Stepping out of the limit order book: Empirical evidence from the EBS FX market

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Abstract:
Most limit orders exit the market as cancellations or revisions without a transaction. Using the EBS dataset, we can measure how long an individual limit order remains in the foreign exchange (FX) market. Thus, we use the measured lifetimes of canceled limit orders and find that post-order-placement changes in market price and limit order book depth affect cancellations, consistent with optimal behaviors that consider both order placement and order exit. FX dealers cancel their limit orders faster as the depth increases at better quotes. When market prices move away from their submitted quotes, patient dealers exhibit greater forbearance for their worsened position.

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Keywords: Foreign exchange market; Lifetime; Limit order; Market microstructure; Order book.

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1. Introduction

As limit order market systems are becoming pervasively adopted in a wide set of asset classes across a variety of financial markets, many studies have begun to investigate the ordering behaviors of traders in the various stock exchanges: Biais, Hillion, and Spatt (1995) on the Paris Bourse; Harris and Hasbrouck (1996) and Yao (2005) on the New York Stock Exchange; Hasbrouck and Sarr (2002) on the Island ECN of the NASDAQ Exchange; Ahn, Bae, Chan (2001) on the Hong Kong Stock Exchange; and Hollifield, Miller, and Sandås (2004) on the Stockholm Stock Exchange. Similarly, as electronic broking systems have overtaken traditional systems, foreign exchange (FX) markets are now considered the most actively traded electronic limit-order markets in the world. In 2010, the daily average volume in the world FX market is 1,490 billion US dollars (USD) (The Triennial Central Bank Survey, BIS, 2010) whereas the daily average volume in the NYSE Group is slightly greater than 3% of that figure, i.e., 47.5 billion USD (NYSE Statistical Archive).

Reflecting widespread adoption of limit order systems in financial markets, theoretical studies have introduced dynamic models suitable for investigating limit order submissions and order book build-up. In seminal research on the dynamic limit order market, both Foucault (1999) and Parlour (1998) analyze how a trader chooses between market and limit order. In contrast to these models, which are simplified to only two quotes, Hollifield et al. (2004), Foucault et al. (2005), and Rocu (2009) investigate the manner in which limit orders with a variety of quotes are submitted in a dynamic framework. In these models, traders face a tradeoff problem, i.e., choosing between non-execution risk and free-option (pickoff) risk. The increase in the availability of order data has also spurred many empirical investigations of order placement strategies in limit order markets[1].

An interesting phenomenon addressed in several empirical studies is the cancellation or revision of many submitted orders without an actual transaction. For example, Biasis et al. (1995) find that 20% of orders are canceled in the Paris Bourse, whereas Hasbrouck and Sarr (2002) find that 93% of limit orders on the INET are canceled. Cancellation rates are approximately 90% for EUR/USD in the EBS FX market in 2010, which is not surprising because traders in FX markets must adjust to rapidly changing market conditions. If a trader optimizes her order choices, such as market or limit order and quotes at order placement, she should also optimally choose her revision/cancellation behaviors in line with changing market conditions, such as bid and ask quotes and the order book. Lo, MacKinlay, and Zhang (2002), Liu (2009), and

[1] See, for example, Biais et al. (1995), Hollifield et al. (2004), and Fong and Liu (2010). For more studies, see the literature review in section 2.

Fong and Liu (2010), among others, investigate revision/cancellation behaviors in stock markets. Unfortunately, this important aspect of order strategy has not been rigorously investigated in the literature.

Moreover, the cancellation/revision behaviors in the FX market—the largest financial market—have not been examined. In this paper, we employ a unique dataset of limit orders in FX markets to characterize the behavioral characteristics of individual limit orders. In particular, we examine all individual orders submitted to the EBS FX market over five consecutive business days and investigate which environments force individual orders to exit from the market before entering a transaction[2].

As an important new contribution to the literature on quote revisions and cancellations in limit order markets, we measure how long individual orders remain in the market until they are revised or canceled, similar to Hollifield et al. (2004). The present study is the first study of FX markets to measure how long individual orders remain at the market. In particular, we compute the lifetime—defined as the time period in which an individual order remains active in the market—from the EBS complete order dataset for five consecutive days in September 2010.

Due to the pervasive use of algorithmic trading in FX markets, a large portion

[2] Mancini, Ranaldo, and Wrampelmeyer (2013) also use the EBS dataset in their empirical study, but the aim of their paper—investigating the liquidity risk in foreign exchange markets—is different from ours..

of the measured lifetime of limit orders fall within fractions of seconds. To wit, 33.5% of all limit orders in the five-day sample are canceled (or revised) within one second. To prevent algorithmic trading from biasing the estimated results, the regression sample is restricted to include only those limit orders with lifetimes that are greater than or equal to two seconds. A robustness check using the same sample that includes all orders confirms that the results remain qualitatively similar.

As with theoretical models of order placement strategy, we argue that order exit strategies should respond to the order book. Moreover, the critical determinant of exit decisions is a change in the order book after a limit order is placed in the market. We constructed two variables for order book changes: 1) a change in the best price with respect to the submitted quote and 2) a change in the depth of the quotes that have higher price priorities than the submitted quote.

Both change variables appear to capture a deterioration of execution probability, which is the key parameter in determining whether and at what quote a trader will submit his limit order. However, after controlling for changes in depth, a mere change in the market price may not indicate a deteriorating execution probability because what matters is the waiting number in line. In fact, we find that the impacts of the two change variables on lifetime have opposite signs. By examining the most paired major currencies in FX markets, EUR/USD, we find that an increased change in depth leads to faster cancellations of limit orders, whereas limit orders remain longer in the order book when the market price moves away from their quotes.

The remainder of the paper is structured as follows. In the next section, we review the literature on limit order markets and connect limit order strategies with cancellation behaviors. Section 3 presents in a simple analytical framework how order placement and order cancellation are similarly determined by traders' optimizing behavior. Section 4 discusses the specific features of the EBS dataset and describes how FX markets operate at the microstructure level; in addition, this section presents the descriptive statistics for the lifetime variable and other covariates. Section 5 describes the lifetime estimation model and the empirical results. In section 6, we show that the qualitative nature of the results remains robust regardless of alternative model specifications. Section 7 concludes.

2. Literature Review: limit order placement, cancellations, and quote revisions

In early microstructure models, limit orders are considered a passive trading strategy that provides liquidity to a market. Limit orders are more costly than market orders because of non-execution risk and free option risk (or free trading option risk), as tested empirically by Fong and Liu (2010). Non-execution risk arises because limit orders accumulate to constitute an order book, and an individual limit order may not be executed unless it becomes the best quote (Hasbrouck and Sarr, 2002; and Liu, 2009). By contrast, a market order is executed instantly with a limit order at the counter-side best quote in the order book. The free option risk arises for limit orders because a trader with private information only submits a market order when the market price offers a fair or a better quote (Copeland and Galai, 1983). For recent models with a dynamic structure, however, limit orders are preferred as an active trading strategy, Foucault (1999), Foucault, Kadan, and Kandel (2005), and Rosu (2009).

Fong and Liu (2010) argue that non-execution risk and free-option risk are two compelling reasons to cancel or revise limit orders. High rates of limit order cancellation/revision are common in stock markets; Biais, Hillion, and Spatt (1995), Harris and Hasbrouck (1996), Hasbrouck and Sarr (2002), Hollifield, Miller, and Sandås (2004), and Yao (2005). Biais et al. (1995) was the first to investigate the order book of the limit order market at the Paris Bourse, which provides traders with the best five quotes and the corresponding volumes at each new order and cancellation; this investigation revealed that approximately 20% of orders (at the best five quotes) are canceled[3]. Harris and Hasbrouck (1996) document that 56.2% of limit orders on the New York Stock Exchange remain unfilled. However, this figure should not be interpreted as active cancellation because some limit orders simply remain unmatched even at the close of the market. Using the complete tick data for a company on the Stockholm Stock Exchange, Hollifield et al. (2004) report that the execution probability for two days is 68, 33, and 12% for limit orders that are 1, 2, and 3 ticks away from the best quote, respectively. Eventually, 88% of limit orders with prices that are 3 ticks away from the best quote are canceled. Yeo (2005) reports that the ratio of cancellations to submitted limit orders on the New York Stock Exchange has recently increased to 40%[4]. Hasbrouck and Saar (2002) show that roughly 25 (40)% of limit orders are canceled after two (ten) seconds on the Island ECN, which represented 11% of the trades on the NASDAQ exchange in 1999.

What are the underlying features that drive the cancellation of so many orders? A number of studies offer several explanations, including order-splitting strategy, undercutting, volatility, and spread. Yeo (2005) argues that many canceled limit orders

[3] This percentage is calculated as the ratio between unconditional new orders and cancellations, as shown in Table III (p. 1670, Biais et al., 1995).

[4] Yeo (2005) compares the percentage of cancellations in all submitted requests, which includes market orders, limit orders, and cancellations. Notably, this percentage has a maximum limit of 50% for cancellations because the number of cancellations cannot exceed the number of limit orders. Approximately 20% of orders became cancellations in 2001, compared with 5% in 1990.

can be attributed to order-splitting strategy and undercutting. Traders split orders in multiple submissions when they do not intend to disseminate their private information. This strategy results in multiple cancellations when traders revise their orders. In addition, traders who compete to undercut other traders must revise their prices frequently. The dynamic limit order market model developed by Foucault (1999) indicates that higher volatility leads to a lower fill rate. Thus, a lower fill rate can be interpreted as a higher probability of cancellation in the FX market because there is no specific closing time. Foucault et al. (2005) theoretically show that the average time to a transaction increases with the size of the spread. This result can be interpreted as indicating a lower fill rate at a fixed time interval during sporadic incoming orders.

Microstructure models for FX markets are notable in the stock market literature. These models emphasize the importance of order flow because of its explanatory power with regard to exchange rate fluctuations. For example, Evans and Lyons (2002) assume that customers with private information initiate trades at the dealer’s quoted price. Then, as dealers trade with one another, the private information contained in customer orders materializes in the order flows at the interdealer stage. Thus, the interdealer order flows aggregate dispersed private information and affect exchange rate movements.

However, the previous literature on the microstructure of FX markets faces two difficult challenges. First, although theoretical models are at the microstructure level, empirical studies use only aggregate order flows at the daily frequency. Second, the models implicitly assume that all limit orders are completely transacted and do not address the prevalence of cancellations/revisions of limit orders. This assumption elides a substantial component of dealer behavior because limit orders that are canceled/revised without any transactions comprise more than 90% of all orders in EBS FX markets[5]. If the order flow (orders with realized transactions) transmits important information to dealers, what information do canceled orders convey to the market? The literature on FX markets has not addressed this issue. Our study attempts to answer this question through the use of empirical information on cancellation/revision of limit orders in FX markets.

3. Optimal strategy for order submission and cancellation

In this section, following the research line that includes Hollifield et al. (2004), we provide a simple model for an optimal strategy for order submission and order cancellation. The aim of this section differs from that of Foucault (1999), Parlour (1998)

[5] The average cancellation/revision rate is 90.0% for the EUR/USD market and 91.8% for the JPY/USD market in our five-day sample from September 2010. Biais et al. (1995) report that only approximately 20% of orders are canceled in the Paris Bourse, but they only observe cancellations at the best five quotes. The smaller figure in their studies is due in part to the omission of cancellations outside of the best five quotes.

and other theoretical studies that provide a complete characterization of the order book as a market equilibrium. As our review indicated in the preceding section, theoretical models treat cancellation as either prohibited or enforced exogenously. We abstract from model specifications and leave functional forms unspecified. We emphasize that both order placement and order cancellation can be treated in a single framework.

