

Programs

TRAMO

(**T**ime Series **R**egression with **AR**IMA Noise,
Missing Observations, and **O**utliers)

and

SEATS

(**S**ignal **E**xtraction in **AR**IMA **T**ime **S**eries)

Instructions for the User

(Beta Version: November 1997)

by

Víctor Gómez

Dirección General de Análisis y
Programación Presupuestaria
Ministerio de Economía y Hacienda
Paseo de la Castellana 162
28046 Madrid
Tel.: +34-1-583.54.39
Fax: +34-1-583.73.17
Email: victor.gomez-enriquez
@analisis.dgip.meh.es

and

Agustín Maravall

Suboficina de Información y
Métodos de Cálculo
Servicio de Estudios
Banco de España
Alcalá, 50
28014 Madrid
Tel.: +34-1-338.54.76
Fax: +34-1-338.51.93
Email: maravall@bde.es

Abstract

Brief summaries and user instructions are presented for the programs TRAMO (“**T**ime Series **R**egression with **AR**IMA Noise, **M**issing Observations and **O**utliers”) and SEATS (“**S**ignal **E**xtraction in **AR**IMA **T**ime **S**eries”).

TRAMO is a program for estimation and forecasting of regression models with possibly nonstationary (ARIMA) errors and any sequence of missing values. The program interpolates these values, identifies and corrects for several types of outliers, and estimates special effects such as Trading Day and Easter and, in general, intervention variable type of effects. Fully automatic model identification and outlier correction procedures are available.

SEATS is a program for estimation of unobserved components in time series following the so-called ARIMA-model-based method. The trend, seasonal, irregular, and cyclical components are estimated and forecasted with signal extraction techniques applied to ARIMA models. The standard errors of the estimates and forecasts are obtained and the model-based structure is exploited to answer questions of interest in short-term analysis of the data.

The two programs are structured so as to be used together both for in-depth analysis of a few series (as presently done at the Bank of Spain) or for automatic routine applications to a large number of series (as presently done at Eurostat). When used for seasonal adjustment, TRAMO preadjusts the series to be adjusted by SEATS.

ACKNOWLEDGEMENTS

This version of TRAMO and SEATS is the result of roughly eight years of work. During this period many persons have helped in innumerable ways, so that thorough recognition is unfeasible. Special mention, however, must be made.

First, there is the crucial role of Gianluca Caporello in the development of the programs. We have relied enormously on his commitment, expertise and ability regarding any issue related to software development and application. Counting on people like Gianluca has only one drawback: it then becomes difficult to imagine life without them.

The starting point for SEATS was a program J. Peter Burman had been developing for seasonal adjustment at the Bank of England, and his work contained very nice features. Thus, to the Bank of England, and most particularly to J. Peter Burman for his generous help, we wish to express our gratitude.

We should next mention the seven years of research support by the European University Institute, in Florence. Two specific mentions should be made. One concerns the very special comments, support, and encouragement afforded by Edmond Malinvaud and Paul Champsaur, the members of Research Council that monitored the research. The second mention goes to the generous help of several doctoral students; two of them, Christophe Planas and Gabriele Fiorentini, should be recognized. Last, but certainly not least, thanks are due to the excellent administrative work of Barbara Bonke.

We also express our gratitude for the institutional support of Eurostat, with which the programs are now closely linked (many thousand times a month). We have deeply appreciated how a large bureaucracy with a huge task can nevertheless be open to new ideas and have the courage to develop them and challenge inertia and routine. We give special thanks to Berthold Feldmann, Björn Fischer and Jens Dossé. Their careful work on large scale applications of TRAMO and SEATS has been invaluable.

We wish to thank the Bank of Spain for its current support and the willingness of many economists in the Research Department to apply and experiment with the programs in their work. Two well-deserved mentions are for Juan Carlos Delrieu and Alberto Cabrero. We also thank the computer assistance of Mercedes Sanz, the research assistance of Fernando Sánchez, and the administrative assistance of Isabel de Blas.

Finally, some names must be added to the list of acknowledgments: Gerhard Thury and Dieter Proske, Bank of Austria; Marco Bianchi, Bank of England; Roberto Sabbatini and Dario Focarelli, Bank of Italy; Dominique Ladiray, INSEE; Eric Ghysels, University of Montreal; Antoni Espasa, Regina Kaiser, and Daniel Pea, Universidad Carlos III; Albert Prat and Manuel Martí-Recover, Universidad Politécnica de Catalua; Domenico Piccolo, Università di Napoli; Pilar Bengoechea, Ministerio de Industria; David Taguas, M^a Dolores García Martos and Angel Sánchez, Ministerio de Economía y Hacienda; and most certainly, we have benefited from the many fruitful discussions with Andrew Harvey, London School of Economics, and with David Findley, U.S. Bureau of the Census.

Contents

1	Program TRAMO	1
1.1	Brief Description of the Program	1
1.2	Instructions for the User	6
1.2.1	Hardware Requirements	6
1.2.2	Expanded Memory Manager Vs. Microway Kernel	6
1.2.3	Installation	8
1.2.4	Execution of the Program	9
1.2.5	Command-Line Options	9
1.2.6	Output File	11
1.2.7	Graphics	11
1.2.8	Printing TRAMO User's Manual	11
1.2.9	Downloading TRAMO Using FTP Anonymous	12
1.3	Description of the Input Parameters	13
1.3.1	Control of the Output File	13
1.3.2	ARIMA Model	13
1.3.3	Minimum Number of Observations	14
1.3.4	Pretest for the log vs. level specification	15
1.3.5	Automatic Model Identification	15
1.3.6	Estimation	17
1.3.7	Forecasting	19
1.3.8	Missing Observations	20
1.3.9	Outliers	21
1.3.10	Regression	23
1.3.11	Others	27
1.3.12	Memory Constraints	28
1.4	Input File and Examples	29
1.5	The File ' <i>Seats.itr</i> '	48
1.6	Identification of the Arrays Produced by TRAMO	54
1.6.1	Series	54
1.6.2	Autocorrelation Functions	54
1.6.3	Regression, Outliers, and Special Effects	55

2	Program SEATS	57
2.1	Brief Description of the Program	57
2.2	Decomposition of the ARIMA Model	63
2.3	Instructions for the User	67
2.4	Description of the Input Parameters	67
2.4.1	Allocation of Regression Effects	67
2.4.2	Specification of the ARIMA Model	68
2.4.3	Estimation of the ARIMA Model	70
2.4.4	Forecasts and Signal Extraction	71
2.4.5	Bias Correction	71
2.4.6	Cyclical Component	72
2.4.7	Smoothing of the Trend; Use of SEATS as a “Fixed Filter”	73
2.4.8	Other Parameters	74
2.5	Output File	75
2.6	Input File and Examples	77
2.7	Identification of the Arrays Produced by SEATS	88
2.7.1	Series	88
2.7.2	Autocorrelation Functions	90
2.7.3	Spectra	90
2.7.4	Filters	91
2.7.5	Forecasts	91
3	Routine use on Many Series	93
3.1	The <i>RSA</i> Parameter	93
3.2	The <i>ITER</i> Parameter	99
3.3	An Application	116
4	References	119
5	Classification of Input Parameters by Function	123
5.1	Program TRAMO	123
5.2	Program SEATS	125
5.3	Routine Use on Many Series	126
	Index	127

1 Program TRAMO

1.1 Brief Description of the Program

TRAMO (“Time Series Regression with ARIMA Noise, Missing Observations, and Outliers”) is a program written in Fortran for mainframes and PCs under MS-DOS. The program performs estimation, forecasting, and interpolation of regression models with missing observations and ARIMA errors, in the presence of possibly several types of outliers. The ARIMA model can be identified automatically. (No restriction is imposed on the location of the missing observations in the series.)

Given the vector of observations:

$$z = (z_{t_1}, \dots, z_{t_M}) \quad (1)$$

where $0 < t_1 < \dots < t_M$, the program fits the regression model

$$z_t = y_t' \beta + \nu_t, \quad (2)$$

where $\beta = (\beta_1, \dots, \beta_n)'$ is a vector of regression coefficients, $y_t' = (y_{1t}, \dots, y_{nt})$ denotes n regression variables, and ν_t follows the general ARIMA process

$$\phi(B) \delta(B) \nu_t = \theta(B) a_t, \quad (3)$$

where B is the backshift operator; $\phi(B)$, $\delta(B)$, and $\theta(B)$ are finite polynomials in B , and a_t is assumed a n.i.i.d. $(0, \sigma_a^2)$ white-noise innovation.

The polynomial $\delta(B)$ contains the unit roots associated with differencing (regular and seasonal), $\phi(B)$ is the polynomial with the stationary autoregressive roots (and the complex unit roots, if present), and $\theta(B)$ denotes the (invertible) moving average polynomial. In TRAMO, they assume the following multiplicative form:

$$\begin{aligned} \delta(B) &= (1 - B)^d (1 - B^s)^D \\ \phi(B) &= (1 + \phi_1 B + \dots + \phi_p B^p) (1 + \Phi_1 B^s + \dots + \Phi_P B^{s \times P}) \\ \theta(B) &= (1 + \theta_1 B + \dots + \theta_q B^q) (1 + \Theta_1 B^s + \dots + \Theta_Q B^{s \times Q}), \end{aligned}$$

where s denotes the number of observations per year. The model may contain a constant μ , equal to the mean of the differenced series $\delta(B)z_t$. In practice, this parameter is estimated as one of the regression parameters in (2).

As explained in Section 1.3, initial estimates of the parameters can be input by the user, set to the default values, or computed by the program.

The regression variables can be input by the user (such as economic variables thought to be related with z_t), or generated by the program. The variables that can be generated are trading day, easter effect and intervention variables of the type:

- a) dummy variables (additive outliers);
- b) any possible sequence of ones and zeros;
- c) $1/(1 - \delta B)$ of any sequence of ones and zeros, where $0 < \delta \leq 1$;
- d) $1/(1 - \delta_s B^s)$ of any sequence of ones and zeros, where $0 < \delta_s \leq 1$;
- e) $1/(1 - B)(1 - B^s)$ of any sequence of ones and zeros.

The program:

- 1) estimates by exact maximum likelihood (or unconditional/conditional least squares) the parameters in (2) and (3);
- 2) detects and corrects for several types of outliers;
- 3) computes optimal forecasts for the series, together with their MSE;
- 4) yields optimal interpolators of the missing observations and their associated MSE; and
- 5) contains an option for automatic model identification and automatic outlier treatment.

The basic methodology followed is described in Gómez and Maravall (1994). Additional documentation is contained in Gómez and Maravall (1992), Gómez (1997) and Gmez, Maravall and Pea (1996).

Estimation of the regression parameters (including intervention variables and outliers, and the missing observations among the initial values of the series), plus the ARIMA model parameters, can be made by concentrating the former out of the likelihood, or by joint estimation. Several algorithms are available for computing the likelihood or more precisely, the nonlinear sum of squares to be minimized. When the differenced series can be used, the algorithm of Morf, Sidhu and Kailath (1974), with a simplification similar to that of Mélard, (1984), is employed. This simplification extends to multiplicative seasonal moving average models, a case discussed, but not implemented, in Mélard.

For the nondifferenced series, it is possible to use the ordinary Kalman filter (default option), or its square root version (see Anderson and Moore, 1979). The latter is adequate when numerical difficulties arise; however it is markedly slower.

By default, the exact maximum likelihood method is employed, and the unconditional and conditional least squares methods are available as options. Nonlinear maximization of the likelihood function and computation of the parameter estimates standard errors is made using Marquardt's method and first numerical derivatives.

Estimation of regression parameters is made by using first the Cholesky decomposition of the inverse error covariance matrix to transform the regression equation (the Kalman filter provides an efficient algorithm to compute the variables in this transformed regression). Then, the resulting least squares problem is solved by applying the QR algorithm, where the Householder orthogonal transformation is used. This procedure yields an efficient and numerically stable method to compute GLS estimators of the regression parameters, which avoids matrix inversion.

For forecasting, the ordinary Kalman filter or the square root filter options are available. These algorithms are applied to the original series; see Gmez and Maravall (1993) for a more detailed discussion on how to build initial conditions on a nonstationary situation.

Missing observations can be handled in two equivalent ways. The first one is an extension to nonstationary models of the skipping approach of Jones (1980), and is described in Gmez and Maravall (1994). In this case, interpolation of missing values is made by a simplified Fixed Point Smoother, and yields identical results to Kohn and Ansley (1986). The second one consists of assigning a tentative value and specifying an additive outlier to each missing observation. If this option is used, the interpolator is the difference between the tentative value and the estimated regression parameter and, if the ARIMA parameters are the same, it coincides with the interpolator obtained with the skipping approach. Also, the likelihood can be corrected so that it coincides with that of the skipping approach. See Gmez, Maravall and Pea (1996) for more details.

When concentrating the regression parameters out of the likelihood, mean squared errors of the forecasts and interpolations are obtained following the approach of Kohn and Ansley (1985).

When some of the initial missing values are unestimable (free parameters), the program detects them, and flags the forecasts or interpolations that depend on these free parameters. The user can then assign arbitrary values (typically, very large or very small) to the free parameters and rerun the program. Proceeding in this way, all parameters of the ARIMA model can be estimated because the function to minimize does not depend on the free parameters. Moreover, it will be evident which forecasts and interpolations are affected by these arbitrary values because they will strongly deviate from the rest of the estimates. However, if all unknown parameters are jointly estimated, the program may not flag all free parameters. It may happen that there is convergence to a valid arbitrary set of solutions (i.e., that some linear combinations of the initial missing observations, including the free parameters, are estimable.)

The program has a facility for detecting outliers and for removing their effect; the outliers can be entered by the user or they can be automatically

detected by the program, using an original approach based on those of Tsay (1986) and Chen and Liu (1993). The outliers are detected one by one, as proposed by Tsay (1986), and multiple regressions are used, as in Chen and Liu (1993), to detect spurious outliers. The procedure used to incorporate or reject outliers is similar to the stepwise regression procedure for selecting the “best” regression equation. This results in a more robust procedure than that of Chen and Liu (1993), which uses “backward elimination” and may therefore detect too many outliers in the first step of the procedure.

In brief, regression parameters are initialized by OLS and the ARMA model parameters are first estimated with two regressions, as in Hannan and Rissanen (1982). Next, the Kalman filter and the QR algorithm provide new regression parameter estimates and regression residuals. For each observation, t -tests are computed for four types of outliers, as in Chen and Liu (1993). If there are outliers whose absolute t -values are greater than a pre-selected critical level C , the one with the greatest absolute t -value is selected. Otherwise, the series is free from outlier effects and the algorithm stops.

If some outlier has been detected, the series is corrected by its effect and the ARMA model parameters are first re-estimated. Then, a multiple regression is performed using the Kalman filter and the QR algorithm. If there are some outliers whose absolute t -values are below the critical level C , the one with the lowest absolute t -value is removed from the regression and the multiple regression is re-estimated. In the next step, using the regression residuals provided by the last multiple regression, t -tests are computed for the four types of outliers and for each observation. If there are outliers whose absolute t -values are greater than the critical level C , the one with the greatest absolute t -value is selected and the algorithm goes on to the estimation of the ARMA model parameters to iterate. Otherwise, the algorithm stops.

A notable feature of this algorithm is that all calculations are based on linear regression techniques, which reduces computational time. The four types of outliers considered are additive outlier, innovational outlier, level shift, and transitory change.

The program also contains a facility to pretest for the log-level specification (based on a trimmed range-mean regression, complemented with the BIC of the default model using both specifications) and, if appropriate, for the possible presence of Trading Day and Easter effects (the pretests are made with regressions using the default model for the noise and, if the model is subsequently changed, the test is redone); it further performs an automatic model identification of the ARIMA model. This is done in two steps. The first one yields the nonstationary polynomial $\delta(B)$ of model (3). This is done by iterating on a sequence of AR and ARMA(1, 1) models (with mean), which have a multiplicative structure when the data is seasonal. The procedure is based on results of

Tiao and Tsay (1983, Theor. 3.2 and 4.1), and Tsay (1984, Corol. 2.1). Regular and seasonal differences are obtained, up to a maximum order of $\nabla^2 \nabla_s$. The program also checks for possible complex unit roots at nonzero and nonseasonal frequencies.

The second step identifies an ARMA model for the stationary series (corrected for outliers and regression-type effects) following the Hannan–Rissanen procedure, with an improvement which consists of using the Kalman filter instead of zeros to calculate the first residuals in the computation of the estimator of the variance of the innovations of model (3). For the general multiplicative model

$$\phi_p(B) \Phi_P(B^s) x_t = \theta_q(B) \Theta_Q(B^s) a_t,$$

the search is made over the range $0 \leq (p, q) \leq 3$, $0 \leq (P, Q) \leq 2$. This is done sequentially (for fixed regular polynomials, the seasonal ones are obtained, and viceversa), and the final orders of the polynomials are chosen according to the BIC criterion, with some possible constraints aimed at increasing parsimony and favoring “balanced” models (similar AR and MA orders).

Finally, the program combines the facilities for automatic detection and correction of outliers and automatic ARIMA model identification just described in an efficient way, so that it has an option for automatic model identification of a nonstationary series in the presence of outliers.

Although TRAMO can obviously be used by itself, for example, as a forecasting program, it can also be seen as a program that polishes a contaminated “ARIMA series”. That is, for a given time series, it interpolates the missing observations, identifies outliers and removes their effect, estimates Trading Day and Easter Effect, etc., and eventually produces a linear purely stochastic process (i.e., the ARIMA model). Thus, TRAMO, can be used as a pre-adjustment process to SEATS (see below), which decomposes then the “linearized series” and its forecasts into its stochastic components.

Both programs can handle routine applications to a large number of series and provide a complete model-based solution to the problems of forecasting, interpolation and signal extraction for nonstationary time series.

1.2 Instructions for the User

This Section is common to both programs, TRAMO and SEATS.

1.2.1 Hardware Requirements

The present versions of SEATS and TRAMO are compiled with the Microway NDP Fortran486 - Ver. 4.2.5 and Microsoft Fortran77 Ver. 5.0, linked with the Microway 486 Linker Ver. 4.2.5 and Microsoft Fortran77 Linker Ver. 5.0.

The present releases break the 640K barrier by utilizing the full 32-bit addressing mode available on 80486 machines; they can run only on 80486-based computers (also PENTIUM) that have at least 4 MB of extended memory.

Executing SEATS and TRAMO requires the following hardware:

- an Intel 80486 or PENTIUM-based IBM-compatible PC;
- a 3.5" diskette drive;
- a hard disk with about 4 MB of free space;
- at least 4 MB of extended memory;
- MS-DOS V3.3 or greater;
- a video graphics adapter VGA, EGA, CGA (color video is recommended).

Note 1: When the execution of TRAMO or SEATS finds an NDP error, the file containing the error is stored in the file *report.bug*, and the program stops.

Note 2: At present, the two programs are compiled for a **maximum number of 600 observations** per series (this limit can be easily modified).

1.2.2 Expanded Memory Manager Vs. Microway Kernel

SEATS and TRAMO are linked with the Microway Dos Extender Kernel (MK). It is an extended memory manager and makes the programs able to access the high memory addresses. The MK is compatible with expanded memory managers (EMM) like CEMM (Version 4.0 or better), EMM386 (Version 4.0 or better) or QEMM (Version 4.1 or better). All these programs adhere to an interface standard called VCPI (Virtual Control Program Interface) to which MK also adheres. If you are running EMM, the primary control program (the EMM) provides the secondary control program (MK) with a set of services, and the two programs coexist sharing the machine's resources.

The MK is not compatible with the EMM only if you have in your CONFIG.SYS a line like this:

```
DEVICE = C : \DOS\EMM386.EXE NOEMS (4)
```

It means you are using an EMM only to address the upper memory area (where you are storing various Dos drivers) in order to increment the quantity of the total conventional memory available (usually the Dos **MemMaker** proposes this kind of configuration). In this case the EMM is not running in VCPI mode so the MK is not able to talk with it. If you are in this kind of situation, you can run SEATS and TRAMO only if you delete the option NOEMS in (4) (you pay for this with something like 64 Kb of conventional memory). Otherwise, you can create a double configuration **config.sys**: the first is your normal one and the other is a special one for SEATS and TRAMO. In order to do it, put in your config.sys:

```
[MENU]
MENUITEM=SEATS
MENUITEM=NORMAL
```

```
[SEATS]
your config.sys without the line where you define the EMM device
```

```
[NORMAL]
config.sys
```

Example:

ORIGINAL CONFIG.SYS:

```
DEVICE=C:\DOS\HIMEM.SYS
DEVICE=C:\DOS\EMM386.EXE NOEMS
FILES=35
DOS=HIGH
DEVICEHIGH=C:\DOS\SETVER.EXE
SHELL=C:\DOS\COMMAND.COM C:\DOS /P/E:2048
DEVICEHIGH=C:\DOS\ANSI.SYS
BREAK=ON
STACKS=9,512
```

DUAL BOOT CONFIG.SYS:

```
[MENU]
MENUITEM=SEATS
MENUITEM=NORMAL
[NORMAL]
DEVICE=C:\DOS\HIMEM.SYS
DEVICE=C:\DOS\EMM386.EXE NOEMS
```

```

FILES=35
DOS=HIGH
DEVICEHIGH=C:\DOS\SETVER.EXE
SHELL=C:\DOS\COMMAND.COM C:\DOS /P/E:2048
DEVICEHIGH=C:\DOS\ANSI.SYS
BREAK=ON
STACKS=9,512
[SEATS]
DEVICE=C:\DOS\HIMEM.SYS
FILES=35
DOS=HIGH
DEVICEHIGH=C:\DOS\SETVER.EXE
SHELL=C:\DOS\COMMAND.COM C:\DOS /P/E:2048
DEVICEHIGH=C:\DOS\ANSI.SYS
BREAK=ON
STACKS=9,512

```

With a config.sys like this, when you boot the machine you can select the NORMAL or the SEATS configuration.

1.2.3 Installation

Insert the diskette in drive A or B and change the default drive (type “A:” or “B:”); when the prompt appears, type **INSTALL**.

The installation procedure asks you for the name of directory in which TRAMO will be installed; by default the directory is TRAMO (in this case be sure it does not already exist).

Three subdirectories are created: SERIES, GRAPH and OUTPUT. The input files should be prepared in the SERIES subdirectory.

TRAMO uses two environment variables **SLIB** and **SERIES** to find the files needed to run. The variable SLIB is the path to look for the graphics library, the variable SERIES is the path to look for the series.

By default (if you install the program on C:\TRAMO) the values for these variables are SLIB = C:\TRAMO\LIB and SERIES = C:\TRAMO\SERIES, so no action is necessary.

If you specified a different directory for TRAMO, you must set them as needed; put in your AUTOEXEC.BAT the following two lines:

```

SET SLIB      =  path\LIB
SET SERIES    =  path\SERIES

```

where *path* is the full path name of the directory where the program is installed.

By following the same procedure, the program SEATS would be installed (by default) in C:\SEATS.

1.2.4 Execution of the Program

Once in TRAMO type: **INPUT**

This is a very simple usable program to prepare the input file for the main program TRAMO. It shows a list of the available series (in the directory specified by variable SERIES) and, after you have selected one of them, it permits to set the values of the program parameters showing a list of all default values.

The program allows some simple facilities:

- “q” to exit;
- “h” to see default parameter values;
- “l” to list already set parameters.

Set the parameters typing them one by one according to the following syntax:

parameter-name = parameter-value

Once all (non-default) parameter values have been set, in the next line type “end”. This creates the file SERIE, containing the data and parameter values for the main program. Of course the file SERIE can be edited directly; this will typically be more convenient when minor changes are desired on an already existing SERIE file.

Having, thus, the SERIE file ready, to run the program type **TRAMO**. Alternatively, TRAMO can be run on a bat file by simply typing Tramo filename.

1.2.5 Command-Line Options

For the two programs, some options can be directly entered in the command-line. These options are the following:

- s (Silent-mode) no output is seen in the screen during execution.
- o *output* Specifies the directory where the output file should be stored (when not used, the output file goes to the directory OUTPUT; see Section 1.2.6).
- i *filename* Specifies the name of the input file (when not used, the input file is always ‘serie’; see Section 1.2.4).

- g graphpath* Specifies the directory where the files for the graphics should be stored. (In DOS this option should not be used because the graphics programs only look in the directory GRAPH.) In the case of SEATS, care should be taken that the subdirectories SERIES, ACF, SPECTRA, FILTERS, and FORECAST are present in the specified path.
- OF filename* Specifies the name of the output file. This file contains all the program output. Thus, even when ITER \neq 0, the two programs contain a single output file each, with all the results for the processed series. The name of this file is '*filename.out*'.

With this option, the files with extension *.tre*, *.sa*, *.cyc* in SEATS, or *.ser*, *.lin* in TRAMO, disappear and instead a single file, '*filename.cmp*' is created. Its structure will be

⋮	⋮	⋮
<i>seriename</i>		
TREND	SA SERIES	CYCLE
<i>xxxx</i>	<i>xxxx</i>	<i>xxx</i>
---	---	---
<i>xxx</i>	<i>xxxx</i>	<i>xxx</i>
<i>seriename</i>		
TREND	SA SERIES	CYCLE
<i>xxxx</i>	<i>xxxx</i>	<i>xxx</i>
---	---	---
<i>xxx</i>	<i>xxxx</i>	<i>xxx</i>
⋮	⋮	⋮

and similarly for TRAMO.

For TRAMO, the following command permits the rename of the file *seats.itr* (see Section 1.3.11).

- k filename* Specifies the name assigned to the file *seats.itr*. (In the examples below it is passed to SEATS as *serie*).

Examples: C : \> SEATS *-s -i alp -o* C : \temp *-OF* alput
 C : \> TRAMO *-k* C : \SEATS\serie

Warning: Options are case sensitive!

1.2.6 Output File

You can see the result of the program by editing or printing the file *serie-name.OUTPUT* in the subdirectory OUTPUT.

As mentioned earlier, several arrays are stored in the subdirectory GRAPH, from which they can be easily retrieved. A table describing the meaning of each array is contained in Subsection 1.6.

1.2.7 Graphics

Typing **GRAPH** you can see some graphics on the screen. The program selects the better graphics resolution for you (if you have any graphics adapter). Running the program, files are created in the subdirectory GRAPH, containing all relevant output arrays (used by the GRAPH program), from which they can be retrieved for further use in packages such as SAS, MATLAB and GAUSS or for further numerical analysis. This version also supports direct laser-jet prints of the graphics produced. Typing the command “egalaser” from the prompt (before calling GRAPH), and calling GRAPH with the option “-P”, the file GRAPH.LHJ is created which can then be printed.

