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"Every move you make, every step you take, I'll be watching you" – the quest for hidden orders in the interbank FX spot market

Katarzyna Bień-Barkowska*

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Abstract

In the paper[2] we seek to investigate different liquidity or information-oriented factors that exert an impact on the submission of iceberg (i.e., partially hidden) orders in the Reuters Dealing Spot 3000 Matching System, the major interbank order-driven market for EUR/PLN spot trading. With this empirical analysis, we present the first – to our knowledge – market microstructure study on the order exposure decisions in FX markets. Our results indicate that the decision whether to hide a part of the submitted order size is significantly influenced by order attributes, measures of the order book shape, and the prevailing market conditions. Thus, we evidence that FX dealers perform a constant monitoring of time-varying market conditions and constantly adjust their individual trading decisions with regard to the continuously changing market environment. The most significant factors explaining order exposure include the size of submitted order and the level of its aggressiveness, different measures of the instantaneous liquidity of the market, the time of a day, previously observed returns, volatility, and the types of orders previously observed. When having taken into account all of these explanatory factors that may be either observable or unobservable by other market participants, the prediction accuracy of the endogeneity-corrected probit model for the decision whether to submit an iceberg order is very high.

Keywords: hidden orders, market microstructure, interbank FX spot market

JEL: C35, C58, F31, G15

* Warsaw School of Economics, Institute of Econometrics; Narodowy Bank Polski, Financial System Department; e-mail: katarzyna.bien@sgh.waw.pl.

[1] The title is taken from the lyrics of the song *Every breath you take* by the Police.

1. Introduction

Throughout the last two decades there has been a large upsurge in the number of research studies concerning order submission strategies on automated order-driven markets. Many theoretical models have described individual order submission decisions as a kind of inter-temporal economic game between different market participants (i.e., Parlour 1998; Foucault 1999; Foucault, Kadan, Kandel 2005; Goettler, Parlour, Rajan 2005; Rosu 2009). These formal models have been consequently followed by empirical studies suggesting adequate econometric tools to depict the dynamic sequencing of different order types in an effort to account for possible causality or contemporaneous interdependence between actions undertaken by individual traders (i.e., Hautsch 2004; Bauwens, Hautsch 2006; Bowsher 2007; Large 2007; Hall, Hautsch 2006; Hall, Hautsch 2007; Lo, Sapp 2008; Bień-Barkowska 2014).

Identifying different factors that determine decisions about the timing of different order types may be important from the viewpoint of: (i) the academics, as it permits deeper insight into the process of price and liquidity formation at the micro level; (ii) the market regulator, as it helps to design a proper institutional framework for the most efficient market (i.e., a quick process of the price discovery) and a safe and smooth trading process;[2] (iii) the traders, as it allows to set up a most advantageous high-frequency trading strategy. Therefore, much effort should be taken in order to describe order submission rules while taking into account the timing of order arrivals, continuously changing order attributes and other various measures of instantaneous market conditions.

In the order-driven markets (i.e. limit order markets) a trader can submit two major types of orders (i.e., market orders or limit orders) to a central marketplace called a limit order book (LOB). Buy and sell orders are continuously and automatically matched once their prices agree. Market orders are perceived as liquidity consuming and the most aggressive in nature since they are always immediately executed against the most competitive limit orders waiting in the order book. For a limit order that is always liquidity-supplying and sometimes termed as a "patient" order, a trader specifies its attributes (a price and a size) and an order waits in the LOB for execution in the future when it will be matched against an incoming market order. Nowadays, limit order markets dominate trading within the stock markets. Examples of this include the Euronext Paris, the SEAQ, the NASDAQ and the UTP system at the Warsaw Stock Exchange. According to the literature on market microstructure and limit order markets, the pace of different orders arriving to the market can provide insight into the trading intentions of market participants in terms of their heterogeneous expectations and preferences. Recent access to high-frequency databases that contain information on the exact timing and detailed characteristics of different order placements have encouraged many empirical studies that have investigated how different information or liquidity dependent factors influence the choice between limit orders and market orders (i.e., Bae, Jang, Park 2003; Ranaldo 2004; Verhoeven, Ching, Ng 2004; Ellul et al. 2007; Lo, Sapp 2008; Lo, Sapp 2010).

[2] The safe and smooth trading process is particularly important from the viewpoint of the predominant use of algorithmic trading (AT) strategies in many order-driven markets. ATs are pre-programmed computer algorithms that automatically submit or cancel different orders on the electronic trading platform, usually without any human intervention. Commercial banks use algorithmic trading on FX markets in order to profit from any possible arbitrage opportunities, in order to alleviate the price impact of large market orders, and to perform ultra-high-frequency trading strategies (often based on speculation). In stock markets, ATs were responsible for the severity of the "Flash Crash" of 6 May 2010, i.e. an instantaneous stock market crash in the United States where the Dow Jones Industrial Average rapidly decreased in value by about 9% yet recovered its previous value just a few minutes later (see SEC, CFTC 2010).

There is a growing branch of literature on order exposure strategies within the mainstream of market microstructure studies on limit and market order submission rules (i.e., submissions of hidden orders). Two major types of hidden limit orders can be distinguished: (i) iceberg (i.e., reserve) orders where only the small part (i.e., the peak) of the order size is visible in the order book whereas the residual and typically predominant portion of the order size cannot be observed by other market participants;[3] and (ii) entirely hidden orders where the size and the price of a limit order remains undisclosed. The latter constitutes a so called "dark liquidity" since it is not possible to know either the standard order attributes nor the location of these entirely invisible orders.

The aim of this paper is to identify the explanatory variables that exert an impact on the submission of hidden orders in the Reuters Dealing 3000 Spot Matching System, which is a major order--driven platform for interbank trading of the EUR/PLN. Hidden orders are limit orders where the trader decides to hide at least a fraction of the corresponding order size. Our explorative study is made possible as a result of access to the detailed datasets on the attributes of different orders submitted within the trading system. With this data we will trace hidden order submission patterns based on their time of a day, the shape of the order book, market trends and the type of the previously observed orders. Accordingly, we aim to check for liquidity or information oriented factors that might impact hidden order submissions at different levels of the order book.

Reserve orders have become extremely popular in stock markets all over the world. Bessembinder, Panayides and Venkatamaran (2009) states that such undisclosed orders constitute about 44% of the trading volume of stocks traded on the Euronext-Paris. Nowadays, the majority of stock exchanges worldwide (i.e., NASDAQ, Toronto Stock Exchange, Euronext, London Stock Exchange, Australian Stock Exchange, Warsaw Stock Exchange) enable some form of a reserve order to match the rising expectations of investors that are reluctant to make their trading motives blindingly obvious by disclosing all of their order attributes. In the interbank EUR/PLN spot market undisclosed orders account for about 18% of submitted limit orders, thus their share is not as considerable as for stocks markets. However, the literature on order submission rules in FX markets is extremely scarce and – to our knowledge – there are no empirical studies focused on order exposure. Henceforth our intention is to fill in this gap and provide some insights about the major motives of currency dealers when keeping the full size their limit orders disclosed or not.

This paper consists of five distinct sections. In the Section 2 we sum up the current knowledge about hiding orders and we present an overview of the literature on the order exposure strategies. In Section 3 we describe the trading environment of the Reuters 3000 Spot Matching System and describe the datasets used for the empirical study. In Section 4 we present an endogeneity-corrected probit model for the binary indicator of a reserve order submission. Section 5 evaluates and discusses the estimation results of the econometric model and in Section 6 we sum up and conclude our findings.

2. Literature background

According to the literature on order exposure rules, there are three major reasons for an extensive use of hidden orders in trading strategies. First, hiding at least a fraction of the order size alleviates the

[3] If the peak of an iceberg order gets executed against an upcoming market order, another portion of the order reappears (i.e., another peak comes above the surface). However, this new visible part of an order loses price priority to other orders submitted at the same price (i.e., it lands as the last in the queue).

so-called "free trading option risk" of a limit order. Copeland and Galai (1983) introduced this term when they argued that the submission of a limit buy (sell) order is equivalent to writing a free put (call) option to the market, where the exercise price of an option is equal to the price of the order. Obviously the price of a limit order is "frozen" from the moment the order is submitted; therefore, it does not have to be the same as the posterior value of the asset (at the moment of a trade execution). Accordingly, this leads to a loss if the limit order is executed at an unfavorable price. This kind of danger arising from adverse movements of price is always impounded in the nature of limit orders and is called the "risk of being picked-off" whereas a limit order is sometimes referred to as a "sitting duck". Hiding the full size of a limit order allows the investor to reduce the option value of a stale limit order[4] (i.e. an order which does not reflect current market information), thus it constrains the risk that the entire size of the order will be hit by an upcoming market sell order or taken by an upcoming market buy order causing ex-post regret. Accordingly, hidden orders limit the cost of continuous monitoring, canceling, or revising submitted limit orders to keep in step with constantly changing market conditions.

