An Application of TRAMO-SEATS: Changes in Seasonality and Current Trend-Cycle Assessment

The German Retail Trade Turnover Series.[1]

Regina Kaiser and Agustín Maravall

Abstract

The paper details an application of programs Tramo and Seats to seasonal adjustment and trend-cycle estimation. The series considered is the German Retail Trade Turnover series, for which, when adjusting with X12-Arima, the Bundesbank had identified two problems. One had to do with heteroscedasticity in the seasonal component, associated with very different moving patterns for some of the months. The other one was related to the stability of the trend-cycle at the end of the series. It is seen how, starting with the fully automatic procedure and adding some simple modifications, the ARIMA-model-based approach of Tramo-Seats deals properly with both problems and provides good results, that are stable and robust.

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Regina Kaiser
D. de Estadística y Econometría
Universidad Carlos III de Madrid
Madrid,126
28903 Getafe (Madrid)
Email: kaiser@est-econ.uc3m.es

Agustín Maravall
Información y Métodos de Cálculo
Servicio de Estudios - Banco de España
Alcalá 50
28014 Madrid
Email: maravall@bde.es

1 Introduction; Description of the Problem

We present an application of the programs TRAMO, "Time Series Regression with ARIMA Noise, Missing Observations and Outliers", and SEATS, "Signal Extraction in ARIMA Time Series", described in Gómez and Maravall (1996). TRAMO is a program for estimation and forecasting of regression models with possibly nonstationary ARIMA errors and 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 effects. SEATS is a program for estimation of unobserved components in time series following the so-called ARIMA-model-based (AMB) method, and was originally motivated by a program developed by J.P. Burman at the Bank of England. The basic components are the trend-cycle, seasonal, and irregular components (some additional component may be present). The components are estimated and forecast with signal extraction techniques applied to ARIMA models. The two programs are structured so as to be used together, both for in-depth analysis of few series or for automatic routine applications to a large number of them, and can be run in an entirely automatic manner. When used for seasonal adjustment, TRAMO preadjust the series to be adjusted by SEATS. The two programs have experienced an explosion in their use by data producing agencies and short-term economic analysts, and are officially used (and recommended) by Eurostat and by the European Central Bank (together with X12ARIMA; see Findley et al 1998).

The AMB methodology for seasonal adjustment was originally proposed by Burman (1980) and Hillmer and Tiao (1982). A more complete description of the methodology behind TRAMO and SEATS can be found in Gómez and Maravall (2000 a,b). In essence, given the vector of observations $y = (y_{t1}, \ldots, y_{tm})$ where $0 < t1 < \ldots < tm$, TRAMO fits the regression model

$$y_t = z_t'\beta + x_t,$$

where β is a vector of regression coefficients, z_t' denotes a matrix of regression variables, and x_t follows the stochastic general ARIMA process

$$\phi(B)\delta(B)x_t = \theta(B)a_t,$$

where B is the backshift operator, a_t is assumed a n.i.i.d. $(0, V_a)$ white-noise variable, and $\phi(B), \delta(B), \theta(B)$ are finite polynomials in B that have, in general, the multiplicative form:

$$\delta(B) = (1 - B)^d(1 - B^s)^D;$$

$$\phi(B) = (1 + \phi_1 B + \ldots + \phi_p B^p)(1 + \Phi_1 B^s);$$
$$\theta(B) = (1 + \theta_1 B + \ldots + \theta_q B^q)(1 + \Theta_1 B^s),$$

where s denotes the number of observations per year. SEATS decomposes x_t as in

$$\begin{aligned} x_t &= n_t + s_t, \\ n_t &= p_t + u_t, \end{aligned}$$

where n_t, p_t, s_t, u_t, are the seasonally adjusted (SA) series, the trend-cycle, seasonal, and irregular components, which also follow ARIMA-type models, possibly with deterministic effects added.

This paper illustrates application of the programs to the monthly German Retail Trade (RT) Turnover series, for the 24-year period 1/1975 - 12/1998, comprising 288 observations. The series is displayed in Figure 1, and was made available by the Bundesbank to participants in its October 1999 workshop on seasonal adjustment. The series had been already corrected for several effects, namely, those due to the number of working days in the month, holidays, Easter, and German shopping hours. Some additional information that could be of relevance in analyzing the series was also provided:

(a) in July 90 the D-Mark was made the sole legal tender in Germany;

(b) in January 93 there was a VAT increase;

(c) in April 94 there was another VAT increase;

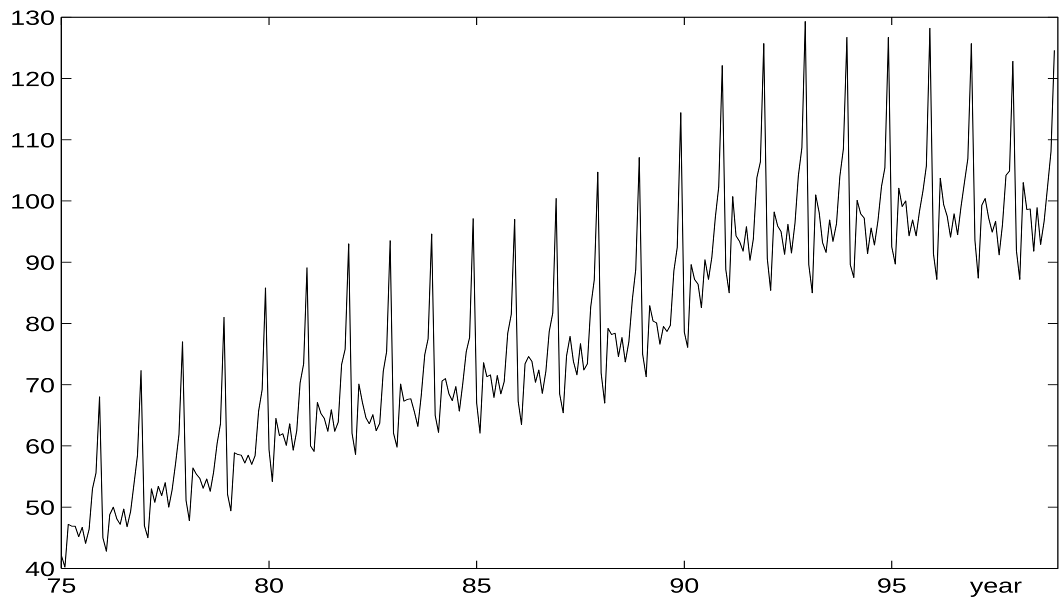
(d) in January 94 part of the reporting sample was new;

(e) in January 95 there was a legal change concerning the declaration of acquired firms by companies;

(f) in November 98 there was a special promotional sales campaign by a large company;

(g) special emphasis was given to the evolution of the Christmas Bonus (CB) during the sample period. The bonus, usually paid in November, had been gradually decreasing, and eventually been frozen in November 94.

Figure 1: The RT series



Besides general interest in the TRAMO-SEATS results, two points of special concern were made:

1) The treatment of different seasonal factor variability for different months. This was related to the CB effect on the November-December seasonality.

2) The assessment of the current situation by means of the trend-cycle component. This was related to the effect on the trend-cycle of treating (or not) as an outlier an observation at the end of the series (the November 98 sales campaign).

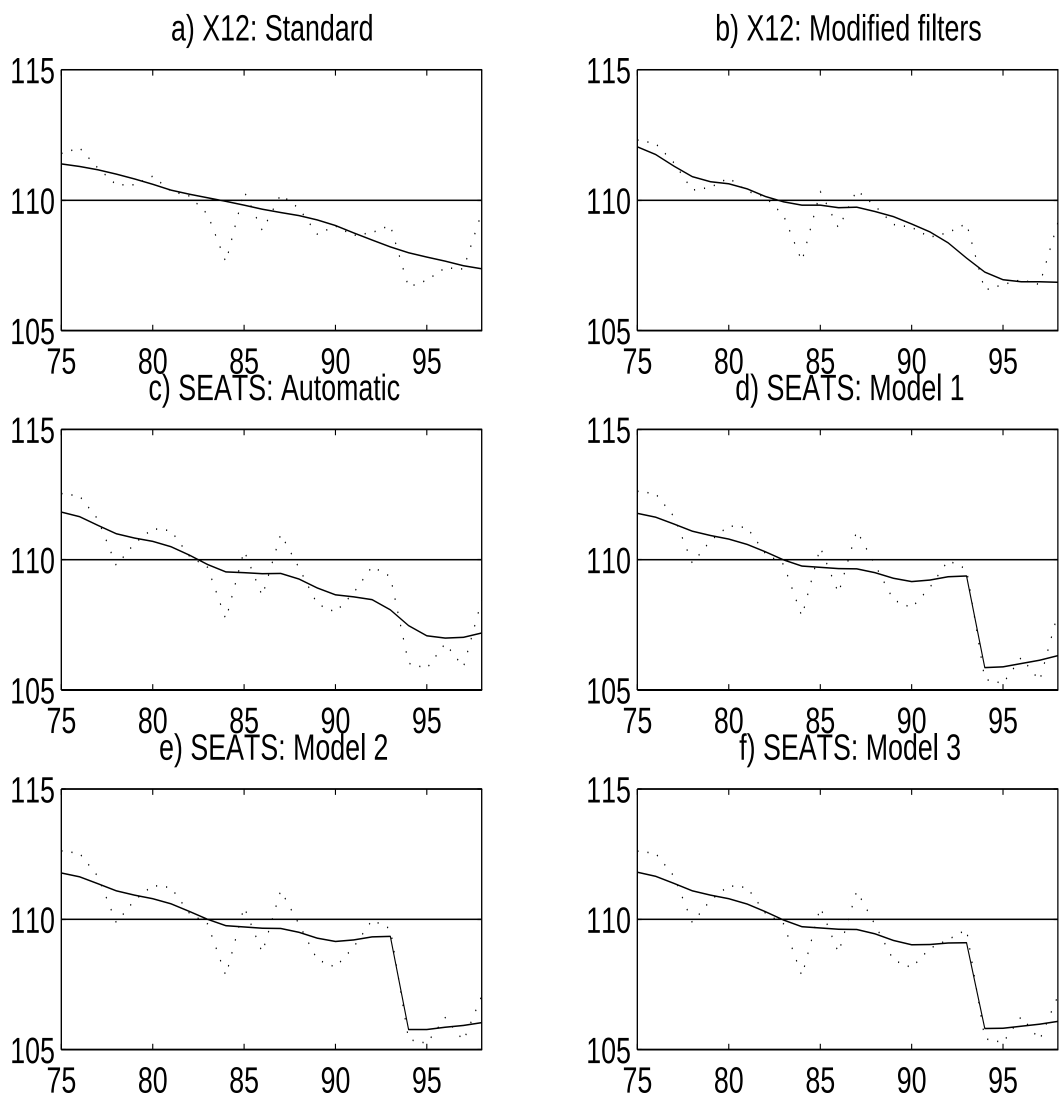
2 An X11-X12ARIMA-Type Approach

The two points of concern mentioned emerge from the X11-X12ARIMA (X12A)-type treatment of the RT series by the Bundesbank. In brief, the problem can be detected from the plot of the preliminary seasonal-irregular (SI) factors versus the final seasonal factors (S). Figure 2a presents the plot for the month of November when the standard Bundesbank (3×9) X11-seasonal filter is used. Two things can be noticed:

1. Starting in 94, there seems to be a break in the pattern of the (SI)-(S) difference, which in the years (94-97) displays a new pattern.

