The Impact of Strategic Limit Order Submissions on Foreign Exchange Market Liquidity

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Abstract

In this paper, we empirically investigate the short-term impact of human/algorithmic limit order submissions on the liquidity provision and withdrawal process of other human/algorithmic traders. Using a high-frequency dataset containing over 1.5 million limit orders in the USD/JPY and EUR/JPY foreign exchange spot markets (amounting to a limit order volume of approximately $2 trillion), we document three key findings. First, order-splitting strategies widely adopted by algorithmic traders to disguise the true order size seem to go detected and are perceived as more information-rich or predatory than orders of the corresponding size typically submitted by human traders. Second, the inverse relationship between limit order size and price aggressiveness is less consistent than expected – both concerning traders' strategic order submissions and their impact on the liquidity withdrawal by others. Third, we find that traders appear to be more sensitive to limit orders submitted from the same side (non-execution risk) than to the opposite side of the order book (free option risk), but that the 'recovery' of the limit order book primarily is driven by a reassessment of free option risk.

JEL Classification Numbers: D4, F3

Keywords: market microstructure, limit order book, foreign exchange, high-frequency trading, volume-based liquidity

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1. Introduction

In this paper, we use a high-frequency dataset to empirically study strategic limit order submissions in the USD/JPY and EUR/JPY FX spot markets, and the impact they have on other traders' immediate behaviour regarding liquidity provision and withdrawal.

One of the most visible features in markets increasingly populated by algorithmic and high-frequency traders is the dramatic increase in the share of limit orders at the expense of market orders (Biais et al., 1995). However, such markets have also tended to be associated with frequent order cancellations and a shortening of the lifetime of limit orders. In the academic literature, therefore, limit order submissions have become seen as active trading strategies (Foucault et al., 2005; Rosu, 2009). However, traders using electronic trading platforms face a range of strategic choices when submitting limit orders. On the one hand, limit orders allow traders to 'buy time' in the hope of a better fill, in contrast to market orders which aim to be executed immediately. On the other hand, limit orders are associated with monitoring costs as traders may be picked off (free-option risk) or be required to repeatedly cancel and resubmit the order at a more competitive price (non-execution risk) (Fong and Liu, 2010; Liu, 2009). Limit orders contain information and to avoid front-running, traders, therefore, need to select the appropriate aggressiveness and size of the limit orders (Cao et al., 2004; Griffiths et al., 2000; Lo and Sapp, 2010; Ranaldo, 2004). As a result, traders could resort to stealth trading or order-splitting – strategies intended to camouflage the true information content transmitted to the market (Barclay and Warner, 1993; Chan and Lakonishok, 1995; Chou and Wang, 2009; Pérold 1988). Put differently, a limit order submission might trigger an immediate reaction by other liquidity providers – depending on its perceived information content. This behaviour, in turn, could affect the volume composition of the limit order book and ultimately result in a short-term price movement.

Whereas the trend towards to algorithmic and high-frequency trading has been most prominent in exchange-traded stock markets, some over-the-counter markets hitherto dominated by human traders have lately also undergone a similar transformation. This is particularly evident in the $5.1 trillion-a-day FX market, which traditionally consisted of banks making markets to end-users on demand, and to each other to maintain liquidity. The share of algorithmic trading on Electronic Broking System (EBS), together with Reuters Matching the most widely used FX spot trading platform used by market-making banks, increased from 2% in 2004 to around 70% in 2013 (Moore, Schrimpf and Sushko, 2016). However, microscopic research on strategic limit order submissions has so far primarily been conducted on equity markets, partly due to data availability from stock exchanges. FX has a very different market structure and is considerably more opaque, which makes investigations into behavioural aspects more challenging.

Fortunately, having obtained a full order book dataset provided by EBS from 9-13 September 2010 enables us to make use of approximately 1.5 million limit orders in the USD/JPY and EUR/JPY FX spot markets (amounting to a limit order volume of roughly $2 trillion). The purpose of this paper is to empirically explore three separate, but interlinked, questions related explicitly to strategic trading behaviour and limit order volume in the FX spot market. First, how do other traders respond to relatively large and/or aggressive limit order submissions? Second, how do other traders react to algorithmic order-splitting strategies adopted to disguise the true order size? Third, do traders on the opposite side (free-option risk) react differently than traders on the same side of the limit order book (non-execution risk) to new limit order submissions? Notably, in contrast to the vast majority of research conducted on limit order books and market liquidity, we specifically focus on short-term changes in the limit order *volume* rather the price-impact as a consequence thereof.

We document empirical results that confirm as well as contradict conventional anecdotes from financial market participants in the FX spot market. First, order-splitting strategies widely adopted by algorithmic traders to disguise the true order size seem to go detected and are perceived as more information-rich or predatory than orders of the corresponding size typically submitted by human traders. Second, the inverse relationship between limit order size and price aggressiveness is less consistent than expected – both regarding traders' strategic order submissions and their impact on the liquidity withdrawal by others. Third, we find that traders appear to be more sensitive to limit orders submitted from the same side (non-execution risk) than to the opposite side of the order book (free option risk), but that the 'recovery' of the limit order book largely is driven by a reassessment of free option risk. Separately, we also find indicative evidence of an 'illusion of liquidity' in both the USD/JPY and the EUR/JPY market.

By doing so, our investigation contributes to the growing literature on limit order books (conducted mainly on stock markets) and the FX market microstructure literature (hitherto focusing on market orders). However, fresh insights into FX trading behaviour are not only of interest to academics and market participants. Following the recent revelations of widespread misconduct by numerous banks, the FX spot markets has come under intense scrutiny by financial regulators, compliance officers and lawyers alike (see, in for instance, FCA, 2014; CFTC, 2014; OCC, 2014; Freifeld, Henry and Slater, 2015; Federal Reserve, 2017). The controversies have concerned manipulation and collusion in relation to various types of orders (market orders, limit orders and benchmark fix orders). However, human traders are not alone in having been caught up in the 'FX scandal'. Single-bank electronic trading platforms have resulted in regulatory settlements too. For instance, in November 2015, Barclays was fined \$150 million for its use of a "Last Look" system on its electronic trading platform BARX (DFS, 2015). The authorities found that Barclays not only had adopted the policy defensively (e.g. to reject toxic order flow by high-frequency traders), but also to distinguish which customer traders would be potentially (un)profitable for the bank.[1] Moreover, the volume-based liquidity provision process on electronic limit order books is also of relevance from a systemic perspective. Despite becoming increasingly electronic like the stock markets, the global FX market still lacks circuit beakers. It could, therefore, be more vulnerable in the event of severe liquidity shocks (BIS, 2011).

The paper is structured as follows. Section 2 provides a brief overview of the related literature and formulates the research questions. Section 3 describes the data used and Section 4 outlines the model. Following the three research questions, the empirical results are then discussed in Section 5. Section 6 concludes.

[1] In 2017, BNP Paribas and Credit Suisse were fined for similar misconduct (DFS, 2017ab).

2. Related literature and formulation of the research questions

The important role of order flow for exchange rate determination is well established in the FX market microstructure literature (see, for instance, Lyons, 1997; Evans and Lyons, 2002). Market orders contain information, and subsequent empirical studies using FX spot transaction data confirm that, at least in the short-run, a buy [sell] initiative is more likely to lead to a higher [lower] price (Daniélsson et al., 2012; Evans and Lyons, 2005; King and Rime, 2010; Payne, 2003). However, given their interconnectedness, order flow affects not only price, but also liquidity (Bjønnes et al., 2005; Daniélsson and Payne, 2012). The knowledge that order flow is likely to have an impact on the price (but also the liquidity) therefore becomes part of the strategic order submission process by traders. For instance, whereas a large and information-rich transaction might not have an impact in the long run, the likelihood that it could cause a change in the price and liquidity in the short term is much higher. Hence, the shorter the time window (or the 'investment horizon'), the more crucial the attention to the potential change in the order book becomes.

Traditional theoretical market microstructure models saw limit orders mainly as passive trading strategies, whereby informed traders, instead, resorted to market orders (Glosten, 1994; Seppi, 1997). Daniélsson and Payne (2012), using data from 1997 on the USD/DEM FX spot market, find that market orders are more information-rich than limit orders. However, more sophisticated technology, accompanied by the rise of algorithmic and high-frequency trading, has resulted in a dramatic increase in the number of limit order submissions on electronic trading venues (see, for instance, Biais et al., 1995 (Paris Bourse); Harris and Hasbrouck, 1996; Yeo, 2005 (NYSE), Hollifield et al., 2004 (Stockholm Stock Exchange); Hasbrouck and Saar, 2002 (Island ECN)). Susai and Yoshida (2014) also document that the trend in the FX spot market has been towards a much higher proportion of limit orders rather than market orders. Overall, the increasing prevalence of algorithmic (at the expense than human) FX trading appears to be associated with a higher proportion of limit order submissions and cancellations, as well as a shortening of the lifetime of limit orders (BIS, 2011; Susai and Yoshida, 2015; Yeo, 2005). What previously tended to be regarded as a standard benchmark in terms of a time horizon (one year, one month, one day etc.) is considered extremely long when seen from the perspective of a computer algorithm comfortable with slicing each second into thousands, or millions, of time periods.

Consequently, limit orders, rather than market orders, are also increasingly becoming seen as active trading strategies in the literature (Foucault, 1999; Foucault et al., 2005; Rosu, 2009; Yeo, 2005). However, limit orders are more complicated than market orders insofar as they are associated with monitoring costs. Put differently, traders resorting to limit orders are, on the one hand, 'buying time' in the hope of a better fill but are, on the other hand, required to pay the costs of monitoring the limit order (Fong and Liu, 2010; Liu, 2009). Constantly 'taking the pulse' of the market concerning the limit order submitted is a time-consuming effort for humans, or requires sophisticated algorithmic programming. More importantly from the perspective of our study, an assessment also has to be made with regards the effect the limit order will have on the *behaviour of others*. Each new limit order submission changes the dynamic of the limit order book, which, in turn, might prompt other (human or algorithmic) traders to react according to its perceived impact at that specific moment in time.

