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AN APPLICATION OF PROGRAM TSW TO A SET OF MACROECONOMIC TIME SERIES

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Abstract

The paper presents a "prototype" application of programs TRAMO and SEATS to a set of 17 aggregate National Accounts series that illustrates a sensible strategy for seasonal adjustment of sets of series. Starting with a purely automatic procedure, the results are analyzed on the basis of the summary output provided by the program. Then, it is seen how problematic series can be identified and how the associated problems can be solved, until satisfactory model specifications for all series have been found. Besides the standard TRAMO diagnostics, it is shown how the SEATS output can be of help in the choice of the most appropriate model. Throughout the paper, guidelines are provided to deal with a variety of problems related to seasonal adjustment. The usefulness of some recently incorporated tools not yet available in the versions that are distributed is also illustrated.

All series are analyzed one by one and used to illustrate some relevant issues, such as stability of the results, interpolation of missing observations, out-of-sample forecasts, non-normality, residual seasonality, deterministic seasonality, stationary seasonality, residual TD effect, bias induced by the log transformation, the use of intervention variables, approximation to non-admissible decompositions, short-term monitoring, cyclical analysis, revisions in the data, error control, and direct versus indirect adjustment under temporal and sectorial aggregation.

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1. INTRODUCTION

The so-called "ARIMA-model-based" (AMB) approach to seasonal adjustment was originally proposed by Burman (1980), and Hillmer and Tiao (1982). It consists of:

- Minimum Mean Square Error (MMSE) estimation (or "signal extraction") of unobserved components hidden in an observed time series,
- for which an ARIMA model has been identified.
- Typically, the components (or signals) are the seasonal, trend-cycle, and transitory-irregular components, the latter two comprising the seasonally adjusted (SA) series.
- The components are orthogonal, and follow ARIMA-type models.
- The models for the components aggregate into the ARIMA model identified for the observed series.
- Estimators of the components are computed via the Wiener-Kolmogorov (WK) filter. This filter yields, in our application, the conditional expectation of the component, given the available series observations.
- In general, the aggregate ARIMA model can be decomposed in an infinite number of ways, mostly depending on the allocation of noise to the components. The AMB approach chooses the decomposition whereby no white-noise can be extracted from the components that are not the irregular one, and hence maximizes the stability of the trend-cycle and seasonal component, given the model for the observed series. (This decomposition is termed "canonical").

The AMB methodology had appealing features:

- compliance with the ARIMA model of the observed series provides protection against spurious results or model misspecification.
- the parametric model-based framework should facilitate analysis and inference.

It is however a fact that, before it can be modeled by an ARIMA process, the series often needs prior treatment ("preadjustment"); see, for example, Findley et al (1998) and Gómez and Maravall (2001a). Important preadjustments are:

- outlier correction,
- the removal of calendar, intervention variable, and other possible regression effects,
- interpolation of missing values,

see, for example, Tsay (1986); Chen and Liu (1993); Hillmer, Bell, and Tiao (1983); Gómez and Maravall (1994).

What with the complexities of preadjustment and model identification, real-world application proved elusive, in particular, for large-scale applications. It seemed to require:

- heavy time-series analyst resources,
- considerable computing resources.

The appearance of programs TRAMO and SEATS [Gómez and Maravall (1996)] changed the situation. First, they provided a satisfactory and reliable solution to the problem of Automatic Model Identification (AMI). Second, highly efficient algorithms made the programs very fast. Thus the problem of heavy resources (of whatever type) practically disappeared.

TRAMO and SEATS have experienced an explosion in their use, in particular at data producing and monitoring agencies (such as central banks and statistical institutes). Given that TRAMO/SEATS are relatively recent and present a drastically different methodological approach, the demand for advice on their use is very large. This paper intends to contribute to the satisfaction of this demand (at a relatively basic level), and to provide some guidelines concerning their application.

2. BRIEF DESCRIPTION OF PROGRAMS TRAMO AND SEATS.

TRAMO ("Time series Regression with ARIMA noise, Missing values, and Outliers") estimates and forecasts regression models with ARIMA errors when there may be:

- missing observations
- contamination by outliers and other special (deterministic) effects.

Missing observations are interpolated, outliers and calendar effects are identified and corrected. Among the calendar effects, an important case is the trading day (TD) one, which classifies the days as working/non-working days, or captures separate effects for each day of the week. In automatic outlier detection and correction, three types of outliers are considered: Additive Outlier, Transitory Change, and Level Shift.

Let B denote the lag operator, such that $B\,x(t) = x(t-1)$. Given the observations $y = [y(t_1), y(t_2), \ldots, y(t_m)]$, $0 < t_1 < \ldots < t_m$, TRAMO fits the model

$$y(t) = \sum_{i=1}^{n_{out}} \omega_i \, \lambda_i(B) \, d_i(t) + \sum_{i=1}^{n_c} \alpha_i \, cal_i(t) + \sum_{i=1}^{n_{reg}} \beta_i \, reg_i(t) + x(t), \quad (2.1)$$

where:

$d_i(t)$: dummy variable that indicates the position of the i-th outlier;

$\lambda_i(B)$: polynomial in B reflecting the type of outlier;

cal_i : calendar-type variable (TD, Easter Effect (EE), Leap Year (LY) and Moving Holidays);

reg_i : regression or intervention variable,

$x(t)$: ARIMA error.

Regression variables can be entered by the user or built by the program (as Intervention Variables, see Box and Tiao, 1975).

ω_i : instant i-th outlier effect,

α_i , β_i : coefficients of the calendar and regression-intervention variables,

n_{out} , n_c and n_{reg} : total number of variables entering each summation term in (2.1).

Expression (2.1) can be rewritten as

$$y(t) = z'(t)\,b + x(t) \quad , \tag{2.2}$$

with b denoting the vector with the ω, α and β coefficients, and

$z'(t)$: matrix with the columns

$[\,cal_1$ (t),…, cal_{n_c} (t), λ_1 (B) d_1 (t),…, $\lambda_{n_{out}}$ (B) $d_{n_{out}}$ (t), reg_1 (t),…, $reg_{n_{reg}}$ (t)].

First term of r.h.s. of (2.2) is the **preadjustment component**. Removing this component from the series yields

$x(t)$: **"Linearized" series**, namely, that part of y(t) which can be assumed to be the output of an ARIMA process.

ARIMA model for $x(t)$:

$$\phi(B)\ \delta(B)\ x(t) = \theta(B)\ a(t) \quad , \tag{2.3}$$

where

$a(t)$: white-noise (0, V_a) innovation.

$\phi(B)$, $\delta(B)$, and $\theta(B)$: finite polynomials in B.

The polynomial $\phi(B)$ contains the stationary autoregressive (AR) roots, $\delta(B)$ contains the nonstationary (unit) AR roots, and $\theta(B)$ is an invertible moving average (MA) polynomial.

Denote by s the number of observations per year. In TRAMO-SEATS

$$\delta(B) = \nabla^{d}\ \nabla_s^{d_s} \quad ,$$

$$\phi(B) = \left(1 + \phi_1 B + \ldots + \phi_p B^p\right)\left(1 + \Phi_1 B^s\right),$$

$$\theta(B) = \left(1 + \theta_1 B + \ldots + \theta_q B^q\right)\left(1 + \Theta_1 B^s\right),$$

where $\nabla = 1 - B$, $\nabla_s = 1 - B^s$; $d = 0,1,2$; $d_s = 0,1$; $0 \le (p,q) \le 3$.

This yields the ARIMA $(p,d,q)(p_s, d_s, q_s)_s$ model.

The model consisting of (2.2) and (2.3): is called a regression **(reg)-ARIMA** model.

When used automatically, TRAMO:

- tests for the log transformation and for the presence of a deterministic mean,

- tests for the possible presence of calendar effects,
- detects and corrects for three types of outliers: additive outliers (AO), transitory changes (TC), and level shifts (LS),
- identifies and estimates by maximum likelihood the reg-ARIMA model,
- interpolates missing values,
- computes forecasts of the series.

The program yields estimates and forecasts of the preadjustment component, $z'(t)\ b$, and of the series $x(t)$ in (2.2), which is the series that can be assumed the output of a linear stochastic process (the "linearized" series) and hence the one that will be treated by SEATS.

Program SEATS ("Signal Extraction in ARIMA Time Series"):

- estimates and forecasts unobserved components in series that follow ARIMA models.
- SE of estimates and forecasts are also provided.

A fairly complete description of SEATS is contained in Gómez and Maravall (2001b).

Unobserved components: trend-cycle, $p(t)$, seasonal, $s(t)$, transitory, $c(t)$, and irregular, $u(t)$, components, as in

$$x(t) = p(t) + c(t) + u(t) + s(t) \quad = \quad n(t) + s(t) \quad , \qquad (2.4)$$

where

$n(t)$: SA-series = trend-cycle + transitory comp + irregular comp.

Trend-cycle: captures spectral peak around zero frequency (if large enough),

seasonal component: captures spectral peaks around seasonal frequencies (if large enough),

irregular component: captures white-noise variation,

transitory component: captures transitory variation that differs from white noise.

The models obtained for the components are fully derived from the model for the observed series $x(t)$. They are of the type

$$\nabla^D\ p(t) = w_p(t) \quad , \qquad D = d + d_s \qquad (2.5)$$

$$S\ s(t) = w_s(t), \qquad S = 1 + B + \ldots + B^{s-1}, \qquad (2.6)$$

$w_p(t)$, $w_s(t)$ are stationary ARMA processes.

The models for p_t and s_t are "balanced", that is the total orders of the AR and MA parts are the same.

Transitory component: a stationary ARMA process,
irregular component: white noise.
$w_p(t)$, $w_s(t)$, $c(t)$, and $u(t)$ are mutually uncorrelated.

Note 1: Aggregation of the models for p, s, c, and u yields the ARIMA model (2.3) for the series $x(t)$.

Note 2: Model for the SA-series is obtained from the aggregation of $p(t)$, $c(t)$, and $u(t)$. Its structure is of the type (2.5), with p replaced by n.

Note 3: The model and associated decomposition –equations (2.1) and (2.4)- have been presented in an additive form. If the additive representation is appropriate for the log of the series, the decomposition will be multiplicative and, for example, (2.4) would be replaced by

$$x(t) = p(t)\ s(t)\ c(t)\ u(t)\ .$$

In this case, the series is expressed as a trend-cycle in levels, modified by seasonal, transitory and irregular factors. By convention, these factors are always multiplied by 100, so that if, for a given period, the seasonal factor is 108.5, the SA-series is obtained by dividing $x(t)$ by 1.085.

The component estimator and forecast are obtained with the WK filter extended to non-stationary series as in Bell (1984), which provides the MMSE estimators of the signal given the observed series (under the normality assumption, equal to the conditional expectation).
The WK filter is a two-sided, centered, symmetric, and convergent filter, with a simple analytical representation (see, for example, Maravall, 1995).
Let the series $x(t)$ follow the invertible ARIMA model

$$\phi(B)\ x(t) = \theta(B)\ a(t)\ ,\quad a(t) \sim wn(0, V_a)\ , \tag{2.7}$$

where $\phi(B)$ contains the unit roots.

Consider the decomposition of $x(t)$ into "signal plus non-signal"

$$x(t) = s(t) + n(t)\,.$$

Let the model for the signal be

$$\phi_s(B)\ s(t) = \theta_s(B)\ a_s(t)\ ,\quad a_s(t) \sim wn(0, V_s)\ ,$$

$\phi_s(B)$: polynomial in B that contains the roots of $\phi(B)$ associated with the component s (including unit roots).

$\phi_n(B)$: polynomial in B with the roots of $\phi(B)$ that are not in $\phi_s(B)$ (that is, the AR roots of the non-signal, including unit roots).

Then, if F = B $^{-1}$ denotes the forward operator [such that $F\,x(t) = x(t+1)$,] for a doubly infinite series, the WK filter to estimate the signal is

$$\nu_s(B,F) = \frac{V_s}{V_a}\ \frac{\theta_s(B)\ \phi_n(B)}{\theta(B)}\ \frac{\theta_s(F)\ \phi_n(F)}{\theta(F)}\ , \tag{2.8}$$

or, equivalently, the ACF of the stationary ARMA model

$$\theta(B)\ z(t) = \left[\ \theta_s(B)\ \phi_n(B)\ \right] b(t)\ ,\ b(t) \sim wn(0, V_s / V_a)\ .$$

The estimator of the signal is obtained through

$$\hat{s}(t) = \nu_s(B,F)\ x(t)\ . \tag{2.9}$$

Because of the filter convergence -implied by the invertibility of the model (2.7),- for a (long enough) finite series, say $\left[x(1), x(2), \ldots, x(T)\right]$, the estimator of the signal for the mid-years of the sample can be assumed to be equal to the estimator obtained through (2.9), to be denoted the final or historical estimator.

More generally, given the series $[x(1), \dots, x(T)]$, MMSE estimators and forecasts of the components are obtained by applying the two-sided WK filter to the series extended at both ends with forecasts and backcasts (Cleveland and Tiao, 1976) by means of the Burman-Wilson algorithm (Burman, 1980). The model-based framework can be exploited to provide approximate Standard Errors (SE) of the estimators and forecasts.

The component estimators at the end points of the series will be preliminary, and will suffer revisions as future data becomes available.

The model-based framework is also exploited to analyze revisions (size, speed of convergence) and to provide further elements of interest to short-term monitoring.

When used together,

TRAMO preadjusts the series,

SEATS decomposes the linearized series into its stochastic components.

Final component = stochastic one estimated by SEATS + deterministic effect estimated by TRAMO.

For example, an AO outlier will be added to the irregular component, a LS outlier will be added to the trend-cycle, TD and EE will go to the seasonal component, and so on.

TRAMO, SEATS, and TSW, a Windows version that integrates both programs, are freely available at the Bank of Spain web site (http://www.bde.es → Professionals → Econometrics Software).

Documentation on the general methodology of the programs can be found in Gómez and Maravall (2001a, 2001b, 1994); Gómez, Maravall and Peña (1999); Maravall (1995), and Maravall and Pierce (1987). Documentation on specific features is contained in Kaiser and Maravall (2003), Maravall (2003, 1994, 1993, 1989, 1987), and Maravall and Planas (1999). A general discussion of the approach and its relation to alternative ones is contained in Kaiser and Maravall (2005), and Maravall (1998, 1985). Applications and extensions of the programs are presented in Kaiser and Maravall (2005, 2001a, 2001b), Fiorentini and Maravall (1996), Maravall and del Río (2006), Maravall and Sánchez (2000), and Maravall (2006, 2002, 2000). Most of these references can be downloaded from the above mentioned web site, together with additional documentation, interfases and macros, manuals, and information. A considerable amount of additional papers having to do with TRAMO-SEATS can be found at the US Bureau of the Census and Eurostat web sites.

For the rest of the paper, all applications will be based on program TSW (version of March 2006). Given that input parameters will be used without prior explanation, the paper should be read with the following document readily available:

- "Program TSW: Revised Reference Manual", Caporello and Maravall (2004).

The document

- "Brief Description of the Programs", Maravall (2005),

may also be of help.

Both documents are found at the same web site.

3. THE APPLICATION

Monthly National Accounts (as measured in July 2002) of a Latin American country.

A total of 17 series with 101 observations (Jan 1994 – May 2002) each.

Series 14 (Global Supply) is equal to the first one (Global Demand), but, for the first 3 years it only contains quarterly observations. (Monthly data are missing for the first 3 years.)

Figures 3.1 to 3.16 plot the series. Direct inspection indicates different trend behavior (steadily increasing, increasing and then decreasing, oscillating, and perhaps absence of trend). Seasonality is clearly discernible in some case and difficult to detect in others. Some series seem strongly affected by outliers, mostly of the additive type, but some also display sudden jumps. Heroscedasticity appears to affect some of the series, and perhaps occasional regime changes (in particular, in what concerns starting conditions) are present. For practically all series, there seems to be a considerable amount of noise.

Fig 3.1: Global Demand

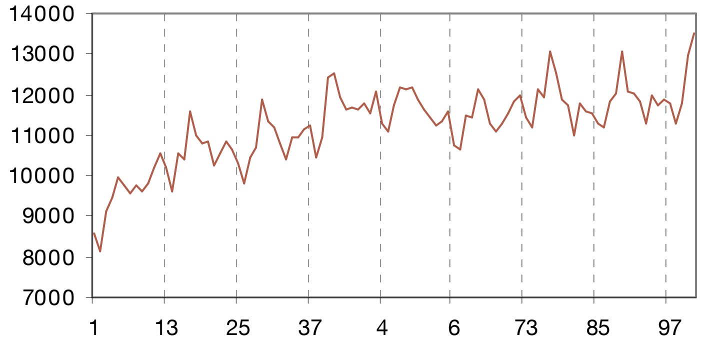


Fig 3.2: Domestic Demand

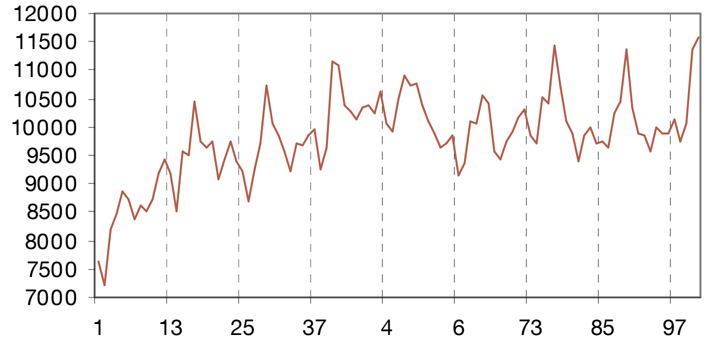


Fig 3.3: Private Consumption

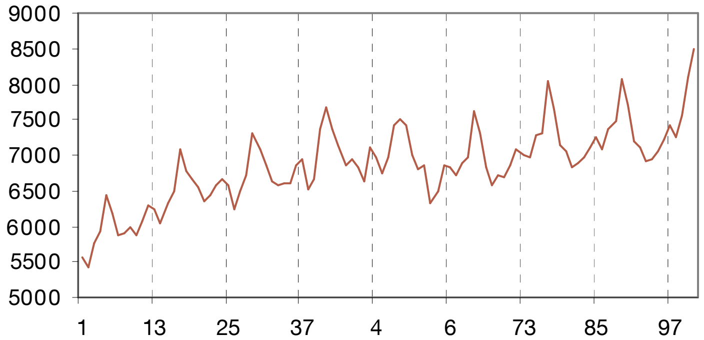
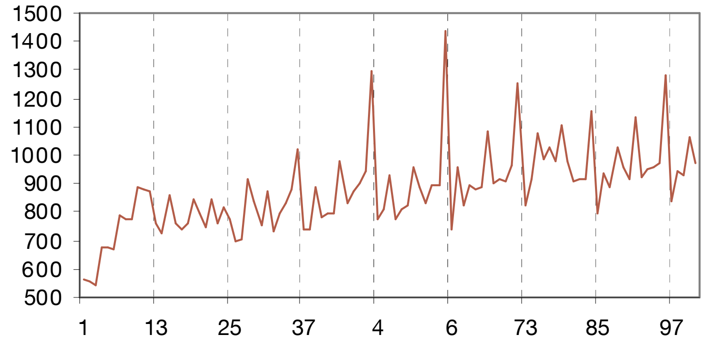


Fig 3.4: Public Consumption



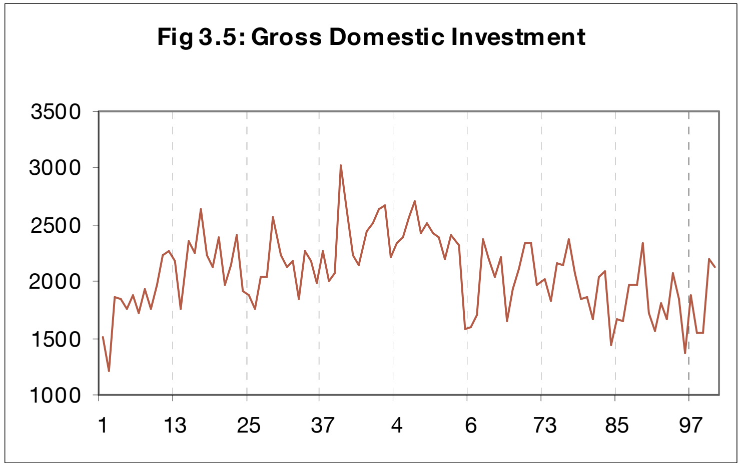


Fig 3.5: Gross Domestic Investment
3500
3000
2500
2000
1500
1000
1
13
25
37
4
6
73
85
97

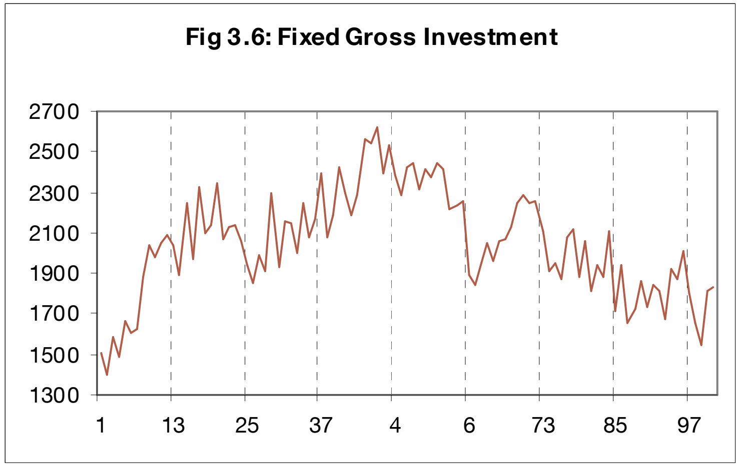


Fig 3.6: Fixed Gross Investment
2700
2500
2300
2100
1900
1700
1500
1300
1
13
25
37
4
6
73
85
97

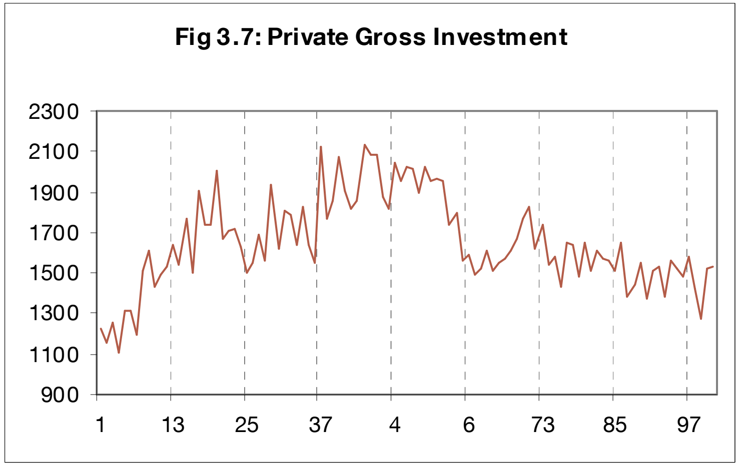


Fig 3.7: Private Gross Investment
2300
2100
1900
1700
1500
1300
1100
900
1
13
25
37
4
6
73
85
97

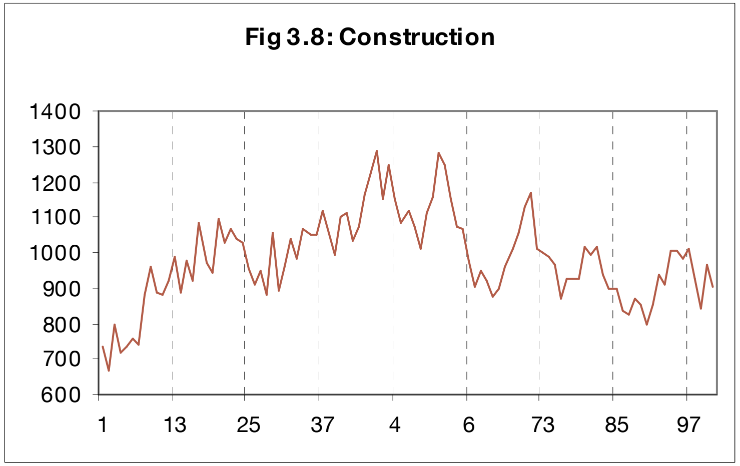


Fig 3.8: Construction
1400
1300
1200
1100
1000
900
800
700
600
1
13
25
37
4
6
73
85
97

Fig 3.9: Imports of Capital Goods

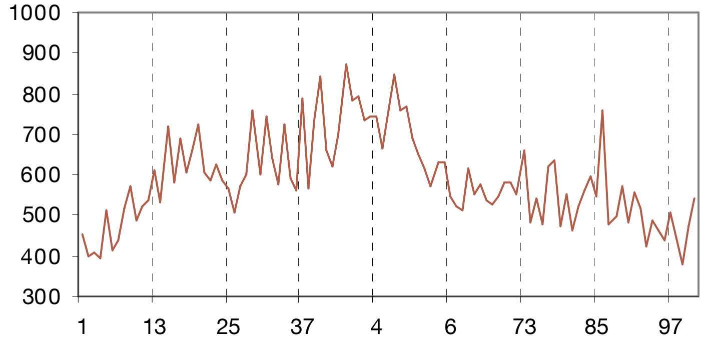


Fig 3.10: Domestic Production of Capital Goods

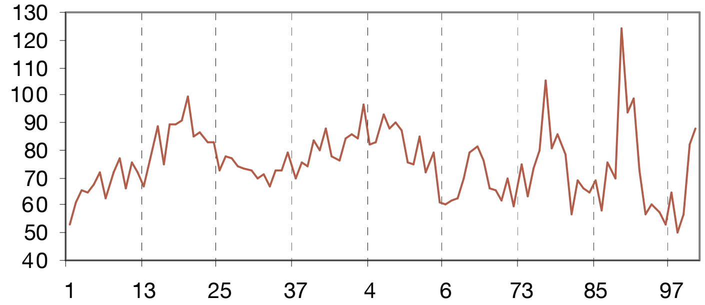


Fig 3.11: Gross Public Investment

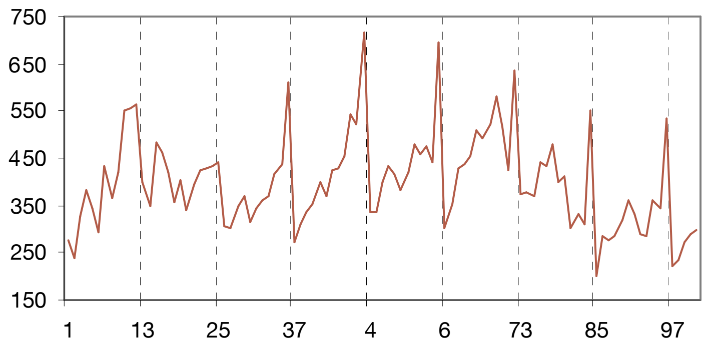
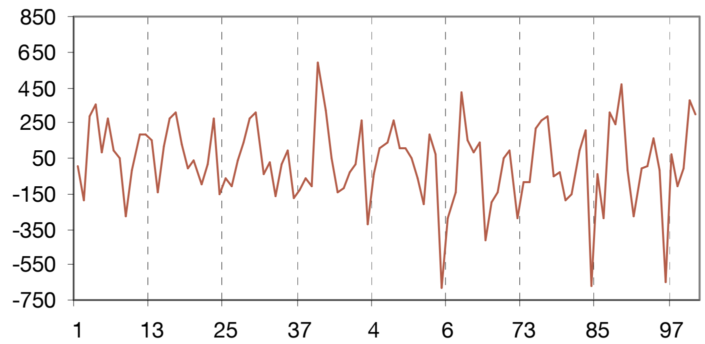


Fig 3.12: Variation of Stocks



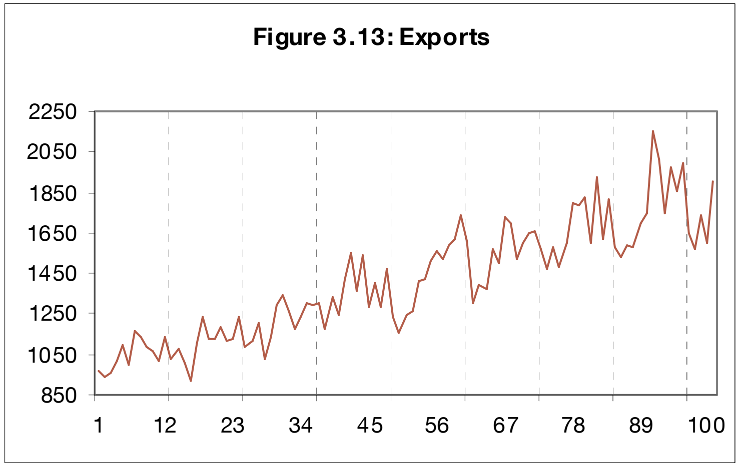


Figure 3.13: Exports
2250
2050
1850
1650
1450
1250
1050
850
1
12
23
34
45
56
67
78
89
100

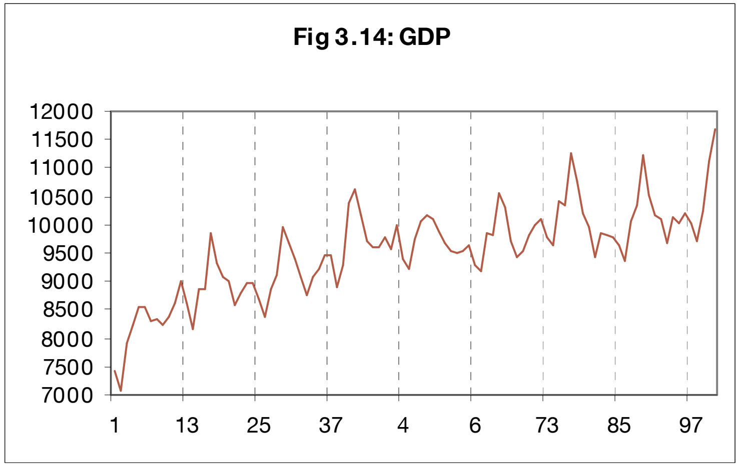


Fig 3.14: GDP
12000
11500
11000
10500
10000
9500
9000
8500
8000
7500
7000
1
13
25
37
4
6
73
85
97

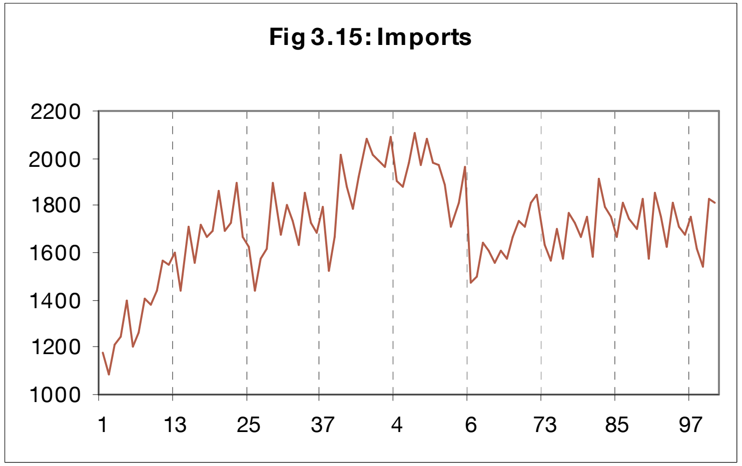


Fig 3.15: Imports
2200
2000
1800
1600
1400
1200
1000
1
13
25
37
4
6
73
85
97

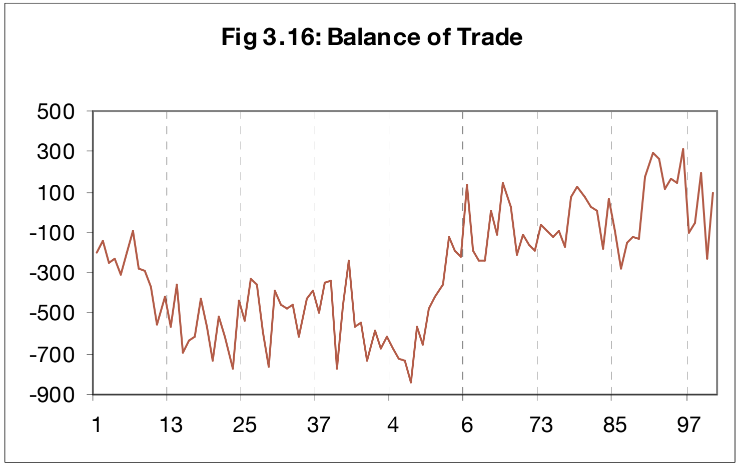


Fig 3.16: Balance of Trade
500
300
100
-100
-300
-500
-700
-900
1
13
25
37
4
6
73
85
97

Next, the results of the automatic option are presented and discussed, and problematic series are identified. The problems have to do with autocorrelation; with nonnormality, nonlinearity, and lack of randomness in the signs of the residuals; with the presence of seasonal and calendar effects in the residuals; with the danger of seasonal overdifferencing, the possible presence of deterministic seasonality, and instability of the seasonal component and of the trend-cycle; with bias in the level of the seasonally adjusted series, and with models that do not accept an admissible decomposition.

It is seen how simple modifications, such as changes in the model specification, in the threshold for outlier detection, or in the sample period treated, and addition of some effects can be of help in correcting the problems.

The example is also used to illustrate some applications relevant to seasonal adjustment, such as model selection (and the use of the SEATS output in the selection), the dilemma direct versus indirect adjustment (both under temporal and sectorial aggregation,) the possible presence of deterministic seasonality, data revisions, error control with out-of-sample forecasts, short-term monitoring, and business-cycle analysis.

4. STARTING POINT: AUTOMATIC PROCEDURE AND OVERALL RESULTS

A good starting point is to treat the full set of series with an automatic procedure.

All are activity-type series, and may well be affected by Trading Day and/or Easter effects.

Given that the series are of moderate length, the parsimonious Trading Day specification is used in the pretesting.

Hence we start with

ITER = 2 same input for all series.

RSA = 4
- Pretest for log/level and for deterministic mean.
- Automatic model identification, joint with
- automatic outlier detection and correction.
- Complete TRAMO-SEATS treatment.

Hence we enter the parameters:

ITER = 2, RSA = 4.

4.1 Aggregate Results

File: "*Model Summary*" (set MODELSUMM= 1 in input; this needs to be done when the number of series in the set is <25. Otherwise it is the default value).

SERIES PROCESSED : 17

SUMMARY RESULTS

TABLE 1 : GENERAL FEATURES

	# of series	%
Levels	3	17.65
Logs	14	82.35
Regular Diff.	14	82.35
Seasonal Diff.	14	82.35
Stationary	1	5.88
Non Stationary	16	94.12
Purely Regular ARIMA	1	5.88
Nz Too Small for complete AMI	0	0.00
Airline Model (Default)	11	64.71

TABLE 2 : DIFFERENCES

# of series with	D = 0	D = 1	D = 2	Total
BD = 0	1	2	0	3
BD = 1	2	12	0	14
Total	3	14	0	17

D = # of regular differences
BD = # of seasonal differences

TABLE 3 : ARMA PARAMETERS

% of series with	P	Q	BP	BQ	Total
0	70.6	29.4	88.2	11.8	
1	17.6	58.8	11.8	88.2	
2	11.8	11.8	0.0	0.0	
3	0.0	0.0	0.0	0.0	
Total > 0	29.4	70.6	11.8	88.2	
Average # of param. per series	0.4	0.8	0.1	0.9	2.2

P = Order of regular AR polynomial
Q = Order of regular MA polynomial
BP = Order of seasonal AR polynomial
BQ = Order of seasonal MA polynomial

TABLE 4 : MISSING VALUES AND REGRESSION

	Outliers					Calendar Var.		
	MO	AO	TC	LS	Tot	TD	EE	Tot
% of series with	5.9	35.3	17.6	23.5	52.9	76.5	58.8	88.2
average # per series	24.0*	0.4	0.2	0.3	0.8			
maximum # per series	24	1	1	2	3			
minimum # per series	0	0	0	0	0			

* Only series with MO are considered

TABLE 5 : SUMMARY STATISTICS

	Mean	SD	Max	Min	Approx 1% CV	Beyond 1% CV	% of series that pass the test (99%)
Length	101	0.0	101	101			
# of ARMA param. per serie	**2.2**	0.9	5	1			
# of outliers per serie	**0.8**	0.9	3	0			
Q	19.5	8.2	36.1	9.4	40.29	0.0	**100.0**
N	2.2	2.9	12.53	0.2	9.21	5.9	**94.1**
SK	0.5	0.9	2.8	-0.7	2.58	5.9	**94.1**
Kur	0.0	1.0	2.3	-1.4	2.58	0.0	**100.0**
QS					9.21	0.0	**100.0**
Q2	26.4	8.9	48.2	13.5	42.98	5.9	**94.1**
Runs	0.4	0.8	2.4	-1.0	2.58	0.0	**100.0**

The last 7 rows of Table 5 contain **Diagnostics on the Residuals**. In short,

Q tests for lack of Autocorrelation;

N for Normality;

SK for Skewness;

Kur for Kurtosis;

QS for the presence of Seasonality;

Q2 for Non-linearity;

Runs for randomness in signs.

