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# SEASONAL ADJUSTMENT OF ITALIAN INDUSTRIAL PRODUCTION INDEX USING TRAMO-SEATS

by

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**ABSTRACT**[1]

This paper analyses the use of TRAMO-SEATS to seasonally adjust Italian industrial production index. The problem of preliminary transformation of the series is illustrated, together with the way to deal with this issue with TRAMO-SEATS.
The subject of the revisions and, in general, of the use of seasonally adjusted and trend data is addressed, with some suggestions for the final user of these data.

JEL Classification: C220.

Key words: Seasonal Adjustment, ARIMA models, trading days, data revisions.

[1] A preliminary version of this paper was presented at the meeting "L'applicazione delle nuove tecniche di destagionalizzazione presso l'ISTAT", ISTAT, 27/09/2000, benefiting from the discussion arisen there. Moreover, comments from Edoardo Otranto, Claudio Lupi and an anonymous referee are gratefully acknowledged. Thanks to Gianna Foschi for her efficient editorial assistence. The author is responsible for all remaining errors.

## NON TECHNICAL SUMMARY

This paper presents an application of TRAMO-SEATS for the seasonal adjustment of Italian industrial production index. The relevance of this subject lies in the adoption, by many official statistical agencies (among them Italian statistical office), of TRAMO-SEATS as the current procedure for this purpose.

The paper reviews very briefly the basic methodology underlying this procedure, which is based on ARIMA models to represent a time series and the unobserved components by which it is hypothesized tobe constituted. In the second step, the general industrial production index and some sub-indices are described, showing the importance of the seasonal component and the contribution of the trading days to the short term variability of these series. This latter problem is then analysed more in detail, because of its importance as a preliminary step in seasonal adjustment, concluding that the current procedure adopted to correct the production indexes for the trading days effect (the so called *proportional* approach) leads to an over-adjustment. A competing way to pursue this objective is implemented in TRAMO-SEATS, basically by means of a regression, and shows clearly a better performance.

After the evidence on preliminary adjustment, the seasonal component is successfully extracted, and the main features of TRAMO-SEATS output are described.

Nevertheless, the use of seasonally adjusted data is discussed more in detail, dealing with the problem of the usefulness of such data. It is showed, also by means of a historical simulation, that the monthly growth rate of the seasonally adjusted index, often considered by business cycle analysts, is hardly significant from a statistical point of view. A more reliable picture is offered by a smoothed version of the trend-cycle (the growth rate of a three-term moving average) which is a good compromise between early detection of turning points and avoiding false signals.

# LA DESTAGIONALIZZAZIONE DELL’INDICE DELLA PRODUZIONE INDUSTRIALE CON TRAMO-SEATS


## SINTESI

Questo lavoro analizza l’uso della procedura TRAMO-SEATS per la destagionalizzazione dell’indice della produzione industriale dell’Italia. Viene analizzato, in particolare, il problema delle trasformazioni preliminari della serie, oltre al modo in cui utilizzare TRAMO-SEATS per trattare questo aspetto. Si affronta, inoltre, il tema delle revisioni delle serie destagionalizzate e di ciclo-trend. Infine, vengono discusse alcune implicazioni per gli utenti di questo tipo di dati.



Classificazione JEL: C220.

Parole chiave: destagionalizzazione modelli ARIMA, effetti di calendario, revisioni dei dati.

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## INTRODUCTION

This paper analyses the problem of the seasonal adjustment of Italian Industrial Production Index by using TRAMO-SEATS procedure. The relevance of the problem exposed lies in the fact that TRAMO-SEATS has replaced X-11-ARIMA as the official seasonal adjustment procedure at ISTAT - Italian statistical office (ISTAT, 1999b). The adoption of the new procedure has been pursued after a careful comparison with a competing one, X-12-ARIMA (ISTAT, 2000). Anyway, still remains some areas to be explored (e.g. Piccolo, 2000), particularly concerning the practical implementation of TRAMO-SEATS in a large-scale production context. In this paper the question of seasonal adjustment is explored, with a particular emphasis put on the problem of preliminary adjustment. We will see that, as advocated by Piccolo (2000), it is still necessary the joint use of TRAMO-SEATS and X-12-ARIMA to get a more satisfactory seasonal adjustment. This implicitly suggests some useful developments of TRAMO-SEATS in order for it to be used as a completely self-contained procedure.

The paper is organised as follows: the first section reviews the basic methodology upon which TRAMO-SEATS is based; the second gives some information about the series analysed. Section 3 describes the issue of preliminary transformation. Section 4 goes through the application of TRAMO and SEATS. Section 5 and 6 discuss the use of the seasonally adjusted and trend series. In the end, some conclusions are drawn.

## 1. A CONCISE DESCRIPTION OF TRAMO-SEATS

A seasonal adjustment procedure carries out the decomposition of a time series $z_t$ into a seasonal and a non seasonal component. In particular, TRAMO-SEATS provides for the following decomposition:

$$z_t = r_t + t_t + s_t + i_t \qquad [1]$$

where $z_t$ is the original series, $t_t$ is the trend, $s_t$ represents the seasonal component and $i_t$ the irregular; $r_t$ sums up the so-called deterministic effects, e.g. outliers, calendar effects etc.. A multiplicative relation among the components can be introduced by considering the logs of $z_t$. The seasonal adjusted series is then obtained leaving out of the original series the seasonal component and the deterministic part attributed to seasonality.

TRAMO-SEATS is actually composed by two main programs: TRAMO (Time series Regression with ARIMA Noise, Missing Observations, and Outliers) and SEATS (Signal Extraction in ARIMA Time Series). Although they could be used separately, we will consider here only their joint utilisation. The procedure is based on the ARIMA model based approach (Burman, 1980; Maravall, 1995) to decompose a time series: that is an ARIMA model is identified for the series of interest, and ARIMA models for the components are derived which are consistent with the aggregate one. Given that there may be many (possibly infinite) decompositions which meet this requirement, an identification problem arises, and is solved by means of the so called *canonical decomposition* (Box, Hillmer and Tiao, 1978; Pierce, 1978) which insures the existence of a unique decomposition, specifying the components of interest as clean of noise as possible. This implies they have a zero in their spectrum, i.e. they are non-invertible. In our case the canonical components are the trend and seasonal; all the remaining noise is then concentrated in the irregular component.

The logical sequence of the procedure is as follows (Gómez and Maravall, 1997). Given a time series $z_t$, a regression model is fitted:

$$z_t = y_t' \beta + v_t \qquad [2]$$

where $\beta$ is a vector of coefficients, $y_t$ a vector of n regression variables, which includes calendar effects, outliers and other user defined effects, and $v_t$ follows an ARIMA process:

$$\phi(B)\delta(B)v_t = \theta(B)a_t \qquad [3]$$

B is the backshift operator, $\delta(B)$, $\varphi(B)$ and $\theta(B)$ are finite polynomials in $B$ and $a_t$ is a n.i.i.d. $(0,\sigma^2_a)$ white noise innovation. The polynomial $\delta(B)$ is associated with the differencing operation, hence it has roots on the unit circle, while $\varphi(B)$ and $\theta(B)$ have their roots outside the unit circle.

TRAMO can automatically identify the order of the polynomials in [3] as well as outliers and the need for a correction for regression effects input by the user or generated by the program; among the latter there are calendar, Easter effect, various intervention variables. Once a model is identified the coefficients are estimated by maximum likelihood, missing observations are interpolated and forecasts are obtained.

Afterwards, the regression effects are eliminated and the series $v_t$ is decomposed by SEATS, following the canonical requirement, obtaining the stochastic components (usually trend, seasonal and irregular). In the end, the deterministic parts (i.e. the regression effects) are reintroduced, obtaining the final components (e.g. the final seasonal component will include also the calendar effects, while transitory outliers are included in the irregular).

