Working Papers in Economics & Finance
2021-02

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Alexis Stenfors[*] and Masayuki Susai[**]

10 February 2021

Abstract

We investigate if and how other traders react to algorithmic order-splitting tactics. Studying over 1.4 million limit orders in the EUR/USD foreign exchange (FX) spot market, we find that stealth-trading strategies adopted by algorithmic traders seem to go detected and are perceived as more market-moving than orders of the corresponding size typically submitted by human traders. We also document that algorithmic traders appear to be more sensitive to limit orders submitted from the opposite side (free-option risk) than to the same side of the order book (non-execution risk). Once human traders have had time to react, however, the pattern reverses.

JEL Classification Numbers: D4, F3

Keywords: algorithmic trading, foreign exchange, limit order book, market microstructure, order splitting, stealth trading

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1. Introduction

One of the most visible features in financial 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; Harris and Hasbrouck, 1996; Hollifield et al., 2004; Hasbrouck and Saar, 2002). Such markets have also tended to be associated with frequent order cancellations and a dramatic shortening of the lifetime of limit orders (Susai and Yoshida, 2015). At the same time, limit order submissions have increasingly become seen in the context of active trading strategies in the academic literature (Foucault et al., 2005; Rosu, 2009). Traders using electronic trading platforms, in particular, 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 involve monitoring costs as traders may be picked off or be required to repeatedly cancel and resubmit the order at a more competitive price (Fong and Liu, 2010; Liu, 2009).

Limit orders contain information and to avoid front-running by others; traders need to select the appropriate aggressiveness and size of the order submissions (Cao et al., 2004; Griffiths et al., 2000; Lo and Sapp, 2010; Ranaldo, 2004). As a result, traders might resort to stealth trading strategies intended to camouflage the true information content transmitted to the market (Kyle, 1985, Barclay and Warner, 1993; Chakravarty; 2001; Alexander and Peterson, 2007). In particular, it has been shown that informed investors often slice their orders into smaller pieces to prevent front-running by others. The aim with such limit order submission strategies is to influence other traders' *perception* of the future supply and demand in the market.

This paper is an investigation into stealth trading and the price discovery process within arguably the largest and most liquid market in the world: the EUR/USD foreign exchange (FX) spot market. With a daily turnover of $416 billion in 2019 in just one currency pair, the trading volume comfortably surpasses that of the global equity market as a whole (BIS, 2019). Instead of focussing on prices or transactions, however, our emphasis lies on the complete limit order book volume. The reason for this is that the FX spot market is so deep and competitive that price changes are relatively rare in comparison to changes in the limit order book volume. The depth provides more frequent signals to traders in their information gathering. By studying the change in the complete limit order book volume, we can capture signals that are crucial in the price determination process – yet not visible in the actual prices.

We first explore how other traders react to algorithmic order-splitting strategies adopted to disguise the true order size. We then dig deeper and investigate whether traders on the opposite side react differently than traders on the same side of the limit order book to new limit order submissions. Interestingly, we find that stealth-trading strategies widely adopted by algorithmic traders seem to go detected and are perceived as more market-moving or predatory than orders of the corresponding size typically submitted by human traders. We also document that algorithmic traders appear to be more sensitive to limit orders submitted from the opposite side (free-option risk) than to the same side of the order book (non-execution risk). Once human traders have had time to react, however, the pattern reverses.

By investigating stealth trading in an extremely deep over-the-counter (OTC) market, our study makes several contributions to the empirical market microstructure literature. In particular, it provides a unique perspective on a trading strategy largely examined on assets in exchange-traded markets (Blau et al., 2009, Chae and Lee, 2011; Chou et al., 2009, Kato and Katayama, 2017; Menkhoff and Schmelling, 2010). It also adds to the
FX literature addressing order flow and limit order submission strategies (Lyons, 1997; Evans and Lyons, 2002; Payne, 2003; Daníelsson et al., 2012; Stenfors and Susai, 2019; 2021). More broadly, by focussing on volume rather than price, our paper provides new insights into the sources of information and the behaviour of traders in limit order markets. We find that information is transmitted via a range of factors that go beyond direction, order size and price aggressiveness (see, for instance, Glosten and Milgrom, 1985; Liu, 2009; Lo and Sapp, 2010).

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

2. Related literature

Order flow influences FX spot prices (Lyons, 1997; Evans and Lyons, 2002). A number of empirical studies show that this relationship holds, at least in the short run (see, for instance, Daníelsson et al., 2012; Evans and Lyons, 2005; Payne, 2003). However, whereas the vast majority of studies on FX markets have been conducted using transaction data or market orders, a similar logic can be applied to limit orders. A limit order, in contrast to a market order, is not intended to be executed immediately. Nonetheless, it contains information that, when it becomes visible to the market, may influence other traders' perception of the direction of the future market price.

Limit orders are more complex than market orders insofar as they are associated with monitoring costs. Traders submitting 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). More importantly from the perspective of our study, an assessment has to be made with regards the effect the limit order submission 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 traders to react depending on the perceived market impact. In other words, 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. This is because 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, traders on the same side of the order book may also revise their expectations, and consequently cancel and resubmit their orders. They are less likely to be picked off. Instead, as the market is more likely to move against them, they face non-execution risk (Hasbrouck and Saar, 2002; Liu, 2009).

A limit order submission involves a strategic trade-off, in particular between size and price aggressiveness. A market order is, per definition, an aggressive order as the intention is to execute a trade immediately at the prevailing best market price. However, the probability of a limit order being executed depends on how far away it is submitted from the market price (Griffiths et al., 2000; Cao et al., 2004; Ranaldo 2004). Lo and Sapp (2010), using USD/DEM and USD/CAD FX spot data from 1997 and 2005, observe that more aggressive limit orders in the FX market tend to be smaller in size. This suggests that large limit orders might be interpreted as potentially market-moving, and, therefore, more likely to trigger order cancellations by other traders.

Theoretically, however, informed traders could camouflage large and potentially market-moving orders by gradually spreading them throughout the trading day (Kyle, 1985). Following the logic of Keim and Madhavan (1995, 1996), order-spitting strategies could be adopted by ‘informed traders’ as well as ‘liquidity traders’. Whereas an informed trader would prefer to disguise his private information as transmitted through a large order submission, a trader demanding liquidity would want to hide his full amount to avoid front-running by others. Empirical studies conducted using data from exchange-traded markets show that informed investors often opt split large orders into medium-sized blocks, making split orders more informative than non-split orders (Barclay and Warner, 1993; Chakravarty; 2001; Alexander and Peterson, 2007). The ‘medium-sized’ category is often classified as in the range of 500 to 9,900 shares, but would, naturally, vary depending on the market.

Studies on NYSE-listed stocks (Blau et al., 2009), the Tokyo Stock Exchange (Kato and Katayama, 2017), Korean KOSPI 200 index options (Chae and Lee, 2011) confirm that stealth-trading strategies tend to be more common when the market is relatively thin. These empirical findings provide support to the logic that informed traders could opt to camouflage large orders by submitting them when the market is liquid (Admati and Pfleiderer, 1988). Furthermore, Chou et al. (2009), using TAIEX futures data from the Taiwan Stock Exchange, and Stenfors and Susai (2019; 2021), who use the same EBS dataset as in this paper, find that split orders tend to be more are aggressive than non-split orders. This suggests that such stealth trading strategies can be adopted not only to minimise the market impact of large orders, but also to maximise the likelihood of a fill through the submission of aggressive, but small, orders. Using USD/RUB FX spot data from Moscow's MICEX exchange in 2002, Menkhoff and Schmelling (2010) find that informed traders engage in stealth trading through medium-sized orders in the range of $50,000.

