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INFORMED TRADING IN AN ELECTRONIC FOREIGN EXCHANGE MARKET

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Informed trading in an electronic foreign exchange market

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Abstract

We examine a recent set of high-frequency spot EUR-USD foreign exchange transaction data from an electronic foreign exchange market. Our framework is based on a continuous time-sequential microstructure trade model that measures the market makers beliefs directly. We present evidence of the strategic arrival of informed traders on a particular day of the week, time of day and geographic location (market).

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

JEL No: G0, G1, F3

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1. Introduction

Theoretical market microstructure models have extensively utilized a setting that involves a risk-neutral competitive market maker who faces two types of traders: informed and uninformed (noise) traders. Within the context of equity markets, some notable research contributions include Easley *et al.* (1996a, 1997a,b). Easley *et al.* (2002) further extend these theoretical models to allow the arrival rates of informed and uninformed trades to be time-varying. They show that both informed and uninformed traders are highly persistent in equity markets.[1]

Until recently, the lack of transaction data for prices and trading volume has precluded such research avenues in foreign exchange (FX) markets.[2] This paper introduces high-frequency FX data from EBS (Electronic Broking Services) that cover one year (2005) of trading volume in the global interdealer spot market. To control for high-frequency noise effects and no-trade periods, we aggregate to 10-minute data and also focus only on EUR-USD transactions. The electronic market for the EUR-USD currency pair is largely dominated by EBS, followed by Reuters.

The FX market can generally be described as decentralized and worldwide, but the actual trading is processed in the bookkeeping of particular markets, with the major ones being London, New York and Tokyo. Thus, the total trading activity of informed and uninformed traders is comprised of the *geographic contributions* of individual market centers. The hours of operation of the market centers are different, but they jointly contribute to the aggregate market trading activity. For instance, the London Stock Exchange (LSE) and the New York Stock Exchange (NYSE) are both open from 09:30 to 11:30 EST. In contrast, the lowest market presence outside weekends can be found during the lunch break at the Tokyo Stock Exchange (TSE), when it is night in North America and Europe.

In this article, we investigate the risk of information trading in the spot EUR-USD market. Our analysis utilizes the information in the trade data to estimate the arrival rates of both informed and uninformed traders as well as the probability of informed trading (PIN). In particular, we can extract a geographical (or the time-of-day) component of the activity of informed and uninformed traders. Considering the low-transparency feature of the FX market, this exercise is of immense importance to our understanding of market dynamics. We find strong support for an intraday geographic component in the arrival of both classes of traders. Our analysis reveals that the target market for informed traders is the NYSE. The activity of the informed traders is particularly strong after lunchtime in New York until 16:00 EST, when the market closes. Noteworthy is the fact that the above-average activity of informed traders generally coincides with the above-average activity of

[1] Another related strand of literature (dynamic heterogeneous agent models) assumes that traders follow two different types of strategies: fundamental and technical trading rules (LeBaron, 2006; Brock and Hommes, 1998). While fundamentalists make decisions based on some perceived fundamental value, chartists rely on past prices or past microstructure variables such as order flow.

[2] The exceptions are Lyons (1995), Payne (2003), and Marsh and O'Rourke (2005). The first two papers use one week of trade-by-trade data, while Marsh and O'Rourke (2005) use about one year of daily data.

uninformed traders, and vice-versa. This indicates to a certain extent the strategic arrival timing of informed traders who tend to conceal their activity by transacting together with uninformed traders. This result is confirmed by the day-of-week analysis and is similar to evidence presented by Kyle and Villa (1991) for the equity market, where “noise trading” provides camouflage for a profitable takeover by a large corporate outsider.[3]

2. Independent Arrival Model

The model consists of informed and uninformed traders and a risk-neutral competitive market maker.[4] The traded asset is a foreign currency for the domestic currency. The trades and the governing price process are generated from the quotes of the market maker over a trading day of twenty-four hours (or 144 ten-minute intervals). Within any trading interval, the time is continuous, and 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 makers information set at the time of the trade.

