

Building a Business Time-series Forecasting System*

With the Intervention Analysis of Japanese Yen Exchange
Rate Behavior

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1 Introduction

Forecasting a business time series is a complex process involving several phases of statistical work. One rather simple, popular method of forecasting is the Box-Jenkins (1976) (B-J) univariate time-series analysis; the other, less simple, multivariate method is the vector autoregressive (VAR) type. The present paper builds a business time-series forecasting system based on the B-J univariate method, and applies the system to the intervention analysis¹ of the Japanese yen per U.S. dollar (yen-dollar) exchange rate behavior.

Special events or circumstances that affect time-series behavior are here called intervention events, two specific types of which to be considered in the paper are additive outlier (AO) and permanent shift (PS) in the observed yen-dollar exchange rate. (Two other general types of intervention events are innovational outlier (IO) and transient shift (TS);

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¹See, for example, Box, Jenkins and Reinsel (1994, ch.12) and Kojima (1994b, chs.3,4,5) for intervention analysis methods.

these are not studied in the paper, however.)²

The time-series forecasting system comprises the RATS (Regression Analysis of Time Series) programs listed in Table 1, where the italic files with “_er” attached are written specifically for the yen-dollar rate forecasting.³ The exchange rate data file “RF_JY_USD.wks” will be created and detailed in section 2.

Table 1 The Japanese Yen Exchange Rate Forecasting System with an Intervention Analysis: The RATS Data File and Programs

Exchange rate data file: ^a RF_JY_USD.wks	
*.prg	*.src
<i>Stats_er.prg</i> ^b	hist.src histscatter.src
RandSample.prg ^c	hist.src
SacfSpacf.prg ^d	bjidentCF.src
<i>BJidentify_er.prg</i> ^e	bjident.src
<i>BJestimate_er.prg</i> ^f	<i>bjest_er.src</i> histnew.src kolmtest.src
<i>BJidentify_erAOPS.prg</i> ^g	bjident.src
<i>BJestimate_erAOPS.prg</i> ^h	<i>bjest_erAOPS.src</i> histnew.src kolmtest.src
<i>InterventionModel_er.prg</i> ⁱ	<i>bjest_erIntrvModel.src</i>
<i>BJforecast_er.prg</i> ^j	<i>bjfore1_er.src</i> <i>bjfore2_er.src</i>

^aSee section 2.1 on the data file.

^bSections 2.1 and 2.2 (on data plots, data summary statistics).

^cSection 3.1 (on white noise).

^dSection 3.2.1 (on simulated models).

^eSection 3.3 (on model identification).

^fSection 4 (on model estimation).

^gSection 5.3 and Appendix A (on model identification with intervention events).

^hSections 5.2, 5.3 and Appendix A (on model estimation with intervention events).

ⁱSection 5.4 (on estimation of intervention analysis model).

^jSection 6.2.3 (on forecasting with intervention events, forecast performance).

The B-J type univariate time-series forecasting is composed of several steps as summarized in the table below. The intervention analysis plays

²See, for example, Kojima (1994b, chs.3,4,5) for IO and TS.

³All the RATS programs are written by the author of the paper. The programs, along with the data file, are all stored at his website <<http://www.seinangu.ac.jp/kojima/BJTS/>>, an access to which is open to the public for free. See Appendix C for how to upload and download RATS-related files. Appendix B gives a list of RATS programs for forecasting general time-series data, including non-italic programs in Table 1 below.

a critical role in Steps 2 and 3; the presence of intervention events to be observed in the exchange rate in Step 2 is most likely to affect the future forecasts in Step 3. It will be shown that the B-J type time-series forecasting system built here is effective to model the intervention analysis of Japanese yen exchange rate behavior in the sense that the system is capable of appropriately detecting intervention events, thereby contributing to better exchange rate forecast performance.

		Section
Step 0	Collecting data up to present.	2
Step 1	Time-series analysis of data up to present (1): Model identification.	3
Step 2	Time-series analysis of data up to present (2): Model estimation and diagnostic checking, with an intervention analysis.	4, 5
Step 3	Forecasting the future, based on the analysis in earlier steps.	6

Foreign exchange rate modeling may be naturally extended in the multivariate framework, for there are a multitude of managerial and economic factors affecting, and being affected by, exchange rate behavior. Yen exchange rate variability affects Japanese corporate decisions with regard to foreign-currency denominated goods prices: This is a problem of exchange-rate pass-through, a microeconomic analysis of which is conducted, for example, by Kojima (1995). Further, the PPP (purchasing power parity) theory is a simplest structural model of foreign exchange rate determination, which Kojima (1993, 1994a, 1994b) studies in the empirical context of intervention analysis. VAR modeling, cointegration and error corrections constitute critical elements in all these multivariate analyses. The multivariate modeling and forecasting is beyond the scope of the paper; the concluding section of the paper will again refer to the multivariate research in the exchange rate forecasting context.

The rest of the paper is organized as follows: Section 2 describes how to get exchange rate data, plots the data, and computes the data summary statistics. Section 3 identifies exchange rate time-series models through two phases; sections 4 and 5 estimate the models with an intervention analysis; section 6 forecasts and compares two models with and without the presence of intervention events being adjusted for; the former model is shown to achieve better forecast performance. Section 7 summarizes and concludes the paper. Appendices detail the iterative search for intervention events, tabulate another set of RATS programs for a general time-series forecasting, and describe how to upload and download RATS files.

2 Collecting Data and Computing Data Summary Statistics: Yen-dollar Exchange Rate

2.1 Collecting and plotting the data

International Monetary Fund's (IMF's) International Financial Statistics (IFS) Online Service provides both real and financial data in the .xls format. How to download the the monthly yen-dollar rate for the period from January 1985 through March 2004, from the IFS Online Service consists of the following steps:

1. Enter Logon ID and Password at <<http://www.imfstatistics.org/imf/>>.⁴
2. Click the "Change" button on the immediate right of "Retrieval Period: 1994 - 2003." Follow the Frequency Retrieval Wizard: Single Frequency → Monthly Frequency → Start Period: M1/1985 → End Period: M3/2004 → Table → SAVE.
3. Country Tables → Choose country.
4. Check the data to be downloaded (✓) in the SELECT column → Click + on the right up → Click the "Retrieve" button on the immediate right → Click again the "Retrieve" button above.
5. The data will be available in the Excel format in the IFS Browser; click it for downloading.
6. Create an Excel file that works for the RATS: Save the data file as RF_JY_USD.wks.⁵ In the .wks file,
 - (6-a) enter Monthly in the very first cell under left-most column;
 - (6-b) leave the date cell as given by the IFS;
 - (6-c) Variable name: RF_JY_USD;
 - (6-d) (i) choose the .wks format; answer Yes to save (Filename= RF_JY_USD.wks); (ii) the .wks file so created will look as follows:⁶

Monthly	M1 1985	M2 1985	...	M2 2004	M3 2004
RF_JY_USD	254.180	260.240	...	106.548	108.623

The first few lines of Stats_er.prg executed to plot the monthly yen-dollar rate as in Fig. 1 are as follows:

⁴For the registration fee required to purchase the IFS Online Service, click and see Pricing Information/Subscribe. The thirty-day trial account is available to those wishing to try out IFS. The CD-ROM version is available to researchers for an annual contract at the price of 36,750 Japanese yen (as of July, 2004).

⁵Note that the .xls format failed using the Macintosh RATS (6/29/04).

⁶The file is processed successfully by the RATS programs in Table 1.

```

RATS Program Stats.er.prg :
Stats.er.prg
calendar 1985 1 12
allocate 2004:3
open data RF_JY_USD.wks
data(format=wks,organization=row) 1985:1 2003:12 RF_JY_USD
The remainder omitted.

```

Stats.er.prg produces several graphs such as Fig. 1, where shaded areas represent recession periods as defined in the program:

```

Part of Stats.er.prg :
RATS programming for oil crisis and recession periods:
* < For monthly data only:
set oilcr2 = t==1978:12.or.t==1979:3
set depression = t>= 1980 : 3.and.t<= 1983 : 2.or.
t>= 1985 : 9.and.t<= 1986 : 11.or.
t>= 1991 : 3.and.t<= 1993 : 10.or.
t>= 1997 : 4.and.t<= 1999 : 4
*/>
/* < For quarterly data only:
set oilcr2 = t==1978:4.or.t==1979:1
set depression = t>= 1980 : 1.and.t<= 1983 : 1.or.
t>= 1985 : 3.and.t<= 1986 : 4.or.
t>= 1991 : 1.and.t<= 1993 : 4.or.
t>= 1997 : 2.and.t<= 1999 : 2
*/>

```

The sample period, here and throughout the paper, is a 19-year long 1985:1-2003:12, with the 3-month long out-of-sample (postsample), forecast period being 2004:1-2004:3. From Fig. 1, it might appear that, when analyzing *raw* series RF_JY_USD, or its first differenced series DRF_JY_USD, the high-yen recession period (1985:9-1986:11) should be deleted and thus the sample period would be from 1987:1 on. At the same time, the figure also suggests that when modeling the *logged* series logRF_JY_USD and its first differenced series DlogRF_JY_USD, the initial month can be 1985:1. Our final choice is the latter month.

In Fig. 1, the Japanese yen against the U.S. dollar is readily seen to experience sharp appreciations at several points in time during the sample period: See the asterisked data points of (raw) RF_JY_USD in Table 2. These sharp yen appreciations (*) in the table may be identified as intervention events such as additive outliers (AOs) or permanent level shifts (PSs).⁷ Their direct and/or indirect causes are identified as follows:

- * 1985:10: Plaza Accord was signed in September, 1985.
- * 1995:4: 79 yen per dollar, a post-war record high, was reached in the same month.
- * 1998:9, 1998:10: The Russian economic/financial crisis (a significant depreciation of the currency Louvre) occurred on 8/17/1998.⁸ Asian

⁷Later, section 2.2 will touch upon AO and PS.

⁸Note that the Russian economic/financial crisis was essentially caused by the

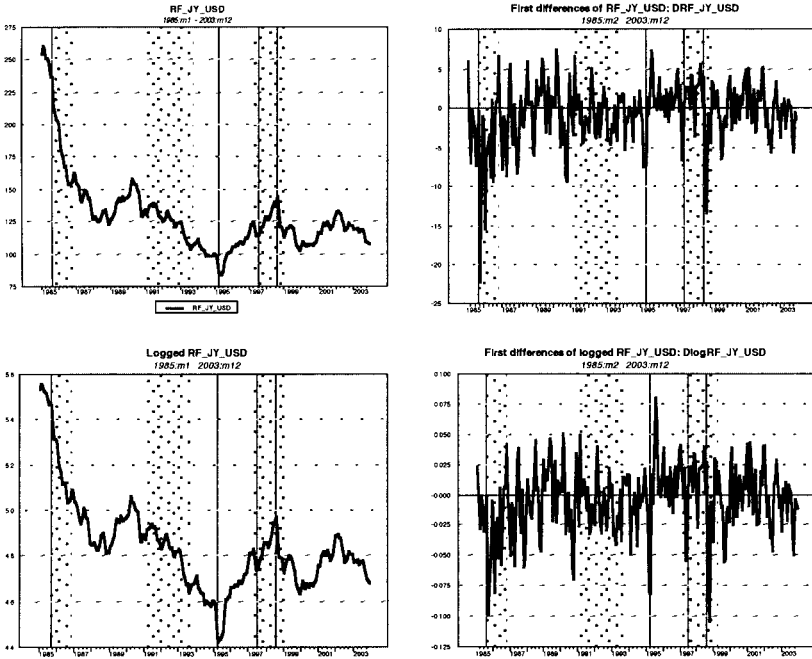


Figure 1 Monthly yen-dollar rate (IMF, IFS line RF); sample period = 1985:1-2003:12. Top = raw data; bottom = logged data; right column = first differences of left column.

currency crisis started in July, 1997 → Russia → Latin America → Industrial nations: The continuous chain of all these crises occurred due to the Russian crisis that had caused the sharp fall in the U.S. GDP (for 1995 on) and in the stock prices in Europe (Germany, in particular), Latin America, NYSE (on 8/27-31/1998), Asia, and Japan (on 8/28/1998). Note also Ito (2004, pp.242-243): “The yen depreciation from 1995 to 1997 is often identified as one of the few important factors that led Asian countries into a currency crisis.”

vulnerability of the Russian banks borrowing a huge amount from American and European banks.

Table 2 Possible Intervention Events in (Raw) Monthly Yen-dollar Exchange Rate^a

1985:08 237.2100	1995:02 98.2430	1998:07 140.7340
1985:09 236.9500	1995:03 90.7886	1998:08 144.6550
1985:10 214.7300*	1995:04 83.6675*	1998:09 134.5940*
1985:11 203.7200	1995:05 85.0970	1998:10 121.2980*
1985:12 202.8200	1995:06 84.5295	1998:11 120.5820

^aData source: IMF, IFS line RF.

2.2 Data summary statistics

As pointed out in the foregoing subsection, the sample period “1987:1 2003:12” should apply to raw data RF_JY_USD and its first differenced series DRF_JY_USD (the corresponding sample size = 204 and 203, respectively), while “1985:1 2003:12” applies to the logged data logRF_JY_USD and its first differenced series DlogRF_JY_USD (the corresponding sample size = 228 and 227, respectively).⁹ In Fig. 2, frequency tables and histograms are all drawn for 1987:1 to 2003:12.

In the RATS Output from Stats_er.prg below, we will only look at the first differenced series DlogRF_JY_USD, drawn in Figs. 1 and 2. For 1985:1 to 2003:12 (in Fig. 1), in particular, negative Skewness (-0.49149) and positive Kurtosis (0.68640) suggest, respectively, a left-skewed distribution and a distribution with a kurtosis; the former is confirmed graphically by histogram for DlogRF_JY_USD in Fig. 2. Jarque-Bera suggests non-normality: It is most likely due to the presence of AO and PS as mentioned in the previous subsection; see Table 2 there. AO and PS will be further studied in section 5.

RATS Output from Stats_er.prg :

```
*— COMPUTED RESULTS
*— Summary statistics
Series Obs Mean Std Error Minimum Maximum
RF_JY_USD 204 121.739242647 15.169933453 83.667500000 158.470000000
Series Obs Mean Std Error Minimum Maximum
DRF_JY_USD 203 -0.229285714 3.485597688 -13.296000000 7.550000000
Series Obs Mean Std Error Minimum Maximum
DLOGRF_JY_USD 227 -0.0037731872 0.0293944759 -0.1040125119 0.0806558131
*— Frequency table, histogram and scatter
*— %nobs = 204
For RF_JY_USD :
Endpoints of Class Intervals:
```

⁹See the RATS Output from Stats_er.prg below for sample size here.

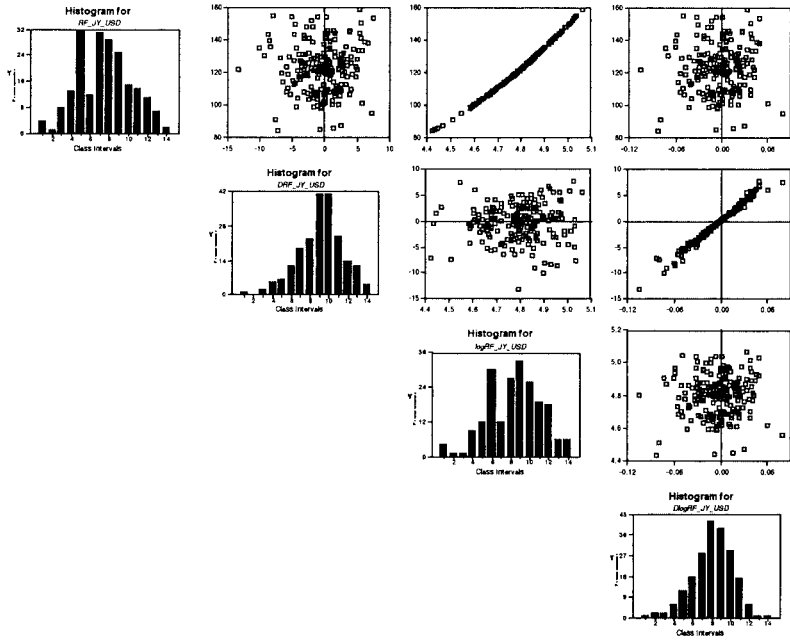


Figure 2 Raw yen-dollar rate and its first differenced series, logged yen-dollar rate and its first differenced data; sample period = 1987:1 2003:12. (The scatter diagrams here are not of much significance.)

```

bar low high counts
1 83.66750 89.06397 4
..... ["....." in every output and program throughout the paper means
"Partly omitted."] 10
14 153.82156 159.21802 2
.....
*— Inferential statistics
Statistics on Series DLOGRF_JY_USD
Monthly Data From 1985:01 To 2003:12
Observations 227 (228 Total - 1 Skipped/Missing)
Sample Mean -0.0037731872 Variance 0.000864
Standard Error 0.0293944759 SE of Sample Mean 0.001951
t-Statistic -1.93400 Signif Level (Mean=0) 0.05436231
    
```

¹⁰The italic remarks given in brackets [,] are inserted in outputs and programs in the paper as output remarks and program remarks to be noted.

Skewness -0.49149 Signif Level (Sk=0) 0.00267253
 Kurtosis 0.68640 Signif Level (Ku=0) 0.03765982
 Jarque-Bera 13.59517 Signif Level (JB=0) 0.00111647
 Minimum -0.1040125119 Maximum 0.0806558131
 01-%ile -0.0813129299 99-%ile 0.0504851599
 05-%ile -0.0547243706 95-%ile 0.0404512017
 10-%ile -0.0414957821 90-%ile 0.0317158489
 25-%ile -0.0214428401 75-%ile 0.0155029644
 Median -0.0009260167
 Statistics on Series DLOGRF_JY_USD

Monthly Data From 1987:01 To 2003:12

[Fig. 2 is drawn for this sample period.]

