# Does Transparency in Central Bank Intervention Policy Bring Noise to the FX Market? The Case of the Bank of Japan*

Jean-Yves Gnabo† Sébastien Laurent‡ Christelle Lecourt§

**Abstract**

This paper empirically investigates the induced effect of a more and less transparent central bank intervention (CBI) policy on rumors that can emerge. Using the case of Japan, we estimate a dynamic-probit model that explains the main determinants of false reports (i.e. falsely reported interventions) and anticipative rumors (i.e. rumors about future interventions) with reference to the intervention strategy adopted by the central bank for actual and oral interventions, and to the uncertainty climate of the market captured by two volatility measures. Our results suggest that the induced effect of a transparent CBI policy on market rumors critically depends on the type of speeches made by officials.

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†CeReFiM, University of Namur; jean-yves.gnabo@fundp.ac.be

‡CeReFiM, University of Namur and CORE; Sebastien.Laurent@fundp.ac.be

§CeReFiM, University of Namur; Christelle.Lecourt@fundp.ac.be

# 1 Introduction

The exchange rate policies managed by many countries have changed radically since the mid-1990s. Before then, central banks (CBs hereafter) had a tendency to entertain secrecy by not clarifying their objectives. Along with a trend towards greater independence and under pressure from governments, there has been a move towards more communication and transparency in both monetary and exchange rate policy. As a matter of fact, most CBs, 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. Only Japan has continued to intervene actively and unilaterally in recent years, and it has done so both actually and orally.

This shift towards the use of official communications coupled with unclear results on the effectiveness of actual interventions[1] led research on exchange rate policies to focus on the desirability of a more transparent intervention policy (Bhattacharya and Weller 1997, Enoch 1998, Vitale 1999, Popper and Montgomery 2001, Gnabo and Lecourt 2005) and more specifically on the effectiveness of communication policies (Fatum and Hutchinson 2002, Fratzscher 2004, Jansen and de Haan 2005, Beine, Janssen, and Lecourt 2006). The goal pursued by most of these studies is to test the direct effect of CBs' transparency and communication policy on the dynamics of exchange rates. In particular, Fratzscher (2004) shows empirically for the CBs of the G3 that "oral interventions" concerning the exchange rate and interventions policy are useful policy tools to influence exchange rates independently of whether or not they are supported by actual FX interventions. By contrast, Beine, Janssen, and Lecourt (2006) argue that official speeches aimed at confirming or commenting on the intervention operations complement, rather than substitute for, actual foreign exchange interventions.

Up to now, few studies have focused on the indirect effect of CBs' transparency and communication in the intervention policy. Chiu (2003) suggests that the degree of transparency adopted by the monetary authorities in their exchange rate policy may favor or reduce the speculation and the dissemination of rumors in the market. More precisely, Gnabo and Lecourt (2005) in a descriptive empirical paper, find that the ambiguous policy practiced by the Japanese authorities increased the market uncertainty about past and future actions of the CB, resulting in the emergence of false intervention reports.[2] Inversely, a too transparent policy on CB targets may favor speculative attacks from market participants by giving explicit targets for speculators to challenge, increasing the occurrence of anticipative rumors, i.e. news reporting the expectations of the market concerning a future intervention.

In line with these studies, the aim of this paper is to analyze the economic desirability of transparency in central bank intervention (CBI hereafter) policy and more precisely to assess the effects of a more and less transparent intervention policy on the market's perception and rumors. Using the case of the Bank of Japan which has continued to intervene actively and unilaterally in recent years we estimate a dynamic-probit model that explains the main determinants of the BoJ's intervention rumors in the foreign exchange market.

[1] Edison (1993), Sarno and Taylor (2001), Humpage (2003) and Neely (2005) provide comprehensive surveys of the literature on actual interventions in the 1980s and 1990s.

[2] To the best of our knowledge, Dominguez and Panthaki (2005) is the first paper analyzing the (intra-daily) direct effect of anticipative intervention rumors on exchange rate. They call an intervention expected by the market that did not occur during the day under consideration an "unrequited intervention".

Two sets of determinants are clearly identified:

- the intervention strategy adopted by the CB concerning actual as well as oral interventions;
- market factors summarizing the uncertainty climate of the market, measured in our case by volatility and jumps.

The Bank of Japan is an interesting case study because in the recent years the Japanese authorities have made several changes in their intervention policy, alternating transparency and ambiguity (see Ito 2006, Chiu 2003). After a period of transparency, recent interventions by the Bank of Japan have been conducted secretly, leading to the emergence of numerous market rumors.

This paper addresses two central questions.

Question 1: *Does transparency in CBI policy introduce noise into the market?*

Literally "noise is contrasted with information" (Black 1986). In our context, we consider market rumors and more precisely rumors about CBI episodes as noise. We make the distinction between false intervention reports (called *false reports*) - when the market mistakenly believes that a CB has intervened - and *anticipative interventions rumors* - news reporting the expectations of the market about a future intervention. These rumors are considered as potentially disturbing for the market because they affect currency values and increase the exchange rate volatility, as shown by Dominguez and Panthaki (2005) and Beine, Bénassy-Quéré, and McDonald (2006).[3]

Question 2: *Do market factors, such as the misalignment of the exchange rate, volatility and jumps, influence the dissemination of these rumors?*

The idea is that uncertainty in the FX market should have an influence on all types of market rumors (Schindler 2003) and more specifically on intervention.

To this end, we developed a novel dataset, based on newswire service releases, to collect and classify different types of BoJ intervention news reports during the period 1991-2004. We distinguished reported actual interventions, falsely reported interventions (false reports), anticipative reported interventions (anticipative rumors) and oral interventions (statements concerning the exchange rate and intervention policy).

The paper is organized as follows. Section 2 provides information on the econometric specification and on the data. The results are reported in Section 3 while Section 4 discusses some robustness issues. Finally, Section 5 concludes.

# 2 Empirical strategy

## 2.1 Defining and measuring the degree of transparency of the FX policy

Transparency in economic policy usually refers to the absence of information asymmetries between monetary policymakers and the private sector (Geraats 2002). As CBs generally have priority access to information concerning their future monetary or exchange rate policies, this definition of transparency

[3]Dominguez and Panthaki (2005) find that both actual interventions and "unrequited interventions" have a statistically significant influence on both exchange rate returns and volatility, suggesting that the expectation of intervention, even when governments do not intervene, can affect currency values.

suggests that CBs pass information to the market faithfully and precisely. One debate that emerges from this definition is whether "*more is better*" with respect to information. To enjoy a direct benefit from this extra information that is to make better informed decisions, the receiver must understand it properly. Then the quality of this information (i.e. its degree of clarity) is also expected to play a key role in the degree of transparency of the policy (Winkler 2002).

In the context of foreign exchange operations, transparency should obviously involve several aspects.[4] One important dimension is the use of official statements aimed at: *i)* informing the market about the authorities' point of view on the level or volatility of the exchange rate and in this way giving information about the future exchange rate policy; *ii)* confirming and commenting on actual intervention operations at the time they are launched and hence clarifying the policy of the CB. The underlying idea is that by revealing its point of view on the exchange rate target to the market, the CB makes future action more understandable and potentially more efficient.

Another important aspect of transparency is to promote clear and understandable procedures for intervention policy. As a matter of fact, although CBs may not formally announce or confirm their operations, they may deliberately conduct them in a visible way in order to leak the intervention operations to the market. For this, the CB has three main strategies at its disposal: *i)* to conduct the intervention in the market through visible channels; *ii)* to intervene in a concerted way, that is to intervene simultaneously with other CBs in support of (or against) the same currency;[5] and *iii)* to intervene with large amounts (Enoch 1998, Beine and Bernal 2006).

