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

A Simultaneous Equations Approach Using Realized Volatility

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Abstract

We use realized volatility to study the influence of central bank interventions on the yen/dollar exchange rate. The observability of volatility enables us to model a system of three equations for returns and volatility of the exchange rate and interventions. In the past, the latent volatility was modeled in GARCH frameworks and the mean equation then suffered from simultaneous equation bias. Realized volatility is a technical innovation that allows a comprehensive view on the problem for the first time. We find that the success of interventions both in pushing the exchange rate into the desired direction and in smoothing volatility changed around the year 2000. From 1995–2000, the effect on returns was negligible and

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interventions actually increased volatility. From 2000–2005, interventions had the desired effect on returns and also reduced volatility.

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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 motivations and 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, 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 seminal paper of Dominguez (1998), the studies of Ito (2002), Frenkel, Pierdzioch and Stadtmann (2005), Watanabe and Harada (2005) as well as Hillebrand and Schnabl (2005) have used daily yen/dollar time series in a GARCH framework to scrutinize 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. Separate estimations of reaction functions of the monetary authorities commonly find that interventions are not related to exchange rate volatility, so that endogeneity does not seem to be a problem. The findings are mixed with evidence that Japanese foreign exchange intervention 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 of the endongeneity issue, in particular in the GARCH mean equation, a new strand of literature has evolved which 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 strong evidence in favor of successful Japanese intervention, as mean exchange rate changes after intervention are statistically smaller than the mean pre-intervention change. Event studies have been criticized for the arbitrary choice of the window size and success criteria.

Up to now, few papers have chosen a structural model to identify the effects of foreign exchange intervention. Kearns and Rigobon (2005) estimate a multiple equation non-linear model for Australian foreign exchange intervention and find successful intervention. Their innovation resolves the endogeneity issue by modeling simultaneous equations. Kim (2003) uses a structural VAR model to identify the effects of intervention and monetary policy providing evidence that sterilized US foreign exchange intervention "leaning against the wind" had a significant impact on the trade weighted dollar exchange rate.

The concept of realized volatility introduced by Andersen and Bollerslev (1998) allows to consider volatility as observed rather than latent, as is done in GARCH models. Therefore, realized volatility enables us to study the interplay of interventions, exchange rate returns, and volatility directly.

We follow Kearns and Rigobon (2005) and estimate a simultaneous system of equations. Unlike Kearns and Rigobon, we study the yen/dollar realized volatility obtained from high-frequency data in a system consisting of equations for the exchange rate return, the realized volatility, and the intervention. We also estimate a reduced form VAR in the same three variables to support our findings. Unlike Kim (2003) we use daily data, which allows us to study the relation between exchange rate and intervention more carefully at the cost of not being able to include macroeconomic variables such as the monetary base and CPI inflation measured at monthly frequencies. We estimate the systems on the sample period 1995–2004 as well as the sub-periods 1995–1999 and 2000–2004.

We find that during the period 1995–1999, Japanese foreign exchange interventions were not successful, neither in influencing the returns nor the volatility of the yen/dollar rate. In the period 2000–2004, interventions were successful in moving the exchange rate in the desired direction as well as in reducing volatility. The results indicate a change toward a more successful intervention policy.

2 Realized Volatility

Returns on 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. Volatility is not observable, however, and squared or absolute daily returns are used as estimators of latent volatility.

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 gets finer. The quadratic variation, in turn, is the variance of increments of the continuous martingale. In the asset price model, the quadratic variation is therefore 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 function of time. The function may be deterministic or stochastic. The quadratic variation $< X > (t)$ is given by

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

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

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

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

$$< X > (t) = \int_0^t \sigma^2(s) ds,$$

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

$$< X > (t) - < X > (t-1) = \sum_{j=1}^{n} |X(\tau_j) - X(\tau_{j-1})|^2, \tag{3}$$

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. The availability of high-frequency intra-day price data therefore enables us theoretically to find an estimator for volatility with arbitrarily small estimation error. Therefore, volatility can be treated as *observable* rather than latent. In practice, microstructure effects like the bid-ask bounce prevent too fine a grid and 5-minute intervals have become something of a standard. Andersen, Bollerslev, Diebold and Labys (2001), and Andersen, Bollerslev, Diebold, and Ebens (2001) use 5-minute quotes to analyze the distribution of daily stock and exchange return volatility.