2. November 98 clearly departs from the new pattern, and could be thus considered and outlier.

Figure 2: SI versus S factors



Consultation with experts provided an explanation for the new November seasonal pattern: the evolution of the CB mentioned above. According to this information, the change in 94 was of a permanent nature, leading to a more stable seasonal factor. Further, the November 98 sales campaign, mentioned in (f), could justify treating the month as an outlier. The need to accommodate a seasonal pattern with an important change, lead to the use of a (3×3) seasonal filter, considerably more flexible than the (3×9) one, for the months of November and December. Figure 2b presents the (SI)-(S) plot, with the modification implemented: the systematic difference after 1994 has disappeared, and the November 98 factor appears to be, as before, an outlier; the estimated seasonal factors are shown in Figure 3a. (The possibility of using different seasonal filters for different months is a nice nonlinear feature of X11/X12, yet it seems somewhat paradoxical that, in order to estimate seasonality that has become more stable, one selects filter designed for highly moving seasonality.)

The decision concerning November 98 is important because its consideration (or lack thereof) has a relevant impact on the trend-cycle at the end of the series. (Not having been able to obtain the complete Bundesbank decomposition, we use as trend-cycle the one automatically selected by the program. The following discussion is, therefore, independent of the Bundesbank specific procedures.) Using the trend-cycle selected by the program, as Figure 4a shows, the messages the two trend-cycles convey are different: in one case, the series is experiencing explosive growth; in the other it seems to be approaching a minimum. Short-term extrapolation of the trend-cycle would lead, in this example, to drastically different cyclical implications.

Figure 3: Seasonal Factors

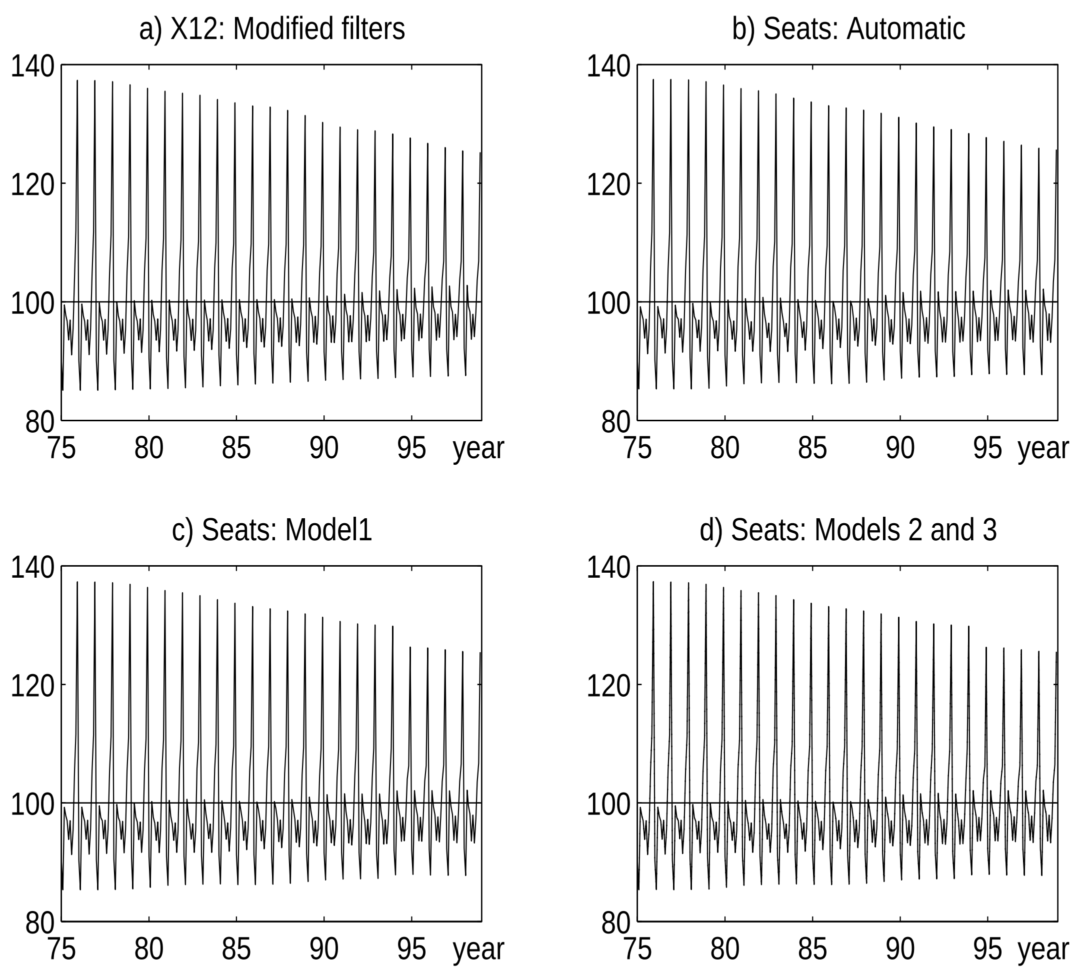
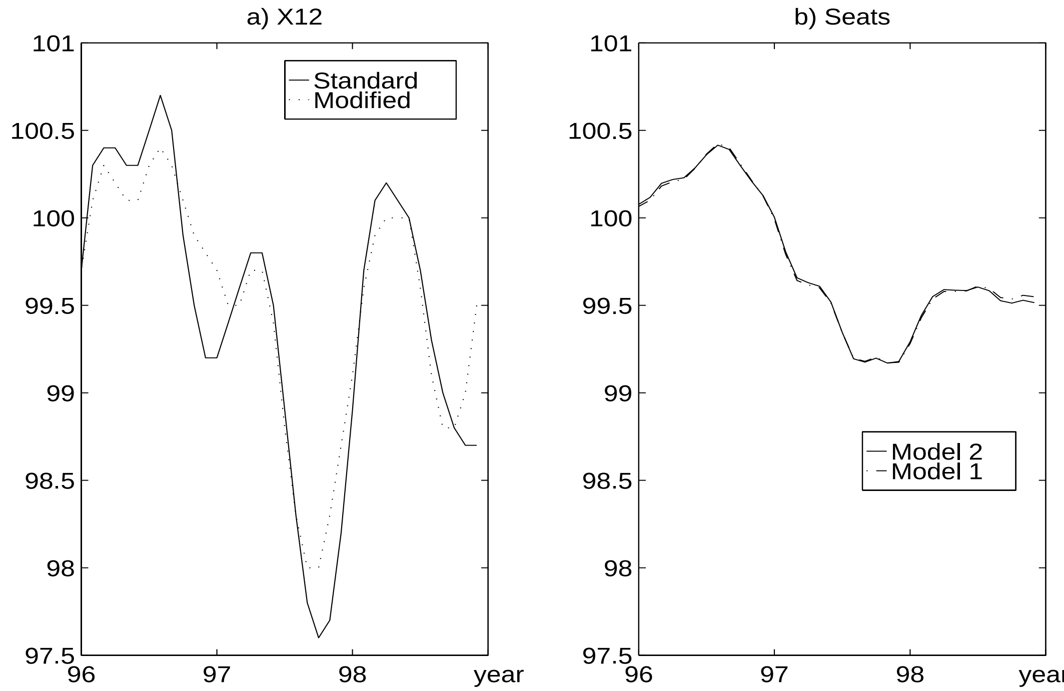


Figure 4: Trend−cycle: last three years



3 The Tramo-Seats Results

As a starting point, we use the purely automatic procedure which yields in this case the "Airline model", in the logs and with no mean. The July 90 outlier, associated with German monetary reunification, is automatically detected as a Level Shift, with a t-value of 4.5 (the effect is estimated as 5.3% of the total). The model provides a good fit, and the first column of Table 1 summarizes the results. The evolution of the estimated seasonal factors (Figure 3b) shows the gradual decrease for the November and December factors, which appears to be levelling off towards the end; the factors are seen to be very close to the ones in Figure 3a. Figure 2c displays the (SI)-(S) plot for the Seats November factors, and the systematic difference for the last year is smaller that the one in Figure 2a. This is due to the larger flexibility of the Seats filters, compared to the fixed (3×9) filter-X11 case. Nevertheless, some systematic difference between (SI) and (S) still remains, and hence it seems sensible to test for whether the CB evolution has produced a change in the November-December seasonal factors pattern. A simple way to do this is by means of the Seasonal Level Shift (SLS) outlier of Kaiser and Maravall (1999). Several specifications are possible and the BIC criterion led to the one whereby the effect of the outlier (in the one-month case) is modelled as $\omega \nabla_{12}^{-1} d_{it}$, where $d_{it} = 1$ for the month when the outlier effect starts, and $d_{it} = 0$ otherwise; the SLS produces a correction in the level of the seasonal factors for the months that correspond to the outlier, after and including the month of its appearance; the correction also has a small effect on the mean.

Given that the effect presumably affects both months, two SLS outliers were introduced for November and December 94. For both, the t-values were significant (close to -2.4), and the parameter estimates of similar sign and magnitude. Setting the two parameters equal, a t-value of -3.52 is obtained, and overall results are improved. The results are indeed excellent, and a summary of them is presented in the second column of Table 1. The estimator of the seasonal factor is presented in Figure 3c: it reflects exactly the "a priori" expected shape (a gradual decrease that stabilizes in November 94).

