Competition, signaling and non–walking through the book: effects on order choice*

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August 2, 2012

Abstract

We investigate the effects of competition and signaling in a pure order driven market and examine the trading patterns of agents when walking through the book is not allowed. We show that the price information does not matter for an impatient trader in her decision of fitting the order size under this market mechanism. Also, our results suggest that the competition effect is persistent beyond the best quotes and dominates the signaling effect at every level, being strongest for the volume at the second best bid and ask for both sides of the market. Finally, we find that institutional traders' order submission strategies are less sensitive to the state of the limit order book compared to individual ones.

Keywords: Limit orders, market orders, limit order book, order aggressiveness, order–driven markets

*We sincerely thank Jon Danielsson, Christian Julliard, Christopher Polk, Dong Lou, Andrea Vedolin, Mikhail Chernov, Thorsten Rheinlander, Piotr Fryzlewicz, Cumhur Ekinci, Sercan Atak, Wolfram Jahn and seminar participants of ICMFE, FEBS 2012 for their useful comments. Moreover, we thank to Recep Bildik, Ozkan Cevik and Huseyin Eskici from Istanbul Stock Exchange for providing us the data and support for undertstanding market mechanism. Finally, we would like to thank to Coskun Gunduz for his invaluable help for the reconstruction of the limit order book.

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1 Introduction

The limit order book and the characteristics of an asset, such as volatility, provide essential information for a trader who wants to design an appropriate order submission strategy. The choice of order aggressiveness in turn affects the price formation of an asset and the liquidity dynamics in the market. Following this, there has been a growing research interest on investors' choice of order submission over the last decade. By undertaking an empirical study of a pure order driven market, this paper aims to contribute to this literature.

Our contribution is twofold: first, we examine the trading patterns of agents when walking through the book is not allowed, i.e. when orders that would otherwise walk through the book are converted into limit orders. Second, we test whether 'competition' or 'signaling' effects, two theories that have been proposed in the existing literature, dominate each other for depth beyond the best quotes. To the best of our knowledge, both of these analyses are the first attempts in the literature.

In Istanbul Stock Exchange, walking through the book is not allowed. That is, a 'large' market order will first be matched with the available volume at the best corresponding quote. Then, the remaining part is converted to a limit order at the quoted price instead of walking up or down the limit order book to be fully executed.[1] This market rule obviously affects the cost of a market order. When walking down/up the book is allowed, the cost of execution of a large market order is higher since it matches with less favorable prices. This in turn should affect the market order trader's submission strategy. By focusing on the order choice of an impatient (market order) trader, we analyse the informativeness of the price information contained in the book.

In an early work, Parlour (1998) suggests that an increase in the same–side thickness of the limit order book (LOB) reveals high *competition*, which in turn increases the submission of more aggressive orders[2] in order to jump the queue ('competition effect'). On the other hand, in their recent theoretical work, Goettler et al. (2009) argue that if the total volume of orders waiting beyond the best bid (ask) is 'too high', then this will *signal* to the market that the current quotes are mispriced and should decrease (increase) ('signaling effect'). By calculating the volume of orders waiting in the queue for the 10 best quotes separately, we analyze which effect dominates at every level.

Our analysis requires considering the reaction of the patient (limit order) and

[1] This is similar to Paris Bourse, Tokyo Stock Exchange, and the Stock Exchange of Hong Kong for example.

[2] The order aggressiveness is defined in Section 3.2.1.

impatient (market order) traders separately to the changing market conditions. Hence following Pascual and Veredas (2009) we employ a two-stage sequential ordered probit (SOP) model. Although our methodology coincides with their study, our research questions are different. In order to test whether competition effect is more persistent than the best quotes, we focus on the actions of patient traders. On the other hand, to analyse whether/how non–walking through the book affects the trading strategy of an aggressive market order trader, our focus is on trading strategies of impatient traders.

Using the unprocessed order flow and trade data provided by Istanbul Stock Exchange (ISE), we first reconstruct the limit order book dynamically. We use the order flow, trade book and limit order book to analyze the effects of the information content of the books on the order choice of the traders on a sample of 30 stocks for the period of June and July 2008.

Our data set has one major advantage compared to many studies: since ISE is a fully computerized and centralized stock exchange (unlike NYSE, there is no specialist and unlike Paris Bourse for instance, none of the trades are occurring outside ISE), the data generated *fully* captures the order flow and execution process.

Moreover, in our data set we can distinguish whether an order is initiated by an institutional or individual investor. By using this classification we examine whether the trading behavior is different for institutional traders compared to the individual ones.

Our main findings can be summarized as follows:

- The competition effect is stronger compared to the signaling effect for both sides of the market, in every stage.
- For a limit order agent, the competition effect is the strongest for the volume at the second best quotes for both, buyer and seller. For a seller, it disappears after the fourth best ask, whereas it is more persistent for a buyer.
- While fitting the size of her market order, for an impatient trader none of the price information, neither spread nor price distance variables, matters in our market. We believe this is specific to markets in which walking through the book is not allowed.
- Institutional traders' order submission strategies are less affected by the state of the limit order book compared to individual ones. If institutions are informed traders as proposed by the existing literature, this may

imply that institutions are placing their orders based more on their own private valuations than the limit order book information.

The paper is organized as follows: Next section briefly presents the related literature. In section 3, we describe data and introduce the order aggressiveness categories. Section 4 introduces the econometric methodology; two-stage sequential ordered probit model. In Section 5, we list the explanatory variables used in sequential ordered probit regressions and discuss the empirical questions. Section 6 presents the findings. The robustness check of the results is provided as well. Finally section 7 concludes.

2 Literature Review

Being one of the first dynamic equilibrium models on limit order markets, Parlour (1998) analyses the effects of the information contained in the limit order book (LOB) on order choice. She suggests that an increase in the same–side thickness of the LOB 'crowds out' the limit orders on that side, since higher competition decreases the execution probability. Similarly, an increase in the opposite-side thickness is anticipated as a decreasing execution risk, hence encouraging more aggressive behavior. This crowding-out effect is symmetric for both sides of the book.

In another dynamic equilibrium model, Foucault (1999) proposes that the order choice depends mainly on the asset volatility. When volatility increases, a limit order trader demands larger compensation for the risk of being picked off by posting higher ask and lower bid prices. This makes market orders more costly, which in turn increases the proportion of limit orders on the total order flow.

Foucault et al. (2005) consider the actual spread as a determinant of the order choice of the strategic liquidity traders that differ in their waiting costs. They conclude that for certain levels, high cost traders (impatient ones) will submit market orders, whereas others submit limit orders. However if spread increases over a cutoff level, all traders will supply liquidity to the market. Goettler et al. (2005) solve numerically for the stationary Markov perfect equilibrium in a model in which traders endogenously choose whether to submit a market or a limit order and the order size. On the other hand, Rosu (2009), similar to Foucault et al. (2005), models a continuous-time market, but with a dynamic investor decision problem, i.e. an agent can modify her strategy decision continuously.

Two of the very recent theoretical works allow asymmetric information for

pure order driven markets; Goettler et al. (2009) and Rosu (2010). In Goettler et al. (2009), informed traders are liquidity providers, i.e. they are submitting limit orders. However, in high volatility states, they are switching their order choice to market orders to take the advantage of the mispriced orders waiting in the queue. Rosu (2010), on the other hand, proposes that the informed traders can be patient or impatient based on how far the fundamental value is from the public price. That is; if the fundamental value of an informed trader is well above the public price plus a cutoff value, which is proportional to the volatility, then the agent will be aggressive and submit a market order to take advantage of her information instead of waiting to be compensated by a limit order.

