EUROPEAN CENTRAL BANK

Seasonal Adjustment

# Seasonal Adjustment

EUROPEAN CENTRAL BANK

# Seasonal Adjustment

Editors:

Michele Manna and Romana Peronaci

EUROPEAN CENTRAL BANK

**Published by:**

| | |
|---|---|
| Address | Kaiserstrasse 29<br>60311 Frankfurt am Main<br>Germany |
| Postal address | Postfach 16 03 19<br>60066 Frankfurt am Main<br>Germany |
| Telephone | +49 69 1344 0 |
| Internet | http://www.ecb.int |
| Fax | +49 69 1344 6000 |
| Telex | 411 144 ecb d |

This publication is also available as an e-book to be downloaded from the ECB's website.



**Editors:**
Michele Manna and Romana Peronaci

**Typeset and printed by:**
Kern & Birner GmbH + Co.
As at January 2003.

ISBN 92-9181-412-1 (print)
ISBN 92-9181-413-X (online)

# Contents

# Foreword

The main objective of the European Central Bank is the maintenance of price stability over the medium term. The challenge faced by central banks is that monetary policy decisions taken today will affect the price level only in the future. The ECB's monetary policy strategy aims to ensure that the Governing Council receives all the relevant statistics, analysis and additional information to take the monetary policy decisions needed today in order to maintain price stability over the medium term. The strategy assigns a prominent role to money. In the long run, the relationship between money and the price level is stable, especially when money is measured using broad monetary aggregates such as M3. In the short run, however, monetary developments may be subject to special influences and distortions, which make forward-looking monetary policy decisions more complex. The monetary analysis of the ECB intends to filter the underlying long-term relationship in the statistics from repercussions by short-term effects. One main approach is the seasonal adjustment of monetary and economic statistics. Seasonally adjusted data allows monitoring short-term developments irrespective of seasonal patterns and trading-day effects where relevant.

Each month, the ECB derives seasonally adjusted results for the principal euro area monetary aggregates and counterparts. In addition, in collaboration with the European Commission (Eurostat, the Statistical Office of the European Communities), it produces seasonally adjusted measures of a wide range of other real economy and price statistics for the euro area, including the Harmonised Index of Consumer Prices (HICP) and GDP.

The compilation of seasonally adjusted data for the euro area implies some challenges, because the concept of a "euro area" is new and harmonised euro area statistics only available for a short period of time and a limited set of indicators. Of particular interest in the context of euro area statistics is the discussion of "direct" versus "indirect" seasonal adjustment. Advantages and drawbacks of a direct adjustment of euro area results as compared to an indirect adjustment via the aggregation of seasonally adjusted sub-components such as country results, need to be carefully considered.

The ECB organised this one-day seminar to bring together professionals in the area of seasonal adjustment from central banks and statistical offices. The exchange of ideas stimulates further theoretical and practical work in seasonal adjustment, which would be of benefit for the monetary and economic analysis of the ECB.

Frankfurt am Main, November 2002

Eugenio Domingo Solans
Member of the Executive Board of the European Central Bank

## Note from the Chairman

Michele Manna

Seasonal adjustment plays a central role in the set-up of the statistical basis used by decision-makers to assess the economic outlook. Seasonally adjusted data are one of the tools used by the ECB to measure the growth of its key monetary aggregate M3. Likewise, the EU statistical office, Eurostat, gives priority to seasonally adjusted data in communicating the growth of euro area GDP, as do the US Federal Reserve (in respect of its index of industrial production) and the US Bureau of Economic Analysis (as regards the US GDP).

At the same time, seasonal adjustment receives comparatively limited attention from academic researchers. A search in the database Helecon International returned 35 entries for "seasonal adjustment", while two other terms applicable to time series interpolation techniques, "trend cycle" and "trend estimates", had 306 and 257 entries respectively.

It was thus with a view to reflecting on the needs of both official producers of statistics and academic researchers that on 12 November 2002 the ECB's Money and Banking Statistics Division organised a one-day seminar on the subject of seasonal adjustment. The seminar involved presentations and discussions by staff members from the ECB, EU and accession country central banks, the US Census Bureau and Eurostat.

When should a researcher judge the seasonal adjustment of a time series to be adequate? In other words, when has the seasonal component been sufficiently whitened so that no seasonal effect can be detected in the seasonally adjusted series? Already at this rather general level, the researcher faces a number of highly empirical issues. For example, the question arises of whether one should adjust directly the series under examination, or rather proceed indirectly, by first adjusting some sub-components and then aggregating. Moreover, the producer of adjusted statistics must tackle the issue of the optimal frequency of review of the seasonal models/parameters/factors. It is also of interest for the expert in the field to monitor the developments in the two main paradigms used in the industry, X12-REGARIMA and TRAMO/SEATS. Finally, further light should be shed on the properties of the seasonal adjustment estimates of short time series.

The discussion at the seminar revolved around these themes. Please refer to the papers for a thorough presentation. I should like here to flag some of the main results which are noteworthy for their general applicability, both within and outside the field of statisticians working in central banks or statistical institutes. I hope I can do justice to the efforts made by the authors.

First and foremost, it can never be emphasised enough that there is no fundamental reason why a seasonally adjusted series should be smooth. This reflects the fact that the irregular component is an integral part of the seasonally adjusted series.

Second, in addition to the visual inspection of the spectrum, the researcher can rely on a class of tests to assess the under/overestimation of the seasonality, and the stability of the seasonal components. In this respect, as a good rule of thumb, it should be borne in mind that when the seasonality of the series is very stable, with little stochastic variation, the filter may over-adjust (remove too much variation as seasonal), and vice versa.

Third, as to the issue of direct versus indirect adjustment, empirical work undertaken on broad sets of time series provides only mixed evidence on which of the two approaches is superior to the other. The applied researcher may, however, wish to note that the indirect adjustment tends to be more effective if the sub-components do not have similar time-series properties or if their relative importance (in terms of weight) changes very rapidly. At the same time, while neither of the two approaches systematically dominates the other, it is only under rather restrictive conditions that the two approaches yield the same seasonally adjusted results. In theory, the issue of the direct versus the indirect approach could be solved by means of a system-based estimation. In practice, given its computational complexity and its shortcomings with respect to revision errors, this approach has rarely been used, and univariate approaches are generally preferred.

Fourth, as regards the optimal frequency of updating models/parameters/factors, it can be shown that frequent updates of the model do not necessarily improve the quality of seasonally adjustment data. Same remark holds true in respect to the frequency of re-estimation of the seasonal factors. Conversely, the analyst avails of more degrees of freedom as regards the updating of the parameters of the model.

Fifth, when seasonal adjustment is run on fairly short time series, e.g. five years of monthly data, simulations point to serious distortions in the results for the first two years of the sample. Furthermore, when outliers occur at the beginning of a short time series, the distortions introduced may be very large compared with the situation in which additional past data are available. More generally, the use of longer series is particularly recommended when the seasonal component is highly volatile.

Sixth and finally, to quote Agustín Maravall, "While X12 provides a quality assessment of the estimated component […], the SEATS diagnostics provide specification-type tests […]. Viewed in this way the information given by the two approaches can be seen as complementary." It is in this light that work is ongoing to establish a facility integrating X12 and TRAMO/SEATS.

In sum, I am convinced that the seminar provided the opportunity for a stimulating exchange of ideas among professional economists and statisticians working on the seasonal adjustment of "official" time series. The outcome of this exchange was a good mix of theoretical and applied results which I hope can also be of use outside the circle of experts dealing with seasonal adjustment in central banks and statistical offices.

At this point, I should once again like to thank all those who participated in the seminar for their contributions, whether in the form of papers or active involvement in the discussion. At the ECB, I should like to express special thanks to Romana Peronaci and Helena Roland, who took over most of the burden involved in the practical organisation of the seminar.

European Central Bank
Frankfurt am Main, November 2002

# 1

# Comparing direct and indirect seasonal adjustments of aggregate series

Catherine C. Hood and David F. Findley

If a time series is a sum (or other composite) of component series that are seasonally adjusted, we can sum the seasonally adjusted component series to get an indirect adjustment for the aggregate series. This kind of adjustment is called an indirect adjustment of the aggregate series. The alternative is the direct adjustment obtained by applying the seasonal adjustment procedure directly to the aggregate data. For example, when we seasonally adjust export series at the individual end-use-code level and then sum the adjustments to get Total Exports, we have an indirect adjustment of Total Exports. If we sum the individual series first to get Total Exports and then seasonally adjust the total, we have a direct adjustment of Total Exports. Under most circumstances, the direct and indirect adjustments for an aggregate series are not identical.

This paper discusses the methodological practices of adjusting aggregate series and the diagnostics we use at the U.S. Census Bureau to help us judge the quality of the adjustments, including indirect adjustments generated from two different seasonal adjustment programs such as X-12-ARIMA and SEATS.

We will discuss attributes of an acceptable seasonal adjustment and how to look for signs of inadequacy in the adjustment, particularly with aggregate series. We will also discuss briefly some diagnostics for judging the quality of the adjustment, including smoothness and revisions.

## 1. Methods

The Census Bureau uses its X-12-ARIMA software to produce seasonally adjusted numbers. X-12-ARIMA and its predecessors, X-11 and Statistics Canada's X-11-ARIMA, are widely-used seasonal adjustment programs. One of the major improvements of X-12-ARIMA is its additional diagnostics. For more information, see Findley, Monsell, Bell, Otto and Chen (1998) or the *X-12-ARIMA Reference Manual, Final Version 0.2* (U.S. Census Bureau 2002).

Different estimates of the seasonal effects in an economic time series can arise from different choices of the options in the seasonal adjustment software. Or, in an aggregate series, different estimates can also result from different choices of the level of aggregation at which seasonal adjustment is performed.

Our larger aggregate series, such as Total Retail Sales, Total Value of Construction, Total Imports, and Total Exports, are seasonally adjusted indirectly. For any aggregate series that is published, staff at the Bureau also looks at the diagnostics for the aggregate's seasonal adjustment.

For the U.S. Import and Export series, the Census Bureau publishes the monthly data, so we look at the diagnostics for the monthly seasonal adjustment. However, the data are also

This paper reports the results of research and analysis undertaken by Census Bureau staff. It has undergone a Census Bureau review more limited in scope than that given to official Census Bureau publications. This report is released to inform interested parties of ongoing research and to encourage discussion of work in progress.

summed to quarters and published quarterly elsewhere (based on our monthly seasonal adjustments), so we also look at diagnostics for the quarterly series and the quarterly aggregates.

With regard to aggregate series, staff at the Census Bureau looks at the diagnostics for each component series to decide if the series is seasonal or not and to decide on the options to produce the best possible seasonal adjustment. We look very carefully at every series to determine if the series is seasonal and if it can be adjusted reliably. When deciding on the best possible options, if we have many series to look at in a short period of time, we focus on the larger-valued series first.

## 2. Diagnostics for direct and indirect adjustments used at the Census Bureau

Whether direct or indirect adjustment is better for a given set of series depends on the set of series in question (Dagum 1979; and Pfefferman, Salama, and Ben-Turvia 1984). Generally speaking, when the component series that make up the aggregate series have quite distinct seasonal patterns and have adjustments of good quality, indirect seasonal adjustment is usually of better quality than the direct adjustment. On the other hand, when the component series have similar seasonal patterns, then summing the series may result in noise cancellation, and the direct seasonal adjustment is usually of better quality than the indirect adjustment. How do we know if it’s better to use direct or indirect adjustment for a given set of series? How similar do the component series need to be in order for direct adjustments to be of superior quality? If the component adjustments are acceptable, will the indirect adjustment always be acceptable as well? The best way to answer these questions is to look at the diagnostics.

### *2.1 Features of a quality adjustment*

The most fundamental requirement of a seasonal adjustment, regarding quality, is that there be no estimable seasonal effect still present in the seasonally adjusted series or in the detrended seasonally adjusted series (i.e., in the irregular component).

Other important qualities of a good adjustment are the lack of bias in the level of the series and the stability of the estimates. A lack of bias in the level means that the local level of the series will be similar for both the original series and the seasonally adjusted series. Stability of the estimates means that as new data are added and incorporated into the estimation procedure, the revisions to the past estimates are small. Large revisions can indicate that the original estimates are misleading or even meaningless.

There are other features that may be desirable in an adjustment. Some users may prefer a smoother adjustment. However, it is important to remember that achieving such desired features can conflict with the quality requirements mentioned earlier. For example, the smoother of two adjustments may also be the one that is more susceptible to large revisions as future data become available and are included in the adjustment calculations. Some users may find an adjustment with large revisions to be unsuitable. Analysis of seasonal adjustment filters shows that increased smoothing is often associated with great delay in detecting turning points (Findley, Martin, and Wills 2002), and delayed turning point detection may be unsuitable to users also. Therefore, it is important to balance all the qualities and features desired.

It is important to always check the quality of the adjustment. This applies to the direct and indirect adjustments, as well as the adjustments of all the component series. We will give examples later in the paper to show the importance of diagnostics.

### *2.2 Diagnostics for residual seasonality*

One of the most important diagnostics is the spectral diagnostic for residual seasonality and trading day effects, examples of which will be given below. For series with at least 60 observations, the Census Bureau encourages users to look at this diagnostic to see if there are any residual calendar effects.

The spectrum of an observed time series shows the strength, or amplitude, of each frequency component when the data are decomposed into such components. For a monthly series with a strong seasonal effect, the spectrum will have especially large amplitudes at the frequencies associated with components that repeat every year, i.e., every twelve months, every six months, every three months, etc. Therefore, for monthly series with a strong seasonal effect, we will see peaks in the spectrum at frequencies $\boldsymbol{k}/12$ cycles per month, for $1 \le \boldsymbol{k} \le 6$. For a quarterly series with a strong seasonal effect, we will see peaks in the spectrum at the frequencies ¼ cycle per quarter and at ½ cycle per quarter. See also Findley *et al* (1998).

With inadequate seasonal adjustments that contain residual seasonality, the residual effects are usually rather weak, and it is necessary to remove any very strong frequency components from the adjusted series before the spectrum calculation, to enable the spectrum to reveal the presence of the seasonal component. Since the irregular component of the seasonal adjustment decomposition is the detrended seasonally adjusted series, X-12-ARIMA plots the spectrum of the irregulars to help the user detect residual seasonality. Examples of spectral graphs are given below.