Thus, traders not only choose between market orders and limit orders. When submitting a limit order, a trader also needs to select the appropriate aggressiveness and size of the order. Whereas a market order, per definition, is an aggressive order as the intention is to execute a trade immediately at the prevailing best market price, the probability of a limit order being executed is dependent on how far away it is submitted from the market price (see, for instance, Griffiths et al., 2000; Cao et al., 2004; Ranaldo 2004). However, as Lo and Sapp (2010) find, more aggressive limit orders in the FX market tend to be smaller in size, suggesting that there is a strategic trade-off between aggressiveness and size. A large limit order might be interpreted as information-rich and therefore trigger other traders to cancel their limit orders – thereby decreasing the likelihood of being filled.

However, several studies show that traders adopt order-splitting strategies in attempts to disguise the 'true' size of the limit order, thereby allowing them to submit relatively more aggressive orders without having the corresponding negative impact on the liquidity of the market. Following the logic of Keim and Madhavan (1995, 1996), order-spitting strategies might be ‘informed traders’ as well as ‘liquidity traders’. Whereas an informed trader would prefer to disguise his private information as signalled by a large order submission, a trader demanding liquidity would want to hide his full amount to avoid front-running.[2] Algorithmic traders have an advantage in slicing orders into smaller pieces to reduce the price impact and the transaction costs resulting from disappearing liquidity (Bertsimas and Lo, 1998).

Furthermore, the reaction by traders might also depend on the side from which a new limit order is submitted. As a buy [sell] initiative is more likely to lead to a higher [lower] price, a limit buy [sell] order submissions ought to cause some traders on the *opposite* side of the order book to cancel their existing sell [buy] orders as they incorporate the new information and revise their price expectations accordingly. Traders withdrawing liquidity might then, perhaps, resubmit their orders at a higher [lower] price. Thus, a limit order contains ‘free-option risk’, i.e. the risk of being picked off by a trader with private information (Copeland and Galai, 1983). However, some traders on the *same* side of the order book also revise their expectations (and consequently cancel and resubmit their orders). They are less likely to be picked off. However, as the market is more likely to move against them, they face ‘non-execution risk’ (Hasbrouck and Saar, 2002; Liu, 2009).

In our dataset, market orders count for less than 1%. Moreover, most limit orders are small in size (€/$1 million, which is the minimum allowed on EBS) and according to our classification, around 20-25% are split orders. The dominance of (small) limit orders and the fact that order-splitting strategies are common is consistent with a market highly populated with algorithmic traders. At the same, however, our dataset also contains some very large limit orders (the largest orders being €250 million and €100 million for USD/JPY and EUR/JPY respectively), which is consistent with the fact that EBS also is the most widely used electronic trading platform among *human* market-makers at banks in the FX spot market.

In this paper, we explore the impact of strategic limit order submissions on the liquidity withdrawal by other traders. In light of the data observations and the

[2] On stealth trading and order-splitting strategies, see: Baclay and Warner, 1993; Engle et al., 2012; Chan and Lakonishok, 1995; Chou and Wang, 2009; Pérold 1988; Yeo, 2005.

literature review above, our research questions are three-fold: Regarding the short-term change of the limit order book,

i) How do other traders react to relatively large and/or aggressive limit order submissions?

ii) How do other traders react to algorithmic order-splitting strategies adopted to disguise the true order size?

iii) Do traders on the opposite side (free-option risk) respond differently than traders on the same side of the limit order book (non-execution risk) to new limit order submissions?

3. Data

We use a high-frequency dataset from 21:00:00 (GMT) on 8 September 2010 to 20:59:59 (GMT) on 13 September 2010 (including the weekend) obtained from EBS, the most widely used electronic trading platform among market-making banks. The share of algorithmic trading on EBS rose from just 2% in 2004 to around 50% in 2010, and anecdotal evidence and surveys among banks suggest that the change has been most visible among the major currency pairs.[3] We study the 2nd and 3rd most actively traded currency pairs (USD/JPY and EUR/JPY).

On EBS, traders can either initiate a quote (i.e., submit a limit order) or match a posted quote (i.e., submit a market order). In the dataset we have acquired, all data entries are assigned one of five indicators (QS, QD, HS, HAD or DSM). A new limit order begins with QS (i.e., a limit order submission) and ends with QD (i.e., a limit order cancellation). A market order starts with HS and ends with HAD. When two counterparties are matched in a transaction on EBS, the information for the deal is recorded as a DSM. In addition to price, volume, buy or sell indicator, we also use the millisecond timestamp. A unique 20-digit Trader ID is attached to each indicator, allowing us to match order submissions and order cancellations. However, the identities or institutions are not revealed. Limit orders count for more than 99% of all

[3] Although no official figures are available, estimates indicate that 25% of the spot market (which makes up close to half of the global foreign exchange market as a whole) is done by algorithmic traders. The real figure might be considerably higher, however, given that the share of algorithmic trading on EBS) rose from just 2% in 2004 to around 50% in 2010 (King and Rime, 2010; BIS, 2011).

orders in our dataset (consistent with the literature on high-frequency trading above, showing the increasing importance of limit orders on electronic trading platforms).

Having filtered the dataset for limit order submissions and limit order cancellations only, and removed all new limit orders that do not have a corresponding cancellation within the same day (less than 0.005% of all limit order submissions), we are left with 787,252 and 751,263 limit orders for USD/JPY and EUR/JPY respectively. In sum, the total limit order book for the three trading days amounts to approximately \$1.0 trillion for USD/JPY and €0.9 trillion for EUR/JPY.

4. The models

4.1 The model and the dependent variables

In contrast to the vast majority of empirical market microstructure studies, we are, in this paper, not dealing with a standard time series with fixed time intervals. Instead, each data point (the time stamp of each limit order submission) occurs irregularly. The focus of our investigation is the immediate reaction to new limit order submissions on the order book as a whole. Therefore, rather than approaching the dataset from a conventional time-series approach with fixed intervals, the reference points are the timestamps of each limit order submission. We then investigate the change in a set of variables from each reference point to various pre-defined points in the future, and refer to these as 'time windows'. Given that computer algorithms have the ability to react faster than humans, we have chosen four different time windows (0.1, 1, 10 and 60 seconds) to investigate potential differences when allowing for human traders to have time to react – thus providing a deeper insight into the dynamics of the liquidity withdrawal process as a whole.

The dependent variable in the model (Equation 1) is the change in limit order buy [sell] volume (LOV) from the buy [sell] side, where d = [buy / sell], within a specified time window (w), where w = 0.1, 1, 10 or 60 seconds following the ith limit order (LOS_i) submitted at time $t(i)$ – but excluding the limit order submission itself:

$$LOV_d^{t(i)+w} - LOV_d^{t(i)} = \alpha_i + \beta_1 Market\ activity_i + \beta_2 Market\ liquidity_i + \beta_3 Volatility_i + \beta_4 Bid - offer\ spread_i + \delta_1 TZ1_i + \delta_2 TZ2_i + \delta_3 TZ3_i + \delta_4 Split_i * \delta_8 MAgg_i * \delta_{11} D_i + \delta_4 Split_i * \delta_9 Agg_i * \delta_{11} D_i + \delta_4 Split_i * \delta_{10} VAgg_i * \delta_{11} D_i + \delta_5 Medium_i * \delta_8 MAgg_i * \delta_{11} D_i + \delta_5 Medium_i * \delta_9 Agg_i * \delta_{11} D_i + \delta_5 Medium_i * \delta_{10} VAgg_i * \delta_{11} D_i + \delta_6 Large * \delta_8 MAgg_i * \delta_{11} D_i + \delta_6 Large_i * \delta_9 Agg_i * \delta_{11} D_i + \delta_6 Large_i * \delta_{10} VAgg_i * \delta_{11} D_i + \delta_7 VLarge * \delta_8 MAgg_i * \delta_{11} D_i + \delta_7 VLarge_i * \delta_9 Agg_i * \delta_{11} D_i + \delta_7 VLarge_i * \delta_{10} VAgg_i * \delta_{11} D_i \quad (1)$$

The limit order volume from the buy [sell] side at each time stamp is equal to the total limit buy [sell] order book – thus containing the total amount of outstanding limit buy [sell] orders (A^b) [(A^a)] from n, where $t(0)$ = 21:00:00 GMT. Hence, $LOV_{buy}^{t(i)} = \sum_{k=t(n)}^{k=t(i-1)} A_k^b$, $LOV_{buy}^{t(i)+w} = \sum_{k=t(0)}^{k=t(i)+w} A_k^b$, $LOV_{sell}^{t(i)} = \sum_{k=t(0)}^{k=t(i-1)} A_t^a$ and $LOV_{sell}^{t(i)+w} = \sum_{k=t(0)}^{k=t(i)+w} A_k^a$.

For instance, if the limit order book consists of 25 million buy orders and 10 million sell orders immediately prior to a new limit order submission, the limit buy order volume from the buy [sell] side is 25 [–25] million and the limit sell order volume from the sell [buy] side is 10 [–10] million. If, 1 second after a limit order has been submitted, the limit order book contains 20 million buy orders and 8 million sell orders, the change in the limit buy order volume from the buy [sell] side is – 5 [5] million and the change in the limit sell order volume from the sell [buy] side is –2 [2] million.

