Do jumps mislead the FX market?

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PRELIMINARY AND INCOMPLETE

Abstract

This paper investigates the causality between jumps in the exchange rate process and rumors of central bank interventions. Using the case of Japan, we analyze in particular whether jumps trigger false reports of intervention (i.e. an intervention is reported whereas it did not occur). Intra-day jumps are extracted using non-parametric techniques recently proposed by Lee and Mykland (2007). Rumors are identified by using a unique database of Reuters and Dow Jones newswires. Our results suggest that a significant amount of jumps on the YEN/USD have been falsely interpreted by the market as the result of a central bank intervention. The paper has policy implications in terms of central bank interventions. We show that in times where the central bank is known to intervene, some investors may attach a lot of weight to central bank interventions as a source of exchange rate movement, leading to an false "intervention explanation" for observed jumps. We provide empirical support to the scapegoat theoretical model of Bachetta and van Wincoop (2004).

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…the dollar spiked [jumped] a yen higher within minutes in a move which a Tokyo trader identified as having been caused by BOJ buying [Bank of Japan intervention] in the Y120.30-40 rang,... (Reuters, July 15, 1999)

1. Introduction

For many years, researchers have studied how economic news affect financial asset prices in general and exchange rates in particular. It might not be exaggerated to say that hundreds of papers have been written in the field, during decades. This paper raise the exact opposite question: how do exchange rates movements affect news? More precisely, we study how exchange rate movements tend to create a particular type of rumor: those of a central bank intervention on the market.

To the best of our knowledge, the general question of "how price movement cause news" has not received empirical attention so far. We conjecture that there are two main reasons that explain this gap in the literature: a potential lack of theoretical understanding about how such an event (i.e. a news caused by a price movement) could occur, and second, the difficulty to empirically capture and scientifically report these (potential) events. These two main difficulties can now be overcome, making such a study possible and the gap in the literature, at least partially filled.

Theoretically, the fact that market participants sometimes falsely interpret as intervention unusual movements of the exchange rate is consistent with the microstructure approach where private information can be transmitted through order flows (Evans and Lyons 2002). In this framework, the market is usually made up of different types of agents, some having access to private information. Their trades induce order flows that in turn influence the prices. Others have no private information and trade according to their hunches or public information. Baillie and al. (2000) emphasize that prices might then "*perform a dual role of describing the terms of trade and of transferring information from more to less informed agents*". Consistent with this idea, some agents might naturally try to extract some information from the developments of prices and especially from exceptional movements as jumps. More formally, Bachetta and van Wincoop (2004) have provided an elegant theoretical explanation for how heterogeneous rational investors can end up using, wrongly, macroeconomic fundamentals as scapegoats for the movement they observe. We will argue that our findings provide empirical support to this theory. Loosely speaking, it is rational for investors to blame fundamentals as the cause for observed exchange rate movements when they receive noisy signals about the true value of fundamentals. Moreover, raising the question whether investors blame a central bank intervention for observed movements, as we do in this paper, is equivalent to the question whether they blame fundamentals as an intervention is a signal about the fundamental value of exchange rate. The theoretical model of Bachetta and van Wincoop (2004) is thus closely related with our empirical investigation.

Second, we overcome the measurement difficulty through the use of a unique news database regarding bank of Japan interventions on the JPY/USD market. We collected Dow Jones/Reuters newswire reports concerning these interventions. Since the BoJ has made public the true data and intervention calendar, we can observe when false news was reported. This data set gives a unique opportunity study how market movement can create false news, or rumors of central bank intervention. Moreover, contrasting with newspaper reports (e.g. Financial Times, Wall Street Journal) newswire reports allow to properly depict the market perception (Oberlechner and Hocking, 2003) and to collect intra-daily information about the occurrence of news. So we can now formulate our research question in a more precise way. This paper examines how investors blame central bank interventions for observed exchange rate movements, as manifested through news providers. We will argue that when such a news is reported by news providers, it reflects properly traders beliefs.

What causes these false rumors to occur? We thus have a theoretical background to understand the false reports we observe. There remains to define precisely what type of market movement we wish to examine as a potential cause for these rumors. In this paper, we consider the effect of very large exchange rate movements in very short period of time, i.e. jumps. It seems indeed natural to consider highly visible market movements as a potential cause for false rumors. We thus consider events defined by large intraday returns relative to local volatility. To achieve jump estimation, we use a new non-parametric technique due to Lee and Mykland (2007) that formalize the idea that an intraday return cannot be considered to come from a pure diffusion when it is large compared to prevailing volatility conditions. Jumps are not necessarily large in absolute terms. If volatility is low, a relatively small return can be detected as a jump. It is thus necessary and original to use this formal jump detection technique rather than determine arbitrarily what constitutes an abnormal exchange rate movement. So our paper can also be seen as a contribution to the jump literature, as we study what can be seen as the consequences of jumps on financial markets. Up to now, few studies have focused on this causality between jumps and intervention report news. Beine and al. (2006) analyze the reverse relation, i.e. do intervention reports create jumps? They find that coordinated interventions tend to cause few, but large jumps.[1] And to the best of our knowledge, this study is the first to investigate a reversed relationship between jumps and false reports.

Last but certainly not least, our paper significantly and originally contributes to the literature about central bank intervention. At least for practical reasons and policy implications, a very large literature has studied the effects of central bank intervention on exchange rates. It has been shown that official interventions[2] and unofficial reports of intervention in the public press cause volatility.[3] But the question raised here is about the reverse relationship. Can market participants detect (rightly or wrongly) an intervention operation when there is a sharp movement of the exchange rate? According to the signalling channel (Mussa, 1981), central banks affect the exchange rate by transmitting a signal to the market. Once perceived, market participants might theoretically adjust their trading behavior accordingly. This signal usually takes the form of a newswire announcing central bank's purchases or sales of domestic currency against foreign currency. As noted by Schwartz (2000), however, it may happen that, in practice, market participants mistaken and "*detect a signal where none was sent*". This is what we confirm in our study. The emerge of false signals is obviously of overwhelming importance for policymakers as it shows that the central bank's policy can indirectly create substantial confusion in the market. Moreover, the credibility of the future central bank's signals and more generally of the central bank's policy

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[1] In the same spirit, some papers have focused on the impact of macroeconomic announcements on the discontinuities in asset prices (Andersen and al. 2003, 2005; Beine and al. 2006).

[2] Official data on currency by major central banks are released periodically and the only contemporaneous accounts of intervention activity are unofficial reports in the public press (Reuters, Dow Jones…).

