Japanese Foreign Exchange Intervention and the Yen/Dollar Exchange Rate:

A Simultaneous Equations Approach Using Realized Volatility

Eric Hillebrand* Gunther Schnabl‡ Yasemin Ulu§

July 23, 2007

Abstract

We use realized volatility to study the influence of Japanese central bank interventions on the yen/dollar exchange rate. A system of equations for returns, realized volatility, and interventions provides a comprehensive view on the problem without endogeneity bias, unlike earlier GARCH-type specifications. We find that during the period 1995 through 1999, interventions of the Japanese monetary authorities could not move the yen-dollar rate into the desired direction. We measure an increase in volatility associated with interventions. During the period 1999 through 2004, the estimations are consistent with successful interventions, both in depreciating the yen and in reducing exchange rate volatility.

Key Words: Realized Volatility, Structural Change, GMM, Foreign Exchange Intervention, Japan

JEL Classification: C32, E58, F31, F33, G15

*Corresponding author. Louisiana State University, Department of Economics, Baton Rouge, LA 70803, erhil@lsu.edu, phone 225-578-3795, fax 225-578-3807

‡Universität Leipzig, Institute for Economic Policy, Marschnerstrasse 31, D-04109 Leipzig, Germany

§St. Cloud State University, Department of Economics, 720 4th Avenue South, St. Cloud, MN 56301

1 Introduction

Since the Japanese monetary authorities have released data on their foreign exchange intervention activities in 2001, a steadily increasing number of studies have scrutinized the effects of Japanese foreign exchange intervention. One of the main challenges to address is an endogeneity problem: If there is significant correlation between interventions and exchange rate returns or volatility, does this support the hypothesis that interventions cause changes in exchange rate movements or does this support the reverse direction that exchange rate movements trigger interventions? Building upon the paper of Dominguez (1998), the studies of Ito (2003), Frenkel, Pierdzioch and Stadtmann (2005), Watanabe and Harada (2006), and Hillebrand and Schnabl (2006), among others, have used daily yen/dollar time series in a GARCH framework to study the impact of Japanese foreign exchange intervention on the volatility of the yen/dollar exchange rate. Instead of trying to measure the success of interventions in pushing the exchange rate to a desired level, these studies use the smoothing of exchange rate volatility as a success criterion. The coefficients in the GARCH mean equations were rendered uninterpretable by endogeneity bias. Separate estimations of reaction functions for the monetary authorities usually found that interventions correlated with exchange rate returns but not with volatility. Therefore, endogeneity did not seem to be a problem in the conditional volatility equation, at least not if one accounted for linear effects only. These studies found mixed evidence that Japanese foreign exchange interventions have increased or decreased exchange rate volatility, depending on the time period.

As the GARCH time series approaches have not been able to fully resolve the endogeneity issue, a new strand of literature has evolved that has used event studies to analyze the success of Japanese foreign exchange intervention (Neely 2005). Fatum and Hutchison (2003) separate intervention episodes and analyze the subsequent effects on the exchange rate. They find evidence in favor of successful Japanese intervention, as mean exchange rate changes after intervention are statistically smaller than the mean pre-intervention change.

Kearns and Rigobon (2005) specify a multiple equation model for returns and interventions that uses a change in intervention policies to identify the parameters. Kim (2003) proposes a structural VAR model for returns and interventions and estimates the effects of intervention and monetary policy with monthly data.

The concept of realized volatility introduced by Andersen and Bollerslev (1998) allows us to consider volatility as an observed rather than as a latent variable. Therefore, we can specify a system of equations that contains not only returns and interventions but also realized volatility. Such a system provides a comprehensive framework to study the interplay of the first and the second moment of the return distribution of the yen/dollar rate with interventions without endogeneity bias.

Using a total sample period from 1995 through 2004, we find a change-point in the time series of realized volatility in December 1999. Estimating the system of equations on the resulting sub-periods, we find that during the period 1995–1999, Japanese foreign exchange interventions were not successful, neither in influencing the returns nor in reducing the volatility of the yen/dollar rate. On the contrary, we measure a significantly positive coefficient of interventions in the volatility equation. In the period 1999–2004, the estimations are consistent with successful interventions, both in depreciating the yen and in reducing volatility. The results therefore indicate a change toward a more successful intervention policy.

2 Realized Volatility

Returns of financial assets display volatility clustering: large movements in prices tend to be followed by more large movements. In other words, current and past volatility can be used to predict future volatility. This serial correlation motivates almost all extant volatility models. Before the introduction of the concept of realized volatiity, however, volatility was not directly observable, and models like GARCH or Stochastic Volatility use squared or absolute returns calculated from daily or lower frequency time series to estimate a latent volatility process.

Andersen and Bollerslev (1998) argue that squared daily returns are a very noisy estimator and introduce realized volatility as a new volatility measure. Realized volatility is the sum of high-frequency intra-day squared returns. The motivation for this statistic is the common practice to model the log price process of an asset as a continuous martingale. For continuous martingales the sum of squared increments converges to the quadratic variation as the partition on which the increments are computed becomes finer. The quadratic variation, in turn, is the variance of increments of the continuous martingale. In an asset price model, the quadratic variation therefore is the integrated volatility. Andersen, Bollerslev, Diebold, and Labys (2001) show this in a general framework.