Quantifying the change in the limit buy and sell order book separately, and approaching the market from the buy-side as well as the sell-side, enables us to distinguish free-option (FO) risk from non-execution (NE) risk as perceived by other traders:

a) Change in the limit buy order volume from a the buy-side perspective (FO)
b) Change in the limit buy order volume from the sell-side perspective (NE)
c) Change in the limit sell order volume from the sell-side perspective (FO)

d) Change in the limit sell order volume from the buy-side perspective (NE)

The liquidity withdrawal process might be influenced by a range of factors. We include both control variables, which relate to the market in which the orders are submitted and not (directly) associated to the limit order submissions themselves, and 'strategic variables' containing the specific characteristics of the new limit order submissions which might have an impact on the volume-based liquidity of the market.

4.2. Strategic variables

Our models include variables, which are constructed to capture both the behaviour of traders submitting limit orders – and the reaction to such orders by other traders in the market. The 12 buy [sell] dummy variables include direction, price aggressiveness, size and order-splitting strategies.

Direction

Traders with private information take into account the current and perceived future liquidity on the other side of the order book, as this is a key factor in determining the ability to execute (potentially large) orders at a fair price. Using the same logic, traders might react to incoming orders from the other side by cancelling their orders (and then, perhaps, resubmitting their orders at a more favourable price to them). By including dummy variables for limit buy order submissions (Buy_i) and limit sell order submissions ($Sell_i$), we can test the free option risk hypothesis by investigating the impact of limit buy [sell] order submissions on the sell [buy] side of the order book.

However, traders might also react to incoming orders from the *same* side of the order book, depending on how information-rich they are perceived to be. As such orders might move the market away from them, these traders, too, would be more inclined to cancel their orders (to resubmit and them at a rate closer to the best market price at the time). Thus, we can test the non-execution risk hypothesis by investigating the impact of limit buy [sell] order submissions on the buy [sell] side of the order book.

Price aggressiveness

A limit order should be perceived to be more likely to have a market-moving impact if it improves, matches or is submitted very close to the current best bid-offer spread. In the models, we, therefore, include dummy variables for orders that are 'very aggressive', 'aggressive' or 'moderately aggressive', and would expect the reaction to these to be stronger. We use the following scale:

> Very aggressive (*VAgg*$_i$) = if the new limit order submission price p_i *improves* the best bid-offer spread ($p^{ba}_{t(i)-1} - p^{bb}_{t(i)-1}$).
>
> Aggressive (*Agg*$_i$) = if the new limit order submission price p_i *matches* the best bid-offer spread ($p^{ba}_{t(i)-1} - p^{bb}_{t(i)-1}$).
>
> Moderately aggressive (*MAgg*$_i$) = if the new limit order submission price p_i is *outside, but within 2 pips*[4] of the best bid-offer spread ($p^{ba}_{t(i)-1} - p^{bb}_{t(i)-1}$).

The logic is the same as for the direction of the limit order. However, we would expect other traders to react faster and stronger to relatively more aggressive orders.

Size

Following Lo and Sapp (2010), FX spot traders not only consider price aggressiveness when submitting limit orders but also the amount. Although our dataset contains some very large limit orders indeed (the most significant orders being \$250 million and €100 million for USD/JPY and EUR/JPY respectively), the overwhelming majority is for precisely the minimum amount allowed on EBS, namely \$1 million or €1 million (see Table 1). To capture the potential impact of size, we use three dummy variables. $Medium_i$, a 'medium-sized limit order', is a dummy variable for order amounts larger than (\$ or €) 1 million but smaller than (\$ or €) 5 million. $Large_i$, a 'large limit order', is a dummy variable for order amounts larger than or equal to (\$ or €) 5 million but smaller than (\$ or €) 10 million. $VLarge_i$, a 'very large limit order' is a dummy variable for order amounts larger than or equal to (\$ or €) 10 million. As the size dummies refer to amounts larger than the \$1 million or

[4] Following the market convention, 1 pip is the 2nd decimal for USD/JPY and EUR/JPY.

€1 million baseline limit order, they should be considered more information-rich. A medium-sized limit order should, *ceteris paribus*, trigger a stronger reaction than a baseline limit order. Large and very large orders should, likewise, trigger stronger responses than medium-sized orders.

Order-splitting strategies

As result of the predictable market reaction following a large order submission, a well-established trading strategy is that of order-splitting. Assuming that other traders react stronger (and faster) to large limit orders, a string of relatively small order submissions could act to disguise the 'true' order size and hence trigger a more muted market reaction.

Algorithmic traders have a far greater ability than human traders to split large orders into many small orders. As a consequence, a high number and proportion of very small orders is often observed in financial markets where algorithmic trading is prominent. In our model, $Split_i$, a 'split limit order', is a dummy variable. To be counted as a split order, all of the following four criteria need to hold. First, the price of limit order submission, p_i, is the same as the price of limit order, p_j, where $j \neq i$. Second, the direction of limit order submission i (i.e. bid or ask) is the same as the direction of limit order submission j. Third, limit order i and limit order j are submitted within less than 0.1 seconds of each other. Fourth, no other orders are submitted or cancelled in between the submissions of limit order i and limit order j.[5] If an order splitting-strategy is successfully used to conceal the 'true' (larger) order size, it should, *ceteris paribus*, trigger relatively fewer order cancellations (and less liquidity withdrawal) on the other side of the order book than a strategy involving an amount equivalent to the sum of the split orders.

[5] Our classification of a split limit order is more conservative than that of Yeo (2005) on the stock market. Obviously, orders submitted within more than 0.1 seconds of each other or at different prices might still be part of an order-splitting strategy. However, given that our methodology already results in around 20-25% of all orders being classified as split limit orders for the major currency pairs, we do not believe a less conservative measure is necessary to capture potential differences.

4.3. Control variables

Traders are, of course, not only reacting to the perceived information content of new limit orders but also the state of the market as a whole. We, therefore, include a set of control variables: market activity, market depth, volatility, bid-offer spread and time zone.

Market activity

In our model, we define market activity as $Market\ activity_i = \sum_{k=t(i)-60s}^{k=t(i)} LOS_k$. Thus, our proxy is the number of limit order submissions to the EBS platform in the respective currency pair within a fixed time interval (60 seconds) before each limit order submission. Hartmann (1998) shows that, in the long run, trading volume contributes to narrower bid-offer spreads in the FX spot market. Using similar logic, a higher level of market activity could also have a positive impact on volume-based liquidity measures. However, bid-offer spreads have been found to widen with trading activity, order size and quoting frequency (Bollerslev and Domowitz, 1993; Glassman, 1987; Lyons, 1995; Melvin and Yin, 2000). Consequently, higher market activity could also indicate greater uncertainty in the market, which, in turn, could prompt traders to cancel limit orders and withdraw liquidity from the market. The net impact in the short-term is, therefore, unclear.

Market liquidity

The limit order volume might also be affected by how liquid the market is at the prevailing best bid-offer spread, where $Market\ liquidity^{t(i)} = \sum_{k=t(0)}^{k=t(i-1)} A_k^{bb} + \sum_{k=t(0)}^{k=t(i-1)} A_k^{ba}$, where A^{bb} [A^{ba}] is the amount of outstanding limit buy [sell] orders at best bid [offer]. Using this proxy for market liquidity, a more liquid market should, theoretically, act to increase the limit order book for two reasons. First, an increase in the liquidity on the same side of the market should trigger competing traders to cancel and resubmit their orders at more competitive price levels, as well as trigger new traders to enter the market (Biais et al., 1985; Hall and Hautsch, 2006, 2007). Second, an increase in the liquidity on the opposite side of the market should increase the likelihood that traders cancel and resubmit their orders at a different price due to the expected change in the cost of transacting (Goettler et al., 2005; Lo and Sapp, 2010).

Volatility

Given the short time windows used in our estimation, we also apply a very short-term measure of volatility. Hence, volatility is the standard deviation of the mid-market price of the best limit buy and sell orders (p^{bm}) at each second during a 60-second interval before the new limit order submission. Theoretically, higher short-term volatility should have a negative impact on the net limit order book (i.e. trigger relatively more order cancellations). This logic is similar to Foucault (1999) and Foucault et al. (2005), where price volatility is connected to a change in information asymmetry among market participants.

Bid-offer spread

Volume-based liquidity could be dependent on the current bid-offer spread, i.e. the difference between the best bid and offer prices, $(p_{t-1}^{bo} - p_{t-1}^{bb})$ measured vis-à-vis the mid-price, p_{i-1}^{bm}, on the EBS platform immediately before the limit order submission. Thus, $Bid - offer\ spread = (p_{t(i)-1}^{bo} - p_{t(i)-1}^{bb})/p_{t(i)-1}^{bm}$. In the literature, higher volatility tends to be associated with wider bid-offer spreads (Bassembinder, 1994; Bollerslev and Melvin, 1994; Glassman, 1987; Hartmann, 1998; Hua and Li, 2011). Thus, a wider bid-offer spread might indicate uncertainty in the market (Foucault et al., 2007), acting to increase cancellations and to reduce the limit order volume. On the other hand, a wide bid-offer spread might induce traders to supply liquidity (at better price levels) (see Lo and Sapp, 2010). If so, the bid-offer spread could have the opposite effect.