[3] Indeed, with the end of Bretton Woods and the shift to a floating exchange rate regime, misalignment and excessive volatility have become well known features of financial markets. Central banks have regularly intervened in the FX market through actual purchases and sales of foreign exchange in order "to calm the disorderly markets" and to limit adverse effects on their international competitiveness. This is despite the fact that such operations have been shown to be ineffective, as documented in the empirical literature. The main body of the literature reveals that official and unofficial interventions do not move the exchange rate very successfully in the desired direction except in the very short run (Fisher and Zurlinden 1999; Beine and al. 2002; Dominguez 2003; Payne and Vitale 2003). Furthermore, such interventions generally increase foreign exchange volatility (Humpage 2003) and this result is robust to the choice of volatility measure: i.e. univariate GARCH models (Baillie and Osterberg 1997; Dominguez 1998; Beine and al. 2002); implied volatility extracted from option prices (Bonser-Neal and Tanner 1996; Dominguez 1998, Galati and Melick 1999); realized volatility (Beine, Laurent and Palm, in press; Dominguez 2003) and continuous volatility vs. jumps (Beine and al. 2006).

is at play.

To summarize, our paper is important for several reasons:

1. The paper has policy implications in terms of central bank interventions. We show that in times where the central bank is known to intervene and to use opaque strategies (e.g. a combination of oral and secret interventions), some investors may attach a lot of weight to central bank interventions as a source of exchange rate movement, leading to an false “intervention explanation” for observed jumps.
2. We provide empirical support to the scapegoat theoretical model of Bachetta and van Wincoop (2004)
3. We estimate jump using non-parametric techniques and document what are the consequences of jumps, of interest in general with respect to the jump literature.

Finally, our work is of interest for a technical empirical question in the news impact research field. We point out a reverse causality from exchange rate movements to reported news. This may be an issue in any empirical work that studies the impact of news on exchange rates, assuming exogeneity of news.[4]

The paper is organized as follows. Section 2 proposes a discussion on central bank interventions policy and rumors, providing motivation for our approach. Section 3 details the procedure used to identify jumps. Section 4 provides some details about the data. Section 5 describes the approach that consists in testing the causality between jumps and false reports of intervention recently and reports our empirical findings. Finally, Section 6 concludes.

2. Central bank interventions policy, false reports and scapegoat effects

[4] See for example Evans and Lyons (2006, p. 4): “A number of other factors give us confidence that our analysis is not significantly exposed to feedback from the DM/$ market to macro news flow. The potential here is that increased volatility in the DM/$price creates incentives for reporters to initiate news items to explain it, which are then posted to the Headline screen. Our fourth filter helps to protect against this form of endogeneity insofar as the news item makes reference to the DM/$ market. The well-defined editorial process described also helps protect against spurious news creation. Perhaps most important, the Headline screen is used by traders in many markets (money markets, bond markets, currency markets, and others), so the audience is much wider than just the DM/$ market. We find the hypothesis of feedback to news flow patently strained when it comes to our analysis at the five-minute frequency: the intermittency of arrivals shown in Table 1 makes this kind of ultra-high-frequency feedback hard to imagine.”

In this section, we describe how central banks intervene on forex markets and the process that leads to news wire reports fixing the belief that the central bank has intervened. Given this process, we argue that the theoretical “scpaegoat” model of Bachetta and van Wincoop (2004) applies particularly well to our empirical findings.

According to the so-called signaling theory, central bank interventions affect the exchange rates by conveying some inside information (i.e. information known to central banks but not to the market) about fundamentals or the future path of the exchange rate to the market**.** A sale of domestic currency for instance may indicate that the exchange rate is currently undervalued or likely to appreciate in the near future, leading market participants to react accordingly**.** In practice, however, this signal is rarely explicit (e.g. written or oral official communiqué). Central banks often prefer to trade with a high degree of visibility or to contact a small number of banks which are in charge of either informing the overall market afterwards or keeping the transaction secret. Most of traders and bankers have thus to rely on unofficial, and then uncertain, sources information as the financial press.

While uncertain, this information remains of overwhelming importance for the different actors in the market. Beyond the fact that it provides private information about the “true value” of the exchange rate, intervention often deeply modifies the overall financial environment in short, medium and long term (e.g. volatility, exchange rate level). Traders need then to adjust their trading behavior in a timely fashion to avoid losses in their portfolio. All piece of information about the central bank activity became naturally interesting and relevant’ for their trading strategies. And newswire journalists are required to collect and broadcast a maximum of information about the central bank activity in very short delays. Schindler(2007) noticed that this context creates a perfect ground for the dissemination of news and rumors either true or false.

Rumors may also be favored by the design of information processing in financial markets. According to Oberlecher and Hocking’ (2001) market survey, newswire are the main and the most reliable source of information for market participants. As this information is made up with journalist’s own analyze and information collected through their personal network in the market, a “*circular cycle of collective information emerge*”. A false and vague rumor may then appear among a small number of market participants and be rapidly reinforced by this "*resonance circuit*" ending up as a firm news (but still false). This dynamics naturally exists when the central bank is intervening.

In practice, the signal sent by the central bank generally evolves in three steps. First depending on whether the central bank wants its action to be perceived or not, some agents detect its presence in the market. The signal is perceived by a small audience and is not considered as publicly known (some agents can also be explicitly informed by the central bank itself). Then it is reported to newswire journalists through their personal network in the market made up of traders, bankers and brokers. Finally, this news is communicated to the overall market with a sentence such as "*BOJ seen buying dlrs at around 104.00 yen in Tokyo*" (Reuters, August 11, 1993) through newswire, making it public.[5] In this case, the intervention is considered "reported" if the news clearly states that the bank has intervened. As explained by Evans and Lyons (2006), the competition between the major news providers such as Reuters, Bloomberg or Dow Jones results in minimal publication delays. Breaking news are then released through headlines or short articles. Given the absence of official information, there are inevitably circumstances in which the financial press mistaken (Oberlecher and Hocking, 2001) and reports interventions that did not occur. Naturally, this false information could bear close resemblance to information making them difficult to disentangle *a priori*. In turn, these events may have critical impact on the exchange rate (Dominguez and Panthaki, 2006).

On what theoretical grounds an exchange rate movement, as a jump, could cause a false rumor? Bachetta and van Wincoop (2004) provide a theoretical justification in a noisy rational expectation monetary model framework. They show that when rational investors receive noisy private signals about the true structural parameters driving macro variables, it is rational to blame observed macro variables for observed exchange rate movements. This is despite the fact that the source of exchange rate variation may be due unobserved factors; unrelated to macro news, as for example liquidity trades.

In their model, agents are heterogeneous because they receive different noisy signals concerning macro variables dynamics. Agents thus attach different weight to macro variables, leading to "confusion" in the market concerning the importance of fundamentals as the source

[5] Dominguez (2006) suggests that this information process may take approximately 15 minutes.

of exchange rate variation. In this context, it is natural for agents to use macro variables as scapegoats for exchange rate fluctuations. They thus set up a monetary model, but deal with average expectations rather then individual expectations, due to heterogeneous agents. In this context, it is shown that the structural parameters driving macro variables average expectation is a function of the exchange rate itself. Loosely speaking, this leads under certain conditions to wrongly relate exchange rate movements to macro news. Even if an investor receives a private signal indicating relative weak importance of, say, money supply, he might rationally use this fundamental as scapegoat, because by definition, he observes nor other agent's private signals (that may give more importance to fundamentals), neither non-fundamentals variables driving exchange rates, as liquidity trades.