Our data set consists of the yen/dollar exchange rate (5-minute quotes from Olsen Financial Technologies), the daily interventions of the Japanese authorities reported on the web site of the Japanese Ministry of Finance, and the daily Nikkei 300 (Bloomberg series NEY). 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 cut the weekends from Friday 21:05 GMT until Sunday 21:05 GMT. Christmas (Dec 24-26), New Year (Dec 31–Jan 2) and the Fourth of July are 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). Figure 1 shows plots of the three considered series.

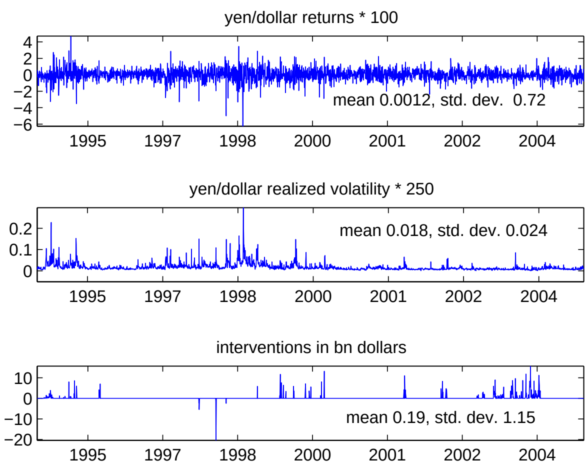

Figure 1: Yen/dollar returns and realized volatility, interventions by Japanese and U.S. authorities during 1995 to 2004.

3 A VAR Model of Exchange Rate Moments and Intervention

In this section, we estimate the system $y_t = (r_t,\, \sigma_t^2,\, I_t)$ in a vector autoregression (VAR), 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 estimated model is

$$y_t = c + \sum_{i=1}^{p} \Phi_i y_{t-i} + Bx_t + \varepsilon_t, \tag{4}$$

where $c \in \mathbb{R}^3$ is a vector of constants, $\Phi_1, \ldots, \Phi_p \in \mathbb{R}^{3\times 3}$ are the autoregressive coefficient matrices, and ε_t is 3-dimensional vector white noise. The vector $x_t \in \mathbb{R}^k$ contains the daily log returns and the daily volatility of the Nikkei 300 index as exogenous variables, the coefficient matrix is $B \in \mathbb{R}^{3\times k}$. We cannot make standard distribution assumptions on the error terms ε_t because of the structure of our data. Realized volatility does not take negative values or zero, and the intervention time series is equal to zero most of the time (more than 90%). Therefore, we only report the impulse response functions without significance intervals, since standard inference does not apply. We understand this analysis as a preliminary study to be complemented by the structural model studied in the next section.

The Bayes Information Criterion indicates that $p = 3$ is a good choice for the lag structure. Figure 2 shows the impulse response functions of yen/dollar

[1] There are two periods where the Federal Reserve intervened during the sample period. The first was between Mar 2, 1995 and Aug 15, 1995. All interventions were coordinated with the Japanese authorities, had the same sign and purpose, and occurred on the same 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 that period. The purchases of the Federal Reserve amounted to \$3.3bn. The only other time was Jun 17, 1998, where the Federal Reserve supported a Japanese sale of Dollars (\$1.6bn) by selling \$0.8bn.

returns and yen/dollar realized volatility with respect to interventions (top row), and the impulse responses of interventions with respect to yen/dollar returns and yen/dollar realized volatility (bottom row). The graphs report the impulse responses for the two sub-segments and for the entire sample ("global").

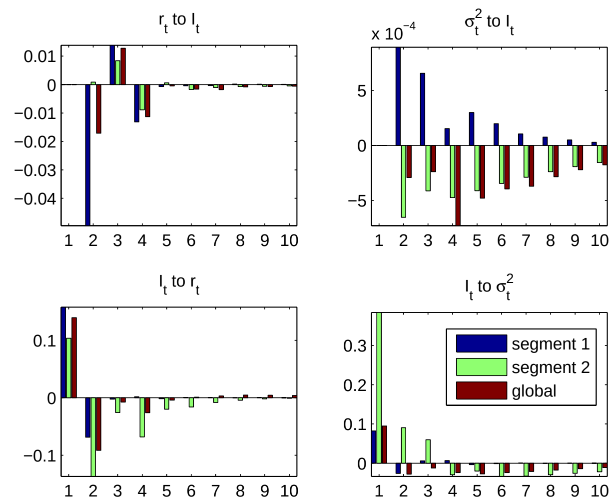

Figure 2: Impulse response functions of yen/dollar returns and yen/dollar realized volatility with respect to interventions (top row), impulse responses of interventions with respect to yen/dollar returns and yen/dollar realized volatility (bottom row).

