Official Central Bank Interventions and Exchange Rate Volatility: Evidence from a Regime Switching Analysis*

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Forthcoming in *European Economic Review*

December 2001

Abstract

In this paper, we investigate the effect of central bank interventions on the weekly returns and volatility of the DEM/USD and YEN/USD exchange rate returns. In contrast with previous analyzes, we allow for regime-dependent specifications and investigate whether official interventions can explain the observed volatility regime switches. It is found that, depending on the prevailing volatility level, coordinated central bank interventions can lead to either a stabilizing or a destabilizing effect. Our results lead us to challenge the usual view that such interventions always imply increases in volatility.
JEL Classifications: C22, E44, F31, G15.
Keywords: Central bank intervention, exchange rate volatility, Markov switching regimes.

*We are indebted to S. Gray and J. Hamilton for sharing their codes that served as a starting point in our analysis. This paper has benefitted from helpful comments from M. Aglietta, A. Benassy, J. Breitung, B. Candelon, C. Croux, R. Djouad, R. Lafrance, H. Lütkepohl, L. Reichlin, A. Ruttiens and particularly P. Giot and F. Palm. Comments and suggestions made during presentations at the Bank of Canada, at the Forecasting Financial Market Meeting in London, at the Humboldt University and at the University of Brussels are gratefully acknowledged. Of course, the usual disclaimer applies.
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1 Introduction

Since the beginning of the 90's, the release of high frequency data by several major central banks has led to a renewed interest in the empirical assessment of the effect of direct interventions on the short run evolution of foreign exchange rates. In particular, the empirical literature investigated whether direct purchases and sales made by the central bank on the foreign exchange market could be effective in moving the nominal exchange rate in one direction or another. These sought-after dynamics have been implicitly defined in two well known major international agreements: the 1985 Plaza Agreement that favored central bank cooperation in order to induce a sharp depreciation of the US dollar (USD hereafter) and the 1987 Louvre Agreement that emphasized the need to decrease excess exchange rate volatility. More recently, the interest for direct interventions on the foreign exchange market has been fostered at the European level by the sharp depreciation of the Euro against the major currencies, i.e. the USD and the Japanese Yen (YEN hereafter) and, to a lesser extent, its relatively high volatility. In September 2000, the European Central Bank directly intervened in support of the Euro in coordination with the major other central banks (the Federal Reserve, the Bank of Japan, the Bank of Canada and the Bank of England). This was followed by three official unilateral interventions carried out in November 2000. Recently, central bank interventions have also been used extensively as an instrument by the Bank of Japan to depreciate the YEN, in order to support its expansive monetary policy.

In the 80's, the inference of the empirical literature was mainly based on the use of quarterly variations of official reserves as proxies to the direct interventions of central banks on the foreign exchange markets. The public release of daily data regarding these direct interventions by the Federal Reserve, the Bundesbank and the Swiss bank (among others) has nevertheless allowed the study of the short-run impact on exchange rates or interest rates. More recently, the Bank of Japan also decided to publish (ex-post) the official interventions made since April 1991. Accordingly, the econometric techniques using these data have been adjusted to account for some of the key features associated with such high frequency financial data (conditional heteroskedasticity for instance).

The results of the empirical literature on foreign exchange rate interventions seem quite surprising. General speaking, there is only some weak evidence that interventions can affect the level of the exchange rate (Baillie and Osterberg, 1997a).[1] When some effects are however detected, net purchases of a particular currency appear to be associated with a subsequent depreciation of this currency (Almekinders and Eijffinger, 1993; Dominguez and Frankel, 1993; Baillie and Osterberg, 1997a and Beine, Bénassy-Quéré, and Lecourt, 2002), suggesting leaning-against-the-wind phenomena.[2] Regarding the second moment of the distribution of returns, the main findings of the literature emphasize a significant increase of volatility subsequent to the foreign exchange rate interventions. This last effect is extensively documented in the previously quoted papers and also by Connoly and Taylor (1994), Dominguez (1998) and Baillie and Humpage (1992) that use an ex-post characterization of volatility (ARCH and subsequent developments). Focusing on some ex-ante measure of volatility leads to the same conclusion (Bonser-Neal and Tanner, 1996 for instance). All in all, these reported effects raise some doubts on the efficiency of such an instrument, at least in the very short run.

As far as the methodological part of the study is concerned, most of the empirical analyzes use an ARCH-type specification to model the heteroskedasticity observed on these series at a high-frequency basis. For instance, Baillie and Osterberg (1997a,b) as well as Dominguez (1998) use GARCH models while Beine, Bénassy-Quéré, and Lecourt (2002) allow for long memory in the conditional variance through a FIGARCH specification. To study the impact of central bank interventions (CBI in short), explanatory variables are usually added in the conditional mean and/or the conditional variance equations. As a result, these approaches implicitly assume linear impacts of CBI, either on the mean or on the volatility of exchange rate returns.

In this paper, we propose an alternative approach to the GARCH specification (Bollerslev, 1986) and the single-regime framework that are commonly used in the

[1] Although Baillie and Osterberg(1997b) find some effects on the risk premium in the forward market.

[2] Leaning-against-the-wind refers to an intervention aiming at reverting the evolution of a particular currency.

empirical literature on the effectiveness of central bank interventions in the foreign exchange markets. In contrast with earlier analysis, we allow for regime-dependent frameworks to assess the impact of direct interventions. More specially, and following the approach proposed by Hamilton (1994), we assume that the evolution of the spot exchange rates depends on a latent regime variable whose dynamics is driven by a first-order Markov switching process. Then, in the spirit of Filardo (1994) or Diebold, Lee, and Weinbach (1994), the probabilities of switching from one regime to another depend on exogenous variables, in our case central bank interventions.

Compared to single-regime GARCH type models, one important advantage of such an approach is that it explicitly allows for different outcomes of central bank interventions with respect to the initial state of the economy. For instance, central bank purchases can lead to an increase in volatility when the markets are calm, but not if the market is in a state of high volatility. Similarly, the effect on the level of exchange rate could be different depending on whether the dollar is depreciating or appreciating. The economic rationale is as follows. The literature tends to favor the signalling channel as the prevailing channel of transmission of central bank interventions on foreign exchange rates. As pointed out by Dominguez (1998), according to the intervention signalling hypothesis, the expected effect of an intervention depends on whether its associated signal is unambiguous and consistent with the official goals of these operations. As indicated in Dominguez (1999), the motivations of the FED include among others influencing trend movements in exchange rates and calming disorderly markets. Therefore, depending on the prevailing state of the market, the signal of an intervention will be ambiguous or not and the effect on the two first moments of exchange rate changes will be different. Our results dealing with the effects of the central bank interventions on exchange rate volatility turn out to be consistent with this idea.