Among the advantages of using a model based approach, there are the possibility to tailor the procedure to the stochastic behaviour of the series and the opportunity to get the standard errors of the estimated components. In so far as the first aspect is concerned, TRAMO-SEATS produces a wide set of tests to let the user check the appropriateness of the model chosen; these include standard tests to insure residuals are white noise and normally distributed. Considering the second aspect, the theoretical models for the components are derived and displayed to the user, who can check the closeness to them of the estimated components.

One of the most used model in TRAMO-SEATS is the so called Airline model, which is an ARIMA (0 1 1)(0 1 1). This model, which is often found to approximate fairly well many economic time series (Fischer and Planas, 2000), is characterised by the nice property that the coefficients have an immediate interpretation in terms of the components. In fact the MA coefficient is directly linked to the "randomness" of trend component and the seasonal MA coefficient to that of the seasonal component. Actually, these components are closer to be deterministic as long as the related coefficients are closer to 1.

## 2. AN EXPLORATORY ANALYSIS OF THE INDUSTRIAL PRODUCTION SERIES

In this section, the main features of the industrial production general index as well as the end-use sub-indices (consumer, capital and intermediate goods) are shortly reviewed. All the series start in January 1981 and end in December 1999. During this span various changes of the base year took place (1980, 1985, 1990 e 1995), so the original series have been chained (see also ISTAT, 1996) to get indices with base 1995=100.

The choice of the starting period has been influenced by different considerations. First, it must be taken into account that every seasonal adjustment procedure requires a large number of observations over the same months of different years; on the other hand, very long series might be characterised by structural breaks which could cause some problems when seasonal adjustment is carried out; these problems could be even more pronounced in a model based framework.

In the case analysed it has been taken into account the fact that from 1981 onward, indices classified following the scheme NACE rev.1 are available at a sufficiently high breakdown, thus making it possible the extension of this exercise. Of course, ex-post evaluation of the estimated models has not shown any presence of a structural break.

In figure 1 the raw series are plotted; they clearly show a strong seasonal component, whose behaviour is characterised by a sharp fall in the level of activity occurring at August. In figure 2 the estimated spectral density is plotted; it confirms the concentration of power for all the series at the fundamental seasonal frequency and at its harmonics.

**Figure 1. Industrial production index – raw series**

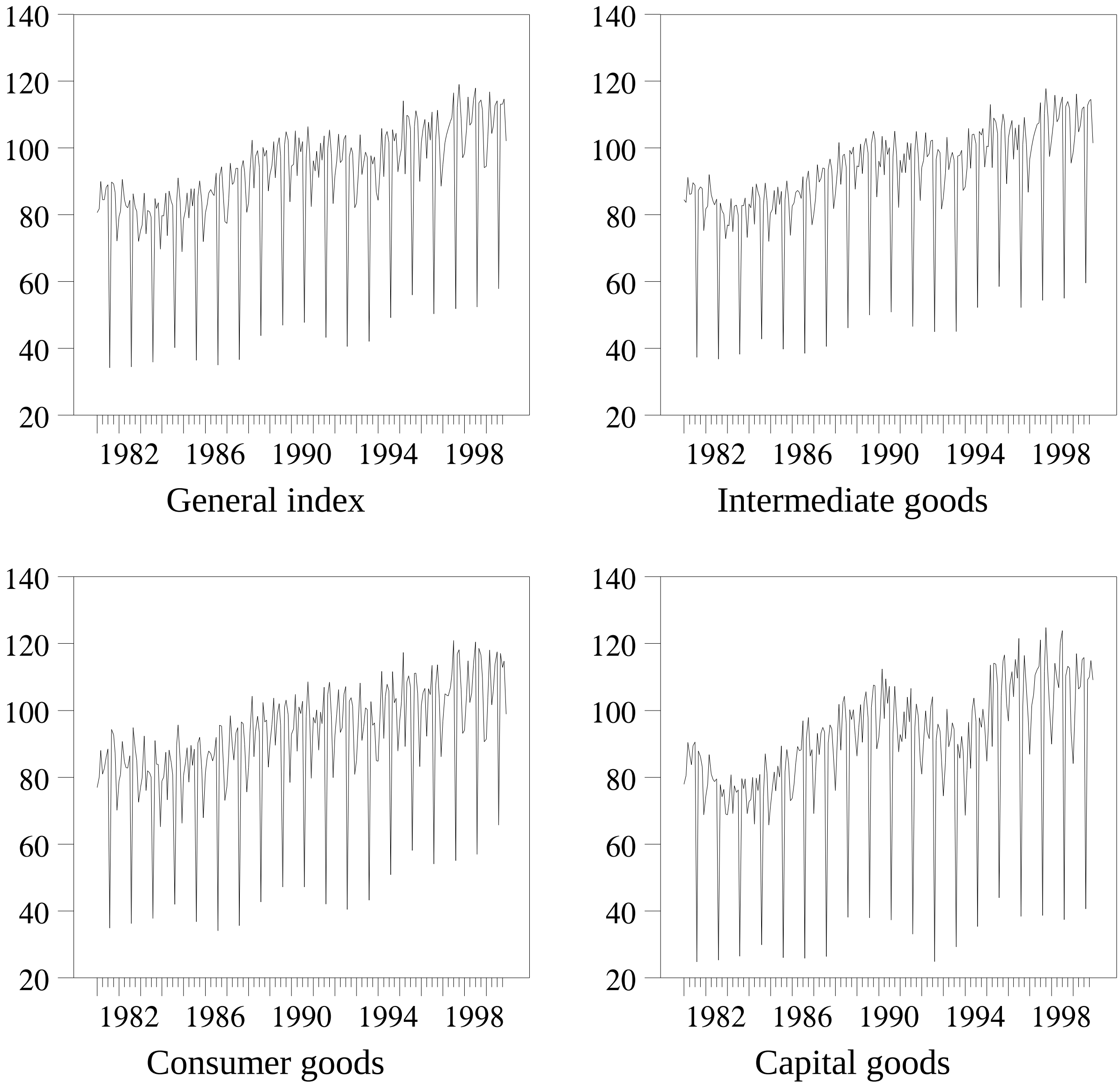
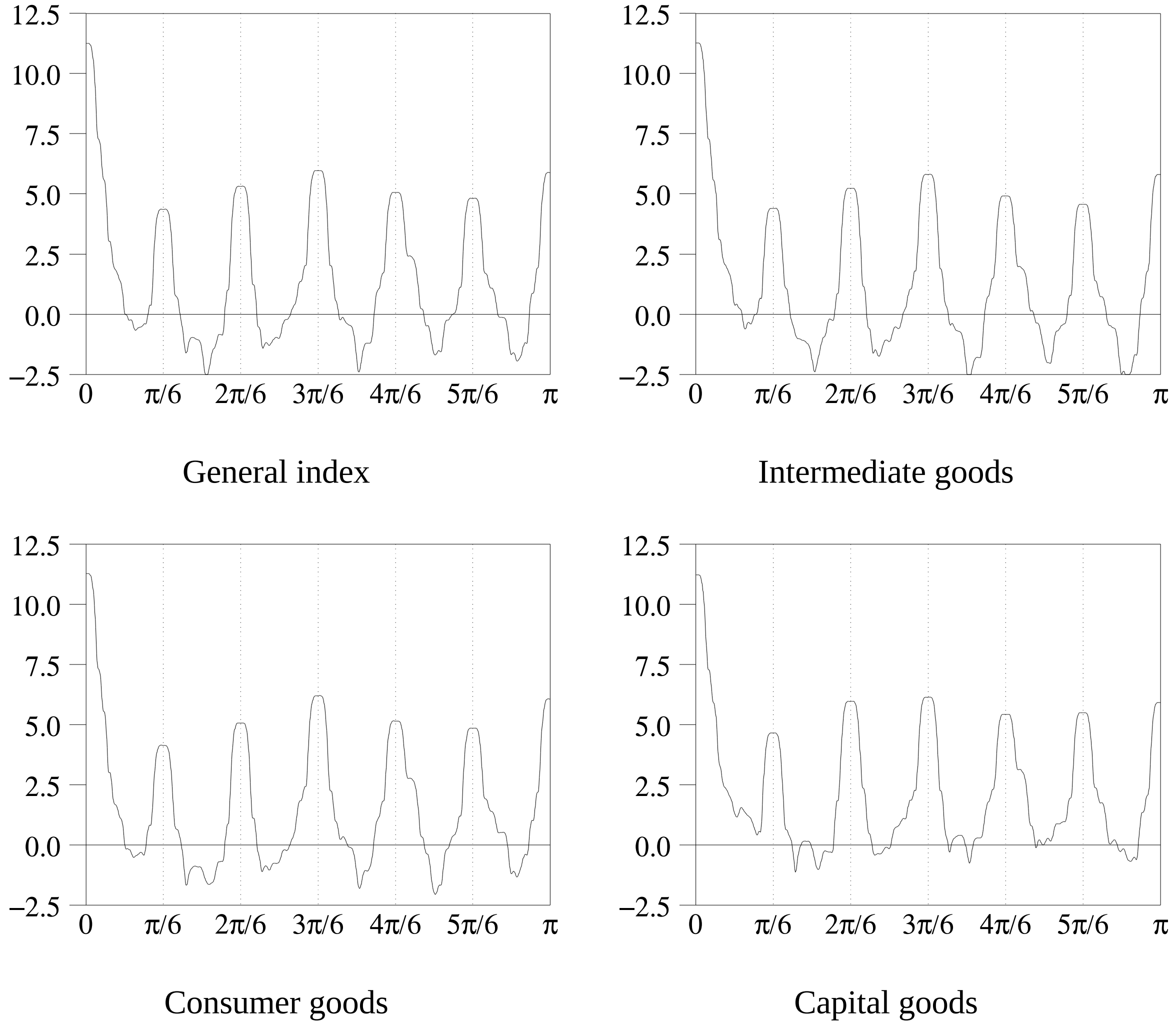