Let us consider the special case of an Itô process with constant drift, that is, the log asset price $X(t)$ at time t is given by the stochastic differential equation

$$dX(t) = \mu dt + \sigma(t) dW(t),$$

where $W(t)$ denotes standard Brownian Motion, μ is the drift parameter and $\sigma(t)$ is the diffusion parameter as a function of time. The function may be deterministic or stochastic. The quadratic variation $\langle X \rangle(t)$ is given by

$$\langle X \rangle(t) = \lim_{||\Pi|| \to 0} \sum_{j=1}^{n} |X(\tau_j) - X(\tau_{j-1})|^2, \qquad (1)$$

where $||\Pi||$ is the mesh of the partition $\Pi = \{\tau_0 = 0, \tau_1, \ldots, \tau_n = t\}$ of the interval $[0, t]$. The increment

$$r(t) := X(t) - X(t-1) = \mu + \int_{t-1}^{t} \sigma(s) dW(s)$$

is normally distributed

$$r(t) \sim \mathcal{N}(\mu, \int_{t-1}^{t} \sigma^2(s) ds). \qquad (2)$$

If $\sigma(t)$ is a stochastic process (the more appropriate model for financial volatility), then the distribution (2) is conditional on the sigma-algebra generated by the path of $\sigma(s)$, $0 \leq s \leq t-1$. It follows from the Itô isometry that the quadratic variation is given by

$$\langle X \rangle(t) = \int_0^t \sigma^2(s) ds,$$

or $\int_0^t \mathbb{E}_0 \sigma^2(s) ds$ in the case of a stochastic volatility process. This *integrated volatility* and equation (1) suggest that the volatility in (2) can be measured arbitrarily exactly by calculating

$$\langle X \rangle(t) - \langle X \rangle(t-1) = \sum_{j=1}^{n} |X(\tau_j) - X(\tau_{j-1})|^2, \qquad (3)$$

on the partition $\Pi = \{\tau_0 = t-1, \tau_1, \ldots, \tau_n = t\}$ of the interval $[t-1, t]$ and choosing the mesh $||\Pi||$ sufficiently small. Therefore, as an estimator of integrated volatility that uses intra-day data, realized volatility is much more precise than estimators using daily data or lower frequencies.

Microstructure effects like the bid-ask bounce and discreteness of prices prevent too fine a grid. Barndorff-Nielsen and Shephard (2002) study the properties of the estimation error of realized volatility. For the purposes of our study, the main advantage of realized volatility is that volatility can be treated as *observable* rather than latent. This allows us to set up a system of equations for returns and volatility of the yen/dollar exchange rate as well as interventions in the yen/dollar market.

3 Data

We use high-frequency intra-day and daily data provided by Olsen Financial Technologies, Bloomberg, the Japanese Ministry of Finance, and the Federal Reserve Board. The sample period is 2-Jan-1995 through 30-Dec-2004. This corresponds to a sample size of 2601 days. The start point of the sample period in 1995 is dictated by our base of high-frequency data.

Following Andersen, Bollerslev, Diebold and Labys (2001), Andersen, Bollerslev, Diebold, and Ebens (2001) as well as Barndorff-Nielsen and Shephard

(2002), we use 5-minute returns on the yen/dollar exchange rate. The provider Olsen Financial Technologies filters the high frequency data for outliers and the 5-minute prices are obtained by linearly interpolating the average of log-bid and log-ask for two closest ticks. We delete the weekends from Friday 21:05 Greenwich Mean Time (GMT) until Sunday 21:05 GMT. Christmas (Dec 24-26), New Year (Dec 31–Jan 2) and the Fourth of July are also removed from the data set. The daily realized volatilities are constructed by the sum of the square of the 5-minute intra-day returns as in (3).

The daily interventions of the Japanese monetary authorities are reported on the web site of the Japanese Ministry of Finance. The exact intervention time, the number of interventions within a day, the intervention market (Tokyo, London, or New York), and the exchange rate at the time of intervention remain undisclosed. The reported amounts are in billion yen; we convert them into billion dollars based on daily exchange rates. The US foreign exchange intervention data are provided by the Federal Reserve Board.

Other time series used are the daily Nikkei 300 (Bloomberg series NEY), the Federal Funds Rate (Bloomberg: FDFD), and the Japanese uncollateralized overnight interbank interest rate (Bloomberg: JYMU1T). The latter is available only after 11-Apr-1996. Figure 1 shows plots of the three main considered series that we will model in a system of equations: The daily returns on the yen/dollar exchange rate, the realized volatility of the yen/dollar exchange rate, and the time series of pooled Japanese and US interventions.

FIGURE 1 ABOUT HERE

4 Structural Breaks in Volatility

The periods of high and low volatility that can be seen in the first and second panel of Figure 1 can be understood as different parameter regimes interrupted by structural breaks, that is, changes in the data-generating parameters of the volatility model under study. The possibility of structural breaks and its implications for the estimation of serial correlation and persistence in volatility has been discussed widely (Andreou and Ghysels 2002, Bos, Franses, and Ooms 1999, Diebold and Inoue 2001, Granger and Hyung 1999, Hillebrand 2005, Lamoureux and Lastrapes 1990, LeBaron 2001, Mikosch and Starica 2004). Earlier studies in the intervention literature have indeed found evidence for structural breaks in the yen-dollar exchange rate (Ito 2003, Hillebrand and Schnabl 2006).

