Private information and its origins in an electronic foreign exchange market

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1 It is worth noting that such issues do not arise with equities. In the equities case, in addition to public information, some traders may have information about firm characteristics (such as future asset prices) that other traders do not have (Glosten and Milgrom, 1985). In line with this notion, 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. Some notable research contributions include Easley et al. (1996a, 1997a,b, 2008). They showed that both informed and uninformed traders are highly persistent in equity markets.

Abstract

We study the risk of informed trading in an electronic foreign exchange market and test whether informed trading is driven by marketwide private information. Our framework is based on a structural microstructure trade model that measures the market makers’ beliefs directly. Evidence of high concentration of informed trades is found to be inversely related to the overall 24-hour trading activity, i.e., early morning and late afternoon GMT rounds of trading involve the highest risk of informed trading. We structurally identify that the trades due to region-specific private information are dominant and explain between 5 and 25% of the variation in currency returns. In contrast, marketwide private information explains only about 1–5% of the variation in returns.

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1. Introduction

Structural macroeconomic spot exchange rate models ignore the role of asymmetric information in exchange rate determination. These models assume that markets are efficient in the sense that information is widely available to all market participants and that all relevant and ascertainable information is already reflected in exchange rates. In other words, from this point of view, exchange rates are not informed by microstructure variables. Even if price effects from currency order flows arise, they are quickly incorporated through the error term of an exchange rate equation. Furthermore, as currency valuation depends primarily on macroeconomic information, the absence of firm-specific information implies a reduced potential for market maker losses to better informed traders (Bessebinder, 1994). In this context, the existence of private information in the foreign exchange (FX) market implies traders privately informed about macroeconomic fundamentals. However, the large volatility of currency returns can not be understood by the slow-moving macroeconomic variables.

In an alternative view, private information in the FX market can originate from proprietary trading models and non-common knowledge private news sources such as direct interdealer transactions and customer orders (Evans, 2002). For example, Lyons (2001) notes that currency orders from firms engaged in international trade convey private signals about the shift in demand for foreign currency because the orders are observed in advance of trade statistics. Foreign exchange orders by central banks placed with FX dealers represent another example of price-relevant private information that can be exploited by the dealers (Peiers, 1997). Recently, Albuquerque et al. (2008) demonstrate that the private information relevant for exchange rates could be

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contained in the equity market order flows, thus, reflecting information such as that on future mergers and acquisitions or cash flows of firms.

The heterogeneity of expectations in the FX market may also be understood as differences in valuation: some traders may place a higher value on a particular currency than others. These differences may originate in taxes, liquidity shocks or behavioral considerations (e.g., overconfidence) (Daniel et al., 1998). For example, Handa et al. (2003) show that the spread widens as valuation differences increase. Further, time-of-day variations in liquidity could also give rise to time-of-day variations in price impact. Particularly, as financial centers around the world open and close, there are changes in the depth of the market that might naturally change the price’s sensitivity to order flow. Finally, as outlined in Evans and Lyons (2002), order flow drives exchange rates because it represents an uninformative portfolio shift that requires a risk premium in order to clear the market. These portfolio shifts, however, could embody regional information content about such shifts, which is generally in line with the premise of the current paper.

This paper addresses a number of important issues and contributes to the study of private information effects in FX markets. First, using a structural model, 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 arrival of informed traders in FX markets. Moreover, by investigating intraday fluctuations in the probability of informed trading and arrival rates of the traders, we uncover the origins of private information in an electronic spot FX market. Specifically, we adapt the model from Albuquerque et al. (2008) to identify the role of marketwide private information in price discovery. In addition, we estimate the impact of region-specific private information on currency returns. In general, our approach can help validate and complement the recent market microstructure literature on the existence of private information in FX markets.5

This strand of research was pioneered by Lyons (1995) and Yao (1998), and extended by Payne (2003) who revealed substantial informed trading effects in an electronic FX market. More recently, Evans and Lyons (2007) show that the private information content in transaction activity (such as customer order flow) can predict exchange rates as well as macroeconomic fundamentals. Marsh and O’Rourke (2005) conclude that order flows of leveraged and unleveraged financial institutions contain price-relevant information. Similarly, Osler and Vandrovyč (2009) show that the trades by leveraged investors are consistently informative. Further, Bjo̩nnes et al. (2008) document information asymmetries based on the interdealer transactions at a large Scandinavian bank. A theoretical model involving asymmetric information in FX markets is provided in Vitale (2007). The model demonstrates how informed traders influence exchange rates by inventory management as well as through their private information. Finally, in a related recent contribution, Gençay et al. (2011) search for a more direct evidence of informed trading using a small retail FX trading platform. They find that both the estimates of the trade model parameters and model-free analysis of the data suggest a time-varying, strategic pattern of arrival of informed traders. Although their data set is exceptionally rich and allows for tracking of individual currency orders, in contrast to the current paper, they do not explore the potential commonality of private information across exchange rates.

