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Informativeness of the Trade Size in an Electronic Foreign Exchange Market

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Informativeness of the Trade Size in an Electronic Foreign Exchange Market

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Abstract

This article studies a trading strategy that relies on private information in an electronic spot foreign exchange market. The framework is a high-frequency extension of a structural microstructure model by Easley et al. (1996). The results relate the informational content of trading to the trade size and suggest that the probability of the informed large trading is significantly higher than the probability of uninformed large trading.

Keywords: Foreign Exchange Markets; Volume; Informed Trading; Noise Trading; Market Microstructure

JEL No: G0, G1, F3

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1. The Model

The model consists of informed and uninformed traders and a risk neutral competitive market maker. The traded asset is a foreign currency for the domestic currency. Similar to the portfolio shifts model (Evans and Lyons, 2002), the trades and the governing price process are generated by the quotes of the market maker over a twenty-four hour trading day. Within any trading hour, the market maker is expected to buy and sell currencies from his posted bid and ask prices. The price process is the expected value of the currency based on the market maker's information set at the time of the trade.

The hourly arrival of news occurs with the probability α. This represents bad news with probability δ and good news with $1-\delta$ probability. Let $\{p_i\}$ be the hourly price process over $i = 1, 2, \ldots, 24$ hours. p_i is assumed to be correlated across hours and will reveal the intraday time dependence and intraday persistence of the price behavior across these two classes of traders. The lower and upper bounds for the price process should satisfy $p_i^b < p_i^n < p_i^g$ where p_i^b, p_i^n and p_i^g are the prices conditional on bad, no news and good news, respectively. Within each hour, time is continuous and indexed by $t \in [0, T]$.

In any trading hour, the arrivals of informed and uninformed traders are determined by independent Poisson processes. At each instant within an hour, uninformed buyers and sellers each arrive at a rate of ε. Informed traders only trade when there is news, and arrive at a rate of μ. All informed traders are assumed to be risk neutral and competitive, and are therefore expected to maximize profits by buying when there is good news and selling otherwise. For good news hours, the arrival rates are $\varepsilon + \mu$ for buy orders and ε for sell orders. For bad news hours, the arrival rates are ε for buy orders and $\varepsilon + \mu$ for sell orders. When no news exists, the buy and sell orders arrive at a rate of ε per hour.

The market maker is assumed to be a Bayesian who uses the arrival of trades and their intensity to determine whether a particular trading hour belongs to a no news, good news or bad news category. Since the arrival of hourly news is assumed to be independent, the market maker's hourly decisions are analyzed independently from one hour to the next. Let $P(t) = (P_n(t), P_b(t), P_g(t))$ be the market maker's prior beliefs with no news, bad news, and good news at time t. Accordingly, his or her prior beliefs before trading starts each day are $P(0) = (1-\alpha, \alpha\delta, \alpha(1-\delta))$.

Let S_t and B_t denote sell and buy orders at time t. The market maker updates the prior conditional on the arrival of an order of the relevant type. Let $P(t|S_t)$ be the market maker's updated belief conditional on a sell order arriving at t. $P_n(t|S_t)$ is the market maker's belief about no news conditional on a sell order arriving at t. Similarly, $P_b(t|S_t)$ is the market maker's belief about the occurrence of bad news events conditional on a sell order arriving at t, and $P_g(t|S_t)$ is the market maker's belief about the occurrence of good news conditional on a sell order arriving at t.

The probability that any trade occurring at time t is information-based is

$$i(t) = \frac{\mu(1 - P_n(t))}{2\varepsilon + \mu(1 - P_n(t))} \tag{1}$$

Since each buy and sell order follows a Poisson Process at each trading hour and orders are independent, the likelihood of observing a sequence of orders containing B buys and S sells in a bad news hour of total time T is given by

$$L_b((B,S)|\theta) = L_b(B|\theta)L_b(S|\theta) = e^{-(\mu+2\varepsilon)T}\frac{\varepsilon^B(\mu+\varepsilon)^S T^{B+S}}{B!S!}, \tag{2}$$

where $\theta = (\alpha, \delta, \varepsilon, \mu)$.