Time zone

Finally, although USD/JPY and EUR/JPY can be classified as currency pairs that trade 24 hours a day, the London and Tokyo markets tend to be most active for these two. Hence, we use three dummy variables (TZ1, TZ2 and TZ3) to account for this variation, where:

TZ1 = 21:00:00–02:59:00 GMT (Pacific)
TZ2 = 03:00:00–08:59:00 GMT (Tokyo)
TZ3 = 09:00:00–14:59:00 GMT (London)
TZ4 = 15:00:00–20:59:00 GMT (New York)

4.4. Estimation and diagnostics

We run 32 regressions using OLS.[6] After checking the diagnostic results of the residuals, we found heteroskedastic behaviour. Thus, we use the Huber-White covariance matrix. As our dataset starts on a Friday and ends on a Tuesday, it excludes the weekend when no trading takes place. However, we do not conduct a time-series analysis because the time interval between the dependent variables is uneven. Instead, we study pre-defined time windows with different starting points (the time stamp of a new limit order submission to the order book). The weekend is therefore not problematic. As a robustness check, however, we run the three days individually, and also separate tests where we exclude the first 50 and 100 observations from the raw datasets. We find that the results are very similar.

Furthermore, we estimate the model using additional time windows (0.2, 0.5 and 5 seconds). However, we do not find any significant breaks in the patterns reported in Section 5 below.

Finally, we run the same regressions using a different dependent variable, namely the difference between the number of limit buy [sell] order cancellations and new limit buy [sell] order submissions. This methodology captures the change of buy/sell order cancellations/submissions regardless of their size (see Jones et al., 1994). Given that the overwhelming proportion of limit orders are for 1 million precisely, however, the estimations do not yield significant changes in the overall results. Consequently, we

[6] Because the range of our dependent variables range from positive to negative, TOBIT is not appropriate here.

opt for a model incorporating the limit order volume information in the dependent variable.

5. Empirical Results

Tables 3–10 show the results. Given the large number of regressions and variables in this study, we concentrate on the highlights relevant to our research questions in the discussion below.

5.1. Descriptive statistics

Before discussing the empirical results, a few notes on the descriptive statistics are helpful (see Table 2). As can be seen, the market activity is very high for the two currency pairs. Each new limit order submission in the USD/JPY market is preceded by an average of 333 limit order submissions during the previous 60 seconds. The corresponding number for EUR/JPY is 231. Given that volatility is based upon price movements during the 60-second time window before each new limit order submission, the average volatility is very low (USD/JPY: 0.0174% and EUR/JPY: 0.0226%). The average bid-offer spread is exeptionally tight for USD/JPY (0.0134%). To put this into perspective, suppose the best prices in this market were 83.49–83.50. This would correspond to a bid-offer spread of 0.0120%. The price-based liquidity measure is somewhat wider (0.0213%) in the EUR/JPY market. The volume-based market liquidity indicator paints a similar picture. Whereas an average of $17.1 million is posted at the current best bid-offer spread at the time of each new limit order submission in the USD/JPY market, the EUR/JPY market is somewhat less deep (€6.7 million). This pattern is consistent with EUR/JPY being an FX cross – reflecting the higher transaction costs associated to deal at two, rather than one, bid-offer spread.

Turning to the strategic variables, four observations are notable from Tables 1–2. First, as mentioned previously, a very high proportion of limit order submissions are for the minimum allowed size on the electronic trading platform, namely 1 million. Medium-sized orders account for around 10%, large and very large orders for about

1% or less. Thus, the size distribution seems to follow a power law, similarly to what has been observed in stock markets (see, for instance, Gopikrishnan et al., 2000; Maslow and Mills, 2001). Second, despite using a conservative classification, a very high proportion of the limit order submissions are split orders (20.4% and 25.2% for USD/JPY and EUR/JPY respectively). Third, whereas there appears to be a trade-off between size and price aggressiveness for medium sized-orders, Table 1 illustrates that the relationship breaks down for large or very large order submissions, as these tend to be very aggressive. On a scale from 1 to 4 (where non-aggressive = 1, moderately aggressive = 2, aggressive = 3 and very aggressive = 4), we can see that medium-sized order submissions are not only less aggressive than large and very large orders, but also less aggressive than split orders for both currency pairs.

5.2. Algorithmic orders-splitting strategies

The first observation relates to split orders, typically submitted by algorithmic traders. An informed trader would typically resort to an order-splitting strategy to disguise a larger amount. If successfully submitted (i.e. if it goes undetected by other market participants), such a plan should trigger fewer order cancellations on the other side of the order book than a strategy involving an amount equivalent to the sum of the split orders. Our dataset contains a substantial number of both split orders and medium-sized orders. The share in terms of total orders are comparable and, more importantly, all orders-splitting strategies involve amounts larger than 1 million but smaller than 5 million (typically 2 million). Thus, the two categories are comparable.

As can be seen from Tables 3–6, medium-sized and split orders submitted maximum two pips from the current best bid-offer spreads consistently triggers in a thinner USD/JPY order book when using time horizons of 0.1 and 1 seconds. Interestingly, however, our empirical results show that split orders in the USD/JPY market only trigger a more muted reaction than medium-sized orders when they are very aggressive. When submitted to match the prevailing bid-offer spread, or within 2 pips from it, orders-splitting strategies trigger a *stronger* reaction by other traders than medium-sized orders. Using Table 3, let us illustrate this with an example. Suppose that the limit buy order volume from the buy-side perspective is \$20 million. Following *a* new limit order submission (but excluding the limit order submission itself), the limit buy order volume changes by \$0.1003 million to \$20.1003 million within 0.1 seconds. However, the change in the limit buy order volume following a moderately aggressive, aggressive and very aggressive split order from the opposite side of the order book is –\$1.1198, –\$1.1455 and –\$0.8161 million respectively. The corresponding results for medium-sized orders are –\$0.5867, –\$0.4504 and –\$0.8515 million.

In the EUR/JPY market, which contains an even higher share of split orders (25.2%), the results are even more pronounced. As Tables 7–10 demonstrate, split orders classified as moderately aggressive, aggressive *and* very aggressive trigger a more substantial withdrawal of liquidity than medium-sized orders. The results are reasonably similar for the change in the limit buy and sell order volume, and regardless whether the perspective is from the buy-side or sell-side. Notably, however, the negative impact on the limit order volume fades after 1 second and frequently turns *positive* when studying the 60-second time window.

Nonetheless, the empirical results seem to contradict the logic of adopting an order-splitting strategy in the FX spot market on EBS (at least in USD/JPY and EUR/JPY). Split orders are, on average, not only considerably less aggressive than medium-sized orders (see Table 1), but also more likely to trigger liquidity withdrawal than medium-sized orders submitted at the equivalent level of aggressiveness. After all, the aim with orders-splitting strategies is to disguise the true order size with, first and foremost, an intent to avoid an immediate reaction by other traders. We, by contrast, show that most order-splitting strategies (in all likelihood exclusively submitted by algorithmic traders) are detected and are perceived as more information-rich than medium-sized orders (logically submitted by human traders).

5.3. Order size and price aggressiveness

The second observation relates to the trade-off between limit order size and price aggressiveness. We already noted that the inverse relationship might be less consistent than suggested by Lo and Sapp (2010). Instead, we find that very large limit orders not only also tend to be very aggressive in the USD/JPY and EUR/JPY markets, but also that large and very large orders (as well as split orders) tend to be more aggressive than medium-sized orders. However, regardless of the chosen strategy at the time of the limit order submission, we would expect *other* traders to react strongly to incoming orders that should be perceived as information-rich.

In the USD/JPY market (see Table 3), the 0.1-second impact on the change in the limit buy order volume following a very aggressive medium-sized, large and very large order from the opposite side of the order book is –\$0.8515, –\$1.4873 and –\$2.2259 million, respectively. The coefficients for the 1-second window are even larger: –\$1.7597, –\$3.1855 and –\$7.0484 million. A similar pattern can be seen when studying the short-term impact of opposite-side orders on the change in the limit *sell* order volume (Table 5). Thus, overall, the empirical results seem to confirm that size and price aggressiveness matter significantly in the USD/JPY market – but *only if* the limit orders are medium-sized and submitted no more than two pips from the best bid-offer spread, or if they are (very) large and very aggressive – i.e. submitted within the prevailing best bid-offer spread.

Being a less liquid market in terms of price and volume, the impact is somewhat less pronounced in the EUR/JPY market (Table 7). When studying the shortest time window, the impact on the change in the limit buy order volume following a very aggressive medium-sized, large and very large order from the opposite side of the order book is –€0.8954, –€0.5551 and –€0.9110 million, respectively, whereas the coefficients for the 1-second window are –€1.3099, –€3.0584 and –€3.1723 million. The corresponding results for the change in the limit sell order volume are, however, mixed or insignificant (Table 9).

5.4. Free-option versus non-executions risk

As outlined above, the empirical results show that the submission of medium-sized orders or (very) large and very aggressive orders immediately triggers traders on the other side of the order book to cancel orders. This short-term liquidity withdrawal process confirms the free-option risk hypothesis. In other words, traders view such orders as potentially market-moving and instantly cancel their orders in the hope that the market will shift to their advantage – allowing them, perhaps, to resubmit their limit orders at more favourable price levels. However, a potentially market-moving limit order might also trigger traders on the *same* side of the order book to reassess their order submission strategies. They face non-execution risk as such an order increases the likelihood of not being filled. Here, two findings are notable.

First, potentially information-rich orders tend to have a similar, but more consistent, impact on the liquidity withdrawal process when submitted from the same, rather than opposite, side of the order book. Our empirical results thus lend support to the theory that a buy [sell] initiative is more likely to lead to a higher [lower] price, as a potentially information-rich limit buy [sell] order ought to cause more limit order cancellations on the opposite side of the order book, and more limit order submissions on the same side of the order book. What is more, same-side orders have a stronger impact than opposite-side orders in the short run. For instance, the 1-second coefficients for very aggressive medium-sized, large and very large orders are –\$3.2413, –\$5.0856 and –\$8.0360 for same-side orders, compared to –\$1.7597, –\$3.1855 and –\$7.0484 for opposite-side orders in the USD/JPY market (see Tables 3 and 4).