The second important reason for the increasing popularity of hidden orders is the need to defend against the parasitic trading strategies of other market participants. Studies on this matter date back to the works of Harris (1996 and 1997) who treats the limited limit order exposure as a weapon against predatory traders, who are always eager to use information concerning order size to the disadvantage of the order submitter. A parasitic trader who suspects that another trader is going to buy (or sell) a large amount of the security may front run such an order (i.e., quote a better, more competitive bid (ask) price) by submitting an in-the-quote limit order or even a market buy (sell) order with the intention to excessively move the price. This kind of practice results in an artificial overshooting (overbidding) of the best bid price or, respectively, undercutting the best ask price at the expense of an initial trader who has exposed his large order. Predatory traders profit from these temporary price movements since they absorb liquidity at a price that might have been proposed to the initial trader. When the large trader wants to finish his trades, the predatory traders may sell back (buy back) an asset at a price that is inferior for him. Harris (1996) shows that the scale of front running strategies increases when lowering the size of the minimum price variation (i.e., tick) because it is cheaper for front runners to quote a price that is only a little more competitive than the best price prevailing in the order book. The front running phenomenon has been studied by Brunnermeier and Pedersen (2005), who propose a formal model that investigates the interaction between a distressed trader who wants to liquidate his position and a predators profiting from the price impact of his trades and the temporary induced price swings. Brunnermeier and Pedersen (2005) show that predatory trading strategies tend to magnify a trader's liquidation cost and therefore the default risk may also have an impact on the systemic risk of the market.

The third reason why traders may want to keep the size of their orders undisclosed is the information-oriented motives of their trades. The decision whether or not to hide an order may be significantly associated with the amount of private information[5] possessed by a trader. If the informed

[4] An option value of a limit order is the value of this order to other market participants (cf., Harris 2003, p. 75).

[5] Trading on private information is widely recognized to be an important feature of FX markets. A vast discussion of this topic has been recently provided by King, Osler, Rime (2013). Accordingly, an access to different information can result from different scale of exposure to bank clients (i.e. large banks have an informational advantage over small ones), private research on market fundamentals or even being a member of a social network of traders (a platform for sharing views). Heterogeneous pieces of private information that are dispersed amongst market participants are to be impounded in asset prices through the mechanism of order flow. Order flow, defined as the imbalance between the number (or volume) of market buy and market sell orders, can therefore be perceived as a measure of the backed-by-money expectations, i.e. voting of the market (cf., Lyons 2000, pp. 6–8).

trader wants to exploit this information and gain profit against other uninformed market participants he may opt for aggressive large limit orders while at the same time keeping their large size secret. This is because informed traders avoid spreading their superior information across the market, which would destroy any profit gained from the adverse selection. Clearly, if a trader exposes his order size and other market participants discover its informational content, they will not supply liquidity at the specified price but will withdraw liquidity from the market. Hence, the opposite side of a market will "escape" from a large trader. This reasoning supports the opinion that hidden orders should go in line with a high order size and increased execution priority (i.e., price aggressiveness).

There are just a few theoretical models that aim to formally describe the order exposure rules. Esser and Mönch (2007) propose a model that allows the establishment of an optimal peak size for an iceberg order. Their framework establishes the best compromise between the advantage of a large peak size that improves the price priority of a reserve order and the large adverse selection costs associated with disclosing a large order to the market. Monais (2010) presents a sequential trade model, which shows that hidden orders may be used not only by informed traders but also by liquidity traders who wish to soften the informational impact of their large orders. She also assumes that the exposure of large orders discourages liquidity (defensive) market participants from trading, as they believe that large orders may signal an inflow of some inside information. Buti, Rindi and Werner (2011) build a formal model that allows orders to be split between two market places: the LOB and the dark pool. Dark pools are the non-transparent alternative trading venues where the exchange of entirely hidden liquidity takes place. They do not disclose the best price orders (i.e., the pre-trade prices are not made public) thus the adverse price impact of a trade is kept at a minimum. Traders who want to sell an asset can access a dark pool, place a bid quotation, and eventually have their order matched with a buyer electronically and with full anonymity.[6] Therefore, the reduced transparency of dark pools gives protection to institutional traders placing large orders that would otherwise suffer from front-running strategies. The theoretical model of Buti, Rindi and Werner (2011) shows that trader decisions about order direction relies on the current shape of the order book; for example, large depth and small spread encourages traders to use dark pools.

The empirical literature concerning the use of hidden orders is not that scarce. Aitken, Berkman, Mak (2001) provides an empirical analysis of undisclosed limit orders at the Australian Stock Exchange. These results indicate that hidden orders may be used by informed or uninformed traders to limit the free option risk of limit orders. Their study proves a positive impact of volatility and average order size and a negative impact of trading activity on using undisclosed orders. Anand and Weaver (2004) investigate the liquidity of the Toronto Stock Exchange around two exogenous shocks to the market mechanism: abolishment of the hidden orders on the Electronic Computer Aided Trading System (CATS) in 1996 and their subsequent reintroduction in 2002. They found that the general level of market liquidity (i.e., quoted bid-ask spread, quoted depth, and trading volume) did not change after the abolition of hidden orders. However, the frequency of quote updates increased after traders were allowed to use hidden orders, which indicates that traders who actively use the information impounded in the order book may use the ability to hide orders more eagerly. Beltran-Lopez, Giot and Grammig (2009) analyze data from the Xetra trading system of the Frankfurt Stock Exchange concerning commonalities amongst different

6 The popularity of these dark-trading facilities is constantly growing. There are currently about 50 dark pools in the United States alone (cf., Patterson 2012). The upsurge in non-transparent markets has recently evoked concerns about evaporation of liquidity in regulated public stock exchanges and the establishment of an unsupervised and unregulated two-tier asset exchange system.

measures of the order book shape. They show that the visible and hidden parts of the order books are driven by distinct, although correlated, latent factors. Chakrabarty and Shaw (2008) examine hidden orders for stocks traded on the electronic marketplace INET. They show that the number and average trade size of executed hidden orders rises significantly around earnings announcements. Thus, hidden orders supply liquidity in periods when the quoted liquidity is usually scarce. Buti, Rindi and Werner (2010) explore the data collected on 11 of 32 dark pools that were active in the US equity market in 2009. Their analysis shows that the equities actively traded in dark pools are more liquid, and have a higher average price. They also have a lower quoted and effective spread and lower intraday volatility. Hautsch and Huang (2012) analyze the use of entirely hidden orders at NASDAQ. They investigated a wide cross--section of stocks and showed that market microstructure variables such as the bid-ask spread, depth, recent price movements, and trading indicators all influence the aggressiveness of entirely hidden orders. Moreover, what is crucial from the viewpoint of our analysis is that according to Hautsch and Huang (2012), the existence of hidden liquidity may be predicted given the visible state of the market.

The empirical analysis conducted in this paper has been greatly inspired by the research studies of De Winnie and D'Hondt (2007) and Bessembinder, Panayides and Venkatamaran (2009). De Winnie and D'Hondt (2007) investigate the variables affecting trader decisions to conceal a full order size for CAC40 stocks traded on the Euronext. Using the logit regression approach they showed that traders are more inclined to hide their entire order sizes if the size of an order is large relative to the visible depth of the LOB or if the price of an order is competitive and the bid-ask spread is small. The quality of data that they use allows them to also differentiate between market participants. Thus, they show that the probability of submitting a reserve order is higher for client orders (i.e., orders submitted by brokers on account on their clients) than for principal orders (i.e. orders submitted by brokers on their own account). They also show that the discovery of hidden depth on the opposite side of the market increases the aggressiveness of submitted orders. Bessembinder, Panayides and Venkatamaran (2009) also analyze Euronext Paris stocks and show that the existence of hidden orders in the order book can be predicted to a significant degree by observable market conditions and different order characteristics.

3. Market and data

The Reuters Dealing 3000 Spot Matching System is a major order-driven market for interbank trading of the EUR/PLN currency pair in Poland and the offshore market (i.e., mainly between London banks). It is an electronic automated system that can match incoming buy and sell orders once their prices agree. Interbank currency dealers can submit either market or limit orders. If a limit order enters the order book and it cannot be immediately matched against the most competitive order on the other side of a market, it must wait a predetermined period of time for possible future execution or can also be cancelled at any time. For every limit order a currency dealer selects an order size as well as a bid (or ask) price at which he agrees to buy (or sell) euro against the Polish zloty. The EUR/PLN exchange rate is quoted as a quantity of zlotys per one euro and the transaction (base) currency is euro. The smallest order size is 1 million EUR. The submission of iceberg orders is allowed, although an arbitrarily chosen "peak" of an order size must be visible (submissions of entirely hidden orders in not allowed in the trading system). For example, a trader may wish to buy 30 million EUR against PLN at a given rate (quote) of 3.1541 but at the same time this trader may be reluctant to disclose his trading intentions to the entire market. Accordingly, he may submit a limit order to buy EUR against PLN with an observable peak of 3 million EUR and an unobservable size equal to 27 million EUR, all at the same predefined price. The order enters the market and lands at the appropriate level of the LOB, which depends on the competitiveness of its price in comparison to the prices of other limit orders awaiting execution. Other market participants cannot see the full size of the submitted order, only its visible smaller portion of 3 million EUR.[7]

The datasets used in this study consisted of all incoming market and limit orders between 2 January 2008 and 30 March 2008[8] submitted to the Reuters Dealing 3000 Spot Matching System for the EUR/PLN currency pair. Each limit order is marked with the exact time of its submission (measured to one hundredth of a second), execution or cancellation, a price, the hidden and visible size of the order, and an indicator of the market side. Trading on the interbank market can take place 24 hours a day, 7 days a week. However, it is heavily concentrated on working days from 8:00 to 18:00 Central European Time (GMT+1, with Daylight Saving Time). In order to limit the undesired impact of periods where trading activity was particularly thin, we excluded days with exceptionally small trading activity, weekends, national holidays and periods outside the usual working hours (i.e., between 18:00 and 8:00 CET). As a result, our sample includes data on 154,967 order submissions.