**Figure 2. Industrial production index – raw series – log spectrum[2]**

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[2] Actually, the spectral density is correctly defined only for stationary series; in particular, when some unit roots are present in correspondence of certain frequencies, the usual expression for the spectral density would take the value $+\infty$ at those frequencies; nevertheless, discarding those frequencies the so called *pseudo-spectrum* (Bell, 1984) can be considered. In this case it has been estimated smoothing a periodogram by means of a rectangular spectral window. A cosine taper has been applied to the data. The spectral bandwidth is $0.048\pi$.

# 3. THE PRELIMINARY TRANSFORMATION OF THE SERIES

## 3.1. The relevance of the problem

The operations which conceptually precede the decomposition operated by SEATS and to which we refer as *preliminary transformation* comprise a wide set of tasks performed either by TRAMO in an automatic way or by the user. These operations are the choice of the relationships among the components, additive or multiplicative (the latter implies a log transformation of the series to be adjusted); the inclusion of the trading days correction, which can take several forms; the identification of outlying observations. All these operations interact, moreover, with the choice of the ARIMA model of eq. [3]. Given the large number of possible combinations of preliminary transformations, it seems quite too ambitious to model correctly a series by means of an automatic procedure only. A good compromise could be represented by a mixed approach, combining the user *a priori* knowledge with the facilities offered by the program to test a smaller number of competing models.

In our case the *a priori* elements are represented by the assumption of the presence of significant calendar and Easter effects, in the following referred to as *trading days* correction.

The relevance of detection and removing of a trading days pattern in monthly data derives from the observation that it can account for much of the variability of a time series. The following table shows the reduction of variance of a trading days adjusted stationary transformation of the industrial production index, respectively coming out from TRAMO-SEATS and from the so called proportional approach currently adopted by ISTAT (Politi, 2000).

**Table 1. Variance reduction of the trading days adjusted industrial production index (twelfth difference of logs) in comparison to the raw series**

| | General index | Consumer goods | Investment goods | Intermediate goods |
|---|---|---|---|---|
| TRAMO-SEATS | 31.2 | 41.6 | 19.1 | 23.4 |
| Proportional method | 22.0 | 27.5 | 12.6 | 17.8 |

From table 1 it seems possible to hypothesize a better correction operated by the regression method of TRAMO-SEATS in comparison to the proportional method. The former, in fact, reduces the variance of the series considerably more than the latter, in particular for the consumer goods and the general index.

Sometimes it is argued that the trading days correction can be too "strong", particularly using the proportional method; in fact, the calendar is a completely deterministic effect, so known in advance, and the firms are likely to smooth in some way its effects. If a firm is able to pursue this objective efficiently, the trading days adjusted production should be approximately uncorrelated with the trading days themselves.

Table 2 is quite instructive in this case. Raw data are, as expected, strongly correlated with trading days; what is particularly upsetting is the negative correlation of trading days adjusted series, obtained with the proportional method. This negative correlation (always significant at 1% confidence level) is a sign of a possible over-adjustment. So, if the analyst is correctly aware about the danger implicit in the use of the yearly rate of growth of the raw series (because of the significance of trading days pattern), one must know that the use of the trading days corrected series officially issued by ISTAT can be quite misleading too.

A much better picture is the one coming from the use of the series adjusted by TRAMO-SEATS, which presents a small negative correlation with the number of trading days, but never significantly different from zero.

**Table 2. Correlation among trading days (twelfth differences) and some industrial production indexes (twelfth difference of logs)**

| | General index | Consumer goods | Investment goods | Intermediate goods |
|---|---|---|---|---|
| Raw index | 0.51* | 0.59* | 0.39* | 0.44* |
| Trading days corrected (proportional method) | -0.26* | -0.34* | -0.18* | -0.22* |
| Trading days corrected (TRAMO-SEATS) | -0.10 | -0.07 | -0.11 | -0.07 |
| Seasonally adjusted | -0.09 | -0.08 | -0.11 | -0.07 |

(*) Significant at 1%.

## 3.2. Testing for alternative preliminary transformations

Once assessed the relevance of the problem, we illustrate how to choose among alternative model specifications for preliminary transformation. Consider then a general statistical model as follows:

$$f(z_t) = y_t'\beta + v_t \qquad [4]$$

where $f$ can be a linear or a log function of the argument, and the right hand side has the same meaning as in [2]. The particular models considered differ each other concerning both the different form of $f$ (log vs. levels) and the different form of calendar effects correction. The latter were specified in six different forms:

**Table 3. Different specifications for trading days**

| Name | Specification |
|---|---|
| TD7 | Six trading days variables, one variable for length-of-month effect, one variable for Easter effect |
| TD2 | One trading days variables, one variable for length-of-month effect, one variable for Easter effect |
| TD7+ | as in TD7, plus a variable for Italian specific holidays |
| TD2+ | as in TD2, plus a variable for Italian specific holidays |
| TD7f | as in TD7, correcting the six trading days variables for Italian specific holidays |
| TD2f | as in TD2, correcting the trading days variable for Italian specific holidays |

The first two specifications are the standard ones in TRAMO-SEATS; the third and the fourth add a regressor for Italian specific holidays. The last two preserve the same number of variables as in TD7 and TD2, respectively, but change them slightly, so as to be consistent with Italian calendar; e.g. in model TD2f the number of working days is diminished by the number of holidays falling between Mondays and Fridays.

