Do jumps mislead the FX market?

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Abstract

This paper investigates the link between jumps in the exchange rate process and rumors of central bank interventions. Using the case of Japan, we analyze specifically whether jumps trigger false reports of intervention (i.e. an intervention is reported when it did not occur). Intraday jumps are extracted using a non-parametric technique recently proposed by Lee and Mykland (2007) and by Andersen et al. (2007), and later modified in Boudt et al. (2008). Rumors are identified by using a unique database of Reuters and Dow Jones newswires. Our results suggest that a significant number of jumps on the YEN/USD have been falsely interpreted by the market as being 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 a false "intervention explanation" for observed jumps.

JEL Classification: E58; F31; G14, G15

Keywords: Central banks; FX interventions; Jumps; Rumors; Scapegoat

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This text presents research results of the Belgian Program on Interuniversity Poles of Attraction initiated by the Belgian State, Prime Minister's Office, Science Policy Programming. Scientific responsibility is assumed by the authors. The authors thank Philippe Bachetta and Frederick H. Wallace for their helpful comments. Gnabo and Lahaye thank Richard Lyons, and the participants at the GREQAM summer school/workshop on the "New Microstructure of Financial Markets" for their helpful comments and discussions.

…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 range... (Reuters, July 15, 1999)

1. Introduction

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. In response, central banks have conducted foreign-exchange interventions (i.e. actual purchases and sales of foreign currency against domestic currency) to "calm the disorderly markets" and to limit adverse effects on their international competitiveness. In practice, however, such operations have often been shown to be ineffective. The main body of research 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 et al. 2002; Dominguez 2003; Payne and Vitale 2003). Furthermore, such interventions generally increase foreign-exchange volatility (Humpage 2003), whatever the volatility measure: univariate GARCH models (Baillie and Osterberg 1997; Dominguez 1998; Beine et al. 2002); implied volatility extracted from option prices (Bonser-Neal and Tanner 1996; Dominguez 1998, Galati and Melick 1999); realized volatility (Beine et al. 2008) and volatility divided into a continuous part and a jump component (Beine et al. 2007).

If official interventions and unofficial reports of intervention in the public press cause volatility, is the reverse also true?[1] More precisely, we can raise the question as to whether market participants may detect (rightly or wrongly) an intervention operation when there is a sharp movement in the exchange rate.

One of the ways that this relationship can be explained is in the light of the microstructure approach where private information is transmitted through order flows (Lyons 2001). In this framework, the market is usually made up of different types of agent. Some have access to private information. Their trading induces order flows, which in turn influence prices. Others have no private information and they trade according to their hunches or public information. Baillie et al. (2000) emphasize that prices might therefore "perform a dual role of describing the terms of trade and of transferring information from more to less informed agents" (see also Admati 1991). Consistent with this idea, some agents might naturally try to extract some

[1] 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…).

information from prices and especially from jumps. This is shown explicitly in Jiang et al. (2008), who show empirically the impact of jumps on price discovery on the U.S. treasury market.

Our paper aims to shed light on whether or not jumps trigger news stories related to central bank intervention in the foreign-exchange markets, namely rumors. The type of rumor we consider corresponds specifically to false reports of intervention. That is, some market participants wrongly interpret a jump on the JPY/USD as being caused by an official intervention; then this false information is transmitted to the overall market through a newswire release by the main financial news media. An example of this causality is given by the news Reuters quoted above (page 2). For our empirical analysis, we use the case of the Bank of Japan (BoJ), which has continued to intervene actively and unilaterally in recent years.

Identifying the origin of false reports is of interest for several reasons. First, it may facilitate our understanding of why false information emerges in the financial market (Bachetta and van Wincoop, 2004). Second, it might help central bankers to determine the extent to which their intervention policy may have a disruptive effect on exchange rate developments. Indeed, while unfounded, this type of news can, at least theoretically, influence the traders' behavior and therefore negatively affect the financial environment (see also empirical evidence from Dominguez and Panthaki, 2007).

The false signals or false reports are identified by comparing systematically the dates of official intervention and the dates of financial press reports announcing an intervention. Along with the literature, we use newswire reports from two of the main news providers: Reuters and Dow Jones. This allows for an accurate portrayal of the market perception (Oberlechner and Hocking, 2004) and the collection of intradaily information regarding the occurrence of the news.

To isolate jumps, we use a modified version of the non-parametric technique proposed by Lee and Mykland (2007) and by Andersen et al. (2007). This parsimonious technique allows the identification of jumps at an intraday level. The intuition behind this technique is to consider that a jump has occurred when a return is too big to plausibly have come from a pure diffusion, that is, when a return is big relative to local volatility conditions. Jumps are not necessarily large in absolute terms. If volatility is low, a relatively small return can be detected as a jump. A recent criticism that has been leveled at the Lee and Mykland approach is that it does not account for the presence of intra-daily volatility periodicity. As shown by Boudt et al. (2008), disregarding this well known feature of the volatility pattern may have a remarkable impact on the accuracy of the jump detection method. To deal with this issue, the modified version of the Lee and Mykland's statistic recently proposed by Boudt et al. (2008) is applied here.

The paper is organized as follows. Section 2 presents a discussion on central bank intervention policy and rumors. Section 3 details the procedure used to identify jumps. Section 4 provides some details regarding the data. Section 5 describes the approach, which consists of testing the causality between jumps and false reports of intervention, and it also reports our empirical findings. Finally, Section 6 concludes.

2. Central bank intervention policy, false reports and the scapegoat effect

In this section, we describe how central banks intervene in the foreign-exchange markets and the process that leads to newswire reports anchoring the belief that the central bank has intervened. Given this process, we argue that the theoretical "scapegoat" model of Bachetta and van Wincoop (2004) applies particularly well to our empirical findings.

2.1 Signaling theory and false reports of intervention

The occurrence of false intervention reports can first be explained by the weight traders attach to any news on central bank intervention. According to the so-called signaling theory, central bank interventions affect the path of the currency by transmitting to the market inside information (i.e. information known to central banks but not to the market) regarding the value of fundamentals or future developments of the exchange rate. A sale of domestic currency for instance may indicate that the currency is undervalued or likely to appreciate in the near future. Once perceived, this operation might lead market participants to adjust their trading behavior accordingly. In practice, the signal is rarely explicit in the sense that it is essentially transmitted through an unofficial information source (i.e. the financial press). Monetary authorities, for instance, tend at best to intervene with a high degree of visibility (e.g. through the anonymous but highly visible Electronic Broking System platform) instead of confirming clearly and unambiguously their intervention in a written or oral communiqué.[2,3] Because the signal emanates from the financial press and not directly from the central bank, there are inevitably circumstances in which it turns out to be wrong (Schwartz, 2000).