The same goes for the EUR/JPY market. Whereas the overall results for the short-term time windows are more mixed than for the USD/JPY market, information-rich orders tend to have a stronger impact and/or more significant impact when submitted from the same side of the limit order book. Thus, although the impact is relatively evenly split, when studying traders' immediate reaction in the USD/JPY and EUR/JPY markets, the results suggest that 'non-execution risk', rather than 'free-option risk' tends to be the primary driver behind the liquidity withdrawal process triggered by information-rich limit orders.

Second, a significant shift in the pattern occurs when studying the more extended time windows. As can be seen from Tables 4 and 6, the coefficients indicating traders' reaction as a result of non-execution risk in the USD/JPY market gradually decrease after 10-60 seconds. Information-rich limit orders from the opposite side of the order book, however, overwhelmingly shift from triggering liquidity withdrawal to triggering liquidity *provision* (Tables 3 and 5). Although the results are less significant (one minute is, after all, a relatively long time in the FX markets), the vast majority of the dummy variables shift from being negative and strongly significant in the short-term, to being largely positive after 60 seconds. Overall, this suggests that the dynamic change of the limit order book regarding volume is more pronounced when studying the opposite side of the order book. Put differently, the ‘recovery’ of the limit order book following relatively large and aggressive orders is caused by a reassessment of free option risk.

5.5. Dependent variable and control variables

An interesting observation also relates to the dependent variables themselves. As can be seen from Tables 3 and 4, a new limit order submission immediately triggers more liquidity provision. The change in the limit buy [sell] order volume from the buy [sell] side is \$0.1003 and \$0.1243 million. However, this marginal but positive impact is extremely short-lived. Within 1 second, the sign switches and the volume-based liquidity impact is negative (–\$0.9712 and –\$0.9972 million respectively) and remains for at least 10 seconds. Given that human traders are unable to react within 0.1–0.2 seconds (but comfortably within 10 seconds), the results are revealing. On the one hand, liquidity provision as proxied by limit order volume has a *positive* short-term effect on the order submission process by others. On the other hand, by the time human traders have had the time to react to the new information, the impact is *negative* (liquidity withdrawal is more prominent than liquidity provision). A similar pattern can be seen in the EUR/JPY market, although the negative impact lasts for a shorter period.

Finally, although the emphasis of this paper is on the strategic variables, a few notes on the control variables are also useful. As the empirical results show, the bid-offer spread is a positive predictor of the liquidity withdrawal process for both currency pairs – consistent with the notion that a wider spread might tempt traders to supply liquidity to the market as a whole (Lo and Sapp, 2010). By contrast, volatility triggers the opposite reaction in the USD/JPY market (but unstable results for EUR/JPY), in line with traders tending to withdraw liquidity from the limit order book as volatility increases (Foucault, 1999 and Foucault et al., 2005). As expected, market liquidity (the total limit order volume at the current best bid-offer spread) has a positive impact on the limit order volume, whereas the results for market activity are unstable.

6. Conclusions

In this paper, we have investigated the short-term impact of strategic limit order submissions on the liquidity provision and withdrawal process of other traders in the FX spot market for USD/JPY and EUR/JPY on EBS under three relatively stable trading days. Studying four different time windows (from 0.1 to 60 seconds), our findings can be summarised as follows.

First, our empirical results seem to contradict the logic of adopting order-splitting strategies in the FX spot market (at least on EBS). Despite being very frequently selected, we find that most order-splitting strategies submitted by algorithmic traders seem to go 'detected' and are perceived as more information-rich than comparable medium-sized orders (logically submitted by human traders). The reason for this is not clear. However, an explanation for the unusual pattern could probably be found in the market microstructure of EBS itself. Whereas order-splitting strategies have become increasingly common in the trading of a range of assets on numerous electronic platforms, the 1-million minimum order rule on EBS acts as an important floor for the 'race to the bottom'. A remarkably high proportion of all orders in our dataset consists of *precisely* 1 million. In fact, the percentage of split orders (despite the fact that we use a very conservative definition) is higher than the combination of limit orders larger than 1 million. In such a setting, it is quite logical that a trader submitting a limit order of 2-3 million might be perceived as *less* informed or predatory than a trader submitting 2-3 1-million limit orders at the same price and in less than 0.1 seconds after each other.

Second, our high-frequency dataset set suggests that the inverse relationship between limit order size and limit order price aggressiveness might be less consistent than indicated by Lo and Sapp (2010). For instance, we find that very large limit orders (at least $/€10 million) tend to be very aggressive, i.e. submitted within the current best bid-offer spread. Unexpectedly, we also detect that medium-sized orders (between $/€2 and $/€4 million) are inclined to be less aggressive than orders of at least $/€5 million, as well as split orders. Our empirical results confirm that orders, which should be perceived as information-rich, orders matter for *other* traders. Interestingly, however, a significant change in the limit order volume only seems to follow as a result of relatively aggressive medium-sized orders or, alternatively, (very) large and very aggressive limit orders.

Third, investigating orders triggering a significant change in the limit order volume, we also explore how sensitive other traders are to limit orders submitted from the opposite side (free option risk) compared to the same side of the order book (non-execution risk). Here, we find that the impact related to non-execution risk is somewhat more significant than to free option risk. Put differently, following a potentially market-moving limit order; there is a stronger tendency of traders to immediately 'jump on the bandwagon' than to cancel their orders to 'avoid being picked off'. However, by studying different time windows, we also find that it takes approximately 5–10 seconds for the limit order volume to 'recover' following such orders. This process mainly is driven by a reassessment of free option risk (an increase in the liquidity provision by traders on the opposite side of the order book).

Finally, we document that provision as proxied by limit order volume, overall, has a positive short-term effect on the order submission process by others. This finding lends support to the argument that high-frequency trading enhances market liquidity (Broogard et al., 2014; Conrad et al., 2015; Hendershott et al., 2011). However, by the time human traders have had the time to react to the new information, the impact is *negative* (liquidity withdrawal is more prominent than liquidity provision). It could, therefore, be claimed that the benefit is unclear, or perhaps even detrimental. Regardless, it suggests that there is an element of truth in anecdotal claims of there being an 'illusion of liquidity' in markets populated by high-frequency traders – including the FX spot market. Given that psychologists estimate that it takes 0.1–0.4 seconds for a human to blink, the liquidity might, quite literally, not always as it seems.

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Table 1: Overview of limit order submissions 9-13 September 2010

	USD/JPY	EUR/JPY
Total limit orders	787,213	751,239
Base line limit orders	511,499	476,134
Split limit orders / %	160,892 / 20.44%	189,671 / 25.25%
Level of aggressiveness	2.52	2.55
Medium-sized limit orders / %	101,050 / 12.84%	77,774 / 10.35%
Level of aggressiveness	1.96	1.75
Large limit orders / %	10,693 / 1.36%	6,467 / 0.86%
Level of aggressiveness	2.14	1.79
Very large limit orders / %	3,079 / 0.39%	1,193 / 0.16%
Level of aggressiveness	2.78	2.00
Minimum limit order size	$1,000,000	€1,000,000
Maximum limit order size	$250,000,000	€100,000,000
Total limit order volume	$1,020,022,000,000	€897,039,000,000
Low	83.49	105.965
High	84.50	107.94

Sources: EBS and authors' calculations. Notes: Low [High] = Lowest [Highest] mid-market price. Level of aggressiveness uses the following scale: non-aggressive = 1, moderately aggressive = 2, aggressive = 3 and very aggressive = 4.

Table 2: Descriptive statistics

Currency pair	USD/JPY		EUR/JPY	
Time zone 1	0.1692		0.0975	
Time zone 2	0.2367		0.2329	
Time zone 3	0.3907		0.4352	
Market activity (mean / median)	332.613 / 263		231.194 / 166	
Market liquidity (mean / median)	17.15 / 14		6.71 / 6	
Volatility (mean / median)	0.0174 / 0.0162		0.0226 / 0.0220	
Bid-offer spread (mean / median)	0.0134 / 0.0119		0.0213 / 0.0188	
Direction	Buy	Sell	Buy	Sell
Split * MAgg	0.0373	0.0375	0.0482	0.0475
Split * Agg	0.0557	0.0578	0.0678	0.0609
Split * VAgg	0.0014	0.0015	0.0066	0.0061
Medium * Magg	0.0284	0.0299	0.0280	0.0261
Medium * Agg	0.0092	0.0096	0.0017	0.0017
Medium * VAgg	0.0046	0.0045	0.0027	0.0030
Large * Magg	0.0011	0.0012	0.0016	0.0013
Large * Agg	0.0006	0.0007	0.0001	0.0002
Large * VAgg	0.0017	0.0018	0.0005	0.0006
VLarge * Magg	0.0003	0.0002	0.0001	0.0001
VLarge * Agg	0.0005	0.0004	0.0001	0.0001

Sources: EBS and authors' calculations.

