine market outcome, one cannot simply transfer the knowledge gained in dealership markets to the new world of limit order markets. Recent research has, indeed, shown that earlier insights may not hold any longer for pure limit order markets (see for example Bloomfield, O'Hara and Saar, 2005). Due to a new data set being available here we are able to analyze a limit order market in a very comprehensive manner. Inspired by Hasbrouck and Saar (2004) we find that the traditional distinction into market and limit orders may usefully be extended into a trinary order choice, reflecting the particular role that aggressive limit orders – we call them screen orders – play. Examining the issues of price impact and liquidity provision by informed traders, we do not only reveal screen orders to be particularly important. More generally, we provide evidence that several particularities associated with limit order markets documented in the recent literature all hold at the same time and for one market.

The traditional view of order choice, information processing and liquidity provision states – somewhat oversimplified – that informed (impatient) traders use market orders to capitalize on their private information and thereby consume liquidity. In contrast, uninformed (patient) traders produce liquidity by means of limit orders. We realize that many studies are nagging at the generality of these simple relations and refer to some studies in the next section. Nevertheless, the traditional view still serves as an analytical reference point which can be contrasted with very recent insights for limit order markets: Hasbrouck and Saar (2004) state that the group of limit orders is not necessarily homogeneous but that limit orders are used for different reasons in

the trading process. We apply this insight to our data and split the group of limit orders into ordinary limit and screen orders. Screen orders are priced aggressively so that they are displayed on the trading screen of all dealers in the market immediately. They represent a general form of order aggressiveness which is also studied by e.g. Goettler, Parlour and Rajan (2004), or Hollifield, Miller, Sandås (2004). Ordinary limit orders are priced to line up in the order book without being noticed by the market. As can be expected, we find that screen orders are filled to a high degree and very fast compared to ordinary limit orders due to their superior pricing. We argue that screen orders serve economic functions in between the categories of market and (ordinary) limit orders. Consequently, traders' qualitative order choice is not between two but between three kinds of order types. For this reason it may be called a trinary choice.

This new differentiation already indicates that the role of market and limit orders may be not as clearcut as seen by the traditional view. Detailed experimental studies by Bloomfield, O'Hara and Saar (2004) – in the following short: BOS – have shown that informed traders heavily use limit orders too. It follows that limit orders may transport information. Kaniel and Liu (2004) have explicitly analyzed this presumption and find that limit orders in total, by informed and uninformed traders as well, are helpful to predict future prices and are thus informative. We directly conduct conventional price impact analyses and confirm their finding for informed traders' (market and) limit orders. Disaggregating limit orders, information is mainly conveyed by screen orders. This is our first main finding and underscores the idea that screen orders are used for different purposes than ordinary limit orders. It also implies that speculation and liquidity supply need not be antithetic processes in limit order markets.

Due to the new role of limit orders in general and of screen orders in particular, we investigate whether the experimental findings of BOS hold in a real world limit order market. It is our second main finding that we can largely reproduce BOS' results: the behavior of informed and uninformed traders with respect to liquidity provision over time is significantly different, reflecting their asymmetric endowment with information.

Furthermore, our analysis confirms results from theoretical models on the relation of volatility and liquidity provision and shows that informed traders supply even

[1] Ito and Hashimoto (2004) for example report a share of 90% for electronically brokered trades for Japan in 2001. In 1998 this figure was just 36% and in 1995 an even more mar-

more liquidity when uncertainty in the market is high. Again it turns out that screen and ordinary limit are used differently in times of changing market volatility and that screen orders behave similar to market orders. The results make up our third main finding and strongly suggest that informational asymmetries benefit the provision of liquidity and help to maintain it in times of higher uncertainty.

Finally, we examine limit orders in a currency market, which has not been done before. As results fit well into the general literature on limit order markets, this study complements earlier studies that are based on stock or bond market data. It also suggests that limit orders should not be neglected in microstructure work on foreign exchange.

This study relies on a new data set that provides comprehensive information about trading on the electronic Russian rouble-US dollar market. This currency market is organized around an electronic limit order book and descriptive statistics reveal the well-known intraday patterns almost universally found for financial markets. The data base provides similar microstructure information on each single transaction in the market as the popular TORQ data base on trading in the NYSE does.[2] In particular, we are able to investigate the complete electronic market without missing orders or incomplete identifications. Furthermore, all events in the dataset can unambiguously be assigned to order types and order cancellations as well as initiating parties and counterparties. Finally, our data allow the attribution of all events to specific trader groups that differ in their likely endowment with information.

This paper continues with a literature overview in Section 2. A description of the market structure under consideration, data and descriptive statistics are provided in Section 3. Section 4 analyzes price impacts of different order types. Endogenous liquidity provision is investigated in Section 5. Section 6 concludes.

2 Previous studies

The question whether informed traders would prefer limit or market orders was often answered in favor of market orders in the earlier literature. It is argued that the benefit of direct execution would outweigh the disadvantage of paying a spread. By contrast, liquidity traders were assumed to be more patient in waiting for an opportu-

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ginal 12% for spot trades (see BIS, 1999, p.15).

[2] Applications of the TORQ data include among others Harris and Hasbrouck (1996), Dufour and Engle (2000), Bae, Jang and Park (2003), Anand, Chakravarty and Martell (2004), and Kaniel and Liu (2004).

nity to trade at a better price (e.g. Rock, 1990, Glosten, 1994, Seppi, 1997). There are further studies, however, modeling the use of limit orders by informed traders (e.g. Kumar and Seppi, 1994, Chakravarty and Holden, 1995, Kaniel and Liu, 2004).[3] Thus, one may conclude that order choice is not exclusively dependent on the degree of an agent's information – informed or uninformed – but may be influenced by other determinants as well. According to arguments put forward limit orders are more often used by informed traders when prices are further away from fundamentals (Angel, 1994, Harris, 1998), when transitory volatility is higher (Handa and Schwartz, 1996) and when private information is long-lived (Kaniel and Liu, 2004).

Empirical work has also underlined the existence and some conditions for the use of limit orders by informed traders. Keim and Madhavan (1995) were among the first to show that informed traders may rely heavily on limit orders. Biais, Hillion and Spatt (1995) find that large limit orders are placed at prices indicating that these orders are used by informed traders. Subsequent work found that market conditions play a role for order choice and that higher volatility and wider spreads attract more limit orders (Handa and Schwartz, 1996, Chung, Van Ness and Van Ness, 1999, Ahn, Bae and Chan, 2001, Bae, Jang and Park, 2003). However, a rigorous examination of how informed versus uninformed traders behave under different conditions is impeded by data availability.

A seminal paper in this respect is the experimental study of BOS, who investigate the role of informed and uninformed traders in completely order driven markets. Due to the experimental approach they can precisely control for the degree of information each trader possesses. Another methodological advantage is that they literally cover the whole market for a specific asset and the whole population of traders operating in it. Their study provides strong evidence that informed traders actively use limit orders, that this use is time-varying and that it depends on several market conditions. Thus, in purely order driven markets, liquidity emerges endogenously from the changing behavior and interaction of informed and uninformed market participants.

Other recent studies analyze the behavior of informed traders in equity markets by drawing on the TORQ data base. Kaniel and Liu (2004) find that informed traders prefer limit to market orders and that limit orders are indeed informative for future

[3] Studies modelling the analogous decision for *uninformed* traders are provided for example by Parlour (1998), Foucault (1999) and Foucault, Kadan and Kandel (2002).

price movements. Anand, Chakravarty and Martell (2004) also observe that informed traders use market orders more often in the first half of the trading day. However, compared to the clear-cut evidence from the BOS study, the earlier evidence is hampered by some data limitations and the fact that the NYSE is not an entirely order driven market like the one in the experimental setting. It rather operates with specialists whose presence is hard to reconcile with the study of endogenous liquidity supply. On the other hand, data for equity markets organized solely around electronic order books like the Paris Bourse (Biais, Hillion and Spatt, 1995) or the Stockholm Stock Exchange (Sandås, 2001, and Hollifield, Miller and Sandås, 2004) do not feature traders' identities.

A recent study by Hasbrouck and Saar (2004) concentrates on different forms of limit orders and their economic implications. They find so called "fleeting orders", i.e. limit orders that are cancelled within two seconds after submission, to be different from other limit orders and provide strong evidence that they serve to search for immediacy in different trading venues. This further questions the traditional view that limit orders only serve to provide liquidity. Rather, fleeting orders are closer substitutes to market orders.

Taken together, there is a new strand of literature on electronic limit order books that does not take traditional roles of order types and trader groups as given but examines how their respective roles change in pure electronic markets. While Hasbrouck and Saar (2004) analyze different types of limit orders, Kaniel and Liu (2004) examine the price impact of limit orders and BOS focus on the role of informed traders in providing liquidity. We contribute to the literature by examining linkages between these three issues and show several interrelations between types of (limit) orders, information aggregation and liquidity provision.

3 Market structure, data, and descriptive statistics

3.1 Market structure and dealing system

The institutional structure of the Russian electronic FX interbank market is quite typical for a modern electronic market. Although volumes are low compared to the leading currencies in the world,[4] a very similar market structure and behavior seems to allow transfer of insights to other electronic currency and security markets.

[4] Trading in the Russian rouble (RUR) has a tiny but steadily increasing share of total turnover which amounts to 0.4% of total world currency trading volume (BIS, 2002, Table E.1.1).

The market is organized as a multiple dealer market without designated market makers or brokers as currency markets used to be organized until some years ago (see Evans, 2002). In our electronic market, only dealers located at one of the market's participating banks may trade so that we observe interbank trades only. Much of this trade is clearly driven by customer orders that are executed by the trading banks. We do not, however, have any information about the motivation of trading but just observe the interbank market transactions.

The inter-dealer RUR/USD market we consider is based at the MICEX in Moscow and plays a key role in Russia, since the official exchange rate to the US dollar is determined exclusively in this trading session.[5] This means that the rouble price per unit USD that results from trading at the MICEX serves as the official country-wide rate to convert rouble into dollar. For this reason the country-wide trading at the MICEX we deal with is officially called the "unified trading session" (UTS).

During the time we consider in March 2002, trading took place only one hour a day from 10.30 to 11.30 Moscow time and the only instrument traded was the spot exchange rate. Nowadays, trading is prolonged to four hours per day and dealing also takes place in other instruments such as forwards.

Furthermore, there are eight regional currency exchanges based in the capitals of certain regions which also trade RUR/USD.[6] These regional exchanges were opened up to five hours (e.g. 9.30-13.30 at the Moscow local exchange) a day in 2002. However, dealing at the regional exchanges occurs among local bank dealers only.

Trading in the UTS takes place on the electronic system SELT that is very similar to the systems introduced by Reuters or the EBS consortium, which are widely used in major currency markets. SELT features only two order types, namely limit orders and cancellation orders. A limit order is an order to buy or sell a quantified US dollar volume to a pre-specified price or better, i.e. higher for selling and lower for buying orders. Submitted limit orders are stored in an electronic order book that has clear priority rules. Marketable limit orders are executed immediately against the best price available. If several limit orders on the same side of the book share an identical limit price, the earlier submitted limit order is executed. Cancellation orders may be used to cancel existing limit orders that have not yet been executed. Trading takes

[5] The MICEX is also the main Russian exchange for all kinds of financial assets such as equities and bonds.

place anonymously, i.e. the details of a direct transaction are reported only to the participating traders. However, the trading screen displays the cumulated buy and sell volume for the actual trading session and the last traded price and thus allows market participants to infer the volume and direction of the last trade(s).

One particular characteristic of SELT is the non-existence of "pure" market orders. Unlike in other electronic trading systems, where direct market orders are to be executed immediately against the best available prices, traders wishing to buy or sell immediately in SELT have to submit a limit order that crosses the best available price. In the following analysis we refer to all crossing limit orders that are submitted directly at the best limit price as market orders to distinguish them from limit orders submitted at a price that does not immediately execute them.[7] Likewise, we use the terms marketable limit orders, crossing limit orders and market orders interchangeably.