While news regarding central bank intervention is uncertain, it remains of overwhelming importance for many actors in the market. The first reason lies in the informational content of intervention. As discussed above, interventions theoretically provide private information

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[2] Alternatively, they can also contact a small number of banks that are in charge of informing the market once the operation has been carried out.

[3] Only a quarter of public interventions conducted by the Bank of Japan were officially confirmed by an oral announcement during the period 1991-2004 (Gnabo and Lecourt, 2008).

regarding the "true value" of the exchange rate. This type of information is, therefore, key for a broad range of traders whose trading strategies are based on their guess or beliefs about the accurate value of fundamentals. Other types of trader do not rely so much on fundamentals to price their assets, preferring alternative sources of information such as the past value of the exchange rate or strong momentums (e.g. Chartists). In this case too, this sort of news can be important, as intervention operations are known to affect the exchange rate dynamics (e.g. reverse momentums) and more generally to increase volatility. In this context, all pieces of information regarding central bank orders become interesting and critical for trading strategies. Market participants need to react in a timely fashion. And newswire journalists are required to collect and broadcast a maximum amount of information regarding central bank activity within a very short time. Schindler (2007) notes that this climate creates the perfect basis for the dissemination of news and rumors, true and false alike.

2.2 Design of the financial market's information processing system and false reports of intervention

Another factor potentially involved in the dissemination of a rumor of an intervention is the design of the information processing system within financial markets. According to Oberlechner and Hocking's (2004) market survey, newswires are the main and the most reliable source of information for market participants. This information is made up of journalists' own analysis and information collected through their personal network in the market. Hence, a "*circular cycle of collective information emerges*" (Oberlechner and Hocking, 2004). 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 story (even though it is still false).

The way in which such information is processed within the financial markets can be corroborated by a close scrutiny of newswire reports and official statements. Such a scrutiny leads to conjecture on how the central bank signal is transmitted. First, depending on whether or not the central bank wants its action to be perceived, some agents will detect its presence in the market. The signal is perceived by a small audience and is not considered as publicly known (some agents may also be explicitly informed by the central bank itself). Then the signal 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 newswires, making it public.[4] In this case, the intervention is considered to be "reported"

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

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 and Dow Jones results in minimal delays in publication. Breaking news is then released through headlines or short articles. Given the frequent absence of official information noted above, there are inevitably circumstances in which the financial press has been mistaken (Oberlechner and Hocking, 2004) and has reported interventions that did not occur.[5] This false information can emerge at any time in the process described above. And it may have a critical impact on the exchange rate (Dominguez and Panthaki, 2007), as it bears a close resemblance to true information (i.e it is difficult to disentangle the false information *a priori*).

2.3. The scapegoat effect

Recently Gnabo et al. (2007) have empirically studied the determinants of false reports. They account for two specific sets of factors: those related to the nature of the central bank policy and those related to market phenomena. Regarding market components, Gnabo et al. (2007) specifically identify jumps as a key factor in the appearance of a false report (i.e. false news). At a theoretical level, the link between exchange rate movements and the occurrence of false news is supported by the work of Bachetta and van Wincoop (2004). While the type of information discussed by these two authors does not directly concern central bank interventions, their model is particularly well suited to our purpose. This paper provides a justification for the emergence of false information within a noisy rational expectation monetary model framework. Bachetta and van Wincoop show that when rational investors receive noisy private signals regarding 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 to unobserved factors unrelated to macro news, such as liquidity trades.

In Bachetta and van Wincoop's model, agents are heterogeneous because they receive different noisy signals concerning macro variable dynamics. Thus agents attach a different weight to macro variables, leading to "confusion" in the market concerning fundamentals as the source of exchange rate variation. In this context, it is natural for agents to use macro variables as scapegoats for exchange rate fluctuations.

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[5] Given the path followed by the central bank signal (described above), it is also likely that traders themselves attempt to initiate false rumors, that is to provide false information to the journalist, in order to make a profit on it. Schindler's survey in particular indicates that of all the respondents, 70% claim the source was, at least possibly, able to profit systematically from the rumor.

Given the process described above, through which a central bank intervention is eventually reported via newswires, the link between jumps and false reports is consistent with the idea underlying the scapegoat model. Indeed, the literature regarding sterilized central bank interventions has widely validated the signaling channel theory (see Edison, 1993; Dominguez and Frankel, 1993 and Sarno and Taylor, 2001 for surveys), according to which an intervention affects the exchange rate because it is perceived by market participants as a piece of information regarding fundamentals. Therefore, raising the question of whether investors blame a central bank intervention for observed movements, as we do in this paper, is closely related to the question of whether they blame fundamentals.

In this paper, we focus on exceptional movements of the exchange rate, known as jumps. The following section provides some details on the appropriate way to measure the jumps in financial series.

3. Estimating jumps

This section describes the testing strategy for jumps, as implemented here. We first describe the original tests of Andersen, Bollerslev and Dobrev (2007) and of Lee and Mykland (2007) before tackling the deterministic volatility component issue in jump estimation, as developed in Boudt, Croux and Laurent (2008).

3.1. First step towards intraday jump detection

Andersen, Bollerslev and Dobrev (2007) and Lee and Mykland (2007) assume a continuous time jump-diffusion data generating process. The log price process evolves as follows:

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

where $p(t)$ is a log asset price, $W(t)$ is a standard Brownian motion, $q(t)$ is a counting process, possibly a non-homogenous Poisson process, independent of $W(t)$, and $\kappa(t)$ $(= p(t) - p(t-))$ is the identically distributed jump size. The Brownian motion, $W(t)$, jump sizes, $\kappa(t)$, and the counting process, $q(t)$, are independent of each other. In the absence of jumps, the drift $\mu(t)$ and instantaneous volatility $\sigma(t)$ are such that the underlying DGP is an Itô process with continuous sample paths. The drift and diffusion coefficients may not change dramatically over short periods of time.

The intuition behind the jump test proposed simultaneously by Andersen, Bollerslev and Dobrev (2007) and by Lee and Mykland (2007) is straightforward: In the absence of jumps, standardized instantaneous returns are increments of a standard Brownian motion. Standardized returns that are too large to plausibly come from a standard Brownian motion must reflect jumps.[6] These authors propose the following statistic to test for the presence of jumps in an intraday return:

(2) $$J_{t+j\Delta} \equiv \frac{\left|r_{t+j\Delta,\Delta}\right|}{\sigma_{t+j\Delta}},$$

where $r_{t+j\Delta,\Delta} \equiv p(t+j\Delta) - p(t+(j-1)\Delta)$ is the discretely sampled Δ-day return, with $1/\Delta$ observations per day. To simplify notation, we omit the Δ subscript from returns, henceforth denoting $r_{t+j\Delta,\Delta}$ as $r_{t+j\Delta}$.