In this paper, different Markov switching models are estimated and a selected specification is then used for the study of the DEM/USD exchange rate over the 1985-1995 period. Some evidence is also provided for the YEN/USD in order to assess to which extent our results are only valid for the DEM. Due to data availability, the analysis of the YEN is performed over a shorter period, 1991-1995. It is found that this regime-switching framework fits the data rather well on the one hand, and compares very well with usual GARCH specifications when investigating the respective out-of-sample forecasting properties on the other hand. One of our main conclusions is that official central bank interventions explain a significant part of the observed switches between volatility regimes. Our results lead us to challenge the previous conclusions according to which central bank interventions cannot have any stabilizing influence on the short run dynamics of exchange rates.

The paper is organized as follows. Section 2 investigates the relevance of several statistical models and presents some evidence in favor of a regime-switching model. Section 3 is devoted to the analysis of the effects of central bank interventions. Section 4 concludes.

2 Regime-dependent frameworks

This section introduces the Markov switching model on which our analysis is based. A comparison with the traditional GARCH model is carried out in order to justify such a regime dependent model. Some statistical model selection search within this class of models is also conducted so that a preferred model can be chosen and extended to time-varying transition probabilities.

2.1 Regime-dependent models versus single regime (G)ARCH models

Most of the statistical models used in the literature to study the impact of foreign exchange rate interventions are single-regime models in the sense that the parameters are assumed to be constant over the whole sample. In this paper, we introduce a more flexible framework by allowing the value of parameters to depend on the prevailing regime. Our data set consists of weekly returns of spot exchange rates $y_t = 100 \times \ln(p_t/p_{t-1})$, where p_t denotes the number of units of the foreign currency (the DEM or the YEN) per unit of USD. The data has been provided by the Bank of International Settlements. These are mid-day spot exchange rates quoted at Frankfurt at 2:00 pm (DEM) and at Tokyo at 10 am (YEN) in local time.[3] For the DEM, the data range from

[3]In contrast with the previous literature, we use weekly data rather than daily data. Indeed, it is unclear (and controversial) what is the exact horizon of the central bank interventions. As reported by Neely (2000), an important proportion of central banks believe that the full effect of the intervention is seen over a few days or more. This suggests that the weekly frequency is relevant, at least from

the first week of 1985 to the last one of 1995, yielding 573 observations. This period turns out to include most central bank operations undertaken on the foreign exchange market during the 80's and the 90's. It also corresponds to the period subsequent to the two major agreements in this field, namely the Plaza (September 1985) and the Louvre (February 1987) agreements.[4]

To a certain extent, some substitutions are possible between ARCH and regime-switching modelling.[5] Although the variance is constant *within* each regime in the latter model, the estimated conditional variance of this model is allowed to vary over time due to the evolution of the probabilistic assessment of being in the first or the second regime. In turn, this suggests that a two-regime model with a constant variance may be an alternative candidate to single-regime (G)ARCH-type models traditionally used in the empirical assessment of central bank interventions. As a starting point, we estimate a two-regime model with shifts allowed both in the conditional mean and variance. Such a framework is proposed by Hamilton (1994). Bollen, Gray, and Whaley (2000) have recently shown that such a model fits the exchange rate data rather well on the one hand and tends to outperform the usual GARCH model on the other hand. In the two-regime case, one has:

$$y_t \mid \Omega_t \sim \Delta(\mu_1, \sigma_1^2) \text{ if } s_t = 1 \tag{1}$$

$$y_t \mid \Omega_t \sim \Delta(\mu_2, \sigma_2^2) \text{ if } s_t = 2, \tag{2}$$

where Ω_t denotes the information set at time t and Δ the Gaussian distribution function. In this framework, the dynamics of y_t is assumed to depend on an unobserved random variable s_t that can take on the values 1 or 2. This unobserved variable is then supposed to follow a first-order Markov process of the type:

the point of view of the central banks. Furthermore, it was implicit that the Plaza and the Louvre agreements focused on lower frequencies than the daily one which is usually considered in the literature. Nevertheless, extending this analysis to the daily frequency should be interesting but it is obviously beyond the scope of this paper.

[4]For the YEN, given the availability of official central bank interventions of the Bank of Japan, the investigation period ranges from April 1991 to December 1995; this amounts to 272 observations.

[5]Kim and Kon (1999), Granger and Hyung (1999) or Beine and Laurent (2001) have recently provided some specific evidence on the strong interaction between structural change (captured for instance through regime switching models) and volatility persistence.

$$
\begin{aligned}
p_1 &= \text{Prob}(s_t = 1 \mid s_{t-1} = 1) && (3)\\
p_2 &= \text{Prob}(s_t = 2 \mid s_{t-1} = 2). && (4)
\end{aligned}
$$

In turn, these transition probabilities can be collected in the following P matrix:

$$
P = \begin{bmatrix} p_1 & 1-p_2 \\ 1-p_2 & p_2 \end{bmatrix}. \tag{5}
$$

Because of the persistence of each regime (a stylized fact of Markov switching models applied to empirical finance[6]) captured by p_1 and p_2, the model accounts for the volatility clustering observed in the data. Persistence and thus the relevance of the Markov switching approach require p_1 and p_2 to be significantly higher than 0.5. This contrasts with single-regime (G)ARCH approaches in which the evolution of the conditional variance is driven by volatility innovations and past values of variances.