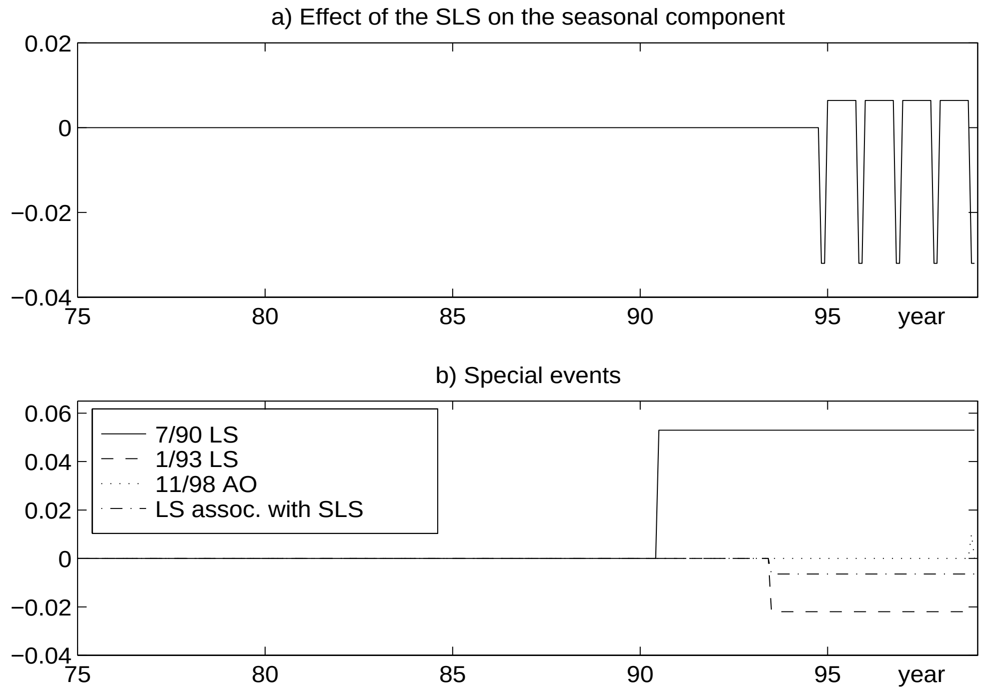
It is worth pointing out that the November and December seasonal factor correction could have been enforced in TRAMO-SEATS without external information on CB payments. From Figure 3b, it is clear that the seasonal component obtained with the purely automatic procedure exhibits some heteroscedasticity that mostly affects November and December. As shown in Kaiser and Maravall (1999), seasonal heteroscedasticity may be successfully corrected with the SLS outlier and hence its use would have seemed appropriate. The SLS effect on the seasonal component for the RT series is displayed in Figure 5a.

Using the previous model (obtained with the automatic procedure with the 2-month SLS included) which already incorporates effects (a) and (g) above, we proceed to test for the significance of effects (b) to (f), introducing them as regression variables in TRAMO. Each variable is specified as an additive outlier (AO), a transitory change (TC), and a level shift (LS), and the most significant specification is chosen; the results are in Table 2. Given that the regression variables are basically orthogonal, the result for one is little affected by inclusion of the others. In summary, with the (borderline) exception of the January VAT increase, the other effects are clearly not significant.

Model	Default	Model 1	Model 2	Model 3
Parameter estimates:				
θ_1	-.689	-.694	-.692	-.690
θ_{12}	-.636	-.686	-.687	-.675
Outliers:				
LS 7/90	.053	.053	.053	.053
t-value	(4.47)	(4.58)	(4.57)	(4.54)
SLS 11-12/94	-	-.032	-.033	-.030
t-value		(-3.52)	(-3.58)	(-3.23)
LS 1/93	-	-	-	-.022
t-value				(1.86)
Residual statistics:				
BIC	-7.989	-8.014	-8.019	-8.010
SE(a_t)*100	1.796	1.759	1.754	1.747
N(a_t)	2.62	1.57	1.44	1.76
$Q_{24}(a_t)$	25.3	25.8	25.3	25.6
$Q_S(a_t)$	.78	.72	.76	.68
$Q_{24}(a_t^2)$	27.5	25.6	26.3	24.1

Table 1. Summary of TRAMO results. BIC denotes the Bayesian information criterion, and SE(a_t) the residual standard error; both should be as small as possible. N denotes the Bowman-Shenton test for normality, and is asymptotically distributed as a χ^2_2; it should be smaller than 6. $Q_{24}(a_t)$ denotes the Ljung-Box test for residual autocorrelation using the first 24 autocorrelations, and is asymptotically distributed as a χ^2 with (24-# of parameter estimates) degrees of freedom; for the Airline model it should be smaller than 34. $Q_{24}(a_t^2)$ is the McLeod-Li test for linearity, equal to the previous test, but computed on the squared residuals; it has the same asymptotic distribution as the Ljung-Box one. The N, Q(a_t), and Q(a_t^2) test are described in, for example, Harvey (1993). $Q_s(a_t)$ is a test for residual seasonal autocorrelation described in Pierce (1978); it is distributed approximately as a χ^2_2 distribution, and should be smaller than 6.

Figure 5: Deterministic Corrections



Event	(b)	(c)	(d)	(e)	(f)
Aprox. t-value	-1.9	-0.1	-1.3	1.2	1.4
Specification	LS	LS	LS	LS	AO

Table 2. Special event effects.

The fact that an event does not seem to produce a significant effect does not imply, of course, that there was no effect, but rather that its magnitude is not large enough to merit correction. For example, based only on the sample evidence, to correct for the November 98 AO would be hard to justify. For the size implied by accepting t=1.4 as significant, and assuming the other 287 observations of the series do not contain AOs, on average, 52 AOs would be spuriously detected. However, for the November 98 AO, there is a presumably very precise independent expert estimation of the effect, equal to 1% of the level of the series for that month. Considering that the SD of the series monthly innovation is 1.8%, it is understandable that a 1% effect is not detected as significant. Be that as it may, given the reliability of the expert's estimate, the 1% November 98 effect can be directly applied to the series, avoiding parameter estimation.

In summary, three models seem worth comparing. All are obtained with the automatic TRAMO procedure, with the 2-month seasonal level shift of November 94 incorporated. This yields, in fact, Model 1. Adding the "ad-hoc" 1% November 98 correction, Model 2 is obtained. Model 3 also includes the January 93 VAT increase effect. In all three cases the Airline model was obtained, with the LS outlier for January 90 (monetary reunification). No additional outlier was detected. Writing the general model as

$$y_t = \omega_1 \frac{1}{\nabla} d_{1t} + \omega_2 \frac{1}{\nabla_{12}} d_{2t}^{(2)} + \omega_3 d_{3t} + \omega_4 \frac{1}{\nabla} d_{4t} + x_t,$$

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

The first equation specifies the outlier-intervention regression variables, that is, the deterministic part of the series; the second equation specifies the ARIMA model, that is, the stochastic part. The d-variables are such that

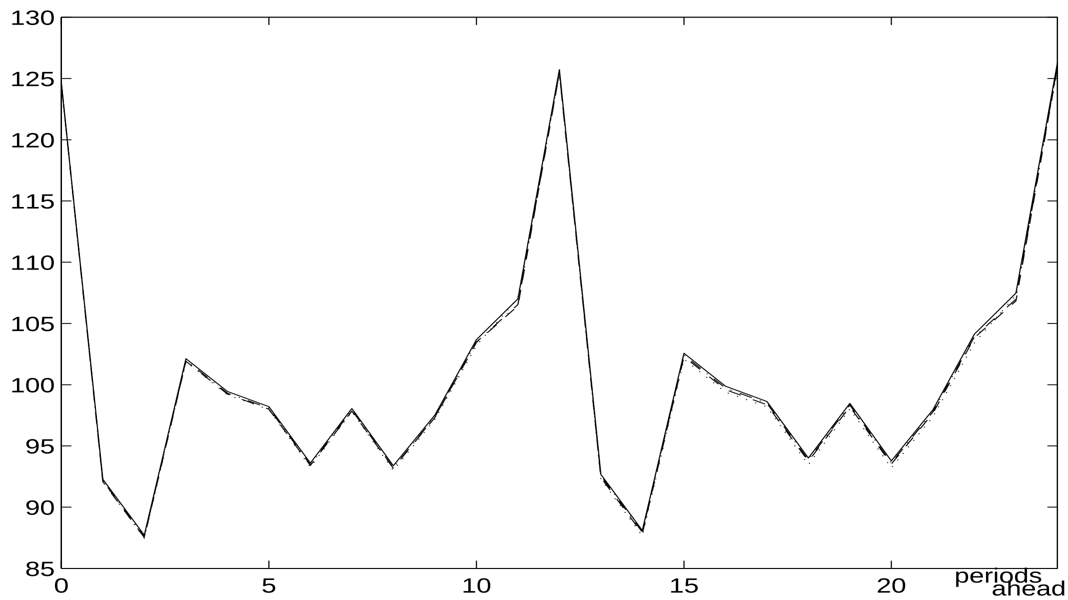
$d_{1t} =$	1	for January 90 (monetary reunification),
	0	otherwise;
$d_{2t}^{(2)} =$	1	for November and December 94 (CB effect) ,
	0	otherwise;
$d_{3t} =$	1	for November 98 (sales compaign),
	0	otherwise;
$d_{4t} =$	1	for January 93 (VAT increase),
	0	otherwise.

Model 1 sets $\omega_3 = \omega_4 = 0$; Model 2 sets $\omega_3 = .01, \omega_4 = 0$; and Model 3 sets $\omega_3 = .01$.

The last 3 columns of Table 1 summarize the TRAMO results: they are good and close. Very marginally, the "ad-hoc" November 98 modification does more good than damage, while the VAT January 93 correction is mostly neutral. The closeness of the models is appreciated in Figure 6, which displays the 2-year ahead forecast function of the 3 models. (The purely automatic result, with no SLS, is also included; it is seen that missing the CB correction has little effect on the series forecasts.)