The detailed outlay of our datasets encouraged us to rebuild the exact detailed shape of the LOB at each centisecond of market activity. To this end, we attempted to exploit the extraordinary richness of information that prevails in the ultra-high-frequency data and capture each movement of the LOB that may exert a direct or indirect impact on the actions undertaken by individual traders. In Figure 1 we present the exemplary picture of the LOB on 23 January 2008, exactly 13.74 seconds after 14:48 (CET). At this particular moment the best (most competitive) ask price available in the market was 3.6315 EUR/PLN whereas the best (most competitive) bid price was 3.6280 EUR/PLN. These two prices correspond to the first level of the order book. Accordingly, the observable bid-ask spread is equal to 35 pips (hundredths of a Polish grosz[9]). The depth available at the best quotes amounts to 1 million EUR on the bid and ask side of the market. A discrepancy between the prices of limit orders posted on the bid and ask side of the market becomes larger as we depart from the most competitive quotes. As far as hidden liquidity is concerned, we can see a hidden depth of 5 million EUR on the fifth level of the ask side of the LOB and, analogously, on the fifth level of its bid side (at rates 3.6365 and 3.6226, respectively). All of this information is useful not only for measures of instantaneous market liquidity, but it might also provide a proxy for the amount of information possessed by market players and expectation heterogeneity among them.

Our intention is to depict the systematic patterns of hidden order submissions that take place on different levels of the dynamically reconstructed LOB. As the first level of the LOB plays the first fiddle in market play, the decision whether to hide an order between the best quotes should be, possibly, the most vulnerable with respect the prevailing market conditions. The most aggressive limit order is always the first to be hit (by an incoming market sell order) or to be taken (by an incoming market sell order) and thus it is the most endangered by the changing information content of upcoming market orders. By contrast, the decision to submit a hidden order behind the first line of the market stage could result from awaited price movements; otherwise the hidden order would have never been executed.

[7] A reserve order might get fully executed if it is matched against most aggressive limit order submitted on the opposite side of a market.

[8] In the period studied the Polish zloty followed an appreciation trend towards euro.

[9] A Polish grosz is a one-hundredth subdivision of the Polish zloty.

Therefore, we decided to categorize incoming limit orders according to their level of aggressiveness as in the study of Bień-Barkowska (2014):

IQB – submission of an inside-the-quote limit buy order. In this case the price of the incoming buy order is higher than the best bid price but lower than the best ask price. Such orders improve the best bid price. There are 29,153 IQB orders in the sample, which accounts for 18.8% of all submitted orders.

IQS – submission of an inside-the-quote limit sell order. In this case the price of the incoming sell order is lower than the best ask price but higher than the best bid price. Such orders improve the best ask price. There are 31,697 IQS order submissions in the sample, which accounts for 20.5% of all order placements.

AQB – submission of an at-the-quote limit buy order. In this case the price of the incoming buy order is equal to the best bid price in the order book. These orders increase the depth at the best bid. There are 7,979 AQB orders, which accounts for 5.1% of all order submissions.

AQS – submission of an at-the-quote limit sell order. In this case the price of the incoming sell order is equal to the best ask price prevailing in the system. These orders increase the depth at the best ask. There are 9,205 AQS orders, which accounts for 5.9% of all order placements.

BQB – submission of a behind-the-quote limit buy order. In this case the price of the buy order is lower than the highest (most competitive) bid price in the order book. There are 15,407 BQB order submissions in the sample, which accounts for 9.9% of our sample.

BQS – submission of a behind-the-quote limit sell order. In this case the price of the sell order is higher than the lowest (most competitive) ask price in the order book. There are 15,874 BQS order submissions, which accounts for 10.2% of all orders submissions.

The residual 29.6% of all order submissions are market orders or, to a much lesser extent, marketable limit orders, which result in immediate execution.[10] In Figure 2 we depict the "dark" content of upcoming limit orders that were classified according to the aforementioned scheme. We can see that the frequency of iceberg order placements (i.e., the number of iceberg orders in the overall number of limit order submissions) as well as the share of hidden liquidity in the overall supply of liquidity (i.e., the cumulated hidden size of submitted limit orders to the cumulated entire size of submitted limit orders) increases with order aggressiveness. In other words, both of these ratios rank highest for orders placed inside or at the best quotes. Additionally, we observe the latent portion of order size for all iceberg orders constitutes the predominant part of these orders and average peaks of such orders accounts for only 20–30% of the order size, which is in line with the conviction that dealers prefer to hide large orders.

We assume that currency dealers are continuously monitoring time-varying trading conditions, which are reflected by market trends, instantaneous liquidity of the order book, and previously submitted orders. This constant watching enables them to harness all favorable trading conditions and undertake an optimal (i.e., most profitable) action at any given point in time. We define the following explanatory variables:

The order size, defined as the natural logarithm of the entire size of a submitted limit order or its peak only (the visible portion of its size). One or the other variable has been used in two different model parameterizations.

The price aggressiveness indicator, defined for the bid side of the market as the difference between the price of the submitted buy limit order and the best bid price, and for the ask side of the

[10] Marketable limit orders account for less than one third of all orders resulting in immediate execution.

market as the difference between best ask price and the price of the submitted order (the difference is then divided by the bid-ask spread to eliminate the impact of instantaneous liquidity). Accordingly, the greater the aggressiveness indicator variable, the more aggressively priced is the order and shorter is the distance to the opposite side of a market.

The bid-ask spread, defined as the difference between the best ask price and the best bid price in the LOB just before the moment of the order submission (measured in number of pips).

The visible ask depth and the visible bid depth, defined as the cumulated sizes of limit orders offered to sell (buy) at the best ask and bid prices, respectively (measured in million EUR).

The hidden ask depth and the hidden bid depth, defined as the cumulated sizes of hidden portions of limit orders offered to sell (buy) at the best ask and bid prices, respectively (measured in million EUR).

Ask and bid quote slopes measuring the shape of the LOB. The ask quote slope is defined as the ratio of the difference between the highest ask price prevailing in the system (P_{ask}^{worst}) and the lowest ask price (P_{ask}^{best}) to the cumulated ask depth ($\sum_{i=1}^{m} Size_{ask,i}$). Bid quote slope is defined as the ratio of the difference between the best bid price (P_{bid}^{best}) and the lowest bid price in the system (P_{bid}^{worst}) to the cumulated bid depth ($\sum_{i=1}^{n} Size_{bid,i}$).

$$askQS = \frac{P_{ask}^{worst} - P_{ask}^{best}}{\sum_{i=1}^{m} Size_{ask,i}}, \quad bidQS = \frac{P_{bid}^{best} - P_{bid}^{worst}}{\sum_{i=1}^{n} Size_{bid,i}} \tag{1}$$

EUR/PLN return, calculated as the log return of the EUR/PLN mid-price in the 10-minute period prior to the moment of the order submission (measured in basis points).

EUR/PLN order flow, measured as the difference between the quantity of market buy and market sell orders submitted in the 10-minute period prior to a limit order submission.

The EUR/PLN return volatility, constructed as a realized volatility estimate for the 10-minute period prior to the order submission. In order to calculate the realized volatility estimate, log returns of all observable mid prices have been used.

The trading volume, measured as the number of trades on the interbank EUR/PLN spot market for the 10-minute period before order submission.

EUR/USD return, measured as the log return of the EUR/USD mid price in the 10-minute period prior to order placement (measured in basis points).

EUR/USD order flow, taken as the difference between the quantities of market buy and market sell orders submitted for the EUR/USD currency pair in the 10-minute period prior to the order submission.

Six binary variables indicating the types of previously submitted orders (i.e., MB denoting a market buy, MS denoting a market sell, IQS, IQB, BQS, BQB).

The selection of the explanatory variables stems from our initial assumption that currency dealers want to profit from all possible pieces of new information at a moment's notice in order to take advantage of any favorable trading opportunity. First, some of explanatory variables aim to depict the ex-ante instantaneous liquidity of the market just before any action is undertaken by a dealer. These variables are: ask (bid) depth, bid-ask spread, ask (bid) quote slopes. Other factors aim to assess the inflow of new information (or market trending behavior) during the past ten minutes prior an limit order submission. These variables are: EUR/PLN return volatility, return on the EUR/PLN, EUR/PLN order flow, order flow and return on the EUR/USD, types of previously submitted orders, number of previously executed trades. Due to a constant "watching behavior" performed by currency dealers, each of these diverse exploratory factors might carry an important piece of news for the profitability of instantaneous trading decisions. As in the studies of De Winnie and D'Hondt (2007) or Bassembinder et al. (2009) we also account for measurable properties of limit orders under study such as their sizes and the levels of their aggressiveness.