3. Data

EUR/USD is the most actively traded currency pair in the world. According to BIS (2019), the average daily turnover in the EUR/USD FX spot market amounted to $416 billion. EBS and Reuters Matching are the two leading FX trading platforms. EBS, controlling a more significant portion of the electronic trading of the major currency pairs, has witnessed a massive influx of algorithmic traders in recent years – increasing from just 2% in 2004 to approximately 50 % in 2010 and 70% in 2013 (Moore et al., 2016).

We use the same EBS high-frequency dataset as Stenfors and Susai (2019; 2021), which runs from 21:00:00 (GMT) on 8 September 2010 to 20:59:59 (GMT) on 13 September 2010 (including the weekend). The dataset contains 100% of all order submissions, cancellations and transactions on the platform. Apart from the price, volume, buy/sell indicators, we also use the millisecond timestamp. Each limit order submission and cancellation is attached with a unique and anonymous 20-digit Trader ID. This permits us to match each submission with its corresponding cancellation.

In line with the literature on high-frequency trading in equity markets, market orders account for only a fraction of all orders in our dataset. Having removed market orders, transactions, as well as limit order submissions that do not have a corresponding order cancellation the same day, we are left with 1,419,630 limit orders and an equal number of cancellations. These account for more than 99.5% of all EUR/USD activity on EBS during the period studied. In sum, the total limit order book for the three trading days amounts to approximately €1.8 trillion.

On EBS, a trader can choose how to view the depth of the limit order book. For instance, the book can be displayed according to individual amounts of bids [offers] at different price levels, the cumulative amounts of bids [offers] or the best bid [offer] for a specific amount (EBS, 2011). Importantly for our subsequent analysis, iceberg orders, which permit traders to display just a proportion of their complete order amount, were not introduced on EBS until October 2013 (ICAP, 2014).

4. The model

4.1 The model and the dependent variables

The focus of our investigation is the immediate market reaction to stealth-trading strategies adopted by algorithmic traders. However, each data point (the time stamp of each limit order submission), which marks the starting point of new information entering the market, occurs irregularly. Therefore, rather than approaching the dataset from a conventional time-series approach with fixed intervals, we use the limit order timestamps as reference points. We then investigate the change in the limit order volume from each reference point to a set of pre-defined points in the future, and refer to these as 'time windows'.

FX spot has a historically been one of the fastest markets in the world. As articulated by ACI (2009), the trade organisation for dealers in FX and money markets, "a dealer has to assume that a price given to a voice/traditional broker is good only for a short length of time, typically a matter of seconds." However, computer algorithms can react much faster than human traders. To enable us to investigate potential differences between the reaction by algorithmic and human traders, we include five different time windows in our study: 0.1, 0.2, 0.5, 1 and 5 seconds.

In our model, we quantify the change in the limit buy and sell order book separately. We also distinguish between buy and sell orders. This enables us to investigate the change in the limit order book from four perspectives:

a) Buyers reacting to a new sell order (free-option risk)
b) Sellers reacting to a new buy order (free-option risk)
c) Buyers reacting to a new buy order (non-execution risk)
d) Sellers reacting to a new sell order (non-execution risk)

To do so, we define the dependent variable in the model (Equation 1) as the change in limit order buy [sell] volume (LOV_d), where d = [buy / sell], within a specified time window (w), where w = 0.1, 0.2, 0.5, 1 or 5 seconds following the ith limit order (LOS_i) submitted at time $t(i)$ – but excluding the limit order submission itself:

$$LOV_d^{t(i)+w} - LOV_d^{t(i)} = \alpha_i + \beta_1 Market\ activity_i + \beta_2 Market\ depth_i + \beta_3 Volatility_i + \beta_4 Bid-ask\ spread_i + \delta_1 TZ1_i + \delta_2 TZ2_i + \delta_3 TZ3_i + \delta_4 NS_i \cdot Small_i \cdot VAgg_i \cdot D_i + \delta_5 NS_i \cdot Small_i \cdot Agg_i \cdot D_i + \delta_6 NS_i \cdot Small_i \cdot MAgg_i \cdot D_i + \delta_7 NS_i \cdot Medium_i \cdot VAgg_i \cdot D_i + \delta_8 NS_i \cdot Medium_i \cdot Agg_i \cdot D_i + \delta_9 NS_i \cdot Medium_i \cdot MAgg_i \cdot D_i + \delta_{10} NS_i \cdot Large_i \cdot VAgg_i \cdot D_i + \delta_{11} NS_i \cdot Large_i \cdot Agg_i \cdot D_i + \delta_{12} NS_i \cdot Large_i \cdot MAgg_i \cdot D_i + \delta_{13} LS_i \cdot Small_i \cdot VAgg_i \cdot D_i + \delta_{14} LS_i \cdot Small_i \cdot Agg_i \cdot D_i + \delta_{15} LS_i \cdot Small_i \cdot MAgg_i \cdot D_i + \delta_{16} LS_i \cdot Medium_i \cdot VAgg_i \cdot D_i + \delta_{17} LS_i \cdot Medium_i \cdot Agg_i \cdot D_i + \delta_{18} LS_i \cdot Medium_i \cdot MAgg_i \cdot D_i + \delta_{19} LS_i \cdot Large_i \cdot VAgg_i \cdot D_i + \delta_{20} LS_i \cdot Large_i \cdot Agg_i \cdot D_i + \delta_{21} LS_i \cdot Large_i \cdot MAgg_i \cdot D_i + \varepsilon_i \quad (1)$$

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 (A^b) [sell (A^a)] orders where $t(0)$ = 21:00:00 GMT. Hence, $LOV_{buy}^{t(i)} = \sum_{k=t(0)}^{k=t(i-1)} A_k^b$, $LOV_{buy}^{t(i)+w} = \sum_{k=t(0)}^{k=t(i)+w} A_k^b$, $LOV_{sell}^{t(i)} = \sum_{k=t(0)}^{k=t(i-1)} A_t^a$ and $LOV_{sell}^{t(i)+w} = \sum_{k=t(0)}^{k=t(i)+w} A_k^a$.

For instance, suppose that the limit order book consists of €25 million buy orders and €10 million sell orders immediately prior to a new limit order enters the market. In other words, the limit buy [sell] order volume is €25 [€10] million. If, 1 second after a new order has been submitted, the limit order book (excluding the new order itself) contains €20 million buy orders and €8 million sell orders, the change in the limit buy [sell] order volume is –€5 [–€2] million. Thus, when measuring the change in the limit order book following a new limit order submission, we take into account both cancellations and new submissions induced by this new information.

4.2. *Independent variables*

Our model includes 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 18 buy [sell] dummy variables include direction, size, order-splitting strategies and price aggressiveness.

