Intervention of the Bank of Japan in Foreign Exchange Market and Its Effects on Volatility of Returns

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Abstract

In this article, we perform several tests to determine whether the intervention of the Bank of Japan has an asymmetric effect through GARCH type models. Furthermore, we use realized volatility calculated by high-frequency exchange rate data to check the adequacy of the estimated volatility from GARCH type models.

Key Words : Intervention; Realized volatility; GARCH type models; High-frequency exchange rate data
JEL Classification : C20; E58; F31

1 Introduction

One of the main roles of the central bank of any country is to stabilize its exchange rate. As is often observed the exchange rate is volatile randomly over time and the central bank often intervenes to mitigate the volatility. However, the effect of the intervention by the central bank seems so vague and inconclusive that many researchers in economics and econometrics have been investigating its effectiveness for long time. Chang and Taylor (1998) and Dominguez (1998) have introduced intervention variables as explanatory variables into the mean and volatility equations in the ARCH model proposed by Bollerslev (1986) to investigate the effects of intervention. Ito (2002) has found that the intervention of the Bank of Japan (abbreviated as BOJ hereinafter) was effective in the late 1990s and the first few years of the 2000s (from June 21, 1995 to March 31, 2003). Watanabe and Harada (2006) identify new evidence on the effects of the BOJ's intervention on the yen/dollar exchange rate volatility based on the component GARCH model. In empirical studies it is often pointed out that the shocks to the financial market do not generate equal responses. For stock markets, negative shocks have been found to generate a larger response than positive shocks of equal magnitude. This empirical phenomenon is often referred to as asymmetric volatility in the literature (see Engle and Ng, 1993; Zakoian, 1994). This phenomenon has been attributed to the leverage effect for stock markets. For exchange rates, asymmetry has also been documented with no apparent economic reason. Yet, ARCH models that allow asymmetric responses have been successfully fitted to exchange rate data (see Hsieh, 1989; Byres and Peel, 1995; Kam, 1995; Hu et al., 1997; Tse and Tsui, 1997; Kim, 1998, 1999; Lu, 2007). McKenzie (2002) attributes the presence of asymmetric responses in exchange rate volatility to the intervention activity of the central bank, which suggests that intervention might do more harm than good in volatile markets.

In this article, we perform several tests to determine whether the intervention of Bank of Japan has an

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asymmetric effect through GARCH type models. For this purpose we will take two approaches: First, to determine whether there is any asymmetric effect on the exchange rate volatility, we analyze GJR, EGARCH and APGARCH models, which can reflect asymmetry of the volatility under the constant mean equation. In addition, we introduce the dummy variable D_t , which takes 1 when the intervention takes place and 0 elsewhere, in the variance equations in keeping the mean equation constant in GARCH type models. The significant estimate of the coefficient of D_t suggests that the intervention has an effect on the exchange rate volatility. We call the first approach as 'variance equation approach'. Second, to determine whether the intervention has an effect on the mean equation of the exchange rate, we apply Ito's (2002) model whose mean equation has explanatory variables associated with the intervention in assuming that the variance equation is a symmetric GARCH process. We use the volume of intervention as an explanatory variable directly in the mean equation with symmetric variance equation. We call the second approach as 'mean equation approach'.

We also apply analysis of variance by F-test to test the effectiveness of the intervention using two sample periods divided by intervention day. Furthermore, we use realized volatility (abbreviated as RV hereinafter) calculated by high-frequency exchange rate data to check the adequacy of the estimated volatility from GARCH type models.

This article is organized as follows: In Section 2 we inspect the time series of exchange rate, returns, RV and intervention by BOJ by graphs. In Section 3 we analyze the various GARCH type models in keeping the mean equation constant and test if the intervention by BOJ has asymmetric effects on the volatility. In Section 4 we investigate the asymmetric effects of the intervention on the mean equation of Ito model in assuming that the volatility is symmetric. Section 5 concludes our analysis.

2 Intervention of BOJ

2. 1 Graphical Inspection

We analyze the effect of the intervention of BOJ in the foreign exchange market by using the data of intervention by BOJ (called intervention data hereafter) and high-frequency data of Yen/Dollar exchange rate. The intervention data can be obtained from the Web site of Ministry of Finance Japan, Foreign Exchange Intervention Operations (www.mof.go.jp/1c021.htm). We use the one-minute high-frequency data supplied by Olsen. However, as is generally recognized one-minute high-frequency data are contaminated by micro structure noise. To remove this noise we convert the one-minute frequency to five minutes by taking the last observation of the bid-ask average within every five-minute segment in time series. We omitted the data on Saturday, Sunday and the days which the number of trade is less than 100 times. The data period is from 1991/04/01 to 2006/08/31 (whole sample period, hereinafter), with a total of 3959 observations. At first we visually inspect the data by graphs. Fig.1 is the series of Yen/Dollar exchange rate and Japanese intervention of the whole sample period. Throughout this article the scale in the left side is for the exchange rate (¥/$) and in the right side is for the amount of intervention (¥) when the two time series are shown in one graph and the scale of the horizontal line does not denote the real time but the consecutive number of the observations (y_t). We introduce the following notations and definitions:

$y_{t,j}$: j-th five-minute high-frequency exchange rate in a day t, $j=1,...,n$

$r_{t,j}$: j-th log-return of the exchange rate in a day t, or $r_{t,j}=\log(y_{t,j})-\log(y_{t-1,j})$.

The RV is defined by

$$RV=\sum_{j=1}^{n} r_{t,j}^{2}$$

By using Olsen's five-minute high-frequency time series data of Yen/Dollar exchange rates from 1991/05/01 to 2006/08/31, we calculated the returns and the RV which are shown in Fig.2. Fig.3 is the histogram and descriptive statistics of the returns. We can see the distribution of the returns has a long tail and a sharp peak around the origin. Fig.4 is the histogram and descriptive statistics of the RV. It seems like lognormal distribution. Fig.5 is the histogram and descriptive statistics of the Log-RV. It looks like normal distribution but has a longer tail.

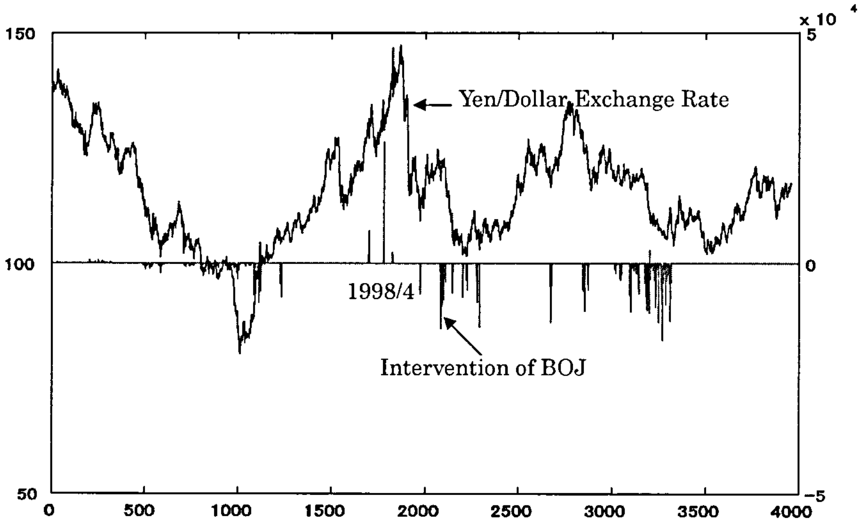

Fig.1 : The ¥/$ Exchange Rate and BOJ's Intervention from 1991/05/01 to 2006/08/31

