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# Informativeness of trade size in foreign exchange markets

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## HIGHLIGHTS

- We investigate the informativeness of trade size in an electronic spot foreign exchange market.
- Large currency orders are likely placed by informed traders.
- Large trades are associated with increased exchange rate volatility.
- Small orders increase the likelihood of extreme events.
- Large orders from informed traders tend to be more concentrated.

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## ABSTRACT

This article investigates a trading strategy that relies on private information in an electronic spot foreign exchange market. In a structural microstructure model extended for high-frequency data, our analysis links the informational content of trading activity to order size. We find that large currency orders are likely to be placed by informed traders during increased price volatility episodes. In addition, the data suggest that excess kurtosis in exchange rate returns (corresponding to large price-contingent trades) is significantly lower than that in small trades.



## 1. Introduction

Do heterogeneously informed currency traders differ in their use of information? If so, how does private information impact their trade size? What is the relationship of trade size to foreign exchange (FX) rate volatility? This paper seeks answers to these questions by linking the information process to order size patterns while relying on a trading strategy designed in an electronic FX market. Extending (Easley et al., 1997b; Easley and O'Hara, 1987), our high-frequency trading setup allows informed and uninformed traders to place orders sequentially in continuous time.[1] To test the predictions of the strategies, we derive tractable likelihood

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[1] While informed traders utilize information surprises as principal motivation for their trading, uninformed traders consider non-news factors, such as liquidity or trade-driven shocks. See also Osler and Savaser (2011) and Osler (2005), who empirically show that extreme FX price movements could result from stop-loss orders even in the absence of any macroeconomic news announcements.

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functions that identify the variation in trade size associated with the orders of informed and uninformed FX traders.

Based on a retail electronic trading platform dataset, our empirical analysis reveals several notable findings. First, we empirically show that large orders are likely to be executed by informed traders rather than uninformed traders. This evidence is particularly pronounced for buy orders and remains strong regardless of the choice of size thresholds. These results highlight the importance of the information content of trade size (i.e., *informativeness*) in characterizing currency transaction data. More broadly, a direct implication of this analysis is that order flow size could be informative by itself even in the absence of information shocks.[2] Second, an estimated logit model suggests that large trade size appears to be an *endogenous* factor that depends on price volatility. This finding supports the *intraday trading invariance principle* proposed by Andersen et al. (2015). Finally, we assess the distributional characteristics of price increments and show that excess kurtosis in exchange rate data, corresponding to large price-contingent trades, is significantly lower than that in small trades. Our motivation for this assessment directly builds on the argument of Osler and Savaser (2011) and Osler (2005), who provide evidence that price-contingent trading could solely explain the extreme price cascades in the transactions of an FX dealer. We emphasize that the source of extreme events could be attributed to the informativeness of trade size: uninformed traders tend to place small orders as a range of extreme stop-loss and take-profit trades. This may result in jump cascades or excess kurtosis observed in transaction data. In addition to quotation bursts in equities (Gençay et al., 2016), the size and informational content of trades could thus be additional drivers of currency jumps.

The remainder of the paper is organized as follows. Section 2 introduces the model and outlines the trading environment. Section 3 describes our data. In Section 4, we present and discuss the empirical results. Section 5 concludes the paper.

## 2. 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 24-hour trading day. Within any trading hour, the market maker is expected to buy and sell currencies from his posted bid and ask prices.[3] The price process is the expected value of the currency based on the market maker's information set at the time of the trade.

### 2.1. Arrivals of news, traders and orders

The hourly arrival of news occurs with the probability $\alpha$. This represents bad news with probability $\delta$ and good news with $1-\delta$ probability. We define the price process as follows.

**Definition 1.** 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 news, 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 $\varepsilon$. Informed traders trade only when there is news, arriving at a rate of $\mu$.[4]

### 2.2. The market maker and measuring the likelihood of orders

The market maker is assumed to be Bayesian, using the arrival of trades and their intensity to determine whether a particular trading hour belongs in the category of no news, good news or bad news. Because 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.

**Definition 2.** 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, the prior beliefs before trading starts each day are $P(0) = (1-\alpha, \alpha\delta, \alpha(1-\delta))$.

Given the definition above, let $S_t$ and $B_t$ further 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 occurs at time $t$ (based on information) is then

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

Because 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

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

and in a good-event hour, this likelihood becomes

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

[2] Prior research on currency markets has focused on the link between expectations and shocks hitting currency markets (Evans, 2002; Evans and Lyons, 2002). While information-driven shocks change expectations and often increase market volatility (see, e.g., Jiang et al., 2011; Ederington and Lee, 1995; Ederington and Lee, 1993), price-contingent trading could also trigger large FX market swings even in the absence of any news arrivals (Osler, 2005; Osler and Savaser, 2011). Non-information shocks may include, for instance, liquidity (or trading-based) shocks (Caballero and Krishnamurthy, 2008), real shocks (i.e., innovations of preferences as in Allen and Gale, 2000) and structural shocks (see, e.g., Dungey et al., 2010).

[3] For ease of notation and exposition, we present our model based on hourly time scales. The predictions of the trading strategy remain the same at higher frequencies, such as 5 or 10 min.

[4] We also assume that all informed traders are risk neutral and competitive, and we therefore expect them 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 $\varepsilon$ for sell orders. For bad news hours, the arrival rates are $\varepsilon$ for buy orders and $\varepsilon+\mu$ for sell orders. When no news exists, the buy and sell orders arrive at a rate of $\varepsilon$ per hour.