4.2.1. Size and order-splitting

A large order should, *ceteris paribus*, trigger a stronger reaction than a small order, as it would be considered as more likely to move the market. The minimum order size allowed on EBS is €/$ 1 million. Although our dataset contains some very large EUR/USD FX spot limit orders (up to €250 million), the overwhelming majority (88.5%) is for precisely €1 million:

Table 1: Overview of EUR/USD FX spot limit order submissions

Total number of limit order submissions	1,419,630
Small orders	88.50%
Medium-sized orders	12.07%
Large orders	1.43%
Split orders	17.42%
Minimum order size	€1,000,000
Maximum order size	€250,000,000
Total limit order volume	€1,818,803,000,000
Low	1.2662
High	1.2893

Sources: EBS and authors' calculations. Low [High] = Lowest [Highest] mid-market price.

To capture the impact of order size in our model, we use three size categories:

- *Small*$_i$: If the limit order size is equal to €1 million.
- *Medium*$_i$: If the limit orders size is greater than €1 million but smaller than €5 million.
- *Large*$_i$: If the limit order size is equal to, or greater than €5 million.

However, as a 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 promptly react 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. Chae and Lee (2011) and Kim and Ryu (2012) define a split buy [sell] order as buy [sell] orders for the same financial asset or instrument submitted by a specific trader at least twice during the same trading day. Yeo (2005) is more conservative and restricts split orders to those submitted within a shorter time frame (10 to 300 seconds).

Algorithmic traders have a far greater ability than human traders to split large orders into many small orders. Following the increase of high-frequency trading on electronic platforms, 10 seconds would not be considered a long time. This is especially true in the famously fast-paced FX spot market. As each order in our dataset contains an individual trader ID, we are unable to ascertain, with absolute certainty, which orders form part of stealth trading strategy. Nevertheless, the sheer magnitude of limit order submissions within one specific market enables us to employ considerably more strict criteria for split orders.

To be precise, we define a limit order as a split order i) if the price of limit order submission i, $p_{t(i)}$, is the same as the price of limit order submission j, $p_{t(j)}$, where $j \neq i$ and $j > i$, ii) if the direction (i.e. buy or sell) of limit order submission i is the same as the direction of limit order submission j, iii) if limit order i and j are submitted within less than 0.1 seconds of each other, and iv) if no other orders are submitted or cancelled in between the submissions of limit order i and j (Stenfors and Susai, 2019; 2021). It could be argued that, in particular, the 100-millisecond requirement is overly stringent. However, with 17.42% being categorised as split orders (see Table 1), we do not believe it is necessary to adopt a more flexible methodology. Changing the requirement from 100 to 200 or 500 milliseconds only marginally increases the proportion of split orders. What is more, given that it takes 300–400 milliseconds for a human being to blink (Geiger and Mamudi, 2014), the criterium rules out all stealth trading strategies adopted by human traders with certainty.

According to our definition, a split order is preceded or followed by an identical limit order in the same direction. Given that we study the impact of orders within relatively short time frames, we, therefore, exclude the initial orders in an order-splitting sequence.[1] In sum, to capture the impact of split orders in our model, we use two dummy categories:

- Last split order (LS_i): If the limit order is the last split order in an order-splitting sequence.
- Non-split order (*NSi*): If the limit order is a non-split order.

4.2.2. Price aggressiveness

Limit orders are not intended to be executed immediately. Therefore, the choice of price aggressiveness is critical in limit order submission strategies. According to Lo and Sapp (2010), FX spot traders strategically chose between size and price

[1] The results from robustness checks where we include the initial orders in an order-splitting sequence are, however, almost identical.

aggressiveness when submitting orders – resulting in a trade-off between the two variables. However, price aggressiveness is also an important ingredient in stealth trading strategies. Chou et al. (2009), using TAIEX futures data from the Taiwan Stock Exchange, find that split orders tend to be relatively aggressive – although the impact of price aggressiveness, as such, is left unexplored. Using a high-frequency dataset in a deep and liquid market allows us to analyse these strategies in detail.

In general, 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-ask spread. The EUR/USD FX spot market is extremely competitive and the typical bid-ask spread is often no more than 1 pip (with 1 pip being the 4th decimal for EUR/USD). Thus, we employ a highly granulated price aggressiveness scale, and incorporate the following variables in our model:

- Very aggressive limit order ($VAgg_i$): If the new limit order submission price p_i improves or matches the best bid-ask spread ($p^{ba}_{t(i)-1} - p^{bb}_{t(i)-1}$).
- Aggressive limit order (Agg_i): If the new limit order submission price p_i is outside, but within 2 pips of the best bid-ask spread.
- Moderately aggressive limit order ($MAgg_i$): If the new limit order submission price p_i is further than 2 pips from, but within 4 pips of, the best bid-ask spread.

4.2.3. 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 and/or aggressive) 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 limit sell [buy] order book.

However, traders might react to incoming orders from the *same* side of the order book. 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 limit buy [sell] order book.

4.2.4. 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, the bid-ask spread and the time zone[2]:

- *Market activity$_i$* : Let us define the *i*th limit order submission as LOS_i. As a proxy for market activity, where $Market\ activity_i = \sum_{j=t(i)-60s}^{j=t(i)} LOS_j$, we use the number of limit orders submitted to the EBS platform in the respective currency pair during the previous 60 seconds.

- *Market depth$_i$*: The market depth at the current best bid-ask spread, where $Market\ depth_i = \sum_{j=t(0)}^{j=t(i-1)} A_j^{bb} + \sum_{j=t(0)}^{j=t(i-1)} A_j^{ba}$, where A^{bb} [A^{ba}] is the amount of outstanding limit buy [sell] orders at best bid [ask] and $t(0)$ = 21:00:00 GMT.

- *Volatility$_i$*: Volatility which is measured using the mid-market price of the best limit buy and sell orders (p^{bm}) at each second during a 60-second interval prior to the new limit order submission, i.e. $Vol_i = \sqrt{252 \times 24 \times 60 \times \sigma(\sum_{j=t(i)-61s}^{j=t(i)-1s}((p_{j-1s}^{bm}/p_{j-2s}^{bm}) - 1)}$, where σ is the variance.

- *Bid-ask spread$_i$*: The difference between the best ask and bid prices, $(p_{t(i-1)}^{ba} - p_{t(i-1)}^{bb})$ measured vis-à-vis the mid price, $p_{t(i-1)}^{bm}$, on the EBS platform immediately prior to the limit order submission. Thus, $Bid - ask\ spread_i = (p_{t(i-1)}^{ba} - p_{t(i-1)}^{bb})/p_{t(i-1)}^{bm}$.

[2] See Stenfors and Susai (2019; 2021) for the first 4 control variables.

- $TZ1_i$, $TZ2_i$ and $TZ3_i$: Although EUR/USD can be classified as a currency pair that trades 24 hours a day, the London market tends to be most active. Hence, we use three dummy variables to account for this variation, where TZ1 = 21:00:00–02:59:59 GMT (Pacific), TZ2 = 03:00:00–08:59:59 GMT (Tokyo), TZ3 = 09:00:00–14:59:59 GMT (London) (and TZ4 = 15:00:00–20:59:59 GMT (New York))

4.3. Estimation and diagnostics

We run 20 regressions using OLS.[3] 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.