The explanatory variables that exhibited intraday periodicity (i.e., the bid-ask spread, the ask and bid quote slopes, the number of trades, and the volatility measure) have been initially deseasonalized by dividing the value of a given variable by a corresponding diurnality factor.[11]

In order to account for repetitive fluctuations (i.e., intraday seasonality pattern) in the use of hidden orders, we use the flexible Fourier form (FFF) defined as:

$$S(\mathbf{v},\tau) = \nu_0 \cdot \tau + \sum_{l=1}^{2}\left(\nu_{2l-1}\sin(2\pi l\tau) + \nu_{2l}\cdot\cos(2\pi l\tau)\right) \tag{2}$$

where τ denotes time-of-day variable standardized to [0, 1].

In order to calculate such a rescaled time-of-day variable, every moment of an order submission (measured as the number of seconds from 8.00 CET on each day) was divided by the number of seconds from 8.00 to 18.00 CET. $\mathbf{v}$ denotes a [5×1] parameter vector to be estimated (cf., Andersen, Bollerslev 1997). The FFF seasonality component has been treated as an additional additive explanatory factor, whereas different classes of limit orders may be characterized by different seasonality factors. Application of the FFF allows for a smooth pattern of systematic variation in the probability of submitting given type of iceberg orders throughout the trading day.

4. Econometric approach

Our modeling framework relies on an endogeneity-corrected probit model for a binary indicator of an iceberg order. The correction for endogeneity stems from the presence of an order size variable as one of the potentially most influential explanatory factors determining a dealer's "hide or not to hide" decision. We suspect that the larger the order size the more inclined a trader is to hide its full size in order to limit the spread of such private information, to limit the risk of being picked-off, or to avoid being front run by other traders. However, both decisions (i.e., what size of an order to choose and whether to hide a part of the order) are intertwined and determined jointly. As suggested by Bassembinder et al. (2009), we can anticipate a strong dependency between the two variables; however, the causality cannot be determined *ex ante*. In order to avoid an endogeneity bias in the probit model, we use a simple endogeneity correction, which requires building a bivariate model for two endogenous

[11] A diurnality factor is a functional description of an intraday seasonality characterizing given explanatory variable. This function has been obtained as a nonparametric (kernel) regression of the given regressor (i.e. explanatory variable) on a time-of-day variable (number of seconds after 8.00 CET on each day). We use the quartic kernel; whereas an optimal smoothing parameter has been selected with the standard Silverman's rule of thumb (see Silverman 1998). Bauwens and Veredas (2004) proposed estimating diurnality in this fashion.

variables: the binary variable y_t indicating the submission of an iceberg order and the continuous variable s_t for the (log) size of an order.[12] The starting point of this modeling framework is a bivariate Gaussian distribution of: (i) a latent continuous variable underlying the dichotomous "hide or not to hide" indicator y_t (this continuous Gaussian variable reflects an unobservable inclination to submit a reserve order); and (ii) a continuous variable depicting the (log) size of an order. The model is given as the following:

$$y_t^* = \alpha s_t + \mathbf{x}_t'\boldsymbol{\beta} + \varepsilon_t \tag{3}$$

$$s_t = \mathbf{x}_t'\boldsymbol{\gamma} + \sum_{i=1}^{p} \lambda_i s_{t-i} + \xi_t \tag{4}$$

where $y_t = 1$ if $y_t^* > 0$, $\mathbf{x}_t'$ denotes a vector of exogenous explanatory variables at t, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the parameter vectors corresponding to exogenous explanatory variables, and α and λ_i denote the scalar parameters.

In a standard extension to the univariate probit model, we assume the bivariate normality of the random terms ε_t and ξ_t:

$$(\varepsilon_t, \xi_t) \sim i.i.d.\, N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & \rho\sigma_\xi \\ \rho\sigma_\xi & \sigma_\xi^2 \end{bmatrix}\right) \tag{5}$$

Accordingly, the contemporaneous dependence between the size and the aptness to hide an order is separated into its directional impact (causality) and its residual correlation ρ of the random errors ε_t and ξ_t. The model can be easily estimated by maximizing the log-likelihood function[13] given as:

$$\ln L = \sum_{t=1}^{T}\left[\ln\Phi\left((2y_t - 1)\left(\alpha s_t + \mathbf{x}_t'\boldsymbol{\beta} + \rho\frac{1}{\sigma_\xi}\left(s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p}\lambda_i s_{t-i}\right)\right)\frac{1}{\sqrt{1-\rho^2}}\right) + \ln\left(\frac{1}{\sigma_\xi}\phi\left(\frac{s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p}\lambda_i s_{t-i}}{\sigma_\xi}\right)\right)\right] \tag{6}$$

where $\phi(\cdot)$ denotes the density function of a standard normal distribution and $\Phi(\cdot)$ is a corresponding cumulative distribution function.

As far as our econometric approach is concerned, most studies on hidden orders do not operate in a time-series framework but investigate determinants of hidden liquidity by means of cross-sectional

[12] Another potentially endogenous variable in our model could be the "price aggressiveness indicator". However, the empirical results of the Wald test confirmed, that the null hypothesis of the exogeneity could not be rejected at the significance level 5%.

[13] Derivation of the log-likelihood function has been presented in the Appendix.

linear regressions for different stocks (cf., Aitken, Berkman, Mak 2001 or Chakrabarty, Shaw 2008). The binary response models have been previously used by De Winnie and D'Hondt (2007) and Bassembinder et al. (2009) as a tool for possible investigation of undisclosed orders in a time-series setup. De Winnie and D'Hondt (2007) applied a standard logit model, whereas Bassembinder et al. (2009) corrected the logit model with respect to the endogeneity of the order size by means of the two-step instrumental variables estimator. In this framework, we suggest to profit from the merits of the one-step full information maximum likelihood approach.[14]

5. Empirical results

Having separated all of the incoming orders into six distinct classes (i.e., IQB, IQS, AQB, AQS, BQB, BQS) we estimate two different endogeneity-corrected probit models for each of the order types. The first model (model I) is where we take into account only these explanatory factors that may be directly observed or easily deduced by other market participants (i.e., visible size of the submitted limit order, order aggressiveness indicator, bid-ask spread, best ask and bid prices with the corresponding depths, EUR/PLN return, EUR/PLN order flow, EUR/PLN return volatility, number of trades, EUR/USD return and EUR/USD order flow, the type of previously submitted orders, and the time-of-day). The second model (model II) is where we account for the explanatory variables that cannot be observed by other market participants (i.e., hidden depths at the best bid and ask quotes, bid and ask quote slopes,[15] and the entire size of the submitted order instead of its visible peak only). Such a partition resembles the one used in the study of Bassembinder et al. (2009). Accordingly, for orders placed inside the best quotes or at the best quotes, the first model is built from the perspective of market participants, especially liquidity-takers (the demand side of the market), and can be perceived as a hint for discovering hidden liquidity from the observable attributes of recently submitted orders and the visible proxies for the current state of the market. However, the second model takes into account much more information and is specified from the viewpoint of an "all-knowing" econometrician who can monitor not only the entire size of the incoming orders but also other potentially informative but not publicly observable features of the order book. Thanks to impounding publicly unobservable variables, the second model is also much more precise in describing the aggregated behavior of the market as a whole from the "micro perspective". We estimate the models for the period of 2 January – 15 March 2008, whereas the data for the two weeks between the 16 and 31 March 2008 have been used for the sake of the out-of-sample evaluation of the models. The obtained estimation results of equation (3)[16] have been gathered in Table 1 (buy orders) and Table 2 (sell orders).

[14] Even if the likelihood-function were misspecified, due to the application of the bivariate normal distribution for the error terms, the estimation method can be treated as the quasi-maximum likelihood. Thus, the obtained parameter estimates are consistent and asymptotically normally distributed.

[15] Market participants in the Reuters Dealing 3000 Spot Matching System can directly observe only the first level of the LOB.

[16] Results of the Wald test showed that we have to reject the null of exogeneity (i.e. the null that the correlation coefficient ρ is equal to zero, see equation (5)). However, estimation results for the size variable are beyond the scope of this paper. The inclusion of equation (4) has been required for technical reasons (to limit the endogeneity bias) and the discussion of parameter estimates for the size variable does not correspond with the aim of this study and is therefore left for future research.

5.1. Order attributes

As far as the order features are concerned (i.e., the order sizes and the order aggressiveness indicators), there are two striking observations that can be inferred from the model estimates. First of all, the visible size of the submitted limit orders have a significantly negative impact on the probability that the order contains a hidden "tail", which confirms the results obtained by Bassembinder et al. (2009). Estimation results of the first model show that for all classes of submitted orders, the coefficients corresponding to the visible size of a submitted orders are statistically significant and negative in value. In contrast to this, all parameter estimates that correspond to the entire (unobservable) sizes of submitted orders in the second model are positive in value. This finding provides strong support for our initial suspicion that traders tend to hide the size of large orders. Such orders tend to have the largest informational content and the highest impact on the price. At the same time, large traders are most endangered by possible adverse selection risks and are eagerly attacked by predatory trading strategies. Because traders are reluctant to inform the entire market when they want to exchange a large amount of zlotys against euro (regardless if this is for information-motivated or liquidity reasons) they often decide to show only the very small peak of their orders. Our results show that the smaller the visible size of a limit order, the more probably it represents only a small fraction of a large size offered to the market. Analogously, large visible order sizes indicate that there is not much liquidity to be consumed underneath such an "encouraging" peak.