Because $\sigma_{t+j\Delta}$ is unobserved, one must estimate it with a robust-to-jumps estimator. Asymptotic results of Barndorff-Nielsen and Shephard (2004, 2006) show that realized bipower variation (RBV) converges to integrated volatility, even in the presence of jumps, and estimates that quantity fairly efficiently. Consequently, Andersen et al. (2007) and Lee and Mykland (2007) propose estimating $\sigma^2_{t+j\Delta}$ as a scaled RBV over a local K-period-window:

(3) $$\hat{\sigma}^2_{t+j\Delta} = \frac{\pi}{2}\frac{1}{K-2}\sum_{l=1-K+2}^{j-1}\left|r_{t+l\Delta}\right|\left|r_{t+(l-1)\Delta}\right| .$$

The window K must be big enough to eliminate the effects of jumps on the instantaneous volatility estimation: $K = O_p(\Delta^{\alpha})$, with $-1 \prec \alpha \prec -0.5$. Lee and Mykland (2007) recommend the smallest possible window size ($K = \Delta^{-0.5}$), as larger windows only raise the computational burden. For returns sampled at frequencies of 60, 30, 15, and 5 minutes, Lee and Mykland (2007) recommend using windows of 78, 110, 156 and 270 observations, respectively.

Under the null of no jumps, $J_{t+j\Delta}$ follows the same distribution as the absolute value of a standard normal variable. Brownlees and Gallo (2006) propose comparing $J_{t+j\Delta}$ with the $1-\alpha/2$ quantile of the standard normal distribution. This rule might spuriously detect many jumps, however. Andersen, Bollerslev and Dobrev (2007) use a Bonferroni correction to minimize spurious jump detection. To minimize the risk of falsely finding jumps, Lee and Mykland (2007) propose the inferring of jumps from a conservative critical value, which they obtain from the distribution of the statistic's maximum over the sample size. If the statistic exceeds a plausible maximum, one rejects the null of no jumps. Under the stated assumptions and no jumps in the interval $(t+(j-1)\Delta, t+j\Delta]$, then when $\Delta \to 0$, the sample maximum of the

[6]The drift is nearly zero and can be ignored in practice.

absolute value of a standard normal (i.e. the jump statistic in Equation 2) follows a Gumbel distribution. We reject the null of no jump if

(4)
$$J_{t+j\Delta} > G^{-1}(1-\alpha)S_n + C_n,$$

where $G^{-1}(1-\alpha)$ is the $1-\alpha$ quantile function of the standard Gumbel distribution, $C_n = (2\log n)^{0.5} - \frac{\log(\pi)+\log(\log n)}{2(2\log n)^{0.5}}$ and $S_n = \frac{1}{(2\log n)^{0.5}}$, *n* being the total number of observations. So if we choose a significance level of $\alpha = 0.0001$, then we reject the null of no jump at testing time if $J_{t+j\Delta} > S_n\beta^* + C_n$ with β^* such that $P(\psi \leq \beta^*) = exp(-e^{-\beta^*}) = 0.9999$, i.e. $\beta^* = -log(-log(0.9999)) = 9.21$.

3.2. The problem of instantaneous volatility periodicity

The previous subsection explained that high persistence of instantaneous volatility prompted Andersen, Bollerslev and Dobrev (2007) and Lee and Mykland (2007) to estimate instantaneous volatility using average RBV on the K observations preceding the tested return.

For the average RBV to be a consistent estimate of instantaneous volatility, one must assume slowly varying volatility on this K-sized window. When K tends to zero, this assumption is realistic. For values of K suggested by Andersen, Bollerslev and Dobrev (2007) or by Lee and Mykland (2007) (typically one day), this assumption is questionable. Indeed, many financial time series display considerable deterministic periodic variation within a day or a week (see e.g. Andersen and Bollerslev, 1997, 1998 or Martens, Chang and Taylor, 2002). Estimating volatility using RBV rolling windows inappropriately smoothes these periodic patterns, because such an estimator is necessarily slowly time varying. Boudt, Croux and Laurent (2008) show that the $J_{t+j\Delta}$ statistic might be inappropriate in this case and spuriously detect jumps in cyclical patterns.

Following Boudt, Croux and Laurent (2008), we assume that the instantaneous volatility in Equation 1 decomposes into a slowly varying component $\delta(t)$ and a deterministic circadian component $f(t)$, i.e.

(5)
$$\sigma(t) = \delta(t)f(t).$$

We assume, without loss of generality, that this deterministic variance process integrates to one on a daily basis,

(6)
$$\int_t^{t+1} f^2(s)ds = 1,$$

and we standardize periodic volatility estimates accordingly.

To correctly infer jumps, we must estimate and remove this deterministic periodicity with a robust-to-jumps volatility estimator. Boudt, Croux and Laurent (2008) propose a modified jump statistic that equals $J_{t+j\Delta}$ divided by a robust estimate of the periodicity factor $f_{t+j\Delta}$, i.e.

(7) $$FiltJ_{t+j\Delta} \equiv \frac{|r_{t+j\Delta}|}{\delta_{t+j\Delta} f_{t+j\Delta}},$$

where $\delta_{t+j\Delta}$ is estimated using RBV over a window of K observations, as in Equation 3.

Andersen, Bollerslev and Dobrev (2007) use Taylor and Xu's (1997) approach to estimate $f_{t+j\Delta}$. Due to the fact that, in the absence of jumps, standardized returns follow a zero-mean normal distribution with variance equal to the squared periodicity factor, Taylor and Xu (1997) estimate the periodic component as the mean of squared standardized returns, for each intraday period of the day or week. While being very efficient in the absence of jumps, this estimator is not appropriate in the presence of jumps because even one jump makes the periodicity estimate extremely large. To overcome this problem, Boudt, Croux and Laurent (2008) propose applying Taylor and Xu's (1997) estimator with weighted returns, where returns receive a weight equal to 1 when they are not suspected of being contaminated by jumps, and are deemed to have a weight of 0 otherwise. See Boudt, Croux and Laurent (2008) for full details.

In the remainder of the text, $Jump_{t+j\Delta}$ denotes significant jumps based on the jump statistics given in Equation 7. It equals the tested return $r_{t+j\Delta}$ when there is a significant jump (i.e. $FiltJ_{t+j\Delta} > G^{-1}(1-\alpha)S_n + C_n$) and it equals 0 otherwise.