We apply the change-point detector statistic proposed in Bai (1994, 1997) to the series of realized volatilities displayed in the second panel of Figure 1. The asymptotic theory developed by Bai will hold as long as realized volatility can be described by a linear time series model. We need an estimator of the variance of the realized volatility series in order to compute the statistic. We choose the VARHAC estimator of Den Haan and Levin (1997) for this purpose. At the 99% confidence level, the detector returns one significant change-point at 1-Dec-1999. The corresponding test statistic converges in distribution under the null to a standard Brownian Bridge. The test statistic is 3.10, which implies a 1e-8 probability under the null. Visually inspecting the second panel of Figure 1, an estimated change-point around the year 2000 is no surprise.

5 A Simultaneous Equations Model of Exchange Rate Moments and Intervention

In this section, we estimate the system $y_t = (r_t, \log \sigma_t^2, I_t)$, where r_t are the daily log returns of the yen/dollar exchange rate, σ_t^2 is the daily realized volatility of the yen/dollar exchange rate, and I_t are the pooled interventions by the Japanese and U.S. monetary authorities. The U.S. interventions make up only a very small fraction in this sample.[1] The interventions are recorded at Tokyo

[1]There are two periods where the Federal Reserve intervened during the sample period. The first was between 2-Mar-1995 and 15-Aug-1995. All interventions were coordinated with the Japanese monetary authorities, had the same sign and purpose, and occurred on the same

time. The high-frequency quotes of the yen/dollar exchange rate are recorded at Greenwich Mean Time, which lags Tokyo time by nine hours. Therefore, interventions I_t at (Tokyo-) time t clearly precede the returns r_t and the realized volatility σ_t^2 (at GMT). Sometimes, the Federal Reserve intervenes on behalf of the Japanese authorities. There are no publicly available data on these transactions. Since the high-frequency quotes cover the entire day until 24:00 GMT corresponding to 19:00 Eastern Standard Time, any immediate effects of these interventions will still be reflected in the returns r_t and realized volatility σ_t^2.

5.1 Specification

We will consider the following linear system of equations

$$r_t = \alpha_0 + \alpha_1 I_t + u_t, \tag{4}$$

$$\log \sigma_t^2 = \beta_0 + \beta_1 \log \sigma_{t-1}^2 + \beta_2 \log \sigma_{t-1,w}^2 + \beta_3 \log \sigma_{t-1,m}^2 + \beta_4 I_t + v_t, \tag{5}$$

$$I_t = \gamma_1 I_{t-1} + \gamma_2 r_t + \gamma_3 r_{t-1} + \gamma_4 \sigma_t^2 + \gamma_5 \sigma_{t-1}^2 + w_t, \tag{6}$$

where r_t are the daily log returns of the yen/dollar exchange rate, σ_t^2 is the daily realized volatility, $\sigma_{t,w}^2$ is realized volatility aggregated at the weekly level (5 days), $\sigma_{t,m}^2$ is realized volatility aggregated at the monthly level (20 days), and I_t are the interventions. The specification of the volatility equation is in the spirit of the HAR-RV model (Corsi 2004).

The parameter vector to be estimated is

$$\theta = (\alpha_0,\, \alpha_1,\, \beta_0,\, \beta_1,\, \beta_2,\, \beta_3,\, \beta_4,\, \gamma_1,\, \gamma_2,\, \gamma_3,\, \gamma_4,\, \gamma_5).$$

We cannot make standard distribution assumptions on the error terms because the intervention time series is equal to zero most of the time and has pronounced

days. During this time, the Japanese authorities intervened on 34 days. The Federal Reserve supported these interventions on 8 days. The Dollar purchases of the Japanese authorities amounted to \$35.4bn during this period. The purchases of the Federal Reserve amounted to \$3.3bn. The other instance was 17-Jun-1998, when the Federal Reserve supported a Japanese sale of Dollars (\$1.6bn) by selling \$0.8bn.

clusters of large interventions (Figure 1). We therefore estimate the system by GMM, which does not require a specific error distribution to derive inferences.

In order to capture the influence of other asset markets on the exchange rate and interventions, we include the returns on the daily Nikkei 300 index in equation (4) (with coefficient α_2), its squared returns in equation (5) (with coefficient β_5), and both returns and squared returns in equation (6) (with coefficients γ_6, γ_7). This results in a nuisance parameter vector

$$\tilde{\theta} = (\alpha_2, \beta_5, \gamma_6, \gamma_7),$$

which we estimate alongside θ.[2] Changes in the interest rate are another possible transmission channel of interventions and we will extend the system to include the Japanese overnight rate and the US-Japanese interest rate differential in a second set of estimations.[3]

Before the theory of realized volatility was available, equations (4) and (5) were usually specified in a GARCH framework with interventions as exogenous variables. Equation (6), the reaction function of the monetary authorities, had to be estimated separately. Examples for studies that follow this approach are Dominguez (1998), Bonser-Neal and Tanner (1996), and Hillebrand and Schnabl (2006), among others. In this setup, volatility was latent and the equations (4) and (5) of the GARCH regression suffered from simultaneous equation bias because equation (6) was not part of the system. Separate estimations of the reaction function (6) routinely indicated that interventions were triggered by changes in returns, underlining the endogeneity problem in equation (4). The conditional volatility equation on the other hand seemed to be statistically fine since volatility (squared daily returns or fitted GARCH series) did not seem to influence interventions in the reaction function estimation. Therefore, the estimated coefficients of the mean equation of the GARCH model could not be

[2] We also included the Dow Jones Industrial Average in addition to the Nikkei and replacing the Nikkei. The results were very similar.