Several papers investigate the state of the book and its effect on order choice in an empirical framework (Ahn et al. (2001), Ranaldo (2004), Beber and Caglio (2005), Ellul et al. (2007), Pascual and Veredas (2009), Menkhoff et al. (2010), among others). They find that the traders consume liquidity when it is plentiful. In other words, when the spread is tight, traders submit more market orders compared to limit orders.

The depth available at the best quotes has also been examined extensively. Ranaldo (2004), Ellul et al. (2007) and Hall and Hautsch (2006) show that aggressiveness increases with the depth on the same side. That is, investors submit more aggressive orders that can jump in the queue when competition increases. On the other hand, traders submit less aggressive orders when the opposite side of the book is thicker, that is when the execution risk decreases.

Most of the previous work considers the informativeness of the limit order book only at the best quotes. Relevant exceptions are Cao et al. (2009), Pascual and Veredas (2009) and Lo and Sapp (2010). Using data from the Australian Stock Exchange, Cao et al. (2009) investigate whether the prices beyond the best bid and offer and their corresponding depths matter in price discovery. They conclude that the contribution of beyond the book to the price discovery is 22%, whereas the remaining part comes from the current bid and ask prices as well as the transaction price. Pascual and Veredas (2009) empirically confirm many of the Goettler et al. (2005) predictions. Using a two stage sequential ordered probit model, they conclude that not only the best quotes, but the information beyond the best quotes matters in explaining the degree of patience of incoming orders. Moreover, they note that although the impatient traders strongly rely on the prevailing best quotes, for patient traders, strategic decisions are primarily based on the state of the book beyond the best quotes. Lo and Sapp (2010) empirically show the trade-off between order aggressiveness and quantity. Using simultaneous equations framework in a foreign exchange market, they conclude that

order size tends to be smaller when an order is more aggressive. That is, by submitting smaller size market orders, traders avoid the higher execution costs. Although their aim is not to examine the effects of the state of the book on order choice, they still consider the depth behind the best prices as an indication of asymmetric information.[3]

3 The Market and Data

3.1 Trading Structure in Istanbul Stock Exchange

The Istanbul Stock Exchange (ISE) is a fully computerized order-driven market. Similar to all other major exchanges, double auction continuous order matching is used for trading and the usual price and time priorities apply. However, there are still some differences of market mechanisms and three of them are worth to emphasize: First, ISE is a non-anonymous open market.[4] All traders can observe all of the orders submitted/traded, with the corresponding prices and volumes. Hence, before submitting an order, traders are aware of the quantity available for a given price, for various prices, not limited to the best five or ten quotes. Moreover, for the executed orders only, they can see the name of the corresponding party who initiated the trade.

Second, walking through the book is not allowed. Hence, the unexecuted portion of a market order is converted to a limit order. If an investor wishes to buy (sell) shares by walking up (down) the book, she needs to use appropriate LOs.

Finally, trading occurs in two sessions with a lunch break and every order is valid for a corresponding session or for a day.

3.2 Data and Descriptive Analysis

For the purpose of the study, we pick the 30 stocks from ISE30 index for the period of June and July 2008. The 30 stocks in our sample correspond to 73% of the total trading volume of ISE for the period under consideration.

By using the unprocessed order flow and trade data, we first reconstructed the limit order book (LOB) dynamically. To do so, we incorporate every

[3]In their data set, agents can only observe the best bid and ask and the corresponding depth. Hence depth beyond the best prices is private information

[4]Non-anonymity has changed by January 2011, but for the sample under consideration, traders can identify the name of the trading parties.

order according to the price and time priority rules and fill in LOB one by one.[5]

If a new order is a market order, it will be matched with the corresponding order(s) from the other side of the book and removed from the LOB. To detect whether an incoming order is a limit or a market order, we create the actual bid and ask prices. If the new–coming buy (sell) order proposes a price higher (lower) than or equal to the ask (bid) price, we identify it as a market order. Moreover, if an order revision (including the split) is submitted, the original order is removed from the limit order book. The volume available at the best, second best, and up to the 10th best prices are calculated as the cumulative volume of the orders waiting for that given prices. Hence the reconstruction methodology will enable to provide snapshots for the order book for any given time.

In 2008, the ISE index had a $248 billion value of shares traded and $11 billion of market capitalization. The total value of shares trading and the market capitalization were 0.7% and 5% of NYSE respectively. In terms of shares trading, it is 5^{th} within the emerging countries, just below the Johannesburg, higher than Thailand, Singapore and Indonesian Stock Exchanges.[6]

Table 1 reports the descriptive statistics of the order flow and trade book, averaged across the sample period.[7] Results show that, on average 2300 orders are submitted in a day, equivalent to 83 million TRL.[8] The highest number of orders is submitted/traded by GARAN investors, whereas the smallest one is for MIGRS. In terms of volume submitted, GARAN is 8 times bigger than the average, whereas MIGRS, is 16 times smaller than the average. Although our sample is composed by the 30 biggest stocks traded in ISE, this results show a high degree of heterogeneity in the sample of study.

On average, the number of buy orders is slightly less than the number of sell orders, roughly 15% of all orders have been revised or split and the number of limit orders constitute about 70% of all the submitted orders.

3.2.1 Order Aggressiveness

In order to analyze how the state of the book effects the order choice of the investor, we divide orders into five categories based on limit price position,

[5]See Valenzuela and Zer (2011) for a details of reconstruction of the limit order book procedure.

[6]Source: World Federation of Stock Exchanges.

[7]Opening session executions have been excluded during the analysis.

[8]On 25th of July 2008, the exchange rate was 1.20USD/TRL.

i.e. order aggressiveness, following Biais et al. (1995):

- Category 1 ('large MO buy'): $Q_{\text{buy}} \geq Q_{\text{ask}}$ and $P_{\text{buy}} \geq P_{\text{ask}}$.
- Category 2 ('small MO buy'): $Q_{\text{buy}} < Q_{\text{ask}}$ and $P_{\text{buy}} \geq P_{\text{ask}}$.
- Category 3 ('buy LO within the quote'): $P_{\text{ask}} > P_{\text{buy}} > P_{\text{bid}}$.
- Category 4 ('buy LO at the quote' order): $P_{\text{ask}} > P_{\text{buy}} = P_{\text{bid}}$.
- Category 5 ('buy LO away from the quotes'): $P_{\text{buy}} < P_{\text{bid}} < P_{\text{ask}}$.

Sell side is constructed analogously.

Table 2 suggests that for the buy side, the most frequent events are small buy market orders (category 2) followed by orders submitted at the quotes whereas, for the sell side the ones away from the best quotes (category 5) have the most frequent arrivals, contradicting the findings of Biais et al. (1995), Beber and Caglio (2005),Griffiths et al. (2000) for Paris Bourse, NYSE and Toronto Stock Exchange respectively. However this inconsistency is intuitive when we take into account the volatile nature of ISE compared to other developed economy stock exchanges.[9] Orders placed far from the best prices may suggest that investors believe large jumps in the price of stocks are always possible, and by placing orders far from the current price they want to take advantage of these large potential fluctuations.

Table 2 also shows a very little frequency of orders within the quotes (for both sides of the book), which can be explained by the small inside spread.[10]

Results regarding the execution rate, i.e. the proportion of orders executed, suggest that only around 20% of orders away from the quotes are executed compared to 67% of execution rate for the orders at the quotes. That is, going from category 4 to 5, traders are facing a substantial non-execution risk. This figures are very similar to Griffiths et al. (2000) for Toronto Stock Exchange.

[9]The daily volatility for July 2008 was 7% for CAC40, 6% for SP500 and 5% for DowJones, whereas it was 12% for ISE30.

[10]For example, say the actual spread is equal to the tick size. If an investor would like to submit a limit order, the most aggressive order he can submit would be at the quote, since 'mechanically' he cannot position his price within the quotes. Indeed, as Table 1 suggests, more than half of the stocks has a (tick size adjusted) spread less than 2.