Given the above described process through which a central bank intervention is eventually reported in news wires, our empirical findings can be well explained by this scapegoat model. And we thus provide empirical support to it. Indeed, the literature about sterilized central bank interventions has widely validated the signaling channel as the mean for central bankers to move exchange rates through buying and selling currencies. So raising the question whether investors blame a central bank intervention for observed movements, as we do in this paper, is equivalent to the question whether they blame fundamentals.

In the following section we provide some details on the appropriate way to measure the jumps in financial series.

3. Estimating jumps using Lee-Mykland statistic

This section describes the methodology used to extract the jumps. To test whether a jump occurred in a small interval (e.g. 5 minutes), we use the Lee and Mykland's (2007) statistic. The intuition behind their test is that, assuming an underlying continuous diffusion, a jump can be inferred when we observe, in discrete data, a big return relative to a local volatility measure. To test whether a given return is a jump or comes from the continuous diffusion, they derive an "infill" asymptotic distribution for the ratio of the tested intraday return to a local volatility measure (bipower variation).

Formally, let $p(t)$ be a logarithmic asset price at time t. Consider the continuous-time jump diffusion process

(1) $$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), 0 \le t \le T,$$

where $\mu(t)$ is a continuous and locally bounded variation process, $\sigma(t)$ is a strictly positive stochastic volatility process with a sample path that is right continuous and has well defined limits, $W(t)$ is a standard Brownian motion, and $q(t)$ is a counting process with intensity $\lambda(t)$ ($P[dq(t)=1] = \lambda(t)dt$ and $\kappa(t) = p(t) - p(t-)$ is the size of the jump in question). Moreover, let $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$ be the discretely sampled Δ-period return.[6]

As a local robust-to-jumps estimator, Lee and Mykland (2007) use bipower variation and the asymptotic results of Barndorff-Nielsen and Shephard (2004, 2006). The realized bipower variation is defined as the sum of the product of adjacent absolute intraday returns standardized by a constant:

(2) $$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} | r_{t+j\Delta,\Delta} || r_{t+(j-1)\Delta,\Delta} |,$$

where $\mu_1^{-2} \equiv \sqrt{2/\pi} \simeq 0.79$. It can be shown that even in the presence of jumps, bipower variation converges to integrated volatility:

(3) $$BV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds .$$

Lee and Mykland's statistics, denoted L_μ, tests whether a jump occurred between any intraday time periods $t+(j-1)\Delta$ and $t+j\Delta$, for an integer j.[7] It compares the tested return (e.g. 5 or 15 min return) with volatility conditions (estimated with bipower variation) immediately preceding the return. It is defined as

(4) $$L_\mu(t+j\Delta) \equiv \frac{r_{t+j\Delta,\Delta} - \widehat{m}(t+j\Delta)}{\widehat{\sigma}(t+j\Delta)},$$

with[8]

(5) $$\widehat{m}(t+j\Delta) = \frac{1}{K-1} \sum_{l=j-K+1}^{j-1} r_{t+l\Delta,\Delta} .$$

$\widehat{\sigma}(t+j\Delta)$ is the realized bipower variation, redefined such that a K-length window

[6] We use the same notation as in Andersen and al. (2005), and normalize the daily time interval to unity.

[7] In the Lee-Mykland setting, $q(t)$ is a counting process that may be non homogenous, independent of $W(t)$, and $\kappa(t)$ is independent from $q(t)$ and $W(t)$. Moreover, the drift and diffusion coefficients are not allowed to change dramatically over short period of time.

[8] The term $\widehat{m}(t+j\Delta)$ reduces to zero in the case of no drift. In that case, the statistic is denoted by $L(t+j\Delta)$.

immediately preceding the tested return is covered by the sum of the product of adjacent returns, and re-scaled by a factor $\mu_1^2/(K-2)$:

(6) $$\hat{\sigma}^2(t+j\Delta) \equiv \frac{1}{K-2}\sum_{l=j-K+2}^{j-1} |r_{t+l\Delta,\Delta}||r_{t+(l-1)\Delta,\Delta}|.$$

Under the null of no jumps at the testing time, the stated assumptions and a suitable choice of the window size for local volatility K (see below), $L_\mu \overset{as}{\sim} N(0,\pi/2)$.

There is a tradeoff in choosing the window size K. While larger values impose a greater computational burden, K must be large enough to retain the advantage of bipower variation as a robust-to-jump estimator. A range of values satisfy the condition for K ($K = O_p(\Delta^\alpha)$, with $-1 < \alpha < -0.5$). Lee and Mykland (2007) recommend the smallest possible window size within the range given by α, as their simulations show that greater windows only increase the computational burden. So K is chosen as $\Delta^{-0.5}$. For example, suppose $\Delta = \frac{1}{252 * nobs}$, $nobs$ being the number of observations per day, the integers between 15.87 and 252 are within the required range. More specifically, they recommend the following window sizes for sampling at frequencies of one week, one day, one hour, 30 minute, 15 minute and 5 minute: 7, 16, 78, 110, 156, and 270, respectively.

Finally, Lee and Mykland (2007) propose a rejection region using the distribution of their statistics' maximum over the sample. Therefore unlike bipower variation, the sample size plays a role here in jump detection, as the sample maximum distribution depends of the asymptotic distribution of the statistic, but also on the number of observations. Under the stated assumptions and no jumps in $(t+(j-1)\Delta, t+j\Delta]$, then when $\Delta \to 0$, they show that

(7) $$\frac{\max|L_\mu(t+j\Delta)| - C_n}{S_n} \to \varphi,$$

where φ has a cumulative distribution function $P(\varphi \le x) = \exp(-e^{-x})$,

$C_n = \frac{(2\log n)^{0.5}}{c} - \frac{\log\pi + \log(\log n)}{2c(2\log n)^{0.5}}$ and $S_n = \frac{1}{c(2\log n)^{0.5}}$, n being the number of sample observations. So if we choose a significance level α =0.0001, we reject the null of no jump at testing time if $\frac{|L_\mu(t+j\Delta)| - C_n}{S_n} > \beta^*$ with the threshold β^* such that

$P(\varphi \le \beta^*) = \exp(-e^{-\beta^*}) = 0.9999$, i.e. $\beta^* = -\log(-\log(0.9999)) = 9.21$.

Using this statistics we can create a 5-min jump series J_t^α for day t whose elements $J_{t+j\Delta}^\alpha$ are computed as follows :

(8) $$J_{t+j\Delta}^\alpha = \begin{cases} \left| r_{t+j\Delta} \right| \text{ if } L_\mu(t+j\Delta) \text{ is significant at level } \alpha \text{ using (7)} \\ 0 \quad \text{otherwise} \end{cases}.$$

We can now move on in the next section to a description of the data used in our analysis before turning to the empirical results.