Several other features of SELT are worth mentioning. As is the case for the trading systems EBS or Reuters, only the best bid and offer price plus respective volumes are displayed on the trading screen. For this case we distinguish between ordinary limit orders that line up in the order book and aggressively priced limit orders. The latter are placed within the prevailing spread and are thus directly visible on everybody's trading screen. Consequently, we term them "screen orders". Limit orders that are not priced to improve the spread are termed ordinary limit orders.

3.2 Data

The analysis below employs a unique dataset collected at the Russian FX interdealer market for RUR/USD over nine days in March 2002 which provides comprehensive microstructure information.

First, our data provide information on an important share of country-wide interbank dealing each day. Except for the minor volume traded at the regional exchanges these data give a clear picture of trading activity in the RUR/USD. Since the official rate is determined in UTS each day, the local exchanges stick to this rate very closely.

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[6] The regions and some of their important characteristics are detailed in Section 2.3.

[7] Hasbrouck and Saar (2004) analyze a similar trading system and use the same classification. Payne (2003, p.312) also classifies crossing limit-orders as market orders, though the trading system Reuters D2000-2 analyzed there contains a pure "market order" type.

Second, our data mirror the complete trading activity of this market, including all entered and deleted limit orders as well as market orders and a timestamp with a one second accuracy. Furthermore, we have the size of each trade. The initiator of a deal, i.e. whether it is buyer or seller initiated, is easily but exactly recovered from the data, so that we do not need to use a classification algorithm.

Last, but most important, we also have coded identities for each event in our data set. This permits us to recover which regional exchange a trader is located at and it allows us to group traders by the regions they work at. In the case of executed trades we have this information both for initiators and counterparties. This is a major vehicle for our analyses below. This information is, to the best of our knowledge, unique for an electronic currency market.

From the raw data we construct an event time data set that contains the mid-quote, a signed transaction indicator, signed transaction volume, the inside spread, aggregate buy and sell volume queued in the order book, the number of buy and sell limit orders outstanding and several measures of entered limit order flows which we detail later. Furthermore, we also construct the same series sampled at the one minute frequency to eliminate some of the microstructure noise.

However, a disadvantage of our data set is that we cannot construct precise inventories for our traders since we do not have information about any of their customer trades.

3.3 Descriptive statistics

Overall, our full data set spans 15 trading days in March 2002. For the following analysis we focus on nine trading days only, namely March 11 to March 21. The reason is that the Russian Central Bank heavily intervenes on the remaining days and significantly influences the exchange rate. This can easily be seen in Figure 1, which plots the RUR/USD spot rate over the 15 trading days. Central bank activity is shaded in gray. The figure shows that the central bank pins down the spot rate in the first five days so that there is almost no intraday variation in prices. For the sake of brevity we do not present further results relating to the central bank's activity here, but it turns out that their trading also markedly changes the way the other dealers trade. Since this paper is not dealing with this issue we drop all days shaded gray in Figure 1 from the sample.

In the remaining sample of nine days, the market is populated by 722 traders who produce 38,442 observations, made up by 15,959 limit order entries, 8374 order deletions and 14,109 market orders. Total trading volume amounts to almost 700 mill. USD, i.e. about 78 mill. USD per day, with an average market order size of about 50,000 USD. The market volume at the electronic exchange makes up roughly 5 per cent of daily spot interbank trading in Russia, assuming that this trading is basically a RUR/USD trading (see BIS, 2002, Table E.1.2). Considering, however, that total trading is distributed over eight more exchanges over five hours each plus some direct interbank trading, there is no other place and time of more intense rouble trading than the one hour UTS. Most importantly, the fixing of the official exchange rate in the UTS guarantees this market to be of the highest relevance to all Russian market participants. Accordingly, interventions of the central bank take place in this market, which underscores its importance.

Below, we present descriptive statistics for our data set in more detail. We use this to give an impression of the trading activity and to compare our market with major electronic markets, such as the Reuters data set on DEM/USD trading analyzed by Payne (2003).

Table 1, Panel A presents descriptive statistics on the evolution of the order book and order size over the UTS for non-overlapping five minute intervals. It can be seen that our market broadly follows the well-known intraday activity patterns. As measured by ask and bid orders outstanding we have an inverted U-shaped pattern although it is less pronounced for volume outstanding (see Figure 2). This should be due to the fact that our market does not trade continuously but only for one hour per day so that customer orders pile up until market opening. When the market opens the order book fills very quickly within the first minute to a high level of volume on both sides of the book. It seems to be a consequence that some activity figures, such as volume traded (i.e. the sum of market orders in an interval), tend to fall over time. The same was found for electronic currency markets in Tokyo operating on EBS (Ito and Hashimoto, 2004). Despite this fact, the spread shows the expected U-shaped pattern.

Panel B of Table 1 shows return statistics for midquote changes, also calculated over five minute intervals. We find the typical unconditional means of nearly zero for midquote returns and a strong and significant autocorrelation in first moments. The variance is highest at the beginning and at the end of the UTS, which gives rise to

the typical intraday pattern in return volatility. As can be expected midquote returns are also heavily fat-tailed. Lastly, midquote return residual variance is serially correlated.

All in all, intraday dynamics follow diurnality patterns that are well in line with previous studies concerning electronic order markets in currency (see e.g. Payne, 2003) and stock markets (see e.g. Chung, van Ness and van Ness, 1999). The main difference is the comparatively lower volume, both in trade and order book size, which corresponds with the smaller Russian economy.[8] While e.g. Payne (2003) finds a mean transaction size of roughly 1.7 mill. USD in the DEM/USD market we have an average order size of 0.05 mill. USD. It seems noteworthy from this perspective that the median of quoted spreads amounts to about 10.0 pips. Given an average midquote of about 31 RUR/USD the percentage spread is low when compared to other foreign exchange markets.[9]

3.4 Informed and uninformed traders

Next, we focus on the different traders in our dataset. Many studies that are interested in information differences have to rely on ex post identification, so that trades are classified as informed that have been identified through some sort of data-based algorithm (see for example Beber and Caglio, 2004). We are able, by contrast, to exploit an ex ante characteristic of our data, i.e. their regional affiliation. This classification is truly exogenous and not based on outcomes of the trading process we are investigating below.

We present financial and economic characteristics of the eight regions differentiated by Russian statistics in Table 2. All data used in this table come from the "Analytical System of Economic Activities" provided by the Russian central bank. Russia's financial, political and economic centers are Moskow and St. Petersburg. As can be seen from Table 2, Moscow has the highest number of, the largest and most profitable, banks in the country. Moreover, Moscow also takes the lead in international orientation, as its banks have the highest customer foreign currency account volume in absolute and relative terms. St. Petersburg ranks second in all of these categories in Russia. In contrast to these financial indicators, industrial production as a proxy of

[8] Russian GDP was 345.6 bn. USD in 2002, and 10400 bn. USD for the United States. Thus, Russia's economy was one thirtieth the size of the latter.
[9] Interbank spread in the most liquid USD/EUR market is 1 or 2 pips but this has to be put in relation to an exchange rate of about 1. From this perspective, the Russian spread is low.

economic activity is much more evenly distributed among the eight regions. Thus, Moscow and St. Petersburg significantly outweigh all other six regions in absolute financial size, in financial outward orientation and in further ratios indicating a financial center.

If there is any private information concerning exchange rates in Russia it will be concentrated in the two financial centers.[10] Of course, there will be liquidity traders in the financial centers and possibly informed traders in the peripheral regions, too, which makes our measure of the degree of information imprecise. As a consequence, we cannot expect such clear-cut results as BOS found in an experimental situation. If, however, our necessarily imprecise distinction between informed and uninformed traders yields a plausible outcome, the result seems to be even more credible.

To underline the findings from the above regional characteristics statistically, we investigate the information share of both trader groups for price discovery (see Hasbrouck, 1995 and Hasbrouck and Seppi, 2001).[11] To do this we construct two time series of midquotes. The first series is made up by the midquotes of informed dealers from Moscow and St. Petersburg. They are calculated by considering only those limit orders in the order book which were placed by informed traders. The second series is the obvious equivalent for uninformed traders This yields two midquote series that are cointegrated with the CI vector $\beta = [1 \ \ -1]$ and which can be used to calculate upper and lower bounds for the information shares of each respective trader group with respect to price discovery in our market. We only give a brief overview of the procedure (for details, see Hasbrouck, 1995). The dynamics of the two cointegrated price series may be written via their common trends representation as

$$\mathbf{p_k} = \mathbf{p_0} + \boldsymbol{\psi}\left(\sum_{\mathbf{s}=1}^{\mathbf{k}} \mathbf{e_s}\right)\boldsymbol{\iota} + \tilde{\boldsymbol{\Psi}}(\mathbf{L})\mathbf{e_k} \qquad (1)$$

where $\mathbf{p_k}$ denotes the (2x1) vector of midquotes, $\mathbf{p_0}$ is a constant vector, the term in brackets is the common stochastic trend with (1x2) adjustment vector $\boldsymbol{\psi}$, $\boldsymbol{\iota}$ is a vector

[10] It seems plausible ex ante that information on financial prices is concentrated in financial centers. This relation is supported by some studies in foreign exchange finding that financial customer orders are informative in contrast to orders from commercial customers (Lyons, 2001, Mende, Menkhoff and Osler, 2004).

[11] Here and for the rest of the paper we estimate dynamic models by treating overnight observations as missing. This is common practice and prevents the assumption that the information set of traders is constant overnight.

of ones and $\tilde{\Psi}$ is polynomial in the lag operator. The increment $\boldsymbol{\psi e_k}$ is permanently incorporated in midquotes and hence presumably due to new information. Since both midquote series are cointegrated, they share the same long-run impact of news shocks. If we denote the covariance matrix of **e** by **Ω** then the variance of this term is **ψΩψ'**. Thus the total variance of a news-related shock can be broken down by the increments of the two midquote series. Furthermore, if **Ω** is not diagonal, a cholesky factorization of **Ω** and its permutation can be used to obtain upper and lower bounds for the respective share of price discovery.

We apply this procedure to the midquotes of both trader groups in event time to assess the relative importance of midquote changes in each of the series for long-run price discovery. The results are clear und statistically underscore our argumentation based on the ex ante regional characteristics. A DF-GLS test for the null of a unit root in each series (with automatic lag length selection via the SIC) cannot be rejected at any convenient significance level. As measured over the whole nine trading days, the group of informed dealers contributes at least 76.61% to price discovery whereas uninformed traders contribute at most 23.39% depending on the cholesky ordering.[12]

As a final prerequisite for the following analysis we provide details about the trading behavior of informed and uninformed investors in Table 3 where we calculate average volumes for each of the three order types and trading profits. According to Easley and O'Hara (1987) one may expect that informed trade is related to larger order size. Indeed, we reveal this pattern for all three order types.[13] Informed traders from the two Russian financial power houses trade and submit higher volumes as measured per trader over the nine trading days and per event in the data set.

Moreover, one would expect that better informed traders earn higher profits. Due to our data, however, profit calculation has three limitations: first, information is restricted to earnings and not to costs, second, we do not know inventories and, third, we only know the interbanking leg of transactions but have no information about the customer leg. So calculations are indicative but not fully revealing. Assuming that trading banks would keep eventual inventories arising from trading at the UTS until the next day, we calculate the profit figures in Table 3. Despite limitations

[12] We do not report results for cointegration tests and VECM parameter estimates since they are not informative in themselves for the point we want to make here. However, results are available from the authors upon request.

[13] We also find these results separately for Moscow and St. Petersburg based traders but do not present them here for the sake of brevity.

of measurement, the relative higher profitability of informed versus uninformed traders is obvious and robust towards some modifications.

Ordinary limit orders and screen orders are also different in terms of their fill rates. Whereas screen orders are filled by about 75%, only 45% of ordinary limit orders are filled. However, informed traders' orders have only slightly higher fill rates. The remaining orders are mostly cancelled. This is the first qualitative evidence that screen orders may be quite different from ordinary limit orders. The risk of non-execution is much lower, which has to be compensated by paying a price that is less favorable compared to ordinary limit orders but still better than that of a market order. We will investigate this in more detail in the following sections.