[3] Note, however, that Japanese money market interest rates became almost zero in early 1999 and did not change substantially since then.

interpreted.

Realized volatility allows us to treat σ_t^2 as an observed variable rather than as a latent variable and set up a system of equations. Multiple equation models have been employed before to analyze the effects of interventions on exchange rates (Kim 2003, Kearns and Rigobon 2005, Neely 2005). Our contribution to this literature is that we include volatility in the system and therefore disentangle the interplay of returns, volatility, and interventions. This resolves the endogeneity problem of the approach using GARCH and exogenous interventions.

5.2 Identification

Model (4) through (6) has 16 structural parameters to be estimated. To identify these structural parameters, we need 16 parameters in a reduced-form model

$$y_t = \Phi x_t + \varepsilon_t,$$

where $y_t = (r_t, \log \sigma_t^2, I_t)$ is the vector of endogenous variables, x_t is a vector of exogenous or pre-determined variables, and ε_t is white noise. The exogenous variables in the system are the returns and squared returns of the Nikkei. The lags of realized volatility sampled at weekly and monthly frequency are pre-determined. Given the three equations and four exogenous or pre-determined variables, the model has twelve reduced-form parameters. Therefore, for the system to be identified, we need to supply two instrumental variables, increasing the number of reduced-form model parameters to 18.

Using the third equation of the system as an example, a valid instrument is a variable z_t that decomposes w_t into

$$w_t = \gamma_6 z_t + w_t', \tag{7}$$

such that $\operatorname{cov}(z_t, w_t') = 0$ by construction. Further, by assumption, $\operatorname{cov}(z_t, v_t) = 0$ and $\operatorname{cov}(z_t, u_t) = 0$ must hold. Then, the instrumental variable estimators of the parameters α_1 and β_4 of main interest are given by

$$\alpha_1 = \frac{\text{cov}(z_t, r_t)}{\text{cov}(z_t, I_t)}, \quad \text{and} \quad \beta_4 = \frac{\text{cov}(z_t, \log \sigma_t^2)}{\text{cov}(z_t, I_t)}. \tag{8}$$

In order for the instrumental variable estimators to exist, the instrument z_t must correlate with the intervention I_t. Only if the instrument z_t also correlates with r_t and $\log \sigma_t^2$, the estimators will not be zero. This correlation with r_t and $\log \sigma_t^2$ must be through I_t only, because the instrument z_t must not correlate with any of the errors u_t, v_t and w_t'.

We propose lags of the intervention variable $z_t := (I_{t-2}, I_{t-3})$ as instruments. Many studies have shown that daily intervention data have significant low order autocorrelations and the first few lags are routinely included in the specification of reaction functions (e.g., Ito 2003, Dominguez 1998). Therefore, (I_{t-2}, I_{t-3}) fulfill the condition $\text{cov}(I_t, z_t) \neq 0$. By equations (4) and (5), z_t will also correlate with r_t and $\log \sigma_t^2$, such that the instrumental variable estimators will not be zero. The sample partial autocorrelation function for the Japanese intervention series drops off after the first two lags, so that $\text{cov}(z_t, w_t') = 0$ does not seem too much of a stretch. The zero correlation with the shocks u_t and v_t means that the interventions at lags 2 and 3 do not lead to shocks to exchange rate returns and volatility today. This seems reasonable if surprising interventions unfold their immediate effect on the day of the intervention and possibly one day later. Note that this assumption does not preclude systematic long term effects of interventions on the returns and volatility. These are still captured by the first lag of interventions in equation (6).

An alternative instrument that is discussed in the literature is announcements about major macroeconomic variables, in particular trade balances (Neely 2005). This variable correlates with the exchange rate r_t and is used to instrumentalize equation (4). To be a valid instrument, it then must not correlate with the residual error in the mean equation ($\text{cov}(z_t, u_t') = 0$), with shocks to interventions ($\text{cov}(z_t, w_t) = 0$), and with shocks to volatility ($\text{cov}(z_t, v_t) = 0$). In particular the latter requirement is unlikely to be fulfilled for this instrument.

In Neely (2005) this does not pose a problem since that study does not consider volatility.

An entirely different approach to solve the identification problem is the two-segment threshold intervention model of Kearns and Rigobon (2005) that they estimate by simulated method of moments. Their setup also does not consider volatility. It allows for changes in the threshold intervention only, all other coefficients remain constant. Earlier studies have shown that both the reaction of the exchange rate returns to intervention (Ito 2003) and the reaction of volatility to intervention (Hillebrand and Schnabl 2006) varies with time, therefore Kearns' and Rigobon's approach is not appropriate for our problem.

5.3 Estimation

The system (4) through (6) is estimated using the instruments $z_t = (I_{t-2}, I_{t-3})$. Because of the unique structure of the intervention time series that has a substantial probability point mass at zero, we employ a GMM approach that does not require a specific distribution assumption for the error. We use a heteroskedasticity and autocorrelation consistent estimator with quadratic spectral kernel for the covariance matrix of the moment conditions and bandwidth selected according to Newey and West (1994). Tables 1 and 2 report the results for the sub-samples identified by the change-point detection in Section 4.