(For more information on these tests, see Section 5.1.a below.)

In summary, for the 17 series in the set,

- 14 in logs
- 16 Non-stationary
    - o 2 only need ∇
    - o 2 only need ∇_{12}
    - o 12 need $\nabla\nabla_{12}$
- Most frequent model: Airline.

  Average # of ARMA parameters per series = 2.2 .

  Average # of outliers per series = 0.8 .

  (mostly AO),

  max # outliers/series = 3 .

  77% subject to TD effect.

  60% subject to Easter effect.

  Diagnostics show few problems.

  Results of automatic procedure are good.

4.2 Data Error Control and Out-of-Sample Forecasts

Often, these series are analyzed every month, once a new observation becomes available. When this happens, it is of interest to look at the forecasting performance of the models that had been previously identified. This forecasting check can also reveal errors in the new data because typically these errors will be associated with abnormally large forecast errors. To do this out-of-sample forecast check, select the application

TERROR = ☑ .

In this case, the program performs out-of-sample 1-period-ahead forecasting of the 17 series, ignoring the last observation in each series. Next, comparing the forecast with the new observation, t-values associated with the forecast errors are computed.
Then, the t-values are compared (in absolute value) to two preset parameter k_1 and k_2 ($k_1 \leq k_2$).
The series with $|t|$ values larger than k_2 or in the interval $k_1 < |t| \leq k_2$ are displayed (see the TERROR Manual in Caporello and Maravall (2003), available at the same web site).
In our application, the 17 $|t|$ values were < 2.
Setting $k_1 = 1$, $k_2 = 1.65$, the program yields the following result

LAST OBSERVATION: Out-of-Sample Forecast Error

Terror TSW Series List

Input Parameters :

mq=12 out= 0 int2=-3 terror= 1 sens= 3 modelsumm= 1 k1= 1.000 k2= 1.65

SERIES TITLE	Date	New Value	Forecast	Log(New Value)	Log(Forecast)	Diff.	StdDev	T-Value
7. Privada	05-2002	1535.665	1385.991	7.336719	7.231366	0.1053532	0.0748958	1.406664
9.- M Ks K	05-2002	542.9360	441.6292	6.296991	6.082583	0.2144080	0.1255948	1.707140
10.- Bs K Nac	05-2002	87.73346	102.6913	4.474303	4.625658	-0.151355	0.1101797	-1.373708
13.Exportaciones	05-2002	1902.287	1773.064	7.550812	7.478409	0.0724031	0.0641119	1.129324
17.Balanza comer.	05-2002	95.10140	-65.25528	-	-	160.3567	148.1458	1.082425

For the meaning of the input parameters, see Caporello and Maravall (2004).

The largest $|t|$ value is about 1.7, and 4 more values are > 1.

Given that $|t| > k_1$ should –on a rough average– occur one out of 3 cases, and $t > k_2$ one out of 10, the above list indicates no anomalies in the last observations. It also evidences the good forecasting performance of the automatic procedure.

4.3 Extended series

The set of series discussed covers the period 01/1994 – 05/2002. (NZ = 101)

I have been kindly provided with an update that adds 44 observations (up to 01/2006).

I shall use this extended set (NZ = 145) mostly to validate some of the results obtained for the first set.

(*Remark*:

The extended series contain revisions for the original period 1/1994 – 5/2002. These revisions are, in general, moderate although certainly not trivial; the series that have been more affected are series 10, 12, and to a lesser extent, 1, 2 and 5.)

I enclose the Model Summary for the fully automatic procedure of RSA = 4, applied to this extended set.

Input Parameters :
mq=12 out= 0 rsa= 4 modelsumm= 1
SERIES IN FILE : 17
SERIES PROCESSED : 17

SUMMARY RESULTS

TABLE 1 : GENERAL FEATURES

	# of series	%
Levels	7	41.18
Logs	10	58.82
Regular Diff.	15	88.24
Seasonal Diff.	16	94.12
Stationary	0	0.00
Non Stationary	17	100.00
Purely Regular ARIMA	0	0.00
Nz Too Small for complete AMI	0	0.00
Airline Model (Default)	13	76.47

TABLE 2 : DIFFERENCES

# of series with	D = 0	D = 1	D = 2	Total
BD = 0	0	1	0	1
BD = 1	2	14	0	16
Total	2	15	0	17

TABLE 3 : ARMA PARAMETERS

% of series with	P	Q	BP	BQ	Total
0	88.2	17.6	94.1	5.9	
1	0.0	82.4	5.9	94.1	
2	11.8	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
Total > 0	11.8	82.4	5.9	94.1	
Average of param. per series	0.2	0.8	0.1	0.9	2.1

TABLE 4 : MISSING VALUES AND REGRESSION

		Outliers				Calendar Var.		
	MO	AO	TC	LS	Tot	TD	EE	Tot
% of series with	5.9	58.8	35.3	41.2	76.5	88.2	76.5	88.2
average # per series	24.0	1.1	0.5	0.8	2.3			
maximum # per series	24	5	2	4	6			
minimum # per series	0	0	0	0	0			

TABLE 5 : SUMMARY STATISTICS

	Mean	SD	Max	Min	Approx 1% CV	Beyond 1% CV	% of series that pass the test (99%)
Length	145.0	0.0	145	145			
# of ARMA param. per serie	2.1	0.4	3	1			
# of outliers per serie	2.3	2.0	6	0			
Q	21.8	6.6	38.4	11.6	40.29	0.0	100.0
N	1.9	1.5	4.82	0.3	9.21	0.0	100.0
SK	-0.3	1.1	1.7	-1.8	2.58	0.0	100.0
Kur	0.2	0.8	1.5	-0.8	2.58	0.0	100.0
QS					9.21	0.0	100.0
Q2	22.9	7.2	36.0	6.3	42.98	0.0	100.0
Runs	0.4	1.0	2.1	-1.6	2.58	0.0	100.0

Brief comment on the extended set

Bearing in mind that adding 44 months to a series with 101 monthly observations is far from being a trivial extension, we compare these last results with the results for the original series and the shorter period:

- The number of series modelled in level increases to 7; all series are non-stationary.
- The ARIMA models are rather close. The average number of ARMA parameters per series is 2.1 .
- The average number of outliers per series is 2.3, more than for the (shorter) original series, but still less that 1 outlier every 5 years.
- TD affects 88% of the series; EE affects 77%; calendar effect has become more significant.
- All diagnostics are passed.
- Revision and extension of the series has lead to an increase in the number of regular and seasonal differences (from 14 to 15, and from 14 to 16, respectively).

Thus seasonality and nonstationarity are more discernible in the more complete series.

Except for the small increase in the number of outliers, the results seem even better.

Given that the vast majority of outliers occur during the first half of the period, one is tempted to conclude that the first years of the series contained some instability that is more properly identified when the full sample is considered.

Both sets of series (the original ones with 101 observations, and the extended and revised ones with 145 observations) are available at the same web site.

5. SUMMARY OF INDIVIDUAL SERIES

Having looked at some aggregate results for the set, we turn to the individual series and to detection and correction of problematic cases. The series considered are the ones with 101 observations.

Our aim will be to remove these problems so as to reach final specifications for all series that are acceptable.

Needless to say, further improvements could still possibly be made.

In the discussion, some relevant features will emerge and be briefly discussed. In some cases, use will be made of the extended series.

The output of the program includes several matrices that summarize the results of the application. They are the following. (Each matrix row corresponds to one of the series in the set.)

5.1 Summary Results

5.1.a TRAMO matrices

Matrix: Fitted model

For each series, the columns provide the following information:

Log/level

Mean/no mean

$(p,d,q)\ (bp,bd,bq)_{12}$: Model orders, in Box-Jenkins notation.

$SE(a_t)$

BIC

Residual Diagnostics:

1) $Q(24)$ is the "portmanteau" Ljung-Box test for residual autocorrelation, computed with 24 autocorrelations, asymptotically distributed (a.d.) as $\chi^2\ ([24-(p+q+bp+bq)]\ d.f.)$.

2) N is the Behra-Jarque test for Normality of the residuals, a.d. as $\chi^2\ (2\ d.f.)$.

3) $SK(t)$ is the t-value associated with H_0 : skewness (residuals) = 0.

4) $KUR(t)$ is the t-value associated with H_0 : kurtosis (residuals) = 3.

5) **QS** is the Pierce test for the presence of seasonality in the residual autocorrelation, a.d. approximately as $\chi^2\ (2\ d.f.)$.

6) $Q2$ is the McLeod and Li test on linearity of the process versus bilinear or ARCH-type structures, computed with 24 autocorrelations, and a.d. as $\chi^2\ (24\ d.f.)$.

7) RUNS is the t-value associated with H_0 : signs of the residuals are random.

Approximated critical values (CV) at the 95% level, for the 7 test, are given in the last row of the table.

Matrix: Deterministic effects

Presence/absence of:

TD

EE

Outliers (A0, TC, and LS)

Other regression variable effects (none in this example)

Missing observations that have been interpolated.

Matrix: ARMA parameters

TRAMO-SEATS notation: always "+" sign $(1+\phi_1 B+...)$

SE of the parameter estimates given in parenthesis

Matrix: Outliers

Type of outlier, date of occurrence, and associated t value.

Matrix: Calendar effects

Parameter estimates and associated t value.

Matrix: Model Summary

A summary of the aggregate results for the set. (Already shown in the previous section.)

Fitted model

n	TITLE	Nz	Lam	Mean	P	D	Q	BP	BD	BQ	SE(res)	BIC	Q-val	N-test	SK(t)	KUR(t)	QS	Q2	RUNS
1	"1_Demanda global"	101	0	0	0	1	1	0	1	1	0.02087	-758.189	13.8	0.731	0.767	-0.38	1.09	19.62	0.868
2	"2_Demanda interna"	101	0	0	0	1	1	0	1	1	0.0249549	-722.437	23.95	1.17	0.643	-0.87	0	26.57	0
3	"3_Consumo privado"	101	0	0	0	1	0	0	1	1	0.0156992	-811.240	29.84	1.52	0.966	-0.77	0	30.78	0.659
4	"4_Consumo publico"	101	0	1	2	0	0	0	1	1	0.0833499	-473.661	13.53	12.5	2.75	2.23	1.66	48.18	0.434
5	"5_Inversion bruta in"	101	1	0	1	1	2	0	1	1	189.8492	107.271	15.9	0.45	-0.57	0.351	0	33.8	2.39
6	"6_ Inversion bruta"	101	0	1	1	0	2	1	0	1	0.0585364	-539.318	11	0.197	0.229	0.38	0	16.62	-1.02
7	"7_ Privada"	101	0	0	2	1	0	0	0	0	0.0745437	-508.504	17.88	2.84	1.51	0.747	6.61	29.55	0.606
8	"8_- Const"	101	0	0	0	1	1	0	1	1	0.0569649	-557.365	9.759	0.444	-0.65	-0.13	0	20.77	0.434
9	"9_- M Ks K"	101	0	1	0	1	1	0	1	1	0.104	-433.083	15.52	1.06	0.069	-1.03	0	25.32	0.218
10	"10_- Bs K Nac"	101	0	0	1	1	0	1	0	0	0.0964419	-449.866	34.72	5.41	-0.32	2.3	0	36.71	0.408
11	"11_ Publica"	101	0	0	0	1	1	0	1	1	0.1233618	-402.827	26.31	0.499	0.409	-0.58	0.041	15.34	-0.22
12	"12_ Variacion de e"	101	1	0	0	0	0	0	1	1	153.1623	101.411	15.8	0.574	-0.66	0.374	0	20.88	0.643
13	"13_Exportaciones"	101	0	0	0	1	1	0	1	1	0.0612444	-550.700	36.06	1.45	0.514	-1.09	0	13.5	0.429
14	"14_Oferta global"	101	0	0	0	1	1	0	1	1	0.0211959	-618.447	15.99	0.642	0.792	-0.12	1.49	18.35	1.55
15	"15_PBI"	101	0	0	0	1	1	0	1	1	0.0178446	-785.622	9.375	1.15	0.543	-0.92	0.245	36.59	-0.87
16	"16_Importaciones"	101	0	1	0	1	1	0	1	1	0.0506197	-565.511	15.17	3.51	1.87	0.109	0	30.35	0.222
17	"17_Balanza comer_"	101	1	0	0	1	1	0	1	1	136.7911	995.486	26.31	2.59	-0.71	-1.44	0	26.56	0
Approx. 95% CRITICAL VALUES: (AV: absolute value)													**< 34**	**< 6**	**AV < 2**	**AV < 2**	**< 6**	**< 36**	**AV < 2**

Deterministic Effects

n	TITLE	TD	EE	#OUT	AO	TC	LS	REG	MO	MEAN	(t)
1	"1_Demanda global"	1	1	0	0	0	0	0	0	0	
2	"2_Demanda interna"	1	1	0	0	0	0	0	0	0	
3	"3_Consumo privado"	1	1	2	1	1	0	0	0	0	
4	"4_Consumo publico"	1	0	1	1	0	0	0	0	0.0417	(-5.05)
5	"5_Inversion bruta in"	1	1	0	0	0	0	0	0	0	
6	"6_ Inversion bruta"	1	0	1	0	0	1	0	0	7.3958	(-65.57)
7	"7_ Privada"	1	0	0	0	0	0	0	0	0	
8	"8_- Const"	1	1	0	0	0	0	0	0	0	
9	"9_- M Ks K"	1	0	1	1	0	0	0	0	-0.004	(-2.43)
10	"10_- Bs K Nac"	0	1	2	0	1	1	0	0	0	
11	"11_ Publica"	0	0	2	1	0	1	0	0	0	
12	"12_ Variacion de e"	0	1	0	0	0	0	0	0	0	
13	"13_Exportaciones"	0	0	0	0	0	0	0	0	0	
14	"14_Oferta global"	1	1	1	1	0	0	0	24	0	
15	"15_PBI"	1	1	1	1	0	0	0	0	0	
16	"16_Importaciones"	1	1	3	0	1	2	0	0	-0.0029	(-4.44)
17	"17_Balanza comer_"	1	0	0	0	0	0	0	0	0	

ARMA Parameters

n	TITLE	PHI1	(t)	PHI2	(t)	PHI3	(t)	BPHI	(t)	TH1	(t)	TH2	(t)	TH3	(t)	BTH	(t)
1	"1_Demanda global"	-	(-)	-	(-)	-	(-)	-	(-)	-0.31468	(-3.0)	-	(-)	-	(-)	-0.72882	(-5.7)
2	"2_Demanda interna"	-	(-)	-	(-)	-	(-)	-	(-)	-0.25767	(-2.4)	-	(-)	-	(-)	-0.64876	(-5.6)
3	"3_Consumo privado"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.67049	(-8.5)
4	"4_Consumo publico"	-0.15187	(-1.5)	-0.27788	(-2.6)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.55712	(-5.2)
5	"5_Inversion bruta in"	0.561961	(-2.8)	-	(-)	-	(-)	-	(-)	0.253345	-1.3	-0.50862	(-5.1)	-	(-)	-0.72033	(-5.5)
6	"6_ Inversion bruta"	-0.92128	(-19.)	-	(-)	-	(-)	-0.85332	(-7.6)	-0.51191	(-4.6)	0.1905	-1.7	-	(-)	-0.52123	(-2.7)
7	"7_ Privada"	0.649511	-6.6	0.216598	-2.1	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
8	"8_- Const"	-	(-)	-	(-)	-	(-)	-	(-)	-0.31503	(-3.0)	-	(-)	-	(-)	-0.64762	(-5.5)
9	"9_- M Ks K"	-	(-)	-	(-)	-	(-)	-	(-)	-0.64065	(-7.8)	-	(-)	-	(-)	-0.98798	(-60.)
10	"10_- Bs K Nac"	0.426654	-4.3	-	(-)	-	(-)	-0.62275	(-5.9)	-	(-)	-	(-)	-	(-)	-	(-)
11	"11_ Publica"	-	(-)	-	(-)	-	(-)	-	(-)	-0.52933	(-5.6)	-	(-)	-	(-)	-0.45378	(-3.9)
12	"12_ Variacion de e"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.50882	(-5.6)
13	"13_Exportaciones"	-	(-)	-	(-)	-	(-)	-	(-)	-0.86365	(-14.)	-	(-)	-	(-)	-0.79606	(-3.8)
14	"14_Oferta global"	-	(-)	-	(-)	-	(-)	-	(-)	-0.25191	(-2.3)	-	(-)	-	(-)	-0.65422	(-6.6)
15	"15_PBI"	-	(-)	-	(-)	-	(-)	-	(-)	-0.1907	(-1.8)	-	(-)	-	(-)	-0.71233	(-5.8)
16	"16_Importaciones"	-	(-)	-	(-)	-	(-)	-	(-)	-0.7366	(-8.7)	-	(-)	-	(-)	-0.78182	(-5.1)
17	"17_Balanza comer_"	-	(-)	-	(-)	-	(-)	-	(-)	-0.40782	(-4.1)	-	(-)	-	(-)	-0.6629	(-5.1)

Roots

n	TITLE	REGULAR AR INVERSE ROOTS						REGULAR MA INVERSE ROOTS					
		root(1)		root(2)		root(3)		root(1)		root(2)		root(3)	
		mod	per	mod	per	mod	per	mod	per	mod	per	mod	per
1	"1_Demanda global"							0.315	-				
2	"2_Demanda interna"							0.258	-				
3	"3_Consumo privado"												
4	"4_Consumo publico"	0.457	2.0	0.609	-								
5	"5_Inversion bruta in"	0.562	2.0					0.598	-	0.851	2.0		
6	"6_ Inversion bruta"	0.921	-					0.436	6.7	0.436	6.7		
7	"7_ Privada"	0.465	2.7	0.465	2.7								
8	"8_- Const"							0.315	-				
9	"9_- M Ks K"							0.641	-				
10	"10_- Bs K Nac"	0.427	2.0										
11	"11_ Publica"							0.529	-				
12	"12_ Variacion de e"												
13	"13_Exportaciones"							0.864	-				
14	"14_Oferta global"							0.252	-				
15	"15_PBI"							0.191	-				
16	"16_Importaciones"							0.737	-				
17	"17_Balanza comer_"							0.408	-				

Outliers

1	"1_Demanda global"	- - - - - - - - - -		
2	"2_Demanda interna"	- - - - - - - - - -		
3	"3_Consumo privado"	AO01(0498, 4.45);	TC01(1098, -5.06);	
4	"4_Consumo publico"	AO01(0394, -3.30);		
5	"5_Inversion bruta in"	- - - - - - - - - -		
6	"6_ Inversion bruta"	LS01(0994, 3.62);		
7	"7_ Privada"	- - - - - - - - - -		
8	"8_- Const"	- - - - - - - - - -		
9	"9_- M Ks K"	AO01(0201, 4.97);		
10	"10_- Bs K Nac"	TC01(0501, 4.29);	LS01(1298, -3.25);	
11	"11_ Publica"	AO01(0196, 4.93);	LS01(0900, -3.64);	
12	"12_ Variacion de e"	- - - - - - - - - -		
13	"13_Exportaciones"	- - - - - - - - - -		
14	"14_Oferta global"	AO01(0499, -2.77);		
15	"15_PBI"	AO01(0499, -3.11);		
16	"16_Importaciones"	TC01(1098, -4.42);	LS01(0199, -6.51);	LS02(1295, -3.95);
17	"17_Balanza comer_"	- - - - - - - - - -		

Calendar Effect

n	TITLE	TD1	(t)	TD2	(t)	TD3	(t)	TD4	(t)	TD5	(t)	TD6	(t)	LY	(t)	EE	(t)
1	"1_Demanda global"	0,003284	-6.7	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.02921	(-4.0)
2	"2_Demanda interna"	0.004111	-7.4	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.03262	(-4.0)
3	"3_Consumo privado"	0.001987	-6.5	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.01745	(-3.7)
4	"4_Consumo publico"	0.006264	-2.7	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
5	"5_Inversion bruta in"	20.8947	-4.2	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-265.89	(-4.3)
6	"6_ Inversion bruta"	0.007538	-4.7	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
7	"7_ Privada"	0.009634	-4.1	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
8	"8_- Const"	0.006644	-5.1	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.04287	(-2.2)
9	"9_- M Ks K"	0.011876	-3.8	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
10	"10_- Bs K Nac"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.10544	(-3.5)
11	"11_ Publica"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
12	"12_ Variacion de e"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-171.182	(-2.5)
13	"13_Exportaciones"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
14	"14_Oferta global"	0.003537	-5.8	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.03027	(-3.8)
15	"15_PBI"	0.002429	-6.3	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.02629	(-4.5)
16	"16_Importaciones"	0.007192	-4.7	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.06335	(-2.8)
17	"17_Balanza comer_"	-19.3964	(-5.9)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)

5.1.b SEATS matrices

Matrix: General

Preadjusted by TRAMO: Y/N

Model changed by SEATS: Y/N

(if so, is it an approximation to a Non-admissible-decomposition model?: Y/N)

Summary of model finally used by SEATS.

(SEATS may change the model passed by TRAMO, even when there is an admissible decomposition; see Section 5.2 below.)

Checks on the SEATS decomposition of the series:

- Spectral factorization (0 / Error)
- Comparison of the theoretical and empirical 2nd order moments (ACF and CCF)

Matrix: Parameters I

Standard Deviation of the component's innovations (in units of the series)

SE of the trend-cycle (TC) and SA series concurrent estimators (in units of the series)

SE of the revision error: TC and SA series concurrent estimates (in units of the series)

SE of the rates of growth estimates (in % points)

- monthly rate of growth: TC and SA series,
- annual rate of growth centered at the present period and completed with forecasts: original series, TC and SA series.

Note 1: The main output of SEATS presents the previous standard errors in units of the standard deviation of the series innovations.

Note 2: The SE are computed under the assumption of a semi-infinite realization.

Matrix: Parameters II

Convergence of the concurrent to the final estimator:

Percentage reduction in the RMSE of the revision error after 1 and 5 additional years of data have become available: TC and SA series.

Significance of stochastic seasonality:

Number of months per year that have a seasonal component significantly different from zero: historical estimator, last year of observations (preliminary estimator), and 1 to 12-months-ahead forecasts.

Average of differences in absolute value between the annual means of the original series, on the one hand, and the TC and SA series, on the other. (Measured as fractions of 1% of the level.) This measure indicates the bias effect in the levels of the components induced by the log transformation.

Seats: General

n	Title	Pread.	Model Changed	Approx To NA	m	p	d	q	bp	bd	bq	SD(a)	Spectr. Factor	Check on ACF	Check on CCF
1	"1.Demanda global"	Y	N	N	0	0	1	1	0	1	1	2.06E-02	0	0	0
2	"2.Demanda interna"	Y	N	N	0	0	1	1	0	1	1	2.47E-02	0	0	0
3	"3.Consumo privado"	Y	N	N	0	0	1	0	0	1	1	1.53E-02	0	0	0
4	"4.Consumo publico"	Y	N	N	1	2	0	0	0	1	1	7.95E-02	0	0	0
5	"5.Inversion bruta in"	Y	N	N	0	1	1	2	0	1	1	186.6	0	0	0
6	"6. Inversion bruta"	Y	Y	Y	0	0	1	1	0	1	1	6.06E-02	0	0	0
7	"7. Privada"	Y	N	N	0	2	1	0	0	0	0	7.45E-02	0	0	0
8	"8.- Const"	Y	N	N	0	0	1	1	0	1	1	5.63E-02	0	0	0
9	"9.- M Ks K"	Y	N	N	1	0	1	1	0	1	1	0.1028	0	0	0
10	"10.- Bs K Nac"	Y	N	N	0	1	1	0	1	0	0	9.81E-02	0	0	0
11	"11. Publica"	Y	N	N	0	0	1	1	0	1	1	0.1219	0	0	0
12	"12. Variacion de e"	Y	N	N	0	0	0	0	0	1	1	152.3	0	0	0
13	"13.Exportaciones"	Y	N	N	0	0	1	1	0	1	1	6.12E-02	0	0	0
14	"14.Oferta global"	Y	N	N	0	0	1	1	0	1	1	1.76E-02	0	0	0
15	"15.PBI"	Y	N	N	0	0	1	1	0	1	1	1.75E-02	0	0	0
16	"16.Importaciones"	Y	N	N	1	0	1	1	0	1	1	4.93E-02	0	0	0
17	"17.Balanza comer."	Y	N	N	0	0	1	1	0	1	1	136	0	0	0

Seats: Parameters I

n	Title														
													SE : Rates of Growth		
									SE Rev.		SE T11			SE T1Mq	
				SD(innov)			SE Est. (Conc.)		(Conc.)		(One Period)			(Annual Centered)	
		TC	S	Trans	U	SA	TC	SA	TC	SA	TC	SA	X	TC	SA
1	"1.Demanda global"	6.14E-03	3.04E-03	0	1.17E-02	1.80E-02	1.10E-02	8.40E-03	7.84E-03	5.97E-03	0.73	0.93	4.03	3.81	3.99
2	"2.Demanda interna"	7.57E-03	4.79E-03	0	1.28E-02	2.06E-02	1.36E-02	1.14E-02	9.94E-03	8.12E-03	0.89	1.17	5.12	4.86	5.04
3	"3.Consumo privado"	6.43E-03	2.98E-03	0	6.41E-03	1.29E-02	9.24E-03	7.97E-03	6.60E-03	5.71E-03	0.67	0.68	4.06	3.96	4.01
4	"4.Consumo publico"	1.98E-02	2.15E-02	1.59E-02	3.67E-02	6.26E-02	3.36E-02	3.79E-02	2.09E-02	2.52E-02	2.51	5.23	8.46	5.73	7.88
5	"5.Inversion bruta in"	38.5	129.7	0	50.19	89.37	100.2	102.1	71.91	65.86	50.61	79.07	298.42	256.34	263.86
6	"6. Inversion bruta"	1.20E-02	1.22E-02	0	3.64E-02	4.92E-02	2.95E-02	2.65E-02	2.22E-02	1.88E-02	1.57	3.25	9.52	8.34	9.29
7	"7. Privada"	2.00E-02	0	2.31E-02	3.40E-02	7.45E-02	3.04E-02	0	2.16E-02	0	2.38	0	12	11.02	12
8	"8.- Const"	1.59E-02	1.08E-02	0	3.05E-02	4.70E-02	3.04E-02	2.53E-02	2.22E-02	1.80E-02	1.93	2.73	11	10.34	10.82
9	"9.- M Ks K"	1.84E-02	6.82E-04	0	8.38E-02	0.1023	4.81E-02	8.65E-03	3.25E-02	5.46E-03	2.43	1.21	13.7	11.12	13.7
10	"10.- Bs K Nac"	1.42E-02	5.57E-02	3.91E-04	3.76E-02	5.55E-02	5.53E-02	5.57E-02	4.52E-02	3.93E-02	2.11	4.82	19.22	16.75	17.42
11	"11. Publica"	2.06E-02	3.28E-02	0	6.78E-02	9.05E-02	5.73E-02	5.69E-02	4.48E-02	4.04E-02	2.77	6.86	18.61	15.84	17.76
12	"12. Variacion de e"	3.117	54.71	0	110.8	113.9	26.23	73.97	18.75	46.09	4.4	107.5	152.29	21.05	136.03
13	"13.Exportaciones"	3.80E-03	8.49E-03	0	5.11E-02	5.53E-02	2.00E-02	2.23E-02	1.48E-02	1.52E-02	0.54	3.23	6.46	2.74	6.36
14	"14.Oferta global"	5.45E-03	3.36E-03	0	9.09E-03	1.47E-02	9.71E-03	8.06E-03	7.07E-03	5.76E-03	0.64	0.83	3.66	3.49	3.61
15	"15.PBI"	6.10E-03	2.84E-03	0	8.94E-03	1.52E-02	9.74E-03	7.74E-03	6.94E-03	5.52E-03	0.69	0.78	3.89	3.75	3.85
16	"16.Importaciones"	5.83E-03	6.68E-03	0	3.80E-02	4.42E-02	2.03E-02	1.77E-02	1.47E-02	1.22E-02	0.8	2.5	5.86	3.99	5.79
17	"17.Balanza comer."	33.61	24.04	0	79.6	114.5	70.18	57.87	51.45	41.11	42.11	67.3	239.6	220.16	235.84

Seats: Parameters II

n	Title	Convergence (in %) 1Y		5Y		Signif. Stoch. Season. (95%)			DAA	
		TC	SA	TC	SA	Hist.	Prel.	Fore.	TC	SA
1	"1.Demanda global"	67.6	26.6	90.9	79.3	6	6	6	0.08	0.02
2	"2.Demanda interna"	66.2	34.3	94	88.4	8	7	7	0.08	0.03
3	"3.Consumo privado"	52.9	32.5	90.5	86.4	8	8	8	0.04	0.02
4	"4.Consumo publico"	63.3	43.7	96.5	94.6	3	3	3	0.46	0.3
5	"5.Inversion bruta in"	83.6	77.5	95.6	93.8	8	6	0	0	0
6	"6. Inversion bruta"	80.5	39	97.5	92.3	4	3	2	0.42	0.06
7	"7. Privada"	100	0	100	0	0	0	0	0.42	0
8	"8.- Const"	69.2	34.4	94.6	88.5	8	7	5	0.25	0.08
9	"9.- M Ks K"	96.4	1.8	96.7	9	7	7	6	1.41	0.07
10	"10.- Bs K Nac"	95	88.6	100	100	8	9	4	0.97	0.84
11	"11. Publica"	84.9	51.9	99.4	98	5	5	3	0.85	0.69
12	"12. Variacion de e"	49.1	49.1	96.6	96.6	8	5	3	0	0
13	"13.Exportaciones"	84.1	20.4	98.1	68	9	8	8	0.67	0.11
14	"14.Oferta global"	65.8	33.8	93.7	87.9	7	7	6	0.07	0.02
15	"15.PBI"	60.8	28.3	89.9	81.5	9	9	7	0.06	0.02
16	"16.Importaciones"	91.4	21.7	96.9	70.8	7	2	2	0.38	0.07
17	"17.Balanza comer."	73.9	32.8	95	87	5	4	3	0	0

5.2 Model Selection and Identification of Problematic Series

5.2.a General Remarks

From the results displayed in the output matrices it is possible to make a first judgement on whether the model finally selected with the automatic procedure seems appropriate or not.

Problematic series, that fail to pass some important test or that present problems having to do with the decomposition into unobserved components, can be identified.

In fact, an Excel macro (*Problematic.xls*) performs this task automatically. The macro reads the Excel files with the matrices and selects the problematic series according to some pre-set (default) or user-defined values for the different criteria; further, input files with the problematic series are created. The macro is particularly useful with sets containing many series and/or many problems; our present example is not one such case. The macro is also available at the same web site.

It should be born in mind that the criteria to judge the appropriateness (or lack thereof) of the model identified for the observed series depends, to some extend, on the purpose of the analysis. Thus, for example, a model selected for forecasting may display poor decomposition properties. In this case, SEATS may modify the model identified by TRAMO.

It may often happen that, from the TRAMO results, more than one model seem acceptable. In this case, as shall be seen, the output from SEATS can be of help in pointing out which one should be chosen.

The following is a list of the main criteria in judging the appropriateness of a model, that are available in the output matrices.

From the TRAMO matrices:

Main concerns (in “Fitted model”): Q,
QS,
N,
SK,

with the order reflecting priority, with some consideration given to RUNS.

ARCH-and bilinear-type structures (kurtosis in general) have relatively mild effects on point estimators, and hence only fairly large values of KUR and Q2 need to be considered.

Another main concern is the number of outliers in "Deterministic effects". Roughly, 4% (or one outlier every two years for monthly data) is considered the acceptable limit for the proportion of outliers.

From the SEATS matrices:
Main concerns are

Whether SEATS has changed the model (perhaps because of a Non-Admissible decomposition)

Possible errors in the spectral factorization (unlikely).

Large discrepancies between 2nd order moments of theoretical and empirical estimators.

Large biases due to log transformation.

Unstable seasonality (as evidenced by clearly stationary seasonal components.)

Of course, there are other considerations. Examples:

5.2.b Changes to an ARIMA model

Interest in:

1 PARSIMONY. (Few parameters.)

2 "BALANCED" MODELS. (Orders of full AR and MA polynomials are the same.)

Example: Assume "regular" orders of model are (2 0 0) ,

and that the regular AR polynomial factorizes as: $(1-.94B)(1+.3B)$.

It may make sense to replace the regular part by the (0 1 1) structure.

$(1-.94B)$ is replaced by ∇ and $(1+.3B)^{-1}$ is not far from $(1-.3B)$ when $NZ = 101$ observations.

The alternative specification has one less parameter (perhaps two if a mean was present) and the model becomes balanced. Also, the trend is likely to be more stable.

5.2.c Imposing some effects (Calendar effects)

Example 1: Assume a set of homogeneous series (say, IPIs of EU countries).

Automatic procedure yields significant TD for all but one or two. It may be sensible to try imposing TD in all cases. In fact, in order to avoid spurious TD effects, TRAMO has a slight bias towards underdetection of TD and EE in automatic modelling.

Example 2: Inspection of the outliers detected (which are restricted to the AO, LS, and TC specification) may suggest a sensible intervention variable that groups several of them, increasing thereby the degrees of freedom.

5.2.d Improving the characteristics of the signal

Often, fitting criteria may show that more than one model could be accepted.

Assume SA is the main objective.

We look at the SEATS output, in particular, at the

- SD of the seasonal innovation:
  The smaller it is, the more stable the seasonal component will be.
- SD of the seasonal component concurrent estimation error:
  We seek reliable estimators; in particular for recent periods.
- SD of the revision in the concurrent estimator:
  Obviously, the smaller the revision, the better.

These features may help in model selection.

5.2.e Model Specification and ARMA Parameters

It is advisable that the "ARMA parameters" estimates be checked. The following are considerations that might, on occasion, be helpful.

(1) AR and MA parameters for the same lag

In general, simultaneous AR and MA parameters for the same lag should be avoided. Typically, for example, the AR and MA parameters in a $(1\,0\,1)$ specification will be highly correlated and may foster model instability. It may be worth replacing them with $(1\,0\,0)$ or $(0\,1\,1)$ specifications.

(2) Simplifying models and correlation between parameter estimates

When simplifying AR or MA polynomials, care should be taken with the effect of possible **correlation between the parameter estimates**. (These correlations are given in the TRAMO output.)

For example, assume an AR(2) polynomial, let $t_1 = .95$ and $t_2 = 2.2$ be the t-values of $\hat{\phi}_1$ and $\hat{\phi}_2$, and $\rho = .9$ the correlation between the two estimators. Noticing that $\hat{\phi}_1$ is not significant, one may set $\hat{\phi}_1 = 0$. Reestimating the polynomial $(1 + \phi_2 B^2)$, because of

the positive correlation, the t value for $\hat{\phi}_2$ may become $t_2 = 1.7$. Removing ϕ_2 because of its lack of significance, the residuals now may display significant autocorrelation.
If, instead, $\rho = -.9$, setting $\phi_1 = 0$ will yield a more significant estimator of ϕ_2.