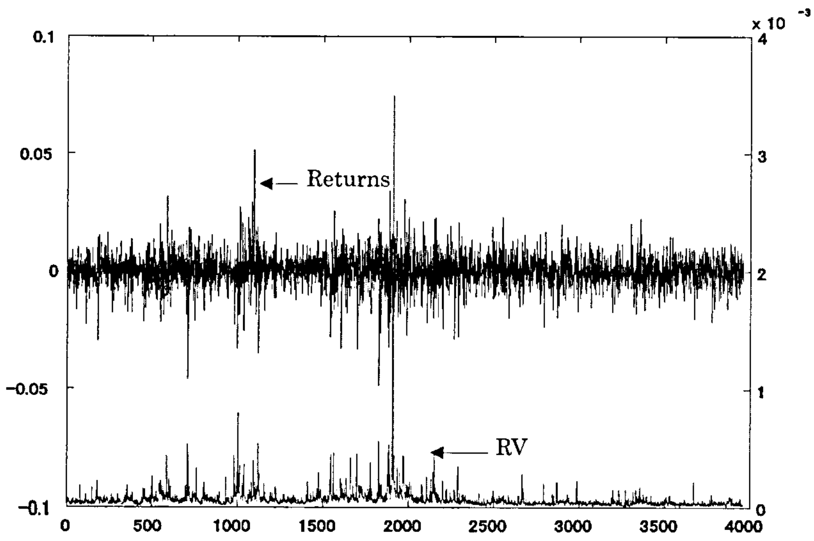

Fig.2 : The Returns and the Realized Volatility from 1991/05/01 to 2006/08/31

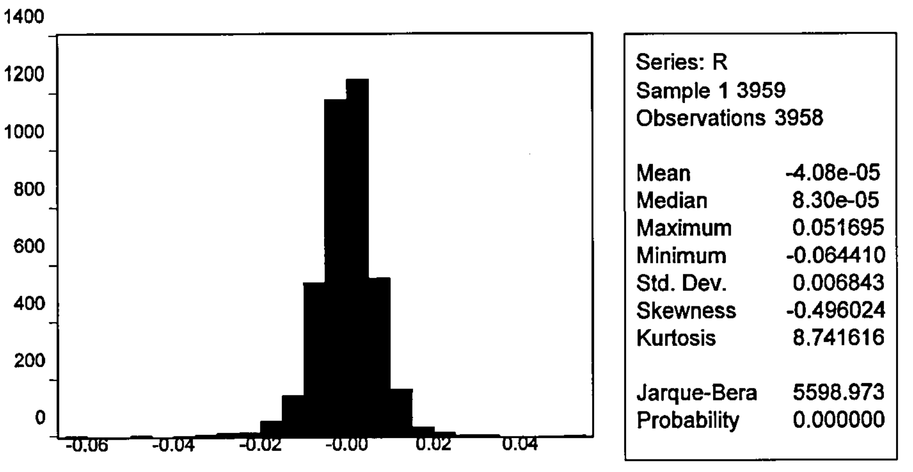

Fig.3 : The Histogram and Descriptive Statistics of the Returns from 1991/05/01 to 2006/08/31

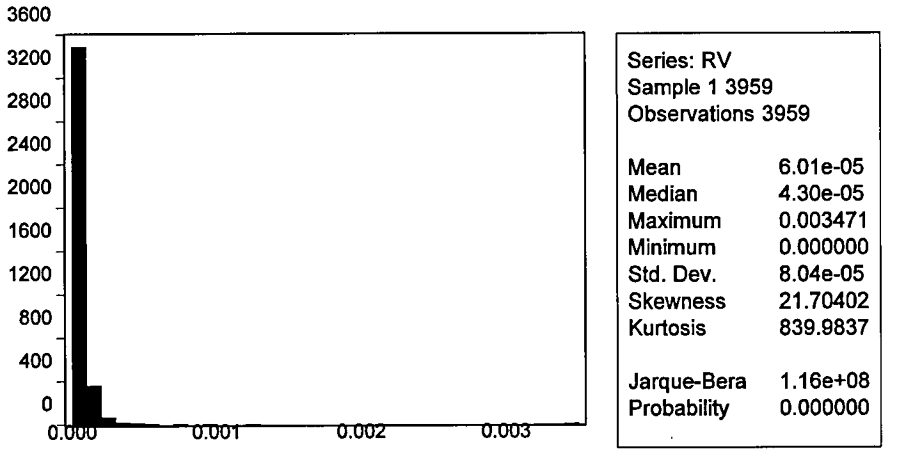

Fig.4 : The Histogram and Descriptive Statistics of the RV from 1991/05/01 to 2006/08/31

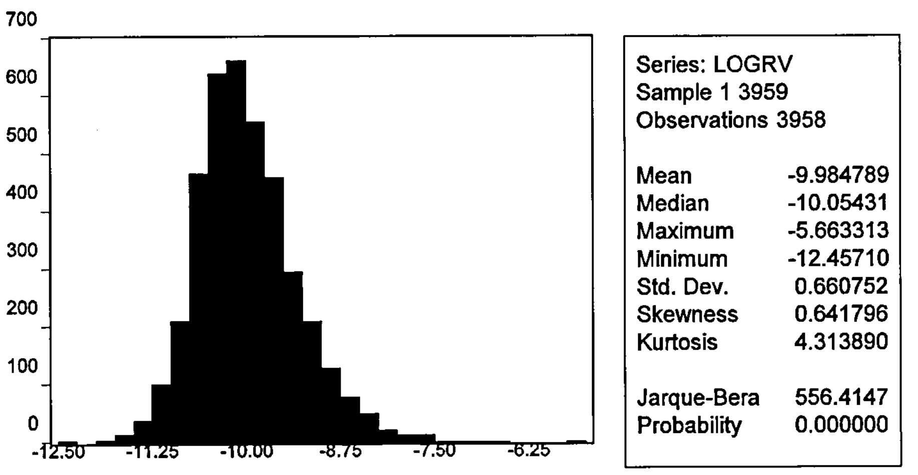

Fig.5 : The Histogram and Descriptive Statistics of the Log-RV from 1991/05/01 to 2006/08/31

2. 2 1998 Intervention

As shown in Fig.1 there is a striking intervention on 1998/04/10. We focus on this occasion and analyze the effect of this intervention by Olsen's five-minute high-frequency exchange rate data. We take a close-up of the period of 1998/01/01-1998/12/31. The data of the level and return in this period are shown in Fig.6 and Fig.7 respectively. A large jump is observed in Fig.6, which is due to Russian economic crisis. The RV series is shown in Fig.8.