A total of 12 models for each variable has been tested, by means of likelihood criteria; as pointed out in Soukup and Findley (2000), these are applicable in selecting among competing models as long as the same outliers and the same differencing order are considered. The last point does not present any problem, because in all the cases the Airline model was chosen; anyway, the outliers found were sometimes different. The solution chosen was to apply to all the models all the outliers identified for every case, consistently with the suggestion made in Soukup and Findley (2000).

The likelihood criteria applied was the so called AICC (Findley *et al.*, 1998)[3]. In two cases (general index and consumption goods) model TD2+ in levels is favoured. The other two variables (investment and intermediate goods) appear to be better represented by the TD2f model in levels. The same results are obtained considering the AIC criteria, while the BIC one prefers always the more parsimonious specification TD2f.

Overall, the choice not to apply the log transformation seems to be valid for all the variables. Concerning the modelling of calendar effects, the more parsimonious specifications with two variables are preferred with respect to the seven variables ones, while the use of Italian specific holidays improves considerably the fit. The only doubt remains about the use of TD2+ vs. TD2f model; the latter, which are preferred on the basis of AICC for investment and intermediate goods, causes a deep worsening of the model performance in terms of residual diagnostic for intermediate goods, which show significant residual autocorrelation. This has led us to choose for all the variables considered the TD2+ model[4].

**Table 4. AICC value for different models *(the best model is the one showing the minimum value of the AICC statistic)***

| | General index | Consumption goods | Intermediate goods | Investment goods |
|---|---|---|---|---|
| *Outliers* | *1984.8*<br>*1995.8* | *1984.8*<br>*1999.8* | *1984.8*<br>*1995.8* | *1986.12*<br>*1992.8*<br>*1998.12* |
| TD7 (logs) | 1017.72 | 1106.34 | 960.63 | 1211.10 |
| TD2 (logs) | 1010.46 | 1101.38 | 955.30 | 1202.09 |
| TD7+ (logs) | 980.59 | 1080.99 | 932.44 | 1190.05 |
| TD2+ (logs) | 977.03 | 1079.07 | 929.90 | 1181.32 |
| TD7f (logs) | 1020.98 | 1105.98 | 973.77 | 1209.82 |
| TD2f (logs) | 983.90 | 1087.33 | 931.91 | 1185.01 |
| TD7 (levels) | 980.62 | 1059.09 | 954.57 | 1189.10 |
| TD2 (levels) | 974.47 | 1052.65 | 949.78 | 1182.05 |
| TD7+ (levels) | 910.81 | 1009.93 | 888.74 | 1140.59 |
| TD2+ (levels) | 909.20 | 1008.12 | 887.11 | 1134.14 |
| TD7f (levels) | 968.35 | 1043.86 | 942.69 | 1174.89 |
| TD2f (levels) | 909.93 | 1011.23 | 885.73 | 1132.89 |

[3] For the sake of simplicity, X-12-ARIMA was used to apply the test. Actually, in the output of the present version of TRAMO-SEATS there is not enough information available to carry out in a simple way the test, while in the output of X-12-ARIMA likelihood criteria are presented directly in the original scale of the observations.
[4] It must be stressed that the difference for all the criteria between TD2+ and TD2f models is always very small.

The choice of the trading days pattern has been further investigated. In particular, X-12-ARIMA has been used to test for a significant regime change in the trading days regressor. The test used is based on a t-statistic (U.S. Census Bureau, 2000) and need for the user to specify the breaking point. January 1990 has been chosen as a cut-off period, being close to the centre of the series and coincident with a base change and a classification break. The following lines illustrate how the test has been implemented with X-12-ARIMA:

```
series{...}
transform{function=none}
arima{model=(0 1 1)(0 1 1)}
regression{file="...”user=fest usertype=holiday start=1981.jan
           variables=(td1coef/1990.1/ easter[6])}
estimate{}
```

**Table 5. Test of a break in trading days pattern. Break at January 1990. Additive relation** *(t-statistics are reported).*

| General index | Consumer goods | Investment goods | Intermediate goods |
|---|---|---|---|
| -2.02 | -1.82 | -1.47 | -2.30 |

The results in table 5 show a break significant at 5% in two cases. Note that the negative sign means that the coefficients associated to the trading days are smaller in the first sub-period. This seems quite difficult to accept, in that implies less flexibility in the production process, in relation to the calendar structure. An alternative explanation could be given once the retained transformation is considered; in fact the additive relation between the component associated to the growth of the production in the period considered (at an average yearly rate of 1,43%), implies a relative decrease in time of the importance of the trading days.

Given these results the same test has been applied with a multiplicative relation among the variables, obtaining the results in table 6.

**Table 6. Test of a break in trading days pattern. Break at January 1990. Multiplicative relation** *(t-statistics are reported).*

| General index | Consumer goods | Investment goods | Intermediate goods |
|---|---|---|---|
| 0.13 | -0.15 | -0.33 | -0.35 |

These results confirm the null hypothesis of no break in the trading days patterns during the period considered, even though they cast some doubt about the choice of the additive relation.

## 4. APPLICATION OF TRAMO-SEATS

Once defined the preliminary adjustment of the series, identification of the ARIMA model and of the outliers and the estimation of the parameters has been carried out using TRAMO-SEATS, with the following specifications[5]:

LAM=1, INIC=3, IDIF=3, ITRAD=2, IEAST=1, IDUR=6, IATIP=1, AIO=1, VA=4.0, + HOLIDAYS

which corresponds to the following actions:

LAM=1: additive relation;
INIC=3, IDIF=3: automatic identification of the ARIMA model;
ITRAD=2, IEAST=1, IDUR=6, HOLIDAYS: trading days as specified before (TD2+);
IATIP=1, AIO=1, VA=4.0: identification of transitory outliers (AO - *additive outlier* - and TC - *temporary change* - in the terminology of TRAMO-SEATS), with a sensitivity parameter of 4.0, which is larger than the default (3.5). In setting this we have followed U.S. Census Bureau (2000), which advises the user to select this value according to the number of observations.

**Table 7. Main results of TRAMO**

| | General index | Consumer goods | Investment goods | Intermediate goods |
|---|---|---|---|---|
| Model | (0 1 1)(0 1 1) | (0 1 1)(0 1 1) | (0 1 1)(0 1 1) | (0 1 1)(0 1 1) |
| MA(1) (a) | -0.505 (-8.42) | -0.626 (-11.68) | -0.537 (-9.15) | -0.404 (-6.29) |
| MA(12) (a) | -0.590 (-9.78) | -0.526 (-8.33) | -0.535 (-8.70) | -0.622 (-10.33) |
| TD1 (a) | 0.788 (23.44) | 0.920 (20.39) | 1.038 (17.16) | 0.653 (21.58) |
| TD2 (a) | 2.289 (2.90) | 1.667 (1.66) | 2.765 (2.00) | 2.280 (3.10) |
| Holidays (a) | -2.203 (-8.67) | -2.379 (-7.17) | -2.837 (-6.28) | -1.971 (-8.44) |
| Easter (a) | -1.588 (-3.20) | -1.646 (-2.54) | -1.732 (-1.98) | -1.581 (-3.49) |
| Constant (a) | no | no | no | no |
| Outliers | none | none | none | none |
| *Test of residuals (p-values)* | | | | |
| Lijung-Box | 0.36 | 0.20 | 0.89 | 0.10 |
| Lijung-Box (squared residuals) | 0.37 | 0.57 | 0.38 | 0.89 |
| Normality test | 0.45 | 0.99 | 0.14 | 0.48 |

(a) Estimated value; t-statistics between brackets.