Different graphs (such as the original, outlier corrected, and linearized series, for example) can be compared through an OVERLAY facility. Further, graphs from different runs of TRAMO can be simultaneously plotted. When exiting GRAPH (after its execution), you will be asked if you wish a backup copy of the graphics. By typing Y, the graphs are copied in the directory GRAPH, in the files *seriesname.bk1*, and *seriesname.n1*. (If a backup was previously made, then the files become *.bk2* and *.n2*.) In the next execution of GRAPH, you will have the option of comparing the new and old graphics (by typing 77). The maximum number of models that can be compared is 3.

Warning: The files *seriesname.bk1* and *seriesname.n1* are not automatically erased at the next execution of TRAMO. By typing (from \TRAMO)

CLEAN,

all previous backups will be erased from the directory GRAPH.

1.2.8 Printing TRAMO User's Manual

In the directory MANUAL you can find the file EXTMAN.EXE, a self-extracting compressed file. It contains a POSTSCRIPT copy of the TRAMO and SEATS user manual.

In order to print it, type EXTMAN from the DOS prompt; this command produces a file MANUAL.PS, and then you can print it in your POSTSCRIPT printer.

1.2.9 Downloading TRAMO Using FTP Anonymous

The PC MS-DOS programs TRAMO and SEATS, together with the user instructions manual, are made available by the Bank of Spain at the following Internet address

<http://www.bde.es>

Note: Eurostat has developed a WINDOWS application of TRAMO and SEATS under Microsoft EXCEL (5.0), which allows the user to seasonally adjust series stored in an EXCEL spreadsheet, using most parameter specifications. The results (seasonally adjusted series, trend-cycle data, forecasts), plus a short diagnostic sheet, are again stored in the EXCEL data file. The program can be obtained from Eurostat, e-mail

berthold.feldmann@eurostat.cec.be

1.3 Description of the Input Parameters

1.3.1 Control of the Output File

In TRAMO and SEATS, the output file is controlled with the following parameter:

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>OUT</i>	= 0	Detailed output file for each series	0
	= 1	Reduced output file for each series	
	= 2	Very brief summary for all series in one file (TRAMO); in one file per series (SEATS)	
	= 3	No output file	
	= -2	As <i>OUT</i> = 0, but also a very brief summary for all series is given in a separate file (only TRAMO)	

In the case of *OUT* = ± 2 , the very brief summary from TRAMO can be seen in the file *table.out*, in the OUTPUT directory.

When the two programs are used together, *OUT* is entered in TRAMO, and passed on to SEATS through the file *seats.itr*.

1.3.2 ARIMA Model

<i>MQ</i>	=	Number of observations per year (12 for monthly, 6 for bimonthly, 4 for quarterly, 1 for annual, and so on).	12
<i>LAM</i>	= 1	No transformation of data	0
	= 0	Take logs of data	
<i>IMEAN</i>	= 0	No mean correction	1
	= 1	Mean correction	
<i>D</i>	=	# of non-seasonal differences	1
<i>BD</i>	=	# of seasonal differences	1
<i>P</i>	=	# of non-seasonal autoregressive terms	0
<i>BP</i>	=	# of seasonal autoregressive terms	0
<i>Q</i>	=	# of non-seasonal moving average terms	1

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>BQ</i>	= # of seasonal moving average terms	1
<i>TH</i>	= <i>Q</i> initial estimates of the regular moving average parameters (not input if <i>INIT</i> =0 and <i>JQR(I)</i> =0 for all <i>I</i>).	All -.1
<i>BTH</i>	= <i>BQ</i> initial estimates of the seasonal moving average parameters (not input if <i>INIT</i> =0 and <i>JQS(I)</i> =0 for all <i>I</i>).	All -.1
<i>PHI</i>	= <i>P</i> initial estimates of the regular autoregressive parameters (not input if <i>INIT</i> =0 and <i>JPR(I)</i> =0 for all <i>I</i>).	All -.1
<i>BPHI</i>	= <i>BP</i> initial estimates of the seasonal autoregressive parameters (not input if <i>INIT</i> =0 and <i>JPS(I)</i> =0 for all <i>I</i>).	All -.1
<i>JPR(I)</i>	= 1 Parameter number <i>I</i> in the regular autoregressive polynomial fixed to the value set in <i>PHI(I)</i> (it is not estimated). = 0 Parameter not fixed.	0
<i>JPS(I)</i>	= 1 Parameter number <i>I</i> in the seasonal autoregressive polynomial fixed to the value set in <i>BPHI(I)</i> (it is not estimated). = 0 Parameter not fixed.	0
<i>JQR(I)</i>	= 1 Parameter number <i>I</i> in the regular moving average polynomial fixed to the value set in <i>TH(I)</i> (it is not estimated). = 0 Parameter not fixed.	0
<i>JQS(I)</i>	= 1 Parameter number <i>I</i> in the seasonal moving average polynomial fixed to the value set in <i>BTH(I)</i> (it is not estimated). = 0 Parameter not fixed.	0

1.3.3 Minimum Number of Observations

The minimum number of observations depends on *MQ*, on the particular model, and on the options requested. By default, if *m* denotes the minimum number of observations,

- for $MQ \geq 12$, $m = 36$
- for $MQ < 12$, $m = \max(12, 4 \times MQ)$.

If the number of observations satisfies these minima, but is not enough for some additional option requested, the option is removed and its default value reset.

1.3.4 Pretest for the log vs. level specification

The program can pretest for the level-versus-log specification. This is controlled as follows:

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>LAM</i>	= 0	As before (logs).	0
	= 1	As before (levels).	
	= -1	The program tests for the log-level specification.	

The test is based, first, on the slope (b) of a range-mean regression, “trimmed” to avoid outlier distortion. This slope b is compared to a constant (β), close to zero, that depends on the number of observations and on the value of *RSA*. When the results of the regression are unclear, the value of *LAM* is chosen according to the *BIC* of the default model, using both specifications.

Note 1: The value *LAM* = -1 is recommended for automatic modelling of many series.

Note 2: The value β increases when *RSA* > 0, so as to favor the choice of the log transformation when a large number of series are routinely adjusted.

1.3.5 Automatic Model Identification

<i>INIC</i>	= 0	No automatic model identification is performed	0
	= 2	The program searches for regular polynomials up to order 2, and for seasonal polynomials up to order 1.	
	= 3	The program searches for regular polynomials up to order 3, and for seasonal polynomials up to order 1.	
	= 4	The program searches for regular polynomials up to order 3 and for seasonal polynomials up to order 2 (not input if <i>IDIF</i> =0).	
	= -1	No automatic model identification is made in TRAMO, and SEATS performs the model selection (essentially, a comparison of four models) described in p. 92 of this Manual (case <i>RSA</i> =1). Thus, the model selection of SEATS can be activated without having to set <i>RSA</i> = 1 or 2.	

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>IDIF</i>	= 0 No automatic model identification.	0
	= 2 Used for automatic model identification. The program accepts the regular (<i>D</i>) and seasonal (<i>BD</i>) differences entered by the user. Used with <i>INIC</i> >1.	
	= 3 Used for automatic model identification. The program searches first for regular differences up to order 2 and for seasonal differences up to order 1. Then, it continues with the identification of an ARMA model for the differenced series. Used with <i>INIC</i> >1.	
	= 5 Same as <i>IDIF</i> =3, but the program also searches for unit complex roots.	

When TRAMO is run with *SEATS* $\neq 0$, if *INIC* = 4, it is automatically changed to *INIC* = 3.

<i>UB1</i>	= If one of the roots in the “AR(2) \times AR _s (1) plus mean” estimation in the first step of the automatic identification of the differencing polynomial is larger than <i>UB1</i> , in modulus, it is set equal to unity.	.96
<i>UB2</i>	= If one of the roots in the “ARMA(1,1) \times ARMA _s (1,1) plus mean” estimation in the second step of the automatic model identification is larger than <i>UB2</i> , in modulus, it is set equal to unity.	.88
<i>CANCEL</i>	= If the difference in moduli of an AR and an MA root (when estimating ARMA(1,1) \times ARMA _s (1,1) models in the second step of the automatic identification of the differencing polynomial) is smaller than <i>CANCEL</i> , the two roots cancel out.	.10
<i>IMVX</i>	= See Section 1.3.9 (“Outliers”).	
<i>PCR</i>	= α Level of significance for the Ljung-Box Q-test used in automatic model identification.	.95
<i>IFAL</i>	= 0 Normal Procedure	0
	= 1 If, in the first round the default model passes the test, the model is accepted and the search stops.	

For automatic identification of a model, there are two steps: First, the program identifies the degrees of differencing (*IDIF*=2,3,5) and later, the program identifies an ARMA model for the differenced series (*INIC*=2,3,4). If *IDIF*=2, the

program accepts the degrees of differencing entered by the user (D and BD), together with the mean specification, and goes on to obtain the ARMA model identification ($INIC=2,3,4$). If $INIC=3$, the program obtains the degrees of differencing and goes on to obtain the ARMA model identification ($INIC=2,3,4$). $IDIF=5$ is as $IDIF=3$, but the program also checks for the presence of unit complex roots. With $IDIF=3,5$, the program generates mean correction if needed, so $IMEAN$ should be input as 0. When the series is thought to contain many outliers, the use of $IMVX=2$ is recommended.

Warning: In so far as they represent alternatives, the program does not accept the simultaneous presence of seasonal differences and seasonal dummy variables, nor of a regular difference and a linear deterministic trend. To incorporate deterministic trends or seasonals in automatic model identification, $IDIF=2$ should be used.

TRAMO and SEATS reproduce well simulated deterministic trends or seasonals by setting MA roots close (but not equal) to one. The programs are not devised to be used with dummy seasonals or linear deterministic trends when regular and seasonal differences are present. When $RSA \neq 0$ and a solution is needed, the deterministic seasonal and trend components are modelled as extremely stable stochastic components, and the program proceeds. For actual series, in our experience, the stochastic formulation works much better even for nearly-deterministic series.

1.3.6 Estimation

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
$INCON$	= 0	Exact maximum likelihood estimation	0
	= 1	Unconditional least squares (only to use with $IFILT=1,2$ or 3).	
$INIT$	= 0	Estimation of unknown parameters and starting values computed by the program	0
	= 1	Estimation of unknown parameters with starting values input by the user	
	= 2	No estimation.	

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>IFILT</i>	= 1	Square root filter	2
	= 2	Morf, Sidhu and Kailath algorithm, as improved by Mèlard	
	= 3	Ordinary Kalman filter	
	= 4	Conditional least squares.	
<i>IDENSC</i>	= 1	Denominator of residual sum of squares is that of Ansley and Newbold (1981) = number of non-initial observations minus number of unknown parameters (AR and MA parameters plus regression parameters, including outliers and initial missing observations)	1
	= 0	Denominator of residual sum of squares is equal to the number of non-initial observations.	
<i>TOL</i>	=	Convergence criterion in Gauss-Marquardt's method.	1.E-4
<i>ICONCE</i>	= 1	σ^2 and regression parameters (including outliers and missing initial observations) concentrated out of the likelihood	1
	= 0	Only σ^2 concentrated out of the likelihood.	
<i>UBP</i>	=	If an AR root found in the estimation of the ARMA model parameters is larger than <i>UBP</i> , it is set equal to one.	.97
<i>M</i>	=	# of autocorrelations and partial autocorrelations printed.	36
<i>IQM</i>	=	# of autocorrelations used in computing <i>Q</i> -statistics.	24*
<i>IROOT</i>	= 1	Roots of all AR and MA polynomials are computed	2
	= 0	Roots not given	
	= 2	Roots of all AR and MA polynomials are computed, and the former are set automatically as unit roots if their modulus is larger than <i>UBP</i> .	
<i>IGRBAR</i>	= 1	Graph of autocorrelations printed.	0
	= 0	Graph of autocorrelations not printed.	
<i>TSIG</i>	=	<i>t</i> -value under which the mean or the ARIMA parameters should be excluded from the model in the last step of the automatic model identification in TRAMO.	1

(*) The default value of *IQM* depends on *MQ*. For $MQ = 12$, $IQM = 24$; for $MQ = 2, 3, 4, 6$, $IQM = 4 \times MQ$; for $MQ = 1$, $IQM = 8$.

1.3.7 Forecasting

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>NBACK</i>	<p>= > 0 # of observations back from the end of the data that the multistep forecasts are to begin.</p> <p>= < 0 When <i>NBACK</i> < 0, then (- <i>NBACK</i>) observations are omitted from the end of the series. The model is estimated for the shorter series, one-period-ahead forecast errors are sequentially computed for the last (- <i>NBACK</i>) periods (without reestimation of the model), and an <i>F</i>-test is performed that compares the out-of-sample forecast errors with the in-sample residuals.</p> <p>The forecast function is printed, as well as the one-period-ahead forecasts, together with the associated forecast errors.</p>	0

When *SEATS* ≠ 0, the program automatically sets *NBACK*=0. When *SEATS*=0 and *NBACK*≠ 0, the program sets *NPRED*=ABS(*NBACK*).

<i>NPRED</i>	= # of multistep forecast values to compute.	0
		if <i>SEATS</i> =0; max(8,2× <i>MQ</i>) if <i>SEATS</i> ≠ 0.

When *NPRED* = 0, if *SEATS* ≠ 0, the forecasts of the series, as well as their standard errors, are computed and printed, up to the *TF*-step-ahead forecast (*TF* = max(8, 2 × *MQ*)).

<i>LOGN</i>	= 0 Levels are obtained as exponents of the logs.	1
	= 1 Levels and Standard errors are obtained through the Lognormal distribution (only for <i>LAM</i> = 0).	

Note 1: The forecast when *LOGN* = 1 is larger than the forecast for *LOGN* = 0, and the difference will increase with the forecast horizon.

Note 2: At present, when *SEATS* ≠ 0, *LOGN* is set = 0.

1.3.8 Missing Observations

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>INTERP</i>	= 0	No interpolation of unobserved values and missing observations treated using the skipping approach	1
	= 1	Interpolation of unobserved values and missing observations treated using the skipping approach	
	= 2	Missing observations are treated as additive outliers (initial values are constructed as the sum of the two adjacent observations; interpolation is always performed).	
<i>ICDET</i>	= 1	A proper correction is made in the determinantal term of the likelihood when missing observations are treated as additive outliers	1
	= 0	No correction is made in the determinantal term.	

Missing observations can be treated in two ways: Skipping approach (*INTERP*=0,1) and additive outliers approach (*INTERP*=2). If *ICDET*=1 and *INTERP*=2, the determinantal term in the function to be minimized is adjusted so that it coincides with that of the function used in the skipping approach.

The automatic model identification facility of TRAMO can be used in the presence of outliers only if these are treated as additive outliers (*INTERP*=2). When this is the case, in order to identify the degree of differencing (*IDIF* = 3, 5), the missing observations are first replaced with tentative values which are the sum of the two adjacent observations. Then, for ARMA model identification (*INIC* = 2, 3, 4) of the differenced series, the program estimates all regression parameters, included those of the missing observations. In this way, the missing observations are implicitly estimated as the difference between the tentative value and the estimated regression parameter of the additive outlier.

1.3.9 Outliers

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>VA</i>	= If <i>IATIP</i> =1, it is used to set the critical value for outlier detection (not input if <i>IATIP</i> =0).	4.0
<i>IATIP</i>	= 1 Automatic detection and correction of four types of outliers (<i>IO</i> , <i>AO</i> , <i>LS</i> , <i>TC</i>) is performed. If <i>IMVX</i> =0, the fast method of Hannan–Rissanen is used for estimation of parameters. If <i>IMVX</i> =1,3 (see below), then maximum likelihood estimation is used. After correcting for the outliers found in the first round, the program performs a new automatic model identification, and a new search for outliers if the model has been changed. In this second round, the critical value <i>VA</i> is reduced by the fraction <i>PC</i> . If the second round does not provide a satisfactory model, a third round is carried out. (The model obtained with automatic identification is always compared with the default model.) = 0 No outlier detection is performed.	0
<i>IMVX</i>	= 0 The fast method of Hannan–Rissanen is used for parameter estimation in the automatic detection and correction of outliers (not input if <i>IATIP</i> =0) = 1 Maximum likelihood estimation is used for parameter estimation in the automatic detection and correction of outliers (not input if <i>IATIP</i> =0) = 2 First, unconditional least squares and then exact maximum likelihood is used in the estimation of the unit roots in the automatic model identification. If <i>IATIP</i> >0, then estimation of outliers is made with the Hannan–Rissanen procedure = 3 As <i>IMVX</i> =2, but, if <i>IATIP</i> >0, outliers correction is made with the exact maximum likelihood procedure. This procedure, although relatively time consuming, may be of interest when the series contains many outliers.	0
<i>PC</i>	= Percentage by which <i>VA</i> is reduced in the second round when <i>IATIP</i> =1.	.14286
<i>DELTATC</i>	= δ $0 < \delta < 1$ It affects only the <i>TC</i> outlier, which is equal to an impulse divided by $(1 - \delta B)$.	.7

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>ISTDV</i>	= 0	The residual variance used in automatic outlier detection is obtained through the MAD estimator.	0
	= 1	The residual variance used in automatic outlier detection is obtained through the leave-one-out trimmed estimator.	
<i>AIO</i>	= 0	The program corrects for the four types of outliers described below.	2
	= 1	All outliers are treated as additive outliers or transitory changes (in this way the level of the series is preserved).	
	= 2	Additive Outliers, Transitory Changes, and Level Shifts are considered (Innovations Outliers are not included).	
	= 3	Only Level Shifts and Additive Outliers are considered.	

When TRAMO is run with $SEATS \neq 0$, $AIO = 1$ or 2 is now the standard option. When $SEATS \neq 0$, if $AIO = 0$, it is automatically set equal to 2. Transitory Changes and Additive Outliers will be assigned in SEATS to the irregular component, and Level Shifts to the trend.

Two parameters, $INT1$ and $INT2$, can be used to define the interval ($INT1$, $INT2$) over which outliers have to be searched. By default

$$INT1 = 1; \quad INT2 = NZ.$$

A facility has been introduced to **avoid outlier correction in the last observations of the series**, which may cause instability in the series forecasts. In particular:

When $INT2 < 0$, outliers are automatically detected and corrected in the interval ($INT1$, $NZ + INT2$). Then, the detection procedure is applied to the last $-INT2$ observations, and if some outlier is detected a warning is printed, but no correction is made. Example: if $NZ = 200$ and $INT2 = -6$, outliers are detected and corrected for the interval (1, 194). For the last 6 observations they are only detected.

Detection and correction of outliers is made with a procedure based on those of Tsay (1986) and Chen and Liu (1993). This procedure has some notable features (namely, exact residuals are used; estimation, based on two simple regressions, is fast; the parameter estimates are modified at each iteration; and it uses a robust method to incorporate or reject outliers which is similar to the stepwise regression procedure to select the “best” regression equation).

Four kinds of outliers can be identified and corrected by the program: innovational outliers (*IO*), additive outliers (*AO*), level shifts (*LS*) and temporary changes (*TC*). This last one being equal to an impulse divided by $1-\delta B$. If $IATIP=1$ and $INIC=0$, the program performs the identification and correction of the four kinds of outliers using the model entered by the user. Recommended critical values depend on the series length, and are given in Section 3.1.

If automatic outlier identification and correction ($IATIP>0$) is to be performed along with automatic model identification ($INIC>2$), the sequence of actions is as follows. After obtaining the degrees of differencing, either automatically ($IDIF=3$) or accepting those entered by the user ($IDIF=2$), if $IATIP=1$, the program obtains first a model using the BIC criterion and then performs the automatic identification and correction of outliers using the previously identified model. There are two rounds: first, the program accepts the model entered by the user and corrects the series for the outlier effects. Then, it returns to model identification and further outlier identification and correction, using the model obtained in the second round and a critical level equal to $(1-PC)$ times that of the first round.

Since innovational outliers (specially at the beginning of the series) may have very drastic effects on the level of the series, by default $AIO=2$, so that only level shifts are allowed to affect the trend. When the preservation of constraints between aggregates and components is an important consideration, the value $AIO = 1$ may be the most sensible choice.

1.3.10 Regression

The regression variables used to make the trading day or easter effect adjustment are generated by the program in the same way as that described in Hillmer, Bell, and Tiao (1983), or in Harvey (1989, p. 334). The aggregate trading day and Easter effects are normalized so as to preserve the mean level of the series.

a) Easter and Trading Day Effects

The program contains a **pretest for Easter and Trading Day effects**; this is done by running a regression on the default model. In automatic model identification, if the model is changed, both tests are then redone. (When these effects are to be estimated, if the starting year in the input file contains only the last two digits, the program adds 1900 to this number.)

The input parameters *IEAST* and *ITRAD* are as follows:

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>IEAST</i>	= 0	No Easter effect.	0
	= 1	Easter effect adjustment.	
	= -1	The program pretests for Easter effect.	
<i>IDUR</i>	=	Duration of easter affecting period (# of days).	8
<i>ITRAD</i>	= 0	No Trading Day effect is estimated.	0
	= 1	# of (M, T, W, Th, F) - # (Sat, Sun) $\times \frac{5}{2}$.	
	= 2	As the previous case, but with length-of-month adjustment.	
	= 6	# M - # Sun, # T - # Sun, ..., # Sat - # Sun.	
	= 7	As the previous case, but with length-of-month correction.	
	= -1	As <i>ITRAD</i> = 1, but a pretest is made.	
	= -2	As <i>ITRAD</i> = 2, but a pretest is made.	
	= -6	As <i>ITRAD</i> = 6, but a pretest is made.	
	= -7	As <i>ITRAD</i> = 7, but a pretest is made.	

Length-of-month correction = # (total days in month) - 365.25/12.

Two parameters, *INTD1* and *INTD2*, can be used to define the interval (*INTD1*, *INTD2*) over which the Trading Day effect is to be estimated. By default

$$INTD1 = 1; \quad INTD2 = NZ.$$

Warning: At present, Trading Day and Easter corrections are aimed at monthly data.

b) Regression and Intervention Variables; Holiday Effect.

<i>IREG</i>	= # of regression variables (entered by the user or calculated by the program as intervention variables).	0
<i>RG</i>	= <i>IMEAN+IREG+ITRAD+IEAST</i> initial estimates of the regression parameters, not including initial missing observations (not input if there are not missing observations or <i>ICONCE=1</i>).	All 0.1

If *IREG* in namelist *INPUT* is greater than zero, then namelist *INPUT* should be followed by a certain number of namelist *REG*, to be specified below. Each

namelist *REG* starts with $\$REG$, terminates with $\$$ and contains the set of instructions for the corresponding regression variable(s).

The total number of namelists *REG* is as follows: There must be as many namelists *REG* following namelist *INPUT* as there are regression variables not entered by the user, plus one namelist *REG* for each file containing regression variables entered by the user.

The parameters in namelist *REG* are:

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>																
<i>IUSER</i> = 1	The user will enter a series for this regression variable. After the present namelist <i>REG</i> , the user will write the series X(I): I=1, <i>ILONG</i> (free format). After the series, next namelist <i>REG</i> should be written	0																
= -1	The program will read <i>NSER</i> series from the file whose name is written after the present namelist <i>REG</i> . There must be <i>NSER</i> columns of length <i>ILONG</i> in this file separated by blanks, containing the <i>NSER</i> series (<i>NSER</i> >0 must be input)																	
= 0	The user does not provide any series																	
= 2	The user specifies the presence of some outliers. Then <i>NSER</i> is equal to the number of specified outliers, and is followed, in a new line, by a sequence of pairs of numbers (free format): $t_1 \ j_1 \ t_2 \ j_2 \ \dots \ t_{NSER} \ j_{NSER}$ where $t_1 \ \dots \ t_{NSER}$ denote the position of the outlier ($t = 1, \dots, T$), and j_1, \dots, j_{NSER} denote the type of outlier according to the following code: <table border="0" style="margin-left: 2em;"> <tr> <td>j_i</td> <td>=</td> <td><i>IO</i></td> <td>Innovation outlier</td> </tr> <tr> <td></td> <td>=</td> <td><i>AO</i></td> <td>Additive outlier</td> </tr> <tr> <td></td> <td>=</td> <td><i>LS</i></td> <td>Level shift</td> </tr> <tr> <td></td> <td>=</td> <td><i>TC</i></td> <td>Temporary change.</td> </tr> </table>	j_i	=	<i>IO</i>	Innovation outlier		=	<i>AO</i>	Additive outlier		=	<i>LS</i>	Level shift		=	<i>TC</i>	Temporary change.	
j_i	=	<i>IO</i>	Innovation outlier															
	=	<i>AO</i>	Additive outlier															
	=	<i>LS</i>	Level shift															
	=	<i>TC</i>	Temporary change.															
= -2	Holidays are incorporated in an external file.																	

The program contains a facility to incorporate in an external file **holidays** that do not fall on Sunday (when *ITRAD* = 6, 7, -6, -7), or on a Saturday or Sunday (when *ITRAD* = 1, 2, -1, -2). The input namelist should contain the parameter:

- a) when *ITRAD* = 6, 7, -6, -7,
IREG = # of regression variables + 6,
- b) when *ITRAD* = 1, 2, -1, -2,
IREG = # of regression variables + 1,

where # of regression variables includes those entered by the user and the ones generated by the program. Holidays are treated as non-working days. That is,

for each month, the number of working days is decreased and the number of non-working days is increased by the amount of the holidays.

A namelist *REG* has to be added, with the parameter values:

$$IUSER = -2,$$

NSER = 6 or 1 and the value of *ILONG*. This namelist is followed by a line with the name of the file from which the holidays will be read.

