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 (2008) and by Andersen et al. (2007b), and later modified by Boudt et al. (2011). 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.

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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 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[1] 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).[2] 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., 2009) and volatility divided into a continuous part and a jump component (Beine et al., 2007).[3]

If official interventions and unofficial reports of central bank intervention in the public press cause volatility, is the reverse also true?[4] 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 agents. 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

[1] 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).

[2] The uncertainty about asset prices grows linearly with the time horizon. Therefore it is difficult to tell whether intervention is effective at any but the shortest horizons.

[3] See Neely (2005) for a survey of this literature.

[4] Official data on currency held 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. 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 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 in 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 at the head of the article. For our empirical analysis, we use the case of the Bank of Japan (BoJ), which has been the most active central bank from industrialized countries in the FX market over the past decade. Identifying the origin of false reports 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).

To the best of our knowledge, the literature has overlooked the question whether jumps affect the occurrence of news and specifically the occurrence of false reports focusing rather on the determinants of jumps. The main result of this literature is that a substantial proportion of jumps are associated with announcements. Goodhart et al. (1993) underline the importance of accounting for financial and macroeconomic news for modeling exchange rates. Fair (2002, 2003) uses various types of newswire reports and high frequency data to identify events (including foreign exchange market interventions) that cause spikes in asset prices (stock, bond and exchange rate). He finds that each event extracted by newswire led to a large and a rapid price changes but many large price changes have no events associated with them. Using new techniques for estimating jumps, a large recent literature concludes that many jumps appear to correspond to macro-news announcements (see among others Barndorff-Nielsen and Shephard, 2004; Andersen et al. 2007a, 2007b and Lahaye et al., 2011). In particular, Lahaye et al. (2011) conclude that exchange rates are subject to frequent jumps but a relatively small proportion of these jumps is explained by the release of macroeconomic news.[5] Focusing on news related to central bank interventions, Gnabo, Laurent and Lecourt (2009) examine, in a study in the same spirit as this paper, the determinants of false reports of intervention at a daily frequency and find that jumps explain the appearance of false reports of intervention. The question we address here is whether the probability of false intervention reports in the FX market increases shortly – i.e. within a few minutes or a few hours – after the occurrence of a jump.

Comparing systematically the dates of official interventions and the dates of financial press reports announcing an intervention, we identify the false reports. 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 (2008) and by Andersen et al. (2007b). This 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 big relative to the 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 addressed at Lee and Mykland's test is that it does not account for the presence of intra-daily volatility periodicity. As shown by Boudt et al. (2011), 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 Lee and Mykland's statistic, recently proposed by Boudt et al. (2011), is applied here.

The paper is organized as follows. Section 2 presents a discussion on central bank intervention policy and false reports. 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 offering an informal tabular and graphical analysis before performing a formal probit regression analysis to test whether the occurrence of jumps increases the probability of false reports. Finally, Section 6 concludes.

[5] See Neely and Dey (2010) for an extensive survey about announcement effects on FX volatility and jumps.

2. Central bank intervention policy 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 interventions as it is known to affect the exchange rate dynamic in the short, medium and long term. According to the coordination channel for instance, official intervention may act as a coordinating signal (Reitz and Taylor, 2008). Specifically, central bank interventions can change the path of the currency by providing the market with a focal point in order to coordinate market beliefs. A sale (purchase) of domestic currency may signal that the central bank wants to move up (drive down) the exchange rate value. 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.[6,7] 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 and Schindler, 2007).

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 for the case of Japan 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 can be transmitted. First, depending on whether or not the central bank wants its action to be

[6] 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.

[7] See Lecourt and Raymond-Feingold (2006) and Neely (2007) on the practice of foreign exchange market interventions and its change in recent years.

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.[8] In this case, the intervention is considered as "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 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.[9] 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)*.

3. Detecting jumps

This section describes our testing strategy for jumps. Andersen et al. (2007b) and Lee and Mykland (2008) assume a continuous time jump-diffusion data generating process. The log price process evolves as follows:

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

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 $\kappa(t)$ is the 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 and therefore is conditionally Gaussian.

8 Dominguez (2006) suggests that this information process may take approximately 15 minutes.

9 Given the path followed by the central bank signal (described above), it is also likely that traders themselves attempt to initiate false rumors, i.e. 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.