(3) AR Polynomials and Unit Roots

Let A_i denote the roots (for B^{-1}) in the factorization of the **regular AR polynomial** $\phi(B)$, that is

$$\phi(B) = \Pi_i \ (1 - A_i B) \ .$$

If a root A_i is close to 1, it may be worth it to replace it with $(1 - B)$, increasing thus d by one and reducing p by one.
A possibly better strategy is to replace the A_i root by a $(0\,1\,1)$ IMA structure, so that d and q are increased and p reduced all by one. This is likely to yield more stable model and trend.
In both cases, if IMEAN = 1 in the original model, it should be replaced by 0.
A similar consideration applies to **seasonal AR polynomials**. Thus, for example, it may be advisable to replace a $(1\,0\,0)_s$ AR seasonal structure with BPHI =-.95 by a $(0\,1\,1)_s$ one. This is likely to improve model stability as well as seasonal component stability.
However, when the seasonal structure is a $(1\,1\,0)_s$ one, the parameter BPHI is left untouched.

Remark: Notice that seasonality implies that the mean depends on the particular period of the year (i.e., depends on time). Thus it is somewhat linked to non-stationarity, and **stationary specifications for the seasonal component** should be avoided.

(4) Pure regular MA models

Model consisting of **pure regular MA** structures will not be decomposed. They basically consist of highly transitory and erratic behavior.
Pure MA seasonal structures are modified in the following way:

* if $-1 < \theta_s < -.5$, the seasonal autocorrelation is deemed relevant and an IMA$(1,1)_{12}$ structure is used to attempt to capture it.
* Otherwise, it is judged to imply highly short-term behavior and it is simply assigned to the irregular. (Therefore the seasonal specification becomes $(0\,0\,0)_s$. The

forecasts of the original model of TRAMO –with the seasonal MA- will be nevertheless preserved.)

(5) Seasonal Overdifferencing

When the seasonal structure is of the type $(0\,1\,1)_s$ and BPHI is close to -1, it can be that seasonality is close to deterministic, or that seasonal overdifferencing has been performed.

The output contains several statistics that can help in assessing the presence/absence of seasonality in the series:

First, a check of whether the lag-s and lag-2s autocorrelations of the differenced series (with only regular differences!) are positive. Second, the significance of the Q_s-Pierce statistics for the model residuals. Third, an out-of-sample forecast comparison of the model with and without the seasonal structure can be performed. Finally, some additional diagnostics are given below.

In practice, one seldom finds that seasonal overdifferencing has been performed.

(6) "Wrong" Models

The way SEATS identifies the components allegedly present in the series (besides the irregular and transitory "pure MA" components) is by, first, factorizing the AR polynomial of the observed series model and, second, by assigning the roots to the component according to their associated frequency.

Thus, for example, the model

$$(1-.6B)\, x_t = (1+\theta B)\, a_t$$

would, in principle, decompose x_t into a trend plus a white-noise irregular. The trend, p_t, would follow the model

$$(1-.6B)\, p_t = (1+B)\, a_{pt} \;,$$

where a_{pt} would be the trend innovation, and the root (1+B) in the MA polynomial would impose the canonical condition on the trend component.

However, when $(-1<\theta<-.6)$, the spectrum of x_t is monotonically increasing in the interval $(0,\pi)$, with a minimum at 0 and a maximum at π (see Figure 5.1).

This spectrum obviously cannot be decomposed into a trend (with a spectral peak around 0) plus a constant spectrum irregular component. The SEATS standard procedure in this case does not work.

Something similar occurs with the decomposition of the model

$$(1-.6B^{12})\,x_t=(1+\theta_{12}B^{12})\,a_t\ .$$

The standard decomposition procedure would yield the trend component

$$(1-.98B)\,p_t=(1+B)\,a_{pt}\ ,\quad (.6^{1/12}=.98),$$

a seasonal component, s_t, of the type

$$(1-.98B+.98^2B^2+...+.98^{11}B^{11})\,s_t=\theta_s(B)\,a_{st}\ ,$$

plus a white-noise irregular.

When $(-1<\theta_{12}<-.6)$, as in the previous example, the spectrum of the series shows no peak for the 0 frequency. Moreover, the spectral peaks of x_t will be found for intraseasonal frequencies, and for the seasonal ones the spectrum will present local minima (see Figure 5.2).

Fig 5.1: Misleading ARMA (1,1)

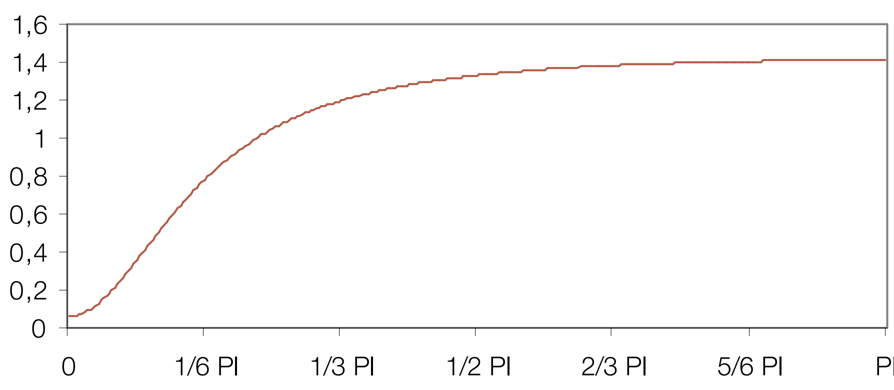
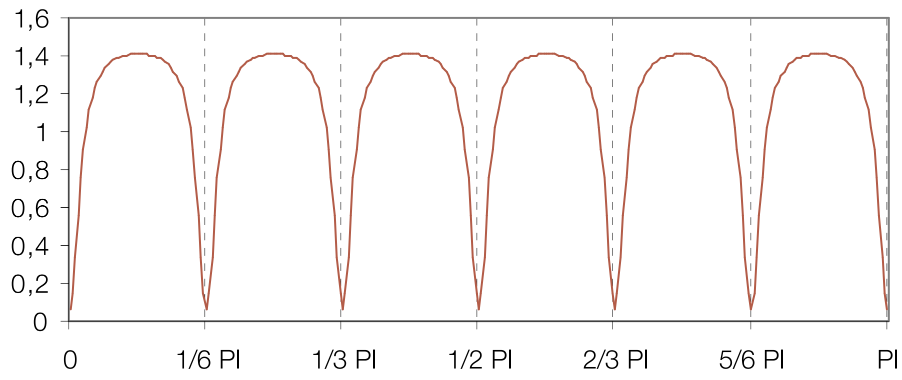


Fig 5.2: Misleading Seasonal ARMA (1,1)



If the model found by TRAMO is of the above type –i.e., contains on ARMA(1,1) structure with $(-1<\theta<\phi<0)$- SEATS does not apply the standard procedure and the series is considered (as it should) simply a "transitory + irregular" component series.

Wrong models such as the above are very rarely found.

5.2.f A Final Remark

The previous criteria and comments refer to the TRAMO, SEATS, and TSW versions that are available at present at the Bank of Spain web site. Some additional diagnostics will be included in future versions, such as one for assessing in-sample model stability, a non-parametric test for detecting seasonality, and model-based complements of the sliding-spans and revision history diagnostic of X12 ARIMA.

Besides, work accomplished at the US Bureau of the Census (available at www.census.gov/srd/www/sapaper.html) has shown the usefulness of spectral diagnostics to detect residual seasonality or Trading Day effects, and the need to analyse spectral properties of preliminary estimators (in particular, phase and gain of the concurrent estimator). Thanks to the help of the USBC, these spectral analysis and diagnostics will also be available in future versions of TRAMO, SEATS, and TSW.

These added features will be illustrated in some of the examples that follow.

6. INDIVIDUAL SERIES

The matrices already displayed in Section 5.2 contain the summary results for each series. (Problematic features are indicated in bold letters.) Next I proceed to briefly discuss each one of the series.

Note: In order to obtain the full set of graphs, the parameter ITER should be changed to 0, and the program re-run.

6.1 SERIES 1 : GLOBAL DEMAND; Out-of-Sample Forecast and Some (Mostly Frequency Domain) Additional Diagnostics.

Output. Looking at the matrices (from TRAMO and SEATS) everything seems OK.

The series in logs is modelled as:

$$y_t = \alpha_{TD}\ TD_t + \alpha_{EE}\ EE_t + x_t \ , \qquad (6.1)$$

$$\nabla\nabla_{12}\ x_t = (1+\theta_1 B)(1+\theta_{12} B^{12})\ a_t \ , \qquad (6.2)$$

with no outliers detected.

Figure 6.1.1 compares the original with the final SA series (also adjusted for calendar effects) and evidences the quantitative importance of the seasonal component. Figure 6.1.2 compares the final SA series with the Trend-Cycle component, which is seen to display strong cyclical oscillations. Figure 6.1.3 plots the forecast functions of the series and of the trend, with the associated 95% Confidence Intervals (CI). Figures 6.1.4, 6.1.5, and 6.1.6 present the stochastic seasonal and irregular components, and the calendar effect. Seasonality is fairly stable, and dominates over the other two components. Figure 6.1.7 exhibits the TRAMO residuals: they appear to be random and homoscedastic, with only 3 outliers beyond the 95% CI (none of them by much).

Fig 6.1.1 GLOBAL DEMAND: Original and SA series

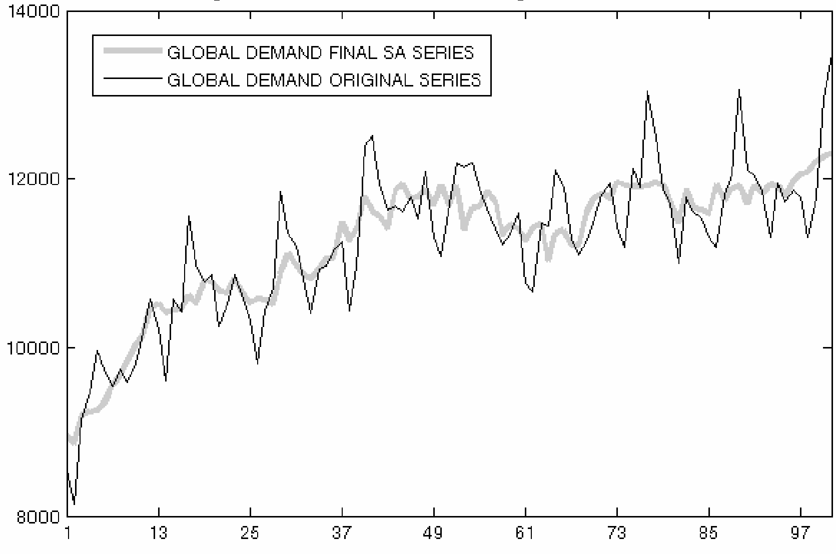


Fig 6.1.2 GLOBAL DEMAND: SA series and Trend-Cycle

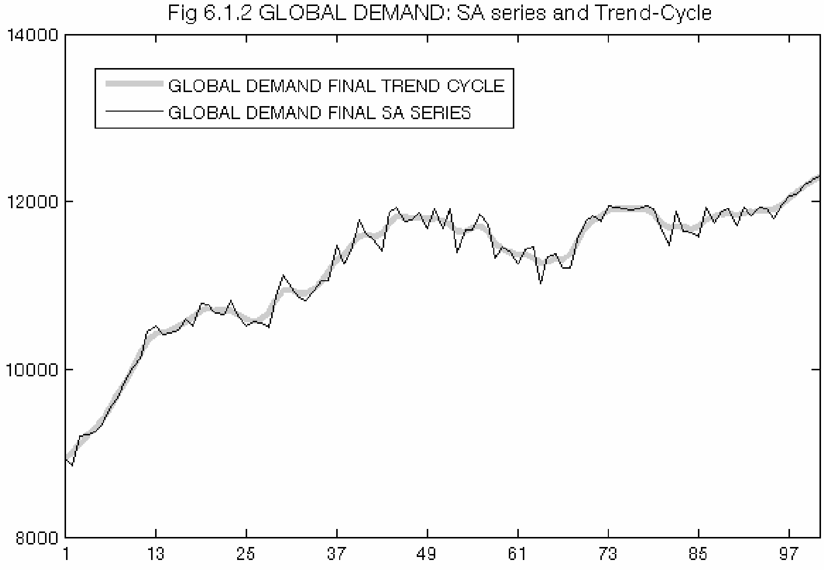


Fig 6.1.3: GLOBAL DEMAND:
Forecast Function of series and Trend-Cycle

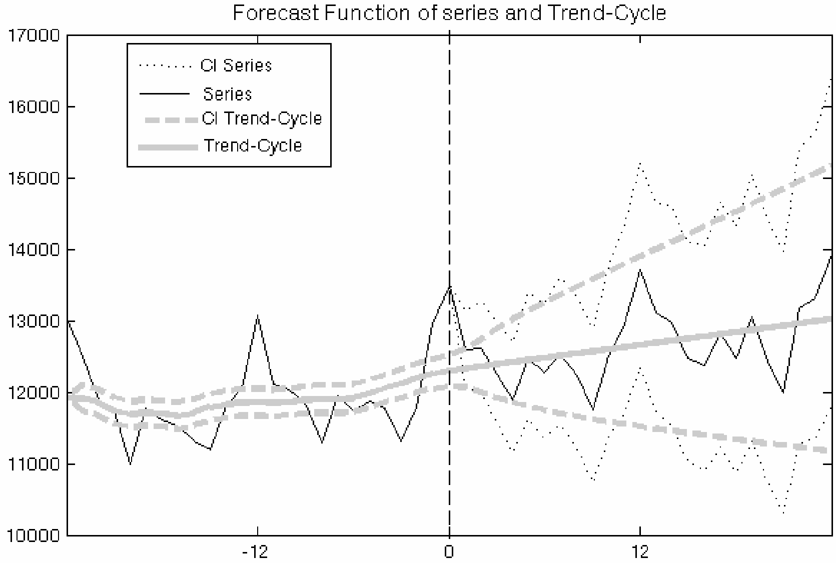


Fig 6.1.4 GLOBAL DEMAND: SEASONAL COMPONENT

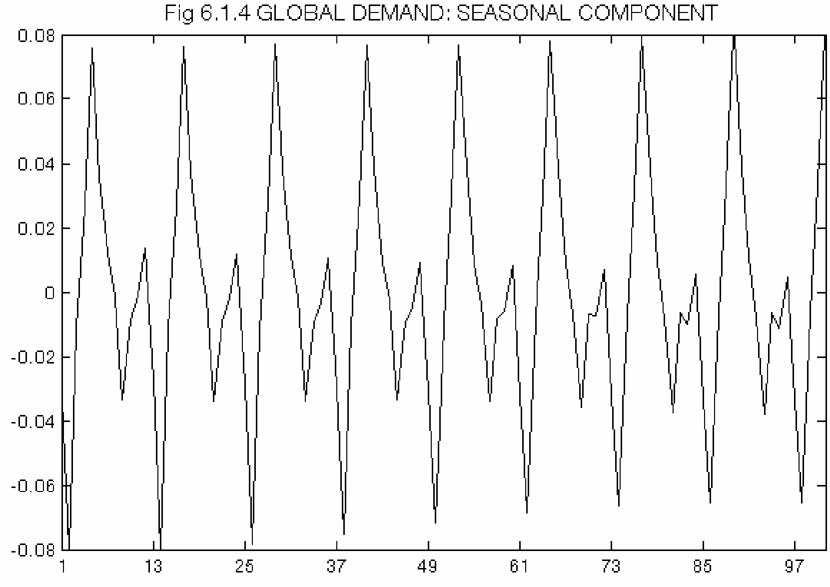


Fig 6.1.5 GLOBAL DEMAND: Calendar Effect

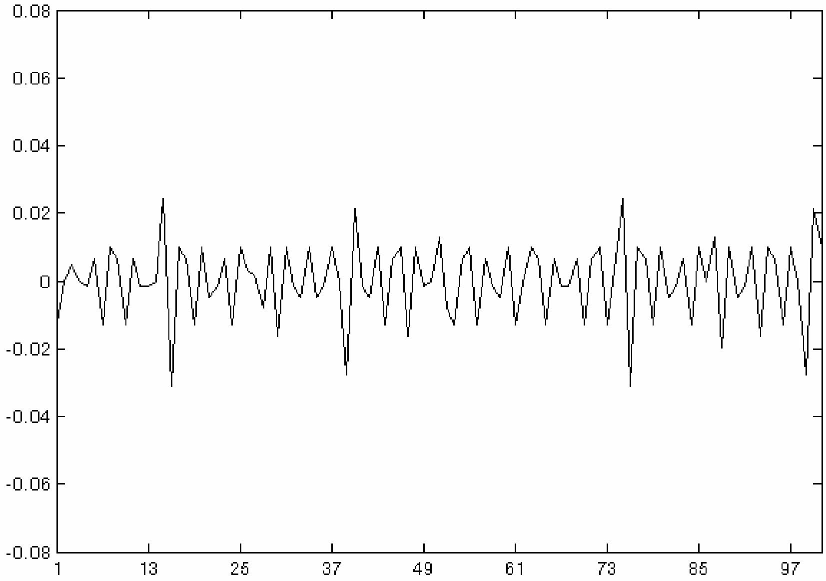


Fig 6.1.6 GLOBAL DEMAND: Irregular Component

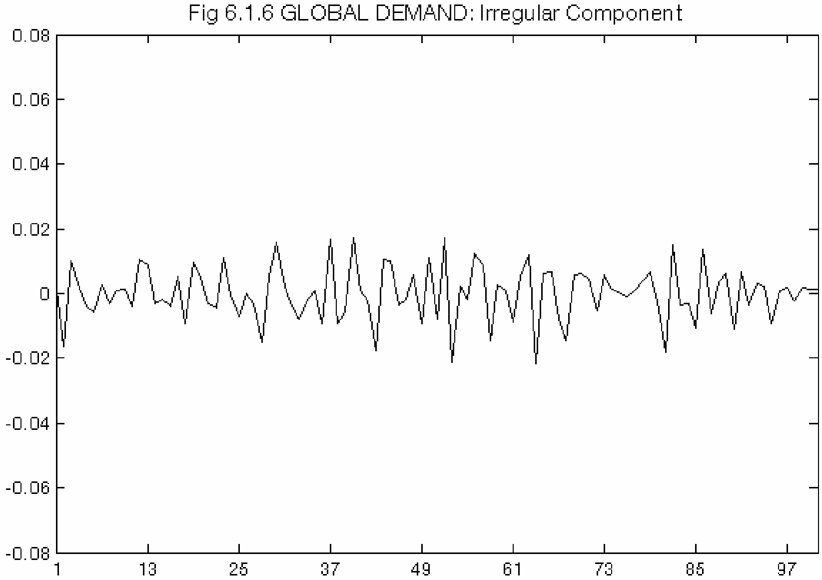
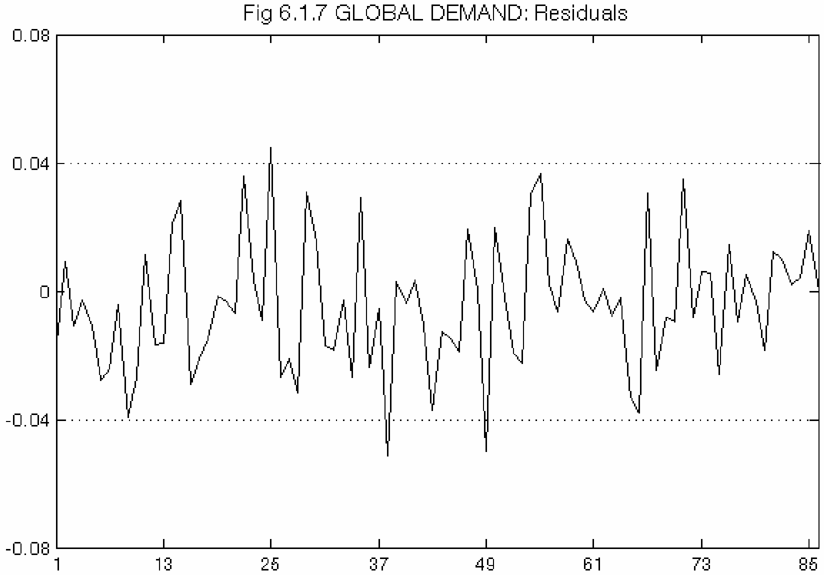


Fig 6.1.7 GLOBAL DEMAND: Residuals



None of the information and diagnostics contained in the matrices already mentioned flags a possible problem. I will use this example to illustrate additional diagnostics and tools that can be of help. (Some are already available in the programs; others will be available in future versions.)

Out-of-Sample Forecast test

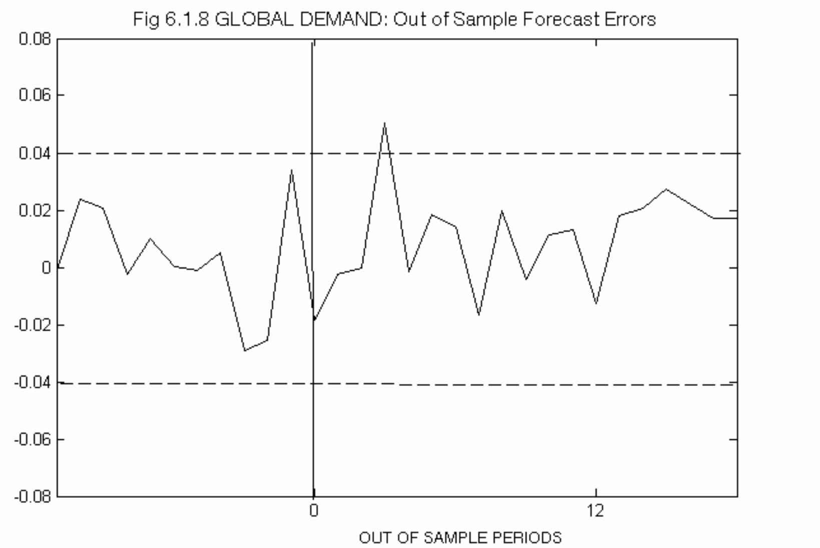
The last 18 observations are removed from the series, and automatic testing for the log/level transformation, automatic model identification (AMI), automatic outlier detection and correction (AODC), and automatic test for TD and EE are performed on the series with 83 observations. The model consisting of (6.1) and (6.2) is identified with –as before- TD and EE, but no outliers.

Then, with this model fixed and no reestimation performed, one-period-ahead forecasts are sequentially computed for the 18 additional periods. In this way, 18 out-of-sample one-period-ahead forecast errors are obtained (see Figure 6.1.8), and their variance is compared to the in-sample residual variance. This exercise implies the following input specification:

NBACK = -18
LAM = -1, ITRAD = -2, IEAST = -1, IATIP = 1, INIC = 3,
IDIF = 3

(Notice that, as explained in the TSW Manual, the out-of-sample test requires, at present, specification of the full set of parameters implied by the configuration RSA = 4.)

The out-of-sample forecast error variance is $.26\,(10^{-3})$, while the in-sample variance is $.47\,(10^{-3})$. Therefore, the model clearly passes the forecast test.



Two **additional diagnostics** that will be available in future versions of TRAMO-SEATS are the following:

(1) **Friedman-Kendall-Ord non-parametric test for detecting seasonality** in the regularly differenced series (Kendall and Ord, 1990). For Series 1 the test statistics, distributed as a Chi-Square (11), under the null hypothesis of no-seasonality, is equal to 61.2, strongly evidencing the presence of seasonality.

(2) **Model Stability Test**, whereby the model identified by TRAMO is used to filter the first and second half of the series. First, a test for the equality of the two means is performed. The ratio of the residual variances can be (roughly) compared to an F distribution. For Series 1, the stability check is comfortably passed.

Additional functions mentioned in Subsection 5.2.f. are displayed next.

Figure 6.1.9 shows the **Phase Delay Function** of the asymmetric concurrent filter for the trend-cycle component and SA series (see Findley and Martin, 2006). Only the frequencies ranging from 0 to the first (fundamental) seasonal frequency (one cycle per year) is presented. Phase effects for high frequency movements are of little interest.

As should be expected, the additional smoothing implied by the trend-cycle increases the phase effect. Still the effect is moderate: as shown in the figure, for the range of cyclical frequencies (comprising cycles with periods between 2 and 16 years) the phase delay goes from .96 months to .56 months. For the SA series, the phase delay is small, varying between .43 months for the 2-year and .22 for the 16-year cycles.

Figures 6.1.10 and 6.1.11 exhibit the **Squared Gain Functions** of the asymmetric concurrent filters and compares them to the Squared Gain Functions of the final (historical) filter, for the trend-cycle and SA series. For the trend-cycle, the final estimator is seen to basically remove noise from the preliminary estimator. For the SA series, the distorsion induced by the asymmetric filter is moderate.

Fig 6.1.9 GLOBAL DEMAND:
Phase Delay of Concurrent Trend filter and SA filter

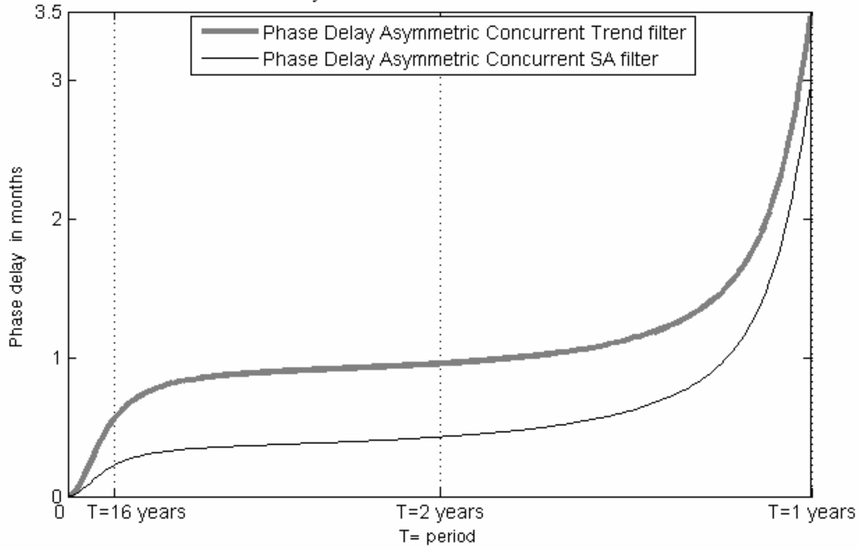


Fig 6.1.10 GLOBAL DEMAND: Squared Gain of Trend Filter:
Concurrent and Historical

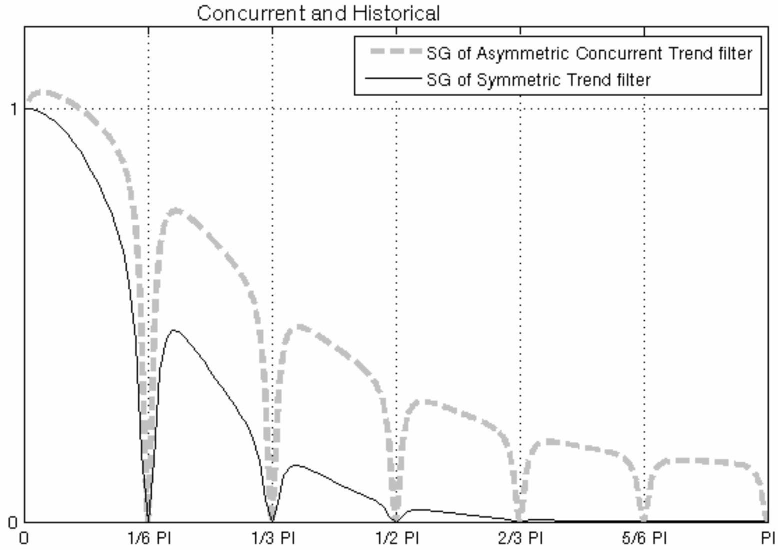
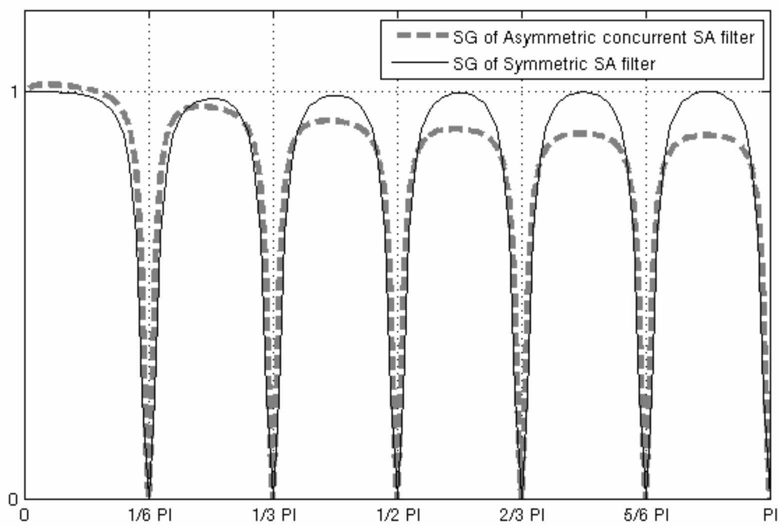


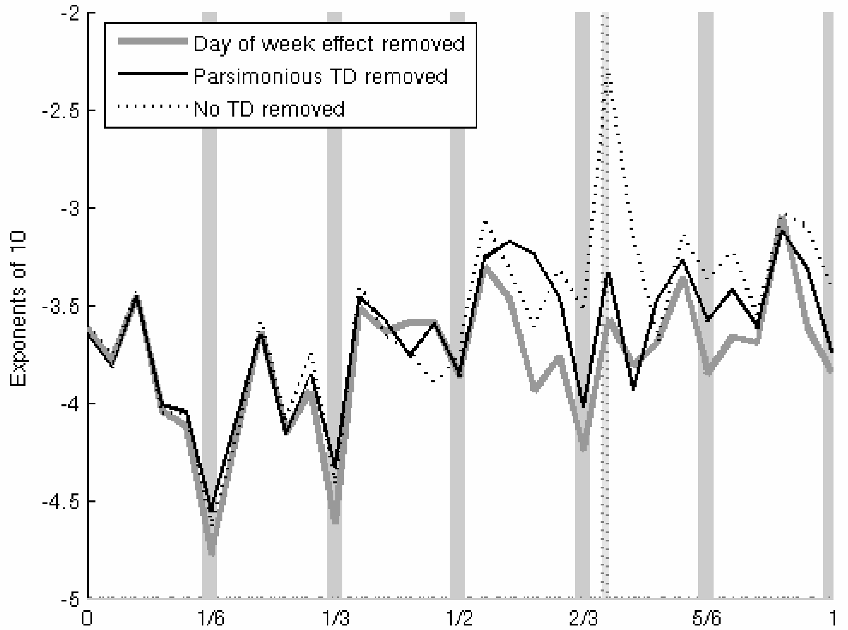
Fig 6.1.11 GLOBAL DEMAND: Squared Gain of (Diff) SA SERIES FILTER:
Concurrent and Historical



Spectral diagnostics to assess the presence of seasonality or Trading Day effects in the (differenced) SA series and model residuals (in the line of McElroy and Holan, 2005, and Soukup and Findley, 1999) are presented in figures 6.1.12 to 6.1.15. The TD frequency is represented by a vertical dotted line at the frequency $\omega = 0.6964\,\pi$. The grey thick vertical lines correspond to the seasonal frequencies.SEATS offers two spectral estimates: the parametric AR(30) spectrum of X12 ARIMA, and the non-parametric Tukey spectrum (with windows computed with m = 60). Both are seen to yield results that are in rough agreement. The AR(30) spectrum tends to display more volatility, with more (and more pronounced) peaks and throughs; this makes the peaks more discernible, although it may also induce a larger number of spurious peaks, damaging identification of the relevant ones. Further, while the Tuckey spectrum with m = 60 computes the spectrum for the exact seasonal and TD frequencies, the AR(30) spectrum on occasion displays some imprecision around these frequencies (see, for example, figure 6.1.15), possibly due to the variability of the AR coefficients estimates. As a consequence, it seems advisable to consider the information provided by the two spectral estimators.

Each of the four figures present three spectra: One (small dots) does not have the TD effect removed; one (black line) has the TD effect removed with the parsimonious specification (ITRAD = 1); and one (thick grey line) has the TD effect removed with the full day-of-week specification (ITRAD = 6). All three share the same $(0\ 1\ 1)(0\ 1\ 1)_{12}$ ARIMA model in the logs, with no mean and no outliers, and with EE removed.