Table 3 also shows, contrary to traditional microstructure theory, that informed traders extensively use limit orders and, that uninformed traders make heavy use of market orders. Furthermore, about one quarter of limit orders are priced aggressively. These screen orders are particularly interesting since we find them to have much higher fill rates. The traditional argument against the use of limit orders by informed traders, is the fact that their execution is not guaranteed. So why should informed traders risk non-execution when they are able to capitalize on their information via market orders? A natural answer is that limit orders are cheaper. Accordingly, it is intuitive to assume that informed traders use screen orders to improve their probability of execution while avoiding payment of the full market spread.

To underscore this idea let us look at the speed of order execution in Figure 3 that shows survival probabilities of screen and ordinary limit orders that are executed or cancelled for both investor groups. The figure has a clear and expected message: screen orders are executed faster than ordinary limit orders. Screen orders that are not executed are cancelled faster than ordinary limit orders that are not executed. To take a concrete example, look at the survival probability of executed screen orders. Only 40% of informed traders' screen orders survive ten seconds after submission. For uninformed traders the corresponding probability is somewhat higher and about 45%, again implying that informed traders are better able to place their orders. Moreover, this shows that using limit orders for speculative, informed trading is not necessarily very risky. The trade-off between the certainty of execution and costs can be largely controlled in limit order markets by pricing limit orders accordingly.

Survival probabilities for cancelled orders are shown in Figure 3. It is obvious that screen orders are not the same as the fleeting orders analyzed in Hasbrouck

and Saar (2004), who also focus on aggressively priced orders. The cancellation of our orders is rather sluggish and not extremely fast as in their market. Since the employed trading technology is very similar in both markets, it seems as if market fragmentation is the driving force behind this difference as hypothesized by the authors (p. 29).[14]

4 Price impact of different order types

According to standard theory, market orders are used to take advantage of better information before others detect and exploit the same information. Thus, market orders should have a price impact whereas limit orders have not. However, recent literature points to limit orders as a trading vehicle of informed traders, too. In this line, Kaniel and Liu (2004) present a Glosten-Milgrom type model to analyze which order mix is chosen by informed traders in equilibrium. They show that these traders may prefer limit orders and that in some settings limit orders can be even more informative than market orders. The critical variable driving this decision in their model is the horizon of the private information they want to exploit. An empirical investigation of their model using the TORQ data base yields the conclusion that limit orders are indeed more informative than market orders.

In line with the extensive use of limit orders by informed traders documented in the last subsection we further find that screen orders are informative and thus impact prices. This has important implications for market design. Orders that have long-run price impacts are commonly thought of as being information based. Hence, we show that liquidity supply and speculation are not necessarily antithetic in limit order books.

4.1 Econometric methodology

To measure the long-run impact of market and limit order flow shocks on spot rates we use vector autoregressions.[15] This flexible class of time series models has been successfully applied to several microstructure settings. These include, among others, Hasbrouck (1991a, 1991b) for equities, Payne (2003) and Froot and Ramadorai (2002) for foreign exchange markets and Brandt and Kavajecz (2004) for bond markets. Chordia, Sarkar and Subrahmanyam (2004) also use VARs to analyze

[14] Hasbrouck and Saar (2004) analyze a market structure that rests on several electronic trading venues whereas our market is the only electronic device to trade this asset, at least at the time and the time zone under investigation.
[15] A comprehensive introduction to this method is given in Hamilton (1994).

cross-market liquidity dynamics between bond and stock markets. While Hasbrouck (1991a, 1991b) and Payne (2003) employ a specialized version of a standard VAR to adopt it to the transaction level, Brandt and Kavajecz (2004) use a restricted VAR in the sense that they regress bond yields on past common factors to get a more parsimonious structure and to save degrees of freedom. Our approach is quite common, employs a VAR without a priori parameter restrictions and is thus similar to that of Froot and Ramadorai (2002) and Chordia, Sarkar and Subrahmanyam (2004).

Our VAR differs from the method introduced by Hasbrouck (1991a, 1991b), who directly links order flow to midquote returns and thus measures the impact of a single trade on the subsequent midquote adjustment. The reason for this is our interest in the relative price impact of several order flow measures for two different groups of traders as well as their contemporaneous and dynamic correlations. In this setting a structural model in the sense of Hasbrouck (1991a, 1991b) would require strong a priori assumptions about the causal relationships between different types of order flows of informed and uninformed traders. Since virtually nothing is known about such causalities we do not want to impose them here.

Moreover, we opt to minimize the exposure to noise in our data and to stay consistent with the lower sampling frequencies employed in the following sections by aggregating our tick-by-tick data into one-minute intervals.[16]

Since we are interested in price impacts of both screen and market orders and the interrelations of different order types we construct order flow variables for both order types. In the case of screen orders, a bid is coded as plus one whereas ask side orders are coded as minus one. Market order flow is measured the standard way: buyer initiated trades occurring at the ask are coded as plus one whereas seller initiated trades occurring at the bid are coded as minus one.

We employ the following five variables in our VAR: the midquote return in percent (r), market order flow of informed dealers (x^i), screen order flow of informed dealers (s^i), market order flow of uninformed dealers (x^u) and aggressive limit order flow of uninformed dealers (s^u).

Estimation proceeds via OLS and we compute standard errors for the impulse response functions via 300 bootstrap replications and by delta method. As the results do not lead to different conclusions we report the usual linearized standard errors.

[16] All of the results described below are qualitatively unchanged if we redo the analysis on tick-by-tick data anyway.

Furthermore, we use the following Cholesky ordering: x^i - s^i - x^u - s^u - r. This ordering, especially placing r in the last position is motivated by economic reasons since trades or aggressive order submissions naturally cause midquote revisions in event time. The causality of order flow for price changes on lower frequencies has also been demonstrated by Evans and Lyons (2002). Moreover, we will explicitly test for Granger causality in the next subsection.[17] Long-run price impacts of market and aggressive limit order shocks are measured by cumulated impulse-responses which we truncate after ten minutes.

4.2 Estimation results

Our results confirm that screen orders of informed traders have a significant and permanent price impact which is robust to several specifications and varying market conditions.[18] Reassuringly, market and screen orders of uninformed traders have no significant price impact and seem to largely follow informed traders' orders.

Exact results of the estimation are shown in Table 4. Uninformed traders' flow shocks have significant long-run price impacts for both order types neither in the full sample nor in several sub-samples sorted by time of the trading session. Informed traders' flows - both screen and market orders – exhibit highly significant impacts on midquote returns that are roughly equal in size. This is our first main finding. The similarity of price impacts remains unchanged over the three first quarters of the trading session but changes remarkably for the last quarter. Here, the price impact of market orders vanishes, whereas aggressively priced limit orders are still highly significant and of much larger size.

How can these findings be interpreted? First, the fact that both order types are informative for future price movements underscores recent findings in the literature (e.g. Kaniel and Liu, 2004) that at least certain limit orders carry information for future price movements. Second, our first main finding that both order types have almost equally sized price impacts strengthens the finding of Hasbrouck and Saar (2004) that certain kinds of limit orders are closer substitutes to market orders than to traditional, liquidity supplying limit orders. Third, the price impact of informed traders' mar-

[17] Permutating the first four elements of the chosen cholesky ordering does not qualitatively change any of the results shown below.

[18] Pooling all limit orders regardless of the price they are submitted also leads to a statistically significant price impact for informed traders. However, the price impact almost com-

ket orders declines over time. This again is ample evidence supporting BOS' experimental finding with real world trading data. BOS argue that informed agents capitalize on their information by market orders early in the day and use limit orders afterwards. Our findings imply that this is indeed true but additionally suggest that certain types of limit orders, here screen orders, are information based and used throughout the whole trading session for informed trading. Thus, we are able to show that speculative trading is not necessarily consuming liquidity. Rather, these results reveal that informed trading may take place in a way that supplies liquidity and instantaneously lowers the prevailing spread.

Another striking result of our VAR analysis is shown in the last two columns of Table 5. These report responses of uninformed flows to informed flows, where we restrict our attention to flows of the same type, i.e. the response of uninformed market order flow (screen order flow) to informed market order flow (screen order flow). Clearly, there can be no long-run effects in these responses, so we investigate the short run dynamics only and present two minute flow impulse responses for convenience. As measured over the whole trading period there is a significantly positive relation between informed order flow shocks and subsequent order flows of uninformed traders for both order types. However, this relationship does not turn out to be statistically significant for all of the four sub-periods of the trading session although all responses are positive.

Tests for Granger Causality (block exogeneity) can be found in Table 5, Panel A. They statistically justify our choice of the cholesky ordering since they reveal that both screen and market order flow Granger cause midquote returns. Furthermore, informed screen order flow also Granger causes informed market order flow. What fits neatly into this picture is that informed flows taken together explain more than 35% of midquote return variance (Panel B). Flows from uninformed traders only contribute a meager 3.5%.[19] Panel C finally shows contemporaneous residual correlation coefficients. These show that all shocks to the system are positively correlated and that correlation is highest for shocks to midquote returns and informed traders' flows.

This positive correlation also gives credence to our former result that uninformed traders learn from informed order flows and that this result is not simply driven by inventory adjustments. The fact that informed traders' order flows lead the

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pletely vanishes if we exclude the aggressively priced screen orders and work with the remaining ordinary limit orders.

flows of uninformed traders in the following minutes would only be explained by inventory adjustments in a situation where informed and uninformed traders contemporaneously trade in opposite directions. However, since innovations to their order flows are positively correlated, both groups tend to buy and sell at the same time so that inventory adjustment fails to explain this result. This finding further supports theoretical predictions by Mendelson and Tunca (2004), who model a market with endogenous liquidity trading and find that liquidity traders benefit from the information acquisition of informed traders since they can infer information from their trading activity. Even though the adverse selection component of the spread rises with higher asymmetric information in the market, welfare of the uninformed traders can still be higher since only a trader with superior information will supply liquidity and is paid for this by his trading profits. This argumentation fits neatly into our analysis.

4.3 Price impacts and market conditions

To check our results for robustness and plausibility, we also run VARs on several sub-samples not sorted by time but by other variables reflecting certain market conditions typically found to be important in microstructure analysis. All variables used for sorting are detrended to eliminate typical intraday patterns and thus to rule out the indirect influence of time.[20] Figure 4 plots price impacts of informed traders sorted by high and low trading volume (TV), order book volume (BV) and spreads, respectively. We use transacted volume as a proxy for market activity, order book volume as a measure of market liquidity and spreads to reflect the degree of asymmetric information. Sub-samples of low and high values are created by splitting the whole sample along the median of the detrended sorting variable.

As can be seen from Figure 4, price impacts for both market and screen orders vary markedly in the sub-samples. Again, screen and market orders' price impacts vary in the same direction, which underscores the idea that both are close substitutes. The findings also serve to test several microstructure theories and to check earlier empirical findings. Figure 4 shows that price impacts for both flow measures

[19] These relations change only marginally when we alter the cholesky ordering.
[20] Specifically, we regress each of the sorting variables on 60 time dummies representing the minute of the trading session each. We then use the fitted values of this regression as the typical intraday pattern and divide the actual observations by the fitted value of the corresponding minute. We run this procedure on our tick-by-tick data set and aggregate to the one-minute interval used here afterwards.

are rising functions of spreads and trading volume and that they are negatively related to liquidity supply. This deserves some discussion.

First, consider price impacts and trading activity. Our results are consistent with the empirical findings of Dufour and Engle (2000), that market activity boosts the size of quote revisions. They also confirm the theory of Foster and Viswanathan (1990), who model high volume as a result of informed trading, which deters the uninformed from trading.[21] Moreover, this finding is also in line with the "Mixture of Distribution Hypothesis" (Clark, 1973) which posits that trading volume and return variance are both driven by an unobservable factor related to news diffusion. Second, the positive relation between spreads and price impacts seems logical since spreads are commonly thought to compensate for asymmetric information risk. Spreads should thus positively correlate with information arrival and, in view of the argumentation above, with market volume. Table 1 reveals that this is indeed the case. Information arrival then implies higher price impacts. Lastly, higher liquidity supply as measured by the size of the order book decreases the price impact of informed traders. A plausible argument for this is as follows. In a market without a market maker, within which spread trading serves to earn market maker profits, low liquidity is most plausibly seen to correspond with uncertainty about the true fundamental price. Thus, low outstanding limit order volume leads to higher price impacts of informed traders since uninformed agents should rely more heavily on observed flows to update their belief on the fundamental value of the traded asset.