Similarly, in a no-event hour, the likelihood of observing any sequence of orders that contains B buys and S sells is

$$L_n((B,S)|\theta) = L_n(B|\theta)L_n(S|\theta) = e^{-2\varepsilon T}\frac{\varepsilon^{B+S} T^{B+S}}{B!S!} \tag{3}$$

In a good-event hour, this likelihood is

$$L_g((B,S)|\theta) = L_g(B|\theta)L_g(S|\theta) = e^{-(\mu+2\varepsilon)T}\frac{\varepsilon^S(\mu+\varepsilon)^B T^{B+S}}{B!S!} \tag{4}$$

The likelihood of observing B buys and S sells in an hour of unknown type is the weighted average of equations (2), (3), and (4) using the probabilities of each type of hour occurring.

$$
\begin{aligned}
L((B,S)|\theta) &= (1-\alpha)L_n((B,S)|\theta) + \alpha\delta L_b((B,S)|\theta) + \alpha(1-\delta)L_g((B,S)|\theta) \\
&= (1-\alpha)e^{-2\varepsilon T}\frac{\varepsilon^{B+S}T^{B+S}}{B!S!} + \alpha\delta e^{-(\mu+2\varepsilon)T}\frac{\varepsilon^{B}(\mu+\varepsilon)^{S}T^{B+S}}{B!S!} \\
&\quad +\alpha(1-\delta)e^{-(\mu+2\varepsilon)T}\frac{\varepsilon^{S}(\mu+\varepsilon)^{B}T^{B+S}}{B!S!} \qquad (5)
\end{aligned}
$$

Because hours are independent, the likelihood of observing the data $M = (B_i, S_i)_{i=1}^{I}$ over twenty-four hours ($I = 24$) is the product of the hourly likelihoods,

$$
\begin{aligned}
L(M|\theta) &= \prod_{i=1}^{I} L(\theta|B_i, S_i) = \prod_{i=1}^{I} \frac{e^{-2\varepsilon T}T^{B_i+S_i}}{B_i!S_i!} \times \qquad (6) \\
&\quad \left[(1-\alpha)\varepsilon^{B_i+S_i} + \alpha\delta e^{-\mu T}\varepsilon^{B_i}(\mu+\varepsilon)^{S_i} + \alpha(1-\delta)e^{-\mu T}\varepsilon^{S_i}(\mu+\varepsilon)^{B_i}\right]
\end{aligned}
$$

The log likelihood function is

$$
\begin{aligned}
\ell(M|\theta) &= \sum_{i=1}^{I} \ell(\theta|B_i, S_i) \\
&= \sum_{i=1}^{I}[-2\varepsilon T + (B_i+S_i)\ln T] \\
&\quad + \sum_{i=1}^{I} \ln\left[(1-\alpha)\varepsilon^{B_i+S_i} + \alpha\delta e^{-\mu T}\varepsilon^{B_i}(\mu+\varepsilon)^{S_i} + \alpha(1-\delta)e^{-\mu T}\varepsilon^{S_i}(\mu+\varepsilon)^{B_i}\right] \\
&\quad - \sum_{i=1}^{I}(\ln B_i! + \ln S_i!) \qquad (7)
\end{aligned}
$$

As in Easley *et al.* (2008), the log likelihood function, after dropping the constant and rearranging[1], is given by

$$\ell(M|\theta) = \sum_{i=1}^{I} \left[-2\varepsilon + M_i \ln x + (B_i + S_i)\ln(\mu+\varepsilon)\right] + \sum_{i=1}^{I} \ln\left[\alpha(1-\delta)e^{-\mu}x^{S_i-M_i} + \alpha\delta e^{-\mu}x^{B_i-M_i} + (1+\alpha)x^{B_i+S_i-M_i}\right], \quad (8)$$

where $M_i \equiv \min(B_i, S_i) + \max(B_i, S_i)/2$, and $x = \frac{\varepsilon}{\varepsilon+\mu} \in [0,1]$.