Nevertheless, as reported by Bollen, Gray, and Whaley (2000), this two-regime framework imposes some restrictions that can be too strong to capture the dynamics of exchange rates. In particular, since the switching process involves both the mean and the variance, a particular combination of the level of returns and variance of exchange rates is enforced within each regime. For instance, if $\mu_1 > \mu_2$ and $\sigma_1^2 < \sigma_2^2$, the first regime necessarily associates patterns of low volatility with patterns of high returns (appreciation of the USD), while the second regime captures high volatility episodes associated with phases of USD depreciation. Such a restriction can be rejected by the data and thus needs to be tested statistically. As analyzed by Bollen, Gray, and Whaley (2000), the model may be generalized to include independent shifts in the mean and in the variance. In this case, one has to define two latent variables, $s_{\mu,t}$ and $s_{\sigma,t}$, relative respectively to the mean and to the variance process. As before, each of these two variables is governed by a first-order Markov process. The transition probabilities are denoted by $p_{1,\mu}$ and $p_{2,\mu}$ for the mean process and $p_{1,\sigma}$ and $p_{2,\sigma}$ for the variance one, respectively. This corresponds to a four-regime model with a new latent variable s_t ($s_t = 1, 2, 3, 4$) taking values depending on the mean and variance regimes:

[6]See for instance Kim and Nelson (1999).

$$y_t \quad | \quad \Omega_t \sim \Delta(\mu_1, \sigma_1^2) \text{ if } s_t = 1 \tag{6}$$

$$y_t \quad | \quad \Omega_t \sim \Delta(\mu_2, \sigma_1^2) \text{ if } s_t = 2 \tag{7}$$

$$y_t \quad | \quad \Omega_t \sim \Delta(\mu_1, \sigma_2^2) \text{ if } s_t = 3 \tag{8}$$

$$y_t \quad | \quad \Omega_t \sim \Delta(\mu_2, \sigma_2^2) \text{ if } s_t = 4. \tag{9}$$

In this case, one ends up with a (4×4) matrix of transition probabilities (see for details Bollen, Gray, and Whaley, 2000 or Ravn and Sola, 1995).

The Markov switching regimes are estimated by the Expected Maximum Likelihood (EML) procedure (see for details Hamilton, 1994). In short, the EML estimation relies on the maximisation of the log-likelihood function $\sum_{t=1}^{T} [Ln(\Delta(y_t \mid \Omega_t)]$ which is computed from the sum of the log-likelihood values conditional upon each regime:[7]

$$Ln(\Delta(y_t \mid \Omega_t)) = Ln \left[\sum_{i=1}^{S} (\Delta(y_t \mid \Omega_t, s_t = i) \Pr(s_t = i \mid \Omega_t) \right], \tag{10}$$

where S denotes the total number of regimes (1, 2 or 4 in our analysis). One has to be cautious in assessing the relevance of the two-regime model against either the one-regime model or the four-regime model since the standard conditions are not fulfilled to carry out usual likelihood ratio tests (LRT). Several solutions have been proposed (see for instance Hansen, 1992), including the adjustment of critical values proposed by Garcia (1998) for a set of specific two-regime models. When these adjusted critical values are not available, several features, like results from the usual diagnostic tests (Ljung-Box or information criteria for instance) or the forecasting performances, should be computed.

2.2 Results and comparison with GARCH model

Before using the Markov switching model to tackle the issue of central bank interventions, the different competing specifications should be compared and assessed and a preferred model should be selected. Tables 1 and 2 present the results obtained from the various Markov switching specifications.

[7]For the estimation of the smoothed probabilities $\Pr(s_t = i \mid \Omega_t)$, we rely on the algorithm developed by Kim (1994). Similar results have also been obtained with the alternative procedure developed by Gray (1996).

INSERT TABLES 1 and 2 about HERE

Table 1 indicates that the model with two dependent regimes is validated by the data. The one-regime model [model (1)] is clearly rejected in favor of the two-regime model with a switching mean [model (3)] using the χ^2 adjusted critical values provided by Garcia (1998) for this specific model. Indeed, the LRT amounts to 32.672, well above the critical value at the 99% confidence level (17.52). Comparing the four-regime model [model (4)] with model (3), a LRT clearly rejects the hypothesis of independence between mean and variance regime, but once again, because of the identification issue of some parameters under the null hypothesis, one cannot discriminate between these models on these grounds.[8] Nevertheless, information criteria (not reported here) and other standard diagnostics tend to favor the two-regime model. Another way to discriminate between these regime-switching models but also to compare them with the standard single-regime GARCH model is to investigate their relative out-of-sample forecasting properties. This is done in the next sub-section and will confirm that the four-regime model is clearly dominated.

From the results of model (3), it is also obvious that the estimated models capture volatility regimes rather than mean regimes, which is quite consistent with the literature on Markov switching models applied to exchange rates. The first regime is basically the high volatility regime with a variance σ_1^2 roughly three times larger than the one in the second regime (σ_2^2).[9] By contrast, the two unconditional means do not significantly differ across regimes, neither for the DEM nor the YEN. Restricting the mean to be constant leads to model (2) that can be compared to model (3); this restriction is supported by a LRT, which implies that model (2) is finally our preferred model for assessing the impact of interventions on both the mean and variability of exchange rate returns. Basically, the same result holds for the YEN: model (2) with a switching variance and a constant mean turns out to be the preferred model.

[8]It should also be noticed that as emphasized by Garcia (1998), unadjusted critical values tend in general to be too *low*. Therefore, it should be expected that using adjusted critical values would also lead to the rejection of the four-regime model in favor of the two-regime model.

[9]Notice that Tables 1 and 2 report the estimated standard errors. In turn, this suggests that the variables introduced to explain the transition probabilities in model (3) should be mainly variables thought to influence exchange rate volatility and not the returns. In particular, one should use absolute values of central bank interventions.

Interestingly, the Ljung-Box statistics at lag 20 for the residuals (Q_{20}) and the squared residuals (Q_{20}^2) suggest that the Markov switching models are supported by the data. In particular, allowing for a switching variance accounts for the heteroskedasticity present in the data without using the GARCH specification. By contrast, the model does not require a switch in the mean to account for the autocorrelation in the data, as suggested by the Q_{20} statistics for model (2). To illustrate this point and to compare these non-nested specifications, one may investigate the out-of-sample forecasting properties of each model.

2.3 Forecasting Performance

We compare the out-of-sample variance forecasts of five volatility models: the GARCH $(1,1)$, the random walk (RW) and three regime switching models (two-regime with constant mean, two-regime with varying mean and four-regime models). The models are estimated for the DEM/USD[10] using the first 521 observations (up to 1994) with the rest of the data (52 points) left for post-sample forecast evaluation. Variance forecasts at 1, 4 and 8 weeks horizons are constructed for each model.