A trader, *i*, must evaluate the common value of asset, *V*, and personal valuation, σ_i, before arriving at the market. Gains accrue from trade due to the heterogeneity of personal valuation among traders. The common value of an asset is evaluated by observing the market. The order book is observable to all traders, represents the current accumulated stocks of past order placements, and yields the best bid and ask prices. Let $\boldsymbol{B_t}$ represent the information set of the order book at time t. By monitoring the market, a trader continues to compare the benefit of submitting his limit order with the benefit of staying out of the market. If the trader chooses to place an order at time *t*, his order submission includes a specific quote, q_{it}, and positive amount of volume, v_{it}. In terms of expected utility, this optimization problem can be shown as follows:

$$(\hat{q}_{it}, \hat{v}_{it}) = \arg\max E[u^i(q_{it}, v_{it}; B_t)] \tag{1}$$

where $u^i()$ is a utility function of trader *i* and a variable with hat represents an optimal choice. Notably, the optimization in equation (1) does not necessarily lead to the same outcome for different individuals because individuals may have different preferences and personal valuations.

Although we avoid focusing on a specific form of equation (1), an example of a buy limit order in the spirit of Foucault (1994) and Parlour (1998) is the following:

$$E[u^i(q_{it}, v_{it}; B_t)] = \rho(q_{it}, v_{it}, B_t) \cdot \left\{ \left\{ \tilde{V}(B_t) + \sigma_i \right\} - q_{it} \right\} \cdot v_{it}, \tag{2}$$

where $\rho()$ is the execution probability, which is a function of the submitted quote, volume, and order book. $\tilde{V}()$ is an estimated value of V and is a function of order book. Liu (2009) extends the model using individual monitoring costs, which generates another source of heterogeneous responses of traders. The trader must estimate the uncertainty of the common value of asset V using the order book information, $\boldsymbol{B_t}$. The solution for the dynamic equilibrium requires solving for the execution probability function at a game-theoretic equilibrium, but we neglect that task and instead focus on the optimal behaviors of order placement and order exit[6].

If a trader chooses to place an order at time t, $\hat{v}_{it} > 0$, and we label this submission time $t^s(i)$. Note that before entering the market, the order volume is zero, i.e., $\hat{v}_{it} = 0$ for all $t \leq t^s(i)$. This part of the order strategy is order placement and is

6 We are fully aware that it would not be possible to obtain the equilibrium solution with this degree of complexity introduced in the model. One issue is the timing of arrival to the market. Even in the order placement literature, arrival rates are exogenously given for other incoming traders.

thoroughly investigated in both theoretical and empirical studies. However, the order book changes after $t^s(i)$, and the trader may find it best at some time t' not to keep an order in the market and to therefore cancel the order. We label this cancellation time as $t^e(i)$. The time framework labeled with decision making is shown in Figure 1.

{Insert Figure 1}

The optimization problem in equation (1) can be simplified if a trader chooses between ordering (with a specific quote and volume) and not ordering. The following two inequalities hold for a canceled order:

$$E[u^i(q_{it}, v_{it}; B_t)] > E[u^i(q_{it}, 0; B_t)] \text{ at the time of order placement, } t = t^s(i), \quad (3)$$

$$E[u^i(q_{it'}, 0; B_{t'})] > E[u^i(q_{it'}, v_{it'}; B_{t'})] \text{ at the time of order cancellation, } t' = t^e(i). \quad (4)$$

From the two inequalities, we can deduce some relevant issues for empirical modeling. For explanatory variables, it is clear that changes in the order book, i.e., $\Delta B_{t,t'} = B_{t'} - B_t$, lead to alternative decision outcomes. Traders respond to the change in market conditions, including depth at each tick and best quotes on both sides. There are a few candidates for dependent variables. First, the volume change, $\Delta v_{it,t'}$, is always $-v_{it}$ because partial cancellation is not allowed in the EBS system. Using this information will lead to biased results, and we will not pursue this course. Second, the time elapsed between order placement and cancellations, $t^e(i) - t^s(i)$, can be measured by the time stamp attached to all order submissions. We refer to this time span as the “lifetime”. Finally, if our dataset can provide a link between the original order and a resubmitted order at a later time, we can also compare the change in quotes, $\Delta q_{t,t'} = q_{t'} - q_t$. Unfortunately, the EBS dataset in this study does not permit this analysis.

What are the effects of a change in order book on lifetime? In this paper, we particularly focus on the two dimensions of order book: Quote change and depth (at quotes with price priority) change. An increase in depth (at quotes with price priority) is induced by other orders cutting in line and as a result waiting cue becomes longer. This decreases the execution probability in equation (2) and, therefore, the expected utility of the submitted order. Consequently, no order (= cancellation) may become the optimizing choice. In terms of lifetime, an increase in depth should lead to an earlier exit.

On contrary, an increase (decrease) in the best bid (offer) signals an increase (decrease) in the common value, *V*, and therefore increases the expected utility. It should be noted that this price change must not accommodate depth change discussed in the paragraph just above. A pure price change (not accommodating depth change) deters the second inequality to hold and, therefore, lengthens the lifetime of the submitted order.

The traders' types can be deduced by comparing the different strategies of traders responding to the same order book, ***B***. If $\hat{q}_{i\cdot} > \hat{q}_{j\cdot}$ holds for two traders *i* and *j* for the same ***B*** (depth, bid and ask), then trader *i* is more patient (impatient) for a sell (buy) order. A higher volume indicates liquidity traders because traders have stronger demand for transactions. A general trading strategy consists of choosing quotes and volumes after processing information such as order flows and outstanding orders from the market, which are dependent on a trader's preferences or valuations and waiting or monitoring costs. By analogy to revealed preference in microeconomics, studying the placement of a quote with respect to the best quote should reveal traders' characteristics.

4. Limit orders at the EBS and the construction of variables

After a limit order is submitted to the market by a dealer, the order waits to be hit by other dealers for a transaction to occur. The outcome of a limit order can be classified into three categories: (1) the total volume of the limit order is filled by a transaction(s); (2) the limit order is canceled before a transaction is realized; and (3) the limit order is withdrawn after part of the volume ordered is transacted.

Traders can either initiate a quote (i.e., submit a limit order) or transact at a posted quote (i.e., submit a market order). In the EBS dataset, all data entries are assigned one of five indicators: QS, QD, HS, HAD, and DSM. A quote begins with QS and a specific 20-digit ID and ends with QD. A hit begins with HS and ends with HAD. When two parties are matched in a transaction, DSM records the information related to the transaction. The outcome of a quote can be described by the four cases shown in Figure 2: (1) the quote is deleted by cancellation; (2) the quote is filled by either another quote or a market order; (3) the quote is canceled after part of the order is executed; or (4) the quote is filled by multiple transactions. We purchased the EBS dataset with a limited proprietary contract, and all data cannot be made public unless aggregated to conceal the characteristics of individual transactions.

{Insert Figure 2 about here}

When submitted, each limit order is identified by a distinguishing 20-digit code with information on the side (i.e., bid or offer), volume, quote price, and the time stamp in a fraction of a second. The dataset also records all the market orders and transactions realized. Importantly, there are certain drawbacks to using the EBS dataset. A 20-digit ID is ascribed to each order-trader pair. Therefore, consecutive orders by the same trader receive randomized distinct IDs, and these orders cannot be connected. Unfortunately, a revised order cannot be distinguished from canceled orders. In the remainder of this paper, we treat all orders without a transaction as cancellations, although distinguishing between (pure) cancellation and quote revision would provide a good research agenda if such a distinction becomes possible.

Each limit order reappears in the dataset when all volume is exhausted by transactions with other dealers or when the order is canceled. A limit order is time-stamped when the order is placed and removed from the order book. The lifetime of limit orders is then calculated based on the difference between the two time stamps as shown in Figure 3. The lifetime we calculate in this study must be distinguished from the duration (i.e., what we call arrival lag in this study), which is measured by the time elapsed between two consecutive quotes, e.g., Manganelli (2005).

{Insert Figure 3 about here}

Because of the data structure of this particular EBS database, in contrast to the (limited) book order dataset readily constructed by ICAP, we must reconstruct the entire order book by adjusting for each moment whenever a new submitted quote, a new transaction, or a new cancellation arrives to the market. By reconstructing the entire order book for the sample period, we can calculate the best bid, the best ask, and the bid-ask spread that corresponds to the time series at the incoming order frequency.

Next, we ascribe the set of information from the EBS dataset with precise notations. For each limit order i, clock times are measured at the start of the order, $t^s(i)$, and at the end of the order, $t^e(i)$. The volume and quote are recorded as v_{it} and q_{it}. The best bid and ask are time-varying and are $b(t)$ and $o(t)$, respectively. I_i is an indicator function, taking the value of one for bid orders and zero for offer orders. The order book is maintained as the sum of the volume at the rate by each tick, i.e., 0.0001 EUR, on the bid and offer sides, $bv(t, tick)$ and $ov(t, tick)$, respectively

For this study, we use all orders submitted to the EUR/USD spot markets for five consecutive business days in September 2010, beginning with the 8th of September. In the following, we provide definitions of variables and their descriptive statistics later in the empirical section. These variables are classified into three groups: order characteristics, market conditions, and changes in priority.

4-1. Order characteristics

The variables in the order characteristics group include lifetime (the dependent variable), order size, and distance from the best quote.

Lifetime

As the dependent variable, we calculated the lifetime for each limit order using the following formula.

$$Life_i = t^e(i) - t^s(i) \tag{5}$$

Descriptive statistics for lifetime are also shown in Table 1. The EUR/USD lifetime distributions are heavily distorted toward zero. Although the mean values range from 34.09 to 46.00 seconds, the median values range between 1.62 and 2.78. In the regression analysis, however, we restrict the sample as follows. First, we begin the sample from the 90th order because one of the explanatory variables requires at least 80 preceding observations. Second, we exclude orders with a lifetime of less than 2 seconds. Market orders are genuinely different from limit orders because market orders are intended for execution at the moment of submission, whereas a limit order trades off a non-execution risk for a better execution quote. In the regression analysis, market orders can be excluded by restricting the lifetime to greater than zero seconds.

{Insert Table 1}

Another concern is the order strategy pursued by algorithmic trading, which mechanically submits orders and makes cancellations in fractions of seconds. To analyze the rational response of (human) traders' strategies, we set a threshold value for lifetime. However, it should be noted that we use all order data to construct the entire order book and extract the best market quotes from the constructed order book. We restrict the sample for the above reasons only in the regression analysis.

The lifetime is described as the length of an arrow in Figure 3. As with the magnitude of arrival lags discussed above, a large proportion of orders exit the market within a fraction of a second, making the lifetime heavily distributed toward zero. In fact, 23.5% of orders exit from the market in the 0.2–0.3 second lifetime bin in the EUR/USD market. Quote revisions or cancellations associated with the 0.2–0.3 second bin must be associated with computer-based or algorithmic trading. At the other extreme, orders with lifetimes exceeding 10 seconds also represent a large portion of all orders, 27.5% of the EUR/USD market.