4 Sequential Ordered Probit Regressions

We investigate how the information content of the limit order book affects the order choice of the investor, by considering the order choice as a two-stage process.

As a first step in her order choice, observing market dynamics and limit order book information, the agent is patient, i.e. submits a limit order, or she is impatient, i.e. submits a market order.[11]

In the second stage, given the agent is patient, she decides the position of her limit price (decides to submit category 1, 2 or 3 order), whereas the impatient trader decides whether to submit a large or small market order (category 1 or 2 order).

To allow this sequential decision, we employ a sequential ordered probit (SOP) model for the empirical investigation. The attractiveness of the SOP model, compared to the ordered probit (OP) model is that the former enables us to compare the reaction of the patient and impatient trader to the changing market conditions separately.

4.1 First stage–arrival of a market or limit order trader

In the first stage of the SOP model, the market conditions and the limit order book information determines the arrival rate of patient or impatient traders to the market. Although the degree of patience of the incoming trader, Y^*, is unobservable, we assume that it is a function of K observable (LOB) variables, Xs. We consider volatility, price trend, volume and price distance as explanatory variables. A detailed explanation of the regressors is provided in the next section.

[11] One can argue that the degree of patience is based on a trader's information level, preferences or waiting costs, hence exogenously determined. However, recent theoretical works suggest that market conditions and the state of the book affects the degree of patience. For example Goettler et al. (2009) claim that although a patient informed agent submits limit orders, when she observes high volatility, she switches to market orders to take advantage of the mispriced quotes. Similarly, in Foucault et al. (2005), if spread increases over a cutoff level, all traders, even the ones with high waiting costs, will submit limit orders. Moreover, Ranaldo (2004), Beber and Caglio (2005) among others show empirically that a trader considers the state of the book while formulating her order strategies. Hence, we allow the arrival rate of patient and impatient agents to be influenced by the state of the book and market conditions.

$$Y_t^* = \sum_{k=1}^{K} \beta_k X_{k,t-1} + \varepsilon_t \quad (1)$$

$$Y_t = \begin{cases} 0 & \text{if } -\infty < Y_t^* \leq \delta \\ 1 & \text{if } \delta < Y_t^* < \infty \end{cases} \quad (2)$$

Here, t refers to transaction time, not clock time. Hence, our first-stage-dependent variable is equal to 1 if the trader is impatient and 0 otherwise.

Assuming that error terms are normally distributed, the probability of the incoming trader being patient is:

$$P(Y_t = 0) = P(-\infty < Y_t^* \leq \delta) \quad (3)$$

$$= P(-\infty < \sum_{k=1}^{K} \beta_k X_{k,t-1} + \varepsilon_t \leq \delta) \quad (4)$$

$$= \Phi(\delta - \sum_{k=1}^{K} \beta_k X_{k,t-1}) \quad (5)$$

4.2 Second stage–patient trader

In the second stage, both patient and impatient traders choose their level of aggressiveness given the information content of the book. A patient trader has three choices: submitting a limit order within, at or away from the best quotes. That is;

$$LO_t^* = \sum_{k=1}^{K} \theta_k X_{k,t-1}^{lo} + \varepsilon_t^{lo} \quad (6)$$

$$LO_t = \begin{cases} 1 & \text{if } -\infty < LO_t^* \leq \delta_1^{lo} \\ 2 & \text{if } \delta_1^{lo} < LO_t^* \leq \delta_2^{lo} \\ 3 & \text{if } \delta_2^{lo} < LO_t^* < \infty \end{cases} \quad (7)$$

Our dependent variable is equal to 1 if a trader submits a limit order away from the best quotes (category 5), is equal to 2, if the order is submitted at the best quotes (category 4) and finally is equal to 3 if the order is submitted within the quotes (category 3). Hence, our dependent variable increases as aggressiveness increases.

Assuming that the error terms are normally distributed, the probability of the incoming patient trader being type $i = 1, 2, 3$ is:

$$P(LO_t = i) = \Phi(\delta_i^{lo} - \sum_{k=1}^{K} \theta_k X_{k,t-1}) - \Phi(\delta_{i-1}^{lo} - \sum_{k=1}^{K} \theta_k X_{k,t-1}) \quad (8)$$

where $\delta_0^{lo} = -\infty$ and $\delta_3^{lo} = \infty$.

4.3 Second stage–impatient trader

Finally, the impatient trader decides the quantity she wants to trade; whether she submits an aggressive market order (category 1), or submits a small market order (category 2).

$$MO_t^* = \sum_{k=1}^{K} \gamma_k X_{k,t-1}^{mo} + \varepsilon_t^{mo} \quad (9)$$

$$MO_t = \begin{cases} 0 & \text{if } -\infty < MO_t^* \leq \delta_1^{mo} \\ 1 & \text{if } \delta_1^{mo} < MO_t^* < \infty \end{cases} \quad (10)$$

As the coefficients of the sequential ordered probit measure the change in the latent variable with respect to a change in one of the explanatory variables, they are difficult to interpret. A direct interpretable measure is given by the marginal probabilities (marginal effects):

$$\frac{\partial P(Y=0)}{\partial X_j} = \frac{\partial \Phi(\delta - \sum_{k=1}^{K} \beta_k X_{k,t-1})}{\partial X_j}$$

$$= -\phi(\delta - \sum_{k=1}^{K} \beta_k X_{k,t-1})\beta_j \quad (11)$$

$$\frac{\partial P(LO=i)}{\partial X_j} = \frac{\partial(\Phi(\delta_i^{lo} - \sum_{k=1}^{K} \theta_k X_{k,t-1}) - \Phi(\delta_{i-1}^{lo} - \sum_{k=1}^{K} \theta_k X_{k,t-1}))}{\partial X_j}$$

$$= [\phi(\delta_{i-1}^{lo} - \sum_{k=1}^{K} \theta_k X_{k,t-1}) - \phi(\delta_i^{lo} - \sum_{k=1}^{K} \theta_k X_{k,t-1})]\theta_j \quad (12)$$

$$\frac{\partial P(MO=0)}{\partial X_j} = \frac{\partial \Phi(\delta_1^{mo} - \sum_{k=1}^{K} \gamma_k X_{k,t-1})}{\partial X_j}$$

$$= \phi(\delta_1^{mo} - \sum_{k=1}^{K} \gamma_k X_{k,t-1})\gamma_j \quad (13)$$

where $i = 1, 2, 3$ and $\delta_0^{lo} = -\infty$ and $\delta_3^{lo} = \infty$.

Marginal effects show how the probability of order choices are effected given a marginal change in any of the explanatory variables.

5 Empirical Analysis

Empirically we ask the following questions: whether 'competition' or 'signaling' effects dominate each other at every level of the depth, how/whether walking through the book affects the order decision of an impatient trader, and finally, how the trading behavior is different for institutional traders compared to the individual ones.

5.1 Covariates for the impact of depth at and beyond the best quotes

We test whether the competition and signaling effects, proposed by Parlour (1998) and Goettler et al. (2009) respectively, dominates each other for depths beyond the best quotes. To do so, we calculate the volume of orders waiting in the queue for the 10 best prices separately.

We define a proxy separately for every stage of the sequential ordered probit (SOP) regressions. In the first stage of the SOP, when a trader decides whether to submit a market or a limit order, she considers only the increase of the volume at the best quotes (Vsame^1 and/or Vopp^1) as an increased competition.

In the second stage, when a limit order trader decides her limit price, we consider two states: first, (tick–adjusted) inside spread greater than 1 and second, spread equal to 1. If an agent observes the inside spread greater than 1, then by submitting an order *within* the quotes (category 3 order) she can jump the queue. In this case, Vsame^1 and (possibly) depth beyond the best quotes captures the competition effect.