We conduct a series of robustness tests. First, 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. Second, we estimate the model using additional time windows (10 and 60 seconds). As expected, the results are considerably less significant for longer time windows. However, we do not find any significant breaks in the patterns reported in Section 5 below. Third, we run the regressions with different sets of dummy variables (all split orders instead of last split orders, more/less granulated levels of price aggressiveness). The results are, however, similar. Fourth, 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 opt for a model incorporating the limit order volume

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

information in the dependent variable. Finally, we conduct the same tests on the 2nd and 3rd most actively currency pairs (USD/JPY and EUR/JPY), which also contain a significant proportion of split orders. Although the results occasionally are somewhat less significant, the overall results remain similar to those for EUR/USD and, more importantly, do not contradict the findings presented and discussed in Section 5. Hence, due to a limitation of space, we opt to include EUR/USD only.

5. Empirical Results

Table 2 shows the descriptive statistics.

Table 2: Descriptive statistics (included observations: 1,419,630)

TZ1	10.8178%	
TZ2	25.6757%	
TZ3	42.7079%	
Market activity (mean / max / min)	613.10 / 4,479.00 / 0.00	
Market depth (mean / max / min)	16.17 / 306.00 / 0.00	
Volatility	1.7047%	
Bid-ask spread	0.0083%	
	Buy	Sell
NS ·Small ·Vagg	10.8013%	10.8756%
NS ·Small ·Agg	12.3678%	12.0612%
NS ·Small ·Magg	4.8020%	4.4577%
NS ·Medium ·Vagg	1.8392%	1.9561%
NS ·Medium ·Agg	1.8178%	1.8091%
NS ·Medium ·Magg	0.7136%	0.7123%
NS ·Large ·Vagg	0.2627%	0.2825%
NS ·Large ·Agg	0.2243%	0.2326%
NS ·Large ·Magg	0.0637%	0.0622%
LS ·Small ·Vagg	0.9497%	0.9196%
LS ·Small ·Agg	1.2084%	1.1739%
LS ·Small ·Magg	0.4194%	0.3709%
LS ·Medium ·Vagg	0.0828%	0.0938%
LS ·Medium ·Agg	0.0926%	0.1062%
LS ·Medium ·Magg	0.0353%	0.0356%
LS ·Large ·Vagg	0.0056%	0.0054%
LS ·Large ·Agg	0.0062%	0.0067%
LS ·Large ·Magg	0.0013%	0.0016%

Sources: EBS and authors' calculations.

Tables 3–6 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. Algorithmic order-splitting strategies

Before discussing stealth trading strategies, let us first study the impact of size and price aggressiveness – and the trade-off between the two strategic variables. These do not contain orders that are submitted further than 4 pips away from the best bid-ask spread, or initial orders in an order-splitting sequence. Hence, we focus on orders that might or should be perceived by other traders as market-moving. These orders ought to be significant. Table 3 shows the impact of sell orders on the buy order volume.

Table 3: The impact of sell orders on the buy order volume (EUR/USD, 9-13 September 2010)

Time window	0.1		0.2		0.5		1.0		5.0	
$LOV_{buy}^{t(i)+w} - LOV_{buy}^{t(i)}$	0.106		-0.114		-0.932		-0.999		-0.849	
Constant	0.419**	(0.016)	0.217**	(0.021)	-0.845**	(0.032)	-0.767**	(0.040)	0.254**	(0.062)
TZ1	-0.514**	(0.013)	-0.575**	(0.017)	-0.767**	(0.024)	-1.116**	(0.031)	-2.080**	(0.050)
TZ2	-0.265**	(0.011)	-0.320**	(0.014)	-0.496**	(0.020)	-0.757**	(0.025)	-0.903**	(0.042)
TZ3	-0.045**	(0.011)	-0.008	(0.014)	0.066**	(0.019)	0.076**	(0.023)	0.817**	(0.043)
Market activity (*1,000)	0.225**	(0.013)	0.239**	(0.017)	0.210**	(0.024)	0.280**	(0.031)	0.145*	(0.066)
Market depth	-0.029**	(0.001)	-0.052**	(0.001)	-0.100**	(0.002)	-0.118**	(0.003)	-0.247**	(0.004)
Volatility	-0.026**	(0.007)	-0.048**	(0.011)	-0.098**	(0.024)	-0.120**	(0.027)	-0.143**	(0.039)
Bid-ask spread (*1,000)	0.047**	(0.001)	0.097**	(0.002)	0.229**	(0.003)	0.255**	(0.004)	0.386**	(0.006)
NS Small VAgg Sell	-0.479**	(0.012)	-0.536**	(0.015)	-0.530**	(0.021)	-0.557**	(0.027)	-0.543**	(0.048)
NS Small Agg Sell	-0.545**	(0.012)	-0.740**	(0.016)	-0.945**	(0.022)	-1.015**	(0.027)	-1.130**	(0.046)
NS Small MAgg Sell	-0.552**	(0.018)	-0.767**	(0.024)	-0.797**	(0.032)	-0.867**	(0.041)	-0.807**	(0.073)
NS Medium VAgg Sell	-0.835**	(0.026)	-0.960**	(0.033)	-0.853**	(0.047)	-0.826**	(0.063)	-0.557**	(0.108)
NS Medium Agg Sell	-0.693**	(0.027)	-0.908**	(0.036)	-0.884**	(0.049)	-0.929**	(0.062)	-0.504**	(0.112)
NS Medium MAgg Sell	-0.623**	(0.043)	-0.836**	(0.055)	-0.722**	(0.082)	-0.758**	(0.105)	-0.790**	(0.188)
NS Large VAgg Sell	-1.630**	(0.069)	-2.418**	(0.095)	-2.129**	(0.129)	-2.350**	(0.171)	-1.013**	(0.295)
NS Large Agg Sell	-1.573**	(0.078)	-2.547**	(0.108)	-2.672**	(0.139)	-2.985**	(0.170)	-0.961**	(0.320)
NS Large MAgg Sell	-1.443**	(0.179)	-2.273**	(0.238)	-2.258**	(0.295)	-2.847**	(0.340)	-0.936	(0.659)
LS Small VAgg Sell	-1.440**	(0.034)	-1.876**	(0.050)	-1.917**	(0.067)	-1.926**	(0.087)	-1.070**	(0.151)
LS Small Agg Sell	-1.388**	(0.035)	-1.958**	(0.046)	-2.235**	(0.063)	-2.147**	(0.082)	-1.237**	(0.135)
LS Small MAgg Sell	-1.368**	(0.081)	-1.788**	(0.097)	-2.029**	(0.126)	-1.945**	(0.145)	-1.250**	(0.236)
LS Medium VAgg Sell	-1.648**	(0.097)	-2.195**	(0.154)	-2.269**	(0.223)	-2.087**	(0.295)	-1.433**	(0.481)
LS Medium Agg Sell	-1.635**	(0.104)	-2.341**	(0.142)	-2.850**	(0.250)	-2.257**	(0.307)	-0.620	(0.488)
LS Medium MAgg Sell	-1.160**	(0.343)	-1.970**	(0.391)	-2.264**	(0.462)	-2.852**	(0.711)	-1.727	(0.987)
LS Large VAgg Sell	-2.523**	(0.899)	-4.511**	(1.380)	-4.486**	(1.612)	-4.942**	(1.532)	-2.613	(2.050)
LS Large Agg Sell	-1.397**	(0.360)	-2.512**	(0.723)	-3.118**	(1.108)	-4.700**	(1.531)	-3.247	(2.719)
LS Large MAgg Sell	-1.204	(0.633)	-1.888*	(0.800)	-0.205	(1.258)	-0.820	(1.435)	2.171	(3.785)
Adjusted R-squared	0.013		0.020		0.036		0.030		0.032	
Included observations	1,419,630									

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level. Standard errors in parentheses. See Section 4 for definitions of the variables.