4. The data

4.1 Exchange rate

We use a long span (about 9 years of data, from the 3rd of January 1995 to the 29th of September 2004) of high frequency data on the yen/dollar (JPY/USD) exchange rate. The original series is provided by Olsen and Associates at a 5-minute frequency, sampled using last mid-quotes (average of log bid and log ask) of each 5-minute interval.

The currency markets are decentralized, traded around the clock, and around the world. A 24 hour trading day is thus divided into 288 5-minute intervals. As standard in the literature, we define trading day *t* to start at 21.00 GMT on day *t-1* and end at 21.00 GMT on day *t*.[9] So the first price of day *t* is the last price of the 21.00-21.05 interval (of day *t-1*).

We remove week-ends and a set of fixed and irregular holidays, from the intraday return series, as well as days where there are too many missing values, constant prices, and/or days with the longest constant runs activity. The regular holidays removed are Christmas plus the day before and the day after, New Year's day plus the day before and the day after, and the fourth of July. Irregular holidays include Good Friday, Easter Monday, Memorial Day, Labor Day, Thanksgiving and the day after.

Table 1 and Figure 1 summarize information about the exchange rate series. Our

[9] This is motivated by the ebb and flow in the daily FX activity patterns. See Bollerslev and Domowitz (1993).

filtering procedure leaves us with T=697248 5-min returns over the 9 years sample. We detect from 306 to 974 jumps, depending on the retained significance level. In other words, the unconditional probability of a jump at the 5-min frequency (P(jump)) ranges from about 0.001 to 0.004. In terms of jump days, the probability of observing a day that contains at least one jump (P(jump day)) is about 10% for a significance level $\alpha = 0.0001$, and can be as high as 30% for $\alpha = 0.5$. We observe the usual stylized facts for the high frequency returns: a mean close to zero and a high kurtosis. Concerning jumps moments, they are on average about half a percent high with a standard deviation of about 0.33%. Figure 1 allows visualizing the time series of returns and jumps over the whole sample. The third panel of Figure 1 provides further information concerning jumps: it shows at what time jumps usually occur. We observe that jumps are not equally likely, depending on the time of the day. Indeed, they are concentrated mostly during opening hours of major trading segments around the world: Japan, Europe and the U.S.

Table 1. Descriptive statistics for 5-min returns and detected jumps

	Returns 5 min.	Absolute value of jumps					
Sig. Level	-	0.0001	0.001	0.01	0.05	0.1	0.5
Sample size	697248	725	935	1258	1565	1712	2219
Mean	0.00	0.38	0.36	0.33	0.31	0.30	0.28
Std. dev.	0.05	0.22	0.21	0.19	0.18	0.18	0.17
Skew.	-0.14	2.73	2.91	3.16	3.33	3.39	3.56
Kurt.	37.82	14.76	16.21	18.92	20.58	21.47	23.69
Min.	-2.21	0.11	0.08	0.08	0.07	0.07	0.07
Max.	1.65	2.21	2.21	2.21	2.21	2.21	2.21
P(jump)	-	0.0010	0.0013	0.0018	0.0022	0.0025	0.0032
P(jumpday)	-	0.22	0.27	0.34	0.41	0.44	0.52

Note: the table gives descriptive statistics (sample size, first four moments, minimum and maximum) for 5-min returns and detected jumps in absolute value (with columns corresponding to different significance level) over the whole sample (3rd of January 1995 - 29th of September 2004). For jumps, the table also reports the estimated jump probability (probability that an intraday period contains a jump, computed as the ratio of detected jumps to the total number 5-min returns), as well as the probability of a jump day (probability to observe a day that contains at least one jump, computed as the ratio of the number of days containing at least one jump to the total number of days in the sample).

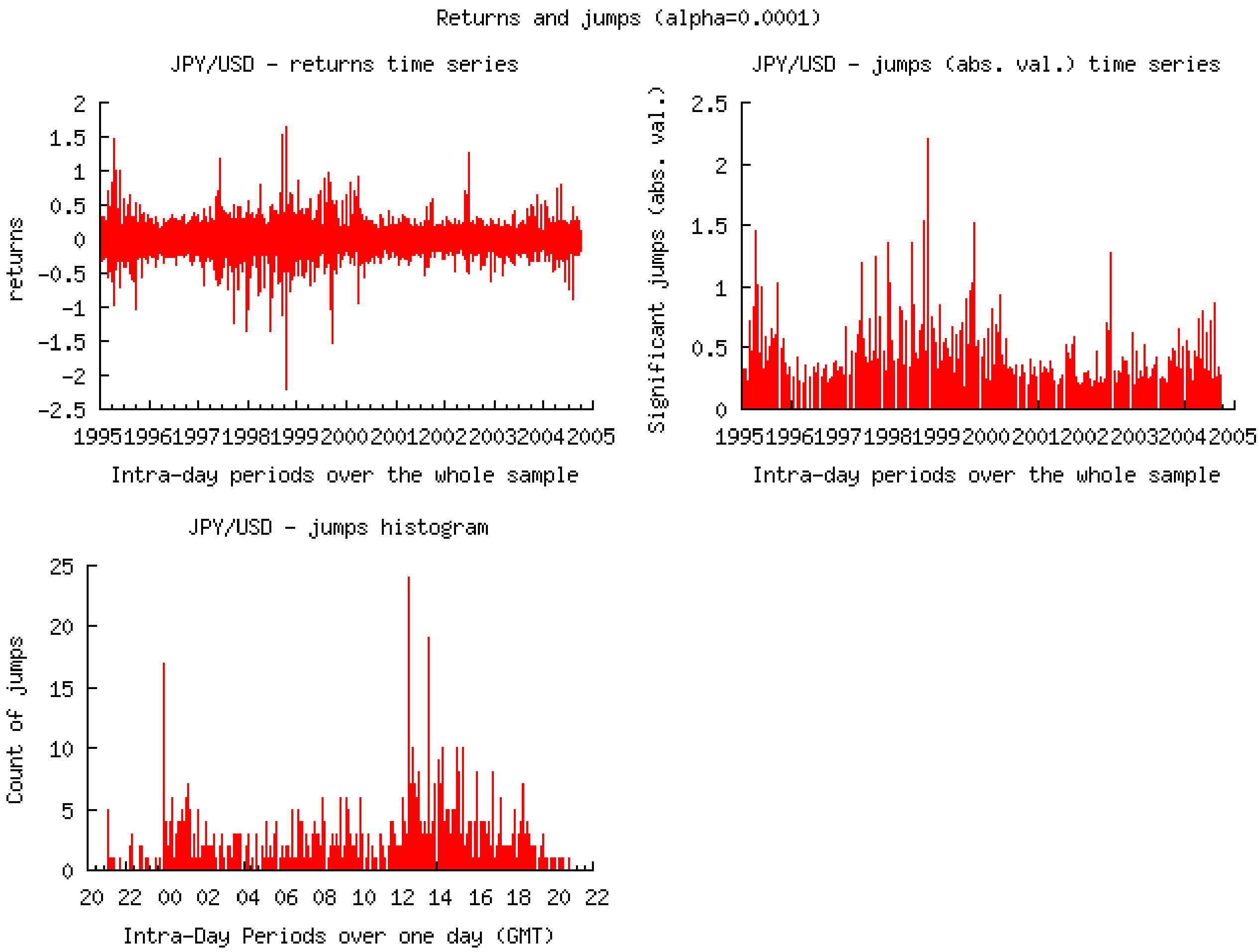
Note that whenever jump estimation is performed using recent non-parametric techniques, choices must be made with respect to two important dimensions: the sampling frequency and the significance level above which a jump is considered significant.