TABLES 1, 2 ABOUT HERE

There are two concepts of "success" of interventions discussed in the literature: Either (1) interventions push the exchange rate in the desired direction or (2) interventions reduce volatility. The desired direction in the case of Japan is a depreciation of the yen most of the time.[4] For the case (1) of returns on the yen/dollar rate, this means that interventions should have a significantly

[4] On 10-Apr-1998, the Japanese monetary authorities sold \$20.4bn. This is the only instance in our sample where an intervention to appreciate the yen against the dollar was undertaken. Deleting this "outlier" does not substantially change the results.

positively estimated coefficient.

Judging by these standards, interventions have not done well on the first segment between 1995 and 1999: The coefficient α_1 of interventions in the returns equation (4) is significantly negative; it has the wrong sign. The coefficient β_4 of interventions in the log realized volatility equation (5) is significantly positive. We cannot conclude that interventions caused an appreciation of the yen and an increase in volatility: The statistical method can still only capture correlations. The simultaneity of the system estimation, however, ensures that the estimates do not suffer from endogeneity bias. The interventions clearly did not prevent movements in the direction opposite to the desired one. The reaction function (6) displays significant coefficients for the returns and insignificant coefficients for volatility, confirming the results commonly found in the literature.

On the second segment from 2-Dec-1999 to 30-Dec-2004, interventions have a marginally significant positive coefficient α_1 in the return equation (4) and a highly significant negative coefficient β_4 in the volatility equation (5). These are the expected signs for a successful intervention that depreciates the yen and reduces volatility. The reduction in volatility is more convincing than the influence on the returns, however, if judged by the significance of the estimated coefficients.

Estimated on the entire sample 2-Jan-1995 through 30-Dec-2004, the coefficient α_1 of interventions in the return equation (4) is insignificant. The estimated coefficient β_4 in the volatility equation (5) is highly significantly negative. These estimates are not reported for brevity.

The extant literature discusses several possible causes for a change in the effects of interventions. Among these are, to name a few, a change in the intervention policy from frequent small to infrequent large interventions (Ito 2003), the deregulation of the Japanese foreign exchange market (Ito and Melvin 1999), and a switch from sterilized interventions to factually unsterilized interventions in the liquidity trap (Hillebrand and Schnabl 2006). The timing of these events differs widely, though, and does not coincide conclusively with the change-point found in 1999 in Section 4. We do not intend to be authoritative about any of these possible causes, the contribution of this study is methodological.

TABLES 3, 4 ABOUT HERE

Another potentially important channel for interventions of the Japanese monetary authorities in the yen/dollar market is the interest rate. Tables 3 and 4 report estimations of the system (4) through (6) including concurrent and lagged values of the Japanese uncollateralized overnight interbank rate $i_{t,\mathrm{jap}}$ as well as the interest rate differential with the US Federal Funds Rate $i_{t,\mathrm{US}} - i_{t,\mathrm{jap}}$. The estimated coefficients are insignificant throughout in the first sub-sample. In the second sub-sample, the interest rate differential is marginally significant in equations (4) and (6), but the signs are inconclusive. On the total sample (not reported) all coefficients of the interest rate variables are insignificant. The interest rate does not seem to be a direct channel of intervention policy in the yen/dollar market.

6 Conclusion

We examine the interplay of returns and realized volatility of the yen/dollar exchange rate with interventions of the Japanese monetary authorities in the yen/dollar market. The concept of realized volatility allows us to treat volatility as an observed variable and enables us to employ a simultaneous equations model for returns, realized volatility, and interventions. This resolves the endogeneity problem that plagued earlier approaches to measure the success of interventions.

We find a change-point in the time series of realized volatility of the yen/dollar exchange rate in Dec 1999. We estimate the system of equations on the resulting sub-periods using GMM. The results show that during the first sub-period from 1995 through 1999, interventions were unsuccessful in devaluating the yen against the dollar and reducing volatility. On the second sub-period 1999 through 2004, the estimated coefficients are consistent with interventions that depreciate the yen and reduce exchange rate volatility.

Acknowledgments

The idea for this paper was the result of a conversation with Marcelo Medeiros. We gratefully acknowledge the comments from participants of the CIREQ Conference on Realized Volatility in Montreal 2006, in particular Greg Bauer, Tim Bollerslev, and Peter Reinhard Hansen, as well as from the participants of the Realized Volatility Conference in Konstanz in 2006, in particular Eric Renault. These comments have substantially improved the paper. All remaining errors are ours.

References

Andersen TG, Bollerslev T. 1998. Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts. *International Economic Review* **39(4)**: 885–905.

Andersen TG, Bollerslev T, Diebold FX, Labys P. 2001. The Distribution of Realized Exchange Rate Volatility. *Journal of the American Statistical Association* **96(453)**: 42–55.

Andersen TG, Bollerslev T, Diebold FX, Ebens H. 2001. The Distribution of Realized Stock Return Volatility. *Journal of Financial Economics* **61**: 43–76.