The volatility forecasts should be compared with the realized variance over the forecast period. The usual measure for the observed volatility in the literature is the square of the returns or the absolute returns (Pagan and Schwert, 1990). However, in a recent paper dealing with daily volatility, Andersen and Bollerslev (1998) have shown that this measure is not fully relevant and have proposed an alternative measure. This new measure uses cumulated squared intradaily returns, also called "integrated volatility", which is a more precise measure of the daily volatility. In our analysis, the integrated volatility is defined as:

$$\sigma_t^2 = \sum_{i=1}^{5} y_{i,t}^2, \tag{11}$$

where $y_{i,t}^2$ is the squared return on day i of week t. For the two-regime and four-regime Markov switching models, the volatility forecast is of course a function of the regime probabilities.[11]

[10]This experience is not conducted for the YEN/USD due to the small sample size.
[11]See Appendix for further details.

To compare the forecasting performances of the different models, we use the following criteria:

- the Root Mean Squared forecast Error (RMSE) generally used in the volatility forecast literature;
- the Heteroskedastic Mean Average Error (HMAE) of Andersen, Bollerslev, and Lange (1999) which is adjusted for ARCH effects;
- the Logarithmic Loss Function (LL) of Pagan and Schwert (1990) as well as Bollerslev, Engle, and Nelson (1994), which stresses the influence of low volatility periods.

The forecast horizon has been set to 1, 4 and 8 weeks. Summary statistics are given in Table 3, respectively in panels A, B and C.

INSERT TABLE 3 about HERE

Results in Table 3 show that the two-regime model with constant mean often leads to a reduction of the variance forecasts errors relative to others models. Such a result is obtained for each forecast length, at least using one criterion. Exceptions are the HMAE and the LL criteria at the one-week horizon and the RMSE criterion at the eight-week horizon. As a whole, it comes out that our preferred model compares very well with the GARCH(1,1) model. More importantly, in almost all cases, the two-regime model clearly outperforms the four-regime model.[12] This may be due to the fact that the uncertainty regarding the estimates of the mean parameters is quite important in the four regime model. Thus, this legitimates the use of the two-regime with constant mean model compared to a GARCH (1,1) specification or to the four-regime model and tends to support the findings drawn from the estimations reported in Tables 1 and 2. Figure 1 plots the conditional variances implied by model (2) and by a GARCH specification. It is seen that both models give rise to similar episodes of high and low volatility.

INSERT FIGURE 1 about HERE

[12]Except for the HMAE criteria at four-week horizon.

3 The impact of central bank interventions

3.1 The TVTP model

As explained in Section 2.1, the change over time of the probabilities of being in one particular regime is in the Markov switching framework the only driving force of the dynamics of the conditional mean and variance of the exchange rate returns. Within each regime, these mean and variance remain constant. Up to now, the transition probabilities of remaining in a particular regime only depend on the previous state of the economy, i.e. the volatility level of past week. To study the impact of central bank interventions on the dynamics of exchange rate returns, we follow Filardo (1994) and Diebold, Lee, and Weinbach (1994) and extend the constant transition probability assumption (see Eq. (3) and (4)) by conditioning the transition probabilities on exogenous variables (in our case central bank interventions) through a logistic specification. For instance, in the two-regime model similar to model (2) that involves only volatility regimes, one has:

$$
\begin{aligned}
p_{1,t} &= Prob(s_t = 1 \mid s_{t-1} = 1, |x_{t-1}|) \\
&= 1 - \left[1 + \exp(\eta_{1,0} + \sum_{i=1}^{k} \eta_{1,i}\, |x_{i,t-1}|)\right]^{-1} \qquad (12) \\
p_{2,t} &= Prob(s_t = 2 \mid s_{t-1} = 2, |x_{t-1}|) \\
&= 1 - \left[1 + \exp(\eta_{2,0} + \sum_{i=1}^{k} \eta_{2,i}\, |x_{i,t-1}|)\right]^{-1}, \qquad (13)
\end{aligned}
$$

where x_t is a matrix of k explanatory variables, i.e. $x_t = (x_{1,t}, \ldots, x_{k,t})$. In our framework, these explanatory variables are of course the central bank interventions. In the subsequent estimations we use $k = 1$ when dealing with coordinated interventions and $k = 2$ with unilateral interventions.

We use model (2) and also introduce interventions as explanatory variables of the conditional mean of exchange rate returns. This implies that we allow only for linear effects on the returns:

$$
y_t = \mu + \sum_{i=1}^{k} \varpi_i x_{i,t-1} + \varepsilon_t. \qquad (14)
$$

By contrast, since interventions influence the transition probabilities of volatility regimes, they should be introduced in a non-linear way in the conditional variance specification. Filardo (1998) provides the necessary conditions to ensure that the estimation of models with time-varying transition probabilities (TVTP) with a ML procedure is possible and relevant. According to the main condition of Filardo (1998), the explanatory variables should be conditionally uncorrelated with the latent regime variable (s_t). Thus one should check that the central bank interventions are not caused in a systematic way by the level of exchange rate volatility. From an econometric point of view, this is similar to the well-known simultaneous bias problem which has been investigated in the literature of central bank interventions. In this respect, evidence presented in the literature is rather mixed: regarding the mean, central banks tend to lean against the wind (Almekinders and Eijffinger, 1993; Dominguez, 1998; Baillie and Osterberg, 1997b and Beine, Bénassy-Quéré, and Lecourt, 2002). In other terms, it is the tendency to depreciate rather than the mere previous change in the level that matters. Concerning volatility, the results appear rather mixed. Baillie and Osterberg (1997a) find that volatility caused interventions on the 1985-1991 period. Nevertheless, using another measure of conditional variance over the same period, Beine, Bénassy-Quéré, and Lecourt (2002) find less evidence according to which volatility levels motivate the intervention of the major central banks, at least for the DEM. As a whole, it turns out that the condition of non-causality from the current state of the market to the central bank interventions is far from being fulfilled. As a result, one should use one-week lagged interventions($|x_{i,t-1}|$) rather than the contemporaneous ones ($|x_{i,t}|$) in the TVTP in order to ensure that such a simultaneous bias does not occur. Given that we work with volatility regimes, both specifications are used to assess the robustness of the results.[13] Before proceeding to the ML estimation, we describe the central bank intervention data.

3.2 The intervention data

Our data consists of weekly official central bank interventions of the Federal Reserve (FED) and the Bundesbank (BB) on the DEM/USD market over the 1985-1995 period

[13] This is especially important in the DEM case. For the YEN, all results emphasize some causality from exchange rate volatility to interventions (see Beine, Bénassy-Quéré, and Lecourt, 2002 for details). Not lagging these interventions would definitely result in endogeneity biases.

and the interventions of the Federal Reserve (FED) and the Bank of Japan (BoJ) on the YEN/USD market over the 1991-1995 period. As in Bonser-Neal and Tanner (1996), Dominguez and Frankel (1993) or Dominguez (1998), we distinguish between the nature of these interventions.