However, if the spread is 1, then 'mechanically' it is not possible to submit a category 3 order, i.e. a trader cannot gain a priority over the orders already waiting at Vsame^1. In this case, while positioning her limit price, she may consider just the depth beyond the best quotes as an increased competition, at least up to some *cutoff* level, discarding the depth at the quotes as part of the competition effect.

In order to determine the cutoff point in the analysis for the second stage, we

run the SOP regressions with accumulated volume of orders from the second to the third, from the second to the fourth and from the second to the fifth best prices ($\text{Vsame}^{2\text{-}3}$, $\text{Vsame}^{2\text{-}4}$ and $\text{Vsame}^{2\text{-}5}$). The signaling effect will then be captured by $\text{Vsame}^{4\text{-}10}$, $\text{Vsame}^{5\text{-}10}$ and $\text{Vsame}^{6\text{-}10}$ respectively.

Table 3 reports the results. For both sides of the market, volume at the second best bid has the strongest competition effect. The marginal effects as well as the significance of the estimated coefficients are decreasing with the additional quotes added.[12] Moreover, at every level, competition effect dominates the signaling effect. Finally, results suggest an asymmetry between the sell and the buy side. The signaling effect is more persistent and stronger for the sell side.

As suggested, we pick the volume at the second best quote as the cutoff level. Hence, we define the competition effect, Vcomp and the signaling effect, Vsign regressors as follows:

- Step 1– arrival rate of patient/impatient traders:

$$\begin{aligned} \text{Vcomp}_t &= \text{Vsame}_t^1 \\ \text{Vsign}_t &= \text{Vsame}_t^2 + \text{Vsame}_t^3 + ... + \text{Vsame}_t^{10} \end{aligned}$$

- Step 2– order choice of patient traders:

$$\begin{aligned} \text{Vcomp}_t &= \begin{cases} \text{Vsame}_t^2 & \text{if} \quad \text{spread}_t = 1 \\ \text{Vsame}_t^1 + \text{Vsame}_t^2 & \text{if} \quad \text{spread}_t > 1 \end{cases} \\ \text{Vsign}_t &= \text{Vsame}_t^3 + \text{Vsame}_t^4 + ... + \text{Vsame}_t^{10} \end{aligned}$$

- Step 2– order choice of impatient traders:

$$\text{Vsign}_t = \text{Vsame}_t^2 + \text{Vsame}_t^3 + ... + \text{Vsame}_t^{10}$$

5.2 Covariates for the impact of non–walking through the book

In markets where walking through the book is allowed, an aggressive, i.e. category 1 market order (MO) has to walk up or down the order book to

[12]For the sake of brevity we did not report the marginal effects, but only report the median coefficient for the statistically significant stocks. Note that the marginal effect of an order submitted at the quotes (category 4) is positively related to the coefficient reported.

be fully executed. For markets in which walking through the book is not allowed, any excess that cannot be executed at the pre–specified limit price, joins the queue at the quoted price instead of walking through and executed with an unfavorable price. By focusing on the order choice of a MO trader, we test the relevance of price information for her while fitting her order size when walking through the book is not allowed. In addition to the depth variables, we define the inside spread and the price distance variables.

i) SPR: The actual bid-ask spread (tick size adjusted) just prior to the submission of the order.

ii) Price Distances:

- Dsame^{1_2} (Dopp^{1_2}): The price difference between the best and the second best quotes for the same and the opposite side of the book.
- Dsame^{2_max} (Dopp^{2_max}): The price difference between the second best and the highest or lowest available quote for the same and the opposite side of the book.

The price distance variables for the opposite side capture the (weighted) average execution price of an aggressive order for markets in which walking through is possible. Because, in that case, when a large buy (sell) MO is submitted, it will eat up all the available volume at the best ask (bid) and then move up (down) to the second best ask, and if necessary move up to third after consuming the second, etc. So since the cost of a MO increases with Dopp^{1_2} or/and Dopp^{1_max}, this should lead to a submission of less aggressive market orders.

5.3 Additional Explanatory variables

Besides our key explanatory variables discussed above, following the previous theoretical literature (e.g., Parlour (1998), Foucault (1999), Goettler et al. (2005), Foucault et al. (2005), Goettler et al. (2009) and Rosu (2010)) as well as the empirical literature (e.g Ranaldo (2004), Beber and Caglio (2005), Pascual and Veredas (2009) and Cao et al. (2009)), we use volatility and price trend as additional explanatory variables.

1. Trading–Time Volatility (Vola):

Following Beber and Caglio (2005), we define the volatility as the exponential moving average of the squared returns, computed on the mid-quote prices

prior to the submission of the order.

$$\hat{\sigma}_t = \sqrt{\lambda \hat{\sigma}^2_{t-1} + (1-\lambda) r^2_{t-1}}; \tag{14}$$

The decay factor λ is equal to 0.95, hence the measure gives the highest weight to the latest observation.

Expected signs: Existing literature identifies a negative relationship between volatility and order aggressiveness using various different reasoning. Foucault (1999), Foucault et al. (2005), Goettler et al. (2009) among others, claim that in high volatility states, since the picking off risk increases, the aggressiveness of an incoming agent decreases.

2. Previous price trend (TREND):

We would like to identify the previous trend in the prices observed by the agents. We define TREND as the percentage change in the mid-quote prices for the last 100 observation at the time of the order arrival.

Expected signs: Given that a trader observes an increasing price trend upon arrival, this may indicate a possible future price increase as well. Since this movement will move the prices away from the current levels, a buy trader may interpret it as an increased non-execution risk of her limit order; hence she prefers to submit more aggressive orders. This works opposite for the seller.

3. Control variables:

In all of the regressions, we use the five previous lags of the dependent variables. Moreover, to control the seasonality on the arrival rate of orders, we use time of the day dummy, indicating which half–an–hour of the day the order is submitted.

6 Results

As mentioned in Section 3, the 30 stocks in our sample present a high degree of heterogeneity. Hence we estimate the sequential ordered probit (SOP) regressions for each stock separately, for buyer and seller initiated traders and report the median coefficient for the significant stocks. Table 4, Table 5 and Table 6 present the results of the first, the second stage for a limit order (LO) trader and the second stage for a market order (MO) trader of the SOP model respectively. We report the median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant.

6.1 Impact of depth at and beyond the best quotes

Table 4 reveals that an increase in the depth at the best quotes is perceived as an increased competition and lead to an increase in the arrival rate of MO traders for both sides of the market. On the other hand, when the competition on the opposite side of the book (Vcompopp) increases, agents predict that the MO arrivals increases on the opposite side of the book, implying an increased probability of execution for their limit orders, so they submit more limit orders.

The signaling effect is more pronounced on the sell side of the book compared to the buy side. An increase in the volume of orders waiting beyond the best quotes is perceived as a disagreement on the current price. An increase in the accumulated volume beyond the best bid (Vsignalopp) is signaling a possible future price decrease, resulting an increase on the arrival rate of aggressive sellers. An increase on the ask side (Vsignal) has an opposite effect.

Table 5 presents the regression results for a patient trader. It suggests that only the same side of the book matters for both, buyer and seller. Vcomp and Vsignal has expected signs. An increase in the competition lead to a submission of aggressive limit orders to jump the queue, whereas an increase on the same-side-depth away from the quotes (Vsignal) is perceived as a possible mispricing of the best quotes as Goettler et al. (2009) predict and lead to a submission of less aggressive limit orders.

Marginal effects regarding the depth variables reveal that the volume at the best quotes is particularly emphasized while determining the degree of patience of the incoming trader compared to depth beyond the best quotes. Moreover, the competition effect is stronger compared to the signaling effect for both sides of the market in all stages of the SOP.