Table 3: USD/JPY, 9-13 September 2010, Change in LBOV from the buy-side perspective (included observations: 787,213)

Time window	0.1		1.0		10.0		60.0	
$LOV_{buy}^{t(i)+w} - LOV_{buy}^{t(i)}$	0.1003		-0.9712		-0.5448		0.5082	
Constant	0.4460**	(0.0158)	-0.9318**	(0.0393)	-0.3525**	(0.0723)	-0.6844**	(0.1079)
TZ1 (dummy)	-0.4534**	(0.0120)	-0.6558**	(0.0299)	-1.5973**	(0.0643)	-1.287**	(0.1022)
TZ2 (dummy)	-0.1810**	(0.0122)	-0.6212**	(0.0288)	-1.5034**	(0.0550)	-0.0599	(0.0955)
TZ3 (dummy)	-0.0367**	(0.0120)	-0.4904**	(0.0241)	-1.2202**	(0.0508)	-2.7004**	(0.0902)
Market activity	-0.0001**	(<0.0000)	0.0000	(<0.0000)	0.0025**	(0.0001)	0.0084**	(0.0002)
Market liquidity	-0.0159**	(0.0006)	-0.0920**	(0.0028)	-0.1875**	(0.0042)	-0.2162**	(0.0048)
Volatility	-0.1550**	(0.0227)	-1.1067**	(0.0734)	-2.1859**	(0.1605)	-3.0434**	(0.3859)
Bid-offer spread	18.4526**	(0.8706)	164.2846**	(2.5026)	250.8715**	(4.2083)	242.2891**	(5.5195)
Split*MAgg*Sell (dummy)	-1.1198**	(0.0220)	-1.5537**	(0.0447)	-0.6542**	(0.0945)	0.5152**	(0.1686)
Split*Agg*Sell (dummy)	-1.1455**	(0.0152)	-1.6821**	(0.0353)	-0.4055**	(0.0705)	1.4699**	(0.1294)
Split*VAgg*Sell (dummy)	-0.8161**	(0.0951)	-1.6466**	(0.2066)	-0.6066	(0.3929)	0.9430	(0.7025)
Medium*MAgg*Sell (dummy)	-0.5867**	(0.0219)	-0.2534**	(0.0460)	0.4715**	(0.0981)	1.6394**	(0.1732)
Medium*Agg*Sell (dummy)	-0.4504**	(0.0373)	-0.2333**	(0.0790)	0.8040**	(0.1584)	2.1745**	(0.2964)
Medium*VAgg*Sell (dummy)	-0.8515**	(0.0445)	-1.7597**	(0.1128)	-1.0649**	(0.2754)	-0.0790	(0.4893)
Large*MAgg*Sell (dummy)	-0.3448**	(0.0796)	0.1499	(0.2478)	0.4357	(0.5458)	1.0468	(0.8874)
Large*Agg*Sell (dummy)	-0.2084	(0.1313)	0.8694**	(0.3297)	-0.3914	(0.8027)	1.5740	(1.1955)
Large*VAgg*Sell (dummy)	-1.4873**	(0.1019)	-3.1855**	(0.2106)	-1.5490**	(0.4138)	2.7953**	(0.8237)
VLarge*MAgg*Sell (dummy)	0.0407	(0.1333)	2.2352	(1.4288)	1.1529	(1.6974)	-5.3044	(3.6507)
VLarge*Agg*Sell (dummy)	-0.0095	(0.1230)	2.1422**	(0.4229)	5.6935**	(1.0153)	7.8453**	(1.4835)
VLarge*VAgg*Sell (dummy)	-2.2259**	(0.2301)	-7.0484**	(0.4440)	-1.3340	(0.8531)	4.8890**	(1.7958)
Adjusted R-squared	0.0153		0.0377		0.0252		0.0149	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 4: USD/JPY, 9-13 September 2010, Change in LBOV from the sell-side perspective (included observations: 787,213)

Time window	0.1		1.0		10.0		60.0	
$-(LOV_{buy}^{t(i)+w} - LOV_{buy}^{t(i)})$	-0.1003		0.9712		0.5448		-0.5082	
Constant	-0.0086	(0.0158)	1.4560**	(0.0396)	0.5229**	(0.0728)	0.3223**	(0.1082)
TZ1 (dummy)	0.2610**	(0.0119)	0.4546**	(0.0300)	1.5528**	(0.0644)	1.4760**	(0.1023)
TZ2 (dummy)	0.0656**	(0.0122)	0.4978**	(0.0288)	1.4711**	(0.0550)	0.1554	(0.0956)
TZ3 (dummy)	0.0102	(0.0119)	0.4620**	(0.0241)	1.2178**	(0.0509)	2.7292**	(0.0903)
Market activity	0.0001**	(<0.0000)	0.0000	(<0.0000)	-0.0025**	(0.0001)	-0.0084**	(0.0002)
Market liquidity	0.0181**	(0.0006)	0.0955**	(0.0028)	0.1887**	(0.0042)	0.2135**	(0.0048)
Volatility	0.1734**	(0.0220)	1.1561**	(0.0721)	2.2175**	(0.1622)	3.0383**	(0.3867)
Bid-offer spread	-21.5498**	(0.8684)	-169.7519**	(2.5038)	-253.2946**	(4.2218)	-239.7117**	(5.5275)
Split*MAgg*Buy (dummy)	-1.5953**	(0.0255)	-0.8463**	(0.0563)	0.4545**	(0.1025)	2.1016**	(0.1664)
Split*Agg*Buy (dummy)	-2.0261**	(0.0173)	-2.1892**	(0.0355)	-1.0421**	(0.0735)	0.5279**	(0.1276)
Split*VAgg*Buy (dummy)	-2.2936**	(0.1062)	-2.6407**	(0.2040)	-1.4350**	(0.4370)	-0.1924	(0.8391)
Medium*MAgg*Buy (dummy)	-1.1169**	(0.0313)	-1.6151**	(0.0528)	-0.9398**	(0.1020)	0.3250	(0.1775)
Medium*Agg*Buy (dummy)	-0.4469**	(0.0391)	-1.1398**	(0.0869)	-0.6825**	(0.1613)	1.5986**	(0.2952)
Medium*VAgg*Buy (dummy)	-0.9354**	(0.0506)	-3.2413**	(0.1731)	-2.6802**	(0.2729)	-0.8851*	(0.4132)
Large*MAgg*Buy (dummy)	0.1724*	(0.0736)	-1.9652**	(0.2449)	-3.3299**	(0.5599)	-3.6158**	(1.0786)
Large*Agg*Buy (dummy)	-0.0701	(0.0911)	-2.2443**	(0.2950)	-1.3075	(0.9022)	0.5214	(1.2887)
Large*VAgg*Buy (dummy)	-1.4927**	(0.0870)	-5.0856**	(0.1708)	-4.6046**	(0.3962)	-1.6531*	(0.7189)
VLarge*MAgg*Buy (dummy)	-0.0271	(0.2563)	-2.4431*	(1.2057)	-2.3156	(1.6495)	1.7233	(2.3958)
VLarge*Agg*Buy (dummy)	-0.6849**	(0.0754)	-3.7693**	(0.3234)	-3.3520*	(1.4215)	0.5572	(1.6191)
VLarge*VAgg*Buy (dummy)	-3.1712**	(0.2005)	-8.0360**	(0.3380)	-6.7269**	(0.8078)	-2.4119*	(1.1854)
Adjusted R-squared	0.0330		0.0414		0.0259		0.0148	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 5: USD/JPY, 9-13 September 2010, Change in LSOV from the sell-side perspective (included observations: 787,213)

Time window	0.1		1.0		10.0		60.0	
$LOV_{sell}^{t(i)+w} - LOV_{sell}^{t(i)}$	0.1243		-0.9972		-0.4786		-0.1399	
Constant	0.4039**	(0.0227)	-0.8811**	(0.0649)	-0.4064**	(0.0894)	-1.4185**	(0.1083)
TZ1 (dummy)	-0.3611**	(0.0157)	-0.5361**	(0.0433)	-1.2159**	(0.0781)	0.3354**	(0.1061)
TZ2 (dummy)	-0.1367**	(0.0158)	-0.5914**	(0.0435)	-0.6025**	(0.0610)	0.5509**	(0.0786)
TZ3 (dummy)	0.0179	(0.0123)	-0.1316**	(0.0268)	-0.0754	(0.0494)	0.6960**	(0.0741)
Market activity	-0.0002**	(<0.0000)	-0.0001	(<0.0000)	0.0024**	(0.0001)	0.0058**	(0.0001)
Market liquidity	-0.0178**	(0.0018)	-0.1308**	(0.0059)	-0.2601**	(0.0073)	-0.3651**	(0.0073)
Volatility	-0.1497**	(0.0211)	-1.3075**	(0.1026)	-1.6592**	(0.2028)	-1.0634*	(0.4753)
Bid-offer spread	22.2569**	(1.3233)	196.0437**	(4.2510)	300.8224**	(5.7679)	371.9824**	(6.4055)
Split*MAgg*Buy (dummy)	-1.0912**	(0.0211)	-1.4540**	(0.0495)	-0.5989**	(0.0926)	0.6289**	(0.1416)
Split*Agg*Buy (dummy)	-1.0958**	(0.0153)	-1.5515**	(0.0358)	-0.2666**	(0.0722)	1.6452**	(0.1133)
Split*VAgg*Buy (dummy)	-0.8857**	(0.1014)	-2.2025**	(0.2140)	-0.7124	(0.4382)	0.8471	(0.6353)
Medium*MAgg*Buy (dummy)	-0.5666**	(0.0209)	-0.2956**	(0.0475)	0.2900**	(0.0986)	1.4809**	(0.1561)
Medium*Agg*Buy (dummy)	-0.4813**	(0.0377)	-0.2450**	(0.0810)	0.9508**	(0.1683)	2.9898**	(0.2801)
Medium*VAgg*Buy (dummy)	-0.8813**	(0.0584)	-1.8559**	(0.1133)	-1.3144**	(0.2801)	0.1980	(0.4235)
Large*MAgg*Buy (dummy)	-0.2433**	(0.0695)	0.7620**	(0.2144)	1.0748	(0.6183)	-1.5796	(1.0416)
Large*Agg*Buy (dummy)	-0.2238*	(0.1016)	0.6520*	(0.2773)	1.7590*	(0.8815)	2.5449*	(1.2431)
Large*VAgg*Buy (dummy)	-1.3771**	(0.0971)	-2.7226**	(0.2084)	-0.6415	(0.4290)	1.1437	(0.6641)
VLarge*MAgg*Buy (dummy)	-0.4113**	(0.1277)	0.2838	(0.3307)	1.2174	(1.2614)	0.8628	(1.6241)
VLarge*Agg*Buy (dummy)	0.2161*	(0.1071)	3.0851**	(0.4348)	5.7833**	(1.1458)	9.9025**	(1.7201)
VLarge*VAgg*Buy (dummy)	-3.0577**	(0.2438)	-6.1052**	(0.4048)	-1.5356	(1.2058)	4.4765**	(1.5590)
Adjusted R-squared	0.0155		0.0542		0.0424		0.0359	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 6: USD/JPY, 9-13 September 2010, Change in LSOV from the buy-side perspective (included observations: 787,213)

