Abstract

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Analysis using a Bivariate Stochastic Volatility Model

Foreign Exchange Intervention by the Bank of Japan: Bayesian
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High volumes may signal the presence of an informed trader in the market. Intervention con-
taining volume as additional (and valuable) information to prices. For example, unsual
market microstructure heterogeneity (Hansen and O'Hara, 1987) provides a theoretical basis for
the dummy variable (see, for example, Kim, 2004) estimating a dummy variable (1) model for the effect of OIR

Introduction

Bank of Austria,

inserted empirical and quantitative stochastic volatility in their study of intervention by the Reserve

Hoesch (2003) examined the impact of the OIR, however, Szhul, Malzmann and Shoen (2004)

and Shin (2000) examined the effectiveness of intervention by the Reserve Bank of Austria;

while also conducting a dummy variable stochastic volatility model on central bank intervention, Schuh.

Most of the existing empirical literature on central bank intervention employs CARCH-

function.

price of accounting for the endogeneity between the volatility in returns and the OIR region.

posterier inference is computed jointly for both models using MC MC, which is the admi-

packed. In turn, intervention by the OIR is modeled using a hierarchical model. Based on

the Bank of Japan (BOJ) on daily returns and volume in the USD/JPY foreign exchange

we employ a dummy variable stochastic volatility model to measure the effect of intervention by

inference. we considered combining with information from the other models proposed above, the

case: see D'Amico and Shepherd (1996), D'Amico and Shepherd (1999), and D'Amico and

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D'Amico and Shepherd (1999), and D'Amico and Shepherd (1999), and D'Amico and
and discuss their implications in context of the existing literature. Section 7 concludes the paper.

In the USD/VEF foreign exchange markets, while section 6 contains the empirical results on the yen/VEF exchange rates, Section 9 outlines the specific model employed to study BID/ask intervention in these markets to demonstrate the reliability of the dollar-based price for the precision matrix of the joint posterior, with details provided in the appendix. In section 4, a simulated dataset is provided in an overview of the MCMC sampling scheme employed to complete inference from the multivariate stochastic volatility and threshold models, and the priors employed. Section 7 introduces both the

The remainder of the paper is structured as follows. Section 2 introduces both the

induced volume due to an exogenous variable in the threshold model.

SV model via simulation. We extend this approach to the BID/ask application and call it also
is able to estimate an integrated model for observed information jointly with the univariate
contrast. The authors obtain estimates of the implied conditional volatility models
of currency movements, which can then be best addressed in model
of certain bank information is to call disorderly markets. Second, another central bank
these models is the volatility of returns, which is included for two reasons. First, one objective
made use of a hybrid model for BID/ask intervention. One of the key exogenous variables in
intervention and dispersion (McCulloch and Weisbenner (1994)) employ a local specification; and Shoven and Kinn (1992) use a hybrid model;
and a number of authors have estimated limited dependent variable models for observed
The Intervention literature also examines the motivation for intervention by central banks

Joint returns-volume process modeled by a multivariate stochastic volatility model.

We extend the work of Shoven and Kinn (1994) to consider the effects of intervention on the
are associated with smaller rises in volume than more moderate interventions. In this paper
between intervention and volume, through cumulative and lagged dummy variables
information have on volume. Shoven and Kinn (2004) find evidence of a positive relationship
studies information to the market and an interesting question is whether, what impact does

BE
\[
\begin{align*}
\Phi & \Phi \\
0 = f & \sum_{t=0}^{N} = \mathbb{V} \\
1 = m & \sum_{t=0}^{N} = \mathbb{V}
\end{align*}
\]

where

\[
\begin{align*}
\mathbb{V} + (\nu^{-1}I - \nu^{-1}\eta)\Phi & = \nu^{-1}I - \nu^{-1}\eta \\
\mathbb{V} & = \nu^{-1}I
\end{align*}
\]

re-written on \( \{\nu_1, \ldots, \nu_N\} \) can be the

The coefficient matrix \( \mathbb{C} \), and the correlation matrix \( \mathbb{G} \), are distributed as \( \mathbb{G} \) and \( \mathbb{C} \) are independent, and

\[
\begin{align*}
\mathbb{Z} & \mathbb{Z} \\
\mathbb{I} & \mathbb{O}
\end{align*}
\]

\( \Phi \). \( \mathbb{I} \) is assumed that the coefficient matrix is appropriate for the correlation matrix with the corresponding coefficients.

\[
\begin{align*}
\mathbb{Z} & \mathbb{Z} \\
\mathbb{I} & \mathbb{O}
\end{align*}
\]

The bivariate stochastic volatility (BSV) model is defined as

\[
\begin{align*}
\mathbb{V} + (\nu^{-1}I - \nu^{-1}\eta)\Phi & = \nu^{-1}I - \nu^{-1}\eta \\
\mathbb{V} & = \nu^{-1}I
\end{align*}
\]