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>NSER</i>	= <i>k</i> (<i>k</i> a positive integer) number of series entered by the user in an external file (if <i>IUSER</i> =-1), or number of outliers specified by the user (if <i>IUSER</i> =2)	0
	= 0 No series entered by the user in any external file.	
<i>ILONG</i>	= Length of the series entered by the user if <i>IUSER</i> =1, -1, -2. If forecasts are to be computed, <i>ILONG</i> should be equal to <i>NZ</i> + <i>NPRED</i> , where <i>NZ</i> is the length of the series; if smaller, the rest of the series, up to a total length of <i>NZ</i> + <i>NPRED</i> is filled up with zeroes (not input if <i>IUSER</i> =0).	0
<i>ISEQ</i>	= <i>k</i> (<i>k</i> = a positive integer). The program will generate one intervention variable of length <i>NZ</i> + <i>NPRED</i> consisting of <i>k</i> sequences of ones. After the present namelist <i>REG</i> , the user will write <i>k</i> pairs of numbers (free format); the <i>k</i> -th pair indicates the time index where the <i>k</i> -th sequence of ones is to begin and its length, respectively. The <i>k</i> pairs of numbers are to be followed by the next namelist <i>REG</i> (no input if <i>IUSER</i> =1,-1)	0
	= 0 The program will generate no regression variable.	
<i>DELTA</i>	= δ ($0 < \delta \leq 1$); the filter $1/(1 - \delta B)$ will be applied to the <i>k</i> -sequences of ones generated by the program (no input if <i>IUSER</i> =1,-1).	0
<i>DELTAS</i>	= δ_s ($0 < \delta_s \leq 1$); the filter $1/(1 - \delta_s B^s)$, $s=MQ$, will be applied to the <i>k</i> -sequences of ones generated by the program (no input if <i>IUSER</i> =1,-1).	0
<i>ID1DS</i>	= 1 The program will generate $1/(1-B)(1-B^s)$, $s=MQ$, of the <i>k</i> -sequences of ones generated by the program (no input if <i>IUSER</i> =1,-1).	0

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>REGEFF</i> = k	($k = 0, 1, \dots, 5$). Only active with <i>SEATS</i> $\neq 0$. It determines the way the regression effects are allocated to the components of the series. See “Allocation of Regression Effects”, Section 2.4.1.	0

Note 1: *IREG* should equal the number of namelists *REG* with *IUSER*=1, plus *NSEK* for each namelist *REG* with *IUSER*=-1 or 2.

Note 2: When *IATIP* $\neq 0$, the parameter *IUSER* should not be 2. The user could still impose outliers specified a priori by entering them as intervention variables in the usual way (i.e., *IUSER* = 0, and setting the parameters *ISEQ*, *DELTA*, *DELTAS*, *ID1DS*, *REGEFF*).

Note 3: The order of the regression variables in TRAMO is as follows. Mean, Missing Observations (when appropriate), Regression variables entered by the user or generated by the program, Trading Day variables, Easter variable, and Outliers.

Note 4: For the allocation of the regression effects to the series components, when TRAMO is used as a preadjustment program for SEATS, see Section 2.4.1 below.

1.3.11 Others

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>PG</i> = 0	Creates output files in the subdirectory <i>GRAPH</i>	0
<i>PG</i> = 1	No output files in <i>GRAPH</i> .	
<i>SEATS</i> = 0	No input file for SEATS is created	0
<i>SEATS</i> = 1	Creates input file for SEATS redoing estimation in SEATS. The name of this file will be SEATS.ITR	
<i>SEATS</i> = 2	Creates input file for SEATS and no estimation is performed in SEATS. The name of this file will be SEATS.ITR .	
<i>UR</i> , <i>XL</i>	When <i>SEATS</i> =2, if the modulus of an estimated root in the AR polynomial falls in the range (<i>XL</i> , 1), it is set equal to <i>UR</i> . If the root is in the MA polynomial, it is set equal to <i>XL</i> . (Used only when <i>SEATS</i> =2.)	1, .98

In order to execute SEATS, the file *seats.itr* should be passed on to the directory *SEATS* as “*serie*”.

1.3.12 Memory Constraints

The user should be aware of the following memory constraints:

$IFILT=2$	$2+2 \times IMRTE \leq 64$ $IR+2 + ICON \leq 64$
$IFILT=3$	$1+2 \times IMRTE + IMISP \leq 64$ $MAX\{IR+1, ICON\} + ICON \leq 64$
$IFILT=1$	like $IFILT=3$
In all cases	$MAX\{N, ICON\} + N+1 \leq 64,$ $NZ \leq 600$ $NZ+NPRED \leq 664,$

where NZ is the length of the series, $IMRTE = IMEAN + IREG + ITRAD + IEAST$, $IMISP$ = number of initial missing values in the skipping approach, $ICON = (MIN\{ICONCE, 1\}) \times (IMRTE + IMISP) + 1$, $IR = MAX\{ID + IP, IQ + 1\}$ if $IFILT = 1$ or 3 , $IR = MAX\{IP, IQ + 1\}$ if $IFILT = 2$ or 4 , $ID = D + MQ \times BD$, $IP = P + MQ \times BP$, N = number of parameters to be estimated by Gauss–Marquardt’s method.

Note: $IREG$ includes all outliers (and missing observations treated as additive outliers). In the case of automatic model identification, $ITRAD$ and $IEAST$ are the ones resulting after the testing process, that is, they are assigned non-negative values.

1.4 Input File and Examples

The input starts with the series to be modelled, comprising no more than 600 observations, followed by one set of control parameters for the series model plus a list of instructions for the regression variables.

To specify the set of control parameters for the series model, as well as the instructions for the regression variables, the NAMELIST facility is used, so that only those parameters which are not at their default values need to be set.

The series is set up as:

Card 1 TITLE (no more than 72 characters)
Card 2 NZ NYER NPER NFREQ (free format)
Card 3 et seq. Z(I): I = 1, NZ (free format),

where NZ is the number of observations, NYER the start year, NPER the start period, and NFREQ is an instruction to control table format (the number of columns). Z(.) is the array of observations. For each missing observation, the code -99999. must be entered. (The first nonblank characters of TITLE are used by the program to create a file named *****.OUT in the subdirectory OUTPUT containing the output of the program.)

This is followed by namelist INPUT. The namelist starts with \$INPUT and terminates with \$.

Eight examples of input files for TRAMO are provided. They illustrate some of the most relevant features of the program.

Note: the format '\$INPUT ... \$' can be replaced by others such as '&INPUT .../'.

Example 1

The series is the airline passengers series of Box and Jenkins (1970). The program performs first a test for the log/level specification, and fits the default model

$$\nabla \nabla_{12} \log z_t = (1 + \theta_1 B)(1 + \theta_{12} B) a_t$$

with automatic outlier detection and correction. Exact maximum likelihood estimation is used, with starting values computed by the program. A simplified Morf-Sidhu-Kailath algorithm is employed for likelihood evaluation. Three types of outliers are considered: additive outliers, transitory outliers and level shifts, with a relatively low critical level (notice that $AIO = 2$ is unnecessary, since it is the default value).

A *seats.itr* file is created for SEATS, and if the ARIMA model passed by TRAMO does not accept an admissible decomposition, SEATS will replace it with a decomposable approximation.

EXAMPLE 1

AIRLINE DATA (Box-Jenkins)

```
144 1949 1 12
112 118 132 129 121 135 148 148 136 119 104 118
115 126 141 135 125 149 170 170 158 133 114 140
145 150 178 163 172 178 199 199 184 162 146 166
171 180 193 181 183 218 230 242 209 191 172 194
196 196 236 235 229 243 264 272 237 211 180 201
204 188 235 227 234 264 302 293 259 229 203 229
242 233 267 269 270 315 364 347 312 274 237 278
284 277 317 313 318 374 413 405 355 306 271 306
315 301 356 348 355 422 465 467 404 347 305 336
340 318 362 348 363 435 491 505 404 359 310 337
360 342 406 396 420 472 548 559 463 407 362 405
417 391 419 461 472 535 622 606 508 461 390 432
$INPUT lam=-1,iatip=1,aio=2,va=3.3,
noadmiss=1,seats=2,$
```

Example 2

The monthly series y_t of oxidant (O_3) level recordings in downtown Los Angeles, for the period January 1955 / December 1972, is considered. The series was analyzed by Box and Tiao (1975) and the identified model is of the form

$$y_t = \frac{\omega_1}{1-B} \xi_{1t} + \frac{\omega_2}{1-B^{12}} \xi_{2t} + \frac{\omega_3}{1-B^{12}} \xi_{3t} + n_t$$
$$(1 + \phi B) \nabla_{12} n_t = (1 + \theta_{12} B^{12}) a_t,$$

where ξ_{1t} , ξ_{2t} and ξ_{3t} are three “intervention” variables such that

$$\xi_{1t} = \begin{cases} 1 & t = \text{January 1960;} \\ 0 & \text{otherwise;} \end{cases}$$
$$\xi_{2t} = \begin{cases} 1 & \text{months June–October, beginning in 1966;} \\ 0 & \text{otherwise;} \end{cases}$$
$$\xi_{3t} = \begin{cases} 1 & \text{months November–May, beginning in 1966;} \\ 0 & \text{otherwise.} \end{cases}$$

Eight observations were randomly removed and estimated as missing values using the “additive outlier approach” with the appropriate determinantal correction in the likelihood. The missing observations can be identified by the number -99999 . in the file. For this model, the three regression variables are constructed by the program. (For their particular meaning, see the paper by Box and Tiao.) The 1-to-36 periods-ahead forecast function (and associated standard errors) is computed. Estimation of the model will be made by exact ML; the regression parameters and (in this case) the additive outlier parameters corresponding to the missing observations, will be concentrated out of the likelihood.

EXAMPLE 2

OZONE LEVEL L.A. (BOX-TIAO)

```

216 1955 1 12
2.7 2.0 -99999. 5.0 6.5 6.1 5.9 5.0 6.4 7.4 8.2 3.9
4.1 4.5 5.5 3.8 4.8 5.6 6.3 5.9 -99999. 5.3 5.7 5.7
3.0 3.4 4.9 4.5 4.0 5.7 6.3 7.1 8.0 5.2 5.0 4.7
3.7 3.1 -99999. 4.0 4.1 4.6 -99999. 4.2 5.1 4.6 4.4 4.0
2.9 2.4 4.7 5.1 4.0 7.5 7.7 6.3 5.3 5.7 4.8 2.7
1.7 2.0 3.4 4.0 4.3 5.0 5.5 5.0 5.4 3.8 2.4 2.0
2.2 2.5 2.6 3.3 2.9 4.3 4.2 4.2 3.9 3.9 2.5 2.2
2.4 1.9 2.1 4.5 3.3 3.4 4.1 5.7 4.8 5.0 2.8 2.9
1.7 3.2 2.7 3.0 3.4 3.8 5.0 4.8 4.9 3.5 2.5 2.4
1.6 2.3 2.5 3.1 -99999. 4.5 5.7 5.0 4.6 4.8 2.1 1.4
2.1 2.9 2.7 4.2 3.9 4.1 4.6 5.8 4.4 6.1 3.5 1.9
1.8 1.9 3.7 4.4 3.8 5.6 5.7 5.1 5.6 -99999. 2.5 1.5
1.8 2.5 2.6 1.8 3.7 3.7 4.9 5.1 3.7 5.4 3.0 1.8
2.1 2.6 2.8 3.2 3.5 3.5 4.9 4.2 4.7 3.7 3.2 1.8
2.0 -99999. 2.8 3.2 4.4 3.4 3.9 5.5 3.8 3.2 2.3 2.2
1.3 2.3 2.7 3.3 3.7 3.0 3.8 4.7 4.6 2.9 1.7 1.3
1.8 2.0 2.2 3.0 2.4 3.5 3.5 3.3 2.7 2.5 1.6 1.2
1.5 2.0 3.1 3.0 3.5 -99999. 4.0 3.8 3.1 2.1 1.6 1.3

```

```
&INPUT NPRED=36,LAM=1,IREG=3,INTERP=2,IMEAN=0,P=1,Q=0,D=0,/
```

```
&REG ISEQ=1, DELTA=1.DO,/
```

```
61 1
```

```
&REG ISEQ=8,DELTAS=1.DO, /
```

```
138 5 150 5 162 5 174 5 186 5 198 5 210 5 222 5
```

```
&REG ISEQ=8,DELTAS=1.DO, /
```

```
143 7 155 7 167 7 179 7 191 7 203 7 215 7 227 7
```

Example 3

Example 3 is the same as in Harvey and Pierse (1984) and in Data Set 2 of Kohn and Ansley (1986). It consists of removing, from the 12 years of monthly data of the Airline passengers series of Example 1, all January through November data in the last 6 years. Since the estimation problem is identical when the missing values are placed at the beginning, the example illustrates an important possible application of the program: Interpolation of data for frequencies higher than the observed one.

There are no regressors, and the ARIMA model is the default model of Example 1 (the “Airline Model”).

Interpolation of the missing values is made with the “skipping approach” and a simplified version of the fixed point smoother. Computation of the likelihood is made with the ordinary Kalman filter ($IFILT = 3$ is in this case unnecessary, since it would be set automatically by the program).

A file *seats.itr* is produced ready for SEATS. In this case, however, only the model orders are passed, and SEATS reestimates the ARIMA model parameters.

EXAMPLE 3

```
MONTHLY INTERPOLATION, AIRLINE MODEL (HARVEY-PIERSE)
144  1949 1 12
112 118 132 129 121 135 148 148 136 119 104 118
115 126 141 135 125 149 170 170 158 133 114 140
145 150 178 163 172 178 199 199 184 162 146 166
171 180 193 181 183 218 230 242 209 191 172 194
196 196 236 235 229 243 264 272 237 211 180 201
204 188 235 227 234 264 302 293 259 229 203 229
-99999. -99999. -99999. -99999. -99999. -99999. -99999. -99999.
-99999. -99999. -99999. 278
-99999. -99999. -99999. -99999. -99999. -99999. -99999. -99999.
-99999. -99999. -99999. 306
-99999. -99999. -99999. -99999. -99999. -99999. -99999. -99999.
-99999. -99999. -99999. 336
-99999. -99999. -99999. -99999. -99999. -99999. -99999. -99999.
-99999. -99999. -99999. 337
-99999. -99999. -99999. -99999. -99999. -99999. -99999. -99999.
-99999. -99999. -99999. 405
-99999. -99999. -99999. -99999. -99999. -99999. -99999. -99999.
-99999. -99999. -99999. 432
$INPUT INTERP=1,IFILT=3,SEATS=1,$
```

Example 4

The series is the monthly series of sales in retail variety stores in Chen, Liu and Hudak (1990). The example illustrates what could be a standard way of executing TRAMO for a series for which there is no a priori information (other than the fact that Trading Day and Easter effect are surely not present).

The program pretests for the log/level specification, performs identification of the 3 types of outliers of Example 1 and of the ARIMA model, and joint exact maximum likelihood estimation of the model parameters. (Notice that after correction for the outliers, the full ARIMA model is identified again, and a second outlier detection and correction will be made.) It further computes the 1-to-24 periods-ahead forecast function (in this case, $NPRED = 24$ would be automatically set by the program). The identified model is of the type

$$(1 + \phi_1 B + \phi_2 B^2) \nabla \nabla_{12} z_t = (1 + \theta_{12} B^{12}) a_t,$$

and 3 outliers have been detected and removed.

A *seats.itr* file is created (for use by SEATS) which includes the series forecasts, the outlier effects, the ARIMA model and the parameter estimates. $NOADMIS = 1$ guarantees that, if the model is nonadmissible, an approximation will be provided.

EXAMPLE 4

RETAIL SALES VARIETY STORES (CHEN-LIU-HUDAK)

153	1967	1	12									
296	303	365	363	417	421	404	436	421	429	499	915	
331	361	402	426	460	457	451	476	436	464	525	939	
345	364	427	445	478	492	469	501	459	494	548	1022	
370	378	453	470	534	510	485	527	536	553	621	1122	
394	411	482	484	550	525	494	537	513	521	596	1069	
393	425	503	529	581	558	547	588	549	593	649	1191	
463	459	554	576	615	619	589	637	601	642	737	1279	
490	490	598	615	681	654	637	694	645	684	749	1245	
489	511	612	623	726	692	623	734	662	684	781	1386	
503	537	636	560	607	585	559	608	556	596	665	1229	
427	450	573	579	615	601	608	617	550	616	673	1199	
438	458	548	584	639	616	614	647	588	648	713	1261	
483	483	593	620	672	650	643	702	654				

\$INPUT LAM=-1, IDIF=3, INIC=3, VA=3.5, IATIP=1, NPRED=24, SEATS=2, NOADMISS=1, \$

Example 5

The series is the monthly sales os U.S. men's and boys' clothing stores in Hillmer, Bell and Tiao (1983). The program fits the model (z_t denotes the logged variable)

$$z_t = \alpha H(\tau, T) + \sum_{i=1}^7 \beta_i T_{it} + n_t,$$

where $H(\cdot)$ denotes the easter effect, T_{1t}, \dots, T_{7t} are the trading day effects, and n_t follows the model

$$(1 + \phi_1 B) \nabla \nabla_{12} n_t = (1 + \theta_2 B^2)(1 + \theta_{12} B^{12}) a_t,$$

with θ_1 constrained to be zero. The Trading Day effect includes length-of-month correction. Estimation is carried out by exact maximum likelihood, and automatic detection and correction of outliers is made (in this case, maximum likelihood is used instead of the (default) Hannan-Rissanen method.) So as to preserve the level, all outliers are forced to be either additive outliers or transitory changes. Since SEATS $\neq 0$, by default, the 1-to-24 periods-ahead forecast function will be obtained. The original series and forecasts, and the Easter, Trading Day, and outlier effects, are passed on to SEATS, together with the ARIMA model, including the parameter estimates. SEATS will assign transitory changes and additive outliers to the irregular, and level shifts to the trend. After removing the mean effect, trading day and easter effect will go to the seasonal component.

EXAMPLE 5

retailmen-EXAMP(HILL-BELL-TIAO)

153 1967 1 12

237	187	241	245	259	296	252	260	271	267	320	549
266	216	252	297	302	310	270	288	280	316	372	594
319	249	287	320	342	329	291	321	315	361	400	680
338	268	304	313	348	350	321	317	333	364	396	719
336	267	303	375	382	401	341	351	357	382	447	771
364	310	379	408	439	451	390	413	424	469	534	884
452	361	426	470	477	502	424	442	442	479	562	961
437	368	427	495	514	492	443	500	458	492	542	889
459	403	490	467	556	542	474	510	483	527	591	1044
495	404	463	540	518	552	505	502	496	558	629	1137
511	440	496	578	542	550	492	518	507	569	708	1141
480	421	532	536	542	563	508	554	552	609	763	1293
561	462	564	582	586	615	553	612	570			

\$INPUT P=1,Q=2,JQR(1)=1,TH(1)=0,IEAST=1,IDUR=9,ITRAD=7,IMVX=1,
IATIP=1,VA=3.5,AIO=1,SEATS=2,\$

Example 6

The series is the Spanish monthly currency series for the period January 1962 / June 1996 (414 observations).

After pretesting for the log/level specification, and for the possible presence of trading and easter effects ($IDUR = 8$ is unnecessary, since it is the default value), the program estimates the model

$$(1 + \phi_1 B + \phi_3 B^3) \nabla \nabla_{12} z_t = (1 + \theta_{12} B^{12}) a_t,$$

and, if they are significant, Trading Day and Easter effect as in Example 5 without length-of-month correction. Automatic outlier detection considers 4 types of outliers: the 3 of Example 1, plus innovation outliers.

An out-of-sample forecasting test is performed by removing the last 36 observations and estimating the model for the shorter series. Since $SEATS = 0$ and the series is in logs, forecasts and their standard errors are obtained from the lognormal distribution.

EXAMPLE 6

CURRENCY (SPAIN)

414 1962 1 12

\$INPUT

80749.0	81657.0	83087.0	84105.0	84349.0	86411.0	91068.0
91106.0	93129.0	92934.0	92497.0	97939.0	93797.0	95108.0
97981.0	97652.0	97646.0	100647.0	105937.0	107500.0	107928.0
106691.0	106928.0	112787.0	108410.0	110187.0	112182.0	112059.0
113323.0	115939.0	123244.0	123333.0	123324.0	124220.0	123265.0
131607.0	127102.0	128422.0	127429.0	131009.0	131344.0	134800.0
145869.0	143125.0	143381.0	143558.0	140657.0	150992.0	145175.0
146167.0	146731.0	150458.0	150990.0	153483.0	166238.0	162480.0
163716.0	162375.0	160782.0	174724.0	165948.0	168290.0	169464.0
175355.0	173243.0	177366.0	190555.0	184811.0	188206.0	183973.0
181084.0	198512.0	185297.0	184629.0	188044.0	187480.0	187482.0
196032.0	206040.0	203712.0	201853.0	201699.0	201175.0	217786.0
203241.0	205184.0	210139.0	209162.0	213486.0	219616.0	231983.0
228617.0	226438.0	226291.0	226557.0	242556.0	229587.0	231572.0
231640.0	232409.0	233821.0	239838.0	256887.0	246510.0	242589.0
242071.0	239784.0	262443.0	245681.0	247670.0	247572.0	252718.0
254556.0	261353.0	282739.0	270481.0	268609.0	270531.0	266021.0
293428.0	272572.0	274446.0	283718.0	286162.0	283087.0	294135.0
316972.0	301683.0	305644.0	300148.0	299126.0	333543.0	308943.0
310072.0	323361.0	325780.0	326073.0	345897.0	370499.0	355535.0
357633.0	346400.0	349015.0	385848.0	354006.0	360003.0	373985.0
373249.0	375170.0	395671.0	423729.0	410594.0	406391.0	402824.0
405173.0	445536.0	416308.0	420538.0	435008.0	434998.0	451074.0
464630.0	503855.0	487626.0	477471.0	485156.0	486591.0	522895.0
493089.0	499272.0	502081.0	517195.0	514108.0	533640.0	595271.0
557488.0	551964.0	559517.0	545659.0	613143.0	572375.0	580387.0
591155.0	605288.0	609262.0	635876.0	733017.0	685732.0	693714.0
687075.0	683418.0	774949.0	725403.0	730767.0	759548.0	779477.0
775237.0	821211.0	899950.0	850135.0	862509.0	847086.0	838964.0
941333.0	863132.0	889486.0	919678.0	916402.0	911226.0	951011.0
1011834.0	971615.0	965410.0	947635.0	949412.0	1034509.0	955952.0
969336.0	991731.0	1004983.0	1043806.0	1075890.0	1158956.0	1129516.0
1103354.0	1102569.0	1095916.0	1178749.0	1114695.0	1126970.0	1126251.0
1157901.0	1172236.0	1192817.0	1287438.0	1236819.0	1216405.0	1229796.0
1208277.0	1326169.0	1234957.0	1237795.0	1240812.0	1281810.0	1283614.0
1309776.0	1417090.0	1347697.0	1344917.0	1407518.0	1379432.0	1522492.0
1426039.0	1449417.0	1551421.0	1543814.0	1529508.0	1550461.0	1664231.0
1581117.0	1577438.0	1569263.0	1531475.0	1686025.0	1575002.0	1570508.0
1606137.0	1615848.0	1610194.0	1707524.0	1792333.0	1752320.0	1746958.0
1724439.0	1706245.0	1862317.0	1738270.0	1741670.0	1803989.0	1799391.0
1817325.0	1891098.0	1981484.0	1953517.0	1934181.0	1923631.0	1909981.0
2080475.0	1973705.0	1987698.0	2039946.0	2052700.0	2096532.0	2152733.0
2256375.0	2221750.0	2202084.0	2217482.0	2209439.0	2401538.0	2283857.0
2292791.0	2291027.0	2363031.0	2382624.0	2430718.0	2584309.0	2510903.0
2491158.0	2524560.0	2502926.0	2735085.0	2595287.0	2583233.0	2714407.0

2698838.0 2728301.0 2823803.0 3028582.0 2930976.0 2970772.0 2961751.0
2928581.0 3236372.0 3058637.0 3092100.0 3201705.0 3265178.0 3269589.0
3452948.0 3609238.0 3530098.0 3577245.0 3563007.0 3535416.0 3835085.0
3588925.0 3600298.0 3699697.0 3748496.0 3752974.0 3896207.0 4024489.0
4017622.0 4045448.0 4094299.0 4198839.0 4533315.0 4335905.0 4396405.0
4555778.0 4570908.0 4689841.0 4832722.0 5001618.0 4986642.0 5019116.0
5074417.0 5143576.0 5607216.0 5441625.0 5447093.0 5454243.0 5537138.0
5555099.0 5612722.0 5820069.0 5707524.0 5704235.0 5671382.0 5664833.0
6024621.0 5804886.0 5853287.0 5883084.0 5917969.0 5911491.0 6009142.0
6222621.0 6106814.0 6113668.0 6122138.0 6101660.0 6508926.0 6275246.0
6280564.0 6442236.0 6412478.0 6471637.0 6612456.0 6819418.0 6730737.0
6813779.0 6782683.0 6772993.0 7164429.4 6897069.0 6925122.4 7027932.7
7031466.0 7042994.7 7214445.5 7306794.4 7212305.0 7257089.9 7183808.0
7186599.5 7535256.9 7207819.9 7231233.6 7334642.1 7316523.3 7422156.8
7505553.6

\$INPUT

p=3, itrad=-6, idur=8, ieast=-1, imean=0, jpr(2)=1, phi(2)=0, jqr(1)=1, th(1)=0,
aio=0, iatip=1, va=4, lam=-1, NBACK=-36, \$

Example 7

The series is the monthly series of the Spanish industrial production index for the period January 1983 / May 1996. First, there are missing observations that are interpolated. Second, a pretest is made for the log/level specification and for the Trading Day and Easter effects. (Notice that the Trading Day specification is the most parsimonious one, and different from the ones in examples 5 and 6). TRAMO performs full automatic model identification and MLE of the parameters.

The model contains two regression variables and is of the type

$$z_t = \beta_1 x_{1t} + \beta_2 x_{2t} + \nu_t$$

where ν_t is found to follow the default Airline model, and:

- x_{1t} is a regression variable that includes holidays (the forecast period is considered). It is provided in the external file *holidays*.
- x_{2t} is a level shift outlier specified a priori. It corresponds to the date at which the base of the index was changed.

TRAMO will produce a file *seats.itr* for SEATS containing the ARIMA model, together with parameter estimators, the forecasts of the series, the Trading Day and Easter effects, plus the effect of the two regression variables. After being removed of the mean effects, the Trading Day, Easter, and holiday effects will be assigned to the seasonal component; the change in levels due to the new base will be assigned to the trend. (Trading Day, Easter, and outlier effects are automatically extended over the forecast period.)