The next section describes the data 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 the 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 $1/\Delta = 288$ 5-minute intervals. As is standard in the literature, we define trading day *t* to start at 16.00 ET on day *t-1* and to end at 16.00 ET on day *t*.[7,8] So the first price of day *t* is the last price of the 16.00-16.05 interval (of day *t-1*).

We remove weekends 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 regarding the exchange rate series. Our filtering procedure leaves us with T=697248 5-min returns over the 9 year sample. We detect from 919 to 2735 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 0.003. In terms of jump days, the probability of observing a day that contains at least one jump (P(jump day)) is about 27% for a significance level $\alpha = 0.0001$, and can be as high as 61% 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 jump moments, the mean is about 0.25%, while the standard deviation is about 0.20%. Figure 1 shows the time series of returns and jumps over the whole sample. Figure 2 provides further information concerning jumps: it shows at what time jumps usually occur. The upper panel is based on the Lee and Mykland (2007) statistic (i.e. without considering the intradaily volatility seasonality); while the lower panel is based on its modified version. A rapid comparison of the two figures emphasizes some similarities but also remarkable differences. The first notable feature is that jumps are not equally likely. They depend on the time of day. In the upper panel, jumps are concentrated mostly during the opening hours of major trading segments around the world: Japan, Europe and the U.S. When using a statistic robust to seasonality, however, this pattern is different: jumps mainly appear between 16.00 ET and 20.00 ET, that is when the liquidity in FX markets is low (i.e. when major markets are closed) and periods of market overlap are characterized by a low number of jumps. This finding illustrates the weight of the methodology when identifying jumps, and the importance of removing seasonality before applying the Lee-Mykland test, as shown in Boudt et al. (2008).

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

[8] Note that we adjust the definition of the trading day to the daylight saving time in the US due to its potential impact on the intradaily seasonality. Specifically, the day *t* starts at 21 GMT-5 from November to March and at 20 GMT-4 the rest of the year. By making these adjustments, the end of the day always corresponds to market closing time in New York.

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

	5-min returns	Absolute value of jumps					
Alpha Level	-	0.0001	0.001	0.01	0.05	0.1	0.5
Sample size	697248	919	1184	1557	1924	2122	2735
Mean	0.000	0.320	0.290	0.270	0.260	0.250	0.240
St. dev.	0.050	0.220	0.210	0.190	0.180	0.170	0.160
Skewness	-0.140	2.890	3.070	3.220	3.350	3.430	3.590
Kurtosis	37.910	15.830	17.750	19.700	21.670	22.770	25.260
Min	-2.210	0.060	0.050	0.050	0.050	0.030	0.030
Max	1.650	2.210	2.210	2.210	2.210	2.210	2.210
Jump days	-	652	806	995	1154	1233	1465
P(jump)	-	0.0013	0.0017	0.0022	0.0028	0.0030	0.0039
P(jumpday)	-	0.270	0.330	0.410	0.480	0.510	0.610

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 levels) over the whole sample (3rd January 1995 - 29th September 2004). For jumps, the table also reports the number of days containing at least one jump, the estimated jump probability (probability that an intraday period contains a jump, computed as the ratio of detected jumps to the total number of 5-min returns), as well as the probability of a jump day (probability of observing 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).

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

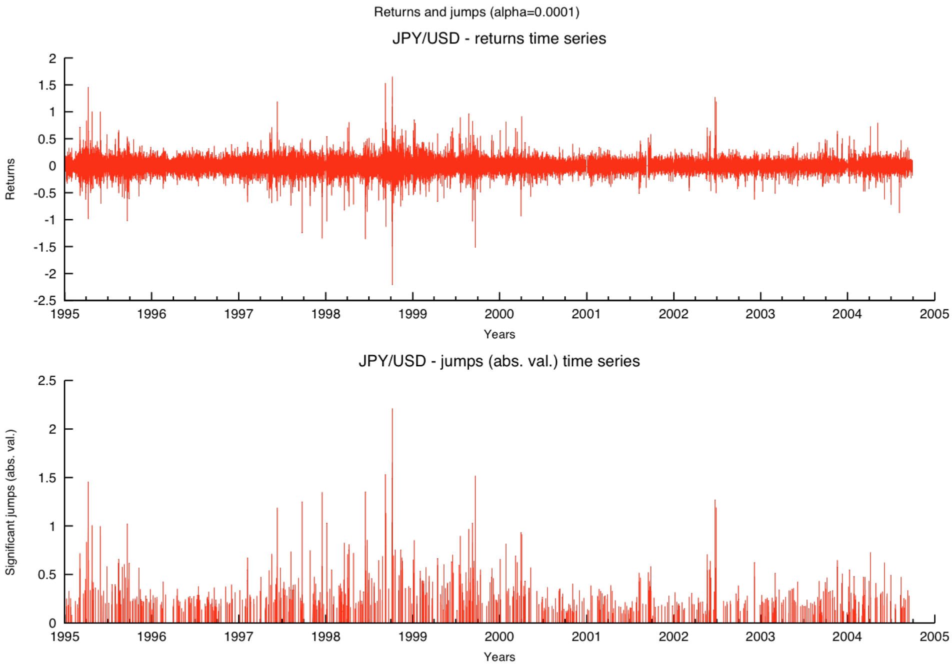
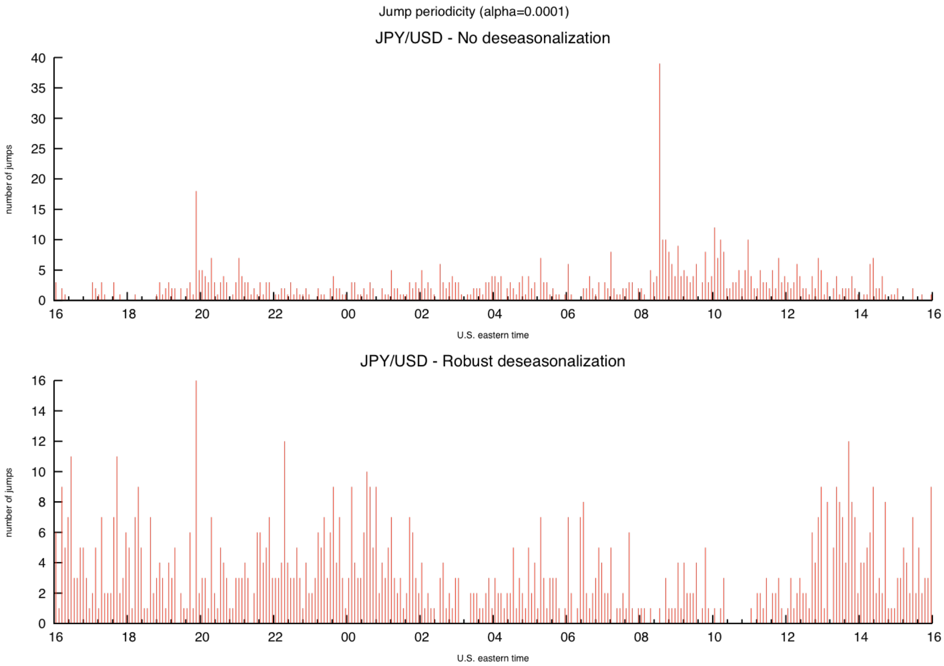