Andreou E, Ghysels E. 2002. Detecting multiple breaks in financial market volatility dynamics. *Journal of Applied Econometrics* **17**: 579–600.

Bai J. 1994. Least Squares Estimation of a Shift in Linear Processes. *Journal of Time Series Analysis* **15(5)**: 453–472.

Bai J. 1997. Estimating Multiple Breaks One at a Time. *Econometric Theory* **13**: 315–352.

Barndorff-Nielsen OE, Shephard N. 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society B* **64(2)**: 253–280.

Bonser-Neal C, Tanner G. 1996. Central Bank Intervention and the Volatility of Foreign Exchange Rates: Evidence from the Options Market. *Journal of International Money and Finance* **15**: 853-878.

Bos CS, Franses PH, Ooms M. 1999. Long memory and level shifts: Re-analyzing inflation rates. *Empirical Economics* **24**: 427–449.

Corsi F. 2004. A Simple Long Memory Model of Realized Volatility. Manuscript. University of Lugano.

Den Haan W, Levin A. 1997. A Practitioner's Guide to Robust Covariance Matrix Estimation. In *Handbook of Statistics Vol. 15: Robust Inference*, Maddala G, Rao C (eds). North-Holland: Amsterdam.

Diebold FX, Inoue A. 2001. Long memory and regime switching. *Journal of Econometrics* **105**: 131–159.

Dominguez K. 1998. Central Bank Intervention and Exchange Rate Volatility. *Journal of International Money and Finance* **17**: 161-190.

Fatum R, Hutchison M. 2003. Is Sterilized Foreign Exchange Intervention Successful after All? An Event Study Approach. *Economic Journal* **113**: 390-411.

Frenkel M, Pierdzioch C, Stadtmann G. 2005. The Effects of Japanese Foreign Exchange Market Interventions on the Yen/U.S. Dollar Exchange Rate Volatility. *International Review of Economics and Finance* **14**: 27-39.

Granger CWJ, Hyung N. 1999. Occasional structural breaks and long memory. UC San Diego Discussion Paper 99-14.

Hillebrand E. 2005. Neglecting Parameter Changes in GARCH Models. *Journal of Econometrics* **129**: 121–138.

Hillebrand E, Schnabl G. 2006. A Structural Break in the Effects of Japanese Foreign Exchange Intervention on Yen/Dollar Exchange Rate Volatility. European Central Bank Working Paper 650.

Ito T. 2003. Is Foreign Exchange Intervention Effective? The Japanese Experience in the 1990s. In *Monetary History, Exchange Rates and Financial Markets. Essays in Honour of Charles Goodhart Vol. 2*, Mizen P (ed). Edward Elgar: Cheltenham.

Ito T, Melvin M. 1999. Japan's Big Bang and the Transformation of Financial Markets. NBER Working Paper 7247.

Kearns J, Rigobon R. 2005. Identifying the Efficacy of Central Bank Interventions: Evidence from Australia and Japan. *Journal of International Economics* **66(1)**: 31-48.

Kim S. 2003. Monetary Policy, Foreign Exchange Intervention, and the Exchange Rate in a Unifying Framework. *Journal of International Economics* **60**: 355-386.

Lamoureux CG, Lastrapes WD. 1990. Persistence in variance, structural change, and the GARCH model. *Journal of Business and Economic Statistics* **8**: 225–234.

LeBaron B. 2001. Stochastic volatility as a simple generator of apparent financial power laws and long memory. *Quantitative Finance* **1**: 621–631.

Mikosch T, Starica C. 2004. Nonstationarities in Financial Time Series, the Long-Range Dependence, and the IGARCH Effects. *Review of Economics and Statistics* **86(1)**: 378–390.

Neely CJ. 2005. Identifying the Effects of U.S. Intervention on the Levels of Exchange Rates. Federal Reserve Bank of St. Louis Working Paper 2005-031B.

Newey W, West K. 1994. Automatic Lag Selection in Covariance Matrix Estimation. *Review of Economic Studies* **61**: 631–653.

Watanabe T, Harada K. 2006. Effects of the Bank of Japan's Intervention on Yen/Dollar Exchange Rate Volatility. *Journal of Japanese and International Economies* **20**: 99–111.

Table 1: ESTIMATION OF MODEL (4) THROUGH (6) FOR SAMPLE 2-JAN-1995 THROUGH 1-DEC-1999.

dep. var.	coeff.	indep. var.	estimate	std. err.	t-stat.	prob.
r_t	α_0	const	0.0421	0.0203	2.0771	0.0379
	α_1	I_t	-0.3218	0.1078	-2.9863	0.0028
	α_2	$r_{t,\text{Nikkei}}$	-0.0262	0.0171	-1.5335	0.1252
$\log \sigma_t^2$	β_0	const	-0.8706	0.0815	-10.6825	0.0000
	β_1	$\log \sigma_{t-1}^2$	0.3986	0.0317	12.5770	0.0000
	β_2	$\log \sigma_{t-1,w}^2$	0.2556	0.0423	6.0475	0.0000
	β_3	$\log \sigma_{t-1,m}^2$	0.1489	0.0350	4.2593	0.0000
	β_4	I_t	0.3950	0.1053	3.7517	0.0002
	β_5	$r_{t,\text{Nikkei}}^2$	0.7708	0.1341	5.7478	0.0000
I_t	γ_1	I_{t-1}	0.2226	0.0713	3.1204	0.0018
	γ_2	r_t	1.7675	0.8200	2.1554	0.0312
	γ_3	r_{t-1}	-0.1167	0.0665	-1.7533	0.0796
	γ_4	σ_t^2	0.0439	0.1993	0.2200	0.8259
	γ_5	σ_{t-1}^2	-0.0246	0.1967	-0.1248	0.9007
	γ_6	$r_{t,\text{Nikkei}}$	0.0535	0.0440	1.2164	0.2239
	γ_7	$r_{t,\text{Nikkei}}^2$	0.3501	0.5551	0.6307	0.5283