As a last robustness check we split our sample along two dimensions, namely transacted volume and outstanding order book volume to assess interrelations between market activity and liquidity. Again we use medians to distinguish between states of high and low realizations of the detrended sorting variable. The VAR is estimated for each of the so constructed four sub-samples and results are depicted in Figure 5.

Conditional on both market activity and liquidity, we again find that low trading volume is associated with low price impacts for both order types. However, transacted volume seems to dominate the effect of changing liquidity. Both order types' price impacts are much higher in the high volume state. Our previous finding that

[21] However, they run counter to the models of Lyons (1996) and Admati and Pfleiderer (1988) and It should be kept in mind that all three theoretical models are not designed for pure electronic markets.

price impacts of limit and market order flows vary in the same direction still holds under this twofold sorting procedure.

In summary, these results show that screen orders serve different economic functions than ordinary limit orders. They are a not just different in times of their execution speed and probability which would render the differentiation into these two groups superfluous but they differ in their use for information processing.

5 Trinary order choice of informed and uninformed traders

Beyond the fact that informed traders heavily rely on limit orders, some of them being used for informed trading, we find that the use of different order types depends on clock time and changing market conditions such as the spread and volatility. Results from our real world electronic currency market further increase the importance of BOS' experimental findings. They also serve to check the robustness of liquidity provision to changing market conditions and interrelations between trading, liquidity supply and relevant market statistics.

5.1 Endogenous market making

Liquidity is crucial for functioning markets, but who provides it in a purely electronic market without any market maker? We show – for the first time according to our knowledge – how informed and uninformed traders contribute to liquidity provision over time, confirming experimental results of BOS.

In their experimental study, BOS find that when trading starts, all traders rely comparatively more on market orders. This seems quite self-evident as informed traders utilize their information advantage and make money on mispriced limit orders. Afterwards limit orders become more important for the purpose of spread trading, i.e. informed traders engage as market makers. This leads to the endogenous provision liquidity since their superior knowledge of the true fundamental asset value prevents informed traders from being picked off by uninformed traders. The latter, however, may use market orders when trading starts to realize some of their trading targets, i.e. to fill customer orders. Towards the end of a trading session it may be expected that uninformed traders – mainly interested in liquidity trading throughout the day – shift towards market orders again to fill their targets from customer trading.

To set the stage we redo BOS' analysis and present the relative use of market and limit orders for both trader groups in Figure 6. This figure shows average sub-

mission and taking rates over five minute non-overlapping intervals for informed and uninformed traders. BOS (p.180 and p.182) define submission rates as the number of limit orders a trader submits divided by the sum of her limit and market orders. Taking rates on the other hand equal the number of market orders divided by the sum of market orders and executed limit orders. Therefore, submission and taking rates may be interpreted as being measures of the share of actively produced and consumed liquidity.

The figure leaves out the first five trading minutes to mimic the pre-trading period in BOS although the overall results do not change when they are included. The depicted curves are very similar to those found in BOS' experimental study. Informed traders increase their liquidity provision almost linearly with time whereas uninformed or liquidity traders heavily turn towards market orders when time left to trade expires. Due to this different behavior submission rates of both groups may graphically cross, which is indeed the case in the experiment (BOS, Fig. 3A) as well as in our market (Fig. 4A). Also, taking rates of informed and uninformed traders, reflecting actively consumed liquidity, do cross each other over time in the experiment (BOS, Fig. 3B) as well as in our electronic market (Fig. 4B).

Overall, informed traders choose differently between market and limit orders than uniformed traders do. BOS attribute this to the changing value of private information over the day and the need of traders to fill customer trades.

How does this time-varying behavior relate to the use of screen, market and ordinary limit orders? First, it may be expected that informed traders still shift from market to both types of limit orders as time passes since the value of private information declines. Therefore, submission rates for ordinary limit and screen orders should rise over the trading session. The reverse should hold for uninformed traders due to the reasons discussed above. Furthermore, as BOS argue, informed traders who use limit orders to earn on spread trading will compete in setting the best price to attract market orders. Thus, the submission of aggressively priced limit orders should increase over time due to this reason, too. We present submission rates for ordinary limit and screen orders for both trader groups in Figure 7 to investigate these hypotheses.[22]

[22] We do not plot taking rates here to conserve space and because results are completely analogous to those of submission rates presented here.

As it turns out, the movement in submission rates for informed traders over time as presented in Figure 6 is mainly driven by the submission of screen orders. This confirms findings from BOS that an increasing competition between informed traders engaging as market makers makes limit order pricing more aggressive towards the end of trading. The fact that we found screen orders to have price impact does not contradict these findings. Aggressive pricing may well only occur on the opposite side of the bid-ask spread that informed traders think the market will be going. This is also in line with the results on the price impact of informed traders in the previous section. There we found screen orders to have higher price impact towards the end of the trading day. Results for uninformed traders suggest that time-variation in their provision of liquidity is not solely driven by any of the two limit order types.

Taken together, we confirm and extend the experimental findings of BOS with real-world trading data. This is out second main finding. As it turns out, informational asymmetries foster the provision of liquidity by different types of traders at different times of the trading session. Given that informed traders act as suppliers of liquidity, how does their behavior change under different market conditions? Is liquidity provision jeopardized when market movements become rapid and volatility rises? We investigate these questions in the next subsection to assess the soundness of liquidity provision in limit order books.

5.2 Liquidity provision and volatility

It is theoretically expected that market conditions influence the use of limit (versus market) orders and we can show for our electronic market that informed traders increase their submission of liquidity with higher volatility. As we will argue below, this further strengthens the assumption that informed traders use limit orders to exploit their informational advantage at the expense of uninformed traders. Furthermore, it is shown that liquidity provision in pure order driven markets does not dissipate in times of uncertain market conditions as it was questioned in BOS (p. 168).

The literature considers at least two antithetic effects of volatility on the relative attractiveness of limit versus market orders, a discussion which is largely independent of the degree of information. The first effect posits a positive correlation of volatility with limit order submission. This relation is simply driven by the fact that higher volatility increases the probability that a limit order executes (Angel, 1994 and Lo et al., 2002), in short a "probability effect". Since limit orders do not incur the cost of

spreads, this clearly makes them more attractive in times of high volatility. In an empirical analysis, Handa and Schwartz (1996) find that returns to limit orders are indeed positive when the non-execution of orders is not penalized.

The second effect, called “option effect”, holds that a limit order is more likely to be picked off when the true underlying value of an asset has changed in a way that makes it mispriced.[23] Hasbrouck and Saar (2002) note that this pick-off risk is similar to the private information risk faced by a dealer in a sequential trade model since it is possible that limit orders cannot be revised or deleted fast enough in case of information arrivals. Harris (1998) models this by including a penalty for bad fills in a trader’s objective function and finds that in this setting the option effect dominates and that higher volatility makes limit orders relatively less preferable.

Our motivation in the following analysis goes beyond earlier empirical work as the focus is on the effects of volatility on order choice, separated for informed and uninformed investors.[24] Economic intuition suggests that the option effect should not dominate for informed investors since their pick-off risk is likely to be small. We therefore expect a positive influence of volatility on limit order submission for informed investors. The case for uninformed investors is less clear. They should be subject to both effects and it is not clear a priori which effect will dominate for them. Furthermore, it is unclear how volatility affects order choice which is trinary in our analysis.

To investigate the role of volatility for order choice we use VARs again, since there is little theoretical guidance about causality, and in particular no guidance for the use of different types of limit orders. The VAR includes the (log of) screen and ordinary limit order submission rates, the taking rate, realized volatility, the average spread, average volume outstanding in the book and the number of trades for non-overlapping intervals of one minute. Although we are primarily interested in the dynamic relation of volatility and liquidity provision we include the spread and the number of trades as measures of market activity and outstanding book volume as a measure of liquidity stock in the market to control for these factors. We further net out intraday patterns in market variables, submission and taking rates by including two

[23] See also Foucault (1999) in this respect.

[24] There is a number of empirical studies relating the (optimal) composition of limit and market orders to market conditions. Biais et al (1995) relate order choice to spreads and find that a higher spread increases the probability of an incoming limit order or Sandås (2001) who among other things shows that spreads positively react to shocks in volatility. Ahn, Bae and Chan (2001) and Bae, Jang and Park (2003) analyze the relations of transitory volatility and market depth.

exogenous regressors: a minute variable and a squared minute variable. This should suffice to capture deterministic time effects since most variables have clear U-shaped patterns or linear trends. Furthermore, we opt to estimate two separate VARs, one for informed and one for uninformed traders to keep the size of the system manageable.[25] More formally, we estimate

$$\begin{pmatrix} \mathbf{y}_t^o \\ \mathbf{w}_t \end{pmatrix} = \begin{pmatrix} \mu^o \\ \mu^w \end{pmatrix} + \begin{pmatrix} \mathbf{A}_1^o & \mathbf{A}_2^o \\ \mathbf{A}_1^w & \mathbf{A}_2^w \end{pmatrix} \cdot \begin{pmatrix} \mathbf{y}_{t-1}^o \\ \mathbf{w}_{t-1} \end{pmatrix} + \begin{pmatrix} \Gamma^o \\ \Gamma^w \end{pmatrix} \cdot \begin{pmatrix} \min_t \\ \min_t^2 \end{pmatrix} + \begin{pmatrix} \xi^o \\ \xi^w \end{pmatrix}, \text{ for } o \in \{i,u\} \qquad (2)$$

where $\mathbf{y}^o$ contains the submission and taking rates for informed (o=i) or uninformed (o=u) traders and $\mathbf{w}$ contains the remaining market statistics described above. $\mathbf{A}^o$ and $\mathbf{A}^w$ are coefficient matrices for the endogenous variables of conformable size whereas Γ^o and Γ^w contain the coefficients corresponding to the exogenous time variables, respectively.

Accumulated five minute impulse responses for informed traders are depicted in Table 6.[26] Since diagnostics of the VAR show heavy signs of heteroscedasticity we report p-values based on 250 bootstrap replications. The cholesky ordering employed ranks volatility first, followed by logs of screen order submission rates, taking rates and ordinary limit order submission rates. The mean spread, number of trades and mean outstanding order book volume come last in the ordering. The ordering represents the goal of our analysis, namely to examine the effect of volatility shocks, which we treat as the arrival of information, on liquidity provision. Spreads, the number of trades per minute and therefore order book volume also, are implicitly taken to respond to information arrival and the provision and consumption of liquidity. The qualitative results remain unchanged upon permutations of the cholesky ordering although statistical significance obviously varies with permutations.

As it turns out, there are clear and intuitive interdependencies between the production of liquidity by screen and ordinary limit orders and volatility. A higher submission rate of ordinary limit order lowers the volatility of midquote changes and the mean spread over five minute intervals. Contrary to this, an increasing submission of screen orders or taking rates lead to higher volatilities and consequently to higher spreads. Again, these findings show that screen orders behave similar to market or-

[25] The results presented in the following do not depend qualitatively on this separation but save valuable degrees of freedom for statistical inference.

ders corroborating the findings in our price impact analyses. Although they provide liquidity to the market, which can be inferred from the reaction of outstanding book volume, it seems as if their information based character dominates over short and medium horizons and raises volatility and the spread.

Reversing the direction of the impulse-response analysis we also find several effects. Both volatility shocks and shocks in the bid-ask spread raise the submission rate of ordinary limit orders. This lends credence to our hypothesis that informed traders are not subject to the option effect or pick-off risk inherent to limit order submission. It also represents a first step to answering the question raised in BOS (p. 168). They state that endogenous liquidity provision in general makes costly market makers redundant. The question is, however, whether endogenous liquidity provision survives in hectic markets. Our results support this. [27] Not only do informed traders supply more liquidity when price movements become more rapid, but the liquidity they supply via ordinary limit orders also helps to calm the market by lowering volatility and spreads as the foregoing analysis has shown. This is our third main finding. Estimation of equation (2) and calculation of impulse-responses for uninformed traders yields several plausible but mostly insignificant results so we do not present them here. The main conclusion is that shocks in the submission rate of ordinary limit orders leads to a reduction in volatility and spreads over five minute horizons which underscores the role of these limit orders for liquidity provision. However, screen order submission and taking rates do not have significant impacts on these two market statistics. Moreover, volatility itself has no significant impact on order choice. In terms of the two competing effects, the probability and the option effect, this could be interpreted as evidence that both effects outweigh.