Next, the paper utilizes a procedure similar to Easley *et al.* (1997b), theoretically outlined in Easley and O'Hara (1987). This approach allows for informed and uninformed traders to place both large and small orders. The extended model relies on the number of unique large buy (LB), small buy (SB), large sell (LS) and small sell (SS) trades that represent the set of possible trade outcomes.[2] This introduces two new parameters: ϕ (the probability that an uninformed trader trades a large amount) and ω (the probability that an informed trader trades a large amount). Naturally, $(1-\phi)$ denotes the probability of a small uninformed trade and $(1-\omega)$ is the probability of a small informed trade. All other parameters (α, μ, δ and ε) follow the previous notation.

The likelihood of observing a sequence of orders with LB large buys, SB small buys, LS large sells and SS small sells in a bad news hour is

$$L_b((LB, LS, SB, SS)|\theta) = L_b(LB|\theta)L_b(LS|\theta)L_b(SB|\theta)L_b(SS|\theta)$$
$$= e^{-(\mu+2\varepsilon)T}\frac{(\varepsilon\phi)^{LB}[\varepsilon(1-\phi)]^{SB}(\varepsilon\phi+\mu\omega)^{LS}[\varepsilon(1-\phi)+\mu(1-\omega)]^{SS}T^{LB+LS+SB+SS}}{LB!LS!SB!SS!},$$

where $\theta = (\alpha, \delta, \varepsilon, \mu, \omega, \phi)$. On a no-event day, the likelihood of observing a sequence of LB

[1] To derive equation (8), the term $\ln[x^{M_i}(\mu+\varepsilon)^{B_i+S_i}]$ is simultaneously added to the first sum and subtracted from the second sum in equation (7). This is done to increase computational efficiency and to ensure convergence in the presence of a large numbers of buys and sells.

[2] For simplicity, the no-trade outcome considered in Easley *et al.* (1997b) for a much smaller dataset of stock prices is ignored.

large buys, SB small buys, LS large sells and SS small sells is

$$\begin{aligned} L_n((LB, LS, SB, SS)|\theta) &= L_n(LB|\theta)L_n(LS|\theta)L_n(SB|\theta)L_n(SS|\theta) \\ &= e^{-2\varepsilon T}\frac{\phi^{LB+LS}(1-\phi)^{SB+SS}(\varepsilon T)^{LB+LS+SB+SS}}{LB!LS!SB!SS!} \end{aligned}$$

On a good-event day, the likelihood is

$$\begin{aligned} L_g((LB, LS, SB, SS)|\theta) = L_g(LB|\theta)L_g(LS|\theta)L_g(SB|\theta)L_g(SS|\theta) \\ = e^{-(\mu+2\varepsilon)T}\frac{(\varepsilon\phi)^{LS}[\varepsilon(1-\phi)]^{SS}(\varepsilon\phi+\mu\omega)^{LB}[\varepsilon(1-\phi)+\mu(1-\omega)]^{SB}T^{LB+LS+SB+SS}}{LB!LS!SB!SS!} \end{aligned}$$

As before, the likelihood of observing LB large buys, SB small buys, LS large sells and SS small sells is the weighted average of the above equations:

$$L((LB, LS, SB, SS)|\theta) = (1-\alpha)L_n(.|\theta) + \alpha\delta L_b(.|\theta) + \alpha(1-\delta)L_g(.|\theta)$$