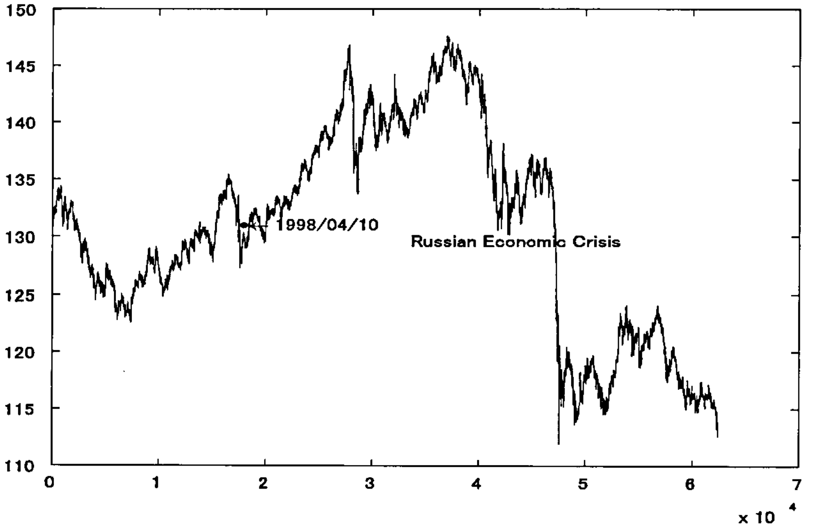

Fig.6 : The ¥/$ Exchange Rate from 1998/01/01 to 1998/12/31

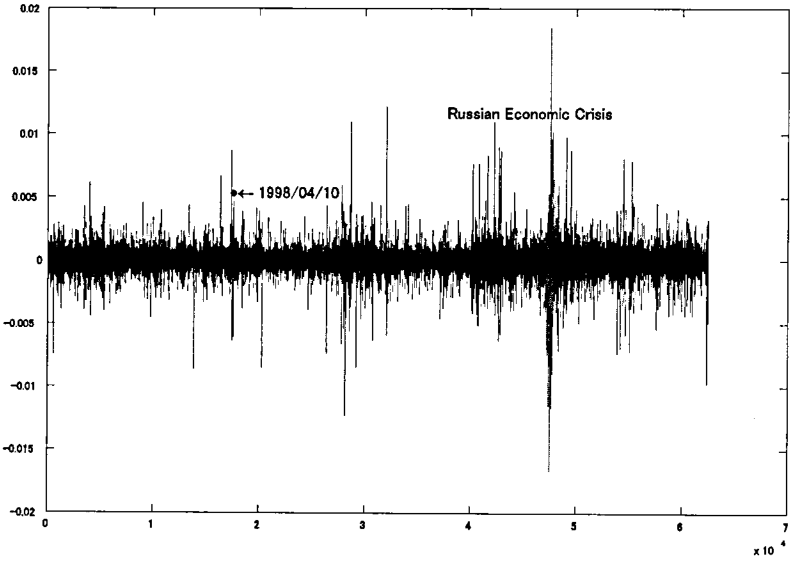

Fig.7 : The ¥/$ Exchange Rate Returns from 1998/01/01 to 1998/12/31

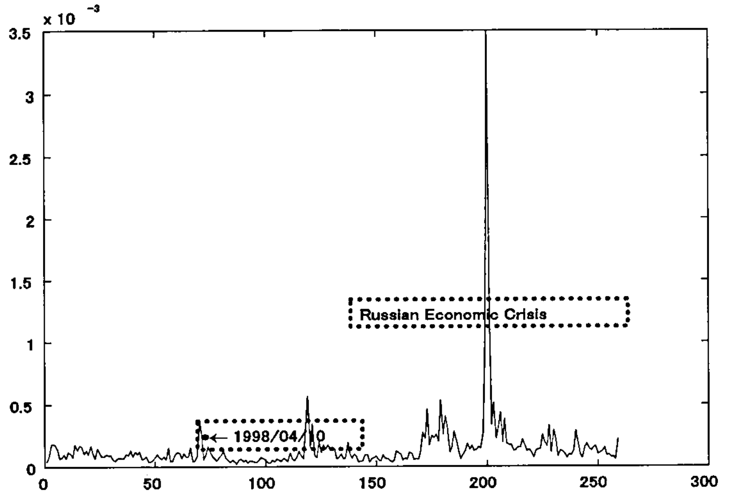

Fig.8 : The ¥/$ Exchange Rate Realized Volatility from 1998/01/01 to 1998/12/31

To focus the largest intervention on 1998/04/10 we visually inspect the data of exchange rate and the return from 1998/03/10 to 1998/05/10 which is shown in Fig.9 and Fig.10 respectively. Fig.11 is the graph of the RV calculated from the five-minute high-frequency data of the exchange data of this period. As far as this graph shows the intervention does not have any significant effect on RV in this short range of time except the day of the intervention.

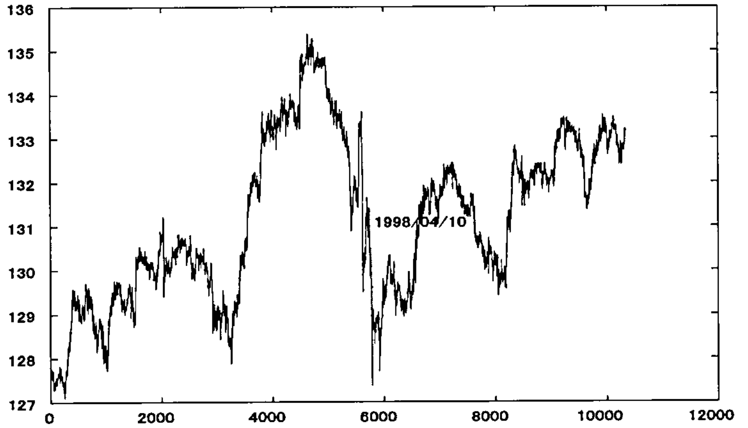

Fig.9 : The ¥/$ Exchange Rate from 1998/03/10 to 1998/05/10

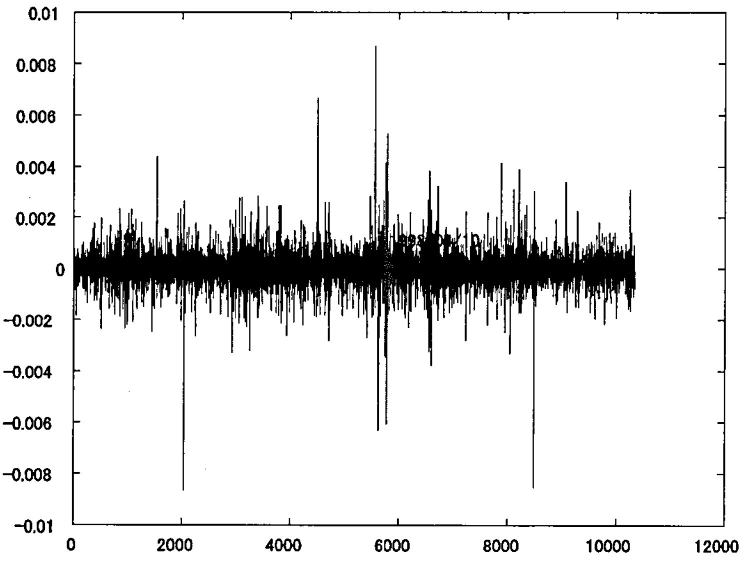

Fig.10 : The ¥/$ Exchange Rate Returns from 1998/03/10 to 1998/05/10

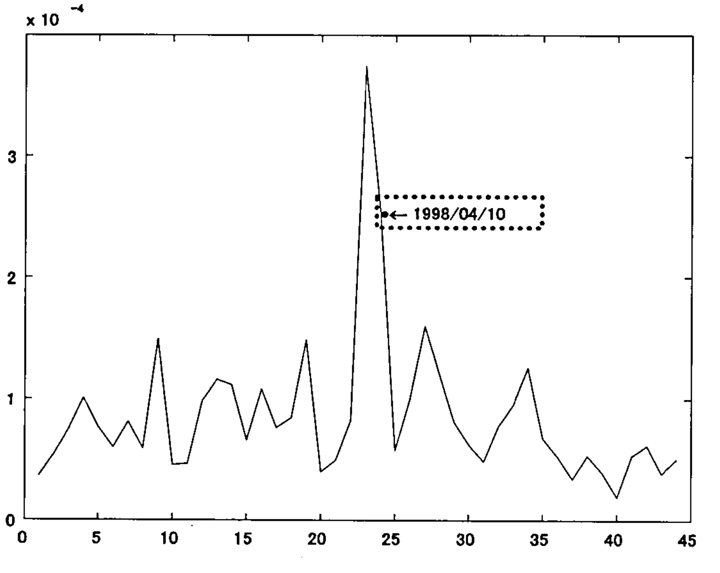

Fig.11 : The ¥/$ Exchange Rate Realized Volatility from 1998/03/10 to 1998/05/10

3 Asymmetric Effect of the Intervention on Volatility

3. 1 Models of Asymmetric Volatility

One of our aims in this article is to test whether the intervention of BOJ has an asymmetric effect on volatility. To see this we investigate the following volatility models, which can reflect asymmetry of the volatility except GARCH (1,1) model.