There are also some other statistical procedures, including F tests, that can be used to detect residual seasonality, but for series that are long enough, the spectral graph is the most sensitive diagnostic to test for residual seasonality.

### *2.3 Stability diagnostics*

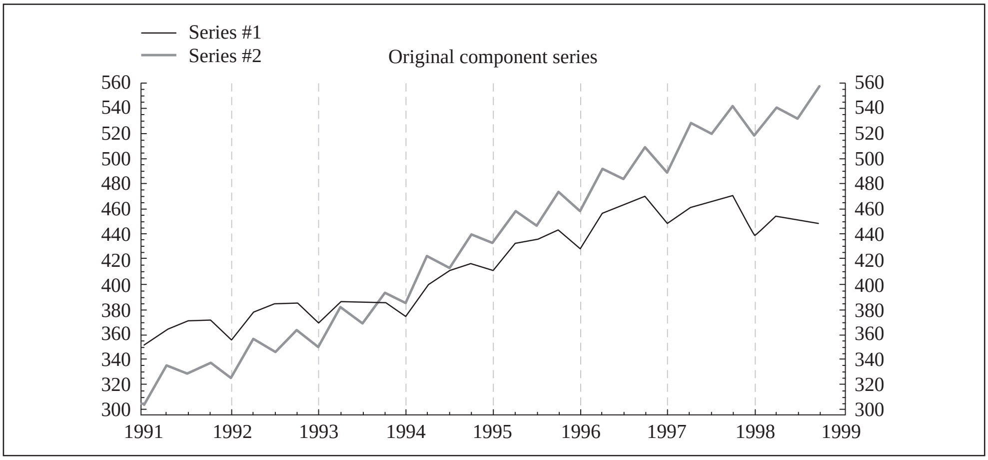
Two different adjustments can both be successful in the sense that their adjusted series have no residual seasonality but one may be more attractive to some users but less attractive to others. For this reason, we believe that once we have determined there is no residual seasonality, it is important to look at additional diagnostics.

Seasonal adjustments for any given month will change as new data are introduced into the series. Included in X-12-ARIMA are diagnostics for stability: the sliding spans and revision history diagnostics.

The sliding spans diagnostic computes separate seasonal adjustments for up to four overlapping subspans of the series. For more infomation on sliding spans diagnostics, please see Findley, Monsell, Shulman, and Pugh (1990), Findley et al (1998), or the *X-12-ARIMA Reference Manual* (U.S. Census Bureau 2002).

Another way to look at the revisions for a series is to compare the initial adjustment for any given point (the adjustment when that particular point is the latest point in the time series) to the final adjustment for that point (the adjustment when all the data in the time series are included in the adjustment). For more information on the revision diagnostics, see Findley *et al* (1998) or the *X-12-ARIMA Reference Manual* (2002). For more information on graphs of the revision diagnostics, see Hood (2001). Examples of revision history graphs are given below.

Figure 1: Graph of the two components
*(thousands)*




### 2.4 Example – residual seasonality in the aggregate series

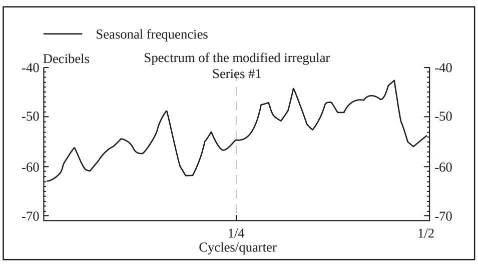
If the component series have no residual seasonality, are we guaranteed that the indirect adjustment will have no residual seasonality? We will demonstrate that it is possible to have two series with no apparent residual seasonality, and yet still have residual seasonality in the aggregate series.

It is possible to set inappropriate options in seasonal adjustment software. It is also the case that when options are used that were set many years before, one can get adjustments that are not optimal. And when we add together several series with suboptimal options, we can sometimes see residual seasonality in the aggregate series. This is why, at the Census Bureau, we believe it is important to check the seasonal adjustment diagnostics every year, including the diagnostics for the aggregate series as well as for the component series.

For the purpose of an example, we've selected a simple aggregate series. The two original (unadjusted) composite series are shown below. The two composite series are real series, and the Census Bureau publishes the aggregate series, but not in the way described below. For the published series, all the diagnostics have been checked carefully. We chose seasonal filter lengths for one series that were inappropriate given the diagnostics from the series. Using these filters, it is possible to create an aggregate series where there is residual seasonality in the aggregate, even though the component series have apparently acceptable adjustments.

The spectral graphs for the components are shown in Figure 2.

Figure 2: Spectral graphs for the component series



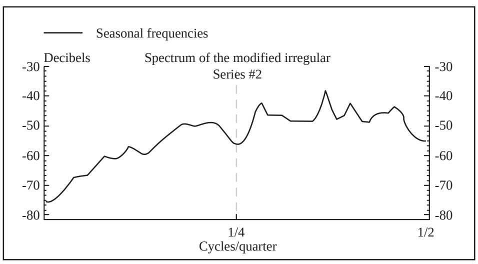
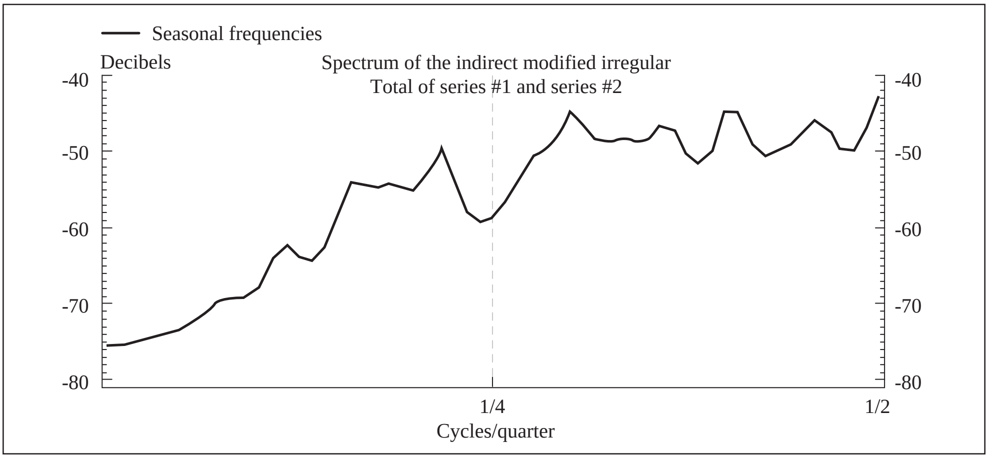



Figure 3: Spectral graph of the indirect adjustment for the total




We would expect that seasonal frequencies at ¼ and ½ would have been suppressed in the spectrum of the seasonally adjusted series. In the first graph in Figure 2, there is a slight seasonal peak on the right of the graph at ½. However, the peak is not marked as "visually significant" by X-12-ARIMA, nor is it the dominant peak of the graph. Therefore, there is no strong signal of residual seasonality for this series alone. The spectral graph for the total of the two series, shown in Figure 3, has a peak on the right side of the graph at the frequency ½ of a cycle per quarter. This peak is marked by X-12-ARIMA as "visually significant" and is the dominant peak of the graph.

Note, however, that while it is possible to get this adjustment for the aggregate series, it is not the adjustment you get from a default run of X-12-ARIMA for the component series. The spectral graph for the default run of the component series is shown in Figure 4. There are no seasonal peaks whatsoever.

Figure 4: Spectral graph of the indirect adjustment, using default X-12 runs for the component series

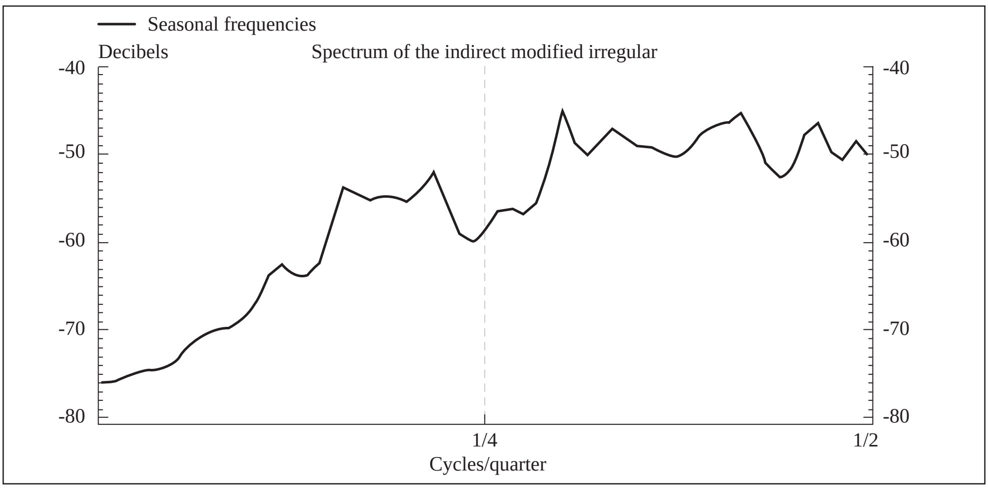
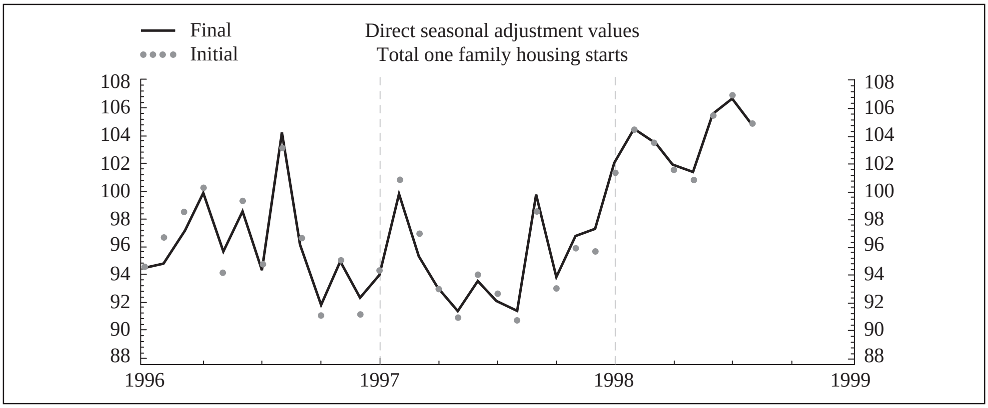


Figure 5: Revisions, initial to final, for the direct adjustment for US housing starts *(thousands)*



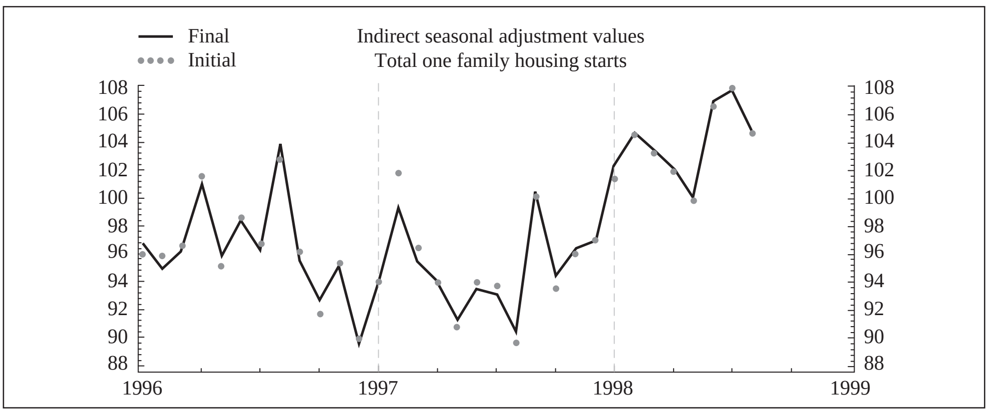

### *2.5 Example – revisions and smoothness in the aggregate series*

The Census Bureau publishes U.S. Single-Family Housing Starts for four regions of the United States: Northeast, Midwest, South, and West. All four series have somewhat similar seasonal patterns in that housing starts are higher in the summer and lower in the winter. Yet the drop in housing starts in the winter months is more pronounced in the Northeast and Midwest regions than in the South and West regions. Are the seasonal patterns similar enough for the direct adjustment to be of better quality than the indirect adjustment? We will look at some diagnostics.

We first checked the direct and indirect seasonal adjustments for residual seasonality. Both adjustments are acceptable. The next step is to make some decisions based on revisions.

The direct adjustment, initial and final, is shown in Figure 5, and the indirect adjustment, initial and final, is shown in Figure 6. The final seasonal adjustment is plotted with the solid line. Initial estimates for the adjustment are shown as the dots. We are looking for small revisions, i.e., the initial estimates that are as close as possible to the final adjustment. Both

Figure 6: Revisions, initial to final, for the indirect adjustment for US housing starts *(thousands)*



the direct and indirect adjustments have some places were there are large revisions – February and October of 1997 are two examples. However, there are more points with large revisions for the direct adjustment – see, for example, early 1996, December 1996, and November and December 1997.

We prefer the indirect adjustment for US Total Single Family Housing Starts because of the smaller revisions.

## 3. Other features of direct and indirect adjustments

### *3.1 Additional diagnostics in X-12-ARIMA*

X-12-ARIMA also contains the M and Q quality diagnostics developed at Statistics Canada and included in X-11-ARIMA. The M diagnostics are a set of 11 numbers that help the users see possible problems in the quality of the adjustments, and the Q diagnostic is a weighted average of the M diagnostics. They were designed so that any number greater than 1.0 signals a possible problem. X-11-ARIMA and X-12-ARIMA provide Ms and Qs for both the direct and indirect adjustment. While these numbers are useful in helping the user see some potential problems with the adjustments, they were not designed to be used to choose between the direct and indirect adjustment. In other words, if the diagnostics pass for both the direct and indirect adjustment, we should not base our decision on the superiority of direct or indirect adjustment on the adjustment with the superior M and Q statistics.

X-12-ARIMA also contains diagnostics for month-to-month (or quarter-to-quarter) percent changes to compare the smoothness of two adjustments. In addition, X-12-ARIMA computes smoothness measures for comparing the direct and indirect adjustment as introduced by X-11-ARIMA. Again, while smoothness may be a desirable property for some, it is not a priority at the Census Bureau.