The paper’s first contribution is the study of the relation between the time of day and the risk of informed trading in an electronic FX market. We utilize high-frequency FX data from Electronic Broking Services (EBS) that cover one year (2005) of trading in the global interdealer spot market for the EUR/USD, USD/JPY and USD/CHF exchange rates. To control for high-frequency noise effects and no-trade periods, we aggregate to 10-minute data. This enables us to structurally investigate intraday (geographical) patterns in the arrival of informed and uninformed traders as well as the intraday patterns in the probability of informed trading (PIN).6 Consistent with the findings for equity markets (Goldstein et al., 2006), we show that the time of day is an important determinant of the risk of informed trading in the FX market. We also find that the PIN is inversely related to the trading activity, measured by the number of buy and sell orders. Furthermore, we reveal that for all exchange rates the highest PIN values correspond to late GMT afternoon North American and early GMT Asian trading. Therefore, it appears that North American and Asian traders are better informed than traders in other geographic regions. Our findings extend and complement the contributions by Dufour and Engle (2000), Payne (2003) and Menkhoff and Schmelings (2010). The latter two papers suggest that price impacts of unexpected trades are highest in non-peak trading periods, when the order book is relatively thin. It is also worthwhile to note that we document relatively high average PIN levels (≈0.2) that are comparable to those in equity markets. This is a novel and surprising evidence for a market that is considered to be largely driven by public information, and to have no or limited private information.

Next, to uncover the origins of informed trading, as in Albuquerque et al. (2008), we differentiate between marketwide private information that affects all geographic regions of the FX market and region-specific private information. Using the assumption that marketwide private information generates trading simultaneously in several currencies, we test whether such information drives currency returns. Our findings suggest that marketwide private information plays a minor role in price discovery as it is able to explain only between 1 and 5% of the variation in high-frequency currency returns. In line with the observed intraday patterns in the PIN, the origins of the potentially informed trading activities lie in region-specific private information. Our measure of region-specific private information is derived from the parameter estimates for each exchange rate and it explains roughly 5–25% of the variation in currency returns. This paper is the first to provide a structural evidence for the geographic origins of private information in FX markets. Other studies either investigate the informativeness of orders by different end-users or utilize non-structural models (Bjo̩nnes et al., 2008; Osler and Vandrovyč, 2009; Schumleiner, 2006).

The remainder of the paper is organized as follows. In Section 2, we derive a high-frequency version of the theoretical model by Easley et al. (1996b). Section 3 describes the EBS data and presents the estimates of the model. Section 4 extends the model in the spirit of Albuquerque et al. (2008) to uncover the origins of private information in the FX market. Section 5 concludes the paper.

2. Independent arrival model

The model consists of informed and uninformed traders and a risk-neutral competitive market maker.7 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 24 h (or 144 ten-minute intervals). Within any trading interval, the time is continuous, and the market maker is expected to buy and sell currencies at his posted bid and ask prices.

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4 The region-specific private information is comprised of “local knowledge” that traders from other geographic regions may have difficulties obtaining. Although there has not been any formal evidence for the existence of such information, these effects may, for instance, arise from the leakage of information from central bank officials that have been reported in Japan (The Wall Street Journal 12, March, 1998). Temporary informational advantage by local banks can also be achieved via aggregation of information extracted from currency orders of large regional corporations (Govir and Melvin, 2002).

5 For an excellent review of FX market microstructure literature see Osler (2009).

6 As in Dacorogna et al. (2001) and, recently, Kaul and Sapp (2009) we use the following geographic regions to cover the 24-hour trading day: 00:00-08:00 GMT (Asia), 08:00-12:00 GMT (Europe only), 12:00-16:00 GMT (both Europe and North America), 16:00-20:00 GMT (North America only), and 20:00-00:00 GMT (post-North America).