The arrival of news to the market occur with probability α. This is comprised of bad news with probability δ and good news with $1-\delta$ probability. Let $\{s_i\}$ be the price process over $i = 1, 2, \ldots, 144$ periods. s_i is assumed to be correlated across trading periods and will reveal the intraday temporal effects and intraday persistence of price behavior across these two classes of traders. The lower and upper bounds for the price process should satisfy $s_i^b < s_i^n < s_i^g$, where s_i^b, s_i^n and s_i^g are the prices conditional on bad news, no news and good news, respectively. Within each time period, time is continuous and is indexed by $t \in [0, T]$.

On any trading period, the arrivals of informed and uninformed traders are determined by independent Poisson processes. At each instant, 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 they are thus expected to buy when there is good news and to sell otherwise to maximize their profits.[5] For good news, the arrival rates are $\varepsilon + \mu$ for buy orders and ε for sell orders. For bad news, the arrival rates for buy orders are ε, 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 period belongs to a no news, good news or bad news category. Since the arrival of news is assumed to be independent, the market maker's hourly decisions are analyzed independently from one period to the next. Let $P(t) = (P_n(t), P_b(t), P_g(t))$

[3]In contrast to our paper, Easley *et al.* (2002) do not find any evidence of strategic behavior by informed traders. They document that uninformed traders seem to avoid informed traders by “herding.”

[4]In this section, our framework follows Easley *et al.* (1996b).

[5]This assumption may seem inappropriate given that it rules out any strategic behavior. As will be shown later, informed traders have some tendency for strategic trading. Therefore, we concur that the assumption of risk-neutrality needs more defending, but for the sake of the model applicability, it will not be dropped.

be the market maker's prior beliefs at no news, bad news, and good news at time t. Accordingly, his/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.

It can be shown that the probability of any trade occurring at time t is information-based by using:

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

Since each buy and sell order follows a Poisson process at each trading hour and is independent, the likelihood of observing the data $M = (B_i, S_i)_{i=1}^{I}$ over twenty-four hours (I=144 ten-minute intervals) is as follows:

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

The log-likelihood function is

$$\begin{aligned} \ell(M|\theta) &= \sum_{i=1}^{I} \ell(\theta|B_i, S_i) \\ &= \sum_{i=1}^{I} [-2\varepsilon T + (B_i + S_i)\ln T] \\ &\quad + \sum_{i=1}^{I} \ln\left[(1-\alpha)\varepsilon^{B_i+S_i} + \alpha\delta e^{-\mu T}\varepsilon^{B_i}(\mu+\varepsilon)^{S_i} + \alpha(1-\delta)e^{-\mu T}\varepsilon^{S_i}(\mu+\varepsilon)^{B_i}\right] \\ &\quad - \sum_{i=1}^{I} (\ln B_i! + \ln S_i!) \end{aligned} \tag{3}$$

As in Easley *et al.* (2002), the log-likelihood function, after dropping the constant and rearranging[6],

[6] To derive Equation 4, 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 3. This is done to increase computing efficiency and ensure convergence in the presence of a large number of buy and sell orders, as is the case with our data set.

is given by

$$\ell(M|\theta) = \sum_{i=1}^{I} [-2\varepsilon + M_i \ln x + (B_i + S_i)\ln(\mu+\varepsilon)] + \sum_{i=1}^{I} \ln\left[\alpha(1-\delta)e^{-\mu}x^{S_i - M_i} + \alpha\delta e^{-\mu}x^{B_i - M_i} + (1+\alpha)x^{B_i+S_i-M_i}\right] \quad (4)$$

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

3. Data and Estimation Results

3.1. Overview of EBS and Temporal Effects

Our data set is from EBS and consists of tick-by-tick FX transaction prices and volume indicators[7] for the EUR/USD exchange rate spanning January 3 through December 23, 2005 for the total of 51 weeks (255 days). EBS operates as an electronic limit order book and is used for global interdealer spot trading. It is dominant for the EUR-USD and USD-JPY currency trading, while the GBP-USD currency pair is traded primarily on Reuters (Chaboud *et al.*, 2008). The average daily EUR-USD trading volume (in USD) on EBS in 2003 was between 50-70 billion dollars, which is well above that of the NYSE (40 billion dollars). In order to avoid extremely high-frequency noise and no-activity periods in very small time windows, we aggregated the data over 10-minute intervals. This gives us 144 observations over each 24-hour period. On average, there are roughly 8,000 buy orders and 6,000 sell orders on a given day. With regard to trader behavior, as we only focus on the informational component (i.e., informed vs. uninformed), market participants in the FX market can be treated in a fashion similar to those in equity markets.