### *3.2 Features of the ratio and difference of two adjustments of the same series*

In our experience at the Census Bureau, we have seen some users that attempt to judge the quality of the indirect adjustment by comparing it to the direct adjustment. One way to compare direct and indirect adjustments, especially when looking for smoothness, is to look at the ratio or the difference of the two adjustments. Now that we have looked at some ways to measure the adequacy and quality of aggregate adjustments, we will look at the difficulties involved in trying to compare the direct and indirect adjustments.

Under most circumstances, the direct and indirect adjustments for an aggregate series are not identical. There are some very specific cases when the direct and indirect adjustments could coincide, particularly if the adjustments are additive. For a multiplicative decomposition, the conditions required for identical adjustments are very restrictive. For more information, see Pfefferman *et al* (1984).

When comparing two adjustments of the same original series by looking at the series of their numerical ratios or differences, seasonal adjusters and data users sometimes see seasonal patterns. We will explain how this can happen even with successful seasonal adjustments.

Note: Any seasonal adjustment is an estimate, and therefore imprecise. If we take two seasonal adjustments of the same series and subtract them, the difference could be smaller in magnitude than the uncertainty surrounding each of the seasonal adjustments. In many cases, the differences between the two adjustments are smaller than the standard error of the irregular component, a natural measure of uncertainty.

To compare multiplicative adjustments, it is more natural to look at ratios instead of differences. With series that are adjusted additively, it is more natural to look at differences instead of ratios.

### *3.2.2 Apparent seasonality in the ratios and differences*

It is simple to show algebraically that residual seasonality in the ratio (and the difference if the adjustment is additive) of two adjustments of the same series can be a natural occurrence and not necessarily an indication of a problem in either adjustment. If you have two adjustments of the same series, and if the seasonal factors of both adjustments show very little evolution over time, then the ratio of the two adjusted series will be seasonal.

We will focus on quarterly adjustments in the equations below because they are somewhat simpler than the equations for monthly adjustment. Similar equations also hold for monthly series.

Let $Y_t$ be the original series. Let $St^{(1)}$ be one series of seasonal factor estimates. Let $St^{(2)}$ be a second series of seasonal factor estimates.

For multiplicative adjustment, the adjusted series, $A_t$ is the original series divided by the seasonal factor estimates. So from the two series of seasonal factors we have two different adjustments:

$$A_t^{(1)} = \frac{Y_t}{S_t^{(1)}} \text{ and } A_t^{(2)} = \frac{Y_t}{S_t^{(2)}}$$

If both seasonal factor estimates are periodic, i.e., $S_{t-4}^{(1)} = S_t^{(1)}$ and $S_{t-4}^{(2)} = S_t^{(2)}$ for all $\boldsymbol{t}$, then the ratio will be periodic also, and we will see a seasonal pattern in the ratio since

$$\frac{A_t^{(1)}}{A_t^{(2)}} = \frac{Y_t/S_t^{(1)}}{Y_t/S_t^{(2)}} = \frac{S_t^{(2)}}{S_t^{(1)}} = \frac{S_{t-4}^{(2)}}{S_{t-4}^{(1)}} = \frac{A_{t-4}^{(1)}}{A_{t-4}^{(2)}} \tag{1}$$

Let's look at a conceptual example. Suppose the seasonal factor for the first adjustment, $S_t^{(1)}$ is 1.07 for quarter one in the most recent year, telling us the original unadjusted quarter one numbers should be decreased by 7%. Let's also assume that the estimates of the seasonal factors for quarter one are reasonably stable ($S_{t-4}^{(1)} \approx S_t^{(1)}$), so that the estimates for the first quarter of every year are approximately 1.07. Let's say that the seasonal factor for the second adjustment, $S_t^{(2)}$, is 1.04 for quarter one in the most recent year and the estimates of the seasonal factors are stable. Therefore, when we divide both seasonal factors into the same original series, the ratio of the two seasonal factors (see equation (1) above) for every first quarter is 1.04/1.07 = 0.972. If the same kind of stability is found in the quarterly estimates for quarters two, three, and four, then we have a series of ratios that are periodic, we will observe a seasonal pattern in the ratio.

For additive adjustment, the basic principles are the same. The adjusted series, $A_t$ is the original series minus the seasonal factor estimates. To compare the two adjustments, we would take differences instead of ratios.

$$A_t^{(1)} - A_t^{(2)} = (Y_t - S_t^{(1)}) - (Y_t - S_t^{(2)}) = S_t^{(2)} - S_t^{(1)}$$

If both seasonal factor estimates are periodic, then the difference of the seasonal factors would also be periodic and therefore seasonal.

### 3.3 Example – direct/indirect ratio for total exports

We will compare a default X-12-ARIMA run for the direct adjustment to the indirect adjustment for US Total Exports. We will show that we can find residual seasonality in the ratio of the two adjustments. This finding does not suggest there is residual seasonality in either the direct or the indirect adjustment.

We first point out that the range of the differences (and of the ratios) are very small in magnitude compared to the original series. The differences are in the range of $1 or $2 billion, compared to the approximately $170 billion of Total Exports – on the order of 1% of Total Exports.

#### 3.3.1 Indirect adjustment for total exports

We can look at the spectral diagnostics in X-12-ARIMA to see if there is evidence of seasonality. The spectral graphs for the original (unadjusted) series and for the seasonally adjusted series are shown below.

Note that the spectrum of the original series in Figure 7 has a somewhat broad peak at both seasonal frequencies: ¼ cycle per year and ½ cycle per year. This is an indication of changing seasonality present in the original series. Notice that peaks at the seasonal frequencies are suppressed by the seasonal adjustment as shown in Figure 8. Therefore, we can conclude there is no estimable seasonal effect still present in the seasonally adjusted series.

Figure 7: Spectrum of the original series, quarterly total exports

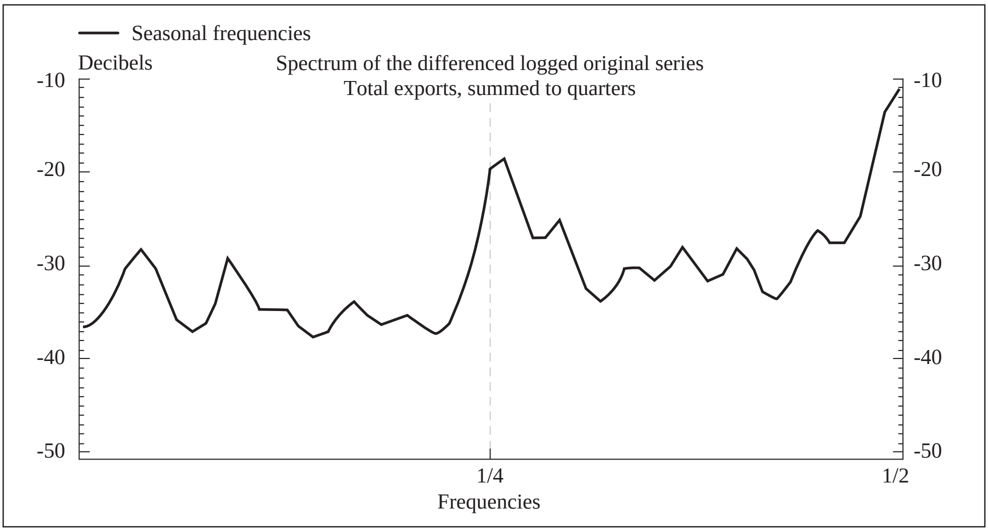
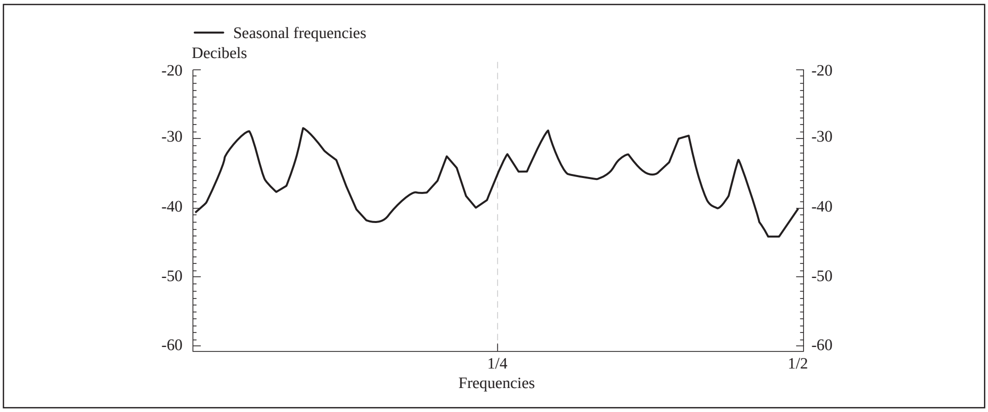


Figure 8: Total exports, spectrum of the seasonally adjusted series
*(Indirect adjustment)*




### *3.3.2 Direct adjustment for total exports*

We can do a similar analysis of the direct adjustment for Total Exports. If we do a default X-12-ARIMA run for Total Exports, we see no sign of residual seasonality for the direct adjustment as well.

### *3.3.3 Direct/indirect ratio*

Figure 9 shows the ratio of the direct and indirect adjustment for Total Exports in a year over year graph. We can see the indications of seasonality in the ratio. Generally, we see a first quarter to second quarter increase, a third quarter to fourth quarter decrease, and a fourth quarter to first quarter increase.

Figure 9: Total exports, ratio between the direct and indirect adjustments

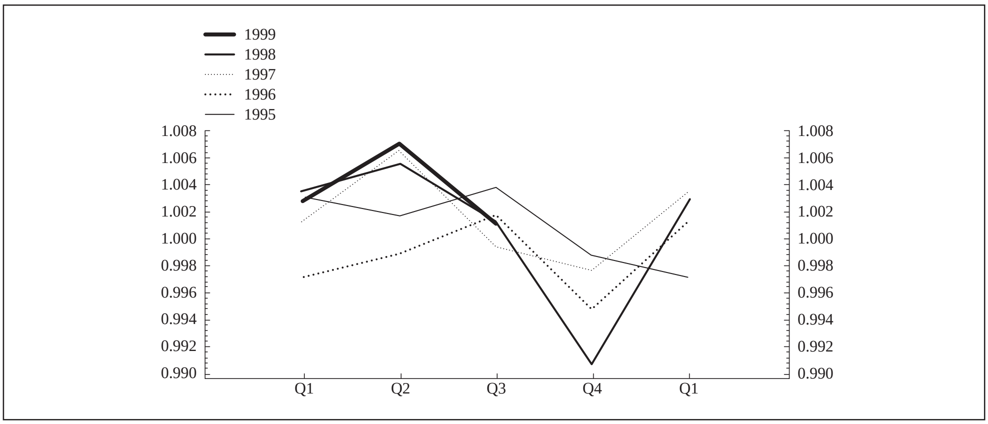
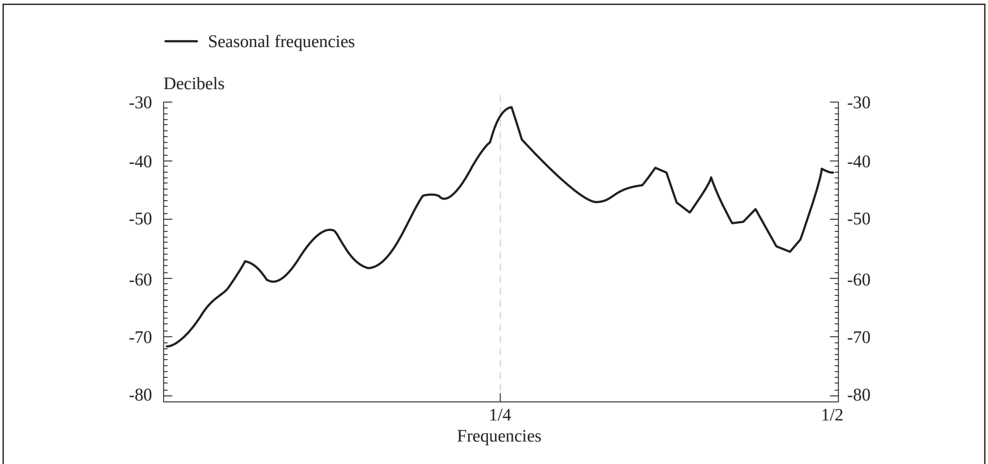


Figure 10: Spectral graph, ratio between the direct and indirect adjustments
*(Spectrum of the differenced original series – direct/indirect ratio using default direct adjustment)*




The X-12-ARIMA diagnostics showed signs of estimable seasonality, among them, the F test for stable seasonality was large enough, at 33.1, to show possible seasonality present. The spectral graph shown in Figure 10 also shows signs of moving seasonality in the ratio – broad peaks at ¼ and ½.

## 4. Possible future SEATS adjustments for selected series

We are researching the use of SEATS adjustments for some series. We expect that in the next two or three years, we might produce seasonal adjustments for some series from SEATS and for the rest from X-12-ARIMA, giving us an indirect adjustment from the seasonal adjustment of choice.

### *4.1 Potential benefits*

For some of our more irregular series, we can get smaller revisions with a SEATS adjustment. If the series is large enough in value, the improvement in the revisions can also be seen at the Total Import or Total Export level. There are other series where the adjustments from X-12-ARIMA have better diagnostics.

We have also found that for a majority of series, the seasonal adjustments from SEATS and X-12-ARIMA are almost identical. For this reason also, we are not concerned with mixing the adjustments from the two programs for an indirect adjustment. We expect that the totals will be very close even if we use SEATS for some series. We also intend to use SEATS only when there is a clear preference for the seasonal adjustment for SEATS.

Even with our expectations, we would still be very careful to investigate the diagnostics for the monthly and quarterly totals no matter the program that produced the adjustment.

### 4.2 Potential problems

In several of our earlier studies at the Bureau (Hood and Findley 1999; Hood, Ashley, and Findley 2000; and Hood 2002) we found that SEATS needs more diagnostics before we can recommend using SEATS for production work at the Bureau. We have been able to get X-12-ARIMA's spectral graphs for individual series run in SEATS, or in aggregate series with some SEATS adjustments by running the final seasonally adjusted series back through X-12-ARIMA. However, it was very difficult to get revision information from SEATS.

At the Census Bureau, we have a test version of X-12-ARIMA that has access to the SEATS algorithm. This allows computation of similar diagnostics for both programs to compare adjustments between the two programs, including revision diagnostics, and the ability to graph both adjustments in X-12-Graph.