The intuition behind the jump test simultaneously proposed by Andersen et al. (2007b) and Lee and Mykland (2008) is straightforward. Consider the (intraday) discrete-time version of (1), i.e.

(2) $$r_{t,i} = \mu_{t,i} + \sigma_{t,i} z_{t,i} + \kappa_{t,i} q_{t,i},\ t = 1,\ldots,T \text{ and i} = 1,\ldots,M,$$

where $r_{t,i} = p_{t,i} - p_{t,i-1}$ is the *i*th intraday return of day *t*, *T* denotes the total number of days, *M* is the number of equidistant intraday returns per day (e.g. *M=288* for 5-minute returns of FX data), $z_{t,i}$ is an i.i.d. standard normal random variable, $\kappa_{t,i}$ is the size of the jumps arriving during the *i*th interval of day *t* and $q_{t,i}$ is a dummy variable taking the value 1 when at least one jump arrived on that intraday interval and 0 otherwise.

In absence of jumps, $\mu_{t,i}$ and $\sigma_{t,i}$ are respectively the conditional mean and conditional variance of $r_{t,i}$ and therefore standardized returns $(r_{t,i} - \mu_{t,i})/\sigma_{t,i}$ follow a standard normal distribution. Consequently, standardized returns that are too large to plausibly come from a standard normal distribution must reflect jumps. These authors propose the following statistic to test for the presence of jumps in $r_{t,i}$:

(3) $$J_{t,i} \equiv \frac{\left|r_{t,i} - \hat{\mu}_{t,i}\right|}{\hat{\sigma}_{t,i}},$$

where $\hat{\mu}_{t,i}$ and $\hat{\sigma}_{t,i}$ are robust to jumps estimates of respectively $\mu_{t,i}$ and $\sigma_{t,i}$ (defined below).

Under the null of no jumps, the test statistic, $J_{t,i}$, follows the same distribution as the absolute value of a standard normal variable. Brownlees and Gallo (2006) propose comparing $J_{t,i}$ with the $1-\alpha/2$ quantile of the standard normal distribution. This rule might spuriously detect many jumps, however. Andersen et al. (2007b) use a Bonferroni correction to minimize spurious jump detection. To minimize the risk of falsely finding jumps, Lee and Mykland (2008) 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 jump. Under the stated assumptions and no jumps in the *i*th interval of day *t*, the sample maximum of the absolute value of a standard normal, i.e. the maximum of the normalized returns from (3) follows a Gumbel distribution. We reject the null of no jump if

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

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

(MT). So if we choose a significance level of $\alpha = 0.0001$, then we reject the null of no jump at testing time if $J_{t,i} > \beta^* S_n + C_n$, with β^* such that $P(\psi \leq \beta^*) = exp(-e^{-\beta^*}) = 0.9999$, i.e. $\beta^* = -\log(-\log(0.9999)) = 9.21$. Note that a significance level of $\alpha = 0.0001$ implies that one expects to reject the null assumption of no jump in the sample while the null is true in 0.0001 % of the cases (called percentage of global spurious detection under the null of no jump). The number of spurious jumps detected for one given sample of n observations is virtually 0. In the remainder of the text, $Jump_{t,i}$ denotes significant jumps based on this test. It equals the tested return $r_{t,i}$ when there is a significant jump and 0 otherwise.

As mentioned above, the $J_{t,i}$ statistic requires estimates of $\mu_{t,i}$ and $\sigma_{t,i}$ that are robust–to–jumps. $\mu_{t,i}$ being nearly zero for most high-frequency return series, it can safely be ignored and set to zero as suggested by Lee and Mykland (2008). Andersen et al. (2007b) and Lee and Mykland (2008) propose estimating $\sigma_{t,i}$ by a transformation of the realized bipower variation (BV) computed on a local window of K observations around, preceding or following $r_{t,i}$. Indeed, Barndorff-Nielsen and Shephard (2004, 2006) show that BV converges to the integrated volatility, even in the presence of jumps. Lee and Mykland (2008) advise to take a local window of one day when M is about 288 (as in our case) and assume that the spot volatility is constant during that period of time. This corresponds to the following $\hat{\sigma}_{t,i}^{BV}$ estimator:

(5) $$\hat{\sigma}_{t,i}^{BV} = \sqrt{\frac{\pi}{2}\frac{1}{M-1}\sum_{i=2}^{M}|r_{t,i}||r_{t,i-1}|}.$$