Simply relating the magnitudes of the impulse responses to those of the time series (Figure 1), all impulse responses seem at least not negligible. Considering the first column of graphs in Figure 2, we point out that initially there is positive correlation between yen/dollar returns and interventions. This is the desired direction of the authorities: As the interventions hit the market (positive = dollar purchases), the dollar appreciates against the yen, driving up the yen/dollar rate. However, this desired correlation appears only in the response of interventions to returns, not vice versa, where we would have expected it. At higher lags, we see more negative correlation, most plausibly explained by "leaning against the wind": The authorities intervene in favor of the dollar (positive interventions) after the yen appreciated (negative movements in the yen/dollar rate).

Considering the second column, which reflect correlation between interventions and realized volatility, we see in the second upper panel the structural break documented in Hillebrand and Schnabl (2005): While interventions correlate positively with realized volatility in the first sub-segment, they correlate negatively in the second segment and on the entire sample. With view to the last panel, it seems that realized volatility correlates with interventions. Inference statements are not possible in this setup, however, since we could not make any distribution assumptions that would facilitate these.

4 A Structural Model of Exchange Rate Moments and Intervention

In this section, we impose more structure on the system $y_t = (r_t, \sigma_t^2, I_t)$ and estimate a system of simultaneous equations using the Generalized Method of Moments (GMM). This will allow us to make inferences about the system.

4.1 Specification

We will consider the following linear system of equations

$$r_t = \alpha_0 + \alpha_1 I_t + u_t, \tag{5}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \sigma_{t-1}^2 + \beta_2 I_t + v_t, \tag{6}$$

$$I_t = \gamma_1 r_t + \gamma_2 r_{t-1} + \gamma_3 \sigma_t^2 + \gamma_4 \sigma_{t-1}^2 + w_t, \tag{7}$$

where r_t are the daily log returns of the yen/dollar exchange rate, σ_t^2 is the daily realized volatility, and I_t are the interventions. The parameter vector to be estimated is

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

As a consequence of the data characteristics (realized volatility being always positive and interventions being equal to zero most of the time), we cannot make standard distribution assumptions on the error terms. We will therefore estimate the system by GMM, which does not require a specific error structure 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 (5) (with coefficient κ_1), its squared returns in equation (6) (with coefficient κ_2), and both returns and squared returns in equation (7) (with coefficients κ_3, κ_4). This results in a nuisance parameter vector

$$\tilde{\theta} = (\kappa_1, \kappa_2, \kappa_3, \kappa_4),$$

which we estimate alongside θ.[2]

Before the theory of realized volatility was available, equations (5) and (6) were usually specified in a GARCH framework with interventions as exogenous variables. Equation (7), 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 (2005), among others. In this setup, volatility was latent and the mean equation (5) of the GARCH regression suffered from simultaneous equation bias because equation (7) was not part of the system. The conditional volatility equation seemed to be statistically fine since separate estimations of the reaction function (7) routinely showed that volatility (squared daily returns or fitted GARCH series) did not influence interventions. Therefore, the estimated coefficients of the mean equation of the GARCH model could not be interpreted.

Realized volatility allows us to treat σ_t^2 as an observed variable and study the effect of interventions on exchange rates with multiple equation models directly. Multiple equation models have been employed before to analyze the effects of

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

interventions on exchange rates but the analysis considered the effect on returns only (Kearns and Rigobon 2005, Neely 2005). Kim (2003) studies a structural VAR for the U.S. incorporating the exchange rate, interventions, and an array of macroeconomic series (interest rates, price indices, etc.)