Diagnostics for the SEATS adjustments are useful not only to make the comparison between the two programs much easier; in addition, the diagnostics can point to problems with the SEATS adjustment. For example, SEATS can induce residual seasonality into the seasonally adjusted series when the original series isn't seasonal. It is also possible to have unreasonably large revisions when TRAMO selects certain types of models. For more information, please see Hood (2002).

Because of the potential problems with SEATS adjustments, we want to be very careful before recommending a SEATS adjustment for a particular series.

## 5. Conclusions

Spectral and revision diagnostics for the aggregate adjustment can be very helpful in determining the best level of aggregation for a particular set of series.

When two competing estimates of the seasonal factors of a time series are both rather stable, in the sense that each calendar month's (or calendar quarter's) factor changes little from one year to the next, then the factors from the two adjustments will differ in a consistent way. The presence of such a seasonal component does not, by itself, indicate inadequacy in either of the adjustments.

No matter the seasonal adjustment software used, it is very important to be able to have access to diagnostics. Though we see potential for SEATS adjustments at the Census Bureau, some care should be taken with SEATS adjustments. SEATS can induce seasonality into the seasonal adjustment of a nonseasonal series. The spectral diagnostics available in X-12-SEATS are very important to be able to see if the original series is seasonal or not and if there exists residual seasonality in the seasonally adjusted series or the irregular component.

## 6. Acknowledgements

We are grateful to Brian Monsell for his software support with X-12-ARIMA and to Kathy McDonald-Johnson for her help with the research. We also thank Agustin Maravall for his advice and instruction on how to use TRAMO/SEATS, and Kathy, Brian, David Dickerson, Diane Oberg, William Bell, Michael Shimberg and Nash Monsour for comments on earlier versions of the paper.

## 7. References


Dagum, E. B., (1979), On the Seasonal Adjustment of Economic Time Series Aggregates: A Case Study of the Unemployment Rate, *Counting the Labor Force, National Commission on Employment and Unemployment Statistics*, Appendix, 2: 317-344.

Findley, D. F., D. E. K. Martin, and K. C. Wills, (2002), Generalizations of the Box-Jenkins Airline Model, to be published in the *Proceedings of the Business and Economics Section*, American Statistical Association: Alexandria, VA.

Findley, D. F., B. C. Monsell, W. R. Bell, M. C. Otto and B.-C. Chen, (1998), New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program (with discussion), *Journal of Business and Economic Statistics,* 16: 127-176.

Findley, D. F., B. C. Monsell, H. B. Shulman, and M. G. Pugh, (1990), Sliding Spans Diagnostics for Seasonal and Related Adjustments, *Journal of the American Statistical Association*, 85: 345-355.

Hood, C. C., (2001), X-12-Graph: A SAS/GRAPH® Program for X-12-ARIMA Output, User's Guide for the X-12-Graph Interactive for PC/Windows, Version 1.2, Bureau of the Census, U.S. Department of Commerce.

Hood, C. C., (2002), Comparison of Time Series Characteristics for Seasonal Adjustments from SEATS and X-12-ARIMA, to be published in the *Proceedings of the Business and Economics Section*, American Statistical Association: Alexandria, VA.

Hood, C. C., J. D. Ashley, and D. F. Findley, (2000), An Empirical Evaluation of the Performance of TRAMO/SEATS on Simulated Series, *Proceedings of the Business and Economics Section*, American Statistical Association: Alexandria, VA.

Hood, C. C. and D. F. Findley, (1999), An Evaluation of TRAMO/SEATS and Comparison with X-12-ARIMA, *Proceedings of the Business and Economics Section,* American Statistical Association: Alexandria, VA.

Pfefferman, D., E. Salama, and S. Ben-Turvia, (1984), On the Aggregation of Series: A New Look at an Old Problem, Working paper, Bureau of Statistics, Jerusalem, Israel.

U.S. Census Bureau, (2002), *X-12-ARIMA Reference Manual, Final Version 0.2,* Washington, DC: U.S. Census Bureau.

# 2

# A class of diagnostics in the ARIMA-model-based decomposition of a time series

Agustín Maravall

## 1. Introduction

At present, the most widely used methods for seasonal adjustment are X12 (or X11)-ARIMA (thereafter, X12A; see Findley et al., 1998) and TRAMO/SEATS (see Gómez and Maravall, 1996). The former emerged from the X11 filters, which have provided for nearly four decades an evolving paradigm. TRAMO/SEATS originated from the ARIMA-model-based (AMB) approach to seasonal adjustment of Burman (1980), Hillmer and Tiao (1982), and others.

Over the years, X12A has incorporated an important set of diagnostics and quality assessment checks, often based on prior beliefs on how "reasonable" components (such as the seasonal, trend-cycle or irregular ones) should behave. But, despite the fact that one of the large potentials of the model-based approach is the possibility of using parametric statistical inference to derive statistical tests in a straightforward manner and, despite a considerable amount of methodological work, this potential has not yet been developed. (Some references of this work are Bell, 1995; Bell and Hillmer, 1984; Box, Pierce and Newbold, 1987; Burridge and Wallis, 1985, 1984; Cleveland and Pierce, 1981; Cleveland and Tiao, 1976; Hillmer, 1985; Maravall, 1987, 1995; Maravall and Planas, 1999; Pierce, 1980, 1979; Tiao and Hillmer, 1978.)

In this paper I focus on tests derived from the joint distribution of the optimal (Minimum Mean Square Error, or MMSE) estimators of the unobserved components. Knowledge of this joint distribution (derived simply from the ARIMA model for the observed series) provides a powerful tool for inference, and it is seen how a large variety of tests can be obtained, some of which are closely related to X12A diagnostics. Yet the information provided by the two approaches is notably different. While X12A provides a quality assessment of the estimated component (is seasonality reasonably stable? is the trend contaminating the irregular? …), the SEATS diagnostics provide specification-type test (is the sample estimate of the variance of the seasonal component in agreement with the theoretical variance of the MMSE estimators? Are the sample autocorrelation estimates in agreement with these implied by the estimator model? Are empirical revisions too large for what they should theoretically be?) Viewed in this way, the information given by the two approaches can be seen as complementary. In the AMB approach, the failure of some test is likely to point out some weak part of the model, and hence the test can be of help in finding an improved specification.

## 2. The motivation: an introductory example

Some years back, when seasonally adjusting a component of a monetary aggregate (Maravall, 1987), an X11ARIMA (Dagum, 1980) quality assessment check said: "too much autocorrelation in the irregular component". I asked myself: Why is it too much? How much should there be? After all, different series yield X11A-irregulars with different autocorrelation. When is the autocorrelation too much? What the diagnostic meant was that, although we do not know how much autocorrelation should be present in the irregular estimator, we do not like an irregular with that amount of correlation. It is more a Quality Assessment check (which can certainly be useful), but not a statistical test. This remark also characterizes other X12A diagnostic checks, such as, for example, the "sliding spans" diagnostics (Findley et al., 1990).

These quality assessment checks can also be applied in an identical manner to the estimates obtained with the ARIMA-model-based procedure of SEATS (and, in fact, work is being presently done at the US Bureau of the Census in this direction.) But there is also another important application that emerges from translating these checks into statistical tests, by means of the model-based structure. The (asymptotic) joint distribution of the estimators can be derived, and for example, it is possible to find the theoretical autocorrelation for the irregular estimator, from which the question: "how much is *too much*?" can be answered.

## 3. One type of model-based tests (or diagnostics)

Assume that the variable $x_t$ follows the ARIMA model

$$\phi(B)\ \delta(B)\ x_t = \theta(B)\ a_t, \tag{1}$$

where $a_t$ is a white-noise (w.n.) variable (i.e., a $\text{niid}(0, V_a)$ variable), $\phi(B)$ denotes the stationary AutoRegressive (AR) polynomial in the backward operator B, $\delta(B)$ denotes the non-stationary polynomial containing the unit roots (or differences, such as for example, $\delta(B) = \nabla\nabla_{12}$), and $\theta(B)$ is the invertible Moving Average (MA) polynomial in B (see Box and Jenkins, 1970). To standardize units, I set $V_a = 1$.

Let $x_t$ be the sum of two uncorrelated unobserved components (UC)

$$x_t = s_t + n_t, \tag{2}$$

(as in, for example, $x_t$= Seasonal Component + Seasonally Adjusted (SA) series.) Finding the roots of the AR polynomials and assigning them to $s_t$ or $n_t$ according to their associated frequency, $\delta(B)$ and $\phi(B)$ can be factorized as

$$\delta(B) = \delta_s(B)\ \ \delta_n(B)$$
$$\phi(B) = \phi_s(B)\ \ \phi_n(B)$$

(For example, if $\delta(B) = \nabla\nabla_{12} = \nabla^2 S$, where $S = 1 + B + B^2 + ... + B^{11}$ contains the seasonal unit roots, then, $\delta_s(B) = S$, $\delta_n(B) = \nabla^2$.) Models for the UC are derived in SEATS, that are of the type:

$$\phi_s(B)\ \ \delta_s(B)\ \ s_t = \theta_s(B)\ \ a_{st}, \tag{3}$$

$$\phi_n(B)\ \ \delta_n(B)\ \ n_t = \theta_n(B)\ \ a_{nt}, \tag{4}$$

where $a_{st}$ and $a_{nt}$ are mutually uncorrelated UC innovations, with zero mean and variances equal to $V_s$ and $V_n$, respectively. The MA polynomials $\theta_s$ (B), $\theta_n$ (B), as well as the variances $V_s$ and $V_n$, are determined from the identity

$$\theta(B)\ \ a_t = \theta_s(B)\ \ \phi_n(B)\ \ \delta_n(B)\ \ a_{st} +\ \theta_n(B)\ \ \phi_s(B)\ \ \delta_s(B)\ \ a_{nt}$$

together with some additional assumptions (see Maravall, 1995). The previous identity assures consistency between the model for the observed series and the ones for the components; the rest of the discussion is valid for any admissible decomposition, independently of the identification assumptions.

Expressions (3) and (4) provide models for the theoretical components. These components are never observed and will be estimated by their MMSE estimators. For the case of $s_t$, and assuming a doubly infinite realization, the estimator is given by

$$\hat{s}_t = \nu_s(B,F)\ x_t\ ,\ (F = B^{-1}),$$

where $\nu_s(B,F)$ is the Wiener-Kolmogorov (WK) filter. In a symbolic manner, the filter can be obtained from

$$\nu_s(B,F) = V_s\ \frac{\psi_s(B)\ \psi_s(F)}{\psi(B)\ \psi(F)}\ x_t\ ,$$

where $\psi_.(B) = \dfrac{\theta_.(B)}{\phi_.(B)}$. Replacing $x_t$ by $\psi(B)\ a_t$, after cancellation of terms, it is obtained:

$$\delta_s(B)\ \hat{s}_t = V_s\left[\frac{\theta_s(B)}{\phi_s(B)}\ \frac{\theta_s(F)\ \delta_n(F)\ \phi_n(F)}{\theta(F)}\right]\ a_t\ , \tag{5}$$

where the left-hand-side (l.h.s.) is the stationary transformation of the component, and the r.h.s. is an MA (convergent in B and in F) which can be easily obtained. Writing, in compact form,

$$\delta_s(B)\ \hat{s}_t = \eta_s(B)\ a_t \tag{6}$$

where $a_t$ is, as before, the innovation in the observed series, $\eta_s(B)\ a_t$ is a stationary, zero mean process, and its variance and autocorrelations can be computed. In this way, the variance and autocorrelations of the (theoretical) MMSE estimator are obtained. They will be different from the variance and autocorrelations of the theoretical component, given by (3).

In summary, in the AMB approach (SEATS), we know the asymptotic distribution of (the stationary transformation) of the optimal estimator, and we can use this for testing. (A similar conclusion holds for $\delta_n(B)\ \hat{n}_t$.)

Back to the example that gave the message: “Too much autocorrelation in the irregular component”, assume the irregular component $u_t$ is w.n. $(0,V_u)$. Letting $s_t$ become $u_t$, expression (5) implies that the estimator $\hat{u}_t$ has the AutoCorrelation Function (ACF) of the model

$$\theta(B)\ y_t = \phi(B)\ \delta(B)\ a_t^*, \tag{7}$$

where $a_t^*$ is a w.n. $(0, V_u)$ variable. (Model (7) is the “Inverse Model” of model (1).) Hence, having the model for $x_t$, we know the ACF of the irregular component estimator.

Assumed we have to treat many, many series and that no automatic model identification procedure such as TRAMO is available. We decide thus to use an “ad-hoc” fixed filter, namely the WK filter associated with the model

$$\nabla\nabla_{12}x_t = (1 - .4B)\ (1 - .6B^{12}), \tag{8}$$

for all series. (This model is the original Airline model of Box-Jenkins, 1970.) Cleveland-Tiao (1976) showed that this model yields filters not far from those of the default application of X11. Besides, it seems safe to assert that it is not far from what could be the "mode model" of a hypothetical overall empirical distribution of models.

Consider one of the treated series, with, say, 144 monthly observations we look at the actual estimate of the irregular, and compute the first-order sample autocorrelation

$$\hat{\rho}_1(\hat{u}_t) = .32$$

(having one year removed at both ends to attenuate end-point effects.) Is .32 "too much AC"?

The AMB answer is straightforward. For model (8), the ACF of $\hat{u}_t$ is that of the model:

$$(1-.4B)\ (1-.6B^{12})\ y_t = (1-B)\ (1-B^{12})\ a_t^*,$$

so that the theoretical $\rho_1$ of $\hat{u}_t$ is

$$\rho_1(\hat{u}_t) = -.30\,.$$

The empirical and theoretical values ($\hat{\rho}_1$ = .32 and $\rho_1$ = -.30, respectively) seem far, but we need a measure of distance. From Bartlett's approximation (see Box and Jenkins, 1971; Priestley, 1981),

$$V(\hat{\rho}_k) \doteq \frac{1}{T} \sum_{j=-m}^{m} \left[\rho_j^2 + \rho_{j+k}\ \rho_{j-k} + 2\ \rho_k^2\ \rho_j^2 - 4\ \rho_k\ \rho_j\ \rho_{j-k}\right]$$

where all ρ's refer to $\hat{u}_t$, and the ones in the r.h.s. are those in the theoretical ACF of $\hat{u}_t$; m denotes the truncation point, such that $\rho_j \approx 0$ for $|j| > m$.