EXAMPLE 7

IPI(Spain)

161 1983 1 12

83.6	83.3	-99999.	-99999.	89.3	86.9	82.8
49.9	87.8	86.8	88.9	86.6	86.5	87.2
-99999.	-99999.	89.8	85.6	85.8	53.3	85.4
91.6	90.2	82.6	88.6	84.6	89.2	84.8
90.6	83.8	89.5	52.4	88.3	99.0	92.9
86.2	88.4	88.0	87.5	94.6	91.2	92.5
93.7	50.4	92.1	100.3	94.9	88.1	87.6
91.9	96.6	91.4	96.3	97.3	102.9	53.1
98.4	102.0	101.1	92.1	90.2	96.5	103.4
95.0	101.2	100.3	99.6	56.4	100.8	100.9
105.8	94.5	100.7	98.7	103.4	102.1	104.8
107.7	104.6	60.0	105.0	107.3	108.8	92.7
105.0	98.9	108.4	96.0	107.1	107.1	104.4
59.8	102.4	105.7	109.2	92.4	103.7	99.0
96.8	102.2	104.0	102.3	104.5	58.9	102.8
111.8	106.1	95.3	100.3	101.1	104.3	98.3
100.3	102.8	104.5	58.8	98.9	100.7	97.3
86.7	88.2	90.3	98.0	90.2	95.3	96.8
97.5	56.9	97.1	97.0	99.5	92.0	91.1
95.2	103.5	97.0	102.1	-99999.	102.7	64.2
104.9	104.4	109.2	99.9	104.2	101.5	113.9
97.4	112.0	112.7	106.2	67.4	105.6	108.1
110.4	95.2	102.7	102.4	106.4	98.4	108.4

\$INPUT lam=-1,itrads=-1,ieast=-1,idif=3,inic=3,ireg=2,interp=1,
noadmiss=1,seats=2,\$

\$REG iuser=-1 nser=1 ilong=185 regeff=2 \$

examples\holidays

\$REG iuser=2 nser=1 regeff=1 \$

119 ls

FILE *holidays*

The file is read with free format, which means that the data can be organized in many different ways. For example, the data may consist of one column array.

1	0	0	0	0	2	1	1	0	1
1	1	1	0	1	0	1	1	1	1
0	1	1	1	1	0	1	0	1	1
1	1	0	0	1	1	2	0	0	0
2	0	1	1	0	0	0	2	2	0
1	0	1	1	0	0	0	1	0	2
2	0	0	0	0	1	1	1	0	1
1	2	1	0	0	0	2	0	1	1
0	1	1	3	1	0	1	0	1	0
0	1	0	1	1	2	2	0	1	0
1	0	1	1	0	0	1	2	2	0
1	0	1	0	0	0	0	1	0	3
2	0	1	0	0	0	0	0	0	1
1	2	1	0	0	0	1	0	1	1
0	1	1	3	1	0	0	0	1	0
1	1	0	1	1	3	1	0	1	0
1	0	0	1	0	0	1	2	2	0
1	0	1	0	1	1	0	1	0	2
2	0	1	0	1					

Example 8

The series consists of the aggregate index of “art price”, observed every 6 months, in Czujack et al (1996).

The example illustrates the use of TRAMO/SEATS for frequencies different from the quarterly and monthly ones. The program pretest for the log/level specification, does automatic outlier detection and correction, and automatic model identification (in this case, the regular AR and MA polynomials are constrained to a maximum order of 2).

The ARIMA model obtained is of the type

$$\nabla_2 z_t = (1 + \theta B)a_t,$$

and a level shift outlier is corrected.

By default, the missing observations are interpolated, and (since SEATS $\neq 0$) the 1-to-8 periods-ahead forecast function is obtained. A file *seats.itr* is produced, ready for SEATS.

EXAMPLE 8

```
ART PRICE INDEX (U.L.B)
53 1971 1 2
    0.006097    0.575264    0.236069    0.439334    0.135483
    0.690869    1.051329    0.486760    1.194987    0.600609
-99999.        0.997317 -99999.        0.997617    1.586138
    1.333425    1.530939    0.932150    1.196279    0.871909
    1.065290    1.200343    0.703766    1.006899    1.201516
    1.565287    1.572131    1.620713    1.745179    1.694186
    2.025192    2.083175    1.988166    2.128631    2.151246
    2.228820    2.349033    2.732166    2.712100    2.405184
    2.867629    2.807326    3.097908    3.274386    3.466686
    3.668304    3.824994    4.015861    3.930079    2.913271
    3.580308    3.062043    2.942187
$INPUT
inic=2, idif=3, aio=2, iatip=1, va=3.5, lam=-1,
MQ=2, seats=2, $
```

1.5 The File ‘*Seats.itr*’

When the input parameter *SEATS* is not zero, TRAMO creates the file ‘*seats.itr*’ as input file for SEATS. This file has the following structure.

First line: Title of series.

Second line: *NZ NYEAR NPER NFREQ*.

Next lines: “Linearized” series. This is the original series, with the missing observations interpolated, the outliers corrected, and the effect of regression and intervention variables removed, including Easter and Trading Day effects. Thus, it is the series corrected for deterministic effects (except for the mean), and hence is the series that will be decomposed by SEATS into stochastic components.

Next lines: Namelist *INPUT*, with the parameter values for SEATS.

Next lines: A ($k \times 5$) matrix, where:
 $k = NZ$ (the length of the series) $+TF$,
where $TF = \max(8; 2 \times MQ)$.

The first column of this matrix contains the original series for TRAMO.

The second column contains the Level Shift outliers.

The third column contains the aggregate effect of the Additive Outliers and the Transitory Changes.

The fourth column contains the Easter effect.

The fifth column contains the Trading Day effect.

For each column, the first NZ elements contain the “in-sample” values; the last TF elements contain the forecasts. (When $LAM = 0$, the effects are expressed as factors; when $LAM = 1$, as additive components.)

Next lines: (Only when $IREG > 0$).
A ($k \times 6$) matrix, where k is as before.

The first column contains the regression variable effects that are to be considered a separate component in SEATS.

The second column contains the regression variable effects that are assigned to the trend.

The third column contains the regression variable effects that are assigned to the seasonal component.

The fourth column contains the regression variable effects that are assigned to the irregular component.

The fifth column contains the regression variable effects that are to be considered an additional component of the seasonally adjusted series.

The sixth column contains the regression variable effects that are assigned to the cycle.

For each column, the first NZ elements are in-sample values; the last TF are forecasts.

Note: Recall that, for its execution by SEATS, the file '*seats.itr*' should be transferred to the directory SEATS as '*serie*'.

Example of a ‘*Seats.itr*’ File

The *seats.itr* file produced by TRAMO in example 7 (the monthly Spanish industrial production index) is presented.

The model contains a level shift outlier, to be assigned to the trend, Trading Day and Easter effects that, after being removed of the mean effect, will be assigned in SEATS to the seasonal component. Finally, the holiday effect is treated as a regression effect to be assigned also to the seasonal (after removing the mean). Notice that, since the decomposition is multiplicative, all effects are expressed as factors.

The file starts with the “linearized” series, that is, the series with the missing values interpolated and all deterministic effects removed. This will be the series that will be decomposed into stochastic components by SEATS. Then follows the INPUT namelist for SEATS, with the model orders and parameter estimates. Next comes a 185×5 matrix. The first column is the original series entered in TRAMO, the second column contains the outlier affecting the trend (the LS outlier), the third column contains outliers assigned to the irregular; in this case there are none and the column has all elements equal to 1. The 4th and 5th columns contain the Easter and Trading Day effects, respectively.

The first 161 rows contain the values for the sample period; the last 24 rows are the 1-to-24 periods-ahead forecasts.

After this first matrix comes another 185×6 matrix with the regression effects grouped according to the value of *REGEFF* (0, 1, 2, 3, 4, 5). Since in this example there is only one regression variable and it is assigned to the seasonal (*REGEFF* = 2), its effect appears in the 3th column of the matrix; all elements of the other 4 columns are 1. As with the first matrix, the first 161 rows correspond to the sample period, and the last 24 contain the forecast function.

EXAMPLE OF A *seats.itr* FILE

The following file is not exactly like the one produced by TRAMO. The formatting has been slightly changed in order to minimize the size of the file. This does not affect the results, however, since SEATS reads the data with free format.

IPI(Spai

```
161 1983 1 12
87.25379616670881 83.30000000000018 89.20040625035404
84.31317774698576 89.55652102474194 89.38420354568424
86.41883161008957 50.03086631361259 86.79835492662872
90.59365439318574 89.64596554945960 88.58815512731081
88.48585933617071 86.70117317356838 90.91361105528229
85.60257569814021 90.03550691307444 88.06899512122364
87.76978879819018 53.43978305642386 87.88513518138967
91.84022754162157 90.95687393207264 86.21009047093474
88.83235982737631 84.60000000000007 91.71325210780084
85.09884091124451 90.83760497020647 87.96574456729948
89.73472014164986 53.60299455740283 89.06313331289694
97.31071463576690 95.57955194815042 88.17897196275045
90.40693635211201 88.00000000000010 92.25623461712712
90.75832790397787 95.16223070379746 93.29943183967121
93.94573494159319 52.60276706701101 91.04929941620165
98.58853210068106 97.66158464536161 90.10012548213869
91.40582686022661 91.90000000000012 95.89881997240978
93.10752935156006 100.50885850303895 98.11645048326680
101.14416703050924 54.33260958198771 97.27742738929686
104.34170696288334 101.97375739449474 94.19093708178185
96.02771637924627 95.94797260607052 103.17080529968084
94.39523180382847 101.49070467753512 101.14162367391225
103.95308729909324 56.54791302781067 99.65004756952369
105.30990470359944 106.68777452342884 98.60560089373756
103.01186167806233 98.70000000000020 104.72916350851153
101.96747564685005 107.17926391064856 106.47133058767555
109.17161577796347 60.15735428490494 105.90746316935646
109.76338389330765 109.71294771407425 100.66576719117104
105.27536999858364 98.90000000000015 107.61316858187604
99.77692789274784 107.38087739855526 108.02561243274364
104.69989692030305 59.95682977062189 105.37983422218154
105.97720579857413 110.11630413949364 98.36985580313022
106.05429072074674 99.00000000000014 104.10582723916204
98.04969462776471 104.27274742716854 105.27692422782395
104.77405871287604 60.25222098150815 103.68844965533195
109.89230198261355 109.16028484067554 99.44035730341999
102.57710086105024 102.56045355924653 103.54292881079034
100.13643474024462 104.68368128613504 101.62723105304595
102.71686544886504 60.16492360491297 97.77172326017747
103.01186167806233 104.28541994628984 96.10679237884099
99.77738932462627 95.95359221629859 101.32471997930774
97.63794544694581 103.61733826927946 101.68709095671554
103.90198841054254 60.63613477497307 102.00223689976325
```


1.6 Identification of the Arrays Produced by TRAMO

Description of the Files in GRAPH that can be plotted (all are in ASCII format).

1.6.1 Series

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
Original series	Original Series	<i>xorig.out</i>
Series with missing observations interpolated	Interpolated series	<i>xint.reg</i>
Forecast of the series	Forecast of the series	<i>pred.out</i>
Forecast of the logged series (only if $LAM = 0$)	Forecast of trans. series	<i>predl.out</i>
Interpolated series with the effect of regression variables removed (the regression variables are those included in the namelists REG)	Reg. corr. series	<i>xcreg.reg</i>
Interpolated series corrected for outliers	Outlier corr. series	<i>xcout.reg</i>
Interpolated series corrected for special effects (Easter and Trading Day)	S.E. corr. series	<i>xcetd</i>
Interpolated series corrected for outliers, special effects, and for the effect of regression variables, not including the mean. (This is the series passed on to the companion program SEATS.)	Linear series	<i>xlin.reg</i>
White-noise residuals	Residuals	<i>resid.out</i>

1.6.2 Autocorrelation Functions

ACF of white-noise residuals	ACF residuals	<i>auto.out</i>
Partial ACF of white-noise residuals	PACF residuals	<i>pauto.out</i>
ACF of differenced series	ACF diff. series	<i>dauto.out</i>

1.6.3 Regression, Outliers, and Special Effects

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
Effect of the first regression variable	Reg1	<i>reg1.out</i>
...
Effect of the n^{th} regression variable	Regn	<i>regn.out</i>

The ordering of the regression variables is determined by the order in which the REG namelists have been entered in the input file. Note that n should be equal to the total number of variables in the namelists REG of the input file.

Aggregate regression effect	Total Reg.	<i>regsum.out</i>
Effect of the first outlier identified by the program	outreg1	<i>outl1.out</i>
...
Effect of the k^{th} outlier	Outregk	<i>outlk.out</i>

The ordering of outliers is determined by the order in which they are detected in the program (i.e., the order in which outliers appear in the output file).

Aggregate outlier effect	Total Outliers	<i>outsum.out</i>
First trading day effect	Trad 1	<i>trad 1.out</i>
...
Seventh trading day effect	Trad 7	<i>trad 7.out</i>
Aggregate trading day effect	Total Trad. Day	<i>tradsum.out</i>
Easter effect	East	<i>east.out</i>
Aggregate special effects (easter plus trading day)	Special Effects	<i>etdsum.out</i>
Aggregate regression, outlier, and special effects (i.e., difference between interpolated/original series and linearized series)	Total Reg-O-SE	<i>totrose.out</i>

2 Program SEATS

2.1 Brief Description of the Program

SEATS (“Signal Extraction in ARIMA Time Series”) is a program in Fortran for mainframes and MS-DOS computers. The program falls into the class of so-called ARIMA-model-based methods for decomposing a time series into its unobserved components (i.e., for extracting from a time series its different signals). The method was originally devised for seasonal adjustment of economic time series (i.e., removal of the seasonal signal), and the basic references are Cleveland and Tiao (1976), Box, Hillmer, and Tiao (1978), Burman (1980), Hillmer and Tiao (1982), Bell and Hillmer (1984), and Maravall and Pierce (1987). These approaches are closely related to each other, and to the one followed in this program. In fact, as already mentioned, SEATS developed from a program built by Burman for seasonal adjustment at the Bank of England (1982 version).

The program starts by fitting an ARIMA model to the series. Let x_t denote the original series, (or its log transformation), and let

$$z_t = \delta(B) x_t, \quad (5)$$

represent the “differenced” series, where B stands for the lag operator, and $\delta(B)$ denotes the differences taken on x_t in order to (presumably) achieve stationarity. In SEATS,

$$\delta(B) = \nabla^d \nabla_s^D, \quad (6)$$

where $\nabla = 1 - B$, and $\nabla_s^D = (1 - B^s)^D$ represents seasonal differencing of period s . The model for the differenced series z_t can be expressed as

$$\phi(B)(z_t - \bar{z}) = \theta(B) a_t, \quad (7)$$

where \bar{z} is the mean of z_t , a_t is a white-noise series of innovations, normally distributed with zero mean and variance σ_a^2 , $\phi(B)$ and $\theta(B)$ are autoregressive (AR) and moving average (MA) polynomials in B , respectively, which can be expressed in multiplicative form as the product of a regular polynomial in B and a seasonal polynomial in B^s , as in

$$\phi(B) = \phi_r(B) \phi_s(B^s), \quad (8)$$

$$\theta(B) = \theta_r(B) \theta_s(B^s). \quad (9)$$

Putting together (5)–(9), the complete model can be written in detailed form as

$$\phi_r(B) \phi_s(B^s) \nabla^d \nabla_s^D x_t = \theta_r(B) \theta_s(B^s) a_t + c, \quad (10)$$

and, in concise form, as

$$\Phi(B) x_t = \theta(B) a_t + c, \quad (11)$$

where $\Phi(B) = \phi(B) \delta(B)$ represents the complete autoregressive polynomial, including all unit roots. Notice that, if p denotes the order of $\phi(B)$ and q the order of $\theta(B)$, then the order of $\Phi(B)$ is $P = p + d + D \times s$.

The autoregressive polynomial $\phi(B)$ is allowed to have unit roots, which are typically estimated with considerable precision. For example, unit roots in $\phi(B)$ would be present if the series were to contain a nonstationary cyclical component, or if the series had been underdifferenced. They can also appear as nonstationary seasonal harmonics.

The program decomposes a series that follows model (7) into several components. The decomposition can be multiplicative or additive. Since the former becomes the second by taking logs, we shall use in the discussion an additive model, such as

$$x_t = \sum_i x_{it}, \quad (12)$$

where x_{it} represents a component. The components that SEATS considers are:

- x_{pt} = the TREND component,
- x_{st} = the SEASONAL component,
- x_{ct} = the CYCLICAL component,
- x_{ut} = the IRREGULAR component.

Broadly, the trend component represents the long-term evolution of the series and displays a spectral peak at frequency 0; the seasonal component, in turn, captures the spectral peaks at seasonal frequencies. Besides capturing periodic fluctuation with period longer than a year, associated with a spectral peak for a frequency between 0 and $(2\pi/s)$, the cyclical component also captures short-term variation associated with low-order MA components and AR roots with small moduli. Finally, the irregular component captures erratic, white-noise behavior, and hence has a flat spectrum. The components are determined and fully derived from the structure of the (aggregate) ARIMA model for the observed series, which can be directly identified from the data. The program is mostly aimed at monthly or lower frequency data and the maximum number of observations is 600.

The decomposition assumes orthogonal components, and each one will have in turn an ARIMA expression. In order to identify the components, we will require that (except for the irregular one) they be clean of noise. This is called the “canonical” property, and implies that no additive white noise can be extracted from a component that is not the irregular one. The variance of the latter is, in this way, maximized, and, on the contrary, the trend, seasonal and cycle are as stable as possible (compatible with the stochastic nature of model

(7)). Although an arbitrary assumption, since any other admissible component can be expressed as the canonical one plus independent white-noise, it seems sensible to avoid contamination of the component by noise, unless there are a-priori reasons to do so. (Moreover, the component estimates for any other admissible decomposition can be obtained from the canonical ones simply by removing a constant fraction of the irregular component estimate and adding it to the trend and/or the seasonal ones.)

The model that SEATS assumes is that of a linear time series with Gaussian innovations. In general, SEATS is designed to be used with the companion program, TRAMO (“**T**ime Series **R**egression with **AR**IMA Noise, **M**issing Observations, and **O**utliers”), described in part 1 of this manual; besides ARIMA estimation, TRAMO “linearizes” the original series. To do that, TRAMO removes from the series special effects, such as Trading Day, Easter, holiday, and intervention or regression variable effects, identifies and removes several types of outliers, and interpolates missing observations. It also contains an automatic model identification facility. When used with TRAMO, estimation of the ARIMA model is made by the exact maximum likelihood method described in Gómez and Maravall (1994). When used by itself, SEATS uses the quasi-maximum likelihood method described in Burman (1980). In both cases, a (faster) least-squares algorithm is also available. SEATS contains a facility whereby the automatic model identification procedure of TRAMO is replaced by a faster, though rougher, automatic model identification procedure done in SEATS (see Section 3.1). This simplified procedure starts directly by fitting the default model and, if found inappropriate, tries a sequence of models according to the results.

When used by itself, the program starts with estimation of the ARIMA model. The (inverse) roots of the AR and MA polynomials are always constrained to remain in or inside the unit circle. When the modulus of a root converges within a preset interval around 1 (by default $(.98, 1)$), the program automatically fixes the root. If it is an AR root, the modulus is made 1; if it is an MA root, it is fixed to the lower limit. This simple feature, we have found, makes the program very robust to over- and under-differencing.

In the standard case in which SEATS and TRAMO are used jointly, SEATS does the control of the AR and MA roots mentioned above, uses the ARIMA model to filter the linearized series, obtains in this way new residuals, and produces a detailed diagnosis of them. The program proceeds then to decompose the ARIMA model. This is done in the frequency domain. The spectrum (or pseudospectrum) is partitioned into additive spectra, associated with the different components. (These are determined, mostly, from the AR roots of the model.) The canonical condition on the trend, seasonal, and cyclical components identifies a unique decomposition, from which the ARIMA models for the components are obtained (including the component innovation variances).

For a particular realization $[x_1, x_2, \dots, x_T]$, the program yields the Minimum Mean Square Error (MMSE) estimators of the components, computed with a Wiener–Kolmogorov–type of filter applied to the finite series by extending the latter with forecasts and backcasts (see Burman, 1980). For $i = 1, \dots, T$, the estimate $\hat{x}_{it|T}$, equal to the conditional expectation $E(x_{it}|x_1, \dots, x_T)$, is obtained for all components.

When $T \rightarrow \infty$, the estimator $\hat{x}_{it|T}$ becomes the “final” or “historical” estimator, which we shall denote \hat{x}_{it} . (In practice, it is achieved for large enough $k = T - t$, and the program indicates how large k can be assumed to be.) For $t = T$, the concurrent estimator, $\hat{x}_{iT|T}$, is obtained, i.e., the estimator for the last observation of the series. The final and concurrent estimators are the ones of most applied interest. When $T - k < t < T$, $\hat{x}_{it|T}$ yields a preliminary estimator, and, for $t > T$, a forecast. Besides their estimates, the program produces several years of forecasts of the components, as well as standard errors (SE) of all estimators and forecasts. For the last two and the next two years, the SE of the revision the preliminary estimator and the forecast will undergo is also provided. The program further computes MMSE estimates of the innovations in each one of the components.

The joint distributions of the (stationary transformations of the) components and of their MMSE estimators are obtained; they are characterized by the variances and auto- and cross-correlations. The comparison between the theoretical moments for the MMSE estimators and the empirical ones obtained in the application yields additional elements for diagnosis (see Maravall, 1987). The program also presents the Wiener–Kolmogorov filter for each component and the filter which expresses the weights with which the different innovations a_j in the observed series contribute to the estimator $\hat{x}_{it|T}$. These weights directly provide the moving average expressions for the revisions. Next, an analysis of the estimation errors for the trend and for the seasonally adjusted series (and for the cycle, if present) is performed. Let

$$\begin{aligned} d_{it} &= x_{it} - \hat{x}_{it}, \\ d_{it|T} &= x_{it} - \hat{x}_{it|T}, \\ r_{it|T} &= \hat{x}_{it} - \hat{x}_{it|T}, \end{aligned}$$

denote the final estimation error, the preliminary estimation error, and the revision error in the preliminary estimator $\hat{x}_{it|T}$. The variances and autocorrelation functions for d_{it} , $d_{it|t}$, $r_{it|t}$ are displayed. (The autocorrelations are useful to compute SE of linearized rates of growth of the component estimator.) The program then shows how the variance of the revision error in the concurrent estimator $r_{it|t}$ decreases as more observations are added, and hence the time it takes in practice to converge to the final estimator. Similarly, the program computes the deterioration in precision as the forecast moves away from the

concurrent estimator and, in particular, what is the expected improvement in Root MSE associated with moving from a once-a-year to a concurrent seasonal adjustment practice. Finally, the SE of the estimators of the linearized rates of growth most closely watched by analysts are presented, for the concurrent estimator of the rate and its successive revisions, both for the trend and seasonally adjusted series. All SE computed are exact given that the ARIMA model for the observed series is correct. Further details can be found in Maravall (1988, 1995) and Maravall and Gómez (1992).

The default model in SEATS is the so-called Airline Model, analyzed in Box and Jenkins (1970). The Airline Model is often found appropriate for actual series, and provides very well behaved estimation filters for the components. It is given by the equation

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

with $-1 < \theta_1 < 1$ and $-1 < \theta_{12} \leq 0$, and x_t is the log of the series. The implied components have models of the type

$$\begin{aligned} \nabla^2 x_{pt} &= \theta_p(B) a_{pt}, \\ S x_{st} &= \theta_s(B) a_{st}, \end{aligned}$$

where $S = 1 + B + \dots + B^{11}$, and $\theta_p(B)$ and $\theta_s(B)$ are of order 2 and 11, respectively. Compared to other fixed filters, the default model allows for the observed series to estimate 3 parameters: θ_1 , related to the stability of the trend component; θ_{12} , related to the stability of the seasonal component; and σ_a^2 , a measure of the overall predictability of the series. Thus, to some extent, even in this simple fixed model application, the filters for the component estimators adapt to the specific structure of each series.

Programs TRAMO and SEATS provide a fully model-based method for forecasting and signal extraction in univariate time series. (The relation between them is somewhat similar to the one between the programs REGARIMA and X11 ARIMA that form the new method X12 ARIMA; see Findley et al, 1996). The procedure is flexible, yet robust and reliable. Due to the model-based features, it becomes a powerful tool for detailed analysis of important series in short-term policy making and monitoring (as is done, for example, at the Bank of Spain; see Bank of Spain (1996)). Yet TRAMO-SEATS can efficiently be used for routine application to a large number of series (as is done, for example, at Eurostat (see EUROSTAT, 1996a). For this routine-application case, fully automatic procedures are available, as described in Section 3. The standard procedure pretests for the log-level specification and, if appropriate, for the possible presence of Trading Day and Easter effects; it further performs an automatic model identification and outlier detection and correction procedures (for several types of outliers), interpolates the missing values if any, and

decomposes the series net of the previous (deterministic) effects into a seasonal, trend, cyclical, and irregular components (If the identified ARIMA model does not accept an admissible decomposition, it is automatically replaced by a decomposable approximation).

Finally, the components (and forecasts thereof) estimated by SEATS are modified to reincorporate the deterministic effects that were removed by TRAMO.

As mentioned earlier, a simple-and-fast or a more sophisticated automatic model identification procedures can be used. In practice, the difference does not amount to much. Using, for example, a 133 Mhz Pentium, it is rather unlikely that execution of either program in the automatic mode will take more than a very few seconds.

Finally, the program contains a relatively complete graphics facility.

2.2 Decomposition of the ARIMA Model

Let the total AR polynomial, $\Phi(B)$, of the ARIMA model (11) be factored as

$$\Phi(B) = \phi_r(B)\phi_s(B^s)\nabla^d\nabla_s^D.$$

The roots of $\Phi(B)$ are assigned to the unobserved components as follows:

Roots of $\nabla^d = 0 \Rightarrow$ Assigned to trend component.

Roots of $\nabla_s^D = 0 \Rightarrow$ Factorizing it as $(\nabla S)^D = 0$, where $S = 1 + B + \dots + B^{s-1}$:

- the root of $\nabla = 0$ goes to the trend;
- the roots of $S = 0$ go to the seasonal component.

Roots of $\phi_r(z)$, \Rightarrow Real positive roots:
where $z = B^{-1}$.

- If modulus $\geq k$, assigned to trend.
- If modulus $< k$, assigned to cycle.

Real negative roots:

- If $s \neq 1$, assigned to seasonal.
- If $s = 1$, assigned to cycle.

Complex roots: Let w denote the frequency of the root.

- If $w \in [\text{a seasonal frequency} \pm \epsilon]$, assigned to seasonal.
- Otherwise, assigned to cycle.

Roots of $\phi_s(z^s)$, \Rightarrow Letting ϕ denote the real positive root of
where $z = B^{-1}$. $(-BPHI)^{1/s}$:

- when $\phi \geq k$, the AR root $(1 - \phi B)$ is assigned to the trend;
- when $\phi < k$, it is assigned to the cycle.

(Note: The parameters k and ϵ can be entered by the user.)