Overall, these findings indicate, that time left to trade is not the only influential variable that determines the use of limit orders and that informed traders use limit orders in response to changing market conditions. Specifically, they use ordinary limit

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[26] We also estimated different versions of these equations with volume-weighted submission and taking rates. The results remain unchanged in these settings. Excluding the last one to five minutes of the trading day also does not affect the results.

[27] BOS find little evidence for the role of volatility in choosing between market and limit orders. This may be due to the fact that they can exactly control for factors such as price extremity, i.e. the size of stock prices' deviations from true asset values. As we are using real trading data, different effects mix up so that findings cannot be directly compared. Nevertheless, our finding of a positive correlation of volatility and submission rate fits into a situation of relatively high extremity in BOS' table 2. As high extremity reflects a high value of private

and screen orders to supply liquidity. This is indeed good news for market designers. Liquidity in electronic order books is maintained even in times of hectic and volatile markets by informed traders who exploit their informational advantage.

6 Conclusions

Financial markets are changing in a way that electronic brokerage systems significantly gain market share. It cannot be expected that this structural change will be without any impact on traders' behavior. We thus examine trading at such a limit order market in two dimensions: first, informed and uninformed traders are differentiated and, second, market, screen and ordinary limit orders are differentiated. By combining these characteristics, we investigate the interdependencies of six categories – i.e. screen orders of informed traders, marketable limit orders of informed traders, etc. – that make up 100 per cent of the market and can be analyzed separately. This data allows us to examine the use of different kinds of limit orders by informed traders that is new in its focus and comprehensiveness and it allows us in particular to test experimental findings of BOS.

This study obviously requires order book data that provide a detailed record of all transactions conducted at the market under investigation. Here we use nine days in March 2002 of trading at the Russian electronic interbank foreign exchange spot market in Russian rouble to US dollar. This is where the daily official exchange rate is fixed. Despite the limited overall volume of this market, banks from all over the country participate and trade actively during this one hour, leading to more than 1,500 transactions over 60 minutes each day. Accordingly, it is no surprise that this market reveals microstructural patterns that are well known from bigger bond, stock and currency markets. This data provide a useful basis to analyze the two core issues of order choice and price impact. Motivated by recent literature, the leading question is about the use of different kinds of limit orders by informed investors and their importance for information aggregation as well as endogenous liquidity provision.

Our data reveal clear findings for the use of limit orders by informed traders: all limit orders are not alike and order choice is trinary rather than binary. There is a sharp difference in the performance and impact of aggressively priced screen orders, ordinary limit orders and pure market orders. We document this by our first main find-

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information, and as emerging markets are regarded as tentatively less transparent than mature markets, our finding may be well in line with BOS.

ing, namely that limit orders of informed traders carry information. It is particularly screen orders that show similar characteristics to market orders both in terms of their price impact as well as their effect on volatility and market spreads. Our second main finding is, that liquidity provision follows intriguing patterns found in experiments before (see BOS). Order choice depends on time as limit orders become more important during the trading hour. Finally, our third main finding is that ordinary limit orders are used more by informed investors when volatility is high, indicating that they exploit their informational advantage, which benefits the maintenance of liquidity supply under market stress. Our three main findings are closely linked and affirmative of each other. Price impacts of informed traders' screen orders are higher towards the end of the trading day just when they are used more heavily. The substitutional character of screen and market orders is found when we investigate liquidity provision under changing market conditions and in the analysis of price impacts.

In summary, the role of limit orders in electronic markets does not conform to the traditional notion that they would be the preferred order choice of liquidity traders and a passive instrument of informed traders only. By contrast, our evidence reveals more complexity, as we find two types of limit orders, that certain limit orders have price impact and that (informed) traders' use of limit orders depends on time, volatility and further market statistics. This new differentiation of limit orders may thus be fruitfully incorporated into theoretical models of order choice.

We can only speculate on the degree to which our results hold for other asset markets as well. However, there are several findings indicating that our results may hold in general. First, the trading technology SELT employed at this market is highly similar to those used in developed countries (Hasbrouck and Saar, 2004, Payne, 2003) and to the technology in BOS' experiment. Second, intraday patterns of market statistics have well-known and expected shapes. Third, our basic results concerning endogenous liquidity provision, price impact of limit orders and the differences between certain limit orders are in line with the literature. So it will be interesting to learn whether and in what way other studies confirm and modify this strand of literature initiated by Hasbrouck and Saar (2004).

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Figure 1. RUR/USD exchange rate

This figure shows exchange rate movements of the RUR/USD over the sample of fifteen trading days in March 2002. Shaded areas correspond to days with central bank activity.

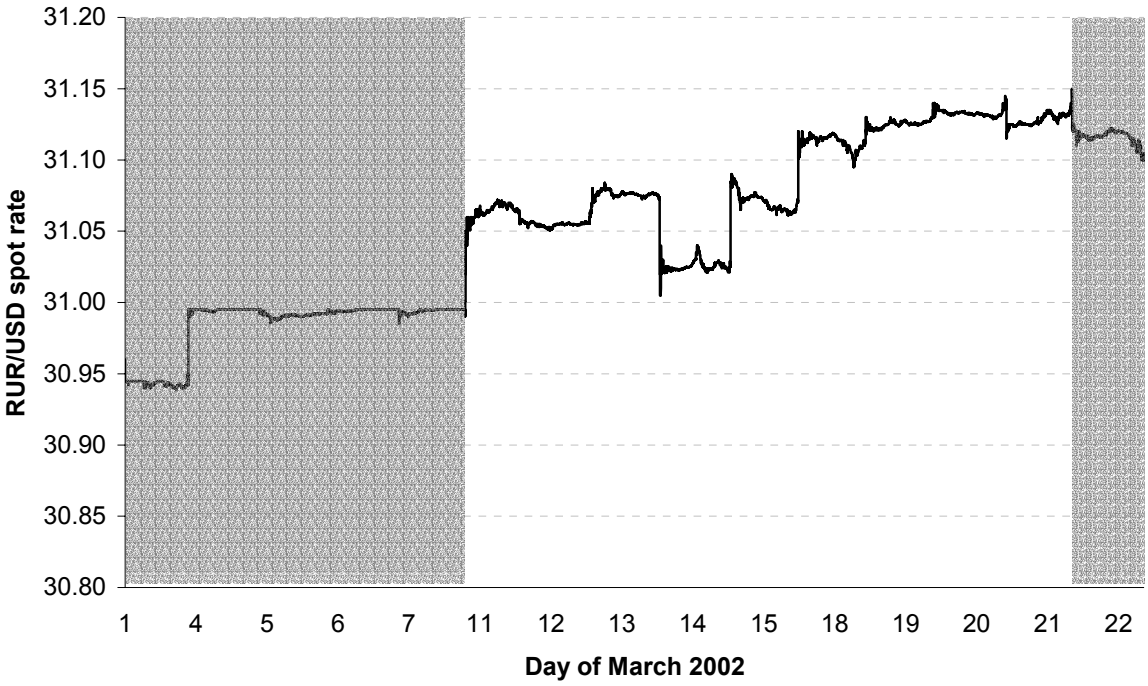


Table 1. Summary descriptive statistics for SELT order book and return data

Panel A of the table gives descriptive statistics for order book data. Column Min. gives the 5 minute sub sample, Q_a and Q_b show ask and bid volume in $m outstanding. Similarly Asks and Bids show the number of ask and bid orders queued in the order book. The next column ''spread'' shows the average percentage spread. $\overline{LO}$ ($\overline{MO}$) and Σ LO (Σ MO) show the average and total trading volume in mill. USD of limit (market) orders. Panel B shows basic statistics for midquote returns (in pips). The first four columns show the first four sample moments of the return series. Columns headed ρ_{-1}, $Q(5)$ and $Q^2(5)$ give the first order autocorrelations, fifth order Ljung-Box test statistics for returns and fifth order Ljung-Box test statistics for squared residual returns respectively. Note that residual returns are calculated by using an MA(1)-Model for returns. The critical values for the test statistics in the seventh and eighth column are 11.07 and 15.09 respectively.

Panel A: Order book statistics

Min.	Obs	Q_a	Q_b	Asks	Bids	spread	$\overline{LO}$	Σ LO	$\overline{MO}$	Σ MO
5	9115	7.03	11.90	65.35	72.53	0.0055	0.1229	565.00	0.0558	175.00
10	5903	11.04	11.86	106.52	97.88	0.0022	0.0894	211.00	0.0522	126.00
15	4561	8.31	10.73	92.94	100.94	0.0021	0.0967	170.00	0.0490	93.46
20	3509	7.45	10.32	86.68	102.02	0.0031	0.0882	128.00	0.0474	58.82
25	2745	7.09	8.61	95.66	88.27	0.0023	0.0903	97.36	0.0468	47.95
30	2256	6.87	8.77	93.29	81.26	0.0025	0.1038	93.84	0.0392	32.61
35	1662	5.75	9.26	87.52	83.54	0.0025	0.0961	62.83	0.0449	26.27
40	2154	4.87	8.52	82.78	69.78	0.0028	0.1040	83.10	0.0500	38.00
45	1769	3.61	7.93	68.62	71.08	0.0030	0.0737	51.21	0.0514	30.70
50	1653	2.91	7.63	58.79	70.91	0.0021	0.0843	50.11	0.0427	23.12
55	1574	1.93	8.24	39.34	63.06	0.0037	0.1078	57.01	0.0399	23.18
60	1541	1.95	8.26	23.58	51.43	0.0097	0.1105	58.34	0.0444	22.04

Panel B: Return statistics

Min.	Mean	Var.	Skew.	Kurt.	ρ_{-1}	$Q(5)$	$Q^2(5)$
5	0.3520	24.9184	5.1387	168.6030	-0.1939	126.46	86.90
10	-0.0250	4.0390	-0.9981	58.9012	-0.2778	200.09	124.45
15	0.1300	3.1008	-0.3600	29.1595	-0.2324	108.11	52.57
20	-0.0620	5.4197	0.6199	32.7976	-0.2771	120.29	195.58
25	-0.1338	4.1408	0.7347	27.5155	-0.1988	59.28	121.71
30	-0.1442	4.2614	0.6517	32.2278	-0.1450	57.92	115.58
35	0.1043	4.0087	0.2024	19.9866	-0.1852	31.87	102.93
40	0.0092	5.7416	0.5517	51.3059	-0.2712	79.15	239.22
45	-0.0787	3.4352	-0.5075	20.5200	-0.1315	16.86	77.25
50	0.1017	3.2788	-1.0582	19.1347	-0.0170	44.27	38.08
55	0.4355	4.9111	2.3719	52.1263	-0.0923	6.85	3.48
60	0.3266	12.3240	0.7148	25.8205	-0.2652	28.45	23.91

Figure 2. Order book intraday pattern

This figure shows the intraday pattern of order book volume and the corresponding number of limit orders outstanding. The left axis and lower lines show order book volume in $m, whereas the right axis and upper lines refer to number of orders in the order book. Time at the x-axis refers to non-overlapping five minute intervals.