For our example, it is obtained that SD ($\hat{\rho}_1$) = .074, thus a 95% Confidence Interval around $\hat{\rho}_1$, equal to [$\hat{\rho}_1 \pm 2$ SD ($\hat{\rho}_1$) ], yields the interval [.17, .47 ]. Clearly, $\rho_1$ = -.30 is not inside the interval, and hence we can conclude "there is too much (positive) AC in the irregular component".

This (unacceptable) positive autocorrelation in the irregular component could be due to misspecification of the trend-cycle component. In fact, for this series, a (0, 2, 2) (0, 1, 1) $_{12}$ model performs considerably better. The irregular autocorrelations become $\rho_1(\hat{u}_t) = -.83$ and $\hat{\rho}_1(\hat{u}_t) = -.82$, with $SD(\hat{\rho}_1) = .04$. The value $\rho_1 = -.84$ now lies comfortably in the 95% confidence interval [-.74 , -.90 ].

## 3. Testing versus quality assessment

In the previous example, the theoretical $\rho_1$ was $\rho_1$ = -.83, which implies that $\hat{u}_t$ has important autocorrelation for the 6-times-a-year seasonal frequency, a somewhat "ugly" feature for an irregular component.

What the AMB test says is, in essence, "your empirical results are in agreement with your model". Thus it is basically a specification test. Of course, the data and the model can be in agreement, but perhaps the model has an ugly decomposition (a clearly stationary seasonal component would provide a good example of an ugly seasonal component). Therefore, quality assessments of the X12 ARIMA type can be of help in this respect: they can, for example, discriminate among models that offer nice or nasty decomposition.

## 4. Tests based on the distribution of the estimators

The previous example provided a test for the first-order autocorrelation of the irregular component estimate. This test was based on the distribution of the stationary transformation of the estimator.

Extensions are straightforward. For example, we can compare $\rho_{12}(\hat{u}_t)$ with $\hat{\rho}_{12}(\hat{u}_t)$, test for $H_0 : \hat{\rho}_{12} = \rho_{12}$, and, for example, when $\hat{\rho}_{12}$ is significantly larger than $\rho_{12}$, conclude that: "there is too much seasonality in the irregular". The test can also be extended to other components such as, for example, the SA series (say $\hat{n}_t$). From the model for $\hat{n}_t^{ST} = \delta_n(B)\ \hat{n}_t$, we derive $\rho_{12}(\hat{n}_t^{ST})$. From the actual estimate, we compute the empirical autocorrelation $\hat{\rho}_{12}(\hat{n}_t^{ST})$. Using Bartlett's approximations, we obtain SD $(\hat{\rho}_{12})$. Again, we can test for $H_0 : \hat{\rho}_{12} = \rho_{12}$ and, if $\hat{\rho}_{12}$ is significantly larger than $\rho_{12}$, conclude that: "there is too much seasonal autocorrelation in the SA series".

We can also think of more general tests. For example, a test for under/over-estimation of seasonality (or under/over-adjustment).

A given filter may, on occasion, capture too much variation as seasonal, or not capture all seasonal variation. This will happen when the widths of the filter squared gain peaks for the seasonal component (or dips for the SA series) are too wide or too narrow, when compared to the seasonality actually present in the series. To see what goes on, consider for example the (default) model

$$\nabla \nabla_{12}\ x_t = (1 + \theta_1\ B)\ (1 + \theta_{12}\ B^{12})\ a_t , \qquad (9)$$

As $\theta_{12} \rightarrow -1$, in the limit, the model becomes

$$\nabla x_t = \sum_{i=1}^{11} \beta_i\ d_{it} + (1 + \theta_1\ B)\ a_t + \mu ,$$

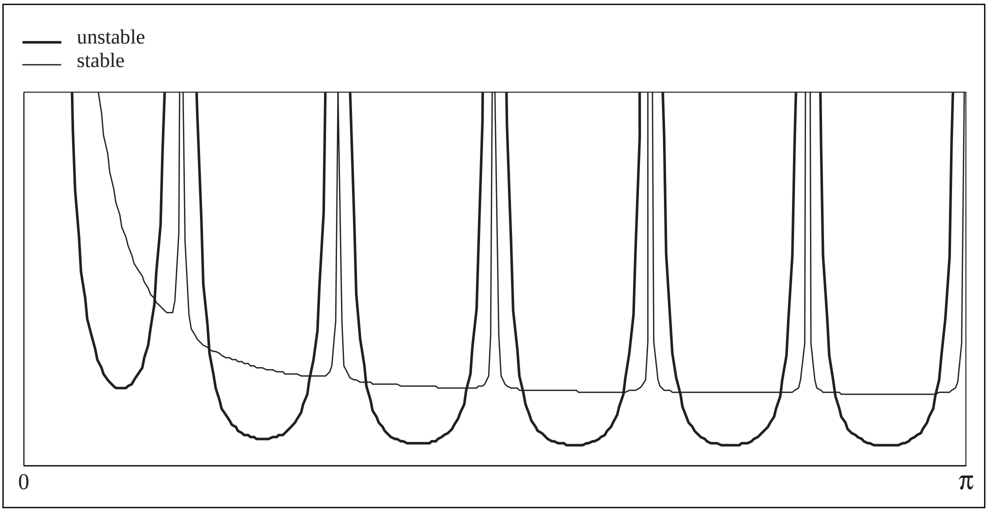
where $d_{it}$ represents the seasonal dummies, and hence the series displays perfectly stable seasonality. In general, values $\theta_{12} \cong -1$ will produce stable seasonality, while values of $\theta_{12}$ far from $-1$will produce unstable (highly moving) one. We set $V_a = 1$, $\theta 1 = -.6$, and consider two values for $\theta_{12}$:

* $\theta_{12} = 0 \quad \Rightarrow$ unstable seasonality.

* $\theta_{12} = -.9 \quad \Rightarrow$ stable seasonality.

Comparison of the two spectra evidences the difference in width of the seasonal peaks.

Figure 1: Series with stable and unstable seasonal




Denote by $\nu(B, F)$ the fixed (ad-hoc) filter to estimate the seasonal component (or SA series). Set, for example, $\nu(B, F)$ = (linear) X11 default filter, which we represent as

$$\nu(B, F) = \nu_0 + \sum_{j=1}^{k} \nu_j (B^j + F^j)$$

The Fourier Transform (F.T.) of the filter is called the filter gain, equal to

$$G(\omega) = \nu_0 + 2 \sum_{j=1}^{k} \nu_j \cos(j\omega) \ ,$$

where $\omega$ is the frequency measured in radians and $0 \le \omega \le \pi$; the squared gain of the filter is given by

$$SG(\omega) = [G(\omega)]^2$$

Let $g_y(\omega)$ denote the spectrum (or pseudo-spectrum) of the variable $y_t$.
From $\hat{s}_t = \nu(B, F)\, x_t$, one obtains

$$g_{\hat{s}}(\omega) = SG_s(\omega)\; g_x(\omega) \tag{10}$$

Likewise, for the SA series ($n_t$)

$$g_{\hat{n}}(\omega) = SG_n(\omega)\; g_x(\omega)\,. \tag{11}$$

The functions $g_{\hat{s}}(\omega)$ and $g_{\hat{n}}(\omega)$ are the spectra of the estimators of the seasonal component and SA series. We can compare them to the spectrum of the series.

a) Unstable seasonality and underestimation

Figure 2a: Underestimation of seasonality: seasonal component

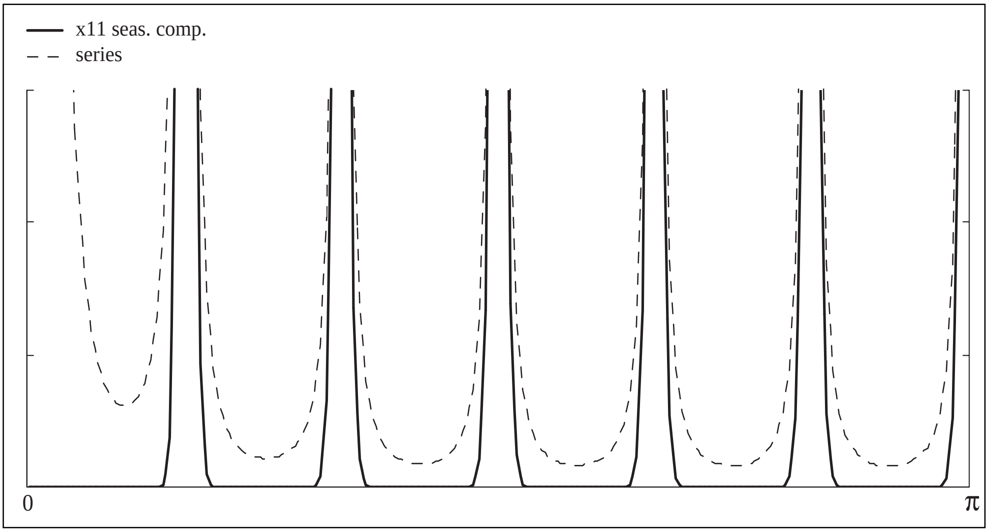
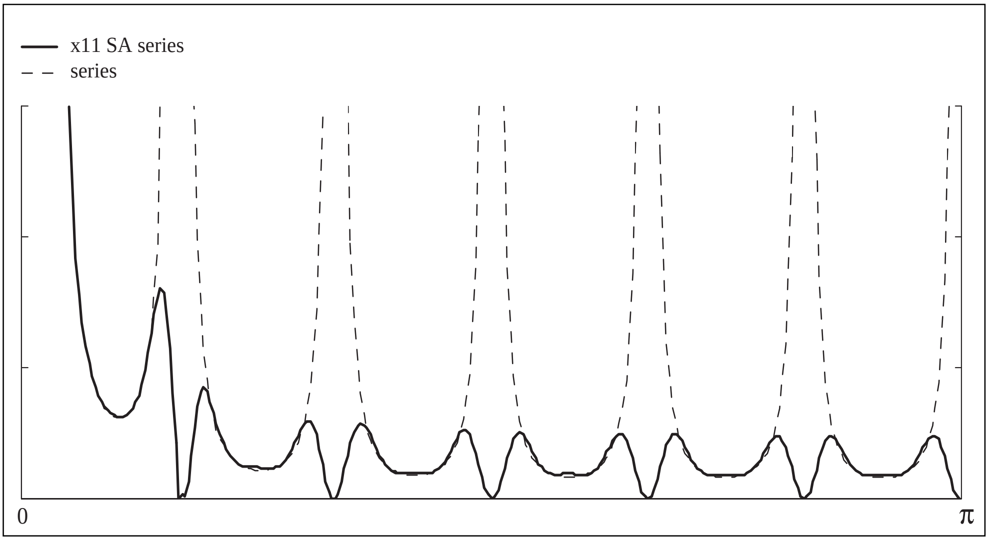



Figure 2b: Underestimation of seasonality: SA series




Residual seasonality (evidenced by peaks in the neighbourhood of the seasonal frequencies) shows up – in an awkward manner – in the SA series.

b) Stable seasonality and overestimation

Figure 3a: Overestimation of seasonality: seasonal component

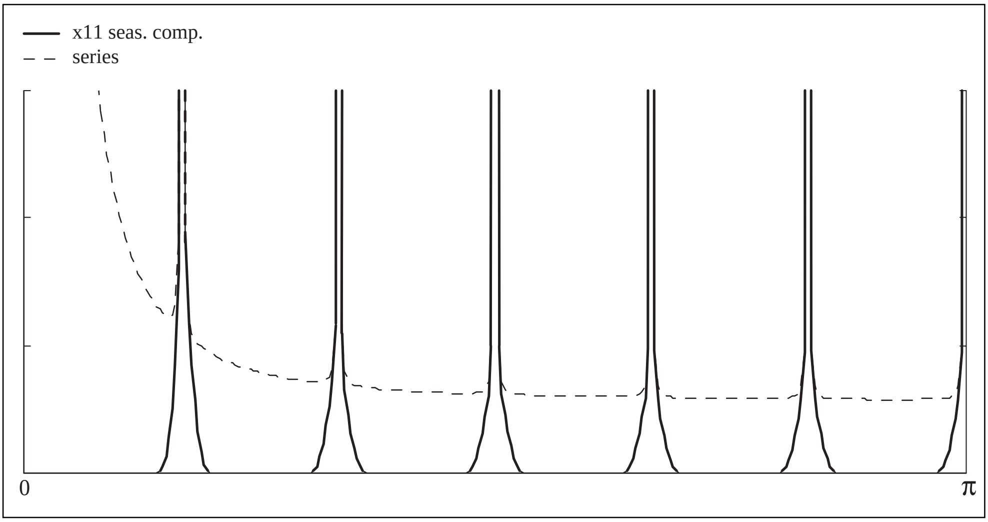
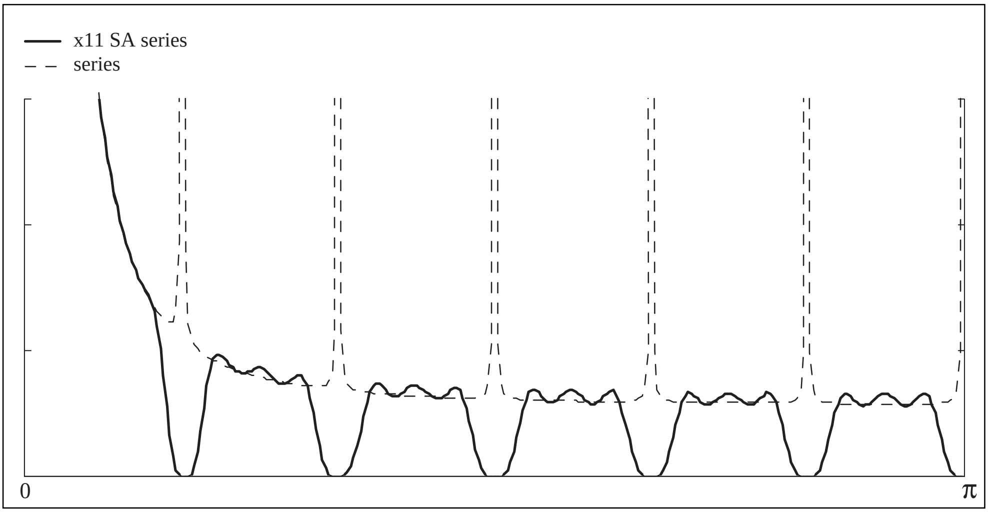



Figure 3b: Overestimation of seasonality: SA series




Holes induced in the SA series are clearly too wide.