Since this work uses hourly data, the likelihood of observing the data $D = (LB_i, LS_i, SB_i, SS_i)_{i=1}^{I}$ over twenty-four hours ($I = 24$) is the product of the hourly likelihoods as follows

$$L(D|\theta) = \prod_{i=1}^{I} L(\theta|LB_i, LS_i, SB_i, SS_i)$$

The log likelihood function is

$$\begin{aligned}\ell(D|\theta) &= \sum_{i=1}^{I}\ell(\theta|LB_i, LS_i, SB_i, SS_i)\\ &= \sum_{i=1}^{I}[-2\varepsilon + M_i\ln x + N_i\ln y]\\ &\quad+\sum_{i=1}^{I}[(LB_i+LS_i)\ln(\varepsilon\phi+\mu\omega)+(SB_i+SS_i)\ln(\varepsilon(1-\phi)+\mu(1-\omega))]\\ &\quad+\sum_{i=1}^{I}\ln[(1-\alpha)x^{LB_i+LS_i-M_i}y^{SB_i+SS_i-N_i}+\alpha\delta e^{-\mu}x^{LB_i-M_i}y^{SB_i-N_i}\\ &\quad+\alpha(1-\delta)e^{-\mu}x^{LS_i-M_i}y^{SS_i-N_i}],\end{aligned}$$

where $M_i \equiv \min(LB_i, LS_i) + \max(LB_i, LS_i)/2$, $N_i \equiv \min(SB_i, SS_i) + \max(SB_i, SS_i)/2$, $y = \frac{\varepsilon(1-\phi)}{\varepsilon(1-\phi)+\mu(1-\omega)} \in [0,1]$ and $x = \frac{\varepsilon\phi}{\varepsilon\phi+\mu\omega} \in [0,1]$. Here, to receive the final expression, the terms $\ln[x^{M_i}(\mu\omega+\varepsilon\phi)^{LB_i+LS_i}]$ and $\ln[y^{N_i}(\mu(1-\omega)+\varepsilon(1-\phi))^{SB_i+SS_i}]$ are added to and subtracted from the right-hand side of the likelihood equation.

2. Data

In the early 1990s, the practice of switching from voice brokers to electronic trading systems rendered the foreign exchange (FX) market more transparent. However, early over-the-counter (OTC) FX market participants had no means of observing the market-wide order flow. The introduction of centralized electronic broking systems, such as Reuters and EBS, thus provided a new platform for research on the FX market microstructure. Although Reuters and EBS are dominant in electronic FX markets, they do not publicly report high-frequency volume data or the identity of the traders.

The dataset from the OANDA FXTrade internet trading platform consists of tick-by-tick foreign exchange transaction prices and the corresponding volumes for several exchange rates from October 1, 2003 to May 14, 2004. The number of active traders during this period is 4,983, and they mainly trade four major exchange rates.[3] The data show that the overall trading frequency increases from Monday to Wednesday (the peak) and falls from Thursday to Saturday. Using the trader's identity (trader ID), it is found that about 33% of the investors specialize in exactly one currency pair, about 11% in two currency pairs, and about 9% in three currency pairs. This decreasing trend leads to only 2-4% of active traders who deal in between 10 and 13 currency pairs. Hence, traders appear to specialize in a small number of currency pairs, in line with OANDA FXTrade's intention to attract small investors.

Since the bulk of all transactions (approximately 40 percent[4]) involve only U.S. Dollar - Euro (USD-EUR) trading, the focus is on transactions involving only USD-EUR. In particular, the research analyzes all USD-EUR buy and sell transactions (market, limit order executed, margin call executed, stop-loss, and take-profit transactions). In addition to price and volume, the trader ID for each transaction is known and it ranges from 123 to 5904. The average number of USD-EUR transactions per trader is 512. It can also be observed that a few traders transact very frequently in this currency pair (between 10,000 and 25,000 times) over the time period that spans the data (Figure 1). The day-of-the-week trading patterns for the USD-EUR transactions (trading frequency and volume) are similar to those of other currency pairs.