Table 2: Estimation of model (4) through (6) for sample 2-Dec-1999 through 30-Dec-2004.

dep. var.	coeff.	indep. var.	estimate	std. err.	t-stat.	prob.
r_t	α_0	const	0.0029	0.0166	0.1776	0.8590
	α_1	I_t	0.0302	0.0158	1.9132	0.0558
	α_2	$r_{t,\text{Nikkei}}$	-0.0374	0.0147	-2.5491	0.0108
$\log \sigma_t^2$	β_0	const	-1.0477	0.1868	-5.6082	0.0000
	β_1	$\log \sigma_{t-1}^2$	0.2560	0.0401	6.3889	0.0000
	β_2	$\log \sigma_{t-1,w}^2$	0.3039	0.0754	4.0331	0.0001
	β_3	$\log \sigma_{t-1,m}^2$	0.2252	0.0573	3.9316	0.0001
	β_4	I_t	-0.1198	0.0246	-4.8777	0.0000
	β_5	$r_{t,\text{Nikkei}}^2$	0.5346	0.1411	3.7884	0.0002
I_t	γ_1	I_{t-1}	0.3470	0.0526	6.5987	0.0000
	γ_2	r_t	0.1526	1.7858	0.0854	0.9319
	γ_3	r_{t-1}	-0.1170	0.1295	-0.9035	0.3663
	γ_4	σ_t^2	0.1224	0.1713	0.7141	0.4752
	γ_5	σ_{t-1}^2	-0.1427	0.1721	-0.8293	0.4070
	γ_6	$r_{t,\text{Nikkei}}$	0.0094	0.0516	0.1818	0.8557
	γ_7	$r_{t,\text{Nikkei}}^2$	-0.0238	0.4762	-0.0501	0.9601

Table 3: ESTIMATION OF MODEL (4) THROUGH (6) FOR SAMPLE 4-NOV-1996 THROUGH 1-DEC-1999.

dep. var.	coeff.	indep. var.	estimate	std. err.	t-stat.	prob.
r_t	α_0	const	0.1638	0.3220	0.5086	0.6111
	α_1	I_t	-0.1823	0.0870	-2.0962	0.0362
	α_2	$r_{t,\text{Nikkei}}$	-0.0600	0.0180	-3.3365	0.0009
	α_3	$i_{t,\text{jap}}$	-0.5365	0.9948	-0.5393	0.5897
	α_4	$i_{t,\text{US}} - i_{t,\text{jap}}$	-0.1016	0.0933	-1.0900	0.2758
	α_5	$i_{t-1,\text{jap}}$	-1.2157	0.9487	-1.2814	0.2002
	α_6	$i_{t-1,\text{US}} - i_{t-1,\text{jap}}$	0.0766	0.0904	0.8475	0.3968
$\log\sigma_t^2$	β_0	const	-0.7857	0.2425	-3.2395	0.0012
	β_1	$\log\sigma_{t-1}^2$	0.3783	0.0323	11.700	0.0000
	β_2	$\log\sigma_{t-1,w}^2$	0.2467	0.0484	5.0926	0.0000
	β_3	$\log\sigma_{t-1,m}^2$	0.1822	0.0417	4.3644	0.0000
	β_4	I_t	0.5863	0.1264	4.6373	0.0000
	β_5	$r_{t,\text{Nikkei}}^2$	0.8679	0.1538	5.6444	0.0000
	β_6	$i_{t,\text{jap}}$	-0.3854	0.5212	-0.7394	0.4597
	β_7	$i_{t,\text{US}} - i_{t,\text{jap}}$	-0.0581	0.0516	-1.1257	0.2604
	β_8	$i_{t-1,\text{jap}}$	0.1699	0.4372	0.3887	0.6976
	β_9	$i_{t-1,\text{US}} - i_{t-1,\text{jap}}$	0.0459	0.0587	0.7824	0.4340
I_t	γ_1	I_{t-1}	0.1299	0.0197	6.5807	0.0000
	γ_2	r_t	0.5537	0.1268	4.3667	0.0000
	γ_3	r_{t-1}	-0.0544	0.0340	-1.6000	0.1097
	γ_4	σ_t^2	0.0852	0.0898	0.9484	0.3430
	γ_5	σ_{t-1}^2	-0.0447	0.0884	-0.5059	0.6130
	γ_6	$r_{t,\text{Nikkei}}$	0.0316	0.0197	1.6087	0.1078
	γ_7	$r_{t,\text{Nikkei}}^2$	-0.2320	0.2677	-0.8665	0.3863
	γ_8	$i_{t,\text{jap}}$	0.6111	0.8474	0.7212	0.4709
	γ_9	$i_{t,\text{US}} - i_{t,\text{jap}}$	-0.0070	0.0654	-0.1072	0.9146
	γ_{10}	$i_{t-1,\text{jap}}$	0.9338	0.7898	1.1824	0.2372
	γ_{11}	$i_{t-1,\text{US}} - i_{t-1,\text{jap}}$	0.0349	0.0701	0.4975	0.6189