Order size (Vol)

With respect to the distribution of order sizes in the EUR/USD market, the most frequently used is the minimum size of one million USD (86.7%). From Table 1, we observe that volumes are almost always one million dollars. Even in the third quartile, volume is only one million dollars. The mean value of volume is greater than one million simply because approximately 15% of the orders are greater than one million dollars. In addition to the prominent role of the one-million-dollar order, the proportion of small orders is also notable. This clustering of small orders is consistent with the limit on open positions for traders (Cheung and Chinn, 2001). The limit on the intraday position for most dealers in the US is 50 million USD or less. In their survey, Cheung and Chinn (2001) report that 54% (74%) of dealers are authorized to have a maximum open position of less than 25 (over 50) million USD. Orders exceeding 50 million USD are exceptionally high with respect to the open position limits of most trading institutions.

Another interpretation of small orders, particularly for the skewed use of minimum one-million-dollar orders, is that currency traders tend to split their bulk orders to avoid an unfavorable effect on the market price based on Yeo's (2005) arguments that an order splitting strategy will increase the cancellation rate. This type of strategy has been augmented in recent years by the use of algorithmic trading.

Distance from the best quote (Gap)

Using quotes recorded in the original dataset and the constructed best-bid and best-offer price, we calculate the price gap, Gap_i, between an individual quote and the best quote at the time of the order submission. This gap or distance should reflect the degree of the liquidity motive. If a dealer must have her submitted order executed quickly, this gap must be small or even negative in value. Biais et al. (1995) categorize market orders that must always be negative under our definition of *Gap* as aggressive orders [7]. By contrast, if a dealer expects her order to be placed at a more advantageous price with the risk of the transaction not occurring, this gap becomes large.

Formally, *Gap* is defined as

$$Gap_i \equiv scale\left\{I_i\left|b(t^s(i))-q_i\right|+(1-I_i)\left|o(t^s(i))-q_i\right|\right\}, \quad (6)$$

where *scale* takes a value of 10,000 for EUR/USD to make *Gap* represent the number of ticks. The mean value of *Gap* is two for the five-day sample in the EUR/USD market. We excluded orders with *Gap* greater than 50 ticks to prevent the regression results from being driven by a few absurdly high or low quotes. In fact, *Gap* is zero up to the 1st quartile, 1 up to the median, and 2 or 3 up to the 3rd quartile. In other words, at least 75% of orders are submitted within 4 ticks including the best market price.

{Insert Figure 4 here}

In the theoretical section above, we indicated that the *Gap* of a limit order at entry reveals a trader's characteristics. Placing an order at the market price or at a better quote yields a higher execution probability. Figure 4 decomposes limit orders by those executed and those canceled at distance from the best quote on September 8, 2010. This

[7] Biais et al. (1995) defines the first three categories for market orders and the other three for limit orders. Ranaldo (2004) investigates order placement decisions based on order aggressiveness, whereas Degryse et al. (2005) examine interactions between order aggressiveness and the order book. Rakowski and Beardsley (2008) examine less-aggressive limit orders behind the best quote. This paper also focuses on less-aggressive orders.

figure indicates that aggressive limit orders that improve the market price by one or two ticks are more likely to be executed than canceled. The number of executed limit orders is greater than the number of canceled limit orders at *Gap* = -2 or -1. However, limit orders placed at the market price have a greater likelihood of being canceled than being executed.

{Insert Figure 5 here}

Figure 5 shows the mean and median lifetimes of both executed limit orders and canceled limit orders on September 8, 2010. In terms of lifetime, executed limit orders remain for a shorter time at the market than canceled orders at *Gap* = -2 or -1. At the market price, executed and canceled limit orders have approximately equivalent lifetimes. However, limit orders placed behind the market price have much longer lifetimes if executed. Limit orders on other days show the same features as those observed on September 8, 2010, in Figure 4 and 5. The statistical summary is presented in the appendix table.

4-2. Changes in market conditions

As indicated in previous sections, cancellations/revisions should respond to changes in market conditions. Changes in market price—particularly when moving away from a submitted quote—indicate a fall in a trader's price priority in the order book. Additionally, a change in the volume of the order book, particularly those with higher price priority, increases the length of the queue for standing orders. Both of these changes affect the probability of execution of traders' current orders and prompt traders to cancel or revise quotes.

Best quote change (Δ Priority(Gap))

The first variable measures the change in the distance between the best quote and the submitted order.

$$\Delta \mathit{Priority(Gap)}_i \equiv \begin{array}{l} scale\left\{I_i \left|b(t^e(i)) - q_i\right| + (1-I_i)\left|o(t^e(i)) - q_i\right|\right\} \\ \quad - scale\left\{I_i \left|b(t^s(i)) - q_i\right| + (1-I_i)\left|o(t^s(i)) - q_i\right|\right\} \end{array} \tag{7}$$

For example, a trader placed a limit buy order at one tick below the best bid. The execution probability depends on the standing orders at the best bid that have price priority to this limit buy order. The execution probability is further reduced when the best bid moves one tick upward. Δ *Priority(Gap)* is (positive) one in this example. The effects of Δ *Priority(Gap)* on lifetime are twofold. By reducing the execution probability, lifetime will be lengthened if the order is not canceled, ceteris paribus. However, a change in execution probability may lead to a different optimal behavior, and the order may be canceled immediately.

{Insert Table 2 here}

The basic statistical summary for Δ*Priority(Gap)* is provided in Table 1. First, limit orders experience relatively large movements in market price in the extreme case. The market price moves toward limit orders by four ticks at the top (first) percentile, whereas limit orders at the 99th percentile experience the market price moving away by six or seven ticks. Limit orders in the middle percentile experience no change in market price. This lack of change in market price is also shown in Table 2. Approximately 54–60% of canceled limit orders exit the market without observing a change in market price[8].

Change in depth with price priority (*Δ*Priority(Depth))

The second variable is constructed from the change in depth. The depth relevant to an order includes those with price priority, i.e., those ahead in the queue. For a limit buy order *i*, this depth at the time of submission, $t^s(i)$, is represented by the following:

$$\sum_{j \in \{j > q_i\}} bv(t^s(i), j).$$

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[8] This statement is actually too strong. We only observe *Gap* at the entry and exit, and the market price may have moved between these points of time.

Notably, depth is counted only for volumes at quotes with higher price priority ($j>q_i$) and excludes those at submitted quotes ($j=q_i$). The reason for not including volumes at a submitted quote is that the change in volumes at this quote cannot be correctly associated with a change in price priority. As an obvious example, the volume at the submitting quote may remain unchanged although some orders with time priority, i.e., those orders submitted prior to this limit order, are canceled and the same amount of volume is placed after the limit order (coincidentally). To avoid this ambiguity, the definition in the following two equations omits the volume at the submitting quote.

In the following, we present two similar but alternative definitions for a change in depth between entry and exit. The first definition for Δ*Priority(Depth)*$_i$ is referred to as 'unconditional' in equation (6), in which an indicator variable is used to control for the side.

$$\Delta \mathit{Priority(Depth)}_i \equiv \begin{matrix} I_i \left\{ \sum_{j=q_i+0.0001}^{b(t^e(i))} bv(t^e(i), j) - \sum_{j=q_i+0.0001}^{b(t^s(i))} bv(t^s(i), j) \right\} \\ + (1-I_i) \left\{ \sum_{j=o(t^e(i))}^{q_i-0.0001} ov(t^e(i), j) - \sum_{j=o(t^s(i))}^{q-0.0001} ov(t^s(i), j) \right\} \end{matrix} \tag{8}$$

With this definition, there is a high correlation between Δ*Priority(GAP)* and Δ*Priority(Depth)* because a change in the best quote affects both variables in the same direction. Table 3 indicates that the correlation between Δ*Priority(GAP)* and Δ*Priority(Depth)* is approximately 0.7. The multicollinearity issue hinders the simultaneous use of these variables in the regression. With respect to orthogonalization, we removed the factor induced by a change in the best quote from Δ*Priority(Depth)*. The orthogonalized version for EUR/USD is defined as follows.

$$\Delta Priority(Depth)_i \equiv \begin{matrix} I_i \left\{ \sum_{j=q_i+0.0001}^{\min(b(t^s(i)),b(t^e(i)))} bv(t^e(i),j) - bv(t^s(i),j) \right\} \\ +(1-I_i)\left\{ \sum_{j=\max(o(t^s(i)),o(t^e(i)))}^{q_i-0.0001} ov(t^e(i),j) - ov(t^s(i),j) \right\} \end{matrix} \quad (9)$$

Figure 6 presents an illustrative example of a buy limit order submitted at 1.0001. After placement of the order, three cases for the best bid are shown: the rising case in A, remaining unchanged in B, and the falling case in C. Both definitions in equations (8) and (9) exclude volumes at quote (1.0001) at which a limit order is submitted. In Figure 6, along with these definitions in (8) and (9), a modified version of the definition that includes volume at the quote (1.0001) at which a limit order is submitted is shown.

We now show in more detail how Δ*Priority(Depth)* is calculated. For the case of an increase in the best bid of case A, the unconditional version in equation (8) accounts for a five-unit increase from six units to eleven units in depth. At the time of entry, two units at 1.0003 (best bid) and four units at 1.0002 sum to six units; note that the three units that are submitted at quote (1.0001) are not included. At the time of exit, three units at the new best bid (1.0004), three units at 1.0003, and five units at 1.0002 sum to eleven units. The orthogonalized version in equation (9) only counts volumes at the quotes that have non-zero depth both at entry and exit; therefore, it ignores an increase in volume at the new best bid (1.0004). Thus, the depth at entry is six, which is the same as in the unconditional definition, but the depth at exit is reduced to only eight units. The orthogonalized version of the definition ignores the effect of price changes on the depth.

Table 3 shows the correlation between Δ *Priority(GAP)* and Δ *Priority(Depth)*. These correlations are sufficiently low to assure that multicollinearity does not appear to be a concern for the orthogonalized version defined in equation (9).

{Insert Table 3}

4-3. Control variables: market condition at entry

Market condition variables include market calmness (the reciprocal of volatility) and the overall size of the order book (i.e., not only those with price priority).

Market volatility (Calm)

The arrival lag or duration, i.e., the elapsed time in seconds from the last order submission to a new order submission in the market, is calculated as follows.

$$lag_i = t^s(i) - t^s(i-1) \tag{10}$$

Calculations of arrival lags and lifetime are depicted in Figure 3. For example, the arrival lag between order (i=3) and order (i=4) is t_7 - t_3. A large portion of orders are submitted literally within a fraction of a second following the preceding order in the market. The orders submitted within a second after the preceding order comprise 94.5% of orders on average for the five-day sample of two foreign spot markets[9]. In addition, approximately 1 percent of all orders are submitted simultaneously (measured in terms of milliseconds) with another order. This extremely fast speed of orders is explained in part by the pervasive use of algorithmic trading by computers[10]. The asymmetric information models in Easley and O'Hara (1987, 1992) suggest that large orders and short durations are evidence of trading by informed traders. Manganelli (2005) find supporting evidence for the link between short durations and trading by informed traders in the NYSE. We later introduce a new variable called *CALM* for representing the market conditions regarding the speed of activities by summing over the past several durations.