Figure 2: Count of jumps ($\alpha = 0.0001$) across the day



4.2. False reports

We consider a newswire intervention report to be a false rumor or a false intervention report if there is no official intervention on that particular day (Klein 1993; Frenkel et al. 2004).[9] For example, on March 23, 1994 the news "*BOJ buys dlrs at around 103.95-104.00 yen in Tokyo*" (Reuters) was reported when no official intervention had been made. Of course, this type of news is considered as a rumor *a posteriori*, when knowledge of official interventions becomes available.

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 through intervention and oral statements.[10] Second, the Japanese authorities have made several changes to their intervention policy, sometimes deliberately practicing transparency and sometimes ambiguity (Ito, 2007). In fact, after a period of transparency in intervention policy during the Sakakibara period[11] of 1995-2002, recent interventions by the Japanese government have been conducted secretly (Beine and Lecourt 2004). This regime change in the level of transparency of

[9] 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).

[10] 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.

[11] Mr. Sakakibara, who was at the head of the Japanese Finance Ministry from 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.

the policy led to the emergence of numerous market rumors and, in particular, of false reports of interventions (Gnabo et al., 2007). As shown in Table 2 below, the financial press, which transmits the perception of market participants was mistaken 98 times during the period 1995-2004,[12] reporting interventions through the Reuters or Dow Jones newswires when they did not occur. It should be the case that the number of false reports are reduced when intervention policy is practiced in a visible way (with interventions being systematically confirmed thereafter by an official speech). That was what happened during the Sakakibara period: there were false reports on only 4.04% of days, in comparison with 5.48% of days for the two year period 2003-2004 (see Table 2 below). This recent period was qualified as "opaque" in terms of intervention policy (80% of interventions were carried out secretly during this period (Beine and Lecourt, 2004)), favoring a climate of uncertainty in the market and therefore the emergence of false reports.

5. Empirical results

5.1. The link between jumps and false reports

Table 2 provides insights into the matching between jumps and false reports at the daily level. We report the number of false reports and the number of days where both a jump and a false report occurred (as well as percentages relative to the total number of days in the period excluding official intervention days).[13] These figures are given for the full period (1995-2004) as well as for the Sakakibara period (June 1995 - December 2002) and for the most recent period (2003-2004). We also condition on the jump significance level α. Over the full sample period, false reports were issued on 98 trading days, while jumps occurred on 652 days (at the very conservative significance level $\alpha = 0.0001$). Using this significance level for jumps, we detect 37 matching days, meaning that about one third of the false reports occurred during a jump day.

We find that the probability of observing the release of a false report on a jump day is about five percent (i.e. 37 matching days over 652 days with jumps). Although this value seems low at first glance, it is actually not surprising that only a minority of days with jumps are associated with false reports. Indeed, several conditions need to be met to observe a matching

[12] To be more precise, we observed 103 days with false reports. In five cases, however, the timing of the news was not indicated. Without clear information concerning this timing, we are unable to perform any analysis based on intradaily information such as assessing the causality between intradaily jumps and false reports. To deal with this issue and to remain consistent throughout the study, we have excluded these news reports from our sample. Auxiliary investigations show that this exclusion does not affect our analysis (i.e. the proportion of matching days remains similar).

[13] Jumps were also calculated with returns at 15 minutes but the results remained fundamentally unchanged; these results are available upon request.

between the two events on a given day. There is, for instance, little chance that the market will mistakenly associate a jump to an intervention if this jump is already clearly related to a macro announcement (e.g. scheduled macro announcement). More generally, we do not expect any matching when the market can unambiguously associate a jump to auxiliary events such as macro news or political events (for a global review of variables related to jumps see Lahaye et al (2007)).[14] Even if this condition is respected, it is also important that market participants keep expecting an intervention at some point. In other words, it is unlikely that a matching would be observed if monetary authorities have explicitly or implicitly stopped their intervention policy.

Despite few days of matching between the two events, the relationship between jumps and false reports remains of interest for several reasons. First, there are naturally periods where both conditions are met. Given the critical consequences this may have on trader behavior and the broader financial environment, a good understanding of this phenomenon is required,[15] regardless of its frequency.[16] Second, investigating this question with real data provides an illustration of the complete Bachetta and van Wincoop (2004) theoretical approach, which challenges the traditional wisdom according to which news systematically creates jumps and not the other way around.

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[14] Lahaye et al. (2007) investigate the link between macro news and jumps. While some macro news reports appear statistically related to jumps, the conditional probability of observing a news report given a jump is as low as the value reported for the false reports (5 percent). For instance, the probability of having an announcement on trade balance or unemployment given a jump is about 6 percent in both cases.

[15] Again, consistently with the signaling channel, interpreting a jump as a central bank signal may lead market participants to wrongly adjust their trading behavior and this in turn will make significant changes to the future developments of the exchange rate.

[16] It is worth noting that many areas of finance focus on rare events (e.g. studies on extreme events).

Table 2: Descriptive statistics on false reports and detected jumps

Period	False reports (count and percentage)		Days with jumps and false reports (count and percentage)											
			α =0.0001		α =0.001		α =0.01		α =0.05		α =0.1		α =0.5	
1995(06)-2002*	74	4.04%	29	1.58%	33	1.80%	38	2.08%	42	2.29%	43	2.35%	48	2.62%
2003-2004	17	5.48%	6	1.94%	7	2.26%	7	2.26%	7	2.26%	8	2.58%	13	4.19%
1995-2004	98	4.37%	37	1.65%	46	2.05%	54	2.41%	55	2.45%	56	2.49%	64	2.85%

Note: The table gives descriptive statistics both for false reports (count and percentage of the total number of days of the period without intervention) and for the number of days where we identify at least one significant jump (at the alpha level) and one false report on the same day.
*Mr. E. Sakakibara started his term at the Ministry of Finance in June 1995. Accordingly, the first sub-sample also starts in June and not in January 1995, which is the start date of the full sample.[17]

The preliminary analysis discussing the number of matching days over the sample remains naturally incomplete, as it says nothing about the causality link between jumps and false reports, i.e. whether jumps really cause 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 timing of the arrival of false reports.