Conversely, non-transparency is characterized by asymmetry of information, i.e. CBs do not leak to the market some "inside" information about future fundamentals (Humpage 2000). Sometimes, CBs may also wish to retain private information about their preference for either creating surprises (Almekinders and Eijffinger 1996) or facing a strong one way trend (Hung 1997). There may even be a rationale for keeping some secrecy around the timing and/or amounts of intervention operations, even *ex post*, when the operations are inconsistent with monetary and fiscal commitments (Bhattacharya and Weller 1997, Vitale 1999).[6]

Most of the empirical evidence tends to support the desirability of a more transparent exchange rate policy to manage the FX rate (see Dominguez 1998, Beine, Bénassy-Quéré, and Lecourt 2002 for actual interventions and Fratzscher 2004, Beine, Janssen, and Lecourt 2006 for communication policy). Still, only a few studies have investigated the overall economic consequences of transparency and communication in the exchange rate policy.[7] For example, LeRoy and Porter (1981) and Geraats (2002) argue that transparency and communication may be undesirable if it is of poor quality or sufficiently noisy to raise market uncertainty. For Winkler (2002), when oral interventions become almost a daily routine or when comments are inconsistent, transparency may be counterproductive. In an empirical descriptive study, Chiu (2003) discusses the pros and cons of increased transparency in the intervention policy. She argues

[4]While there is an abundant literature on transparency in monetary policy (see inter alia, Winkler 2002, Geraats 2002), here we focus exclusively on transparency in exchange rate policy.

[5]Considering the three major CBs (Bank of Japan, Federal Reserve and Bundesbank), Beine and Lecourt (2004) show that the proportion of secret interventions turns out to be much lower for coordinated operations than for unilateral interventions. They note that this result is not entirely due to the magnitude of the sales or purchases as modest coordinated operations after 1987 were systematically detected by market participants.

[6]See Dominguez (1993) for a summary of the different reasons why CBs could intervene secretly.

[7]This question of the conditions under which communication may be undesirable has been analyzed at a theoretical level with respect to monetary policy (see among others Geraats 2002, Morris and Shin 2002, Amato, Morris, and Shin 2002).

that "*greater transparency of intervention objectives and operations reduces speculation and rumors about CBs actions, which would be helpful when CBs try to reduce market volatility*". But inversely, when communication policy is not consistent with the intervention policy, it may stimulate market rumors and increase the exchange rate volatility.

In line with this literature, we may also expect indirect effects of transparency through the emergence of rumors.

### 2.2 Defining and measuring intervention rumors

As Schindler (2003) explains rumor is contrasted with information.

**Definition 1** *A rumor is a piece of news which is only later confirmed as true or false; at the time the rumor is launched, the market does not know if it will turn out to be true. In contrast, information is a piece of verified news with a true content.*

Schindler (2003) also emphasizes that rumors in financial markets can be considered as a substitute for news and will be disseminated to the market only if their content is interesting and relevant. As already mentioned, a CBI is associated with the arrival of private information as well as sharp moves in the exchange rate level and volatility (see among others Dominguez 1998, Beine, Bénassy-Quéré, and Lecourt 2002). This type of event naturally involves a specific financial risk that should be managed by the different actors in the market. Therefore, all pieces of information concerning this event become interesting and relevant for their trading strategies, creating a fertile ground for the dissemination of market rumors. The market information mainly derives from real-time newswire service such as Reuters and Dow Jones (Oberlechner and Hocking 2004). It is thus bulked out with journalistic analysis or commentary and pieces of information from other sources such as the journalist's own network into the market. Such a design creates a circular pattern of market information processing that in turn may open the door to the dissemination of rumors.

When a CB intervenes the signal usually evolves in three steps. First depending on whether the CB wants its action to be perceived or not, some agents detect the presence of the CB in the market. The signal is perceived by a small audience and is not considered as publicly known (some agents can also be explicitly informed by the CB itself). Then it is reported to newswire journalists through their personal network in the market made up of traders, bankers and brokers. Finally, this news is communicated to the overall market with a sentence such as "*BOJ seen buying dlrs at around 104.00 yen in Tokyo*" (Reuters, August 11, 1993) through newswire, making it public.[8]

**Definition 2** *The intervention is considered "reported" if the news clearly states that the bank has intervened.*

Because there is often uncertainty about whether a given government is intervening or not, explained in part by the fact that governments rarely officially confirm their presence in the market and by the practice of secret interventions, there are inevitably circumstances when the financial press reports interventions over the wire services that have not occurred. In this case, newswire intervention reports are considered

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

as rumors or false intervention reports if there is no official intervention (Klein 1993, Frenkel, Pierdzioch, and Stadtmann 2005).[9]

**Definition 3** *False intervention reports are news explicitly reporting an intervention that has not occurred.*

For example, on March 23, 1994 the news "*BOJ buys dlrs at around 103.95-104.00 yen in Tokyo*" (Reuters) was reported whereas no official intervention had been conducted. Of course, this type of news is considered as rumors *a posteriori*, when knowledge of official interventions becomes available but in practice, rumors bear some resemblance to information making them usually difficult to disentangle *a priori* (Oberlechner and Hocking 2004). Although this type of news does not provide any accurate information on fundamentals, evidence show that it may influence market behavior and the FX prices (Fatum and Hutchinson 2002, Dominguez and Panthaki 2005).

In the same way, there are also frequently some news reports of intervention operations that the market expects which we term "anticipative rumors".

**Definition 4** *Anticipative rumors are interventions which the market expects.*[10]

As explained above, we consider both false reports and anticipative rumors as intervention rumors. It is noteworthy that both types of rumors report the same event, i.e. CBIs, although they differ in their time scale. Anticipative rumors are *ex ante*, i.e. concern future (possible) interventions. False reports are real time or *ex post*, i.e. concern present or past interventions. Moreover, the first is about a guess or belief while the second reflects a fact wrongly reported.

Our empirical investigation of the determinants of intervention rumors is focused on the BoJ intervention policy for two main reasons. First, in recent times the Bank of Japan has been by far the most active major CB in the FX markets, intervening 343 times over the period 1991-2004 and 128 times during the recent short period 2003-2004. This means the BoJ was in the market on more than 10% of business days and more than 40% of the time during the recent period. This pattern is in stark contrast with the other major CBs, like the Fed and the ECB, that have become extremely reluctant to use this stabilization instrument since 1995.[11] Second, the BoJ was chosen because Japanese authorities made several changes in their intervention policy, sometimes practising deliberate transparency and sometimes ambiguity. As a matter of fact, after a long period of intervention policy transparency, the recent intervention policy of the BoJ has undergone a major shift in favor of secret interventions. This shift may contribute to the emergence and dissemination of intervention rumors.

To measure intervention rumors, we adopted the approach developed by Beine and Lecourt (2004) and Gnabo and Lecourt (2005) based on newswire reports of Reuters and Dow Jones.[12] In this way, we were able to identify days with information and rumors about CBI activities.

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

[10] Dominguez and Panthaki (2005) in an intra-daily analysis define "unrequited interventions", as interventions that the market expects but which did not occurred that day. This concept is very close to ours at the notable difference that we do not make distinction between expectations which were and were not followed by an intervention. In fact, such a distinction seems far less relevant at a daily level.

[11] Since 1995, the Fed has intervened only twice in a concerted way and the ECB four times to support the euro.

[12] We restrict our sources to the Dow Jones and Reuters reports, which are considered as the main information providers to the traders.

The identification procedure consists in searching for an appropriate set of key words in the newswire.[13] The newswire reports were extracted using an online database (Factiva) which offers a wide choice of search tools and interesting search features. This search procedure provides numerous advantages compared to the approaches employed in several previous studies such as the use of financial publications (Beine and Lecourt 2004, Frenkel, Pierdzioch, and Stadtmann 2005). Examples of newswire reports for each type of intervention rumor are given in Tables 6-7 of the Appendix.

Some statistics concerning intervention rumors are reported in Tables 1. The methodology described in the previous paragraph allows us to determine that there were 571 days with anticipative rumors and 170 with false reports between April 1991 and September 2004. Within the sample the so-called Sakakibara period (June 1995-2002) known for its high degree of transparency as well as an active communication policy (Gnabo and Lecourt 2005, Ito 2006), appears to be a fertile ground for anticipative rumors (probably due to oral interventions). By contrast, the number of false reports fell sharply during this time, compared to the previous period. The recent period (2003-2004) displays a large increase in both the number of interventions and the proportion of secret interventions (Beine and Lecourt 2004). Along with this, officials regularly threatened to intervene in the market. As a result, the policy was accompanied by a resurgence of false reports and the persistence of anticipative rumors.

Table 1: Number of intervention rumors

| Period | Anticipative rumors | | False reports | |
|---|---|---|---|---|
| 1991-June 1995 | 128 | 12.7% | 72 | 10.4% |
| June 1995-2002 | 370 | 19.6% | 81 | 4.2% |
| 2003-2004 | 73 | 16.7% | 18 | 5.8% |
| Full sample | 571 | 17.1% | 170 | 6% |

Sources: Reuters and Dow Jones.
The first and third columns report the number of days with rumors. The second gives the number of days with anticipative rumors divided by the trading days. The last column shows the number of days with false reports divided by the trading days less days of official interventions (a false report can not emerge the same day as an official interventions).