Table 1 summarizes the institutional characteristics of the OANDA FXTrade trading platform. This platform is an electronic market making system (i.e., a market maker) that executes orders using bid/ask prices that are realistic and prevalent in the marketplace. The prices are determined by their private limit order book or by analyzing prices from the Interbank market. The OANDA FXTrade policy is to offer the tightest possible bid/ask spread (e.g., 0.0009% spread on the USD-EUR, regardless of the transaction size). Like most market makers, they profit from the spreads. Some of the other market features include continuous, second-by-second interest rate payments, no limit on the transaction size, no requirement for minimum initial deposit, no charges for stop or limit orders, free quantitative research tools, and margin trading (maximum leverage of 50:1). Given these market characteristics, the OANDA FXTrade seems to be designed to attract small, uninformed traders. However,

[3] By "active", the paper refers to traders that did not simply receive interest on their positions, but placed orders during this period. The market share of these traders is approximately 86.4%.

[4] The next most active currency pairs are USD-CHF (7.88% share), GBP-USD (7.81% share), USD-JPY (6.42% share), and AUD-USD (5.98% share).

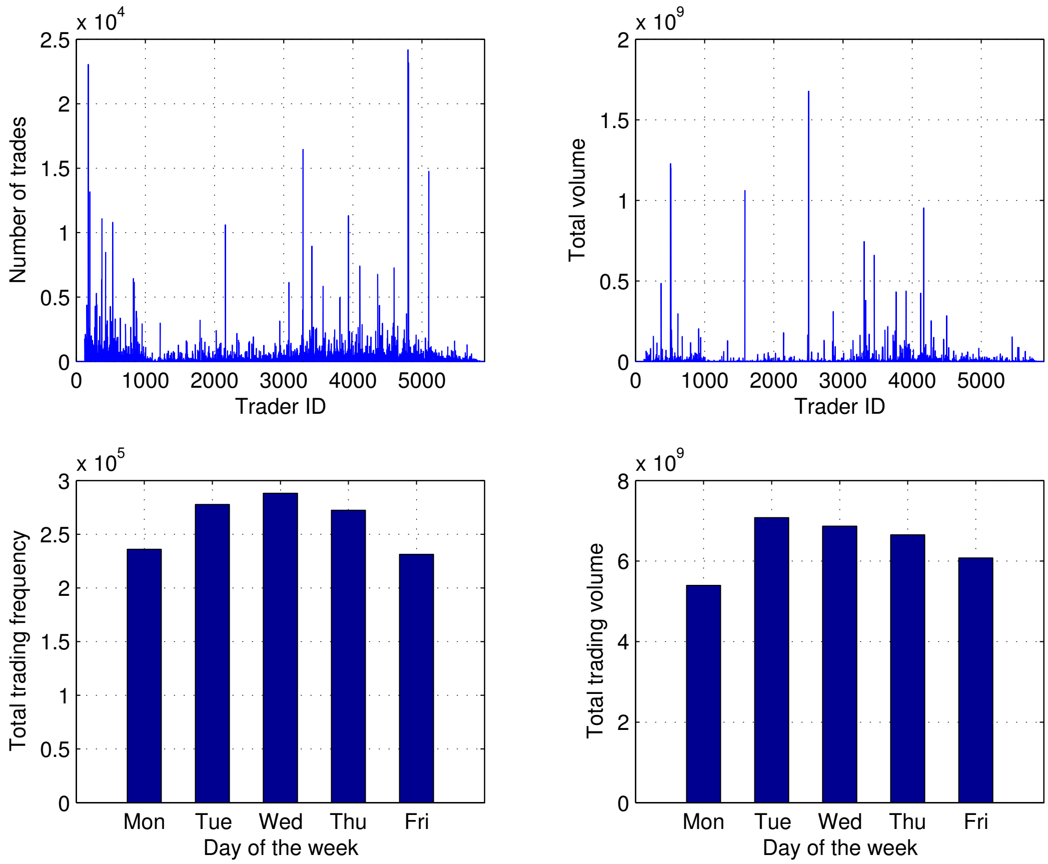

Figure 1: Top left: Total trading frequency (number of trades) per trader (trader ID). Top right: Total trading volume (in the units of base currency - EUR) per trader (trader ID). Bottom left: Total trading frequency (number of trades) for each day of the week. Bottom right: Total trading volume (in the units of base currency - EUR) for each day of the week.

given the above findings, it is reasonable to assume that informed traders are also present in this market.