6.2 Impact of non-walking through the book

Our results suggest that, while fitting the size of her market order (MO), for an impatient trader none of the price information, neither spread nor price distance variables, matters. An MO trader only considers volatility and volume accumulated on the opposite side of the book. We believe that this is a result of non-allowance of walking through the book.

In high volatility states impatient trader submits more aggressive MOs. This can be explained by two: first, an impatient trader may benefit from a high volatility state since it increases the probability of fully execution of large size orders. This is due to the fact that the excess is converted to a limit order

and the execution probability of a limit order increases with volatility.[13]

Second, given that the trader submits an MO in a high volatility state, it is more likely that she is informed as Goettler et al. (2009) predict. She would like to take advantage of the mispricing at the quotes, which makes her to submit an aggressive MO.

An impatient buyer splits her orders into several small quantities rather than submitting a large MO when Vsignalopp (the accumulated volume on the opposite side of the book) increases. Since, the non-executed part of a large MO is converted to a limit order; an increase in the Vsignalopp makes large MOs less attractive. Because, when Vsignalopp increases, this signals a possible future price increase, making the non-execution risk higher for the limit-order-converted-part of the aggressive MO. This result is weak for an impatient seller.

All of the results regarding the actions of an impatient trader contradicts with the previous empirical studies conducted on markets in which walking through the book is allowed. For example, in their study of Spanish Stock Market, Pascual and Veredas (2009) show that spread, the depth at and away from the best quotes and the price differences on the opposite side of the market matters for an impatient trader's decision.

In his study on the Swiss Stock Exchange, Ranaldo (2004) demonstrates that the sensitivity of a large MO with respect to volatility is more negative compared to a small one. Thus in high volatility states, given that the trader is an MO trader, she prefers to submit small MOs.[14]

To analyze further, we use a different proxy to capture the price and volume information contained at the quotes away from the best prices. We fit a second degree polynomial for the total volume available at each price and the corresponding quotes. Then the coefficient of the quadratic term for both sell and buy sides of the book is used in the SOP regressions. Following the discussion above, we expect them to be insignificant for an impatient trader. As expected, neither the fit for the same nor the opposite side of the book matters. The only significant variables are volatility and price trend.[15]

[13]For example Cho and Nelling (2000) and Hasbrouck and Saar (2002) show that execution probability of limit orders are increasing with volatility.

[14]It is worth to stress here that in Ranaldo (2004) study, the actions of patient and impatient are not distinguished separately. However by considering the marginal effects of each type of order aggressiveness, we can still come up to this conclusion.

[15]The results are presented in the working paper version.

6.3 Effects of the Additional Variables

Similar to the existing literature, we find that when volatility increases, the probability of an incoming agent being patient increases since the increased volatility increases the picking off risk.

On the other hand, given that the agent is patient and submits a limit order, she prefers to submit more aggressive limit orders since submitting orders away from the quotes decreases the execution probability significantly.[16]

Our results suggest that, when the previous price trend increases, a buyer submits more limit orders whereas a seller submits more MOs. This contradicts the expected sign proposed. One possible interpretation is the expectation of mean reversion in the prices. If a seller, for instance, believes that prices will revert back, she would submit an aggressive MO to take advantage of this 'mispricing', instead of waiting and to be compensated by a limit order.

In line with the majority of the literature, we found that wider spread increases the probability of an incoming trader being patient. On the other hand, Table 5 shows that, the importance of the inside spread is more pronounced for the limit order trader while positioning their limit price. In line with the predictions of Foucault et al. (2005) and Goettler et al. (2005), we find that a wider spread persuades patient traders to submit more aggressive limit orders.

6.4 Trading Behavior of the Institutions

The current literature points out that individual and institutional investors may differ in their level of information implying that institutions are informed traders.[17]

In our data we can distinguish whether an order is initiated by an institutional or individual investor, with a problem however. Due to internal regulations, some of the foreign institutions are classified as individual instead of institutions. Hence, whenever it is marked as an institution in our data set, it is an institution for sure. However, individual traders are pooled with foreign institutions. This in turn reduces our sample size significantly, but does not affect the conclusions we derived.

[16]For instance, Table 2 suggests that submitting an order away from the quotes instead of at the quotes decreases the execution probability from 60% to 20%.

[17]See Arbel and Strebel (1983), Lo and MacKinlay (1990), Cornell and Sirri (1992), Koski and Scruggs (1998) and Chakravarty (2001).

In our sample, on average 3.7% of all orders are initiated by institutions. When we parse orders initiated by institutional investors only, it is not possible to run the SOP regressions mentioned in Section 4 for four of the stocks in our sample, due to limited number of observations. Hence we excluded those stocks from our analysis in this section.[18]

Results presented in Table 7 show that only the depth available at the same and at the opposite side of the book, matters for institutional investors in their decision to submit a limit or a market order. In other words, competition matters. Comparing with the overall sample, we see that the significance of the volatility is disappeared. This may suggest that the picking off risk that drives uninformed agents to submit more limit orders in high volatility states diminishes in case of institutional trading since they have informational advantage over individual investors.

When we analyze the second stage results, we see that except the Vcomp, the competition effect variable, which matters only half of the sample, the information contained in the book does not matter at all for institutional investors in their price or quantity decision. This may imply that institutions are placing their orders based more on their own private valuations than in the limit order book information. They analyze other traders' actions only for possible competition; however signaling does not influence their order choice.

As a robustness check, we check our results under 1% confidence interval and we see that the conclusions do not change.

6.5 Robustness

We provide three sets of robustness checks to make sure that our findings are not driven by an arbitrary choice. The first robustness check is related to the model specification. Instead of estimating the model with ordered probit, we use ordered logit. The results were qualitatively same and even quantitatively very similar. [19]

We proxy the price fluctuations by using exponential-weighted moving average (EWMA) volatility and price trend as the percentage change in the mid–quote prices for the last 100 observations. The empirical results could depend on those definitions. For this reason, we re–estimate SOP regressions with different transient volatility measures by employing the absolute value and the standard deviation of the mid–quote changes of the previous 60, 100

[18]IHLAS, ISGYO MIGRS and TSKB are excluded.

[19]For the sake of brevity, robustness results are presented only the working paper version.

and 120 orders prior to order submission. Similarly, as a robustness check for the price trend, we employ different window sizes of 60 and 120.

All of the results are qualitatively robust, except the volatility in the second stage for limit order trader. Whereas in our benchmark model, volatility is significant for almost half of the stocks, when we change the definition of the volatility, the significance reduced to one–third.

Finally, we check the robustness of the chosen level of decay factor, λ. We estimate the EWMA volatility by using two different levels of the decay factor other than 0.95 namely 0.97 and 0.93[20]. Similarly, results are very robust for the chosen decay factor.

To sum up, for all of our order book covariates, we find a remarkable robustness over different specifications.

7 Conclusion

This paper investigates how the information content of the limit order book affects the order choice of an investor. Employing a two-stage sequential ordered probit model, we answer the following questions: whether competition or signaling effects dominate each other at every level of the depth, how does non–walking through the book affect order decision of an impatient trader, and finally, how the trading behavior is different for institutional traders compared to the individual ones.

By reconstructing the limit order book for Istanbul Stock Exchange, we show that although competition effect is present only at the best quotes while determining the arrival rate of market or limit orders, a limit order trader, perceives an increase in the depth at the second best quote as an increased competition and go for a more aggressive limit order. On the other hand, an increase in the same–side–depth away from the quotes is perceived as a signal of a possible mispricing of the best quotes and induces agent to submit less aggressive limit orders.

The competition effect is strongest for volume at the second best quotes for both the patient buyer and seller. For sellers, it disappears after the fourth best ask, whereas it is more persistent for a buyer. Moreover, at every level, competition effect dominates the signaling effect.