To measure the calmness of the market, the time span for the previous *Mth*

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[9] This ratio is slightly higher for the EUR/USD market than for the JPY/USD market due to the greater number of submissions in the former market. Simple averages are 96.3 and 92.8% for EUR/USD and JPY/USD, respectively.

[10] Corwin and Lipson (2011) distinguish program (algorithmic) traders, institutional traders, retail traders, and member traders in their empirical analysis on the NYSE-listed securities. See section 2 of their paper for the significant presence of program traders.

limit orders is calculated. This measure, $Calm_i$, is proportionally the reciprocal of the number of limit orders within a fixed period. This measure increases as trading activity in the market slows. When the market is fast-paced, the decisions and responses of dealers must be accelerated.

$$Calm_i(1\_M) \equiv \sum_{j=i-M+1}^{i} lag_j \tag{11}$$

where $lag_j = t^s(j) - t^s(j-1)$.

Size of the order book (depth)

Using the constructed order book, we aggregate the volume of standing orders within N ticks, i.e., 0.0001*N USD, of the best price on both sides as a measure of market depth, $Depth_i$. For EUR, we use 0.001 EUR as 1 tick. The market depth should affect the behavior of dealers, particularly regarding the timing of canceling a submitted order.

$$Depth_i(1\_N) \equiv \sum_{j=b_i-0.0001*(N-1)}^{b_i} bv(t^s(i), j) + \sum_{j=o_i}^{o_i+0.0001*(N-1)} ov(t^s(i), j) . \tag{12}$$

Increasing N allows one to investigate how far from the best quote cumulated orders in the order book can significantly affect a new incoming order.

5. Lifetime estimation model and results

The change in market conditions affects the decision to exit from the order book and therefore the length of the lifetime. Using the market condition variables defined in the previous section, we evaluate the impact of a change—in terms of price and depth—in the order book on how long a limit order remains in the market.

In terms of selecting explanatory variables, most previous studies focus on order placement and include only variables observable at the time of order placement. However, our focus in this paper is order exit or cancellations, and thus the variables of interest should be those observable at the time of exit. To be more precise, a trader makes an entrance by observing the order book at the time of entry and then decides to exit from the market because of changes in the order book that have occurred between the time of entry and the time of exit. Therefore, the important measures are those variables that capture changes observed during the order's stay at the market. These variables include Δ *Priority(Gap)* defined in equation (7) and Δ *Priority(Depth)* defined in equation (9).

In addition, we include those variables that represent the trader's characteristics. First, a patient trader is more likely to place a limit order behind the best quote; such an order consequently has a greater value of *Gap*, which is the distance between the trader quote and the best quote in the market. The lifetime is expected to be longer for a greater *Gap* regardless of whether the order is executed or canceled. This correlation appears as an upward slope of mean (median) lifetime in Figure 5. Second, FX dealers constantly serve their customers and often must meet customer demand by transacting in the interbank limit order market. In this case, *Vol* is greater—if it is not breaking down the block order—as it is reflecting the liquidity trading of dealers. However, liquidity trading itself does not directly relate to the degree of the urge to execute. The unconditional correlation between *Vol* and *Gap* is very low, ranging from -0.010 to 0.002 in our sample. The sign of *Vol* is left open as an empirical question. With these explanatory variables, we estimate the following equation for the lifetime of limit orders in the EBS EUR/USD market:

$$Life_i = \alpha + \beta_1 \Delta priority(Depth)_i + \beta_2 \Delta priority(Gap)_i + \gamma_1 Gap_i + \gamma_2 Vol_i + \varepsilon_i . \qquad (13)$$

where Δ *Priority(Depth)* is the change in depth at better quotes, Δ *Priority(Gap)* is the change in the market price, *Gap* is the distance measured in ticks between the market price and the submitted quote, *Vol* is the volume of a limit order, and ε_i is an error term.

Some cautionary measures taken during data constructions must be explained here. First, the first set of limit orders is removed from the estimation sample because the order book is reconstructed from the limit order submission database and may be incomplete for orders appearing early in the database. In particular, the set of the first 500 orders are only used to reconstruct the order book for later order placements, and the best bid and ask quotes are recovered from the constructed order book. Second, orders with quotes far from market price are removed. These orders may represent simply mispricing or strategic order submission but may inappropriately influence the regression result. Specifically, orders with quotes placed 50 ticks from the best quote at the time of submission are dropped from the regression sample. Finally, to minimize the effects of algorithmic trading, which may be operated with a completely different objective, orders with lifetimes of less than two seconds are removed from the regression sample. After performing this data cleaning, the basic lifetime regressions with four independent variables are estimated for both EUR/USD market for the five consecutive business days in our September 2010 sample.

5-1. Empirical results of basic lifetime regressions

The estimation results may be biased if orders of algorithmic trading are retained in the sample because they have much shorter lifetimes and may differ in the objectives of their order strategies. Thus, we investigate the empirical model of equation (11) using only limit orders with lifetimes greater than or equal to 2 seconds. Notably, later in the robustness section, the qualitative results are shown not to be sensitive to the threshold value of 2 seconds.

{Insert Table 4 about here}

The estimation results for EUR/USD lifetime basic regressions are shown in Table 4. All estimated coefficients are statistically significant at the 1% level. The fitness of the regressions in terms of R^2 is between 18 and 22%. We believe that these explanatory powers are not too low, given that we cannot match consecutive ordering by the same trader. Information on financial institution size and type, i.e., banks or hedge funds, should matter for the lifetimes of the limit orders. For example, Anand, Chakravarty, and Martell (2005) and Kaniel and Liu (2006) find that the likelihood of submitting limit orders over market orders differs between informed institutional investors and uninformed individual traders in the NYSE. Unfortunately, our database does not provide information regarding institutions.

We first report the estimation results of the variables of order characteristics. Patience measured by order placement one tick away from the best quote is related to an extra stay of approximately a half-minute in the order book. A greater volume of a limit order is associated with longer lifetime. A limit order with an extra one million USD generally remains approximately ten seconds longer in the order book.

We now turn to the results for change in market condition variables. An increase in Δ*Priority(Depth)* indicates an increase in depth at the better quotes and hastens the exit from the market of limit orders with worse terms of quotes. Thus, when he observes more orders jumping in line in front of his position, a trader will reevaluate the execution probability of his order and will decide to cancel or revise his order. The impact of one unit (i.e., 100 million USD) of additional depth ranges from minus 1.83 (September 14) to minus 5.52 seconds (September 10). Based on the sign proportion of Δ*Priority(Depth)* in Table 2, the lifetime of approximately 23% (26%) of limit orders is lengthened (shortened) by a change in depth.

When the market price moves away, i.e., when there are positive values of Δ*Priority(Gap)*, a limit order is likely to remain longer in the market. The impact on lifetime of one tick moving away from the market price is approximately 50–70 seconds. This result is consistent with a standard theoretical model as equation (2). An increase in the best bid signals an increase in the common value, *V*, and therefore increases the expected utility of limit buy order.

Caution is required in directly interpreting this result. The coefficient of Δ*Priority(Gap)* in Table 4 is the unconditional impact of a one-tick change in the gap on the lifetime of limit orders. However, as we have shown, limit orders differ greatly in patience and liquidity urges. It is natural to assume that there is an impact of one tick change difference between a limit order placed at the best quote and another order placed three ticks away from the best quote.

Indeed, the cancellation probability, i.e., the reciprocity of execution probability, is much higher when an order is placed far from the best quote. Table 5 shows the cancellation probability for each *Gap* level and each tick change in *Gap*. For example, on the 8th of September, faced with a market price that has moved away one tick, a limit order in the first column that improves the best quote has a cancellation probability of 24%, whereas limit orders placed three ticks away from the best quote are all canceled. Understanding this stark difference in execution probability, FX dealers should behave differently when facing a change in the best quote according to the *Gap* at the time of submission.

{Insert Table 5}

The difference-in-depth variable reflects a change in price priority of a submitted limit order. The difference-in-gap variable, on the other hand, captures a change in the estimated common value of the traded asset. These effects on lifetime in response to price priority changes or the common value change are influenced by traders' characteristics. We will examine these issues with traders' characteristics more carefully in the next section.

5-2. Robustness checks

The estimated results above may be sensitive to alternative threshold values for lifetime and alternative definitions of the depth change variable. We address each of these issues in the following.

Alternative threshold values for lifetime

In the previous section, to exclude possible algorithmic trading, which might affect the results of lifetime regressions, we restricted the sample by using orders with lifetimes greater than or equal to the threshold value of two seconds. However, the results of lifetime regressions may be sensitive to the choice of threshold values. We set alternative threshold values of 0, 0.5, 1, and 5 seconds and re-run the lifetime regressions. Of course, the number of observations varies substantially because a large portion of orders clusters around these seconds. The estimated results are shown for the threshold values of zero and five seconds in Table 4. The estimated coefficients modestly remain at the same level regardless of the threshold values. Notably, the fitness of regression monotonically increases as the sample size is reduced by increasing the value of the threshold. In support of our previous findings, this sensitivity analysis demonstrates that the qualitative results remain the same for alternative threshold values.

{Insert Table 6 about here}

Alternative definition for depth change

As we discussed above in section 4.2, we exclude the volume at the submitted quote in the construction of the Δ*Priority(Depth)* variable because of its ambiguity with regard to a change in price priority. Alternatively, we construct the Δ *Priority(Depth)* variable by including the volume at the submitted quote, and the estimated results are reported in Table 7. Δ*Priority(Gap)* and *Gap* show almost no change. The estimated coefficients of Δ*Priority(Depth)* variable in general decrease approximately 30% compared to the results in Table 4, whereas point estimates of *Vol* increase 20–40%. As expected, including volume at the submitted quote undermines the impact of changes in depth that have ‘price priority’.

{Insert Table 7 about here}

6. Extended Lifetime Regression with Order Characteristics and Market

Conditions

Thus far, the lifetime regression model for the limit order lifetime assumes that the effects of changes in the order book are homogeneous on all orders regardless of possible differences in patience or liquidity urges among traders. For example, a patient trader (or order) should respond differently to a change in the corresponding best quote. Thus far, we find that a limit order remains longer in the order book when the best price moves away, i.e., with positive Δ*Priority(Gap)*. However, it cannot be determined a priori whether an impatient order stays longer in the order book relative to a patient order when the best price moves away. An impatient order placed closer to the best price is more sensitive to price changes and may leave the order book relatively quickly. By contrast, an impatient order with a higher execution probability at entry may have room for the best price to move away for a tick or two. In the absence of a concrete theoretical model, this remains an entirely empirical question.

6-1. Empirical results of the extended lifetime regression

A straightforward means of evaluating the heterogeneous responses of orders is to interact an order's characteristics with the variables of interest. We therefore re-estimate a lifetime equation by adding change-in-book variables interacted with control variables.

$$
\begin{aligned}
Life_i &= \alpha + \beta_1 \Delta priority(Depth)_i + \beta_2 \Delta priority(Gap)_i + \gamma_1 Gap_i + \gamma_2 Vol_i \\
&+ \sum_j \delta^j X_i^j \cdot \Delta priority(Depth)_i + + \sum_j \eta^j X_i^j \cdot \Delta priority(Gap)_i + \varepsilon_i
\end{aligned} \tag{14}
$$

where X_i^j is the j-th control variable. The control variables include two variables for order characteristics and two variables for market conditions at entry. The order characteristic variables are volume (*Vol*) and the difference between the order quote and the best quote in the order book (*Gap*). The market condition variables are the inflow speed of the preceding orders (*Calm*) and the subtotal volume in the order book (*Depth*). All variables are defined above in section 4.