Fig 6.1.12 GLOBAL DEMAND: Tukey Spectrum; Diff SA Series



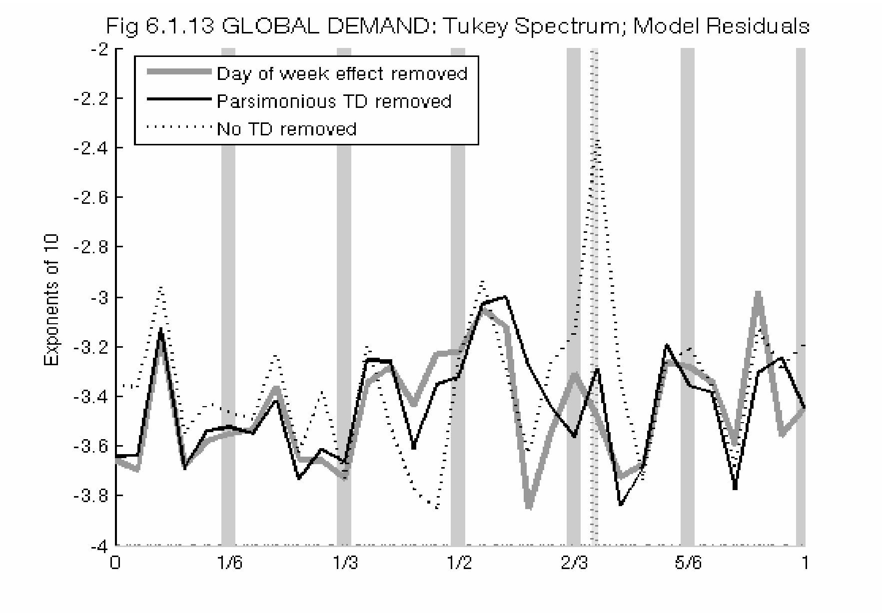


Fig 6.1.13 GLOBAL DEMAND: Tukey Spectrum; Model Residuals
Day of week effect removed
Parsimonious TD removed
No TD removed
Exponents of 10
-2
-2.2
-2.4
-2.6
-2.8
-3
-3.2
-3.4
-3.6
-3.8
-4
0
1/6
1/3
1/2
2/3
5/6
1

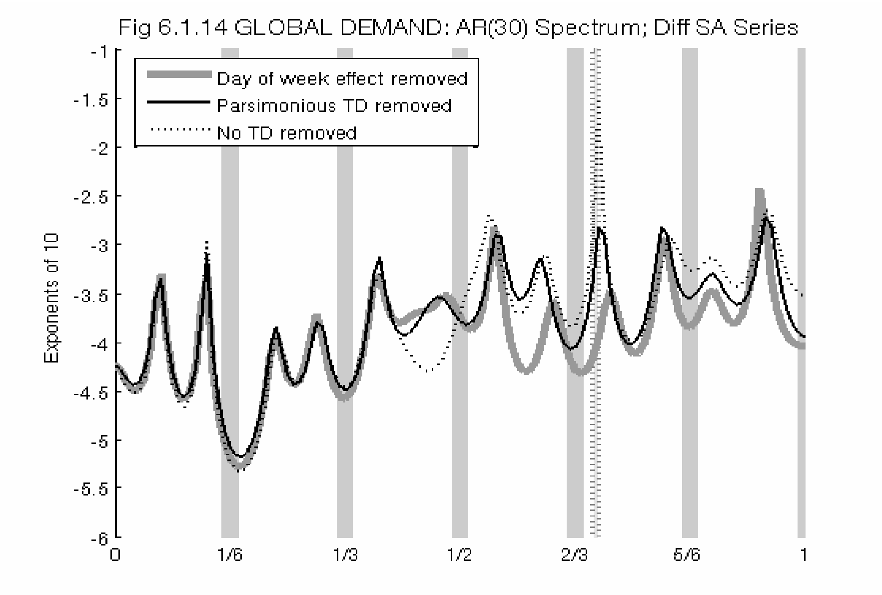


Fig 6.1.14 GLOBAL DEMAND: AR(30) Spectrum; Diff SA Series
Day of week effect removed
Parsimonious TD removed
No TD removed
Exponents of 10
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
-5
-5.5
-6
0
1/6
1/3
1/2
2/3
5/6
1

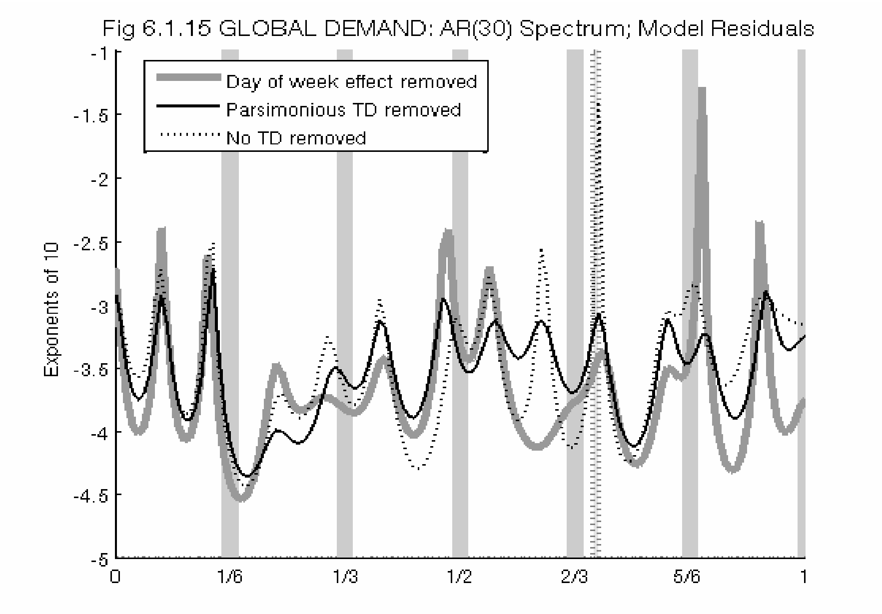


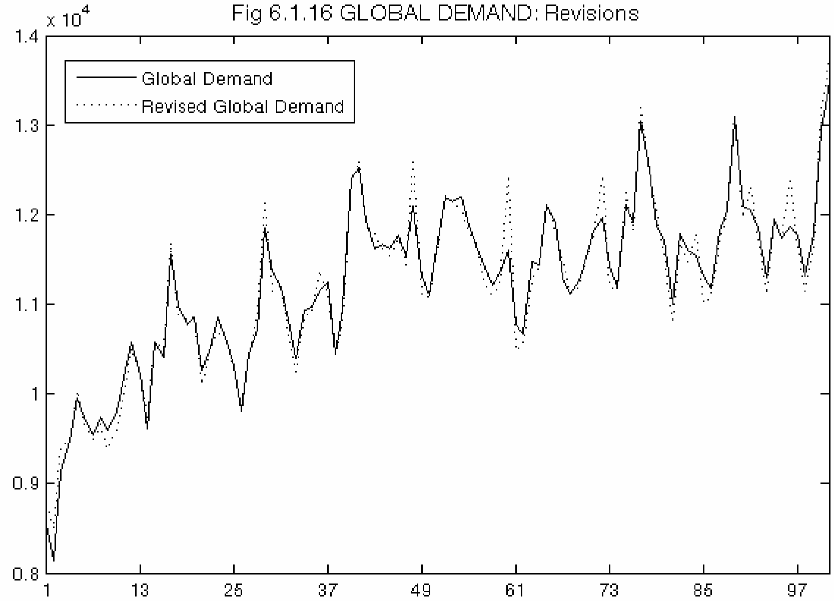
Fig 6.1.15 GLOBAL DEMAND: AR(30) Spectrum; Model Residuals
Day of week effect removed
Parsimonious TD removed
No TD removed
Exponents of 10
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
-5
0
1/6
1/3
1/2
2/3
5/6
1

All four spectra convey the same basic message. No residual seasonality is found (as evidenced by the dips around the seasonal frequencies). The series contains an important TD effect, which is considerably reduced (though not completely removed) with the parsimonious specification, and made practically negligible when different day-of-week effects are considered. Nevertheless, of the 6 TD coefficients, only one is found significant and the model BIC deteriorates.

Thus the choice seems to be between a model with a mild residual TD effect and a model with some parameter instability.

Comparison of the out-of-sample forecasting performance can be seen to be, in this case, of little help. Looking at the extended series (Figure 6.1.16), the revisions are moderate, although they do affect seasonality. The option ITRAD = 6 yields now a clearly significant TD coefficient, and the non-parsimonious specification would seem preferable. Of course, at the time of observation 101, future revisions were not known, and the option RSA = 4 would have possibly seemed the most reasonable choice.

Fig 6.1.16 GLOBAL DEMAND: Revisions



6.2 SERIES 2 : **DOMESTIC DEMAND; the Choice of a Model: The Gain from Parsimony and Use of the SEATS output.**

RSA = 4 → The results of the TRAMO and SEATS matrices flag no problem, and the model is similar to that of series 1: (0 1 1) (0 1 1) + TD(1) + EE, with no mean and no outliers, for the logs.

Figure 6.2.1 shows the two estimators of the spectrum of the differenced SA series. As before, both are in broad agreement, with the AR(30) spectrum displaying more -and more pronounced- peaks. Seasonality has been properly removed, but the figure evidences a moderate peak for the TD frequency, which disappears when the automatic option RSA = 5 (pretesting for a separate variable for each day-of-week effect) is employed. Figure 6.2.2 and 6.2.3 present the TD spectral peak in the AR(30) and Tukey spectra when there is no TD removal, and when it is removed with the parsimonious (working/nonworking day) and non-parsimonious (day-of-week) specifications.

The two options RSA = 4 and 5 yield the same type of model for the series, except for the TD specification. When RSA = 5, TD removal is more complete, at the cost of adding 5 more parameters to the model. Besides,

BIC (RSA = 4) = -7.224

BIC (RSA = 5) = -7.258

And hence the BIC for the 6 variable TD specification is (slightly) smaller. Is this specification preferable?

One would be tempted to answer "yes", yet the example may illustrate the possible gains from **parsimony** because, while RSA = 4 models 88 observations (101 – order of differencing) with 4 parameters, RSA = 5 does it with 9.

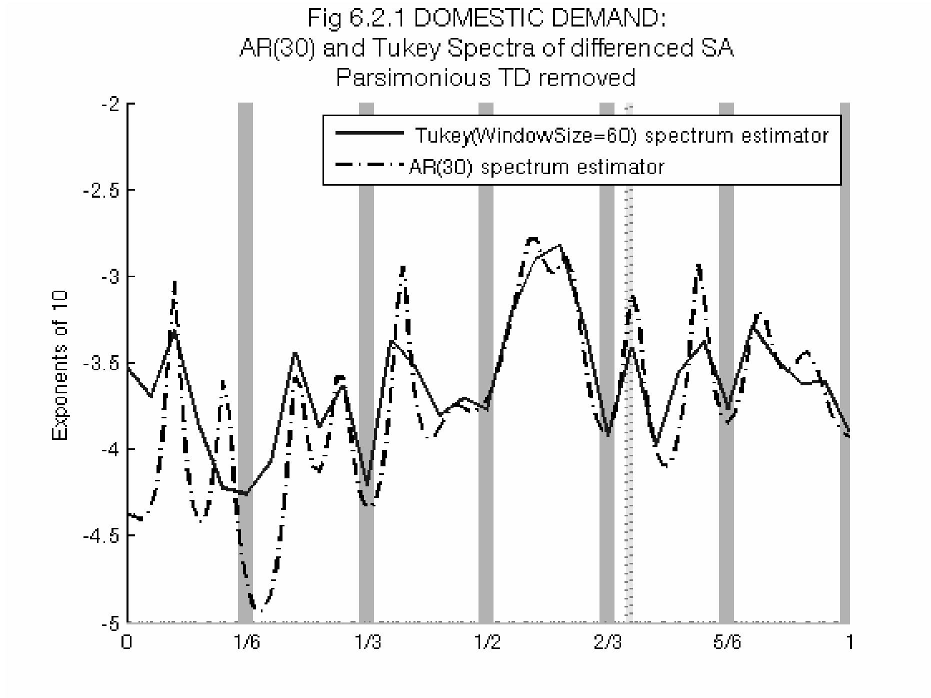


Fig 6.2.1 DOMESTIC DEMAND:
AR(30) and Tukey Spectra of differenced SA
Parsimonious TD removed
Tukey(WindowSize=60) spectrum estimator
AR(30) spectrum estimator
Exponents of 10
-2
-2.5
-3
-3.5
-4
-4.5
-5
0
1/6
1/3
1/2
2/3
5/6
1

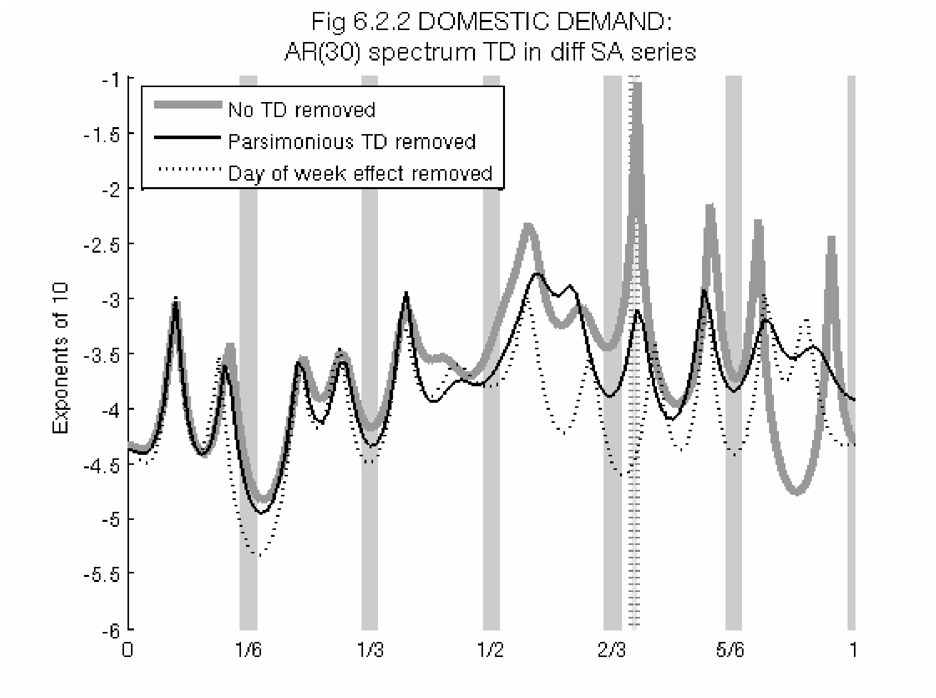
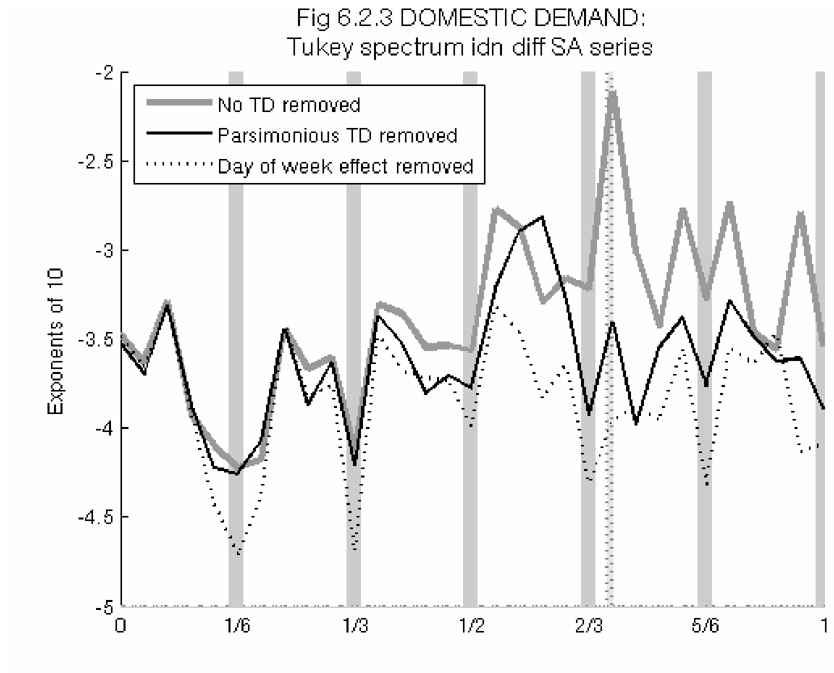


Fig 6.2.2 DOMESTIC DEMAND:
AR(30) spectrum TD in diff SA series
No TD removed
Parsimonious TD removed
Day of week effect removed
Exponents of 10
-1
-1.5
-2
-2.5
-3
-3.5
-4
-4.5
-5
-5.5
-6
0
1/6
1/3
1/2
2/3
5/6
1



Some Remarks on the Choice of a Model: Use of the SEATS Output

Figures 6.2.4 to 6.2.6 display the calendar adjustment, trend-cycle and seasonal components produced by the two automatic options. The differences are rather small. The trend-cycle obtained with RSA = 4 is slightly smoother, and the seasonal components are close although the one for RSA = 4 is marginally more stable. The summary output from SEATS (see the matrix "Parameters I") yields the following information on the decomposition.

SD of:	Component	RSA = 4	RSA = 5	Comparison
Component innovations	TC SC	.0076 .0048	.0081 .0063	Components more stable for RSA = 4
Estimation error in concurrent estimator	TC SA	.0136 .0113	.0142 .0131	Estimation error smaller for RSA = 4
Revision in concurrent est.	TC SA	.0099 .0081	.0105 .0095	Revision smaller for RSA = 4

Although the differences are small, RSA = 4 provides a decomposition with more stable trend-cycle and seasonal components, that can be estimated with more precision, and are subject to smaller revision. Thus SEATS results would point towards the parsimonious TD specification.

The decomposition achieved with RSA = 4 is also preferable on other accounts. Switching the interest from decomposing the series to forecasting, Figure 6.2.7 compares the forecast functions, together with the 95% probability intervals, and RSA = 4 provides more precise forecasts. This better forecasting performance is supported by the following exercise.

Consider the extended Series 2, with 145 observations. (As seen in Figure 6.2.8, although not trivial, the revisions are moderate.)

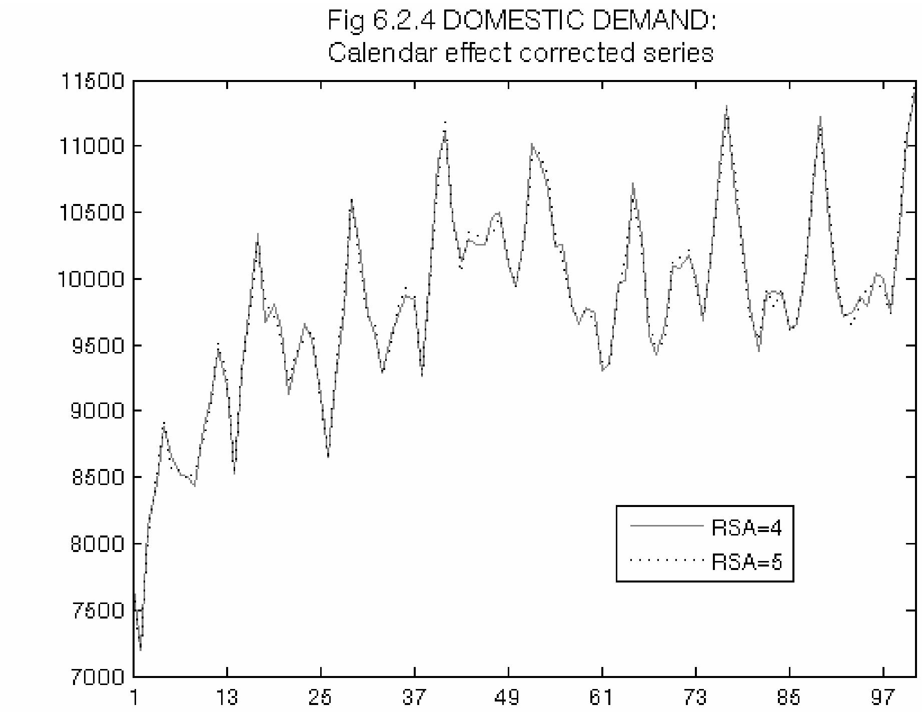


Fig 6.2.5 DOMESTIC DEMAND:
Trend-Cycle

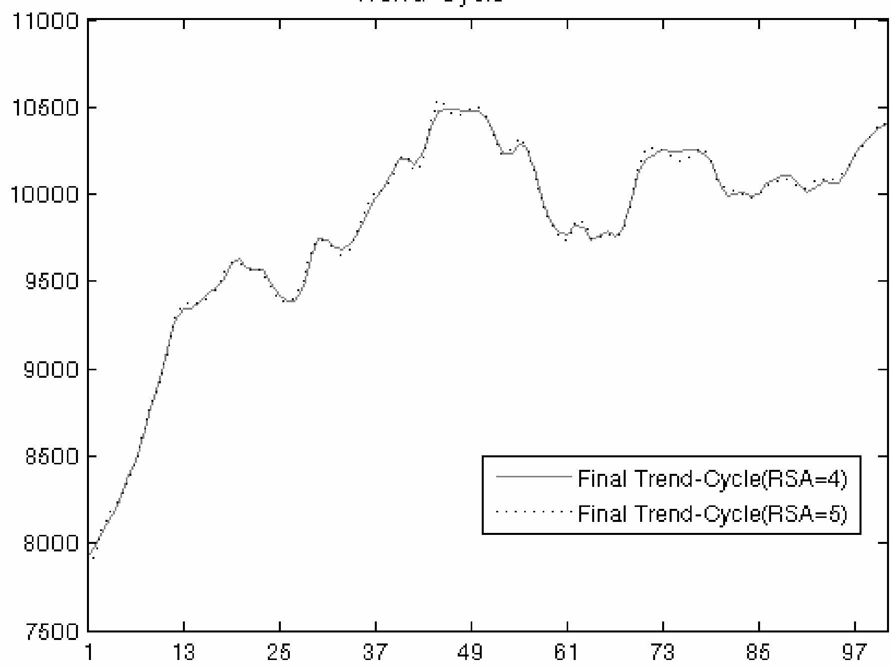
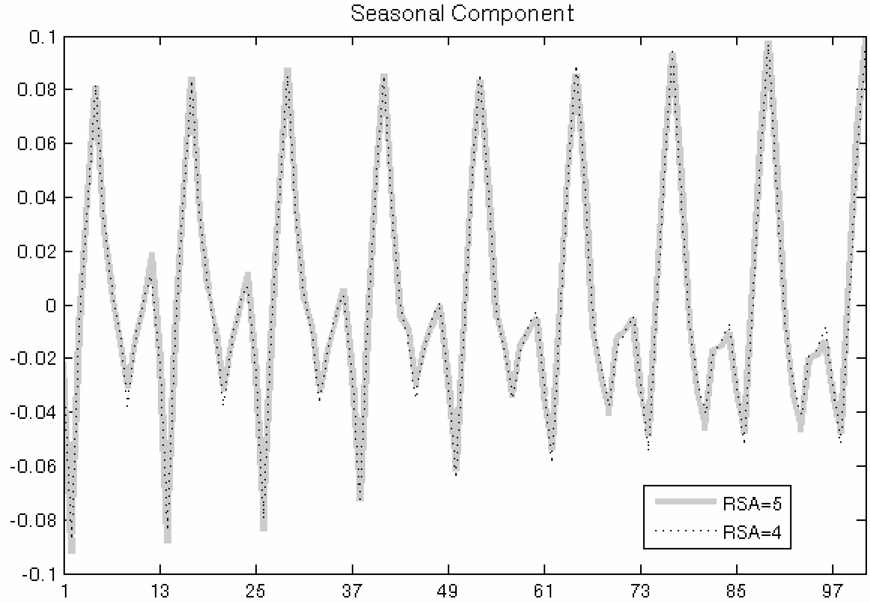


Fig 6.2.6 DOMESTIC DEMAND:
Seasonal Component



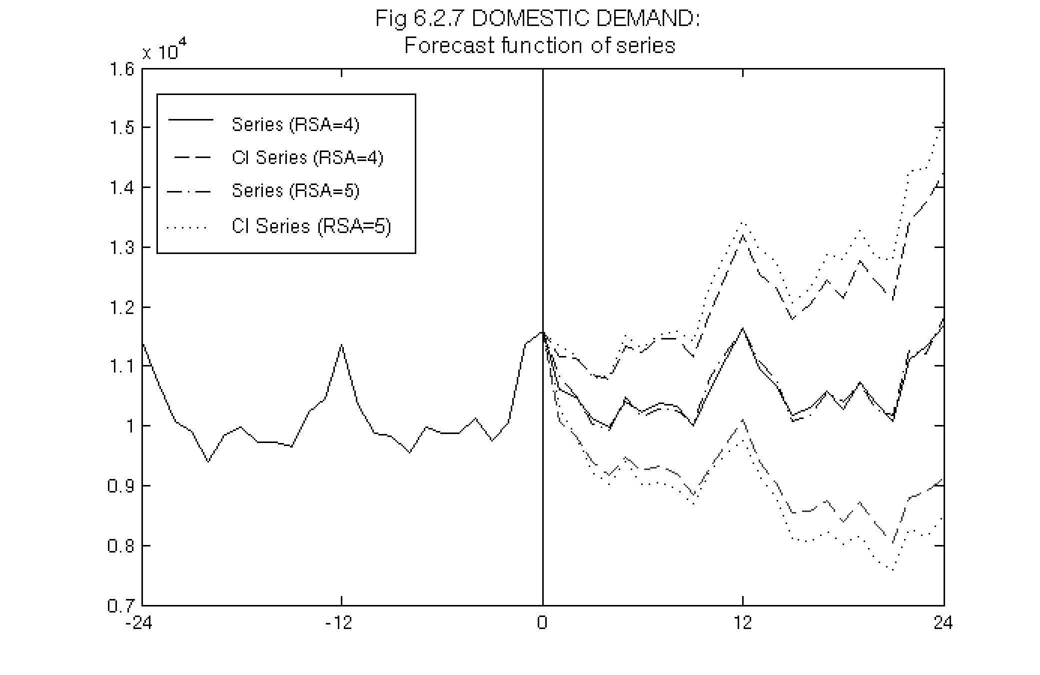


Fig 6.2.7 DOMESTIC DEMAND:
Forecast function of series
x 10^4
Series (RSA=4)
CI Series (RSA=4)
Series (RSA=5)
CI Series (RSA=5)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0.7
-24
-12
0
12
24

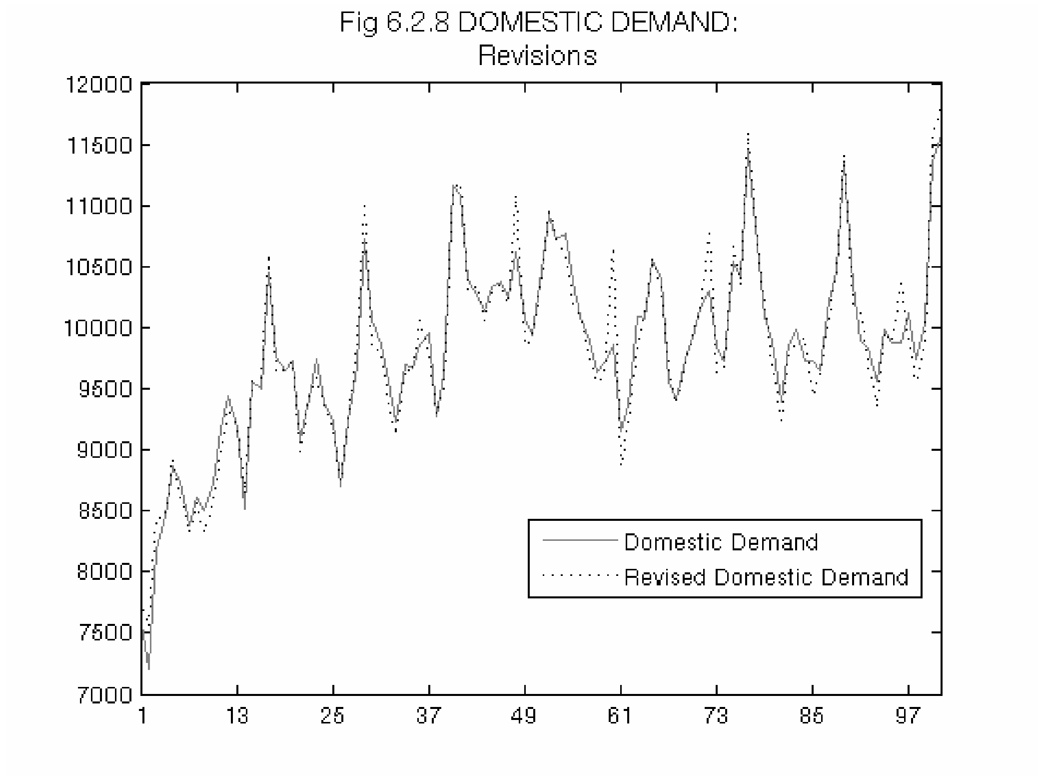


Fig 6.2.8 DOMESTIC DEMAND:
Revisions
12000
11500
11000
10500
10000
9500
9000
8500
8000
7500
7000
1
13
25
37
49
61
73
85
97
Domestic Demand
Revised Domestic Demand

An out-of-sample forecast comparison is performed, with the specifications fixed to those obtained with RSA = 4 and 5 for the shorter series (no re-identification is done). It is obtained that the variances of the 1 period-ahead forecast error for the last 44 observations are:

$$\text{Var (RSA = 4)} = .317\ (10^{-3}) < \text{Var (RSA = 5)} = .562\ (10^{-3}).$$

(Both are smaller than the two, relatively close, in-sample variances.)

Therefore, even at the cost of some TD misspecification, the more stable components and their more precise estimators are seen to be associated, over a relatively long period, with a better overall forecasting performance.

Hence one may well prefer the RSA = 4 option. Nevertheless, as the number of observation increases, stability of the less parsimonious model will also increase and, at some point, the specification obtained with RSA = 5 would likely become the best choice.

6.3 SERIES 3 : PRIVATE CONSUMPTION; Short-term Monitoring and Assessment.

RSA = 4 yields results that, according to the TRAMO and SEATS matrices, can be comfortably accepted.

The model obtained with the automatic (parsimonious TD) option is a (0 1 0) $(0\ 1\ 1)_{12}$ model, with no mean and in the logs, with TD, EE and two outliers (AO and TC). Series 1, 2, and 3 are inter-related aggregate demand-type series, and accordingly their structure turns out to be somewhat similar, with similar ARIMA models and similar ambiguity concerning the specification of the TD effect. A discussion similar to the one for the two previous cases therefore applies, and the results of the automatic RSA = 4 option are maintained. The spectral diagnostics point towards some possible, though small, residual TD effect, but imposing a 6-variable TD specification does not provide a better model. Although the small TD spectral peak becomes negligible, seasonality becomes more erratic, and the instability of the TD parameter estimates damages out-of-sample forecasts. (And, as before, as more observations become available, the 6-variable TD may become a more appropriate specification.)

The next figures illustrate the decomposition of Series 3. Comparison of figures 6.3.1 and 6.3.2 evidences the dominance of the seasonal variations in the short-term evolution of the series. (Notice that Figure 6.1.2 indicates that Global Demand displays much stronger cyclical oscillations than Private Consumption.) Figures 6.3.3 and 6.3.4 show a relatively stable seasonal component, which can be forecast with considerable precision. The calendar effect is displayed in Figure 6.3.5; as is most often the case, its magnitude is small when compared to the seasonal component. Figure 6.3.6 exhibits the (small) irregular component, and figure 6.3.7 the model residuals. Two series of residuals are shown. One is the white-noise residuals produced by TRAMO, which are output of the Kalman filter, equal in number to the number of observations in the series minus the differencing order and minus the degrees of freedom lost in estimation (see Gómez and Maravall, 1994). The other is the "extended residuals" produced by SEATS, which span the full observation period. It is seen how the extension has practically no effect on the white-noise residuals. The residuals are well-behaved and, compared to the irregular component of Figure 6.3.6, evidence the relative importance of the seasonal and trend-cycle innovations when forecasting the series.

Figure 6.3.1 PRIVATE CONSUMPTION: Original series and SA series

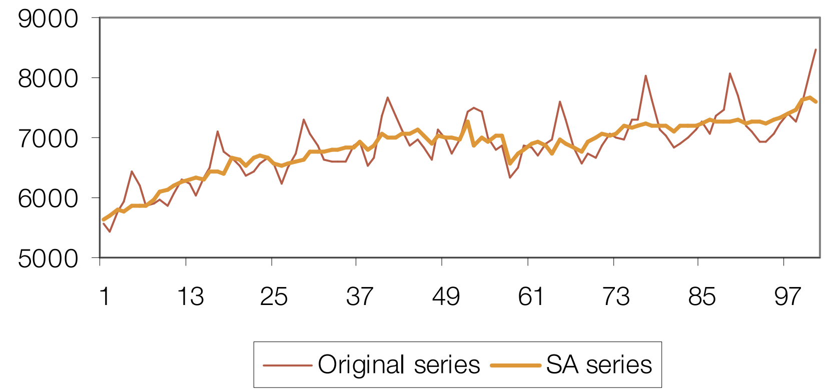


Figure 6.3.2 PRIVATE CONSUMPTION: SA series and Trend-Cycle

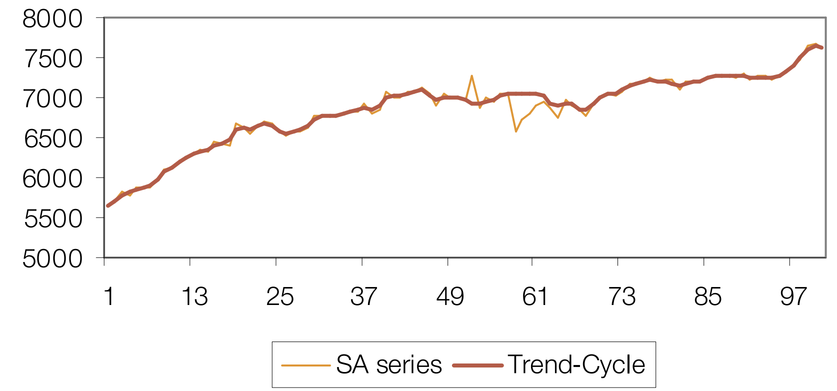


Figure 6.3.3 PRIVATE CONSUMPTION: Seasonal component

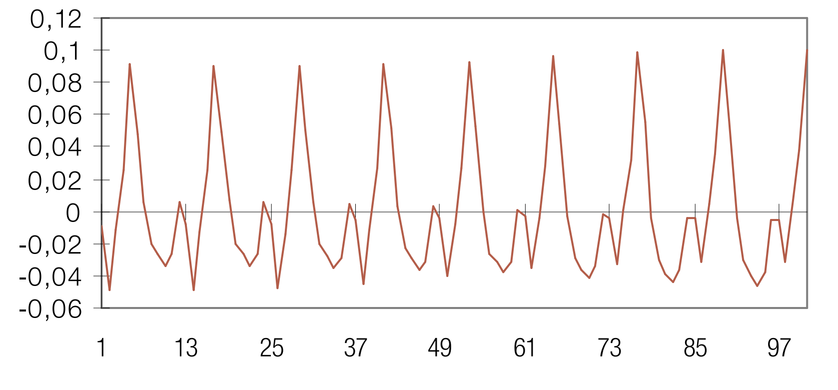
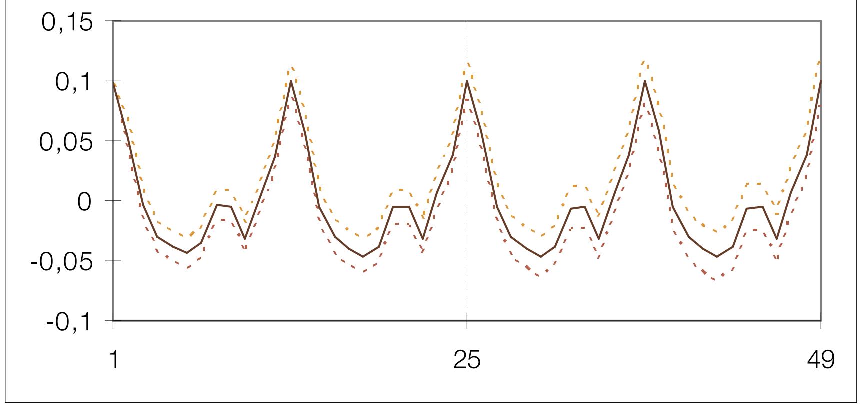


Figure 6.3.4 PRIVATE CONSUMPTION: Forecast of Seasonal Component



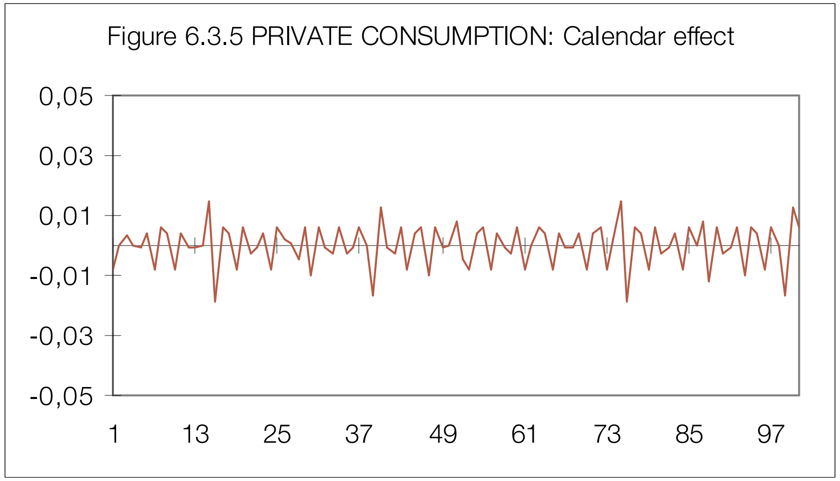


Figure 6.3.5 PRIVATE CONSUMPTION: Calendar effect
0,05
0,03
0,01
-0,01
-0,03
-0,05
1
13
25
37
49
61
73
85
97

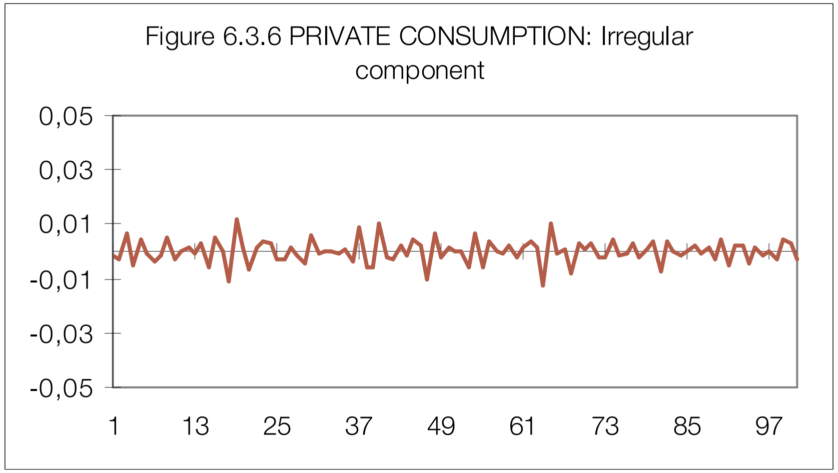


Figure 6.3.6 PRIVATE CONSUMPTION: Irregular component
0,05
0,03
0,01
-0,01
-0,03
-0,05
1
13
25
37
49
61
73
85
97

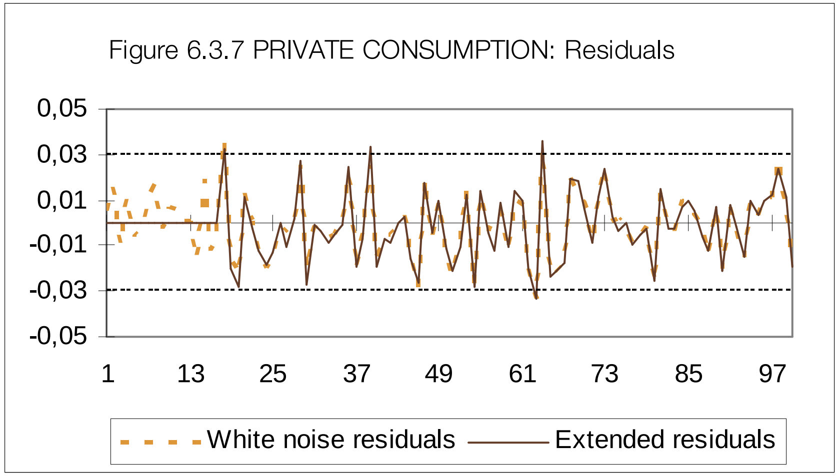


Figure 6.3.7 PRIVATE CONSUMPTION: Residuals
0,05
0,03
0,01
-0,01
-0,03
-0,05
1
13
25
37
49
61
73
85
97
White noise residuals
Extended residuals

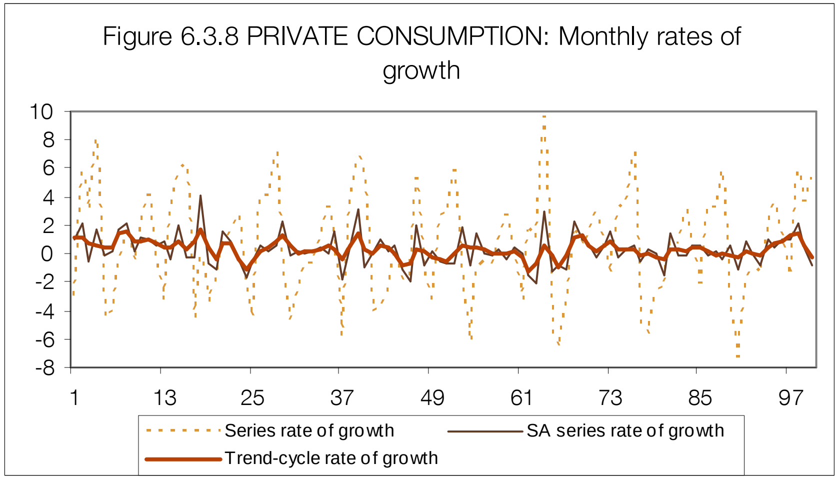


Figure 6.3.8 PRIVATE CONSUMPTION: Monthly rates of growth
10
8
6
4
2
0
-2
-4
-6
-8
1
13
25
37
49
61
73
85
97
Series rate of growth
SA series rate of growth
Trend-cycle rate of growth

For short-term monitoring, rates-of-growth (RG) are usually of more use to the analyst. Figure 6.3.8 plots the monthly RG of the original and SA series, and of the trend-cycle. Based on the results obtained with RSA = 4, I use the Private Consumption series to illustrate an application of TRAMO-SEATS to short-term monitoring. (This output will also appear in future versions; at present, an Excel macro that computes it from the program's output can be made available upon request.) The output presents a battery of rates-of-growth of the original series, SA series, and trend-cycle component, useful for assessing the present situation and for short-term forecasting. It consists of the following.