Concerning the sampling frequency, theory dictates clearly to choose the highest possible frequency as theoretical results rely on infill asymptotics. However, in practice, microstructure noise prevents from using a frequency as high as would be optimal. A trade-off must be made between the precision gained with higher frequencies and the increased presence of noise when increasing the sampling frequency. For example, Bandi and Russel

(2006) or Aït-Sahalia et al. (2005) have provided methods to deal optimally with these issues. Nevertheless, we choose here to retain a very high frequency because the economic problem we are dealing with make it unlikely that the jumps we detect are due to microstructure noise. Indeed, as we show below, we show that jumps tend to create rumors of central bank interventions. If these jumps, causing rumors, were not detected anymore using a smaller frequency, one could argue that we do not detect them because we loose precision using sparser sampling.

Concerning the jump significance level, we choose to consider a very low significance level so that all potential jumps are encompassed in our study. We then discuss what significance level is relevant with respect to our problem at hand. As we will see, we establish a link between jumps and intervention rumors only for highly significant jumps.

Figure 1: 5-min returns, 5-min jumps (α=0.0001) and count of jumps across the day



4.2 False reports

We consider newswire intervention report as false rumor or false intervention report if there is no official intervention on that particular day (Klein 1993; Frenkel and al. 2004).[10] For example, on March 23, 1994 the news "*BOJ buys dlrs at around 103.95-104.00 yen in Tokyo*" (Reuters) was reported whereas no official intervention had been conducted. Of course, this type of news is considered as rumor a posteriori, when knowledge of official interventions becomes available but in practice, rumors bear some resemblance to information making them usually difficult to disentangle a priori (Oberlechner and Hocking 2004).

[10] An official intervention is defined as an intervention conducted by the central bank and confirmed either contemporaneously or in the future by the central bank (e.g. on its website).

The Bank of Japan is an interesting case study for two main reasons. First, only Japan has continued to intervene actively and unilaterally in recent years, and it has done so both actually and orally.[11] Second, the Japanese authorities made several changes to their intervention policy, sometimes deliberately practicing transparency and sometimes ambiguity (Ito, 2007). In fact, after a period of intervention policy transparency during the Sakakibara period[12] in 1995-2002, recent interventions of the Japanese government have been conducted in secret (Beine and Lecourt 2004). This regime change in transparency of the exchange rate policy led to the emergence of numerous market rumors and especially false reports of interventions (Gnabo, Laurent and Lecourt, in press). As a matter of fact, market participants have been mistaken 105 times over the period 1995-2004, reporting interventions through Reuters or Dow Jones newswire whereas there did not occur. The number of false reports should be reduced when intervention policy is practiced in a visible way (interventions systematically confirmed thereafter by an official speech). That was the case during the Sakakibara period since there were only false reports on 4.31% of days, compared to 5.84% of days only for the two years period 2003-2004 (see Table 2 hereafter). This recent period was qualified as “opaque” in terms of intervention policy (80% of interventions were realized secretly during this period), favoring uncertainty climate in the market and therefore the emergence of false reports.

5. Results

5.1 General results

Table 2 provides some descriptive statistics both for false reports and for the number of days where these is both at least one significant jump (at the α level) and one false report the same day.[13] These statistics are given for the total period (1995-2004) as well as the Sakakibara period (June 1995- December 2002) and the recent period (2003-2004). Over the total period, false reports were issued on 105 trading days whereas jumps occurred on 725 days (at the very conservative significance level α =0.0001). Using this significance level for

[11] Most central banks, such as the Fed and the ECB, have become increasingly reluctant to intervene and have shifted towards the use of communication policy to manage their exchange rates.

[12] Mr Sakakibara at the head of the Japanese Finance Minister in June 1995-1999 consciously changed the Ministry’s intervention tactics, by intervening less frequently, with high amounts and systematically confirming thereafter its intervention operations. His successor, Haruhiko Kuroda, followed roughly the same policy so that the overall period June 1995 to January 2003 is usually identified as the Sakakibara-Kuroda period.

[13] Jumps have been also calculated with returns at 15 minutes but results remain fundamentally unchanged and are available upon request.

jumps, we detect 34 matching days, meaning that about one third of the false reports occurred during a jump day. Interestingly the number of matching days between jumps and false reports is higher during the recent period 2003-2004 qualified as “opaque” concerning the FX intervention policy practiced by the Japanese authorities.

On the other hand, only five percent of the days with jumps are associated with a false report. While this proportion can seem very low, it remains highly consistent with our framework. Many factors actually limit the chance of correspondence between these two events. If the jump can be clearly related to macro announcements,[14] for instance, there is little chance that the market mistakenly associates it to an intervention. More generally, we do not expect any correspondence when a jump is clearly associated to auxiliary events (e.g. macro news or political events). Likewise, the market should believe that central bank is still active in the exchange rate market. If monetary authorities have explicitly or implicitly stopped their intervention policy, it is again unlikely to observe this type of link.

Table 2. Statistics on false reports and detected jumps

Periods	False reports		Number of days with jumps and false reports											
			α=0.0001		α=0.001		α=0.01		α=0.05		α=0.10		α=0.5	
June 1995-2002	79	4.31%	27	1.47%	30	1.64%	39	2.13%	42	2.29%	44	2.40%	50	2.73%
2003-2004	18	5.84%	5	1.63%	7	2.27%	8	2.60%	10	3.25%	10	3.25%	11	3.57%
1995-2004	105	4.68%	34	1.55%	41	1.82%	51	2.27%	60	2.67%	61	2.71%	64	2.85%

Note: the table gives descriptive statistics both for false reports (calculated in number and in percentage of the total number of days of the period without intervention) and for the number of days where these is both at least one significant jump (at the α level) and one false report the same day.

This preliminary analysis remains naturally incomplete as it says nothing about the causality link between jumps and false reports, i.e. do jumps stimulate false reports? To investigate this question, we need to identify the timing of the discontinuities that create jumps and to compare this timing to the arrival of false reports.