Secondly, our estimation results indicate that the more aggressively priced is the limit order, the greater the likelihood it will contain a hidden part. Parameter estimates corresponding to the aggressiveness indicator are statistically significant and positive in value for the first model.[17] This finding indicates that hidden orders tend to be the most competitive. After having accounted for the full size of an order as a control variable, the aggressiveness indicator becomes insignificant for inside-the-quote orders (see the second model). This can be explained by the fact that aggressive orders are at the same time large in value; therefore, the size variable takes over the explanatory power of the aggressiveness indicator.

5.2. Liquidity-oriented variables

The instantaneous shape of the LOB just before an order submission tends to have the greatest impact on exposure strategies for the most competitive orders. Because behind-the-quote orders are the least aggressive and cannot be observed by other market participants, their submission rules are not as prone to the changing liquidity of the market as in-the-quote or at-the-quote orders. As far as the publicly observable liquidity measures are concerned, the following conclusions can be drawn. We can see that the bid-ask spread has a negative impact on the placement of reserve orders. Therefore, the greater the distance between the best ask and bid prices the less probability a trader would submit an iceberg order. This finding may seem quite surprising at first glance and it does not agree with the results obtained by Bassembinder et al. (2009). In the literature of market microstructure, the

[17] We do not account for the aggressiveness indicators in models of the at-the-quote orders since in this case they are always equal to zero (i.e., the prices of submitted orders are always equal to the most competitive quotes on the same side of a LOB).

bid-ask spread is usually perceived as a measure of market uncertainty; therefore, one should rather await its positive impact on the probability of submitting hidden orders. However, our results seem robust because we have obtained the same outcome for different classes of orders. We have already inferred that undisclosed orders are nearly always large. Therefore, in periods of deteriorated liquidity when the bid-ask spread is wide, traders either deter from supplying liquidity to the market in the form of large orders (and thus they do not have an incentive to hide them) or if they submit large orders they deter from hiding them in order to encourage other traders to prompt execution. If the bid-ask spread is large, it is simply more expensive to cross the market and execute an immediate trade with a market order. To this end, considerable undisclosed sizes of limit orders may serve as an encouragement for full execution of a market order on the other side of a market.

The coefficients for the bid and ask depths are significant and negative in value for inside-the-quote orders. This indicates that large visible depth on both sides of the market discourages traders from submitting iceberg orders. Large-sized orders placed on the first level of the LOB usually encourage more market orders from the opposite side of the market because such large depth is a guarantee that these most aggressive orders will be executed at a best price. We also show that in the presence of large depths the mix of limit orders will be shifted towards fully disclosed orders. This finding agrees with the results of Chakrabarty and Shaw (2008), who state that hidden orders supply liquidity in periods when the quoted liquidity is usually scarce. The hidden depths have also influenced order exposure strategies. From the value of the estimated coefficients we can see that there is a kind of autocorrelation in a pattern of the hidden liquidity supply, as for the IQS orders the coefficient corresponding to the hidden ask depth is significant and positive, whereas for the IQB orders significant and positive coefficient can be found for the hidden bid depth. Accordingly, dealers tend to offer more hidden liquidity on this side of the market where it has been supplied previously. As traders cannot see if other market participants have submitted iceberg orders, they cannot simply mimic each other's behavior. Therefore, this finding can be explained only by the common reaction of different individuals to the same information flows or to the same market conditions. The existence of a common unobservable factor that is responsible for the commonalities among individual trader decisions has been evidenced by Nolte and Voev (2011). Trading decisions cannot be, to a full extent, explained by observable and measurable factors describing market conditions or the LOB liquidity. For example, different FX dealers might behave in the similar manner because they all react to the same news announcements or to similar changes in an order flow in the client market. Accordingly, the dynamics of such a latent factor may be correlated with the variables as quote slopes or the amount of hidden liquidity on the given side of LOB. Although these explanatory variables are directly unobservable to market participants, they ought to influence their trading decisions in an indirect manner.

Accordingly, we also see that the unobservable shape of the LOB is associated with the probability of submitting hidden orders. Coefficients corresponding to the ask quote slopes are significantly positive for IQS and ASQ orders and significantly negative for IQB orders. Symmetrically, the coefficients for the bid quote slope are positive for IQB, AQB and BQB orders. As the quote slope increases and the market becomes less liquid,[18] iceberg orders are more frequently placed on the weaker (less liquid) side

[18] According to the definition of the quote slope measures (see equation (1)), the infinitely illiquid market would be obtained if the ask or bid depth was approaching zero or the difference between the best bid price (worst ask price) and the worst bid price (best ask price) was approaching infinity. The infinitely liquid market would be obtained for the depth tending to infinity or the best bid (ask) price equal to the worst bid (ask) price. Accordingly, the ask and bid quote slope values are bound between 0 (an infinitely liquid market) and infinity (an infinitely illiquid market).

of the market. This confirms the results obtained by De Winnie and D'Hondt (2007). The reasoning is that large liquidity on the ask (bid) side of the market, where the limit orders to sell (buy) euro against zloty are gathered, signals a downward (upward) pressure on the quoted price and directly precede the movement of the EUR/PLN rate. Accordingly, a trader who wants to execute a large buy order at a pre-specified quote while exposing the size of the order to the public faces the risk of being picked-off if the rate moves excessively downwards (upwards).

As the frequency of executed trades increases so does the probability of hiding the full size of the submitted orders, especially in the case of the most aggressive inside-the-quote orders. The finding seems obvious for the first model since large orders that are placed as iceberg orders usually go in line with increased trading activity. Moreover, increased trading activity may signal the arrival of new information to the market (cf., Easley, O'Hara 1987; Easley, O'Hara 1992); therefore, dealers may not be eager to disclose their full knowledge or may want to reduce the free option risk of the submitted order.

5.3. Market trends and volatility

The decision whether to submit a reserve order seems to be very vulnerable to the prevailing market trends. Previously observed EUR/PLN returns or the EUR/PLN order flow are significant for all of the estimated models. The parameter estimates are positive for the bid side of the market (limit orders to buy euro against zloty) and negative for the ask side of the market (limit orders to sell euro against zloty). If the zloty has been weakening against the euro within the 10-minute period prior to the order submission and thus the observable return on the EUR/PLN rate was positive, traders would likely hide their limit orders to buy euro against the zloty. On the other hand, traders are also significantly more reluctant to conceal their full orders to sell euro (buy zloty). In the case of an upward-going trend of the EUR/PLN, a dealer that would disclose a large limit order to buy euro reinforces signals about the weakening of the zloty, which may accelerate the upward movement of the EUR/PLN rate by unleashing the front running activities undertaken by other traders. If the price quoted by the other market participants was at least one pip higher than the price of the initially submitted large order, the market would "escape" from the trader and he would not be able to execute a trade at the predefined quote. This finding is in line with the trend-following strategies performed by currency dealers. As shown by Bień-Barkowska (2014), the upward (downward) slope trend is typically followed by an increased number of market buy (sell) orders. The impact of the past return on the decision to hide the full size of submitted AQS, IQB and BQB orders has also been echoed by the significant impact of the order flow in the same direction. The volatility of EUR/PLN returns has had a negative impact on submitting hidden orders; although, its significance holds true only for the most aggressive inside the quote orders. Bessembinder, Panayides and Venkatamaran (2009) have obtained similar findings.

5.4. Previously submitted orders

Our results suggest that actions undertaken by other traders also exert a significant impact upon the order exposure rules. Previously observed market sells raise the probability of hiding the entire size of limit buy orders. Similarly, if a previously submitted order was a market buy, currency dealers will tend to hide their limit orders to sell euro against the zloty. This finding holds true irrespective of whether we control for the full size of the submitted orders or not. Market sell (buy) orders absorb liquidity at the best bid (ask) price, which increases the bid-ask spread. According to the market microstructure model of Parlour (1998), even in the absence of new information arrival, an aggressive market buy (sell) order erodes the LOB creating room for a limit sell (buy) order of the same size as the previously executed limit order. Therefore, a market buy order makes a limit sell order more probable and a market sell order that erodes liquidity at the best bid makes a limit buy order more probable. This systematic sequence within the micro phases of liquidity consumption by market sell (buy) orders and its replenishment by limit buy (sell) orders has been empirically evidenced by Hall and Hautsch (2007) and Bień-Barkowska (2014). Since this is a usual yet systematic cycle of liquidity absorption--replenishment, the incidence of a large limit order may indicate its potential informational content, hence traders would rather hide the excessive size of their orders. Interestingly enough, the submission of market sell orders discourages currency dealers from hiding their order sizes when they submit at-the-quotes or behind-the-quotes limit buy orders. This is because after a market sell dealers may await a downward shift in the price and a subsequent execution of their orders. A similar effect can be observed for the ask side of a market where after a market buy traders are reluctant to place reserve BQS orders (coefficients are significant at the 10% level).

We also see that the previous submission of inside-the-quotes orders generally discourages further submission of inside-the-quote hidden orders (for the ask side of the market the coefficients are significant and negative in value for the last IQB indicator and the last AQS indicator whereas for the bid side of the market the coefficients for last IQB are significant). Submissions of this kind always supply liquidity; therefore, the results remain in line with those previously obtained suggesting that increased market depth, either on the bid or ask side of the market, renders the submission of hidden orders less probable.