Absence of autocorrelation in residuals and squared residuals is largely accepted, as well as their normality. A by-product of the process is the trading

[5] The values of the options are reported for ease of the reader; anyway the software used in this work is the seasonal adjustment user interface Demetra, version 1.4, developed by Eurostat.

days corrected series[6] (the $v_t$ term of [2]), which is the series actually decomposed by SEATS.

The following table shows SEATS results:

**Table 8. Main results of SEATS**

| | General index | Consumer goods | Investment goods | Intermediate goods |
|---|---|---|---|---|
| *Variance of innovation components (in unit of the variance)* | | | | |
| Trend | 0.03879 | 0.02039 | 0.03145 | 0.05873 |
| Seasonal | 0.04200 | 0.06447 | 0.05169 | 0.03935 |
| Irregular | 0.35807 | 0.37904 | 0.34792 | 0.32424 |
| Seasonal adjusted | 0.65292 | 0.59899 | 0.61134 | 0.67692 |
| *Variance of components, estimators and estimates (stationary transformation)* | | | | |
| Trend (theoretical components ) | 0.074 | 0.039 | 0.060 | 0.113 |
| Trend (estimator) | 0.009 | 0.003 | 0.006 | 0.019 |
| Trend (estimate) | 0.007 | 0.002 | 0.005 | 0.017 |
| Seasonal (theoretical components ) | 0.297 | 0.220 | 0.314 | 0.412 |
| Seasonal (estimator) | 0.041 | 0.053 | 0.057 | 0.039 |
| Seasonal (estimate) | 0.023 | 0.067 | 0.031 | 0.018 |
| Irregular (theoretical components ) | 0.358 | 0.379 | 0.348 | 0.324 |
| Irregular (estimator) | 0.214 | 0.232 | 0.205 | 0.185 |
| Irregular (estimate) | 0.200 | 0.220 | 0.192 | 0.171 |
| Seas. adjusted (theoretical compon.) | 2.223 | 2.313 | 2.147 | 2.058 |
| Seas. adjusted (estimator) | 1.765 | 1.738 | 1.646 | 1.667 |
| Seas. adjusted (estimate) | 1.774 | 1.674 | 1.632 | 1.577 |
| *Percentage reduction in the standard error of revision after* n *periods (in comparison with concurrent estimator) – seas. adj. / trend* | | | | |
| After 1 year | 39.6 / 80.6 | 46.0 / 87.7 | 44.7 / 83.3 | 36.7 / 74.6 |
| After 2 years | 64.4 / 88.5 | 71.6 / 93.5 | 91.1 / 70.4 | 60.6 / 84.2 |
| After 3 years | 79.0 / 93.2 | 85.0 / 96.6 | 95.2 / 84.2 | 75.5 / 90.2 |
| After 4 years | 87.6 / 96.0 | 92.1 / 98.2 | 97.4 / 91.5 | 84.7 / 93.9 |
| After 5 years | 92.7 / 97.7 | 95.9 / 99.1 | 98.6 / 95.5 | 90.5 / 96.2 |
| *Growth rates standard error (percentage points) – seas. adj. / trend* | | | | |
| Monthly growth rate – concurrent | 1.047 / 0.502 | 1.434 / 0.481 | 1.930 / 0.820 | 0.938 / 0.564 |
| Monthly growth rate – 1st revision | 1.047 / 0.463 | 1.433 / 0.453 | 1.930 / 0.761 | 0.938 / 0.511 |
| Monthly growth rate – 2nd revision | 0.884 / 0.430 | 1.197 / 0.414 | 1.605 / 0.701 | 0.800 / 0.480 |
| Monthly growth rate – final estimate | 0.782 / 0.422 | 1.093 / 0.409 | 1.453 / 0.689 | 0.698 / 0.468 |
| 3-month centred mov.av. – concurrent | 1.773 / 1.116 | 2.157 / 1.085 | 3.081 / 1.836 | 1.726 / 1.242 |
| 3-month centred mov.av. – 1st revision | 1.195 / 0.985 | 1.543 / 0.993 | 2.168 / 1.642 | 1.137 / 1.063 |
| 3-month centred mov.av. – 2nd revision | 1.098 / 0.826 | 1.418 / 0.820 | 1.980 / 1.363 | 1.042 / 0.901 |
| 3-month centred mov.av. – final estim. | 0.887 / 0.796 | 1.168 / 0.802 | 1.621 / 1.319 | 0.841 / 0.858 |

(a) Estimated value; t-statistics between brackets.

We find a small innovation variance for seasonal and trend series, and a larger one for the irregular. This implies that the final seasonally adjusted series is quite volatile, with negative consequences for its use in short term analysis.

[6] This is true in this particular case, where no outliers were identified.

Variances of estimators are always less than those of theoretical components, and quite close to those of the estimates, which is consistent with an acceptable decomposition.

An interesting result emerges when looking at the revision errors, which are quite large for the seasonally adjusted series even after four or five years; this implies that stopping the publication of revisions after a smaller span (e.g. two or three years) can be quite an unadvisable practice.

In the end, the standard errors of some growth rates are displayed. It is interesting to note that monthly rates of growth do not seem to provide a robust signal, as it will be shown in section 5.

An assessment of how good the performance of a seasonal adjustment method is, can be given by the use of spectral methods. In particular, the spectrum of the seasonally adjusted series should be characterized by the absence of significant spectral peaks at the seasonal frequencies, while leaving unchanged the others.