Observations 204
 Sample Mean -0.0019992925 Variance 0.000817
 Standard Error 0.0285860127 SE of Sample Mean 0.002001
 t-Statistic -0.99894 Signif Level (Mean=0) 0.31901475
 Skewness -0.43653 Signif Level (Sk=0) 0.01151549
 Kurtosis 0.62665 Signif Level (Ku=0) 0.07253421
 Jarque-Bera 9.81677 Signif Level (JB=0) 0.00738442
 Minimum -0.1040125119 Maximum 0.0806558131
 01-%ile -0.0787056288 99-%ile 0.0505676501
 05-%ile -0.0524666097 95-%ile 0.0404553834
 10-%ile -0.0397643695 90-%ile 0.0335102798
 25-%ile -0.0179313082 75-%ile 0.0176578737
 Median 0.0010558748

3 Two-phase Identification of Model

Time-series models will be generally identified through two phases:

The first-half phase: The stationarity of the raw data X_t will be examined: If it is found nonstationary, then some work will be required to transform it into stationary series W_t . The stationarity conditions are that neither the expected value of W_t nor the population autocovariance $Cov(W_t, W_{t-l}), l \geq 1$ depends on t :

$$E[W_t] = \mu; \quad (1)$$

$$\sigma_{W_t, W_{t-l}} = \gamma_l. \quad (2)$$

The second-half phase: Time-series model(s) that suit well the data at hand will be selected as candidate(s). Again, those selected models must satisfy both usual stationarity and invertibility conditions.¹¹

¹¹See Box, Jenkins and Reinsel (1994, pp.50-51) for invertibility conditions: "To sum up, a linear process $z_t - \mu_z = a_t + \sum_{j=1}^{\infty} \psi_j a_{t-j}$, with a_t being a white noise, is stationary if $\sum_{j=0}^{\infty} |\psi_j| < \infty$ and is invertible if $\sum_{j=0}^{\infty} |\pi_j| < \infty$, where $\pi(B) = \psi^{-1}(B) = 1 - \sum_{j=1}^{\infty} \pi_j B^j$." For π see also Appendix A.

3.1 First-half phase: Transforming raw, nonstationary data into stationary series

Time-series models for the raw data X_t to be considered in this phase are multiplicative SARIMA($p, d, q; P, D, s, Q$) models (seasonal ARIMA models): X_t is assumed to have not only trend but seasonal variation. Its ($d; D, s$)-th differenced series

$$W_t = (1 - B)^d(1 - B^s)^D X_t, \tag{3}$$

where d denotes a consecutive difference order and D a seasonal difference order, is assumed to satisfy stationarity conditions (1) and (2). With T denoting the sample size (the end of the sample period), the effective sample size (the effective end of the differenced series) is $T' = T - d - sD$.

Let now

$$X_t^\ell = \log X_t, \tag{4}$$

with which $W_t = (1 - B)^d(1 - B^s)^D X_t^\ell$ will be interpreted as a growth rate from previous period (for $d = 1, D = s = 0$) or a growth rate from same period of previous year (for $d = 0, D = 1, s = 12$ for monthly data or $s = 4$ for quarterly data). Then, with a_t denoting the white noise, SARIMA($p, d, q; P, D, s, Q$) for X_t^ℓ will be written as

$$\phi(B)\Phi(B^s)(1 - B)^d(1 - B^s)^D X_t^\ell = \theta(B)\Theta(B^s)a_t \tag{5}$$

where $\phi(B), \Phi(B^s), \theta(B), \Theta(B^s)$ are, respectively, AR, SAR, MA, SMA multinomials of backshift operator B , which, with $\phi_0 = \Phi_0 = \theta_0 = \Theta_0 = -1$, are written as:

$$\begin{aligned} \phi(B) &= -\sum_{i=0}^p \phi_i B^i; & \Phi(B^s) &= -\sum_{i=0}^P \Phi_i B^{is}; \\ \theta(B) &= -\sum_{i=0}^q \theta_i B^i; & \Theta(B^s) &= -\sum_{i=0}^Q \Theta_i B^{is}. \end{aligned} \tag{6}$$

The multiplicative SARIMA($p, d, q; P, D, s, Q$) model (5) may then be written, too, as:

$$\begin{aligned} (1 - B)^d(1 - B^s)^D X_t^\ell &= c - \sum_{\substack{i=0 \\ \text{Not}\{i=0, j=0\}}}^p \sum_{j=0}^P \phi_i \Phi_j (1 - B)^d(1 - B^s)^D X_{t-i-j s}^\ell \\ &+ \sum_{i=0}^q \sum_{j=0}^Q \theta_i \Theta_j a_{t-i-j s} \end{aligned} \tag{7}$$

where: $Not\{i = 0, j = 0\}$ means i and j cannot be both zero simultaneously; the overall constant c is¹²

$$c = \mu \left(1 - \sum_{i=1}^p \phi_i \right) \left(1 - \sum_{i=1}^P \Phi_i \right)$$

where μ is as given by (1).

3.1.1 How to determine the set of orders ($d; D, s$)

Corresponding to (population) autocorrelation and partial autocorrelation are, respectively, sample autocorrelation function of lag l (abbreviated as SACF, and called also sample correlogram) and sample partial autocorrelation function (abbreviated as SPACF).¹³

To determine the set of orders ($d; D, s$) in ($p, d, q; P, D, s, Q$), one draws SACF and SPACF for the logged series X^l (or the raw series X_t) possibly exhibiting trend. If both are dying out very gradually, then the consecutive difference order would be $d = 1$, thereby removing the observed trend. For seasonal series, $D = 1$ and $s = 12$ will be appropriate

¹²The interpretation of c in the SARIMA model (7) is given as follows: The overall constant c is included in the model technically to take into account the possibility that the differenced series W_t in (3) has mean $\mu \neq 0$ (Nelson 1973, p.174), which in turn suggests the presence of upward or downward trend in the raw, undifferenced data X_t .

Not including the constant, then, would imply the contrary: W_t has $\mu = 0$ and the raw data has neither type of trend (Nelson 1973, p.63).

¹³They are formally given as:

$$\text{SACF: } R_l \equiv \frac{G_l}{G_0}, \quad G_l = \frac{1}{T'} \sum_{t=1}^{T'-l} (W_t - \bar{W}_{T'}) (W_{t+l} - \bar{W}_{T'}), \quad \bar{W}_{T'} = \frac{1}{T'} \sum_{t=1}^{T'} W_t,$$

$$T' = T - d - sD, \quad l = 0, 1, 2, \dots, L;$$

$$\text{SPACF: } PR_{ll} = \begin{cases} R_1, & l = 1 \\ \frac{R_l - \sum_{j=1}^{l-1} PR_{l-1,j} R_{l-j}}{1 - \sum_{j=1}^{l-1} PR_{l-1,j} R_j}, & l = 2, 3, \dots, L \end{cases}$$

$$PR_{lj} = PR_{l-1,j} - PR_{ll} PR_{l-1,l-j}, \quad j = 1, 2, \dots, l-1.$$

to remove seasonal regularity from monthly data. After computing the untrended, non-seasonal W_t by (3) with specific $(d; D, s)$, one moves on to the second phase.

3.2 Second-half phase: Model selection based on sample autocorrelations and the principle of parsimony

With the untrended, non-seasonal W_t at hand, Table 3 will be useful to in determining the remaining orders in $(p, d, q; P, D, s, Q)$. The principle of parsimony should be practiced aiming at a simple model with small orders of parameters.

Table 3 Features of Multiplicative SARMA($p, q; P, s, Q$) Model (8)

Model	ACF (correlogram)	PACF
Without seasonal parameters		
white noise ^a	zero	zero
AR(p) ^b	die out gradually	zero from lag p on
MA(q) ^c	zero from lag q on	die out gradually
ARMA(p, q) ^d	die out gradually	die out gradually
With seasonal parameters		
SAR(P, s) ^e	die out gradually but with spikes at every s	zero from lag sP on
AR(p) \times SAR(P, s) ^f	die out gradually but with spikes at every s	zero from lag $p + sP$ on
SMA(Q, s) ^g	zero from lag sQ on	die out gradually
MA(q) \times SMA(Q, s) ^h	zero from lag $q + sQ$ on	die out gradually
SARMA($p, q; P, s, Q$) ⁱ	die out gradually	die out gradually

^aThe corresponding SACFs and SPACFs are drawn in Fig. 3-left.

^bSee Fig. 3-center and -right, Fig. 4-left.

^cSee Fig. 4-center and -right.

^dSee Fig. 5-left and -center.

^eSee Fig. 5-right.

^fSee Fig. 7-left.

^gSee Fig. 6-left.

^hSee Fig. 7-right.

ⁱSee Fig. 6-center and -right.

Time-series models for W_t to be considered in this phase are multiplicative SARMA($p, q; P, s, Q$) models. Denoting the deviation from mean as $\tilde{W}_t = W_t - \mu$, the Multiplicative SARMA($p, q; P, s, Q$) model for \tilde{W}_t takes the following form of multiplication of the ϕ, Φ and θ, Θ parameters:

$$\phi(B)\Phi(B^s)\tilde{W}_t = \theta(B)\Theta(B^s)a_t. \tag{8}$$

3.2.1 SACF and SPACF simulated by SacfSpacf.prg

Sample autocorrelations and partial autocorrelations for SARMA models are simulated and drawn by the RATS program `SacfSpacf.prg`. Assuming in Eq. (8) that $\mu = 0$ and $\tilde{W}_t = W_t$, `SacfSpacf.prg` produces, by simulation, Figs. 3 through 7. In the figures, the dotted lines represent $\pm 2 \times [\text{standard error of SACF and SPACF}]$; the spikes above or below the dotted lines are autocorrelations being significant approximately at the 5% level.

In Fig. 3, the left-most graphs are white noise; the remaining SACFs and SPACFs in Figs. 3 through 7 are indeed consistent, respectively, with ACFs and PACFs in Table 3. See the footnotes in Table 3 for the association between Figs. 3 through 7 and (theoretical) ACFs and PACFs.

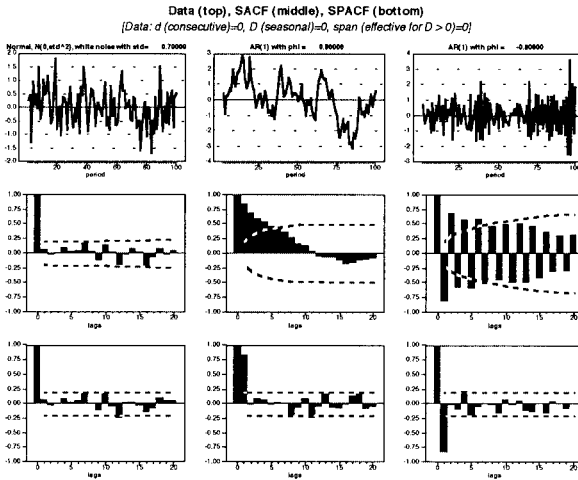


Figure 3 SACFs and SPACFs generated by simulation. The dotted lines represent $\pm 2 \times [\text{standard error of SACFs and SPACFs}]$. See the footnotes in Table 3 for the association between Figs. 3 through 7 and (theoretical) ACFs and PACFs.

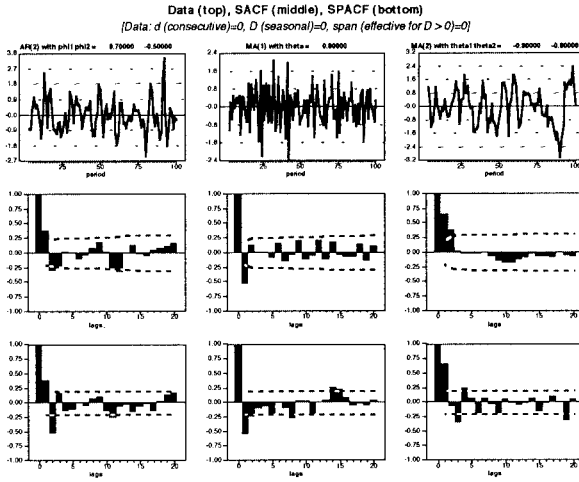


Figure 4 SACFs and SPACFs generated by simulation. (Continued from the previous graph.)

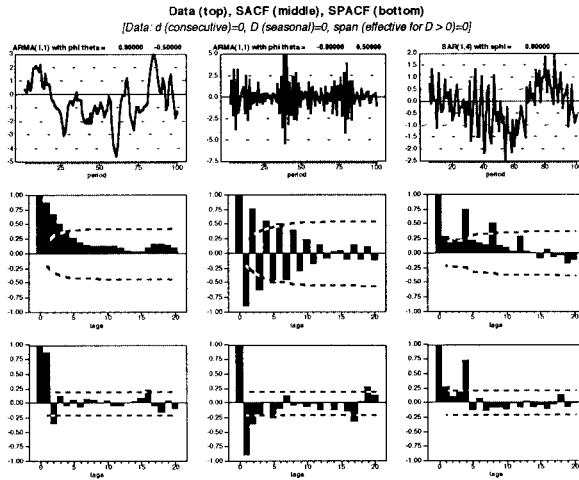


Figure 5 SACFs and SPACFs generated by simulation. (Continued from the previous graph.)

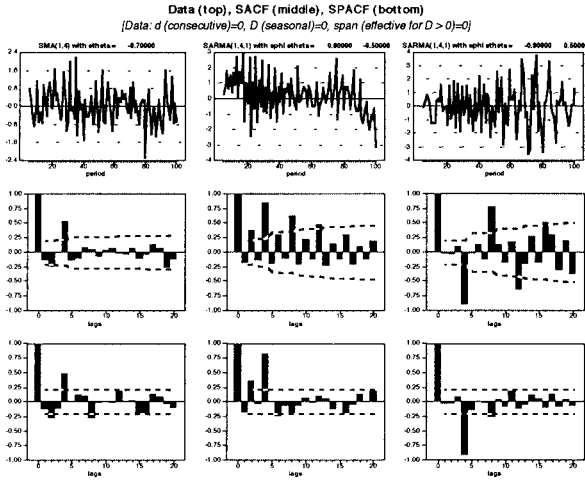


Figure 6 SACFs and SPACFs generated by simulation. (Continued from the previous graph.)

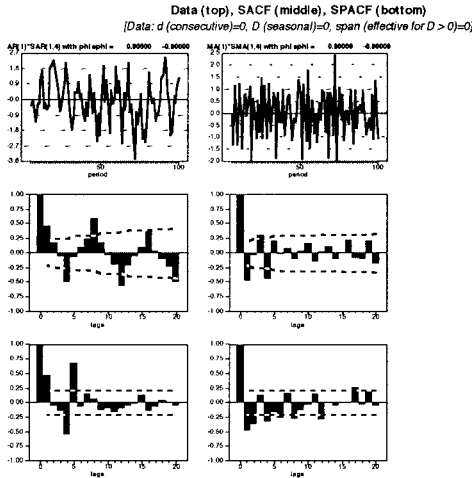


Figure 7 SACFs and SPACFs generated by simulation. (Continued from the previous graph.)

3.3 Identifying yen-dollar exchange rate model by BJidentify_er.prg

With the sample period 1985:1-2003:1 for the yen-dollar rate RF_JY_USD, the program BJidentify_er.prg produces an output, based on which a time-series model is identified as follows: Comparing Fig. 8 with Fig. 4-center, the first-differenced, logged series DlogRF_JY_USD may be identified as MA(1); letting $X_t = \text{RF_JY_USD}$,

$$X_t^\ell = \log X_t$$

$$W_t = (1 - B)X_t^\ell \tag{9}$$

$$W_t = c + (1 - \theta B)a_t \tag{10}$$

In RATS: $W_t = c + (1 + \theta B)a_t$.

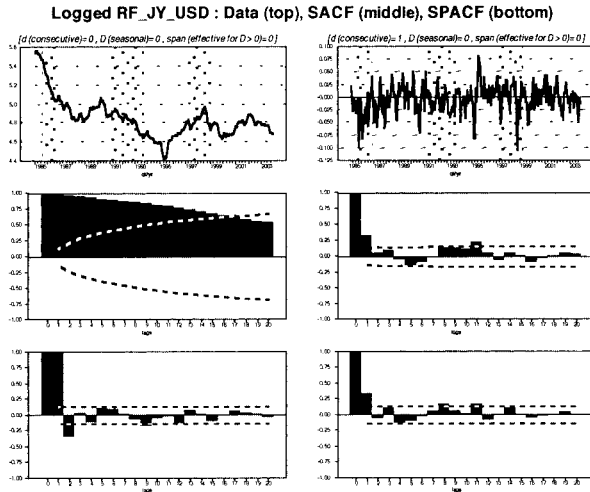


Figure 8 SACF and SPACF plots for logged yen-dollar rate; sample period = 1985:1-2003:12.

With a first-order moving average parameter included, W_t ($=\text{DlogRF_JY_USD}$) is not a white noise: X_t^ℓ ($=\log\text{RF_JY_USD}$) is *not* identified as a

random walk. This non-random walk identification could be due to the presence of intervention events as pointed out in sections 2.1 (see Table 2 there) and 2.2. The next two sections will investigate this issue.

4 Estimation and Diagnostic Checking: Ignoring Intervention Events

Two approaches to estimating time-series models are studied in the paper: One ignoring the presence of AO and PS, and the other adjusting for it in an appropriate statistical framework. The present section employs the former approach, the RATS program for which is `BJestimate_er.prg`, leaving the latter approach to section 5. (Later, in section 6.2.3, the two resulting forecasts will be contrasted with regard to forecasting performance/accuracy.)

In the first-half phase of estimation, model(s) identified in section 3 is (are) estimated to compute *initial* estimates, and the stationarity and invertibility conditions of the AR/SAR and MA/SMA estimates, respectively, are checked.¹⁴ With these estimates, one goes on to the second-half phase of an *iterative* model estimation,¹⁵ which is followed by the model diagnostic checking.¹⁶ The models will be re-estimated based on the checking results to further improve their model adequacy.

¹⁴See Kojima (1994b, Appendix A.1) for details.

¹⁵See Kojima (1994b, pp.11-16) for details.