Table 3 shows the dates and the false report and jump arrival times.[18] Columns labeled "Jump *i*" show the size of the *i*th most significant jump on the corresponding day, while columns labeled "Stat *i*" and "Time *i*" report respectively the modified Lee-Mykland/Andersen et al. statistics and the jump arrival time (at a 5-min frequency), where *i*=1,2,3. Column "FR Time" gives the arrival time of the (first) false report (FR). Column "I(J & FR <2h)" is a dummy equal to 1 when a jump occurs within one hour before or after an FR. Column "Min(J-FR)<-60" reports the distance (in min.) between the closest jump to the FR and the FR when this jump occurs at a maximum of 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 occurs at a maximum of one hour after the FR. Importantly, the table is sorted according to the column "Stat1" in decreasing order. So the first row concerns the day with the most significant jump, the second is the day with the second most significant jump, etc. The table is divided into 5 parts, representing days with at least one significant jump at the critical level α = 0.0001, 0.001, 0.01, 0.05, 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.

[17] Statistical tests of population proportions based on the z-statistic cannot reject the null hypothesis that the proportions of days with jumps and false reports over the Sakakibara and post-Sakakibara periods are equal, regardless of the level of alpha but 0.5. Results of the tests are available upon request.
[18] Table 3 reports a maximum of four jumps per day. For a few dates, more jumps were detected (with a maximum of 6). As these jumps are not crucial for our purposes, we do not report them in Table 3, in order to save space.

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

Date	jump 1	stat 1	time 1	jump 2	stat 2	time 2	jump 3	stat 3	time 3	jump 4	stat 4	time 4	FR time	I(J&FR<2h)	Min(J-FR) <-60	Min(J-FR) <60
Jumps significant at alpha=0.0001, i.e. whose test statistic >9.2102																
20040406	0.73	98.6	30	0.28	11.16	20	-0.21	13.25	45	0.12	15.8	2350	148	0	0	0
19980320	-0.83	65.72	1945	0	0	0	0	0	0	0	0	0	1944	1	1	0
19990416	-0.67	60.41	2320	0.59	36.05	2350	0;22	4.65	2325	-0.2	3.91	2300	2358	1	0	-8
19990825	0.97	49.78	2020	-0.28	1.33	2040	0	0	0	0	0	0	2030	2	10	-10
19980403	0.71	48.6	2040	-0.46	20.79	40	0.24	3.62	2110	0	0	0	42	1	0	-2
19950921	-1.02	48.57	1350	-0.61	3.52	1220	-0.47	3.09	545	0.36	17.32	1745	2037	0	0	0
19990715	0.6	47.29	340	0.18	5.53	1420	0	0	0	0	0	0	342	1	0	-2
19950426	1.01	43	2040	-0.43	11.14	1845	0.42	3.73	2035	0	0	0	2208	0	0	0
19980812	-0.64	41	2020	-0.26	1.19	2005	0	0	0	0	0	0	2039	1	0	-19
19980616	-0.8	39.29	2230	-0.42	11.74	2235	0.38	8.4	2240	-0.37	18.03	2120	2216	2	14	-56
19990202	-0.53	32.63	155	-0.46	30.35	120	-0.24	6.83	110	0.13	3.46	5	958	0	0	0
20040331	-0.43	32.03	2100	-0.26	26.43	2315	-0.18	5.79	30	0.14	1.83	15	2244	1	31	0
19980428	-0.72	30.35	2005	-0.15	7.19	35	0	0	0	0	0	0	2011	1	0	-6
19980624	-0.85	30.14	235	0.5	9.48	240	0.37	24.83	2325	0	0	0	236	2	4	-1
20000417	0.43	27.41	2020	0.31	7.41	540	-0.27	21.37	2135	0.21	0.97	2155	2027	1	0	-7
19950914	-0.47	26.86	15	-0.29	12.16	2310	0.23	6.32	1900	-0.21	5.78	2255	222	0	0	0
19990428	-0.3	21.9	2335	-0.29	30.03	2315	0.27	1.31	740	-0.21	13.23	2215	20	1	0	-45
19950814	0.28	18.84	1645	-0.26	8.87	1640	0.26	5.54	1825	0	0	0	138	0	0	0
19950831	-0.58	18.77	145	-0.34	13.66	2245	0	0	0	0	0	0	201	1	0	-16
19960229	-0.29	18.4	1850	-0.25	12.73	1835	0.24	0.75	1855	0	0	0	1917	1	0	-22
19950801	0.4	17.44	355	0	0	0	0	0	0	0	0	0	300	1	55	0
20030922	-0.33	15.92	1850	0	0	0	0	0	0	0	0	0	1932	1	0	-42
19970116	0.24	15.48	1810	-0.22	29.97	1805	-0.15	0.65	2250	0	0	0	1001	0	0	0
19950929	-0.62	15.01	2155	0.34	0.38	2200	0	0	0	0	0	0	2152	1	3	0
19970220	0.27	14.54	1350	0.21	9.44	1535	0	0	0	0	0	0	2034	0	0	0
19980318	0.45	14.31	2005	0	0	0	0	0	0	0	0	0	2251	0	0	0
19990107	0.51	12.78	545	0.49	3.06	700	0.44	2.48	525	0	0	0	534	2	11	-9
19990728	0.41	11.84	255	-0.26	3.78	300	-0.19	2.02	200	0	0	0	257	2	3	-2
20030221	0.11	11.83	745	0	0	0	0	0	0	0	0	0	1219	0	0	0
19951024	0.25	11.51	1945	0	0	0	0	0	0	0	0	0	2031	1	0	-46
19990812	0.18	10.91	1900	0	0	0	0	0	0	0	0	0	2040	0	0	0
20010920	0.3	10.52	455	-0.26	4.75	745	0	0	0	0	0	0	515	1	0	-20
19950718	0.19	10.48	1625	0	0	0	0	0	0	0	0	0	122	0	0	0
19950719	-0.4	9.61	2110	-0.32	14.27	2050	-0.29	0.68	2250	0.28	1.83	1350	2001	1	49	0
Jumps significant at alpha=0.001, i.e. whose test statistic >6.9072																
19960509	-0.22	9.12	355	0	0	0	0	0	0	0	0	0	501	1	0	0
19970501	-0.45	8.89	1015	-0.13	3.97	1815	0	0	0	0	0	0	1402	0	0	0
19950724	-0.31	8.7	2035	-0.28	4.12	2020	0	0	0	0	0	0	2047	0	0	-12
20030328	-0.15	8.68	1315	-0.15	4.7	1340	-0.14	3.28	130	0	0	0	1308	1	7	0
19950918	0.19	8.64	1540	0	0	0	0	0	0	0	0	0	259	1	0	0
19970115	-0.26	8.25	1455	0.16	3.99	1230	0	0	0	0	0	0	1003	0	0	0
20030311	0.19	8.22	950	0	0	0	0	0	0	0	0	0	33	0	0	0
20040326	-0.14	8.01	1910	0	0	0	0	0	0	0	0	0	2359	0	0	0
19951023	-0.23	7.91	1820	0	0	0	0	0	0	0	0	0	2143	0	0	0
Jumps significant at alpha=0.01, i.e. whose test statistic >4.6001																
19980415	-0.19	5.71	1320	0.17	3.51	1515	-0.16	10.59	1520	0	0	0	1027	0	0	0
19951018	-0.15	5.34	2300	0.15	5.32	2305	0.15	0.63	2055	0	0	0	2213	0	47	0
19970124	-0.28	5.24	1820	0	0	0	0	0	0	0	0	0	2137	1	0	0
19960530	-0.19	5.19	655	0	0	0	0	0	0	0	0	0	927	0	0	0
19950308	-0.5	4.84	45	-0.4	6.54	1735	-0.34	5.92	50	0	0	0	2108	0	0	0
Jumps significant at alpha=0.05, i.e. whose test statistic >2.9702																
19951005	-0.27	3.23	1220	0	0	0	0	0	0	0	0	0	2105	0	0	0
19980625	0.35	2.9	1810	-0.31	11.78	1805	0	0	0	0	0	0	1314	0	0	0
Jumps significant at alpha=0.5, i.e. whose test statistic >0.3665																
19950907	-0.26	2.86	2015	0	0	0	0	0	0	0	0	0	2329	0	0	0
19950419	0.42	2.04	610	0.34	16.96	1335	-0.31	4.8	2055	-0.22	0.67	35	2003	1	52	0
19980626	-0.33	2.04	1455	0.25	5.15	1510	-0.23	3.18	1450	0	0	0	710	0	0	0
19980813	-0.31	2	1955	0.29	6.55	1925	-0.22	1.94	550	0	0	0	503	1	47	0
19970407	-0.18	1.36	55	0	0	0	0	0	0	0	0	0	2100	0	0	0
19950731	0.26	1.22	1140	0.1	5.79	1750	0	0	0	0	0	0	203	0	0	0
19950720	-0.13	1.11	1350	0	0	0	0	0	0	0	0	0	2215	0	0	0
19950829	0.13	1.05	120	0.09	0.45	100	0	0	0	0	0	0	320	0	0	0
19950905	-0.18	0.99	2240	-0.13	1.3	35	0.13	5.82	2220	0	0	0	2338	2	57	-58
20040325	-0.16	0.82	950	0	0	0	0	0	0	0	0	0	2212	0	0	0
19980416	0.23	0.82	1750	0	0	0	0	0	0	0	0	0	2136	0	0	0
19950515	-0.33	0.6	1445	0	0	0	0	0	0	0	0	0	2040	0	0	0
20031204	-0.09	0.5	2255	0	0	0	0	0	0	0	0	0	31	0	0	0
20010918	-0.18	0.38	155	0	0	0	0	0	0	0	0	0	2106	0	0	0