2.1 Bivariate Stochastic Volatility Model
\[ \begin{align*} 
\theta > \frac{1}{b} & \quad \text{or} \quad \theta < \frac{1}{b} \\
\theta \geq \frac{1}{b} & \quad \text{or} \quad \theta \leq \frac{1}{b} \\
\theta & = \frac{1}{b} 
\end{align*} \]

These thresholds are due to the existence of both direct and indirect effects of intervention. Therefore, at time \( t \) if it exceeds some upper threshold, \( \theta \), or falls below a lower threshold, \( \theta \), the model is employed for certain bank intervention. Here, several interventions are only observed during crises and risk periods (2003) and Smith, Mclenton, and Shreen (2004), a threshold

2.6 Thresholds Model and Endogeneity

\[ (4) \]

\[ \left\{ \left( \Omega Z - 1\eta \right)_{1-1} \Pi \left( \Omega Z - 1\eta \right) \frac{c}{1-1} \right\} \text{d}x = \left[ \frac{1}{L} \right] \Pi (\Omega Z) N \sim \Pi 1 \eta \]

\[ \text{so that (Rebula, 1997)} \]

The process \( \{ \eta \} \) is assumed to be stationary where \( \{ \eta \} \) and \( \{ \eta_1, \cdots, \eta_1 \} = \nu \)

\[ (5) \]

\[ \left( \Pi 1 \eta \right) d(1-1\eta \Pi 1 \eta) d \prod_{u} (\Pi 1 \eta \Pi 1 \eta) d \prod_{u} = \left( \Pi 1 \eta \right) d(1 \eta \Pi 1 \eta) d \\
= (\Pi 1 \eta) d(1 \eta \Pi 1 \eta) d 
\]

Let \( \Pi \) be the parameter vector, then the likelihood associated with the latent volatilities

Section 3.

However, computing inference on such a model proves more complex than that outlined in dynamics that underlie equation (4) (\[ 6 \]) and discusses the underlying spatial partition. Note that an alternative discrete time model could be defined by taking the continuous time

We left this as a univariate stochastic volatility model with missing observations (BSYMO).
and assume a proper Wishart prior \( W^{-1} \) for \( \Sigma \). Hence, we set \( a = 2 \) to ensure a high

Instead, we assume \( P(d) \propto (d - 1)^{1 - (n - 1) \beta} \), ensuring that \( C \), is a correlation matrix,

both complex and computationally burdensome, and the effect of the posterior is hard to

issue by extending the informative prior of Wong et al. (2003) to the multivariate SV

because the estimated likelihood is expressed in terms of the posterior with respect to \( \alpha \).

Selection of appropriate priors for \( \alpha \) and \( \beta \) is more difficult. First, much of the evidence

and \( (\nu, \phi) \) is line, so that the indicator function \( I_{\nu > \phi > 1 - \nu} \) is zero when \( \nu \) is

which means that priors for \( \alpha \) and \( \beta \). The log-likelihoods are assumed to follow standard discounted

and the two models are equivalent. This is accounted for by computing

In modeling causal interactions, in section 2, the elements in the vector \( \nu \) are

when the latent variables are properly transformed to

In modeling causal interaction, in section 2, the elements in the vector \( \nu \) are
3 Estimation

on the likelihoods and Chib's (1995) for the parameters in the likelihood model that prior is assumed
The proposed density is \( \psi \), which is the mean density of the mixture distribution at \( t = 1 \). The proposal is made using random walk Metropolis-Hastings steps, and proposals are accepted with probability given by the acceptance probability, which is determined by the ratio of the proposal density to the conditional density, as calculated in the second step of the sampler.

In step (2) of the Metropolis-Hastings steps, the proposal density is \( \psi \), with a normal density centered at \( t = 1 \), where \( \psi \) is the mean density of the mixture distribution. The proposal is made using random walk Metropolis-Hastings steps, and proposals are accepted with probability given by the acceptance probability, which is determined by the ratio of the proposal density to the conditional density, as calculated in the second step of the sampler.

The conditional posterior densities, and corresponding normal densities, where 1 is the mode of \( \psi \) and is found using the gradient of the target density:
do not differ much and that both are lower than the true value. However, the data-based prior is not informative when the posterior means $E(\theta) = 0$, so it is not surprising that the posterior means $E(\theta)$ are lower than the true value.

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Table 1 and Figure 1 above--

In this section, a simulated dataset is employed to illustrate the impact of the data-based prior on posterior inference.

4 Data-Based Prior

Estimated ($1 - 95\%$) posterior probability intervals do not contain zero.

and the posterior intervals are calculated using the smooth distribution of the Monte Carlo estimates.

Monte Carlo estimates of the (1 - $\alpha$)% posterior probability intervals are used, instead of estimates of posterior probability intervals. Otherwise, Bayesian estimates and the sample mean ± standard deviation of the Monte Carlo estimates are used as point estimates and these are calculated using the marginal distribution of the posterior.

Once the sampling scheme above is run, Monte Carlo estimates of the parameters and

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Chi$^2$(1997), and a brief summary is provided in the appendix.

and Shier (2000) applied the data augmentation approach of Albert and
The BOJ has made the historical record of its FX intervention public and it is this data that is measured as a proxy for the total volume of transactions in the market.