As we can see from the regressions, the coefficients for all non-split (NS) variables are negative and, in 44 out of 45 cases (9 variables and 5 time windows), strongly significant. Such sell orders trigger buyers in the market to withdraw liquidity (i.e. cancel their buy orders) in the short-term.

Table 4 shows the impact of buy orders on the sell order volume.

Table 4: The impact of buy orders on the sell order volume (EUR/USD, 9-13 September 2010)

Time window	0.1		0.2		0.5		1.0		5.0	
$LOV_{sell}^{t(i)+w} - LOV_{sell}^{t(i)}$	0.103		-0.135		-0.968		-1.048		-0.769	
Constant	0.259**	(0.016)	0.124**	(0.024)	-0.878**	(0.034)	-0.966**	(0.040)	-0.773**	(0.061)
TZ1	-0.511**	(0.013)	-0.725**	(0.018)	-0.978**	(0.025)	-1.286**	(0.029)	-1.595**	(0.047)
TZ2	-0.183**	(0.011)	-0.269**	(0.015)	-0.461**	(0.021)	-0.685**	(0.025)	-0.908**	(0.043)
TZ3	0.007	(0.011)	0.050**	(0.016)	0.043*	(0.021)	0.038	(0.026)	0.130**	(0.045)
Market activity (*1,000)	0.214**	(0.013)	0.343**	(0.019)	0.694**	(0.027)	1.095**	(0.032)	2.224**	(0.060)
Market depth	-0.032**	(0.001)	-0.072**	(0.002)	-0.142**	(0.002)	-0.179**	(0.003)	-0.261**	(0.003)
Volatility	-0.029**	(0.006)	-0.059**	(0.012)	-0.129**	(0.027)	-0.156**	(0.033)	-0.172**	(0.042)
Bid-ask spread (*1,000)	0.058**	(0.001)	0.125**	(0.002)	0.270**	(0.003)	0.329**	(0.003)	0.421**	(0.005)
NS Small VAgg Buy	-0.273**	(0.012)	-0.299**	(0.017)	-0.369**	(0.024)	-0.450**	(0.029)	-0.561**	(0.050)
NS Small Agg Buy	-0.300**	(0.012)	-0.482**	(0.016)	-0.718**	(0.022)	-0.833**	(0.028)	-1.058**	(0.048)
NS Small MAgg Buy	-0.453**	(0.016)	-0.693**	(0.022)	-0.741**	(0.031)	-0.825**	(0.039)	-0.671**	(0.070)
NS Medium VAgg Buy	-0.771**	(0.025)	-0.874**	(0.035)	-0.714**	(0.051)	-0.776**	(0.069)	-0.672**	(0.120)
NS Medium Agg Buy	-0.503**	(0.028)	-0.708**	(0.040)	-0.736**	(0.053)	-0.885**	(0.068)	-0.567**	(0.119)
NS Medium MAgg Buy	-0.485**	(0.038)	-0.655**	(0.053)	-0.391**	(0.077)	-0.411**	(0.098)	-0.272	(0.190)
NS Large VAgg Buy	-1.292**	(0.078)	-1.970**	(0.103)	-1.720**	(0.138)	-1.955**	(0.180)	-1.195**	(0.330)
NS Large Agg Buy	-1.209**	(0.075)	-2.086**	(0.105)	-2.140**	(0.158)	-2.249**	(0.184)	-1.005**	(0.354)
NS Large MAgg Buy	-1.011**	(0.146)	-1.916**	(0.215)	-2.001**	(0.296)	-2.104**	(0.413)	-1.584*	(0.728)
LS Small VAgg Buy	-1.254**	(0.039)	-1.640**	(0.051)	-1.630**	(0.071)	-1.621**	(0.086)	-1.126**	(0.156)
LS Small Agg Buy	-1.227**	(0.036)	-1.698**	(0.048)	-2.009**	(0.064)	-2.008**	(0.086)	-1.293**	(0.136)
LS Small MAgg Buy	-1.279**	(0.056)	-1.748**	(0.073)	-1.758**	(0.121)	-1.600**	(0.143)	-0.584*	(0.230)
LS Medium VAgg Buy	-1.768**	(0.132)	-2.400**	(0.165)	-2.525**	(0.211)	-2.906**	(0.337)	-1.713**	(0.572)
LS Medium Agg Buy	-1.330**	(0.149)	-1.897**	(0.193)	-2.221**	(0.254)	-1.759**	(0.312)	-0.474	(0.506)

LS Medium MAgg Buy	-1.314**	(0.170)	-1.997**	(0.251)	-2.246**	(0.361)	-1.955**	(0.483)	0.611	(0.853)
LS Large VAgg Buy	-1.803**	(0.405)	-1.884*	(0.746)	-1.304	(0.971)	-1.449	(1.281)	0.025	(2.098)
LS Large Agg Buy	-0.721	(0.396)	-1.129*	(0.515)	-0.686	(0.908)	-5.260	(3.181)	-3.165	(3.960)
LS Large MAgg Buy	-1.315*	(0.653)	-1.617	(0.882)	-1.700	(1.376)	0.933	(1.836)	3.781	(3.509)
Adjusted R-squared	0.013		0.027		0.051		0.050		0.033	
Included observations	1,419,630									

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level. Standard errors in parentheses. See Section 4 for definitions of the variables.

The pattern is almost identical. Thus, our empirical results lend support to the theory that a sell [buy] initiative through a potentially market-moving limit order is more likely to lead limit buy [sell] order cancellations, which, consequently, is more likely to result in a lower [higher] price. Furthermore, large non-split orders overwhelmingly trigger a stronger reaction than medium-sized orders, which, in turn, cause more liquidity withdrawal than small orders. For instance, the 0.1-second change in the buy order volume following a very aggressive small, medium-sized or large non-split order from the opposite side of the order book is –€0.273, –€0.771 and –€1.292 million, respectively. The impact when studying the 1-second window even more significant: –€0.450, –€0.776 and –€1.955 million. Thus, given the level of price aggressiveness, a larger order has a greater impact. Interestingly, however, we do not find evidence that the trade-off holds both ways. Given the size, price aggressiveness seems to matter less as long as they are submitted within 4 pips of the best bid-ask spread.