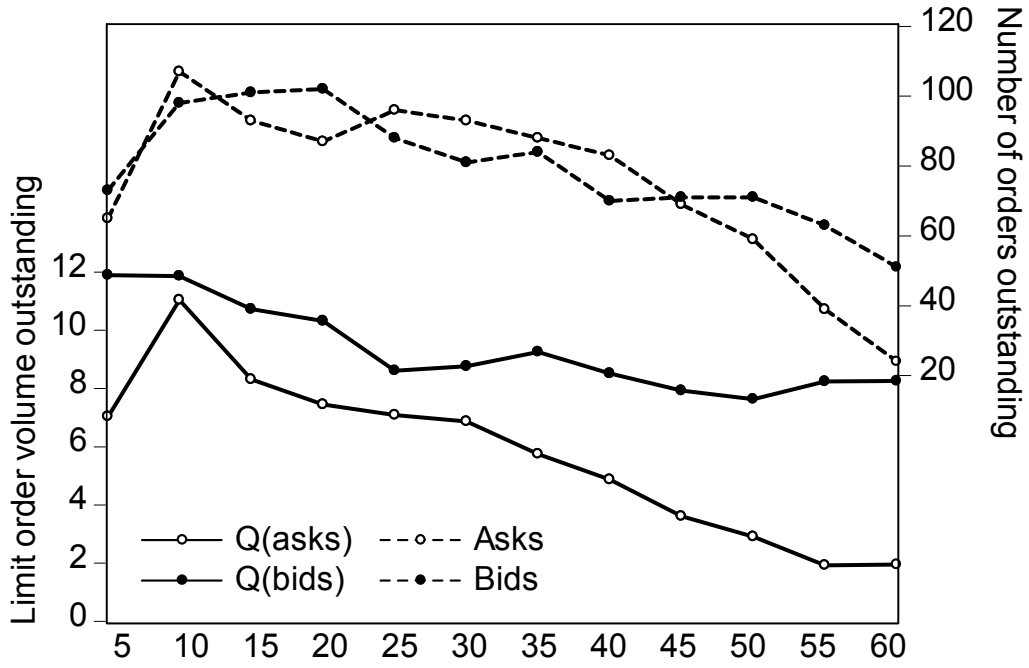


Table 2. Regional characteristics

This table shows aggregate data for eight regions represented by traders in our sample. All data used in this table come from the "Analytical System of Economic Activities" provided by the Russian central bank. For all numbers below we use average quarterly values for the period April 1, 2001 to March 31, 2002. The respective headings stand for the number of banks operating in the region (# Banks), the volume of foreign currency accounts (FCAV) in m USD, the profits in mill. RUR earned by these banks, the debt investments (DI) in mill. RUR in local bank portfolios, the equity investments (EI) in m. RUR in local bank portfolios, and industrial production (IP) in mill. RUR. The fifth and sixth columns shows foreign currency account volume per number of local banks and as a share of industrial production, column ten gives profits per number of local banks, and the last two columns report debt and equity investments as share of industrial production.

Region	# Banks	FCAV	IP	FCAV/ # Banks	FCAV/ IP	Profits	DI	EI	Profits/ # Banks	DI / IP	EI / IP
Moscow	595	70,506	155,652	118.50	45.30%	24,937.56	31,163	358,022	41,911.86	20.02%	230.01%
St. Petersburg	40	4,262	83,730	106.54	5.09%	531.32	570	9,783	13,280.58	0.68%	11.68%
Ekaterinburg	28	295	111,986	10.53	0.26%	95.26	101	1,415	3,402.11	0.09%	1.26%
Rostov	24	53	42,330	2.22	0.13%	25.35	52	57	1,056.38	0.12%	0.13%
Samara	22	556	96,152	25.27	0.58%	119.41	219	719	543.05	0.23%	0.75%
N. Novgorod	20	233	66,239	11.63	0.35%	73.73	54	423	3,686.65	0.08%	0.64%
Novosibirsk	13	75	25,849	5.74	0.29%	39.26	29	251	3,020.15	0.11%	0.97%
Vladivostock	6	89	34,912	14.80	0.25%	37.79	4	74	6,298.83	0.01%	0.21%

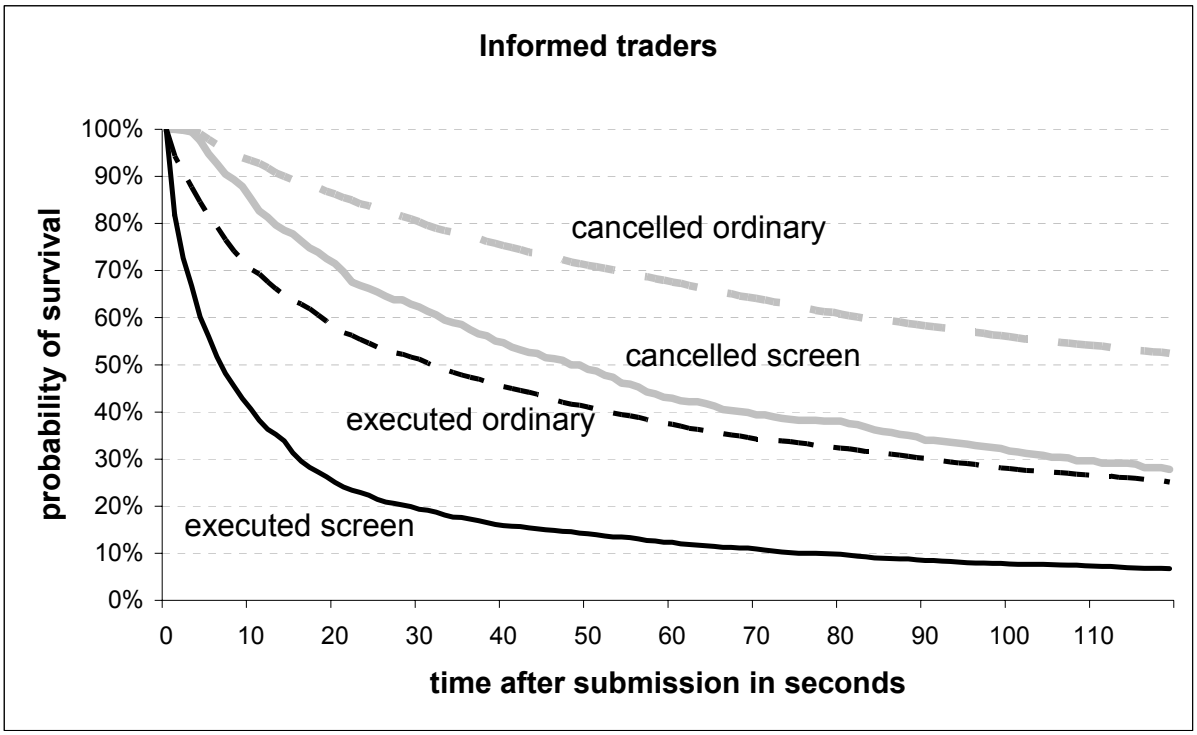
Table 3. Trading volume and liquidity submission of different dealer groups

This table provides descriptive statistics for market activities and a characterization of the different trader groups in the sample. The rows stand for all traders, informed traders and uninformed traders. The columns separate results in ordinary limit orders, screen orders (aggressively priced limit orders) and market orders. The first block gives the number of events for each order type and trader group in the sample. The second block shows volume in million USD per trader in each group for each order type and the third block shows volume in million USD per number of events. Fill rates correspond the fraction of filled limit orders relative to all submitted limit orders. The last block shows trading profits for per trader in million USD.

	Number of events		
	ordinary	screen	market
all	12,562	3,397	14,109
informed	7,612	2,072	10,476
uninformed	4,950	1,325	3,633
	Average volume per trader		
	ordinary	screen	market
all	1,839,297.37	413,258.64	963,930.78
informed	2,338,305.86	520,470.72	1,232,325.29
uninformed	964,954.02	225,475.10	493,563.23
	Average volume per event		
	ordinary	screen	market
all	102,886.81	79,464.36	49,395.56
informed	137,144.91	103,421.12	54,228.90
uninformed	49,724.19	40,867.36	35,458.30
	Fill rates		
	ordinary	screen	both
all	44.98%	74.87%	51.21%
informed	46.02%	75.67%	52.53%
uninformed	42.87%	73.66%	49.68%
	Trading profits		
informed	0.0043		
uninformed	-0.0076		

Figure 3. Survival probabilities for screen and ordinary limit orders

This figure shows survival probabilities for executed and cancelled limit orders separately for screen orders (solid lines) and ordinary (dashed lines) limit orders. Panel A shows results for informed traders whereas Panel B depicts results for uninformed traders. Survival probabilities are calculated from empirical frequencies.



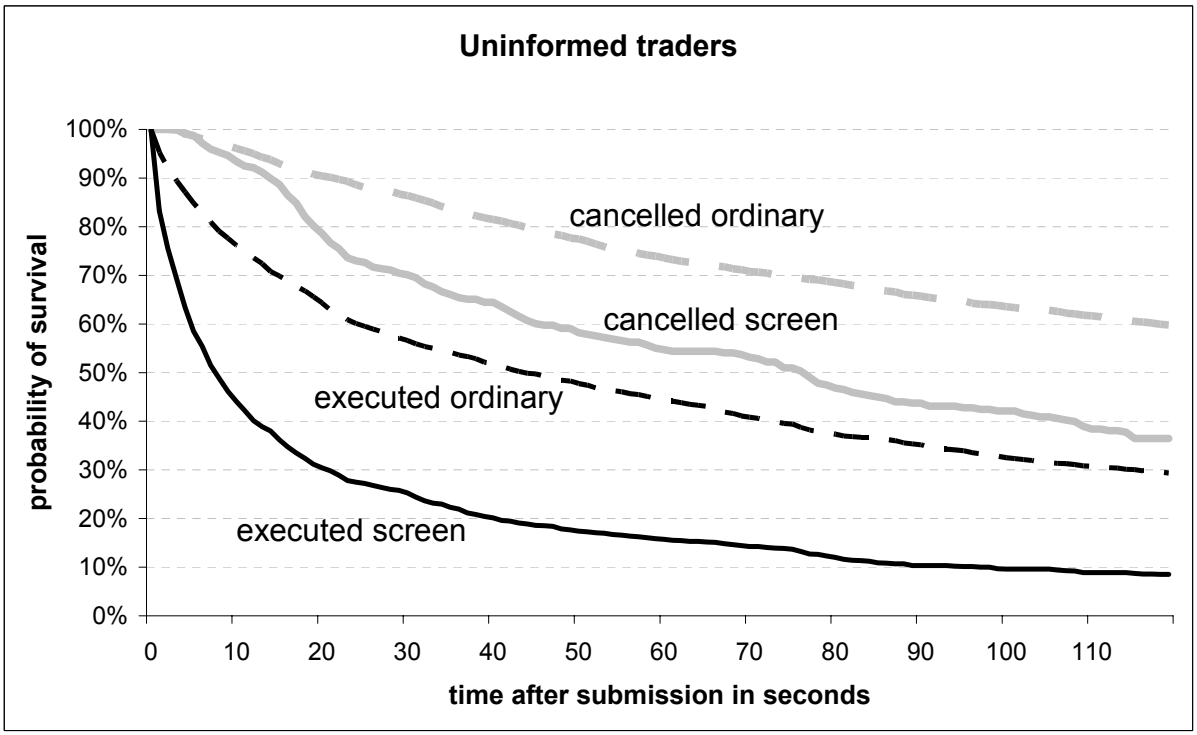


Table 4. VAR analysis results

This table shows results from the VAR analysis in section 4. Variables in the VAR are midquote returns (r), market order flow (x^i and x^u) and aggressive limit order flow (w^i and w^u) for both informed (superscript i) and uninformed (superscript u) traders. The results below correspond to the cholesky ordering: x^i - w^i - x^u - w^i - w^u – r. The first column refers to the (sub-)samples of trading days, the next four columns show the long-run response of midquote returns to market and limit order flows, i.e. the 10 minute responses of midquote returns to one standard deviation shocks in the respective variables. R^2 corresponds to the equation of midquote returns, $Q_2(5)$ shows the multivariate Portmanteau test statistic for no residual autocorrelation, lag gives the number of lags employed for estimation and AIC stands for value of the Akaike Information Criterion which is used to select the lag lengths. The last two columns show two minute responses of market and limit order flows of uniformed dealers to shocks in informed dealers' order flows. P-values are given in parentheses.