## 2.3 Model

### 2.3.1 Binary choice model

The aim of this paper is to find the determinants of both anticipative rumors and false rumors. Since these two variables are dichotomous, we rely on the standard approach of binary response models.

Defining $y_t = 1$ when a rumor occurs on day $t$ and 0 otherwise (for ease of presentation we do not make the distinction between anticipative rumors and false rumors here), the binary choice model is defined as:

$$\begin{aligned} y_t &= 1 \text{ if } \pi(X_t, \beta) \geq u_t, \\ y_t &= 0 \text{ if } \pi(X_t, \beta) < u_t, \end{aligned} \tag{1}$$

where $X_t$ is a set of $k$ explanatory variables (including a constant), $\beta$ is a vector of $k$ unknown coefficients

[13] The search criteria we used were : a) "BoJ" or "Bank of Japan" or"MoF" or "Ministry of Finance" or "Interventions" to find reports and rumors of interventions; b) the name or title of the principal policy maker to find official statements. Both were conducted on the whole text. After that each item was systematically analyzed before being classified.

to be estimated and $u_t$ is an iid random variable. $u_t$ plays the role of a disturbance term but can also be interpreted as critical values determining whether or not a rumor is likely to be observed.
Standard binary choice models assume that $\pi(X_t, \beta)$ (henceforth $\pi_t$) is a linear function of $X_t$ (note that the determinants of both unrequited interventions and false rumors will be presented in the next section), i.e.

$$\pi_t \equiv X_t\beta = \sum_{i=1}^{k} \beta_i x_{it}. \tag{2}$$

Defining $E_{t-1}(y_t)$, the conditional expectation of $y_t$ given the information set up to time $t-1$, we have: $E_{t-1}(y_t) = Prob_{t-1}(\pi_t \geq u_t)$.

The probit model assumes that $u_t$ is iid $N(0,1)$ which implies that $E_{t-1}(y_t)$ is related to $\pi_t$ through the standard normal cumulative distribution function, i.e. $E_{t-1}(y_t) = \Phi(\pi_t) = p_t$.

### 2.3.2 Dynamic binary choice model

The '*iid*-ness' assumption of $u_t$ is essential to prove the asymptotic normality of the maximum likelihood estimators (MLE) of the binary choice model presented above. However, due to the nature of the data, the relevance of this assumption might be questioned when considering a static model of the rumors.

In fact the probability of a rumor on a given day if there was a rumor on the previous day is around 30% for false reports and 50% for anticipative rumors. It is evident from this that rumors are clustered over time, i.e. there are sustained periods with rumors and periods of calm.

Based on this empirical evidence, two strategies are possible. First, like Estrella and Rodrigues (1998), we can assume that the MLE of the static binary choice model are still consistent and asymptotically normal when $u_t$ is not *iid* (see also Poirier and Montgomery 1988). However, the standard variance-covariance matrix of the estimates is no longer valid and robust standard errors have to be implemented to make correct statistical inferences. A second and more efficient method is to extend the generating mechanism of the rumors by including lagged values of $y_t$. The most commonly used specification assumes that

$$\pi_t = \sum_{i=1}^{k} \beta_i x_{it} + \sum_{j=1}^{q} \delta_j y_{t-j}, \tag{3}$$

where the $\delta_j$s are $q$ additional parameters to be estimated. Recently, de Jong and Woutersen (2003) derive sufficient conditions for this process to be stationary and strong mixing and showed that MLE behaves well in large samples. This specification has been used in the context of CBI to estimate the CB reaction function by Beine, Bénassy-Quéré, and Lecourt (2002).

In Equation (3), a dynamic approach is introduced through the lagged values of $y_t$. For instance, setting $q = 1$, the probability of a rumor occurring is obviously related (in a non-linear way) to $\delta_1$. A high positive value of $\delta_1$ would imply that, conditional on the occurrence of a rumor in $t-1$, i.e. $y_{t-1} = 1$, the probability of a rumor in $t$ is high. However, the impact on day $t+1$ is nil, implying that the memory of the process is very short and it is not able to replicate the clusters of rumors.

Alternatively, we could be tempted to consider a dynamic probit model in which lagged values of $\pi_t$ appear on the right hand side of the probit equation.

This approach leads to:

$$\pi_t = \sum_{i=1}^{k} \beta_i x_{it} + \sum_{j=1}^{q} \delta_j y_{t-j} + \sum_{j=1}^{p} \alpha_j \pi_{t-j}, \tag{4}$$

where the $\alpha_j$s are $p$ additional parameters to be estimated. High values of the $\alpha_j$s (but $< 1$) would mean that the probability of occurrence of a rumor takes a long time to die out.

As shown recently by Kauppi and Saikkonen (2006), this model is easily estimated by conditional maximum likelihood by setting the unobserved latent variables $\pi_0, \pi_{-1}, ...$ to their unconditional mean (e.g. $\pi_0 = \frac{\sum_{i=1}^{k} \beta_i \bar{x}_i + \delta \bar{y}}{1-\alpha_1}$ when $p = q = 1$). This model can be estimated by conditional maximum likelihood and the log-likelihood takes the form:

$$L(\beta) = \sum_{t=0}^{T} l_t(\beta) = \sum_{t=0}^{T} \left\{ y_t \log \Phi[\pi_t(\beta)] + (1 - y_t) \log[1 - \Phi(\pi_t(\beta))] \right\}, \tag{5}$$

where $\pi_t(\beta)$ is given by Equation (4) or its restricted versions (2) and (3).

As explained above, we consider two types of intervention rumors, i.e. false reports ($y_{FR}$) and anticipative rumors ($y_{UI}$). Consequently, two distinct models are estimated. In both models, we disentangle determinants of rumors (i.e. $X_t$) between variables representing CBI policy and those reflecting the market uncertainty. The first set of variables is related to the intervention strategy adopted by the BoJ concerning actual and oral interventions; the second, to market factors and the uncertainty climate of the market. We now turn to the issue of the determinants of intervention rumors.

## 2.4 Determinants of intervention rumors

### 2.4.1 CB policy variables

The analyzes of Gnabo and Lecourt (2005) and Beine and Bernal (2006), both considering the intervention policy of the BoJ, provide some clues to variables that influence the probability of intervention as well as the probability of detecting the presence of the CB in the market. These determinants pertain to the transparency policy of the CB in its intervention strategy as well as in its communication policy. If CB policy variables such as oral interventions influence the probability of intervention, they may also influence the probability of false reports and anticipative rumors. In the same way, factors that favor the CBs operations being regularly detected by the market (the size of the operation; whether the operation was carried out in concert with other monetary authorities; confirmation of the operation) should influence (reduce) the probability of false reports. These determinants are presented below.

*Statements and threats*

Among CB policy variables that influence the probability of intervention, communication policy can have an impact on the occurrence of intervention rumors. According to the literature, communication policy is measured by official statements (Fatum and Hutchinson 2002, Jansen and de Haan 2005, Fratzscher 2004, Beine, Janssen, and Lecourt 2006, Gnabo and Lecourt 2005). As a matter of fact, policymakers can express their views regarding the exchange rate value and the usefulness of interventions. Two types of statements are considered:

i) statements giving pieces of information about the future exchange rate policy, i.e. informing the market of the authorities' point of view on the level or the volatility of exchange rate (e.g. *"Finance Minister Hikaru Matsunaga and vice minister Koji Tanami said once again that the yen was undervalued..."* June 8, 1998 Dow Jones);

ii) statements indicating clearly the possibility of a future intervention (e.g. *"Sakakibara said Japanese authorities would be ready to intervene in the foreign exchange markets..."* December 28, 1997 Dow Jones).

The impact of these two types of statement on rumors is not straightforward. If oral interventions are considered as tools that substitute for actual interventions, they can convey a signal to the market and so reduce the uncertainty (Fratzscher 2004).

However, when oral interventions become almost a daily routine and are no longer credible, transparency may be counterproductive, increasing speculation and stimulating the emergence of intervention rumors.