**Figure 3. Industrial production index – raw and seasonally adjusted series**

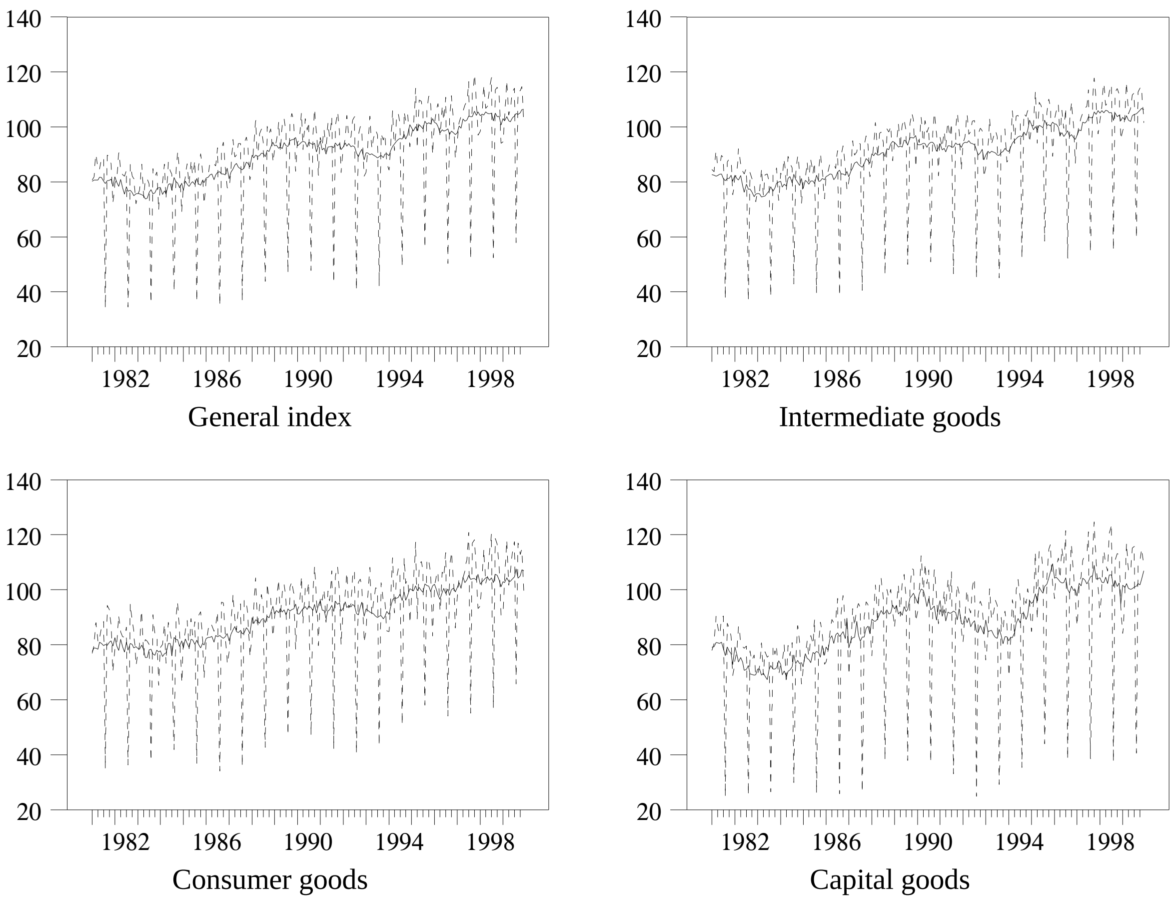
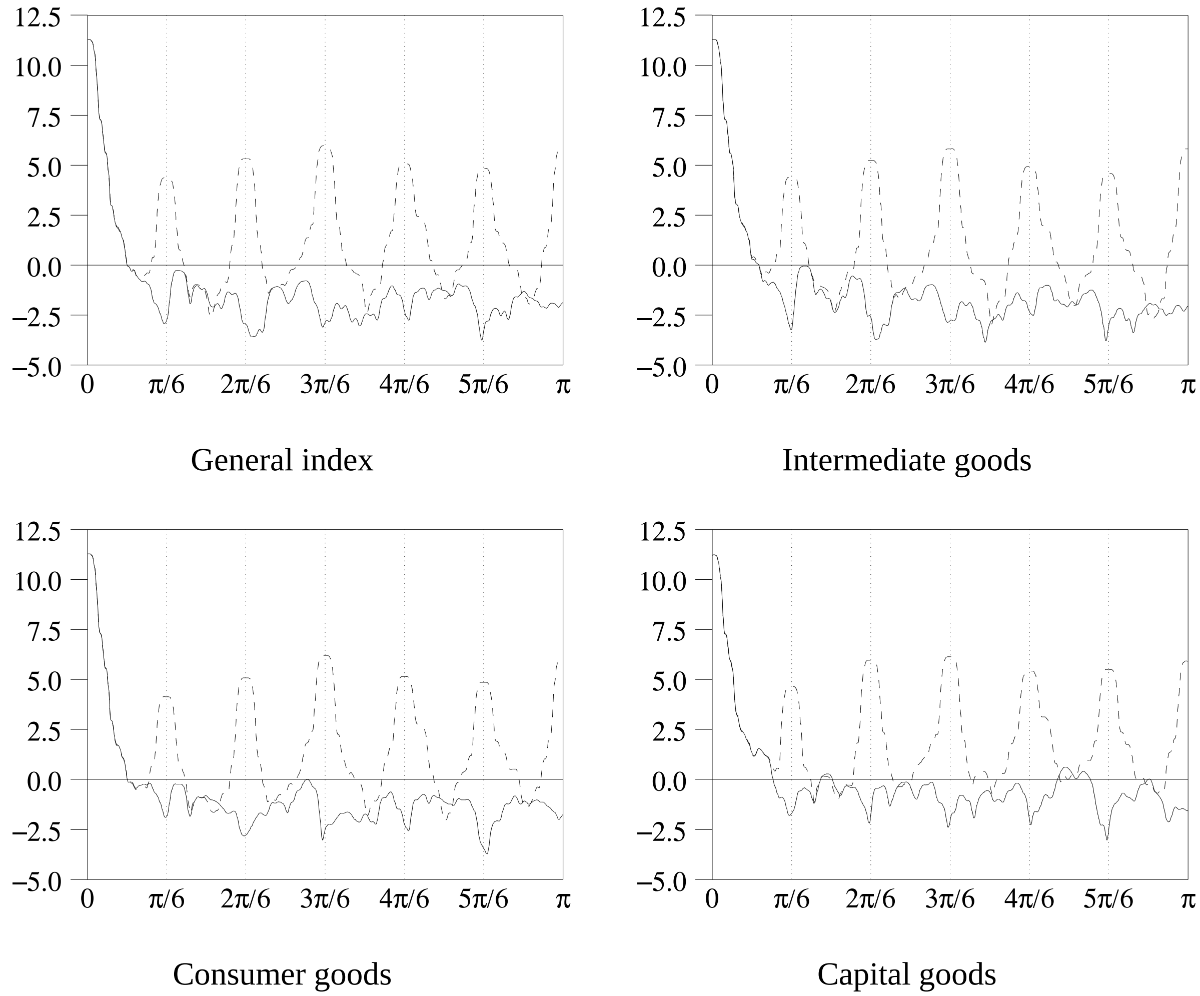


**Figure 4. Industrial production index – raw and seasonally adjusted series – log spectrum**[7]




The graphs show quite clearly that the procedure has successfully removed the seasonal peaks. In some cases it is also evident that it has removed "too much", creating dips at some seasonal frequencies; indeed, the filters used by TRAMO-SEATS always produce a non-invertible seasonal adjusted component, which implies a zero in its spectrum at the seasonal frequency and at its harmonics.

Spectral techniques are also useful in order to assess the bias seasonal adjustment could have induced at frequencies other than the seasonal ones. In particular, cross-spectral techniques can be used (Granger and Newbold, 1977).

[7] See note 2.

Squared coherency can be estimated between the linearised and the seasonal adjusted series. The value of the squared coherency at frequency ω can be interpreted as the square of coefficient of correlation between ω-frequency components of two series.

**Figure 5. Industrial production index – Estimated squared coherency between linearised and seasonally adjusted series[8]**