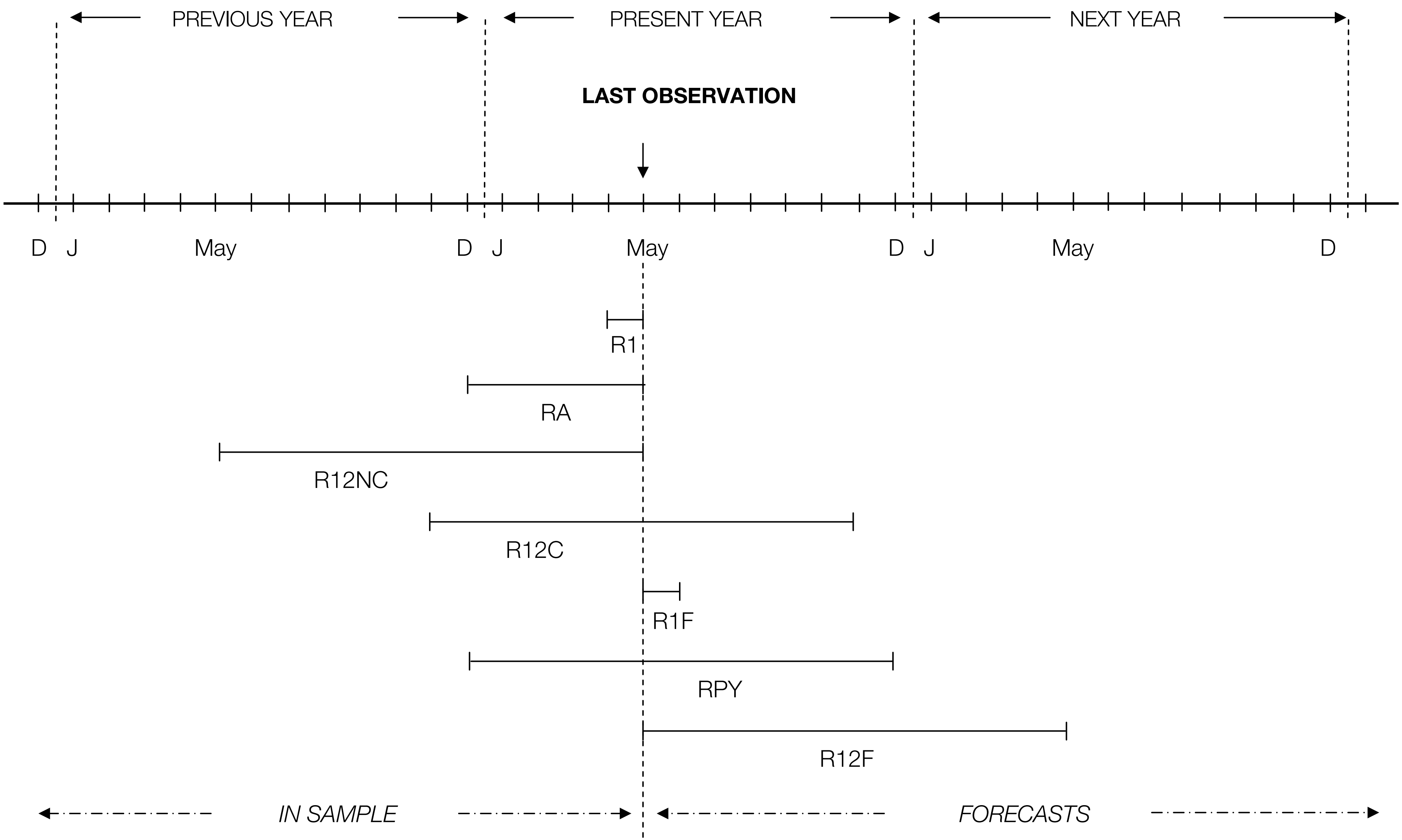
SHORT-TERM ASSESSMENT

Rates-of-growth (RG) considered:

Last observed month: MAY.

1. **R1**: RG for **last month** = $\left(\frac{z_t}{z_{t-1}} - 1 \right) 100$.
2. **RA**: **Accumulated** RG during last year (over first 5 months) = $\left(\frac{z_t}{z_{t-5}} - 1 \right) 100$.
3. **R12NC**: (Annual RG not centered) RG over the **last 12 months** = $\left(\frac{z_t}{z_{t-12}} - 1 \right) 100$.
4. **R12C**: (Annual RG centered) **Present rate of annual growth** (last 6 observed periods and next 6 forecasts) = $\left(\frac{\hat{z}_t(6)}{z_{t-6}} - 1 \right) 100$.
5. **R1F**: Forecast of RG for **next month** = $\left(\frac{\hat{z}_t(1)}{z_t} - 1 \right) 100$.
6. **RPY**: RG for **present year** = $\left(\frac{\hat{z}_t(7)}{z_{t-5}} - 1 \right) 100$.
7. **R12F**: RG for the **next 12-month** period = $\left(\frac{\hat{z}_t(12)}{z_t} - 1 \right) 100$.

$\hat{z}_t(j)$: j-periods ahead forecast of variable z made at period t.


PREVIOUS YEAR
PRESENT YEAR
NEXT YEAR
LAST OBSERVATION
D J May D J May D J May D
R1
RA
R12NC
R12C
R1F
RPY
R12F
IN SAMPLE
FORECASTS

RATES OF GROWTH (in %)

1. Recent Assessment: Series 3 (Private Consumption)

Rate of growth	Original series	Trend-cycle	SA series
Last month (**R1**)	**4.82**	**-0.21**	**-0.80**
	---	(0.31)	(0.46)
Accumulated in present year (**RA**)	**17.23**	**4.14**	**3.99**
	---	(0.72)	(0.74)
Growth for the last 12 months (**R12NC**)	**5.05**	**4.99**	**4.98**
	---	(0.23)	(0.20)
Present rate of annual growth, centered with forecasts (**R12C**)	**5.37**	**6.26**	**6.14**
	(2.87)	(2.62)	(2.78)

2. Forecasts

One-month ahead (**R1F**)	**-5.4**	**0.00**	**0.27**
	(1.4)	(0.45)	(1.00)
Present year (**RPY**)	**6.60**	**5.77**	**5.91**
	(3.1)	(2.8)	(3.0)
Next 12 months (**R12F**)	**2.45**	**2.89**	**3.17**
	(3.9)	(3.6)	(3.8)

In parenthesis: SD of revision error.

Note: In this table, because the "true" SA series and Trend-cycle will never be observed, concern is with the distance between their preliminary estimators and the historical ones (that will remain as final). Thus theoretical estimation error in these historical estimators is of little applied interest and, in the table, ignored.

Some Comments on the Rate-of-Growth Output

Original series can be quite misleading.

Strong difference in seasonal effect between first and second half of the year (growth in 2nd half will be considerably smaller).

Growth for last year $\cong$ 5%.

This rate is being maintained (perhaps slightly higher) at present, so that growth for present year can be expected to be in the order of 6%. But for the next year, forecasts indicate a slowing down.

> Growth $\cong$ 0 for last month.
>
> Growth $\cong$ 0 forecasted for next month.
>
> Difference between the accumulated rate in the present year (RA), and the expected rate for the year (RPY) implies that most of the growth for present year has already been achieved in the first 5 months.

Forecast for next 12 months: Growth $\cong$ 3%, but, considering the forecast error, it is not significantly different from zero, nor from 6.

Standard deviations are computed in SEATS using linear approximations, and under the standard Box-Jenkins assumption of an infinite past (see Section 8.9 in Gómez and Maravall, 2001), Martin and Bell (2002), and McElroy and Gagnon (2006), have shown that the SE obtained with this later assumption can be misleading for short time series and for some models. In this example, however, the distortions are, in all cases, moderate.

6.4 SERIES 4 : **PUBLIC CONSUMPTION: Non-normality; Modifying the Sample Period.**

This is a problematic series due to the high values of the diagnostics related to **non-normality/non-linearity**. In the matrix "Fitted Model" one finds

N = 12.5 (> 6),

Q2 = 48 (> 36),

and there is also excess skewness and kurtosis.

The model obtained is a (2 0 0) $(0\ 1\ 1)_{12}$ model in the logs and with mean. The AR polynomial factorizes as $(1+.457B)(1-.609B)$, and hence the roots are of moderate size and induce relatively short-term oscillations in the SA series and trend-cycle component. TD is significant, although EE is not. One AO is detected.

Direct inspection of the series (Figure 3.4) shows very abnormal behaviour for the first year suggesting perhaps that the monthly series has been artificially extended backwards.

Removing this first year and considering the interval [13, 101], that is, setting RSA = 4, INT1 = 13, the diagnostics improve, but the number of outliers (6) is excessive.

Noticing that TD and EE are not detected a rare exception for the set, it seems worth it to check for underdetection. Imposing the two effects, it is found that

RSA = 3, ITRAD = 1, int1 = 13,

yields excellent results on all accounts.

The model is simplified to:

$$\nabla_{12} \log x_t = (1-.7B^{12})\, a_t + \mu + TD(1) + 1AO + 1TC \ .$$

TD is barely significant, yet its inclusion improves substantially the results. All diagnostics are passed, and in particular

N = 3 ,

Q2 = 26.9 ,

and skewness and kurtosis are now acceptable.

As seen in Figures 6.4.1 - 6.4.3, the decomposition provided by the new model is more attractive, in the sense that both the trend-cycle and seasonal components are now considerably more stable. Comparing the two trend-cycles, the drastic effect of simply removing the first year of (abnormal) data is somewhat shocking.

Figure 6.4.1 PUBLIC CONSUMPTION: Trend-cycle components

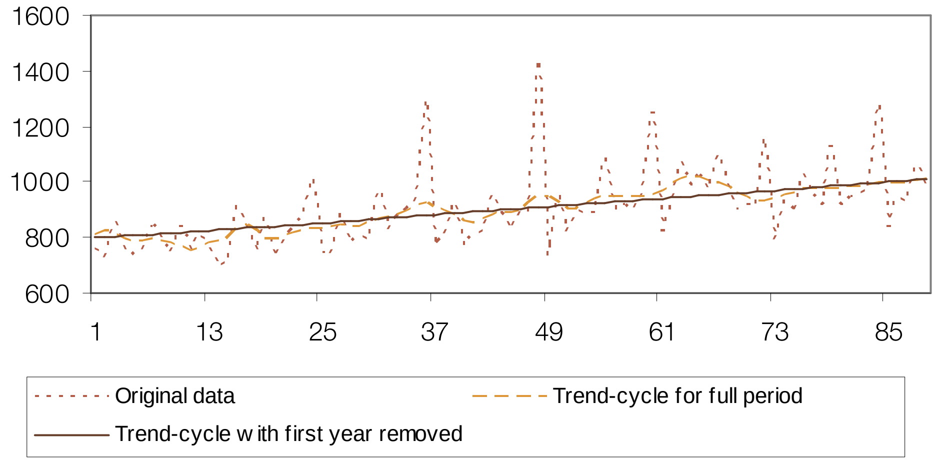


Figure 6.4.2 PUBLIC CONSUMPTION: Seasonal component;
(estimated for full sample)

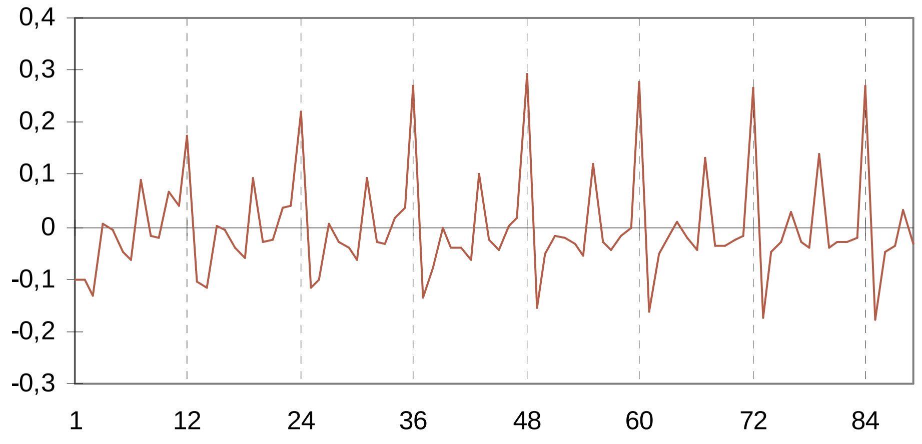
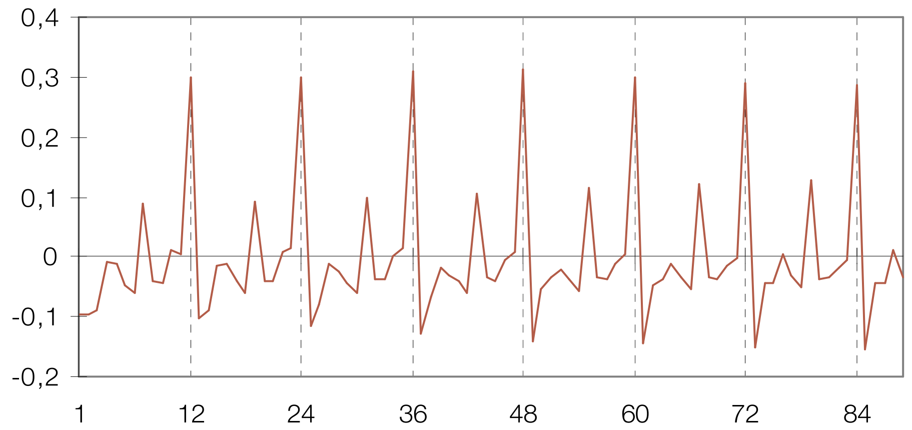


Figure 6.4.3 PUBLIC CONSUMPTION: Seasonal component;
first year has been removed



6.5 SERIES 5 : **GROSS DOMESTIC INVESTMENT: Non-random signs in residuals; transitory component.**

Mildly problematic: test of **randomness in signs of residuals** yields t = 2.39 .

The automatic option RSA = 4 is maintained, but noticing that no outliers are detected, the detection threshold is slightly lowered to VA = **3** .

The model, originally a

$(1\ 1\ 2)\ (0\ 1\ 1)_{12}$ + TD (1 var) + EE, in levels and with no outliers

becomes

$(2\ 1\ 0)\ (0\ 1\ 1)_{12}$ + TD (1 var) + EE + 1 TC outlier, in levels.

The AR (2) polynomial has a pair of complex conjugate roots with:

mod = .65

period = 3.35 months.

It produces, thus, (stationary) transitory movements for a frequency between the 2 and 3 times/year ones. It is captured in SEATS through a **transitory component**. Its model is the stationary ARMA (2,2) model

$$(1+.390B-.418B^2)\ c_t = (1+B)(1-.474B)\ a_{ct}\ ,$$

$$Var(a_{ct}) = .104\ \ Var(a_t)$$

Its spectrum is shown in Figure 6.5.1.

Figures 6.5.2 and 6.5.3 display:

Irregular component,

Transitory component.

From an applied point of view, both play a similar, erratic, role. The irregular component corresponds to purely white-noise behavior, while the transitory component corresponds to colored highly short-term behavior.

All diagnostics are now satisfactory, and hence the choice of input is: RSA = 4, VA = 3.

Figure 6.5.1 GROSS DOMESTIC INVESTMENT: Spectrum of Transitory Component

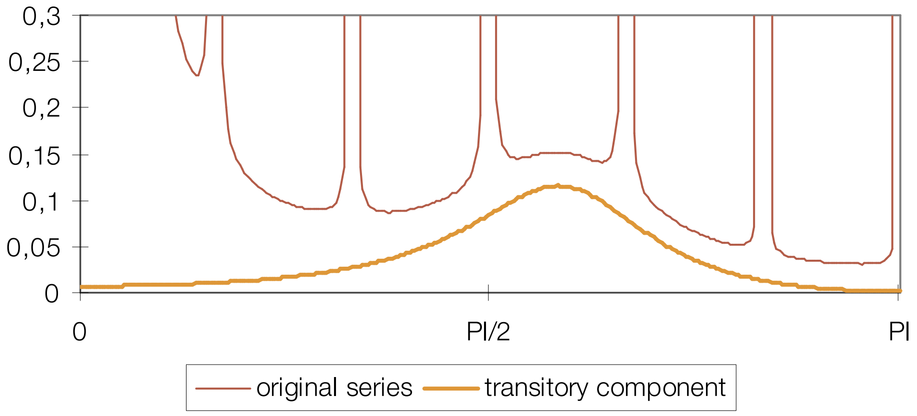


Figure 6.5.2 GROSS DOMESTIC INVESTMENT: Transitory Component

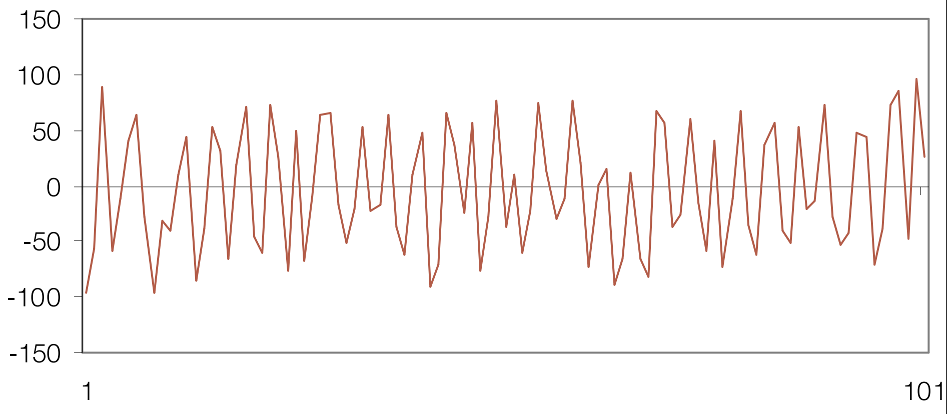
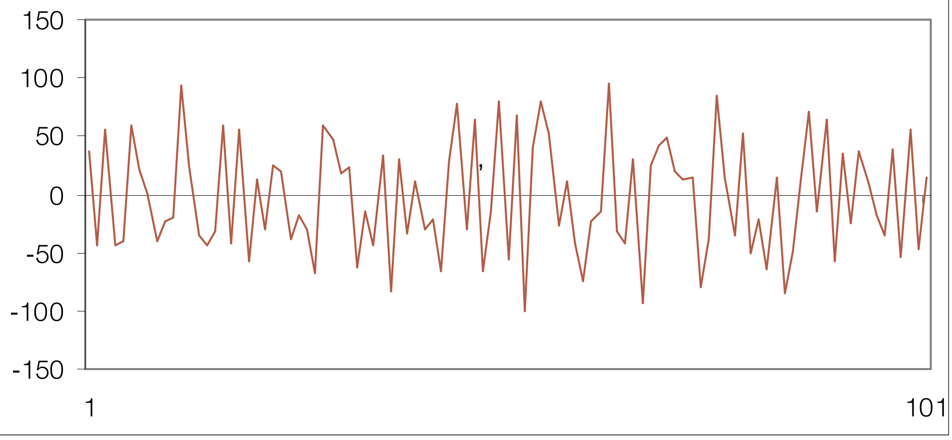


Figure 6.5.3 GROSS DOMESTIC INVESTMENT: Irregular Component



6.6 SERIES 6 : **FIXED GROSS INVESTMENT: Approximation to a Non-admissible decomposition.**

This series is also classified as problematic because the model identified by TRAMO does **not** accept an **admissible decomposition**.

The model is given by

$$(1-.92B)(1-.86B^{12})\ \log x_t = (1-.51B+.19B^2)(1-.52B^{12}) + \mu + TD(1) + 1LS\ .$$

Although stationary, both AR parameters are close to -1. The correlation between $\hat{\phi}_{12}\ (=-.86)$ and $\hat{\theta}_{12}\ (=-.52)$ is .9, so that lowering $\hat{\phi}_{12}$ towards -1 will also lower $\hat{\theta}_{12}$, and yield a more sensible seasonal component. Further, $\hat{\theta}_2\ (=-.19)$ is borderline significant; EE is not significant.

Direct inspection of the series (Figure 3.6) brings serious doubts about the appropriateness of the stationary specification.

SEATS automatically replaces the model with one that accepts an admissible decomposition.

Regular AR: $(1-.92B) \rightarrow \nabla$,

Seasonal AR: $(1-.86B^{12}) \rightarrow \nabla_{12}$,

and removes θ_2.

Results for the approximated model are OK. In fact, they are slightly better than for the original one.

The SEATS approximation is an Airline-type model, which suggests the use of the "bench mark" automatic procedure parameter RSA = 2 as an alternative input. The difference between the results obtained with the automatic approximation with RSA = 4 and the ones obtained with RSA = 2 is that, in the first case, the forecasts of the observed series and the linearized series are the ones obtained with the "(1,0,2) $(1,0,1)_{12} + \mu$" model, while in the second case they are obtained with the (0,1,1) $(0,1,1)_{12}$ model. Thus in both cases the ARIMA model in SEATS is the Airline model; TRAMO however uses different models, and hence the two preadjustments will in general differ.

Running Series 6 with RSA = 2, the results are good, but the number of outliers (4) is perhaps too high. Besides, EE (which is close to being significant) is not detected. Increasing the outlier detection threshold and imposing EE, that is, setting

RSA = 1, ITRAD = 1, IEAST = 1, VA = 3.3,

the results are very good, and improve upon those for RSA = 4 presented in the previous matrices of Section 5.1. Only one outlier (an AO) is detected, and EE is now significant.
When ITER = 0 (only the series, only one input specification) the results contained in the TRAMO matrices described in Section 5.1 are summarized into a one-page file, *summaryt.txt*; those in the SEATS matrices are summarized in the file *summarys.txt*. For Series 7, the two summary files are the following.

6. **Fixed Gross Investment**

NZ =101; PERIOD=01-1994/05-2002; MQ=12;

Input Parameters

mq=12 itrad= 1 ieast= 1 out= 0 rsa= 1 va= 3.300

Model Fit

Nz	Lam	Mean	P	D	Q	BP	BD	BQ	SE(res)	BIC	Q-val	N-test	SK(t)	KUR(t)	QS	Q2	RUNS
101	0	1	0	1	1	0	1	1	0.0586083	-5.43910	21.10	2.24	-0.20	1.48	0.	23.90	0.220

ARMA Parameters

PHI1	(t)	PHI2	(t)	PHI3	(t)	BPHI	(t)	TH1	(t)	TH2	(t)	TH3	(t)	BTH	(t)
-	(-)	-	(-)	-	(-)	-	(-)	-0.36691	(-3.4)	-	(-)	-	(-)	-0.60745	(-4.9)

Deterministic Effect (total)

TD	EE	#OUT	AO	TC	LS	REG	MO
1	1	1	1	0	0	0	0

Calendar Effect

TD1	(t)	TD2	(t)	TD3	(t)	TD4	(t)	TD5	(t)	TD6	(t)	LY	(t)	EE	(t)
0.006747	(4.9)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.04846	(-2.4)

Outliers

AO01(0201, 3.88)

Summary SEATS

6. **Fixed Gross Investment**

NZ =101; PERIOD=01-1994/05-2002; MQ=12;

Decomposition : General

Pread.	Model Changed	Approx. to NA	m	p	d	q	bp	bd	bq	SD(a)	Spectr. Factor	Check on ACF	Check on CCF	Determ. Comp. Modif. TC	S	U	Trans
Y	N	N	1	0	1	1	0	1	1	.5758E-01	0	0	0	N	Y	Y	N

Decomposition : Standard Errors

SD(innov) TC	S	Trans	U	SA	SE Est. (Conc.) TC	SA	SE Rev. (Conc.) TC	SA	SE : Rates of Growth SE T11 (One Period) TC	SA	SE T1Mq (Annual Centered) X	TC	SA
.1467E-01	.1204E-01	0.000	.3163E-01	.4694E-01	.3041E-01	.2618E-01	.2259E-01	.1868E-01	1.83	2.91	10.62	9.83	10.41

Decomposition : Properties

Convergence (in %) 1Y TC	SA	5Y TC	SA	Signif.Stoch. Season. (95%) Hist.	Prel.	Fore.	DAA TC	SA
73.0	38.1	96.3	91.6	5	4	3	0.37	0.11

Figure 6.6.1 and 6.6.2 present the seasonal components obtained with the final specification and with the SEATS approximation. Seasonality is clearly moving, more markedly so when the SEATS approximation is used. Figures 6.6.3 and 6.6.4 compare the two irregular components; the one obtained with the model approximation is seen to display some heteroscedasticity. Figure 6.6.5 shows that the two series of extended residuals present notable differences. Figure 6.6.6 presents the original series, the SA series, and the trend-cycle component obtained with the final specification.

Figure 6.6.1 FIXED GROSS INVESTMENT: Seasonal Component with approximation

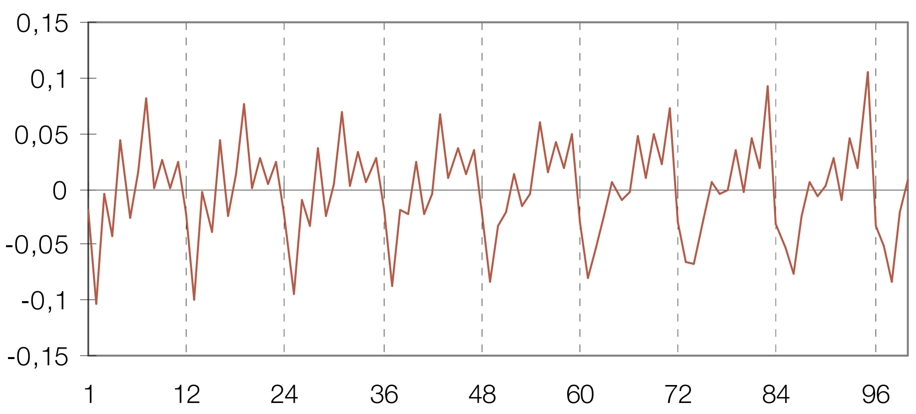


Figure 6.6.2 FIXED GROSS INVESTMENT: Seasonal Component with final model

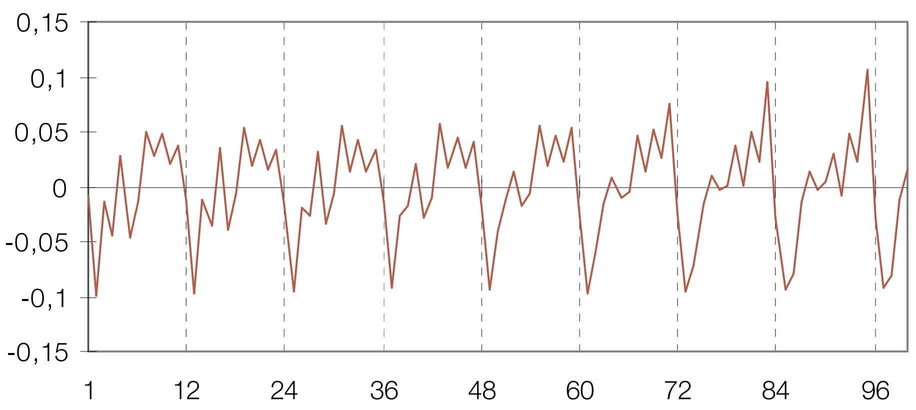


Figure 6.6.3 FIXED GROSS INVESTMENT: Irregular Component with approximation

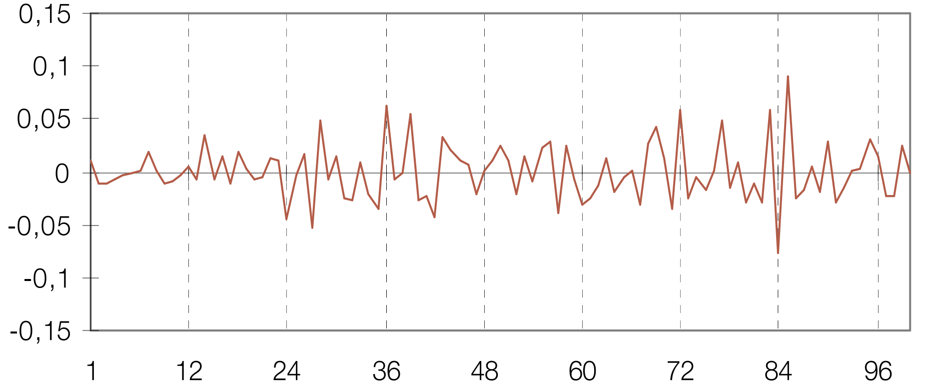


Figure 6.6.4 FIXED GROSS INVESTMENT: Irregular Component with final model

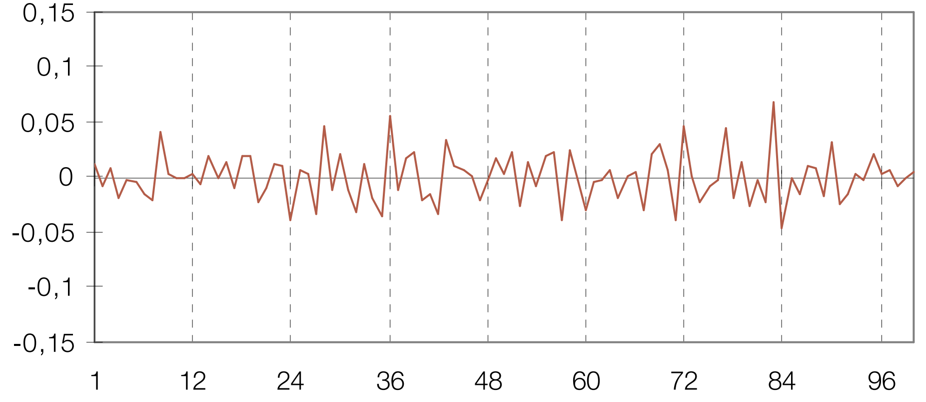


Figure 6.6.5 FIXED GROSS INVESTMENT: Residuals

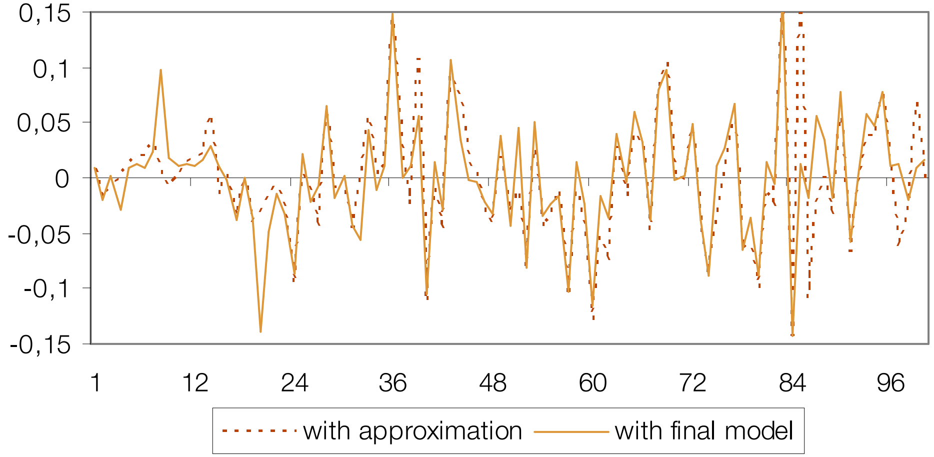
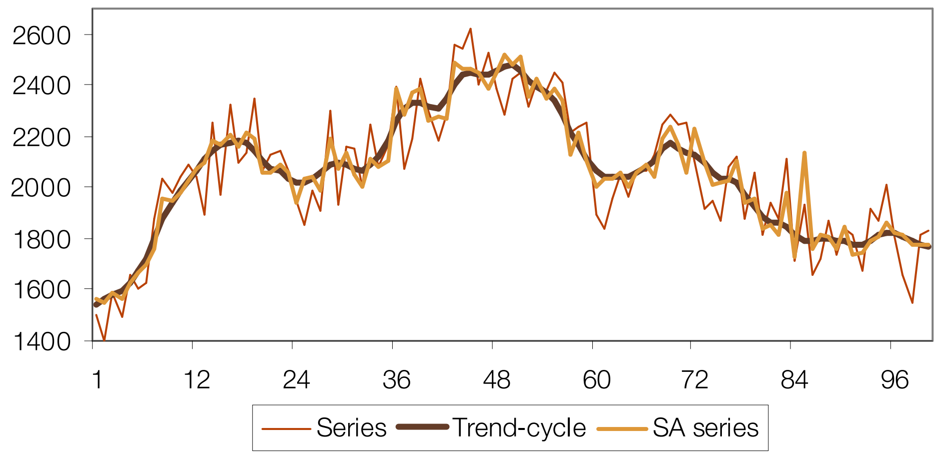


Figure 6.6.6 FIXED GROSS INVESTMENT: Original series, SA series, and Trend-cycle



6.7 SERIES 7 : **PRIVATE GROSS INVESTMENT: Seasonality in residuals.**

The input RSA = 4 also yields a (barely) problematic series:

$Q_s = 6.61$ $\rightarrow$ **Residual (stochastic) Seasonality**.