For $\hat{\sigma}_{t,i}^{BV}$ to be a consistent estimate of $\sigma_{t,i}$, the volatility must vary only slowly in this local window. This assumption is questionable, however. Indeed, many financial time series display considerable deterministic periodic variations within a day or a week (see e.g. Andersen and Bollerslev, 1997, 1998 or Martens, Chang and Taylor, 2002). Boudt et al. (2011) show that $\hat{\sigma}_{t,i}^{BV}$ inappropriately smoothes these periodic patterns and that such cyclical patterns might induce the $J_{t,i}$ statistic to spuriously detect or under-detect jumps. Following Boudt et al. (2011), we assume that the conditional variance in Equation (2) decomposes into a slowly varying component $s_{t,i}$ and a deterministic circadian component $f_{t,i}$, i.e. $\sigma_{t,i} = s_{t,i} f_{t,i}$. Andersen and Bollerslev (1997, 1998) and Boudt et al. (2011) assume that $s_{t,i}$ is constant during day t (i.e. $s_{t,i} = s_t \forall t$) and propose to estimate s_t by $\hat{\sigma}^{BV}_{t,i}$. Boudt et al. (2011) propose two estimators for $f_{t,i}$ that are robust to jumps (one parametric and one non-parametric, generalizing respectively Andersen and Bollerslev, 1997 and Taylor and Xu, 1997). We implement their non-parametric weighted standard estimator, denoted $\hat{f}^{WSD}_{t,i}$ (see Boudt et al. (2011) or Appendix A-1 of Lahaye et al. (2011) for a description of this estimator). Finally, our estimator of $\sigma_{t,i}$ used when computing $J_{t,i}$ and denoted $\hat{\sigma}^{BCL}_{t,i}$, is

$$\hat{\sigma}^{BCL}_{t,i} = \hat{\sigma}^{BV}_{t,i} \hat{f}^{WSD}_{t,i} .$$

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 and traded around the clock, and around the world. A 24 hour trading day is thus divided into *M=288* five-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*.[12,13] 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 and/or constant prices (in a row or spread over the trading day). 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.

[12] This is motivated by the ebb and flow in the daily FX activity patterns (see Bollerslev and Domowitz, 1993).
[13] 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 intraday periodicity. 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 and Figure 1 summarize information regarding the exchange rate series. Our filtering procedure leaves us with $n=MT=697248$ five-min returns over the 9 year sample. We detect from 919 to 2735 jumps, depending on the significant level employed. 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 27% for a significance level $\alpha = 0.0001$, and can be as high as 61% for $\alpha = 0.5$. Recall that expected number of spurious jumps detected by the test is in any cases smaller than one and therefore jumps that are significant at the level $\alpha = 0.5$ and not at the level $\alpha = 0.0001$ are not necessarily spurious but of smaller magnitude. Note also that when a jump is found to be significant at a certain level of significance (e.g. 0.0001) it is necessarily significant at a higher level of significance (e.g. 0.001).

We observe the usual stylized facts for the high frequency returns: a mean close to zero and a high kurtosis. We report some summary statistics about $\left|Jump_{t,i}\right|$ for several levels of significance. The mean is about 0.25%, while the standard deviation is about 0.20%, irrespectively of the level of significance. 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 (2008) statistic (i.e. without considering the intradaily volatility periodicity), 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 accounting for the intraday periodicity in the estimation of the spot volatility, 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.

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

	5-min returns	Absolute value of jumps					
α 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 jumps ($\alpha = 0.0001$)