¹⁶In the diagnostic checking, the white noise a_t in (5) and (8) is assumed to follow the normal distribution (the white noise normality assumption), under which the residuals distribution and independence are looked into. Here is a list of critical items to be checked:

(i) Is each parameter statistically significant? (ii) Do those final parameter estimates satisfy the stationarity and invertibility conditions? (iii) Is there detected any abnormal behavior in the residuals series? Is the behavior cyclical in nature? (iv) Can the residuals be considered normal? If yes, then one could check on their serial independence by their serial correlations (see the preceding footnote). (v) Would adding a new parameter contribute to improving the model? Or, is there any room for simplifying the model based on the principle of parsimony?

A remark is in order about residuals distribution and independence. Generally, the necessary and sufficient condition that random variates, like the white noise time series, follow a multivariate normal distribution is that they are uncorrelated (i.e., the covariance matrix of the multivariate distribution is diagonal) (Ferguson 1967, p.110). Note here that the random variates following normal marginal distributions but non-normal multivariate distribution are *not* independent even if they are uncorrelated (Ferguson 1967, p.111).

Those diagnostic checks listed in the previous footnote are carried out later in Outputs 1 and 2 as follows:

For (i) in the footnote, see (A) in Outputs 1 and 2.

For (iii) and (iv), see (B) Check the normality of RESIDS in Outputs 1 and 2.

For (v), see, in Outputs 1 and 2, (C) SCCF Check: A large SCCF at a lag $l < 0$ suggests an AR parameter to be inserted at that l ; the parameter value should be close to that SCCF, and (D) SACF Check: A large residuals SACF at a lag l suggests an MA term to be added at l ; the parameter value should be close to the negative of that SACF.¹⁷

The MA(1) model (10) as identified for the yen-dollar rate in section 3.3 is now estimated, and then a diagnostic checking of the estimated model follows to improve model adequacy.

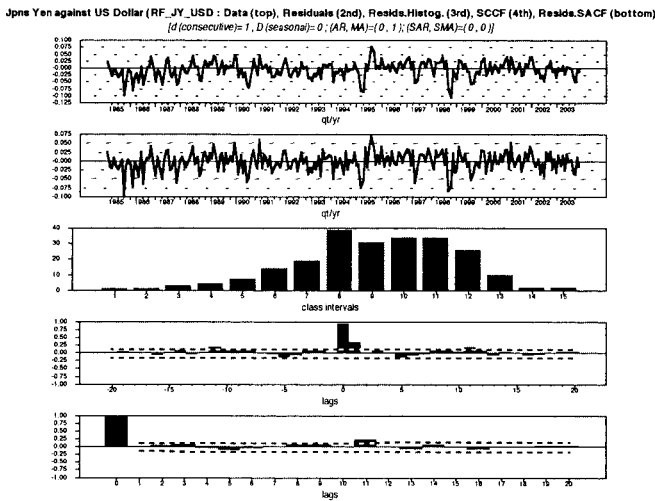


Figure 9 Model (10): Logged yen-dollar rate; sample period = 1985:1-2003:12. From top: Differenced series W_t (1985:2 to 2003:12), residual series, residual histogram, SCCF plot, and residual SACF plot.

Based on Fig. 9 (the residual SACF, in particular) and the diagnos-

¹⁷See Hokstad (1983) for these diagnostic checking techniques.

tic checking of RATS Output 1 below, one will get the following more adequate model:

$$W_t = (1 - \theta_1 B - \theta_{11} B^{11}) a_t \quad (11)$$

$$\text{In RATS: } W_t = (1 + \theta_1 B + \theta_{11} B^{11}) a_t. \quad (12)$$

The left-skewed distribution of the residuals as observed in Output 1 is possibly due to the sharp yen appreciation at three points in time (AO and PS) as indicated in section 2.

RATS Output 1 from BJestimate.er.prg for the model (10) :

```
*— COMPUTED RESULTS
*— BJ model estimation
START=
STARTL= 2
end=
endL= 228
(A)
Box-Jenkins - Estimation by Gauss-Newton
Convergence in 6 iterations. Final criterion was 0.0000012 < 0.0000100
Dependent Variable TRANSFRM
Monthly Data From 1985:02 To 2003:12
Usable Observations 227 Degrees of Freedom 225
Centered R**2 0.981036 R Bar **2 0.980952
Uncentered R**2 0.999968 T x R**2 226.993
Mean of Dependent Variable 4.8439736226
Std Error of Dependent Variable 0.2005543498
Standard Error of Estimate 0.0276795548
Sum of Squared Residuals 0.1723854943
Durbin-Watson Statistic 2.003803
Q(36-1) 43.923790
Significance Level of Q 0.14329078
Variable Coeff Std Error T-Stat Signif
*****
1. CONSTANT -0.003730004 0.002511424 -1.48521 0.13888663
2. MA{1} 0.369112348 0.062037337 5.94984 0.00000001
.....
(B) Check the normality of RESIDS.
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0000467328 Variance 0.000763
Standard Error 0.0276182092 SE of Sample Mean 0.001833
t-Statistic -0.02549 Signif Level (Mean=0) 0.97968338
Skewness -0.50507 Signif Level (Sk=0) 0.00202820
Kurtosis 0.44765 Signif Level (Ku=0) 0.17523856
Jarque-Bera 11.54635 Signif Level (JB=0) 0.00310987
.....
Studentized Range = 6.00043
(C) SCCF Check: Large SCCF at a lag l < 0 below suggests
the AR term at l, whose value is close to that SCCF.
.....
Ljung-Box Q-Statistics
Q(1 to 20) = 59.2377. Significance Level 0.00000272
Q(-20 to -1) = 32.1530. Significance Level 0.02108781
Q(-20 to 20) = 292.8742. Significance Level 0.00000000
```

(D) SACF Check: Large resids SACF at a lag l below suggests the MA term at l , whose value is close to negative of that SACF.

 Ljung-Box Q-Statistics
 $Q(20) = 30.8977$. Significance Level 0.02958080
The remainder omitted.

The graph output for the modified model (11) is given in Fig. 10; the associated RATS Output 2 below, to be checked again in section 5, indicates that the residual normality is still rejected.

RATS Output 2 from BJestimate.er.prg for the model (11) :

```
*— COMPUTED RESULTS
.....
(A)
Box-Jenkins - Estimation by Gauss-Newton
Convergence in 7 Iterations. Final criterion was 0.0000037 < 0.0000100
Dependent Variable TRANSFRM
Monthly Data From 1985:02 To 2003:12
Usable Observations 227 Degrees of Freedom 225
..... [Similar to Output 1.]
Sum of Squared Residuals 0.1672362285
Durbin-Watson Statistic 1.954515
Q(36-2) 24.774498
Significance Level of Q 0.87632979
Variable Coeff Std Error T-Stat Signif
*****
1. MA{1} 0.3430948547 0.0609216294 5.63174 0.00000005
2. MA{11} 0.2092140716 0.0624985945 3.34750 0.00095571
.....
(B) Check the normality of RESIDS.
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0024686445 Variance 0.000734
Standard Error 0.0270898900 SE of Sample Mean 0.001798
t-Statistic -1.37298 Signif Level (Mean=0) 0.17111928
Skewness -0.43935 Signif Level (Sk=0) 0.00726358
Kurtosis 0.70307 Signif Level (Ku=0) 0.03325086
Jarque-Bera 11.97820 Signif Level (JB=0) 0.00250592
.....
Studentized Range = 6.35765
(C) SCCF Check: Large SCCF at a lag  $l < 0$  below suggests
the AR term at  $l$ , whose value is close to that SCCF.
.....
Ljung-Box Q-Statistics
Q(1 to 20) = 56.1869. Significance Level 0.00000833
Q(-20 to -1) = 18.3203. Significance Level 0.43474601
Q(-20 to 20) = 272.0368. Significance Level 0.00000000
(D) SACF Check: Large resids SACF at a lag  $l$  below suggests
the MA term at  $l$ , whose value is close to negative of that SACF.
.....
Ljung-Box Q-Statistics
Q(20) = 16.0372. Significance Level 0.58995251
The remainder omitted.
```

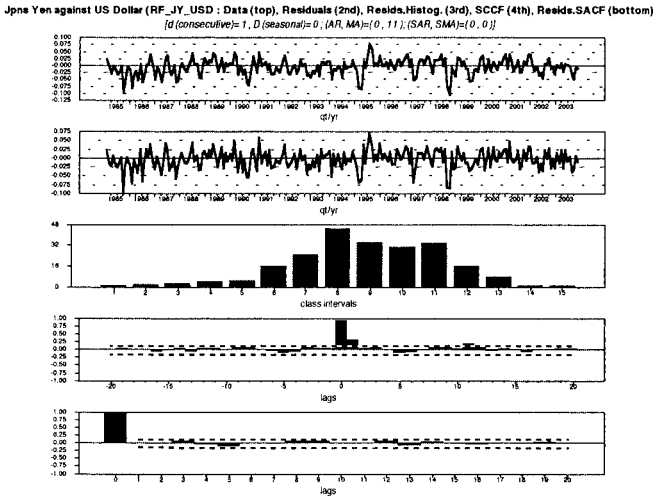


Figure 10 Model (11): Logged yen-dollar rate; sample period = 1985:1-2003:12. From top: Differenced series W_t (1985:2 to 2003:12), residual series, residual histogram, SCCF plot, and residual SACF plot.

5 The Intervention Analysis: Estimation Adjusting for Intervention Events

Even with the improved model (11), the residual normality again failed to obtain, which strongly suggests the need for an intervention analysis in which the presence of such intervention events as AO and PS is appropriately adjusted for in the model. The intervention analysis that follows is detailed in Kojima (1994b, pp.90-94,117-121).¹⁸ The method of iteratively detecting AO and PS in the estimation procedure is, first, very briefly described, and then, will be applied to the model (11) for the intervention analysis of the yen-dollar exchange rate behavior.

¹⁸Later, section 6 will study AO and PS with regard to their effects on forecast performance.

5.1 Intervention model and the iterative procedure of detecting AO and PS

Let Z_t denote a time series *not contaminated* (i.e., an *intervention-free* time series) and described by the SARIMA($p, d, q; P, D, s, Q$) model (5), which is here rewritten as:

$$\begin{aligned} W_{zt} &= (1 - B)^d(1 - B^s)^D Z_t \\ E[W_{zt}] &= \mu \\ \tilde{W}_{zt} &= W_{zt} - \mu \\ \phi(B)\Phi(B^s)(1 - B)^d(1 - B^s)^D Z_t &= \theta(B)\Theta(B^s)a_t. \end{aligned} \tag{13}$$

The model is assumed to satisfy both stationarity and invertibility conditions. The corresponding SARMA($p, q; P, Q$) model is (8) with \tilde{W}_t replaced by \tilde{W}_{zt} .

Let now X_t^ℓ denote a *contaminated* (logged) observed time series (X_t^ℓ is that given by Eq. (4) in section 3.1). The contaminated series is related with the intervention-free data Z_t as in the following intervention model (Box, Jenkins and Reinsel 1994, ch. 12; RATS UG, pp.277-280):

$$X_t^\ell = \sum_{k=1}^m \omega_{d_k} \left\{ \nu_k(B) \xi_t^{(d_k)} \right\} + Z_t, \tag{14}$$

which, put in the differenced form, will be written as

$$\tilde{W}_t = \sum_{k=1}^m \omega_{d'_k} \left\{ \nu_k(B) \xi_t'^{(d'_k)} \right\} + \tilde{W}_{zt} \tag{15}$$

where W_t is a differenced series of X_t^ℓ as computed by Eq. (3), m =number of intervention events observed in X_t^ℓ , d_k =point in time when k th intervention event is detected (this notation applies to X_t^ℓ), ω_{d_k} =size of the initial impact of k th intervention event (this applies to $\omega_{d'_k}$ as well), $\xi_t^{(d_k)} = 1$ (for $t = d_k$); $= 0$ (for $t \neq d_k$), and $d'_k = d_k - d - sD$ (this notation applies to differenced series W_t), and $\xi_t'^{(d'_k)} = (1 - B)^d(1 - B^s)^D \xi_t^{(d_k)}$.

In Eqs. (14) and (15), ω are computed by the formulas as shown in Kojima (1994b, pp.119-120). $\nu_k(B)$ exhibits different structure depending on type of the k th intervention event (see Kojima 1994b, pp.91-94):

AO If k th intervention event is AO,

$$\nu_k(B) = 1; \tag{16}$$

substituting this into (14) with $m = 1$ leads to

$$\begin{aligned} X_t^\ell &= Z_t, & t \neq d_k \\ X_{d_k}^\ell &= \omega_{A,d_k} + Z_{d_k}, & t = d_k. \end{aligned}$$

PS If k th intervention event is PS (assuming $|B| < 1$),

$$\nu_k(B) = \frac{1}{1-B} = \sum_{i=0}^{\infty} B^i; \tag{17}$$

substituting this into (14), with $m = 1$, leads to

$$\begin{aligned} X_t^\ell &= Z_t, & t < d_k \\ X_{d_k+i}^\ell &= \omega_{P,d_k} \psi_i + Z_{d_k+i}, & i = 0, 1, \dots \end{aligned}$$

where the ψ weights, equal to 1 here for all i , are those in the random-shock form of the model (13), as given by

$$\tilde{W}_{zt} = \psi(B)a_t \tag{18}$$

with $\psi(B) = \sum_{i=0}^{\infty} \psi_i B^i$ and $\psi_0 = 1$.¹⁹

The number m of intervention events and their observed points in time d_k (or d'_k) are unknown in the models (14) or (15). Details are given in Kojima (1994b, pp.117-121) on the procedure that will iteratively detect AO and PS and determine m and d_k in outer and inner loops. Just two remarks are in order:

(i) The series adjusted for the presence of AO and PS (AO-PS adjusted series) is computed by

$$X_t^{\ell*} = X_t^\ell - \hat{\omega}_{d_k} \left\{ \nu_k(B) \xi_t^{(d_k)} \right\}, \quad d_k = t_{\max} + d + sD \quad (t = 1, \dots, T); \tag{19}$$

it will be an estimate of unobservable, theoretical Z_t , computed in the final outer loop of the iterative detection procedure. Substituting the random-shock form of (13) with $\mu = 0$ into Eq. (14) yields the general form of an intervention model (to be applied subsequently in section 5.4):

$$X_t^\ell = \sum_{k=1}^m \omega_{d_k} \left\{ \nu_k(B) \xi_t^{(d_k)} \right\} + \frac{\theta(B)\Theta(B^s)/\phi(B)\Phi(B^s)}{(1-B)^d(1-B^s)^D} a_t. \tag{20}$$

¹⁹The ψ weights of a general ARIMA model can be recursively determined: See Box, Jenkins and Reinsel (1994, pp.100-102). The random-shock form will be again a critical element in the forecasting stage: See Remark 1 in section 6.1.

²⁰See Kojima (1994b, pp.115-119) for t_{\max} and other related details.

After all the iterations are completed, the intervention model of this form will be estimated simultaneously with regard to all of ω_{d_k} , $k = 1, 2, \dots, m$, and parameters ϕ , θ , Φ , Θ . The initial estimates to use then are those estimates obtained in the iterative procedure, $\hat{\omega}_{d_k}$ and parameters computed in the final outer loop. Such simultaneous estimation will be illustrated for the yen-dollar exchange rate in section 5.4.

(ii) Has the intervention model (20) been improved as compared to the model altogether ignoring the intervention events? This problem will be investigated in the forecast performance context in section 6.

5.2 Detecting intervention events in the yen exchange rate behavior: The very first outer loop

The RATS program BJestimate_erAOPS.prg is designed and written for the specific attempt to statistically and iteratively detect AO and PS in the yen-dollar rate behavior. Its entire set of outputs and related figures is listed in Table 4.

Table 4 Iterative Detection of AO and PS: Outputs, Figs. and Mdoels^a

OL (Outer loop)	IL (Inner loop)	RATS Output and Fig.	Model identified and estimated
1		Outputs 2, A; Figs. 8, 10-12*	(11)
	1	Same as above; same as above	
	2	Outputs A, B; same as above, Fig. 13	
	3	Output C	
2**		Output D; Figs. 18, 19	(11)
	1	Output F; Figs. 21-23	
	2	Output F	
3**		Output G	(11)
	1	Output H	
	2	Output H	
4**		Output I	(11)
	1	Output J	
	2	Output J	
	3	Output J	
5		Output K; Figs. 14, 15	(11)
	1	Output L	
Intervention Model***		Output M; Fig. 16	(21)

^aSee Table 5 at the end of section 5.3 for the summary statistical results of OL 1 through OL 5. *: See sections 3.3 and 4, respectively, for Figs. 8 and 10. **: See Appendix A for details. ***: See section 5.4.

Those outputs that follow are RATS Outputs A, B, C, K and L for the very first outer loop (in the present section) and the very last outer loop (in section 5.3); note the output remarks. (The remaining outputs are in Appendix A.) All the statistical results in the first through final, fifth outer loops are reported in Table 5 at the end of section 5.3.