The model obtained is $(2\ 1\ 0)\ (0\ 0\ 0)$ + TD; with no outlier and no EE.

No stochastic seasonality is implied by the model.

Imposing EE, model changes to

$$(1\ 1\ 0)\ (1\ 0\ 0)\ + \text{TD} + \text{EE} + 1 \text{ TC Outlier}$$

with $\hat{\phi}_{12} = -.40$.

EE is significant, no residual seasonality is left $(Q_s = 0.0)$; BIC improves.

Setting ITER = 0, the input specification RSA = 3, ITRAD = 1, IEAST = 1, yields the following summary files.

7. **Private Gross Investment**

NZ =101; PERIOD=01-1994/05-2002; MQ=12;

Input Parameters

mq=12 itrad= 1 ieast= 1 out= 0 rsa= 3

Model Fit

Nz	Lam	Mean	P	D	Q	BP	BD	BQ	SE(res)	BIC	Q-val	N-test	SK(t)	KUR(t)	QS	Q2	RUNS
101	0	0	1	1	0	1	0	0	0.0679160	-5.20000	17.65	3.09	1.68	0.528	0.	37.81	0.817

ARMA Parameters

PHI1 (t)	PHI2 (t)	PHI3 (t)	BPHI (t)	TH1 (t)	TH2 (t)	TH3 (t)	BTH (t)
0.518021 (5.8)	- (-)	- (-)	-0.39540 (-4.3)	- (-)	- (-)	- (-)	- (-)

Deterministic Effect (total)

TD	EE	#OUT	AO	TC	LS	REG	MO
1	1	1	0	1	0	0	0

Calendar Effect

TD1 (t)	TD2 (t)	TD3 (t)	TD4 (t)	TD5 (t)	TD6 (t)	LY (t)	EE (t)
0.009563 (5.0)	- (-)	- (-)	- (-)	- (-)	- (-)	- (-)	-0.06830 (-2.8)

Outliers

TC01 (0196, -4.19)

7. **Private Gross Investment**
NZ =101; PERIOD=01-1994/05-2002; MQ=12;

Decomposition : General

Pread.	Model Changed	Approx. to NA	Model m	p	d	q	bp	bd	bq	SD(a)	Spectr. Factor	Check on ACF	Check on CCF	Determ. Comp. Modif. TC	S	U	Trans
Y	N	N	0	1	1	0	1	0	0 .	6494E-01	0	0	0	N	Y	Y	N

Decomposition : Standard Errors

SD(innov) TC	S	Trans	U	SA	SE Est. (Conc.) TC	SA	SE Rev. (Conc.) TC	SA	SE : Rates of Growth SE T11 (One Period) TC	SA	SE T1Mq (Annual Centered) X	TC	SA
.1030E-01	.3603E-01	0.000	.2823E-01	.4089E-01	.3619E-01	.3620E-01	.2800E-01	.2249E-01	1.48	3.46	12.14	10.65	11.19

Decomposition : Properties

Convergence (in %) 1Y TC	SA	5Y TC	SA	Signif.Stoch. Season. (95%) Hist.	Prel.	Fore.	DAA TC	SA
95.2	89.0	100.0	100.0	1	0	0	0.53	0.41

The highly **stationary stochastic seasonal** does not look very seasonal (see Fig. 6.7.1). Does it make sense to remove it?

The SEATS summary file indicates that seasonality can hardly be considered significant: Only one month per year has significant seasonality for historical estimators, none for preliminary estimators, and none for forecasts.

Given that the stationary seasonal root implies a spectral peak for seasonal frequencies (see Figure 6.7.2), I opt for its removal, bearing in mind that the resulting seasonal component lacks the persistence properties that one would expect from a seasonal component. Still, the problem is perhaps more academic than real given that preliminary estimates and forecasts of the seasonal component can all be taken as 0 (see Figure 6.7.3).

Notice that, since the forecasts of the seasonal component are close to 0, out-of-sample forecasting would be of no help in the decision "include/not to include" seasonality.

Choice of input: RSA = 3 ITRAD = 1 IEAST = 1

Figure 6.7.1 PRIVATE GROSS INVESTMENT: Seasonal Component

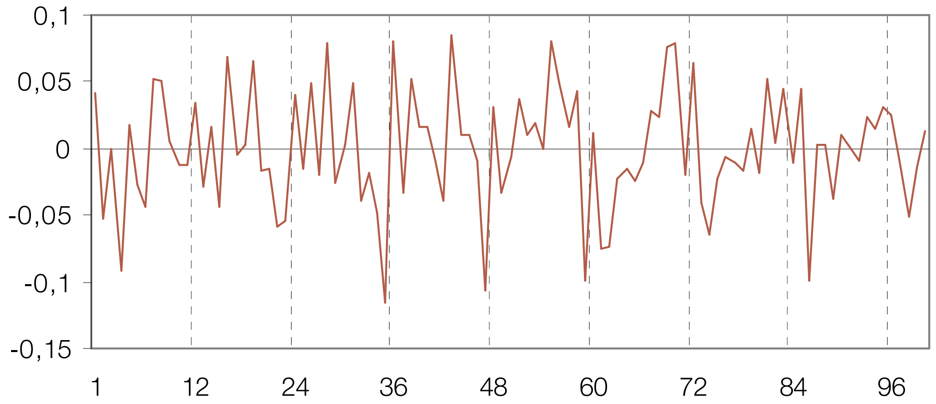


Figure 6.7.2 PRIVATE GROSS INVESTMENT: Spectrum of Seasonal

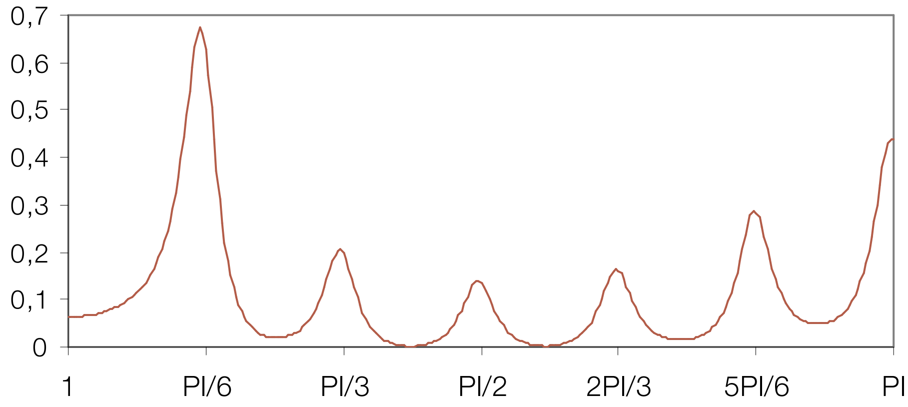
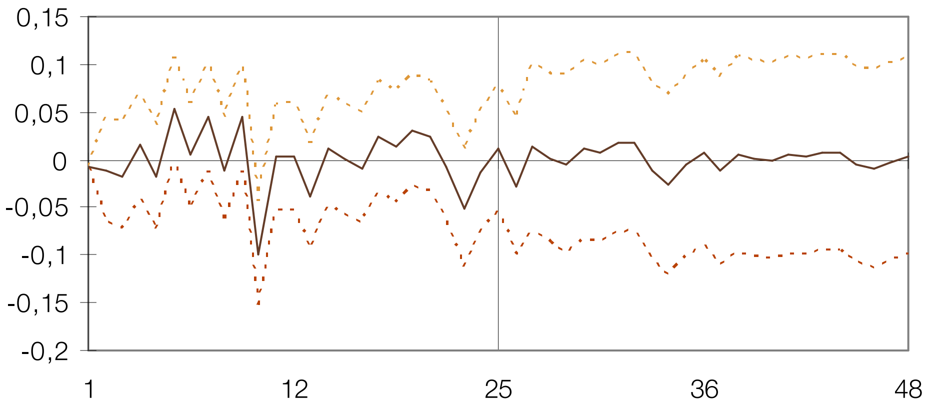


Figure 6.7.3 PRIVATE GROSS INVESTMENT: Forecasts of seasonal



6.8 SERIES 8 : **CONSTRUCTION: Long-term trend and cyclical component.**

RSA = 4. Everything OK.

EXTENSION TO CYCLICAL ANALYSIS

Given that 101 observations are not enough for cyclical estimation, I use for this case the series extended to 145 observations. (As seen in Figure 6.8.1, revisions in the series are rather minor.)

The model identified is a (0 1 1) $(0\ 1\ 1)_{12}$ model, in the logs, with no mean, and with TD and EE. All diagnostics are comfortably passed.

I use this example to illustrate how TRAMO-SEATS can be used to split the trend-cycle component into separate "long-term trend" and "**business-cycle component**", following the approach of Kaiser-Maravall (2001).

Modified Hodrick-Prescott filter

The cyclical component is obtained with the SEATS equivalent of the Hodrick-Prescott (HP) filter with two modifications:

(1) Adding four years of forecasts, obtained with the ARIMA model for the series, to complete the filter at the end-points of the sample period so as to increase end-point stability.

(2) Use of the trend-cycle component from SEATS as input to the HP filter, so as to remove noise contamination of the cyclical signal.

In order to do that, I

- extract the trend-cycle component (p_t) from the observed series setting NPRED = 48.
- The HP filter is obtained as the MMSE estimator of the irregular (wn) c_t in

$$p_t = m_t + c_t \ ,$$

where m_t is the long-term trend, and p_t follows an IMA (2,2) model, say

$$\nabla^2 p_t = (1 + \theta_1 B + \theta_2 B^2)\ a_{pt} .$$

For monthly observations, the MA(2) polynomial equivalent to the usual value of $\lambda = 1600$ for quarterly data is (see Maravall and del Río, 2006).

$$(1 - 1.9255\,B + .9282\,B^2) \ .$$

Thus we proceed as follows.

Use the extended Series 9 (NZ = 145) with

RSA = 4, NPRED = 48 .

From Out-Tables, pick up the trend-cycle component and its 48 forecasts. The component (without the forecasts) is displayed in Figure 6.8.2.

Run SEATS on the trend-cycle extended with forecasts with

D = 2 Q = 2 BD = 0 BQ = 0

IMEAN = 0 LAM = 1

INIT = 2 $\theta_1 = -1.9255$

$\theta_2 = .9282$

The "trend-cycle" yields the **long-term trend**, displayed in Figure 6.8.3.

The "irregular" yields the **cycle**, displayed in Figure 6.8.4.

Cycle is a stationary ARMA (2,2) model.

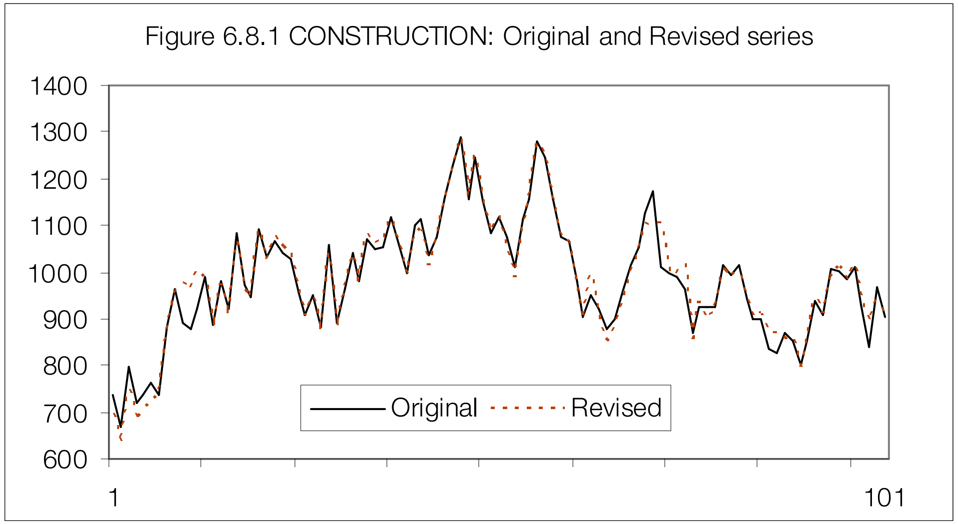


Figure 6.8.1 CONSTRUCTION: Original and Revised series
1400
1300
1200
1100
1000
900
800
700
600
1
101
Original
Revised

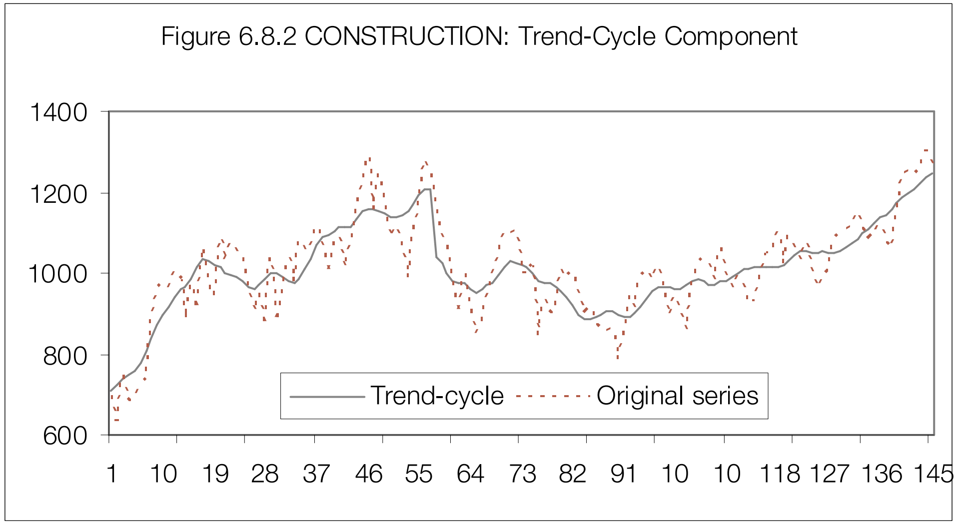


Figure 6.8.2 CONSTRUCTION: Trend-Cycle Component
1400
1200
1000
800
600
1 10 19 28 37 46 55 64 73 82 91 10 10 118 127 136 145
Trend-cycle
Original series

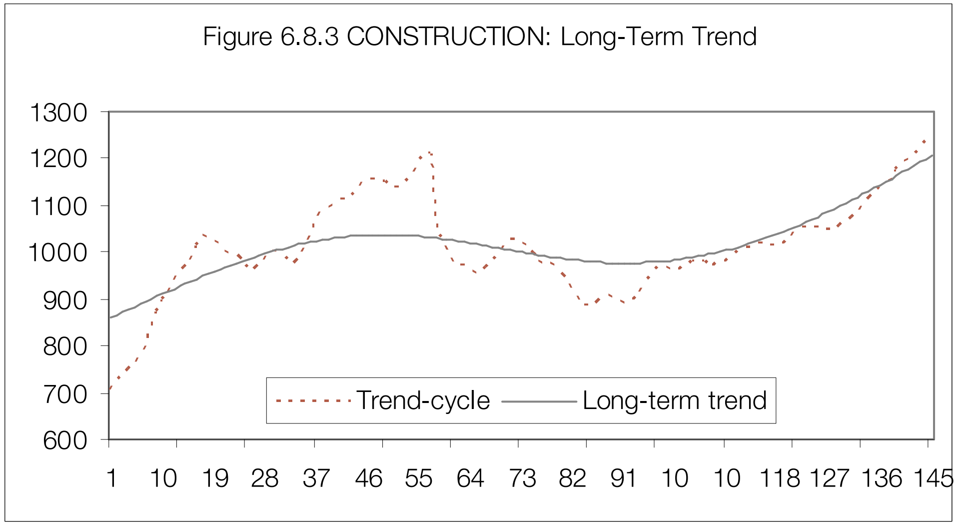


Figure 6.8.3 CONSTRUCTION: Long-Term Trend
1300
1200
1100
1000
900
800
700
600
1 10 19 28 37 46 55 64 73 82 91 10 10 118 127 136 145
Trend-cycle
Long-term trend

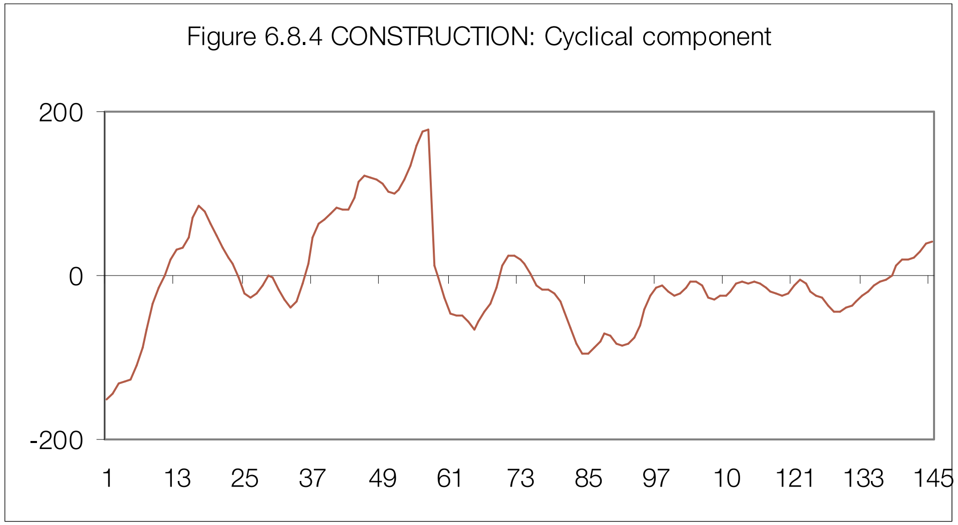


Figure 6.8.4 CONSTRUCTION: Cyclical component
200
0
-200
1 13 25 37 49 61 73 85 97 10 121 133 145

6.9 SERIES 9 : **IMPORTS OF CAPITAL GOODS: Deterministic or stochastic seasonality. Seasonal overdifferencing?**

As before, the automatic option RSA = 4 yields diagnostics that are acceptable. The model is an Airline-type model with mean and in the logs, with TD and 1AO.

Seasonal polynomials: $AR = \nabla_{12}$

$MA = 1 - .988\,B^{12}$

Therefore, this is a clear case of a series that may have nearly **deterministic seasonality**. In fact, SEATS yields

Var (seasonal innov.) = .00004 σ_a^2, a very small value.

On the other hand, the close to -1 value of $\hat{\theta}_{12}$ could be due to **seasonal overdifferencing**. In order to decide which of the two alternatives should be chosen, I consider the following information.

The output of SEATS tells us that:

a) Seasonality is highly significant for historical, preliminary and future estimators.

b) TD is highly significant

c) The residual ACF shows $\rho_{12}(a_t) = .13$, $\rho_{24}(a_t) = .24$, $\rho_{36}(a_t) = .36$, that is all are positive and are slow to converge.

d) Comparing with model with no stochastic seasonality

IMA (1,1) + μ + TD + 1AO ,

BIC (no season.) = -4.13 ;

BIC (season.) = -4.33 .

Q_s (no season.) = 10.2

Q_s (season.) = 0.0

e) We make use of the extended series (NZ = 145), for which the input RSA = 4 yields similar results.

Compute 44 out-of-sample 1-period-ahead forecasts:

Var (forecast errors with no stochastic seasonal specification) = .0114

Var (forecast errors with stoch. season. specif.) = .0080

Conclusion is overwhelming:

- There has been no seasonal overdifferencing,
- There is very stable and significant seasonality of moderate size.

Choice of input: RSA = 4

Implication: What the example basically shows is that there really is **no need for testing deterministic versus stochastic seasonality**. The seasonality present is extremely stable (very close to deterministic), yet the ARIMA model will capture it with no problem.

Figure 6.9.1 plots the original series and the trend-cycle component, figure 6.9.2 the very stable seasonality, and figure 6.9.3 the squared gains of the filters that provide the historical estimates of the trend-cycle and SA series.

The spill-over effects on the trend-cycle filter for frequencies beyond the cyclical range are very small, and the SA series only needs removal of frequencies in a very narrow band around the seasonal ones.

Figure 6.9.1 IMPORTS OF CAPITAL GOODS: Original Series and Trend-Cycle Component

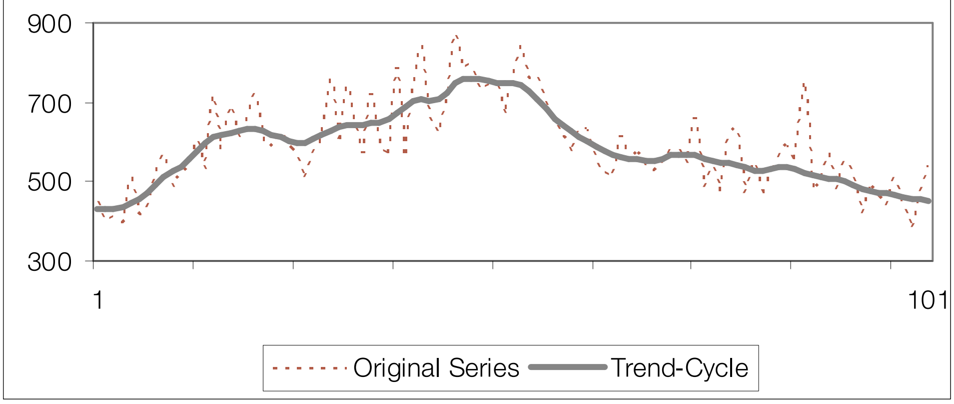


Figure 6.9.2 IMPORTS OF CAPITAL GOODS: Seasonal component

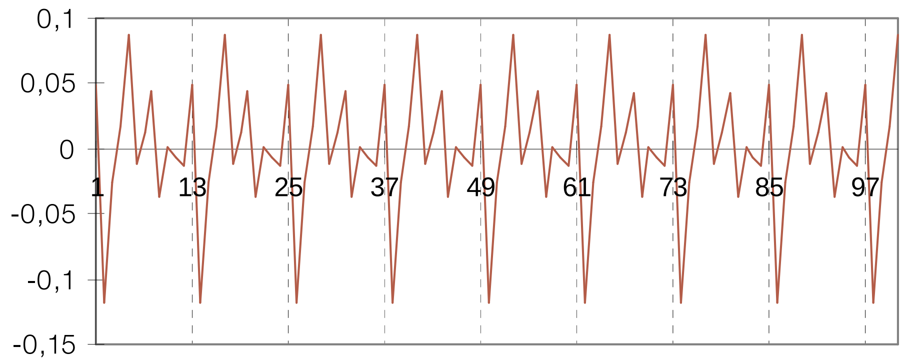
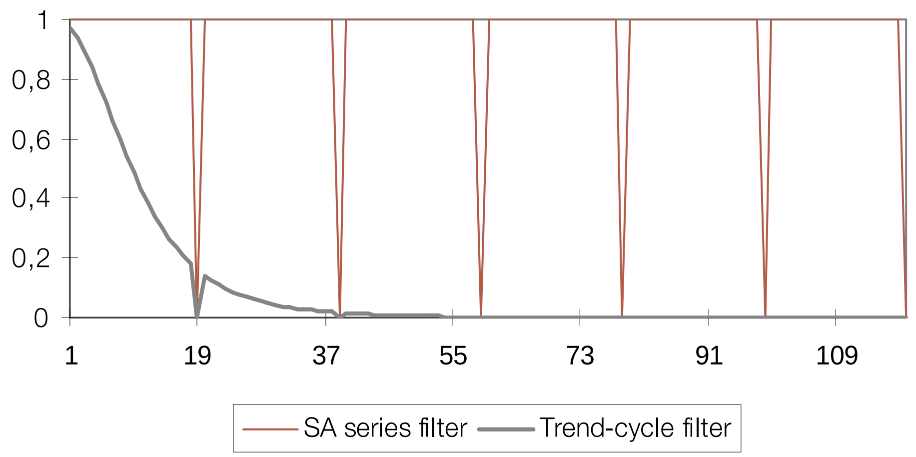


Figure 6.9.3 IMPORTS OF CAPITAL GOODS: Squared Gains



6.10 SERIES 10 : **DOMESTIC PRODUCTION OF CAPITAL GOODS: Data transformation and bias in the seasonally adjusted series; stationary seasonality.**

This is a problematic series because the **Bias in the level of SA series** induced by log transformation is too high. This is evidenced in the SEATS output: the Average of the differences (in absolute value) between the annual average of the original and SA series is DAA = .84 (of 1% of the level). Limit by default = .5 .

Obvious change (as indicated by the program): LAM = 1 (fixed)

The automatic option RSA = 4 LAM = 1 yields a relatively high value for Q.

Further, EE is found significant, but TD is not. Imposing it, with LAM = 1, RSA = 3, ITRAD = 1, IEAST = 1 , results improve, and the model obtained is

$$(2\ 0\ 0)\ (1\ 0\ 0)_{12} + \mu + \text{TD} + \text{EE} + 1\text{TC outlier},$$

a purely stationary specification, which significant TD and EE (the t values are 2.5 and -2.9, respectively). Direct inspection of the series (fig. 3.1.4) and of its ACF shows that the stationary specification may be inappropriate. In fact, the regular and seasonal AR polynomial are:

$$\phi(B) = (1 - .85\,B)\ (1 - .30\,B)$$

$$\Phi(B) = (1 - .50\,B^{12}\ ).$$

An obvious modification to the ARIMA model is to replace the $(1 - .85\,B)$ AR factor by $(1 - B)$, that is, to specify the model:

$$(1 1 0)\,(1 0 0)_{12}\ \text{, with no mean.}$$

This model presents good results. As in the case of Series 7, the seasonal component is a stationary AR(1) model, now with $\phi_{12} = -.57$. Historical and preliminary estimation of seasonality are highly significant, while forecasts are not [as indicated in the *summarys* file, (8 8 1), respectively].

The decomposition can be accepted, and hence the choice of input is

P = 1, Q = 0, BP = 1, BD = 0, BQ = 0, IMEAN = 0, LAM = 1,
ITRAD = 1, IEAST = 1, IATIP = 1.

This specification will be referred to as Model A.

If seasonal adjustment is the main objective, one may be tempted to try

$$(0\ 1\ 1)_{12} \text{ instead of } (1\ 0\ 0)_{12}$$

in the model. This nonstationary specification will be referred to as Model B.

In-sample fit shows very similar seasonal components (figure 6.10.1), both of a highly moving type.

Because of the addition of the seasonal difference, the forecasts are, of course, quite different.

But here we cannot use the series extended to NZ = 145 because the series has been significantly revised backwards (see Figure 6.10.2). For the revised, longer series, the IMA (1,1) seasonal structure is clearly preferable.

Figure 6.10.1 DOMESTIC PROD OF CAPITAL GOODS: Seasonal Component

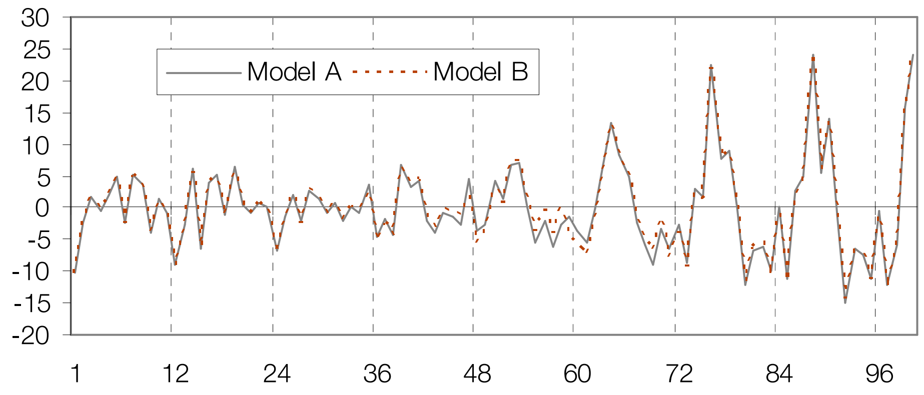
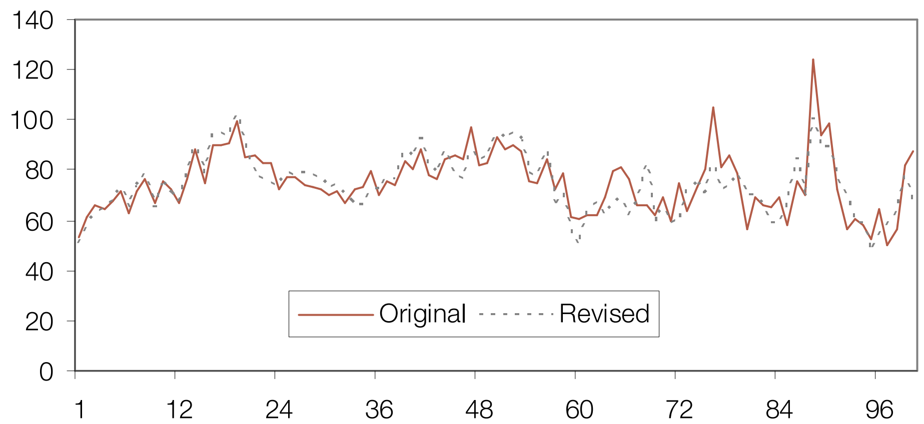


Figure 6.10.2 DOMESTIC PROD OF CAPITAL GOODS: Revisions



6.11 SERIES 11 : **GROSS PUBLIC INVESTMENT: Moving seasonality and seasonal outliers.**

The input specification RSA = 4 yields satisfactory results. The ARIMA model is a $(0\ 1\ 1)(0\ 1\ 1)_{12}$ model in the logs, with no mean, no TD and no EE present, 1AO and 1LS outlier. The ARMA parameter estimates are $\hat{\theta}_1 = -.53$ and $\hat{\theta}_{12} = -.45$. Some of the main statistics are

$$\text{BIC} = -4.028, \qquad Q = 26.3, \qquad SE(a_t) = .123, \qquad N = .5 \ .$$

The spectral diagnostics reveal no seasonality and no TD effect in the SA series or in the residuals. Figure 6.11.1 exhibits the original series, the SA series, and the trend cycle component. Figure 6.11.2 shows the seasonal component, s_t, which displays a clearly

Figure 6.11.1 GROSS PUBLIC DEMAND: Original Series, SA Series and Trend-Cycle.

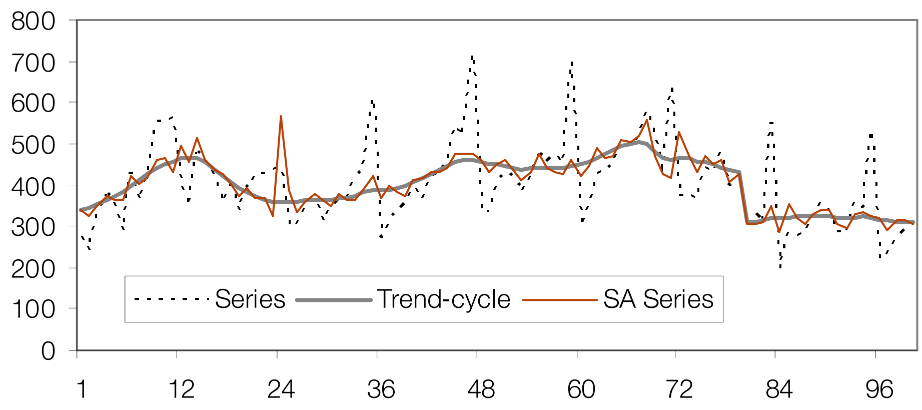
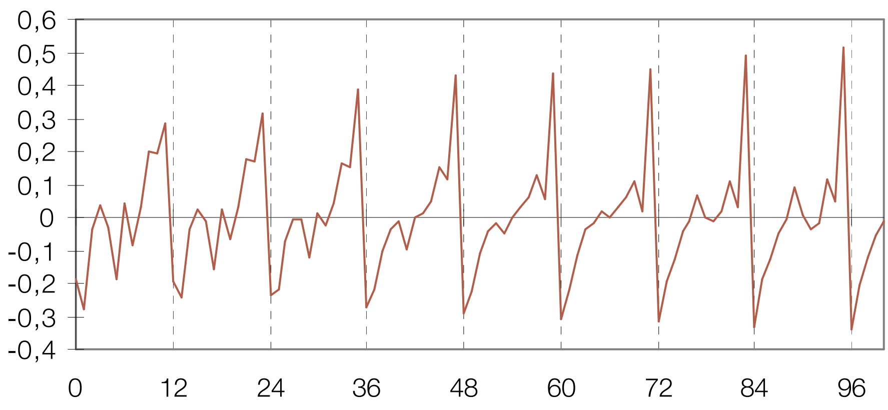


Figure 6.11.2 GROSS PUBLIC DEMAND: Seasonal component



moving behavior. The two most important changes are the one associated with the June effect, which moves from a significantly negative value to approximately 0, and the one associated with December, which evidences a steadily increasing amplitude.

Possibly, the most salient virtue of ARIMA models is their capacity to adapt to moving features, as figure 6.10.2 evidences. Yet seasonal adjusters are, on occasion, reluctant to accept these moving features and prone to intervene the series in order to obtain more stable seasonal factors. Corresponding to the June and December effects just mentioned, one can in fact introduce two **intervention variables** that can also be seen as **Seasonal Outliers**.

Thus, setting IREG = 2, the first intervention uses the input specification:

IUSER = 0 REGEFF = 2 (its effect is thus assigned to the seasonal component)

NSER = 1 ILONG = 125 (the effect is extended over the forecasting period)

ISEQ = 1 DELTAS = .8

Starting position = 6 Length = 1.

This intervention implies a damped effect of the seasonal factor for the months of June, by a factor of 20% a year, starting with a relatively large negative value and converging to zero.

The second intervention uses the same input specification, except for the parameters

DELTAS = 1.1 Starting Position = 12,

and implies a 10% annual increase in the December peak.

Adding the two (seasonal) intervention variables improves the estimation results. The statistics given above become

BIC = -4.194, Q = 22.0, SE($\hat{a}_t$) = .109, N = .2 .

The same type of ARIMA model is obtained, with the same two outliers. The ARMA parameter estimates become $\hat{\theta}_1 = -.52$ and $\hat{\theta}_{12} = -.78$; thus the regular part remains unchanged and the seasonal parameter indicates a more stable seasonal component. The t-values are -3.63 and 3.65 for the first and second intervention variables, respectively.

In summary, the two seasonal intervention variables improve the fit and yield a more stable seasonal component, as shown in figures 6.11.3 and 6.11.4, which display the stochastic seasonality and the deterministic one captured with the intervention variables. Figure 6.11.5 compares the seasonal factors obtained with the model with and without the intervention variables. The most important difference corresponds to the December peak for the last years, which is amplified by the associated intervention variable. This amplification is clearly appreciated in figure 6.11.6, which shows the forecast function associated with the two models.