In our market, in her decision to submit a 'large' or 'small' market order, only volatility and volume accumulated on the opposite side of the book matters

[20]For daily purposes, J.P. Morgan (1995) estimate optimal λ as 0.94.

for an impatient trader. We believe this is specific to markets in which walking through the book is not allowed. None of the price information matters since under this case, the quotes beyond the best do not capture the execution price of an aggressive order.

Finally, we repeat the analysis for institutional investors only. Results show that institutional traders' order submission strategies are less affected by the state of the limit order book compared to individual ones. If institutions are informed traders as proposed by the existing literature, this implies that institutions are placing their orders based more on their own private valuations than the limit order book information.

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Table 1: Descriptive statistics for each stock.
This table reports the daily mean statistics of ISE30 stocks separately for June 2008. Market capitalization is at the beginning of the period.

	Mcap	**Orders (Number)**	**Volume Order (M shares)**	**Value Ordered (M TRL)**	**Trades (Number)**	**Volume Traded (M shares)**	**Value Traded (M TRL)**
AKBNK	16650	2609	26.00	130.63	1643	8.81	44.09
AKGRT	1463	1044	4.28	18.35	714	1.54	6.59
ARCLK	1664	1003	2.39	10.51	576	0.75	3.27
ASYAB	1980	1392	6.50	16.94	954	2.19	5.64
DOHOL	2160	2438	36.75	54.95	1546	12.37	18.45
DYHOL	1082	2991	28.13	46.06	1949	9.45	15.40
EREGL	9995	2286	6.70	61.99	1455	2.19	20.22
GARAN	14448	9260	221.13	749.12	6186	82.39	278.14
GSDHO	277	2074	32.89	35.77	1400	10.91	11.78
HALKB	7750	1656	7.89	49.35	972	2.56	15.99
HURGZ	745	2281	28.63	45.50	1455	9.53	15.09
IHLAS	202	1975	31.92	18.15	942	7.63	4.30
ISCTR	13165	7332	88.64	393.63	4732	32.46	143.32
ISGYO	459	700	5.09	4.94	367	1.35	1.31
KRDMD	670	2016	33.67	38.73	1150	9.91	11.39
KCHOL	7629	1399	11.87	41.51	855	3.93	13.72
MIGRS	3614	346	2.98	60.88	152	0.48	9.84
PETKM	1024	1156	3.70	20.39	688	1.12	6.02
PTOFS	2778	507	1.59	8.47	295	0.48	2.53
SAHOL	8676	1103	6.56	28.25	713	2.19	9.44
SKBNK	876	1872	9.80	21.47	1216	3.23	7.06
SISE	1439	1572	10.29	14.73	975	3.24	4.63
TSKB	490	707	6.08	5.73	448	1.72	1.62
TKFNK	2166	1172	3.04	25.96	747	1.00	8.56
TCELL	17050	1847	14.80	117.95	1095	5.05	40.15
TUPRS	7387	1413	2.71	75.11	761	0.83	22.86
THYAO	919	1252	4.89	26.83	787	1.65	8.99
TTKOM	14350	4447	28.51	119.25	2343	8.48	35.07
VAKBN	4400	4813	86.02	151.08	3169	31.17	54.61
YKBNK	9999	2939	42.24	106.19	1911	14.61	36.47
Average	5184	2253	26.52	83.28	1406	9.11	28.55
Median	2163	1752	10.04	40.12	973	3.24	11.59
Min	202	346	1.59	4.94	152	0.48	1.31
Max	17050	9260	221.13	749.12	6186	82.39	278.14

Table 1: Descriptive statistics for each stock.
This table reports the daily mean statistics of ISE30 stocks separately for June 2008. Market capitalization is at the beginning of the period. (continued)

	Execution Rate (%)	**Execution Time (minutes)**	**Spread/tick**	**Buy Orders (%)**	**Limit Orders (%)**	**Market Orders (%)**
AKBNK	61.06	16.24	1.59	0.47	0.69	0.15
AKGRT	67.95	11.01	2.14	0.52	0.62	0.15
ARCLK	56.62	19.36	2.05	0.46	0.71	0.13
ASYAB	66.68	10.12	2.11	0.49	0.62	0.16
DOHOL	61.02	13.21	1.58	0.44	0.69	0.15
DYHOL	63.33	12.34	1.68	0.49	0.66	0.15
EREGL	61.29	15.47	1.80	0.49	0.68	0.15
GARAN	63.69	14.28	1.50	0.47	0.69	0.16
GSDHO	64.57	12.17	1.58	0.47	0.64	0.15
HALKB	56.17	17.28	1.87	0.46	0.72	0.16
HURGZ	62.14	15.29	1.71	0.47	0.67	0.15
IHLAS	45.21	24.18	1.47	0.48	0.71	0.11
ISCTR	61.48	16.09	1.51	0.49	0.70	0.14
ISGYO	50.46	23.84	1.95	0.45	0.72	0.11
KRDMD	54.70	17.31	1.53	0.46	0.70	0.14
KCHOL	58.68	17.06	1.99	0.45	0.69	0.14
MIGRS	42.17	25.24	1.47	0.39	0.70	0.11
PETKM	57.35	18.40	2.05	0.47	0.71	0.15
PTOFS	57.85	18.58	2.42	0.46	0.69	0.13
SAHOL	63.32	15.11	2.04	0.49	0.66	0.15
SKBNK	62.64	11.16	2.31	0.44	0.64	0.17
SISE	59.48	15.23	2.07	0.51	0.67	0.14
TSKB	60.04	16.26	1.71	0.49	0.63	0.12
TKFNK	62.92	12.86	2.10	0.49	0.65	0.16
TCELL	57.16	16.57	1.73	0.46	0.71	0.18
TUPRS	52.09	22.60	1.56	0.48	0.74	0.16
THYAO	60.72	15.10	1.95	0.51	0.68	0.15
TTKOM	50.44	20.29	1.57	0.39	0.73	0.13
VAKBN	63.21	13.31	1.54	0.47	0.69	0.15
YKBNK	61.82	12.49	1.66	0.48	0.67	0.16
Average	58.87	16.28	1.81	0.47	0.68	0.15
Median	60.87	15.78	1.72	0.47	0.69	0.15
Min	42.17	10.12	1.47	0.39	0.62	0.11
Max	67.95	25.24	2.42	0.52	0.74	0.18

Table 2: Descriptive statistics of order aggressiveness categories.

Orders are divided into five categories based on limit price position, i.e. order aggressiveness, following Biais et al. (1995). Category 1 ('large MO buy'): $Q_{\text{buy}} \geq Q_{\text{ask}}$ and $P_{\text{buy}} \geq P_{\text{ask}}$, Category 2 ('small MO buy'): $Q_{\text{buy}} < Q_{\text{ask}}$ and $P_{\text{buy}} \geq P_{\text{ask}}$., Category 3 ('buy LO within the quote'): $P_{\text{ask}} > P_{\text{buy}} > P_{\text{bid}}$, Category 4 ('buy LO at the quote' order): $P_{\text{ask}} > P_{\text{buy}} = P_{\text{bid}}$, Category 5 ('buy LO away from the quotes'): $P_{\text{buy}} < P_{\text{bid}} < P_{\text{ask}}$. Sell side is constructed analogously. The first two columns report the unconditional frequencies of orders and order sizes for five aggressiveness categories. The last column, execution rate, gives the proportion of orders executed in each category.

	Orders (%)	**Ordersize (%)**	**Execution rate(%)**
Panel A- Buy Side			
Category 1	3.78	14.83	97.97
Category 2	33.24	24.31	99.77
Category 3	0.98	1.90	86.87
Category 4	32.08	34.74	67.35
Category 5	29.92	24.22	21.36
Panel B- Sell Side			
Category 1	3.54	12.78	97.98
Category 2	24.46	22.41	99.74
Category 3	0.85	1.66	88.95
Category 4	28.75	32.27	60.72
Category 5	42.41	30.89	16.04

Table 3: Analysis of depth beyond the best quotes.