7 In this section, our framework follows Easley et al. (1996b).
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 occurs with probability $\alpha$. This is comprised of bad news with probability $\bar{\alpha}$ and good news with $1 - \bar{\alpha}$ probability. Let $[s_t]$ be the price process over $i = 1, 2, ..., 144$ periods. $s_t$ 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 $s_t < s_t' < s_t''$, where $s_t'$, $s_t''$ and $s_t'''$ are the price 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 $\epsilon$. Informed traders only trade when there is news and arrive at a rate of $\mu$. 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. For good news, the arrival rates are $\epsilon + \mu$ for buy orders and $\epsilon$ for sell orders. For bad news, the arrival rates for buy orders are $\epsilon$, and $\epsilon + \mu$ for sell orders. When no news exists, the buy and sell orders arrive at a rate of $\epsilon$ per ten-minute interval.

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 ten-minute decisions are analyzed independently from one period to the next. Let $P(t) = (P_B(t), P_S(t), P_{SB}(t))$ 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 is $P(0) = (1 - \alpha, \alpha, 0(1 - \alpha))$.

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 at $t$ conditional on the history prior to time $t$ and a sell order arriving at $t$. $P_t([S_t])$ is the market maker’s belief about no news conditional on a sell order arriving at $t$. Similarly, $P_t([S_t])$ is the market maker’s belief about the occurrence of bad news events conditional on a sell order arriving at $t$, and $P_t([S_t])$ 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:

$$PIN(t) = \frac{\mu(1-P_{SB}(t))}{2\epsilon + \mu(1-P_{SB}(t))} = \frac{\mu x}{2\epsilon + \mu x}$$

Since each buy and sell order follows a Poisson process at each trading interval and is independent, the likelihood of observing the data $M = (B_t,S_t)_{t=1}^{24}$ over 24 hours ($1 = 144$ ten-minute intervals) is as follows:

$$L(M|\theta) = \prod_{t=1}^{t=24} L(\theta[B_t,S_t]) = \prod_{t=1}^{t=24} \frac{e^{-2\epsilon t}B_t^{S_t}S_t!}{B_t!} \times \left[1 - e^{\mu x} \bar{\alpha} + e^{-\mu x} (\bar{\alpha} - e^{\mu x} + \alpha(1 - \bar{\alpha})e^{\mu x}) \right]$$

The log-likelihood function is

$$l(M|\theta) = \sum_{t=1}^{t=24} l(\theta[B_t,S_t]) = \sum_{t=1}^{t=24} \left[ -2\epsilon t + (B_t + S_t)\ln \bar{\alpha} + \sum_{t=1}^{t=24} \ln \left[1 - e^{\mu x} \bar{\alpha} + e^{-\mu x} (\bar{\alpha} - e^{\mu x} + \alpha(1 - \bar{\alpha})e^{\mu x}) \right] \right]$$

(3)

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

$$l(M|\theta) = \sum_{t=1}^{t=24} \left[ -2\epsilon t + M_t x + (B_t + S_t)\ln(x + \bar{\alpha}) \right]$$

$$+ \sum_{t=1}^{t=24} \ln \left[\alpha(1 - \bar{\alpha})e^{\mu x} x - M_t + e\alpha e^{\mu x} x + (1 + e\alpha e^{\mu x} x - M_t) \right]$$

(4)

$$M_t \equiv \min(B_t,S_t) + \max(B_t,S_t)/2, \text{ and } x = e^{\mu x} [0, 1].$$

3. Data and estimation results

3.1. Overview of EBS and intraday trading patterns

Our data set is from EBS and consists of tick-by-tick FX transaction prices and volume indicators for the EUR/USD, USD/JPY and USD/CHF exchange rates 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 and 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, for the EUR–USD market, there are roughly 8000 buy orders and 6000 sell orders on a given day. The corresponding figures for the USD–JPY and USD–CHF markets are around 5000 buys and 4000 sells, and 2000 buys and 1500 sells, respectively.