The data allow us to identify the number of buy (B'_t) and sell (S'_t) trades for each 10-minute window. When we plot the number of 10-minute buy and sell arrivals (B', S'), strong daily temporal effects and a time trend in both series are evident. Therefore, we first estimate the linear time trend, $\hat{B}_t$ and $\hat{S}_t$, from the trend regression, which is free of temporal and irregular fluctuations. Assuming a set of multiplicative separable temporal effects, we divide the original series by the trend estimates $\hat{B}_t$ and $\hat{S}_t$ to obtain an estimate of the temporal component

$$\tilde{s}_t^B = \frac{B'_t}{\hat{B}_t}, \qquad \tilde{s}_t^S = \frac{S'_t}{\hat{S}_t}.$$

In order to estimate an index for each 10-minute interval, we averaged the values of $\tilde{s}_t^B$ and $\tilde{s}_t^S$ corresponding to the same 10 minutes of the day across the sample and obtained the final 10-

[7]EBS does not provide exact volume figures, but "size indicator values," i.e., the letters A, B, C, D, E, F, G that correspond to volume intervals. For our application, we are only interested in the number of buy/sell orders; consequently, volume indicators are not used in the paper.

minute-of-day indices s_i^B and $s_i^S, i = 1, 2, \ldots 144$ for the 24-hour cycle. The adjusted number of buy and sell arrivals are obtained via:

$$B_i = \frac{B_i'}{s_i^B}, \qquad S_i = \frac{S_i'}{s_i^S}, \qquad i = 1, 2, \ldots, 144$$

for each 255 days in the sample.

Figure 1 shows the final 10-minute-of-day indices s_i^B and $s_i^S, i = 1, 2, \ldots 144$, for the number of buy and sell trades starting at 00:00 EST. The number of buy and sell trades starts to increase after 03:00 EST and becomes above average after 06:00 EST. Another sharp increase is observed around 12:30 EST. The number of trades starts to decline after the NYSE closes. They remain relatively low and stable during the following hours until midnight. In the lower panel of Figure 1, the sample autocorrelation functions of the adjusted number of buy and sell arrivals are studied at 10-minute lags. The strong daily temporal effects are removed, and a strong persistence in both series is revealed.

3.2. Informed traders, uninformed traders and the PIN

According to the Easley *et al.* (1996b) model, the expected value of the total number of trades per unit time, $E(TT) = E(S + B)$, is equal to the sum of the Poisson arrival rates of informed and uninformed trades:

$$E(TT) = \alpha(1-\delta)(\varepsilon + \mu + \varepsilon) + \alpha\delta(\mu + \varepsilon + \varepsilon) + (1-\alpha)(\varepsilon + \varepsilon) = \alpha\mu + 2\varepsilon$$

The expected value of the trade imbalance $E(K) = E(S - B)$ is given by

$$E(K) = \alpha\mu(2\delta - 1)$$

, which provides information on the arrival of informed trades. When μ is large, the following approximate relation holds

$$E(|K|) \simeq \alpha\mu.$$

Accordingly, the absolute trade imbalance $|K|$ provides information on the arrival of informed trades, $\alpha\mu$, while the difference between the total trade TT and the absolute trade imbalance $|K|$ contains information on the arrival of uninformed trades, ε. If we assume that the probability of information events α is constant, the time-of-day average of the absolute trader imbalance $|K|$ provides information on the intraday temporal effects of the orders from informed traders. In other words, it is possible to obtain a measure of the *activity time* of the informed traders, since we know the number of trades occurring during each 10-minute period of the day. Similarly, we can identify whether uninformed traders (liquidity traders) follow a distinct intraday pattern.