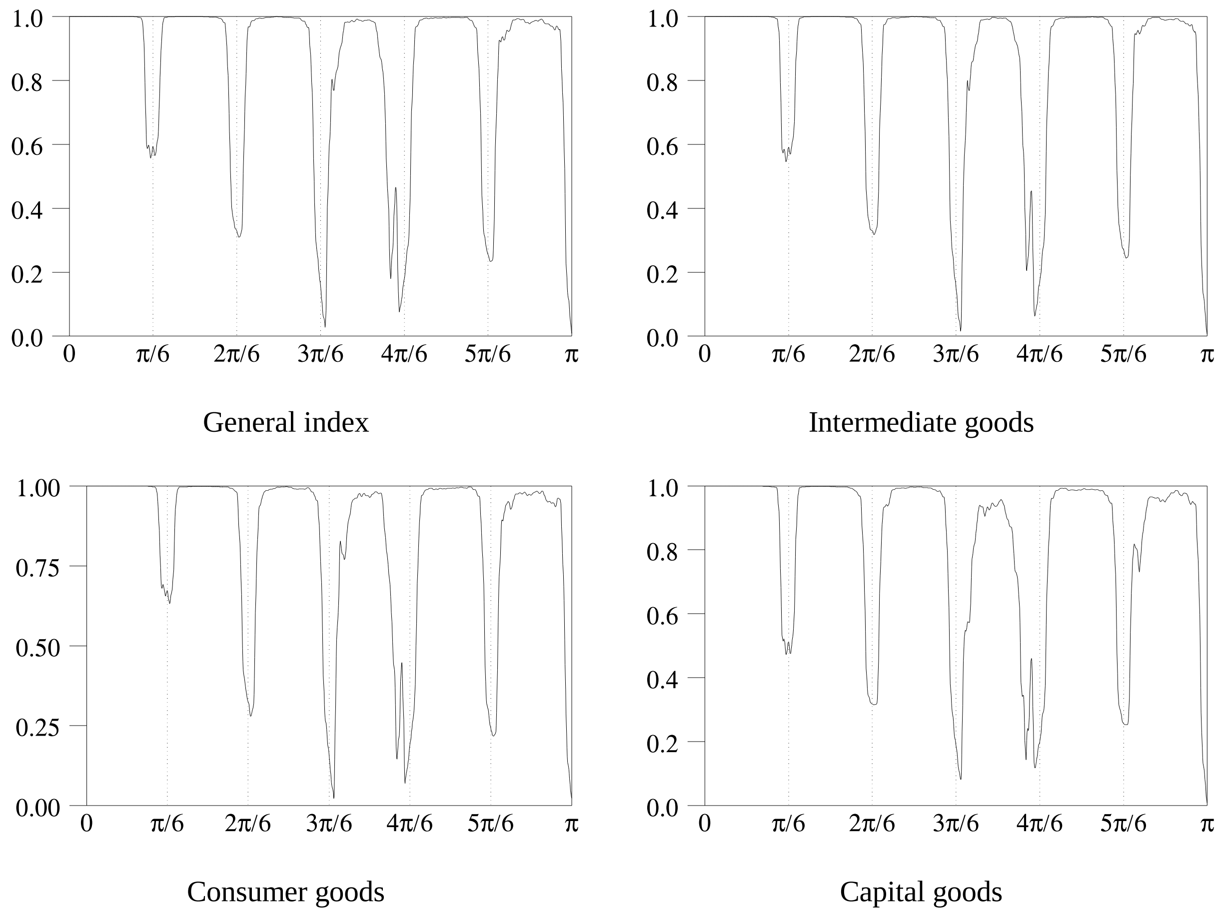



Figure 5 shows that no significant bias seems to have been induced by the procedure at low frequencies, including the cyclical ones. Some problems emerge at frequencies higher than π/2. Anyway, the overall performance seems to be quite satisfactory.

[8] The squared coherency is estimated smoothing the cross-periodogram and taking its magnitude. Seasonally adjusted series have no power at seasonal frequencies, so the squared coherency is not properly defined at those frequencies.

## 5. THE USE OF ADJUSTED DATA FOR SHORT-TERM ECONOMIC ANALYSIS

One important aspect which needs some explanation regards the opportunity to seasonally adjust a series. While it is a well known result that seasonal adjustment can considerably bias the relationships between variables (Wallis, 1974), nevertheless it is a very common practice to produce and use seasonally adjusted data. One of the justification for their use is that they make comparable consecutive months, which is normally not feasible with unadjusted data. This is an important feature because monthly rates of change allow for a faster detection of turning points than yearly rates (normally used with unadjusted data), being less affected by phase shifts.

Actually, the results shown in table 8 enable us to be quite unconfident with monthly rates of change of seasonally adjusted data; indeed, a monthly rate of change of one and half percentage point of the seasonally adjusted series cannot be considered significant, as well as a change of 0.8 in the trend series. Less than 30% of the observed seasonally adjusted series changes could then be considered significant, from a statistical point of view, while this percentage would fall to less than 2% in the case of trend series![9]

Considering a further smoothing of the series (a three-term moving average), monthly changes are significant in 64% of cases for the seasonally adjusted series, and 53% for the trend. In this case, including the revision error leads to a smaller loss in precision: the above percentages would fall, respectively, to 59% and 50%. One could argue that half changes not significant from zero is still a high record; effectively, in this sense seasonal adjustment procedure has revealed itself to be a partially unsatisfactory approach to get a series free of noise, in order to interpret the short term movements of the variable considered in a clearer manner. In addition, trend extracted from TRAMO-SEATS, even though smoother, is still affected by a large error.

A further analysis can be carried out considering the ability of the seasonally adjusted and/or the trend series to help detecting turning points. We consider here just the visual inspection of these series. In order to do that, a historical simulation has been carried out, estimating seasonally adjusted and trend series at every month from January 1993 onward. In this way, we can replicate what would have been the actual procedure. A series of turning points has been

[9] This rather raw indication, based on a standard 5% confidence level, is still optimistic, having been calculated considering just the final estimation error; if we consider the total estimation error (which include also the revision error) the percentage of significant monthly changes is about 18% for the seasonally adjusted series and zero for the trend.

calculated, based on a visual inspection of the final trend series (calculated on the full span of data available).

**Table 9. Turning points**

| Turning points | Monthly change of trend | Monthly change of a 3-term moving average of cycle-trend data | Monthly change of a 3-term moving average of seasonally adjusted data |
|---|---|---|---|
| 1993.8 | 94.3 | 93.12 | * |
| 1996.1 | 96.3 | 96.3 | * |
| 1996.12 | 97.2 | 97.3 | * |
| 1998.1 | 98.12 | 98.8 | 98.1 |
| 1999.2 | 99.6 | 99.7 | 99.7 |

Table 9 shows, in the first column, when the turning points have occurred (the only doubt exists for the location of the turning point at 1998.1, which could be set later), and when they would have been detected in an actual historical situation. We see that the first series tracks quite well the turning points with a delay which is variable from two to eleven months. There is also a small number of false signals in correspondence of most of the points.

Passing to the monthly rate of change of a three-term moving average of the trend, the detection of turning points ranges from two to seven months; in this case the number of false signals is reduced, even if still present.

In the end, considering the rate of change of a three-term moving average of the seasonally adjusted data, there are a large number of false signals, that make it difficult to locate precisely a turning point by visual inspection in the first three cases examined.

## 6. REVISIONS

As we have seen in the two previous sections the revisions can have an important effect in the use of seasonally adjusted and/or trend data to monitor the short term evolution of a variable. While after some years it is possible to give a correct picture of the business cycle looking at the filtered series, in a concurrent situation the extent of possible revisions needs some consideration.

Revisions can arise from different reasons. Firstly, the ARIMA model identified for the series is used to extrapolate future values of the series itself, in order to reduce the impact of asymmetric filters at the end of the available span of data; as new data become available the forecasts are replaced with the true values and seasonally adjusted data can be revised. The diagnostic contained in TRAMO-SEATS are useful to evaluate this problem. A second cause of revision is due to the possible change in the estimated coefficients of model [2], which determines a change in the filters used to estimate the components. A third cause is represented by the change in the identified model, which causes, in general, a much more pronounced modification in the estimated components.

In this paper we have already checked the importance of the first cause of revisions (see table 8). Here we present some results obtained, as in section 5, from a historical simulation. In this case the model is let fixed, but the coefficients are re-estimated each time. Doing so, we take into account the first two sources of revisions presented above, neglecting the third. Actually, the third problem is quite unlikely to occur in practice, because a statistical agency will in general prefer to "freeze" the model identified by the procedure, revising at fixed dates the coefficients. In this exercise we have re-estimated the coefficients every month, form 1993 onward.

The measures used to illustrate the revision process are the following. Denoting the "final" estimator of a component at period *t* by $\hat{s}_t$, its preliminary estimate at period *t+k* as $\hat{s}_{t|t+k}$, the so called *concurrent estimate* is obtained when k=0. The update in the preliminary estimate after one further observation is given by:

$$r_k = \hat{s}_{t|t+k+1} - \hat{s}_{t|t+k} \qquad k = 0,\ldots,T-1 \qquad [5]$$

For every *k* in equation (5) $r_k$ is the monthly revision in the preliminary data, *k+1* months after the concurrent estimate. Two synthetic measures are then derived. The *average absolute percentage revision (AAPR), k+1* months after the concurrent estimate:

$$AAPR(k) = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{r_k}{\hat{s}_t}\right|\cdot 100 \qquad k = 0,\dots,T-1$$

which gives an idea of the average revision one can expect in practice. The second measure considered is the *maximum absolute percentage revision (MAPR), k+1* months after the concurrent estimate:

$$MAPR\ (k) = \max\left(\left|\frac{r_k}{\hat{s}_t}\right|\cdot 100\right) \qquad k = 0,\dots, T-1$$

Both the measures are computed for the seasonally adjusted and the trend series, and are graphed below, with the x-axis representing *k+1*.