{Insert Table 8 here}

The estimated results are shown in Table 8. First, the improvements in the fitness of regression are fairly substantial. In terms of adjusted R-squared, they increase from two to fifteen points over the five-day sample. Second, we find weak evidence that the effect of depth change, Δ *Priority(Depth)*, on the lifetime of limit orders is heterogeneous. All four control variables are statistically significant on some of the sample days, but no variables are always statistically significant on all five days of the sample period. The point estimates of Δ *Priority(Depth)* show a substantial decrease (an increase in absolute term). However, the marginal effect of an increase in depth on lifetime now should be measured with $\beta_1 + \delta^j X_i^j$ for the j-th control variable. In this manner, the marginal effect of Δ*Priority(Depth)* comes back close to the estimates of the basic regression reported in Table 4 because all δ^j are estimated to be positive.

Third, for the estimates of Δ*Priority(Gap)* with interaction terms, we find stronger evidence that heterogeneity represented by the control variables, particularly *Gap* and *Vol*, influence marginal effects. Thus far, with the basic lifetime regression, we find that all trades, whether they are patient or impatient, remain longer in the market when the best price moves away. Now, the results in Table 8 offer additional insight on how a limit order is placed at and removed from the market. A relatively patient trader or a trader with low waiting costs or relatively mild personal valuation places an order far from the best quote. These orders actually respond more slowly to changes in market conditions and therefore exit more slowly from the market.

To quantify the degree of heterogeneity, the marginal effects are compared between the 25th and 75th percentile values of the control variables. For the following comparisons, the five-day averages of the control variables at each percentile are calculated from Table 1. The value of *Gap* at the 25th and 75th percentile is zero and three, respectively[11]. Therefore, the difference in lifetime associated with a market price

[11] The five-day sample average is 0.2 for *Gap*, but here we rounded to use a discrete value.

change would be 5.19 to 14.6 seconds between orders placed at the best quote and those placed three ticks behind when the best price moves one tick away[12]. This additional lifetime is substantial considering that the median value of a lifetime is less than three seconds. We thus have evidence for an order exit strategy when the market price moves away: a patient trader who places his order a few ticks behind the best quote would wait longer for extra time, in addition to a longer lifetime of all orders caused by price moving away.

6-2. Robustness checks

Thus far, we have estimated regressions by ordinary least squares because of asymptotic consistency if the error terms have an expected value of zero and bounded variances. However, non-normal distributed error terms bias the standard errors used for statistical significance in a small sample. The lifetime variable is bounded from below (zero or two seconds), and its error terms should be treated with caution.

First, taking the natural logarithm of the lifetime makes the range of the dependent variable both negative and positive. The estimation results for lifetime in the natural logarithm are shown in appendix table A2. The estimated values of the

[12] The marginal effect of this interaction term at the 25th percentile is zero because *Gap* is zero. The smallest estimated coefficient of this interaction term is 1.73 for September 9, and this value is multiplied by 3 for *Gap* at the 75th percentile to obtain 5.19.

coefficients differ widely because of a large shift in dependent variables. However, the qualitative results hold for the signs and statistical significance of the estimated coefficients. The only difference appears with respect to the signs of the interaction terms for *Gap*.

Second, we applied Tobit regression for the truncated lifetime variable. By exploiting the truncated estimation model, orders with a lifetime of less than two seconds are truncated to zero instead of being dropped from the sample, which increases the number of observations. For example, for the 8^{th} of September, the observations increase from 257,215 to 491,088. The Tobit estimated results are shown along the OLS results in appendix table A3. Again, the qualitative results remain intact. The expanded OLS result in Table A3 is qualitatively similar to the result presented in Table 8. Moreover, the OLS and Tobit results in Table A3 are quite similar. We conclude that the results of this research are robust regardless of the econometric specifications for error terms.

7. Conclusion

The EBS FX markets provide a unique platform to investigate the microstructure behavior of limit orders because the EBS dataset records all submitted orders in time series. We reconstructed the order book and the best market quotes, both varying at the frequency of incoming orders. In addition, we measured the lifetime of all limit orders. Consistent with previous evidence on stock markets, the majority of orders in FX markets are also canceled (or resubmitted with a modified quote) before any transactions occur.

Several features of individual orders in the EBS EUR/USD limit order market are notable. First, more than half of orders have lifetimes of less than three seconds. Second, approximately 85% of orders are submitted with a minimum size of one million USD. Third, submitted quotes are within three ticks from the best quote for 75% of all orders.

Most previously developed theoretical models for a limit order market concentrate on order placement strategies by imposing exogenous restrictions on cancellation behavior. A simple model that encompasses both order placement and order exit suggests that order book information should affect a trader’s decision both at entry and exit. We test this proposition by estimating lifetime regressions by regressing the lifetime of limit orders on changes in the order book. The estimated results demonstrate that support lifetime is influenced by a change in the submitted-and-best quote gap and depth with a higher price priority. A greater distance between the submitted quote and the best quote after order placement contributes to a longer lifetime in the order book. An increased depth of quotes with higher price priority shortens the lifetime of a submitted limit order.

We further test whether individual order characteristics and market conditions (at the time of submitting a new order) affect the degree of the impact of the order book change on the lifetime of limit orders in the FX market. Consistent with the expected financial behaviors of market traders, we find that the response of the lifetime to order book depends on the characteristics of the order. In particular, for a change in the price gap, a patient order, which is defined as placed far from the best quote, leaves the market more slowly than an impatient order.

Whereas most previous studies focus on stock markets, this study contributes to the literature on limit order markets by offering empirical evidence from FX markets. Our suggested specifications for the estimation model for the lifetime of limit orders yield sufficient explanatory power and are robust to the selection of the cut-off level for a lifetime, to the specification of explanatory variables, and to various econometric methods. Kozhan and Salmon (2012) obtain negative results in seeking to determine whether the use of the information content of the order book in the US Dollar-British Pound Sterling market yields economically significant returns. Their results do not contradict our results that a change in the order book affects the exit strategy of traders in FX markets. After the information from the order book is efficiently reflected in the market price via the exit strategies of market participants, there will be no extra profit remaining in the market, which is consistent with the assumptions of the efficient market hypothesis.

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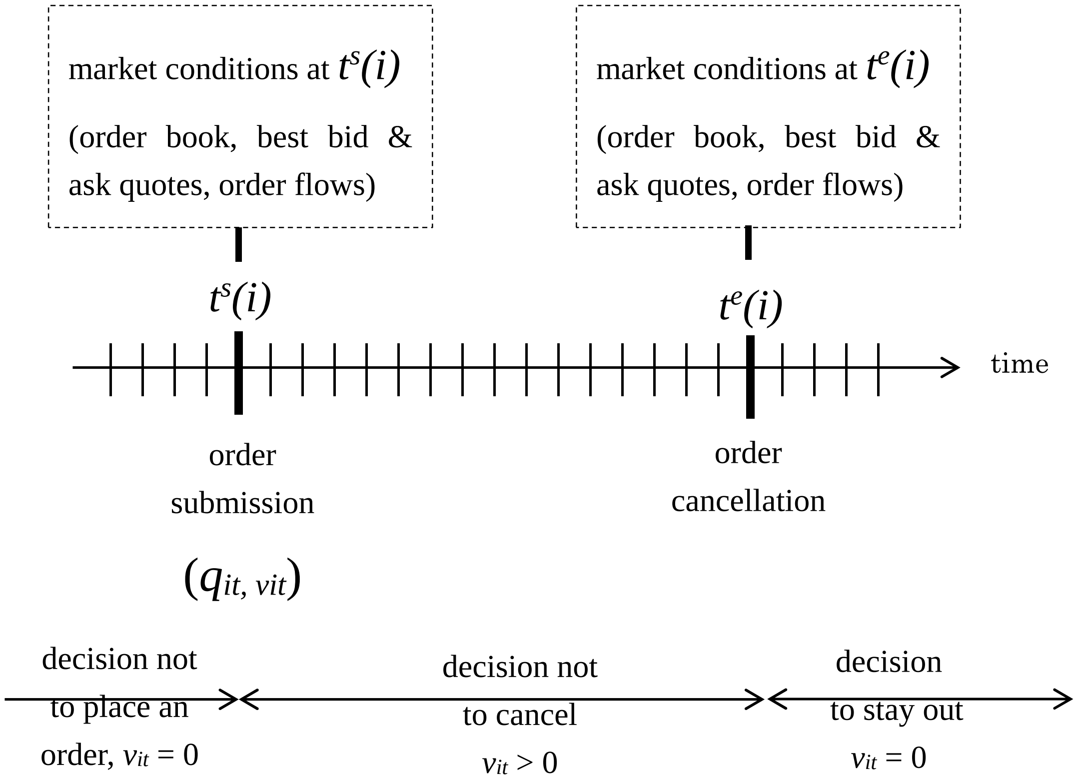
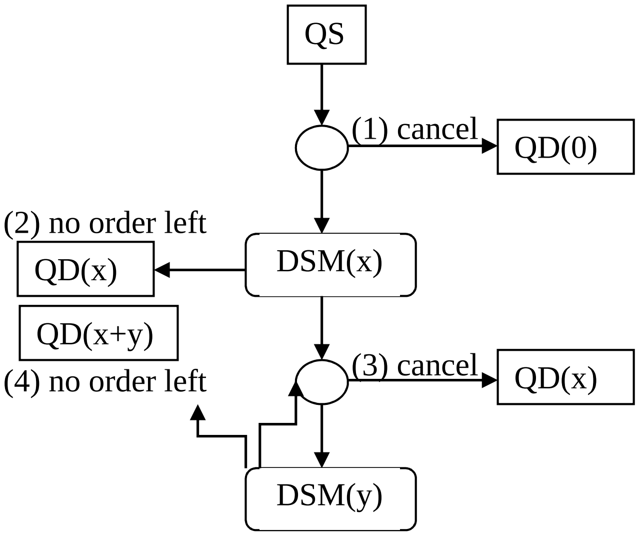
Figure 1. Decision making by an FX dealer



Note: q_{it} and v_{it} are the quote and the volume of submitted order i at time t. A trader observes market conditions (in the dotted square box) and submits his limit orders at $t^s(i)$ when the expected utility of placing an order exceeds that of staying out of the market. After order placement, a trader continues to monitor the market and decides to cancel his order at $t^e(i)$ if staying out maximizes his expected utility.

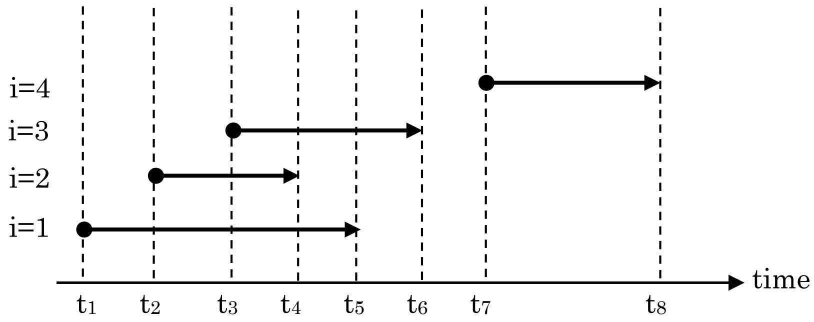
Figure 2. Records of orders on the EBS spot market



Note: QS indicates the beginning of the order. QD indicates the end of the order. DSM indicates a transaction. There are four outcomes for an order: (1) the order is deleted by cancellation; (2) the order is filled with either another counter-side limit order or a market order; (3) the order is canceled after a part of the order is executed; or (4) the order is filled by multiple transactions.