GARCH (1,1) Model (Bollerslev, 1986) of the return R_t :

$$R_t = \varepsilon_t,\ \varepsilon_t = \sigma_t z_t,\ \sigma_t > 0,\ z_t \sim \text{i.i.d.,N(0,1)},$$
$$\sigma_t^2 = \omega + a\,\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,\ \omega > 0,\ \alpha,\beta \geq 0.$$

GJR Model (Glosten et al., 1993) :

$$\sigma_t^2 = \omega + a\,\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma D_{t-1}^{*}\,\varepsilon_{t-1}^2,$$
$$\omega > 0,\ \alpha,\beta,\gamma \geq 0,$$

where $D_{t-1}^{*}=0$, if $\varepsilon_{t-1} \geq 0$, and $D_{t-1}^{*}=1$, if $\varepsilon_{t-1} < 0$.
Alternatively, we can write GJR model as

$$\sigma_t^2 = \omega + a\,\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,\ \text{if } \varepsilon_{t-1} \geq 0,$$
$$\sigma_t^2 = \omega + (a+\gamma)\,\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,\ \text{if } \varepsilon_{t-1} < 0.$$

So we can say, if $\gamma > 0$, there is an asymmetric effect.

EGARCH Model (Nelson, 1991) :

$$\ln(\sigma_t^2) = \omega + \beta\{\ln(\sigma_{t-1}^2) - \omega\} + \theta\varepsilon_{t-1} + \gamma\{|\varepsilon_{t-1}| - \text{E}(|\varepsilon_{t-1}|)\}.$$

There is no need to set the parameters to be non-negative for the $\ln(\sigma_t^2)$ is used as the explained variable.
Alternatively, we can write this model as

$$\ln(\sigma_t^2) = \omega + \beta\{\ln(\sigma_{t-1}^2) - \omega\} + (\gamma + \theta)\,|\varepsilon_{t-1}| - \gamma\text{E}(|\varepsilon_{t-1}|),\ \text{if } \varepsilon_{t-1} \geq 0,$$
$$\ln(\sigma_t^2) = \omega + \beta\{\ln(\sigma_{t-1}^2) - \omega\} + (\gamma - \theta)\,|\varepsilon_{t-1}| - \gamma\text{E}(|\varepsilon_{t-1}|),\ \text{if } \varepsilon_{t-1} < 0.$$

So we can say, if $\theta < 0$, there is an asymmetric effect.

APGARCH Model (Ding et al., 1993) :

$$\sigma_t^{\delta} = \omega + \beta\sigma_{t-1}^{\delta} + \alpha\,(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta},$$
$$\omega,\delta > 0,\ \alpha,\beta \geq 0,\ -1 < \gamma < 1.$$

Alternatively, we can write this model as

$$\sigma_t^{\delta} = \omega + \beta\sigma_{t-1}^{\delta} + \alpha\,(1-\gamma)^{\delta}|\varepsilon_{t-1}|^{\delta},\ \text{if } \varepsilon_{t-1} \geq 0,$$
$$\sigma_t^{\delta} = \omega + \beta\sigma_{t-1}^{\delta} + \alpha\,(1+\gamma)^{\delta}|\varepsilon_{t-1}|^{\delta},\ \text{if } \varepsilon_{t-1} < 0.$$

So we can say, if $\gamma > 0$, there is an asymmetric effect.

We estimate the above models by the maximum likelihood (ML) method by using Olsen's five-minute high-frequency exchange rate data from 1991/04/01 to 2006/09/30. The resulted estimates are shown in Tables 1-4, under the assumption that ε_t is generated from the normal or t-distribution. As the log-likelihood function varies depending on the assumption used, ML estimate differs according to the distributional assumption. All the ML estimates are shown for each assumption in Tables 1-4 and all of them are significant, especially $\gamma > 0$ in the GJR Model and APGARCH Model, $\theta < 0$ in the EGARCH Model which means the asymmetric phenomenon exists in the exchange rate volatility.

Table 1 : MLE for GARCH, $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$, $\omega > 0$, $\alpha, \beta \geq 0$

	Under Normal Distribution	Under t-Distribution
ω	7.80E-07	7.52E-07
	(6.7339)	(3.7528)
α	0.0471	0.0401
	(12.9270)	(6.1368)
β	0.9364	0.9428
	(179.0168)	(101.8351)
Log likelihood	14339.28	14460.28

Note : z-statistic in parentheses.

Table 2 : MLE for GJR, $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma D_{t-1}^{*}\varepsilon_{t-1}^2$, $\omega > 0$, $\alpha, \beta, \gamma \geq 0$

	Under Normal Distribution	Under t-Distribution
ω	8.04E-07	7.61E-07
	(6.8718)	(3.8494)
α	0.0415	0.0322
	(9.3635)	(3.8771)
β	0.9359	0.9438
	(177.2566)	(102.5194)
γ	0.0107	0.0125
	(2.2271)	(1.3394)
Log likelihood	14340.15	14460.61

Note : z-statistic in parentheses.

Table 3 : MLE for EGARCH, $\ln(\sigma_t^2) = \omega + \beta\{\ln(\sigma_{t-1}^2) - \omega\} + \theta\varepsilon_{t-1} + \gamma\{|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)\}$,

	Under Normal Distribution	Under t-Distribution
ω	-0.2811	-0.2565
	(-8.7571)	(-4.6755)
β	0.9813	0.9825
	(348.9340)	(203.7535)
ϑ	-0.0169	-0.0185
	(-4.2361)	(-2.2417)
γ	0.1227	0.1048
	(14.8844)	(6.9679)
Log likelihood	14338.84	14460.99

Note : z-statistic in parentheses.

Table 4 : MLE for APGARCH: $\sigma_t^{\delta} = \omega + \beta\sigma_{t-1}^{\delta} + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta}$,
$\omega, \delta > 0$, $\alpha, \beta > -0$, $-1 < \gamma < 1$

	Under Normal Distribution	Under t-Distribution
ω	1.17E-05	1.64E-05
	(1.2567)	(0.7737)
α	0.0588	0.0499
	(11.1820)	(5.7102)
β	0.9335	0.9419
	(172.1768)	(99.8146)
γ	0.1011	0.1487
	(3.4227)	(1.8966)
δ	1.4703	1.3893
	(9.3736)	(5.4676)
Log likelihood	14342.61	14462.65

Note : z-statistic in parentheses.