The factorization of $\Phi(B)$ can be rewritten as

$$\Phi(B) = \phi_p(B)\phi_s(B)\phi_c(B),$$

where $\phi_p(B)$, $\phi_s(B)$ and $\phi_c(B)$ are the AR polynomials with the trend, seasonal, and cyclical roots, respectively. Let P and Q denote the orders of the polynomials $\Phi(B)$ and $\theta(B)$ in (11):

a) Consider first the case $P \geq Q$. A polynomial division of the spectrum (or pseudospectrum) of model (11) yields a first decomposition of the type

$$\frac{\theta(B)}{\Phi(B)}a_t = \frac{\tilde{\theta}(B)}{\Phi(B)}a_{1t} + v_1,$$

where the order of $\tilde{\theta}(B)$ is $\min(Q, P - 1)$, and v_1 is a constant (0 if $P > Q$).

A partial fraction expansion of the spectrum of $[\tilde{\theta}(B)/\Phi(B)]a_{1t}$ yields the decomposition

$$\frac{\tilde{\theta}(B)}{\Phi(B)}a_{1t} = \frac{\tilde{\theta}_p(B)}{\phi_p(B)}\tilde{a}_{pt} + \frac{\tilde{\theta}_s(B)}{\phi_s(B)}\tilde{a}_{st} + \frac{\tilde{\theta}_c(B)}{\phi_c(B)}\tilde{a}_{ct},$$

where, letting $j = p, s, c$, we have $\text{order}(\tilde{\theta}_j) \leq \text{order}(\phi_j)$. If $\tilde{g}_j(w)$ denotes the spectrum of $[\tilde{\theta}_j(B)/\phi_j(B)]\tilde{a}_{jt}$, let

$$v_j = \min \{ \tilde{g}_j(w) : 0 \leq w \leq \pi \};$$

Imposing the canonical condition

$$g_j(w) = \tilde{g}_j(w) - v_j, \quad j = p, s, c,$$

$$v = v_1 + \sum_j v_j,$$

the spectrum of the final components are obtained, which give the models for the components:

$$\begin{aligned}\phi_p(B)p_t &= \theta_p(B)a_{pt} \\ \phi_s(B)s_t &= \theta_s(B)a_{st} \\ \phi_c(B)c_t &= \theta_c(B)a_{ct} \\ u_t &= \text{white noise } (0, v)\end{aligned}$$

All components have balanced models, in the sense that the order of the AR polynomial equals that of the MA one.

b) When $(Q > P)$, the decomposition proceeds as follows.

A first decomposition is performed, whereby

$$\text{ARIMA}(P, Q) = \text{ARIMA}(P, P - 1) + \text{MA}(Q - P).$$

The first component falls under case a), and hence can be decomposed in the previous way. Let this decomposition be, in general,

$$\text{ARIMA}(P, P - 1) = p_t + s_t + c_t + u_t,$$

where p_t , s_t , c_t and u_t denote the trend, seasonal, cyclical, and irregular component. The $\text{MA}(Q - P)$ component, which represents stationary short-term deviations, is added to the cyclical component. The series is decomposed then, into a balanced trend model, a balanced seasonal model, a top-heavy cycle model, and a white-noise irregular. The first three components are made canonical (i.e., noise-free).

As a general rule, it is recommended that balanced models be favored, since they tend to display good decomposition properties. Models for which Q is much larger than P are discouraged because the excess MA structure may provoke awkward, often nonadmissible, decompositions.

Example: The monthly model

$$(1 + .4B - .32B^2)\nabla\nabla_{12}x_t = \theta(B)a_t,$$

with $\theta(B)$ of order $Q = 16$ ($> P = 15$), would decompose as follows. Factorizing the $\text{AR}(2)$, it can be rewritten as $(1 - .4B)(1 + .8B)$, and hence the first factor goes to the cycle (assuming $k > .4$), and the second factor to the seasonal component (a peak for $w = \pi$). Therefore, the models for the components will be of the type:

Trend:	$\nabla^2 p_t = \theta_p(B)a_{pt}$
Seasonal:	$(1 + .8B)S s_t = \theta_s(B)a_{st}$
Cycle:	$(1 - .4B)c_t = \theta_c(B)a_{ct}$
Irregular:	White noise.

The orders of the polynomials $\theta_p(B)$, $\theta_s(B)$, and $\theta_c(B)$ would be 2, 12, and 1, respectively.

2.3 Instructions for the User

Section 1.2 of the previous TRAMO user instructions, that refers to hardware requirements, installation, execution, graphics, printing, editing, and downloading of the program, apply to SEATS in a straightforward manner, simply by replacing the word TRAMO by SEATS.

2.4 Description of the Input Parameters

2.4.1 Allocation of Regression Effects

Each *REG* namelist in TRAMO contains a value for the parameter *REGEFF*, that determines to which component each of the regression effects should be assigned. The parameter can take the following values.

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>REGEFF</i> = 0	The regression effect is a separate additional component; it is not included in the seasonally adjusted series.	0
= 1	Regression effect assigned to trend. (An example could be the case of two alternating regimes, as captured for instance by the following regression variable in TRAMO: \$REG ISEQ = 2, \$ 50 20 150 20 which creates a series of zeros, except for two stretches of 20 ones, starting at $T = 50$ and $T = 150$.)	
= 2	Regression effect assigned to seasonal component. (An example could be a variable including national festivities.)	
= 3	Regression effect assigned to irregular component. (An example could be an effect similar to that of a transitory change with positive parameter; that is, with effects having alternating signs.)	
= 4	Regression effect is assigned to the seasonally adjusted series, but as an additional separate component. (An example could be if one wished to remove the effect of exchange rate variations before looking at the underlying trend of a variable.)	
= 5	Regression effect is assigned to the cycle (an example could be a leading indicator).	

Note 1: The regression variables with $REGEFF = 2, 3,$ and $5,$ are centered by the program.

Note 2: When in a REG Namelist, $IUSER = -1$ and the external file has $NSER > 1,$ the same $REGEFF$ value will apply to all series in the file.

Note 3: The parameter $REGEFF$ is entered in TRAMO through the REG namelist.

2.4.2 Specification of the ARIMA Model

If MQ denotes the number of observations per year, the general model considered is the multiplicative $(P, D, Q) \times (BP, BD, BQ)_{MQ}$ ARIMA model, subject to the constraints $P \leq 3, D \leq 3, Q \leq 3, BP \leq 1, BD \leq 2, BQ \leq 1.$

The model can be written as

$$\phi_P(B) \Phi_{BP}(B^{MQ}) (z_t - \mu) = \theta_Q(B) \Theta_{BQ}(B^{MQ}) a_t,$$

where

$$z_t = \nabla^D \nabla_{MQ}^{BD} x_t,$$

and μ is the mean of the differenced series $z_t.$ For the most general case,

$$\begin{aligned} \nabla^D &= (1 - B)^D \\ \nabla_{MQ}^{BD} &= (1 - B^{MQ})^{BD} \\ \phi_P(B) &= 1 + PHI(1) \times B + PHI(2) \times B^2 + PHI(3) \times B^3 \\ \Phi_{BP}(B^{MQ}) &= 1 + BPHI(1) \times B^{MQ} \\ \theta_Q(B) &= 1 + TH(1) \times B + TH(2) \times B^2 + TH(3) \times B^3 \\ \Theta_{BQ}(B^{MQ}) &= 1 + BTH(1) \times B^{MQ}. \end{aligned}$$

For seasonal adjustment, it is required that $BPHI(1) \leq 0,$ since $BPHI(1) > 0$ implies a two-year periodic component (with its twelve harmonics).

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>MQ</i>	= Number of observations per year (12 for monthly, 6 for bimonthly, 4 for quarterly, 1 for annual, ...)	12
<i>LAM</i>	= 0 Logs are taken	0
<i>IMEAN</i>	= 0 No mean correction ($\mu = 0$)	1
	= 1 Mean correction ($\mu \neq 0$)	
<i>D</i>	= # of regular differences	1
<i>BD</i>	= # of seasonal differences	1
<i>P</i>	= # of regular autoregressive terms	0
<i>BP</i>	= # of seasonal autoregressive terms	0
<i>Q</i>	= # of regular moving average terms	1
<i>BQ</i>	= # of seasonal moving average terms	1
<i>PHI</i>	= <i>P</i> initial estimates of the regular autoregressive parameters (not input if <i>INIT</i> = 0)	-
<i>TH</i>	= <i>Q</i> initial estimates of the regular moving average parameters (not input if <i>INIT</i> = 0)	-
<i>BPHI</i>	= <i>BP</i> initial estimates of the seasonal autoregressive parameters (not input if <i>INIT</i> = 0)	-
<i>BTH</i>	= <i>BQ</i> initial estimates of the seasonal moving average parameters (not input if <i>INIT</i> = 0)	-

Note: When *INIT* = 1 or 2, the input parameters are entered as *PHI*(*i*); *TH*(*i*); *BPHI*(*i*); *BTH*(*i*), as detailed above.

The default model is thus the ARIMA model

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

the so-called Airline Model, analyzed in Box and Jenkins (1970).

2.4.3 Estimation of the ARIMA Model

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>INIT</i>	= 0	Starting values for parameters computed by the program	0
	= 1	Starting values for parameter input	
	= 2	Starting values for parameter input and no parameter estimation is done.	
<i>TYPE</i>	= 0	Maximum likelihood estimation	0
	= 1	Constrained least squares	
<i>MAXIT</i>	=	A positive integer. Number of iterations in ARIMA estimation	20
<i>EPSIV</i>	=	A small positive number. Convergence criteria for estimation of ARIMA	10^{-3}
<i>M</i>	=	A positive number ($M \leq 48$). Number of ACF and PACF printed in tables	36
<i>IQM</i>	=	A positive number. Number of autocorrelations used in computing Q-statistics	24*
<i>SEK</i>	=	A positive number. Number of standard deviations used for the detection of outliers in residuals	3
<i>XL</i>	=	When the modulus of an estimated root falls in the range ($XL, 1$), it is set equal to <i>UR</i> (see below) if root is in AR polynomial. If root is in MA polynomial, it is set equal to <i>XL</i>	.98
<i>UR</i>	=	Parameter to fix roots of AR polynomial (see <i>XL</i>)	-1
<i>CRMEAN</i>	= 0	Compute mean on total # of observations	0
	= 1	Compute mean on # of observations equal to the largest multiple of <i>MQ</i>	

(*) The default value of *IQM* depends on *MQ*. For $MQ = 12$, $IQM = 24$; for $MQ = 2, 3, 4, 6$, $IQM = 4MQ$; for $MQ = 1$, $IQM = 8$.

2.4.4 Forecasts and Signal Extraction

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
L	= 0 ARIMA estimation only.	-1
	= A positive integer. ARIMA estimation, plus the 1- to L-periods-ahead forecast	
	= -1 ARIMA estimation, plus signal extraction, plus forecasting (determined by the program)	
FH	= A positive integer. Minimum number of forecast horizon for series and components when $L = -1$. When TRAMO has been used as a preadjustment program, $FH = \max(8, 2 \times MQ)$	8
$EPSPHI$	= When $\phi_P(B)$ contains a complex root, it is allocated to the seasonal if its frequency differs from the seasonal frequencies by less than $EPSPHI$ (measured in degrees). Otherwise, it goes to the cycle.	3
$NO SERIE$	= 0 Usual case	0
	= 1 No series is used. An ARIMA model is entered ($INIT = 2$, $PHI(1) = , \dots$), and the program performs the decomposition of the model and the subsequent model-based analysis	
$NO ADMISS$	= 0 When model does not accept an admissible decomposition, no approximation is made	0
	= 1 When model does not accept an admissible decomposition, it is automatically replaced with a decomposable model	

2.4.5 Bias Correction

The next parameters correct for the bias that may occur in multiplicative decomposition when the period-to-period changes are relatively large when compared to the overall mean. This bias implies an underestimation of the seasonally adjusted series and of the trend in levels, caused by the fact that geometric means underestimate arithmetic means.

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>BIAS</i>	= 1	A correction is made for the overall bias for the full length of the series and the forecasting period. (Only when $LAM = 0$.)	1
	= -1	A correction is made so that, for every year (including the forecasting period), the annual average of the original series equals the annual average of the seasonally adjusted series, and also (very approximately) equals the annual average of the trend. (Only when $LAM = 0$.)	
<i>MAXBIAS</i>	= k	A positive number.	.5

When the average value of the differences (in absolute value) between the annual means of the original and seasonally adjusted series is larger than *MAXBIAS*, the parameter *BIAS* is set automatically equal to -1 , and the correction is enforced. The number k is expressed in % points of the level of the series.

2.4.6 Cyclical Component

As mentioned in Section 2.2, a cyclical component can emerge from a variety of reasons. It can be the effect of a complex AR root associated with a cyclical frequency, but it can also contain stationary deviations due to a pure MA component, or to a real positive AR root of small modulus.

A cutting point is defined for the modulus of the AR root; above that point, the root is part of the trend, below that point the root is part of the cycle. The cutting point is controlled by the following parameter:

<i>RMOD</i>	= k	($0 \leq k \leq 1$) Cutting point for the modulus of an AR root.	.5
-------------	-----	--	----

Thus, for example, by default the AR root $(1 - .8B)$ would be assigned to the trend, while the AR root $(1 - .4B)$ would go to the cycle. (Recall that this cutting point also affects the real positive root of a the seasonal AR polynomial).

As a consequence, added to the irregular, the cyclical component represents the deviations with respect to the trend of a seasonally adjusted series, more in line with the concept of a business cycle (see, for example, Stock and Watson, 1988). Care should be taken, however with this interpretation. For some ARIMA models, the derived trend may contain (as the trend-cycle component of X11)

short-term variation thought undesirable by business cycle analysts. The cycle in SEATS should be seen more as a way to absorb part of the stationary variation, so as to improve estimation of the trend.

When a cycle is present, the series is decomposed (in its additive form) into a trend, seasonal, cyclical, and irregular component. The cyclical component is also made canonical and the irregular component is white noise. Of course, in most applications the irregular component can be added to the cycle to provide a “stationary” component containing short-term variations.

2.4.7 Smoothing of the Trend; Use of SEATS as a “Fixed Filter”

For the default model, a facility has been introduced to obtain a smoother trend without significantly affecting the seasonally adjusted series. This is done by simply decreasing the value of the parameter $TH(1)$ of the MA factor $(1 + \theta B)$. It is controlled by two input parameters:

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
$SMTR$	= 0	Inactive	0
	= 1	The trend is further smoothed.	
$THTR$	= k	$-1 < k < 0$	-.4

When $TH(1) \leq THTR$, nothing is done since the trend is already smooth enough. When $TH(1) > THTR$, it is replaced by $THTR$.

Note: Typically, the changes in $TH(1)$ have little effect on the seasonal component estimator, and hence on the seasonally adjusted series. Varying $TH(1)$ amounts thus to a redistribution of the latter into “trend + irregular” where, as the trend becomes smoother, the irregular component increases its variance and exhibits low-order autocorrelation, and hence displays more and more the characteristics of a cyclical component.

Even without the automatic model identification procedures, the use of TRAMO/SEATS with the default model, $SMTR = 1$, and some chosen (negative) value for $THTR$ (that reflects the prior belief on how smooth a trend should be), provides well-behaved filters for the components, and can produce results close to those obtained with many ad-hoc filters, with the advantage of preserving a considerable capacity to adapt to the particular type of seasonality present in the series. This way of proceeding can be seen as the simplest way SEATS can be used as a “fixed filter”.

2.4.8 Other Parameters

OUT and *PG* = See TRAMO User Instructions (Sections 1.3.1 and 1.3.11, respectively).

<u>Parameter</u>	<u>Meaning</u>	<u>Default</u>
<i>NDEC</i>	= A positive number. Controls the number of printed decimals in some of the tables	2
<i>NDEC1</i>	= As <i>NDEC</i> , but for another set of tables	3
<i>HS</i>	= A positive number. Sets the scale for the vertical axis of the spectral graphs	1.5
<i>NANNUA</i>	= 0 Rates of Growth are not annualized	1
	= 1 Rates of Growth are annualized	
<i>SQG</i>	= 0 Fourier Transform of component estimation filter (for graphs)	1
	= 1 (Squared) Gain of component estimation filter (for graphs)	

2.5 Output File

In the most general case, the decomposition of the series that TRAMO/SEATS provide is the following one. (We use the additive version; the multiplicative one is identical, with “+” replaced by “×”, and “component” replaced by “factor”.) Letting *SA* denote “seasonally adjusted”,

serie = final *SA* series + final seasonal component + separate regression component;

the latter is associated with the regression variables for which *REGEFF* = 0. Then,

final *SA* series = final trend + final irregular component + final cyclical component + other regression effects included in the *SA* series;

the latter is associated with the regression variables for which *REGEFF* = 4. Next,

final trend = stochastic trend + level–shift outliers + trend regression component (*REGEFF* = 1);

final irregular component = stochastic irregular + additive outliers + transitory–change outliers + irregular regression component (*REGEFF* = 3);

final cyclical component = stochastic cyclical component + cyclical regression component (*REGEFF* = 5);

final seasonal component = stochastic seasonal component + trading day + easter effect + seasonal regression component (*REGEFF* = 2).

The decomposition covers the sample period and the $\max(8, 2 \times MQ)$ –period–ahead forecast function.

In accordance with the previous decomposition, the end of the output file in SEATS contains (for the most general case) the following tables.

ORIGINAL (UNCORRECTED) SERIES

PREADJUSTMENT COMPONENT (aggregate one from TRAMO)

LINEAR SERIES (generated by ARIMA model)

Stochastic Components

SEASONAL COMPONENT

CYCLICAL COMPONENT

IRREGULAR COMPONENT
TREND COMPONENT
SEASONALLY ADJUSTED SERIES.

First, the table with the point estimators is given, followed by the table with the associated STANDARD ERRORS. Next, the program prints the tables of the stochastic components' FORECASTS, as well as of the associated STANDARD ERRORS. Then follow the tables of

Deterministic Components

LEVEL-SHIFT OUTLIERS
TRANSITORY OUTLIERS (the sum of *AO* and *TC*)
TRADING DAY EFFECT
EASTER EFFECT
TREND REGRESSION COMPONENT
SEASONAL REGRESSION COMPONENT
IRREGULAR REGRESSION COMPONENT
CYCLICAL REGRESSION COMPONENT
OTHER REGRESSION COMPONENT IN *SA* SERIES
SEPARATE REGRESSION COMPONENT (not in *SA* series).

From the combination of the stochastic and deterministic components, the tables of FINAL COMPONENTS are obtained and printed, as well as those of their FORECASTS. This ends the program.

Warning: As mentioned in Section 3.1 below, in order to improve the decomposition of the series, SEATS may change on occasion the model estimated in TRAMO. When this happens, the forecast of the original series in TRAMO and SEATS will differ. But even when the models are the same, the two forecasts will not, in general, coincide. While TRAMO uses the white-noise residuals (equal in number to the degrees of freedom), SEATS uses the residuals obtained from filtering the linearized series with the ARIMA model plus MLE estimates of the residuals lost in differencing (hence the number of residuals equals the number of observations). Further, the conditional expectation computed by TRAMO is a projection on the finite sample, while SEATS uses the projection on the semi-infinite sample (as in Box and Jenkins, 1970). Unless the model has been considerably changed, the difference between the two forecasts is, nevertheless, small.

2.6 Input File and Examples

The input starts with the series to be modelled, comprising no more than 600 observations, followed by one set of control parameters. To specify the set of control parameters for the series model, the NAMELIST facility is used, so that only those parameters which are not at their default values need to be set.

The series is set up as:

Card 1 TITLE (no more than 72 characters)
Card 2 NZ NYER NPER NFREQ (free format)
Card 3 et seq. Z(I): I = 1, NZ (free format),

where NZ is the number of observations, NYER the start year, NPER the start period, and NFREQ is an instruction to control table format (the number of columns). $Z(\cdot)$ is the array of observations. (The first nonblank characters of TITLE are used by the program to create a file named *****.OUT in the subdirectory OUTPUT containing the output of the program.)

This is followed by namelist INPUT. The namelist starts with \$INPUT and terminates with \$. Other formats, such as “&INPUT . . . ,/” can also be used.

Example 9

The series is the monthly series of Italian production of manufactured metal from January 1990 to February 1996 (source: Eurostat).

The example illustrates some of the estimation capabilities of SEATS. In this case, SEATS fits the default model of Example 1, with the mean constrained to be zero, using the quasi-ML method in Burman (1980).

The model obtained yields a decomposition with a negative irregular spectrum and is replaced by a relatively close decomposable model. (The comparison between the components obtained with this approximation and the ones produced by X12-ARIMA is discussed in Fiorentini and Planas, 1996).

EXAMPLE 9

PROD OF MANUFAC METAL (ITALY)

74	1990	1	12
4.5991521		4.7211739	4.6950109
4.6041697		4.7140246	4.6922649
4.6606049		3.2347492	4.7431915
4.7335634		4.6672056	4.5293685
4.6986605		4.7782828	4.7723781
4.7604631		4.7808028	4.7613189
4.6681450		3.4045252	4.8202816
4.7974421		4.7561731	4.5315236
4.8048404		4.8441871	4.8331023
4.8089270		4.7924793	4.7664383
4.7158167		3.5055574	4.8146204
4.7899886		4.8015590	4.5196123
4.7974421		4.8315086	4.7891570
4.8138091		4.7941363	4.8015590
4.8210877		3.6349511	4.8449742
4.8489004		4.8481164	4.4761998
4.8210877		4.9265288	4.8933521
4.9351931		4.8880909	4.8582608
4.8354879		3.8372995	4.9074945
4.8559289		4.8644528	4.6405373
4.7774414		4.9308703	4.9801761
4.9067552		4.9452075	4.9265288
4.8706066		3.8836235	4.9272537
4.8782461		4.8613616	4.7131273
4.7621739		4.8888442	

\$INPUT

NOADMISS=1, imean=0, \$

Example 10

This example illustrates the use of SEATS to analyze the decomposition of an ARIMA model. No series is entered and the model parameters are, of course, fixed. The file can be created directly or by typing INPUT, then 77, and then the parameters (as explained in Section 1.2.4).

The model is given by

$$(1 - .5B^3)\nabla_{12}z_t = (1 + .2B)(1 - .4B^{12})a_t,$$

and is similar to the model used by Cleveland and Tiao (1976) as an example of X11 inadequacy.

Since $RMOD = .8$, the root $1 - .794B$ in the AR polynomial of the model ($.794 = 5^{1/3}$) goes to the cycle, and hence the series is decomposed into a trend, seasonal, irregular, and cyclical component. (The cycle should be interpreted simply as transitory deviations from the trend, other than pure white noise.)

EXAMPLE 10

```
NOSERIE
      0      0      0      0
      0      0      0      0
$INPUT
NOSERIE=1,
INIT=2,rmod=.8,
LAM=1,
P=3,D=0,
PHI(1)=0,
PHI(2)=0,
PHI(3)=-.5,
TH(1)=.2,
BTH(1)=-.4,$
```

Example 11

The series is the quarterly series of US GNP (seasonally adjusted) in Lippi and Reichlin (1994). This example illustrates the capacity of SEATS to approximate “ad hoc” filters, and to produce more stable estimators.

SEATS fixes the ARIMA model to

$$\nabla^2 z_t = (1 - 1.7771B + .7994B^2)a_t,$$

and decomposes the series into a trend and an irregular component with the filters derived from that model.

It can be seen that the model is the one for which the Hodrick–Prescott filter is optimal (in a minimum MSE sense) to estimate a trend of the type

$$\nabla^2 p_t = b_t,$$

contaminated by noise u_t (for the standard value $\lambda = v_u/v_b = 1600$). The trend component generated by SEATS is “canonical” and, as a consequence, the Hodrick–Prescott trend will be equal to the trend of SEATS + orthogonal white noise. Thus, for the same aggregate series, the SEATS trend will be smoother and the SEATS irregular will contain all white–noise variation.

EXAMPLE 11

GNP (USA)						
	165	1947	1	4		
1056.5	1063.2	1067.1	1080.0	1086.8	1106.1	1116.3
1125.5	1112.4	1105.9	1114.3	1103.3	1148.2	1181.0
1225.3	1260.2	1286.6	1320.4	1349.8	1356.0	1369.2
1365.9	1378.2	1406.8	1431.4	1444.9	1438.2	1426.6
1406.8	1401.2	1418.0	1438.8	1469.6	1485.7	1505.5
1518.7	1515.7	1522.6	1523.7	1540.6	1553.3	1552.4
1561.5	1537.3	1506.1	1514.2	1550.0	1586.7	1606.4
1637.0	1629.5	1643.4	1671.6	1666.8	1668.4	1654.1
1671.3	1692.1	1716.3	1754.9	1777.9	1796.4	1813.1
1810.1	1834.6	1860.0	1892.5	1906.1	1948.7	1965.4
1985.2	1993.7	2036.9	2066.4	2099.3	2147.6	2190.1
2195.8	2218.3	2229.2	2241.8	2255.2	2287.7	2300.6
2327.3	2366.9	2385.3	2383.0	2416.5	2419.8	2433.2
2423.5	2408.6	2406.5	2435.8	2413.8	2478.6	2478.4
2491.1	2491.0	2545.6	2595.1	2622.1	2671.3	2734.0
2741.0	2738.3	2762.8	2747.4	2755.2	2719.3	2695.4
2642.7	2669.6	2714.9	2752.7	2804.4	2816.9	2828.6
2856.8	2896.0	2942.7	3001.8	2994.1	3020.5	3115.9
3142.6	3181.6	3181.7	3178.7	3207.4	3201.3	3233.4
3157.0	3159.1	3199.2	3261.1	3250.2	3264.6	3219.0
3170.4	3179.9	3154.5	3159.3	3186.6	3258.3	3306.4
3365.1	3451.7	3498.0	3520.6	3535.2	3568.7	3587.1
3623.0	3650.9	3698.8	3704.7	3718.0	3731.5	3772.2
3795.3	3835.9	3880.8	3915.4			

```

$INPUT
MQ=4,lam=1,imean=0,
D=2,
BD=0,
Q=2,
BQ=0,
TH(1)=-1.7771,
TH(2)=.7994,
INIT=2,
$

```

Example 12

The series is the annual historical series of wheat price in the Toulouse market, discussed in Grenier and Mathis (1991). The example illustrates the use of SEATS outside the context of seasonal adjustment.

The model fitted is of the type:

$$(1 + \phi_1 B + \phi_2 B^2) \nabla z_t = (1 + \theta_1 B) a_t + \mu.$$

The AR(2) polynomial contains a stationary root for a cyclical frequency (of period close to 4 years), and the series is decomposed into a trend, irregular and cyclical components, and the cyclical component represents transitory deviations from a trend, that exhibit now a periodic cycle. The use of SEATS in the context of trend estimation is discussed in Maravall (1993).