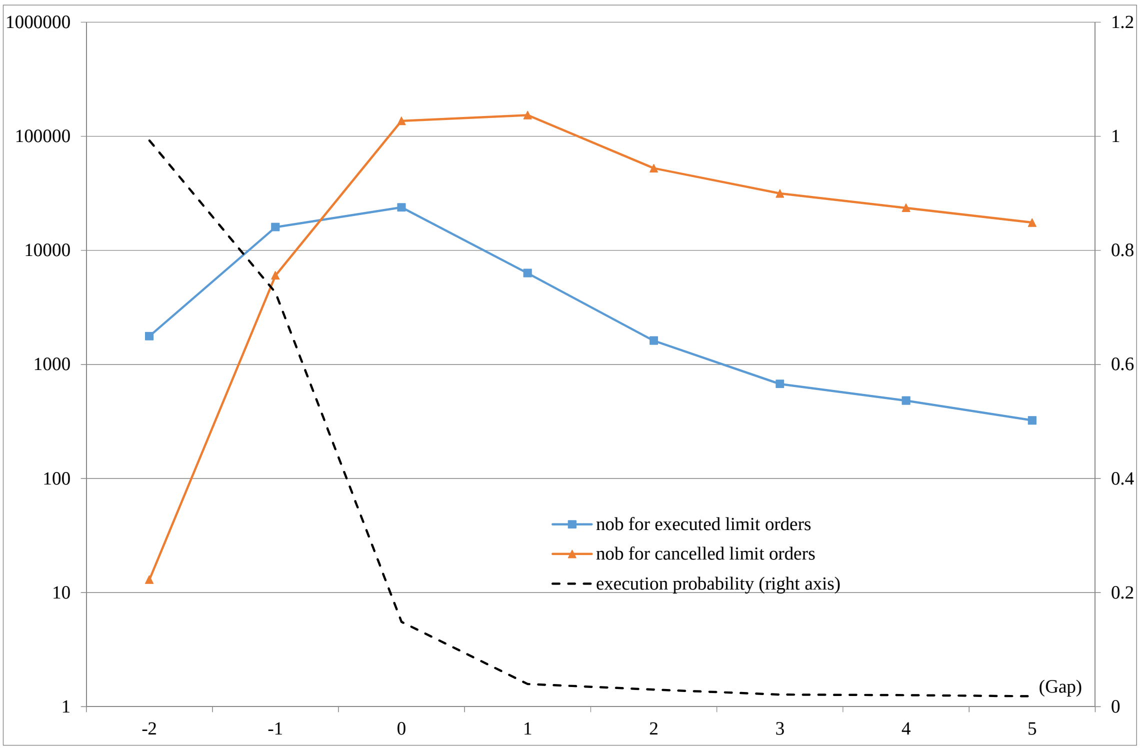
Figure 3. An illustrative example of EBS limit order flows
for arrival lags (duration) and lifetime

time stamp	ID	EBS code	Volume	Side
t1	i=1	QS	1,000,000	bid
t2	i=2	QS	1,000,000	offer
t3	i=3	QS	2,000,000	bid
t4	i=2	QD	0	offer
t5	i=1	QD	0	bid
t6	i=3	QD	0	bid
t7	i=4	QS	1,000,000	offer
t8	i=4	QD	0	offer



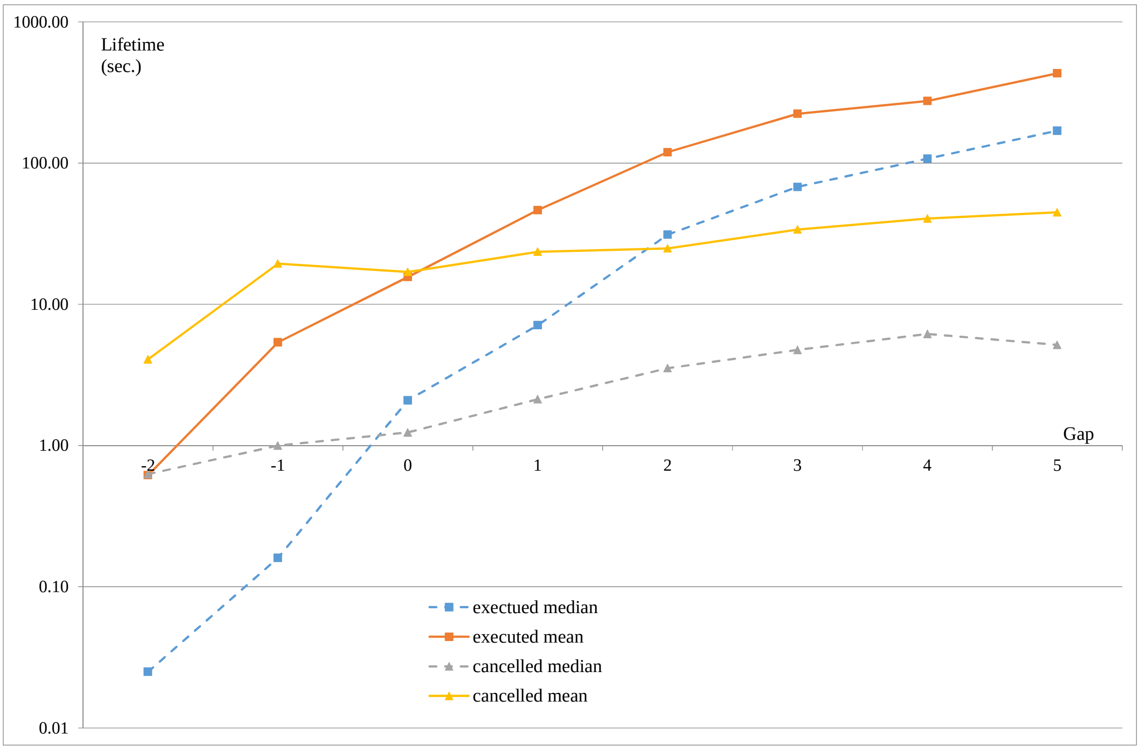
Note: For the top panel, see Figure 2 for the definitions of EBS code and dynamic flow charts. The bottom panel provides a graphical representation of this example. A circle at the left end of the arrow indicates the arrival of an order, and the right end of an arrow indicates the exit of the order. For example, the first order (i=1) arrives at the market at t_1 and exits at t_5. The *arrival lag* is the time elapsed between the previous order's arrival and the current order's arrival; for example, the *arrival lag* is t_2 - t_1, for the second order (i=2) and $t_7 - t_1$ for the fourth order (i=4). *Lifetime* is defined as t_5 - t_1, $t_4 - t_2$, t_6 - t_3, and t_8 - t_7 for the first through fourth order, respectively.

Figure 4. Execution probability



Note: The number of observations (nob) for executed and canceled limit orders by *Gap* are represented by the line with square boxes and the line with triangles, respectively. The execution probability (on the right scale) is calculated by the nob of executed orders divided by the sum of executed and canceled orders. This figure represents the data for September 8, 2010, in appendix table A1.

Figure 5. Difference in lifetime between executed and canceled limit orders



Note: Lifetimes of limit orders are shown by *Gap*. Lines with square boxes indicate executed limit orders, and lines with triangles indicate canceled orders. Solid (broken) lines indicate the mean (median). This figure represents the data for September 8, 2010, in appendix table A1.

Figure 6. Alternative definitions of change in depth

case A (bid rises)		case B (bid remains the same)	
quote at entry	quote at exit	quote at entry	quote at exit
1.0004	1,0004 ***	1.0004	1,0004
1.0003 **	1,0003 ***	1.0003 **	1,0003 ****
1.0002 ****	1.0002 *****	1.0002 ****	1.0002 ****
1.0001 *** +	1.0001 ****	1.0001 *** +	1.0001 ****
1.0000 **	1.0000 **	1.0000 **	1.0000*
0.9999	0.9999	0.9999	0.9999

case C (bid falls)

quote at entry	quote at exit
1.0004	1,0004
1.0003 **	1,0003
1.0002 ****	1.0002 **
1.0001 *** +	1.0001 **
1.0000 **	1.0000 ***
0.9999	0.9999

	unconditional including at-own quote	unconditional without at-own quote	orthogonalized including at-own quote	orthogonalized without at-own quote
case A	+ 6 (9, 15)	+5 (6, 11)	+3 (9, 12)	+2 (6, 8)
case B	+3 (9, 12)	+2 (6, 8)	+3 (9, 12)	+2 (6, 8)
case C	-5 (9, 4)	-4 (6, 2)	-3 (7, 4)	-2 (4, 2)

Note: This figure only accounts for a buy-limit order. The case for a sell-limit order can be shown by analogy. An asterisk (*) indicates one unit (one million USD). In all cases, the best bid (1.0003) and depth are the same for all quotes at order submission (left). The bottom panel shows the change in depth, and the depth at entry and at exit are shown in parentheses. The unconditional version of change in depth counts volumes at all quotes with price priority. The orthogonalized version of change in depth counts volumes only at quotes that have non-zero volume at both entry and exit.

Table 1. Descriptive statistics of EUR/USD (five days in September 2010)

		8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
	NOB	491,092	436,339	408,244	434,997	551,952
lifetime	mean	39.05	42.00	41.85	38.31	30.83
(seconds)	min	0.001	0.005	0.008	0.005	0.005
	1%	0.248	0.249	0.248	0.247	0.246
	25%	0.298	0.370	0.312	0.283	0.268
	50%	2.32	2.95	2.57	2.21	1.70
	75%	12.77	15.69	13.83	12.20	9.20
	99%	563	634	618	652	452
	max	37180	30704	36716	28032	30989
Δ priority(GAP)	mean	0.20	0.19	0.18	0.15	0.21
(ticks)	min	-36	-39	-40	-46	-37
	1%	-4	-4	-4	-4	-4
	25%	0	0	0	0	0
	50%	0	0	0	0	0
	75%	0	0	0	0	0
	99%	7	7	6	6	7
	max	84	75	97	107	179
Δ priority(DEPTH)	mean	1	1	0	0	0
(million US dollars)	min	-1,008	-420	-517	-341	-955
	1%	-31	-30	-29	-30	-33
	25%	0	-1	0	-1	0
	50%	0	0	0	0	0
	75%	1	1	1	1	1
	99%	34	34	31	31	33
	max	995	309	489	483	961

Note: All orders regardless of cancellations or executions are used to construct the order book. The sample includes only canceled orders from the EUR/USD spot foreign exchange market. The first 500 observations are dropped from the regression sample. Orders with quotes placed more than 50 ticks away from the market quote are also dropped. *Lifetime* is measured as the time elapsed between entry to and exit from the market. Δ *Priority(Depth)* is the change in depth at price-priority quotes and Δ *Priority(Gap)* is the change in *Gap*. For the precise definitions, see section 4.