In Output A just below, the backcasts of RESIDS are computed based on Eq. (12): In RATS, with $t = -10, -9, \dots, -1, 0$ [=ENTRY 15, ...,25=1984:03, ...,1985:01],

$$W_t = TRANSFRM_t - TRANSFRM_{t-1}$$

$$a_t = W_t - \theta_1 a_{t-1} - \theta_{11} a_{t-11}.$$

RATS Output A for the model (11), from BJestimate.erAOPS.prg :

```
* --- COMPUTED RESULTS
* --- BJ model estimation
STARTL (=1983:1, as specified by calendar 1983 1 12 in BJestimate.erAOPS.prg)
= 1
ENDL (=2004:3, as specified by allocate 2004:3 in BJestimate.erAOPS.prg) = 255
print / SERIES;* / = smpl, right above @BJEST_erAOPS in BJestimate.erAOPS.prg
(Note that / is NOT= STARTL - ENDL!!):
ENTRY RF_JY_USD
1985:01 254.1800
.....
2003:12 107.9350
STARTL = STARTL+DIFFS+ARS+SPAN*(SDIFFS+SAR):
START=
STARTL= 2 (=1983:2)
end=
ENDL= 255 (=2004:3)
compute ENDL=ENDL-fprd:
ENDL= 252 (=2003:12)
* When backcasting is required (o.w., not needed):
compute STARTL=STARTL+eprd
STARTL= 26 (=1985:2)
(A)
Box-Jenkins - Estimation by Gauss-Newton
..... /Same as RATS output from BJestimate.er.prg at the end of section 4.
The following lines are being added to check on the validity of the author's
own programming for computing standard error of estimate SQUARED:
* --- Resid variance (=standard err. of estimate SQUARED = %SEESQ):
RATS, RM, p.198;UG, p.146): 7.43272e-04
* < Computations by Hirao:
Sum of Squared Residuals = 0.16724
ENDL-(STARTL-1) - numparam (= resids. Degrees of Freedom)= 225
standard err. of estimate SQUARED = 7.43272e-04
standard err. of estimate = 0.02726
* > /
*--- Backcasting TRANSFRM (Tom Maycock of Estima 7/15/2004):
t = 1,2,...,T (smpl STARTL-das ENDL):
ENTRY TRANSFRM
1985:01 5.538042677454
.....
2003:12 4.681529194087
t = T, T-1,...,2,1: /Ignore, for the timebeing, the time index ENTRY; the order
```

only is meaningful.]
 ENTRY TRANSFRM
 1985:01 4.681529194087

 2003:12 5.538042677454
 12 backcasts of TRANSFRM: [*Continued from 2003:12 5.538042677454 immediately above.*]
 Entry TRANSFRM
 2004:01 5.5388401842668

 2004:12 5.5246697242832 [*Same as 2004:11 immediately above.*]
 Reverting the series back into its original order:
 ENTRY TRANSFRM
 1985:01 5.524669724283

 2004:12 4.681529194087
 Store the backcasts in period up to 1984:12: [*The time index ENTRY is meaningful from here on. They are drawn in Fig. 12-top panel, along with observations from 1985:1 on.*]
 TRY TRANSFRM
 1984:01 5.524669724283 [*ENTRY=13 (1983:01 is ENTRY=1); backforecast values start here.*]

 1984:12 5.538840184267 [*ENTRY=24; backforecast values end here.*]
 1985:01 5.538042677454 [*ENTRY=25; actual values start here.*]
 1985:02 5.561604282165 [*ENTRY=26.*]

 2003:12 4.681529194087 [*ENTRY=252; actual values end here.*]
 Check when first-order differenced TRANSFRM backcasts die out to zero [*The differenced series W_t in the model (10) is of first order. Drawn in Fig. 11.*]
 (For backcasts dying out, see Box and Jenkins 1976, pp.212-220):
 The latest dTRANSFRM, printed at the bottom below, is the VERY FIRST backcast:
 ENTRY DTRANSFRM
 1984:01 NA
 1984:02 0.000000000000 [*t=-11.*]
 1984:03 0.001713628841 [*t=-10.*]
 1984:04 -0.001411763555

 1984:12 0.002774148681 [*t=-1.*]
 1985:01 -0.000797506813 [*t=0; = TRANSFRM (1985:01 5.538042677454 minus 1984:12 5.538840184267).*]
 Extreme Values of Series ZS [*Check on where DTRANSFRM (1984:02 0.0) is located as against 1985:01 -0.0007975.*]
 Monthly Data From 1983:01 To 1983:12
 Minimum Value is 0.000000000000 at 1983:12 Entry 12
 Maximum Value is 0.00816494413 at 1983:08 Entry 8
 Qzero = 12 [*DTRANSFRM (1984:02 0.0) is the twelfth from 1985:01 -0.0007975.*]
 %beta(1)= 0.34309
 %beta(2)= 0.20921
 STARTL= 26
 ENDL= 252
 resids(STARTL)= 0.02356
 resids(ENDL-1), (ENDL)= 0.00675 -0.00819
 %nobs for resids = 227
 numr=endl - startl + 1 = Number of residuals computed = 227
 %SEESQ (the standard error of estimate SQUARED):
 its SQRT is displayed earlier and used below: RATS RM, p.198; UG, p.146) =
 7.43272e-04
 sqrt(adjSEESQ)

```

(the standard error of estimate, displayed earlier and used below: RATS RM,
p.198; UG, p.146) = 0.02726
11 (=Qzero-1) backcast residuals, 1984:3 (-10) - 1985:1 (0):
ENTRY RESIDS
1983:01 0.000000000000 [ENTRY=1.]
.....
1984:02 0.000000000000 [ENTRY=14 (=STARTL-Qzero); t=-11; the twelfth
from 1985:01 (=Qzero); RESIDS=0 for the previous periods.]
1984:03 0.001713628841 [ENTRY=15; t=-10; backcasting RESIDS is done by
the equation right above the output.]
1985:01 -0.002618290683 [ENTRY=25; t=0; backcast RESIDS.]
1985:02 0.023561604711 [ENTRY=26; t=1.]
.....
2003:12 -0.008190791508
Plotting for smpl STARTL-das-num_bkcasts ENDL [Drawn in Fig. 12-top panel.]
ENTRY TRANSFRM
1984:01 5.524669724283
.....
2003:12 4.681529194087
ENTRY RESIDS
1984:01 0.000000000000
1984:02 0.000000000000
1984:03 0.001713628841
.....
2003:12 -0.008190791508
    
```

Produced by the output so far are Figs. 11 and 12.

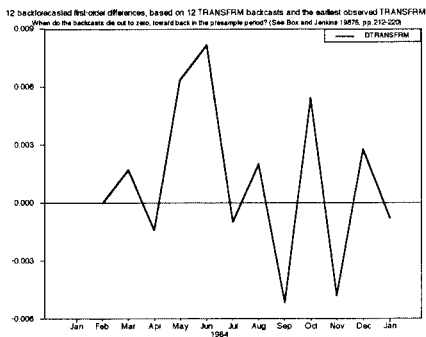


Figure 11 OL 1-IL 1 in Tables 4 and 5: Twelve backcasts of the first differenced series of TRANSFRM (check on when the backcasts converge to zero).

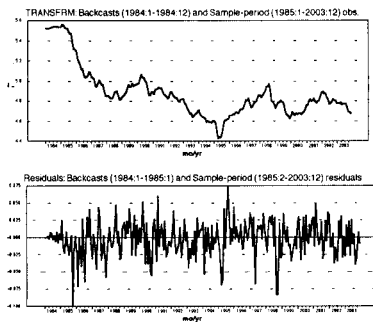


Figure 12 OL 1-IL 1 in Tables 4 and 5: Top panel=backcasts and observations of TRANSFRM; bottom panel=backcasts and observations of residuals.

RATS Output A (continued) :

```

===== To detect additive outlier (AO) and permanent level shift (PS):
* --- inner_round = 1
For AO:
lambdat
NA NA NA NA NA
.....
NA NA NA NA NA
0.2769 0.6182 0.5687 0.0810 0.8094
.....
0.3888 0.3004 NA NA NA
NA NA NA NA NA
.....
NA NA NA NA NA
lambdat(t):
..... [( 25 ) 1985:01 NA]
( 33 ) 1985:09 2.92944 [Rather, 1985:10 is consistent with * in Table 2 in
section 2.1.]
.....
( 42 ) 1986:06 2.23986
.....
( 98 ) 1991:02 2.61735
.....
( 148 ) 1995:04 2.36197 [This is consistent with * in Table 2.]
.....
( 172 ) 1997:04 2.33582 [This seems related to the Asian currency crisis. See
Table 2.]
.....
( 190 ) 1998:10 2.35927 [This is consistent with * in Table 2.]
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00182361144 at 1986:03 Entry 39
Maximum Value is 2.92944113279 at 1985:09 Entry 33
lmax 2.92944
tmax 33
omegat(tmax) = 0.04400
For PS:
lambdat_eta
NA NA NA NA NA
.....
NA NA NA NA NA
0.6949 0.2380 0.7820 0.1563 0.2899
.....
0.3316 0.3004 NA NA NA
NA NA NA NA NA
.....
NA NA NA NA NA
lambdat_eta(t):
..... [( 25 ) 1985:01 NA]
( 34 ) 1985:10 3.39019 [This is consistent with * in Table 2.]
( 99 ) 1991:03 2.38260
( 148 ) 1995:04 2.51630 [This is consistent with * in Table 2.]
( 190 ) 1998:10 2.95575 [This is consistent with * in Table 2.]
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.01179139143 at 1999:11 Entry 203
Maximum Value is 3.39019433354 at 1985:10 Entry 34
lmax_eta 3.39019
tmax_eta 34
omegat_eta(tmax_eta) = -0.08401
lmaxk = max(lmax,lmax_eta) = 3.39019
Crit = 4.00000

```

$l_{\max} = \max(l_{\max}, l_{\max_eta}) = 3.39019$ is below $\text{Crit}=4.0$. Lowering Crit to 3.25 leads to another inner loop: Output B and Fig. 13 follow. See Output C for further inner loops.

RATS Output B (continued from Output A, now with “Crit = 3.25”) :

```

lmax = max(lmax,lmax_eta) = 3.39019
Crit = 3.250000
* --- Adjusted residuals for Adj. series [They are drawn in Fig. 13-bottom
and -center panels.]
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0022274511 Variance 0.000698
Standard Error 0.0264155174 SE of Sample Mean 0.001753
t-Statistic -1.27046 Signif Level (Mean=0) 0.20522612
Skewness -0.31841 Signif Level (Sk=0) 0.05170584
Kurtosis 0.30308 Signif Level (Ku=0) 0.35873158
Jarque-Bera 4.70462 Signif Level (JB=0) 0.09514889
.....
Editing data file "residsBJEST_2.rat" [They are drawn in Fig. 13-bottom panel.]
RESIDS 1985:02 - 2003:12 Monthly
RESIDS
Monthly Data From 1985:02 To 2003:12
=====
1985:01 [A blank space here.] 0.02356160 -0.01428968 -0.02237705
.....
Editing data file "AdjSrs_er.rat" [The AO-PS adjusted data are saved and drawn
in Fig. 13-center panel.]
TRANSFRM 1985:01 - 2003:12 Monthly
TRANSFRM
Monthly Data From 1985:01 To 2003:12
=====
1985:01 5.53804268 5.56160428 5.55539847 5.52811871
.....
Go back to INNER loop < 3 >: current round = 1 next round = 2.

```

RATS Output C (continued from Output B) :

```

* --- inner_round = 2
For AO:
lambdat
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00457394499 at 1992:04 Entry 112
Maximum Value is 2.68536416838 at 1991:02 Entry 98
lmax 2.68536
tmax 98
omegat(tmax) = -0.03930
For PS:
lambdat_eta
.....
* --- inner_round = 3
.....
* --- inner_round = 4
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.01183520509 at 1988:03 Entry 63

```

Maximum Value is 3.03300841695 at 1998:10 Entry 190
lmax_eta 3.03301
tmax_eta 190
omegat_eta(tmax_eta) = -0.07324
lmaxk = max(lmax,lmax_eta) = 3.03301 [See OL 2-IL 1 in appendix section A.1.]
Crit = 3.25000
Current round of the INNER loop = 4
If both of the current OUTER and INNER loops are very first ones,
then Crit should be made smaller to try the inner loop again. See Kojima (1994b, p.120).
Otherwise, the inner loop terminates, and
the detection procedure continues with the next round of the outer loop < 1 >
using the most recent AdjSrs_er.rat.

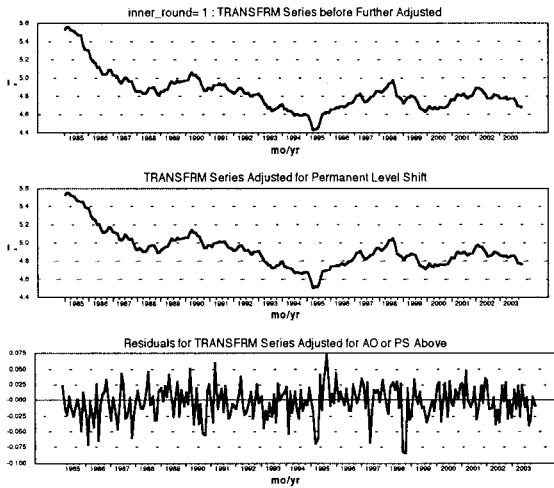


Figure 13 OL 1-IL 2 in Tables 4 and 5: Logged yen-dollar rate; sample period = 1985:1-2003:12. Top=before being further adjusted; center=after being further adjusted; bottom=residuals computed based on further adjusted data (backcasts are used where needed). The AO-PS adjusted series $X_t^{\ell*}$ is computed by (19).

5.3 Detecting intervention events in the yen exchange rate behavior: The second outer loop on

In the second outer loop on, models for data already adjusted for the presence of AO and PS (i.e., $X_t^{\ell*}$ computed by Eq. (19) in section 5.1 and drawn as in Fig. 13-center in section 5.2) will be identified and estimated, respectively, by BJidentify_erAOPS.prg and BJestimate_erAOPS.prg.

5.3.1 Second through fourth outer loops

The iterative search for AO and PS in the second through fourth outer loops is described, along with the outputs, in Appendix A.

5.3.2 Fifth outer loop: Very last outer loop

Model identification The fifth OL here follows the fourth OL in appendix section A.2.2. Based on Fig. 14, which essentially looks the same as Fig. 18 in appendix section A.2.2, the model (11) used previously in OL 2 is again identified.

Adjusted, Logged RF_JY_USD : Data (top), SACF (middle), SPACF (bottom)

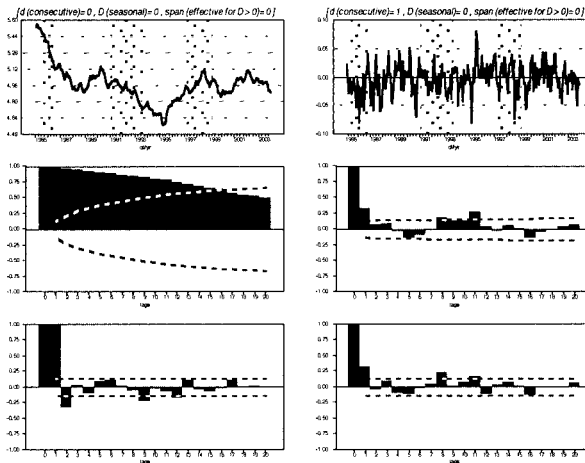


Figure 14 OL 5 in Tables 4 and 5: Model identification.

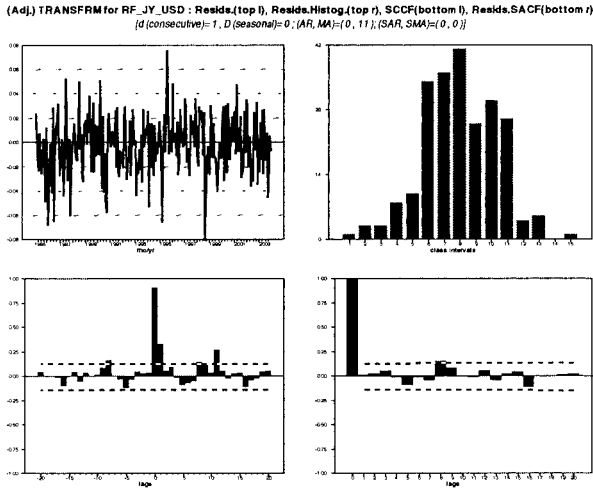


Figure 15 OL 5 in Tables 4 and 5: Estimation and diagnostic check of the model (11).

Model estimation and diagnostic checking Assuming, first, that AO and PS are not present in the present time series, the model (11) is estimated by BJestimate_erAOPS.prg (with skipDetect=1)²¹ and bjest_erAOPS.src. See Output K and Fig. 15.

RATS Output K for the model (11) :

```
* --- COMPUTED RESULTS
.....
(A)
Box-Jenkins - Estimation by Gauss-Newton
Convergence in 7 Iterations. Final criterion was 0.0000039 < 0.0000100
Dependent Variable TRANSFRM
Monthly Data From 1985:02 To 2003:12
Usable Observations 227 Degrees of Freedom 225
Centered R**2 0.980702 R Bar **2 0.980617
Uncentered R**2 0.999976 T x R**2 226.994
Mean of Dependent Variable 4.9736957764
Std Error of Dependent Variable 0.1769674074
Standard Error of Estimate 0.0246381600
Sum of Squared Residuals 0.1365837585
Durbin-Watson Statistic 1.957323
Q(36-2) 27.431790
```

²¹With skipDetect=1, the backcasting step is entirely skipped.

Significance Level of Q 0.77999042
 Variable Coeff Std Error T-Stat Signif

 1. MA{1} 0.3441620487 0.0587360889 5.85946 0.00000002
 2. MA{11} 0.3193090379 0.0610122854 5.23352 0.00000038
The remainder omitted.

OL 5-IL 1 To detect AO and PS (with skipDetect=0 in RATS), C is set at 2.7 (with Crit=2.7 in RATS) in OL 5 here, since, in Output J in appendix section A.2.2, “lmaxk = max(lmax,lmax_eta) = 2.69163” at the end of OL 4. From Output L, the search is seen to terminate here.²²

RATS Output L :

.....{*Sames as Output K; computation of backcasts.*}
 ===== To detect additive outlier (AO) and permanent level shift (PS):
 * --- inner_round = 1
 For AO:
 Extreme Values of Series ZS
 Monthly Data From 1985:02 To 2003:12
 Minimum Value is 0.00227194434 at 1997:04 Entry 172
 Maximum Value is 2.69598739779 at 1986:06 Entry 42
 lmax 2.69599
 tmax 42
 omegat(tmax) = 0.03445
 For PS:
 Extreme Values of Series ZS
 Monthly Data From 1985:02 To 2003:12
 Minimum Value is 0.00144094612 at 1996:11 Entry 167
 Maximum Value is 2.64212581023 at 1998:09 Entry 189
 lmax_eta 2.64213
 tmax_eta 189
 omegat_eta(tmax_eta) = -0.05630
 lmaxk = max(lmax,lmax_eta) = 2.69599
 Crit = 2.70000
 Current round of the INNER loop = 1
 If both of the current OUTER and INNER loops are very first ones,
 then Crit should be made smaller to try the inner loop again. See Kojima (1994b,
 p.120).
 Otherwise, the inner loop terminates, and
 the detection procedure continues with the next round of the outer loop < 1 >
 using the most recent AdjSrs_er.rat.