EXAMPLE 12

WHEAT PRICE TOULOUSE (France)

241 1550 1 4

14.00	14.00	15.00	16.00	23.00	27.00	26.00
28.00	16.00	15.00	20.00	23.00	30.00	43.00
32.00	36.00	37.00	25.00	21.00	21.00	24.00
34.00	63.00	71.00	41.00	57.00	54.00	38.00
30.00	42.00	53.00	43.00	45.00	48.00	43.00
50.00	53.00	45.00	44.00	47.00	54.00	48.00
87.00	90.00	52.00	73.00	48.00	60.00	83.00
74.00	41.00	30.00	29.00	37.00	50.00	65.00
52.00	58.00	44.00	40.00	31.00	33.00	51.00
53.00	66.00	33.00	37.00	38.00	46.00	53.00
54.00	52.00	61.00	46.00	39.00	34.00	35.00
45.00	63.00	55.00	94.00	114.00	62.00	47.00
34.00	33.00	48.00	53.00	40.00	35.00	37.00
40.00	41.00	77.00	98.00	58.00	50.00	49.00
47.00	54.00	66.00	82.00	111.00	144.00	94.00
51.00	57.00	47.00	50.00	70.00	64.00	62.00
72.00	52.00	50.00	53.00	56.00	49.00	50.00
66.00	61.00	50.00	52.00	43.00	41.00	50.00
57.00	62.00	66.00	60.00	57.00	45.00	45.00
57.00	56.00	69.00	62.00	52.00	46.00	36.00
42.00	66.00	75.00	87.00	113.00	62.00	62.00
76.00	80.00	89.00	91.00	85.00	74.00	73.00
79.00	65.00	57.00	51.00	72.00	147.00	114.00
74.00	114.00	126.00	85.00	63.00	62.00	56.00
57.00	90.00	133.00	70.00	74.00	95.00	113.00
108.00	68.00	64.00	92.00	103.00	82.00	69.00
68.00	83.00	91.00	88.00	77.00	98.00	98.00
95.00	85.00	91.00	92.00	75.00	73.00	71.00
77.00	128.00	145.00	120.00	128.00	124.00	129.00
84.00	74.00	75.00	92.00	100.00	113.00	141.00
132.00	109.00	91.00	102.00	128.00	125.00	157.00
147.00	145.00	154.00	151.00	165.00	159.00	177.00
159.00	141.00	126.00	146.00	186.00	132.00	127.00
146.00	181.00	167.00	136.00	146.00	152.00	144.00
166.00	199.00	186.00				

\$INPUT

p=2, imean=1, mq=1, \$

Example 13

The series is the monthly series of Japanese exports, from January 1972 to July 1992 (source: Datastream); it is discussed in Planas (1995). The example further illustrates the allocation of the AR roots to the components and some other features of SEATS.

The model fitted is

$$(1 + \phi_1 B + \phi_2 B^2 + \phi_3 B^3) \nabla \nabla_{12} z_t = (1 + \theta_{12} B^{12}) a_t.$$

The AR(3) polynomial has one root for the 0 frequency (with modulus .64) and a pair of complex conjugate roots for the frequency $\omega = 129^\circ$ (with modulus .75), close to the 4-times-a-year seasonal frequencies. Since, by default, $RMOD = .5$, the first root is assigned to the trend. As for the complex root, given that $EPSPHI = 10$, $\omega \in (120 - EPSPHI, 120 + EPSPHI)$, and hence the root is assigned to the seasonal. Notice that, by default, ω would not have been considered “close to a seasonal frequency” and, since it would represent non-seasonal, non-white noise transitory deviations from the trend, the complex root would have been assigned to the cycle.

In this example, the original series and the seasonally adjusted one are constrained to have identical annual means for every year of the sample and of the forecasting period (notice that the presence of the log makes the decomposition multiplicative). By default and in this case, the correction would not have been enforced.

The reduced output file is produced, instead of the full one obtained by default. This reduced output file should be enough for most applications.

EXAMPLE 13

EXPORTS (JAPAN)

	252	1970		1	12			
393.0	489.0	600.0	550.0	537.0	589.0	616.0	574.0	625.0
639.0	562.0	781.0	452.0	594.0	772.0	682.0	683.0	736.0
778.0	744.0	729.0	706.0	680.0	838.0	481.0	629.0	785.0
693.0	651.0	678.0	754.0	747.0	814.0	770.0	778.0	1026.0
562.0	800.0	798.0	747.0	749.0	791.0	878.0	791.0	882.0
887.0	964.0	1181.0	763.0	1020.0	1227.0	1185.0	1286.0	1365.0
1484.0	1499.0	1439.0	1630.0	1532.0	1791.0	1109.0	1320.0	1463.0
1404.0	1283.0	1303.0	1420.0	1304.0	1358.0	1474.0	1337.0	1798.0
1113.0	1451.0	1795.0	1596.0	1597.0	1713.0	1760.0	1581.0	1761.0
1757.0	1652.0	2155.0	1386.0	1688.0	2019.0	1889.0	1702.0	1837.0
1942.0	1733.0	1812.0	1838.0	1724.0	2077.0	1364.0	1793.0	2078.0
1750.0	1751.0	1806.0	1714.0	1540.0	1699.0	1595.0	1522.0	1914.0
1193.0	1547.0	1925.0	1674.0	1795.0	1906.0	1935.0	1797.0	2055.0
2006.0	2049.0	2650.0	1656.0	2304.0	2655.0	2535.0	2494.0	2435.0
2495.0	2336.0	2553.0	2501.0	2349.0	3071.0	1925.0	2464.0	2903.0
2725.0	2748.0	2857.0	3083.0	2784.0	3028.0	3093.0	2692.0	3166.0
2284.0	2704.0	3196.0	3032.0	2750.0	2862.0	3060.0	2684.0	3010.0
2974.0	2741.0	3135.0	2134.0	2616.0	3070.0	2912.0	2738.0	2935.0
3030.0	2824.0	3130.0	3032.0	2908.0	3581.0	2384.0	3098.0	3557.0
3252.0	3256.0	3418.0	3536.0	3244.0	3560.0	3680.0	3410.0	3931.0
2795.0	3321.0	3783.0	3783.0	3629.0	3614.0	3759.0	3298.0	3534.0
3560.0	3242.0	3639.0	2584.0	2913.0	3177.0	3173.0	2988.0	2957.0
3076.0	2609.0	2948.0	2953.0	2712.0	3201.0	2362.0	2635.0	2963.0
2863.0	2606.0	2685.0	2942.0	2655.0	2910.0	2986.0	2619.0	3070.0
2188.0	2603.0	2923.0	2826.0	2576.0	2762.0	3039.0	2776.0	3109.0
3095.0	2842.0	3202.0	2437.0	2876.0	3392.0	3068.0	2908.0	3247.0
3320.0	3061.0	3529.0	3286.0	3151.0	3548.0	2699.0	3190.0	3876.0
3445.0	3380.0	3624.0	3626.0	3340.0	3686.0	3573.0	3302.0	3717.0

\$INPUT p=3, imean=0, q=0, bias=-1, epsphi=10, out=1, \$

2.7 Identification of the Arrays Produced by SEATS

Description of the Files in GRAPH

2.7.1 Series

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
Original linearized series (from TRAMO)	Original series	<i>serie.t</i>
Transformed series (logs)	Transformed series (logs)	<i>tserie.t</i>
Rate of growth of original series	Series: Rate of growth	<i>rserie.t</i>
Differenced series	Differenced series	<i>differ.t</i>
Seasonally adjusted series	SA series	<i>seasadjo.t</i>
Seasonally adjusted series (logs)	SA series (logs)	<i>seasadjt.t</i>
Rate of growth of seasonally adjusted series	SA series: rate of growth	<i>sarate.t</i>
Seasonal factors (levels)	Seasonal factors	<i>seasfac.t</i>
Seasonal component (logs)	Seasonal component	<i>seas.t</i>
Trend (level)	Trend	<i>trendo.t</i>
Trend component (logs)	Trend component	<i>trendt.t</i>
Rate of growth of trend	Trend: Rate of growth	<i>trate.t</i>
Cyclical factors (levels)	Cyclical factors	<i>cyclefac.t</i>
Cyclical component (logs)	Cyclical component	<i>cycle.t</i>
Irregular factors (levels)	Irregular factors	<i>irregfac.t</i>
Irregular component (logs)	Irregular component	<i>irreg.t</i>
ARIMA residuals	Residuals	<i>resid.t</i>
Pseudoinnovations in the components		
Seasonally adjusted series	Pseudo-inn.: SA series	<i>pisa.t</i>
Trend	Pseudo-inn.: Trend	<i>pitrend.t</i>
Seasonal	Pseudo-inn.: Seasonal	<i>piseas.t</i>
Cyclical	Pseudo-inn.: Cycle	<i>picycle.t</i>

When TRAMO has been used as a preadjustment program, the directory GRAPH \SERIES also contains the following series:

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
Original uncorrected series (from TRAMO)	Orig. uncorrect. series	<i>xorig.t</i>
Aggregate Preadjustment factor	Preadjustment factor	<i>preadf.t</i>
Preadjustment factors (or components) from TRAMO		
Level Shifts		<i>paotrf.t</i>
Transitory Outliers		<i>paoirf.t</i>
Easter Effect		<i>paearf.t</i>
Trading Day Effect		<i>patdf.t</i>
Regression effect allocated to seasonal component (<i>REGEFF</i> = 2)		<i>sregf.t</i>
Regression effect allocated to trend (<i>REGEFF</i> = 1)		<i>tregf.t</i>
Regression effect is part of the irregular component (<i>REGEFF</i> = 3)		<i>iregf.t</i>
Regression effect is allocated to the cycle (<i>REGEFF</i> = 5)		<i>cyregf.t</i>
Regression effect is allocated to the seasonally adjusted series, as an additional component (<i>REGEFF</i> = 4)		<i>saregf.t</i>
Regression effect is a separate component (<i>REGEFF</i> = 0)		<i>spregf.t</i>

Note: When *LAM* = 1, the factors are the components, and the ‘*f*’ before the ‘.’ becomes a ‘*c*’ (for ex., *paotrc.t*).

Final Components

Seasonally Adjusted series	<i>safin.t</i>
Trend	<i>trfin.t</i>
Irregular factor (component)	<i>irfin.t</i>
Seasonal factor (component)	<i>sfin.t</i>
Cyclical factor (component)	<i>cfin.t</i>

When *OUT* = 2 (short summary output), the directory GRAPH only contains the files *series.t*, *seasadjo.t*, *trendo.t*, *irregfac.t*, and *seasfac.t*.

2.7.2 Autocorrelation Functions

Note: ST denotes “Stationary Transformation”.

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
Differenced series	ACF of differenced series	<i>dauto.t2</i>
Residuals	ACF of residuals	<i>autores. t2</i>
Squared residuals	ACF of sqd residuals	<i>autosres.t2</i>
Theoretical component (ST)		
SA series	Comp: ACF of SA series	<i>acftsadj.t2</i>
Seasonal	Comp: ACF of seasonal	<i>acftseas.t2</i>
Trend	Comp: ACF of trend	<i>acfttre.t2</i>
Cycle	Comp: ACF of cycle	<i>acftcyc.t2</i>
Theoretical MMSE estimator (ST)		
SA series	E-tor: ACF of SA series	<i>acfradj.t2</i>
Seasonal	E-tor: ACF of seasonal	<i>acfrseas.t2</i>
Trend	E-tor: ACF of trend	<i>acfrtre.t2</i>
Cycle	E-tor: ACF of cycle	<i>acfrcyc.t2</i>
Irregular	E-tor: ACF of irregular	<i>acfrir.t2</i>
Empirical estimate (ST)		
SA series	E-te: ACF of SA series	<i>acfesadj.t2</i>
Seasonal	E-te: ACF of seasonal	<i>acfeseas.t2</i>
Trend	E-te: ACF of trend	<i>acfetre.t2</i>
Cycle	E-te: ACF of cycle	<i>acfecyc.t2</i>
Irregular	E-te: ACF of irregular	<i>acfeir.t2</i>

2.7.3 Spectra

Aggregate ARIMA model	Spectrum series	<i>spect.t3</i>
Theoretical component		
SA series	Spectrum SA series	<i>spectsa.t3</i>
Seasonal component	Spectrum seasonal	<i>spects.t3</i>
Trend	Spectrum trend	<i>spectt.t3</i>
Cycle	Spectrum cycle	<i>spectc.t3</i>
Theoretical MMSE estimator		
SA series	Spectrum SA series est.	<i>spectesa.t3</i>
Seasonal component	Spectrum seas. est.	<i>spectes.t3</i>
Trend	Spectrum trend est.	<i>spectet.t3</i>
Cycle	Spectrum cycle est.	<i>spectec.t3</i>
Irregular	Spectrum irreg. est.	<i>spectei.t3</i>

2.7.4 Filters

Wiener–Kolmogorov filters (estimator as function of observed series)

Note: TD denotes “Time Domain”; FD denotes “Frequency Domain”.

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
SA series (TD)	SA series filter (TD)	<i>filtadj.t4</i>
SA series (FD)	SA series filter (FD)	<i>filtfadj.t4f</i>
Seasonal component (TD)	Seasonal comp. filter (TD)	<i>filtst.t4</i>
Seasonal component (FD)	Seasonal comp. filter (FD)	<i>filtfs.t4f</i>
Trend (TD)	Trend filter (TD)	<i>filtt.t4</i>
Trend (FD)	Trend filter (FD)	<i>filft.t4f</i>
Cyclical component (TD)	Cyclical comp. filter (TD)	<i>filtc.t4</i>
Cyclical component (FD)	Cyclical comp. filter (FD)	<i>filtfc.t4f</i>
Irregular component (TD)	Irregular comp. filter (TD)	<i>filti.t4</i>
Irregular component (FD)	Irregular comp. filter (FD)	<i>filtfi.t4f</i>

Note: Given that the filters are symmetric, only one side of the filter is kept.

Psi-weights (estimator as function of innovations in observed series)

SA series	Psi-weights: SA series	<i>psisa.t4</i>
Seasonal	Psi-weights: seasonal	<i>psiseas.t4</i>
Trend	Psi-weights: trend	<i>psitre.t4</i>
Cycle	Psi-weights: cycle	<i>psicyc.t4</i>

Note: The Psi arrays contain $4MQ + 1$ elements, and are centered around the coefficient for B^0 . Thus for the estimation of the component at period t , $2MQ$ weights refer to innovations prior to t , and the last $2MQ$ weights refer to innovations posterior to t .

2.7.5 Forecasts

Original series	Forecasts of orig. series	<i>forx.t5</i>
Series in logs	Forecasts of series (logs)	<i>forlx.t5</i>
Seasonal factors	Forecasts of seasonal factors	<i>forsf.t5</i>
Seasonal component	Forecasts of seas. comp.	<i>forsc.t5</i>
Trend (level)	Forecasts of trend	<i>fort.t5</i>
Trend component	Forecasts of trend comp.	<i>fortc.t5</i>
Cyclical factors	Forecasts of cyclical factors	<i>foref.t5</i>
Cyclical component	Forecasts of cyclical comp.	<i>forecc.t5</i>

<u>Meaning</u>	<u>Title of Graph</u>	<u>Name of File</u>
Preadjustment factor or component (when TRAMO has been used as a preadjustment program)	Forecast of preadjustment factor or component	<i>fdetf.t5</i>
Forecast of Regression Effect	Forecast of Regression Effect	<i>freg.t5</i>

Note: Each array of component forecasts consists of three consecutive series: first, the lower and upper limits of the 95% probability interval, and then the point estimators. (The three lines displayed in the graphs.) Thus, if there are N elements in the array, the point estimator series consists of the last $N_1 = N/3$ elements. N_1 is always odd, and the center element corresponds to the last observed period. Therefore, of these last N_1 elements, the first $(N_1 + 1)/2$ are estimates (or observations) for recent periods, and the last $(N_1 - 1)/2$ form the forecast function.

When $L =$ a positive integer, it determines the number of forecasts computed. When $L = -1$ (i.e., when signal extraction is performed), the number of forecasts for the series and components is equal to $\max(2MQ, FH)$, where $FH = 8$ by default; see Section 2.4.4.

For example, for the default (monthly) model, the length of the array is 147. The last 49 represent the point estimates, of which the first 25 represent past and present values, and the last 24 the two-year-ahead forecast function.

Forecasts of the Final Components

Original uncorrected series	<i>funorig.t5</i>
Seasonally Adjusted series	<i>fsafin.t5</i>
Trend	<i>ftrfin.t5</i>
Irregular factor (component)	<i>firfin.t5</i>
Seasonal factor (component)	<i>fsfin.t5</i>
Cyclical factor (component)	<i>fcycfin.t5</i>

Note: The one-to- $\max(2 \times MQ, FH)$ -period-ahead forecast function is given by the last $\max(2 \times MQ, FH)$ elements of each array. (For example, if $MQ = 12$, the forecast function of the final trend consists of the last 24 elements of the array *ftrfin.t5*).

3 Routine use on Many Series

3.1 The *RSA* Parameter

The programs contain a facility for routine treatment (for example, routine seasonal adjustment) of perhaps a very large number of series. This is controlled by the three input parameters *RSA*, *QMAX*, and *DVA*.

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>QMAX</i>	= k	A positive number, which controls the sensitivity of the routine procedure (see below). The parameter <i>QMAX</i> is only active when <i>RSA</i> \neq 0.	50 ^(*)
<p>(*) The default value of <i>QMAX</i> depends on <i>MQ</i>. For $MQ \geq 6$, <i>QMAX</i> = 50; for $MQ = 4, 3$, and 2, <i>QMAX</i> = 36, 30, and 24, respectively.</p>			
<i>DVA</i>	= k	A (small) number to control the criteria for outlier detection in automatic applications (see below).	0
<i>RSA</i>	= 0	Parameter inactive.	0
	= 1	Fast routine procedure. The program TRAMO automatically sets the following parameters: <i>LAM</i> = -1, <i>INTERP</i> = 1, <i>IATIP</i> = 1, <i>AIO</i> = 2, <i>VA</i> = see below, <i>NOADMISS</i> = 1, <i>SEATS</i> = 2.	
	= 2	As before, but the following parameters are added: <i>IEAST</i> = -1, <i>ITRAD</i> = -1.	
	= 3	Detailed routine procedure. As <i>RSA</i> = 1, but the following parameters are added: <i>INIC</i> = 3, <i>IDIF</i> = 3.	
	= 4	As <i>RSA</i> = 3, but the following parameters are added: <i>IEAST</i> = -1, <i>ITRAD</i> = -1.	
	= 5	Equal to <i>RSA</i> =2 with <i>ITRAD</i> =-6.	
	= 6	Equal to <i>RSA</i> =4 with <i>ITRAD</i> =-6.	
	= 7	Equal to <i>RSA</i> =2 with <i>ITRAD</i> =-7.	
	= 8	Equal to <i>RSA</i> =4 with <i>ITRAD</i> =-7.	

The parameter *VA* is also set, but its value depends on the number of observations (*NZ*), in the following way:

$$\begin{array}{ll}
NZ \leq 50, & VA = 3 + DVA \\
50 < NZ \leq 250, & VA = 3.5 + DVA \\
250 < NZ \leq 500, & VA = 3.8 + DVA \\
500 < NZ & VA = 4 + DVA.
\end{array}$$

By default, $DVA = 0$.

Therefore, **when** $RSA = 1$, the program automatically tests for the log/level specification, interpolates missing values, corrects for three types of outliers, and estimates the default (“Airline”) model, which is passed on to SEATS. SEATS checks the autocorrelation of the residuals. If the Ljung–Box Q statistics is larger than $QMAX$, three other models are estimated, within SEATS, to the series linearized by TRAMO, and the results are compared. The one that provides the best fit is chosen. If the model does not provide an admissible decomposition, it is automatically approximated by a decomposable one.

When $RSA = 2$, the same fast routine procedure is followed, except that the pretests for Trading Day and Easter effects are included. This is done by running a regression on the Trading Day and Easter variables, with the noise following the default model.

When $RSA = 3$ (Detailed Routine Adjustment), the program TRAMO automatically sets the same parameters for the case $RSA = 1$, and adds:

$$INIC = 3, \quad IDIF = 3.$$

In this case, thus, the automatic model identification procedure in TRAMO is used to determine the model. As before, nondecomposable models are approximated in SEATS. **When** $RSA = 4$, the detailed procedure is followed, but pretests for Trading Day and Easter effects are included. (The model ultimately selected will be retested for both types of effects.)

Note 1: When $RSA \neq 0$, the user can still enter the following parameters: MQ , DVA , OUT , $MAXBIAS$, XL , $QMAX$, $IMVX$, $IDUR$, $ITER$, VA , $INT1$, $INT2$, plus the parameters for regression variables entered by the user.

Note 2: $RSA \neq 0$ requires $MQ \neq 1$
 $RSA = 2, 4$ requires $MQ = 12$.

Note 3: If there are missing observations, $LAM = -1$ and/or $ITRAD < 0$ and/or $IEAST = -1$, $INTERP$ should not be 1.

Note 4: On occasion, SEATS **can change the model** identified and estimated by TRAMO, and estimate the new model. This will happen, for example, when $RSA = 1$ and $Q(\text{obtained}) > QMAX$. It can also happen in other situations to improve the decomposition of the series.

An important case is when the model identified by TRAMO has the $(0,0,1)_{MQ}$ multiplicative seasonal structure, and the seasonal MA parameter is $BTH > 0$ (for example, the case $(1 + .5B^4)$). Then, the above structure is replaced in SEATS by the standard $(0,1,1)_{MQ}$ multiplicative seasonal structure. Typically, very little is lost in terms of the fit (often, nothing), but the second structure provides much more stable components.

Two examples of an *RSA* input file are presented.

Example 14

The series is the quarterly series of Austrian employment for the full period 1964–1994 (source: Institute of Economic Research, Vienna).

Setting $RSA = 1$ implies for this series, the following parameter configuration:

$$\begin{aligned} LAM &= -1, & IATIP &= 1, & AIO &= 2, \\ SEATS &= 2, & NOADMISS &= 1, & QMAX &= 36 \quad (\text{since } MQ = 4) \\ VA &= 3.5 \quad (\text{since } NZ = 124) \end{aligned}$$

Therefore, after determining the appropriate transformation for the data, TRAMO uses the default model for outlier removal and the results are passed on to SEATS. SEATS filters the linearized series with the model passed by TRAMO, and looks at the Q -Box-Ljung statistics for (in this case) 24 autocorrelations. If $Q < QMAX$, the model is accepted; otherwise SEATS tries a sequence of 3 more models and chooses the best one.

This parameter configuration could be adequate for a very robust and fast procedure for routine adjustment of very large numbers of series. It is based on the close to 50% probability of finding a model that can fit the “Airline Model” (default) structure (see Section 3.3), and on considering alternative models that decompose well or can be well approximated if their decomposition is non-admissible.

The parameter $INT2 = -120$ implies that, for the last $NZ + INT2$ ($= 124 - 120 =$) 4 observations, outliers are detected but not corrected. (This may avoid unpleasant features of some outliers corrected at the end of the series.)

EXAMPLE 14

EMPLOYMENT (Austria)

124 1964	1	4
0.228823300000000D+07	0.236829900000000D+07	0.241292533333333D+07
0.238566366666667D+07	0.231188466666667D+07	0.238593633333333D+07
0.242979566666667D+07	0.239825033333333D+07	0.233790933333333D+07
0.240194200000000D+07	0.242880800000000D+07	0.237785066666667D+07
0.230560966666667D+07	0.236460433333333D+07	0.240656833333333D+07
0.236141866666667D+07	0.227081033333333D+07	0.234188400000000D+07
0.239312600000000D+07	0.235145500000000D+07	0.227850066666667D+07
0.235907066666667D+07	0.241391200000000D+07	0.237913533333333D+07
0.231464700000000D+07	0.237898733333333D+07	0.243716333333333D+07
0.242598200000000D+07	0.238329066666667D+07	0.244352200000000D+07
0.250278700000000D+07	0.248983300000000D+07	0.244354433333333D+07
0.249960866666667D+07	0.255487300000000D+07	0.255284533333333D+07
0.252470100000000D+07	0.259748900000000D+07	0.265455266666667D+07
0.265648000000000D+07	0.260244066666667D+07	0.264554000000000D+07
0.269293866666667D+07	0.268676966666667D+07	0.262494133333333D+07
0.264241866666667D+07	0.268857800000000D+07	0.266982233333333D+07
0.262152633333333D+07	0.266590833333333D+07	0.273306766666667D+07
0.272294433333333D+07	0.268329866666667D+07	0.272307666666667D+07
0.278266400000000D+07	0.275955000000000D+07	0.271692833333333D+07
0.274134866666667D+07	0.280030100000000D+07	0.277224333333333D+07
0.272760700000000D+07	0.276356766666667D+07	0.281539666666667D+07
0.278830500000000D+07	0.274047100000000D+07	0.277315733333333D+07
0.283681966666667D+07	0.280449900000000D+07	0.275880233333333D+07
0.279190700000000D+07	0.284703866666667D+07	0.279648100000000D+07
0.273225800000000D+07	0.276568766666667D+07	0.281190400000000D+07
0.275554933333333D+07	0.269503700000000D+07	0.272404233333333D+07
0.278567700000000D+07	0.273416133333333D+07	0.268498000000000D+07
0.273323900000000D+07	0.280625766666667D+07	0.275354633333333D+07
0.269633333333333D+07	0.274959033333333D+07	0.282475133333333D+07
0.276795466666667D+07	0.271999500000000D+07	0.277405933333333D+07
0.284555266666667D+07	0.278120700000000D+07	0.272500300000000D+07
0.278169600000000D+07	0.285034433333333D+07	0.278438666666667D+07
0.274614400000000D+07	0.279867700000000D+07	0.287390200000000D+07
0.282319033333333D+07	0.279743433333333D+07	0.284603400000000D+07
0.292778833333333D+07	0.287790600000000D+07	0.285727833333333D+07
0.290986066666667D+07	0.299522000000000D+07	0.295228833333333D+07
0.292687400000000D+07	0.298097600000000D+07	0.307062066666667D+07
0.301093600000000D+07	0.299102500000000D+07	0.304995466666667D+07
0.312956233333333D+07	0.305269733333333D+07	0.300399466666667D+07
0.305177266666667D+07	0.312021333333333D+07	0.304365933333333D+07
0.301064733333333D+07	0.306403633333333D+07	0.313829466666667D+07
0.306995033333333D+07		

\$INPUT

MQ=4,

RSA=1,int2=-120,

\$

Example 15

The series is the industrial production index of Example 7.