Table 1. (continued)

		8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
	NOB	491,092	436,339	408,244	434,997	551,952
Vol	mean	1.20	1.20	1.24	1.21	1.23
(million US dollars)	min	1	1	1	1	1
	1%	1	1	1	1	1
	25%	1	1	1	1	1
	50%	1	1	1	1	1
	75%	1	1	1	1	1
	99%	3	3	4	4	5
	max	999	156	250	250	940
Gap	mean	2	2	2	2	2
(ticks)	min	-2	-2	-9	-4	-4
	1%	-1	-1	-1	-1	-1
	25%	0	1	0	0	0
	50%	1	1	1	1	1
	75%	3	3	3	3	3
	99%	12	12	13	13	13
	max	50	50	50	50	50
Depth(10)	mean	299	271	289	324	296
(million US dollars)	min	37	25	12	23	18
	1%	141	111	113	89	92
	25%	250	215	227	213	202
	50%	303	265	277	297	295
	75%	351	336	359	428	379
	99%	480	459	510	639	603
	max	1,328	722	839	911	1,570
Calm(40)	mean	6.2	6.9	7.4	6.8	5.4
(seconds)	min	0.0	0.0	0.0	0.0	0.0
	1%	0.2	0.2	0.2	0.2	0.1
	25%	1.4	1.7	1.8	1.5	1.0
	50%	3.2	3.6	3.8	3.7	2.5
	75%	6.8	7.7	8.3	8.2	6.1
	99%	46	49	54	44	41
	max	399	278	393	238	335

Note: (continued) *VOL* is the size of the order. *GAP* is the difference between the submitted quote and the best quote in the market. *Depth* is measured as aggregate volume in the order-book. *Calm* is calculated as the arrival lags between preceding and incoming orders.

Table 2. Direction of changes in Gap and Depth

		8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Δpriority(GAP)	negative	0.19	0.20	0.19	0.18	0.18
(ticks)	zero	0.56	0.54	0.58	0.60	0.57
	positive	0.25	0.26	0.24	0.22	0.24
Δpriority(DEPTH)	negative	0.22	0.24	0.23	0.23	0.22
(million US dollars)	zero	0.53	0.49	0.52	0.51	0.52
	positive	0.25	0.27	0.25	0.26	0.26

Note: Complementary to the information in Table 1, the proportions of negative change, no change, and positive change for change variables are shown.

Table 3. Correlation between ΔPriority(Gap) and ΔPriority(Depth)

	8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Depth including at-own-quote	0.714	0.738	0.711	0.731	0.613
Depth without at-own-quote	0.746	0.761	0.733	0.752	0.635
Orthogonalized depth including	-0.109	-0.088	-0.107	-0.069	-0.181
Orthogonalized depth without	-0.108	-0.078	-0.105	-0.055	-0.176

Note: Δ*Priority(Depth)* is defined in equations (8) and (9). Equation (8) corresponds with the second row and equation (9) with the fourth row. The first and third rows are modified versions of Δ*Priority(Depth)* that include depth at the submitted quote.

Table 4. EUR/USD Basic Lifetime Regressions (only with change variables)

	8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Δpriority(DEPTH)	-5.00***	-4.91***	-5.52***	-2.95***	-1.83***
	(0.44)	(0.43)	(0.51)	(0.49)	(0.24)
Δpriority(GAP)	70.30***	54.55***	72.37***	56.97***	49.52***
	(4.29)	(3.96)	(5.15)	(4.44)	(2.64)
GAP	49.98***	37.50***	44.33***	35.62***	36.12***
	(2.39)	(1.72)	(2.21)	(1.87)	(1.73)
VOL	12.32***	8.07***	10.58***	10.51***	6.48***
	(2.17)	(1.24)	(1.85)	(1.41)	(2.51)
constant	-91.48***	-50.24***	-71.86***	-43.73***	-55.19***
	(7.38)	(5.11)	(6.54)	(5.31)	(5.53)
R^2	0.22	0.18	0.22	0.18	0.21
NOB	257,215	243,558	219,990	224,778	262,866

Note: All orders regardless of cancellations or executions are used to construct the order book. The sample includes only canceled orders from the EUR/USD spot foreign exchange market. The first 500 observations are dropped from the regression sample. Then, orders with lifetimes of less than two seconds are dropped as they may add noise to the analysis due to algorithmic trading. Orders with quotes placed more than 50 ticks away from the market quote are also dropped. Figures in parentheses are the standard deviations that are robust to heteroskedasticity. *, **, and *** denote statistical significance at the 10, 5, and 1% levels, respectively.

Table 5. Cancellation probability by change in Gap and Gap at entry

8-Sep

change in gap	gap at submission -1	0	1	2	3
-3	(0)	(0)	(0)	(0)	0.631 (1,422)
-2	(0)	(0)	(0)	0.739 (4,921)	0.975 (3,893)
-1	(0)	(0)	0.892 (43,444)	0.987 (16,700)	0.995 (5,518)
0	(0)	0.814 (120,735)	0.985 (93,946)	0.996 (20,858)	0.998 (13,611)
1	0.242 (20,674)	0.960 (29,632)	0.990 (10,272)	0.999 (6,641)	1.000 (4,262)
2	0.740 (847)	0.981 (4,774)	0.998 (3,689)	0.999 (2,080)	1.000 (1,746)
3	0.776 (223)	0.980 (1,418)	0.993 (2,423)	0.998 (1,254)	1.000 (956)

9-Sep

change in gap	-1	0	1	2	3
-3	(0)	(0)	(0)	(0)	0.626 (1,271)
-2	(0)	(0)	(0)	0.780 (4,775)	0.980 (3,533)
-1	(0)	(0)	0.900 (36,780)	0.988 (15,789)	0.997 (6,310)
0	(0)	0.783 (89,999)	0.986 (79,129)	0.997 (24,110)	0.999 (15,682)
1	0.246 (19,368)	0.959 (23,456)	0.993 (9,770)	1.000 (7,354)	1.000 (4,344)
2	0.720 (739)	0.986 (4,493)	1.000 (3,619)	1.000 (2,114)	1.000 (1,732)
3	0.841 (214)	0.988 (1,262)	0.999 (1,993)	0.999 (1,141)	1.000 (965)

10-Sep

change in gap	-1	0	1	2	3
-3	(0)	(0)	(0)	(0)	0.646 (1,300)
-2	(0)	(0)	(0)	0.784 (4,319)	0.974 (3,186)
-1	(0)	(0)	0.900 (35,220)	0.984 (11,713)	0.996 (5,883)
0	(0)	0.808 (105,347)	0.984 (66,012)	0.994 (20,380)	0.999 (16,595)
1	0.242 (18,187)	0.955 (19,482)	0.990 (8,169)	1.000 (6,437)	0.999 (4,372)
2	0.742 (764)	0.977 (3,031)	0.998 (3,122)	1.000 (1,693)	0.999 (1,535)
3	0.749 (191)	0.992 (1,732)	0.998 (1,787)	1.000 (992)	1.000 (892)

13-Sep

change in gap	-1	0	1	2	3
-3	(0)	(0)	(0)	(0)	0.648 (1,136)
-2	(0)	(0)	(0)	0.745 (3,743)	0.970 (2,946)
-1	(0)	(0)	0.892 (34,956)	0.983 (13,836)	0.997 (5,991)
0	(0)	0.798 (110,662)	0.985 (77,456)	0.995 (25,712)	0.997 (13,692)
1	0.222 (18,522)	0.952 (21,857)	0.994 (9,736)	0.999 (7,701)	1.000 (3,632)
2	0.735 (731)	0.978 (3,368)	0.996 (2,950)	0.999 (1,724)	1.000 (1,343)
3	0.780 (191)	0.986 (1,547)	0.999 (1,657)	1.000 (997)	1.000 (748)

14-Sep

change in gap	-1	0	1	2	3
-3	(0)	(0)	(0)	(0)	0.632 (1,969)
-2	(0)	(0)	(0)	0.738 (6,270)	0.962 (4,526)
-1	(0)	(0)	0.864 (45,017)	0.976 (17,450)	0.994 (7,721)
0	(0)	0.787 (138,077)	0.979 (99,871)	0.990 (33,344)	0.997 (19,383)
1	0.219 (24,030)	0.947 (32,273)	0.985 (13,007)	0.998 (9,479)	0.999 (4,887)
2	0.706 (958)	0.970 (5,197)	0.991 (4,164)	0.998 (2,406)	0.999 (1,831)
3	0.802 (243)	0.977 (2,191)	0.995 (2,369)	0.998 (1,329)	0.999 (993)

Note: Cancellation probabilities at each Gap by Δ *Priority(Gap)* are shown. The figures in parentheses are the number of observations in the corresponding cell.

Table 6. EUR/USD Basic Lifetime Regressions (Robustness with thresholds)

Lifetime >= 0

	8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Δpriority(Depth)	-4.39***	-4.32***	-4.95***	-2.49***	-1.65***
	(0.40)	(0.41)	(0.47)	(0.45)	(0.21)
Δpriority(Gap)	67.66***	53.16***	69.99***	54.36***	48.58***
	(4.20)	(3.85)	(5.04)	(4.32)	(2.64)
Gap	29.80***	25.71***	26.63***	17.23***	19.79***
	(1.44)	(1.17)	(1.35)	(0.94)	(0.95)
Vol	4.70***	5.19***	5.73***	6.01***	3.56***
	(1.73)	(0.69)	(0.88)	(0.86)	(1.36)
constant	-45.88***	-34.49***	-39.88***	-19.12***	-28.86***
	(4.12)	(3.10)	(3.62)	(2.75)	(2.90)
R^2	0.18	0.16	0.19	0.14	0.18
NOB	491,088	436,335	408,240	434,995	551,946

Lifetime >= 5

	8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Δpriority(Depth)	-5.16***	-5.31***	-6.00***	-3.15***	-1.81***
	(0.47)	(0.45)	(0.55)	(0.53)	(0.26)
Δpriority(Gap)	71.69***	55.28***	73.54***	58.37***	50.08***
	(4.34)	(4.02)	(5.19)	(4.51)	(2.65)
Gap	61.46***	44.11***	54.97***	45.25***	44.90***
	(2.94)	(2.04)	(2.73)	(2.38)	(2.16)
Vol	21.21***	9.46***	14.56***	12.14***	11.95***
	(3.99)	(1.63)	(3.07)	(1.85)	(2.68)
constant	-123.31***	-56.48***	-91.91***	-54.54***	-73.98***
	(10.36)	(6.40)	(8.70)	(7.00)	(7.12)
R^2	0.24	0.20	0.24	0.19	0.23
NOB	187,749	181,552	161,966	163,726	184,483

Note: Thresholds to exclude limit orders with short lifetimes are changed to zero and five seconds. The zero-second threshold includes the entire sample. See also the note for Table 4.

Table 7. EUR/USD Basic Lifetime Regressions
(Robustness with alternative depth definition)

	8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Δpriority(Depth)	-3.53***	-3.77***	-4.11***	-2.10***	-1.34***
	(0.33)	(0.33)	(0.39)	(0.37)	(0.18)
Δpriority(Gap)	70.61***	54.34***	72.59***	56.82***	49.72***
	(4.35)	(3.99)	(5.23)	(4.46)	(2.67)
Gap	50.22***	37.28***	44.61***	35.68***	36.24***
	(2.40)	(1.72)	(2.23)	(1.87)	(1.73)
Vol	15.92***	11.85***	14.49***	12.62***	7.81***
	(2.18)	(1.31)	(1.89)	(1.42)	(2.51)
constant	-93.28***	-50.50***	-72.97***	-44.10***	-55.70***
	(7.46)	(5.16)	(6.63)	(5.34)	(5.54)
R^2	0.21	0.18	0.21	0.17	0.21
NOB	257,215	243,558	219,990	224,778	262,866

Note: Modified version of equation (9) for Δ *Priority(Depth)* that includes the depth at the submitted quote.