The theoretical model by Easley *et al.* (2008) is developed in the context of equity markets. Adapting it to the FX market requires care. As opposed to the equity market, the FX market is open 24 hours and is decentralized. Further, unlike the NYSE, it does not involve a so-called specialist responsible for maintaining fairness and order, with an insight into the limit order book. While the NYSE has recently introduced an open limit order book that provides a real-time view of the limit order book for all NYSE-traded securities, the FX market exhibits a low level of transparency. Finally, trading in the FX market is motivated by speculation, arbitrage and, importantly, inventory management of currencies. Dealers in the FX market are generally quick to eliminate inventory positions (from below five minutes to half an hour). This process is sometimes referred to as "hot-potato-trading" (Evans and Lyons, 2002; Bjønnes and Rime, 2005). On the NYSE, however, inventory has an average half-life of over a week (Madhavan and Smidt, 1993). Thus, inventory management is an important component of intraday FX trader activity.

The features of the OANDA FXTrade allow for it to be viewed as a "special case" of the FX market that can be approached using the model by Easley *et al.* (2008). First, as a market maker, the OANDA FXTrade promotes transparency: spreads are clearly visible, past spreads are published for public view and current open orders on major pairs are visible to all market participants. In regards to trader behavior, as the only focus is on the informational aspect (i.e., informed vs. uninformed), market participants in the FX market can be treated in a fashion similar to those in equity markets.

The preliminary analysis indicates that overall market activity was extremely low on certain days or during certain weeks. Therefore, the weekends are eliminated, starting from every Friday 15:59:59 to Sunday 15:59:59 (all times are EST), including Christmas week (December 22-26), the first week of the year (December 29-January 2), and the week of Independence Day (April 5-9). This leaves 145 24-hour periods. In order to avoid extremely high-frequency noise and no-activity periods in small time windows, the data are aggregated over one-hour intervals. Aggregating over trading intervals smaller than one hour is not feasible, as this would not cover a sufficient number of buy and sell transactions for the model to be empirically applicable. On the other hand, longer trading intervals would "stretch" the assumptions of the model to a certain extent. For example, the news is assumed to arrive hourly (with probability α). It is unlikely that the flow of information would be less frequent, i.e., over longer time intervals. The final sample size is 3,480 hourly data points covering 145 business days, from October 5, 2003, 16:00 to May 14, 2004, 16:00 EST. There are 667,030 sell and 666,133 buy transactions in the sample period, with an average of approximately 6 transactions (3 buy and 3 sell) per minute. The transaction volume totals 32.6 billion USD-EUR contracts. According to the BIS Triennial Survey for 2004, the daily average turnover in the USD-EUR currency pair was 501 billion USD. Hence, on average, the data represent

Hours of operation	24 hours/7 days per week
Number of currency pairs	30
Number of active traders	4,983
Number of trades (USD-EUR)	667,030 sell transactions
	666,133 buy transactions
Average number of trades per day (USD-EUR)	192 sell transactions
	191 buy transactions
Total volume (USD-EUR)	32.6 billion USD
Average volume per day (USD-EUR)	224 million USD
Transaction types	Buy/Sell market (open or close)
	Limit order Buy/Sell
	Cancel order (reason: bound violation, insuff. funds, none)
	Change order
	Change stop loss (sl) or take profit (tp)
	Sell/Buy tp (close), Sell/Buy sl (close)
	Buy/Sell limit order executed (open or close)
	Order expired
	Sell/Buy margin called (close)
	Interest

Table 1: OANDA FXTrade institutional characteristics.

about 0.045% of the global daily USD-EUR trading volume. Nevertheless, it is one of the largest tick-by-tick FX datasets to be used in an academic study.