Note: Columns labeled "Jump i" show the size of the i[th] biggest jump on that day, while columns labeled "Stat i" and "Time i" report respectively the modified Lee-Mykland/Andersen et al. statistics and the jump arrival time (at a 5-min frequency), where i=1,2,3. Column "FR Time" gives the (first) false report (FR) arrival time. Column "I(J & FR <2h)" is a dummy equal to 1 when a jump occurs within one hour before or after an FR. Column "Min(J-FR)<-60" reports the distance (in min.) between the closest jump to the FR and the FR when this jump occurs at a maximum of one hour before the FR. Finally, the column labeled "Min(J-FR)<60" reports the distance (in min.) between the closest jump to the FR and the FR when the jump occurs at a maximum of one hour after the FR.

Of these 34 matching days,[19] 22 are characterized by at least one jump and a false report within a time interval of two hours (see column "I(J&FR<2h)"). The second feature concerns the causality between jumps and false reports: on these 22 days, 17 support the idea of a causality from jumps to false rumors (see the column labeled: Min(J-FR)<-60). Likewise, one can see this causality in the 15 most significant jumps, where 9 days have at least one discontinuity before a false report within a time interval of one hour and 7 days do so within an interval of 10 minutes. This result reinforces the causality from jumps to false reports, i.e. the fact that the most significant jumps on false report days may have been interpreted by agents as indicating 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 19.45 ET (i.e. a price variation between 19.40 and 19.45 ET), while the false report is recorded at 19:44 ET, i.e. one minute before. Thanks to Olsen and Associates, we were able to gain access to 1-min data for that day. A careful inspection of these data suggests that the jump actually occurred at 19.42 ET, i.e. 2 minutes before the false rumor appeared. This means that, of the 15 most significant matching days, 10 have at least one discontinuity before a false report within a time interval of one hour and 8 do so within an interval of 10 minutes and not respectively 9 and 7 days, as mentioned above. Another important finding is that the evidence of causality from jumps to false rumors is less strong for less significant jumps, in that they occur somewhat less near the false report.

We can summarize our results by referring to Figure 3. This figure illustrates the dispersion of jumps around false reports. The X-axis represents the distance in minutes between jumps and false reports, while the Y-axis represents the test statistic associated to jumps. We find that many false report days also experienced a jump (about one third if we consider highly significant jumps). Many of these jumps occurred before the false report, allowing an interpretation of causality from jumps to false news. And the closer we get to the arrival, the greater the dispersion of the jump test statistic. In other words, the more significant the jump, the more likely its false interpretation by market participants.

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[19] It is noted that the number of matching days is 34 in Table 3 as opposed to 37 in Table 2 (at the same significance level $\alpha = 0.0001$). This is due to a slight difference in the Table's construction. In Table 2, we consider as jump days those with at least one intra daily significant jump. The most significant jump of a given day then determines its ranking in Table 2's columns. In Table 3, intra daily jumps are initially sorted within each day according to their size. Then, jump days are ranked according to the level of significance of the biggest intra daily jump. This lead to slight differences between these two Tables as the biggest jump of a day may be less significant than the second biggest jump of the same day. These Tables' construction slight differences have no impact on our discussion.