Setting $RSA = 4$ implies the same configuration of parameters of the previous Example 14 ($QMAX$ becomes irrelevant), and adding the more sophisticated automatic model identification procedure of TRAMO and the pretesting for log/level specification and for Trading Day and Easter effects.

Compared to Example 7, automatic outlier detection is now included (it yields precisely the “a priori” outlier of Example 7.) Further, holidays are treated as the “holiday effect” of Section 1.3.10, part (b), and implies simply a modification of the Trading Day variable, in the sense that, for each month, the number of working days is decreased and the number of non-working days is increased by the amount of the holidays. (In Example 7, holidays were a separate regression variable, and therefore the results of Examples 7 and 15 should not be identical, even if there were no missing observations in the former.)

EXAMPLE 15

IPI (Spain)

161 1983 1 12

83.60	83.30	90.60	84.50	89.30
86.90	82.80	49.90	87.80	86.80
88.90	86.60	86.50	87.20	89.90
81.60	89.80	85.60	85.80	53.30
85.40	91.60	90.20	82.60	88.60
84.60	89.20	84.80	90.60	83.80
89.50	52.40	88.30	99.00	92.90
86.20	88.40	88.00	87.50	94.60
91.20	92.50	93.70	50.40	92.10
100.30	94.90	88.10	87.60	91.90
96.60	91.40	96.30	97.30	102.90
53.10	98.40	102.00	101.10	92.10
90.20	96.50	103.40	95.00	101.20
100.30	99.60	56.40	100.80	100.90
105.80	94.50	100.70	98.70	103.40
102.10	104.80	107.70	104.60	60.00
105.00	107.30	108.80	92.70	105.00
98.90	108.40	96.00	107.10	107.10
104.40	59.80	102.40	105.70	109.20
92.40	103.70	99.00	96.80	102.20
104.00	102.30	104.50	58.90	102.80
111.80	106.10	95.30	100.30	101.10
104.30	98.30	100.30	102.80	104.50
58.80	98.90	100.70	97.30	86.70
88.20	90.30	98.00	90.20	95.30
96.80	97.50	56.90	97.10	97.00
99.50	92.00	91.10	95.20	103.50
97.00	102.10	105.50	102.70	64.20
104.90	104.40	109.20	99.90	104.20
101.50	113.90	97.40	112.00	112.70
106.20	67.40	105.60	108.10	110.40
95.20	102.70	102.40	106.40	98.40
108.40				

\$INPUT Rsa=4 va=3 ireg=1 \$

\$REG iuser=-2 nser=1 ilong=185 \$

examples\holidays

3.2 The *ITER* Parameter

The programs contains a facility to handle in a single file many series, perhaps with different models each. This is controlled by the parameter *ITER*, which can take the following values

<u>Parameter</u>		<u>Meaning</u>	<u>Default</u>
<i>ITER</i>	= 0	One series, one model (the usual input file)	0
	= 1	several models are provided by the user to be applied by the program to the same series	
	= 2	Several series are to be treated by the program with the same model	
	= 3	Several series, each with its own specified model, are treated by the program	

When *ITER* = 1 the names of the output file are *MODEL1.OUT*, ..., *MODELn.OUT*, where *n* is the number of models (if *ITER* = 2,3 the usual *serienam.out*).

The structure of the input file *serie* if *ITER* > 0 is the following:

- ITER* = 1 You have to append (in any format) at the end of the usual input file the number of namelists *INPUT* (and eventually namelists *REG*) that you want; remember that the structure of the namelists *INPUT* and *REG* is the following:
- ```

$ INPUT parameter-name=parameter-value, ...,
parameter-name=parameter-value, $
$ REG parameter-name=parameter-value, ...,
parameter-name=parameter-value, $

```
- ITER* = 2 You have to append (in any format) at the end of the usual input file the number of series that you want, according to the following convention:
- ```

1st line:      title
2nd line:      number of observations
                starting year
                starting period
                Nfreq
3rd to nth line: observations in any format

```

ITER = 3 You have to append (in any format) at the end of the usual input file the number of pairs series–namelist that you want; the convention for the series is the same as in *ITER* = 2, and for the namelist the same as in the case *ITER* = 1

When *ITER* ≠ 0, TRAMO sends the output file to the subdirectory OUTPUT. The files in GRAPH \ SERIES are

if *ITER* = 1

<i>model#.ser</i>	original series;
<i>model#.lin</i>	linearized series;
<i>model#.pre</i>	forecasts of the original series;

if *ITER* = 2, or *ITER* = 3

<i>title.ser</i>	original series;
<i>title.lin</i>	linearized series;
<i>title.pre</i>	forecasts of the original series;

When *ITER* ≠ 0, SEATS puts the output in the directory OUTPUT. For every iteration it creates the following files in the directory GRAPH \ SERIES:

if *ITER* = 1

<i>model#.ser</i>	series;
<i>model#.tre</i>	final trend component;
<i>model#.cyc</i>	final cyclical component;
<i>model#.sa</i>	final seasonally adjusted series;

if *ITER* = 2, or *ITER* = 3

<i>title.ser</i>	original series;
<i>title.tre</i>	final trend component;
<i>title.cyc</i>	final cyclical component;
<i>title.sa</i>	final seasonally adjusted series,

and, similarly, in the subdirectory GRAPH \ FORECAST:

****.fx	forecast of series;
****.ftr	forecast of final trend;
****.fcy	forecast of final cyclical;
****.fsa	forecast of final SA series,

where **** denotes ‘*model#*’ when *ITER* = 1 and ‘*series title*’ when *ITER* = 2 or 3.

Five examples of *ITER* input files are given next.

Warning: When $ITER \neq 0$, the program *INPUT* should not be executed. The input file is entered directly in “*serie*”, and then SEATS can be run.

Example 16

This example consists of an *ITER* file containing 4 quarterly series. The first series is the Gross Fixed Capital Formation: Building and Construction for the Total Economy. The second series is the Gross Fixed Capital Formation: Residential Building, in the private sector. The third series is the Gross Fixed Capital Formation: Other Building and Construction, in the private sector. All 3 series are for Germany. The fourth series is Employment in Agriculture, Forestry and Fishery in Italy. The source for the 4 series is Eurostat.

With $ITER = 2$, the same input namelist will apply to all series, and in this case they will be treated with $RSA = 1$. The parameter $QMAX = 25$ will imply a more stringent requirement on the cleanness of the residuals for the model to be accepted.

The default model turns out to be comfortably appropriate for the German series. For the Italian series, it is not, but the model

$$\nabla^2 \nabla_4 \log z_t = (1 + \theta_1 B + \theta_2 B^2)(1 + \theta_4 B^4) a_t$$

is found to be quite appropriate.

EXAMPLE 16

```

BUILDING AND CONSTR (TOTAL ECON):GF Capital Form.(Germany)
106 1968 1 4
  14560.00      19660.00      20910.00      21120.00      15040.00
  22430.00      24270.00      23570.00      17060.00      28710.00
  30410.00      29990.00      23010.00      32960.00      34010.00
  33470.00      27600.00      36080.00      35960.00      36790.00
  30880.00      38760.00      37980.00      36370.00      31520.00
  37130.00      36220.00      35480.00      28370.00      33860.00
  34440.00      34690.00      27660.00      37130.00      37310.00
  37470.00      31620.00      38590.00      38660.00      38240.00
  31470.00      42670.00      42600.00      42410.00      32560.00
  49730.00      50000.00      50420.00      43650.00      55090.00
  55250.00      51250.00      41000.00      56950.00      56440.00
  49940.00      39750.00      54520.00      54400.00      51170.00
  40090.00      55220.00      57050.00      53500.00      43710.00
  57310.00      57760.00      54760.00      37130.00      54830.00
  57880.00      52940.00      37700.00      57650.00      60230.00
  57030.00      37450.00      58720.00      62110.00      58070.00
  45310.00      60880.00      62650.00      58600.00      51740.00
  65130.00      65460.00      62720.00      58370.00      71840.00
  73400.00      69600.00      60290.00      80570.00      82470.00
  75990.00      70510.00      86820.00      88060.00      83930.00
  71920.00      90650.00      92350.00      83550.00      76740.00
  95530.00

```

\$INPUT mq=4 rsa=1 qmax=25 iter=2 \$

```

RESID BUILDING (PRIVATE SECTOR):GF Capital Form (Germany)
106 1968 1 4
  7260.00      9560.00      9920.00      10330.00      7100.00
  10220.00     10830.00     10870.00      7510.00     12190.00
  12650.00     13090.00     10120.00     14530.00     15040.00
  15650.00     13430.00     17330.00     17220.00     18210.00
  15740.00     19470.00     18520.00     17850.00     14910.00
  17340.00     16400.00     16230.00     12860.00     15290.00
  15190.00     15770.00     13030.00     17020.00     17040.00
  17690.00     15290.00     18360.00     18340.00     18300.00
  15510.00     20560.00     20150.00     20140.00     16380.00
  24150.00     23870.00     24150.00     21740.00     26850.00
  26370.00     24570.00     20600.00     27920.00     27200.00
  24090.00     19890.00     26580.00     26420.00     24930.00
  20900.00     28360.00     29120.00     27390.00     23620.00
  30290.00     29520.00     27610.00     19580.00     27460.00
  28140.00     25670.00     19000.00     27570.00     28370.00
  26890.00     18840.00     27630.00     28760.00     27350.00
  22320.00     28980.00     29500.00     27810.00     25240.00
  31540.00     31170.00     29980.00     29210.00     35890.00
  36390.00     34370.00     31150.00     40760.00     41390.00
  38130.00     36680.00     45010.00     45600.00     43670.00
  39070.00     48870.00     50210.00     45920.00     43680.00

```

54910.00
 OTHER BUILDING AND CONSTR (PRIVATE SECTOR):GF Capital form.(Germany)
 106 1968 1 4

3940.00	5060.00	5570.00	5440.00	4500.00
6320.00	6790.00	6670.00	5600.00	8550.00
8960.00	8720.00	7410.00	9960.00	10110.00
9630.00	8340.00	10420.00	10370.00	10150.00
9030.00	10780.00	10650.00	10090.00	9300.00
10370.00	10080.00	9420.00	8110.00	9290.00
9590.00	9230.00	8040.00	10580.00	10590.00
9860.00	9540.00	11060.00	10930.00	10220.00
9180.00	11820.00	12030.00	11830.00	9690.00
13570.00	13960.00	13990.00	12550.00	15410.00
15710.00	14760.00	12260.00	16250.00	16470.00
14940.00	12590.00	16650.00	16410.00	15600.00
12580.00	16660.00	17100.00	16230.00	13610.00
17230.00	17650.00	16960.00	12030.00	17290.00
18470.00	17180.00	12820.00	18810.00	19670.00
18730.00	13070.00	19660.00	20680.00	19460.00
15620.00	20490.00	21050.00	19940.00	17640.00
21820.00	22120.00	21250.00	19690.00	23660.00
24020.00	23220.00	19970.00	26230.00	26790.00
24830.00	23150.00	27480.00	27560.00	26210.00
22260.00	27140.00	27250.00	24470.00	22370.00
26550.00				

EMPLOYMENT AGRIC-FORES-FISH (Italy)
 97 1970 1 4

3740.00	3822.00	3819.00	3744.00	3776.00
3867.00	3808.00	3603.00	3489.00	3512.00
3485.00	3378.00	3357.00	3442.00	3455.00
3376.00	3334.00	3378.00	3368.00	3266.00
3208.00	3240.00	3237.00	3151.00	3135.00
3234.00	3276.00	3185.00	3113.00	3126.00
3108.00	3032.00	3038.00	3131.00	3151.00
3059.00	3011.00	3079.00	3089.00	2999.00
2954.00	3018.00	3039.00	2965.00	2898.00
2901.00	2849.00	2733.00	2659.00	2704.00
2716.00	2655.00	2655.00	2758.00	2816.00
2753.00	2695.00	2723.00	2716.00	2611.00
2543.00	2585.00	2629.00	2566.00	2520.00
2567.00	2606.00	2555.00	2513.00	2537.00
2531.00	2450.00	2407.00	2437.00	2421.00
2320.00	2252.00	2282.00	2307.00	2266.00
2236.00	2257.00	2252.00	2195.00	2198.00
2266.00	2280.00	2205.00	2158.00	2178.00
2147.00	2045.00	1980.00	2000.00	2005.00
1951.00	1925.00			

Example 17

The file contains two series, and the same input line applies to both. SEATS is to be run entirely by default and the Airline model will be fit to the log of both series.

The first series is the Spanish consumer price index and the second series is the same price index seasonally adjusted by SEATS run by default. (Both series are monthly). The example illustrates the idempotency properties of the default filter of SEATS. The adjusted CPI and the adjusted adjusted CPI are indistinguishable.

EXAMPLE 17

CPI (Spain)

180 1978 1 12

25.5449980	25.7959900	26.1269990	26.6769870	26.9439850
27.2159880	27.8060000	28.2909850	28.5239870	28.7849880
28.9109950	29.3029940	29.8060000	30.0369870	30.3489990
30.8069920	31.1669920	31.4419860	32.1209870	32.4369960
32.8639980	33.3049930	33.3849950	33.8719940	34.8039860
35.1149900	35.3039860	35.6449890	35.8919980	36.4489900
36.9639890	37.3969880	37.7949980	38.0979920	38.4870000
39.0249940	39.8179930	40.0199890	40.8169860	41.2229920
41.4149930	41.4509890	42.2629850	42.7780000	43.1179960
43.6029970	43.9809880	44.6469880	45.5719910	45.9269870
46.3779910	46.9879910	47.6679990	48.1259920	48.7439880
49.0819850	49.1389920	49.6309970	49.7929990	50.9009860
51.7609860	52.0209960	52.3369900	53.0560000	53.2759860
53.5879970	53.7789920	54.5009920	54.9369960	55.6819920
56.2489930	57.1219940	58.0059970	58.2269900	58.6959990
58.9729920	59.2919920	59.7119900	60.6289980	61.0499880
61.1739960	61.5429990	61.8589940	62.2780000	63.4379880
63.8969880	64.2959900	64.9590000	65.1629940	65.0519870
65.4219970	65.5199890	66.2389980	66.5799870	67.0929870
67.3709870	69.3079990	69.6169890	69.8519900	70.0219880
70.2169950	70.8620000	71.5699920	71.7729950	72.5159910
72.7869870	72.6199950	72.9299930	73.4889980	73.8019870
74.2309880	74.3989870	74.3069920	74.3249970	75.0779880
75.0449980	75.7370000	76.1869960	76.0119930	76.2839970
76.7679900	76.9779970	77.5359950	77.2659910	77.2619930
77.5619960	78.5859990	79.3629910	80.0599980	80.1499940
80.1049960	80.7419890	81.6799930	81.7379910	82.2599950
82.4809880	82.5979920	83.0479890	84.3959960	84.5899960
85.4849850	85.8299870	85.9689940	86.3039860	87.1439970
87.6969910	88.0179900	88.2179870	88.2109990	88.4829860
89.6719970	90.0649870	91.0129850	91.8209990	91.7289890
91.9549870	93.0249940	92.8949890	93.1969910	93.3989870
93.6639860	93.9339900	95.0999910	95.4529880	96.2329860
96.8379970	96.9849850	97.0379940	98.5759890	99.2329860
99.5919950	99.4849850	99.7449950	99.7259980	100.0499900
100.9619900	101.7950000	101.8559900	101.9209900	102.2269900

&INPUT ITER=2, /

SA-CPI

180 1978 1 12

25.414259	25.761105	26.115735	26.617996	26.965040
27.311301	27.745434	28.221437	28.507689	28.801040
29.084870	29.404541	29.646123	29.988956	30.328751
30.743201	31.196269	31.555145	32.061744	32.374499
32.857653	33.330664	33.583299	33.981385	34.600998
35.040593	35.258253	35.567519	35.925574	36.581213
36.911006	37.346890	37.808336	38.143135	38.712876

39.141112	39.577262	39.923908	40.740441	41.121396
41.443656	41.599941	42.218694	42.742797	43.155315
43.668488	44.236697	44.769211	45.289826	45.803918
46.280718	46.871734	47.693474	48.287856	48.705087
49.063179	49.194963	49.709648	50.071714	51.028308
51.431498	51.861944	52.213141	52.929376	53.317147
53.779310	53.763124	54.511909	54.997375	55.758735
56.535185	57.263924	57.635524	58.030128	58.538042
58.843340	59.358648	59.938853	60.615149	61.080835
61.213361	61.607073	62.149520	62.457372	63.048215
63.671117	64.106125	64.829757	65.258189	65.317282
65.414155	65.577146	66.238426	66.609576	67.376804
67.577069	68.903495	69.373184	69.643074	69.924360
70.369648	71.179580	71.555250	71.828875	72.442308
72.746896	72.877345	73.139605	73.097830	73.569848
74.016578	74.342674	74.523905	74.703814	75.069530
75.095074	75.601282	76.082917	76.234291	76.480182
76.380557	76.752858	77.322625	77.255417	77.539008
78.002069	78.585594	79.400897	79.866663	79.995883
80.301153	80.935910	81.272745	81.502903	82.046209
82.501777	82.922125	83.546063	84.406610	84.631473
85.253255	85.628986	86.141026	86.508387	86.709417
87.436472	87.795227	88.260064	88.568205	89.034661
89.712229	90.120812	90.757352	91.582015	91.882259
92.175232	92.551480	92.604017	92.958889	93.454310
94.036563	94.524930	95.177398	95.520815	95.964966
96.593089	97.143888	97.285629	98.068905	98.897638
99.315530	99.535808	100.12312	100.34933	100.16202
101.03657	101.50792	101.60950	102.09001	102.49188

Example 18

This example presents a case in which two different models are estimated for the same series, namely the monthly series of the Spanish monetary aggregate, ALP. The first model is the default one, and the second model is given by

$$\nabla^2 \nabla_{12} \log z_t = (1 + \theta_1 B + \theta_2 B^2)(1 + \theta_{12} B^{12}) a_t.$$

The example illustrates robustness of the results with respect to overdifferencing: the estimates of the components obtained with the two models are practically indistinguishable. Moderate amounts of overdifferencing cause hardly any problem.

EXAMPLE 18

Monetary Aggregate ALP (Spain)

234 1972 1 12

2.4515170000000000E-001	2.4639800000000000E-001	2.4988290000000000E-001
2.5444300000000000E-001	2.5847050000000000E-001	2.6214310000000000E-001
2.6907710000000000E-001	2.7261260000000000E-001	2.7518630000000000E-001
2.8048690000000000E-001	2.8432290000000000E-001	2.9302240000000000E-001
3.0194920000000000E-001	3.0424060000000000E-001	3.0950570000000000E-001
3.1634449999999999E-001	3.2147160000000000E-001	3.2869740000000000E-001
3.3918720000000001E-001	3.4435860000000000E-001	3.4802160000000000E-001
3.5439520000000000E-001	3.5939800000000001E-001	3.6925980000000000E-001
3.7766990000000000E-001	3.7808480000000000E-001	3.8384930000000000E-001
3.9114010000000000E-001	3.9571340000000000E-001	4.0177950000000000E-001
4.1203580000000000E-001	4.1438240000000000E-001	4.1624490000000000E-001
4.2277300000000000E-001	4.2772850000000000E-001	4.3961210000000000E-001
4.5108560000000000E-001	4.4978150000000000E-001	4.5618620000000000E-001
4.6174400000000000E-001	4.6660800000000000E-001	4.7474120000000000E-001
4.8898340000000000E-001	4.9557630000000000E-001	4.9934230000000000E-001
5.0454120000000000E-001	5.1072300000000000E-001	5.2555440000000000E-001
5.3783859999999999E-001	5.3653480000000000E-001	5.4233810000000000E-001
5.4912620000000000E-001	5.5609950000000000E-001	5.6448670000000000E-001
5.8067880000000001E-001	5.8646110000000000E-001	5.8905100000000000E-001
5.9832020000000000E-001	6.0553580000000000E-001	6.2324090000000000E-001
6.3943680000000000E-001	6.3870160000000000E-001	6.4586100000000000E-001
6.5662760000000000E-001	6.6382000000000000E-001	6.7463560000000000E-001
6.9518540000000000E-001	7.0377230000000000E-001	7.0870340000000000E-001
7.1559930000000000E-001	7.2043820000000000E-001	7.4151450000000000E-001
7.5603510000000000E-001	7.5427390000000001E-001	7.6431050000000000E-001
7.7886979999999999E-001	7.9087420000000000E-001	8.0508530000000000E-001
8.3396240000000000E-001	8.4037690000000000E-001	8.4825360000000001E-001
8.5804190000000000E-001	8.6413710000000000E-001	8.8986780000000000E-001
9.1191599999999999E-001	9.1357230000000000E-001	9.2760390000000000E-001
9.4410770000000000E-001	9.5053330000000000E-001	9.6573300000000000E-001
9.9784580000000000E-001	9.9915600000000000E-001	1.0022310000000000
1.0152789000000000	1.0232241000000000	1.0599459000000000
1.079427801682360	1.0745940000000000	1.0894509000000000
1.1095655000000000	1.1143346000000000	1.1291057000000000
1.1628859000000000	1.1765235000000000	1.1838329000000000
1.1979287000000000	1.2049063000000000	1.2351923000000000
1.2527280000000000	1.2496579000000000	1.2650584000000000
1.2850291000000000	1.2976086000000000	1.3085495000000000
1.3493081000000000	1.3671929000000000	1.3739365000000000
1.3920073000000000	1.4001685000000000	1.4412989000000000
1.4684535000000000	1.4675129000000000	1.4900285000000000
1.5206379000000000	1.5411228000000000	1.5587682000000000
1.6043311000000000	1.6198610000000000	1.6340096000000000
1.6576183000000000	1.6638014000000000	1.6970570000000000
1.7356645000000000	1.7336476000000000	1.7562654000000000
1.7861441000000000	1.8019543000000000	1.8114491000000000

1.861327900000000	1.873137100000000	1.888286200000000
1.905671800000000	1.910385500000000	1.965745500000000
2.000236200000000	1.990424800000000	2.009817800000000
2.031432100000000	2.039603800000000	2.067762200000000
2.142653400000000	2.150785300000000	2.167796900000000
2.190538400000000	2.184826600000000	2.248718100000000
2.274066400000000	2.283329700000000	2.311432800000000
2.343535500000000	2.364475500000000	2.394538300000000
2.443022369092340	2.441784700000000	2.463420300000000
2.482427000000000	2.485065600000000	2.547335200000000
2.574159000000000	2.582804100000000	2.619072000000000
2.642971000000000	2.655233900000000	2.695839800000000
2.743640504111572	2.730694500000000	2.751568900000000
2.772322300000000	2.775471700000000	2.854814300000000
2.887130500000000	2.888820200000000	2.926423500000000
2.966250500000000	2.987823300000000	3.012782900000000
3.075060700000000	3.107470300000000	3.139458900000000
3.184725600000000	3.194557000000000	3.272019499999999
3.313497700000000	3.305462700000000	3.349010400000000
3.393362200000000	3.410465900000000	3.429108600000000
3.493090400000000	3.505486400000000	3.532134800000000
3.569820500000001	3.580141700000000	3.669777700000000
3.722117100000000	3.726806100000000	3.764234899999999
3.817833600000000	3.852147299999999	3.906767000000000
4.000905100000000	3.992481400000000	4.013749400000000
4.028433300000000	4.011368300000000	4.067253376256384
4.077508500000000	4.057360000000000	4.098987200000000
4.164747800000000	4.198894200000000	4.261137400000000
4.343988400000000	4.347833500000000	4.368389800000000
4.389004500000000	4.400961600000000	4.526939100000000
4.586332500000000	4.603505900000001	4.674752900000001
4.720417500000000	4.730497800000000	4.767853200000001

\$INPUT ITER=1,\$
\$INPUT D=2,Q=2,IMEAN=0,\$

Example 19

This example applies the default model to 3 series: the Spanish series of exports, of imports, and the trade balance (measured as the ratio of the former two). The example illustrates the behavior of the default filter with respect to aggregation of series (i.e. with respect to seasonal adjustment of composite series). The difference between direct and indirect adjustment is minor.