Indeed, Stenfors and Susai (2019; 2021) find that the inverse relationship between size and price aggressiveness might be less consistent than suggested by Lo and Sapp (2010), who use a dataset that pre-dates algorithmic FX trading. In particular, they show that split orders are significantly more aggressive than non-split orders. These findings echo those by Chou et al. (2009), who investigate TAIEX futures traded at the Taiwan Stock Exchange. This could suggest that order-splitting might not only involve an intent to disguise a larger order size to prevent front-running by others. The strategy could also be chosen with the view that smaller orders are less likely to trigger a reaction, permitting them to be submitted at more aggressive price levels. If so, split orders are likely to be more aggressive than non-split orders. Uniquely, our model enables a direct comparison of the short-term impact of split and non-split orders that are equally aggressive.

Let us now turn to algorithmic order-splitting strategies. An informed trader would normally resort to a stealth trading strategy to disguise a large amount. Alternatively (as discussed above), stealth trading might be chosen as a strategy to enable a series of relatively aggressive, but small, orders to be submitted. If successfully submitted, i.e. if it goes undetected by other market participants, such a plan should trigger a more muted impact on the opposite side of the order book than a strategy involving an amount equivalent to the sum of the split orders. As we distinguish the limit orders according to their level of price aggressiveness and size, we are able to compare the impact by studying the corresponding coefficients.

However, as we can see from the regressions in Table 3, the coefficients for split variables are overwhelmingly more negative for split orders than non-split orders – for a given size and level of price aggressiveness. For instance, the 0.5-second change in the buy order volume following a very aggressive small, medium-sized or large non-split order from the opposite side of the order book is –€0.530, –€0.853 and –€2.129 million, respectively. The impact of split orders is considerably more pronounced: –€1.917, –€2.269 and –€4.486 million. The results are strongly significant for all categories of small split orders and most medium-sized and large split orders. Moreover, the pattern holds for all time windows, and is also similar when testing the
impact of buy orders on sellers in the market (see Table 4).

It could, however, be argued that even through split orders trigger a more substantial reaction than non-split orders for a given size and level of price aggressiveness, the categories are not directly comparable. After all, most order-splitting strategies in the dataset involve submissions of a short sequence of €1-million orders – typically amounting to €2-3 million in total. As a result, such strategies should be compared to the submission of medium-sized, rather than small, non-split orders. Nonetheless, as can be seen from Tables 3 and 4, even when comparing small split orders with medium-sized non-split orders, stealth-trading strategies consistently trigger a stronger reaction by traders on the opposite side of the limit order book.

5.2. Free-option versus non-execution risk

The empirical results in Tables 3 and 4 show that the submission of potentially market-moving limit orders in the EUR/USD FX spot market immediately triggers cancellations from the opposite side of the order book. Given the level of price aggressiveness, the reaction is stronger to medium-sized and large orders – and split orders in particular. The withdrawal of liquidity confirms the free-option risk hypothesis. Because traders believe that such orders will move the market, they fear that they might be "picked off". Alternatively, they hope that the market will shift to their advantage. Both scenarios induce them to cancel and, perhaps, resubmit their limit orders at more favourable price levels.

However, limit orders that are likely to move the market 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 orders increase the probability of not being filled at all. Table 5 shows the impact of buy orders on the buy order volume, and Table 6 the impact of sell orders on the sell order volume. In other words, they display the results for traders facing non-execution risk.

Table 5: The impact of buy orders on the buy order volume (EUR/USD, 9-13 September 2010)

Time window	0.1		0.2		0.5		1.0		5.0	
$LOV_{buy}^{t(i)+w} - LOV_{buy}^{t(i)}$	0.106		-0.114		-0.932		-0.999		-0.849	
Constant	0.113**	(0.016)	-0.239**	(0.021)	-1.436**	(0.032)	-1.413**	(0.040)	-0.373**	(0.062)
TZ1	-0.510**	(0.013)	-0.565**	(0.017)	-0.748**	(0.024)	-1.097**	(0.031)	-2.053**	(0.050)
TZ2	-0.273**	(0.011)	-0.329**	(0.014)	-0.500**	(0.020)	-0.762**	(0.025)	-0.903**	(0.042)
TZ3	-0.049**	(0.011)	-0.012	(0.014)	0.064**	(0.019)	0.073**	(0.023)	0.816**	(0.043)
Market activity (*1,000)	0.223**	(0.013)	0.237**	(0.017)	0.209**	(0.024)	0.281**	(0.031)	0.153*	(0.066)
Market depth	-0.030**	(0.001)	-0.053**	(0.001)	-0.101**	(0.002)	-0.119**	(0.003)	-0.248**	(0.004)
Volatility	-0.025**	(0.007)	-0.047**	(0.012)	-0.098**	(0.025)	-0.119**	(0.028)	-0.143**	(0.040)
Bid-ask spread (*1,000)	0.049**	(0.001)	0.100**	(0.002)	0.232**	(0.003)	0.258**	(0.004)	0.387**	(0.006)
NS Small VAgg Buy	-0.046**	(0.012)	0.163**	(0.016)	0.546**	(0.022)	0.740**	(0.028)	1.117**	(0.047)
NS Small Agg Buy	0.137**	(0.012)	0.253**	(0.016)	0.415**	(0.022)	0.541**	(0.027)	0.603**	(0.047)
NS Small MAgg Buy	0.446**	(0.018)	0.594**	(0.023)	0.791**	(0.031)	0.805**	(0.040)	0.447**	(0.071)
NS Medium VAgg Buy	0.185**	(0.023)	0.627**	(0.033)	1.338**	(0.048)	1.477**	(0.061)	1.721**	(0.111)
NS Medium Agg Buy	0.382**	(0.029)	0.731**	(0.037)	1.248**	(0.053)	1.360**	(0.066)	1.448**	(0.114)
NS Medium MAgg Buy	0.408**	(0.043)	0.696**	(0.056)	1.336**	(0.076)	1.321**	(0.099)	1.148**	(0.186)
NS Large VAgg Buy	0.735**	(0.063)	2.363**	(0.103)	3.670**	(0.138)	3.809**	(0.178)	4.222**	(0.325)
NS Large Agg Buy	1.216**	(0.078)	3.092**	(0.114)	4.607**	(0.160)	4.820**	(0.192)	5.396**	(0.357)
NS Large MAgg Buy	1.074**	(0.122)	2.667**	(0.194)	4.373**	(0.263)	4.893**	(0.359)	4.138**	(0.665)
LS Small VAgg Buy	0.714**	(0.041)	1.199**	(0.053)	1.349**	(0.073)	1.449**	(0.090)	1.402**	(0.147)
LS Small Agg Buy	1.122**	(0.040)	1.494**	(0.051)	1.454**	(0.068)	1.378**	(0.081)	0.743**	(0.136)
LS Small MAgg Buy	1.345**	(0.056)	1.653**	(0.076)	1.254**	(0.113)	1.087**	(0.143)	0.219	(0.237)
LS Medium VAgg Buy	0.517**	(0.162)	1.390**	(0.193)	1.939**	(0.255)	2.139**	(0.321)	1.801**	(0.523)
LS Medium Agg Buy	0.649**	(0.156)	1.360**	(0.217)	1.633**	(0.263)	1.471**	(0.321)	0.471	(0.520)
LS Medium MAgg Buy	1.092**	(0.283)	1.676**	(0.329)	1.654**	(0.421)	0.855	(0.543)	-1.141	(1.079)
LS Large VAgg Buy	0.805**	(0.299)	2.098**	(0.501)	2.342*	(1.050)	2.928**	(1.053)	1.393	(2.363)
LS Large Agg Buy	0.649	(0.491)	1.940**	(0.650)	1.835	(2.098)	2.486	(2.142)	0.961	(3.012)
LS Large MAgg Buy	1.692**	(0.506)	2.460**	(0.818)	4.901**	(1.813)	1.718	(1.599)	-0.541	(3.443)
Adjusted R-squared	0.010		0.017		0.036		0.030		0.032	
Included observations	1,419,630									

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level. Standard errors in parentheses. See Section 4 for definitions of the variables.