Time window	0.1		1.0		10.0		60.0	
$-(LOV_{sell}^{t(i)+w} - LOV_{sell}^{t(i)})$	-0.1243		0.9972		0.4786		0.1399	
Constant	0.0271	(0.0226)	1.4112**	(0.0652)	0.5778**	(0.0897)	1.0504**	(0.1087)
TZ1 (dummy)	0.1738**	(0.0157)	0.3264**	(0.0434)	1.1621**	(0.0783)	-0.1574	(0.1063)
TZ2 (dummy)	0.0204	(0.0157)	0.4647**	(0.0436)	0.5678**	(0.0611)	-0.4542**	(0.0788)
TZ3 (dummy)	-0.0519**	(0.0122)	0.0916**	(0.0267)	0.0563	(0.0494)	-0.6891**	(0.0741)
Market activity	0.0001**	(<0.0000)	0.0001	(<0.0000)	-0.0024**	(0.0001)	-0.0057**	(0.0001)
Market liquidity	0.0199**	(0.0018)	0.1344**	(0.0059)	0.2613**	(0.0073)	0.3624**	(0.0073)
Volatility	0.1638**	(0.0215)	1.3529**	(0.1048)	1.6872**	(0.2027)	1.0551*	(0.4758)
Bid-offer spread	-25.2966**	(1.3244)	-201.8717**	(4.2475)	-303.7647**	(5.7475)	-370.1811**	(6.3895)
Split*MAgg*Sell (dummy)	-1.5891**	(0.0234)	-1.0139**	(0.0555)	0.2562*	(0.1016)	1.9604**	(0.1490)
Split*Agg*Sell (dummy)	-2.0138**	(0.0161)	-2.2407**	(0.0368)	-1.0062**	(0.0697)	0.6252**	(0.1110)
Split*VAgg*Sell (dummy)	-2.1200**	(0.0949)	-2.2032**	(0.2594)	-0.4892	(0.5073)	1.9331**	(0.7476)
Medium*MAgg*Sell (dummy)	-0.9620**	(0.0295)	-1.5048**	(0.0539)	-0.5932**	(0.1041)	0.7093**	(0.1622)
Medium*Agg*Sell (dummy)	-0.2909**	(0.0373)	-0.9093**	(0.0989)	-0.5509**	(0.1972)	0.6004*	(0.2932)
Medium*VAgg*Sell (dummy)	-0.7264**	(0.0473)	-3.2008**	(0.1053)	-2.5325**	(0.2555)	-0.5658	(0.4065)
Large*MAgg*Sell (dummy)	0.3712**	(0.0718)	-2.0078**	(0.3383)	-2.9484**	(0.7417)	0.1990	(1.2412)
Large*Agg*Sell (dummy)	-0.1663	(0.0911)	-2.4478**	(0.2648)	-1.4564	(1.0231)	2.7611	(1.5092)
Large*VAgg*Sell (dummy)	-1.6783**	(0.0867)	-5.9560**	(0.1724)	-5.1643**	(0.5261)	-2.2672**	(0.7585)
VLarge*MAgg*Sell (dummy)	-0.1220	(0.1485)	-2.2410**	(0.5668)	-5.4579*	(2.4040)	9.2578**	(3.4457)
VLarge*Agg*Sell (dummy)	-1.2073**	(0.2118)	-6.5112**	(0.5566)	-4.3865*	(1.7464)	-1.0251	(2.5606)
VLarge*VAgg*Sell (dummy)	-3.2034**	(0.2173)	-8.1390**	(0.6497)	-6.2085**	(1.1070)	-3.2349*	(1.5458)
Adjusted R-squared	0.03304		0.058751		0.042953		0.0357	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 7: EUR/JPY, 9-13 September 2010, Change in LBOV from the buy-side perspective (included observations: 751,239)

Time window	0.1		1.0		10.0		60.0	
$LOV_{buy}^{t(i)+w} - LOV_{buy}^{t(i)}$	0.0131		0.0048		-0.0668		-0.4356	
Constant	0.2987**	(0.0202)	-0.0495	(0.0445)	-0.0649	(0.0928)	1.8913**	(0.1497)
TZ1 (dummy)	-0.2133**	(0.0140)	-0.0761*	(0.0316)	-0.0684	(0.0582)	-0.8243**	(0.0940)
TZ2 (dummy)	-0.0914**	(0.0125)	0.0395	(0.0260)	-0.135*	(0.0572)	-0.3100**	(0.0956)
TZ3 (dummy)	0.0438**	(0.0127)	0.0558*	(0.0256)	0.0639	(0.0596)	-0.4959**	(0.1011)
Market activity	-0.0001**	(<0.0000)	-0.0001*	(0.0001)	-0.0002	(0.0002)	-0.0023**	(0.0002)
Market liquidity	-0.0034	(0.0019)	0.0171**	(0.0057)	-0.0192*	(0.0079)	-0.0945**	(0.0114)
Volatility	-0.1625	(0.6319)	4.5529**	(1.3746)	-5.4528	(3.0218)	-81.9325**	(4.6703)
Bid-offer spread	5.2551**	(0.5893)	6.7191**	(1.4113)	15.3401**	(2.6027)	31.9017**	(4.1142)
Split*MAgg*Sell (dummy)	-2.2924**	(0.0193)	-2.4121**	(0.0453)	-0.9500**	(0.1042)	1.1617**	(0.1641)
Split*Agg*Sell (dummy)	-2.6522**	(0.0181)	-2.2079**	(0.0383)	0.6265**	(0.0879)	4.1400**	(0.1413)
Split*VAgg*Sell (dummy)	-2.3295**	(0.0432)	-1.6711**	(0.1088)	-0.3268	(0.2555)	0.3028	(0.4247)
Medium*MAgg*Sell (dummy)	-1.1384**	(0.0307)	-1.4020**	(0.0635)	-0.4802**	(0.1455)	2.2199**	(0.2335)
Medium*Agg*Sell (dummy)	-0.5363**	(0.1320)	0.0211	(0.2468)	0.4869	(0.4950)	2.6724**	(0.8230)
Medium*VAgg*Sell (dummy)	-0.8954**	(0.0677)	-1.3099**	(0.1796)	-0.7622*	(0.3863)	2.2801**	(0.5908)
Large*MAgg*Sell (dummy)	-0.6795**	(0.1105)	-0.0479	(0.2870)	0.1361	(0.6526)	0.9216	(1.0782)
Large*Agg*Sell (dummy)	-0.5714	(0.3088)	0.4818	(0.6075)	1.7106	(1.5043)	4.7565	(2.8915)
Large*VAgg*Sell (dummy)	-0.5551**	(0.1414)	-3.0584**	(0.4276)	-2.0690*	(0.8762)	0.9383	(1.3241)
VLarge*MAgg*Sell (dummy)	-1.3667**	(0.3454)	1.3803	(0.8689)	3.9221	(2.0346)	6.2839	(3.3852)
VLarge*Agg*Sell (dummy)	0.0231	(0.1724)	-1.1072	(0.9959)	1.7905	(2.0910)	10.0454**	(3.5346)
VLarge*VAgg*Sell (dummy)	-0.9110**	(0.3215)	-3.1723*	(1.3992)	2.7612	(1.7384)	13.2381**	(2.3202)
Adjusted R-squared	0.0434		0.0092		0.0003		0.0032	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 8: EUR/JPY, 9-13 September 2010, Change in LBOV from the sell-side perspective (included observations: 751,239)