	Ten minute accumulated response of midquote returns to shocks in								Response of uninformed flows to informed flow shocks	
Minute	x^i	w^i	x^u	w^u	R^2	$Q_2(5)$	lag	AIC	x^{uninf} to x^{inf}	w^{uninf} to w^{inf}
1 to 60	0.0038	0.0036	0.0006	-0.0009	0.0251	95.5731	2	16.89	0.9775	0.6545
	(0.0006)	(0.0009)	(0.5793)	(0.3981)		(0.0548)			(0.0040)	(0.0000)
1 to 15	0.0042	0.0034	0.0009	-0.0008	0.1378	55.7978	2	18.18	1.0231	0.7584
	(0.0003)	(0.0007)	(0.4327)	(0.4160)		(0.9526)			(0.4706)	(0.0028)
16 to 30	0.0022	0.0019	0.0024	0.0003	0.1589	70.1928	1	13.39	0.4890	1.2741
	(0.0067)	(0.0270)	(0.7311)	(0.6691)		(0.6355)			(0.3627)	(0.0016)
31 to 45	0.0026	0.0020	0.0006	0.0003	0.1889	64.3548	3	10.83	1.5429	0.2612
	(0.0000)	(0.0000)	(0.2394)	(0.5684)		(0.8048)			(0.0154)	(0.2551)
46 to 60	0.0023	0.0044	0.0011	0.0016	0.1372	68.6401	1	12.21	1.0523	0.6476
	(0.0838)	(0.0024)	(0.3878)	(0.2175)		(0.6843)			(0.0685)	(0.0076)

Table 5. Granger causality, variance decompositions and residual correlation

This table shows results from the VAR analysis in section 4. Variables in the VAR are midquote returns (r), market order flow (x^i and x^u) and screen order flow (s^i and s^u) for both informed (superscript i) and uninformed (superscript u) traders. The VAR is estimated with two lags and a constant term. Panel A shows p-values from Granger causality tests for the null that the row variable does not granger cause the column variable. Panel B shows Variance decompositions from the estimated VAR with cholesky ordering: x^i - s^i - x^u - s^u - r. Columns show the forecasted variables whereas rows indicate which innovation is used for forecasting. Results are computed for 10 minute horizons and row "forecast σ" shows forecast standard errors. Panel C presents the contemporaneous correlation of estimated residuals from the VAR. Here, the upper triangular part shows correlation coefficients and the lower triangular part corresponding p-values for the null of no correlation.

Panel A: Granger causality tests

	r	x^i	s^i	x^u	s^u
r		0.5248	0.3599	0.6271	0.0005
x^i	0.0438		0.3178	0.0330	0.6764
s^i	0.0001	0.0041		0.2594	0.1104
x^u	0.4793	0.7105	0.4545		0.0738
s^u	0.5838	0.9771	0.5661	0.3406	

Panel B: Variance decomposition

	r	x^i	s^i	x^u	s^u
forecast σ	0.0050	13.2289	2.4982	5.2288	1.9436
r	60.60	0.02	0.03	0.01	0.79
x^i	22.82	96.04	0.85	2.79	0.39
s^i	13.22	3.82	98.49	0.41	6.32
x^u	3.17	0.11	0.43	96.43	0.93
s^u	0.19	0.01	0.20	0.36	91.57

Panel C: Residual correlation

	r	x^i	s^i	x^u	s^u
r	1	0.5053	0.3100	0.2427	0.1544
x^i	(0.0000)	1	0.1057	0.1386	0.0550
s^i	(0.0000)	(0.0150)	1	0.0177	0.2262
x^u	(0.0000)	(0.0012)	(0.6854)	1	0.0379
s^u	(0.0000)	(0.2101)	(0.0003)	(0.3839)	1

Figure 4. Price impact of market and screen orders under different market conditions

This figure plots price impact of market orders (black bars) and screen orders (grey bars) by informed traders under different market conditions, separated by dashed lines. The price impacts are estimated by Vector Autoregressions as detailed in section 4.1. The first section (all) shows price impacts for the whole sample as given in Table 5. The next three sections show impacts for low and high trading volume (TV), low and high book volume (BV) and low and high spreads. Trading volume is defined as the total volume traded in each one minute interval, book volume is the average size of the order book per interval and spreads are computed as mean values for each interval. The median of these variables serves to split the sample into subsamples of high and low realizations.

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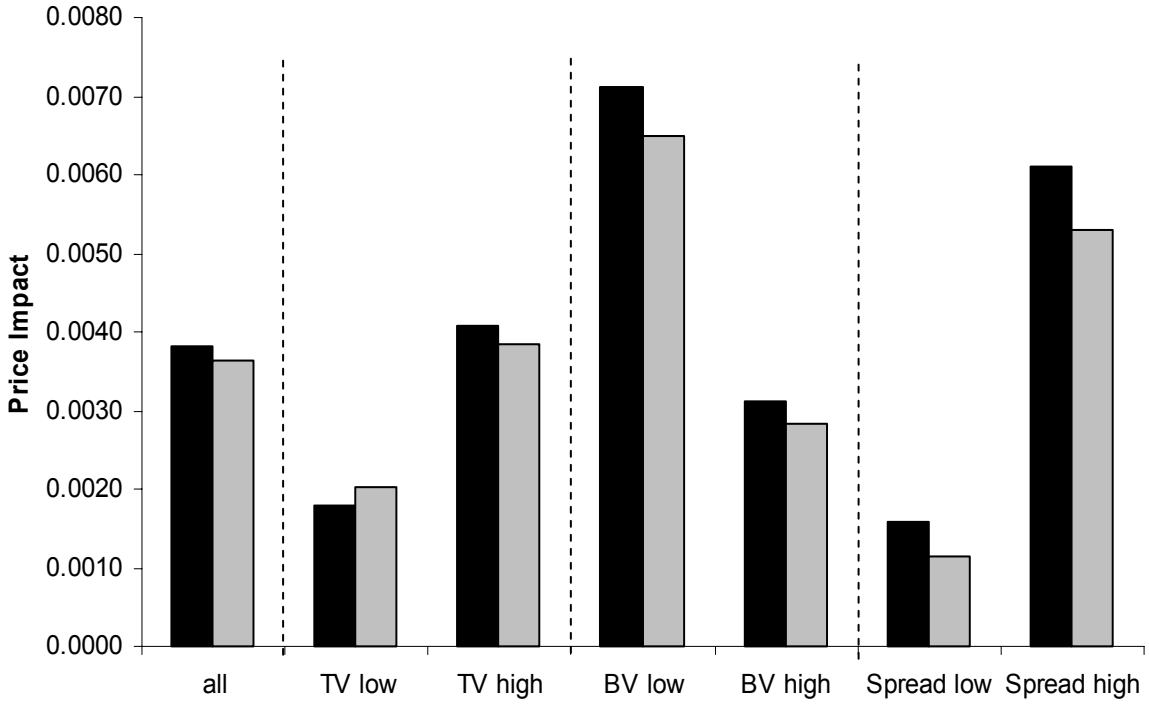


Figure 5. Cross effects of liquidity supply and trading volume on price impacts

This figure shows price impacts for market (black bars) and aggressive limit orders (grey bars) of informed traders under different market conditions. Each of the four cells below represent a market condition that is indicated by the respective row and column headings.

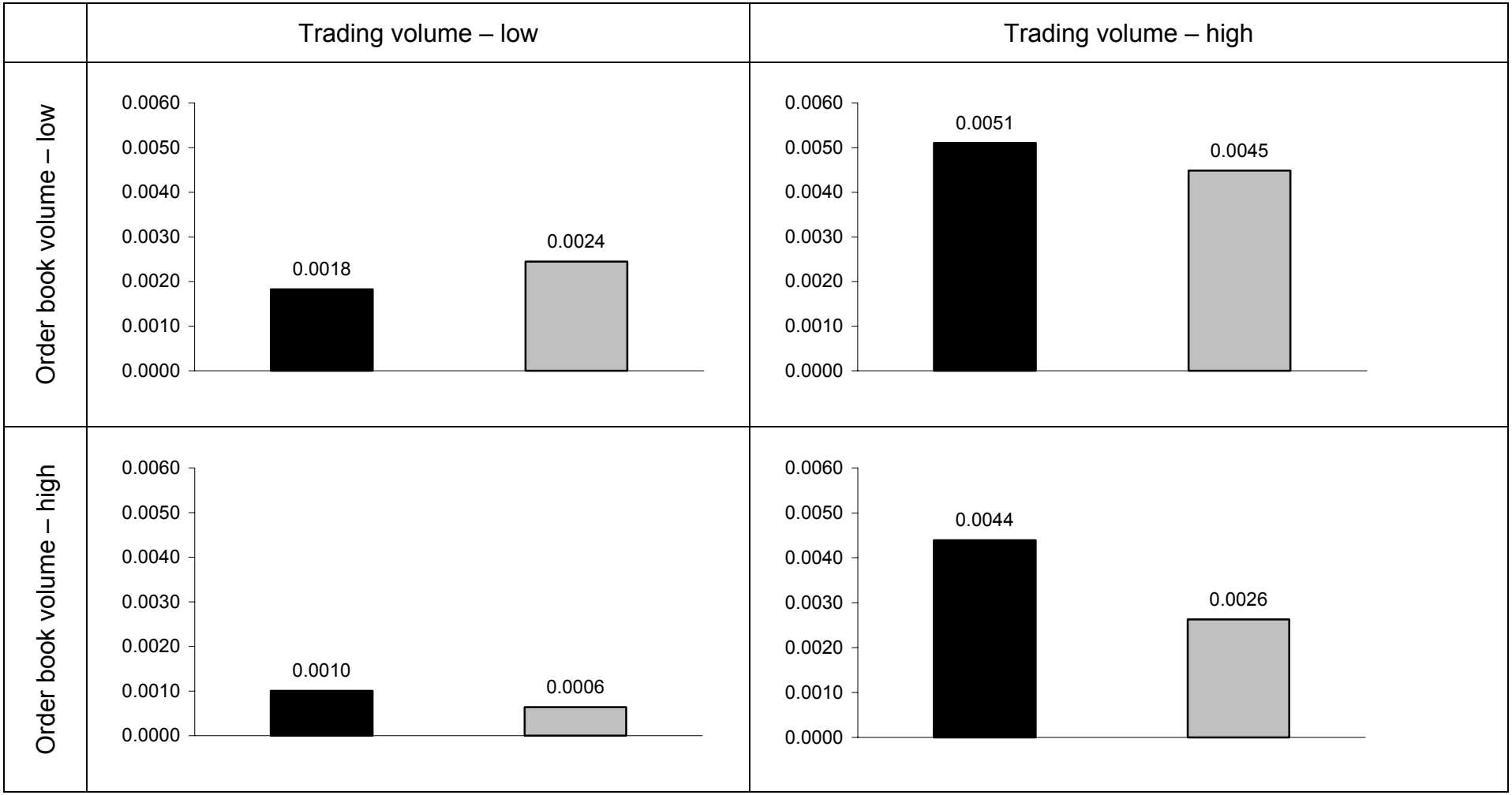
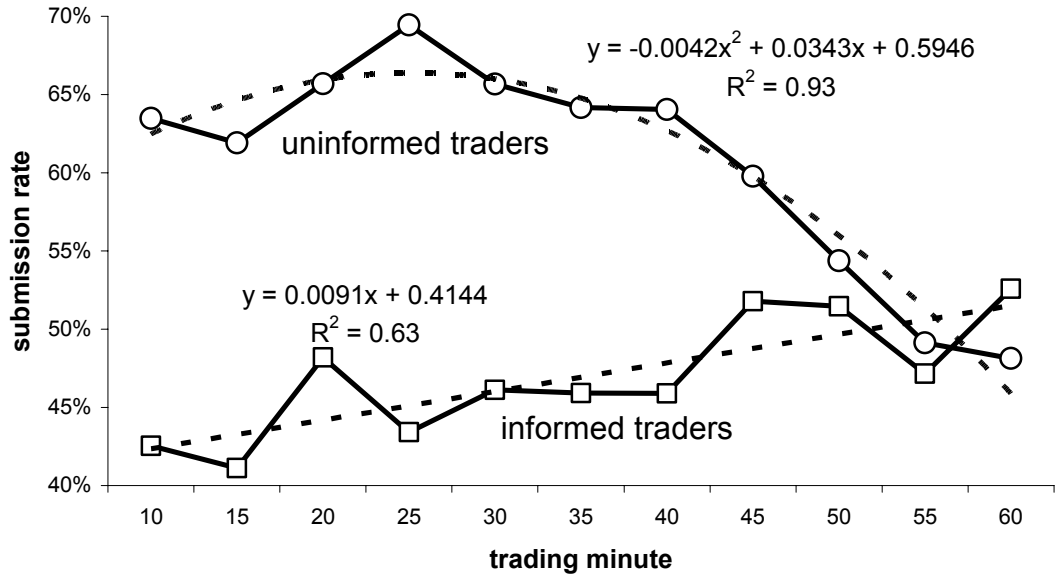


Figure 6. Submission and taking rates

This figure shows submission (Panel A) and taking rates (Panel B) for informed and uninformed traders for non-overlapping five minute intervals, averaged across all trading days in the sample.