Table 6: The impact of sell orders on the sell order volume (EUR/USD, 9-13 September 2010)

Time window	0.1		0.2		0.5		1.0		5.0	
$LOV_{sell}^{t(i)+w} - LOV_{sell}^{t(i)}$	0.103		-0.135		-0.968		-1.048		-0.769	
Constant	0.005	(0.016)	-0.286**	(0.024)	-1.421**	(0.034)	-1.568**	(0.040)	-1.365**	(0.062)
TZ1	-0.503**	(0.013)	-0.710**	(0.018)	-0.951**	(0.025)	-1.256**	(0.029)	-1.562**	(0.047)
TZ2	-0.188**	(0.011)	-0.276**	(0.015)	-0.465**	(0.021)	-0.688**	(0.025)	-0.909**	(0.043)
TZ3	0.005	(0.011)	0.046**	(0.016)	0.039	(0.021)	0.034	(0.026)	0.127**	(0.045)
Market activity (*1,000)	0.213**	(0.013)	0.341**	(0.019)	0.692**	(0.027)	1.093**	(0.032)	2.226**	(0.060)
Market depth	-0.032**	(0.001)	-0.073**	(0.002)	-0.144**	(0.002)	-0.180**	(0.003)	-0.262**	(0.003)
Volatility	-0.029**	(0.006)	-0.059**	(0.013)	-0.129**	(0.028)	-0.156**	(0.034)	-0.171**	(0.043)
Bid-ask spread (*1,000)	0.060**	(0.001)	0.128**	(0.002)	0.274**	(0.003)	0.332**	(0.003)	0.423**	(0.005)
NS Small VAgg Sell	-0.041**	(0.012)	0.193**	(0.017)	0.534**	(0.023)	0.644**	(0.029)	0.861**	(0.050)
NS Small Agg Sell	0.261**	(0.013)	0.411**	(0.017)	0.509**	(0.023)	0.594**	(0.028)	0.636**	(0.048)
NS Small MAgg Sell	0.334**	(0.018)	0.456**	(0.025)	0.629**	(0.035)	0.614**	(0.042)	0.311**	(0.074)
NS Medium VAgg Sell	0.110**	(0.024)	0.605**	(0.035)	1.443**	(0.052)	1.619**	(0.067)	1.807**	(0.116)
NS Medium Agg Sell	0.372**	(0.029)	0.759**	(0.039)	1.371**	(0.055)	1.457**	(0.072)	1.224**	(0.122)
NS Medium MAgg Sell	0.216**	(0.044)	0.499**	(0.058)	1.339**	(0.082)	1.437**	(0.107)	1.473**	(0.184)
NS Large VAgg Sell	0.831**	(0.052)	2.776**	(0.098)	4.376**	(0.129)	4.768**	(0.165)	4.543**	(0.314)
NS Large Agg Sell	1.426**	(0.068)	3.615**	(0.102)	5.362**	(0.139)	5.457**	(0.184)	5.259**	(0.347)
NS Large MAgg Sell	1.066**	(0.139)	3.101**	(0.217)	4.515**	(0.314)	4.748**	(0.505)	5.036**	(0.967)
LS Small VAgg Sell	0.709**	(0.037)	1.252**	(0.051)	1.439**	(0.076)	1.481**	(0.100)	0.943**	(0.163)
LS Small Agg Sell	1.180**	(0.038)	1.639**	(0.051)	1.487**	(0.073)	1.420**	(0.091)	0.667**	(0.148)
LS Small MAgg Sell	1.282**	(0.065)	1.654**	(0.087)	1.484**	(0.115)	1.361**	(0.148)	0.950**	(0.266)
LS Medium VAgg Sell	0.560**	(0.104)	1.445**	(0.139)	1.734**	(0.205)	1.890**	(0.268)	1.696**	(0.514)
LS Medium Agg Sell	0.974**	(0.108)	1.719**	(0.183)	1.752**	(0.224)	1.668**	(0.269)	0.907	(0.540)
LS Medium MAgg Sell	0.709**	(0.226)	1.434**	(0.255)	1.977**	(0.393)	1.869**	(0.488)	0.787	(0.907)
LS Large VAgg Sell	0.389	(0.532)	2.725**	(0.798)	5.519**	(0.983)	6.289**	(1.379)	8.087**	(2.916)
LS Large Agg Sell	0.495	(0.342)	1.822**	(0.701)	3.940**	(1.150)	3.808**	(1.427)	6.060**	(2.160)
LS Large MAgg Sell	0.300	(0.540)	1.838*	(0.768)	3.236**	(1.105)	6.064**	(2.289)	2.669	(4.354)
Adjusted R-squared	0.011		0.026		0.052		0.050		0.033	
Included observations	1,419,630									

Sources: EBS and authors' calculations. Notes: OLS, White heteroskedasticity-consistent standard errors & covariance. * / ** denotes statistical significance at 5% / 1% level. Standard errors in parentheses. See Section 4 for definitions of the variables.

As can be seen, the results are almost "mirror-like" when studying the impact on the same, rather than the opposite, side of the order book. The largely positive (instead of negative) coefficients show that buyers [sellers] jump on the bandwagon when a potentially market-moving buy [sell] order is submitted. Nonetheless, two crucial differences are notable when comparing the coefficients of opposite-side orders (free-option risk) with the coefficients of same-side orders (non-execution risk).

First, opposite-side orders trigger a stronger reaction than same-side orders in the very short run (0.1–0.2 seconds). For instance, when studying the impact of sell orders on buyers in the market (Table 3), the 0.1-second impact of very aggressive small, medium-sized and large non-split orders is –€0.479, –€0.835 and –€1.630 million. However, when studying the impact of sell orders on sellers in the market (Table 6), the reaction is –€0.041, +€0.110 and +€0.831. The corresponding results for split orders are –€1.440, –€1.648 and –€2.523 versus +€0.709, +€0.560 and +€0.389

million. The findings, therefore, suggest that free-option risk, rather than non-execution risk, is the primary driver behind why and how traders react when noticing a new potentially market-moving limit order.