The *Statements* variable is the number of statements concerning the exchange rate policy issued during the past five trading days; the *Threat* variable is the number of statements on (possible) interventions issued during the past five trading days.

<u>*Cluster*</u>

The clustering of interventions should raise traders' awareness of the presence of the CB in the market, increasing the probability of intervention rumors. This CB practice has been well documented in numerous studies (Almekinders and Eijffinger 1996, Ito 2006, Gnabo and Lecourt 2005). It is often viewed as a means of either increasing transparency by indicating the CB target clearly, or of overcoming the political cost of implementing the decision to intervene (Ito and Yabu 2006). In return, this intervention strategy enables agents to observe some regularities and then to infer the authorities' intervention tactics.

To test this idea, we constructed a variable *Cluster* that captures the number of successive reported interventions during the five days immediately preceding an intervention.[14]

<u>*Political transition*</u>

We also take periods of political transition into account as determinant of rumors. These periods are usually characterized by more friction in the communication process. Former codes or habits are replaced by new ones and a new *common language* has to be constructed (de Haan and Amtenbrink 2003, Winkler 2002). This learning process worsens the degree of transparency in the market, favoring the emergence of false reports as well as anticipative rumors during this period. We relied on Ito (2006) and Gnabo and Lecourt (2005) to identify the significant transition periods in Japanese exchange rate policy. The arrival of Sakakibara as the head of foreign affairs in the Ministry of Finance and the departure of Kuroda from the Ministry of Finance were selected (June 1995 and January 2003 respectively). We then created a dummy variable called *Political transition* that takes the value 1 during the first four months of the transition and 0 otherwise.

When discussing the probability that the market is mistaken about the presence of the CB, we consider three types of variables. These three variables aim at capturing the degree of visibility of the policy

[14] It is noteworthy that we restricted our analysis to reported interventions. Traders might well be unaware of secret interventions and clustering interventions will only attract the public's attention if past interventions are clearly visible to the market.

over the sample period. Naturally, we expect that greater transparency will improve the quality of the detection process and so reduces the probability of having false reports. In contrast to previous variables such as threat, these variables explain the probability of detection by the market and not the probability of intervention, so they are only considered as determinants of one type of rumor (i.e. false reports).[15]

*Coord*

First, the joint presence of two or more CBs increases the visibility of CB trades and should reduce the probability of false reports.[16] We therefore built a variable called *Coord* that represents the number of coordinated interventions out of the last five actual interventions. The greater the variable, the higher the degree of transparency over the period.

*Amount*

The amount of the intervention is also expected to influence the extent to which market participants might be mistaken about the presence of the CB. More precisely, if market participants are used to detecting interventions by observing large trades from the central bank (Beine and Bernal 2006), they might not wrongly detect an intervention when the FX authorities remain out of the market. To account for this, we built an *Amount* variable, computed as the amount invested in the last five interventions (trillion yen).

*Confirmed*

Finally, the systematic confirmation of interventions issued in press communiqués just after the operation by the CB such as: *"Shiokawa confirms Japan intervened in FX market."* (June 24, 2002 Reuters) is also expected to influence the extent to which market participants might be mistaken about the presence of the CB. Confirmation speeches are definitely an instrument of transparency that complements the actual intervention since they help both to remove all ambiguity about the intervention and to clarify the signal (Beine, Janssen, and Lecourt 2006). Therefore, they should reduce the probability of false reports, as was the case during the Sakakibara period. Like the variable *Coord*, the variable *Confirmed* is computed as the number of interventions officially confirmed out of the last five interventions.

### 2.4.2 Market factor variables

A second set of market factor variables is introduced in both models. These market variables, calculated from historical exchange rate data, are supposed to reflect the state of the Japanese exchange rate market, i.e. the degree of misalignment of the exchange rate JPY/USD and the level of volatility.

It is expected that uncertainty in the market has an influence on both the dissemination of false reports and anticipative rumors. As a matter of fact, periods of uncertainty are considered by traders themselves to be fertile breeding grounds for all types of rumors (Schindler 2003).[17] In order to capture these periods of uncertainty in the FX markets, we use two volatility measures.

[15]The three variables capturing the degree of transparency of actual interventions are not included in the model for anticipative rumors. While the main motivation to exclude them lies in economic arguments, auxiliary estimations made as a robustness check confirm this specification. The variables *Coord*, *Amount* and *Confirmed* are not significant and general conclusions concerning the other variables remain the same. These estimations are not reported in order to save space but are available upon request.

[16]Beine and Lecourt (2004) identify a low proportion of secret interventions when they are coordinated with at least one other CB. These results are reinforced by Beine and Bernal (2006) who tested it empirically and found a significant impact on the detection process.

[17]More than 60% of traders answered in the affirmative the question "Do you heard more rumors in volatile market?" (Schindler 2003).

The recent widespread availability of databases providing the intra-daily prices of financial assets (stocks, stock indexes, bonds, currencies, *etc*) has led to new developments in applied econometrics and quantitative finance to measure daily volatility. Andersen and Bollerslev (1998) proposed a consistent nonparametric estimate of the price variability that has occurred over a given discrete interval. This measure is called *realized volatility.* It corresponds to the summation of high-frequency (intraday) squared returns. As long as there are no jumps, this measure is a consistent estimate of the integrated volatility (Barndorff-Nielsen and Shephard 2004). In the presence of jumps, the realized volatility consistently estimates the sum of two components: the integrated volatility (continuous and persistent part of the volatility) and the jumps (i.e. the sum of the squared discontinuities). Recently, Barndorff-Nielsen and Shephard (2004) have proposed an elegant method of isolating the jump component of the realized volatility using the concept of bi-power variation.

$\underline{CV_t}$

The variable $CV_t$ captures the effect of the continuous and persistent part of the volatility. Since rumors are expected to raise volatility, we used the one day lagged continuous volatility to avoid potential endogeneity problems in our estimations. This variable, $CV_t$, is obtained from intra-daily data sampled every 5-minutes.[18]

$\underline{Jump_t}$

Besides the continuous volatility, we naturally consider the remaining part of the realized volatility by including the one day lagged jumps. Generally speaking, jumps are sharp and unexpected movements in the exchange rate. In line with the literature, we only consider the largest jumps (i.e. 15% of the observations). The variable $Jump_t$ captures the size of significant jumps and is aimed at capturing their effect on rumors.

$\underline{Jump_{t+1}}$

Market participants may also wrongly detect an intervention when there is a sharp movement of the exchange rate. In this respect, we consider an extension of the specification for modeling the emergence of false reports by including the contemporaneous jumps (denoted $Jump_{t+1}$). This relation can be understood in the light of the microstructure approach where private information can be transmitted through order flows (Evans and Lyons 1999). In this framework, the market is usually made up of different types of agents. Some have access to private information. Their trades induce order flows that in turn influence the prices. Others have no private information and trade according to their hunches or public information. Baillie, Osterberg, and Humpage (2000) emphasize that prices might then "perform a dual role of describing the terms of trade and of transferring information from more to less informed agents". Consistent with this idea, some agents might naturally try to extract some information from prices and especially from jumps.

Beine and Bernal (2006), noticed that sharp movements in the exchange rate the day of an official intervention draw the attention of traders and increase the probability of detection.[19] Therefore, the market may be mistaken and wrongly associate jumps with CBIs. This is at least suggested by a couple

[18] Note that $CV_t$ refers to the continuous volatility of day $t-1$ and not day $t$. This convention comes from the fact that realized volatility and the bi-power variation are *ex post* measures of the volatility, i.e. they are only computable at the end of day $t-1$, i.e. on day $t$.

[19] They noticed that on May 31, 1995 "the first order of the Fed resulted in DEM/USD jumping more than 2 per cent, drawing attention of traders and triggering news reports" (Beine and Bernal 2006).

of newswire reports extracted from Reuters and Dow Jones such as: "*... 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).

This discussion justifies the inclusion of the variable $Jumps_{t+1}$ to explain the occurrence of false reports but not anticipative rumors. Of course, one might be tempted to include it in both models anyway, at least by analogy. But this would introduce serious econometric problems, while exchange rate volatility can create rumors, it can be the other way around too. Consequently, the inclusion of a contemporaneous measure of volatility is exposed to a problem of endogeneity. This caveat is handled for false reports in Section 4. Thanks to a very precise timing of news reports, we can control whether most discontinuities creating jumps occur before the arrival of rumors (when considering only the days characterized by both a significant jump and a rumor).
Unlike false reports which report a fact, anticipative rumors reflect a market sentiment, i.e. market participants guess that an intervention may be conducted during the following day or days. This is something latent in the market which is expressed at certain points in time during the day without a precise intra daily timing.[20] In this respect, we cannot properly control the relation of causality between the two variables. This feature coupled with the absence of clear economic motivation definitely led us to include the contemporaneous jumps only in the model that explains the emergence of false reports.