Since the trader's identity is known in each transaction, one is able to identify the number of unique traders in each one-hour window. For estimation purposes, the number of buy arrivals in each hour (B'_t) is defined as the number of unique traders involved in buy transactions in that hour. The number of sell arrivals in each hour (S'_t) is defined similarly. Therefore, the arrival of an individual trader who conducts several buy (sell) transactions in a given hour is counted as one buy (sell) arrival in that hour.

3. Results

The goal of this research is twofold: first, to compare the estimated ω and ϕ over 145 days ($\omega > \phi$ would mean that trade size conveys additional information to market participants); and second, to observe how changes in the cutoff trade size impact the estimates. The procedure of testing for trade size effects involves comparing the estimates of the restricted ($\omega = \phi$) and unrestricted ($\omega \neq \phi$) models. The cutoff amount that differentiates large from small trades is initially set to 5,000, and it is shown later that this does not affect the major results.[5]

Table 2 lists the average estimates of $\alpha_i, \delta_i, \varepsilon_i, \mu_i, \omega_i$, and ϕ_i $(i = 1, \ldots, 145)$. The paired t-test of the equality of the means of the constrained and unconstrained models shows no significant difference for the first four parameters.[6] However, the difference between the two sets of estimates of ω_i is statistically significant.[7] Furthermore, including the trade size effects (unconstrained model) significantly increases the absolute value of the log likelihood function, thus indicating that the constraint is binding. The informativeness of the trade size is also confirmed by the unpaired t-test of the equality of $\bar{\omega}$ and $\bar{\phi}$ for the unconstrained model. The model concludes that $\bar{\omega}$ is significantly greater than $\bar{\phi}$. On about 68% of the days in the sample, $\omega_i > \phi_i$ and the difference in the probabilities $(\omega_i - \phi_i)$ ranges from -0.12 to 0.14 $(i = 1, \ldots, 145)$. Although there are 47 days when the probability of uninformed large trading exceeds the probability of informed large trading, it can be concluded that this is not the case on average.

It is essential to investigate whether the findings above are robust to the choice of the cutoff amount for a "large" trade. Table 3 reports the results for 2000, 8000 and 12000 cutoff rates. The focus is on the difference column from Table 2 and the mean values of the unconstrained estimates.

It is found that in the cutoff range between 3000 and 8000, all the estimates are stable and the informed large trade size is more informative than the uninformed large trade size. The choice of cutoff values above 8000 (e.g., 12000 in Table 3) distorts the results due to the low frequency of such large trades. Similarly, it is unreasonable to consider trades above small cutoff values (e.g., 2000 in Table 3) to be "large," in which case the observed effects diminish. These findings confirm the work of Chakravarty (2001) and Anand and Chakravarty (2007), who find that medium-sized trades are the most informative. This can also be interpreted as a "separating equilibrium" outcome in which informed traders submit

[5] Trade size is expressed in currency units of the base currency, i.e., the Euro.

[6] The null hypothesis for this test is that the mean difference ($\bar{d}$) between paired observations (constrained and unconstrained) of the estimated parameters is zero. The test statistic is calculated as $t = \frac{\bar{d}}{\sqrt{s_{\bar{d}}/145}}$, where $s_{\bar{d}}$ is the sample standard deviation for $\bar{d}$.

[7] Also, the standard errors of $\hat{\omega}_i$ and $\hat{\phi}_i$ for the unconstrained model are consistently on the order of 10^{-4} and 10^{-5}, respectively, thus indicating statistically significant differences in the probabilities.