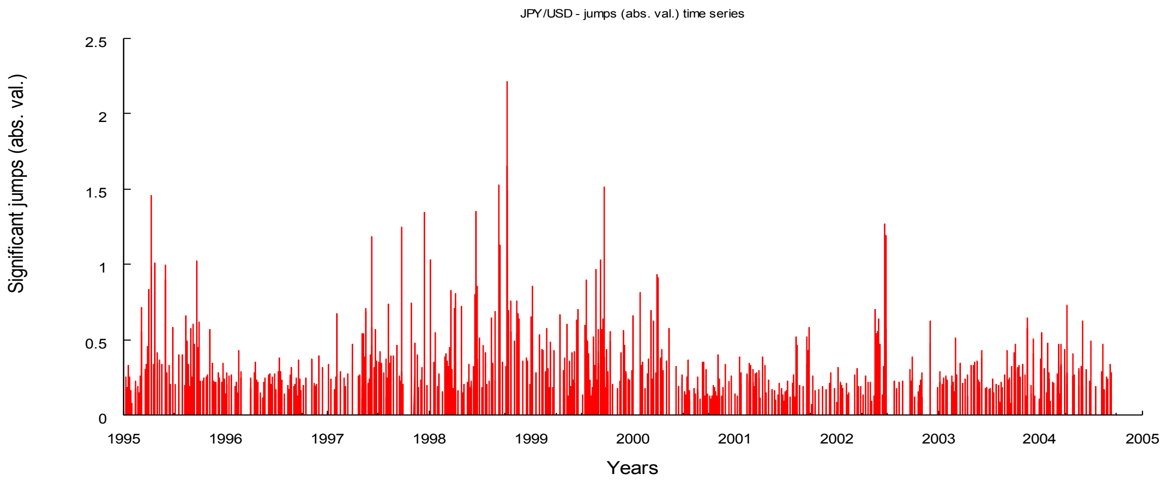
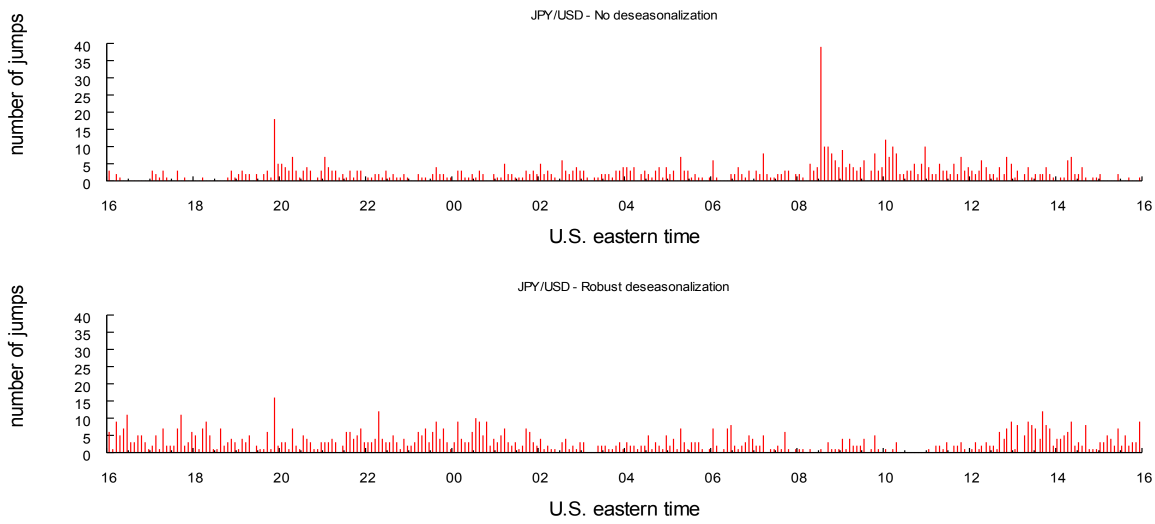


Figure 2: Count of jumps ($\alpha = 0.0001$) across the day



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). For example, on March 23, 1994 the news "*BOJ buys dlrs at around 103.95-104.00 yen in Tokyo*" (Reuters) was reported while 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.[15] 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[16] of 1995-2002, the last intervention campaign conducted by the Japanese government has been done secretly (Beine and Lecourt, 2004). This regime change in the level of transparency of the policy led to the emergence of numerous market rumors and, in particular, of false reports of interventions (Gnabo et al., 2009). 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,[17] 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 is 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

[15] Most central banks, such as the Fed and the ECB, have become increasingly reluctant to intervene.

[16] 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.

[17] 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).

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).[18] 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 α =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 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 (Lahaye et al., 2011 review the main variables related to jumps).[19] 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.

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

[19] Lahaye et al. (2011) 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.