First, we use discrete variables focusing on the number of official interventions days rather than on the (cumulated) amounts of daily interventions. Basically, this allows us to assess the influence of the presence of the banks in the markets, and emphasizes the signalling channel of interventions rather than the basic portfolio effect. Table 4 provides the number of (official) intervention days for each central bank.[14] The number of coordinated interventions is also given. Two interventions are said to be coordinated if they happen on the same day and in the same direction. For the DEM, we take FED interventions at day $t-1$ but Bundesbank interventions at time t in order to account for time lags between the markets. For the YEN, we consider FED and BoJ interventions at day $t-1$.[15]

INSERT TABLE 4 about HERE

Because the number of coordinated interventions is large, one may expect that the weekly intervention data will be highly correlated. Table 5 confirms that, in the case of the DEM, the correlation between interventions measured through discrete variables, both in levels[16] and in absolute value (used in the conditional volatility specification) is very high.[17]

INSERT TABLE 5 about HERE

Such a high correlation would give rise to multicollinearity problems and poor estimates of standard errors. To account for this problem, we isolate unilateral interventions, i.e. interventions made by a single central bank on a particular day. The

[14] Table 4 provides the number of official and reported interventions. Reported interventions are obtained from reports extracted from the financial newspapers (we are grateful to K. Bonser-Neal for providing the reported interventions on the DEM market over the 1985-1991 period). Given the important discrepancy between reported and official interventions (see for instance the reported interventions for the YEN), we prefer to focus on official interventions.

[15] The German market is six hours ahead of the US market and lags the Japanese market by 8 hours.

[16] In this case, the variable is trinomic: -1 indicates that the bank is selling dollars, 0 means that the bank does not intervene and 1 that the bank is buying dollars.

[17] Similar results are also obtained for the YEN (although the problem seems less important given the lower proportion of coordinated interventions. These results are not reported in order to save space.

cross correlations between these adjusted interventions given in Table 6 show that the correlations have dramatically decreased and thus multicollinearity should not be a problem in our estimations. We run two types of regressions with discrete variables: the first one relies only on the unilateral interventions while the second one uses only the coordinated interventions. This distinction makes sense from an economic point of view as some authors have argued that the effect of coordinated interventions is more powerful than the one obtained by unilateral ones (see among others Catte, Galli, and Rebecchini, 1992; Dominguez and Frankel, 1993 and Weber, 1996).

INSERT TABLE 6 about HERE

3.3 The results

Tables 7 and 8 report the estimation results for the DEM and the YEN respectively. In both cases, the two-regime specification with a constant conditional mean is used. In these models, central bank interventions enter linearly the conditional mean equation. The official central bank interventions are modelled using discrete variables giving the number of intervention days over a particular week. For both currencies, we study the effect of coordinated and unilateral interventions.[18]

INSERT TABLES 7 and 8 about HERE

Basically, our results are in agreement with the literature as far as the conditional mean of exchange rate returns is concerned. This is not surprising since the basic specification (i.e. linear impacts of the interventions) is consistent with the previously adopted approaches: the Bundesbank purchases of dollars lead to a subsequent depreciation of the USD, which is also documented in Almekinders and Eijffinger (1993), Dominguez and Frankel (1993), Baillie and Osterberg (1997a) and Beine, Bénassy-Quéré, and Lecourt (2002). Baillie and Humpage (1992) interpret this result as a smoothing effect, suggesting that the depreciation might have been even sharper without such an intervention. The FED interventions do not give similar results, at least

[18]However, in the case of the YEN, it is impossible to consider the effect of unilateral interventions of the FED, given that there is only one occurrence over the considered period (see also Table 4). This unilateral intervention occurred on the May 24^{th}, 1993.

over the 1985-1995 period.[19] The results for the YEN suggest that coordinated interventions or unilateral operations of the BoJ have a limited impact on exchange rate returns.

Our results present a quite different view regarding the effects of interventions on exchange rate volatility. In contrast with the single regime GARCH framework, our regime-dependent specification allows us to account explicitly for the initial state of the market in which a specific intervention occurs. Almost all regression results of Tables 7 and 8 clearly show that when the market is in the low volatility state, central bank interventions tend to increase volatility (see estimates of $\eta_{2,i}$ $(i = 1, 2)$).[20] Our results also suggest that the unilateral interventions had less power than coordinated ones in "moving" the markets. This tends to be consistent with the main results of the literature.

Nevertheless, it is also found that, when the market is quite volatile (i.e. when the high volatility regime prevails), direct coordinated interventions can have a stabilizing impact. In the second column of Tables 7 and 8 (labelled "Coordinated"), the $\eta_{1,1}$ parameter is negative and significant at the 5% level. To a certain extent, such a result is fairly new in the literature.[21] Furthermore, it holds for *both* pairs of currencies. As suggested by the results reported in the third column of Table 7 (labelled "Coordinated (no lag)"), this stabilizing impact is robust to the choice of the one-week lagging procedure whose goal is to account for the potential endogeneity problem.[22] Quite interestingly, this stabilizing impact occurs in the case of coordinated interventions only when the high volatility regime prevails. It should be stressed that such a result is fully consistent with the signalling approach presented in Dominguez (1998) who shows that an intervention can reduce exchange rate volatility only if such an intervention is credible and its associated signal is unambiguous. If the intervention occurs in the high

[19] Beine, Bénassy-Quéré, and Lecourt (2002) obtain different results across sub-periods concerning the effects of the FED interventions on the conditional mean. While the full period (1985-1995) is associated with positive signs (albeit not always significant), the estimations relative to the 1985-1991 sub-period yield negative signs (net purchases associated to a depreciation).

[20] For instance, when $\eta_{2,1}$ is significantly negative, this means that coordinated interventions tend to reduce the probability of remaining in the low volatility regime and thus tends to increase exchange rate volatility.

[21] Note that this dampening effect of central bank intervention is also found by Murray, Zelmer, and McManus (1996). They show that this effect is specific to some circumstances (including the size of the intervention) but do not make any distinction concerning the prevailing level of volatility.