3. 2 Intervention Effect in the Asymmetric Volatility Models

To determine whether the intervention of BOJ has any asymmetric effects on the volatility, we add the dummy variable D_t in the right side of the variance equations, where 1 is assigned for intervention and 0 elsewhere. If the coefficient of D_t is significant, we can say that the intervention has an effect on the exchange rate volatility. The variance equation with the dummy variable in GARCH family is written as follows :

for GARCH (1,1) Model : $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \phi D_t,$

for GJR Model : $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma D_{t-1}^{*}\varepsilon_{t-1}^2 + \phi D_t,$

for EGARCH Model : $\ln(\sigma_t^2) = \omega + \beta\{\ln(\sigma_{t-1}^2) - \omega\} + \theta\varepsilon_{t-1} + \gamma\{|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)\} + \phi D_t,$

for APGARCH Model : $\sigma_t^\delta = \omega + \beta\sigma_{t-1}^\delta, + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \phi D_t.$

We estimate the above models under the normality assumption of ε_t by using the same exchange rate data from 1991/04/01 to 2006/09/30. The resulted estimates are shown in Tables 5-7.

The estimates are not significant under the assumption of ε_t is t-distribution except the GARCH Model, and the estimates are significant under the assumption of ε_t is normal distribution in both the asymmetric coefficients, $\gamma > 0$ in the GJR Model and in the EGARCH Model, and the dummy coefficient ϕ. That means the asymmetric phenomenon exists in the exchange rate volatility, and the intervention has an effect on the volatility.

Table 5 : MLE for GARCH (t-Distribution), $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \phi D_t,\ \omega > 0,\ \alpha, \beta \geq 0$

ω	7.31E-07
	(6.2463)
α	0.0467
	(12.9443)
β	0.9371
	(179.8163)
ϕ	4.22E-07
	(2.2342)
Log likelihood	14340.36

Note : z-statistic in parentheses.

Table 6 : MLE for GJR (Normal Distribution), $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma D_{t-1}^{*}\varepsilon_{t-1}^2 + \phi D_t,\ \omega > 0,\ \alpha, \beta, \gamma \geq 0$

ω	7.59E-07
	(6.3990)
α	0.0419
	(9.3582)
β	0.9364
	(177.5532)
γ	0.0094
	(1.9261)
ϕ	3.79E-07
	(2.0184)
Log likelihood	14341.01

Note : z-statistic in parentheses.

Table 7 : MLE for EGARCH (Normal Distribution), $\ln(\sigma_t^2) = \omega + \beta\{\ln(\sigma_{t-1}^2) - \omega\} + \theta\varepsilon_{t-1} + \gamma\{|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)\}$

ω	-0.2701
	(-8.5634)
β	0.9825
	(353.6671)
ϑ	-0.0134
	(-3.3472)
γ	0.1217
	(14.9891)
ϕ	0.0197
	(3.8938)
Log likelihood	14341.41

Note : z-statistic in parentheses.

3. 3 A Comparison of RV and Estimated Volatility

As we are interested in how accurate the variance equation σ_t^2 in GARCH (1,1) is estimated, we compare RV and estimated volatility $\hat{\sigma}_t^2$ by the following magnified image graphs to distinguish the two series clearly. Fig.12a (for the period of t=900,...,1150) and Fig.12b (for the period of t=3709,...,3959) show the observed RV and the estimated $\hat{\sigma}_t^2$. We can see the estimated volatility can catch the movement of the RV very well. In other words the estimated volatility looks like a smoothed line of RV. The same phenomenons were seen in the case of the GJR model, the EGARCH model and the APGARCH model. We omit them here for brevity. We also omit the graphs in the case of the models with a dummy variable.

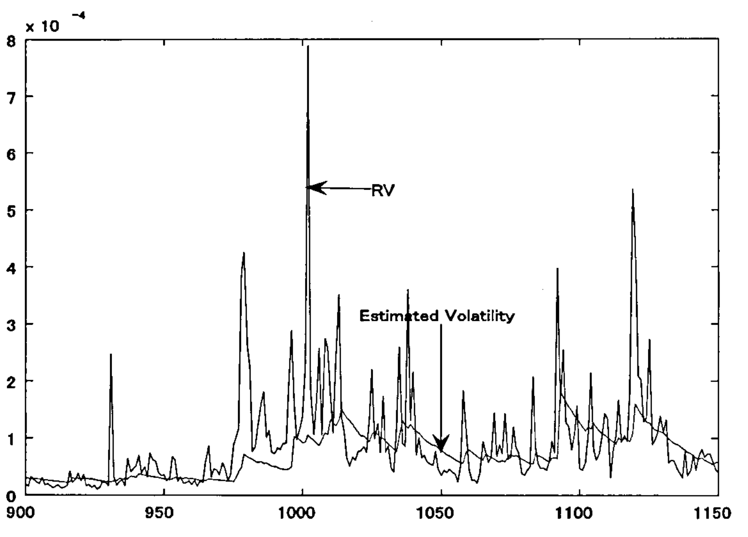

Fig.12a : Realized Volatility and the Estimated Volatility $\hat{\sigma}_t^2$ for t =900,...,1150

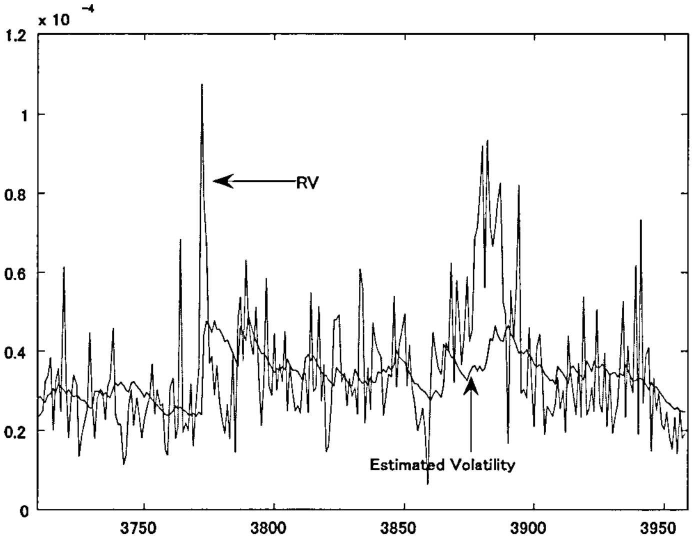

Fig.12b : Realized Volatility and the Estimated Volatility $\hat{\sigma}_t^2$ for t =3709,...,3959

As we can regard RV as the proxy variable of the true volatility, we can evaluate the performance of the asymmetric GARCH type model by comparing RV and the estimated volatility $\hat{\sigma}_t^2$ by RMSE (root mean squared error), RMSPE (root mean squared percentage error), MAE (mean absolute error) and MAPE (mean absolute percentage error). These measures are defined as follows :

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(RV_t - \hat{\sigma}_{t|t-1}^2\right)^2} \qquad \mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|RV_t - \hat{\sigma}_{t|t-1}^2\right|$$

$$\mathrm{RMSPE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\frac{RV_t - \hat{\sigma}_{t|t-1}^2}{RV_t}\right)^2} \qquad \mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{RV_t - \hat{\sigma}_{t|t-1}^2}{RV_t}\right|$$

The results are shown in Table 8. We find : (1) The estimated volatility $\hat{\sigma}_t^2$ in GJR Model is the best approximation to RV when evaluated by RMSPE. (2) APGARCH Model is the best when evaluated by RMSE, MAE and MAPE. (3) In any case, the performance of the model with asymmetric volatility is better than pure GARCH model. We omit results in the case of the models with a dummy variable.