*Misalignment*

Finally, the misalignment of the exchange rate with the fundamentals can influence the likelihood of an intervention and in turn the emergence of rumors. Following the literature on FX reaction functions which estimates the probability of having an intervention, we include a measure of misalignment as the difference between the current exchange rate and a measure of its fundamental value. As there is still no real consensus on the accurate measurement of fundamentals, the literature usually considers different proxies such as the *purchasing power parity* (Beine, Bénassy-Quéré, and Lecourt 2002) or the Funabashi 125 JPY/USD *ad hoc* value (Baillie and Osterberg 1997). In this study, we follow Beine and Bernal (2006) by using the equilibrium rates computed by Bénassy-Quéré, Lahrèche-Revil, and Mignon (2006).[21] This reflects the level of the exchange rate needed to reach a global equilibrium among the G-20 economies.[22] More precisely, we include a dummy variable that takes the value 1 on days of high misalignment and 0 otherwise (denoted *Misalignment*). We consider the 10% of days with highest positive misalignment and the 10% of days with the highest negative misalignment as high misalignment.

[20] In practice, these rumors are usually captured by journalist's comments within the body of the text (e.g. "*The yen has been very volatile in overnight trading, with gains in the currency prompting rumors that the Bank of Japan would intervene to sell the currency.*"(March 20, 2000 Reuters)) and news containing these comments are repeated several times throughout the day, contrasting with false reports which are announced through newswire headlines.

[21] It is noteworthy that our measure is slightly different from Beine and Bernal (2006) since we use the equilibrium rate at a quarterly frequency and not at an annual frequency.

[22] We use the equilibrium rate computed by Bénassy-Quéré, Lahrèche-Revil, and Mignon (2006). This is an extension of equilibrium rate proposed by Alberola, Humberto, and Ubide (2000) (see also Alberola, Garcia-Cervero, Lopez, and Ubide 2005), where the equilibrium exchange rate of each currency is calculated as the weighted average of bilateral exchange rates against the 14 other currencies (from the G-20). In contrast to the standard model, Bénassy-Quéré, Lahrèche-Revil, and Mignon (2006) simply account for other parities by adding a synthetic, rest-of-the world currency to the sample. Then, bilateral equilibrium exchange rates are derived by inverting the weighted matrix of effective rates. The estimations are performed using panel cointegration techniques. Eventually, this method provides a quarterly measure of the equilibrium exchange rate JPY/USD that was used to compute our measure of misalignment.

# 3 Results

The estimated coefficients of the econometric models described in Section 2.3.1 applied to the two dependent variables - false reports and anticipative rumors - are reported in Tables 3 and 4. Different specifications are estimated for the two models. The column labeled 'Static' corresponds to the static probit model given in Equation (2), while the columns labeled 'Dynamic(1)' and 'Dynamic(2)' refer to the dynamic probit models described in Equations (3) and (4) and the column labeled 'Parsimonious' corresponds to the most parsimonious specification (excluding variables that are not significant at the 10% level).

Table 2 summarizes the different variables used as determinants of false reports and anticipative rumors as well as their expected effects.

Table 2: Expected effects of FX regulation policy and market factors on rumors

| Variables | Definition | Expected effects UI | FR |
|---|---|---|---|
| CB policy variables | | | |
| *Statements* | Number of statements indicating the authorities' point of view during the past 5 trading days | ? | ? |
| *Threat* | Number of statements indicating the possibility of an intervention in the near future during the past 5 trading days | + | + |
| *Cluster* | Number of successive reported interventions during the 5 days immediately preceding an intervention | + | + |
| *Political Transition* | 1 if there is a political transition during the first 4 months of transition | + | + |
| *Coord* | Number of coordinated interventions in the last 5 interventions | . | - |
| *Amount* | Amount invested in last 5 interventions (trillion yen) | . | - |
| *Confirmed* | Number of confirmed interventions in the last 5 interventions | . | - |
| Market factors | | | |
| $CV_t$ | Daily continuous volatility estimated at the end of the preceding day | + | + |
| $Jump_t$ | Daily jumps estimated at the end of the preceding day | . | + |
| $Jump_{t+1}$ | Daily jumps estimated at the end of the day | . | + |
| *Misalignment* | 1 if the current rate is far from its fundamental value | + | + |

Note: UI and FR stand for anticipative rumors and false reports respectively . Positive (+), negative (-) or neutral (.) effects are expected when rumors emerge. (?) indicates that the expected effect is undetermined.

There is no doubt that the choice of a dynamic binary choice model seems justified. Furthermore, comparing the likelihood values of the first three models, there is strong evidence that the model proposed by Kauppi and Saikkonen (2006) outperforms the other two models, both for false rumors (Table 3) and for anticipative rumors (Table 4). This is mechanically confirmed by the McFadden pseudo $R^2$ which also emphasizes that a large part of the model remains unexplained since its value is around 20%. Actually, there is no doubt that other factors may influence the emergence of rumors. For example, some traders can open a position and then initiate a rumor to influence the exchange rate in a certain way (Schindler 2003).[23] Additionally, the central bank can indirectly stimulate rumors by regularly "*checking rate*" that is calling traders to collect some piece of news about the state of the market before intervening (they can also stay out of the market): who buys or sells and to what extent. As all these factors are unfortunately not observable they are included in the error term. The quality of our estimates should, however, not be affected as long as the assumption of strict exogeneity holds.

[23]This scenario is, at least, suggested by a market survey by Schindler (2003) which reports that "among all respondents (of his survey) 70% claim the source (the person initiating the rumor) is, at least possibly, able to profit systematically from the rumor"

Table 3: Determinants of false reports: BOJ, 1992-2004

| Variables | Static | | Dynamic(1) | | Dynamic(2) | | Parsimonious | |
|---|---|---|---|---|---|---|---|---|
| *Constant* | -1.489 | | -1.565 | | -0.412 | | -0.441 | |
| | [0.096] | *** | [0.098] | *** | [0.164] | ** | [0.157] | *** |
| $y_{FR,t-1}$ | | | 0.761 | | 0.423 | | 0.467 | |
| | | | [0.125] | *** | [0.146] | *** | [0.144] | *** |
| $\pi_{t-1}$ | | | | | 0.754 | | 0.765 | |
| | | | | | [0.096] | *** | [0.086] | *** |
| *Statements* | 0.140 | | 0.124 | | 0.059 | | 0.056 | |
| | [0.065] | ** | [0.059] | ** | [0.021] | *** | [0.019] | *** |
| *Threat* | 0.112 | | 0.096 | | 0.010 | | | |
| | [0.054] | ** | [0.051] | * | [0.019] | | | |
| *Cluster* | 0.191 | | 0.193 | | 0.168 | | 0.161 | |
| | [0.074] | *** | [0.081] | ** | [0.051] | *** | [0.053] | *** |
| *Political transition* | 0.946 | | 0.781 | | 0.193 | | 0.180 | |
| | [0.160] | *** | [0.154] | *** | [0.079] | ** | [0.081] | ** |
| *Coord* | 0.136 | | 0.118 | | 0.033 | | | |
| | [0.059] | ** | [0.061] | * | [0.021] | | | |
| *Amount* | -0.233 | | -0.213 | | -0.041 | | | |
| | [0.074] | *** | [0.073] | *** | [0.025] | | | |
| *Confirmed* | -0.087 | | -0.078 | | -0.022 | | -0.027 | |
| | [0.037] | ** | [0.038] | ** | [0.013] | * | [0.011] | ** |
| $CV_t$ | 0.034 | | 0.015 | | -0.031 | | | |
| | [0.030] | | [0.032] | | [0.024] | | | |
| $Jump_t$ | 0.018 | | -0.132 | | -0.506 | | -0.592 | |
| | [0.313] | | [0.338] | | [0.294] | * | [0.292] | ** |
| $Jump_{t+1}$ | 0.756 | | 0.803 | | 0.816 | | 0.837 | |
| | [0.312] | ** | [0.275] | *** | [0.262] | *** | [0.259] | *** |
| *Misalignment* | -0.106 | | -0.078 | | -0.043 | | | |
| | [0.117] | | [0.113] | | [0.032] | | | |
| Log-Likelihood | -546.90 | | -528.38 | | -511.31 | | -519.86 | |
| $R^2$ | 0.13 | | 0.16 | | 0.19 | | 0.18 | |

Notes: *, **, ***, indicate significance at the 1%, 5%, 10% levels respectively. Robust standard errors are reported in square brackets. $R^2$ corresponds to MacFadden's $R^2$.