The measure is defined as:

$$\text{Volume} = \sum_{t=1}^{T} |\Delta V_t|$$

where $\Delta V_t$ is the change in the FX rate at time $t$. The data is sourced from the Bank of Japan and consists of daily FX transactions in USD million.

This section outlines the model used to compute intervention by the BOJ in the VND/USD.

2 Bank of Japan Foreign Exchange Intervention

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In Figure 2, allows for the accurate recovery of the initial volatility.

In Figure 3, allows for the accurate recovery of the initial volatility. This demonstrates how the data-based prior and sample-based smoothed estimates differ. Figure 2 plots the time-series volatility for the first 200 observations, while Figure 3 plots the model posterior mean from the model in the same manner as the Watanabe (2014) prior.

The model posterior mean is used in the same manner as the Watanabe (2014) prior, which is used to infer the true intervention. Figure 2, which is a plot of the data-based prior model, suggests that the intervention was significant. Figure 3, which is a plot of the sample-based smoothed estimate, further reinforces this conclusion. Notice that the posterior mean is used in the same manner as the Watanabe (2014) prior, which is used to infer the true intervention.
They are similar to those specified in Sheen and Kim (2004) and others employed in the

The following parameters for the first moments of returns and volume

and other authors and estimate $\hat{\gamma'}$ by OLS before estimating the BSVMO model

is difficult to estimate the parameters $\gamma'$, in conjunction with $\hat{\gamma}$ as the likelihood based

univariate SV literature (Harvey and Snyder, 1996; Kroner and Sultan, 2003) that $\gamma'$

model in equation (7.2), so that

The daily returns and volume data were mean-corrected and then modeled using the BSVMO

5.2 Bi-arch Model for Returns and Volume

correct completely.

significantly larger. Also, information by the Federal Reserve on behalf of the BSVMO model

in 1992. It would appear that among the implications information became less frequent but

appointment of Dr. Swebah by the position of Director of the International Finance

However, this may be attributable to the

If it appears from Figure 3 that there are marked differences in the intervention decisions

Figure 3 about here—

days' fees to 37%. The returns, volume and intervention data are summarized in Figure 3.

days, the proportion of interventions on days, given that the BSVMO intervened on the previous

and a maximum of 14.0 billion VEN. Although the BSVMO intervened on less than 6% of

The average size of intervention is 14.9 billion VEN, with a minimum of 2.1 billion VEN.

transactions, they are modeled using a separate variable, $\gamma'$. For example, on the

days during the sample. To differentiate between these

the period. The BSVMO also on occasion requested the US Federal Reserve to intervene
The proportion of trades cancelled out by brokers has diminished substantially over time. The

The evidence suggests that lagged volume is also included in the second equation. Similar to

Previous studies (Hillier, 1987; Jones et al., 1994) also suggest that lagged volume

The lagged in the interest rate differential between Japan and the US, 

The interest rate differential is calculated as the difference in rates of interest between a period of interest rate. For any other reason than a weekend, the first variable is included in the model. Following Sheen and Kim (2004) the authors conclude that

The effect of the variable is lagged one trading day in the volume equation.

The lagged variable, which is lagged by the current day, is included in the model. Since the volume equation refers to the lagged volume, it is zero. The lagged in the model is equal to one if the absolute value of the lag is not included.

The former leads on the value of one if lagged correlation on day i was preceded by

The explanatory variable of primary interest is BO/INTER and the effect on returns

\[ \frac{\text{BO/INTER}}{\text{RET}} = \beta_0 + \beta_1 \text{BO/INTER} + \beta_2 \text{RET} + \epsilon \]

The variable $ET_{t-h}^\nu$ measures potential exchange rate developments from fundamentals.

That immediately low volumes are unlikely to induce intervention by the BOJ.

The first two terms aim to capture the degree of disorder in the market. The first

$$\left(1^2\right) \quad 1 - \frac{1}{\eta} \frac{d}{dt} \hat{\eta} \hat{\eta} + \frac{1}{\eta} \frac{d}{dt} \hat{\eta} \hat{\eta} + \frac{1}{\eta} \delta \frac{\delta}{\eta} + \frac{1}{\eta} \frac{1}{\eta} \delta \frac{\delta}{\eta} = \left(\frac{\eta}{\delta}\right) \mathcal{F}$$

Intervention function

where the explanatory variables are defined above.

A similar parametric model was employed for the mean of the log-returns.