Fitting criteria are not enough to clearly select a model. Given that the main purpose of the application is seasonal adjustment, perhaps differences in the way the series are decomposed can be of help. Table 3 presents some results from SEATS that are of relevance. First, the variances of the component innovations are displayed. Interest centers on more stable seasonal signals and hence we seek to minimize the innovation variance of the seasonal component.

Figure 6: Different model forecasts



Second, the percent reduction in the revision variance of the concurrent estimator, after one more year of data has become available, is presented. The next rows present the variances of the concurrent estimation error. Finally, the table contains the variance of the full revision error in the concurrent estimator. Naturally, we would like a fast convergence, a small estimation error, and small revisions. The table shows how not including the CB correction produces a more unstable seasonal component, and SA series that are estimated with larger error and subject to larger revisions.

Among the 3 models that include the CB correction, the differences are very small and unlikely to have applied relevance. Marginally, model 3 performs systematically worse on practically all accounts. Adding the fact that it is less parsimonious, models 1 and 2 seem preferable. Figure 4b displays the SEATS trend-cycles produced by Models 1 and 2. The difference reflects the effect of incorporating the "ad hoc" November 98 AO correction. The correction has a very small effect, and the two trend-cycles show similar behavior at the end. The closeness of the results is also shown in Figure 7 which displays the components obtained with the two models. The differences between them are, for all practical purposes, negligeable, as are the differences between the (SI)-(S) plots (see Figure 2). Figure 8 compares the complete X12A and TRAMO-SEATS decomposition of the series. The two SA series are close, the SEATS trend-cycle is more stable (less noisy), the SEATS seasonal component is also more stable, and the irregular component more homocedastic. Figure 9 compares the trend-cycle of X12A (with all corrections enforced) and of Model 2 in SEATS, together with the original series. The short-term oscillations of the X12A trend-cycle around the SEATS trend are clearly discernible.

Model	Default	Model 1	Model 2	Model 3
SD of component innovation variance:				
• Trend	.230	.229	.230	.228
• Seasonal	.387	.329	.326	.337
• Irregular	1.230	1.249	1.274	1.229
Convergence of concurrent estimator in 1 year (% decrease in revision variance):				
• Trend	90	90	89	89
• SA series	36	31	31	32
SD of concurrent estimation error				
• Trend	.753	.742	.742	.739
• SA series	.756	.710	.706	.712
SD of revision in concurrent estimator				
• Trend	.568	.533	.552	.553
• SA series	.517	.488	.487	.488

Table 3. Summary of SEATS results. SD: Standard deviation; all are expressed in 10^{-2} (i.e., in percent points), and are obtained from the standarized variances provided by SEATS. To express them in the series units, they have been multiplied by the residual SD.