One should keep in mind that the hypothetical “market maker” in the model has access to all EBS data (like ECB does), but this is not what EBS traders normally do. An EBS trader selects a given number of counterparties with which he/she is willing to make business. He/she will then see only their quotes. The information set depends on the counterparties and it is unlikely that individual traders will have information about the market-wide order flow. Furthermore, it is important to stress that, unlike OANDA FXTrade trading platform that is an electronic market making system, EBS is not a market maker. However, prices are made by a relatively few dealers (market making banks) that specialize in individual currency pairs. For this reason, EBS platform can be

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

9 To derive Eq. (4), the term $\ln [\alpha^x (1 + e^x + \alpha (1 - \bar{\alpha}) e^x)]$ is simultaneously added to the first sum and subtracted from the second sum in Eq. (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.

10 EBS (level 1.5) 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. It is worth noting that, except for data levels 2.0, 4.0 and 5.0, released in 2008, EBS and also Reuters neither reveal the high-frequency trading volume nor the identity of the traders.
approximately viewed as a “special case” of the FX market and can be approached using the model by Easley et al. (1996b). In regards to trader behavior, as we only focus 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.

An important advantage of our data is that the nature of the EBS currency orders is directly observable and trade classification algorithms such as Lee and Ready (1991) were not required to differentiate between buyer- and seller-initiated trades. This differs from equity markets, where trade classification data is often unavailable.

Fig. 1. Top: The average number of buy trades on each 10-minute interval for a 24-hour trading day. Bottom: The average number of sell trades on each 10-minute interval for a 24-hour trading day. The average number of buys or sells across all geographic regions is marked by a horizontal line.

Fig. 2. Top: The average number of buy trades on each 10-minute interval for a 24-hour trading day. Bottom: The average number of sell trades on each 10-minute interval for a 24-hour trading day. The average number of buys or sells across all geographic regions is marked by a horizontal line.
EBs level 1.5 data allow us to directly observe the average 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 order arrivals, strong intraday effects in all series are evident. Fig. 1 shows \( B_t \) and \( S_t \) (\( t = 1, 2, \ldots, 144 \)), for the EUR–USD transactions starting at 00:00 GMT. The number of buy and sell trades starts to increase after 03:00 GMT and becomes above average after 06:00 GMT. Another sharp increase is observed around 12:30 GMT. The number of trades starts to decline after the European trading closes. They remain relatively low and stable during the following hours until midnight.

We also plot the USD–JPY transactions over 24 h in Fig. 2. As mentioned before, the number of trades in this market is lower that in the EUR–USD market. The trading activity pattern is similar to the EUR–USD market, but it also includes a distinct outburst in Asian trading that is at its peak higher than the Europe-only trading. This is expected because large Japanese banks are making a market in USD–JPY trading. In sub-section 3.2 and Section 4, we explore whether the fact that Japanese banks receive FX orders of the largest Japanese corporations gives them any informational advantage.

Fig. 3 shows that the USD–CHF market has the lowest trading activity with the maximum \( B_t = 50 \) orders and the maximum \( S_t = 40 \) orders per 10-minute trading interval. The bulk of the USD–CHF trading takes place during the North American and European hours. Asian trading contribution is very small, but it is greater than zero. Although it is characterized by lower overall levels, the USD–CHF trading resembles the EUR–USD market trading activity.

### 3.2. Model estimates

#### 3.2.1. Daily parameters

The log-likelihood function in Eq. (4) is maximized every day (\( l = 144 \) ten-minute intervals) for the entire sample period (255 days). As a result, we have 255 different estimates of \( \alpha, \delta, \) and \( \mu \) for each exchange rate. The two probability parameters \( \alpha \) and \( \delta \) are restricted to \((0, 1)\), and the two arrival rates are restricted to \((0.500, \infty)\), since the maximum observed number of buy or sell trades in our sample is 494.\(^{11}\)

Table 1 reports the average estimates and the PIN for all geographic regions and exchange rates. The last column indicates that the estimated PIN figures are surprisingly large and comparable to equity market PIN estimates (Easley et al., 1996b). Specifically, the highest average PIN is observed for the USD/CHF exchange rate and it is driven by the relatively low arrival rates of uninformed traders \( (\lambda) \), relative to the arrival rates of informed traders \( (\mu) \). The PIN estimates for the EUR–USD and USD–JPY markets reflect the high arrival rates of informed traders. To assist in analyzing the results, Fig. 4 provides histograms of the parameter estimates for the EUR/USD exchange rate.\(^{12}\)

The estimated probability of an event \( \alpha \) 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 \((0.06/9) \times 144 \approx 1 \) day). Similarly, the highest estimate 0.48 shows that the most eventful day had 69 ten-minute intervals.