Table 8 : Volatility Forecast Performance (Interpolation)

	RMSPE	RMSE	MAE	MAPE
GARCH_N	8.2666	1.8595	0.2526	0.3881
GARCH_T	8.8795	1.1936	0.2528	0.3846
GJR_N	8.2130	1.7846	0.2517	0.3868
GJR_T	8.8665	1.0908	0.2519	0.3835
EGARCH_N	8.6231	1.7450	0.2492	0.3843
EGARCH_T	9.2049	1.0721	0.2510	0.3826
APGARCH_N	8.4356	1.5491	0.2487	0.3818
APGARCH_T	9.0764	0.8862	0.2501	0.3797

3.4 Intervention Effect on RV

Next we detect the intervention effect on RV by the following equation :

$$RV = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \alpha_2 RV_{t-1} + \alpha_3 D_t, \qquad (1)$$

where D_t is the same dummy variable in Section 3.2 to represent the intervention by BOJ. $\hat{\varepsilon}_t$ is the OLS residual calculated from Ito Equations (2) and (3) in the next section 4.1 and the simplest mean equation of the return : $r_t = c + \varepsilon_t$. The estimated parameters of $\hat{\alpha}_0$, $\hat{\alpha}_1$, $\hat{\alpha}_2$, $\hat{\alpha}_3$, calculated by using the above three kinds of residuals $\hat{\varepsilon}_t$ are shown in Tables 9-11.

Table 9 : Estimated Parameters in Model (1) Based on OLS Residual from Model (2)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\alpha}_0$	2.33E-05	1.19E-06	19.64307	0.0000
$\hat{\alpha}_1$	0.276274	0.008586	32.17670	0.0000
$\hat{\alpha}_2$	0.381322	0.012989	29.35719	0.0000
$\hat{\alpha}_3$	1.39E-05	3.32E-06	4.196554	0.0000
R-squared	0.473099	Mean dependent var		6.00E-05
Adjusted R-squared	0.472699	S. D. dependent var		8.04E-05
S.E. of regression	5.84E-05	Akaike info criterion		-16.65697
Sum squared resid	1.35E-05	Schwarz criterion		-16.65062
Log likelihood	32951.50	Durbin-Watson stat		2.166679

Table 10 : Estimated Parameters in Model (1) Based on OLS Residual from Model (3)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\alpha}_0$	2.37E-05	1.20E-06	19.73339	0.0000
$\hat{\alpha}_1$	0.256136	0.008479	30.21006	0.0000
$\hat{\alpha}_2$	0.387950	0.013194	29.40338	0.0000
$\hat{\alpha}_3$	1.45E-05	3.36E-06	4.324639	0.0000
R-squared	0.459810	Mean dependent var		6.00E-05
Adjusted R-squared	0.459400	S. D. dependent var		8.04E-05
S.E. of regression	5.91E-05	Akaike info criterion		-16.63207
Sum squared resid	1.38E-05	Schwarz criterion		-16.62571
Log likelihood	32902.23	Durbin-Watson stat		2.165455

Table 11 : Estimated Parameters in Model (1) Based on OLS Residual from $r_t = c + \varepsilon_t$

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\alpha}_0$	2.41E-05	1.21E-06	19.94611	0.0000
$\hat{\alpha}_1$	0.239888	0.008249	29.07937	0.0000
$\hat{\alpha}_2$	0.389090	0.013357	29.12971	0.0000
$\hat{\alpha}_3$	1.54E-05	3.38E-06	4.546312	0.0000
R-squared	0.452238	Mean dependent var		6.00E-05
Adjusted R-squared	0.451822	S. D. dependent var		8.04E-05
S.E. of regression	5.96E-05	Akaike info criterion		-16.61840
Sum squared resid	1.40E-05	Schwarz criterion		-16.61205
Log likelihood	32883.50	Durbin-Watson stat		2.156528

From these tables we can see that $\hat{\alpha}_3$ is around 1.4×10^{-5} and significant, which means that the intervention by BOJ has positive effect on RV.

4 Asymmetric Effect of the Intervention on the Mean Equation

4. 1 Estimation of Ito Model

So far have we focused on the variance equation to determine whether BOJ's intervention has any asymmetric effect on the volatility and introduced a variable to represent the asymmetric effect in the variance equation. In this section we change our standpoint from the variance equation to the mean equation of the volatility model to see if the intervention has asymmetric effects in the mean equation. To do so we introduce the amount of intervention as an explanatory variable directly in the mean equation. Instead we use the symmetric variance equation. Along this line Ito (2002) proposed the following model with GARCH (1,1) error term :

$$s_t - s_{t-1} = \beta_0 + \beta_1(s_{t-1} - s_{t-2}) + \beta_2(s_{t-1} - s^T_{t-1}) + \beta_3 Int_t + \beta_4 IntF_t + \beta_5 IntI_t + \varepsilon_t \tag{2}$$

where

$\varepsilon_t = z_t \sigma_t$, with $z_t \sim N(0,1)$, $\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \sigma^2_{t-1}$.

s_t : log of spot rate of day t,

s^T_t : log of long-run equilibrium exchange rate, 125 yen (following Ito, 2002, we set long-run equilibrium at 125 ¥/$, because 125 ¥/$ was the dividing line between yen selling and purchasing),

Int : the Japanese intervention (in 100 million yen),

IntF : the US intervention by Federal Reserve Board (FRB, in million dollars),

IntI : the initial intervention (Int: if no intervention in 5 proceeding business days; 0: otherwise).

The initial intervention and the exchange rate are shown in Fig.13. If the interventions by BOJ are effective, then we expect $\beta_3 < 0$. For example, if the yen-purchasing intervention ($Int > 0$) by BOJ tends to appreciate the yen $s_t - s_{t-1} < 0$, then the negative sign of β_3 should be obtained. The US interventions (positive for yen purchasing) are judged to be effective when β_4 is negative. The total effects of the joint interventions are measured by $\beta_3 + \beta_4$. Because all of the US interventions were joint interventions, the magnitude of β_4 may contain any of the nonlinear effects of the joint interventions. The coefficient of β_5 shows the effectiveness of the first intervention in more than a week beyond just as one of the interventions. Such a variable is originally introduced by Humpage (1998). The full impact of the first intervention is measured by $\beta_3 + \beta_5$.

We basically follow the Ito model but the data of *IntF* are not available for us. As a result we had to omit *IntF* and hence our model is written as

$$s_t - s_{t-1} = \beta_0 + \beta_1(s_{t-1} - s_{t-2}) + \beta_2(s_{t-1} - s^T_{t-1}) + \beta_3 Int_t + \beta_5 IntI_t + \varepsilon_t \tag{3}$$

where we assume ε_t follows GARCH (1,1) as in Model (2). The estimated parameters of Model (3) are shown in Table 12.

Table 12 : Estimation of GARCH (1,1) Model (3) for the Whole Sample Period (1991/05/01-2006/08/31)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\beta}_0$	-0.000280	0.000127	-2.204596	0.0275
$\hat{\beta}_1$	-0.004779	0.015957	-0.299528	0.7645
$\hat{\beta}_2$	-0.002372	0.001017	-2.332115	0.0197
$\hat{\beta}_3$	-3.24E-07	9.40E-08	-3.444624	0.0006
$\hat{\beta}_5$	-7.75 E-06	1.58E-07	-4.892442	0.0000
$\hat{\alpha}_0$	7.64E-07	1.20E-07	6.394569	0.0000
$\hat{\alpha}_1$	0.046269	0.003834	12.06755	0.0000
$\hat{\alpha}_2$	0.937273	0.005491	170.6948	0.0000