Table 4: Determinants of anticipative rumors: BOJ, 1991-2004

| Variables | Static | | Dynamic(1) | | Dynamic(2) | | Parsimonious | |
|---|---|---|---|---|---|---|---|---|
| *Constant* | -1.550 | | -1.605 | | -0.731 | | -0.689 | |
| | [0.051] | *** | [0.047] | *** | [0.138] | *** | [0.118] | *** |
| $y_{UI,t-1}$ | | | 0.713 | | 0.623 | | 0.620 | |
| | | | [0.080] | *** | [0.072] | *** | [0.070] | *** |
| $\pi_{t-1}$ | | | | | 0.561 | | 0.584 | |
| | | | | | [0.086] | *** | [0.073] | *** |
| *Statements* | 0.206 | | 0.163 | | 0.063 | | 0.060 | |
| | [0.034] | *** | [0.031] | *** | [0.021] | *** | [0.020] | *** |
| *Threat* | 0.346 | | 0.266 | | 0.078 | | 0.071 | |
| | [0.031] | *** | [0.029] | *** | [0.028] | *** | [0.024] | *** |
| *Cluster* | 0.137 | | 0.106 | | 0.033 | | | |
| | [0.043] | *** | [0.031] | *** | [0.022] | | | |
| *Political transition* | 0.503 | | 0.426 | | 0.145 | | 0.125 | |
| | [0.133] | *** | [0.114] | *** | [0.063] | ** | [0.055] | ** |
| $CV_t$ | 0.052 | | 0.035 | | 0.004 | | | |
| | [0.055] | | [0.035] | | [0.015] | | | |
| $Jump_t$ | 0.687 | | 0.621 | | 0.414 | | 0.406 | |
| | [0.229] | *** | [0.224] | *** | [0.198] | ** | [0.189] | ** |
| *Misalignment* | 0.082 | | 0.088 | | 0.068 | | 0.078 | |
| | [0.080] | | [0.074] | | [0.034] | * | [0.032] | ** |
| Log-Likelihood | -1239.8 | | -1190.2 | | -1175.3 | | -1176.4 | |
| $R^2$ | 0.16 | | 0.20 | | 0.21 | | 0.21 | |

Notes: *, **, ***, indicate significance at the 1%, 5%, 10% levels respectively. Robust standard errors are reported in square brackets. $R^2$ corresponds to MacFadden's $R^2$.

### 3.1 CB policy variables

Our estimations succeed on the whole in capturing determinants of intervention rumors. Among the CB policy determinants, there is overwhelming evidence that oral interventions aimed at informing the market of the Japanese authorities' point of view on the level or the volatility of exchange rate (variable *Statements*) increase the probability of both false reports and anticipative rumors. Furthermore, other things being equal, statements indicating clearly the possibility of a future intervention (*Threat*) result in a higher probability of anticipative intervention rumors.[24]

However, statements aimed at confirming or providing some details of the operation the day it was carried out (*Confirmed*) have less impact on the occurrence of false reports. This important result means that the way the CB talks to the market can have an impact in terms of rumors. How can this result be explained? As already mentioned, when oral interventions are tools that substitute for actual interventions, the signalling channel states that the quality of the signal sent by the oral intervention is of overwhelming importance identifying its impact on rumors. When the signal is not considered credible or ambiguous by the market, transparency may be counterproductive, increasing speculation and stimulating the emergence of false reports and especially anticipative rumors. This is clearly the case when oral interventions become almost a daily routine or when comments are inconsistent with intervention policy. During the Sakakibara period, oral interventions were frequently used as an autonomous tool to influence the exchange rate, altering the credibility of signals sent by oral interventions and consequently increasing speculation and the emergence of intervention rumors.[25] In the same way, statements clearly indicating the possibility of a future intervention and not followed by an actual intervention are a good example of comments inconsistent with the intervention policy. In contrast, appropriate statements by monetary authorities on their exchange rate policy can be a valuable complementary tool to actual exchange rate operations. As a matter of fact, confirming statements realized by the monetary authorities just after an intervention operation enable the message conveyed by the intervention to be clarified and so decrease uncertainty and rumors about the exchange rate. In accordance with the results of Beine, Janssen, and Lecourt (2006) and Fratzscher (2004), this result suggests that talking to the markets in an appropriate way can remove at least some of the ambiguity that is associated with FX operations.

Our estimations also suggest that successive reported interventions (*Cluster*) increase the probability of false reports. The fact that CBs tend to intervene in a clustered way might raise traders' awareness of order flows. This leads them to anticipate that the CB will probably intervene in the future, and sometimes to falsely detect the presence of the CB in the market.

However, the way the CB intervenes, captured by the variables *Coord* and *Amount* does not seem to affect the probability of false reports. This result completes that of Beine and Bernal (2006) who find that coordinated interventions are more often detected by market participants.

Finally, we find that political transitions exert a significant positive impact on the probability of both false reports and anticipative rumors. This means that the two periods of political transition in June 1995 (at the arrival of Sakakibara as Minister of Finance) and in January 2003 (at the departure of Kuroda)

[24] This variable is insignificant in the false reports model, but it makes less sense for it to explain the probability of false reports than the probability of anticipative rumors.

[25] As reported in Table 1, this period of numerous oral interventions is associated with many anticipative rumors.

were considered as periods of uncertainty by the market, favoring the emergence of both false reports and anticipative rumors.

### 3.2 Market determinants

The results reported in Tables 3 and 4 also reveal some interesting facts about market determinants. First, periods of misalignment result in a higher probability of anticipative rumors (see Table 4). This result is consistent with Ito and Yabu (2006) who find that central banks have a tendency to intervene during periods of misalignment. Importantly, the Japanese authorities have stated in several official statements that they have or had an explicit exchange rate target.

Second, while past volatility, captured by the continuous volatility of the previous day ($CV_t$) does not influence the occurrence of either false reports or anticipative rumors, jumps seem to play an important role. Interestingly, contemporaneous jumps ($Jump_{t+1}$) are strongly associated with false reports while past jumps ($Jump_t$) increase the likelihood of anticipative rumors. At this stage we will not attempt an interpretation of the direction of the causality, from jumps to false reports or the reverse. This issue will be discussed in the next section.

The results reported in Table 3 also suggest that days with unexpected jumps are characterized by significantly fewer false reports the next day (see $Jump_t$). This result is not surprising and is probably related to the nature of the jump series. Indeed, unlike continuous volatility, jumps are unpredictable (i.e. they are not clustered over time). In other words, the probability of having of a jump tomorrow, conditional on a jump today, is almost zero. However, since jumps are associated with false reports, a jump yesterday ($Jump_t$) naturally leads to fewer false reports today.

## 4 Testing the reverse causality between jumps and rumors

Do jumps in the spot exchange rate stimulate false rumors of interventions? At this stage in our study we can hardly propose a satisfying answer. Previous results (see Table 3) clearly reflect a contemporaneous correlation between the two events. But did jumps stimulate rumors? Or did rumors create jumps? Presumably, this double causality risks biasing our estimation, jeopardizing the conclusions. Further investigations are necessary to disentangle the two effects and to check the robustness of earlier results. One way to do this consists of identifying the timing of the discontinuities that create jumps ($\kappa^2$ in Equation (12) of Appendix B). Then, by comparing this timing to the arrival of false reports, we should be able to control the endogeneity problem robustly. Of course, a false report can be repeated several times during the day. Therefore we simply select the first newswire of the day.

To isolate the discontinuities, we used a recent approach developed by Beine, Lahaye, Laurent, Neely, and Palm (2006). The procedure is rather simple. If a day is found to contain one or more significant jumps, we neutralize the highest intra-day return (i.e. we fix it to zero) and re-estimate the realized volatility. We then check whether we still observe a statistically significant jump using the test presented in Equation (15). If we do, we repeat the procedure all over again: we set the second highest intra-day return to zero, re-estimate the jump and so on until the test fails to reject the null hypothesis of no jumps. This allows to precisely identify which discontinuities contributed to making $\sum \kappa^2$ a statistically significant quantity.