[22] In contrast with the DEM, for the YEN, previous empirical evidence emphasizes this simultaneity problem even on the volatility side.

volatility regime, the objective of reducing exchange rate volatility is best understood by the market, especially subsequent to the Louvre Agreement which was made public in 1987. By contrast, when the market is less volatile, the signal associated to the intervention is more ambiguous and the resulting effect on exchange rate volatility is definitely positive, a case clearly identified in the signalling approach.[23] These findings are also in agreement with the recent results of Mundaca (2001) in the special case of the interventions carried out by the bank of Norway.[24]

Moreover, it should be noticed that the size of these effects can be substantial. For example, in the case of the DEM, if both central banks intervene once on a particular week in a concerted way whereas the market is in the high volatility regime, the probability of remaining the next week in this regime drops from 89.62% to 54.4%; in other words, the expected number of weeks of high volatility in this market drops from 9.62 weeks (more than two months) to 2.19 weeks.[25] Ceteris Paribus, when both banks intervene three times during the same week, the probability of remaining in a high volatility regime falls below 3%.[26]

Our results also shed an interesting light on the results found in the literature. As illustrated by Baillie and Osterberg (1997 a,b), all studies emphasize either a positive impact or no effect of interventions on exchange rate volatility. Single regime specifications cannot account for the initial state of the market. As a result, the estimates of the effect of the central bank interventions tend to correspond to an average effect. Because the occurrences of the low volatility regime are more frequent (i.e. $\widehat{p}_1 < \widehat{p}_2$ or equivalently $\widehat{\eta}_{1,0} < \widehat{\eta}_{2,0}$ for both exchange rates), single regime estimates tend to be

[23] Another interpretation involves the traded amounts on the market. Indeed, volatility and traded volumes on the market are often related (see for instance MacDonald (2000) on this point). Furthermore, trading volumes reflect the amount of information processed by the market. This could suggest that the way central bank interventions affect the behavior of market participants depends on market activity and the amount of information flows.

[24] Mundaca (2001) shows that the direct interventions carried out by the Bank of Norway were stabilizing when they occurred while the exchange rate was moving around the central parity of the currency band rather than near the weakest edge of this band, and thus when the objective was to decrease exchange rate volatility rather than to support the level of the exchange rate.

[25] The $\eta_{1,0}$ and $\eta_{2,0}$ parameters are expressed on the logistic scale. Given p_{ii}, the expected value of the number of periods with prevailing regime i is equal to $\frac{1}{1-p_{ii}}$.

[26] These computations of course assume that the marginal effect of one additional intervention during a particular week is constant on the logistic scale. When two concerted interventions occur the same week on the DEM/USD market, the probability of remaining in the high volatility regime amounts to 14.19%. This probability is less than 1% when four coordinated interventions are made in the same week. In our dataset, we observe respectively 4 weeks with 4 concerted interventions, 7 weeks with 3 concerted ones and 14 weeks with 2 coordinated interventions.

driven by the effects related to this regime. Our results confirm that these impacts are definitely positive. Next to this, it is found that the effect of coordinated interventions differs drastically from the effect of unilateral interventions. While coordinated interventions influence the volatility patterns of the DEM and the YEN exchange rates, unilateral interventions do not seem to be effective in "moving" the markets. These results are in agreement with the results obtained by several authors including Catte, Galli, and Rebecchini (1992), Dominguez and Frankel (1993) or Weber (1996).

4 Conclusion

In this paper we study the impact of weekly central bank interventions on the level and the volatility of the DEM/USD and YEN/USD exchange rate returns. In contrast with the usual literature which favors GARCH-type specifications, we rely on a regime dependent approach. Because of this new feature, the interventions can have different outcomes depending on the prevailing state of the market. Our estimations suggest that the dynamics of both series is mainly driven by volatility regimes (a high and a low volatility regime). Thanks to out-of-sample forecasting experiments, it is shown that this specification compares very well with GARCH models and thus offers a relevant statistical alternative to the usual methodology presented in the literature.

Our results partly confirm the positive impact of central bank interventions on exchange rate volatility emphasized in the literature. Nevertheless, it is found for *both* the DEM and the YEN that when the market is highly volatile and when market participants expect the central banks to intervene, concerted interventions can have a stabilizing effect. This new result in the empirical literature is consistent with the signalling approach to central bank interventions on the foreign exchange market. It is also consistent with the 1987 Louvre Agreement objective of decreasing excess volatility of exchange rate through direct coordinated interventions. Such a result also sheds an interesting light on previous results obtained with "single regime" specifications. By not taking into account the volatility regime in which the interventions occur, these models tend to favor the impact observed in the most prevailing state of the market, i.e. the low volatility one.

Regarding economic policy issues, our results have two important implications.

First, they confirm previous results according to which coordinated rather that unilateral interventions lead to large effects in the foreign exchange market. Second, our findings suggest that the signal sent to market participants through central bank interventions and hence its impact on exchange rates crucially depends on the current state of the market and the perceived motivation to intervene. This speaks for a more transparent intervention policy followed by central banks.

5 Appendix

For the two-regime model, the variance forecast at time t of a single observation at time $t+j$ (denoted s_{t+j}^2) is computed as:[27]

$$\begin{aligned} s_{t+j}^2 &\equiv var\left[y_{t+j} \mid \tilde{y}_t\right] \\ &= E_t\left[y_{t+j}^2\right] - E_t\left[y_{t+j}\right]^2 \\ &= p_{1t,t+j}\left(\sigma_1^2+\mu_1^2\right) + \left(1-p_{1t,t+j}\right)\left(\sigma_2^2+\mu_2^2\right) \\ &\quad - \left[p_{1t,t+j}\mu_1 + \left(1-p_{1t,t+j}\right)\mu_2\right]^2, \end{aligned}$$

where $\tilde{y}_t = \{y_t, y_{t-1}, ...\}$ and $p_{1t,t+j} = \Pr\left[S_{t+j}=1 \mid \tilde{y}_t\right]$ which is the first element in a two-element vector of regime probabilities for time $t+j$ given by

$$p_{t+j} = p_t' P^j.$$

The j-week variance forecast is then

$$j - \text{week} = \sum_{i=1}^{j} s_{t+i}^2.$$

For the four-regime forecasts, the variance forecasts are constructed in a similar way. For example, for a one-week forecast, we have:

$$\begin{aligned} E_t\left[\sigma_{t+1}^2 \mid \tilde{y}_t\right] &= E_t\left[y_{t+1}^2\right] - E_t\left[y_{t+1}\right]^2 \\ &= p_{1t,t+1}\left(\sigma_1^2+\mu_1^2\right) + p_{2t,t+1}\left(\sigma_1^2+\mu_2^2\right) \\ &\quad + p_{3t,t+1}\left(\sigma_2^2+\mu_1^2\right) + p_{4t,t+1}\left(\sigma_2^2+\mu_2^2\right) \\ &\quad - \left[\left(p_{1t,t+1}+p_{3t,t+1}\right)\mu_1 + \left(p_{2t,t+1}+p_{4t,t+1}\right)\mu_2\right]^2. \end{aligned}$$

[27]See Bollen, Gray, and Whaley (2000).