Figure 2 plots the hour-of-day indices of informed (top) and uninformed (bottom) traders, based on unbalanced traders ($|K|$) and balanced traders ($TT - |K|$). Note that both $|K|$ and TT are

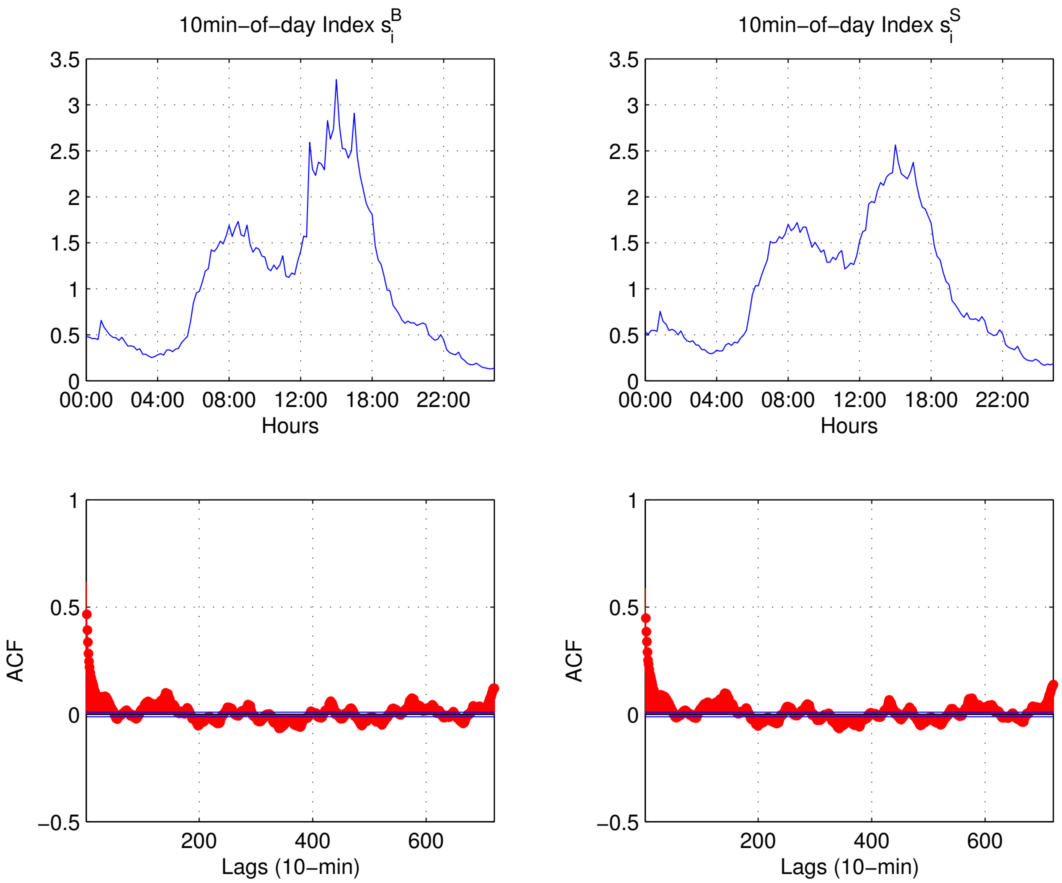

Figure 1: Top: 10-minute-of-day indices s_i^B and $s_i^S, i = 1, 2, \ldots 144$, for the number of buy (top left) and sell (top right) trades starting at 00:00 EST. Bottom: Sample autocorrelation functions at 720 ten-minute lags (5 days) of the adjusted number of buy and sell trades.

calculated from B_t and S_t so that we do not expect any time-of-day effects a priori.[8] However, the hourly activity of uninformed (liquidity) traders starts increasing after the LSE opens (03:00 EST). The activity is above average from 06:00 EST until 17:00 EST. Note that the above-average variation of the 10-minute-of-day index of uninformed traders is between 1 and 2.5 and, in addition, that the fluctuations are relatively smooth. Therefore, we may speculate that uninformed traders

[8]Thus, "hidden" time-of-day patterns are present even after B_t and S_t are adjusted for temporal effects. Since these effects are strong enough to persist even after adjusting for intraday time dependency, we will concentrate on them for the remainder of the paper.