We address the question of structural stability that has been raised in the extant literature by splitting our sample into 1995–1999 and 2000–2004 subperiods. Several authors have found evidence for a change in the effects of Japanese interventions on returns and volatility of the yen/dollar rate in the late 1990s (Ito 2003, Hillebrand and Schnabl 2005).

4.2 Identification

Consider the simplified system

$$r_t = \alpha_0 + \alpha_1 I_t + u_t, \tag{8}$$

$$\sigma_t^2 = \beta_0 + \beta_1 I_t + v_t, \tag{9}$$

$$I_t = \gamma_1 r_t + \gamma_2 \sigma_t^2 + w_t. \tag{10}$$

Equations (8) through (10) can be written as

$$Ay_t = c + \varepsilon_t,$$

where $y_t = (r_t,\, \sigma_t^2,\, I_t)$ is the vector of variables of the system, $c = (\alpha_0,\, \beta_0,\, 0)'$ is the vector of constants, $\varepsilon_t = (u_t,\, v_t,\, w_t)$ is the vector error process, and A is the coefficient matrix

$$A = \begin{bmatrix} 1 & 0 & -\alpha_1 \\ 0 & 1 & -\beta_1 \\ -\gamma_1 & -\gamma_2 & 1 \end{bmatrix}.$$

It is necessary for identification that A be invertible. The inverse is given by

$$A^{-1} = \frac{1}{1 - \alpha_1\gamma_1 - \beta_1\gamma_2} \begin{bmatrix} 1 - \beta_1\gamma_2 & \alpha_1\gamma_2 & \alpha_1 \\ \beta_1\gamma_1 & 1 - \alpha_1\gamma_1 & \beta_1 \\ \gamma_1 & \gamma_2 & 1 \end{bmatrix}.$$

Plugging (8) and (9) into (10), we obtain that

$$I_t = (\alpha_1\gamma_1 + \beta_1\gamma_2)I_t + cu_t + dv_t + w_t.$$

Therefore, $\mathbb{E}I_t = (\alpha_1\gamma_1 + \beta_1\gamma_2)\mathbb{E}I_t$, or $\alpha_1\gamma_1 + \beta_1\gamma_2 = 1$. Thus, the system is not identified; A^{-1} does not exist. One possibility to solve this problem is by instrumental variable estimation.

A valid instrument must be a variable x_t that decomposes w_t into

$$w_t = \gamma_3 x_t + \varepsilon_t, \tag{11}$$

such that $\mathrm{cov}(x_t, \varepsilon_t) = 0$ by construction. Further, by assumption, $\mathrm{cov}(x_t, v_t) = 0$ and $\mathrm{cov}(x_t, u_t) = 0$ must hold. Then, the instrumental variable estimators of the parameters α_1 and β_1 of main interest are given by

$$\alpha_1 = \frac{\mathrm{cov}(x_t, r_t)}{\mathrm{cov}(x_t, I_t)}, \quad \text{and} \quad \beta_1 = \frac{\mathrm{cov}(x_t, \sigma_t^2)}{\mathrm{cov}(x_t, I_t)}. \tag{12}$$

In order for the instrumental variable estimators to exist, the instrument x_t must correlate with the intervention I_t. Only if the instrument x_t also correlates with r_t and σ_t^2, the estimators will not be zero. The instrument x_t must not correlate with any of the errors u_t, v_t and ε_t.

The extended system $\tilde{y}_t = (r_t, \sigma_t^2, I_t, x_t)$ has coefficient matrix

$$\tilde{A} = \begin{bmatrix} 1 & 0 & -\alpha_1 & 0 \\ 0 & 1 & -\beta_1 & 0 \\ -\gamma_1 & -\gamma_2 & 1 & -\gamma_3 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

with inverse

$$\tilde{A}^{-1} = \frac{1}{1 - \alpha_1\gamma_1 - \beta_1\gamma_2} \begin{bmatrix} 1 - \beta_1\gamma_2 & \alpha_1\gamma_2 & \alpha_1 & \alpha_1\gamma_3 \\ \beta_1\gamma_1 & 1 - \alpha_1\gamma_1 & \beta_1 & \beta_1\gamma_3 \\ \gamma_1 & \gamma_2 & 1 & \gamma_3 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

Let $x_t = \delta I_t + \tilde{\varepsilon}_t$. Then, plugging (8), (9), and (11) into (10) and substituting for x_t, we obtain

$$I_t = \gamma_1 \alpha_1 I_t + \gamma_2 \beta_1 I_t + \gamma_3 \delta I_t + w_t + \gamma_1 u_t + \gamma_2 v_t + \gamma_3 \tilde{\varepsilon}_t.$$

Taking expectations, the new condition on the parameters reads

$$\alpha_1 \gamma_1 + \beta_1 \gamma_2 + \gamma_3 \delta = 1,$$

and for $\delta \neq 0$, an essential requirement for a valid instrument, the inverse $\tilde{A}^{-1}$ exists.