The table presents the results of the depth analysis using different cutoff values. Vcomp=Vsame^{j} +...+Vsame$^{\text{cutoff}}$, where $j = 1$, if spread/tick> 1, $j = 2$ otherwise. Whereas, Vsign=Vsame$^{\text{cutoff}+1}$ + ...+Vsame^{10}. Vcompopp and Vsignopp are constructed analogously. Vola is the EWMA volatility (multiplied by 1000), Trend is the previous price change of 100 observations (multiplied by 1000), SPR is the actual spread in ticks. Dsame^{1_2} (Dsame$^{2_\text{max}}$) is the price difference between the best and the second best quotes (is the price difference between the best and the highest or lowest available quote) for the same side of the book. Dopp^{1_2} (Dopp$^{2_\text{max}}$) is the price difference between the best and the second best quotes (is the price difference between the best and the highest or lowest available quote) for the opposite side of the book. All of the volume variables are scaled by 1e-5. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are reported.

BUY		**Vola**	**Trend**	**SPR**	**Vcomp**	**Vcompopp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame$^{2_\text{max}}$**	**Dopp^{1_2}**	**Dopp$^{2_\text{max}}$**
cutoff=2	median given sig.	0.048	0.525	0.761	0.081	0.009	-0.007	0.007	-0.037	0.014	0.231	0.020
	sig. (%)	57	60	97	80	23	60	37	60	50	30	50
	> 0	94	94	100	100	86	6	91	50	60	56	53
cutoff=3	median given sig.	0.047	0.515	0.792	0.046	0.007	-0.011	0.005	-0.032	0.017	0.206	0.018
	sig. (%)	60	57	97	67	43	47	27	60	47	30	53
	> 0	94	100	100	95	85	7	88	50	64	56	56
cutoff=4	median given sig.	0.048	0.532	0.833	0.019	0.012	-0.012	0.002	-0.034	0.018	0.202	0.026
	sig. (%)	57	57	97	67	43	43	33	60	47	30	50
	> 0	94	100	100	80	100	15	60	50	57	56	67
cutoff=5	median given sig.	0.051	0.543	0.822	0.033	0.015	-0.008	-0.002	-0.035	0.020	-0.083	0.029
	sig. (%)	50	57	97	53	53	47	33	60	40	27	47
	> 0	93	100	100	75	100	29	50	50	67	50	64
SELL												
cutoff=2	median given sig.	0.053	-0.609	0.652	0.081	0.010	-0.018	0.005	-0.011	0.045	0.229	0.008
	sig. (%)	63	43	100	93	30	77	47	40	33	33	20
	> 0	95	31	100	100	56	4	79	50	70	60	50
cutoff=3	median given sig.	0.055	-0.452	0.680	0.062	0.007	-0.019	0.003	-0.019	0.042	0.222	0.024
	sig. (%)	63	47	100	77	43	80	43	40	43	33	23
	> 0	95	36	100	100	62	4	62	50	54	60	57
cutoff=4	median given sig.	0.065	-0.449	0.678	0.027	0.009	-0.025	0.001	-0.034	0.041	0.222	0.017
	sig. (%)	60	47	100	70	43	70	50	40	43	33	27
	> 0	94	36	100	90	92	0	53	50	54	60	63
cutoff=5	median given sig.	0.064	-0.612	0.670	0.019	0.008	-0.043	0.001	-0.017	0.038	0.223	0.018
	sig. (%)	60	50	97	43	53	60	37	40	43	33	27
	> 0	94	33	100	77	94	0	55	50	54	60	63

Table 4: First Stage Sequential Ordered Probit.

This table presents the estimated results of the first stage of the two-stage sequential ordered probit model. In this stage, the dependent variable is equal to 1 if the incoming trader is impatient (submits MO), and 0 otherwise. Vola is the EWMA volatility (multiplied by 1000), Trend is the previous price change of 100 observations (multiplied by 1000), SPR is the actual spread in ticks, Vcomp (Vcompopp) is the volume accounting for the competition effect on the same (opposite) side of the book, Vsignal (Vsignalopp) is the volume accounting for the signaling effect on the same (opposite) side of the book. Dsame^{1_2} (Dsame^{2_max}) is the price difference between the best and the second best quotes (is the price difference between the best and the highest or lowest available quote) for the same side of the book. Dopp^{1_2} (Dopp^{2_max}) is the price difference between the best and the second best quotes (is the price difference between the best and the highest or lowest available quote) for the opposite side of the book. All of the volume variables are scaled by 1e-5. All of the regressions include 5 lags of the dependent variable and the time-of-the day dummies. In sake of brevity, those are not reported. The cross sectional median of marginal effects scaled by 1e3 is also reported. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are provided.

Buy	**Vola**	**Trend**	**SPR**	**Vcomp**	**Vcompopp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame^{2_max}**	**Dopp^{1_2}**	**Dopp^{2_max}**
median given sig.	-0.067	-0.707	-0.323	0.161	-0.200	-0.002	0.001	-0.389	-0.031	-0.432	-0.031
Sig.	70	80	77	100	100	57	53	40	37	30	67
Pos. given sig. (%)	5	8	0	100	0	35	56	8	9	11	30
Marginal Effects (x1000)											
median given sig.											
MO	-26.60	-265.50	-122.00	64.05	-77.35	-0.91	0.31	-151.00	-11.80	-165.00	-12.15
Sell											
median given sig.	-0.078	0.565	-0.370	0.165	-0.174	-0.018	0.002	-0.396	-0.025	-0.338	-0.023
Sig. (%)	83	67	77	100	100	80	73	47	37	43	50
Pos. given sig. (%)	0	100	0	100	0	8	64	21	27	8	20
Marginal Effects											
median given sig.											
MO	-26.90	192.00	-128.00	59.00	-62.80	-6.42	0.56	-138.50	-9.08	-113.00	-7.88

Table 5: Second Stage Sequential Probit, Patient Traders.

This table presents the estimated results of the second stage of the two-stage sequential ordered probit model for patient traders. In this stage, given the trader is patient, the dependent variable is equal to 1, 2 or 3 if the trader submits a category 5, category 4 or category 3 order (limit price within, at or away from the best quotes) respectively. All of the explanatory variables are same as noted in Table 4. All of the regressions include 5 lags of the dependent variable and the time-of-the day dummies. For the sake of brevity, those are not reported. The cross sectional median of marginal effects scaled by 1e3 is also reported. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are provided.

Buy-LO	**Vola**	**Trend**	**SPR**	**Vcomp**	**Vcompopp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame^{2_max}**	**Dopp^{1_2}**	**Dopp^{2_max}**
median given sig.	0.048	0.525	0.761	0.081	0.009	-0.007	0.007	-0.037	0.014	0.231	0.020
Sig. (%)	57	60	97	80	23	60	37	60	50	30	50
Pos. given sig. (%)	94	94	100	100	86	6	91	50	60	56	53
Marginal Effects											
Within quotes	0.47	2.99	12.20	0.58	0.06	-0.04	0.01	-0.51	0.07	-1.88	0.00
At quotes	13.60	135.00	282.00	19.85	3.33	-1.12	0.70	18.10	1.94	-49.50	0.21
Above quotes	-13.90	-138.50	-290.00	-20.60	-3.43	1.16	-0.72	-18.40	-1.99	51.60	-0.21
Sell-LO											
median given sig.	0.053	-0.609	0.652	0.081	0.010	-0.018	0.005	-0.011	0.045	0.229	0.008
Sig. (%)	63	43	100	93	30	77	47	40	33	33	20
Pos. given sig. (%)	95	31	100	100	56	4	79	50	70	60	50
Marginal Effects											
Within quotes	0.53	-3.14	8.56	0.94	0.11	-0.20	0.04	-1.58	0.40	1.40	0.05
At quotes	20.70	-234.00	253.00	30.95	4.08	-6.77	1.77	1.30	17.30	88.00	2.99
Above quotes	-21.20	236.00	-260.00	-31.80	-4.19	7.06	-1.81	4.50	-17.55	-90.95	-3.17

Table 6: Second Stage Sequential Probit Regressions, Impatient Traders.