\textit{Intervention Function}
positive) intervention and therefore effectively hides the effect of intervention on returns.

behavior by the BOJ. This is where an appropriate (depreciation) VFN promotes negative
behavior because the negative coefficient is most likely capturing something against the wind.
It would appear that intervention is ineffective. However, this result needs to be interpreted
and since of VFN are associated with an application of the VFN against the USD. Thus,
ship with the first moment of contemporaneous returns. That is, purchases of USD
consistent with previous studies, intervention is found to have a significant negative relationship

6.1 Estimation of the first moment of returns and volume

Table 2 and 3 about here—

Highlighting the suitability of the proposed model.
the full sample only. Table 3 reports the occurrence rates for the Veronez-Heathcote steps
reported in Table 2. Although for brevity the discussions in sections 6.1 to 6.4 correspond to
the potential structural break in BOJ policy. Results for all these periods are
correspond to the potential structural break. In BOJ policy. Results for all these periods are
were also confirmed for the two subsamples 12-2-91 to 29-6-97 and 29-6-97 to 28-6-97, which
were approximately 10 hours to complete on a standard P4 PC. For the full sample. Results
than those with a binning of 10,000 iterations and a Monte Carlo sample of 20,000 iterations. This

This section contains the empirical estimates computed using the simulation scheme in sec-

6 Empirical Results

The condition that a positive relationship is expected between the change in the US inter-
the condition that a positive relationship is expected between the change in the US interest
intervention). In this case the size of the expected to be negative. Similar reasoning leads to
be associated with the purchase of USD assets and the sale of YEN by the BOJ (positive
support domestic monetary policy? Then, a decrease in the Japanese interest rate is expected
the change in the US Federal Funds Rate \( \Delta r_F \), if one of the innovations to intervention is to
The third two equations are the change in the official Japanese discount rates, \( \Delta d_f \) and
Similar results for both returns and volume were obtained for the effects of \( \text{frac{\text{Firm}}}{\text{Cum}} \) and \( \text{frac{\text{Firm}}}{\text{Cum}} \).

Significant from the intervention and there is an increase in the heteroskedasticity of returns.

Interpretation for this purpose may increase volatility because not all agents recover the same
may be more likely to intervene when volatility is high (Packer and Smith, 2004). Secon,

is to influence the first moment of returns. First, to meet the objective of central bank

and volume. Even though one of the measures of volatility is to reduce volatility in the market, the

There is a positive relationship between intervention \( \text{frac{\text{Firm}}}{\text{Cum}} \) and the volatility of both returns

Estimates of the second moment of returns and volume

The negative sign of \( \text{frac{\text{Firm}}}{\text{Cum}} \) is consistent with this result.

is observed in days that immediately follow a holiday (Boads 1994: Kkm and Park 1994).

One of the most robust results concerning volume in the financial literature is that volume

market during the news of intervention by the Federal Reserve.

the positive coefficient of \( \text{frac{\text{Firm}}}{\text{Cum}} \) is consistent with this theory. Whilst not significant,

The positive coefficient of \( \text{frac{\text{Firm}}}{\text{Cum}} \) is consistent with this theory. Whilst not significant,

involves because informed market participants exploit information available and

Furthermore, theory suggests that information external should be associated with an increase

interception when it is paired on by both the BOJ and the Federal Reserve.

Since all interventions by the Federal Reserve observed in the same two-year period as an

Intercepted control on by the Federal Reserve moves the VEN in the intended direction.

In order to move the VEN in the intended direction, the positive coefficient of \( \text{frac{\text{Firm}}}{\text{Cum}} \) indicates that

The remaining consistent with the BOJ remaining against an unambiguously present and over a period

Positive intervention on successive days appears to reinforce the appreciation of the VEN.
6.3 Comparison with a Divariate GARCH Model

The interest rate differential represents a second interest rate relationship in the positive response of volatility to changes in returns. A second interest rate relationship is the positive response of volatility to changes in returns, observed over the holiday period but not observed immediately after the market closes. The interest in volatility can be understood to be a result of events that may occur outside of the market, such as information about the holiday effect in returns. Even though the BGN volatility accounts for missing information to the holiday effect, the results imply that the returns make an interest rate contribution.

Although not the primary interest of this analysis, the results of this study indicate that the returns make an interest rate contribution.

In the case of intervention, the Federal Reserve intervention is considered to have an effect on the returns, because the Federal Reserve Reserve intervention is considered to have an effect on the returns. The results of this study indicate that the intervention of the Federal Reserve Reserve intervention is considered to have an effect on the returns.
found on point estimates for the volatility process. The coefficient of $\theta_1\theta_2$ is positive in the

previous empirical analysis, involving estimation of a simple, dependent variable model. Hence,

the process can be interpreted as the threshold model in a multiple stage fashion. We feel

the main advantage of simulation based estimation in this application is that the volatility


This is associated with the increases in size and change in the nature of BOI interventions

section 2.3. Note that the estimates of $\theta_1\theta_2$ differ substantially in the two sub-samples.