Table 3 displays the dates and the false reports and jumps arrival times (considering a maximum of three discontinuities per day).[15] Columns labeled "Jump *i*" show the size of the *i*th most significant jump on that day, i.e. $J^{\alpha}_{t+j\Delta}$, while columns labeled "Stat *i*" and "Time *i*" report respectively the Lee and Mykland's (2007) statistics and the jump time arrival (at a 5-min frequency), where *i*=1,2,3. Column "FR Time" gives the (first) false report (FR) time

[14] See the study of Lahaye and al. (2007) for the link between macro news and jumps.
[15] The analysis has been extended to a maximum of six discontinuities but the results are qualitatively the same and thus not reported to save space.

arrival. Column "I(J & FR <2h)" is a dummy equal to 1 when a jump occurred within one hour before or after a FR. Column "Min(J-FR)<-60" reports the distance (in min.) between the closest jump to the FR and the FR when this jump occurred maximum one hour before the FR. Finally, Column "Min(J-FR)<60" reports the distance (in min.) between the closest jump to the FR and the FR when the jump occurred maximum one hour after the FR. Importantly, the table is sorted in such a way that the first row concern the day with the most significant jump, the second is the day with the second most significant jump, etc. The table is divided into 6 parts, being respectively days with at least one significant jump at the critical level α = 0.0001, 0.001, 0.01, 0.05, 0.1, and 0.5 respectively (the most significant jump days being in the top panel of the table).

Table 3 highlights two important features. The first is the proximity between jumps and false reports on matching days. The first part of Table 3 concerns the most significant jump days. Out of these 34 matching days, 19 are characterized by at least one jump and a false report in a time interval of two hours (see column “FR Time”). The second feature concerns the causality between jumps and false reports: on these 19 days, 14 speak in favor of the causality from jumps to false rumors. This is even more striking for the 10 most significant jumps since 8 have at least one discontinuity before a false report in a time interval of one hour and 6 in an interval of 10 minutes. This result confirms the causality from jumps to false reports, i.e. the fact that the most significant jumps have been interpreted by agents as the presence of the central bank in the market.

Interestingly, looking at the last column of Table 3, we see that the second most significant jump day might suggest a reverse causality link because the jump is detected at 0:45 GMT (i.e. a price variation between 0:40 and 0:45 GMT) while the false report is recorded at 0:44 GMT, i.e. one minute before. Thanks to Olsen and Associates, we have had access to 1-min data for that day. A careful inspection of these data suggests that the jump actually occurred at 0:42 GMT, i.e. 2 minutes before the false rumor. This means that out of the 10 most significant matching days, 9 have at least one discontinuity before a false report in a time interval of one hour and 7 in an interval of 10 minutes and not respectively 8 and 6 as mentioned above.

Another important finding is that the evidence of causality from jumps to false rumors is no longer true for less significant jumps.

Table 3: Emergence of CBI false reports and jumps on the JPY/USD from 1995 to 2004

Date	Jump 1	Stat 1	Time 1	Jump 2	Stat 2	Time2	Jump 3	Stat 3	Time3	FR Time	I(J & FR <2h)	Min(J-FR)<-60	Min(J-FR)<60
Jumps significant at α = 0.0001, i.e. whose test statistic > 9.2102													
20040406	0.73	73.92	4:30	-0.29	4.98	7:10	0.28	13.14	4:20	5:48	0	0	0
19980320	-0.83	64.61	0:45							0:44	1	0	1
19990825	0.97	63.23	0:20							0:30	1	-10	0
19980624	-0.85	61.01	6:35	0.50	23.28	6:40	0.37	16.65	3:25	6:36	1	-1	4
19990715	0.60	60.71	7:40							7:42	1	-2	0
19980428	-0.72	57.19	0:05							0:11	1	-6	0
19980812	-0.64	53.79	0:20	-0.26	8.52	0:05				0:39	1	-19	0
19980403	0.71	52.67	1:40	-0.46	18.37	5:40				5:42	1	-2	0
19980616	-0.80	44.07	2:30	-0.42	7.16	2:35	-0.37	14.47	1:20	2:16	1	-56	14
19990416	-0.67	41.62	3:20	0.59	23.06	3:50				3:58	1	-8	0
19970501	-0.45	39.84	14:15	0.22	1.42	14:25				18:02	0	0	0
20040331	-0.43	35.15	2:00	-0.26	5.07	4:15				3:44	1	0	31
19950426	1.01	33.76	0:40	-0.43	1.22	22:45				2:08	0	0	0
20030207	0.30	29.11	13:35							10:27	0	0	0
20030307	-0.27	27.53	13:05							22:27	0	0	0
19980318	0.45	27.07	1:05							3:51	0	0	0
19951018	0.49	25.44	12:35	0.27	1.65	12:50	-0.17	2.21	23:55	2:13	0	0	0
19990728	0.41	24.07	6:55	-0.26	6.29	7:00				6:57	1	-2	3
20000417	0.43	23.75	0:20	-0.27	0.45	1:35				0:27	1	-7	0
19950921	-1.02	21.76	17:50	-0.61	4.21	16:20				0:37	0	0	0
19980605	-0.34	21.54	14:15	-0.21	4.38	14:10				11:23	0	0	0
20030930	0.49	20.83	14:35	0.42	26.15	23:10	0.40	9.78	15:00	23:07	1	-2	3
19950831	-0.58	19.52	5:45	-0.34	1.20	2:45				6:01	1	-16	0
20010920	0.30	19.21	8:55	-0.26	10.80	11:45	-0.21	3.03	13:00	9:15	1	-20	0
19950801	0.40	19.09	7:55							7:00	1	0	55
19990202	-0.53	19.06	6:55	-0.46	16.32	6:20				14:58	0	0	0
19950929	-0.62	15.45	1:55							1:52	1	0	3
19950914	-0.47	14.30	4:15	-0.29	1.60	3:10				6:22	0	0	0
20030221	-0.15	13.97	15:20	0.11	0.63	12:45				16:19	1	-59	0
19950719	-0.40	12.67	1:10	-0.32	7.22	0:50				0:01	1	0	49
19970115	-0.26	10.65	19:55	-0.20	4.11	17:25				15:03	0	0	0
20031204	-0.19	10.16	16:00	-0.13	1.51	13:45				5:31	0	0	0
19950731	0.26	9.88	15:40							6:03	0	0	0
20030311	0.19	9.46	14:50	-0.14	0.37	10:20				5:33	0	0	0
Jumps significant at α = 0.001, i.e. whose test statistic > 6.9072											0	0	0
19960509	-0.22	9.02	7:55	-0.19	1.23	18:40				9:01	0	0	0
19970116	0.24	8.33	23:10	-0.22	5.21	23:05				15:01	0	0	0
20030220	-0.19	7.92	16:10	-0.15	2.92	13:35				15:17	1	0	53
19970124	-0.42	7.91	8:15	-0.28	0.55	23:20				2:37	0	0	0
19990428	-0.33	6.99	12:00	-0.30	13.94	3:35	-0.29	15.81	3:15	4:20	1	-45	0
Jumps significant at α = 0.01, i.e. whose test statistic > 4.6001											0	0	0
20030922	-0.33	5.97	22:50							0:32	0	0	0
19980813	-0.31	5.94	23:55	0.29	4.52	23:25				9:03	0	0	0
19980626	-0.36	5.61	5:55							11:10	0	0	0
19960229	-0.29	5.47	23:50	-0.25	3.83	23:35				0:17	1	-27	0
19951024	0.25	5.42	23:45							0:31	1	-46	0
19950814	-0.38	5.30	23:05	0.37	2.65	23:40				5:38	0	0	0
19950724	-0.31	5.26	0:35	-0.28	4.50	0:20	-0.26	4.13	0:05	0:47	1	-12	0
19960802	0.26	5.19	13:25							5:44	0	0	0
20040324	-0.15	4.90	8:25	-0.15	2.77	8:35				5:33	0	0	0
20030328	-0.15	4.15	18:15	-0.15	0.66	18:40	0.14	2.94	13:35	18:08	1	0	7
Jumps significant at α = 0.05, i.e. whose test statistic > 2.9702											0	0	0
19950907	-0.34	4.02	12:55							3:29	0	0	0
19990107	0.51	3.79	10:45	0.49	1.43	12:00	-0.44	2.40	7:35	10:34	1	0	11
19951005	-0.27	3.59	16:20							1:05	0	0	0
19951023	-0.23	3.43	22:20							1:43	0	0	0
19960510	-0.21	3.07	6:35	0.19	0.89	6:40				0:20	0	0	0
19950419	0.42	2.63	10:10							0:03	0	0	0
19970117	0.23	2.37	13:35							0:55	0	0	0
19950928	-0.35	2.34	15:10							6:00	0	0	0
Jumps significant at α = 0.1, i.e. whose test statistic > 2.2503											0	0	0
19950912	0.27	2.09	15:15							0:17	0	0	0
Jumps significant at α = 0.5, i.e. whose test statistic > 0.3665											0	0	0
19970407	0.26	1.59	23:40							1:00	0	0	0
19950718	-0.28	1.57	0:10							5:22	0	0	0
19960530	0.21	1.25	12:45							13:27	1	-42	0
19950222	0.16	0.47	8:00							1:07	0	0	0