EXAMPLE 19

EXPORTS (Spain)

	155	1976	1	12		
49444.0000	48682.0000	45133.0000	38067.0000	39767.0000	47488.0000	
52028.0000	41625.0000	45400.0000	44329.0000	55267.0000	76312.0000	
51291.0000	62050.0000	63352.0000	56173.0000	68656.0000	54479.0000	
60236.0000	60335.0000	61916.0000	73630.0000	71528.0000	91661.0000	
77158.0000	88518.0000	80183.0000	86899.0000	84819.0000	83798.0000	
84636.0000	70119.0000	66863.0000	80402.0000	93158.0000	105046.0000	
92036.0000	103368.0000	98925.0000	94260.0000	101168.0000	104374.0000	
103109.0000	95722.0000	77345.0000	92269.0000	119921.0000	138740.0000	
96795.0000	119534.0000	126831.0000	120935.0000	123494.0000	123797.0000	
103653.0000	96898.0000	105899.0000	133477.0000	125616.0000	216258.0000	
97572.6875	129616.0000	141593.0000	132478.0000	161804.0000	176383.0000	
212728.0000	150908.0000	126844.0000	151760.0000	175499.0000	231237.0000	
146088.0000	203651.0000	196633.0000	170473.0000	183629.0000	160610.0000	
220743.0000	130827.0000	171692.0000	168126.0000	225863.0000	279671.0000	
162446.9375	188385.0625	269524.2500	173623.1250	283792.0000	252020.3750	
234237.7500	196265.9375	228235.8125	251133.4375	292554.4375	306381.5625	
300383.0000	304328.0000	332838.0000	290566.0000	332370.0000	329840.0000	
318266.0000	238763.0000	279975.0000	339210.0000	316525.0000	348064.0000	
319779.0625	315178.0000	334498.0000	312250.0000	387798.0000	306971.0000	
373121.2500	266327.3125	280446.9375	380393.8750	366700.0000	460679.6875	
262048.0000	324444.1250	301816.2500	357067.3125	309480.2500	337888.8750	
358475.6250	202038.0000	261781.7500	360970.5000	346161.0000	378053.0000	
292547.0000	339213.0000	339605.6875	331736.0000	393349.0000	345999.0000	
403641.0000	239238.1875	347911.4375	345673.0000	398127.0000	418583.0000	
294990.0000	406433.0000	419178.0000	374945.0000	414450.0000	397143.0000	
401256.0000	259475.0000	437628.0000	374514.0000	456696.0000		

\$INPUT ITER=2,\$

IMPORTS

	155	1976	1	12		
81340.0000	90740.0000	87283.0000	92280.0000	108751.0000	98371.0000	
96072.0000	97390.0000	95857.0000	93761.0000	105296.0000	123209.0000	
77842.0000	108640.0000	102936.0000	107108.0000	126357.0000	114519.0000	
103206.0000	121754.0000	122954.0000	118206.0000	122513.0000	124490.0000	
122322.0000	131534.0000	103278.0000	110231.0000	129592.0000	136299.0000	
127650.0000	96058.0000	108285.0000	126094.0000	124969.0000	115226.0000	
118058.0000	137256.0000	116264.0000	125669.0000	141187.0000	123371.0000	
159249.0000	130306.0000	138853.0000	163418.0000	171654.0000	178722.0000	
159990.0000	189853.0000	192576.0000	224908.0000	189324.0000	207563.0000	
188045.0000	152988.0000	245218.0000	208279.0000	224281.0000	267627.0000	
174331.0000	225444.0000	247724.0000	244997.0000	272892.0000	269039.0000	
258690.0000	227697.0000	206856.0000	323611.0000	231887.0000	287270.0000	
244025.0000	261139.0000	295343.0000	298748.0000	270346.0000	299403.0000	
292100.0000	228846.0000	266101.0000	238904.0000	361268.0000	409316.0000	
312048.1875	336754.2500	355977.6250	341221.2500	382700.5000	347066.5625	
329253.5000	300734.4375	286826.8750	336327.6250	394985.2500	452574.0000	
395458.6250	380705.3750	370659.1250	340281.0000	416519.8750	364381.8750	

466714.0000 298013.6250 331545.0000 444087.0000 422288.8125 398336.3750
429676.8750 404920.0000 400468.0000 436364.3750 466257.0000 414403.0000
393292.8125 345976.8125 374880.7500 437928.7500 413940.0000 555129.5625
329502.0625 374747.0625 372795.6875 416947.0625 390024.6875 459939.6875
456881.8125 279095.0000 384625.3125 512148.7500 451016.0000 463044.0000
368530.0000 495839.0000 500334.1250 503945.0000 513999.0000 484132.0000
589572.0000 371218.5000 513396.4375 601960.0000 538550.0000 548363.0000
428556.0000 559184.0000 608968.0000 576878.0000 592526.0000 607677.0000
565997.0000 482257.0000 643753.0000 624850.0000 654830.0000

EXP/IMP

155 1976 1 12

6.0786821e-01 5.3649989e-01 5.1708809e-01 4.1251625e-01 3.6567020e-01
4.8274390e-01 5.4155217e-01 4.2740528e-01 4.7362217e-01 4.7278719e-01
5.2487274e-01 6.1937034e-01 6.5891164e-01 5.7115243e-01 6.1545038e-01
5.2445196e-01 5.4334940e-01 4.7572019e-01 5.8364824e-01 4.9554840e-01
5.0357044e-01 6.2289562e-01 5.8384008e-01 7.3629207e-01 6.3077778e-01
6.7296669e-01 7.7638026e-01 7.8833540e-01 6.5450799e-01 6.1481009e-01
6.6303173e-01 7.2996523e-01 6.1747241e-01 6.3763541e-01 7.4544887e-01
9.1165188e-01 7.7958292e-01 7.5310369e-01 8.5086527e-01 7.5006565e-01
7.1655322e-01 8.4601730e-01 6.4747031e-01 7.3459396e-01 5.5702794e-01
5.6461956e-01 6.9862048e-01 7.7628943e-01 6.0500656e-01 6.2961344e-01
6.5860232e-01 5.3770875e-01 6.5228920e-01 5.9643096e-01 5.5121381e-01
6.3336994e-01 4.3185655e-01 6.4085674e-01 5.6008311e-01 8.0805748e-01
5.5969786e-01 5.7493657e-01 5.7157562e-01 5.4073315e-01 5.9292321e-01
6.5560383e-01 8.2232788e-01 6.6275796e-01 6.1319952e-01 4.6895810e-01
7.5682984e-01 8.0494657e-01 5.9865997e-01 7.7985670e-01 6.6577843e-01
5.7062474e-01 6.7923698e-01 5.3643417e-01 7.5571037e-01 5.7168139e-01
6.4521366e-01 7.0373874e-01 6.2519515e-01 6.8326428e-01 5.2058286e-01
5.5941406e-01 7.5713818e-01 5.0882858e-01 7.4155116e-01 7.2614421e-01
7.1142068e-01 6.5262209e-01 7.9572673e-01 7.4669286e-01 7.4067180e-01
6.7697562e-01 7.5958136e-01 7.9937931e-01 8.9796251e-01 8.5390016e-01
7.9796912e-01 9.0520419e-01 6.8192940e-01 8.0118149e-01 8.4445550e-01
7.6383682e-01 7.4954626e-01 8.7379416e-01 7.4423149e-01 7.7837104e-01
8.3526774e-01 7.1557171e-01 8.3172585e-01 7.4075477e-01 9.4871108e-01
7.6978370e-01 7.4809639e-01 8.6862047e-01 8.8587718e-01 8.2985976e-01
7.9528486e-01 8.6576829e-01 8.0960231e-01 8.5638525e-01 7.9348887e-01
7.3463735e-01 7.8461347e-01 7.2390405e-01 6.8061498e-01 7.0481574e-01
7.6751379e-01 8.1645157e-01 7.9382140e-01 6.8411924e-01 6.7875780e-01
6.5827819e-01 7.6527192e-01 7.1467905e-01 6.8463394e-01 6.4446731e-01
6.7766625e-01 5.7424580e-01 7.3925726e-01 7.6333195e-01 6.8833478e-01
7.2683231e-01 6.8834159e-01 6.4995545e-01 6.9946298e-01 6.5354292e-01
7.0893662e-01 5.3804299e-01 6.7980732e-01 5.9936625e-01 6.9742681e-01

Example 20

This example illustrates the case in which each series has a different input. The first series is the Spanish monthly series of car registrations. The automatic treatment of TRAMO is enforced (pretesting for log transformation, automatic model identification, and automatic outlier detection). The second series is the quarterly aggregate of the first one. A similar treatment is made to this series, except that the quarterly frequency has to be specified. The example illustrates the consistency versus time aggregation of the programs.

EXAMPLE 20

CAR-REGISTRATION (Spain)

240	1971	1	12
.2883500	.3392800	.4326900	.4072800
.4114200	.4497600	.4566700	.3018800
.2967100	.3259600	.3220400	.2986300
.3196600	.3841000	.5040700	.4121700
.4454100	.4963700	.4969800	.3427400
.3753500	.4241600	.4203400	.4456400
.5091500	.4493300	.5770900	.5063600
.4997700	.5338200	.5198100	.3361700
.4293500	.5479400	.5456500	.4973200
.4776000	.4765400	.5977800	.5025400
.4930800	.5473700	.6100300	.3765300
.4037000	.4430300	.4296900	.3993400
.4394800	.4721400	.4639400	.5148800
.4365800	.5213600	.6198100	.4059000
.3596800	.5069300	.4851700	.4960100
.4976100	.4276200	.5965000	.5836500
.5690000	.5220000	.6350600	.3025800
.4309300	.5344900	.5333000	.5640300
.4997600	.5922100	.6905500	.5955400
.6492600	.6359200	.6537700	.3746700
.4670200	.4993800	.5005900	.4699200
.5063600	.5096200	.6945600	.7280700
.6018800	.5880100	.5371600	.4141600
.4801600	.5181700	.5222600	.4399200
.5937400	.4342800	.5609800	.5167900
.6707900	.5596000	.5472200	.4383400
.4700500	.4495500	.5994900	.3656900
.3790500	.4519400	.5083300	.4751800
.5825400	.4436300	.5182100	.3547800
.4568400	.5994300	.5035700	.4679900
.3950200	.3913700	.4077500	.4758100
.4936800	.4499700	.4868700	.3049400
.3464800	.4291000	.3993300	.4768400
.4187300	.4309100	.5372900	.4487500
.4566900	.4693100	.5323600	.3069400
.3378800	.4584300	.4893200	.4707200
.4860200	.4233100	.5512100	.4500200
.5360800	.4594500	.4982100	.3696700
.3528800	.4601700	.4419000	.4754400
.4764300	.3971600	.4642200	.5040400
.5064300	.4174400	.5641200	.3619200
.3069700	.4325700	.4026600	.3883300
.4674400	.3754900	.5418500	.5164300
.4378100	.4272000	.6648900	.3339100
.3292700	.5752100	.4904700	.5905500
.2933000	.4108800	.5573200	.5238800

.5940800	.6753700	.8271600	.4439400
.4573400	.7129100	.6844900	.7098400
.5951000	.6865000	.8438000	.8609500
.8028800	.7987800	1.1054300	.5950100
.5576400	.7869000	.7844500	.8652000
.8101200	.8171300	1.0475600	.7591200
.9786800	1.0241900	1.0674100	.7749300
.6943100	.8657600	.8908900	.9621000
.8680300	.9721500	1.0972700	.9481700
1.0078000	1.1788300	1.1387700	.7561000
.7258600	.9460900	.9154300	.9392300
.8548500	.8487200	1.0581000	.9107600
.9656300	.9394200	1.0785700	.7520800
.5184700	.7725800	.7070200	.6637400

\$INPUT RSA=3,ITER=3,\$

QUAT-CAR REG

80	1971	1	4
1.0603200e+00	1.2684600e+00	1.0552600e+00	9.4663000e-01
1.2078300e+00	1.3539500e+00	1.2150700e+00	1.2901400e+00
1.5355700e+00	1.5399500e+00	1.2853300e+00	1.5909100e+00
1.5519200e+00	1.5429900e+00	1.3902600e+00	1.2720600e+00
1.3755600e+00	1.4728200e+00	1.3853900e+00	1.4881100e+00
1.5217300e+00	1.6746500e+00	1.3685700e+00	1.6318200e+00
1.7825200e+00	1.8807200e+00	1.4954600e+00	1.4698900e+00
1.7105400e+00	1.9179600e+00	1.4314800e+00	1.4803500e+00
1.5890000e+00	1.7471800e+00	1.4556100e+00	1.4147300e+00
1.3393200e+00	1.5013500e+00	1.3298300e+00	1.5709900e+00
1.1941400e+00	1.4194600e+00	1.1382900e+00	1.3052700e+00
1.3869300e+00	1.3747500e+00	1.1771800e+00	1.4184700e+00
1.4605400e+00	1.4455500e+00	1.2207600e+00	1.3775100e+00
1.3378100e+00	1.4279100e+00	1.2330100e+00	1.2235600e+00
1.3847800e+00	1.3814400e+00	1.3280700e+00	1.6562300e+00
1.2615000e+00	1.7933300e+00	1.7284400e+00	2.1072400e+00
2.1254000e+00	2.4626100e+00	2.2580800e+00	2.4365500e+00
2.6748100e+00	2.7619900e+00	2.5366500e+00	2.7187500e+00
2.9374500e+00	3.1348000e+00	2.6207300e+00	2.8007500e+00
2.7616700e+00	2.8158100e+00	2.3491200e+00	2.1433400e+00

\$INPUT MQ=4,RSA=3,\$

3.3 An Application

The performance of TRAMO / SEATS, applied in an entirely automatic manner with the more sophisticated model identification procedure of TRAMO, has been analyzed in some detail at Eurostat on 13227 series (EUROSTAT, 1996b). The series were short-term indicators (all activities) for all 15 European Union member states, the European aggregates, USA, and Japan. We summarize some of their findings.

- 64% of the series follow a multiplicative model; for 36% the components are additive.
- 50% of the series can be modelled with the default model (i.e., an Airline-type model).
- For 87% of the series the fit obtained was good, for an additional 11% the fit was reasonably acceptable, and only for 2% the fit was poor. In fact, the authors concluded “(Automatic) modeling works much better than expected !”.
- 15% of the series showed a stationary behavior; for 2% of all series the order of the regular differencing was larger than 1.
- 50% of the series did not require outlier adjustment; 27% presented one outlier; 23% presented two or more outliers,

Split into four groups of indicators, the results are the following

	Production	Other Indicators	Foreign Trade	Business Surveys	TOTAL
No. of Series	2627	2577	6976	1047	13227
Mult/addit model (%)	63/37	59/41 ^{a)}	75/25	7/93 ^{b)}	64/36
Airline model $(0, 1, 1) \times (0, 1, 1)_s$ (%)	71	37	49	31	50
Differencing order $< 1 / > 1$ (%)	8/0.4	5/7	19 /0.3	32/0	15/2
AR or MA regular polynomial > 2 (%)	5	11	6	3	7
Ljung Box: good/ bad (%)	88/1	77/7	90/1	92/0.6	87/2
No seasonality found (%)	1	9	7	47	9
Outliers none/one/more (%)	44/22/34	43/23/34	54/30/26	54/25/21	50/27/23

a) splitted up into indicators, the percentage of the **multiplicative** model is

employment: 29% / turnover: 77% / new orders: 76%

b) since the balance can be negative, the model for most of the series is additive

4 References

- ANSLEY, C.F. and NEWBOLD, P. (1981), “On the Bias in Estimates of Forecast Mean Squared Error”, *Journal of the American Statistical Association*, 76, 569–578.
- ANDERSON, B. and MOORE, J. (1979), *Optimal Filtering*, New Jersey: Prentice Hall.
- BANCO DE ESPAÑA (1996), *Economic Bulletin*, February 1996.
- BELL, W.R. and HILLMER, S.C. (1984), “Issues Involved with the Seasonal Adjustment of Economic Time Series”, *Journal of Business and Economic Statistics* 2, 291–320.
- BOX, G.E.P., HILLMER, S.C. and TIAO, G.C. (1978), “Analysis and Modeling of Seasonal Time Series”, in Zellner, A. (ed.), *Seasonal Analysis of Economic Time Series*, Washington, D.C.: U.S. Dept. of Commerce — Bureau of the Census, 309–334.
- BOX, G.E.P. and JENKINS, G.M. (1970), *Time Series Analysis: Forecasting and Control*, San Francisco: Holden–Day.
- BOX, G.E.P. and TIAO, G.C. (1975), “Intervention Analysis with Applications to Economic and Environmental Problems”, *Journal of the American Statistical Association* 70, 71–79.
- BURMAN, J.P. (1980), “Seasonal Adjustment by Signal Extraction”, *Journal of the Royal Statistical Society A*, 143, 321–337.
- CHEN, C. and LIU, L.M. (1993), “Joint Estimation of Model Parameters and Outlier Effects in Time Series”, *Journal of the American Statistical Association* 88, 284–297.
- CHEN, C., LIU, L.M. and HUDAK, G.B. (1990), “Outlier Detection and Adjustment in Time Series Modeling and Forecasting”, Working Paper and Reprint Series, Scientific Computing Associates, Lyle (IL), August 1990.
- CLEVELAND, W.P. and TIAO, G.C. (1976), “Decomposition of Seasonal Time Series: A Model for the X–11 Program”, *Journal of the American Statistical Association* 71, 581–587.
- CZUJACK, C., FLORES, R. and CINABURGH, V. (1996), “Comovements Between Prices of Paintings and Prints for a Group of 20th Century Painters”, in Ginsburgh, V. and Menger, P.M. (eds.), *Issues in the Economics of the Art Markets*, Amsterdam: North Holland, Forthcoming.
- EUROSTAT (1996a), *Industrial Trends*, monthly statistics.
- EUROSTAT (1996b), “Is the ARIMA Model Adapted to Economic Time Series?” (Presented at Informal Group on Seasonal Adjustment) EUROSTAT/D3/SA/04.
- FINDLEY, D.F., MONSELL, B., OTTO, M., BELL, W. and PUGH, M. (1992), “Towards X–12 ARIMA”, mimeo, Bureau of the Census.

- FINDLEY, D.F., MONSELL, B.C., BELL, W.R., OTTO, M.C., and CHEN, B.C. (1996), “New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program”, U.S. Bureau of the Census, mimeo, May 16, 1996.
- FIorentINI, G. and PLANAS, C. (1996), “Non-Admissible Decompositions in Unobserved Component Models”, mimeo, July 1996, Eurostat.
- GÓMEZ, V. (1997), “Automatic Model Identification in the Presence of Missing Observations and Outliers”, mimeo, Ministerio de Economía y Hacienda, Dirección General de Análisis y Programación Presupuestaria, June 1997.
- GÓMEZ, V. and MARAVALL, A. (1992), “Time Series Regression with ARIMA Noise and Missing Observations — Program TRAM”, EUI Working Paper ECO No. 92/81, Department of Economics, European University Institute.
- GÓMEZ, V. and MARAVALL, A. (1993), “Initializing the Kalman Filter with Incompletely Specified Initial Conditions”, in Chen, G.R. (ed.), *Approximate Kalman Filtering (Series on Approximation and Decomposition)*, London: World Scientific Publ. Co.
- GÓMEZ, V. and MARAVALL, A. (1994), “Estimation, Prediction and Interpolation for Nonstationary Series with the Kalman Filter”, *Journal of the American Statistical Association* 89, 611–624.
- GÓMEZ, V., MARAVALL, A., and PEA, D. (1996), “Missing Observations in ARIMA Models: Skipping Strategy Versus Additive Outlier Approach”, Unpublished Manuscript
- GRENIER, J.Y., and MATHIS, A. (1991), “Séries temporelles, structure et conjoncture: le prix du blé à l’époque moderne”, *Histoire et Mesure* (special issue on Time Series), 1991, Paris: Centre National de la Recherche Scientifique.
- HANNAN, E.J. and RISSANEN, J. (1982), “Recursive Estimation of Mixed Autoregressive-Moving Average Order”, *Biometrika* 69, 81–94.
- HARVEY, A.C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge: Cambridge University Press.
- HARVEY, A.C., and PIERSE, R.G. (1984), “Estimating Missing Observations in Economic Time Series”, *Journal of the American Statistical Association*, 79, 125–131.
- HILLMER, S.C., BELL, W.R. and TIAO, G.C. (1983), “Modeling Considerations in the Seasonal Adjustment of Economic Time Series”, in Zellner, A. (ed.), *Applied Time Series Analysis of Economic Data*, Washington, D.C.: U.S. Department of Commerce — Bureau of the Census, 74–100.
- HILLMER, S.C. and TIAO, G.C. (1982), “An ARIMA-Model Based Approach to Seasonal Adjustment”, *Journal of the American Statistical Association* 77, 63–70.
- KOHN, R. and ANSLEY, C.F. (1985), “Efficient Estimation and Prediction in Time Series Regression Models”, *Biometrika* 72, 694–697.

- KOHN, R. and ANSLEY, C.F. (1986), “Estimation, Prediction and Interpolation for ARIMA Models with Missing Data”, *Journal of the American Statistical Association* 81, 751–761.
- LIPPI, M. and REICHLIN, L. (1994), “Diffusion of Technical Change and the Decomposition of Output into Trend and Cycle”, *The Review of Economic Studies*, January.
- MARAVALL, A. and PIERCE, D.A. (1987), “A Prototypical Seasonal Adjustment Model”, *Journal of Time Series Analysis* 8, 177–193.
- MARAVALL, A. (1987), “On Minimum Mean Squared Error Estimation of the Noise in Unobserved Component Models”, *Journal of Business and Economic Statistics*, 5, 115–120.
- MARAVALL, A. (1988), “The Use of ARIMA Models in Unobserved Components Estimation”, in Barnett, W., Berndt, E. and White, H. (eds.), *Dynamic Econometric Modeling*, Cambridge: Cambridge University Press.
- MARAVALL, A. (1993), “Stochastic Linear Trends: Models and Estimators”, *Journal of Econometrics*, 56, 5–37.
- MARAVALL, A. (1995), “Unobserved Components in Economic Time Series”, in Pesaran, H., Schmidt, P. and Wickens, M. (eds.), *The Handbook of Applied Econometrics*, vol. 1, Oxford: Basil Blackwell.
- MARAVALL, A. (1996), “Short-term Analysis of Macroeconomic Time Series”, in *Economics: The Next ten Years*, Oxford, Oxford University Press.
- MARAVALL, A. and GÓMEZ, V. (1992), “Signal Extraction in ARIMA Time Series — Program SEATS”, EUI Working Paper ECO No. 92/65, Department of Economics, European University Institute.
- MÉLARD, G. (1984), “A Fast Algorithm for the Exact Likelihood of Autoregressive–Moving Average Models”, *Applied Statistics* 35, 104–114.
- MORF, M., SIDHU, G.S. and KAILATH, T. (1974), “Some New Algorithms for Recursive Estimation on Constant, Linear, Discrete–Time Systems”, *IEEE Transactions on Automatic Control*, AC — 19, 315–323.
- PLANAS, C. (1995), “Estimation Error in Unobserved Component Models”, Ph. D. Dissertation, Department of Economics, European University Institute.
- STOCK, J.H., and WATSON, M.W. (1988), “Variable Trends in Economic Time Series”, *Journal of Economic Perspectives*, 2, 147–174.
- TIAO, G.C. and TSAY, R.S. (1983), “Consistency Properties of Least Squares Estimates of Autoregressive Parameters in ARMA Models”, *The Annals of Statistics* 11, 856–871.
- TSAY, R.S. (1984), “Regression Models with Time Series Errors”, *Journal of the American Statistical Association* 79, 118–124.

Some relevant additional references concerning the development and first applications of the model-based approach to seasonal adjustment are the following

- NERLOVE, M., GREYER, D.M. and CARVALHO, J.L. (1979), *Analysis of Economic Time Series: A Synthesis*, New York: Academic Press.
- HYLLEBERG, S. (ed.) (1992), *Modelling Seasonality*, New York: Oxford University Press.
- DEN BUTTER, F.A.G. and FASE, M.M.G. (1991), *Seasonal Adjustment as a Practical Problem*, Amsterdam: North Holland.
- PICCOLO, D. and VITALE, C. (1981), *Metodi Statistici per l'Analisi Economica*, Bologna: Il Mulino.
- ZELLNER, A. (ed.) (1978), *Seasonal Analysis of Economic Time Series*, Washington D.C.: US Dept. of Commerce-Bureau of the Census.
- ZELLNER, A. (ed.) (1983), *Applied Time Series Analysis of Economic Data*, Washington D.C.: US Dept. of Commerce-Bureau of the Census.

5 Classification of Input Parameters by Function

Control of the Output File

OUT 13

5.1 Program TRAMO

ARIMA Model

MQ 13, 69	LAM 13, 69
IMEAN 13, 69	D 13, 69
BD 13, 69	P 13, 69
BP 13, 69	Q 13, 69
BQ 14, 69	TH 14, 69
BTH 14, 69	PHI 14, 69
BPHI 14, 69	JPR 14
JPS 14	JQR 14
JQS 14	

Pretest for the Log vs. Level Specification

LAM 15

Automatic Model Identification

INIC 15	IDIF 16
UB1 16	UB2 16
CANCEL 16	IMVX 16, 21
PCR 16	IFAL 16

Estimation

INCON 17	INIT 17, 70
IFILT 18	IDENSC 18
TOL 18	ICONCE 18
UBP 18	M 18, 70
IQM 18, 70	IROOT 18
IGRBAR 18	TSIG 18

Forecasting

NBACK 19
LOGN 19

NPRED 19

Missing Observations

INTERP 20

ICDET 20

Outliers

VA 21
IMVX 16, 21
DELTATC 21
AIO 22
INT2 22

IATIP 21
PC 21
ISTDV 22
INT1 22

Regression

a) Easter and Trading Day Effects

IEAST 24
ITRAD 24
INTD2 24

IDUR 24
INTD1 24

b) Regression and Intervention Variables; Holiday Effect

IREG 24
IUSER 25
ILONG 26
DELTA 26
ID1DS 26

RG 24
NSER 25, 26
ISEQ 26
DELTAS 26
REGEFF 27, 67

Others

PG 27
UR 27, 70

SEATS 27
XL 27, 70

5.2 Program SEATS

Allocation of Regression Effects

REGEFF 27, 67

ARIMA Model

MQ 13, 69

IMEAN 13, 69

BD 13, 69

BP 13, 69

BQ 14, 69

BPHI 14, 69

LAM 13, 69

D 13, 69

P 13, 69

Q 13, 69

PHI 14, 69

BTH 14, 69

Estimation

INIT 17, 70

MAXIT 70

M 18, 70

SEK 70

UR 27, 70

TYPE 70

EPSIV 70

IQM 18, 70

XL 27, 70

CRMEAN 70

Forecasts and Signal Extraction

L 71

EPSPHI 71

NOADMISS 71

FH 71

NOSERIE 71

Bias Correction

BIAS 72

MAXBIAS 72

Cyclical Component

RMOD 72

Smoothing of the Trend; Use of SEATS as a “Fixed Filter”

SMTR 73

THTR 73

Others

NDEC 74

HS 74

SQG 74

NDEC1 74

NANNUA 74

5.3 Routine Use on Many Series

QMAX 93

RSA 93

DVA 93

ITER 99

Index

AIO 22
BD 13, 69
BIAS 72
BP 13, 69
BPHI 14, 69
BQ 14, 69
BTH 14, 69
CANCEL 16
CLEAN command 11
CRMEAN 70
D 13, 69
DELTA 26
DELTAS 26
DELTATC 21
DVA 93
EPSIV 70
EPSPHI 71
FH 71
GRAPH command 11
HS 74
IATIP 21
ICDET 20
ICONCE 18
ID1DS 26
IDENSC 18
IDIF 16
IDUR 24
IEAST 24
IFAL 16
IFILT 18
IGRBAR 18
ILONG 26
IMEAN 13, 69
IMVX 16, 21
INCON 17
INIC 15
INPUT command 9
INIT 17, 69
INT1 22
INT2 22
INTD1 24
INTD2 24
INTERP 20
IQM 18, 70
IREG 24
IROOT 18
ISEQ 26
ISTDV 22
ITER 99
ITRAD 24
IUSER 25
JPR 14
JPS 14
JQR 14
JQS 14
L 71
LAM 13, 15, 69
LOGN 19
M 18, 70
MAXBIAS 72
MAXIT 70
MQ 13, 69
NANNUA 74
NBACK 19
NDEC 74
NDEC1 74
NFREQ 29, 77
NOADMISS 71
NOSERIE 71
NPER 29, 77
NPRED 19
NSER 25, 26
NYER 29, 77
NZ 29, 77
OUT 13
P 13, 69
PC 21
PCR 16

PG 27
PHI 14, 69
Q 13, 69
QMAX 93
REGEFF 27, 67
RG 24
RMOD 72
RSA 93
SEATS 27, 67
SEATS.ITR 27, 48
SEK 70
SMTR 73
SQG 74
TH 14, 69
THTR 73
TOL 18
TSIG 18
TYPE 70
UB1 16
UB2 16
UBP 18
UR 27, 70
VA 21
XL 27, 70