Figure 6.11.3 GROSS PUBLIC DEMAND: Stochastic seasonal factors

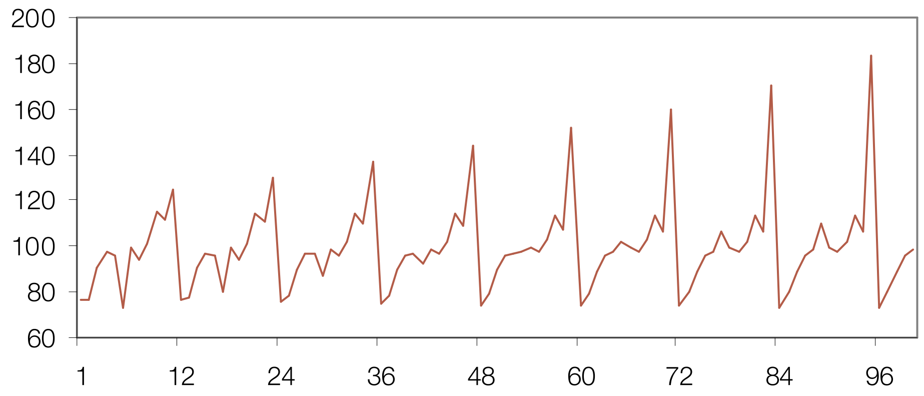


Figure 6.11.4 GROSS PUBLIC DEMAND: Deterministic seasonality; seasonal outliers model

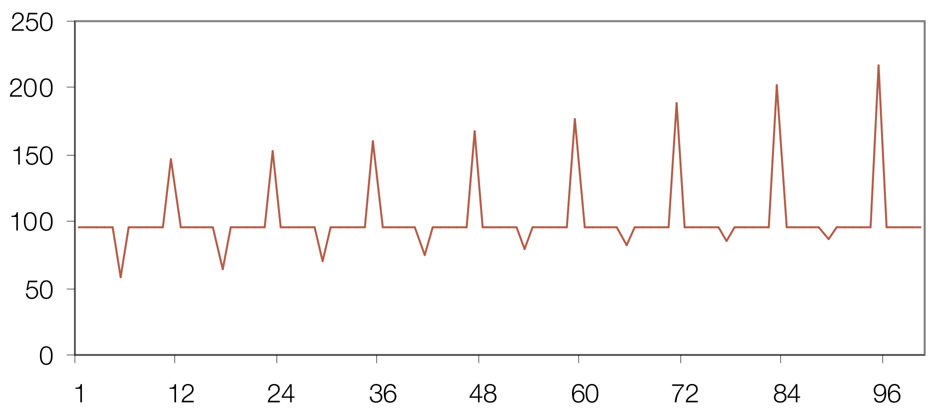


Figure 6.11.5 GROSS PUBLIC DEMAND: Seasonal Factors for the two specifications

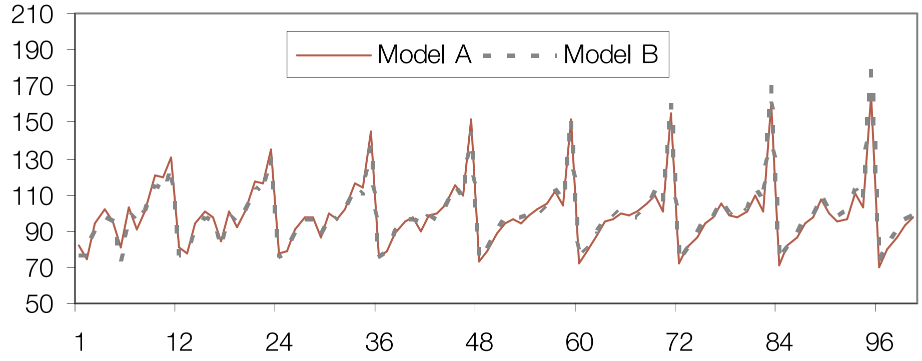
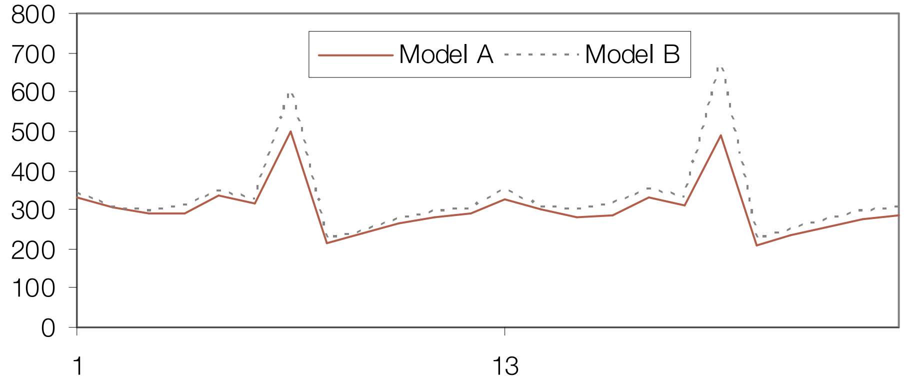


Figure 6.11.6 GROSS PUBLIC DEMAND: Forecast functions for the two specifications



At the end of the day, careful inspection of a series is likely bound to find some particular behavior that could be captured with an appropriate intervention variable, improving thereby the fit. This improvement, however, does not guarantee better inferences. The series extended to 145 observations cannot be of much help in this case in deciding which of the two specifications is preferable because of the revisions that were made on the series. Still, if the model obtained for the series with 101 observations had been maintained for one year, and one-period-ahead forecast errors had been computed using the extended (revised) series, comparison of the MSE of the out-of-sample forecast errors would show a better performance of the model without the intervention variables. (If, instead of one year, the 44 additional months of the extension are considered –a rather unrealistic assumption- the MSE of the out-of-sample one-period-ahead forecast errors is nearly identical for the two specifications; in both cases, the associated F tests are comfortably passed.) Thus, unless external information provides very strong reasons, the practice of imposing ex-post deterministic effects to capture moving features seems rather questionable.

6.12 SERIES 12 : VARIATION OF STOCKS: Stability and phase delay of trend-cycle.

The automatic procedure, again, yields good results. The ARIMA model obtained is a $(0\,0\,0)(0\,1\,1)_{12}$ model, with no mean and in the levels. Trading Day effect is not significant, but EE is. No outliers are detected. The standard diagnostics are comfortably passed and, for example,

BIC = 10.141, SE($\hat{a}_t$) = 153.16, Q = 15.8, N = .6 .

The decomposition shows a very stable trend (very slightly decreasing in the first half; practically constant in the second,) and a moving seasonality, with the December minimum becoming more pronounced over the last 6 years. (See figures 6.12.1 and 6.12.2.)

Figure 6.12.1 VARIATION OF STOCKS: Original Series and Trend-Cycle

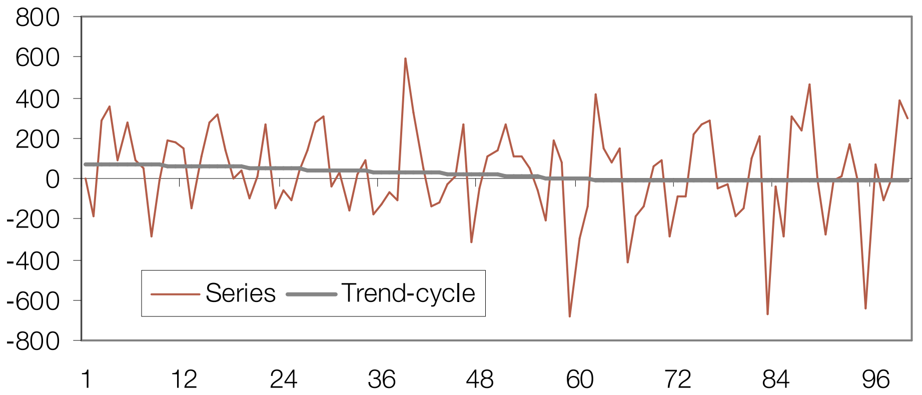
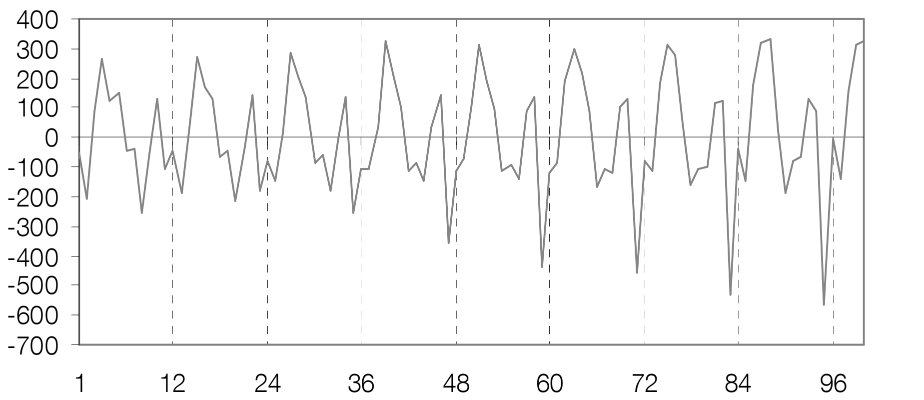
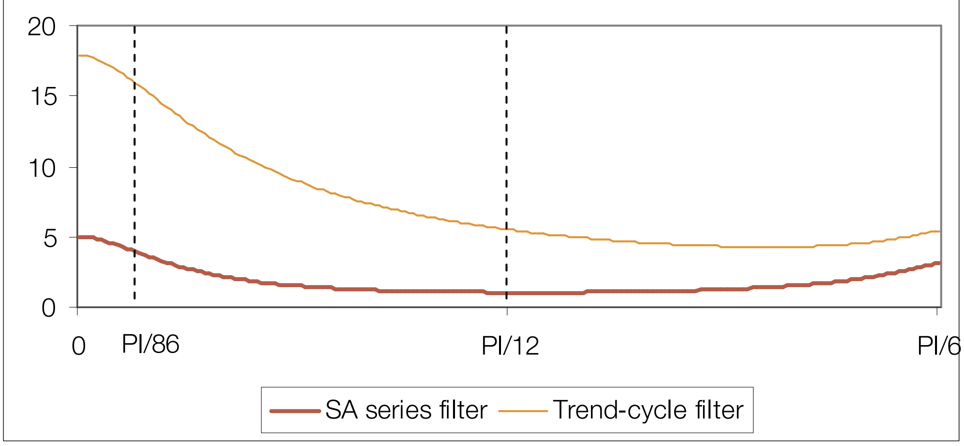


Figure 6.12.2 VARIATION OF STOCKS: Seasonal Component



As seen in figure 6.12.3, the phase delay of the concurrent trend filter is very large, ranging between 18 and 6 months for the range of cyclical frequencies. This large phase delay can be seen as a drawback of the model, but in practice the drawback is more apparent than real: the evolution of the trend is extremely smooth, and variations are close to negligible. It is in fact a general feature than very stable trends, which imply narrow spectral peaks around the zero frequency, display large phase effects; in other words, turning points take a long time to be detected when they are of relatively small importance.

Figure 6.12.3 VARIATION OF STOCKS: Phase delay of SA series and trend-cycle filters



Alternative models can be tried. In particular, noticing a concentration of spectral peaks in the neighborhood of the twice-a-year seasonal frequency, one may try the model $(3\,0\,0)(0\,1\,1)_{12}$ with EE, no mean, and in the levels. The BIC improves slightly, and the regular AR(3) is found significant, with a complex root associated with a period of 4.8 months, and a real root for the 6-times-a-year frequency. The first roots yield a transitory component, and the second one is added to the seasonal one. Moreover, two outliers (1AO and 1TC) are now found.

Further comparison of the two models does not yield a clear answer. The phase delay in the concurrent trend-cycle (and, to a smaller degree, SA series) estimator remains large and, in accordance, the trend-cycle is very stable. Looking at the SEATS output, the model with no regular AR implies a more stable seasonal component, which is estimated with a larger error. The seasonal components obtained with both models are presented in figure 6.12.4: the moderate attenuation of the maxima and minima is clearly appreciated, although the two components are quite similar. In fact comparing the forecast functions of the two models (figure 6.12.5) it is seen that the differences are –to all effects- irrelevant. As a consequence, on the basis of the parsimony principle, the simpler model (obtained with RSA = 4) would be preferable.

Figure 6.12.4 VARIATION OF STOCKS: Seasonal component for the two models

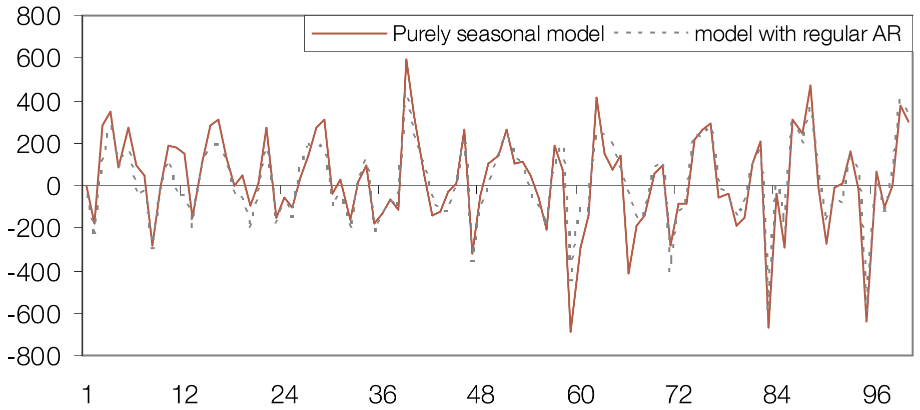
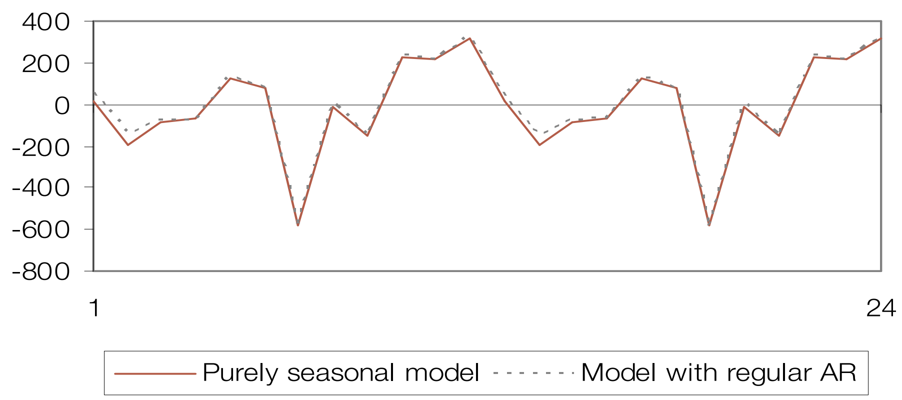


Figure 6.12.5 VARIATION OF STOCKS: Forecast function for the two models



6.13 SERIES 13 : **EXPORTS: Residual autocorrelation and Outlier detection.**

The automatic procedure RSA = 4 produces a model that passes all diagnostics, except the one for **residual autocorrelation** that yields the value Q = 36.1 . The model obtained will be referred to as a Model A. The Q value is barely significant (the 95% critical value is about 34) and could be accepted as the one lying in the 5% critical region among a group of 17 series. Nevertheless, I shall consider it a problematic series.

The model obtained is a $(0\,1\,1)(0\,1\,1)_{12}$ model in the logs, with no mean, no TD and no EE. The associated BIC is -5.507, and the ARMA parameter estimates are $\hat{\theta}_1 = -.86$ and $\hat{\theta}_{12} = -.79$.

Noticing that no outliers are detected, an obvious modification to the input is to lower the threshold value for outlier detection. Thus, running RSA = 4, VA = 2.6, two TC outliers are found towards the middle of the series. The .86 regular AR root approaches 1 and cancels the regular difference, so that the ARIMA model becomes

$$\nabla_{12} \log x_t = (1 - .74 B^{12})\, a_t + \mu .$$

The BIC becomes -5.673, the Q value becomes 24.5, and all diagnostics are passed, including the spectral ones for residual TD effect. This model will be denoted Model B.

From the SEATS outputs (see matrix “Parameters I”), comparison of the two model yields the following results:

Standard Deviation of Innovations

	Trend-Cycle	Seasonal Comp.	SA Series
Model A	.004	.009	.055
Model B	.001	.010	.047

Standard Error of Concurrent Estimator

	Trend-Cycle	SA Series
Model A	.020	.022
Model B	.007	.022

Standard Error of Revision

	Trend-Cycle	SA Series
Model A	.015	.015
Model B	.005	.015

In summary,

- The TRAMO diagnostics point towards Model B as the better one.
- In terms of the SEATS decomposition, the main difference (albeit, rather small) concerns the trend-cycle. Model B provides a more stable series, which is estimated with more precision and is subject to smaller revisions. Differences in the SA series are negligible. Figures 6.13.1 and 6.13.2 display the trend-cycle component and the seasonal component for the two models.

Figure 6.13.1 EXPORTS: Trend-cycle for the two models

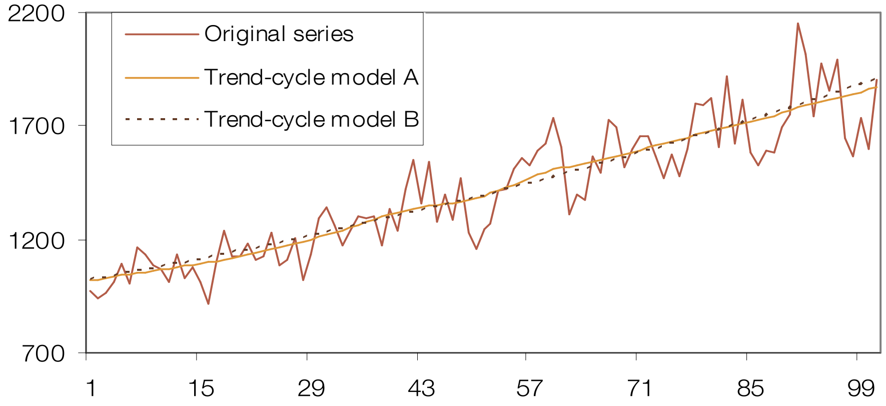
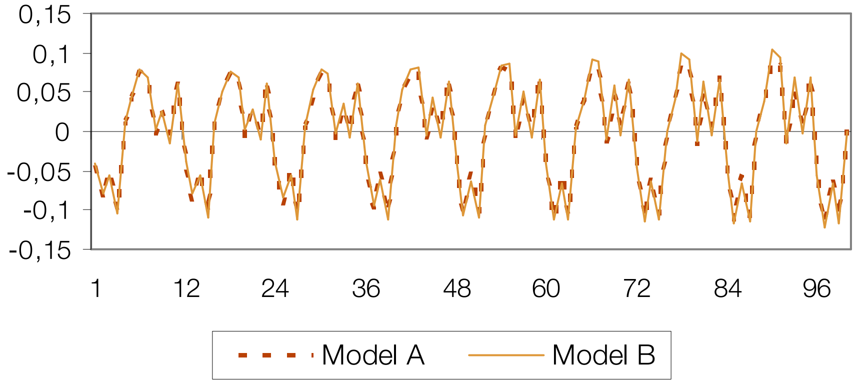


Figure 6.13.2: EXPORTS: Seasonal component for the two models



Even though seasonal adjustment is not much affected, the input specification RSA = 4, VA = 2.6 seems preferable.

6.14 SERIES 14 : **GLOBAL SUPPLY: Missing observations and model stability.**

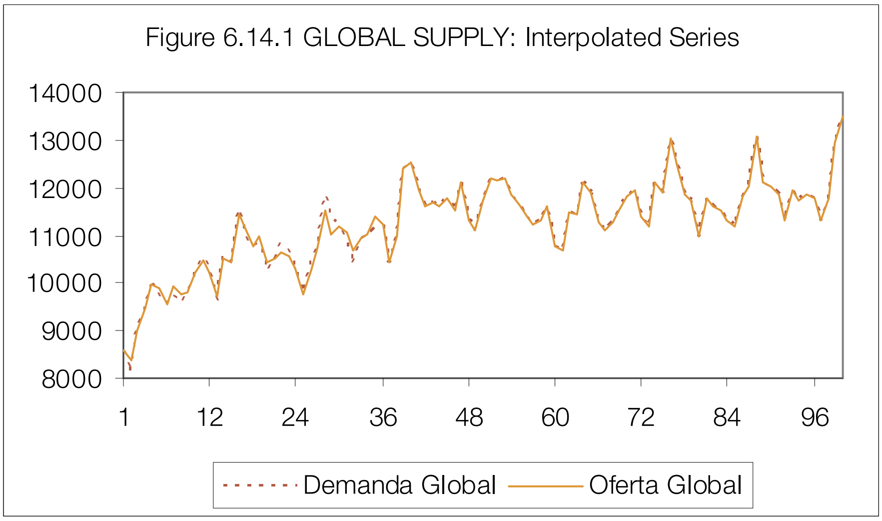
Series 14, Global Supply, is identical to Series 1, Global Demand. I use this example to illustrate interpolation of **Missing Observations**. For the first 3 years, two monthly observations have been removed from each quarter. Thus:

First 3 years: quarterly series;

Next 5(+) years: monthly series.

RSA = 4 interpolates the 24 M.O. (see Figure 6.14.1), and yields the same model obtained for Series 1 (consisting of (6.1) and (6.2)), with close parameter estimates (see Table below).

Only difference is barely significant AO in the middle of the series.



Stability of the model. Considering the series extended to 145 observations, RSA = 4 yields again the model consisting of (6.1) and (6.2). The following table compares the parameter estimates obtained in the three cases (a: series with 101 observations; b: as a, but with 24 missing observations spread –as described- over the first 3 years; c: series with 145 observations.)

	$\hat{\theta}_1$	$\hat{\theta}_{12}$	$\hat{\sigma}_a$	α_{TD}	α_{EE}
a) NZ = 101	-.315	-.729	.021	.0033	-.029
b) MO	-.252	-.654	.022	.0035	-.030
c) NZ = 145	-.459	-.807	.021	.0040	-.026

Considering the number of MO at the beginning, and the length of the extension at the end (close to 50% of the series length), the results for Series 1 and 14 seem remarkably stable.

Out-of-sample forecast tests further confirm this stability.

Thus, for Series 14, the results of RSA = 4 are also accepted.

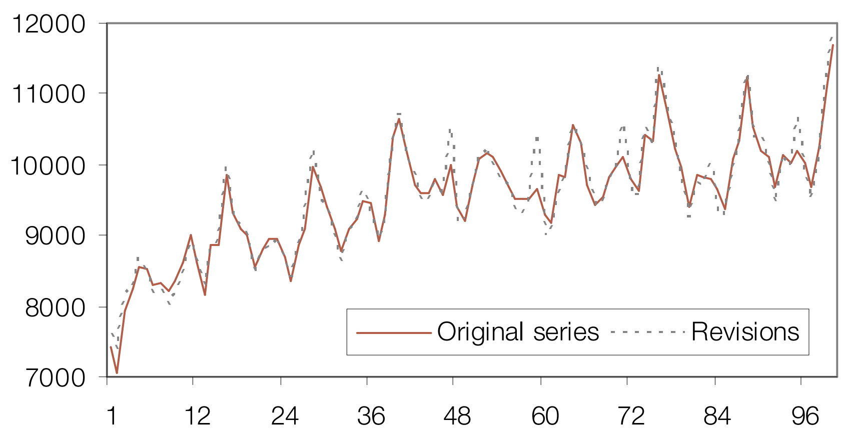
6.15 SERIES 15 : **GDP: Revisions in the raw data.**

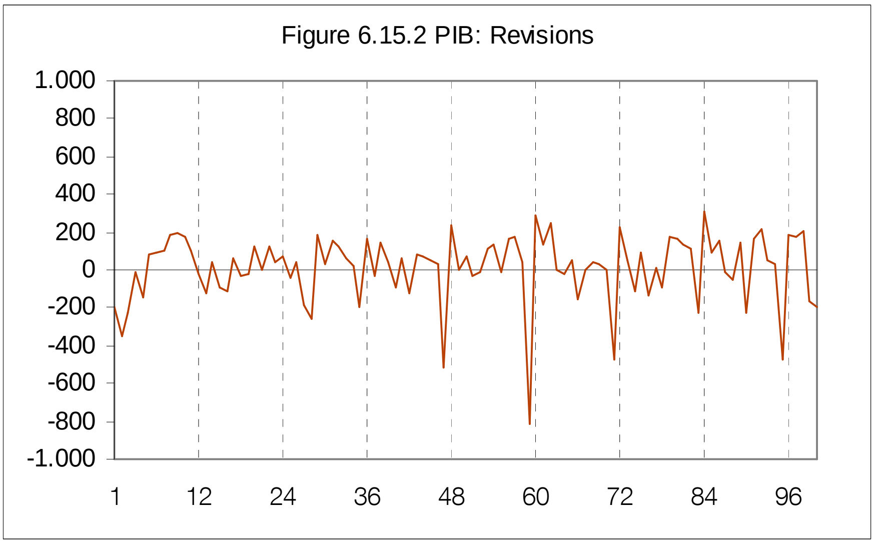
The results of the automatic option RSA = 4 are excellent. The model is, again, a $(0\,1\,1)(0\,1\,1)_{12}$ model, in the logs, with no mean, with significant TD and EE, and with an AO of moderate size towards the middle of the series. The SE of the residuals is 0.178, and all statistics are clearly passed; in particular, Q = 9.4 and N = 1.15.

I shall use this series to illustrate a problem of applied relevance, namely, revisions that are made to raw aggregate macroeconomic series. These revisions may appear because of a variety of reasons. For example: some of the components included in the aggregate may be measured at a lower frequency; there may have been some changes in the definition/construction of the series, in the items that comprise the aggregate, in the base year, some past error may have been corrected, etc. With some notable exceptions, (such as recent work done at Statistics Sweden; see, for example, Teterukovsky, 2006) this type of revisions have not been the subject of much research, yet they can be far from negligible. As already mentioned, the original set of series I have analyzed were resent to me updated with 44 additional months of observations and with revisions made for the first 101 observations.

Figure 6.15.1 presents the original series and their revisions. The revision standard deviation is in the order of 22.5% of the standard deviation of the original series (this represents an intermediate value for the set of series considered), and their size is considerably larger than that of the one-period-ahead forecasts of the original series.

Figure 6.15.1 PIB: Original Series and Revisions





Direct inspection of the series of revisions (Figure 6.15.2) evidences the presence of seasonality. The automatic option RSA = 4 yields a model with some low-order residual autocorrelation which is removed by adding a regular AR(1) polynomial. The model obtained is

$$(1-.281B)\nabla_{12}\, x_t = (1-.326B^{12})\, a_t + TD + 1AO\,,$$

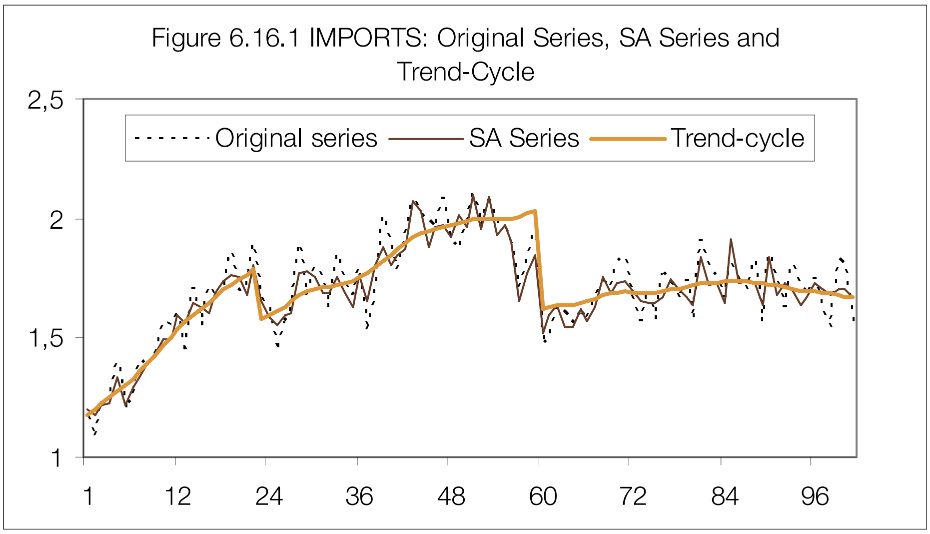
and all diagnostics are acceptable. The standard deviation of the residuals is 118.5, well below that of the revisions (equal to 177.3). This reg-ARIMA structure of the revision raises the possibility of improving estimators at the end of the series by incorporating forecasts of the revisions, a possibility that may be worth investigating.

6.16 SERIES 16 : **IMPORTS: Temporal aggregation; direct versus indirect adjustment; intervention variable.**

The automatic specification RSA = 4 yields satisfactory results. The ARIMA $(0\ 1\ 1)(0\ 1\ 1)_{12}$ model with mean is chosen for the logs of the series. TD and EE are significant and 3 outliers are detected: a LS at the beginning, and an AO and another LS towards the middle of the series. The ARMA parameter estimates are $\hat{\theta}_1 = -.737$ and $\hat{\theta}_{12} = -.782$; some summary statistics are

$$BIC = -5.65; \quad SE(\hat{a}_t) = .051; \quad Q = 15.2; \quad N = 3.5.$$

All diagnostics are comfortably passed. Figure 6.16.1 plots the original and SA series, and the trend-cycle component.



I shall use this example to illustrate some issues having to do with Temporal Aggregation of the series. The quarterly imports series is obtained as the sum of the three months in each quarter. Running RSA = 4 on the quarterly series, the ARIMA $(0\ 1\ 1)(0\ 1\ 1)_4$ model with no mean is found for the levels of the series. TD and EE are not significant and no outlier is detected. All diagnostics are passed with no problem and, in particular, $Q = 6.7$ (CV = 24), $N = .9$.

The example contains some features that are bound to affect consistency under aggregation: first, the use of the logs versus the levels; second, the correction for 3 outliers versus the lack of outlier correction; third, the removal of TD and EE in the monthly, but not the quarterly, series. Figures 6.16.2 and 6.16.3 compare the SA series and trend-cycle components obtained with the direct and indirect procedures. The differences are noticeable, in particular for the case of the trend-cycle component, where the correction for the second LS outlier has a very strong effect.

Figure 6.16.2 IMPORTS (QUARTERLY): Automatic Procedure. Direct versus Indirect Seasonal Adjustment

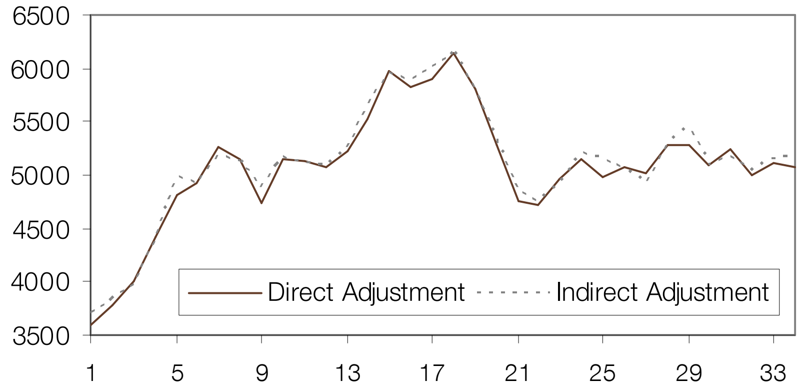
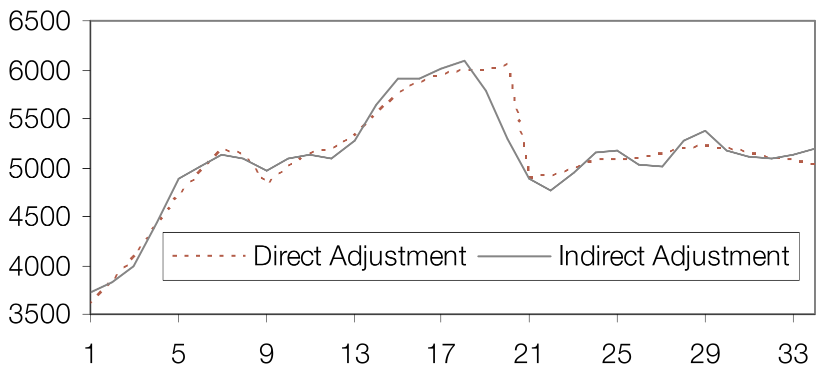


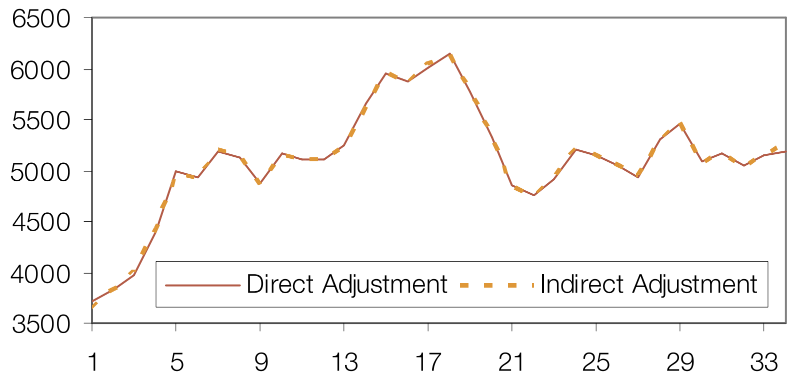
Figure 6.16.3 IMPORTS (QUARTERLY): Automatic Procedure. Direct versus Indirect Trend-Cycle

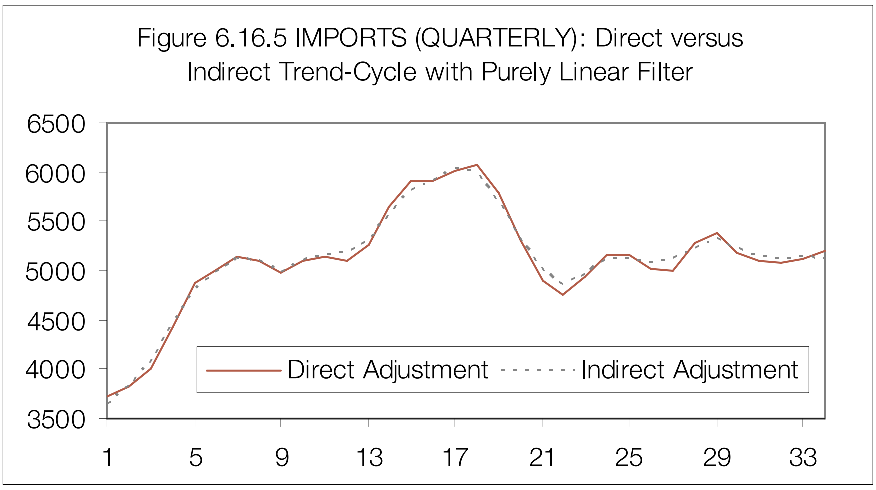


Ultimately, the difference between direct and indirect adjustment has a well-founded justification. The quarterly raw series is a linear transformation of the monthly one, but the aggregate SA series and trend-cycle components are non-linear transformations of the corresponding disaggregate series: this is the result of the different outcomes of the log/level and calendar effects tests, and of the differences in outlier detection. Besides, the estimated ARMA models are not exact aggregates of each other. On the one hand, direct and indirect adjustment do not yield the same results; on the other hand, diagnostics do not allow us to make a clear cut choice between the two types of adjustment. Still, inspection of the filtered series favors the smoother results of the direct procedure, which avoids the drastic effect of the second LS outlier.

Consistency under aggregation could be improved by removing the main causes of non-linearity. This closer behavior of the filtered series is clearly appreciated in Figure 6.16.4 and 6.16.5, where the direct procedure is compared with an indirect one based on the ARIMA $(0\,1\,1)(0\,1\,1)_{12}$ model with mean and in the levels, with no calendar effects removed and no outlier correction. (Therefore, the filters for the monthly series are made similar to those for the quarterly ones). The (nearly negligible) difference between the direct and indirect method is now simply due to the lack of an exact aggregation relationship between the ARMA parameter estimates. Yet the results this procedure yields for the monthly series are unacceptable, with $Q = 58.0$ and residual TD effects. The price paid to achieve consistency under aggregation seems too high, and it may be preferable to use at both levels of aggregation a direct approach, given that the implied inconsistencies are justified.