Time window	0.1		1.0		10.0		60.0	
$LOV_{buy}^{t(i)+w} - LOV_{buy}^{t(i)}$	-0.1201		0.1097		-0.2018		-0.1881	
Constant	0.0655**	(0.0131)	0.9641**	(0.0302)	0.8384**	(0.0586)	0.1663	(0.0909)
TZ1 (dummy)	0.2079**	(0.0093)	0.3687**	(0.0194)	0.5406**	(0.0378)	0.7529**	(0.0597)
TZ2 (dummy)	0.1021**	(0.0079)	0.1023**	(0.0168)	0.2852**	(0.0374)	0.2841**	(0.0613)
TZ3 (dummy)	-0.0385**	(0.0077)	-0.0924**	(0.0164)	-0.1413**	(0.0382)	0.2644**	(0.0642)
Market activity	0.0002**	(<0.0000)	0.0003**	(<0.0000)	0.0000	(0.0001)	0.0016**	(0.0001)
Market liquidity	0.0187**	(0.0015)	0.0977**	(0.0034)	0.1693**	(0.0041)	0.1912**	(0.0060)
Volatility	0.1929	(0.3931)	-1.5228	(0.8569)	-18.5106**	(1.7848)	-21.5435**	(2.6569)
Bid-offer spread	-9.4127**	(0.3881)	-64.4106**	(0.9707)	-82.2688**	(1.5841)	-88.7727**	(2.4341)
Split*MAgg*Buy (dummy)	-1.3343**	(0.0119)	-1.2419**	(0.0282)	-0.7382**	(0.0586)	0.0232	(0.1001)
Split*Agg*Buy (dummy)	-1.6228**	(0.0108)	-1.2113**	(0.0218)	0.1991**	(0.0479)	1.7526**	(0.0764)
Split*VAgg*Buy (dummy)	-1.6927**	(0.0277)	-1.2135**	(0.0689)	-0.5225**	(0.1438)	0.2729	(0.2264)
Medium*MAgg*Buy (dummy)	-0.3555**	(0.0193)	-0.9820**	(0.0380)	-1.1072**	(0.0821)	-0.1610	(0.1349)
Medium*Agg*Buy (dummy)	-0.1571*	(0.0633)	-0.3390*	(0.1485)	-0.7896**	(0.2850)	0.3883	(0.4649)
Medium*VAgg*Buy (dummy)	-0.6151**	(0.0402)	-0.883**	(0.1177)	-0.5698*	(0.2342)	0.1356	(0.3665)
Large*MAgg*Buy (dummy)	0.1012	(0.0622)	-1.4002**	(0.1408)	-3.2585**	(0.3494)	-2.0063**	(0.5079)
Large*Agg*Buy (dummy)	0.0049	(0.2448)	-1.1385**	(0.4216)	-0.7023	(1.2580)	-1.1242	(1.9125)
Large*VAgg*Buy (dummy)	-0.6167**	(0.0702)	-2.4821**	(0.2491)	-2.7102**	(0.6250)	-0.5707	(0.7497)
VLarge*MAgg*Buy (dummy)	-0.1164	(0.2014)	-1.4430**	(0.4825)	-2.8713*	(1.2832)	-1.6683	(1.8194)
VLarge*Agg*Buy (dummy)	-0.8215**	(0.0965)	-4.0494**	(0.3633)	-6.4712**	(1.6336)	-1.9771	(1.7096)
VLarge*VAgg*Buy (dummy)	-0.8235**	(0.1500)	-4.1645**	(0.4392)	-3.5489**	(1.0978)	1.1255	(1.4576)
Adjusted R-squared	0.0472		0.0248		0.0084		0.0046	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 9: EUR/JPY, 9-13 September 2010, 9-13 September 2010, Change in LSOV from the sell-side perspective (included observations: 751,239)

Time window	0.1		1.0		10.0		60.0	
$LOV_{sell}^{t(i)+w} - LOV_{sell}^{t(i)}$	0.1069		-0.1145		0.2685		0.6237	
Constant	0.1278**	(0.0127)	-0.4040**	(0.0308)	-0.5564**	(0.0548)	-2.3401**	(0.0861)
TZ1 (dummy)	-0.3314**	(0.0089)	-0.6348**	(0.0221)	-0.5728**	(0.0345)	0.3711**	(0.0544)
TZ2 (dummy)	-0.1631**	(0.0077)	-0.3062**	(0.0153)	-0.1964**	(0.031)	0.2038**	(0.0518)
TZ3 (dummy)	-0.0054	(0.0076)	0.0348*	(0.0142)	0.0891**	(0.0319)	0.2714**	(0.055)
Market activity	-0.0001**	(<0.0000)	-0.0002**	(0)	0.0002*	(0.0001)	0.0008**	(0.0001)
Market liquidity	-0.0031*	(0.0012)	-0.1055**	(0.0045)	-0.1609**	(0.0059)	-0.1383**	(0.0072)
Volatility	0.1654	(0.4193)	-2.9103**	(0.9126)	23.7948**	(1.7207)	102.3266**	(2.8038)
Bid-offer spread	10.8547**	(0.3816)	62.3967**	(1.0913)	63.8205**	(1.6398)	46.4597**	(2.3982)
Split*MAgg*Buy (dummy)	-0.7680**	(0.0116)	-0.9376**	(0.0249)	-0.6065**	(0.0524)	0.0889	(0.0845)
Split*Agg*Buy (dummy)	-1.0061**	(0.0100)	-0.9065**	(0.0215)	0.4268**	(0.0466)	2.0099**	(0.0748)
Split*VAgg*Buy (dummy)	-0.6994**	(0.0260)	-0.7155**	(0.0598)	-0.2162	(0.1347)	0.5399*	(0.2204)
Medium*MAgg*Buy (dummy)	-0.5697**	(0.0181)	-0.2244**	(0.0352)	0.7007**	(0.0785)	1.7821**	(0.1278)
Medium*Agg*Buy (dummy)	-0.6327**	(0.0657)	0.0044	(0.1357)	0.4206	(0.2685)	2.2224**	(0.4329)
Medium*VAgg*Buy (dummy)	-0.3573**	(0.0490)	-0.1082	(0.1008)	0.6607**	(0.2099)	1.3420**	(0.3353)
Large*MAgg*Buy (dummy)	-0.3600**	(0.0662)	1.2408**	(0.1763)	3.1148**	(0.3532)	4.9181**	(0.5929)
Large*Agg*Buy (dummy)	-0.4763	(0.2536)	0.9677*	(0.4687)	2.6143**	(0.9517)	3.2520*	(1.596)
Large*VAgg*Buy (dummy)	-0.0758	(0.1495)	0.0339	(0.2794)	1.2725*	(0.5464)	4.7998**	(0.8675)
VLarge*MAgg*Buy (dummy)	-0.4964*	(0.2480)	5.0940**	(1.0266)	8.5925**	(1.3576)	11.1267**	(2.0157)
VLarge*Agg*Buy (dummy)	-0.1378	(0.1128)	8.7832**	(1.2802)	10.4187**	(1.3965)	13.3424**	(1.8541)
VLarge*VAgg*Buy (dummy)	-0.7502**	(0.2762)	0.9487	(0.7416)	4.3871**	(1.0097)	9.7215**	(1.6328)
Adjusted R-squared	0.0198		0.0227		0.0078		0.0074	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.

Table 10: EUR/JPY, 9-13 September 2010, 9-13 September 2010, Change in LSOV from the sell-side perspective (included observations: 751,239)

Time window	0.1		1.0		10.0		60.0	
$LOV_{sell}^{t(i)+w} - LOV_{sell}^{t(i)}$	0.1201		-0.1097		0.2018		0.1881	
Constant	0.1808**	(0.0133)	-0.6857**	(0.0303)	-0.6800**	(0.0584)	-0.2541**	(0.0910)
TZ1 (dummy)	-0.3675**	(0.0094)	-0.5521**	(0.0195)	-0.6348**	(0.0377)	-0.6552**	(0.0598)
TZ2 (dummy)	-0.1710**	(0.0080)	-0.1910**	(0.0168)	-0.3352**	(0.0373)	-0.2282**	(0.0614)
TZ3 (dummy)	0.0458**	(0.0079)	0.0955**	(0.0164)	0.1486**	(0.0381)	-0.2444**	(0.0641)
Market activity	-0.0003**	(<0.0000)	-0.0003**	(<0.0000)	0.0000	(0.0001)	-0.0016**	(0.0001)
Market liquidity	-0.0125**	(0.0015)	-0.0913**	(0.0034)	-0.1716**	(0.0041)	-0.2087**	(0.0060)
Volatility	-0.0843	(0.3991)	1.7737*	(0.8595)	18.7806**	(1.7844)	21.3443**	(2.6570)
Bid-offer spread	12.6674**	(0.3971)	66.4976**	(0.9789)	80.7485**	(1.5829)	83.7768**	(2.4339)
Split*MAgg*Sell (dummy)	-0.8327**	(0.0123)	-1.2010**	(0.0267)	-0.7314**	(0.0596)	0.3163**	(0.0944)
Split*Agg*Sell (dummy)	-1.0278**	(0.0111)	-1.0626**	(0.0232)	0.1450**	(0.0552)	1.8779**	(0.0901)
Split*VAgg*Sell (dummy)	-0.6629**	(0.0269)	-0.6869**	(0.0603)	-0.2495	(0.1544)	0.0134	(0.2652)
Medium*MAgg*Sell (dummy)	-0.6823**	(0.0178)	-0.5820**	(0.0389)	-0.0521	(0.0890)	1.1788**	(0.1453)
Medium*Agg*Sell (dummy)	-0.5651**	(0.0654)	-0.4996**	(0.1232)	0.0489	(0.2935)	1.1838*	(0.4593)
Medium*VAgg*Sell (dummy)	-0.4058**	(0.0464)	-0.6879**	(0.1121)	-0.5425*	(0.2463)	1.0914**	(0.3489)
Large*MAgg*Sell (dummy)	-0.7201**	(0.0685)	-0.5896**	(0.1729)	-0.6654	(0.3542)	-0.1144	(0.6339)
Large*Agg*Sell (dummy)	-0.4997*	(0.1982)	0.6331	(0.3571)	1.3960	(0.7584)	3.8836**	(1.4975)
Large*VAgg*Sell (dummy)	-0.2889**	(0.1028)	-1.1740**	(0.3190)	-0.2188	(0.4881)	1.0764	(0.6553)
VLarge*MAgg*Sell (dummy)	-1.0774**	(0.2439)	-0.7835	(0.4883)	-0.8926	(1.1521)	-0.2062	(1.9183)
VLarge*Agg*Sell (dummy)	0.4764**	(0.1313)	2.8383**	(0.4759)	4.9433**	(0.9946)	9.1302**	(1.8157)
VLarge*VAgg*Sell (dummy)	-0.1624	(0.2431)	-0.9294	(0.6703)	3.0019**	(0.9023)	9.1016**	(1.3747)
Adjusted R-squared	0.0206		0.0222		0.0079		0.0048	

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level.