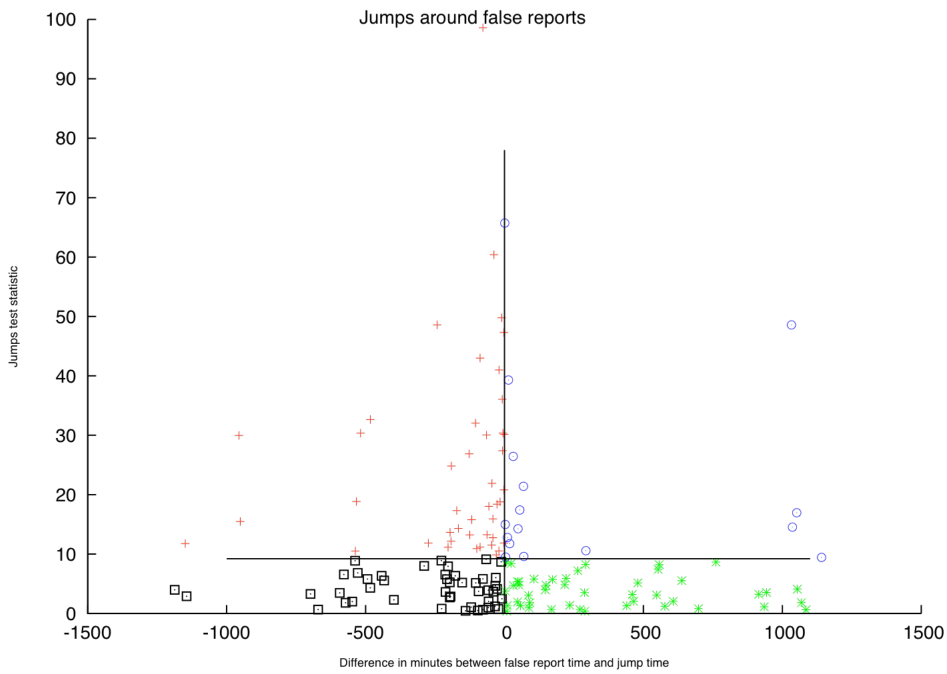

Figure 3: We plot all jumps detected on false report days. The X-axis represents the distance in minutes between jumps and false reports, while the Y-axis represents the test statistics associated to jumps. We divide the graph into four quadrants. The upper part represents highly significant jumps (α =0.0001, i.e. jumps whose test statistic is above 9.2102). The vertical line represents the arrival time of false reports, centered at 0. For instance, the squares in the bottom-left hand corner of the figure displays small jumps occurring before the news. Conversely, the cycles in the top-right hand corner represent big jumps occurring after the news.

5.2. Case studies

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

For example, consider April 28, 1998 (the thirteenth row of Table 3). The first jump occurred at 20.05 ET while the false report occurred 6 minutes later (at 20.11 ET). A few minutes after that, a news story reported that a large order flows had 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 reports also indicated that the market was even more watchful as Japanese officials adopted an active communication policy: *"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).

The fact that the market expected an intervention at some point, because of an aggressive communication policy from Japanese officials for instance, may also have favored the matching between jumps and false reports on June 24, 1998 (the fourteenth row of Table 3). The state of the market is conveyed in the following news: "*We [the market] expect there to be some form of [central bank] intervention around here [*a dealer at a Japanese trust bank*]*" (Dow Jones). The quote was reported in a Dow Jones newswire at 2.32 ET. And three minutes later, at 2.35 ET, a jump was observed in the market and was closely followed, at 2.36 ET, by a headline announcing an intervention: "*Tokyo: Traders Say BOJ [Bank of Japan] May Have Sold Dollars For Yen [intervene]*" (Dow Jones).

Another revealing example concerns July 28, 1999 (the twenty-eighth row of Table 3). Two discontinuities were detected at 2.55 ET and 3.00 ET, while the false report arrived at 2.57 ET. A news report clearly explained that rumors of interventions had appeared as a result of the dollar jump: "*Rumors of BOJ intervention appeared soon after the dollar quickly jumped about Y1 higher around 06.57 GMT [2.57 ET] Wednesday* (Dow Jones, July 28, 1999). However, it is not clear whether the second jump (from an opposite signal) was the consequence of the false rumor.

5.3. Implications

We find that large jumps can cause false rumors. This piece of empirical evidence is consistent with the scapegoat model of Bachetta and van Wincoop (2004). Indeed, our results can be interpreted as heterogeneous agents using interventions, or equally as signals regarding fundamentals, as scapegoats for large jumps. In the theoretical model, the heterogeneity of agents creates confusion on the market. We could argue that this confusion is enhanced when the bank applies an opaque policy. We certainly find a higher probability of jumps causing rumors in the period of BoJ opaque policy. 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, a large jump creates rumors of central bank intervention. In that respect, our study cannot be deemed as a formal test of the scapegoat theory. Instead, it should be viewed as an original illustration of its underlying mechanisms.

From a policy-making perspective, our findings have several implications. As discussed in section 2, intervention operations are generally not officially confirmed on the day they are carried out. Market participants need therefore to rely on sources of unofficial information, such as newswire reports, to detect the central bank signal. The combination of both the weight attached by market participants to the intervention – because the intervention transmits an official signal – and the lack of transparency in the conduct of the policy has led to a number of incidents of wrong detection (see Table 2). On several occasions, these incidents of wrong detection were simply provoked at an intradaily level by the occurrence of jumps. False reports can, in their turn, significantly enhance volatility, as documented in Dominguez and Panthaki (2007). Therefore, because reducing uncertainty is presented as one of the main objectives of intervention (see Beine *et al.*, 2007 and Dominguez, 2006 on the short, medium and long term impact of central bank interventions on the exchange rate), official authorities might need to take this potential indirect effect of their policy into account.

6. Conclusion

According to the signaling channel theory (Mussa, 1981), central banks affect exchange–rate developments by transmitting a signal to the market. In practice, this signal usually takes the form of a newswire announcing the central bank's transactions in the FX market. Because newswires are an unofficial source information, there are inevitably cases in which the news is wrong. And it can happen, as noted by Schwartz (2000), that market participants are mistaken, "*detect[ing] a signal where none was sent*". Understanding the origin of false reports might therefore be important.

This paper is the first to empirically investigate the causality link between jumps and intervention rumors (i.e. false reports of intervention). We used a unique database allowing the identification of false rumors regarding interventions by the Bank of Japan over the period 1995-2004. To identify jumps, we used a modified version of the recent non-parametric technique proposed by Lee and Mykland (2007) and by Andersen et al. (2007). We showed that many false report days also experienced a jump. And many of these jumps occurred shortly before the false report, allowing an interpretation of causality from jumps to false news. The more significant the jump, the more likely its false interpretation by the market.

Therefore, if official authorities aim at "*calming the disorderly market*" as they often claim to, intervention strategies that may enhance false reports as non-transparent policies (i.e. secret interventions) should be used with care.

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