Table 5 summarizes all the search results. Setting C smaller (such as at 2.5), further AO and PS could be detected: Such additional AO and PS would also be statistically significant, which could in turn work to make the forecast performance better. As seen by comparing Table 2 in section 2.1 and Table 5, however, AOs and PSs that have been detected so far do correspond to the “spikes” of the past yen against dollar rate behavior; there would thus be no need for further search.

²²See (5b) in the iterative search procedure in Kojima (1994b, pp.117-119).

Table 5 Yen-dollar Exchange Rate (January 1985 – December 2003): Iterative Detection of AO and PS^a

OL	IL	C ^b	Time	Type ^c	Initial Impact ^d	$\hat{\sigma}_\epsilon^2$ ^e	Jarque-Bera (Signif Level (JB=0))
1						7.43272e-04 ^f	11.97820 (0.00250592)
	1	4.0					No statistically significant AO or PS detected; C is set at 3.25 ^g
	2 ^h	3.25	1985 : 10 (34) ⁱ	PS	-0.08401	7.05886e-04 ^f	4.70462 (0.09514889)
	3	3.25					No statistically significant AO or PS detected; C is set at 3.0 ^k
2						7.04939e-04	4.78205 (0.09153586)
	1	3.0	1998 : 10 (190)	PS	-0.07362	6.75540e-04	2.12742 (0.34517207)
	2	3.0					No statistically significant AO or PS detected; C is again set at 3.0.
3						6.74839e-04	2.08821 (0.35200682)
	1	2.7	1991 : 02 (98)	AO	-0.03985	6.68801e-04	2.47077 (0.29072265)
	2	2.7					No statistically significant AO or PS detected
4						6.50423e-04	2.92645 (0.23148845)
	1	2.7	1995 : 04 (148)	PS	-0.06103	6.29161e-04	3.03022 (0.21978406)
	2	2.7	1997 : 04 (172)	AO	0.03709	6.24954e-04	3.10711 (0.21149513)
	3	2.7					No statistically significant AO or PS detected
5						6.07039e-04	1.58774 (0.45209161)
	1	2.7					No statistically significant AO or PS detected

^aSee section 5.1 and Table 4 in section 5.2 for the iterative search as applied to the table. See also Table 2 in section 2.1 for the “spikes” observed in the yen-dollar rate behavior .

^bCritical value: It is denoted by Crit in RATS Outputs. The minimum of C (= 2.7 here) is the maximum at which the residuals are taken to be normally distributed in the final OL. (With smaller C, more AO and PS could be detected.)

^cPS and AO are, respectively, permanent level shift and additive outlier.

^dThe initial impact is denoted by ω in (14) or (15) and computed by the formulas as shown in Kojima (1994b, pp.119-120).

^eEither the residual variance (= the squared “standard error of estimate, as displayed in the RATS output”) before AO and PS are detected in OL, or the residual variance immediately after AO and PS are detected in IL. Backcast residuals are not taken into account.

^fThe squared “standard error of estimate, in RATS Output for the modified model (11) in section 4”: $(0.0272630176)^2$.

^gSmaller than lmax = max(lmax,lmax.eta) = 3.39019 at the end of Output A.

^hThe results under right columns are from RATS Outputs A and B.

ⁱEntry 1=1983:1, as specified by “calendar 1983 1 12” in BJestimate.erAOPS.prg.

^jThe residual variance for the adjusted series in Fig. 13-bottom.

^kSmaller than lmax = max(lmax,lmax.eta) = 3.03301 at the end of Output C.

5.4 Estimating an intervention model: RATS program InterventionModel_er.prg

After completing the detection procedure, one moves on to specifying and estimating an intervention model, the general form of which is given by (20) in section 5.1.

It is seen from Table 5 that $m = 5$ and that d_k , $k = 1, 2, \dots, 5$ correspond, respectively, to 1985:10 (34), 1998:10 (190), 1991:02 (98), 1995:04 (148), 1997:04 (172), with ω_{d_k} , $k = 1, 2, \dots, 5$ being a magnitude of the respective initial impact. By (17), $\nu_k(B) = \frac{1}{1-B}$, $k = 1, 2, 4$; by (16), $\nu_k(B) = 1$, $k = 3, 5$. The resultant intervention model will be specified as:

$$X_t^\ell = \sum_{k=1,2,4} \omega_{d_k} \left\{ \frac{1}{1-B} \xi_t^{(d_k)} \right\} + \sum_{k=3,5} \omega_{d_k} \left\{ 1 \xi_t^{(d_k)} \right\} + \frac{1 - \theta_1 B - \theta_{11} B^{11}}{1-B} a_t \quad (21)$$

where:

$$\begin{aligned} k = 1, 2, 4 : \omega_{d_k} \left\{ \frac{1}{1-B} \xi_t^{(d_k)} \right\} &= \omega_{d_k} \left\{ \sum_{i=0}^{\infty} B^i \xi_t^{(d_k)} \right\} \\ &= \omega_{d_k} \left\{ \xi_t^{(d_k)} + \xi_{t-1}^{(d_k)} + \dots \right\} \\ &= \begin{cases} 0, & t = d_k + i, i = -1, -2, \dots \\ \omega_{d_k}, & t = d_k + i, i = 0, 1, 2, \dots \end{cases} \quad (22) \end{aligned}$$

$$k = 3, 5 : \omega_{d_k} \left\{ 1 \xi_t^{(d_k)} \right\} = \begin{cases} 0, & t \neq d_k, \\ \omega_{d_k}, & t = d_k. \end{cases} \quad (23)$$

In RATS as well, ω (and its signs) are the same as above (RATS RM, pp.18-21).

The RATS program InterventionModel_er.prg, using another program `bjest_erIntrvModel.src`, estimates the intervention model (21). With X_t^ℓ representing logged raw data *before* adjusted for the presence of AO and PS, the estimation here is done using the logged data and “calendar”, “allocate”, “open” and “data” for `BJestimate_er.prg` which ignores AO and PS; `InterventionModel_er.prg` and `bjest_erIntrvModel.src` are designed as such.

In RATS Output M for the intervention model (21), whose corresponding graph output is Fig. 16, AO and PS are seen to be all significant even at the less than 1% level: In particular, “PS34” that is associated with 1985:10, the month following Plaza Accord, has the largest “Coeff”; its sign and magnitude are consistent with those in Table 5.

The question arises as to whether the intervention model (21) will lead to better forecast performance, as compared to the model (11). An attempt to answer it is made in section 6.2.3.

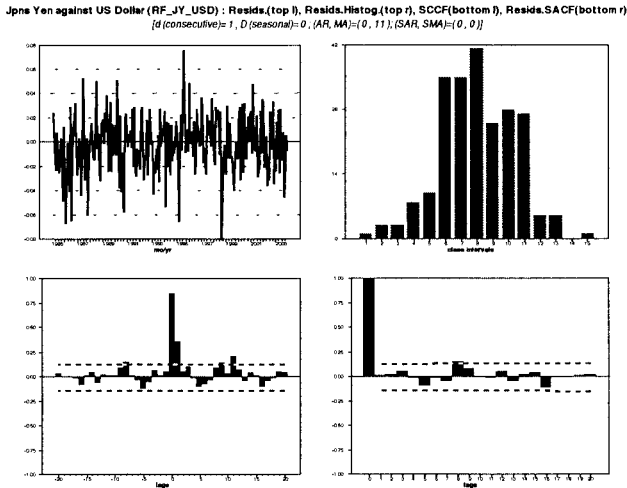


Figure 16 Estimating the intervention model (21).

RATS Output M for the intervention model (21) :

```
* --- COMPUTED RESULTS
* --- Intervention model estimation
.....
```

startv [Initial values when estimating the intervention model (21); the first two are estimates of MA{1} and MA{11} in RATS Output K for the model (11); the remaining are initial impact in Table 5.]

```
0.3442 0.3193 -0.0840 -0.0736 -0.0398
-0.0610 0.0371
(A)
```

Box-Jenkins - Estimation by Gauss-Newton

Convergence in 7 iterations. Final criterion was 0.0000087 < 0.0000100

Dependent Variable TRANSFRM

Monthly Data From 1985:02 To 2003:12
 Usable Observations 227 Degrees of Freedom 220
 Centered R^{**2} 0.984982 R Bar $**2$ 0.984572
 Uncentered R^{**2} 0.999974 $T \times R^{**2}$ 226.994
 Mean of Dependent Variable 4.8439736226
 Std Error of Dependent Variable 0.2005543498
 Standard Error of Estimate 0.0249106766
 Sum of Squared Residuals 0.1365191983
 Durbin-Watson Statistic 1.963048
 $Q(36-2)$ 28.065673
 Significance Level of Q 0.75306881
 Variable Coeff Std Error T-Stat Signif

 1. MA{1} 0.347647470 0.060624720 5.73442 0.00000003
 2. MA{11} 0.323655523 0.062646406 5.16639 0.00000053
 3. N_P34{0} -0.083835189 0.021451246 -3.90817 0.00012382 [*N* denotes nu-
 merator and {0} lag of 0 (*RATS RM*, pp.18-21).]
 4. N_P190{0} -0.070662115 0.022011228 -3.21028 0.00152432
 5. N_AO98{0} -0.043044043 0.012907219 -3.33488 0.00100143
 6. N_P148{0} -0.064797537 0.021667641 -2.99052 0.00310216
 7. N_AO172{0} 0.037270141 0.012911377 2.88661 0.00428220

 RESIDS
 Monthly Data From 1985:01 To 2003:12
 =====
 1985:01 NA 0.02356160 -0.01439695 -0.02227470

 2003:09 -0.04442781 -0.02364588 0.00494839 -0.00577985
 (B) Check the normality of RESIDS.

 Statistics on Series RESIDS
 Monthly Data From 1985:01 To 2003:12
 Observations 227 (228 Total - 1 Skipped/Missing)
 Sample Mean -0.0017217929 Variance 0.000601
 Standard Error 0.0245171279 SE of Sample Mean 0.001627
 t-Statistic -1.05809 Signif Level (Mean=0) 0.29114221
 Skewness -0.15306 Signif Level (Sk=0) 0.34966544
 Kurtosis 0.26243 Signif Level (Ku=0) 0.42679931
 Jarque-Bera 1.53773 Signif Level (JB=0) 0.46353935
 Minimum -0.0798722914 Maximum 0.0752828074

 Median -0.0026445167
 Studentized Range = 6.32844
 (C) SCCF Check: Large SCCF at a lag $l < 0$ below suggests
 the AR term at l , whose value is close to that SCCF.

 Ljung-Box Q-Statistics
 $Q(1$ to 20) = 59.8390. Significance Level 0.00000006
 $Q(-20$ to $-1)$ = 16.9131. Significance Level 0.20330534
 $Q(-20$ to 20) = 242.7127. Significance Level 0.00000000
 (D) SACF Check: Large residS SACF at a lag l below suggests
 the MA term at l , whose value is close to negative of that SACF.

 Ljung-Box Q-Statistics
 $Q(20)$ = 15.9412. Significance Level 0.25231945
 The remainder omitted.

6 Forecasting and Forecast Performance

Two sets of out-of-sample (postsample) exchange rate predictions will be computed based on the the model (11) and the intervention model (21) estimated, respectively, in sections 4 and 5.4; the two models will then be compared with respect to forecast performance. First two subsections here summarize general features of multistep-ahead forecasting and forecast performance; the third, final subsection carefully compares the two models with regard to exchange rate forecast performance.

6.1 Multistep-ahead forecast: logged vs. raw series

Let the conditional, l -step-ahead expectation of the *logged* series X_t^ℓ , (4), be

$$\hat{X}_T^\ell(l) \equiv E[X_{T+l}^\ell | I_T], l = 1, 2, 3, \dots \tag{24}$$

where T is a forecast origin (the end of the sample period), l the number of steps ahead and I_T all information available up until the forecast origin.

Suppose that a model is identified and estimated for X_t^ℓ . The l -step-ahead forecast $\hat{X}_T^\ell(l)$ will be computed based on the estimated SARIMA($p, d, q; P, D, s, Q$) model as follows:²³

$$\begin{aligned} \hat{X}_T^\ell(l) = & c - \sum_{\substack{i=0 \\ \text{Not}\{i=0, j=0, k=0, m=0\}}}^p \sum_{j=0}^P \sum_{k=0}^d \sum_{m=0}^D \phi_i \Phi_j (-1)^{k+m} \binom{d}{k} \binom{D}{m} [X_{T+l-i-j-s-k-m-s}^\ell] \\ & + \sum_{i=0}^q \sum_{j=0}^Q \theta_i \Theta_j [a_{T+l-i-j-s}] \end{aligned} \tag{25}$$

where: $\binom{n}{r} = \frac{n!}{r!(n-r)!}$;

$$\begin{aligned} (1-B)^d(1-B^s)^D X_t^\ell &= \sum_{k=0}^d \sum_{m=0}^D (-1)^{k+m} \binom{d}{k} \binom{D}{m} X_{t-k-m-s}^\ell \\ &= \sum_{k=0}^1 \sum_{m=0}^1 (-1)^{k+m} X_{t-k-m-s}^\ell \\ &\text{when } d = D = 1; \end{aligned} \tag{26}$$

²³See Kojima (1994b, pp.17-18).

$$[X_{T+l-u}^\ell] = \begin{cases} X_{T+l-u}^\ell, & \text{for } l \leq u \\ \hat{X}_T^\ell(l-u), & \text{for } l > u; \end{cases} \quad (27)$$

$$[a_{T+l-u}] = \begin{cases} a_{T+l-u} = X_{T+l-u}^\ell - \hat{X}_{T+l-u-1}^\ell(1), & \text{for } l \leq u \\ 0, & \text{for } l > u. \end{cases} \quad (28)$$

The upper equation in (28) is simply a one-step-ahead forecast error.

With Eqs. (25)–(28), we now move on to forecasting *raw* data X_t ; recall (4). Two crucial remarks are here in order:

Remark 1 While $X_t = \exp(X_t^\ell)$, we have the l -step-ahead forecast of raw data $\hat{X}_T(l) \equiv E[\exp(X_{T+l}) | I_T] \neq \exp\{\hat{X}_T^\ell(l)\}$. Rather, assuming the normality of X_t^ℓ , i.e., the log-normality of X_t , the correct l -step-ahead forecast of raw data is given by

$$\hat{X}_T(l) = \exp\left\{\hat{X}_T^\ell(l) + (1/2)\text{Var}[X_{T+l}^\ell | I_T]\right\} \quad (29)$$

where $\text{Var}[X_{T+l}^\ell | I_T] = \text{Var}[e_T(l)]$, with the l -step-ahead forecast error being

$$e_T(l) \equiv X_{T+l} - \hat{X}_T(l) = \sum_{i=0}^{l-1} \psi_i a_{T-i} \quad (\psi_0 \equiv 1) \quad (30)$$

and its variance (the variance of the l -step-ahead forecast error) being²⁴

$$\text{Var}[e_T(l)] = \sigma_a^2 \sum_{i=0}^{l-1} \psi_i^2. \quad (31)$$

The ψ weights here, also called the error-learning coefficients, are those parameters in the random-shock form of the SARIMA model, as defined by Eq. (18) earlier in section 5.1 (see the footnote there for how to compute them). With $l = 1$, Eq. (30) yields the one-step-ahead forecast error $e_T(1) = a_{T+1}$; by (31), then, $\text{Var}[e_T(1)] = \sigma_a^2$.

As will be seen in section 6.2, the variance of the l -step-ahead forecast error is a critical element in computing the forecast performance of a model.²⁵

²⁴See Nelson (1973, pp.161-163).

²⁵See also Yamamoto (1988, pp.78-80, ps.217,219).

Remark 2 X_T^ℓ and X_T differ in the confidence interval of forecast. Letting $\hat{X}_T^\ell(l) \pm k\sqrt{\text{Var}[e_T(l)]}$ be the confidence interval of forecast for (logged future data) X_{T+l}^ℓ , the confidence interval of forecast for (raw future data) X_{T+l} is given by

$$\exp \left\{ \hat{X}_T^\ell(l) \pm k\sqrt{\text{Var}[T(e_i)]} \right\}. \quad (32)$$

While the confidence interval of forecast for X_{T+l}^ℓ is symmetric, that for X_{T+l} , (32), is asymmetric.²⁶

6.2 Two approaches to computing forecast performance

Two forecasting methods are studied and detailed now in the present section: “Forecasting with fixed parameters” and “forecasting with updated parameters.” These methods provide two approaches to computing forecast performance.

The former approach uses the parameter estimates based only on the in-sample (sample-period) data to compute out-of-sample (postsample) forecasts: The parameter estimates are being fixed. The forecast performance here will be computed only at the forecast origin which is the end of the sample period.

On the other hand, the latter approach uses the out-of-sample data points as they become available: The parameter estimates will be updated using the future data. The forecast performance here will be computed based on the updated (i.e., re-estimated) parameters.

6.2.1 Computing the forecast performance with fixed parameters

As of the end of the sample period (the forecast origin), the future is entirely unknown: The forecast performance of the model is computed at the forecast origin, based on the standard error of the l -step-ahead forecast error $e_T(l)$, which is a square root of Eq. (31), the variance of $e_T(l)$. The forecast is a point estimate and the actual, realized value would likely fall somewhere within the interval centered around this point forecast. The approximate endpoints of this interval may be estimated

²⁶See Nelson (1973, pp.161-165).

by using the standard error of the l -step-ahead forecast error. The l -step-ahead “interval” forecast may be given by the point forecast \pm two standard errors of the l -step-ahead forecast error.

As the standard error here is smaller, the actual value would be anticipated to more likely fall near the point forecast, in which sense the forecast performance is improved: Searching for model(s) with as small standard error as possible will be our primary objective.