5.5. Time-of-day

Our results indicate that the seasonal pattern is important for explaining decisions to hide full order sizes, especially for the most aggressive inside the quote orders. In Figure 3 we depict the obtained diurnality patterns of the second model (i.e., controlling for the full size of submitted orders) for the cases where the FFF component was significant at the 10% level (IQS, IQB, AQS, and BQB orders). We can see that currency dealers tend to hide their limit orders to sell euro against zloty in the morning. At the same time they tend to refrain from hiding the full size of submitted orders to buy euro against zloty. A systematic increase in the probability of keeping full sizes of IQS and AQS undisclosed in the morning corresponds with a large dispersion of information amongst market participants and increased uncertainty when the interbank EUR/PLN spot market "wakes up" after the overnight trading decline (see Bień 2010). However, the decrease in IQB and BQB hidden orders does not support this finding. Bień-Barkowska (2014) shows that in the morning currency dealers will refrain from aggressive buying of euro (selling zloty). This limits the risk of being front run by other market participants when submitting IQB orders. Thus, the trader does not have strong incentives to hide their entire sizes.

5.6. Discriminative power

We evaluate the goodness-of-fit for each endogeneity-corrected probit model by assessing an area under the corresponding Receiver Operating Characteristics (ROC) curves (i.e., the AUC). The ROC curve is a function of a true positive rate (a proportion of true iceberg orders that are correctly identified as iceberg orders, which is a measure of sensitivity) against a false positive rate (a proportion of true negatives or visible orders that are incorrectly identified as positives, which is 1-specificity) for different cut-offs of the discrimination parameter. We depict the ROC curves for the IQS, AQS and BQS orders in Figure 4 (for the bid side of the market the graphs are very similar). The larger the area under the ROC curve (i.e., the AUC) the more accurate the probit model is in identifying hidden orders out of truly hidden orders, while at the same time the number of entirely visible orders being incorrectly identified as iceberg orders decreases. The AUC serves as a standard measure for assessing the performance of a classification model. Random guessing generates an AUC equal to 0.5 whereas a perfect discriminative power will generate an AUC equal to 1.

The results for the in-sample and out-of-sample evaluation of the models, as far as their discriminative power is concerned, have been depicted in Tables 3–4. We can see that in the case of the first model the discriminatory power takes medium-sized values ranging between 0.63 and 0.66 for all types of orders. However, the inclusion of unobservable explanatory factors, where the most important is the entire order size ($p < 0.000$ for nearly all the order types), significantly increases the AUC measure, which reaches 0.91 for BQB orders and 0.94 for IQS orders. These results clearly confirm our initial suspicion that the full order size is the most important driver of the decision to submit reserve orders. The striking discrepancy between the discriminative power of the first and the second models indicates that observable features of the LOB and of the prevailing market conditions are insufficient contributors to a satisfactory discrimination between entirely observable and partially hidden orders. If we choose the cut-off value of the discrimination parameter (i.e. probability) as one corresponding to the shortest distance from the ROC curve to the upper left corner, the second model allows for a correct prediction of over 80% of all submitted inside-the-quote orders. The proper prediction of in-the-quote iceberg order submissions (i.e. sensitivity) reaches over 90% and the specifity – over 80%. This is in opposition to the first model, which provides correct predictions for only about 60% of in-the-quote orders; with sensivity of about 63% and the specifity of about 57%. What must be underlined is that the discriminative power stays on the same level or is only a bit lower in the case of the out-of-sample model evaluation, which proves that the obtained relationships are quite robust. The results clearly show that the full model with all observable and unobservable variables allows for very good accuracy in discriminating between visible and partially hidden orders. However, the model that relies on the variables observable to market participants does not allow for a very precise determination of hidden liquidity.

6. Conclusions

In this paper we have investigated different market microstructure variables that influence dealer decisions about submitting partially undisclosed limit orders on different levels of the order book. To our knowledge, our analysis is the first one to shed light on the determinants on hidden order submission strategies in FX markets. From the concluded empirical analysis we see that FX dealers use undisclosed order to alleviate the free-market option risk of a limit order, to avoid being front run by other dealers or to hide the informational motives of their trades. More specifically, we confirmed the findings of Bessembinder, Panayides and Venkatamaran (2009) with respect to stock markets, which state that the inclination to hide orders increases with the entire size of a limit order. However, the visible size of submitted orders are negatively correlated with a probability of hiding; thus, small peaks may often indicate more liquidity underneath. We also confirm the results of De Winnie and D'Hondt (2007) for stock markets, who state that traders usually hide the size of aggressively priced (competitive) orders. Additionally, we evidence that the decisions to submit reserve orders are more likely when the bid-ask spread is narrow but the displayed depth is scarce. Traders hide their orders on the less liquid (weak) side of the market.

What we contribute to the literature is also an evidence that the provision of hidden liquidity tends to cluster over time and is characterized by pronounced intraday periodicity. Moreover, it reacts strongly to prevailing market trends and order flow, as well as the concrete actions undertaken by other dealers just prior to an order submission. We also show that the prevailing liquidity or information-oriented features of the market exert the largest impact on the properties of the orders submitted at the first level of the LOB (i.e. inside-the-quote orders). Behind the quote orders are much less influenced by the liquidity of the market but are still quite vulnerable to market trends.

All of these findings allow us to conclude that – similarly to stock markets – market participants on FX markets perform a constant monitoring of time-varying market conditions and constantly adjust their individual trading decisions. Although many variables proved significant when explaining hidden orders and the relationships obtained can be understood from the viewpoint of the theoretical literature on market microstructure, nevertheless the observable market characteristics are not sufficient to successfully discriminate between hidden and visible orders. Including unobservable features of the order book, particularly the entire order size, allows for a very successful prediction (both in and out-of-sample).

The analysis performed here contributes to a better understanding of the trading mechanism of automated brokerage limit order markets for the interbank FX spot trading. Although the market microstructure of stock markets in Poland has been previously analyzed by Bień (2006) and Doman (2010; 2011), the literature on different micro-aspects of trade flow in FX market is still rather scarce. We hope to contribute to this body of knowledge on order submission rules and incentives that drive the particular micro-level trading decisions of currency dealers.

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Appendix

In order to build the joint likelihood for y_t and s_t, we decompose the bivariate density function:

$$f(y_t^*, s_t \mid \mathbf{x}_t) = f(y_t^* \mid s_t, \mathbf{x}_t) f(s_t \mid \mathbf{x}_t) \tag{1A}$$

From the standard properties of the bivariate normal density, we obtain:

$$y_t^* \mid (s_t, \mathbf{x}_t) \sim N\left(\alpha s_t + \mathbf{x}_t'\boldsymbol{\beta} + \rho \frac{1}{\sigma_\xi}\left(s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p} \lambda_i s_{t-i}\right), \sqrt{1-\rho^2}\right)$$

Accordingly, in line with the standard probit model for the univariate case, we have:

$$P(y_t = 1 \mid s_t, \mathbf{x}_t) = \Phi\left(\left(\alpha s_t + \mathbf{x}_t'\boldsymbol{\beta} + \rho \frac{1}{\sigma_\xi}\left(s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p} \lambda_i s_{t-i}\right)\right)\frac{1}{\sqrt{1-\rho^2}}\right) \tag{2A}$$

Therefore, the joint bivariate density of y_t and s_t can be derived as:

$$\begin{aligned}
f(y_t, s_t \mid \mathbf{x}_t) &= f(y_t \mid s_t, \mathbf{x}_t) f(s_t \mid \mathbf{x}_t) = \\
&= [f(y_t = 0 \mid s_t, \mathbf{x}_t)]^{1-y_t} [f(y_t = 1 \mid s_t, \mathbf{x}_t)]^{y_t} f(s_t \mid \mathbf{x}_t) = \\
&= \left(1 - \Phi\left(\left(\alpha s_t + \mathbf{x}_t'\boldsymbol{\beta} + \rho \frac{1}{\sigma_\xi}\left(s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p} \lambda_i s_{t-i}\right)\right)\frac{1}{\sqrt{1-\rho^2}}\right)\right)^{1-y_t} \cdot \\
&\cdot \Phi\left(\left(\alpha s_t + \mathbf{x}_t'\boldsymbol{\beta} + \rho \frac{1}{\sigma_\xi}\left(s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p} \lambda_i s_{t-i}\right)\right)\frac{1}{\sqrt{1-\rho^2}}\right)^{y_t} \cdot \\
&\cdot \frac{1}{\sigma_\xi} \phi\left(\frac{s_t - \mathbf{x}_t'\boldsymbol{\gamma} - \sum_{i=1}^{p} \lambda_i s_{t-i}}{\sigma_\xi}\right)
\end{aligned} \tag{3A}$$

Table 1

Estimation results of the endogeneity-corrected probit model for a submission of iceberg order – buy orders (bid side of a market)