Table 4: ESTIMATION OF MODEL (4) THROUGH (6) FOR SAMPLE 2-DEC-1999 THROUGH 30-DEC-2004.

dep. var.	coeff.	indep. var.	estimate	std. err.	t-stat.	prob.
r_t	α_0	const	-0.0570	0.0284	-2.0079	0.0447
	α_1	I_t	0.0498	0.0124	4.0118	0.0001
	α_2	$r_{t,\text{Nikkei}}$	-0.0398	0.0146	-2.7258	0.0064
	α_3	$i_{t,\text{jap}}$	1.6074	1.3247	1.2134	0.2250
	α_4	$i_{t,\text{US}} - i_{t,\text{jap}}$	-0.1470	0.0854	-1.7198	0.0855
	α_5	$i_{t-1,\text{jap}}$	0.4010	1.2329	0.3252	0.7450
	α_6	$i_{t-1,\text{US}} - i_{t-1,\text{jap}}$	0.1647	0.0859	1.9168	0.0553
$\log \sigma_t^2$	β_0	const	-1.1814	0.2044	-5.7785	0.0000
	β_1	$\log \sigma_{t-1}^2$	0.2534	0.0392	6.4685	0.0000
	β_2	$\log \sigma_{t-1,w}^2$	0.3098	0.0715	4.3304	0.0000
	β_3	$\log \sigma_{t-1,m}^2$	0.1951	0.0580	3.3630	0.0008
	β_4	I_t	-0.1215	0.0227	-5.3589	0.0000
	β_5	$r_{t,\text{Nikkei}}^2$	0.6157	0.1458	4.2240	0.0000
	β_6	$i_{t,\text{jap}}$	0.5751	0.7310	0.7868	0.4314
	β_7	$i_{t,\text{US}} - i_{t,\text{jap}}$	0.1286	0.0868	1.4815	0.1385
	β_8	$i_{t-1,\text{jap}}$	-0.8153	0.4469	-1.8244	0.0682
	β_9	$i_{t-1,\text{US}} - i_{t-1,\text{jap}}$	-0.1245	0.0869	-1.4334	0.1518
I_t	γ_1	I_{t-1}	0.2474	0.0563	4.3967	0.0000
	γ_2	r_t	8.2418	2.2070	3.7344	0.0002
	γ_3	r_{t-1}	0.0931	0.1526	0.6098	0.5420
	γ_4	σ_t^2	-0.1474	0.2133	-0.6909	0.4897
	γ_5	σ_{t-1}^2	0.0258	0.1840	0.1402	0.8885
	γ_6	$r_{t,\text{Nikkei}}$	0.3032	0.1132	2.6779	0.0074
	γ_7	$r_{t,\text{Nikkei}}^2$	0.2476	0.5113	0.4844	0.6281
	γ_8	$i_{t,\text{jap}}$	-12.747	9.3519	-1.3631	0.1729
	γ_9	$i_{t,\text{US}} - i_{t,\text{jap}}$	1.1856	0.6603	1.7957	0.0726
	γ_{10}	$i_{t-1,\text{jap}}$	-2.4283	8.0821	-0.3005	0.7638
	γ_{11}	$i_{t-1,\text{US}} - i_{t-1,\text{jap}}$	-1.3484	0.6820	-1.9771	0.0481

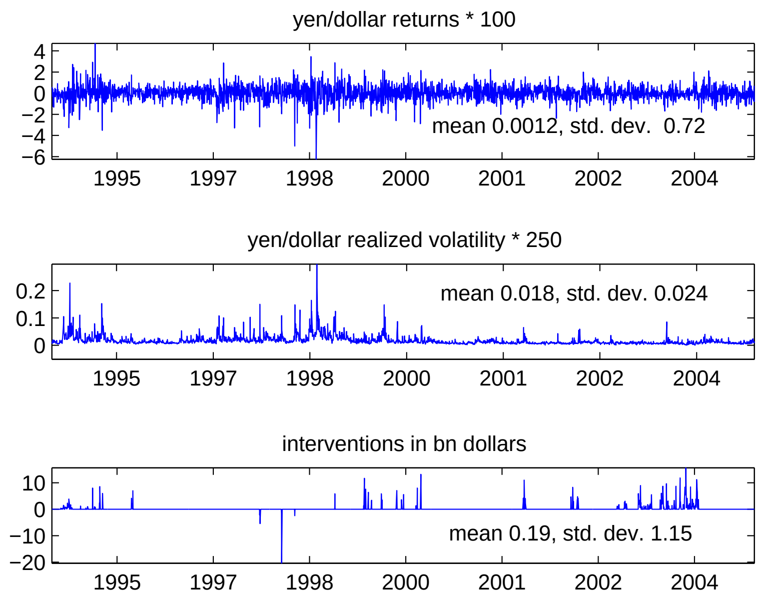

Figure 1: Yen/dollar returns and realized volatility, interventions by Japanese and U.S. authorities during 1995 to 2004.