Figure 4 compares the point estimates of the parameters in the BOI intervention equation in

6.5 Estimates for the Intervention Equation

Figure 5 shows here—

that not accounting for the missing observations partially distorts estimates. The model of

estimation of $\theta_1\theta_2$ does the smoothed volatility estimates from the two models and shows

the autoregressive parameters and higher estimates of the error variance in the transition

the BSV model at Equation (2.1) was also estimated. The BSV has lower estimates for

To demonstrate the effect of taking into account missing observations in Equation (2.2),

6.4 Missing Observations

Figure 4 shows here—

model for the missing observations, so that they are comparable with the baseline EGARCH(1,1)

Note that the volatility estimates obtained are from a BSV model that does not account

the more appropriate specification for the joint analysis of volatility and price volatility is

the latent volatilities, especially in periods of high volatility. This suggests that the BSV model is

Shleen and Kim (2004) using the same returns and volume data. Figure 4 plots the smoothed


relationship with intervention by the BOJ.

central bank interventions. Changes in USD interest rates do not appear to have a meaningful

and scale of VFN. Such a relationship is not surprising because during this period interest

price shocks, a fall in domestic interest rates is associated with the purchase of USD

The coefficient with central bank interventions being used to support domestic monetary

the coefficient of determinations of Dombrish et al (1979). In the second sub-sample there is a strong

and Kim (2002) find a similar relationship and suggest that this may be due to the central

The relationship between Japanese monetary policy and BOJ intervention appears to

the second sub-sample is consistent with the increased scale of intervention observed during

(above trend) so that the VFN rate decreases as expected. The results of the OLS regression

downward trend. In such a situation, the coefficient of the regression is not statistically

As expected in previous studies, the main driver of BOJ intervention is deviation of the ex-

containing some additional information about the level of disorder in the markets over-

Higher volume, when controlling for volatility, appears associated with positive inter-

---Table 4 about here---

with a disorderly market becomes less of a priority.

inherent coefficient indicates that after Dr. Sato’s departure was appointed, intervention associated

This is also the case in the first sub-sample, but in the second sub-sample, the back of a step

full sample, suggesting that the BOJ reacted to patterns of excessive volatility by interventions.
prior to 1997 the FOJ was more concerned with calming the market than with supporting
and to support domestic monetary policy. However, amendments to its policy from 1997
in relation to the market by the desire to calm the market to control developments from then
under the condition that the FOJ was induced to be associated with the financial authority, that movements
and action occurs during disorderly market conditions. However, these results are little due to the FOJ's
to be associated with the financial authority. The empirical results for the

One of the main results of the empirical work is that intervention appears to shift the

Inference for the multivariate SV model,

Sensitivity to this parameter is one of the major challenges in calibrating models in the
future. This paper highlights the importance of parameter estimation, and provides evidence
of the existence of intervention in the conditional mean and variance processes. A data-based
investment process for the prediction of the future

It is shown empirically how accounting for misspecification can improve on the esti-

\[
\mathbb{E}\left\{ \left( \sigma^2 Z - 1 \eta \right)_{1-1}\left( \sigma^2 Z - 1 \eta \right)_{1-1} \right\} dx
\]
\[
\left\{ \left( \sum_{t=1}^{\infty} \sum_{q=1}^{\infty} \left( \Gamma_{1-1} \psi^2 + \eta \psi \right) \right)^{\frac{q}{q+1}} \right\} dx \propto
\]
\[
(b^2 \Pi \eta d(b^2 \Pi \eta d (\Pi \eta) d \prod_{q=1}^{\infty} (\Pi \eta \eta) d \prod_{q=1}^{\infty} (\Pi \eta \eta) d^{(p,b \Pi \{ \eta \eta \})} \right) dx \]
\[
\eta > q > r = 1: (q)\text{ Deriving (1)}
\]

There are three cases to consider:
\[
(b^2 \Pi \eta d(b^2 \Pi \eta d (\Pi \eta) d \prod_{q=1}^{\infty} (\Pi \eta \eta) d \prod_{q=1}^{\infty} (\Pi \eta \eta) d^{(p,b \Pi \{ \eta \eta \})} \right) dx \]
\[
\eta > q > r = 1: (q)\text{ Deriving (1)}
\]

This appendix outlines how to derive key posterior distributions employed in section 3.

Appendix A

The foreign exchange markets.

Reserve Bank of Australia for their general insights regarding central bank intervention in foreign exchange markets, also granted to Chris Beer, Michael Street and other participants at seminars at the Reserve Bank of Australia for their general insights regarding central bank intervention in foreign exchange markets. The authors are also grateful to Chris Beer, Michael Street and other participants at seminars at the Reserve Bank of Australia for their general insights regarding central bank intervention in foreign exchange markets. The authors are also grateful to Chris Beer, Michael Street and other participants at seminars at the Reserve Bank of Australia for their general insights regarding central bank intervention in foreign exchange markets.

Acknowledgments

In the foreign exchange markets, effective tools in assessing both the effects of, and information for, central bank intervention in monetary policy, while the opposite is true after 1999. Overall, the BSV model provides an effective tool in assessing both the effects of, and information for, central bank intervention in monetary policy, while the opposite is true after 1999.
\[ (\tilde{r} \cdot b^* \{ \phi \} \eta d \bar{\Pi} \{ \eta \}) d \bar{\Pi} \{ \eta \} \]

where \((\bar{\Pi} \{ \eta \})\)