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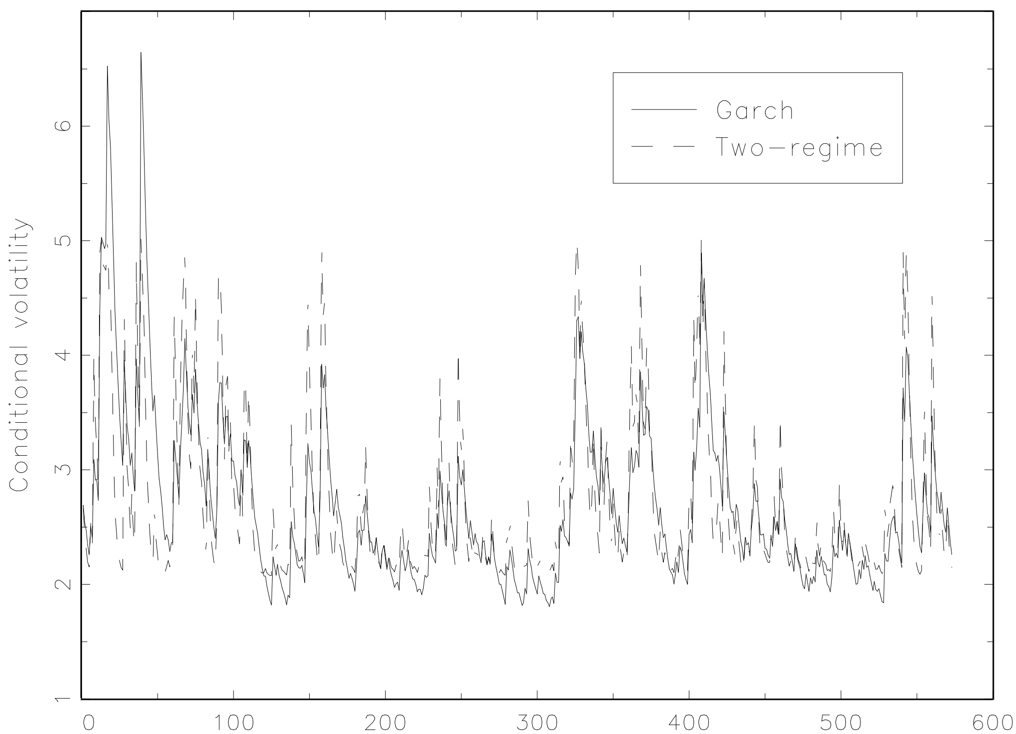

Figure 1: Conditional variances: GARCH vs. two-regime model.

Table 1: Markov Switching models: DEM (1985-1995)

	(1)	(2)	(3)	(4)
μ_1	-0.1381	-0.1513	-0.0241	0.3858
	(0.0685)	(0.0642)	(0.2366)	(0.4141)
μ_2	-	-	-0.1758	-0.3646
			(0.0790)	(0.1410)
σ_1	1.6417	2.3853	2.3872	2.3624
	(0.1033)	(0.3025)	(0.3106)	(0.2962)
σ_2	-	1.2997	1.2997	1.2427
		(0.1020)	(0.1020)	(0.1014)
$p_1/p_{1,\mu}$	-	0.8395	0.8394	0.8576
		(0.0752)	(0.0678)	(0.1714)
$p_2/p_{2,\mu}$	-	0.9466	0.9473	0.9420
		(0.0325)	(0.0339)	(0.0331)
$p_{1,\sigma}$	-	-	-	0.8381
				(0.0760)
$p_{2,\sigma}$	-	-	-	0.9446
				(0.0333)
Q_{20}	25.8038	25.4923	25.5471	26.8022
Q_{20}^2	31.9849	17.9924	18.1727	18.2120
Log-Lik	-1096.594	-1080.408	-1080.264	-1079.185

Standard errors of maximum likelihood estimates are in parentheses. *Log-Lik* refers to the log-likelihood value at maximum. Model (1) has constant mean and variance. In Model (2), only the variance switches. In Model (3), the mean and variance switch simultaneously while in Model (4) they can switch independently.

Table 2: Markov Switching models: YEN (1991-1995)

	(1)	(2)	(3)	(4)
μ_1	-0.1467	-0.1415	-0.1822	0.3736
	(0.0992)	(0.0899)	(0.3884)	(0.6928)
μ_2	-	-	-0.1358	-0.2037
			(0.1108)	(0.2133)
σ_1	1.6364	2.3943	2.3896	2.3846
	(0.2276)	(0.3180)	(0.3307)	(0.3062)
σ_2	-	1.3135	1.3126	1.2991
		(0.0822)	(0.0861)	(0.0944)
$p_1/p_{1,\mu}$	-	0.9481	0.9481	0.8011
		(0.0455)	(0.0455)	(0.1508)
$p_2/p_{2,\mu}$	-	0.9818	0.9816	0.9751
		(0.0156)	(0.0167)	(0.0762)
$p_{1,\sigma}$	-	-	-	0.9469
				(0.0473)
$p_{2,\sigma}$	-	-	-	0.9813
				(0.0159)
Q_{20}	21.0343	17.1436	17.1834	17.1239
Q_{20}^2	29.3048	10.6958	10.6951	11.8250
Log-Lik	-519.422	-508.881	-508.872	-508.835

Note: see Table 1.