This table presents the estimated results of the second stage of the two-stage sequential ordered probit model. In this stage, given the trader is impatient; the dependent variable is equal to 0 if she submits a small MO (category 2) and 1 is she submits large MO (category 1). All of the explanatory variables are same as noted in Table 4. All of the regressions include 5 lags of the dependent variable and the time-of-the day dummies. For the sake of brevity, those are not reported. The cross sectional median of marginal effects scaled by 1e3 is also reported. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are provided.

Buy-MO	**Vola**	**Trend**	**SPR**	**Vcomp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame^{2_max}**	**Dopp^{1_2}**	**Dopp^{2_max}**
median given sig.	0.241	-1.061	-0.413	-0.026	-0.005	-0.025	-0.322	0.048	-0.474	-0.049
Sig. (%)	97	40	13	23	30	73	20	33	23	47
Pos. given sig. (%)	100	0	0	29	44	5	17	90	14	43
Marginal Effects										
Large Market Order	32.90	-94.80	-43.90	-3.45	-0.73	-3.41	-32.30	4.83	-23.00	-2.46
Sell-MO										
median given sig.	0.273	1.014	-0.178	-0.078	-0.020	-0.017	-0.494	-0.041	-0.478	-0.030
Sig. (%)	100	57	7	40	50	53	13	27	37	13
Pos. given sig. (%)	100	94	50	0	7	13	0	38	18	25
Marginal Effects										
Large Market Order	44.65	131.00	-65.10	-10.65	-3.32	-2.67	-62.60	-2.67	-43.90	-3.02

Table 7: First Stage Sequential Ordered Probit Regression–Institutions.

This table presents the estimated results of the first stage of the two-stage sequential ordered probit model for institutions. In this stage, the dependent variable is equal to 1 if the incoming trader is impatient, hence submits a market order, and 0 otherwise. All of the explanatory variables are same as noted in Table 4. All of the regressions include 5 lags of the dependent variable and the time-of-the day dummies. For the sake of brevity, those are not reported. The cross sectional median of marginal effects scaled by 1e3 is also reported. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are provided.

Buy	**Vola**	**Trend**	**SPR**	**Vcomp**	**Vcompopp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame^{2_max}**	**Dopp^{1_2}**	**Dopp^{2_max}**
median given sig.	-0.188	-1.746	-0.840	0.299	-0.320	-0.029	0.008	1.953	-0.108	1.236	0.117
Sig.	19	31	19	100	96	31	31	4	23	8	19
Pos. given sig. (%)	20	25	20	100	0	13	88	100	17	100	60
Marginal Effects											
median given sig.											
MO	-67.8	-634.0	-311.0	109.0	-119.0	-10.8	3.0	750.0	-41.8	442.0	44.7
Sell											
median given sig.	-0.224	2.865	-1.045	0.257	-0.290	0.009	0.003	-1.007	-0.108	-3.889	-0.011
Sig. (%)	23	19	8	96	85	19	27	8	15	4	31
Pos. given sig. (%)	0	100	0	100	0	80	57	0	25	0	50
Marginal Effects											
median given sig.											
MO	-82.0	945.0	-410.0	97.0	-102.3	3.7	0.9	-374.0	-38.7	-1396.0	-5.1

Table 8: Second Stage Sequential Probit Regressions, Patient Institutional Traders.

This table presents the estimated results of the second stage of the two-stage sequential ordered probit model for patient institutional traders. In this stage, given the trader is patient, the dependent variable is equal to 1, 2 or 3 if the trader submits a category 5, category 4 or category 3 order (limit price within, at or away from the best quotes) respectively. All of the explanatory variables are same as noted in Table 4. All of the regressions include 5 lags of the dependent variable and the time-of-the day dummies. For brevity, those are not reported. The cross sectional median of marginal effects scaled by 1e3 is also reported. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are provided.

Buy-LO	**Vola**	**Trend**	**SPR**	**Vcomp**	**Vcompopp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame^{2_max}**	**Dopp^{1_2}**	**Dopp^{2_max}**
Median given sig.	0.291	3.129	1.342	0.206	0.109	-0.030	0.057	-1.900	0.108	1.941	0.122
Sig. (%)	19	35	54	58	8	31	8	12	27	12	31
Pos. given sig. (%)	80	89	93	100	50	13	50	33	71	100	75
Marginal Effects											
Within quotes	0.6	8.3	10.6	1.7	1.0	-0.2	0.0	-3.1	0.1	6.1	0.2
At quotes	90.6	975.0	399.0	73.9	31.5	-11.0	15.3	-692.0	34.2	666.0	27.6
Above quotes	-91.4	-983.0	-415.5	-76.8	-32.0	11.1	-15.4	715.0	-34.3	-666.0	-28.1
Sell-LO											
Median given sig.	-0.168	-2.145	1.528	0.204	0.051	-0.030	-0.053	-1.475	0.125	-1.719	0.104
Sig. (%)	19	35	35	58	27	31	15	8	19	12	19
Pos. given sig. (%)	40	0	100	100	57	38	0	0	80	33	80
Marginal Effects											
Within quotes	-0.7	-19.6	22.6	1.4	0.4	-0.2	-0.1	-8.7	1.2	-13.7	1.2
At quotes	-52.5	-566.0	463.0	56.1	15.4	-8.8	-14.7	-453.0	42.3	-539.0	27.8
Above quotes	53.2	579.0	-473.0	-57.2	-15.8	9.1	15.0	461.5	-44.7	560.0	-29.0

Table 9: Second Stage Sequential Probit Regressions, Impatient Institutional Traders.

This table presents the estimated results of the second stage of the two-stage sequential ordered probit model for impatient institutional traders. In this stage, given the trader is impatient; the dependent variable is equal to 0 if she submits a small MO (category 2) and 1 is she submits large MO (category 1). All of the explanatory variables are same as noted in Table 4. All of the regressions include 5 lags of the dependent variable and the time-of-the day dummies. For the sake of brevity, those are not reported. The cross sectional median of marginal effects scaled by 1e3 is also reported. The median of the estimated significant coefficients for the stocks in our sample, the percentage of statistically significant coefficients at 5% level, and the positive coefficients given that they are significant are provided.

Buy-MO	**Vola**	**Trend**	**SPR**	**Vcomp**	**Vsignal**	**Vsignalopp**	**Dsame^{1_2}**	**Dsame^{2_max}**	**Dopp^{1_2}**	**Dopp^{2_max}**
Median given sig.	0.431	-3.214	1.588	-0.144	-0.020	-0.055	-	0.051	-1.213	-0.135
Sig. (%)	54	27	4	15	12	8	0	23	4	27
Pos. given sig. (%)	100	0	100	0	33	50	-	50	0	43
Marginal Effects										
Large Market Order	113.5	-824.0	159	-41.4	-6.3	-21.7	-	21.0	-341.0	-13.5
Sell-MO										
Median given sig.	0.523	3.862	-2.535	-0.040	-0.064	-0.004	-0.424	-0.228	-	-0.474
Sig. (%)	69	19	4	23	19	15	4	12	0	4
Pos. given sig. (%)	100	100	0	17	0	50	0	33	-	0
Marginal Effects										
Large Market Order	107.5	665.0	-87.6	-5.1	-6.7	-1.3	-32.6	-71.3	-	-3.5