Variable	**IQB model I**		**IQB model II**		**AQB model I**		**AQB model II**		**BQB model I**		**BQB model II**	
	esti-mate	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**
Visible size	**-1.552**	0.000	–	–	**-0.548**	0.027	–	–	**-0.161**	0.017	–	–
Full size	–	–	**1.891**	0.000	–	–	**1.601**	0.000	–	–	**1.509**	0.000
Aggressiveness	**0.204**	0.000	0.114	0.100	–	–	–	–	**0.032**	0.000	**0.051**	0.000
Bid-ask spread	**-0.039**	0.002	**-0.063**	0.001	**-0.095**	0.007	**-0.065**	0.036	-0.036	0.142	**-0.082**	0.022
Ask depth	**-0.010**	0.018	**-0.025**	0.001	-0.015	0.213	-0.012	0.251	-0.007	0.180	-0.007	0.186
Bid depth	**-0.016**	0.000	**-0.017**	0.016	-0.009	0.537	**-0.106**	0.000	**-0.026**	0.006	**-0.046**	0.001
Ask depth hidden	–	–	**-0.020**	0.003	–	–	-0.025	0.111	–	–	0.001	0.932
Bid depth hidden	–	–	**0.009**	0.004	–	–	0.001	0.875	–	–	**0.007**	0.037
Ask quote slope	–	–	**-0.043**	0.011	–	–	-0.056	0.129	–	–	-0.035	0.084
Bid quote slope	–	–	**0.060**	0.000	–	–	**0.061**	0.004	–	–	**0.080**	0.000
Return EUR/PLN	**0.007**	0.000	**0.006**	0.017	**0.006**	0.069	0.004	0.369	**0.011**	0.000	**0.014**	0.000
Order flow EUR/PLN	**0.005**	0.011	**0.009**	0.003	0.004	0.323	0.008	0.139	**0.013**	0.000	**0.016**	0.000
Volatility	**-0.000**	0.023	**-0.000**	0.007	-0.000	0.314	-0.000	0.138	0.000	0.820	0.000	0.867
Volume EUR/PLN	**0.053**	0.000	**0.048**	0.004	0.038	0.123	0.053	0.097	-0.012	0.468	-0.062	0.050
Return EUR/USD	0.002	0.905	-0.037	0.175	-0.002	0.956	-0.006	0.904	0.023	0.460	0.021	0.565
Order flow EUR/USD	0.032	0.160	0.058	0.061	0.087	0.057	0.078	0.179	0.004	0.908	-0.001	0.969
Last market sell	**0.132**	0.000	**0.177**	0.000	-0.143	0.051	**-0.346**	0.000	**-0.123**	0.016	**-0.136**	0.022
Last market buy	-0.030	0.315	**-0.095**	0.033	**-0.208**	0.008	**-0.357**	0.000	-0.041	0.452	-0.011	0.864
Last IQS	-0.012	0.673	-0.023	0.558	-0.125	0.068	-0.162	0.059	0.005	0.896	0.012	0.818
Last IQB	**-0.084**	0.006	**-0.150**	0.001	0.068	0.226	-0.089	0.203	0.063	0.111	**0.118**	0.009
Last AQS	0.010	0.806	-0.022	0.725	0.065	0.493	-0.102	0.369	0.013	0.841	0.009	0.902
Last AQB	-0.062	0.132	0.015	0.788	-0.069	0.436	-0.206	0.081	0.004	0.946	0.019	0.809
τ	**0.387**	0.000	**0.379**	0.001	0.218	0.269	0.105	0.696	0.005	0.970	-0.354	0.055
$\sin(2\pi\tau)$	**0.091**	0.002	**0.116**	0.003	-0.001	0.991	0.017	0.840	-0.058	0.206	**-0.164**	0.006
$\cos(2\pi\tau)$	-0.013	0.313	**-0.070**	0.000	**-0.073**	0.018	-0.043	0.265	**-0.071**	0.003	**-0.184**	0.000
$\sin(4\pi\tau)$	**0.048**	0.005	**0.055**	0.017	-0.040	0.907	-0.048	0.331	0.010	0.710	-0.022	0.499
$\cos(4\pi\tau)$	0.018	0.173	0.026	0.155	0.031	0.296	-0.023	0.540	-0.040	0.087	**-0.157**	0.000
Const	**-0.991**	0.000	**-1.287**	0.000	**-0.929**	0.000	**-0.969**	0.000	**-0.927**	0.000	-0.906	0.000

Notes:
In the model I explanatory variables are observable to other market participants. Model II has been enriched by publicly unobservable explanatory variables. P-values correspond to the robust QML standard errors. Bolded values mark the coefficients significant at 5% level.

Table 2

Estimation results of the endogeneity-corrected probit model for a submission of an iceberg order – sell orders (ask side of a market)

Variable	**IQS model I**		**IQS model II**		**AQS model I**		**AQS model II**		**BQS model I**		**BQS model II**	
	esti-mate	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**	**esti-mate**	**p-value**
Visible size	**-1.250**	0.000	–	–	**-1.218**	0.000	–	–	**-0.553**	0.007	–	–
Full size	–	–	**1.829**	0.000	–	–	**1.956**	0.000	–	–	**0.536**	0.013
Aggressiveness	**0.244**	0.000	-0.032	0.638	–	–	–	–	**0.035**	0.000	**0.035**	0.000
Bid-ask spread	**-0.070**	0.000	**-0.113**	0.000	**-0.103**	0.020	**-0.146**	0.001	**-0.128**	0.000	**-0.131**	0.000
Ask depth	**-0.016**	0.000	**-0.033**	0.000	**-0.053**	0.022	**-0.215**	0.000	-0.002	0.736	-0.002	0.773
Bid depth	**-0.015**	0.001	**-0.018**	0.015	-0.006	0.426	**-0.025**	0.036	-0.012	0.118	-0.012	0.113
Ask depth hidden	–	–	**0.011**	0.049	–	–	-0.019	0.142	–	–	0.011	0.158
Bid depth hidden	–	–	-0.003	0.357	–	–	-0.013	0.112	–	–	-0.005	0.112
Ask quote slope	–	–	**0.083**	0.000	–	–	**0.094**	0.002	–	–	0.012	0.532
Bid quote slope	–	–	-0.010	0.427	–	–	-0.000	0.995	–	–	0.012	0.520
Return EUR/PLN	**-0.010**	0.000	**-0.013**	0.000	-0.005	0.108	-0.005	0.226	**-0.015**	0.000	**-0.015**	0.000
Order flow EUR/PLN	0.002	0.318	0.005	0.081	**-0.009**	0.045	**-0.010**	0.071	0.001	0.732	0.001	0.750
Volatility	**-0.000**	0.085	**-0.000**	0.013	-0.000	0.179	-0.000	0.892	0.000	0.257	0.000	0.279
Volume EUR/PLN	**0.022**	0.047	0.003	0.816	**0.059**	0.008	0.051	0.121	-0.019	0.264	-0.019	0.276
Return EUR/USD	**0.090**	0.000	**0.102**	0.000	-0.023	0.563	-0.050	0.326	0.037	0.283	0.036	0.292
Order flow EUR/USD	-0.045	0.056	-0.053	0.065	0.012	0.791	0.054	0.369	0.004	0.915	0.004	0.909
Last market sell	**-0.101**	0.002	**-0.164**	0.000	-0.022	0.768	-0.113	0.283	0.034	0.567	0.033	0.573
Last market buy	**0.064**	0.019	**0.129**	0.000	-0.022	0.750	-0.012	0.877	-0.091	0.086	-0.092	0.082
Last IQS	-0.027	0.351	**-0.172**	0.000	0.084	0.134	0.063	0.356	0.074	0.073	0.070	0.090
Last IQB	**-0.067**	0.026	-0.032	0.418	0.068	0.298	0.067	0.410	0.025	0.598	0.025	0.587
Last AQS	**-0.084**	0.032	-0.035	0.501	**0.235**	0.004	0.086	0.404	0.075	0.274	0.068	0.318
Last AQB	0.001	0.982	0.220	0.706	**0.188**	0.049	-0.020	0.868	0.053	0.491	0.057	0.458
τ	0.032	0.712	-0.134	0.228	**-0.564**	0.018	**-0.953**	0.001	0.079	0.584	0.074	0.608
$\sin(2\pi\tau)$	-0.009	0.759	-0.063	0.090	-0.132	0.081	**-0.212**	0.024	-0.018	0.703	-0.021	0.670
$\cos(2\pi\tau)$	0.093	0.000	0.019	0.277	0.037	0.240	0.023	0.537	0.020	0.389	0.016	0.492
$\sin(4\pi\tau)$	**-0.059**	0.001	-0.039	0.055	**-0.128**	0.002	**-0.154**	0.002	-0.052	0.071	-0.053	0.066
$\cos(4\pi\tau)$	**0.041**	0.002	0.029	0.099	**0.085**	0.005	**0.085**	0.023	0.033	0.147	0.032	0.158
Const	**-0.925**	0.000	**-1.100**	0.000	**-0.795**	0.000	**-0.581**	0.001	**-1.090**	0.000	**-1.111**	0.000

Notes:
In the model I explanatory variables are observable to other market participants. Model II has been enriched by publicly unobservable explanatory factors. P-values correspond to the robust QML standard errors. Bolded values mark the coefficients significant at 5% level.