Substituting in the Gaussian densities at \((\bar{\Pi} \{ \eta \})\), and completing the square in \(a\) yields \(a\)

\[ \cdot (b^* \{ \phi \} d(b^* \{ \phi \} \eta d \bar{\Pi} \{ \eta \}) \prod_{\eta} \infty \]

\[ (\bar{\Pi} \{ \eta \}) d \cdot (\bar{\Pi} \{ \eta \} \eta d \bar{\Pi} \{ \eta \}) \prod_{\eta} \infty \]

\[ (\bar{\Pi} \{ \eta \}) d \cdot (\bar{\Pi} \{ \eta \} \eta d \bar{\Pi} \{ \eta \}) \prod_{\eta} \infty \]

\[ (\bar{\Pi} \{ \eta \}) d \cdot (\bar{\Pi} \{ \eta \} \eta d \bar{\Pi} \{ \eta \}) \prod_{\eta} \infty \]

\( u = q > v > 1 \cdot (\bar{\Pi} \{ \eta \}) \)
Appendix B

For further details, see Smith, Ackerman, and Shonan (2009a).  

11

This appendix provides the analytical derivatives required to implement step (1) of the sample scheme. 

Denote the (9) steps to (9) of the sample scheme

\[
\left\{ (1-\delta) I-\frac{\bar{\tau}}{I} \right\} \frac{d\tau}{\| B \|} + \left\{ (\omega^T - \frac{I}{2})_{1-\lambda} \frac{\bar{\tau}}{I} \right\} \frac{d\tau}{\| B \|} + \left\{ (\omega^T - \frac{I}{2})_{1-\lambda} \frac{\bar{\tau}}{I} \right\} \frac{d\tau}{\| B \|}
\]

(9)

(9)
\[(\eta_{y_1 - \sigma} \partial \zeta + \eta_{y_1 - \sigma}(\eta_\sigma)\delta_{\eta\lambda} - \gamma)\frac{\zeta}{1} = \frac{\eta_\sigma}{(\eta_\sigma)}\]

Case (e) \( q \leq 1 \) and \( u = q > q > v \):

\[I < f_A \quad 0 = \frac{f^+_{A_1 \Psi}}{(\eta_\sigma)} I_{\delta\sigma} \quad 1 + (1 + \eta_{y_1 - \sigma})(\eta_\sigma)\delta_{\eta\lambda} \frac{\zeta}{1} + (\eta_\sigma)\delta_{\eta\lambda} (\eta_\sigma)\delta_{\eta\lambda} - \gamma = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma}\]

\[I < f_A \quad 0 = \frac{f^+_{A_1 \Psi}}{(\eta_\sigma)} I_{\delta\sigma} \quad 1 - (1 + \eta_{y_1 - \sigma})(\eta_\sigma)\delta_{\eta\lambda} \frac{\zeta}{1} + (\eta_\sigma)\delta_{\eta\lambda} (\eta_\sigma)\delta_{\eta\lambda} - \gamma = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma}\]

Case (a) \( q \leq 1 \) and \( u > q > v > v \):

\[I < f_A \quad 0 = \frac{f^+_{A_1 \Psi}}{(\eta_\sigma)} I_{\delta\sigma} \quad 1 + (1 + \eta_{y_1 - \sigma})(\eta_\sigma)\delta_{\eta\lambda} \frac{\zeta}{1} + (\eta_\sigma)\delta_{\eta\lambda} (\eta_\sigma)\delta_{\eta\lambda} - \gamma = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma}\]

Case (a) \( q \leq 1 \) and \( u > q > v > v \):

\[I < f_A \quad 0 = \frac{f^+_{A_1 \Psi}}{(\eta_\sigma)} I_{\delta\sigma} \quad 1 - (1 + \eta_{y_1 - \sigma})(\eta_\sigma)\delta_{\eta\lambda} \frac{\zeta}{1} + (\eta_\sigma)\delta_{\eta\lambda} (\eta_\sigma)\delta_{\eta\lambda} - \gamma = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma}\]

where the third equation is derived using Remark 6.2 in Dwyer (2000).

\[(\eta_{y_1 - \sigma} \otimes \eta_{\lambda})(\delta_{\eta\lambda}) = 0 = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma} \quad 0 = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma}\]

We also note that

\[\frac{\rho_\sigma \rho_\sigma}{x_{\delta\sigma} (I \otimes V_F \hat{\lambda}) + \frac{\rho_\sigma \rho_\sigma}{x_{\delta\sigma}} V_F \hat{\lambda} = \frac{\rho_\sigma \rho_\sigma}{h_{\delta\sigma}} I_{\delta\sigma} \quad \text{on} \quad x_{V_F} = \hat{\lambda} I_{\delta\sigma}\]

\[2000 \text{ at p. 12}\]

For calculating the second order derivatives we make use of the following result (Dwyer):

\[(1 + \eta_\sigma)\delta_{\eta\lambda} \frac{\zeta}{1} = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma} \quad 0 = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma} \quad 0 = \frac{\eta_\sigma}{(\eta_\sigma)} I_{\delta\sigma}\]
References

\[ I < \gamma \Delta 0 = \frac{\gamma \hat{\eta}_0 \hat{\eta}_0}{(\gamma \hat{\eta}(\gamma \hat{\eta}))} = \frac{\gamma \hat{\eta}_0 \hat{\eta}_0}{(\gamma \hat{\eta}(\gamma \hat{\eta}))} \]

\[ (1 - \lambda + ((\gamma \hat{\eta}_0 \hat{\eta}_0) \circ \gamma \hat{\eta}_0 \hat{\eta}_0) - \gamma \hat{\eta}_0 \hat{\eta}_0) = \frac{\gamma \hat{\eta}_0 \hat{\eta}_0}{(\gamma \hat{\eta}(\gamma \hat{\eta}))} \]

Kim, S. and Sheen, J. (2002), "The Determinants of Foreign Exchange Volatility by Central

comparison with ARCH models, Review of Economic Studies, 69(2), 361-393.