<table>
<thead>
<tr>
<th>Exchange rate</th>
<th>( \alpha )</th>
<th>( \delta )</th>
<th>( \mu )</th>
<th>PIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUR/USD</td>
<td>0.30</td>
<td>0.09</td>
<td>40.66</td>
<td>63.93</td>
</tr>
<tr>
<td>USD/JPY</td>
<td>0.27</td>
<td>0.19</td>
<td>25.74</td>
<td>41.23</td>
</tr>
<tr>
<td>USD/CHF</td>
<td>0.24</td>
<td>0.34</td>
<td>10.08</td>
<td>29.40</td>
</tr>
</tbody>
</table>

\(^{11}\) For the reasonable choice of the starting values, the estimates are stable over the sample period.

\(^{12}\) Histograms for the USD/JPY and USD/CHF exchange rates are very similar and can be available upon request.
with an event. The Shapiro and Wilk (1965) test 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. It is worth noting that the EUR–USD market shows the highest average probability of an event, which is in line with the highest number of orders for this market (Fig. 1).

The estimate that an event is bad news $\delta$ 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 about the EUR currency. According to the Shapiro–Wilk test, the estimate of $\delta$ is not normally distributed with the p-value $= 0.000$. This is a somewhat unexpected result, as the USD appreciated against the EUR in 2005. The other two estimates for average $\delta$ in the second column of Table 1 are reasonable as they suggest more good news about the USD relative to the JPY and CHF currencies (and the USD appreciated against both currencies in 2005).13

The estimated arrival rate of uninformed traders $\epsilon$ 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 $\mu$ 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 $\epsilon$.

### Table 2

<table>
<thead>
<tr>
<th>Geographic region</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\epsilon$</th>
<th>$\mu$</th>
<th>PIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asia 1</td>
<td>0.35</td>
<td>0.16</td>
<td>39.62</td>
<td>63.38</td>
<td>0.19</td>
</tr>
<tr>
<td>Asia 2</td>
<td>0.35</td>
<td>0.10</td>
<td>40.33</td>
<td>68.62</td>
<td>0.17</td>
</tr>
<tr>
<td>Europe only</td>
<td>0.34</td>
<td>0.04</td>
<td>42.81</td>
<td>45.27</td>
<td>0.14</td>
</tr>
<tr>
<td>Europe and North America</td>
<td>0.34</td>
<td>0.03</td>
<td>42.29</td>
<td>45.73</td>
<td>0.14</td>
</tr>
<tr>
<td>North America only</td>
<td>0.31</td>
<td>0.08</td>
<td>40.58</td>
<td>63.41</td>
<td>0.17</td>
</tr>
<tr>
<td>Post North America</td>
<td>0.40</td>
<td>0.21</td>
<td>37.11</td>
<td>68.62</td>
<td>0.25</td>
</tr>
</tbody>
</table>

#### 3.2.2. Regional parameters

If one believes that the FX market has no or limited private information, the above findings necessitate careful consideration of the origins of private information. Extracting time-of-day variations in the PIN could shed light on this issue. For that purpose, we estimate the parameters and the PIN for each geographic region separately. Dividing the 24-hour trading day (144 time intervals) into six non-overlapping regions results in the following sample sizes: Asia 1 ($T_1 = 24$), Asia 2 ($T_2 = 24$), Europe only ($T_3 = 24$), Europe and North America ($T_4 = 24$), North America only ($T_5 = 24$), and post-North America ($T_6 = 24$).

The average regional estimates of the parameters and the PIN for the EUR–USD exchange rate are listed in Table 2. It indicates that high intra-day levels of the PIN reflect high arrival rates of informed traders. The arrival rates of uninformed traders are relatively stable throughout the day. Further, the probability of news arrival ($\alpha$) is stable, while the probability of good news $(1 - \delta)$ is directly related to the overall market activity. In other words, the lowest values of $\delta$ correspond to more intense market activity that takes place between 08:00 GMT and 16:00 GMT. Also, as trading activity decreases, the PIN increases. This is consistent with the findings of Menkhoff and Schmeling (2010) and can be explained by correlated trading strategies that are pursued by informed traders. As liquidity traders attempt to avoid trading in such periods of high PIN, that leads to a reduction in market activity (and liquidity). The relationship between higher spreads (and lower market activity) and the presence of informed traders have also been covered in Admati and Pfleiderer (1988). Finally, it appears that North American traders are better informed than traders in Europe, which is to a certain degree expected given the dominance of large North American banks in making the EUR–USD market. However, the high concentration of Asian informed traders in the EUR–USD market is puzzling, but in line with Ito