6.2.2 Computing the forecast performance with updated parameters

The forecast performance here is based on the updated forecasts as computed by re-estimating the parameters: The forecasts will be updated as future data point becomes available and the parameters are re-estimated with the expanded set of data; the updated forecasts will be thus made for the remaining, fewer future periods (the shorter forecast horizon). See the next subsection for details.

Notice here that the *actual* values of future period are used, in the sense of which the forecast performance is computed using the *post* sample period data. The proxies for such forecast performance include ME (Mean Error), MAE (Mean Absolute Error), RMSE (Root Mean Squared Error) and Theil’s U statistic. They are computed as follows (see RATS, Ver. 5, RM, pp.353-358; UG, ps.253, 269-270):

l -step-ahead ME=average of the l -step-ahead forecast errors (=actual – forecast, as in Eq. (30)): If ME is statistically significantly different from zero, the forecast is biased in either direction.

l -step-ahead MAE=average of absolute values of the l -step-ahead forecast errors.

l -step-ahead RMSE=the square root of average of the squared l -step-ahead forecast errors.

l -step-ahead Theil’s U statistic=[l -step-ahead RMSE above]/[l -step-ahead RMSE for the naive model generating future forecasts all equal to the actual value of the dependent variable at the forecast origin]: If it is less than 1, the model under study performs better with regard to forecast performance than the naive model (RATS RM, pp.353-355).

The smaller all these statistics, the better. The computations are now detailed for the yen-dollar exchange rate in the next subsection.

6.2.3 Comparing the model (11) and the intervention model (21), with regard to yen exchange rate forecast performance

The model (11) and the intervention model (21), respectively, in sections 4 and 5.4 are now compared with regard to exchange rate forecast performance. The RATS programs BJforecast_er.prg, bjfore1_er.src and bjfore2_er.src are designed and written for comparing the two models with respect to forecast performance; note the program remarks.

The RATS programs for forecasting

RATS Program BJforecast_er.prg :

```

BJforecast_er.prg
calendar 1985 1 12
allocate 2004:3
open data RF_JY_USD.wks
data(format=wks,organization=row) 1985:1 2004:3 RF_JY_USD
source(noecho) bjfore1_er.src
source(noecho) bjfore2_er.src
.....
set verlines = t==2003:12 ;* Forecast origin
*
compute bg=2003:1
compute fo=2003:12
compute bt=2004:1
compute et=2004:3
compute nf=3 ;* Number of forecasts to be made = 2004:1 - 2004:3
display '*--- COMPUTED RESULTS'
disp ', '
disp '*--- Model I: '
@bjfore1_er(nf=nf,trans=log,diffs=1,NOCONSTANT,mass=11) RF_JY_USD bt et
JYUSD.Frcst_I upper_I lower_I
disp '*--- Model II: Intervention model'
@bjfore2_er(nf=nf,trans=log,diffs=1,NOCONSTANT,mass=11) RF_JY_USD bt et
JYUSD.Frcst_II upper_II lower_II
The remainder omitted.

```

RATS Program bjfore1_er.src :

```

PROCEDURE BJFORE1_er SERIES START END FORECAST upper lower [START is
bt and END et in BJforecast_er.prg above.]
.....
disp 'Multistep-ahead forecasts of transformed: '
COMPUTE STEPS=END-START+1 [The future period from START =2004:01 to
END=2004:03.]
FORECAST(print) 1 STEPS START [The l-step-ahead forecasts are computed here
by (25).]
# BJEQ FORECAST [FORECAST here is that in "PROCEDURE BJFORE1
SERIES START END FORECAST upper lower" and will be drawn as future
forecasts.]
errors(print) 1 STEPS ;*see Manual, p.14-74, for the standard error of
the forecasts. [See RATS UG, pp.299-301 or RM, pp.105-106.]
set lower START END = FORECAST - 2*stderrors
}

```

```

# BJEQ stderrs START [With trans=log in @bjfore1_er, the standard errors
"stderrs" of the l-step-ahead forecast error are computed and displayed
for logged series; their squared values,  $\text{Var}[X_{T+1}^l | I_T]$ , will be used when l-
step-ahead raw forecasts are computed by (29). See RATS UG, pp.299-301.]
.....
revised (2/7/01):
IF TRANS == 2
{
set upper START END = EXP(FORECAST + 2*stderrs) [Confidence interval,
based on (32) using logged forecasts, for raw data  $X_{T+1}$ .]
set lower START END = EXP(FORECAST - 2*stderrs)
}
ELSE
{
set upper START END = FORECAST + 2*stderrs ;* <<<< [Confidence in-
terval for raw data  $X_{T+1}$  when no log transformation is made.]
set lower START END = FORECAST - 2*stderrs
}
IF TRANS == 2
SET FORECAST START END = EXP(FORECAST+0.5*stderrs**2) [Forecasts based
on (29) for future raw series  $X_{T+1}$ .]
ELSE IF TRANS == 3
SET FORECAST START END = FORECAST**2
*****
disp 'Upper limit - Lower limit'
set ulintvl= upper - lower
print / ulintvl [The confidence interval (=upper limit - lower limit) is
computed by (32), and displayed, for raw data  $X_{T+1}$ .]
disp '----'
theil(setup,estimate=1) 1 nf END ["Forecasting with updated parameters"
by theil for logged series and displaying the forecast performance statistics.
The whole (nf=)3-month long future period from 2004:01 through (END=)2004:03
is covered as one month ahead is added (estimate=1) starting with the month
2004:01.]
# BJEQ [BJEQ of DEFINE=BJEQ in previous BOXJENK.]
do time=START, END,1 [START(=bt)=2004:01, END(=et)=2004:03.]
theil(print) time [First, a forecast and an actual value for each month of
the future period from START to END (i.e., 2004:01 through 2004:03) are
displayed using the data up to the forecast origin 2003:12. Subsequent com-
putations are iterated as programmed and remarked below.
MacDonald and Marsh (1994, pp.42-44) on PPP seems to apply "theil" for
exchange-rate forecast accuracy statistics.]
Model I:
BOXJENK(AR=ars,MA=|1,11|,SMA=SMA,SAR=SAR,DIFFS=DIFFS,
SDIFFS=SDIFFS,$
iterations=100,CONST=CONST,DEFINE=BJEQ) WORKX STARTL time RESIDS [First
re-estimation (see Output Z): First (continued from 'First' for "theil(print)
time" above), time=START for "STARTL time" here, which means to re-
estimate with the data up to START, with the future being START+1 through
END (i.e., 2004:02 to 2004:03). Note, however, that the time-series model
itself remains unchanged throughout all the re-estimations: What changes is
only parameter estimates (that are re-estimated).
Second, with "DEFINE=BJEQ", we go back to theil(print) time, with
time=START+1, which displays the two predictions made above along with
the corresponding actual values for the future START+1 through END. Sec-
ond re-estimation (see Output Z): Further, BOXJENK will be executed with

```

$time=START+1$, meaning the re-estimation with the data up to $START+1$, with the future being only $START+2$, which is equal to END (i.e., 2004:03).

Finally, going back to $theil(print)$ time, with $time=START+2$ which is equal to END , the prediction for 2004:03 is displayed along with the actual value. **Third, final re-estimation** (see Output Z): Eventually, with $time=START+2(=END)$, $BOXJENK$ is executed with the data up to END , without any forecasts being made, and the iteration is thus terminated here; we will no longer return to “ $theil(print)$ time”.

For re-estimation programming here, see RATS Ver. 5, RM, pp.354-356 (p.356 for similar programs).]

```
end do time
theil(dump) [Displayed for each l step are ME (Mean Error), MAE (Mean
Absolute Error), RMSE (Root Mean Squared Error) and Theil's U statistic.]
*****
END BJFORE1_er
```

RATS Program bjfore2_er.src :

```
PROCEDURE BJFORE2_er SERIES START END FORECAST upper lower
.....
compute startv(1)=0.3441620487 ;*  $\theta_1$  [The initial values are taken from
Output M in section 5.4.]
compute startv(2)=0.3193090379 ;*  $\theta_{11}$ 
compute startv(3)=-0.08401 ;* ps34
compute startv(4)= -0.07362 ;*ps190
compute startv(5)=-0.03985 ;* ao98
compute startv(6)= -0.06103 ;*ps148
compute startv(7)=0.03709 ;* ao172
set ao98 = t==1991:2
set ao172 = t==1997:4
set ps34 = t>=1985:10
set ps190 = t>=1998:10
set ps148 = t>=1995:4
.....
Model II:
BOXJENK(inputs=5,initial=startv,applydiff,$ ["inputs=5" here means five
intervention events being detected. Recall no such inputs are present in Model
I.]
AR=ars,MA=|1,1|,SMA=SMA,SAR=SAR,DIFFS=DIFFS,SDIFFS=SDIFFS,$
iterations=100,CONST=CONST,DEFINE=BJEQ) WORKX STARTL ENDL RESIDS
# ps34 0 0
# ps190 0 0
# ao98 0 0
# ps148 0 0
# ao172 0 0
The remainder omitted.
```

The RATS output

RATS Output Z for the model (11) :

```
* - - - COMPUTED RESULTS
* - - - Model I:
Box-Jenkins - Estimation by Gauss-Newton
Convergence in 6 Iterations. Final criterion was 0.0000012 < 0.0000100
Dependent Variable TRANSFRM [Transformed: Logged.]
Monthly Data From 1985:02 To 2003:12
..... [Same as Output for the model (11) in section 4.]
Forecasting equation (BJEQ in BOXJENK above):
Dependent Variable RF_JY_USD
```

Variable Coeff

1. RF_JY_USD{1} 1.0000000000

2. Mvg Avge{1} 0.3430948547

3. Mvg Avge{11} 0.2092140716

ENTRY RF_JY_USD

1985:01 5.538042677454

.....

2003:11 4.693144432603

2003:12 4.681529194087

2004:01 4.668257654858

2004:02 4.668595587838

2004:03 4.687883171448

ENTRY RESIDS

1985:02 0.023561604711

.....

2003:12 -0.008190791508

Multistep-ahead forecasts of transformed: [Forecasts by Eq. (25), whose un-

logged values will be graphed.]

Entry RF_JY_USD

2004:01 4.6823267008997

2004:02 4.6795525522184

2004:03 4.6843365855264

Decomposition of Variance for Series RF_JY_USD

Step Std Error RF_JY_USD

1 0.027263018 100.000

2 0.045651545 100.000

3 0.058522260 100.000

Upper limit - Lower limit

ENTRY ULINTVL

2004:01 11.78576402347

2004:02 19.69801891835

2004:03 25.39532394488

* --- *

Entry RF_JY_USD

2004:01 4.6823267008997

4.6682576548583

2004:02 4.6747255349106

4.6685955878382

2004:03 4.6774064149183

4.6878831714483

Box-Jenkins - Estimation by Gauss-Newton

Convergence in 7 Iterations. Final criterion was 0.0000047 < 0.0000100

Dependent Variable RF_JY_USD

Monthly Data From 1985:02 To 2004:01 [First re-estimation.]

.....

Entry RF_JY_USD

2004:02 4.6606948717676

4.6685955878382

2004:03 4.6681297107039

4.6878831714483

Box-Jenkins - Estimation by Gauss-Newton

Monthly Data From 1985:02 To 2004:02 [Second re-estimation.]

.....

Entry RF_JY_USD

2004:03 4.6759855890629

4.6878831714483

Box-Jenkins - Estimation by Gauss-Newton

Convergence in 7 Iterations. Final criterion was 0.0000049 < 0.0000100

Dependent Variable RF_JY_USD

Monthly Data From 1985:02 To 2004:03 [Third, final re-estimation.]

.....

[No forecasts are computed here.]

```

Forecast Statistics for Series RF_JY_USD
Step Mean Error Mean Abs Error RMS Error Theil U N.Obs
1 0.001909751 0.011289115 0.011574567 0.85619 3
2 0.006811757 0.012941704 0.014624901 0.87997 2
3 0.010476757 0.010476757 0.010476757 1.64885 1

```

RATS Output Z (continued) for the intervention model (21) :

```

* --- Model II: Intervention model
Box-Jenkins - Estimation by Gauss-Newton
Convergence in 7 Iterations. Final criterion was 0.0000087 < 0.0000100
Dependent Variable RF_JY_USD [RF_JY_USD here is a transformed (logged)
series.]

```

Monthly Data From 1985:02 To 2003:12

..... [Same as Output M in section 5.4.]

Forecasting equation (BJEQ in BOXJENK above): [This is Eq. (36).]

Dependent Variable RF_JY_USD

Variable Coeff [Details are given later in the paragraph titled 'Remark on "Variable Coeff" for Model II (Intervention model).']

1. RF_JY_USD{1} 1.000000000 [{1}≡lag of -1; see Eq. (36).]
2. PS34 -0.083835189 [Notation here slightly differs from that of Output M in section 5.4.]

3. PS34{1} 0.083835189

4. PS190 -0.070662115

5. PS190{1} 0.070662115

6. AO98 -0.043044043

7. AO98{1} 0.043044043

8. PS148 -0.064797537

9. PS148{1} 0.064797537

10. AO172 0.037270141

11. AO172{1} -0.037270141

12. Mvg Avge{1} 0.347647470

13. Mvg Avge{11} 0.323655523

ENTRY RESIDS [Same as Output M in section 5.4.]

1985:02 0.023561604711

.....

2003:12 -0.005779847063

Multistep-ahead forecasts of transformed: [Forecasts by (36), whose unlogged values are graphed.]

Entry RF_JY_USD

2004:01 4.6847913670515

2004:02 4.6805110596433

2004:03 4.6890735631531

Decomposition of Variance for Series RF_JY_USD

Step Std Error RF_JY_USD

1 0.024910677 100.000

2 0.041803602 100.000

3 0.053614741 100.000

Upper limit - Lower limit [For raw series.]

ENTRY ULINTVL

2004:01 10.79454163014

2004:02 18.05093347727

2004:03 23.36764365974

* ---

Entry RF_JY_USD

2004:01 4.6847913670515

4.6682576548583

2004:02 4.6747631564282 [Underlined figures are used later in the paragraph titled 'Remark on "Forecast Statistics for Series RF_JY_USD" for Model II (Intervention model).']

4.6685955878382
2004:03 4.6811815203211

4.6878831714483
Box-Jenkins - Estimation by Gauss-Newton

Monthly Data From 1985:02 To 2004:01 [First re-estimation.]

.....
Entry RF_JY_USD
2004:02 4.6582702742499
4.6685955878382
2004:03 4.6703427606417

4.6878831714483
Box-Jenkins - Estimation by Gauss-Newton

Monthly Data From 1985:02 To 2004:02 [Second re-estimation.]

.....
Entry RF_JY_USD
2004:03 4.6805774441288
4.6878831714483

Box-Jenkins - Estimation by Gauss-Newton

Monthly Data From 1985:02 To 2004:03 [Third, final re-estimation.]

..... [No forecasts are computed here.]

Forecast Statistics for Series RF_JY_USD [Details are given later in the paragraph titled ‘Remark on “Forecast Statistics for Series RF_JY_USD” for Model II (Intervention model).’]

Step Mean Error Mean Abs Error RMS Error Theil U N.Obs

1 0.000365776 0.011388251 0.012018727 0.89905 3

2 0.005686421 0.011853990 0.013147336 0.79106 2

3 0.006701651 0.006701651 0.006701651 1.05472 1 [Italic figures are used later in the paragraph titled ‘Remark on “Forecast Statistics for Series RF_JY_USD” for Model II (Intervention model).’]

Two remarks are in order for “Model II: Intervention model” above: “Variable Coeff” and “Forecast Statistics for Series RF_JY_USD”.

Remark on “Variable Coeff” for Model II (Intervention model)

To rewrite the intervention model (21) in the form of (24)-(25) in section 6.1, both sides of (21) are multiplied by $1 - B$:

$$\begin{aligned}
 (1 - B)X_t^\ell &= (1 - B) \left[\sum_{k=1,2,4} \omega_{d_k} \left\{ \frac{1}{1 - B} \xi_t^{(d_k)} \right\} + \sum_{k=3,5} \omega_{d_k} \left\{ 1 \xi_t^{(d_k)} \right\} \right] \\
 &\quad + (1 - \theta_1 B - \theta_{11} B^{11}) a_t \\
 &= \sum_{k=1,2,4} \omega_{d_k} \left\{ \frac{1}{1 - B} \left(\xi_t^{(d_k)} - \xi_{t-1}^{(d_k)} \right) \right\} + \sum_{k=3,5} \omega_{d_k} \left\{ \xi_t^{(d_k)} - \xi_{t-1}^{(d_k)} \right\} \\
 &\quad + (1 - \theta_1 B - \theta_{11} B^{11}) a_t \tag{33}
 \end{aligned}$$

where

$$k = 1, 2, 4 : \omega_{d_k} \left\{ \frac{1}{1 - B} \left(\xi_t^{(d_k)} - \xi_{t-1}^{(d_k)} \right) \right\} = \omega_{d_k} \xi_t^{(d_k)} = \begin{cases} 0, & t \neq d_k \\ \omega_{d_k}, & t = d_k; \end{cases} \tag{34}$$

$$k = 3, 5 : \omega_{d_k} \left\{ \xi_t^{(d_k)} - \xi_{t-1}^{(d_k)} \right\} = \begin{cases} 0, & t \neq d_k \text{ and } t-1 \neq d_k \\ \omega_{d_k}, & t = d_k \\ -\omega_{d_k}, & t-1 = d_k. \end{cases} \quad (35)$$

(See also Eqs. (23) and (22) in section 5.4.) Eq. (33) is, for $t = T + l$,

$$\begin{aligned} X_{T+l}^\ell &= X_{T+l-1}^\ell + \sum_{k=1,2,4} \omega_{d_k} \left\{ \frac{1}{1-B} \left(\xi_{T+l}^{(d_k)} - \xi_{T+l-1}^{(d_k)} \right) \right\} \\ &+ \sum_{k=3,5} \omega_{d_k} \left\{ \xi_{T+l}^{(d_k)} - \xi_{T+l-1}^{(d_k)} \right\} + (1 - \theta_1 B - \theta_{11} B^{11}) a_t; \end{aligned}$$

taking an expectation, as in Eq. (24), leads to

$$\begin{aligned} \hat{X}_T^\ell(l) &= [X_{T+l-1}^\ell] + \sum_{k=1,2,4} \omega_{d_k} \left\{ \frac{1}{1-B} \left(\xi_{T+l}^{(d_k)} - \xi_{T+l-1}^{(d_k)} \right) \right\} \\ &+ \sum_{k=3,5} \omega_{d_k} \left\{ \xi_{T+l}^{(d_k)} - \xi_{T+l-1}^{(d_k)} \right\} \\ &- \theta_1 [a_{T+l-1}] - \theta_{11} [a_{T+l-11}]. \end{aligned} \quad (36)$$

Note here that, since $T + l - 1 > d_k$, $\xi_{T+l}^{(d_k)} = 0 = \xi_{T+l-1}^{(d_k)}$, and that, as pointed out in section 3.3, the moving average part is written in RATS as $\theta_1 [a_{T+l-1}] + \theta_{11} [a_{T+l-11}]$.