Table 3: Variance Forecasts for the models

A. One Week Horizon					
	Two-regime constant mean	*Two-regime*	*Four-regime*	*GARCH(1,1)*	*Random Walk*
RMSE	**4.097**	4.099	4.109	4.164	5.135
HMAE	0.401	0.403	0.411	**0.388**	0.392
LL	1.264	1.273	1.331	**1.157**	1.461
B. Four Week Horizon					
	Two-regime constant mean	*Two-regime*	*Four-regime*	*GARCH(1.1)*	*Random Walk*
RMSE	**4.519**	4.522	4.750	4.533	5.281
HMAE	0.384	0.385	**0.372**	0.413	0.392
LL	**1.226**	1.227	1.275	1.361	1.479
C. Eight Week Horizon					
	Two-regime constant mean	*Two-regime*	*Four-regime*	*GARCH(1.1)*	*Random Walk*
RMSE	4.697	4.703	5.191	**4.642**	5.497
HMAE	**0.364**	0.365	0.464	0.397	0.391
LL	**1.180**	1.184	2.050	1.369	1.526

Bold figures highlight the minimal forecast error.

Table 4: Official and reported central bank interventions, number of days

	Observations	Total number of daily interventions		Coordinated
		(DEM/USD, 1985-1995)		
		FED	BB	
Official	2868	215	264	97
Reported	2868	184	161	-
		(YEN/USD, 1991-1995)		
		FED	BoJ	
Official	1445	16	159	15
Reported	1445	15	22	-

Table 5: Cross correlations between central bank interventions

Discrete variables (DEM/USD, 1985-1995)							
		Levels			Absolute values		
		BB	FED	Coord	BB	FED	Coord
Levels	BB	1	0.647	0.769	-	-	-
	FED		1	0.770	-	-	-
	Coord			1	-	-	-
Absolute values	BB				1	0.594	0.755
	FED					1	0.751
	Coord						1

Table 6: Cross correlations between central bank interventions

Discrete variables (Unilateral) (DEM/USD, 1985-1995)							
		Levels			Absolute values		
		BB	FED	Coord	BB	FED	Coord
Levels	BB	1	0.208	0.346	-	-	-
	FED		1	0.253	-	-	-
	Coord			1	-	-	-
Absolute values	BB				1	0.113	0.289
	FED					1	0.183
	Coord						1

Table 7: Central Bank Interventions, DEM (1985-1995)

	Discrete variables, official interventions		
	Coordinated	Coordinated (no lag)	Unilateral
μ	-0.1475	-0.1627	-0.1760
	(0.0663)	(0.0656)	(0.0696)
ϖ_1 [Coord/BB]	-0.0971	-0.1256	-0.2229
	(0.0964)	(0.1438)	(0.0898)
ϖ_2 [FED]	-	-	0.1398
			(0.0919)
σ_1	2.3100	2.2150	2.3644
	(0.3186)	(0.2000)	(0.4295)
σ_2	1.2771	1.1834	1.2848
	(0.0975)	(0.1173)	(0.0927)
$\eta_{1,0}$	2.1562	1.5501	2.3029
	(1.1973)	(0.6535)	(1.4194)
$\eta_{1,1}$ [Coord/BB]	-1.9778	-2.8840	-0.5312
	(0.9440)	(1.2807)	(0.4362)
$\eta_{1,2}$ [FED]	-	-	-0.4257
			(0.5804)
$\eta_{2,0}$	3.3381	2.4328	3.5558
	(0.9334)	(0.7621)	(0.8762)
$\eta_{2,1}$ [Coord/BB]	-2.1755	-15.2901	-0.3774
	(0.8356)	(2.3933)	(0.3960)
$\eta_{2,2}$ [FED]	-	-	-0.5916
			(0.4626)
p_1	0.8961	0.8249	0.9091
	(0.1113)	(0.0944)	(0.1172)
p_2	0.9651	0.9193	0.9722
	(0.0305)	(0.0565)	(0.0236)
Q_{20}	26.1531	27.1567	25.8283
Q^2_{20}	18.5289	19.9721	18.5653
Log-Lik	-1078.676	-1077.274	-1074.855

Standard errors of maximum likelihood estimates are in parentheses. *Log-Lik* refers to the log-likelihood value at maximum. $y_t = \mu + \sum_{i=1}^{k} \varpi_i x_{i,t-1} + \varepsilon_t$, $p_{s,t} = 1 - [1 + \exp(\eta_{s,0} + \sum_{i=1}^{k} \eta_{s,i} |x_{i,t-1}|]^{-1}$, $p_s = 1 - [1 - \exp(\eta_{s,0})]^{-1}$ and $s = 1, 2$. For coordinated interventions, $x_{1,t}$ stands for the number of official intervention days; for unilateral interventions, $x_{1,t}$ and $x_{2,t}$ stand respectively for the number of official intervention days of the Bundesbank [BB] and of the Federal Reserve [FED]. Column labelled "Coordinated (no lag)" refers to estimations of $p_{s,t}$ based on $|x_{i,t}|$ rather than $|x_{i,t-1}|$.

Table 8: Central Bank Interventions, YEN (1991-1995)

Discrete variables, official interventions		
	Coordinated	Unilateral
μ	-0.1539	-0.1661
	(0.0896)	(0.1520)
ϖ_1 [BoJ/Coord]	-0.6426	0.0122
	(0.4304)	(0.0903)
σ_1	2.7379	2.5407
	(0.5599)	(0.9431)
σ_2	1.3464	1.3117
	(0.0802)	(0.1232)
$\eta_{1,0}$	2.1913	2.7183
	(1.8748)	(2.7587)
$\eta_{1,1}$ [BoJ/Coord]	-12.9226	-1.4253
	(1.6359)	(13.7202)
$\eta_{2,0}$	3.8605	3.6524
	(0.8717)	(2.6839)
$\eta_{2,1}$ [BoJ/Coord]	-3.0663	-0.5383
	(1.6830)	(0.3429)
p_1	0.8995	0.9380
	(0.1695)	(0.1602)
p_2	0.9794	0.9747
	(0.0176)	(0.0661)
Q_{20}	18.0481	17.8551
Q_{20}^2	20.1797	19.2777
Log-Lik	-506.868	-507.742

Standard errors of maximum likelihood estimates are in parentheses. *Log-Lik* refers to the log-likelihood value at maximum. $y_t = \mu + \sum_{i=1}^{k} \varpi_i x_{i,t-1} + \varepsilon_t$, $p_{s,t} = 1 - [1 + \exp(\eta_{s,0} + \sum_{i=1}^{k} \eta_{s,i} |x_{i,t-1}|]^{-1}$, $p_s = 1 - [1 - \exp(\eta_{s,0})]^{-1}$ and $s = 1, 2$. For coordinated interventions, $x_{1,t}$ stands for the number of official intervention days; for unilateral interventions, $x_{1,t}$ stands for the number of official intervention days of the Bank of Japan [BoJ].