Using, on the two series, SEATS by default (in which case, the orders of the model are those of the Airline model), estimation of the parameters allows the WK-filter $\nu_s\,(B, F)$ to adapt to the particular stochastic structure of the series. The F.T. of $\nu_s\,(B, F)$ is the Gain:

$$G_s(\omega) = g_s(\omega) \,/\, g_x(\omega)$$

and as before, the spectra of the estimators of the seasonal component and SA series are given by (10) and (11). Comparing these two spectra to the one of the series:

a) Unstable seasonality case (SEATS)

Figure 4a: Unstable seasonality: SEATS seasonal component

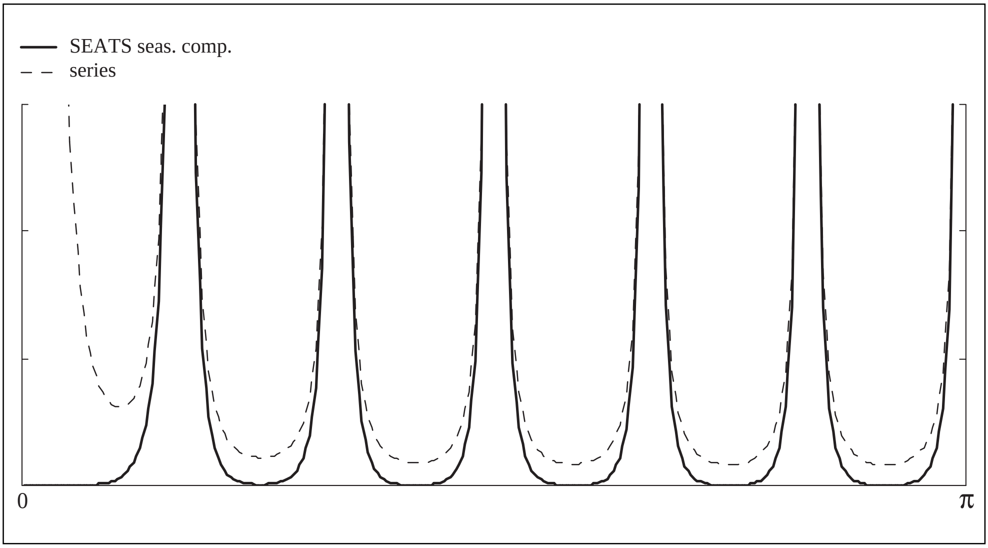
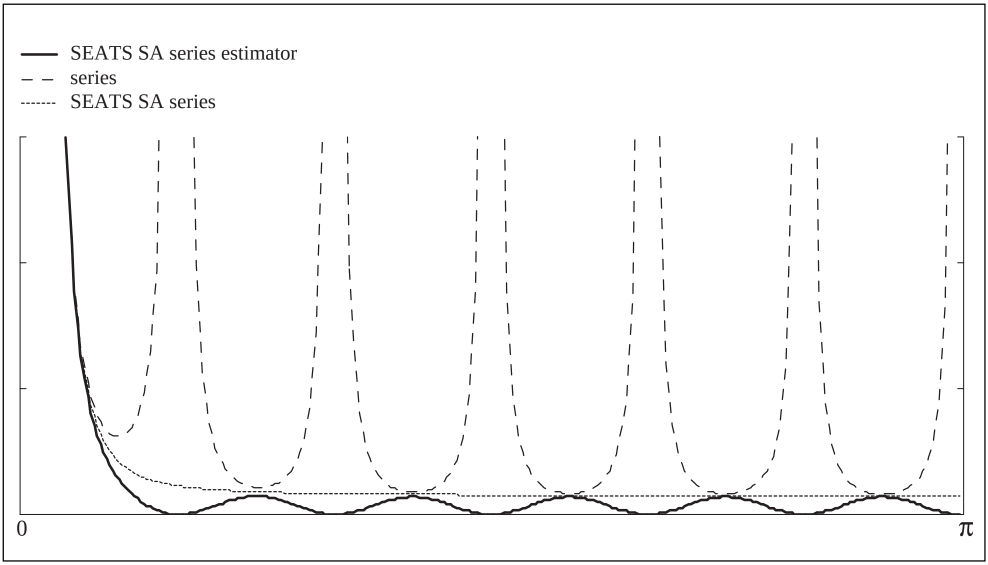



Figure 4b: Unstable seasonality: SEATS SA series




It is seen that the large peaks in the neighbourhood of the seasonal frequencies have disappeared.

b) Stable seasonality case (SEATS)

Figure 5a: Stable seasonality: SEATS seasonal component

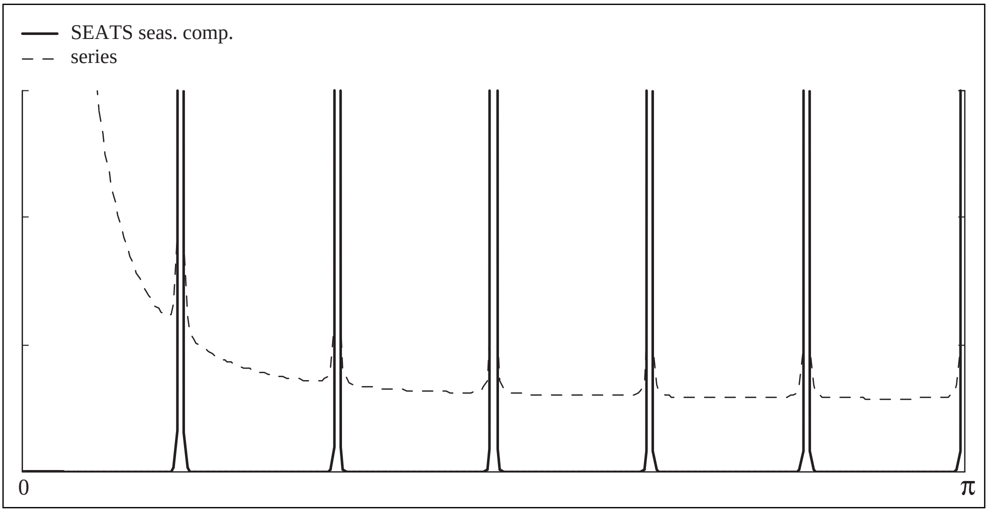
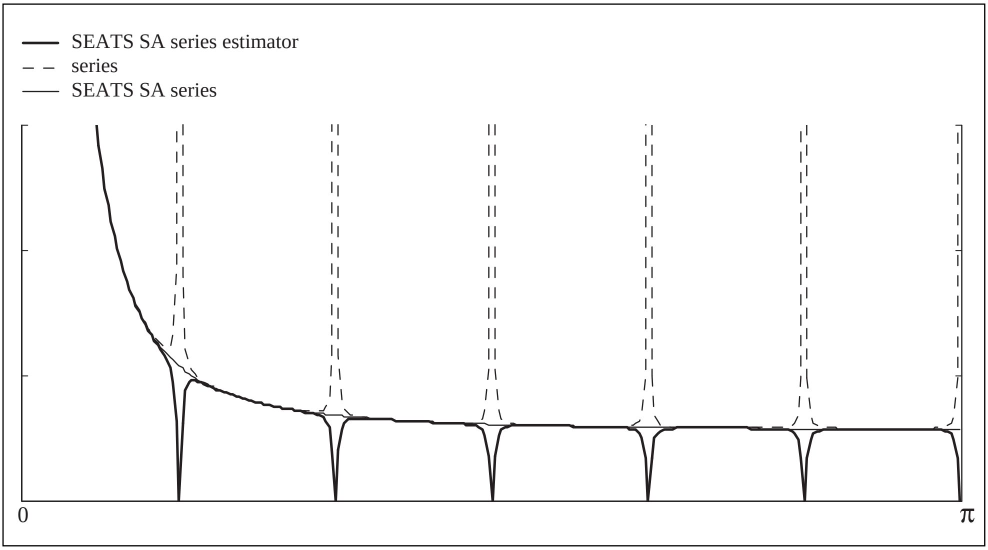



Figure 5b: Stable seasonality: SEATS SA series




The estimator adapts to the structure of the series so that the width of the spectral holes in the SA series are determined from the width of the seasonal peaks in the series spectrum.

### Testing for under/over adjustment

If we compare the spectra of the estimators of the SA series in the previous two examples, it is seen how under estimation of seasonality implies excess variance in the SA series, while over estimation of seasonality implies that the variance of the SA series is too small.

Figure 6a: Unstable seasonality: estimator of the SA series

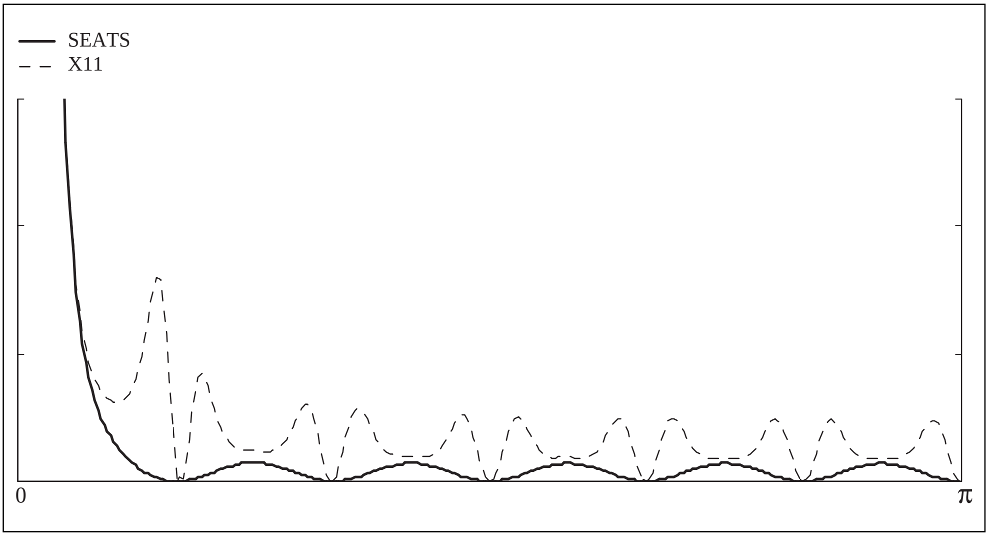
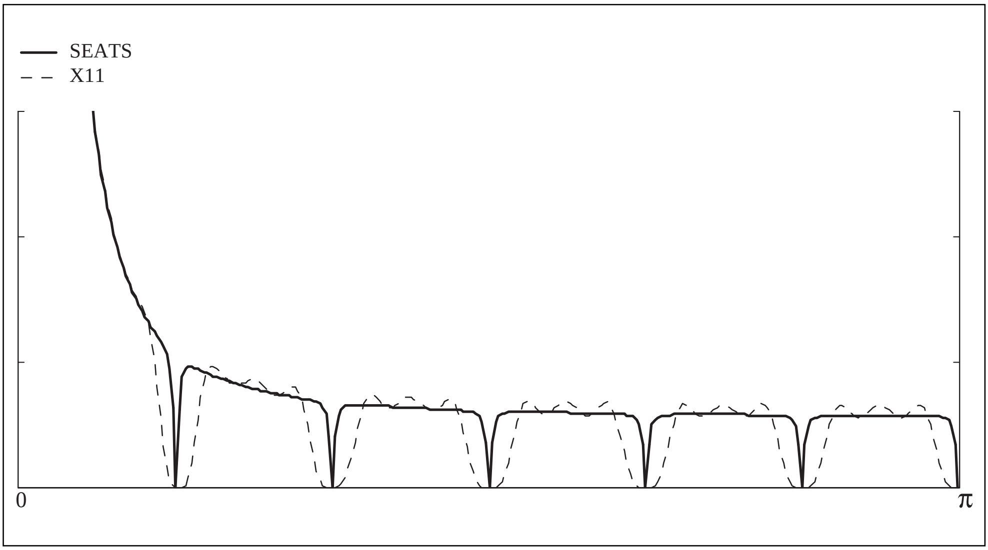



Figure 5b: Stable seasonal: estimator of the SA series



The example illustrates the general fact that, when the seasonality present in the series is very stable, with little stochastic variation, the filter may overadjust (remove too much variation as seasonal). On the contrary, when seasonality is unstable, and the series presents highly stochastic seasonal variation, the filter may underadjust (not remove all seasonal variation). In other words, under adjustment implies underestimation of the seasonal component variance, while over-adjustment implies overestimation of the seasonal component variance; they are, thus, the result of under/over estimation of a component variance.

Proceeding as before, from model (5) for the estimator $\hat{s}_t$, we know the theoretical value of the variance of the stationary transformation of the component estimator $V_{\hat{s}}$. We can use again Bartlett's approximation to compute the standard deviation of this variance estimator

$$\mathrm{SD}\ (\hat{V}_{\hat{s}}) = V_{\hat{s}} \left[ \frac{2}{T} \left( 1 + 2 \sum_{j=1}^{m} \rho_j^2 \right) \right]^{\frac{1}{2}} ,$$

where $\rho_j$ are the autocorrelations implied by model (5). Then, we can test for whether is $H_0 : \hat{V} = V$ rejected or not. If, for example, $S_t$ = seasonal component, and we have obtained

$$V_{\hat{s}} = .067 \qquad \hat{V}_{\hat{s}} = .100 \qquad (\mathrm{SD} = .010)$$

we would conclude that there is "evidence of overestimation of seasonality".

One can think of many extensions. An important one is the following. Although the theoretical components are uncorrelated, it is well known (see Nerlove, Grether, and Carvalho, 1979) that MMSE estimation will induce some crosscorrelation between them. From model (5), and the equivalent expression for $\hat{n}_t$, we can obtain the theoretical crosscovariance and crosscorrelation functions for any pair of estimators (Gómez-Maravall, 2001). Further, the Bartlett's approximations can also be extended to the estimators of these correlations. Therefore, as before, we can for example build a test that may say: "There is too much correlation between the seasonal and irregular estimators".