Table 8. EUR/USD Extended Lifetime Regressions
(with order characteristics and market conditions)

	8-Sep	9-Sep	10-Sep	13-Sep	14-Sep
Δpriority(DEPTH)	-7.03***	-3.49*	-9.27***	-7.41***	-7.97***
	(0.98)	(1.87)	(1.31)	(1.19)	(0.94)
Δpriority(GAP)	40.34**	1.69	81.89***	30.63***	25.12***
	(18.57)	(14.17)	(19.90)	(9.70)	(6.85)
Gap	40.02***	34.99***	38.53***	31.56***	31.14***
	(2.59)	(1.80)	(2.27)	(1.88)	(1.62)
Vol	5.16**	2.81	4.26*	10.60***	3.35*
	(2.18)	(2.36)	(2.37)	(1.70)	(1.92)
Δ priority(Depth) interacted with					
GAP	0.09	0.07	0.13	0.51***	0.24***
	(0.13)	(0.09)	(0.15)	(0.15)	(0.07)
VOL	0.89***	0.08	0.01	-0.09	0.30
	(0.26)	(0.11)	(0.03)	(0.10)	(0.20)
DEPTH	0.00***	0.00	0.01***	0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CALM	0.18*	0.15	0.24***	0.12	0.31***
	(0.09)	(0.17)	(0.06)	(0.09)	(0.10)
Δ priority(Gap) interacted with					
GAP	4.09***	1.73*	4.62***	4.87***	2.22***
	(0.92)	(1.03)	(1.09)	(1.14)	(0.22)
VOL	10.44***	8.96***	7.40***	0.12	3.00***
	(2.34)	(2.83)	(1.84)	(0.90)	(0.99)
DEPTH	-0.10*	0.09*	-0.19***	-0.01	-0.03
	(0.06)	(0.05)	(0.05)	(0.02)	(0.02)
CALM	1.77***	0.64	-0.37	0.49	1.28***
	(0.24)	(0.70)	(0.60)	(0.32)	(0.46)
constant	-46.93***	-35.37***	-39.14***	-25.76***	-29.98***
	(7.83)	(6.09)	(6.90)	(5.74)	(4.52)
R^2	0.37	0.20	0.29	0.23	0.27
NOB	257,215	243,558	219,990	224,778	262,866

Note: See notes for Table 4.

Appendix Tables

A1. Lifetime by Gap for executed and canceled limit orders

8-Sep	executed limit orders							cancelled limit orders					
gap	nob	median	0.95	0.99	mean	std	gap	nob	median	0.95	0.99	mean	std
-2	1769	0.03	0.80	13.28	0.62	5.37	-2	13	0.63	25.32	25.32	4.07	7.63
-1	15988	0.16	16.21	82.53	5.38	59.01	-1	6037	1.00	75.72	378.15	19.42	89.83
0	23820	2.09	56.01	235.99	15.62	88.10	0	136441	1.24	61.51	304.35	16.96	86.27
1	6315	7.12	200.50	716.38	46.44	173.43	1	153217	2.13	98.65	385.01	23.57	122.31
2	1615	31.12	520.57	1324.52	119.46	372.01	2	52464	3.53	94.70	348.59	24.90	150.08
3	675	67.78	1092.11	1996.72	223.62	487.47	3	31540	4.76	131.07	459.82	33.88	183.76
4	482	107.36	1158.27	2488.23	275.36	481.01	4	23616	6.17	157.48	554.00	40.47	174.80
5	323	169.55	1834.43	5005.62	432.01	789.85	5	17514	5.15	181.22	633.13	44.82	264.88

9-Sep	executed limit orders							cancelled limit orders					
	nob	median	0.95	0.99	mean	std		nob	median	0.95	0.99	mean	std
-2	1409	0.08	1.37	14.75	0.81	8.14	-2	8	2.33	16.11	16.11	6.13	6.84
-1	14877	0.15	15.43	88.34	5.21	85.69	-1	5685	1.00	72.31	280.50	16.97	98.87
0	20593	2.32	56.25	248.98	16.25	78.16	0	101635	1.62	82.10	371.18	20.86	127.11
1	4862	8.59	252.38	851.06	57.79	183.48	1	131485	2.82	114.40	438.09	27.69	155.58
2	1325	34.60	508.23	1634.88	122.86	313.10	2	55631	3.80	101.99	375.78	26.16	123.42
3	578	66.44	920.25	1945.79	220.44	522.23	3	33966	4.44	118.22	424.89	31.19	186.46
4	372	115.25	1133.03	3497.84	302.23	727.08	4	26519	4.58	143.77	491.81	35.64	164.60
5	236	170.73	1565.86	2963.40	369.30	688.28	5	23392	3.89	181.74	649.15	46.00	252.48

10-Sep	executed limit orders							cancelled limit orders					
	nob	median	0.95	0.99	mean	std		nob	median	0.95	0.99	mean	std
-2	1299	0.08	2.80	21.55	1.14	9.14	-2	34	2.83	446.35	815.82	45.85	156.46
-1	14073	0.15	19.14	101.90	6.22	61.58	-1	5322	1.03	77.60	459.50	22.87	127.75
0	21198	2.38	69.51	285.62	18.34	126.33	0	111200	1.51	79.79	386.09	20.47	97.42
1	4701	8.25	231.84	821.32	56.19	229.88	1	113787	2.77	119.49	442.89	27.59	113.99
2	1260	36.45	571.25	1459.12	133.28	370.76	2	45667	3.58	112.28	365.59	27.69	137.56
3	582	83.81	945.46	2226.25	226.51	433.22	3	33777	3.59	127.44	442.12	31.44	145.10
4	339	149.66	1153.29	5654.73	359.62	864.88	4	25353	4.28	148.89	479.88	35.47	158.67
5	232	143.93	1276.88	2503.16	367.26	589.52	5	16238	4.01	183.92	623.58	44.69	230.27

13-Sep	executed limit orders							cancelled limit orders					
	nob	median	0.95	0.99	mean	std		nob	median	0.95	0.99	mean	std
-2	1298	0.08	1.53	33.26	1.66	17.88	-2	22	1.23	40.93	43.23	9.46	15.27
-1	14683	0.16	16.43	90.07	5.76	93.51	-1	4957	0.96	66.00	347.17	17.71	80.15
0	23557	2.47	66.28	296.51	18.50	102.55	0	116328	1.45	69.57	426.46	20.46	104.13
1	5043	8.36	245.89	860.85	63.70	393.05	1	125535	2.40	106.36	429.20	26.07	116.38
2	1335	33.76	530.56	1763.92	137.15	411.41	2	53546	3.28	95.50	349.18	24.43	125.32
3	554	87.88	983.70	2710.94	255.26	709.78	3	29568	4.50	156.81	658.35	39.20	159.73
4	304	151.58	1462.66	6612.84	470.74	1614.12	4	20875	5.40	195.29	701.63	47.58	238.27
5	220	225.77	2275.61	3591.07	506.10	739.78	5	21290	2.92	179.86	628.22	43.12	284.51

14-Sep	executed limit orders							cancelled limit orders					
	nob	median	0.95	0.99	mean	std		nob	median	0.95	0.99	mean	std
-2	1991	0.02	0.75	6.25	0.57	5.91	-2	13	1.38	37.08	37.08	5.70	10.51
-1	19174	0.11	11.83	69.26	4.57	128.15	-1	6369	0.77	58.15	327.50	16.82	87.40
0	31342	1.48	50.31	221.39	14.36	98.14	0	150440	1.10	53.56	257.21	14.88	90.04
1	8430	5.45	163.12	655.87	41.28	183.07	1	161860	1.65	74.88	303.15	19.26	108.37
2	2426	12.86	275.09	883.20	64.75	197.96	2	69817	2.36	66.80	266.24	18.37	110.05
3	1011	32.19	718.66	1918.67	146.67	365.19	3	41383	2.99	99.10	393.95	26.87	143.45
4	574	56.39	695.59	2095.46	194.56	553.24	4	28949	3.36	119.62	427.99	32.91	286.96
5	356	104.86	1776.10	5249.53	417.94	1474.96	5	21055	3.08	132.93	454.18	32.42	187.86

Note: Lifetimes decomposed by Gap are shown for executed and canceled limit orders. Along the mean and median, lifetime at the 95th and 99th percentiles are shown.

A2. Natural log of lifetime

	lifetime	ln(lifetime)
Δpriority(DEPTH)	-7.03***	-0.002***
	(0.98)	(0.001)
Δpriority(GAP)	40.34**	0.246***
	(18.57)	(0.010)
Gap	40.02***	0.121***
	(2.59)	(0.001)
Vol	5.16**	0.003
	(2.18)	(0.002)
Δ priority(Depth) interacted with		
GAP	0.09	-0.00091***
	(0.13)	(0.00008)
VOL	0.89***	0.00057***
	(0.26)	(0.00017)
DEPTH	0.00***	0.00000***
	(0.00)	(0.00000)
CALM	0.18*	0.00016***
	(0.09)	(0.00002)
Δ priority(Gap) interacted with		
GAP	4.09***	-0.012***
	(0.92)	(0.001)
VOL	10.44***	0.009***
	(2.34)	(0.001)
DEPTH	-0.10*	0.000***
	(0.06)	(0.000)
CALM	1.77***	0.001***
	(0.24)	(0.000)
constant	-46.93***	2.335***
	(7.83)	(0.005)
R^2	0.37	0.12
NOB	257,215	257,215

Note: Only estimation results for the 8th of September are shown due to space constraints. The results for the remaining four days are readily available upon request.

A3. Tobit regression

	OLS	Tobit
Δpriority(DEPTH)	-5.63***	-4.06***
	(0.92)	(0.90)
Δpriority(GAP)	32.83*	60.43***
	(17.62)	(18.06)
Gap	23.73***	38.30***
	(1.48)	(2.15)
Vol	4.23**	2.17
	(1.98)	(2.34)
Δ priority(Depth) interacted with		
GAP	0.09	-0.02
	(0.13)	(0.13)
VOL	0.64***	0.73***
	(0.23)	(0.20)
DEPTH	0.00***	0.00***
	(0.00)	(0.00)
CALM	0.18*	0.18**
	(0.09)	(0.09)
Δ priority(Gap) interacted with		
GAP	4.54***	3.10***
	(0.89)	(0.90)
VOL	8.95***	9.98***
	(1.93)	(1.93)
DEPTH	-0.09	-0.11*
	(0.06)	(0.06)
CALM	1.83***	1.85***
	(0.25)	(0.24)
constant	-25.32***	-275.45***
	(4.39)	(14.53)
R^2	0.34	
F stat.	99.56	133.10
NOB	491,088	491,088

Note: F stat. denotes F statistics with degree of freedom as the number of coefficient (NOC) and NOB minus NOC, which tests the null hypothesis that all regressors are statistically insignificant. Only estimation results for the 8th of September are shown due to space constraints. The results for the remaining four days are readily available upon request.