We propose the first two lags of the intervention variable (I_{t-1}, I_{t-2}) 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, $x_t = (I_{t-1}, I_{t-2})$ fulfill the condition $\operatorname{cov}(I_t, x_t) \neq 0$. By equations (8) and (9) and the autocorrelation, (I_{t-1}, I_{t-2}) will also correlate with r_t and σ_t^2, such that the instrumental variable estimators (12) will not be zero. The sample partial autocorrelation function for the Japanese intervention series drops from 27.3% to 20.5% to 6.1% for the first three lags, so that $\operatorname{cov}(x_t, \varepsilon_t) = 0$ does not seem too much of a stretch. A more delicate issue is the zero correlation with the shocks u_t and w_t. Economically, this means that the interventions yesterday and the day before yesterday do not lead to shocks to exchange rate returns and volatility today. This seems somewhat reasonable as surprising interventions should have their shock effect on the same day but of course this can be disputed. 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 (8). To be a valid instrument, it then must not correlate with shocks to interventions ($\operatorname{cov}(x_t, w_t) = 0$, Neely does not consider volatility) and with the residual error in the mean equation ($\operatorname{cov}(x_t, \varepsilon_t) = 0$). In particular the latter requirement makes this instrument not much more attractive to us than our candidate. An entirely different approach to tackle the identification problem is the two-segment threshold intervention model of Kearns and Rigobon (2005), which they estimate by simulated method of moments. Their setup allows only for changes in the threshold intervention, however, 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 2005) varies through time, therefore Kearns' and Rigobon's approach does not seem to be the best one for our problem.

4.3 Estimation

The system (5) through (7) is estimated using the following instruments: the first two lags of the intervention series, the first lag of the yen/dollar returns, the first two lags of yen/dollar realized volatility, and the returns and squared returns of the Nikkei 300. We use a heteroskedasticity and autocorrelation consistent estimator with quadratic spectral kernel for the covariance matrix of the moment conditions (Andrews 1991).

On the entire sample period Jan 1, 1995 through Dec 31, 2004, we obtain the following estimated coefficients (t-probabilities in parentheses):

$$r_t = \underset{(0.11)}{0.02} - \underset{(0.59)}{0.01} I_t - \underset{(0.00)}{0.04} r_{t,\text{Nikkei}} + u_t, \tag{13}$$

$$\sigma_t^2 = \underset{(0.00)}{0.006} + \underset{(0.00)}{0.55} \sigma_{t-1}^2 + \underset{(0.68)}{\text{2.4e-4}} I_t + \underset{(0.00)}{0.02} r_{t,\text{Nikkei}}^2 + v_t, \tag{14}$$

$$\begin{aligned} I_t = {} & \underset{(0.00)}{0.32} I_{t-1} + \underset{(0.00)}{3.95} r_t - \underset{(0.00)}{0.16} r_{t-1} - \underset{(0.20)}{9.04} \sigma_t^2 + \underset{(0.09)}{6.91} \sigma_{t-1}^2 \\ & + \underset{(0.00)}{0.12} r_{t,\text{Nikkei}} + \underset{(0.04)}{1.32} r_{t,\text{Nikkei}}^2 + w_t. \end{aligned} \tag{15}$$

The first sub-period between Jan 1, 1995 and Dec 31, 1999 results in the following coefficient estimates.