Table 5 displays the dates and the timing of both false reports and discontinuities, up to a maximum of four discontinuities per day. As we do not have reliable time stamp data for newswires before 1995, the sample period is restricted to February 1, 1995 to September 30, 2004 (2199 trading days). False reports were issued on 104 trading days whereas jumps occurred on 350 days. There were 23 days with both events. Intra-day patterns highlight two important features. First, there are 14 days with jumps with at least one discontinuity before the false report. This is even more striking for the 10 highest jumps since 8 have at least one discontinuity before the rumors. The second feature is the proximity between a discontinuity and the emergence of false rumors. For example on June 24th, 1998 (first row of Table 5), the main discontinuity occurred at 6.35 GMT and the false rumor at 6.36 GMT. At first glance, this seems rather unlikely. But as we work on 5-minutes scaled data the price can actually move between about 6.30 and 6.35 GMT, whereas the corresponding return is recorded at 6.35 GMT. This leaves between 1 and 6 minutes for the traders to react and for the news (false rumor) to arrive on the screens, which is long enough in financial markets.

As a second example, consider April 3, 1998 (third row of Table 5). The jump is due to two distinct discontinuities, at 1.40 and 5.40 GMT while the first false report occurred at 5.42 GMT, i.e. between 2 and 7 minutes after the second jump. The same month, a jump occurred on the 28th (sixth row). This day is characterized by a single discontinuity at 0.05 GMT while the first false report was recorded at 0.11 GMT.

While all these examples speak in favor of a causality from jumps to false reports, there is at least one strong example calling for a reverse causality link. On January 7, 1999 (second row) the two discontinuities responsible for the jump are recorded at 10.45 and 12.00 GMT while the false report arrived at 10.34 GMT. There is only very weak evidence that jumps are created by rumors: out of 350 days with jumps, only 23 observations are associated with rumors (about 6.5%). Furthermore, out of these 23 observations, 14 rumors arrived after the first discontinuity while for the remaining 9 observations the time between the discontinuities and the emergence of the false rumors was often substantial.

These results favor a causality link from jumps to false rumors, even though most jumps do not cause false reports. To check the robustness of our results (presented in Table 3), we have re-estimated the most parsimonious specification by removing the contemporaneous jumps ($Jump_{t+1}$) following the false reports (but occurring the same day). Results, not reported here to save space, are robust to this modification.

# 5 Conclusion

The paper is the first attempt at empirical investigation of the effect of a transparent CBI policy on rumors. We examined the actions of the Bank of Japan over the recent period 1991-2004. The Bank of Japan has been the sole major CB that has continued to use foreign exchange interventions as an instrument, its exchange rate policy alternating between transparency and ambiguity. This has favored the dissemination of intervention rumors, i.e. false reports and anticipative rumors.

Table 5: Emergence of CBI false reports and jumps on the JPY/USD from 1995 to 2004

| Jump size | Timing of discontinuities | | | | Date | False reports | Position |
|---|---|---|---|---|---|---|---|
| 1.324 | 6.35 | 6.40 | 3.25 | 22.10 | 1998-06-24 | 6.36 | 1 |
| 0.731 | 10.45 | 12.00 | - | - | 1999-01-07 | 10.34 | 0 |
| 0.724 | 1.40 | 5.40 | - | - | 1998-04-03 | 5.42 | 1 |
| 0.683 | 3.20 | 3.50 | 3.55 | 3.40 | 1999-04-16 | 3.58 | 1 |
| 0.620 | 0.20 | 23.55 | 23.25 | 0.05 | 1998-08-12 | 0.39 | 1 |
| 0.543 | 0.05 | - | - | - | 1998-04-28 | 0.11 | 1 |
| 0.531 | 9.30 | 13.00 | - | - | 1997-05-16 | 21.05 | 1 |
| 0.380 | 23.45 | 12.55 | - | - | 1995-09-07 | 3.29 | 0 |
| 0.354 | 7.40 | - | - | - | 1999-07-15 | 7.42 | 1 |
| 0.354 | 0.20 | - | - | - | 2000-04-17 | 0.27 | 1 |
| 0.253 | 2.00 | - | - | - | 2004-03-31 | 3.44 | 1 |
| 0.228 | 12.35 | - | - | - | 1995-10-18 | 2.13 | 0 |
| 0.222 | 0.05 | - | - | - | 1995-04-04 | 2.11 | 1 |
| 0.220 | 8.55 | - | - | - | 2001-09-20 | 9.15 | 1 |
| 0.216 | 19.55 | 23.10 | 23.05 | - | 1999-08-12 | 15.03 | 0 |
| 0.199 | 23.55 | - | - | - | 1997-01-15 | 0.40 | 0 |
| 0.195 | 1.05 | - | - | - | 1998-03-18 | 3.51 | 1 |
| 0.102 | 8.00 | - | - | - | 1995-02-22 | 1.07 | 0 |
| 0.092 | 13.35 | - | - | - | 2003-02-07 | 10.27 | 0 |
| 0.090 | 12.10 | - | - | - | 2003-10-15 | 5.45 | 0 |
| 0.086 | 15.25 | - | - | - | 1995-09-11 | 21.02 | 1 |
| 0.083 | 16.10 | 13.35 | 14.10 | 14.30 | 2003-02-20 | 15.17 | 1 |
| 0.071 | 18.15 | 18.40 | 22.20 | 13.35 | 2003-03-28 | 18.08 | 0 |

Columns 1 shows the size of the daily jumps ($\sum \kappa^2$). Columns 2, 3, 4 and 5 report the timing of the first four discontinuities creating the jump. They are ranked from the highest discontinuity (column 2) to the lowest (column 5)(the size of the discontinuities that create the jumps are note reported for the sake of clarity). Columns 6 and 7 give the date and time of the (first) false report. Column 7 is one if there is at least one discontinuity before the false report and 0 otherwise.

Using newswire reports, we collected and classified different types of intervention news reports, i.e reported actual interventions, falsely reported interventions (false reports); anticipative reported interventions (unrequited) and oral interventions. We estimated a dynamic-probit model to find the main determinants of intervention rumors in the foreign exchange market. Our analysis includes two sets of explanatory variables, one related to the intervention strategy adopted by the BoJ concerning actual interventions as well as oral interventions, the other related to market factors such as volatility and jumps. We find that the induced effect of transparent CBI policy on market rumors depends on the type of statement issued by officials: oral interventions aimed at informing the market of the Japanese authorities' point of view on the level or the volatility of exchange rates increase the probability of both false reports and unrequited interventions. But statements aimed at confirming or providing some details about the operation the day it was carried out tend to decrease the probability of false reports. This important result suggests that talking to the market in an appropriate way can remove at least some of the ambiguity that is associated with FX operations. This results fits with the previous evidence by Fratzscher (2004) and Beine, Janssen, and Lecourt (2006).

We also find that the intervention strategy adopted by the CB has an impact on the occurrence of intervention rumors. In particular, the fact that CBs tend to intervene in a clustered way leads the market participants to anticipate that the CB will probably intervene in the future and sometimes to detect the presence of the CB in the market which has not actually occurred. However, the way the CB intervenes (alone or in concert with other monetary authorities, with large or small operation) does not influence the probability of false reports.

Another important result concerns the impact of market variables on the probability of rumors. Periods of exchange rate misalignment are found to be associated with the emergence of both types of rumors. Finally, we have seen that several jumps have been falsely interpreted by the market as the result of a CBI, leading to rumors of interventions.