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.[22]

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.[23] Columns labelled "Jump *i*" show the jump arrival time (at a 5-min frequency, where *i*=1,...,4) of the *i*th most significant jump on the corresponding day. Column "FR" gives the arrival time of the (first) false report (FR). Column "-60<Min(J-FR)<60" answers the question as to whether a jump occurs in a near window (2 hours) centered on the false report, and if so, how many minutes before and/or after the false report. It shows the distance (in min.) between FR and adjacent jumps, when the jumps occurs maximum one hour before and/or after the FR. In that last column, we only report the information for the jumps closest to the FR (a positive number for jumps occurring after the FR and a negative number for those occurring before). The absence of number means that no jump occurred within the two-hour window around the FR. Importantly, the table is sorted 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

[22] 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 α but 0.5. Results of the tests are available upon request.
[23] 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.

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.

Out of these 34 matching days,[24] 22 are characterized by at least one jump and a false report within a time interval of two hours. 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 negative numbers in the column labelled: "-60<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.

[24] 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 α=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 in construction have no impact on our discussion.

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

	Arrival time of					
Date	Jump 1	Jump 2	Jump 3	Jump 4	FR	-60<MIN(J-FR)<60
Jumps significant at α = 0.0001						
06/04/04	00:30	00:20	00:45	23:50	01:48	
20/03/98	19:45				19:44	1
16/04/99	23:20	23:50	23:25	23:00	23:58	-8
25/08/99	20:20	20:40			20:30	-10/10
03/04/98	20:40	00:40	21:10		00:42	-2
21/09/95	13:50	12:20	05:45	17:45	20:37	
15/07/99	03:40	14:20			03:42	-2
26/04/95	20:40	18:45	20:35		22:08	
12/08/98	20:20	20:05			20:39	-19
16/06/98	22:30	22:35	22:40	21:20	22:16	-56/14
02/02/99	01:55	01:20	01:10	00:05	09:58	
31/03/04	21:00	2315	00:30	00:15	22:44	31
28/04/98	20:05	00:35			20:11	-6
24/06/98	02:35	02:40	23:25		02:36	-1/4
17/04/00	20:20	05:40	21:35	21:55	20:27	-7
14/09/95	00:15	23:10	19:00	22:55	02:22	
28/04/99	23:35	23:15	07:40	22:15	00:20	-45
14/08/95	16:45	16:40	18:25		01:38	
31/08/95	01:45	22:45			02:01	-16
29/02/96	18:50	18:35	18:55		19:17	-22
01/08/95	03:55				03:00	55
22/09/03	18:50				19:32	-42
16/01/97	18:10	18:05	22:50		10:01	
29/09/95	21:55	22:00			21:52	3
20/02/97	13:50	15:35			20:34	
18/03/98	20:05				22:51	
07/01/99	05:45	07:00	05:25		05:34	-9/11
28/07/99	02:55	03:00	02:00		02:57	-2/3
21/02/03	07:45				12:19	
24/10/95	19:45				20:31	-46
12/08/99	19:00				20:40	
20/09/01	04:55	07:45			05:15	-20
18/07/95	16:25				01:22	
19/07/95	21:10	20:50	22:50	13:50	20:01	49