Second, a significant shift occurs between 0.2 and 0.5 seconds. When studying the more extended time windows (0.5 seconds to 5 seconds) a completely different pattern emerges. Medium-sized and large non-split orders, as well as large split orders, consistently trigger more liquidity provision (i.e. order submissions) from the same side of the limit order book than liquidity withdrawal (i.e. order cancellations) from the opposite side of the limit order book. For instance, the 1-second impact of very aggressive medium-sized and large orders is +€1.619 and +€4.768 million for same-side non-split orders (Table 6), compared to –€0.826, and –€2.350 for opposite-side orders (Table 3). The corresponding results for large split orders are +€6.289 versus –€4.942. Thus, for up to 5 seconds, free-option risk continues to be the primary driver behind the shift in the limit order book for orders that are seen as somewhat less information-rich (including most split orders). For more market-moving orders, however, non-execution risk surpasses free-option risk after 0.1–0.2 seconds. The patterns are similar when seen comparing the impact of buy orders (Tables 4 and 5).

Our empirical results lend support to the theory that a buy [sell] initiative is more likely to lead to a higher [lower] price. This is because a 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. However, we also find that the short-term drivers of the change in the limit order book depend on the trader types submitting and cancelling orders. Furthermore, this pattern changes over time. Algorithmic traders, who comfortably are able to react within 100–200 milliseconds of new information entering the limit order book, seem to be more inclined to cancel orders due to free-option risk. When human traders have had the chance to react, however, the contribution to the change in the order book is highly dependent on the perceived impact of the new limit order entering the market. Medium-sized and large non-split orders, as well as large split orders, are viewed as more important for the direction of the short-term price-trend – causing traders to jump on the bandwagon and submit same-side limit orders.

6. Concluding discussion

In this paper, we have investigated the short-term impact of EUR/USD FX spot limit order submissions on the liquidity provision and withdrawal process of other traders on EBS. Our findings can be summarised as follows.

First, order splitting enables algorithmic traders to disguise the true order size. Alternatively, it allows for limit orders to be submitted at more aggressive price levels (Chou et al., 2009, Stenfors and Susai, 2019; 2021). Our results show, however, that for a given order size and scale of price aggressiveness, split orders trigger *more* liquidity withdrawal than non-split orders.

Second, our high-frequency dataset enables us to distinguish free-option and non-execution risk within the limit order submission process. We find that potentially market-moving orders have a similar, mirror-like, impact on the liquidity withdrawal process when viewed from the opposite side (free-option risk) and the same side (non-execution risk) of the order book. However, the shift in the order book is dynamic in the short-run and depends on the trader types submitting and cancelling orders. Overall, ultra-fast algorithmic traders seem to be more inclined to cancel orders due to free-option risk. Once human traders have had time to react, however, non-execution risk plays a greater role – particularly with regards to new information entering the market through more sizable orders.

The empirical results seem to confirm as well as contradict the logic of adopting order-splitting strategies in the FX spot market. On the one hand, we find that traders react strongly to sizeable limit order submissions from the other side of the order book. Such orders also trigger other traders to submit orders in the same direction. To minimise the likelihood of such a reaction, order splitting, therefore, seems like a logical strategy to adopt. On the other hand, however, split orders trigger an *even stronger* reaction than non-split orders. Thus, limit orders submitted through algorithmic stealth-trading strategies are, at least in the short term, perceived as more market-moving than equivalent non-split orders likely to be submitted by humans.

Theoretically, the market timing could be a reason for this contradiction. The more liquid the market is, the less impact a potentially market-moving order will have in relative terms. Consequently, traders might choose to adopt order-splitting strategies when the market is illiquid, i.e. when other traders are more sensitive to new information entering the market. In such a scenario, split orders should be more prevalent when the market is thin and more likely to have an impact on other traders' behaviour. Indeed, Blau et al. (2009), using data on NYSE-listed stocks, show that informed investors opt for large orders when the market is deep, and stealth trading strategies when the turnover is low. Likewise, Chae and Lee (2011) and Kato and Katayama (2017), using data from the Korean Exchange and the Tokyo Stock Exchange respectively, find that order-splitting strategies are less frequent when the liquidity is high. These results are consistent with Admati and Pfleiderer (1988), who demonstrate that informed traders camouflage information-rich orders during busy trading hours, often associated with the commonly observed U-shaped intra-day trading pattern in stock markets. Hence, we should expect last split orders to be submitted when indicators show that the market is relatively illiquid, in comparison to non-split orders. However, as we can see from Table 7, the opposite scenario appears to be more accurate.

Table 7: State of the market: EUR/USD

Size	Split	Activity	Depth	Bid-ask spread	Pacific	Tokyo	London	New York
Small	NS	597.9	€15.9 mio	0.0109%	12.8%	26.1%	41.3%	19.8%
	LS	623.5	€16.5 mio	0.0081%	6.4%	28.2%	43.7%	21.7%
Medium	NS	672.6	€17.3 mio	0.0082%	5.9%	19.6%	49.3%	25.2%
	LS	742.0	€19.1 mio	0.0074%	2.6%	17.4%	51.9%	28.1%
Large	NS	659.0	€19.9 mio	0.0061%	11.5%	28.3%	42.5%	17.7%
	LS	881.8	€25.2 mio	0.0071%	3.3%	16.7%	67.6%	12.4%

Sources: EBS and authors' calculations. Notes: NS = non-split, LS = last split.

Four observations are notable. First, the EUR/USD FX spot market is exceptionally competitive. The average bid-ask spread in our dataset is 0.0083% (see Table 2 for the descriptive statistics). This corresponds to approximately 1 pip. However, as can be seen from Table 7, stealth-trading strategies are adopted when the bid-ask spread is tighter, rather than wider, than usual. The only exception is for large orders, which, however, tend to be submitted when the bid-ask spread is even tighter than 0.0083%. Second, the average market depth (i.e. the volume at the best bid-ask spread) is €16.2 million but ranges from €1 million to €316 million. Nonetheless, split orders are submitted when the volume-based market liquidity indicator is higher and not lower than average. Third, the EUR/USD FX spot market is very active on EBS. Each new limit order submission is preceded by an average of 613.1 limit order submissions during the previous 60 seconds. Again, however, stealth-trading strategies are present when the market is more, not less, active. Fourth, being decentralised, the global FX market does not have any formal opening and closing hours. Nonetheless, each currency pair tends to display a regular intra-day pattern in terms of 24-hour trading activity. The EUR/USD FX spot market is busiest during the London time zone and least active during the Pacific time zone. However, as Table 7 shows, split orders are relatively more common during the hectic trading hours (London) and relatively less frequently adopted when the market is least liquid (Pacific).

In sum, despite being very frequently used, we find that stealth-trading strategies submitted by algorithmic traders appear to go 'detected' and are perceived as more market-moving than orders of an equivalent size likely to be submitted by humans. Although the reason for this is unclear, FX market conventions, coupled with the EBS rulebook, are likely to play a significant role. Algorithmic trading, including order-splitting strategies, has become increasingly common in the trading of a range of assets on numerous electronic platforms. This process has not only resulted in a dramatic increase in the number of limit order submissions, but also a reduction in the average limit order size. Importantly, however, €/$ 1 million has traditionally been considered as a 'minimum' amount in the interbank FX spot market and also acts as a floor for the 'race to the bottom' on EBS. An overwhelming majority of orders in our dataset consists of precisely €1 million. Thus, it appears as if the unique market structure is a key driver behind why a human trader submitting a limit order of €2-4 million is perceived as less informed or predatory than a non-human trader submitting a similar order, but using a stealth-trading strategy.

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