Kaminski, M. and Sengen, H. (2003), "Stochastic Volatility and Short-


Market evidence from Daily Dollar-Yen Spot and Daily of Banking and Finance, 23.
models; Econometrica, 90, 809-830.


Figure 1: Summary of the impact of prior choice on \( \gamma_{ij} \) in section 4. Panels (a), (b), (c), and (d) contain the prior and posterior when the identity prior is used. Panels (e) and (f) contain the prior and posterior when the data-based prior is used. In panels (e) and (f), the line value of \( \gamma_{ij} \) is represented by a vertical line.

<table>
<thead>
<tr>
<th>True Value</th>
<th>Identity Prior</th>
<th>Data-based Prior</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.09428</td>
<td>0.11327</td>
<td>0.08386</td>
</tr>
<tr>
<td>0.07233</td>
<td>0.03313</td>
<td>0.0381</td>
</tr>
<tr>
<td>0.00400</td>
<td>0.40608</td>
<td>0.40152</td>
</tr>
</tbody>
</table>

Table 1: The values of the elements of \( \hat{\gamma} \) and posterior estimates under the two priors for the simulated data.
<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th></th>
<th>Sub-sample One</th>
<th></th>
<th>Sub-sample Two</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Returns</td>
<td>Volume</td>
<td>Returns</td>
<td>Volume</td>
<td>Returns</td>
<td>Volume</td>
</tr>
<tr>
<td>( \beta_{10} )</td>
<td>-0.00588</td>
<td>1.86891***</td>
<td>-0.00312</td>
<td>3.63122***</td>
<td>-0.00530</td>
<td>2.85115***</td>
</tr>
<tr>
<td>( \beta_{11} )</td>
<td>-0.00361***</td>
<td>-0.00287</td>
<td>-0.00489***</td>
<td>0.02355***</td>
<td>0.00192</td>
<td>-0.03075***</td>
</tr>
<tr>
<td>( \beta_{12} )</td>
<td>-0.00246***</td>
<td>0.01088***</td>
<td>0.00098</td>
<td>0.00253</td>
<td>-0.00136</td>
<td>0.01088***</td>
</tr>
<tr>
<td>( \beta_{13} )</td>
<td>0.00478***</td>
<td>0.00118</td>
<td>-0.00064</td>
<td>-0.02051**</td>
<td>-0.00088</td>
<td>0.02926***</td>
</tr>
<tr>
<td>( \beta_{14} )</td>
<td>0.00233***</td>
<td>0.00130</td>
<td>0.00077*</td>
<td>-0.00095</td>
<td>0.00541***</td>
<td>0.00714***</td>
</tr>
<tr>
<td>( \beta_{15} )</td>
<td>-0.00856</td>
<td>-0.09182</td>
<td>-0.11694**</td>
<td>-0.62571**</td>
<td>0.05189</td>
<td>0.20362</td>
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<tr>
<td>( \beta_{16} )</td>
<td>0.01256</td>
<td>-2.29592***</td>
<td>-0.08376</td>
<td>-1.05809**</td>
<td>0.08386</td>
<td>-3.23745***</td>
</tr>
<tr>
<td>( \beta_{17} )</td>
<td>-0.03792</td>
<td>0.13119</td>
<td>0.06906</td>
<td>-0.15307</td>
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<td>0.30764</td>
</tr>
<tr>
<td>( \beta_{18} )</td>
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<td></td>
</tr>
<tr>
<td>( \beta_{20} )</td>
<td>-1.06643***</td>
<td>2.00023***</td>
<td>-1.39292***</td>
<td>1.28194***</td>
<td>-0.91099***</td>
<td>2.20877***</td>
</tr>
<tr>
<td>( \alpha_{10} )</td>
<td>0.00671*</td>
<td>0.00533*</td>
<td>0.00631</td>
<td>0.00920**</td>
<td>0.01315*</td>
<td>0.01653***</td>
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<tr>
<td>( \alpha_{11} )</td>
<td>0.00244</td>
<td>-0.00081</td>
<td>0.00409</td>
<td>-0.00279</td>
<td>-0.00483**</td>
<td>-0.00447</td>
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<tr>
<td>( \alpha_{12} )</td>
<td>-0.00630*</td>
<td>-0.00500*</td>
<td>0.00001</td>
<td>-0.00194</td>
<td>-0.01260*</td>
<td>-0.01644***</td>
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<tr>
<td>( \alpha_{13} )</td>
<td>0.00210**</td>
<td>0.00057</td>
<td>0.00163</td>
<td>0.00070</td>
<td>-0.00105</td>
<td>0.00174</td>
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<tr>
<td>( \alpha_{14} )</td>
<td>0.00010</td>
<td>0.00233**</td>
<td>0.00053</td>
<td>0.00030</td>
<td>-0.00162</td>
<td>0.00530***</td>
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<tr>
<td>( \alpha_{15} )</td>
<td>0.08494</td>
<td>-0.02098</td>
<td>0.15780</td>
<td>0.08924</td>
<td>0.01893</td>
<td>-0.18253**</td>
</tr>
<tr>
<td>( \alpha_{16} )</td>
<td>0.44322***</td>
<td>0.02088</td>
<td>0.32110</td>
<td>0.09303</td>
<td>0.51522**</td>
<td>-0.17689</td>
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<tr>
<td>( \alpha_{17} )</td>
<td>0.23490</td>
<td>0.10327</td>
<td>0.14272</td>
<td>0.23941</td>
<td>0.33992*</td>
<td>0.18756</td>
</tr>
</tbody>
</table>