As a last extension, I shall very briefly mention the sliding spans diagnostics included in X12 ARIMA; in short, one finds first the percentage of months with unreliable adjustment. To find if the adjustment for a month is "unreliable", the program adjusts several overlapping subspans of the series, and looks at the variation of the estimated seasonality for that month with the different subspans. When that variation is larger than a pre-selected amount k, the adjustment for that month is judged "unreliable". If the frequency of unreliable months is more than 25%, the series should not be adjusted.

This check can also be applied, in an identical manner, to SEATS as a "quality" diagnostics in the sense of having a "nice" seasonal. But, given that the variation considered in the diagnostic is related to the revisions in preliminary estimators, in the AMB approach, for any given model, one could compute for example the measure (Maravall, 1998),

$$\mathrm{Prob}\ [\ |\hat{s}_t - \hat{s}_{t|t}| > k\ ]$$

where $\hat{s}_t$ = final estimator, and $\hat{s}_{t|t}$ = concurrent estimator of $\hat{s}_t$, obtained with the series finishing with $x_t$. This measure provides the probability that the variation from concurrent to final seasonal component estimator, for any given month, is larger than a threshold level k. Letting $d_t$ denote the revision in the concurrent estimator

$$d_t = \hat{s}_t - \hat{s}_{t|t},$$

the model for $d_t$ is easily obtained (Pierce, 1980) and the probability $P\ (|d_t| > k)$ can be computed. This probability would be the theoretical value associated with the optimal estimator. Given k, P ( $|d_t|$ > k) is something fully determined from the ARIMA model for the observed series. For some models the probability will be large (even above .25); for some models, it will be small. Be that as it may, optimal (MMSE) estimation of the components imply that probabilities such as the above take some particular values. Thus, as was the case with the variance and auto/cross-correlations of the estimators, comparison of this "theoretical" value with the frequency detected in the sample can provide an AMB diagnostic. Large differences between this sample frequency and the probability implied by the model, or failure of the sliding-spans diagnostic in X12 ARIMA would mean different things. So to speak, X12A would be telling us: "$\hat{s}_t$ is not nice because it moves too fast", while failure of the test in the AMB approach would say: "The model specified is not in agreement with the empirical revisions in your concurrent estimates" (again, a specification-type test). Both the X12A and the AMB results provide relevant and different information, that complement each other. However, while a bad diagnostic in X12 ARIMA can be due to the use of an inadequate filter or to the fact that the series is wild beyond hope, in the AMB approach, failure of a test is likely to point out which parts of the model may be mis specified.

## References

Bell, W. R., (1995), Seasonal Adjustment to Facilitate Forecasting. Arguments for Not Revising Seasonally Adjusted Data, *Proceedings of the American Statistical Association*, Business and Economics Statistics Section.

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. and Jenkins, G. M., (1970), *Time Series Analysis: Forecasting and Control*, San Francisco: Holden-Day.

Box, G. E. P., Pierce, D. A. and Newbold, P., (1987), Estimating Trend and Growth Rates in Seasonal Time Series, *Journal of the American Statistical Association* 82, 276-282.

Burman, J. P., (1980), Seasonal Adjustment by Signal Extraction, *Journal of the Royal Statistical Society* A, 143, 321-337.

Burridge, P. and Wallis, K. F., (1985), Calculating the Variance of Seasonally Adjusted Series", *Journal of the American Statistical Association* 80, 541-552.

Burridge, P. and Wallis, K. F., (1984), Unobserved Components Models for Seasonal Adjustment Filters, *Journal of Business and Economic Statistics* 2, 350-359.

Cleveland, W. P. and Pierce, D. A., (1981), Seasonal Adjustment Methods for the Monetary Aggregates, *Federal Reserve Bulletin*, Board of Governors of the Federal Reserve System, December 1981, 875-887.

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.

Dagum, E. B., (1980), The X11 ARIMA Seasonal Adjustment Method, Statistics Canada, Catalogue 12-564e.

Findley, D. F., Monsell, B. C., Bell, W. R., Otto, M. C. and Chen, B. C., (1998), New Capabilities and Methods of the X12 ARIMA Seasonal Adjustment Program (With Discussion), *Journal of Business and Economic Statistics*, 12, 127-177.

Findley, D. F., Monsell, B. C., Schulman, H. B. and Pugh, M. G., (1990), Sliding-Spans Diagnostics for Seasonal and Related Adjustments, *Journal of the American Statistical Association*, 85, 410, 345-355.

Gómez, V. and Maravall, A., (2001), Seasonal Adjustment and Signal Extraction in Economic Time Series, Ch. 8 in Peña D., Tiao G. C. and Tsay, R. S. (eds.) *A Course in Time Series Analysis*, New York: Wiley.

Gómez, V. and Maravall, A., (1996), Programs TRAMO and SEATS. Instructions for the User, (with some updates). Working Paper 9628, Servicio de Estudios, Banco de España.

Hillmer, S. C., (1985), Measures of Variability for Model-Based Seasonal Adjustment Procedures, *Journal of Business and Economic Statistics* 3, 60-68.

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.

Maravall, A., (1998), Comments on the Seasonal Adjustment Program X12ARIMA, Journal *of Business and Economic Statistics*, 16, 155-160.

Maravall, A., (1995), Unobserved Components in Economic Time Series, in Pesaran, H. and Wickens, M. (eds.), *The Handbook of Applied Econometrics*, vol. 1, Oxford: Basil Blackwell.

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. and Planas, C., (1999), Estimation Error and the Specification of Unobserved Component Models, *Journal of Econometrics*, 92, 325-353.

Nerlove, M., Grether, D. M. and Carvalho, J. L., (1979), *Analysis of Economic Time Series: A Synthesis*, New York: Academic Press.

Pierce, D. A., (1980), Data Revisions In Moving Average Seasonal Adjustment Procedures, *Journal of Econometrics* 14, 95-114.

Pierce, D. A., (1979), Signal Extraction Error in Non Stationary Time Series, *Annals of Statistics* 7, 1.303-1.320.

Priestley, M. B., (1981), *Spectral Analysis and Time Series*, London: Academic Press.

Tiao, G. C. and Hillmer, S. C., (1978), Some Consideration of Decomposition of a Time Series, *Biometrika* 65, 497-502.

# 3

# Seasonal adjustment of European aggregates: direct versus indirect approach

Dominique Ladiray and Gian Luigi Mazzi

## 1 Introduction

Most of the European and Eurozone economic short term indicators are computed either through "horizontal" aggregation, e.g. by country, or through "vertical" aggregation, e.g. by sector or product. Three main strategies can be used to obtain seasonally adjusted figures:

- The direct approach: the European indicator is first computed by aggregation of the raw data and then seasonally adjusted;
- The indirect approach: the raw data (for example the data by country) are first seasonally adjusted, all of them with the same method and software, and the European seasonally adjusted series is then derived as the aggregation of the seasonally adjusted national series;
- The "mixed" indirect approach: each Member State seasonally adjusts its series, with its own method and strategy, and the European seasonally adjusted series is then derived as the aggregation of the adjusted national series.

Unfortunately, these strategies could produce quite different results. The choice between the first two approaches has been the subject of articles and discussions for decades and there is still no consensus on the best method to use. On the contrary, some agreement appears in the literature on the fact that the decision has to be made case by case following some empirical rules and criteria (Dagum [2], European Central Bank [3], Lothian and Morry [12], Pfefferman et al. [13], Planas and Campolongo [14], Scott and Zadrozny [15] etc.). The last approach is often used and, as it cannot be derived from a simple adjustment, is rarely compared to the others.

The choice between the methods cannot be based on accuracy and statistical considerations only. To publish timely estimates, Eurostat must often work with an incomplete set of national data. The indirect approaches imply estimation of missing raw and seasonally adjusted data and therefore different models have to be estimated, checked and updated. The direct approach is obviously easier to implement and would be preferred except if there is a strong evidence that an indirect approach is better.

Section 2 of the paper is devoted to a detailed presentation of the direct vs indirect problem, its implications and some non statistical guidelines for the choice of a strategy. Section 3 presents the various quality measures that can be used to make the right choice and the methodology used in the applications. Both of the applications presented in this paper concern the Quarterly National Accounts: the geographical aggregation problem in Section 4 and the sectoral aggregation problem in Section 5. TRAMO-SEATS and X-12-ARIMA were used for these applications; the same quality measures have been computed for both seasonal adjustment programs and, when possible, the mixed indirect approach has been compared to the other approaches.

## 2 The direct versus indirect problem

Nowadays it is common to decompose an observed time series $X_t$ into several components, themselves unobserved, according to, for example, an additive model:

$$X_t = TC_t + S_t + D_t + E_t + I_t \tag{1}$$

where $TC_t$, $S_t$, $D_t$, $E_t$ and $I_t$ designate, respectively, the trend-cycle, the seasonality, the trading-day, the Easter effect and the irregular components.

The seasonality $S_t$ and the calendar component ($D_t + E_t$) are removed from the observed time series to obtain the seasonally adjusted series $A_t = TC_t + I_t$.
We will suppose from now on that $X_t$ is an European indicator computed by linear aggregation of $N$ national indicators ($N = 15$ for the European Union or $N = 12$ for the Eurozone); in this aggregation, each Member State n has a weight $\omega_n$. Therefore we have:

$$X_{n,t} = TC_{n,t} + S_{n,t} + D_{n,t} + E_{n,t} + I_{n,t} \tag{2}$$

and:
$$X_t = \sum_{n=1}^{N} \omega_n X_{n,t}$$

Note that the weights can be positive and sum up to 1, as in the IPI case, or can be all equal to 1, as in the GDP case.

### *2.1 Direct, indirect and mixed indirect seasonal adjustments*

The seasonally adjusted series $A_t$ of the European aggregate $X_t$ can be derived from at least three different strategies:

- The direct approach consists in adjusting directly the aggregate. The direct seasonally adjusted series is noted $A_t^D$;
- In the indirect approach, all the national indicators $X_{n,t}$ are seasonally adjusted, with the same method and software, and the European seasonally adjusted series is then derived as the aggregation of the seasonally adjusted national series. Thus we have:

$$A_t^I = \sum_{n=1}^{N} \omega_n A_{n,t}$$

- In the "'mixed" indirect approach: each Member State seasonally adjusts its series, with its own method and strategy, and the European seasonally adjusted series is then derived as the aggregation of the adjusted national series. The mixed indirect seasonally adjusted series is noted $A_t^M$.

The multivariate approach, which permits to derive simultaneously the seasonally adjusted series for the aggregate and the components, must be mentioned at this stage as an alternative. This method has been proposed for many years (Geweke [6]) but given its computational complexity, the limitations of existing programs and its lack of optimality with respect to revision errors, it is rarely used in practice and the univariate approaches are generally preferred.

The mixed indirect approach is a quite popular strategy but, as it does not result from a simple seasonal adjustment process, it is scarcely studied by itself. The national seasonal adjustment policies can substantially differ for several reasons:

- The methods are often different: some countries use a model-based approach (TRAMO-SEATS, STAMP), other countries a non parametric approach (X-11 family);
- The software, or the release, that implements the method can also differ: X-11, X-11-ARIMA and X-12-ARIMA are currently in use in the European countries, sometimes in the same institute;
- The revision policies can vary and Member States may use current or concurrent seasonal adjustments;
- Member States can perform themselves direct or indirect seasonal adjustments;
- The strategy for the correction of calendar effects is usually not the same, the seasonal adjustments are not performed on the same time span, the treatment of outliers can differ etc.

All these differences show how it is difficult to compare, from the theoretical point of view, the mixed indirect seasonal adjustment to the direct and indirect ones. Furthermore, these three strategies are not the only possible ones and we can imagine for example a mixed approach: a subset of the basic series can be first aggregated in one new component, this component and the remaining sub-series can then be adjusted and the adjusted aggregate derived by implication. In fact this procedure is frequently used since many of what are considered the basic components are themselves aggregates of other components, although the latter are not always observed separately (Pfefferman [13]).

### *2.2 Could direct and indirect approaches coincide?*

As far as the aggregate is a linear combination of the components and the seasonal adjustment is a non-linear process, the answer is generally no, except under some very restrictive conditions (see for example Pfefferman [13]). Thus, if the aggregate is an algebraic sum (GDP for example), if the decomposition model is purely additive (equation 1), if there is no outlier in the series and if the global filter used in the seasonal adjustment process is the same for all series, the two approaches are equivalent. If the decomposition model is multiplicative, it could be shown that the equivalence of the two approaches requires for instance that there is no irregular, that the sub-series have identical seasonality patterns (or that the sub-series have identical or proportional trend-cycles) and that the lter used is the same for all sub-series. On the other hand, if the aggregate is a rate, any seasonal adjustment strategy that produces unbiased estimates will give different results (Dagum [2]).
Clearly the reality is much more complex:

- For the majority of economic series the additive model is not the most appropriate and the series are adjusted using the multiplicative option. Such series may be converted to an additive model by a logarithmic transformation, as in TRAMO-SEATS, but this will not ensure the equivalence since the logarithm of a sum is not the sum of the logarithms.
- Outliers are frequently present in economic time series as the result of structural changes, anomalous conditions, external shocks etc.
- For model-based approaches, such as TRAMO-SEATS, the filter used for the seasonal adjustment is optimally derived from the characteristics of the series. It means that a different filter is associated to each series. In that case, direct and indirect adjustments would never coincide.

On the other hand, it may occur that sub-series are not very noisy, show a very similar trend-cycle or seasonal pattern and are affected more or less by the same external shocks. In these conditions, the direct and indirect approaches could not be too different. These considerations advocate for measures of the differences between the various adjusted series; such indicators will be presented in section 3.2.

### 2.3 A priori advantages and drawbacks

The choice between direct, indirect and mixed indirect adjustment can be guided by some statistical or non statistical considerations or by some *a priori* desirable properties.