Note: columns labelled "Jump *i*" show the size of the *i*th most significant jump on that day while columns labelled "Stat *i*" and "Time *i*" report respectively the Lee and Mykland's (2007) statistics and the jump time arrival (at a 5-min frequency), where *i*=1,2,3. Column "FR Time" gives the (first) false report (FR) time arrival. Column "I(J & FR <2h)" is a dummy equal to 1 when a jump occurred within one hour before or after a FR. Column "Min(J-FR)<-60" reports the distance (in min.) between the closest jump to the FR and the FR when this jump occurred maximum one hour before the FR. Finally, Column "Min(J-FR)<60" reports the distance (in min.) between the closest jump to the FR and the FR when the jump occurred maximum one hour after the FR.

5.2 Case studies

The detected causality can be corroborated by the news reports. In the following paragraphs, we discuss different case studies to illustrate the relation between false reports and jumps.

For example, consider the April 28, 1998 (sixth row of Table 3). The first jump occurred at 0.05 GMT while the false report occurred 6 minutes later (at 0.11 GMT). Few minutes later, a news reported that a large order flows has been interpreted by the market as an intervention of the Bank of Japan: "*... Dollar fell more than one yen in morning trade due to large-lot sales at around 132.50 yen.(. . .) Some speculated the falls might be due to Bank of Japan (BOJ)'s intervention* ..."(Reuters, April 28, 1998). Interestingly, other news also indicated that the market was watchful further to a very active communication policy practiced by Japanese authorities: " *While wary of any large movement in dollar-yen in the wake of a slew of verbal intervention by Japanese authorities, market participants were uncertain that the Bank of Japan had actually stepped in to sell dollars* (Dow Jones). Finally, the rumor was disproved later in the day: "*The fall triggered speculation of dollar-selling intervention by the Bank of Japan and was later attributed by some to selling by the World Bank.* "(Dow Jones).

Market expectation may also have played a key role in the misinterpretation of jumps on June 24, 1998. This day some market participants expected an intervention as illustrated by a dealer at a Japanese trust bank declared "*We [the market] expect there to be some form of [central bank] intervention around here*" (Dow Jones). The quote was reported in a Dow Jones newswire at 6h32. Three minutes later, at 6h35, a jump was observed in the market and was closely followed, at 6h36, by a headline announcing an intervention: "*Tokyo: Traders Say BOJ[Bank of Japan] May Have Sold Dollars For Yen [intervene]*" (Dow Jones).

Another lighting example concerns the July 28, 1999 (eighteens row). Two discontinuities have been detected at 6.55 GMT and 7.00 GMT, while the false report arrived at 6.57 GMT. A news clearly explained that rumors of interventions appeared further to the dollar jump: "*Rumors of BOJ intervention appeared soon after the dollar quickly jumped about Y1 higher around 06.57 GMT Wednesday* (Dow Jones, July 28, 1999). It is however not clear whether the second jump (of opposite sign) has been the consequence of the false rumor.

5.3 Implications

We find that large jumps cause false rumors. Thus, the scapegoat model of Bachetta and van Wincoop (2004) receives empirical support. Our results can indeed interpreted as heterogeneous agents using interventions, or equivalently signals about fundamentals, as scapegoats for large jumps. In the theoretical model, agents' heterogeneity creates confusion on the market. We could argue that this confusion is enhanced when the bank applies an opaque policy. We indeed find a higher probability of jumps causing rumors in the BoJ opaque policy period. Note finally that what we observe might be only a small window on the mechanisms described by Bachetta and van Wincoop (2004). We show that sometimes, large jump create rumors of CBI. But most probably, the effect of different type of movements, or of small jumps, may imply the use of scapegoats in the market that do not end up in news wires, and that cannot be observed.

On a policy-making viewpoint, we observe that most days where jumps are followed by a false report in an interval of one hour concern the recent "opaque" period with a huge number of secret interventions but also surprisingly the period 1995-2002 known for its high degree of transparency as well as an active communication policy. How the market can mislead more easily in period of transparent intervention policy? This period is characterized by large-scale infrequent interventions systematically confirmed by a speech and by a frequent practice of intervention threat statements used as a substitute for real action (Gnabo and Lecourt 2007). This policy may have favored the dissemination of rumors in two ways. First, as actual interventions were particularly effective at that time,[16] the financial cost of missing such information was probably high. Traders and bankers were then more willing to interpret any abnormal movement of the exchange rate as an intervention. Second, the aggressive communication policy put the market continuously on alert; provoking potentially some kind of self-fulfilling prophecy (i.e. the market is expecting an intervention so strongly that it often wrongly detects an operation). This feature is well illustrated in the case studies 1 and 2. The later emphasizes the critical role of market expectation. The former clearly shows that communication policy can increase or decrease the likelihood of an operation and then the expectation of future operations. In turn, these findings reinforce Gnabo and al.'s (2007) conclusions according to which the way authorities talk to the market may play a critical role

[16] The architect of the Japanese intervention policy at that time, Mr. Eisuke Sakakibara, was called "Mr. Yen" by financial journalists for its ability to move the market (i.e. influence the path of the exchange rate).

in the diffusion of false information.