**Figure 6. Average absolute percentage revision of Industrial production index**

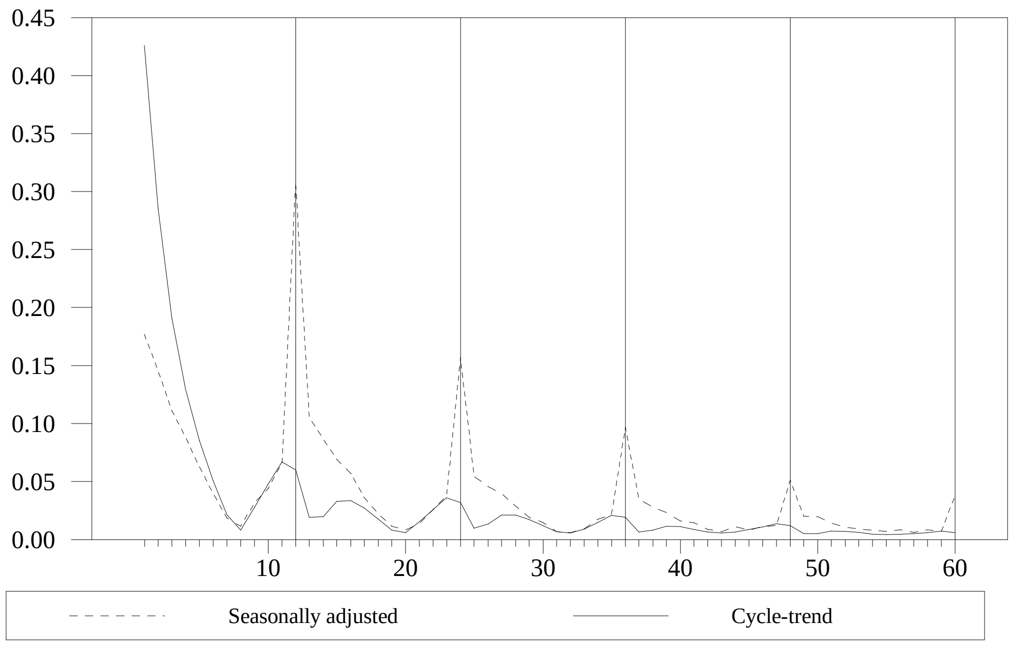
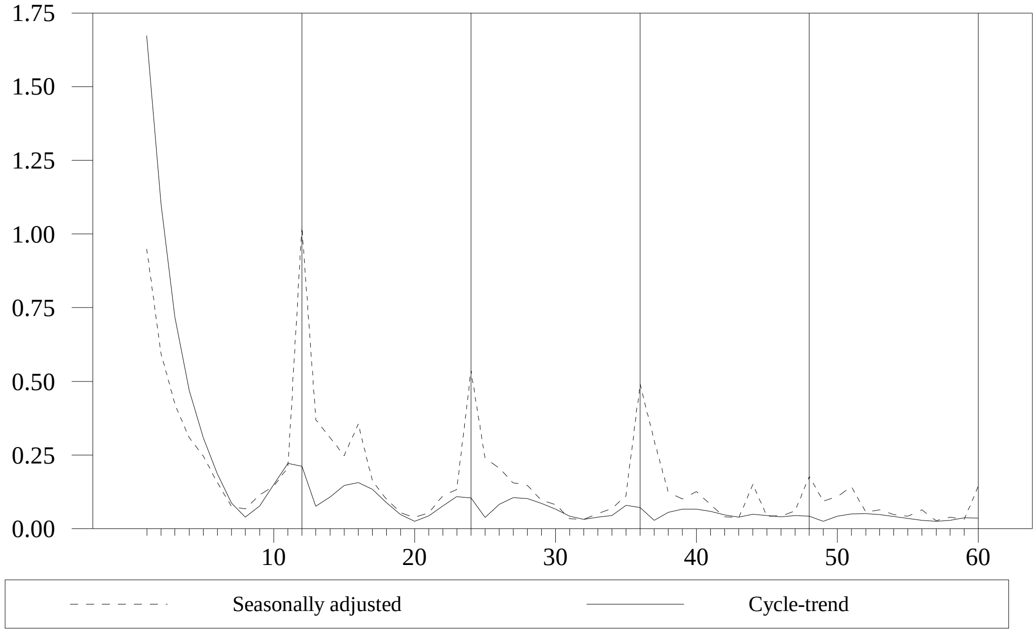


**Figure 7. Maximum absolute percentage revision of Industrial production index**




As evident from the figures, the largest revision for the trend takes place six months after the concurrent estimate is produced; this is true also for the MAPR indicator. The shape in both cases has a small peak around the first year.

AAPR and MAPR have a typical shape also for seasonally adjusted data. In this case the revisions are substantially smaller than in the trend case during the first months. Anyway, large revisions occur after complete years are passed from the concurrent adjustment, mirroring the weighting scheme of the seasonal adjustment filters, which emphasize consecutive observations on the same months.

These results show that seasonally adjusted industrial production index can be revised substantially for at least three or four years. In comparison trend revisions are less persistent; nevertheless, for the first periods they are larger, making clear the intuitive trade-off between a larger revision and a smoother signal.

## CONCLUSIONS AND SOME FINAL REMARKS

This application has confirmed some of the findings of earlier studies on this subject. In particular, the choice of the transformation is still a problematic aspect. The choice of an additive relation among the components raises some problems; as illustrated in Proietti (2000), the seasonal component is in this case less flexible, producing a more volatile seasonally adjusted series. Moreover, in this paper additive decomposition is questioned also by the findings concerning the trading days pattern. This is consistent with the fact that the choice of simple relationships among the components allowed for by TRAMO-SEATS and X-12-ARIMA can be too simple to model efficiently the series considered in this work. In addition, the time invariant behaviour of the trading days component is a limiting characteristic of both the procedures.

The limited amount of break-down allowed for in this exercise has not raised the problem of cross-sectional consistency. The aggregation of the three end-use seasonally adjusted sub-series from 1995 onward is identical to the aggregate (absolute value of the maximum difference is at most 0.1). This makes the problem of the choice between direct and indirect methods practically not relevant. Nevertheless, this is not expected to hold as soon as seasonal adjustment is carried out at a more disaggregated level.

The most relevant evidence stemming from this work regards the use of the estimated components, evaluated looking at the diagnostics of SEATS and at a historical simulation exercise. Overall, monitoring the short term evolution of the series considered, with particular regard to turning points detection, cannot be fully answered, in a concurrent real situation, neither using the seasonally adjusted nor the trend component, or their simple growth rate. In particular, in the case considered the focus usually made on the monthly growth rate of the seasonally adjusted series has revealed itself overwhelming misleading, when used to assess the state of the cycle. Better results have been found using the trend component and the problem of false signals can be partially dealt with taking the growth rate of a three-term uncentered moving average of the latter. Nevertheless, this is not a fully satisfactory result, especially because a phase shift is expected to be introduced in this way.

Further research should perhaps investigate what is the main objective of the user of generally filtered data, tailoring the choice of the “optimal” filter to this objective.

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