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# APPENDICES

## A Example of newswires for data collection

Table 6: Sample of news reports used to build the *anticipative rumor* variable

| Date | Source | Relevant text of the news report |
|---|---|---|
| March 19, 1993 | *Reuters* | *"... **dealers feared the Bank of Japan (BOJ) may intervene** to buy dollars for yen if **the dollar's downward spiral continues** (...) In the morning, Finance Minister Yoshiro Hayashi said Japan will take appropriate steps at the right time to stabilise the currency market."* |
| February 20, 1993 | *Reuters* | *"**Japan may act to stem rapid yen rise**, dealers say. (...) The rise of Japan's currency to record highs against the dollar **could trigger intervention to halt further gains**, currency dealers here said on Saturday."* |
| September 18, 1995 | *Reuters* | *"In addition, **the Bank of Japan is widely expected to intervene aggressively on Wednesday** to prop up the dollar against the yen and magnify the impact of the stimulus package on the currency market."* |
| June 26, 2000 | *Dow Jones* | *"But nervousness in the market about **possible intervention by the BOJ** and other central banks is increasing, particularly because of perceptions that an unchecked dollar rise would make **last week's intervention look like a failure** - something monetary officials want to avoid, dealers said ..."* |

Note: The news reports in this table clearly indicate that the market is expecting an intervention in the near future.

Table 7: Sample of news reports used to build the *false reports* of intervention variable

| Date | Source | Relevant text of the news report |
|---|---|---|
| September 1, 1993 | *Reuters* | *"The **BOJ appeared to have bought dollars twice at just below 105 yen** in Tokyo morning trade, then at 104.65 yen or just above in the afternoon, overwhelming exporter sales at peaks."* |
| Marsh 25, 1994 | *Reuters* | *"But the dollar recovered somewhat in Tokyo trade this morning, helped by **the Bank of Japan's dollar-buying intervention**."* |
| July 15, 1999 | *Reuters* | *"Market attention was focused on action in dollar/yen amid talk of intervention by the Bank of Japan. **Rumours that the BOJ was buying dollar for yen in Tokyo** boosted the dollar to 121.30 yen from a low of 120.27."* |
| March 20, 1998 | *Dow Jones* | *"The currency reversed direction abruptly however, after Eisuke **Sakakibara**, the Japanese deputy finance minister for international affairs, **threatened 'decisive action'** to counter the yen's weakness. Simultaneously **the Bank of Japan entered the market selling U.S. dollars**, according to traders, sending the yen, and Southeast Asian currencies, sharply higher."* |

Note: The news reports in this table clearly indicate that the market perceived an intervention whereas official data show that no interventions were conducted during these days.

## B Realized volatility, bi-power variation and jumps

Let $p(t)$ be a logarithmic asset price at time $t$, i.e. the JPY/USD exchange rate in our study. Consider the continuous-time jump diffusion process

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), \qquad 0 \leq t \leq, T \tag{6}$$

where $\mu(t)$ is a continuous and locally bounded variation process, $\sigma(t)$ is a strictly positive stochastic volatility process with a sample path that is right continuous and has well defined limits, $W(t)$ is a standard Brownian motion, and $q(t)$ is a counting process with intensity $\lambda(t)$ ($P[dq(t) = 1] = \lambda(t)dt$

and $\kappa(t) = p(t) - p(t-)$ is the size of the jump in question). The quadratic variation for the cumulative process $r(t) \equiv p(t) - p(0)$ is the integrated volatility of the continuous sample path component plus the sum of the $q(t)$ squared jumps that occurred between time 0 and time $t$:

$$[r, r]_t = \int_0^t \sigma^2(s)ds + \sum_{0<s\leq t} \kappa^2(s). \tag{7}$$

Now, let us define the daily realized volatility as the sum of the corresponding intra-daily squared returns:[26]

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r^2_{t+j\Delta,\Delta}, \tag{8}$$

where $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$ is the discretely sampled $\Delta$-period return.[27] So $1/\Delta$ is the number of intra-daily periods (288 in our application).

Barndorff-Nielsen and Shephard (2004) show that the realized volatility converges uniformly in probability to the increment of the quadratic variation process as the sampling frequency of the returns increases ($\Delta \to 0$):

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds + \sum_{t<s\leq t+1} \kappa^2(s). \tag{9}$$

In other words, the realized volatility is a consistent estimate of the integrated volatility as long as there are no jumps.

In order to disentangle the continuous and the jump components of realized volatility, we need to consistently estimate the integrated volatility, even in the presence of jumps in the process. This is done using the asymptotic results of Barndorff-Nielsen and Shephard (2004). The realized bi-power variation is defined as the sum of the product of adjacent absolute intradaily returns standardized by a constant:[28]

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2}(1-2\Delta)^{-1} \sum_{j=3}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+(j-2)\Delta,\Delta}|, \tag{10}$$

where $\mu_1 \equiv \sqrt{2/\pi} \simeq 0.79788$

For $\Delta \to 0$

$$BV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds \tag{11}$$

Then the contribution of jumps can be isolated for $\Delta \to 0$

$$RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \to \sum_{t<s\leq t+1} \kappa^2(s) \tag{12}$$

and imposing non-negativity on the empirical measurement, we have:

$$J_{t+1}(\Delta) \equiv max[RV_{t+1}(\Delta) - BV_{t+1}(\Delta), 0]. \tag{13}$$

[26] The realized volatility for day $t$ is usually denoted $RV_{t+1}(\Delta)$ and not $RV_t(\Delta)$ because it is only computable at the end day $t$ (i.e. in $t+1$).

[27] We use the same notation as Andersen, Bollerslev, and Diebold (2005) and normalize the daily time interval to unity. We drop the $\Delta$ subscript for daily returns: $r_{t+1,1} \equiv r_{t+1}$.

[28] Following Andersen, Bollerslev, and Diebold (2005), we use a modified staggered realized bi-power variation measure to tackle first order autocorrelation due to microstructure noise issues.

Applying Equation (13) to extract the daily jump component of the JPY/USD would lead to an implausible number of days associated with jumps (about 90% of days are detected). This result is standard in this literature. For this reason, it might be better to select only statistically significant jumps and consider very small jumps as part of the continuous sample path rather than genuine discontinuities.

Several statistics have been proposed recently to test the significance of the jumps. Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2005), propose to select significant jumps as follows:

$$J_{t+1,\alpha}(\Delta) = I[Z_{t+1}(\Delta) > \Phi_\alpha] \cdot [RV_{t+1}(\Delta) - BV_{t+1}(\Delta)], \tag{14}$$

where

$$Z_{t+1}(\Delta) \equiv \Delta^{-1/2} \frac{[RV_{t+1}(\Delta) - BV_{t+1}(\Delta)]RV_{t+1}(\Delta)^{-1}}{[(\mu_1^{-4} + 2\mu_1^{-2} - 5)max\{1, TQ_{t+1}(\Delta)BV_{t+1}(\Delta)^{-2}\}]^{1/2}}. \tag{15}$$

To compute this statistic, we need first to estimate the integrated quarticity $\int_t^{t+1} \sigma^4(s)ds$. The realized tri-power quarticity measure permits us to estimate it consistently, even in the presence of jumps. Following Andersen, Bollerslev, and Diebold (2005), we use a modified staggered version of the realized tri-power quarticity:

$$TQ_{t+1}(\Delta) \equiv \Delta^{-1} \mu_{4/3}^{-3} (1 - 4\Delta)^{-1} \sum_{j=5}^{1/\Delta} |r_{t+j\Delta,\Delta}|^{4/3} |r_{t+(j-2)\Delta,\Delta}|^{4/3} |r_{t+(j-4)\Delta,\Delta}|^{4/3}. \tag{16}$$

Second, we have to chose a significance level $\alpha$. Of course, a smaller $\alpha$ means that fewer and larger jumps are detected. In our application, we chose a conservative confidence level of 99.99%, i.e $\alpha = 0.9999$.

Finally, to make sure that the jump component added to the continuous one equals the realized volatility, we impose:

$$CV_{t+1,\alpha}(\Delta) = I[Z_{t+1}(\Delta) \leq \Phi_\alpha] \cdot RV_{t+1}(\Delta) + I[Z_{t+1}(\Delta) > \Phi_\alpha] \cdot BV_{t+1}(\Delta). \tag{17}$$

In short, the two quantities we use in our estimations are $CV_{t+1,\alpha}(\Delta)$ and $J_{t+1,\alpha}(\Delta)$ (i.e. the continuous volatility and the jumps respectively).

In line with a large body of the literature, we rely on 5-minute (JPY/USD) series. The raw data were obtained from Olsen and Associates. They were first filtered for outliers and other anomalies. Then the price at each 5-minute mark were obtained by linearly interpolating from the average of the log bid and the log ask for the two closest ticks. Finally, we computed 5-minute returns as the first difference of the logarithmic prices. To remain coherent with the data collection on rumors, a day is defined as the period between 00.00 GMT and 23.55 GMT.