Figure 6.16.4 IMPORTS (QUARTERLY): Direct versus Indirect Adjustment with purely Linear Filter





Be that as it may, it is possible to reduce the differences while remaining inside the model-based approach. For example, it has been mentioned that the second level shift creates important discrepancies between the direct and indirect approach. (This is often the case with LS outliers.) Inspection of Figures 6.16.1 suggests that the AO and LS outliers at positions 58 and 61 could be combined into a **ramp effect** captured with an **intervention variable**. Thus we introduce the regression variable

IUSER = 0 REGEFF = 1 (variable is assigned to trend-cycle)

NSER = 1 ILONG = 125 ISEQ = 1 DEL = 1

Starting position = 56 Length = 6 ,

Representing a ramp effect that starts at period 56 and lasts 6 months. The first LS of the first model is maintained, and a second outlier is detected (an AO at period 86). The diagnostics for this model are very similar to those of the first one ($BIC = -5.62$; $SE(\hat{a}_t) = .052$; $Q = 19.9$; $N = 3.1$) but two improved features are apparent. First, as seen in Figure 6.16.6, the ramp effect produces a more satisfactory trend, and, as seen in figure 6.16.7, a considerably more stable seasonal component. Moreover, indirect adjustment based on this modified model reduces drastically the differences with respect to direct adjustment (see figure 6.16.8 and 6.16.9). Thus a simple modification yields results that perform much better under temporal aggregation.

Figure 6.16.6 IMPORTS: Trend-Cycle; Automatic with and without Intervention Variable

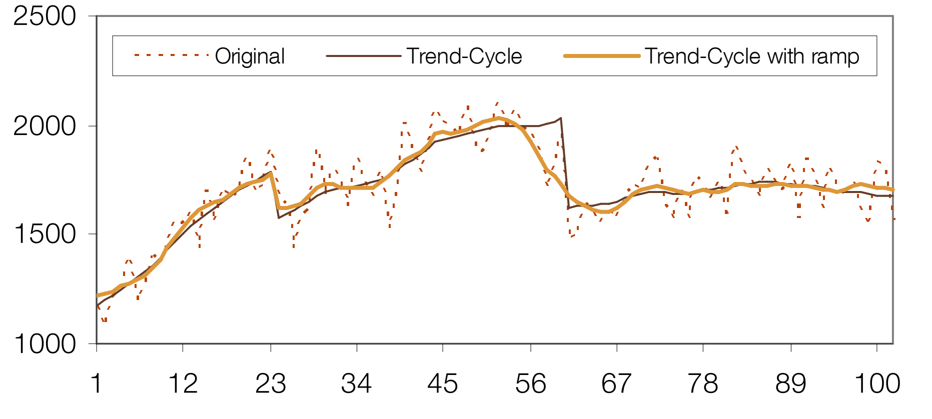


Figure 6.16.7 IMPORTS: Monthly Seasonal Component. Automatic with and without Intervention Variable

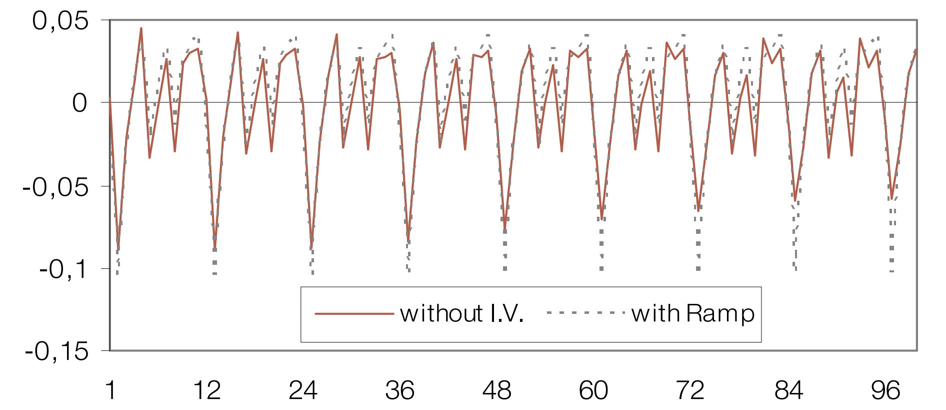


Figure 6.16.8 IMPORTS (QUARTERLY): Automatic Direct Adjustment versus Indirect Adjustment With Intervention Variable

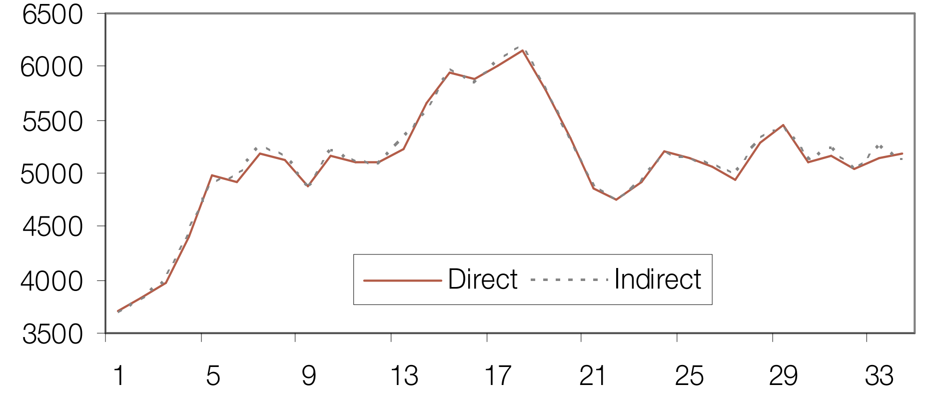
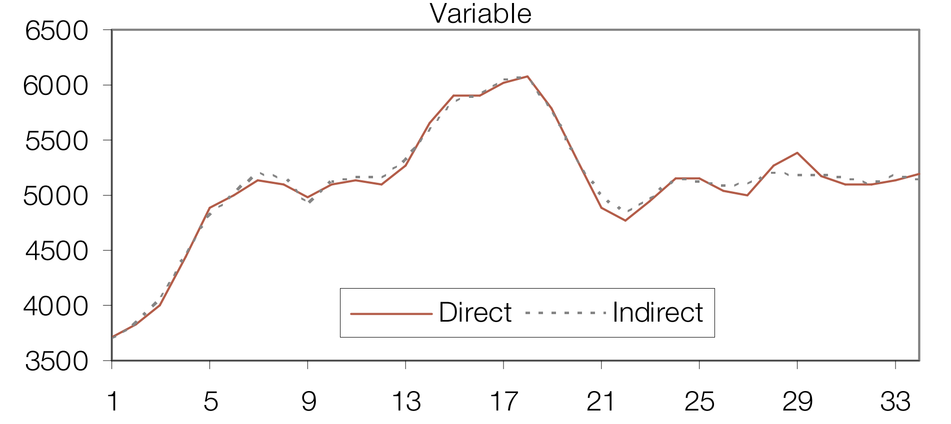


Figure 6.16.9 IMPORTS (QUARTERLY): Automatic Direct Trend-Cycle versus Indirect Trend-Cycle with Intervention Variable



6.17 SERIES 17 : **BALANCE OF TRADE: Sectorial aggregation; direct versus indirect adjustment.**

The automatic option RSA = 4 applied to the Balance of Trade series yields again good results. The $(0\ 1\ 1)(0\ 1\ 1)_{12}$ model with mean and in the levels is obtained, no outliers are detected, TD is found significant while EE is not, and some summary statistics are

$$SE(\hat{a}_t) = 136.8\ ; \qquad Q = 26.3\ ; \qquad N = 2.6\ .$$

In this way, a direct adjustment of the Balance of Trade series is obtained. Given that, by construction,

Balance of Trade = Exports – Imports,

an indirect adjustment of the series could be made using the adjusted export and import series. As already seen, the option RSA = 4, adding VA = 2.6 for the case of exports, yields satisfactory results for the two disaggregate series.

As was the case for temporal aggregation, direct and indirect adjustment will not produce the same results when sectors are aggregated. One important reason is the non-linearity introduced in the adjustment procedure. Thus, for example, while indirect adjustment is based on the log transformation for Exports and Imports, direct adjustment of the Balance of Trade series is made for the levels. Further, indirect adjustment corrects for 5 outliers (2TC outliers for Exports, 1AO and 2LS outliers for imports, all of them for different periods). Another important issue is possible interaction between the components, as discussed in Maravall (2006).

Figures 6.17.1 and 6.17.2 display the trend-cycle component and SA series for the Balance of Trade series, computed with the direct and indirect procedures.

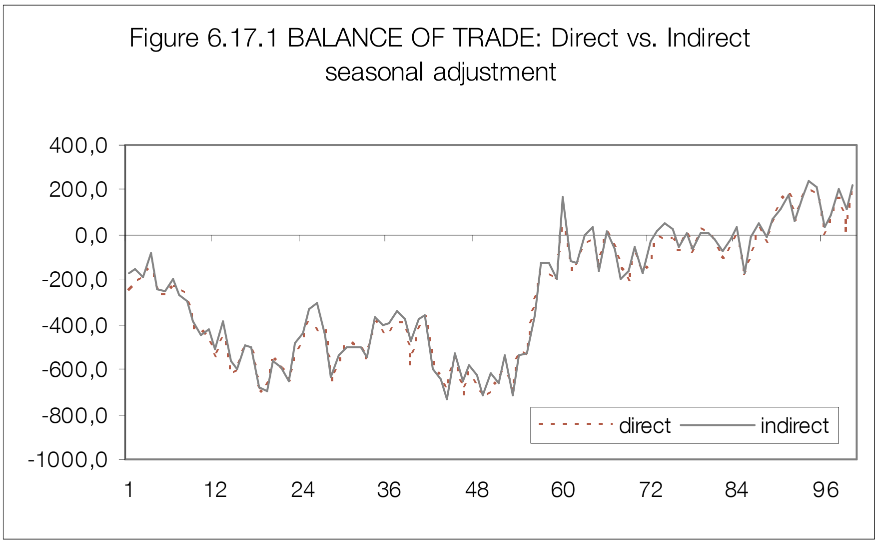


Figure 6.17.1 BALANCE OF TRADE: Direct vs. Indirect seasonal adjustment
400,0
200,0
0,0
-200,0
-400,0
-600,0
-800,0
-1000,0
1
12
24
36
48
60
72
84
96
direct
indirect

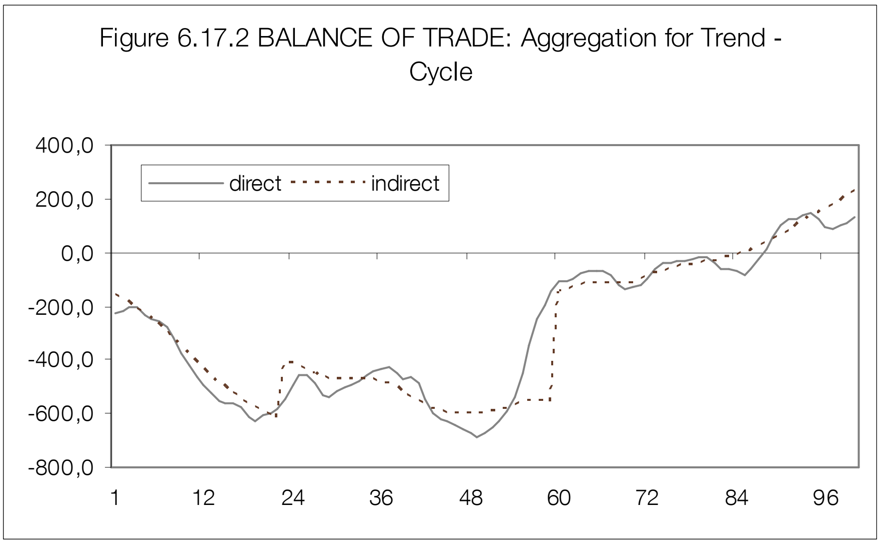


Figure 6.17.2 BALANCE OF TRADE: Aggregation for Trend - Cycle
400,0
200,0
0,0
-200,0
-400,0
-600,0
-800,0
1
12
24
36
48
60
72
84
96
direct
indirect

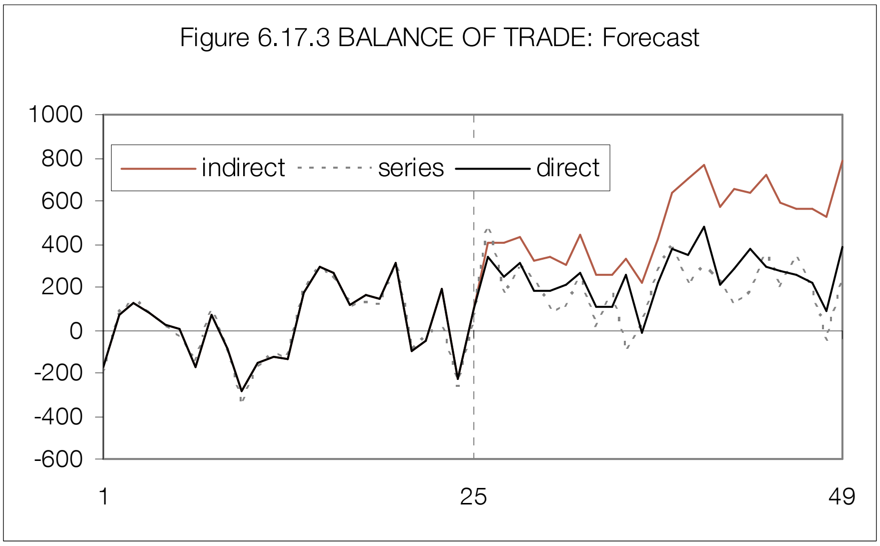


Figure 6.17.3 BALANCE OF TRADE: Forecast
1000
800
600
400
200
0
-200
-400
-600
1
25
49
indirect
series
direct

Similarly to the case of temporal aggregation, the difference in the SA series is moderate, while for the trend-cycle component it is large and related to the presence of a LS outlier. For this component, the direct procedure yields a visually more appealing decomposition.

Figure 6.17.3 plots the forecast function obtained with the direct and indirect procedure, as well as the observations corresponding to the forecasting period contained in the extended series with NZ = 145 (in this case, revisions to the series have been minor).

It is apparent that the direct procedure provides a more appropriate forecast function.

The superiority of the direct approach is by no means a universal law; it is nevertheless an often encountered result.

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7. CONCLUSION: FINAL RESULTS.

The previous discussion has shown how a few, relatively straightforward, modifications to the automatic procedure lead to acceptable models for all series.

(Needless to say, these models could be improved…)

The MODEL SUMMARY for the final specifications achieved is the following

Input Parameters :
mq=12 modelsumm= 1 iter = 3
To see the input parameters used for each series, see the matrix *Input Parameters* (below)
SERIES IN FILE : 17
SERIES PROCESSED : 17

SUMMARY RESULTS

TABLE 1 : GENERAL FEATURES

	# of series	%
Levels	4	23.53
Logs	13	76.47
Regular Diff.	14	82.35
Seasonal Diff.	15	88.24
Stationary	0	0.00
Non Stationary	17	100.00
Purely Regular	0	0.00
Nz Too Small for complete AMI	0	0.00
Airline Model (Default)	11	64.71

TABLE 2 : DIFFERENCES

# of series with	D = 0	D = 1	D = 2	Total
BD = 0	0	2	0	2
BD = 1	3	12	0	15
Total	3	14	0	17

TABLE 3 : ARMA PARAMETERS

% of series with	P	Q	BP	BQ	Total
0	82.4	41.2	88.2	11.8	
1	11.8	58.8	11.8	88.2	
2	5.9	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
Total > 0	17.6	58.8	11.8	88.2	
Average of param. per series	0.2	0.6	0.1	0.9	1.8

TABLE 4 : MISSING VALUES AND REGRESSION

		Outliers				Calendar Var.		
	MO	AO	TC	LS	Tot	TD	EE	Tot
% of series with	5.9	41.2	41.2	17.6	70.6	82.4	70.6	88.2
average # per series	24.0*	0.4	0.5	0.2	1.1			
maximum # per series	24	1	2	2	3			
minimum # per series	0	0	0	0	0			

* Only series with MO are considered

TABLE 5 : SUMMARY STATISTICS

	Mean	SD	Max	Min	Approx 1% CV	Beyond 1% CV	% of series that pass the test (99%)
Length	100.3	2.8	101	89			
# of ARMA param. per serie	1.8	0.5	3	1			
# of outliers per serie	1.1	0.9	3	0			
Q	19.8	6.0	29.8	9.4	41.64	0.0	100.0
N	1.5	1.0	3.51	0.4	9.21	0.0	100.0
SK	0.3	0.9	1.9	-1.1	2.58	0.0	100.0
Kur	-0.1	0.8	1.5	-1.4	2.58	0.0	100.0
QS					9.21	0.0	100.0
Q2	26.7	7.8	41.0	15.3	42.98	0.0	100.0
Runs	0.4	0.6	1.5	-0.9	2.58	0.0	100.0

In summary, for 11 out of the 17 series the results from the purely automatic option RSA = 4 can be accepted as final. Perhaps the most questionable point concerns estimation of the TD effect. The set of series considered is particularly sensitive to the bias towards underestimation of TD in the TRAMO pretesting procedure. Further, for the first 3 series, the 6-variable TD specification offers some advantages, although the relatively short length of the series favors model parsimony. It is worth pointing out that the use of some intervention variables (in particular, ramp effects and seasonal outliers) may also be worth considering.

The specifications finally selected marginally increase the number of series modeled in levels, the number of series that require seasonal differencing, and the number of non-stationary series. The average number of ARIMA parameters per series decreases to 1.8, and the average number of outliers increases to 1.1 per series. (Altogether, the degree of parsimony is very high.) The proportion of series subject to TD and Easter effects increases, and all tests are now passed by all series.

The matrices with the summary results for the individual series are the following.

n	TITLE	Nz	Lam	Mean	P	D	Q	BP	BD	BQ	SE(res)	BIC	Q-val	N-test	SK(t)	KUR(t)	QS	Q2	RUNS
1	"1.Demanda global"	101	0	0	0	1	1	0	1	1	0.0208700	-7.58189	13.80	0.731	0.767	-0.38	1.09	19.62	0.868
2	"2.Demanda interna"	101	0	0	0	1	1	0	1	1	0.0249549	-7.22437	23.95	1.17	0.643	-0.87	0.	26.57	0.
3	"3.Consumo privado"	101	0	0	0	1	0	0	1	1	0.0156992	-8.11240	29.84	1.52	0.966	-0.77	0.	30.78	0.659
4	"4.Consumo publico"	89	0	1	0	0	0	0	1	1	0.0690152	-5.13193	22.18	3.00	1.49	0.884	5.01	26.86	-0.47
5	"5.Inversion bruta in"	101	1	1	2	1	0	0	1	1	180.6082	10.6659	22.77	0.462	-0.62	0.277	0.	41.03	0.220
6	"6. Inversion bruta"	101	0	1	0	1	1	0	1	1	0.0586083	-5.43910	21.10	2.24	-0.20	1.48	0.	23.90	0.220
7	"7. Privada"	101	0	0	1	1	0	1	0	0	0.0679160	-5.20000	17.65	3.09	1.68	0.528	0.	37.81	0.817
8	"8.- Const"	101	0	0	0	1	1	0	1	1	0.0569649	-5.57365	9.759	0.444	-0.65	-0.13	0.	20.77	0.434
9	"9.- M Ks K"	101	0	1	0	1	1	0	1	1	0.1040000	-4.33083	15.52	1.06	0.069	-1.03	0.	25.32	0.218
10	"10.- Bs K Nac"	101	1	0	1	1	0	1	0	0	7.128104	4.14253	26.70	2.03	-1.08	0.930	0.	37.86	1.23
11	"11. Publica"	101	0	0	0	1	1	0	1	1	0.1233618	-4.02827	26.31	0.499	0.409	-0.58	0.041	15.34	-0.22
12	"12. Variacion de e"	101	1	0	0	0	0	0	1	1	153.1623	10.1411	15.80	0.574	-0.66	0.374	0.	20.88	0.643
13	"13.Exportaciones"	101	0	1	0	0	0	0	1	1	0.0542330	-5.67318	24.55	0.609	0.091	-0.77	0.055	15.95	0.434
14	"14.Oferta global"	101	0	0	0	1	1	0	1	1	0.0211959	-6.18447	15.99	0.642	0.792	-0.12	1.49	18.35	1.55
15	"15.PBI"	101	0	0	0	1	1	0	1	1	0.0178446	-7.85622	9.375	1.15	0.543	-0.92	0.245	36.59	-0.87
16	"16.Importaciones"	101	0	1	0	1	1	0	1	1	0.0506197	-5.65511	15.17	3.51	1.87	0.109	0.	30.35	0.222
17	"17.Balanza comer."	101	1	0	0	1	1	0	1	1	136.7911	9.95486	26.31	2.59	-0.71	-1.44	0.	26.56	0.

n	TITLE	PHI1	(t)	PHI2	(t)	PHI3	(t)	BPHI	(t)	TH1	(t)
1	"1_Demanda global"	-	(-)	-	(-)	-	(-)	-	(-)	-0.31468	(-3.0)
2	"2_Demanda interna"	-	(-)	-	(-)	-	(-)	-	(-)	-0.25767	(-2.4)
3	"3_Consumo privado"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
4	"4_Consumo publico"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
5	"5_Inversion bruta in"	0.389910	(3.9)	0.417473	(4.3)	-	(-)	-	(-)	-	(-)
6	"6_ Inversion bruta"	-	(-)	-	(-)	-	(-)	-	(-)	-0.36691	(-3.4)
7	"7_ Privada"	0.518021	(5.8)	-	(-)	-	(-)	-0.39540	(-4.3)	-	(-)
8	"8_- Const"	-	(-)	-	(-)	-	(-)	-	(-)	-0.31503	(-3.0)
9	"9_- M Ks K"	-	(-)	-	(-)	-	(-)	-	(-)	-0.64065	(-7.8)
10	"10_- Bs K Nac"	0.375163	(4.0)	-	(-)	-	(-)	-0.56575	(-5.4)	-	(-)
11	"11_ Publica"	-	(-)	-	(-)	-	(-)	-	(-)	-0.52933	(-5.6)
12	"12_ Variacion de e"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
13	"13_Exportaciones"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
14	"14_Oferta global"	-	(-)	-	(-)	-	(-)	-	(-)	-0.25191	(-2.3)
15	"15_PBI"	-	(-)	-	(-)	-	(-)	-	(-)	-0.19070	(-1.8)
16	"16_Importaciones"	-	(-)	-	(-)	-	(-)	-	(-)	-0.73660	(-8.7)
17	"17_Balanza comer_"	-	(-)	-	(-)	-	(-)	-	(-)	-0.40782	(-4.1)

		REGULAR AR INVERSE ROOTS						REGULAR MA INVERSE ROOTS					
		root(1)		root(2)		root(3)		root(1)		root(2)		root(3)	
n	TITLE	mod	per	mod	per	mod	per	mod	per	mod	per	mod	per
1	"1_Demanda global"							0.21875	-				
2	"2_Demanda interna"							0.17916667	-				
3	"3_Consumo privado"												
4	"4_Consumo publico"												
5	"5_Inversion bruta in"	0.44861111	-3.3	0.44861111	3.03								
6	"6_ Inversion bruta"							0.25486111	-				
7	"7_ Privada"	0.35972222	2.00										
8	"8_- Const"							0.21875	-				
9	"9_- M Ks K"							0.44513889	-				
10	"10_- Bs K Nac"	0.26041667	2.00										
11	"11_ Publica"							0.36736111	-				
12	"12_ Variacion de e"												
13	"13_Exportaciones"												
14	"14_Oferta global"							0.175	-				
15	"15_PBI"							0.13263889	-				
16	"16_Importaciones"							0.51180556	-				
17	"17_Balanza comer_"							0.28333333	-				

n	TITLE	TD	EE	#OUT	AO	TC	LS	REG	MO
1	"1_Demanda global"	1	1	0	0	0	0	0	0
2	"2_Demanda interna"	1	1	0	0	0	0	0	0
3	"3_Consumo privado"	1	1	2	1	1	0	0	0
4	"4_Consumo publico"	1	0	2	1	1	0	0	0
5	"5_Inversion bruta in"	1	1	1	0	1	0	0	0
6	"6_ Inversion bruta"	1	1	1	1	0	0	0	0
7	"7_ Privada"	1	1	1	0	1	0	0	0
8	"8_- Const"	1	1	0	0	0	0	0	0
9	"9_- M Ks K"	1	0	1	1	0	0	0	0
10	"10_- Bs K Nac"	1	1	2	0	1	1	0	0
11	"11_ Publica"	0	0	2	1	0	1	0	0
12	"12_ Variacion de e"	0	1	0	0	0	0	0	0
13	"13_Exportaciones"	0	0	2	0	2	0	0	0
14	"14_Oferta global"	1	1	1	1	0	0	0	24
15	"15_PBI"	1	1	1	1	0	0	0	0
16	"16_Importaciones"	1	1	3	0	1	2	0	0
17	"17_Balanza comer_"	1	0	0	0	0	0	0	0

n	TITLE	TD1	(t)	TD2	(t)	TD3	(t)	TD4	(t)	TD5	(t)	TD6	(t)	LY	(t)	EE	(t)
1	"1_Demanda global"	0.003284	(6.7)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.02921	(-4.0)
2	"2_Demanda interna"	0.004111	(7.4)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.03262	(-4.0)
3	"3_Consumo privado"	0.001987	(6.5)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.01745	(-3.7)
4	"4_Consumo publico"	0.004443	(1.8)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
5	"5_Inversion bruta in"	209.031	(4.3)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-239.719	(-3.8)
6	"6_ Inversion bruta"	0.006747	(4.9)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.04846	(-2.4)
7	"7_ Privada"	0.009563	(5.0)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.06830	(-2.8)
8	"8_- Const"	0.006644	(5.1)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.04287	(-2.2)
9	"9_- M Ks K"	0.011876	(3.8)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
10	"10_- Bs K Nac"	0.471970	(2.5)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-710.678	(-3.1)
11	"11_ Publica"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
12	"12_ Variacion de e"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-171.182	(-2.5)
13	"13_Exportaciones"	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)
14	"14_Oferta global"	0.003537	(5.8)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.03027	(-3.8)
15	"15_PBI"	0.002429	(6.3)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.02629	(-4.5)
16	"16_Importaciones"	0.007192	(4.7)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-0.06335	(-2.8)
17	"17_Balanza comer_"	-193.964	(-5.9)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)	-	(-)

1	"1_Demanda global"			
2	"2_Demanda interna"			
3	"3_Consumo privado"	AO01(0498, 4.45);	TC01(1098, -5.06);	
4	"4_Consumo publico"	AO01(1295, -3.94);	TC01(0300, 3.42);	
5	"5_Inversion bruta in"	TC01(1298, -3.34);		
6	"6_ Inversion bruta"	AO01(0201, 3.88);		
7	"7_ Privada"	TC01(0196, -4.19);		
8	"8_- Const"			
9	"9_- M Ks K"	AO01(0201, 4.97);		
10	"10_- Bs K Nac"	TC01(0501, 5.96);	LS01(1298, -3.04);	
11	"11_ Publica"	AO01(0196, 4.93);	LS01(0900, -3.64);	
12	"12_ Variacion de e"			
13	"13_Exportaciones"	TC01(1198, 3.66);	TC02(0397, 3.37);	
14	"14_Oferta global"	AO01(0499, -2.77);		
15	"15_PBI"	AO01(0499, -3.11);		
16	"16_Importaciones"	TC01(1098, -4.42);	LS01(0199, -6.51);	LS02(1295, -3.95);
17	"17_Balanza comer_"			

n	Input Parameters									
1	mq=12		rsa= 4	modelsumm= 1						
2	mq=12		rsa= 4							
3	mq=12		rsa= 4							
4	mq=12	itrad= 1		rsa= 3						
5	mq=12		rsa= 4		va= 3.000					
6	mq=12	itrad= 1	ieast=1		rsa= 1		va= 3.300			
7	mq=12	itrad= 1	ieast=1		rsa= 3					
8	mq=12		rsa= 4							
9	mq=12		rsa= 4							
10	imean= 0	bd= 0	p= 1	bp= 1	q= 0	bq= 0	mq=12	itrad=1	ieast= 1	iatip= 1
11	mq=12		rsa= 4							
12	mq=12		rsa= 4							
13	mq=12		rsa= 4		va= 2.600					
14	mq=12		rsa= 4							
15	mq=12		rsa= 4							
16	mq=12		rsa= 4							
17	mq=12		rsa= 4							

											SE : Rates of Growth				
							SE Est.		SE Rev.		SE T11		SE T1Mq		
n	Title			SD(innov)			(Conc.)		(Conc.)		(One Period)		(Annual Centered)		
		TC	S	Trans	U	SA	TC	SA	TC	SA	TC	SA	X	TC	SA
1	"1.Demanda global"	6.14E-03	3.04E-03	0	1.17E-02	1.80E-02	1.10E-02	8.40E-03	7.84E-03	5.97E-03	0.73	0.93	4.03	3.81	3.99
2	"2.Demanda interna"	7.57E-03	4.79E-03	0	1.28E-02	2.06E-02	1.36E-02	1.14E-02	9.94E-03	8.12E-03	0.89	1.17	5.12	4.86	5.04
3	"3.Consumo privado"	6.43E-03	2.98E-03	0	6.41E-03	1.29E-02	9.24E-03	7.97E-03	6.60E-03	5.71E-03	0.67	0.68	4.06	3.96	4.01
4	"4.Consumo publico"	8.48E-04	1.49E-02	0	5.69E-02	5.77E-02	9.76E-03	2.97E-02	6.91E-03	1.96E-02	0.12	4.35	6.76	0.57	6.49
5	"5.Inversion bruta in"	42.86	30.14	57.26	75.07	155.2	84.13	70.27	63.36	48.84	54.17	87.56	296.82	269.48	293.6
6	"6. Inversion bruta"	1.47E-02	1.20E-02	0	3.16E-02	4.69E-02	3.04E-02	2.62E-02	2.26E-02	1.87E-02	1.83	2.91	10.62	9.83	10.41
7	"7. Privada"	1.03E-02	3.60E-02	0	2.82E-02	4.09E-02	3.62E-02	3.62E-02	2.80E-02	2.25E-02	1.48	3.46	12.14	10.65	11.19
8	"8.- Const"	1.59E-02	1.08E-02	0	3.05E-02	4.70E-02	3.04E-02	2.53E-02	2.22E-02	1.80E-02	1.93	2.73	11	10.34	10.82
9	"9.- M Ks K"	1.84E-02	6.82E-04	0	8.38E-02	0.1023	4.81E-02	8.65E-03	3.25E-02	5.46E-03	2.43	1.21	13.7	11.12	13.7
10	"10.- Bs K Nac"	1.137	4.131	1.19E-02	2.93	4.349	4.306	4.295	3.468	2.96	1.67	3.66	14.8	13.02	13.53
11	"11. Publica"	2.06E-02	3.28E-02	0	6.78E-02	9.05E-02	5.73E-02	5.69E-02	4.48E-02	4.04E-02	2.77	6.86	18.61	15.84	17.76
12	"12. Variacion de e"	3.117	54.71	0	110.8	113.9	26.23	73.97	18.75	46.09	4.4	107.5	152.29	21.05	136.03
13	"13.Exportaciones"	5.73E-04	1.01E-02	0	4.65E-02	4.71E-02	7.26E-03	2.24E-02	5.14E-03	1.50E-02	0.08	3.29	5.37	0.39	5.22
14	"14.Oferta global"	5.45E-03	3.36E-03	0	9.09E-03	1.47E-02	9.71E-03	8.06E-03	7.07E-03	5.76E-03	0.64	0.83	3.66	3.49	3.61
15	"15.PBI"	6.10E-03	2.84E-03	0	8.94E-03	1.52E-02	9.74E-03	7.74E-03	6.94E-03	5.52E-03	0.69	0.78	3.89	3.75	3.85
16	"16.Importaciones"	5.83E-03	6.68E-03	0	3.80E-02	4.42E-02	2.03E-02	1.77E-02	1.47E-02	1.22E-02	0.8	2.5	5.86	3.99	5.79
17	"17.Balanza comer."	33.61	24.04	0	79.6	114.5	70.18	57.87	51.45	41.11	42.11	67.3	239.6	220.16	235.84

n	Title	Convergence (in %)				Signif. Stoch. Season. (95%)			DAA	
		1Y		5Y						
		TC	SA	TC	SA	Hist.	Prel.	Fore.	TC	SA
1	"1.Demanda global"	67.6	26.6	90.9	79.3	6	6	6	0.08	0.02
2	"2.Demanda interna"	66.2	34.3	94.0	88.4	8	7	7	0.08	0.03
3	"3.Consumo privado"	52.9	32.5	90.5	86.4	8	8	8	0.04	0.02
4	"4.Consumo publico"	30.1	30.1	83.3	83.3	5	3	3	0.82	0.19
5	"5.Inversion bruta in"	72.9	26.2	92.0	78.2	8	6	6	0.00	0.00
6	"6. Inversion bruta"	73.0	38.1	96.3	91.6	5	4	3	0.37	0.11
7	"7. Privada"	95.2	89.0	100.0	100.0	1	0	0	0.53	0.41
8	"8.- Const"	69.2	34.4	94.6	88.5	8	7	5	0.25	0.08
9	"9.- M Ks K"	96.4	1.8	96.7	9.0	7	7	6	1.41	0.07
10	"10.- Bs K Nac"	95.2	88.8	100.0	100.0	8	8	1	0.00	0.00
11	"11. Publica"	84.9	51.9	99.4	98.0	5	5	3	0.85	0.69
12	"12. Variacion de e"	49.1	49.1	96.6	96.6	8	5	3	0.00	0.00
13	"13.Exportaciones"	25.6	25.6	77.2	77.2	9	8	8	0.73	0.13
14	"14.Oferta global"	65.8	33.8	93.7	87.9	7	7	6	0.07	0.02
15	"15.PBI"	60.8	28.3	89.9	81.5	9	9	7	0.06	0.02
16	"16.Importaciones"	91.4	21.7	96.9	70.8	7	2	2	0.38	0.07
17	"17.Balanza comer."	73.9	32.8	95.0	87.0	5	4	3	0.00	0.00

n	Title	Pread.	Model Changed	Approx. to NA	Model m	p	d	q	bp	bd	bq	SD(a)	Spectr. Factor	Check on ACF	Check on CCF	Determ. Comp. TC	S	U	Modif. Trans
1	"1.Demanda global"	Y	N	N	0	0	1	1	0	1	1	2.06E-02	0	0	0	N	Y	N	N
2	"2.Demanda interna"	Y	N	N	0	0	1	1	0	1	1	2.47E-02	0	0	0	N	Y	N	N
3	"3.Consumo privado"	Y	N	N	0	0	1	0	0	1	1	1.53E-02	0	0	0	N	Y	Y	N
4	"4.Consumo publico"	Y	N	N	1	0	0	0	0	1	1	6.76E-02	0	0	0	N	Y	Y	N
5	"5.Inversion bruta in"	Y	N	N	1	2	1	0	0	1	1	177.5	0	0	0	N	Y	Y	N
6	"6. Inversion bruta"	Y	N	N	1	0	1	1	0	1	1	5.76E-02	0	0	0	N	Y	Y	N
7	"7. Privada"	Y	N	N	0	1	1	0	1	0	0	6.49E-02	0	0	0	N	Y	Y	N
8	"8.- Const"	Y	N	N	0	0	1	1	0	1	1	5.63E-02	0	0	0	N	Y	N	N
9	"9.- M Ks K"	Y	N	N	1	0	1	1	0	1	1	0.1028	0	0	0	N	Y	Y	N
10	"10.- Bs K Nac"	Y	N	N	0	1	1	0	1	0	0	7.332	0	0	0	Y	Y	Y	N
11	"11. Publica"	Y	N	N	0	0	1	1	0	1	1	0.1219	0	0	0	Y	N	Y	N
12	"12. Variacion de e"	Y	N	N	0	0	0	0	0	1	1	152.3	0	0	0	N	Y	N	N
13	"13.Exportaciones"	Y	N	N	1	0	0	0	0	1	1	5.37E-02	0	0	0	N	N	Y	N
14	"14.Oferta global"	Y	N	N	0	0	1	1	0	1	1	1.76E-02	0	0	0	N	Y	Y	N
15	"15.PBI"	Y	N	N	0	0	1	1	0	1	1	1.75E-02	0	0	0	N	Y	Y	N
16	"16.Importaciones"	Y	N	N	1	0	1	1	0	1	1	4.93E-02	0	0	0	Y	Y	Y	N
17	"17.Balanza comer."	Y	N	N	0	0	1	1	0	1	1	136	0	0	0	N	Y	N	N

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