Table 3
Discriminative power of the endogeneity-corrected probit model II for the decision to hide a full order (binary hide indicator)

	IQS	AQS	BQS	IQB	AQB	BQB
in-sample						
AUC	0.94	0.93	0.90	0.94	0.93	0.91
Sensitivity (%)	91.47	93.24	94.65	95.50	92.40	88.34
Specifity (%)	85.06	83.63	78.66	80.39	82.07	81.39
Correctly classified (%)	86.15	84.82	80.43	83.68	83.89	82.35
out-of-sample						
AUC	0.94	0.98	0.90	0.94	0.91	0.87
Sensitivity (%)	90.96	89.55	92.54	93.12	90.93	86.52
Specifity (%)	82.78	85.34	79.32	80.26	82.00	78.02
Correctly classified (%)	84.14	86.06	80.83	82.91	83.40	78.95

Note: AUC denotes an estimate of the field under the ROC curve.

Table 4
Discriminative power of the endogeneity-corrected probit model I for the decision to hide a full order (binary hide indicator)

	IQS	AQS	BQS	IQB	AQB	BQB
in-sample						
AUC	0.64	0.65	0.66	0.65	0.63	0.63
Sensitivity (%)	62.09	68.21	61.11	64.55	70.57	47.88
Specifity (%)	57.84	55.04	61.53	56.23	47.52	69.11
Correctly classified (%)	59.56	56.67	61.48	58.04	51.59	66.16
out-of-sample						
AUC	0.64	0.66	0.64	0.62	0.60	0.66
Sensitivity (%)	55.35	65.91	59.46	57.30	70.09	56.82
Specifity (%)	63.90	53.70	60.05	58.10	44.96	68.45
Correctly classified (%)	62.48	55.72	59.98	57.94	48.92	67.20

Figure 1
Graphical visualization of the EUR/PLN order book in the Reuters Dealing 3000 Spot Matching System on 23 January 2008, time (CET): 13.74 sec. after 14:48

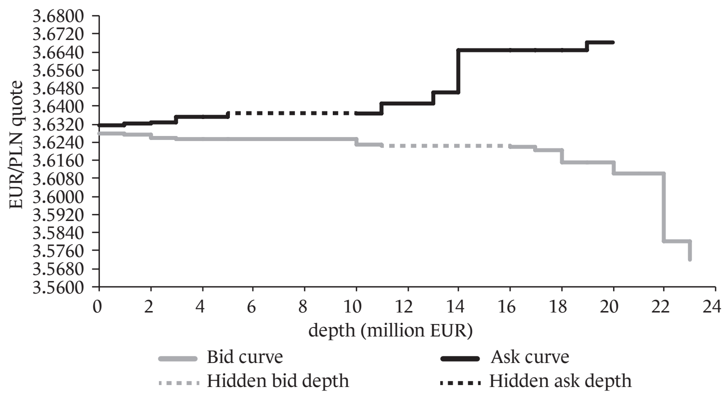


Figure 2
Percentage of hidden liquidity supply in the overall liquidity supply

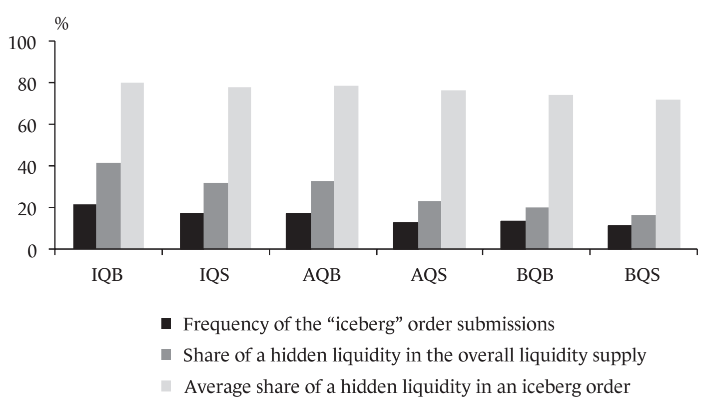
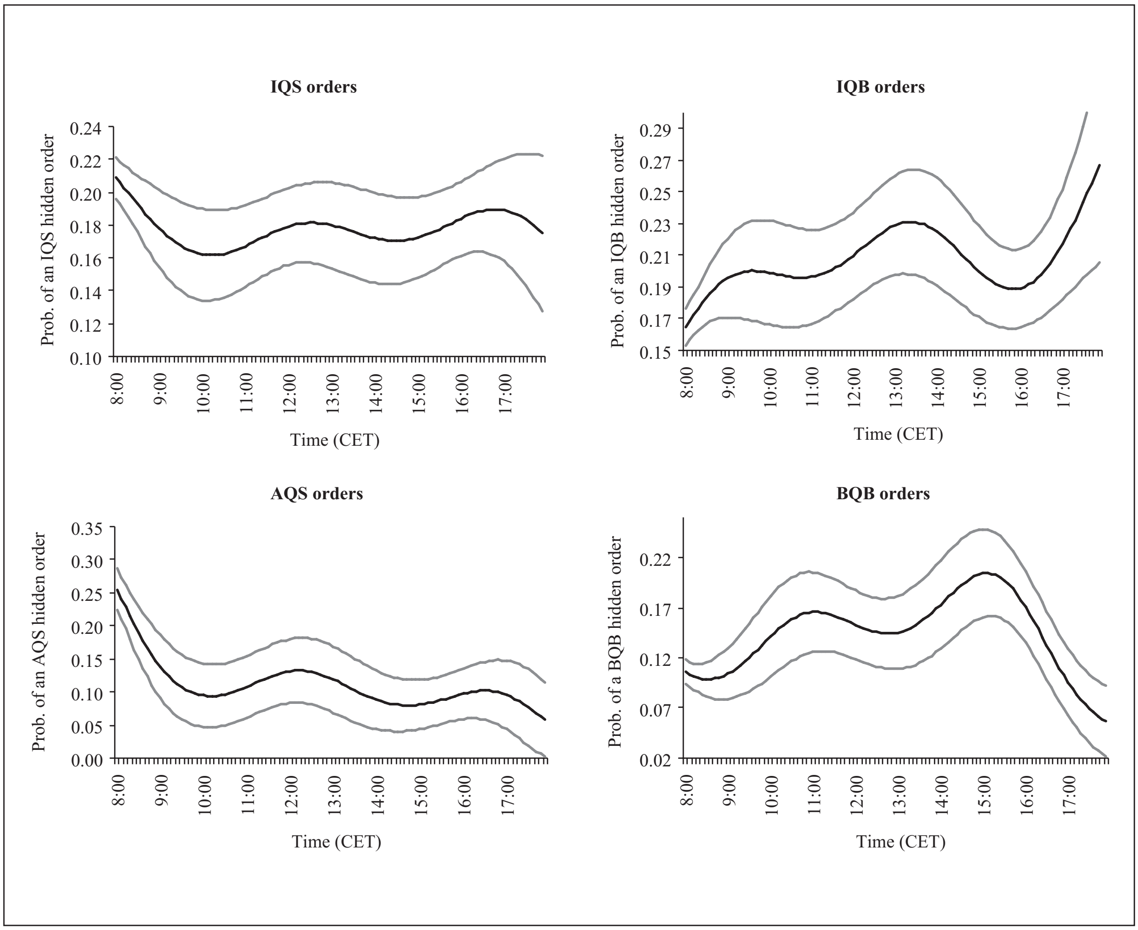
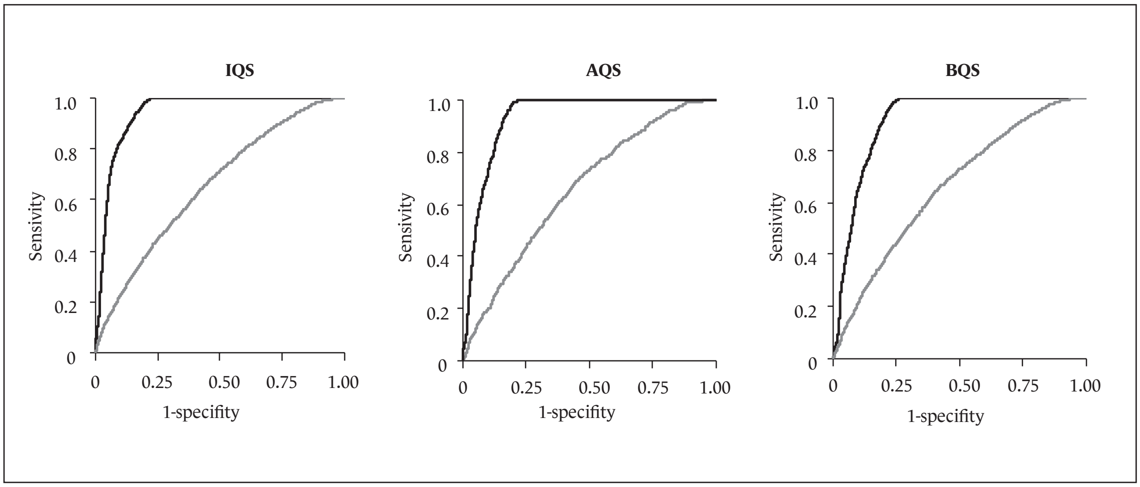


Figure 3
Durnality patterns for the probability of submitting an iceberg order



Note: grey lines depict the 95% confidence intervals obtained with the delta method.

Figure 4
ROC curves corresponding to the probit models for the ask side of the market



Note: black lines correspond to the model II, grey lines to the model I.