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \rho )</td>
<td>-0.05611</td>
<td>-0.10102</td>
<td>-0.03608</td>
<td></td>
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<tr>
<td></td>
<td>( \phi_1 )</td>
<td>0.94309</td>
<td>0.76185</td>
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<td></td>
<td>( \phi_2 )</td>
<td>0.92017</td>
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<td>0.92116</td>
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<tr>
<td></td>
<td>( \omega_{11} )</td>
<td>0.05141</td>
<td>0.16132</td>
<td>0.02584</td>
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<tr>
<td></td>
<td>( \omega_{12} )</td>
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<td>0.02265</td>
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<tr>
<td></td>
<td>( \omega_{22} )</td>
<td>0.08816</td>
<td>0.13993</td>
<td>0.06897</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Parameter estimates for the BSVMO model. One star, two stars and three stars indicate the significance of an explanatory variable at the 90%, 95% and 99% level, respectively. For \( \alpha \), significance is measured using the marginal posterior probability intervals. The 95% posterior probability intervals are provided for a few key parameters.
Probability intervals. For significance is measured using the interval procedure.

The signs indicate the significance of an explanatory variable at the 90%, 95% and 99% level.

<table>
<thead>
<tr>
<th>Parameter estimates for the transformed equation. One, two steps and three step model.</th>
<th>Full Sample</th>
<th>Sub-sample One</th>
<th>Sub-sample Two</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{b}_0$</td>
<td>-3.1873</td>
<td>-3.189</td>
<td>-3.1966</td>
</tr>
<tr>
<td>$\hat{b}_1$</td>
<td>2.1792</td>
<td>2.1879</td>
<td>2.1982</td>
</tr>
<tr>
<td>$\hat{b}_2$</td>
<td>2.2893</td>
<td>2.2893</td>
<td>2.2989</td>
</tr>
<tr>
<td>$\hat{b}_3$</td>
<td>0.0116</td>
<td>0.0114</td>
<td>0.0114</td>
</tr>
<tr>
<td>$\hat{b}_4$</td>
<td>1.1629</td>
<td>1.1629</td>
<td>1.1629</td>
</tr>
<tr>
<td>$\hat{b}_5$</td>
<td>1.8231</td>
<td>1.8231</td>
<td>1.8231</td>
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<tr>
<td>$\hat{b}_6$</td>
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<td>1.4033</td>
<td>1.4033</td>
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<tr>
<td>$\hat{b}_7$</td>
<td>0.3878</td>
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<td>0.3878</td>
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<tr>
<td>$\hat{b}_8$</td>
<td>0.0938</td>
<td>0.0938</td>
<td>0.0938</td>
</tr>
</tbody>
</table>

Table 3: Acceptance rules for the Metropolis-Hastings steps in the full sample. For the
Histogram estimates of the smoothed log-volatilities. The first 500 observations are shown.

Figure 2: Comparison of the true log-volatilities for the simulated returns equation and the

Histogram estimates

True log-volatilities
Federal Reserve on behalf of the BOJ measured in billion yen.

Panel (c) BOJ intervention measured in billion yen. Panel (d) intervention by the
exchange rate. Panel (d) measured-exchanged volume in the Tokyo market measured in USD.

Figure 3: Summary of data. Panel (a) continuously compounded returns on the yen/USD.
Figure 4: A comparison of the volatility estimates obtained from a bivariate EGARCH(1,1) model. The smooth volatility estimates for the returns series are shown for each model. (a) provides the full sample; and (b) a sub-sample of observation 1730 to 2000 (approximately 1998 - 1999).
Figure 3: A comparison of the volatility estimates obtained from a bivariate stochastic volatility model with missing observations (thin line) and a bivariate stochastic volatility model that does not account for missing observations (thick line). The first 100 smoothed volatility estimates for the intervention dataset are shown.