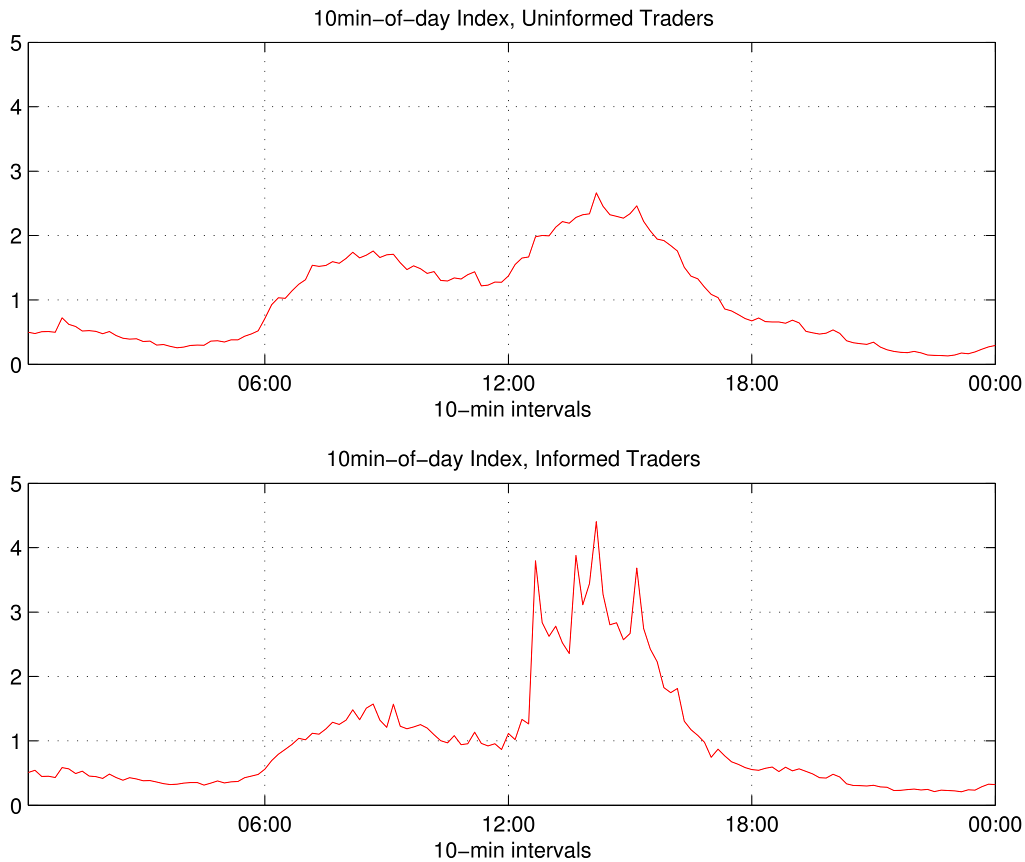

Figure 2: 10-minute-of-day indices of informed (top) and uninformed (bottom) traders over 24 hours, based on unbalanced trades ($|K|$) and balanced trades ($TT - |K|$). The 10-minute-of-day index of uninformed traders is above average from about 06:00 EST to 17:00 EST and is relatively stable, indicating a non-strategic arrival. The same index of informed traders is concentrated in the period after the lunch time in New York until 16:00 EST, when it is highly above average.

arrive during this time non-strategically. In contrast, the 10-minute-of-day index of informed traders reveals a different picture. It is almost entirely focused on the period after the lunch time in New York (13:00 EST) and 16:00 EST. The volatility of informed traders during that period is high: the index fluctuates between 1 and 4.5. It is possible that traders exchange private information during lunch-time and then trade on it, thus generating such excess volatility in their after-lunch arrival. Finally, the Tokyo activity is always below average for both classes of traders.

Index	Monday	Tuesday	Wednesday	Thursday	Friday
SI_α	0.88	0.97	0.99	1.05	1.08
SI_δ	1.42	0.96	0.75	0.87	0.98
SI_ε	0.93	1.07	1.11	1.05	0.82
SI_μ	1.02	1.09	1.04	0.99	0.84
SI_{PIN}	0.87	1.05	1.05	1.05	0.96

Table 1: Day-of-week indices of estimated parameters and the PIN.