Figure 7: Decomposition of series with different models

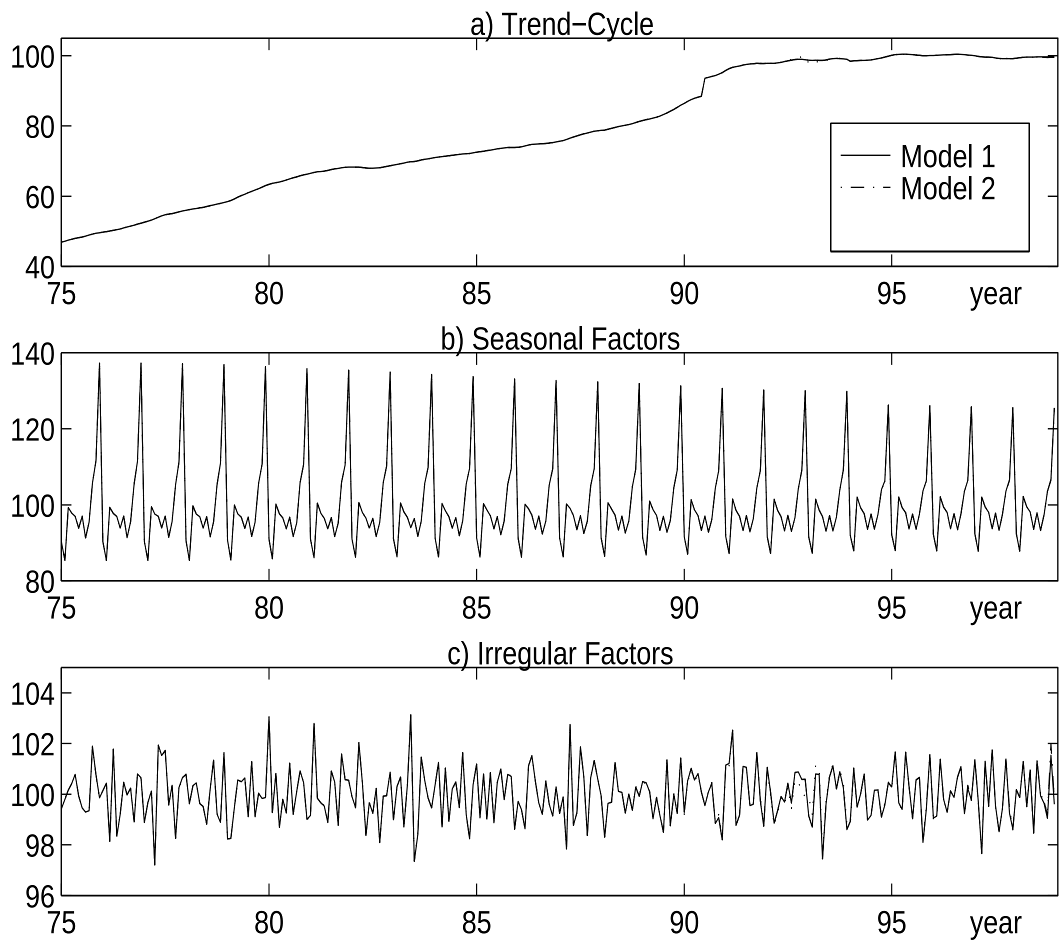


Figure 8: X12 ARIMA and TRAMO−SEATS

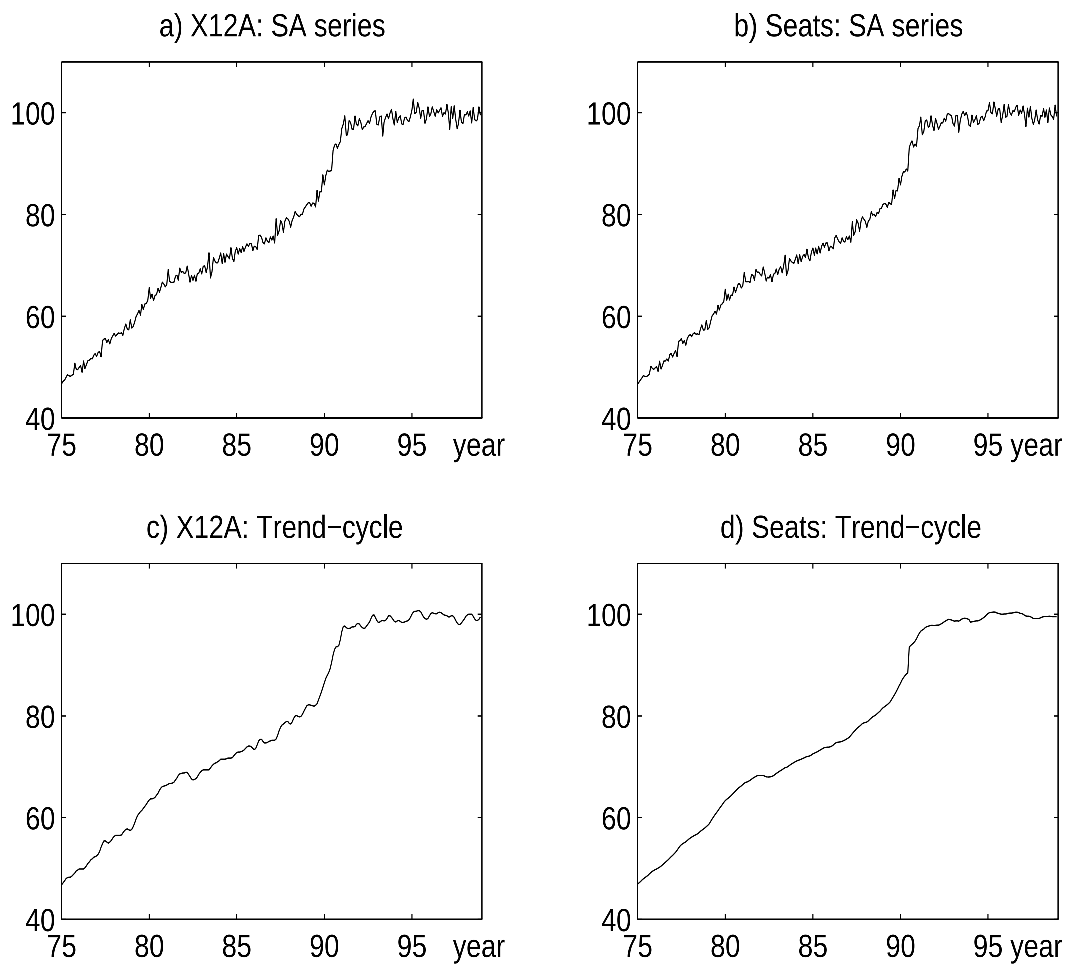


Figure 8 cont.: X12 ARIMA and TRAMO−SEATS

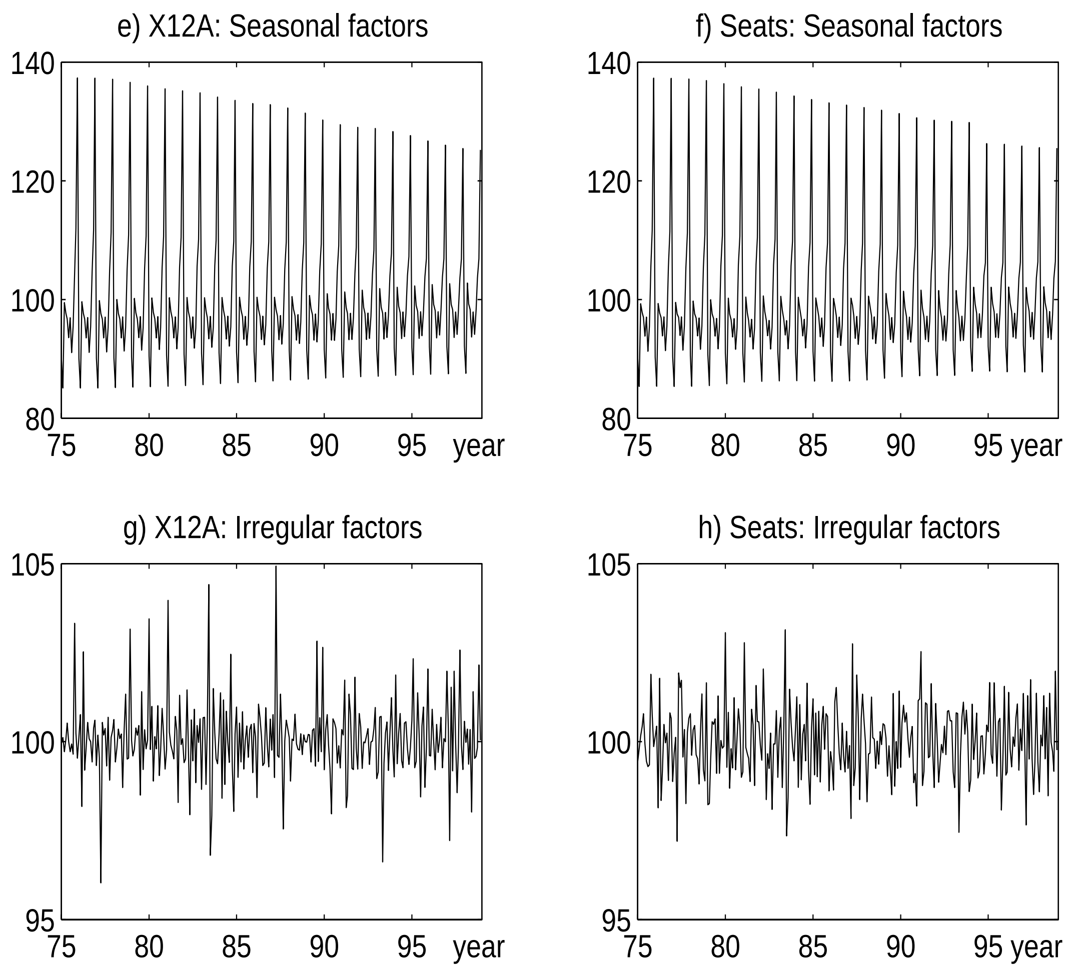
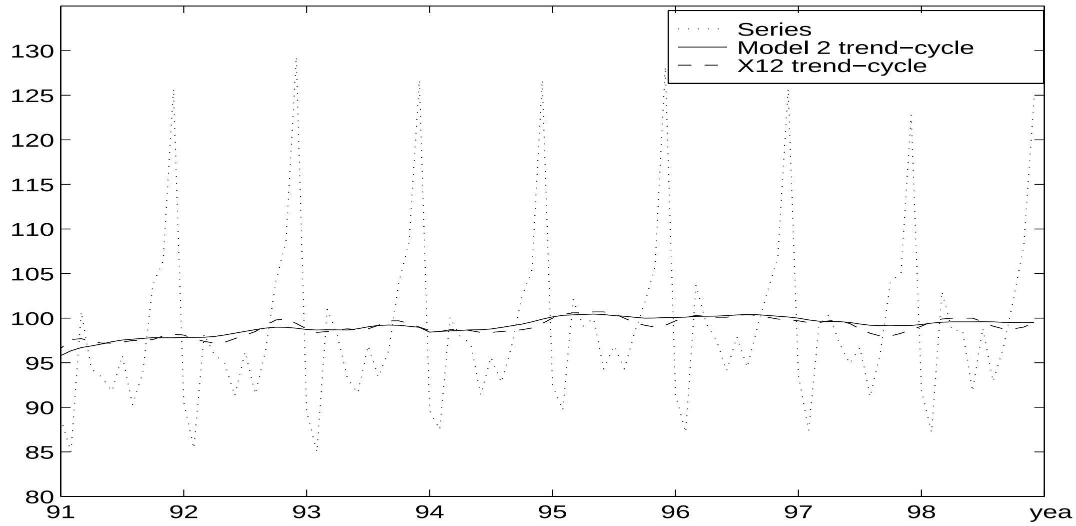


Figure 9: Trend–Cycle comparison



4 Assessment of the Current Trend-Cycle

As mentioned earlier, the current evolution of the X12A trend-cycle component is affected by the treatment of the November 98 observation. Although the AO correction is small, when enforced, the trend-cycle shows a steep increase, with a turning point in September-October 98. If the correction is not enforced, no turning point is detected, and the trend-cycle seems to be approaching a minimum.

When TRAMO-SEATS are employed, the relevance of the dilemma (to correct or to not correct) is greatly decreased. Figure 4b shows how the November 98 AO correction has very little effect, and no discrepancy between the two trend-cycles appears: they both show that growth for the last months has been very close to zero.

To help analysis of the present evolution of the trend-cycle, SEATS offers two additional tools of applied interest: the standard error of the component estimator (as well as of its rates of growth) and its optimal forecast, with the associated standard error. Table 4 presents, for the December 98 observation, information on the rates of growth of the original and SA series and of the trend-cycle. Three rates are considered:

- the (annualized) monthly rate-of-growth,
- the rate of growth for the last 12 months (December 98 versus December 97),
- the present rate of annual growth, centered in December 98 and measured using 6-months ahead forecasts (i.e., June 99 versus June 98);

standard errors of the rates-of-growth are given in parenthesis. First, the trend-cycle is seen to provide a more stable and more precise signal than the SA series. Second, the underlying current rate-of-growth of the series, measured with the trend-cycle, can be comfortably accepted as zero.

	Original Series	SA series	Trend-Cycle
a) Current measures			
Month-to-month rate of growth	15.3 -	-1.9 (0.6)	0.0 (0.1)
Rate of growth for last 12 months	1.5 -	1.6 (0.7)	0.5 (0.5)
Current rate of anual growth (centered in December 98 and using 6 forecasts)	2.0 (2.11)	2.0 (2.0)	0.4 (1.4)
b) Forecasts			
Monthly rate of growth for January 1999	-25.9 (1.7)	0.6 (2.2)	0.2 (1.7)
Rate of gowth for the next 12 months	0.9 (2.5)	0.9 (2.9)	0.5 (2.4)

Table 4. Rates of growth (in percent points); last observation is December 1998.

The table also contains the forecasts of the rate-of-growth for the next month and for the next year; they indicate that the series may experience very mild growth, by an amount that is far from being significant. The table shows how much the month-to-month series growth is influenced by seasonality. Comparing the SA series with the trend-cycle, it is seen that, although non-trivial, the noise plays a second-order role.

If interest goes beyond present evolution of the trend-cycle, and seeks for a judgement having to do with the business cycle, it is also possible to apply SEATS to get an estimator of the latter, along the lines of the Modified Hodrick-Prescott (MHP) filter of Kaiser and Maravall (1999b, 2000). This is done, in essence, by extending the trend-cycle component with forecasts and backcasts, and using the extended trend-cycle series as input to SEATS, run in the fixed model-based Hodrick-Prescott format. The MHP filter depends on a parameter, λ, that for quarterly series usually takes the value 1600 (see Prescott, 1986). We use $\lambda = 129000$, which (as shown in Del Rio and Maravall, 2000) is the monthly equivalent of the 1600 quarterly value. Compared to the standard Hodrick-Prescott filter applied to X11-SA series, the modified procedure brings three improvements:

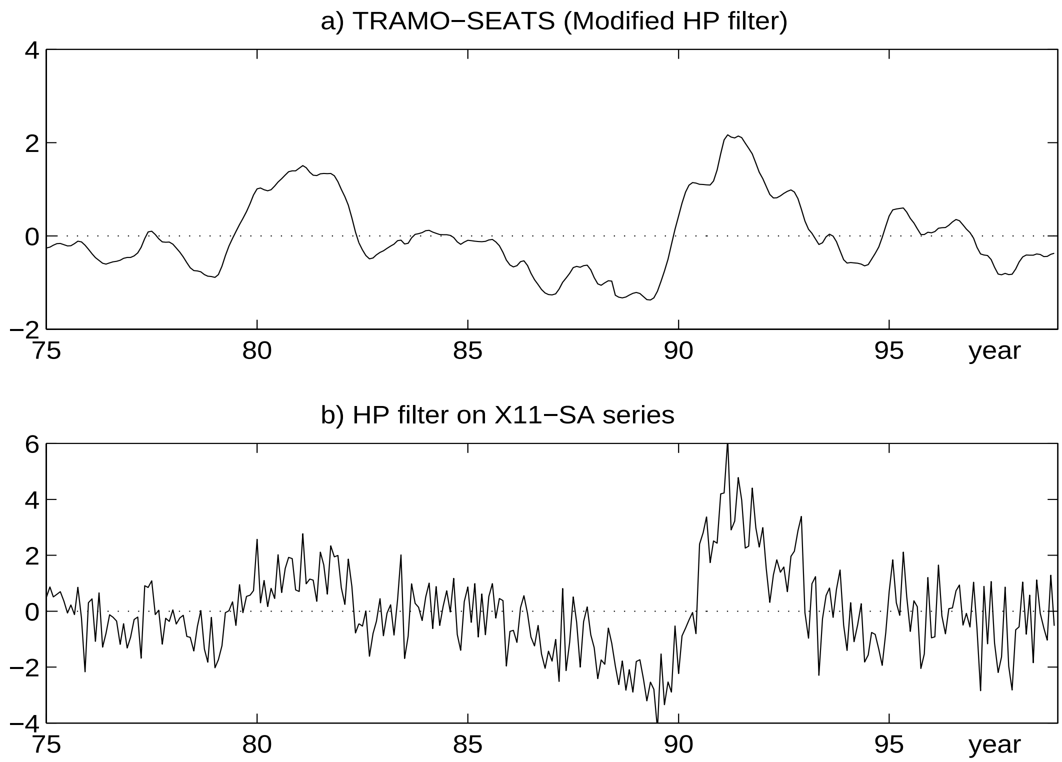
1) it provides a considerably cleaner cyclical signal (Figure 10);

2) it improves end-point estimation and reduces revisions;

3) it can be given a sensible model-based interpretation, based on which confidence intervals and forecasts can be computed (Figure 11).