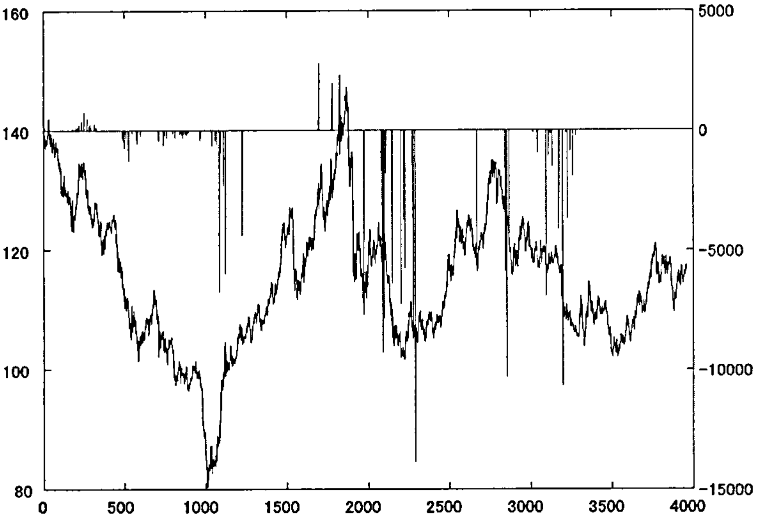

Fig. 13 : The ¥/$ Exchange Rate and Japanese Initial Intervention from 1991/05/01 to 2006/08/31

4. 2 Variants of Ito Model

As depicted in the previous sections there are extreme returns and RVs at Russian economic crisis. To deal with these extreme values we introduce a dummy variable, D_t , in which 1 is assigned for 1998/10/07, 1998/10/08, 1998/10/09, and 0 elsewhere. By using this dummy variable we rewrite Ito Model (3) as follows :

$$s_t - s_{t-1} = \beta_0 + \beta_1(s_{t-1} - s_{t-2}) + \beta_2(s_{t-1} - s^T_{t-1}) + \beta_3 Int_t + \beta_5 IntI_t + \beta_6 D_t + \varepsilon_t \qquad (4)$$

The estimates of the Equation (4) are shown in Table 13. As is seen the estimated coefficient for $\hat{\beta}_6$ is significant. Comparing Table 13 with Table 12, we notice that the significance level of $\hat{\beta}_1$ is slightly improved in Table 13, and $\hat{\beta}_5$ becomes much smaller in Table 13.

Table 13 : Estimation of GARCH (1,1) Model (4) for the Whole Sample Perio (1991/05/01-2006/08/31)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\beta}_0$	-0.000276	0.000127	-2.177101	0.0295
$\hat{\beta}_1$	-0.012031	0.016055	-0.749370	0.4536
$\hat{\beta}_2$	-0.002360	0.001016	-2.323121	0.0202
$\hat{\beta}_3$	-3.23E-07	9.39E-08	-3.440403	0.0006
$\hat{\beta}_5$	-7.70E-07	1.58E-07	-4.869797	0.0000
$\hat{\beta}_6$	-0.038061	0.004833	-7.874894	0.0000
$\hat{\alpha}_0$	7.27E-07	1.16E-07	6.264106	0.0000
$\hat{\alpha}_1$	0.043274	0.003705	11.67876	0.0000
$\hat{\alpha}_2$	0.940762	0.005270	178.5031	0.0000

The RV and the estimated volatility $\hat{\sigma}_t^2$ in Model (4) are compared in Fig.14a and Fig.14b, which show the observed RV and the estimated $\hat{\sigma}_t^2$ respectively. By comparing these two graphs we can see that the estimated variance $\hat{\sigma}_t^2$ can capture the movement of RV to a certain extent.

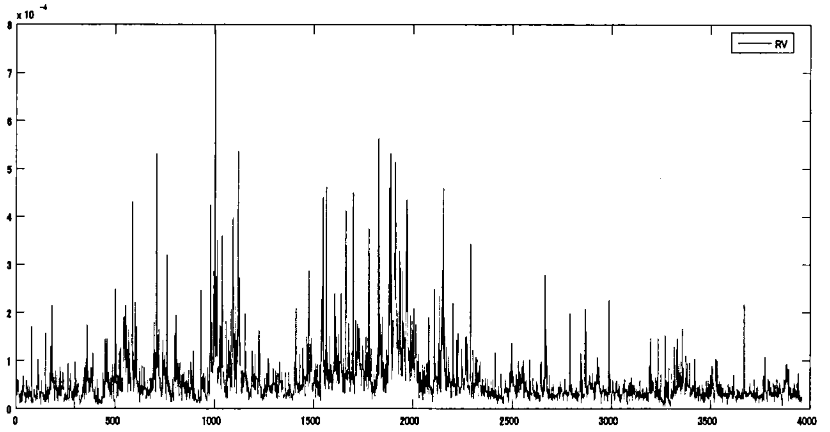

Fig.14a : Realized Volatility in Model (4)

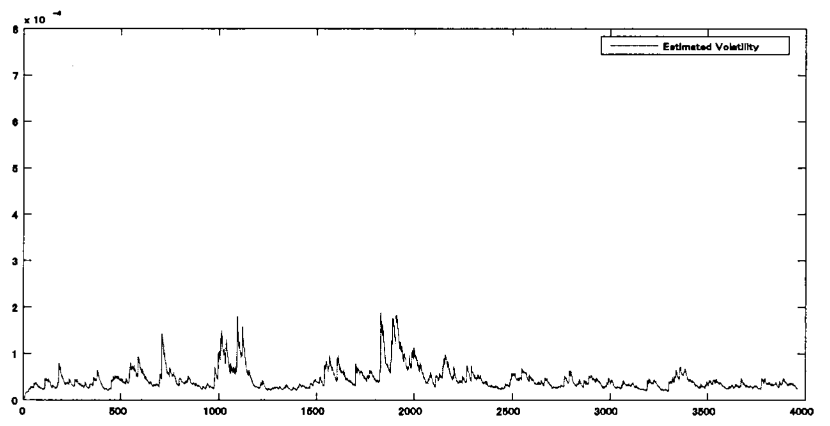

Fig.14b : Estimated Volatility $\hat{\sigma}_t^2$ in Model (4)

Next we introduce a dummy variable AD_t to capture FRB intervention such as

$$AD_t = \begin{cases} 1 & \text{intervention by FRB} \\ 0 & \text{no intervention} \end{cases},$$

and estimated GARCH Model (5) for the whole sample period (1991/05/01- 2006/08/31).

$$s_t - s_{t-1} = \beta_0 + \beta_1(s_{t-1} - s_{t-2}) + \beta_2(s_{t-1} - s^T_{t-1}) + \beta_3 Int_t + \beta_5 IntI_t + \beta_6 D_t + \beta_7 AD_t + \varepsilon_t \qquad (5)$$

As shown in Table 14 the coefficient $\hat{\beta}_7$ is not significant, which means the intervention by FRB may not be effective.