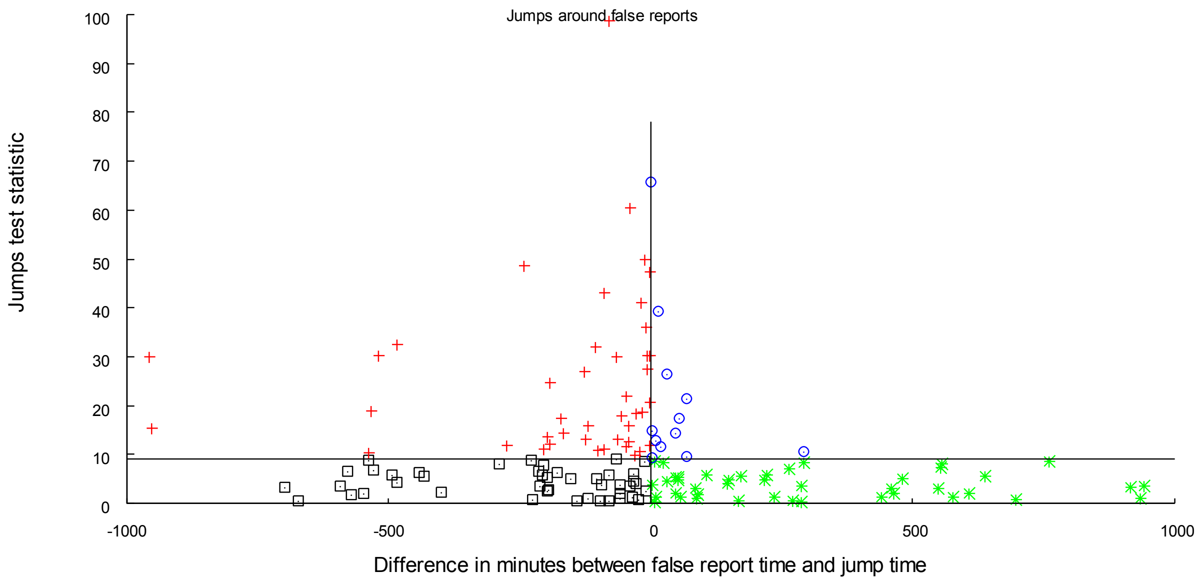
	Arrival time of					
Date	Jump 1	Jump 2	Jump 3	Jump 4	FR	-60<MIN(J-FR)<60
	Jumps significant at α = 0.001					
09/05/96	03:55				05:01	
01/05/97	10:15	18:15			14:02	
24/07/95	20:35	20:20			20:47	-12
28/03/03	13:15	13:40	01:30		13:08	7
18/09/95	15:40				02:59	
15/01/97	14:55	12:30			10:03	
11/03/03	09:50				00:33	
26/03/04	19:10				23:59	
23/10/95	18:20				21:43	
	Jumps significant at α = 0.01					
15/04/98	13:20	15:15	15:20		10:27	
18/10/95	23:00	23:05	20:55		22:13	47
24/01/97	18:20				21:37	
30/05/96	06:55				09:27	
08/03/95	00:45	17:35	00:50		21:08	
	Jumps significant at α = 0.05					
05/10/95	12:20				21:05	
25/06/98	18:10	18:05			13:14	
	Jumps significant at α = 0.5					
07/09/95	20:15				23:29	
19/04/95	06:10	13:35	20:55	00:35	20:03	52
26/06/98	14:55	15:10	14:50		07:10	
13/08/98	19:55	19:25	05:50		05:03	47
07/04/97	00:55				21:00	
31/07/95	11:40	17:50			02:03	
20/07/95	13:50				22;15	
29/08/95	01:20	01:00			03:20	
05/09/95	22:40	00:35	22:20		23:38	-58/57
25/03/04	09:50				22:12	
16/04/98	17:50				21:36	
15/05/95	14:45				20:40	
04/12/03	22:55				00:31	
18/09/01	01:55				21:06	

Note: Columns labeled "Jump i" show the arrival time of the i^{th} biggest jump on that day (at a 5-min frequency), where i=1,2,3,4. Column "FR Time" gives the (first) false report (FR) arrival time. Column "-60<Min(J-FR)<60" reports the distance (in min.) between the FR and the closest adjacent jumps, when these jumps occur at a maximum of one hour before and/or after the FR. In that column, a negative number -x means that a jump occured x minutes before the FR. A positive number x means that a jump occured x minutes after the FR. When the adjacent jumps occur more than one hour before/after the FR, no number is reported.

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.

Figure 3: All jumps detected on false report days



Note: 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, centred at 0. For instance, the squares in the bottom-left hand corner of the figure display 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 flow 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 Regression analysis

The analysis performed in Section 5.1 allows us to glean some clues about whether jumps might trigger false reports of intervention but does not permit any conclusions to be drawn about the significance of the effect. To do so, we now perform a regression analysis with a standard probit model. We are very grateful to one of the anonymous referees for suggesting us this extension.

We now detail the general setup, the specifications that have been adopted and the results. Let $y_{t,i}$ be a binary variable equal to one when there is a false report of intervention on the ith interval of day t, where $i=1,...,M$ and $t=1,...,T$.

The probit model is defined as follows:

$$y_{t,i} = \begin{cases} 1 \text{ if } y^*_{t,i} \geq \varepsilon_{t,i} \\ 0 \text{ if } y^*_{t,i} < \varepsilon_{t,i} \end{cases},$$

where $\varepsilon_{t,i}$ is an i.i.d. random variable. $\varepsilon_{t,i}$ plays the role of a disturbance term but can also be interpreted as critical values determining whether or not a false report is likely to be observed. Standard binary choice models assume that $y^*_{t,i}$ is a linear function of a set of explanatory variables $X_{t,i}$, i.e. $y^*_{t,i} = X_{t,i}\beta$. We use this model to study the connection between jumps and erroneous reports of intervention by conditioning $y^*_{t,i}$ on the occurrence of jumps during a certain period preceding the tested interval.