Those parameters on the right hand side of Eq. (36) are being vertically listed under “Variable Coeff” for “Forecasting equation” in Output Z: In the order there, first, 1.0 for $[X_{T+l-1}^\ell]$; next, $\omega_{d_k}, -\omega_{d_k}, k = 1, \dots, 5$; finally, θ_1, θ_{11} . After all, since with (34) and (35) $\xi_{T+l}^{(d_k)} = 0 = \xi_{T+l-1}^{(d_k)}$, the future, logged forecasts under “Multistep-ahead forecasts of transformed” are computed by Eq. (36) with the two summation terms vanishing. In fact, Eq. (36) can be derived when (24)-(25) in section 6.1 are rewritten for the differenced equation (9) and the intervention model (21):

$$\begin{aligned} \hat{X}_T^\ell(l) &\equiv E [X_{T+l}^\ell | I_T] \\ &= (1-B) \left[\sum_{k=1,2,4} \omega_{d_k} \frac{1}{1-B} \xi_{T+l}^{(d_k)} + \sum_{k=3,5} \omega_{d_k} \xi_{T+l}^{(d_k)} \right] \\ &- \sum_{\substack{i=0 \\ N o t \{i=0, j=0, k=0, m=0\}}}^0 \sum_{j=0}^0 \sum_{k=0}^1 \sum_{m=0}^0 \phi_i \Phi_j (-1)^{k+m} \binom{1}{k} \binom{0}{m} [X_{T+l-i-0j-k-0m}^\ell] \end{aligned}$$

$$+ \sum_{\substack{i=0 \\ i \neq 2, \dots, 10}}^{11} \sum_{j=0}^0 \theta_i \Theta_j [a_{T+l-i-0j}]. \tag{37}$$

Noting (6), (26), (28), (34), (35) and “*Not*{ $i = 0, j = 0, k = 0, m = 0$ },” each term in (37) may be rewritten as: First term = 0; second term = $-\phi_0 \Phi_0 \sum_k (-1)^k [X_{T+l-k}^\ell] = -\phi_0 \Phi_0 (-1)^1 [X_{T+l-1}^\ell] = [X_{T+l-1}^\ell]$; third term = $\theta_0 \Theta_0 [a_{T+l-0}] + \theta_1 \Theta_0 [a_{T+l-1}] + \theta_{11} \Theta_0 [a_{T+l-11}] = -\theta_1 [a_{T+l-1}] - \theta_{11} [a_{T+l-11}]$.

The forecasts thus computed will be drawn as in Fig. 17 in section 6.2.3.

Remark on “Forecast Statistics for Series RF_JY_USD” for Model II (Intervention model) This part of Output Z does “forecasting with updated parameters” for the *logged* series: It computes and displays, for each *l*-step ahead, ME, MAE, RMSE and Theil’s U statistic.²⁷

Figures used in the computations below are all from Output Z:

ME:

3-step-ahead ME=average of the 3-step-ahead forecast error (=actual – forecast)

$$= 0.006701651 = \frac{1}{1} (4.6878831714483 - 4.6811815203211)*;$$

2-step-ahead ME=average of the 2-step-ahead forecast errors

$$= 0.005686421 = \frac{1}{2} \{ (4.6685955878382 - 4.6747631564282)** + (4.6878831714483 - 4.6703427606417)*** \}.$$

1 and 2 in the denominator above are the number of the forecast errors, respectively, for Steps 3 and 2 (“N.Obs” in Output Z). *, **, and *** below denote terms with the corresponding parantheses above.

MAE:

3-step-ahead MAE=average of absolute value of the 3-step-ahead forecast error = $\frac{1}{1} |*|$;

2-step-ahead MAE=average of absolute values of the 2-step-ahead forecast errors = $\frac{1}{2} \{ |**| + |***| \}$.

RMSE:

3-step-ahead RMSE=square root of average of the 3-step-ahead forecast error squared = $\sqrt{\frac{1}{1} (*)^2}$;

2-step-ahead RMSE=square root of average of the 2-step-ahead forecast

²⁷See section 6.2.2 for the detailed description of the computations involved here.

$$\text{errors squared} = \sqrt{\frac{1}{2} \{ (**)^2 + (***)^2 \}}.$$

Theil U:

Theil U at Step l = [RMSE at Step l] / [RMSE at Step l of a naive model that takes the value at (time-1) for “theil time” to be a predictor] where naive means no-change prediction. Tabulated in Table 6 are some Theil U’s computed as shown in RATS, RM, pp.357-358 (figures under “ENTRY RF_JY_USD” for “Model II” in RATS Output Z are used). Those computed Theil’s U statistics indicate that, at Steps 1 and 2, the naive predictions have larger RMSE.

Table 6 Details of Computing Theil’s U Statistic

Step l	$N_l = N$. Obs	Theil’s U
3	1	$SSE_NCF_3 = \sum_{i=1}^1 (y_{i0}^a - y_{i3})^2 = (y_{10} - y_{13})^2$, where SSE_NCF = SSE of no-change forecasts (NCF), $= (X_{2003:12}^{\ell} - X_{2004:3}^{\ell})^2 = (4.681529194087$ $- 4.6878831714483)^2 = 0.000040373$; $RMSE_NCF_3 = \sqrt{SSE_NCF_3 / N_3} = \sqrt{0.000040373 / 1}$ $= 0.006353977$ where $RMSE_NCF$ = RMS of no-change forecasts; $TheilU_3 = RMSE_3 / RMSE_NCF_3$ $= 0.006701651 / 0.006353977$ $= 1.054717481$.
2	2	$SSE_NCF_2 = \sum_{i=1}^2 (y_{i0} - y_{i2})^2$ $= (y_{10} - y_{12})^2 + (y_{20} - y_{22})^2$ $= (X_{2003:12}^{\ell} - X_{2004:2}^{\ell})^2 + (X_{2004:1}^{\ell} - X_{2004:3}^{\ell})^2$ $= (4.681529194087 - 4.668595587838)^2$ $+ (4.668257654858 - 4.687883171448)^2$ $= 0.000552439$; $RMSE_NCF_2 = \sqrt{SSE_NCF_2 / N_2} = \sqrt{0.000552439 / 2}$ $= 0.016619854$; $TheilU_2 = RMSE_2 / RMSE_NCF_2$ $= 0.013147336 / 0.016619854$ $= 0.791062063$.
1	3	Computed similarly as above.

^aNaive (i.e., no-change) prediction = log of RF_JY_USD at (time-1) for the i th “theil time” (in the RATS program).

Contrasting forecast performance

The RATS Output Z and Fig. 17 drawn for *raw* series lead to three types of forecast performance contrast, in which several measures of forecast performance, such as “Decomposition of Variance,” “Upper limit - Lower limit” and “Forecast Statistics” as computed and displayed in Output Z, are checked:

Out-of-Sample Forecasts of Raw (Unlogged) Data (RF_JY_USD): 2004:m1 to 2004:m3 Model I (left) vs. Model II (right)

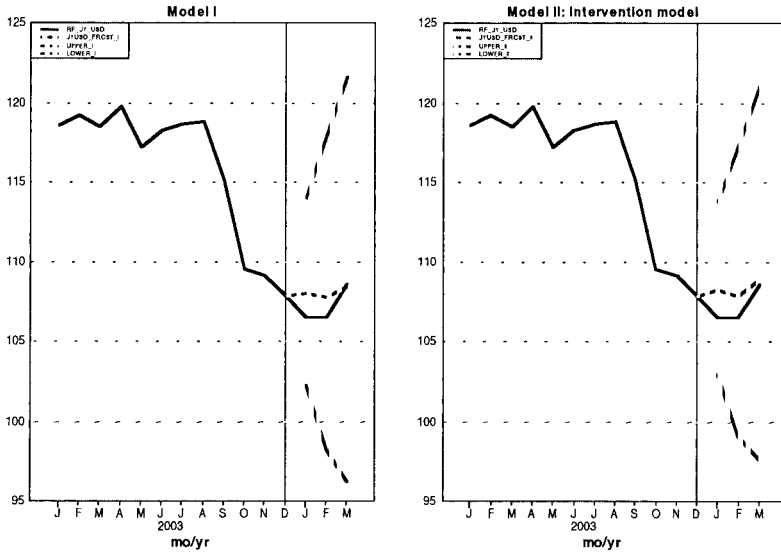


Figure 17 Japanese yen per U.S. dollar exchange rate: Actual raw series RF_JY_US for the last 12 months 2003:1 to 2003:12 of the sample period; forecasts with fixed parameters JYUSD_FRCST for the 3-month long forecast horizon from 2004:1 to 2004:3; upper and lower limits of the interval forecast UPPER, LOWER.

[1] **Future data is not available: “Forecasting with fixed parameters”** Forecasts plotted in Fig. 17 are those made with fixed

parameters.

“Decomposition of Variance” (for *logged* series): The standard error of the l -month-ahead forecast error for the logged forecasts $\hat{X}_T^\ell(l)$ is smaller for the intervention model at every $l = 1, 2, 3$.

“Upper limit - Lower limit” (for *raw* series): The confidence interval for the raw forecasts $\hat{X}_T(l)$ is narrower for the intervention model at every l .

[2] Future data becomes available (a): “Forecasting with fixed parameters” Fig. 17 (drawn for raw series): Based on forecasts with fixed parameters, the forecasts are above the realized values at every l in both models: In retrospect, the Japanese yen was predicted to be less expensive than its actual price throughout the 3-month forecast horizon.

The forecasts made by the intervention model (21) turn out to be slightly more time-varying than those by the model (11). This should be a feature that the model taking into account the intervention events is anticipated to have, along with the desired features in [1] above.

[3] Future data becomes available (b): “Forecasting with updated parameters” “Forecast Statistics” (for *logged* series): ME is smaller for the intervention model; MAE, RMSE and Theil’s U statistic are also smaller for the intervention model at every l except $l = 1$. (Theil’s U statistics at $l = 3$ in both models are above 1, meaning that the models’ RMSE fails to be smaller than that for the naive, no-change forecasts.)

Summary As anticipated, the intervention model (21) performs better with regard to forecast accuracy: Detecting AO and PS and embodying them into a model is seen to help improve forecast performance.

It should be noted that “The effect of the identified disturbances²⁸ on point forecasts is negligible provided that the forecast origin is not too close to the disturbances” (Tsay 1998, p.12). One immediate implication of this is that intervention events observed *near* the forecast origin should *not* be ignored if the forecast accuracy is a major concern. This is indeed confirmed in the present intervention modeling analysis for the 19-year long sample period of 1985:1 to 2003:12: PS in October 1998 is close

²⁸A disturbance is called, in the present paper, an intervention (event).

enough to the forecast origin, December 2003, *and* important enough,²⁹ to *favorably* affect forecast performance as well as point forecasts of the *intervention model*.

7 Concluding Remarks

The paper builds a business time-series forecasting system employing the Box-Jenkins (1976) (B-J) type, univariate time-series analysis. The B-J time-series forecasting system built here has been found effective to model the intervention analysis of Japanese yen exchange rate behavior, as the system appropriately detects special events or circumstances called intervention events, thereby contributing to better exchange rate forecast performance.

One may naturally ponder, however, why univariate, why not multivariate. The other, more sophisticated, structural method of forecasting is the vector autoregressive (VAR) type. The simplest structural modeling of foreign exchange rate determination is said to be PPP (purchasing power parity). While simple with respect to exchange rate determination, the VAR modeling of PPP does require sophisticated, but now widely applied, statistical concepts such as cointegration and error correction (EC).

Roll (1979) presents an innovative, efficient markets view of PPP (EMPPP), supportive of the random walk modeling. Later, MacDonald and Marsh (1994, pp.25-29, 44) raises and studies the question whether the PPP outperforms the random walk in an out-of-sample forecasting context.³⁰ More recently, Chowdhry, Roll and Xia (2004) verify that the relative version of PPP holds when, instead of official price measures such as CPI, “inflation extracted from stock returns” is used as a price inflation proxy. It is, therefore, my future research work to investigate, in a VAR-cointegration-EC framework, MacDonald and Marsh’s (1994) forecast-performance question above in conjunction with Chowdhry, Roll and Xia’s strong, supportive evidence for PPP.

²⁹Recall from Table 5 that the PS is second most significant intervention event. (Recall also the remarks in section 2.1 that are made on the economic/financial sources of those intervention events asterisked in Table 2.)

³⁰If so, then one could argue the PPP would be a better specification of foreign exchange rate behavior, for example, than Roll’s (1979) EMPPP. See also MacDonald and Marsh (1999, pp.50-56).

Appendices

Three appendices follow: “A. Iterative Search for AO and PS: Second Outer Loop On”; “B. A General Business Time-series Forecasting System”; and “C. How to Upload and Download RATS-related Files”.

A Iterative Search for AO and PS: Second Outer Loop On

The iterative search for AO and PS in the second through fourth outer loops in Tables 4 and 5 is summarized here in the appendix.

In the second outer loop on, models for data already adjusted for AO and PS (i.e., $X_t^{\ell*}$ computed by Eq. (19) in section 5.1 and drawn as in Fig. 13-center in section 5.2) will be identified and estimated, respectively, by `BJidentify_erAOPS.prg` and `BJestimate_erAOPS.prg`: See OL 2 through OL 5 in Tables 4 and 5.

A.1 Second outer loop

Model identification The model (11) estimated earlier in OL 1 (in section 4) may be taken to be a model identified here: See Fig. 18 below, drawn for the AO-PS adjusted series (Fig. 13-center) in section 5.2, which may be contrasted with Fig. 8 in section 3.3.

Model estimation and diagnostic checking First, ignoring AO and PS in the data, the model (11) is estimated by `BJestimate_erAOPS.prg` (with `skipDetect=1`) and `bjest_erAOPS.src`. See Output D and Fig. 19.

RATS Output D for the model (11) :

```
* --- COMPUTED RESULTS
.....
(A)
Box-Jenkins - Estimation by Gauss-Newton
.....
Variable Coeff Std Error T-Stat Signif
*****
1. MA{1} 0.3346756743 0.0607357693 5.51036 0.00000010
2. MA{11} 0.2323897206 0.0623786103 3.72547 0.00024656
The remainder omitted.
```

Diagnostic checks of Output D and Fig. 19 will lead to the improved

Adjusted, Logged RF_JY_USD : Data (top), SACF (middle), SPACF (bottom)

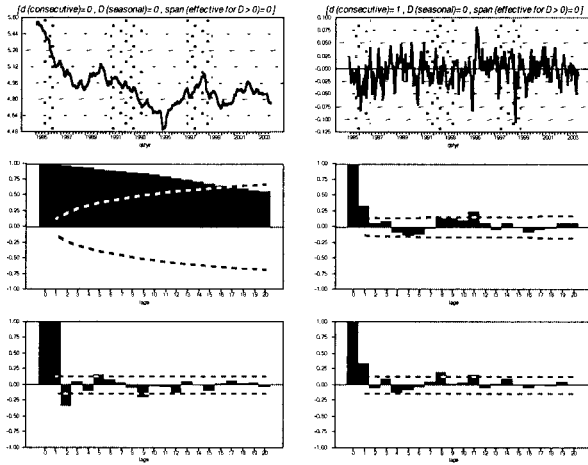


Figure 18 OL 2 in Tables 4 and 5: Model identification.

model having an additional parameter ϕ_8 :

$$(1 - \phi_8 B^8)W_t = (1 - \theta_1 B - \theta_{11} B^{11})a_t \quad (38)$$

In RATS notation: $(1 - \phi_8 B^8)W_t = (1 + \theta_1 B + \theta_{11} B^{11})a_t.$ (39)

See Output E and Fig. 20 for Eq. (38) or (39).

RATS Output E for the model (38) :

```

* --- COMPUTED RESULTS
.....
(A)
Box-Jenkins - Estimation by Gauss-Newton
.....
Variable Coeff Std Error T-Stat Signif
*****
1. AR{8} 0.1376866756 0.0681118612 2.02148 0.04446391
2. MA{1} 0.3281212245 0.0624762573 5.25193 0.00000036
3. MA{11} 0.2168194959 0.0640769814 3.38373 0.00084905
The remainder omitted.
    
```

Comparing Figs. 19 and 20, the model (39) in Fig. 20 appears better, for ϕ_8 turns out statistically significant and the resultant SCCF looks better.

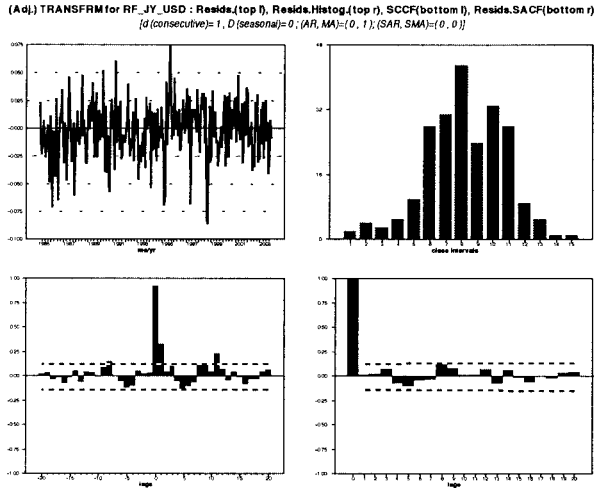


Figure 19 OL 2 in Tables 4 and 5: Estimation and diagnostic check of the model (11).