$$r_t = \underset{(0.08)}{0.03} - \underset{(0.04)}{0.25}\ I_t - \underset{(0.02)}{0.04}\ r_{t,\text{Nikkei}} + u_t, \tag{16}$$

$$\sigma_t^2 = \underset{(0.00)}{0.01} + \underset{(0.00)}{0.53}\ \sigma_{t-1}^2 + \underset{(0.00)}{0.02}\ I_t + \underset{(0.00)}{0.05}\ r_{t,\text{Nikkei}}^2 + v_t, \tag{17}$$

$$\begin{aligned} I_t = {} & \underset{(0.00)}{0.18}\ I_{t-1} + \underset{(0.00)}{1.68}\ r_t - \underset{(0.00)}{0.17}\ r_{t-1} - \underset{(0.27)}{2.63}\ \sigma_t^2 + \underset{(0.23)}{1.77}\ \sigma_{t-1}^2 \\ & + \underset{(0.02)}{0.04}\ r_{t,\text{Nikkei}} + \underset{(0.06)}{1.07}\ r_{t,\text{Nikkei}}^2 + w_t. \end{aligned} \tag{18}$$

The second five-year period from Jan 1, 2000 through Dec 31, 2004 results in the following estimation.

$$r_t = \underset{(0.45)}{0.01} + \underset{(0.01)}{0.03}\ I_t - \underset{(0.00)}{0.05}\ r_{t,\text{Nikkei}} + u_t, \tag{19}$$

$$\sigma_t^2 = \underset{(0.00)}{0.006} + \underset{(0.00)}{0.42}\ \sigma_{t-1}^2 - \underset{(0.00)}{0.001}\ I_t + \underset{(0.09)}{0.004}\ r_{t,\text{Nikkei}}^2 + v_t, \tag{20}$$

$$\begin{aligned} I_t = {} & \underset{(0.01)}{0.26}\ I_{t-1} + \underset{(0.00)}{26.04}\ r_t - \underset{(0.04)}{0.58}\ r_{t-1} - \underset{(0.20)}{38.6}\ \sigma_t^2 + \underset{(0.01)}{-57.22}\ \sigma_{t-1}^2 \\ & + \underset{(0.00)}{1.03}\ r_{t,\text{Nikkei}} + \underset{(0.21)}{1.10}\ r_{t,\text{Nikkei}}^2 + w_t. \end{aligned} \tag{21}$$

The large differences in the coefficients are due to the very different distributional characteristics of the intervention time series in the two different segments. There are two concepts of "success" of interventions discussed in the literature: Either (1) interventions push the exchange rate in the desired direction (positive correlation of interventions with returns in the case of the yen/dollar rate) or (2) interventions reduce volatility.

Judging by these standards, interventions have not done well on the first segment between 1995 and 1999: There is significant negative correlation of interventions with returns in the return equation and positive correlation of interventions with volatility. While we cannot conclude that interventions caused these movements, they clearly also did not prevent them. At the same time, the reaction function displays positive correlation of interventions with returns, repeating what was already apparent in the VAR. On the second segment from 2000 to 2004, interventions have the desired correlation with returns and volatility in the first two equations. The switch in the effect on volatility could already be seen in the VAR. In both segments, the lagged return in the reaction function shows the "leaning against the wind" by the Japanese authorities, frequently found in the intervention literature.[3]

On the entire sample, the correlation of returns and interventions is insignificant in the return equation. Likewise, the relation between realized volatility and interventions is insignificant in the volatility equation. In summary, in the first segment, interventions are unsuccessful in both respects. In the second segment, interventions are successful in both respects. On the global sample, the effect seem to cancel each other out into insignificance.

5 Conclusion

We examine the interplay of returns and realized volatility of the yen/dollar exchange rate with interventions of the Japanese authorities in the yen/dollar market. The concept of realized volatility allows to treat volatility as observed and this enables us to employ a simultaneous equations model for returns, realized volatility, and interventions. On our sample period 1995–2005, we find that in the first sub-period from 1995 through 2000, interventions were unsuccessful in both changing the returns and reducing volatility. On the second sub-period, 2000 through 2005, interventions seem to have influenced returns into the desired direction as well as reduced volatility.

[3]Note that the yen/dollar returns and realized volatilities are stamped at Greenwich Mean Time, that is, after market closing in Tokyo. The daily intervention series is recorded in Tokyo time. Therefore, I_t can directly cause changes in r_t but the other direction can only work through expectations. The lag r_{t-1} can directly cause changes in I_t. Of course, the estimation then only measures correlation.

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