3.3. Model Estimates

The log-likelihood function in Equation 4 is maximized every day ($I = 144$ ten-minute intervals) for the entire sample period (255 days). As a result, we have 255 different estimates of each parameter. The two probability parameters α and δ are restricted to $(0, 1)$, and the two arrival rates are restricted to (0,500), since the maximum observed number of buy or sell trades in our sample is 494.[9]

Table 1 reports the indices (day-of-week index) of the estimated parameters and the PIN.[10] The probability of an event α is higher on Thursdays and Fridays. Given that an event occurs, the probability that it is a bad event δ is lower than the average on all days except on Mondays. Therefore, we may speculate that during the sample period, Thursdays and Fridays were eventful days, with good news for EUR-USD.

The estimated probability of an event $\hat{\alpha}$ fluctuates between 0.06 and 0.48 with an average of 0.30. This implies that there were no days without an event occurring in a ten-minute interval. The lowest estimate 0.06 shows that there was a day with only nine ten-minute intervals with an event ($(0.06/9) \times 24 \approx 1$ day). Similarly, the highest estimate 0.48 shows that the most eventful day had 69 ten-minute periods with an event. The Shapiro-Wilk test (Shapiro and Wilk, 1965) does not reject the null hypothesis of normality at the 1% significance level, as the p-value is 0.123. Thus, for this sample, the market maker views the arrival of news as a normal process. The estimate that an event is bad news $\hat{\delta}$ lies between 0 and 0.32, with an average of 0.09. Note that $(1 - \delta)$ is the probability that an event is good news. This indicates that in 2005 there were on average high expectations of good news. According to the Shapiro-Wilk test, the estimate of δ is not normally distributed with the p-value=0.000. This is an expected result, as there was a significant trend in USD-EUR prices in 2005 (the market was optimistic about the USD).

The estimated arrival rate of uninformed traders $\hat{\varepsilon}$ does not exhibit any sharp increases and is between 5.18 and 65.23. The overall mean of this parameter is 40.66. The estimate follows a normal distribution, as confirmed by the Shapiro-Wilk test. The estimated arrival rate of informed traders

[9]For the reasonable choice of the starting values, the estimates are stable over the sample period.

[10]The day-of-week indices, denoted by SI_i ($i \in \{\alpha, \delta, \varepsilon, \mu, PIN\}$), are found using the ratio-to-moving average method.

$\hat{\mu}$ is volatile with occasional jumps. The Shapiro-Wilk test strongly rejects the null hypothesis of normality (p-value=0.000). The overall average of this parameter is 63.93, which is substantially higher than the average $\hat{\varepsilon}$. From Table 1, we see less-than-average arrival rates for both informed and uninformed traders on Fridays. The highest arrival rates of both informed and uninformed traders are observed on Tuesdays and Wednesdays. Noteworthy is the fact that the market maker attaches a non-normal (i.e., strategic) component to the arrival of the informed traders, which is not in line with the model assumption of the informed traders' risk-neutrality.

Finally, the average estimated PIN is about 0.11 and is thus lower than in equity markets.[11] Over the 255 days in the sample, the PIN ranges between 0.02 and 0.20. The day-of-week indices for the PIN point to Tuesday, Wednesday and Thursday as the above-average days. The PIN is below average on Mondays and Fridays. Therefore, when compared to $\hat{\mu}$, except for Mondays, the PIN appears to be a good indicator of informed trading activity. Although in general, informed traders attempt to camouflage their activity behind uninformed traders, the PIN successfully detects their behavior. In addition, the fact that the distribution of $\hat{\mu}$ is non-normal confirms the evidence of strategic activity by informed traders.

4. Conclusions

Using a high-frequency version of the structural microstructure model by Easley *et al.* (1996b) for the FX market, we address a number of important issues and provide new empirical findings. First, we estimate parameters that reflect market maker's beliefs about the arrival of informed traders to the market and the risk of informed trading. We establish the exact timing of the arrival of not only informed but also uninformed traders. The findings indicate a strategic component in the activity of the informed traders that is not observed for the uninformed traders. This phenomenon operates at different levels starting from the geographic intraday effects to the day-of-week effects. The microstructural analysis presented in this paper is only the first step in our understanding how the features of the electronic FX market are related to the findings.

[11] The estimated PIN in equity markets is usually between 0.15 and 0.25.

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