Parameter	Benchmark model	Constrained	Unconstrained	Difference (p-value)
$\bar{\alpha}$	0.30	0.30	0.30	0.00 (0.17)
$\bar{\delta}$	0.47	0.47	0.47	0.00 (0.42)
$\bar{\varepsilon}$	77.8	77.16	77.12	0.04 (0.19)
$\bar{\mu}$	83.5	82.5	82.5	0.00 (0.99)
$\bar{\omega}$	-	0.43	0.45	-0.02 (0.00)***
$\bar{\phi}$	-	0.43	0.42	0.01 (0.00)***
$\overline{LLF}$	-15111	-12087.25	-12087.46	0.21 (0.08)*

Table 2: The information role of trade size.
The first column lists the average estimates for the model, which do not account for the trade size. The second and third columns represent the average estimates of the parameters in the constrained ($\omega_i = \phi_i$) and unconstrained ($\omega_i \neq \phi_i$; $i = 1, \ldots, 145$) versions of the model, respectively. The last column contains the differences in mean value between the 145 parameters estimated from the constrained and unconstrained models. The p-value comes from the paired t-test for the null hypothesis of the difference being equal to zero. LLF denotes the value of the log likelihood function. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

mainly large orders (Easley and O'Hara, 1987).[8] An interesting observation emerges from Table 3: the probability of both informed and uninformed large trading declines with the cutoff value. This can be explained by the fact that increasing the cutoff value eliminates the majority of the transactions that qualify as "large" trades.

4. Conclusions

The paper reveals that the transactions of informed FX traders are related to larger trade sizes. These findings are robust with regard to reasonable choices for cutoff points that define a "large" trade, though some trade sizes that are found informative can also be interpreted as medium-sized. Therefore, the current paper adds to the literature that provides evidence on the link between informed trading and larger trade sizes (e.g., Easley *et al.*, 1997a, Menkhoff and Schmeling, 2007, Chakravarty, 2001 and Anand and Chakravarty, 2007). The observed behavior can be described as a strong strategic component in the activity of the informed traders that is not observed for the uninformed traders (Gencay and Gradojevic, 2013).

[8] Suppose that the constrained model is found to be more appropriate. This would indicate a "pooling equilibrium," where informed traders submit both large and small orders roughly equally.

Parameter	2000 cutoff			8000 cutoff			12000 cutoff		
$\bar{\alpha}$	0.31	0.00	(0.43)	0.30	0.00	(0.14)	0.30	0.00	(0.33)
$\bar{\delta}$	0.48	0.00	(0.53)	0.47	0.00	(0.66)	0.47	0.02	(0.38)
$\bar{\varepsilon}$	74.43	0.02	(0.59)	78	0.00	(0.15)	77.93	0.05	(0.19)
$\bar{\mu}$	74.54	0.42	(0.40)	83.11	1.34	(0.12)	82.65	0.82	(0.19)
$\bar{\omega}$	0.73	-0.02	(0.00)***	0.36	-0.01	(0.00)***	0.24	-0.00	(0.02)**
$\bar{\phi}$	0.70	0.01	(0.00)***	0.34	0.01	(0.00)***	0.23	0.00	(0.00)***
$\overline{LLF}$	0.12		(0.15)	1.66		(0.09)*	0.97		(0.17)

Table 3: The robustness of the estimates with respect to "large" trade size. For each cutoff amount for a "large" trade (2000, 8000 and 12000), this table presents the average parameter estimates from an unconstrained model along with the average difference between the estimates from the two versions of the model: constrained ($\omega_i = \phi_i$) and unconstrained ($\omega_i \neq \phi_i$; $i = 1, \ldots, 145$). More precisely, each column represents the merged columns 3 and 4 from Table 2 for different cutoff amounts. LLF denotes the average value of difference between the log likelihood function for the two models. The p-value reported in the brackets comes from the paired t-test for the null hypothesis of the difference being equal to zero. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

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