Figure 11 indicates that in December 1998, the series seemed to be slowly recovering from a relatively mild recession. Forecasts of stationary cycles, however, have limited interest given that they will tend to converge relatively fast to zero.

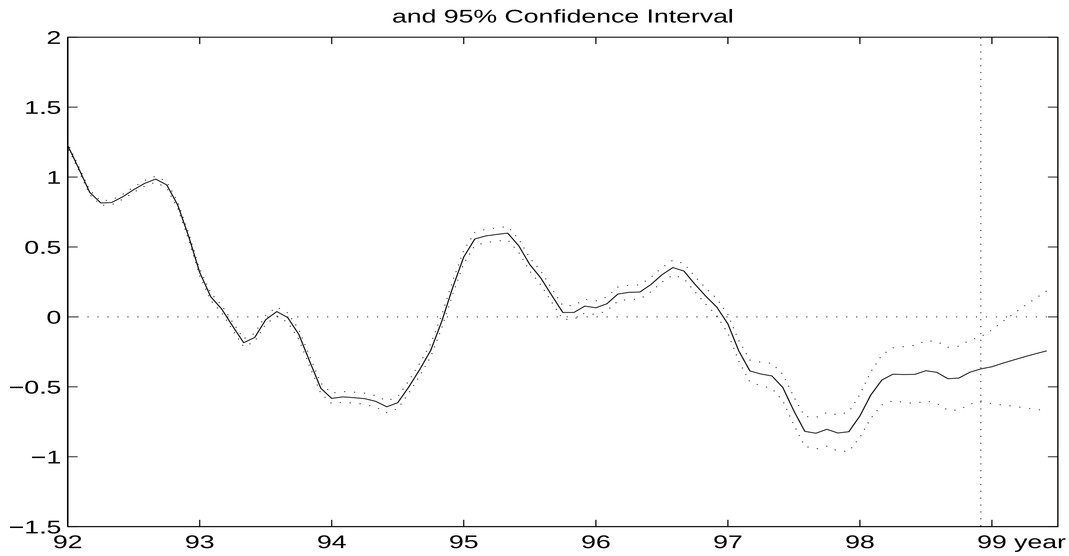
Figure 10: Cycle Estimator



A Comment on Ex-Post Corrections

The X11-Bundesbank type of approach relies heavily on careful analysis of the data using tools supplied by X11-X12A, that are unquestionably of help. Be that as it may, the practice of ex-post corrections to the data can be dangerous. Every year many special events happen (strikes, unusual weather, surprises in economic data, financial shocks, increases in the price of oil or of coffee, wars, earthquakes or floodings, sales campaigns, some politican election, changes in data collection, changes in legislation, to quote a few examples.) Surely God could explain the world in a deterministic manner; we certainly cannot. In the limit, by searching enough, we could possibly find ex-post explanations for any unexpected shock. In practice this is unfeasible, and that is why stochastic models were invented (they have proved, incidentally, most useful). The basic assumption is that there are many unexpected shocks, that are better treated as random inputs. Having a proper model, we can then test for the significance of some specific event. Allowing for ex-post correction

Figure 11: Cycle Estimator for Last Years (with 6 Forecasts)



of non-significant effects cannot be universally recommended. First, ex-post, ad-hoc modifications will increase revisions in the series. Second, these modifications, being analyst-dependent, difficult transparency of the procedure. Further, they introduce an element of arbitrariness that could, in theory, foster data manipulation (i.e., correcting only the ones that are convenient)

In the RT series, the problem came from observation of the November seasonal factors: out of the last five, four seemed to reflect a new pattern, broken by the fifth one. Investigating this behavior lead to the identification of the November 94 freezing of the CB payment, and of the November 98 sales campaign. The first event was dealt with by introducing for some months a more flexible filter; the second, by specifying an outlier. This last correction had an effect on the trend-cycle at the end of the series. As we have seen, however, these problems were partly due to the method. Purely automatic use of TRAMO-SEATS provided better initial results in terms of capturing the seasonal pattern change. By adding a seasonal level shift the new pattern was accurately captured. Further, the trend-cycle was little affected by the November 98 correction. Besides being less affected by (non-major) special events, the TRAMO-SEATS results can be easily duplicated, and the explicit model can be criticized and improved in a systematic manner (a good algorithm for progress in applied science.)

5 Out-of-Sample Analysis

The series made available for the Bundesbank workshop covered the period January 1975-December 1998. From the previous sections, it has been concluded that TRAMO-SEATS with Model 2 (or Model 1) provided good results. Given that more than a year has gone by since December 1998, it is of interest to look at the out-of-sample behavior of the TRAMO-SEATS procedure. We asked the Bundesbank for the more recent observations, but were informed that the series had been revised for the full period (the Federal Statistical office revised the unadjusted data at the end of 1998 and the Bundesbank changed the regression variables to explain Easter effect). Eventually we were provided with the new revised series, for the period January 1975-February 2000; the new series includes thus 14 additional months. Figure 12 displays the new and old series for the last 8 years. The revision seems relatively small though, as Figure 13 shows, for some periods it is not negligeable; this is particularly noticeable towards the end of the series. Despite the series differences, two questions of interest are the following:

A. Would the results from TRAMO-SEATS have been different for the revised series?

B. Would the TRAMO-SEATS procedure have been stable over the 14 additional months?

Figure 12: Revised and old series; last 8 years

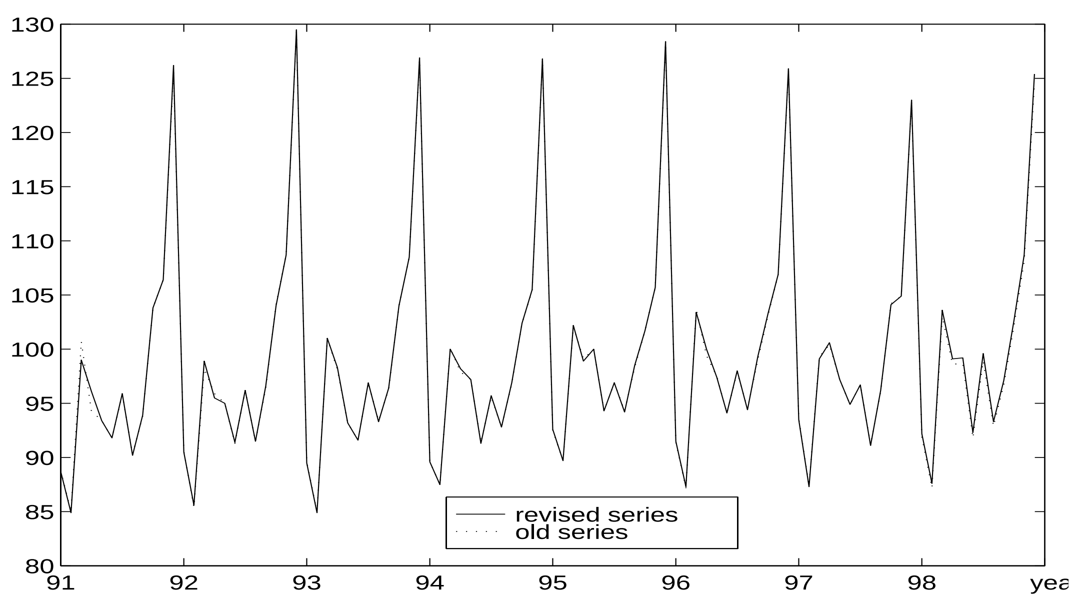
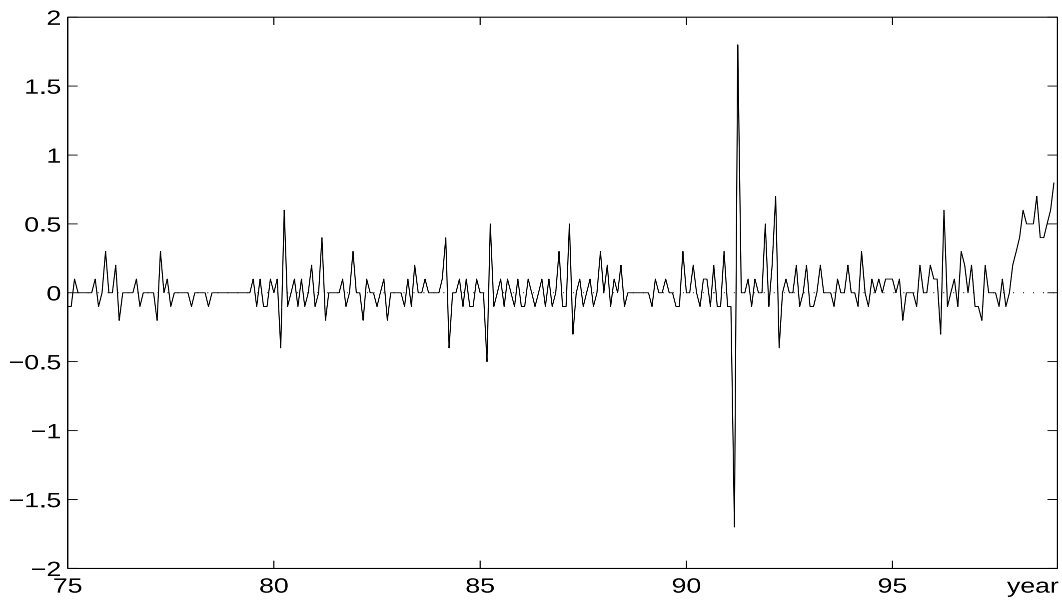


Figure 13: Revision in series



In order to answer question A, we redid the analysis of Sections 3 and 4 for the new series. The purely automatic procedure provided again the Airline model (in the logs and without mean), and the LS outlier associated with monetary reunification. The results were similar to those obtained for the old series (perhaps marginally better). Heteroscedasticity in the seasonal component is nevertheless noticeable, and introduction of the SLS for November and December, associated with the CB freezing, yields a highly significant effect, and an improvement in the model. In particular, the BIC and residual SE decrease, seasonality becomes more stable, is subject to smaller revisions, and estimated with more precision. Adding the November 1998 effect, as the 1% ad-hoc correction, has a very small (though positive) effect. Pretesting for the other special effects shows again that the only possible addition is the January VAT effect, included previously in Model 3. As before, the specifications of Model 1, 2, and 3 seem the best options. A summary of the Tramo and Seats results for the different models is presented in Tables 5 and 6, and, as before, Model 3 is marginally outperformed by Models 1 and 2; the latter possibly remains the best option, although the differences between 1 and 2 are negligeable. Due to the availability of 14 out-of-sample months, Table 5 includes the variance of the 1-period-ahead forecast error for the out-of-sample period. The associated F-test are all equal to 1.3, and hence clearly acceptable. Figure 15 exhibits the 1-period-ahead forecast of the new series obtained with Model 2 for the 14 additional periods, with the parameters fixed at their December 1998 value, and the implied forecast errors. The figure evidences the good out-of-sample behavior of the forecast.