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13 Orders in the EBS market are submitted in units of millions of the base currency which is BBB when an exchange rate is expressed as BBB/LLL; the listed price is the amount of local currency (LLL) that is required to purchase one unit of the base currency (BBB).
and Hashimoto (2006) who found the largest bid-ask spreads for the EUR–USD trading in Asia.\footnote{Increased activities of informed traders might cause other market participants to protect themselves against informative order flows and increase the bid-ask spread.}

Table 3 presents intraday properties of the PIN and the estimated parameters in the USD–JPY market. The highest PIN and the highest arrival rate of informed traders correspond to North American and Asian trading activity. The arrival rate of uninformed traders is stable with a slight decline during North American hours. Note that the bid-ask spread for Asian trading is the largest (Ito and Hashimoto, 2006), thus, confirming significant presence of informed traders in this market. Our findings in general support those by Covrig and Melvin (2002) and also extend them to a longer time period.

The results for the USD–CHF market mirror the ones for the EUR–USD market, except for the fact that the observed “U-shape” in the PIN figures is more pronounced (Fig. 5). It is worth noting that the PIN in Table 4 for Asian trading (Asia 1) reaches 0.35 mainly because of the relatively high probability of the news arrival (\(\pi = 0.34\)). Similar findings are uncovered for North American trading where the PIN is largest. However, it is important to stress that European trading rounds in the USD–CHF currency pair attract highest average arrival rates of informed traders (\(\pi\)). The middle section of Fig. 5 shows that for European trading the PIN (and the arrival rates of informed traders) for the EUR–USD market is greater than the PIN for the USD–CHF market. The opposite can be seen on the far left (Asia) and far right (North America) sections of Fig. 5. In all, the evidence overwhelmingly supports regional (time-of-day) informed trading effects that are inversely related in magnitude to the overall trading activity levels for each currency pair. Another interesting finding is that, from a temporal perspective, less frequently traded currencies may have new information more often than active ones, which can be observed in the first column of Tables 3 and 4 where the values for average \(\alpha\) are located. Specifically, for the USD–CHF currency pair, which is the least active market, the average \(\alpha\) is relatively low for the European and North American time zones. Thus, it can be concluded that infrequently traded currencies show more temporal variation in \(\alpha\), where the arrival of news is inversely related to their trading intensity over 24 h.

4. The origins of private information

FX markets aggregate both private and public information from various sources such as macroeconomic announcements, proprietary forecasting models and technical trading strategies. In the context of private information, the information content of currency order flows can be marketwide or region-specific. Marketwide private information affects a number of exchange rates simultaneously. Such information can be, for instance, obtained from stock market order flows which are shown to predict the FX market movements (Albuquerque et al., 2008). Similarly, this issue can be viewed through the lens of cross-market order flow effects: various markets (i.e., currency pairs) are linked and trading in some exchange rates is able to convey information relevant for other exchange rates. Lyons and Moore (2009) tackle this question using triangular arbitrage and demonstrate that order flows in the JPY/USD market predict USD/EUR and JPY/EUR exchange rates. In contrast to marketwide information, region-specific private information is related to regional informational advantage of the resident traders about their local currency. With regard to the USD–JPY currency pair, Japanese banks receive FX orders from the largest Japanese corporations and this may offer a temporary informational advantage. Likewise, the USD–JPY transactions of non-North American investors are likely not driven by private information about the USD and they are mainly motivated by international portfolio considerations. Hence, we assume that region-specific information about a currency pair reflects the knowledge and activity of traders in both countries.\footnote{The Easley et al. (1996b) model applied to currencies should produce the same result whether one looks at the JPY–USD market or the USD–JPY market because buying USD is the same as selling JPY and vice-versa.}

The impact of region-specific information (RPI) and marketwide private information (MPI) on FX returns.