Table 14 : Estimation of GARCH (1,1) Model (5) for the Whole Sample Period (1991/05/01-2006/08/31, with a Dummy Variable for FRB Intervention)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\beta}_0$	-0.000274	0.000127	-2.149430	0.0316
$\hat{\beta}_1$	-0.012211	0.016036	-0.761433	0.4464
$\hat{\beta}_2$	-0.002383	0.001018	-2.341165	0.0192
$\hat{\beta}_3$	-3.24E-07	9.38E-08	-3.448718	0.0006
$\hat{\beta}_5$	-7.72E-07	1.58E-07	-4.872905	0.0000
$\hat{\beta}_6$	-0.038066	0.004823	-7.891902	0.0000
$\hat{\beta}_7$	-0.001002	0.000712	-1.408324	0.1590
$\hat{\alpha}_0$	7.15E-07	1.16E-07	6.153199	0.0000
$\hat{\alpha}_1$	0.042783	0.003846	11.12299	0.0000
$\hat{\alpha}_2$	0.941502	0.005421	173.6783	0.0000

Although we could not obtain the data of FRB intervention we can estimate it by subtracting the BOJ intervention from the total intervention (FRB+BOJ intervention). This indirect calculation of FRB intervention, denoted by $IntF_t$, is somewhat problematic, but may provide useful information. We estimated GARCH Model (6) by using $IntF_t$ for the whole sample period (1991/05/01- 2006/08/31), and the results are shown in Table 15. From this table we can see that the estimated coefficient for $IntF_t$ is significant and $\hat{\beta}_3 + \hat{\beta}_4 < 0$, which means the joint intervention by FRB and BOJ was effective.

$$s_t - s_{t-1} = \beta_0 + \beta_1(s_{t-1} - s_{t-2}) + \beta_2(s_{t-1} - s^T_{t-1}) + \beta_3 Int_t + \beta_4 IntF_t + \beta_5 IntI_t + \beta_6 D_t + \varepsilon_t \qquad (6)$$

Table 15 : Estimation of GARCH (1,1) Model (6) for the Whole Sample Period (1991/05/01-2006/08/31, with the Intervention by FRB)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\beta}_0$	-0.000251	0.000128	-1.963891	0.0495
$\hat{\beta}_1$	-0.014179	0.016180	-0.876334	0.3808
$\hat{\beta}_2$	-0.001993	0.001036	-1.923485	0.0544
$\hat{\beta}_3$	-3.17E-07	9.36E-08	-3.392296	0.0007
$\hat{\beta}_4$	-1.43E-05	1.98E-06	-7.228333	0.0000
$\hat{\beta}_5$	-7.39E-07	1.63E-07	-4.540924	0.0000
$\hat{\beta}_6$	-0.038155	0.004767	-8.004018	0.0000
$\hat{\alpha}_0$	6.95E-07	1.13E-07	6.148751	0.0000
$\hat{\alpha}_1$	0.041366	0.003984	10.38243	0.0000
$\hat{\alpha}_2$	0.943214	0.005463	172.6567	0.0000

We also used the total intervention by FRB and BOJ denoted by $IntT_t$ and estimated GARCH (1,1) Model (7). As shown in Table 16 the coefficient $\hat{\beta}_7$ for $IntT_t$ is significant, which means the total intervention is effective.

$$s_t - s_{t-1} = \beta_0 + \beta_1(s_{t-1} - s_{t-2}) + \beta_2(s_{t-1} - s^T_{t-1}) + \beta_3 Int_t + \beta_5 IntI_t + \beta_6 D_t + \beta_7 IntT_t\ \varepsilon_t \qquad (7)$$

Table 16 : Estimation of GARCH (1,1) Model (7) for the Whole Sample Period
(1991/05/01-2006/08/31, with the Total Intervention by FRB and BOJ)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\beta}_0$	-0.000252	0.000127	-1.981439	0.0475
$\hat{\beta}_1$	-0.014090	0.016104	-0.874961	0.3816
$\hat{\beta}_2$	-0.002028	0.001030	-1.968381	0.0490
$\hat{\beta}_3$	-3.18E-07	9.37E-08	-3.390195	0.0007
$\hat{\beta}_5$	-7.35E-07	1.73E-07	-4.246302	0.0000
$\hat{\beta}_6$	-0.038143	0.004750	-8.030141	0.0000
$\hat{\beta}_7$	-4.78E-06	3.95E-07	-12.10624	0.0000
$\hat{\alpha}_0$	6.80E-07	1.11E-07	6.113381	0.0000
$\hat{\alpha}_1$	0.040633	0.003859	10.52968	0.0000
$\hat{\alpha}_2$	0.944292	0.005233	180.4453	0.0000

Table 17 shows the results of the estimation of Ito Model (2) for the whole sample period (1991/05/01-2006/08/31).

Table 17 : Estimation of GARCH (1,1) Type Ito Model (2) for the Whole Sample Period
(1991/05/01-2006/08/31)

	Coefficient	Std. Error	t-Statistic	Prob.
$\hat{\beta}_0$	-0.000256	0.000128	-2.000390	0.0455
$\hat{\beta}_1$	-0.006842	0.016016	-0.427171	0.6693
$\hat{\beta}_2$	-0.002011	0.001036	-1.941788	0.0522
$\hat{\beta}_3$	-3.18E-07	9.37E-08	-3.396219	0.0007
$\hat{\beta}_4$	-1.41E-05	2.02E-06	-6.981898	0.0000
$\hat{\beta}_5$	-7.45E-07	1.63E-07	-4.569336	0.0000
$\hat{\alpha}_0$	7.33E-07	1.17E-07	6.247514	0.0000
$\hat{\alpha}_1$	0.044384	0.004044	10.97653	0.0000
$\hat{\alpha}_2$	0.939653	0.005670	165.7323	0.0000

4. 3 F-test

To see the intervention effect we apply a variance analysis by F-test. We divide sample period into "in sample" before the intervention and "out of sample" ("out sample" for short) after that. We compare "in sample variance" and "out of sample variance". If F-test indicates the variance is unchanged in the two sample periods we may say there is no intervention effect. We apply F-test to the period including Russian economic crisis in August 1998. In October 1998 there was a striking aftershock when huge amount of Japanese Yen was bought back by hedge funds. The aftershock was seen as a big downward spike in Fig.6. We choose the period of 1998/08/24 - 1998/12/22 as a whole sample period and divide this period into two periods: 1998/08/24-1998/10/05 as "in sample" and 1998/10/10-1998/12/22 as "out sample". $F = \frac{\sigma^2_{in}}{\sigma^2_{out}} = 1.15$, where σ^2_{in} and σ^2_{out} are the estimated variances in "in sample" and "out sample" period respectively. As the degree of freedom in denominator and numerator are very large, $F=1.15$ is significant. As the result we can say the variances are not equal in the two sample periods. This means that the volatility became smaller after the Russian economic crisis.

5 Concluding remarks

In this article, we have analyzed the asymmetric effect of the intervention of BOJ in the foreign Exchange Market through GARCH models. The effect may be seen in the volatility equation and/or the mean equation of the GARCH models. First, to determine whether there is any asymmetric effect on volatility of the returns of exchange rate, we have applied GJR, EGARCH and APGARCH models, which can reflect asymmetry of the volatility in keeping the mean equation constant. We name this approach 'variance equation approach'. Second, to determine whether the intervention has an effect on the mean equation, we have applied Ito (2002) model and its variants to the real data in assuming that the variance equation is symmetric. We name this approach 'mean equation approach'. We have also applied F-test approach to test the effect of the intervention of BOJ. In the variance equation approach, we tested if the intervention of BOJ has any asymmetric effect on the volatility through the dummy variable D_t in the right side of the variance equations, which takes a value 1 for the intervention and 0 elsewhere. We obtained the significant estimate of the coefficient of D_t, and we can say that the intervention has an effect on the exchange rate volatility. In the mean equation approach, we used Ito model with symmetric GARCH error and with the amount of intervention as an explanatory variable in the mean equation. Especially, we used RV analysis based on high-frequency exchange rate data. In the F-test approach, we obtained the empirical evidence, which supports that the intervention by BOJ makes the exchange rate volatility more fluctuate. The interventions by BOJ have effects in the case of Russian economic crisis.

As our empirical study showed that the intervention by BOJ has significant asymmetric effects on the volatility and the mean equations of the returns of exchange rate, we may conclude that the intervention by BOJ does not have a stabilizer effect on the volatility of returns of exchange rate.

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