Conclusion

The paper is the first to empirically investigate the causality link between jumps and intervention rumors (i.e. false reports of intervention). We examined the actions of the Bank of Japan over the recent period 1995-2004. To identify jumps, we use the recent non-parametric technique recently proposed by Lee and Mykland (2007). We find that the most significant jumps on the YEN/USD have been falsely interpreted as the presence of the central bank in the market, leading just after the jump to the emergence of intervention rumors (i.e. false reports of intervention).

Bibliography

Aït-Sahalia, Y., Mykland, P., Zhang, L. (2005). “A Tale of Two Time Scales: Determining Integrated Volatility with Noisy High-Frequency Data”. *Journal of the American Statistical Association*, 100, 1394-1411.

Andersen, T. G., Bollerslev, T., Diebold, F.X., Vega, C. (2003). “Micro effects of macroeconomic announcements: real-time price discovery in foreign exchange”. *American Economic Review*, 93, 1, 38-62.

Andersen, T. G., Bollerslev, T., Diebold, F.X. (2005). “Roughing It Up: Including Jump Components in the Measurement, Modelling and Forecasting of Return Volatility”. NBER Working Paper 11775.

Bachetta, P., van Wincoop, E. (2004). “A Scapegoat Model of Exchange Rate Fluctuations”. NBER Working Paper 10245.

Baillie, R.T., Humpage, O., Osterberg, W.P. (2000). “Intervention from an intervention perspective”. *Journal of International Financial Markets, Institutions and Money*, 10, pp. 407-421.

Baillie, R. T., Osterberg, W. P. (1997). “Why do central banks intervene?”. *Journal of International Money and Finance*, 16, pp. 909-919.

Bandi F. M., Russell, J R. (2006). "Separating Microstructure Noise from Volatility." *Journal of Financial Economics*, *79*(3), pp. 655-92.

Barndorff-Nielsen, O.E. Shephard, N. (2004). “Power and bipower variation with stochastic volatility and jumps (with discussion)”. *Journal of Financial Econometrics*, 2, pp. 1-48.

Barndorff-Nielsen, O.E., Shephard, N. (2006). “Econometrics of testing for jumps in financial economics using bipower variation”. *Journal of Financial Econometrics*, 4, pp. 1-30.

Beine, M., Bénassy-Quéré, A., Lecourt, C. (2002). “Central bank intervention and foreign exchange rates: new evidence from FIGARCH estimations”. *Journal of International Money and Finance* 21(1), pp. 115-144.

Beine M., Laurent S. and Palm (in press). “Central bank FOREX interventions assessed using realized moments”. Forthcoming in *Journal of International Financial Markets, Institutions and Money*.

Beine, M., Lahaye, J., Laurent, S., Neely, C.J., Palm, F., (2006). “Central bank intervention and exchange rate volatility, its continuous and jump components”. *International Journal of Finance and Economics*, 12, pp. 201-223.

Beine, M., Lecourt, C. (2004). “Reported and secret interventions in the foreign exchange markets”. *Financial Research Letters*, 4, pp. 215–225.

Bollerslev, T., Domowitz, I. (2003). “Trading patterns and prices in the interbank foreign exchange market”. *Journal of Finance*, 12, 5, pp. 511-521.

Bonser-Neal, C., Tanner, G. (1996). “Central-bank intervention and the volatility of foreign exchange rates: evidence from the options market”. *Journal of International Money and Finance* 15(6), pp. 853-878.

Dominguez, K.M. (1998). “Central bank intervention and exchange rate volatility”. *Journal of International Money and Finance* 17(1), pp. 161-190.

Dominguez K.M. (2003). The Market Microstructure of Central Bank Intervention”. *Journal of International Economics*, 59, p. 25-45.

Dominguez, K.M. (2006). “When do central bank interventions influence intradaily and longer-term exchange rate movements?”. *Journal of International Money and Finance*, 25, pp. 1051-1071.

Evans, M.D.D., Lyons, R.K. (2001). “Portfolio balance, price impact, and secret intervention”. *NBER Working Paper* No. 8356.

Evans, M.D.D., Lyons, R. K. (2002). “Order Flow and Exchange Rate Dynamics”. *Journal of Political Economy*, pp. 170-180.

Evans, M.D.D., Lyons, R. K. (2006). “How is macro news transmitted to exchange rates?” NBER Working Paper 9433.

Fischer, A.M. and Zurlinden, M. (1999), “Exchange Rate Effects of Central Bank interventions: An Analysis of Transaction Prices”. *The Economic Journal*, 109(458), pp. 662-76.

Frenkel, M., Pierdzioch, C., Stadtmann, G. (2004). “The Accuracy of Press Reports Regarding the Foreign Exchange Interventions of the Bank of Japan”. *Journal of International Financial Markets, Institutions, and Money*, 14, pp. 25–36.

Galati, G., Melick, W. (1999). “Perceived central bank intervention and market expectations: an empirical study of the yen/dollar exchange rate, 1993-96”. BIS Working Paper No. 77.

Gnabo, J.Y., Laurent, S., Lecourt, C. (in press). “Does transparency in central bank interventions policy bring noise to the FX market? The case of the Bank of Japan”. Forthcoming in *Journal of International Financial Markets, Institutions, and Money*.

Gnabo, J.Y., Lecourt, C. (2005). “How transparent is the intervention exchange rate policy of the Bank of Japan?”. SSRN Working Paper 839188.

Humpage, O.F., (2003). “*Government intervention in the foreign exchange market*”. Federal Reserve Bank of Cleveland, Working Paper 03–15.

Ito, T., (2007). Myths and reality of foreign exchange interventions: an application to Japan. *International Journal of Finance and Economics*,12, 133–154.

Klein, M.W. (1993). “The accuracy of reports of foreign exchange intervention”. *Journal of International Money and Finance*, 12, pp. 644-653.

Lahaye, J., Laurent, S., Neely, C. J. (2007). “Jumps, cojumps and macro announcements”, *Federal Reserve Bank of Saint-Louis Working Paper Series 2007-032A*.

Lee, S. S., Mykland P.A. (2007), “Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics”. Forthcoming in *Review of Financial Studies*.

Oberlechner, T., Hocking, S. (2004). “Information sources, news and rumors in financial markets: insights into the foreign exchange market”. *Journal of Economic Psychology*, 25, pp. 407-424.

Payne, R., Vitale, P. (2003). “A transaction level study of the effects of central bank intervention on exchange rates”. *Journal of International Economics* 61, pp. 331-352.

Schindler, M.P. (2007). Rumors in financial markets: Insights into behavioral finance. Wiley Finance Series.