<table>
<thead>
<tr>
<th>Currency Pair</th>
<th>RPI</th>
<th>MPI</th>
<th>RPI and MPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUR/USD</td>
<td>10.36%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>1.02%</td>
<td>-</td>
</tr>
<tr>
<td>USD/JPY</td>
<td>24.76%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>4.58%</td>
<td>-</td>
</tr>
<tr>
<td>USD/CHF</td>
<td>5.10%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>0.88%</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>5.43%</td>
</tr>
</tbody>
</table>

In this section, we utilize a computationally effective route for estimating the contribution of marketwide private information news (MPI) in generating the average number of buy and sell orders over a trading period. The variable MPI captures the qualitative nature of the marketwide private information embedded in currency trading in all three currency pairs. The idea is to estimate the first principal component in currency...
order flow due to region-specific trading. Albuquerque et al. (2008) show that this amounts to maximizing the log-likelihood Eq. (4) and obtaining relevant parameters for each exchange rate. Hence, we can use the parameter estimates from sub-section 3.2. To assess the MPI, we first estimate the contribution of region-specific private information (RPI) in explaining FX returns as

\[ RPI_{t+1} = \alpha_i \left(1 - \delta_{i,t+1}\right) \mu_{i,t} = \left(\text{EUR/USD, USD/JPY, USD/CHF}\right), t = 1, \ldots, 255. \]  

(5)

Intuitively, the RPI variable is directly related to the exchange rate-specific estimated news arrival rate (\( \alpha \)) and also to the observed arrival of informed traders (\( \mu \)). MPI is the first principal component of the variable in each of the above regressions. Table 5 presents the R^2 with regard to the RPI measure in the second column and those with regard to the MPI measure in the third column. The fourth column shows the R^2 figures when the FX returns were regressed on both private information measures. Next, for each exchange rate (\( S_{ij} \)), we regress daily FX returns (\( R_{ij} = \log S_{t} - \log S_{t-1} \)) on RPI and MPI measures using the variants of the following simple regression:

\[ R_{ij} = \gamma_{i0} + \gamma_{i1} RPI_{ij} + \gamma_{i2} MPI_{ij} + \epsilon_{ij} \]

(6)

where \( i \in [\text{EUR/USD, USD/JPY, USD/CHF}] \), \( t = 1, \ldots, 255. \)

We are interested in the percentage of explained variation in FX returns explained by the two measures, i.e., the R^2 in each of the above regressions. We find weak evidence of contribution of marketwide private information effects in explaining FX returns. However, the variation in region-specific private information measure is able to explain between 5 and 25% of the variation in currency returns. These findings confirm that the vast majority of private information is specific to a currency pair, rather than being common across pairs.

5. Conclusions

We estimate parameters that reflect market maker’s beliefs about the arrival of informed traders to the FX market and the risk of informed trading. Moreover, we uncover intra-day arrival patterns of informed traders in the EUR–USD, USD–JPY and USD–CHF markets. The findings indicate the strongest activity of the informed traders during Asian and North American trading that is inversely related to the overall market activity for all exchange rates. In line with the findings for equity markets i.e.,Goldstein 2006, we show that the time of day and location are important determinants of the risk of informed trading in the FX market. In all, we present a novel and direct way to estimate the presence of informed investors as compared to, for example, contributions by Payne (2003) and Menkhoff and Schmelzing (2010).

We also address the following question: what is the geographic source of private information in the FX market? To answer it, we test whether marketwide private information has a key role in price discovery. Alternatively, we also test the impact of region-specific information on currency returns. We find that the observed PIN effects originate in the prevalence of region-specific private information. In contrast, marketwide private information plays a minor role in price discovery as it is able to explain only between 1 and 5% of the variation in high-frequency currency returns. We conclude that the location of FX traders might offer a temporary informational advantage. Depending on the availability of appropriate end-user data, it remains open to future research to determine who brings private information to regional segments of the FX market.

References


16 Adding lags of MPI to Eq. (7) does not improve the results. In general, we are unable to document any statistically significant forecasting power of FX marketwide private information.

17 For example, Covrig and Melvin (2002) present evidence that Japanese traders are better informed regarding the yen and that they are dominant in their contribution to the JPY/USD exchange rate price discovery, relative to non-Japanese traders. In the same vein, Peiers (1997) identifies periods when Deutschebank acted as a price leader in the DM-USD market.