In summary, the selected TRAMO-SEATS procedure is unaffected by the series revisions. As for the change in the estimated SA series implied by the revision, Figure 16 compares the two SA series for the old and new series: the revision in the SA series implied by the revision in the series is moderate.

Revised Series: Original period (Jan 75-Dec 98) T=288 observations.

Model	Default	Model 1	Model 2	Model 3
Parameter estimates:				
θ_1	-.671	-.669	-.667	-.673
θ_{12}	-.630	-.679	-.680	-.671
Outliers:				
LS 7/90	.052	.052	.052	.052
t-value	(4.41)	(4.45)	(4.46)	(4.50)
SLS 11-12/94	-	-.033	-.033	-.030
t-value		(-3.60)	(-3.67)	(-3.33)
LS 1/93	-	-	-	-.023
t-value				(-1.95)
Residual statistics:				
BIC	-8.040	-8.067	-8.073	-8.066
SE(a_t)*100	1.751	1.713	1.702	1.700
N(a_t)	2.82	1.62	1.46	1.76
$Q_{24}(a_t)$	27.2	28.3	27.8	28.9
$Q_S(a_t)$	.88	.97	1.00	.68
$Q_{24}(a_t^2)$	28.7	29.7	31.5	28.7
Out-of-sample forecast error variance ($*10^3$)	.377	.373	.377	.377

Table 5. Summary of TRAMO results. BIC denotes the Bayesian information criterion, and SE(a_t) the residual standard error; both should be as small as possible. N denotes the Bowman-Shenton test for normality, and is asymptotically distributed as a χ_2^2; it should be smaller than 6. $Q_{24}(a_t)$ denotes the Ljung-Box test for residual autocorrelation using the first 24 autocorrelations, and is asymptotically distributed as a χ^2 with (24-# of parameter estimates) degrees of freedom; for the Airline model it should be smaller than 34. $Q_{24}(a_t^2)$ is the McLeod-Li test for linearity, equal to the previous test, but computed on the squared residuals; it has the same asymptotic distribution as the Ljung-Box one. The N, Q(a_t), and Q(a_t^2) test are described in, for example, Harvey (1993). $Q_s(a_t)$ is a test for residual seasonal autocorrelation described in Pierce (1978); it is distributed approximately as a χ_2^2 distribution, and should be smaller than 6. The last column contains the variance of the one-period-ahead forecasts for the out-of-sample period Jan 1999-Feb 2000.

Revised Series: Original period (Jan 75-Dec 98) T=288 observations.

Model	Default	Model 1	Model 2	Model 3
SD of component innovation variance:				
• Trend	.236	.240	.240	.234
• Seasonal	.376	.318	.315	.325
• Irregular	1.183	1.194	1.190	1.181
Convergence of concurrent estimator in 1 year (% decrease in revision variance):				
• Trend	89	88	88	88
• SA series	36	32	32	32
SD of concurrent estimation error				
• Trend	.747	.741	.740	.731
• SA series	.739	.694	.691	.695
SD of revision in concurrent estimator				
• Trend	.565	.552	.551	.546
• SA series	.508	.478	.477	.479

Table 6. Summary of SEATS results. SD: Standard deviation; all are expressed in 10^{-2} (i.e., in percent points), and are obtained from the standarized variances provided by SEATS. To express them in the series units, they have been multiplied by the residual SD.

Figure 14: Out−of−sample forecasts

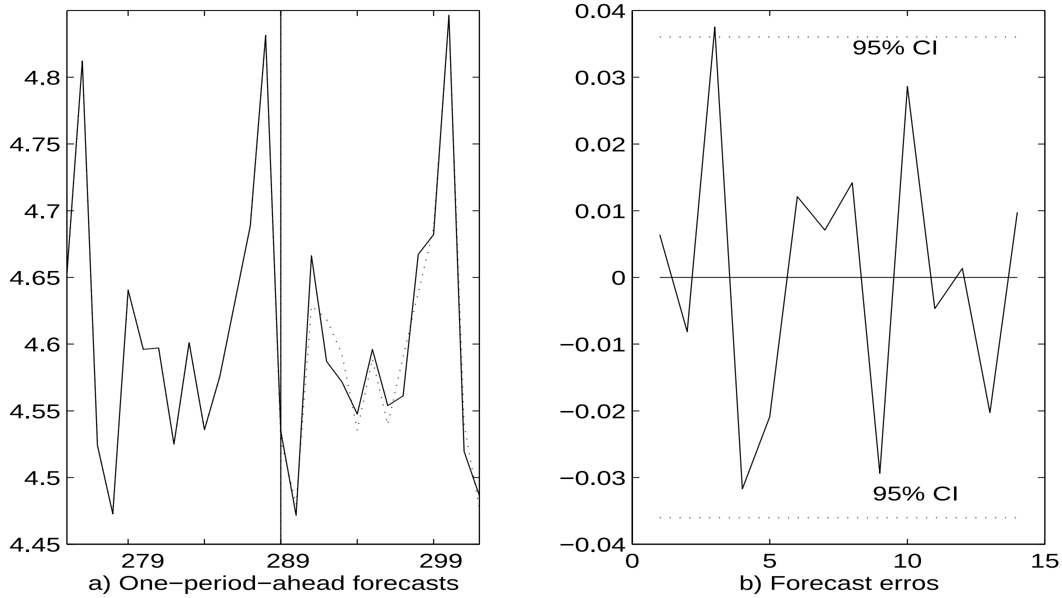
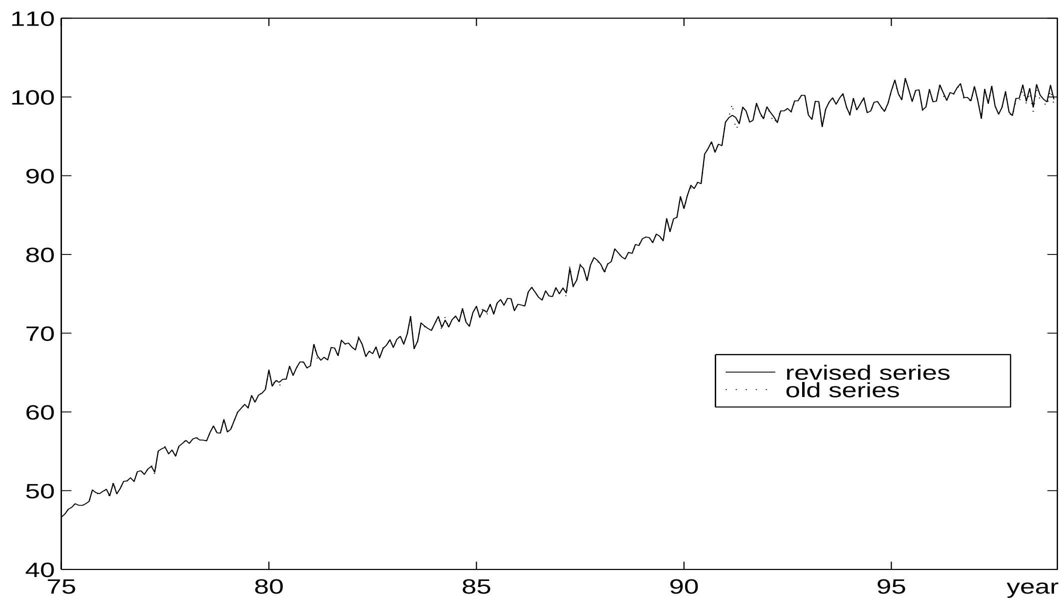


Figure 15: Effect of revisions on the SA series; full period



In order to answer question B, using the new series, and once the model has been identified, we apply the routine procedure recommended in Gómez and Maravall (1998). This implies, in our case, fixing, after December 1998, the $(0,1,1)(0,1,1)_{12}$ -in the logs and with no mean- specification, maintaining the LS outlier (associated with the monetary reunification), the SLS outlier (associated with the freezing of the CB), and the "ad-hoc" AO (associated with the November 1998 campaign). Every month, the model parameters are reestimated and, after the additional 14 months, the complete model is reidentified.

Figure 16 displays the 1-period-ahead forecasts and the implied forecast errors. The forecasts are very similar to those of Figure 14, they track well the series, and none of the forecast errors is cause for alarm. Figure 17 plots the estimators of the ARIMA parameters: they all comfortably lie within the 95% confidence intervals for the parameters estimated in December 1998. The estimators of the two regression variables remain practically unchanged, and no new outliers are detected. In fact, reidentification of the model after the 14 months have became available replicates the arguments of Section 3. Tables 7 and 8 summarize the Tramo-Seats results for the different models, and suggest again Model 2 or Model 1 as the best choice. Comparison of these two tables with Tables 1 and 3, and with tables 5 and 6 shows that:

- the Tramo-Seats procedure seems robust with respect to moderate revisions in the series;
- the Tramo-Seats procedure is very stable over the out-of-sample period considered.

It is of interest to notice that, although the differences between them are quite small, the relative ranking of the models remains basically unchanged.