Panel A: Submission rates over five minute non-overlapping intervals



Panel B: Taking rates over five minute non-overlapping intervals

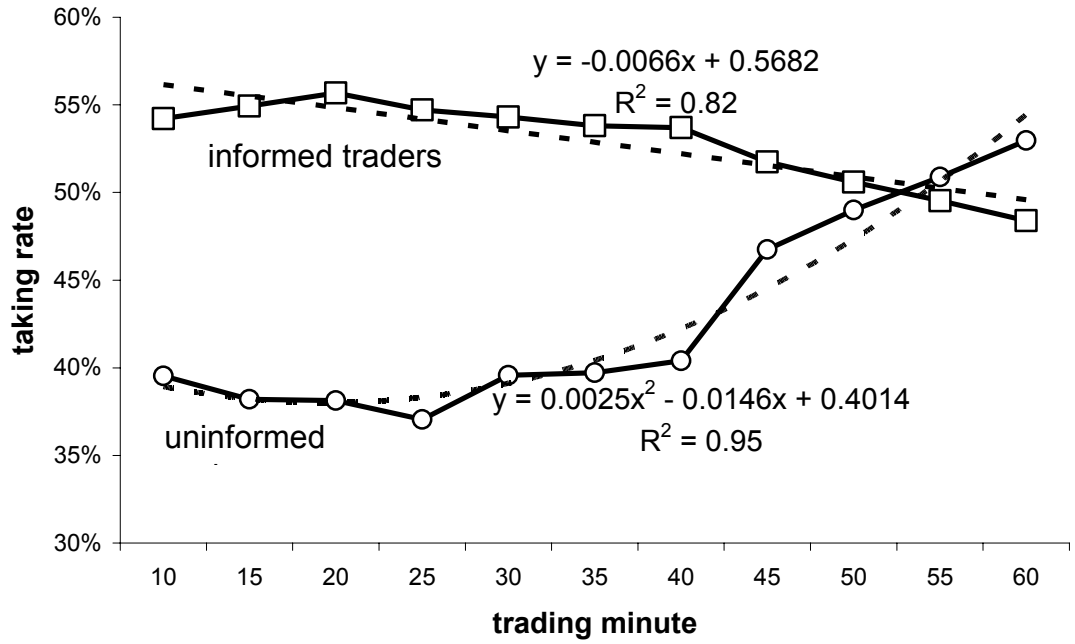
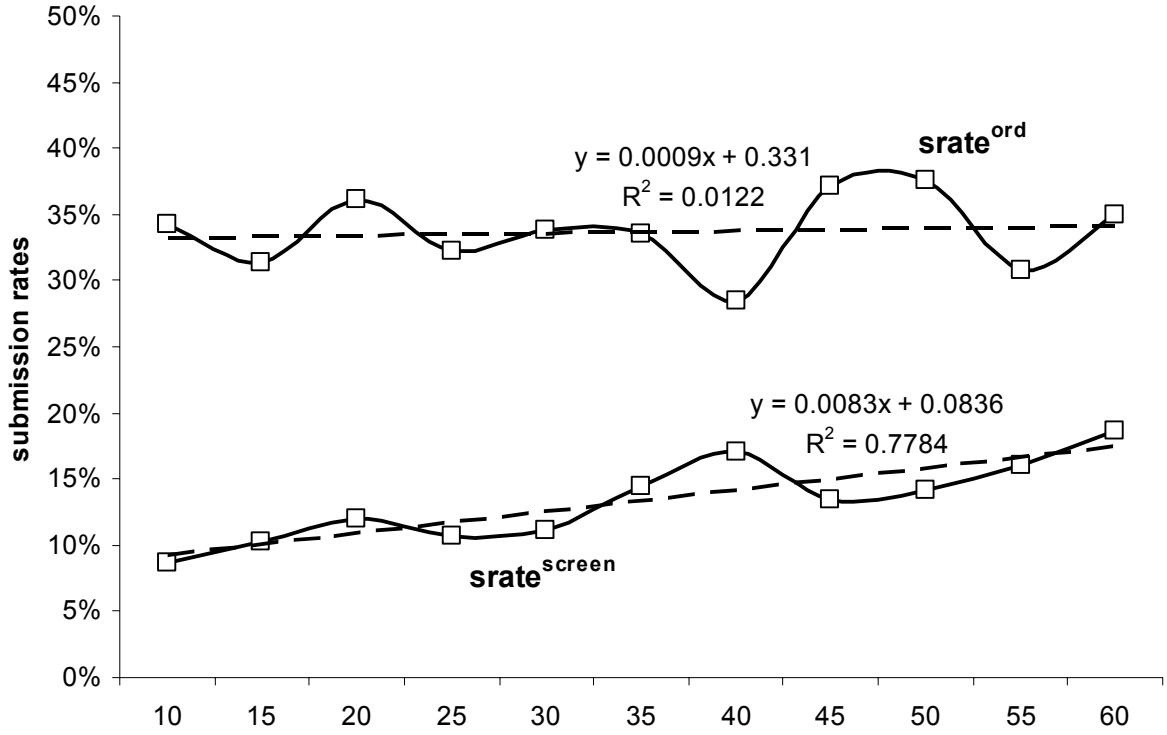


Figure 7. Submission rates for screen and ordinary limit orders

This figure shows submission rates seperately for informed (upper chart) and uninformed (lower chart) traders. The lines "srate^{ord}" correspond to submission rates of ordinary limit orders whereas lines labelled "srate^{screen}" corresponds to the submission rate of screen orders.

Panel A: Submission rates of informed traders over five minute non-overlapping intervals



Panel B: Submission rates of uninformed traders over five minute non-overlapping intervals

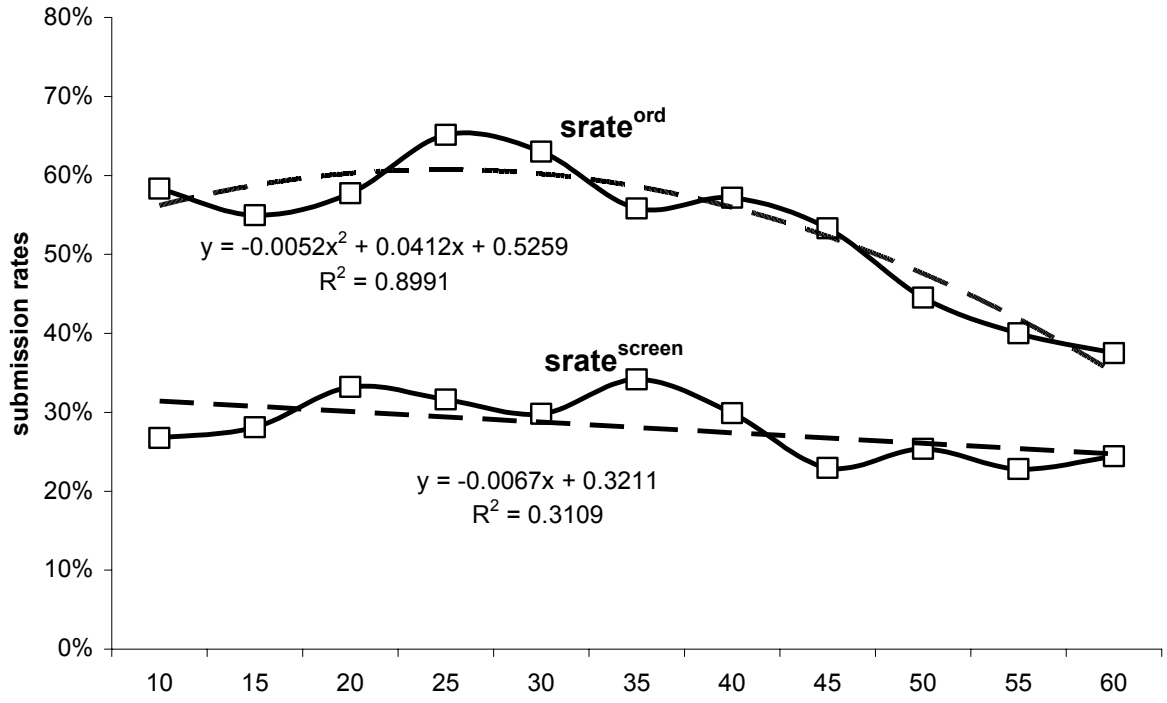


Table 6. Accumulated five minute responses of order choice variables and market statistics for informed traders

This table shows accumulated five minute responses for informed traders' provision and consumption of liquidity as well as several market statistics from a VAR estimated on a one minute frequency. The submission rate of screen orders ($srate^{screen}$) is the number of screen orders divided by the number of screen and market orders. The submission rate of ordinary limit orders ($srate^{ord}$) is defined analogous. The taking rate (trate) equals the number of market orders divided by the number of market orders and executed limit orders. Spread and outstanding order book volume and averages over the respective minutes. The rows "minute" and "$minute^2$" give the estimated coefficients for the two exogenous regressors in the VAR. Bootstrap p-values based on 250 replications are given in parentheses. The cholesky ordering is equal to the ordering of variables in the column headings.

	Accumulated five minute response of						
to one st. dev. shocks in	realized volatilty	$\log(srate^{screen})$	log(trate)	$\log(srate^{ord})$	spread	outstanding book volume	number of trades
realized volatility	3.3136	0.0922	-0.0563	0.1418	14.6724	-0.7492	-0.5461
	(0.0000)	(0.1486)	(0.0006)	(0.0000)	(0.0000)	(0.1518)	(0.6513)
$\log(srate^{screen})$	0.4685	0.8395	-0.0461	-0.1674	3.1592	1.1051	-3.9347
	(0.0602)	(0.0000)	(0.0092)	(0.0000)	(0.0213)	(0.0463)	(0.0025)
log(trate)	0.4927	0.0272	0.2032	-0.1382	1.4654	-0.4385	0.7700
	(0.0109)	(0.5117)	(0.0000)	(0.0000)	(0.1861)	(0.3801)	(0.4838)
$\log(srate^{ord})$	-0.7251	-0.0088	0.0156	0.3304	-3.4948	2.5749	-5.5976
	(0.0001)	(0.8295)	(0.1488)	(0.0000)	(0.0013)	(0.0000)	(0.0000)
spread	0.2079	0.0668	-0.0240	0.0748	9.9223	0.0189	-1.7271
	(0.3198)	(0.1480)	(0.0466)	(0.0022)	(0.0000)	(0.9699)	(0.1268)
outstanding book volume	-1.0257	-0.0110	0.0190	0.0194	-4.2275	-0.5089	14.2508
	(0.0000)	(0.8081)	(0.1114)	(0.4217)	(0.0001)	(0.2972)	(0.0000)
number of trades	-0.6047	-0.0042	0.0005	-0.0703	-3.4366	7.1911	0.7484
	(0.0062)	(0.9341)	(0.9726)	(0.0125)	(0.0021)	(0.0000)	(0.4509)
minute	-0.38082	0.02307	-0.00398	0.00076	-1.55844	-2.47146	-0.14028
	(0.0000)	(0.0273)	(0.5632)	(0.8212)	(0.0000)	(0.0000)	(0.0000)
$minute^2$	0.00544	-0.00023	0.00006	-0.00004	0.02395	0.02820	0.00160
	(0.0000)	(0.1336)	(0.5775)	(0.4213)	(0.0000)	(0.0000)	(0.0009)
adj. R^2	0.3151	0.1200	0.0436	0.1451	0.3785	0.8861	0.6589