While the exact timing of the false reports is known very precisely, the timing of the jumps depends on the frequency at which the test has been performed, i.e. the 5-min frequency in our case. However, to render the estimation of the probit model more tractable, we followed the referee's suggestion and reduced the time frequency to 60 minutes (i.e. *M=24* for this model). Another advantage of working with data at a lower frequency than the initial 5-min frequency is to allow getting more memory in the process without adding too many lags of the jump variable.

We consider the following specification:

$$y^*_{t,i} = \beta_0 + \beta_1 J^{NoMA}_{t,i} + \sum_{j=1}^{q_J} \beta_{1+j} J^{NoMA}_{t,i-j} + \beta_{1+q_J} J^{MA}_{t,i} + \sum_{j=1}^{q_{MA}} \beta_{1+q_J+j} J^{MA}_{t,i-j} + \beta_{2+q_J+q_{MA}} RI_{t,i} \,,$$

where $J^{NoMA}_{t,i} = J_{t,i}\left(1 - MA_{t,i}\right)$ and $J^{MA}_{t,i} = J_{t,i} MA_{t,i}$, with $MA_{t,i}$ a binary variable equal to one if there was macro news during the 2 hours preceding the ith interval of day *t*, $J_{t,i}$ is a binary variable equal to one if a jump occurred during the ith interval of day t (and prior to the false report) and $RI_{t,i}$ is a control binary variable equal to one if a reported intervention occurred the day before.

The reason for using the interaction variables $J^{NoMA}_{t,i}$ instead of $J_{t,i}$ is that all jumps may not have the same impact on the probability of false reports. In particular, we expect the market to make more mistakes when a jump cannot be associated with or explained by auxiliary factors as US macroeconomic news (we used the same US macroeconomic news indicators as Lahaye et al., 2011).

The results of the probit model are reported here below for the most parsimonious specification (the standard errors are listed in parentheses). Note that the lag orders q_J and q_{MA} have been obtained by minimising the Akaike information criterion.

$$y^*_{t,i} = \underset{(0.03)}{-3.03} + \underset{(0.10)}{0.52} J^{NoMA}_{t,i} + \underset{(0.11)}{0.41} J^{NoMA}_{t,i-1} + \underset{(0.13)}{0.28} J^{NoMA}_{t,i-2} + \underset{(0.13)}{0.29} J^{NoMA}_{t,i-3} + \underset{(0.12)}{0.32} RI_{t,i} \,.$$

We find that jumps indeed significantly increase the conditional probability of observing a false report of intervention during the next three hours. The first two coefficients β_1 and β_2 are significant at the 1% level while the next two coefficients are significant at the 5% level. The $J_{t,i}^{MA}$ variables were found to be insignificant at any conventional significance levels and therefore were discarded from the most parsimonious model. Eventually, the coefficient of the variable $RI_{t,i}$ is significant at the 1% level, meaning that the probability of false report is higher when an official intervention occurred the day before.

Overall, the regression exercise supports our initial findings: some investors may mistakenly interpret a jump as an intervention's signal.[26]

6. Conclusion

According to the coordination channel (Reitz and Taylor, 2008), central banks affect exchange–rate developments by providing the market with a focal point. In practice, this point or signal usually takes the form of a newswire announcing the central bank's transactions in the FX market. Because newswires are an unofficial source of 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 (2008) and by Andersen et al. (2007b). 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. The intraday connection between jumps and erroneous reports of intervention is confirmed by a formal regression analysis.

From a policy-making perspective, our findings have several implications. Intervention operations are generally not officially confirmed on the day they are carried out.

[26] The model has been estimated on two sub-samples, 1995 – 2002 and 2003-2004, to account for a potential structural break in the series due to the arrival of H. Kuroda at the head of the Japanese Finance Ministry. Overall, the conclusions remain the same: past jumps are positively correlated to the probability of false reports. Results are available upon request.

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. 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, official authorities might need to take this potential indirect effect of their policy into account.

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