Figure 16: Routine procedure; forecasts

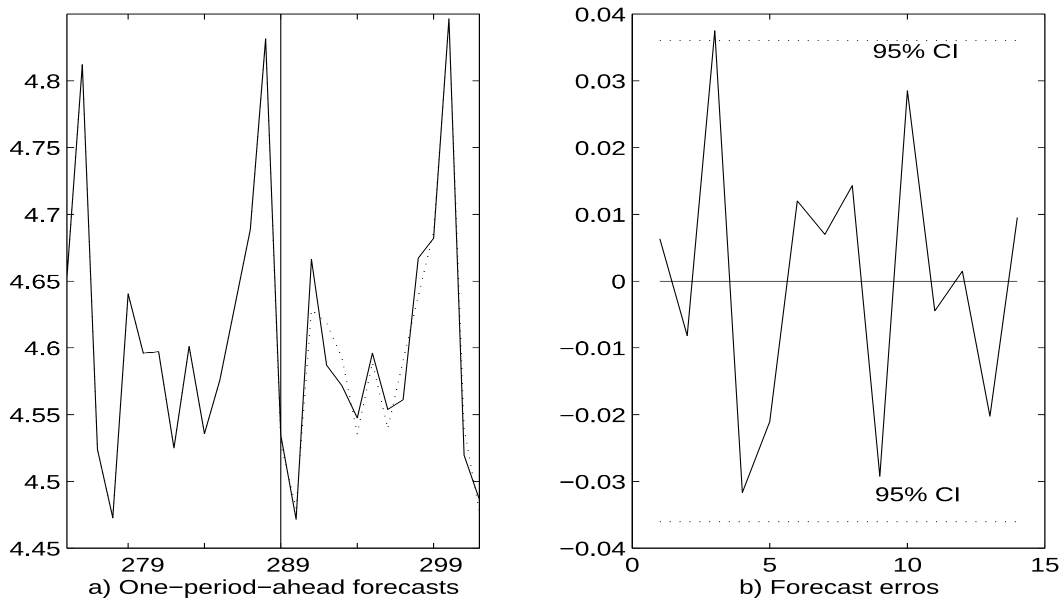
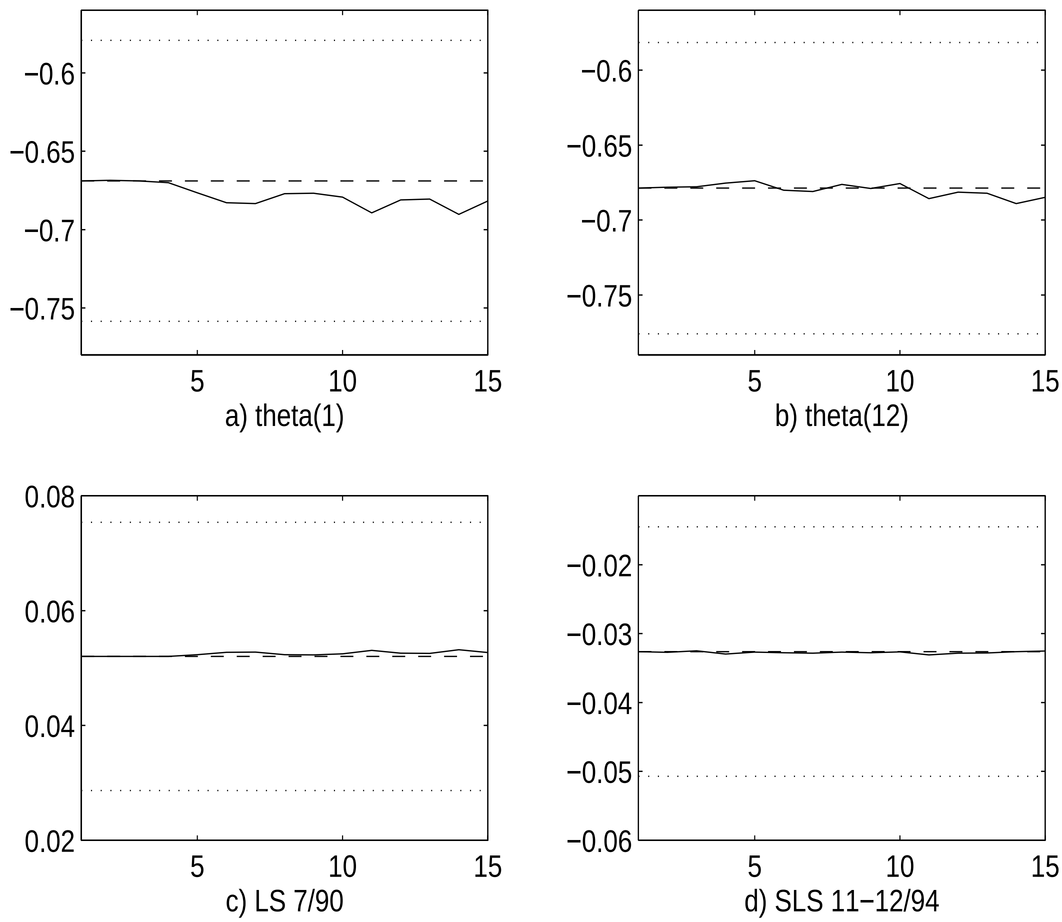


Figure 17: Routine procedure; parameter estimates



— parameter estimate for added months; - - parameter estimate in Dec. 98; .... 95% confidence interval

Revised and Updated Series: Extended period (Jan 75-Feb 2000)
T=302 obs.

Model	Default	Model 1	Model 2	Model 3
Parameter estimates:				
θ_1	-.685	-.682	-.681	-.686
θ_{12}	-.633	-.685	-.686	-.676
Outliers:				
LS 7/90	.053	.053	.053	.052
t-value	(4.52)	(4.55)	(4.55)	(4.59)
SLS 11-12/94	-	-.033	-.033	-.030
t-value		(-3.63)	(-3.70)	(-3.34)
LS 1/93	-	-	-	-.022
t-value				(-1.94)
Residual statistics:				
BIC	-8.031	-8.058	-8.063	-8.055
SE(a_t)*100	1.760	1.723	1.719	1.711
N(a_t)	2.86	1.43	1.28	1.63
$Q_{24}(a_t)$	26.3	26.6	25.6	25.5
$Q_S(a_t)$	1.06	1.24	1.30	.67
$Q_{24}(a_t^2)$	28.0	29.7	30.5	28.4

Table 7. Summary of TRAMO results. BIC denotes the Bayesian information criterion, and SE(a_t) the residual standard error; both should be as small as possible. N denotes the Bowman-Shenton test for normality, and is asymptotically distributed as a χ^2_2; it should be smaller than 6. $Q_{24}(a_t)$ denotes the Ljung-Box test for residual autocorrelation using the first 24 autocorrelations, and is asymptotically distributed as a χ^2 with (24-# of parameter estimates) degrees of freedom; for the Airline model it should be smaller than 34. $Q_{24}(a_t^2)$ is the McLeod-Li test for linearity, equal to the previous test, but computed on the squared residuals; it has the same asymptotic distribution as the Ljung-Box one. The N, Q(a_t), and Q(a_t^2) test are described in, for example, Harvey (1993). $Q_s(a_t)$ is a test for residual seasonal autocorrelation described in Pierce (1978); it is distributed approximately as a χ^2_2 distribution, and should be smaller than 6.

Revised and Updated Series: Extended period (Jan 75-Feb 2000) T=302 obs.

Model	Default	Model 1	Model 2	Model 3
SD of component innovation variance:				
• Trend	.228	.233	.233	.227
• Seasonal	.380	.319	.317	.327
• Irregular	1.201	1.214	1.197	1.202
Convergence of concurrent estimator in 1 year (% decrease in revision variance):				
• Trend	89	89	89	89
• SA series	36	31	31	32
SD of concurrent estimation error				
• Trend	.741	.737	.735	.728
• SA series	.743	.696	.692	.697
SD of revision in concurrent estimator				
• Trend	.559	.548	.546	.541
• SA series	.507	.478	.477	.478

Table 8. Summary of SEATS results. SD: Standard deviation; all are expressed in 10^{-2} (i.e., in percent points), and are obtained from the standarized variances provided by SEATS. To express them in the series units, they have been multiplied by the residual SD.

One important point related to the stability of the TRAMO-SEATS procedure concerns the convergence of the preliminary estimator (in particular, the concurrent one) to the historical estimator. To look at this convergence for the SA series, we started the procedure with the series ending in 1993, and compared the sequence of estimators for the years 1992 and 1993, as more years of data are made available. The results are presented in Table 9; the concurrent estimator suffers a relatively small revision, but converges slowly (in about 5 years). This is in complete agreement with the message given in the output of SEATS.

	12/93	12/94	12/95	12/96	12/97	12/98	12/99
1/92	98.0	98.0	97.9	97.9	97.9	97.8	97.8
2/92	98.0	98.0	97.9	97.9	97.9	97.8	97.8
3/92	98.0	98.0	97.9	97.9	97.9	97.8	97.8
4/92	98.1	98.0	97.9	97.9	97.9	97.9	97.9
5/92	98.2	98.2	98.1	98.1	98.0	98.0	98.0
6/92	98.4	98.4	98.3	98.3	98.3	98.2	98.2
7/92	98.6	98.6	98.5	98.5	98.5	98.4	98.4
8/92	98.8	98.8	98.7	98.7	98.7	98.7	98.6
9/92	98.9	98.9	98.9	98.9	98.9	98.8	98.8
10/92	99.0	99.0	99.0	99.0	99.0	98.9	98.9
11/92	99.0	99.0	99.0	99.0	98.9	98.9	98.9
12/92	98.9	98.9	98.9	98.9	98.8	98.8	98.8
1/93	98.8	98.8	98.7	98.7	98.6	98.6	98.6
2/93	98.8	98.7	98.6	98.6	98.6	98.5	98.5
3/93	98.8	98.7	98.6	98.6	98.6	98.6	98.6
4/93	98.8	98.7	98.6	98.6	98.6	98.6	98.5
5/93	98.7	98.7	98.6	98.6	98.6	98.5	98.5
6/93	98.8	98.8	98.8	98.7	98.7	98.7	98.7
7/93	99.0	99.0	99.0	99.0	99.0	98.9	98.9
8/93	99.2	99.2	99.2	99.2	99.1	99.1	99.1
9/93	99.2	99.2	99.2	99.2	99.2	99.2	99.2
10/93	99.2	99.2	99.2	99.2	99.1	99.1	99.1
11/93	99.1	99.1	99.1	99.1	99.0	99.0	99.0
12/93	99.1	99.0	98.9	98.9	98.9	98.9	98.8

Table 9. SA series: preliminary and final estimators

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