Contrasting Outputs D and E, however, one can see that Resid variance (=standard err. of estimate SQUARED = %SEESQ= $\hat{\sigma}_a^2$) and Signif Level (JB=0) for Jarque-Bera are slightly better for the model (11) in Output D;³¹ in Output D, $\hat{\sigma}_a^2$ is smaller than $\hat{\sigma}_a^2$ in OL 1-IL 2 in Table 5; on the other hand, in Output E, smaller residual Degrees of Freedom for Monthly Data From 1985:10 To 2003:12 causes an increase in $\hat{\sigma}_a^2$, which turns out greater than $\hat{\sigma}_a^2$ in OL 1-IL 2 in Table 5. Following the principle of parsimony, our model selection decision here is *not* to add ϕ_8 : At this point, the model (11) continues to be our choice.

OL 2-IL 1 To search for AO and PS (with skipDetect=0 in RATS proram) in OL 2, C is first set equal to 3.0 (in RATS, Crit=3.0), for at the end of OL 1 in Output C we had “lmaxk = max(lmax,lmax_eta) = 3.03301”. See Output F (“inner_round=1” and “inner_round=2”) for

³¹Resid variance, Signif Level (JB=0) for Jarque-Bera, $\hat{\sigma}_a^2$ and residual Degrees of Freedom are all omitted from the paper for brevity.

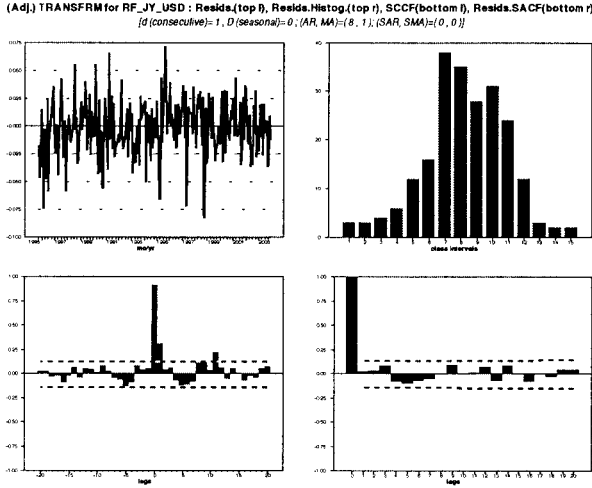


Figure 20 OL 2 in Tables 4 and 5: Estimation and diagnostic checks of the model (38).

details of ILs 1 and 2.

Since the model (11) is still used, there is no need to modify `bjest_erAOPS.src` with regard to π weight computations.³²

RATS Output F :

* --- COMPUTED RESULTS
 * --- BJ model estimation
 [Same as Output D.]

³²The π weights play an important role in the invertibility conditions: See section 3. The π weights for the SARMA model (8) are those in $\pi(B) = -\sum_{j=0}^{\infty} \pi_j B^j$ ($\pi_0 = 0$) in the inverted form $\pi(B)\tilde{W}_t = a_t$. In general, letting $\varphi(B) = \phi(B)(1-B)^d = -\sum_{i=0}^{p+d} \varphi_i B^i$ (with $\varphi_0 = -1$) for ARIMA(p, d, q), the π weights are computed by iteratively solving $\varphi(B) = \theta(B)\pi(B)$ (see Box, Jenkins and Reinsel 1994, ps.99,107) :

$$\begin{aligned} \pi_j &= 0, & j < 0, \\ \varphi_j &= 0, & j > p + d, \\ \pi_j &= \theta_1 \pi_{j-1} + \dots + \theta_q \pi_{j-q} + \varphi_j, & j > 0. \end{aligned}$$

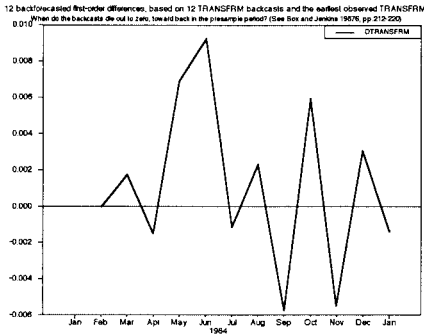


Figure 21 OL 2 in Tables 4 and 5: Twelve backcasts of the first differenced series of TRANSFRM (check on when the backcasts converge to zero).

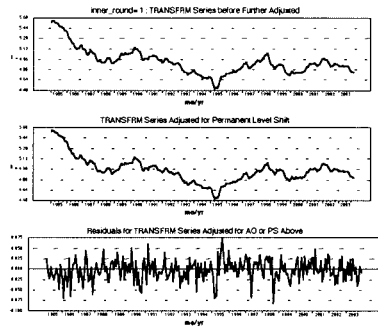


Figure 22 OL 2 in Tables 4 and 5: Top panel=backcasts and observations of TRANSFRM; bottom panel=backcasts and observations of residuals.

```
* --- Backcasting TRANSFRM (Tom Maycock of Estima 7/15/2004):
.....
===== To detect additive outlier (AO) and permanent level shift (PS):
* --- inner_round = 1
For AO:
.....
Extreme Values of Series ZS Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00344407738 at 1992:04 Entry 112
Maximum Value is 2.73059238084 at 1991:02 Entry 98
lmax 2.73059
tmax 98
omegat(tmax) = -0.03984
For PS:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00159046899 at 1998:01 Entry 181
Maximum Value is 3.06323602622 at 1998:10 Entry 190
lmax_eta 3.06324
tmax_eta 190
omegat_eta(tmax_eta) = -0.07362
lmaxk = max(lmax,lmax_eta) = 3.06324
Crit = 3.00000
* --- Adjusted residuals for Adj. series
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0020039816 Variance 0.000669
Standard Error 0.0258557074 SE of Sample Mean 0.001716
t-Statistic -1.16775 Signif Level (Mean=0) 0.24413772
```

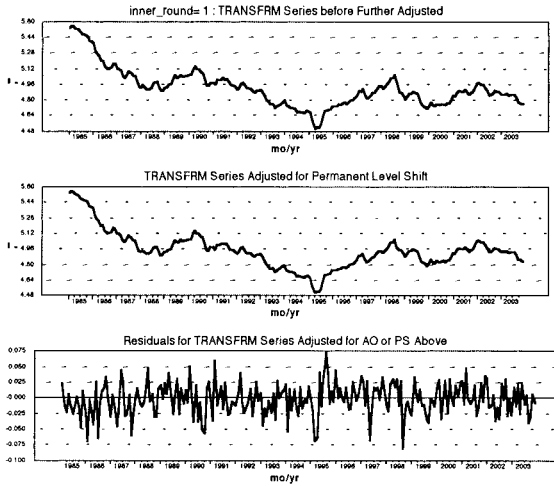


Figure 23 OL 2-IL 1 in Tables 4 and 5: Logged yen-dollar rate; sample period = 1985:1-2003:12. Top=before being further adjusted; center=after being further adjusted; bottom=residuals computed based on further adjusted data (backcasts are used where needed). The AO-PS adjusted series $X_t^{\ell*}$ is computed by (19).

```

Skewness -0.21749 Signif Level (Sk=0) 0.18388299
Kurtosis 0.18901 Signif Level (Ku=0) 0.56708592
Jarque-Bera 2.12742 Signif Level (JB=0) 0.34517207
.....
Editing data file "AdjSrs_er2.rat"
.....
Go back to the next round of INNER loop < 3 >: current round = 1 next round
= 2
* -- inner_round = 2
For AO:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00300565199 at 1992:04 Entry 112
Maximum Value is 2.78910864712 at 1991:02 Entry 98
lmax 2.78911
tmax 98
omegat(tmax) = -0.03984
For PS:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12

```

```

Minimum Value is 0.00000000000 at 1998:10 Entry 190
Maximum Value is 2.65351399623 at 1995:04 Entry 148
lmax_eta 2.65351
tmax_eta 148
omegat_eta(tmax_eta) = -0.06243
lmax = max(lmax,lmax_eta) = 2.78911 [See OL 3-IL 1 in appendix section
A.2.1.]
Crit = 3.00000
Current round of the INNER loop = 2
The remainder omitted.

```

A.2 Third and fourth outer loops

Model identification, estimation and diagnostic checking turn out common to both OL 3 and OL 4. The model (11) estimated earlier in OLs 1 and 2 will be again taken to be a model identified here in both OLs 3 and 4; the initial AO-PS adjusted series in OL 3 is as earlier drawn in Fig. 23-center for OL 2.

Model identification: In both OLs 3 4, the figures omitted from the paper, which are almost the same as Fig. 18 for OL 2, lead to the model (11), as used in OL 2, being again identified for the AO-PS adjusted series.

Estimation and diagnostic check: First, ignoring AO and PS in the data, the model (11) will be estimated by BJestimate_erAOPS.prg (with skipDetect=1) and bjest_erAOPS.src. See Output G for OL 3 and Output I for OL 4.

A.2.1 OL 3

RATS Output G for the model (11) :

```

* --- COMPUTED RESULTS
.....
(A)
Box-Jenkins - Estimation by Gauss-Newton
.....
Variable Coeff Std Error T-Stat Signif
*****
1. MA{1} 0.3057838551 0.0612132848 4.99538 0.00000118
2. MA{11} 0.2462897400 0.0628482756 3.91880 0.00011810
The remainder omitted.

```

Diagnostic checks of Output G and the figure (omitted from the paper) could lead to ϕ_8 being added; just as in OL 2, however, such an expanded model will not be considered.

OL 3-IL 1 To search for AO and PS (with skipDetect=0 in RATS proram) in OL 2, C is first set equal to 2.7 (in RATS, Crit=2.7), for at

the end of OL 2 in Output F we had “ $lmaxk = \max(lmax, lmax_eta) = 2.78911$ ” (C should be in fact greater than 3.0). See Output H.

RATS Output H :

```
* --- COMPUTED RESULTS
* --- BJ model estimation
..... [Same as Output G.]
* --- Backcasting TRANSFRM (Tom Maycock of .....
===== To detect additive outlier (AO) and permanent level shift (PS):
* --- inner_round = 1
For AO:
.....
Extreme Values of Series ZS Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00908431713 at 2001:12 Entry 228
Maximum Value is 2.73990244224 at 1991:02 Entry 98
lmax 2.73990
tmax 98
omegat(tmax) = -0.03985
For PS:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.02345489065 at 2002:02 Entry 230
Maximum Value is 2.68719213394 at 1995:04 Entry 148
lmax_eta 2.68719
tmax_eta 148
omegat_eta(tmax_eta) = -0.06369
lmaxk = max(lmax, lmax_eta) = 2.73990
Crit = 2.70000
* --- Adjusted residuals for Adj. series
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0018488884 Variance 0.000662
Standard Error 0.0257372852 SE of Sample Mean 0.001708
t-Statistic -1.08233 Signif Level (Mean=0) 0.28025806
Skewness -0.22274 Signif Level (Sk=0) 0.17352132
Kurtosis 0.25056 Signif Level (Ku=0) 0.44801124
Jarque-Bera 2.47077 Signif Level (JB=0) 0.29072265
.....
Go back to the next round of INNER loop < 3 >: current round = 1 next round
= 2
* --- inner_round = 2
For AO:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00912523606 at 2001:12 Entry 228
Maximum Value is 2.60845690773 at 1998:08 Entry 188
lmax 2.60846
tmax 188
omegat(tmax) = 0.03776
For PS:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.02356053964 at 2002:02 Entry 230
Maximum Value is 2.69929618269 at 1995:04 Entry 148
lmax_eta 2.69930
tmax_eta 148
omegat_eta(tmax_eta) = -0.06369
```

lmaxk = max(lmax,lmax_eta) = 2.69930 [See OL 4-IL 1 in appendix section A.2.2.]
 Crit = 2.70000
 Current round of the INNER loop = 2
 The remainder omitted.

A.2.2 OL 4

ϕ_8 could be added based on the diagnostic checks of Output I and the figure (omitted from the paper); again, just as in OLs 2 through 3, no such an expanded model will be considered.

RATS Output I for the model (11) :

```
* --- COMPUTED RESULTS
.....
(A)
Box-Jenkins - Estimation by Gauss-Newton
.....
Variable Coeff Std Error T-Stat Signif
*****
1. MA{1} 0.3369693872 0.0595230135 5.66116 0.00000005
2. MA{11} 0.2894384953 0.0615311972 4.70393 0.00000445
The remainder omitted.
```

OL 4-IL 1 To search for AO and PS (with skipDetect=0 in RATS proram) in OL 4, C is first set equal to 2.7 (in RATS, Crit=2.7), for at the end of OL 3 in Output H we had “lmaxk = max(lmax,lmax_eta) = 2.69930”. See Output J; the output will be referred back to in OL 5 in section 5.3.2.

RATS Output J :

```
* --- COMPUTED RESULTS
* --- BJ model estimation
..... [Same as Output I.]
* --- Backcasting TRANSFRM (Tom Maycock of Estima 7/15/2004):
.....
===== To detect additive outlier (AO) and permanent level shift (PS):
* --- inner_round = 1
For AO:
.....
Extreme Values of Series ZS Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00520243885 at 1998:11 Entry 191
Maximum Value is 2.63262225473 at 1998:08 Entry 188
lmax 2.63262
tmax 188 omegat(tmax) = 0.03576
For PS:
.....
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00120757782 at 1998:03 Entry 183
Maximum Value is 2.71206023285 at 1995:04 Entry 148
lmax_eta 2.71206
```

```

tmax_eta 148
omegat_eta(tmax_eta) = -0.06103
lmaxk = max(lmax,lmax_eta) = 2.71206
Crit = 2.70000
* -- -- Adjusted residuals for Adj. series
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0017691135 Variance 0.000623
Standard Error 0.0249646376 SE of Sample Mean 0.001657
t-Statistic -1.06769 Signif Level (Mean=0) 0.28680155
Skewness -0.23706 Signif Level (Sk=0) 0.14747726
Kurtosis 0.30916 Signif Level (Ku=0) 0.34916584
Jarque-Bera 3.03022 Signif Level (JB=0) 0.21978406
.....
Go back to the next round of INNER loop < 3 >: current round = 1 next round
= 2
* -- -- inner_round = 2
For AO:
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00542928925 at 1992:05 Entry 113
Maximum Value is 2.77627109098 at 1997:04 Entry 172
lmax 2.77627
tmax 172
omegat(tmax) = 0.03709
For PS:
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00000000000 at 1995:04 Entry 148
Maximum Value is 2.64189857275 at 1998:09 Entry 189
lmax_eta 2.64190
tmax_eta 189
omegat_eta(tmax_eta) = -0.05847
lmaxk = max(lmax,lmax_eta) = 2.77627
Crit = 2.70000
* -- -- Adjusted residuals for Adj. series
.....
Statistics on Series RESIDS
Monthly Data From 1985:02 To 2003:12
Observations 227
Sample Mean -0.0019324844 Variance 0.000618
Standard Error 0.0248684015 SE of Sample Mean 0.001651
t-Statistic -1.17080 Signif Level (Mean=0) 0.24291399
Skewness -0.23046 Signif Level (Sk=0) 0.15908168
Kurtosis 0.34067 Signif Level (Ku=0) 0.30225324
Jarque-Bera 3.10711 Signif Level (JB=0) 0.21149513
.....
Go back to the next round of INNER loop < 3 >: current round = 2 next round
= 3
* -- -- inner_round = 3
For AO:
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12
Minimum Value is 0.00668194511 at 1998:01 Entry 181
Maximum Value is 2.69163059091 at 1998:08 Entry 188
lmax 2.69163
tmax 188
omegat(tmax) = 0.03583
For PS:
Extreme Values of Series ZS
Monthly Data From 1985:02 To 2003:12

```

Minimum Value is 0.00801606138 at 1999:03 Entry 195
 Maximum Value is 2.65077577506 at 1998:09 Entry 189
 lmax_eta 2.65078
 tmax_eta 189
 omegat_eta(tmax_eta) = -0.05847
 lmaxk = max(lmax,lmax_eta) = 2.69163 [See OL 5-IL 1 in section 5.3.2.]
 Crit = 2.70000
 Current round of the INNER loop = 3
 The remainder omitted.

B A General Business Time-series Forecasting System

The following RATS programs, written and designed for general purposes, are saved and open to the public for free at the website <<http://www.seinan-gu.ac.jp/kojima/BJTS/>>:

*.prg	*.src
Stats.prg	hist.src histscatter.src
RandSample.prg	hist.src
SacSpacf.prg	bjidentCF.src
BJidentify.prg	bjident.src
BJestimate.prg	bjest.src histnew.src kolmtest.src
BJforecast.prg	bjfore1.src bjfore2.src

Many of the programs are also included in the exchange rate forecasting system, listed as non-italic programs in Table 1 in section 1. The data file saved at the website and used in the genral programs here is “sales59-03.dat”; the sample period is from 1977:1 to 2002:2 and the postsample period from 2002:3 to 2003:4.

C How to Upload and Download RATS-related Files

When uploading RATS files by Macintosh G4-Fetch, the formats to be used are as follows: “text” for *.prg, *.src and *.dat files; “raw data” for *.wks file. With these formats, one can successfully download the files (and execute them) by WinRATS for Windows PC as follows:

1. *.prg, *.wks files

Netscape: Right-click *.prg, *.wks files → Save, with name attached to link target, as ... → Save.

Internet Explorer (IE): Left-click *.prg, *.wks files → Save. (IE seems more preferable under the Windows XP OS. 10/28/2004.)

2. *.src files

Netscape, IE: Left-click *.src files → Save.

3. *.dat file

Netscape: Right-click *.dat file → Save, with name attached to link target, as ... → Save.

IE: Right-click *.dat → Save as file ... → Save.

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