**1. The additivity constraint and the indirect approaches**

Sometimes the additivity constraint plays an important role in some domains (quarterly national accounts, balance of payments) or has to be assured as the consequence of a legal act (external trade). Then the indirect or the mixed indirect approaches appear to be the relevant ones. Furthermore, the mixed indirect approach seems to imply there is no discrepancy between national figures and European data. Nevertheless, some points must be precised:

- Even with a direct approach it is always possible to assure ex post the additivity constraint by distributing the discrepancies. Various univariate or multivariate statistical techniques exist to compute these adjustment factors.
- The additivity constraint is veriefied on the levels of the series. But users are more generally concerned with growth rates. Of course, as we have:

$$\frac{A_{t+1}^I - A_t^I}{A_t^I} = \frac{1}{\sum_{n=1}^N \omega_n A_{n,t}} \sum_{n=1}^{N} \left( \omega_n A_{n,t} \times \frac{A_{n,t+1} - A_{n,t}}{A_{n,t}} \right)$$

  the indirect growth rate is a weighted average of the sub-series growth rates, with weights that sum up to 1. Therefore, the indirect growth rate is always between the smaller and the larger sub-series growth rate and in that sense, the indirect approach is consistent. But you can have a majority of sub-series increasing while the global growth rate decreases: see some examples in Section 4.
- The additivity constraint has nothing to do with either the time consistency problem, requiring for example that quarterly and annual figures have to be coherent, or the consistency between raw and adjusted data annual totals.

**2. Some “statistical” considerations**

Most of the statisticians involved in seasonal adjustment agree on one point: if the sub-components do not have similar characteristics or if the relative importance of the sub-series (in terms of weight) is changing very fast, indirect adjustment should be preferred. From the opposite point of view (Dagum [2]), if the sub-series have a similar seasonal pattern and more or less the same timing in their peaks and troughs, the direct approach should be preferred. The aggregation will produce a smoother series with no loss of information on the seasonal pattern.

On one hand, as some studies show a synchronization of the cycles in the European Union (see for example Blake et al. [1]), the direct approach should be preferred. On the other hand, some countries have strong specificities and this point is of great importance with respect to the forthcoming enlargement of the European Union.

A combined two-step approach must therefore be seriously studied: a first direct approach for groups of similar series and then an indirect approach for the estimation of the final seasonally adjusted aggregate. Finally, one must note that following this idea of similarity of the sub-series, the direct approach should be more adapted to "horizontal" aggregation, e.g. by country, and the indirect approach to "vertical" aggregation, e.g. by sector, branch or product.

The mixed indirect approach poses serious methodological problems for further statistical analysis of the aggregate. As Member States use in general different methods, they also implicitly use different definitions of the trend-cycle and the seasonality. As seasonal adjusted series are unfortunately often used in econometric modeling, this could generate artifacts and spurious relationships which could spoil the quality of the estimations and mislead the interpretation of the results. Of course, these undesirable effects are more evident for the end points of the series on which asymmetric filters are used. This can have negative implications for the construction of flash estimates, nowcasting and coincident or leading indicators.

**3. Production consequences**

Eurostat calculates European and Euro-zone aggregates from national data. As national indicators are not produced at the same time by all Member States, Eurostat has to imput missing information using some modeling of the concerned series, in order to publish timely figures. As an example, Eurostat must publish the European IPI 45 days after the end of the month but at that date the results for only six countries are available. A truly mixed indirect approach is impossible because of the delays; an indirect approach implies to estimate and seasonally adjust missing national IPI (6 for the Euro-zone); a direct approach requires much less work as it implies only to estimate and seasonally adjust the aggregate. Once more the usual trade-off between accuracy and timeliness has to be taken into account in the choice of the "optimal" method.

## 3 Methodology

To empirically assess the quality of the different approaches, some problems have to be solved. The first one is that the effect of the aggregation strategy must be isolated from the other numerous sources of variation. The second problem resides in the definition of quality indicators that should be computed for the different approaches. And the last one is a computational problem as the two main programs currently used, TRAMO-SEATS and X-12-ARIMA, do not provide the user with a common set of quality statistics.

### *3.1 Various causes of revisions*

Seasonally adjusted figures are usually subject to revisions that can be the consequence of numerous causes. For example, at the European level, we can underline:

- The imputation of national data. When more national data become available, the preliminary estimates calculated by Eurostat must be updated and the raw and adjusted series have to be revised.
- The usual sources of revisions due to the seasonal adjustment process: adjustment policy (current or concurrent adjustment), modification of the adjustment parameters, treatment of outliers, estimation of calendar effects, impact of new data etc.
- The revisions due to the seasonal adjustment process at the national level.
- The revisions of the corresponding annual figures.

In order to study the direct vs indirect problem, it would be preferable to isolate the variations only due to this problem and therefore to work with quite stable time series and under stable assumptions. For instance, the series could be first cleaned from any calendar effect or outlier, the decomposition model could be fixed etc. Unfortunately, it is quite difficult to measure the relative importance of each source of revision.

### *3.2 Quality measures*

There is no real consensus on the measures to assess the quality of a seasonal adjustment, and that explains the large number of criteria one can find in the literature. Several aspects of the seasonal adjustment can be addressed and, for each of them, some criteria have been defined.

**1. How different the various approaches really are?**

The results of the three approaches are compared to see how important the direct vs indirect problem is.

We compute for the direct and indirect seasonally adjusted series, the two following statistics:

- Mean Absolute Percentage Deviation: $\frac{100}{N}\sum_{n=1}^{N}\left|\frac{A_t^D - A_t^I}{A_t^I}\right|$
- Max Absolute Percentage Deviation: $100 \times \mathrm{Max}\left|\frac{A_t^D - A_t^I}{A_t^I}\right|$

These statistics can be calculated: for each couple of possible approaches (Direct, Indirect), (Direct, Mixed indirect) and (Indirect, Mixed indirect); for the seasonally adjusted series, the trend-cycle estimates and the seasonal components; for the two programs TRAMO-SEATS and X-12-ARIMA; on the complete series and on the last three years.

Users pay a lot of attention to the growth rate of the seasonally adjusted series. The mean and the range of the series of the growth rate differences should therefore be computed and checked.

**2. Inconsistencies**

Moreover, the various seasonally adjusted series should deliver more or less the same message and their growth rates should have the same sign. To measure the degree of consistency in growth rates, two kinds of statistics are computed:

- the first measures the global percentage of concordance between the direct and indirect series;
- the second measures the percentage of concordance between the seasonally adjusted series and the national adjusted series. An inconsistency in the growth rates is detected when the aggregate does not evolve as the majority, in terms of weight, of adjusted sub-series.

**3. Quality of the seasonal adjustment**

X-12-ARIMA proposes a set of M and Q statistics to assess the quality of the seasonal adjustment.[1] These statistics have been adapted when possible to the TRAMO-SEATS

[1] For a precise definition and the interpretation of these statistics, one can refer to Ladiray, Quenneville [11].

estimates.[2] Approximated components linked to the mixed seasonally adjusted series have been computed in order to calculate these statistics.

**4. Roughness of the components**

Dagum [2] proposed two measures of roughness of the seasonally adjusted aggregates.[3] The first one is the $L_2$-norm of the differenced series: $R1 = \sum_{t=2}^{T} (A_t - A_{t-1})^2 = \sum_{t=2}^{T} (\nabla A_t)^2$. The second one is based on the 13-term Henderson filter: the adjusted series is smoothed with the Henderson filter and $R2$ is defined as the $L_2$-norm of the residuals: $R2 = \sum_{t=1}^{T} (A_t - H_{13}A_t)^2 = \sum_{t=1}^{T} [I - H_{13}) A_t]^2$.

The rationale of these measures of roughness is that the involved filters (the first difference operator and $I - H_{13}$) are high-pass filters that remove most of the low frequencies components that correspond to the trend-cycle variations. In other words, these statistics measure the size of the deviations to a smooth trend, e.g. the size of an "irregular component". This is why Pfefferman ([13]) suggested a "natural" third measure, a measure of similarity between seasonally adjusted data and trend: $R3 = \sum_{t=1}^{T} (A_t - TC_t)^2$.

Indeed, there is no fundamental reason why a seasonally adjusted series should be smooth as the irregular component, a characteristic of the series, is a part of the seasonally adjusted series. Gómez and Maravall ([8]) prefer to focus the quality measures on the other components, the trend-cycle and the seasonality. For the seasonality, they use the criteria $Mar(S) = \sum_{t=1}^{T} [(1 + B + B^2 + \ldots + B^{11}) A_t]^2$ where $1 + B + B^2 + \ldots + B^{11}$ is the annual aggregation operator. The smoothness of the trend-cycle is measured by the $L_2$-norm of the first and the second differences: $Mar1(TC) = \sum_{t=1}^{T} (\nabla A_t)^2$ and $Mar2(TC) = \sum_{t=1}^{T} (\nabla A_t)^2$.

All these measures can be computed on the direct, indirect and mixed indirect adjustments, on the estimates obtained from TRAMO-SEATS and X-12-ARIMA, for the complete series or only for the last three years.

**5. Idempotency**

A seasonal (and trading-day and holiday) adjustment that leaves detectable residual seasonal and calendar effects in the adjusted series is usually regarded as unsatisfactory. X-12-ARIMA and TRAMO-SEATS are used on the three seasonally adjusted series and the usual tests proposed by these softwares are used to check the idempotency.

**6. Stability of the seasonally adjusted series**

Even if the seasonal adjustment does not leave residual seasonal or calendar effects, the adjustment will be unsatisfactory if the adjusted values undergo large revisions when they are recalculated as future time series values become available. Frequent and substantial revisions cause data users to lose condence in the usefulness of adjusted data. Such instabilities can be the unavoidable result of the presence of highly variable seasonal or trend movements in the raw series being adjusted. But, in any case, they have to be measured and checked. X-12-ARIMA includes two types of stability diagnostics: sliding spans and revision histories (see Findley et al. [5], US Bureau of Census [17]). Some of these diagnostics are used here:

- The mean and standard deviation of the absolute revisions after $k$ periods;

---

[2] For example, the $M6$ statistic cannot be computed as it refers specifically to the use of a 3x5 moving average in the seasonal adjustment procedure.

[3] In the following definitions, $B$ is the lag operator defined by $BX_t = X_{t-1}$ and $\nabla = I - B$ is the first difference operator.

- The two most important sliding spans: *A*(%), percentage of dates with unstable adjustments, and *MM*(%), percentage of dates with unstable month-to-month percent changes.

Unfortunately, it is quite difficult to compute these statistics for the mixed indirect approach.

**7. Characteristics of the irregular component**

The irregular component should not present any structure or residual seasonality. The irregulars derived from the various approaches are analyzed both with the TRAMO automatic modeling module and the X-12-ARIMA software. The usual tests proposed by these programs are used to check the randomness of the irregular components.

### *3.3 Software, programs and parameters*

TRAMO-SEATS (version 98) and X-12-ARIMA (version 0.2.8) have been used in the applications.[4] A dedicated SAS macro manages the two programs and calculates all the quality statistics for the direct and indirect approach and most of them for the mixed indirect approach. Some specific features have been implemented in order to simulate different adjustment policies. For example, the series can be cleaned from calendar effects or outliers before any adjustment is performed. The decomposition model can be, or not, fixed by the user etc.

Nevertheless, in the applications, we use a default strategy for seasonal adjustment:

- The Trading-Day and Easter effects are tested and corrected only if they are significant.
- The decomposition model is fixed and common to each sub-series.
- In the revision and sliding span analysis, the ARIMA model and the decomposition model are fixed and equal to the ones found for the complete series.

## 4 GDP: Geographical aggregation

Even if this application concerns a specific aggregate, the Gross Domestic Product (GDP), it does not seem unrealistic to assume the results can be generalized to most of the Quarterly National Accounts indicators.[5]

### *4.1 The data*

We use here the Quarterly Gross Domestic Product in volume for the whole economy of the following countries: Belgium, Germany, Spain, France, Italy, Netherlands and Finland. The sample ranges from 1980Q1 to 2002Q2, for a total of 90 observations. These countries are the only ones providing long series for Quarterly National Accounts in the Euro-zone. Other countries, such as Austria, Ireland and Portugal, have not been taken into consideration in this study due to the impossibility of back-recalculating their data: Ireland did not produce any quarterly figures before the adoption of ESA95, whereas Portugal compiled only seasonal

---

[4] The versions of the softwares that can be downloaded from:
• the Banco de España web site http://www.bde.es/servicio/software/softwaree.htm
• the US Bureau of Census web site http://ftp.census.gov/pub/ts/x12a/ nal/pc/.

[5] Nevertheless, some very particular series (e.g. gross added value for agriculture, forestry and fishing) could have a quite different behavior.

adjusted figures. In the case of Austria changes in definitions do not permit any reliable recalculation. Finally Luxembourg and Greece are *a priori* excluded since Luxembourg does not currently compile Quarterly National Accounts and Greece provides only an incomplete set of data which is currently under test by Eurostat.

Before the ESA95 regulation, some Member States (France, Spain) did not compile raw figures. This is the main reason why the official Eurozone GDP series is derived from an estimation procedure based on available national seasonally adjusted data. In order to focus on the direct versus indirect problem only, we decided to compute a "pseudo Euro-zone GDP", not affected by these estimation procedure effects, by summing up the seasonally adjusted data of the seven available countries. This "benchmark" series (the so-called mixed series) ranges from 1991Q1 to 2002Q2, for a total of 46 observations.

### 4.2 A first comparison between seasonally adjusted series

As it has already been mentioned, Member States use different seasonal adjustment techniques to produce Quarterly National Accounts. Moreover, seasonal adjustment policies concerning working day corrections, revisions and so on, are also quite disparate. Table 1 summarizes the seasonal adjustment procedures used by Euro-zone Member States.

There is no consensus neither on the software nor on working day correction policy: two Member States are currently using X11, with or without ARIMA modeling (Portugal and Finland), three X-12-ARIMA (Germany, France and Netherlands) and four TRAMO-SEATS (Belgium, Spain, Italy and Austria); only four Member States provide trading-day seasonally adjusted figures.

Table 1: Seasonal adjustment methods and practices in European Union Member States for Quarterly National Accounts

| Country | Seasonal Adjustment Method | Trading/Working day Correction | |
|---|---|---|---|
| | | Yes | No |
| Euro-zone | Mixed | | X |
| Belgium | TRAMO-SEATS | | X |
| Germany (Bundesbank) | X-12-ARIMA | X | |
| Spain | TRAMO-SEATS | X | |
| France | X-12-ARIMA | X | |
| Greece | - | - | - |
| Ireland | - | - | - |
| Italy | TRAMO-SEATS | | X |
| Luxembourg | - | - | - |
| Netherlands | X-12-ARIMA | X | |
| Austria | TRAMO-SEATS | | X |
| Portugal | X-11 | | X |
| Finland | X-11-ARIMA | | X |

Figure 1: Mixed and TRAMO-SEATS direct and indirect adjustments: GDP geographical aggregation
*(millions)*

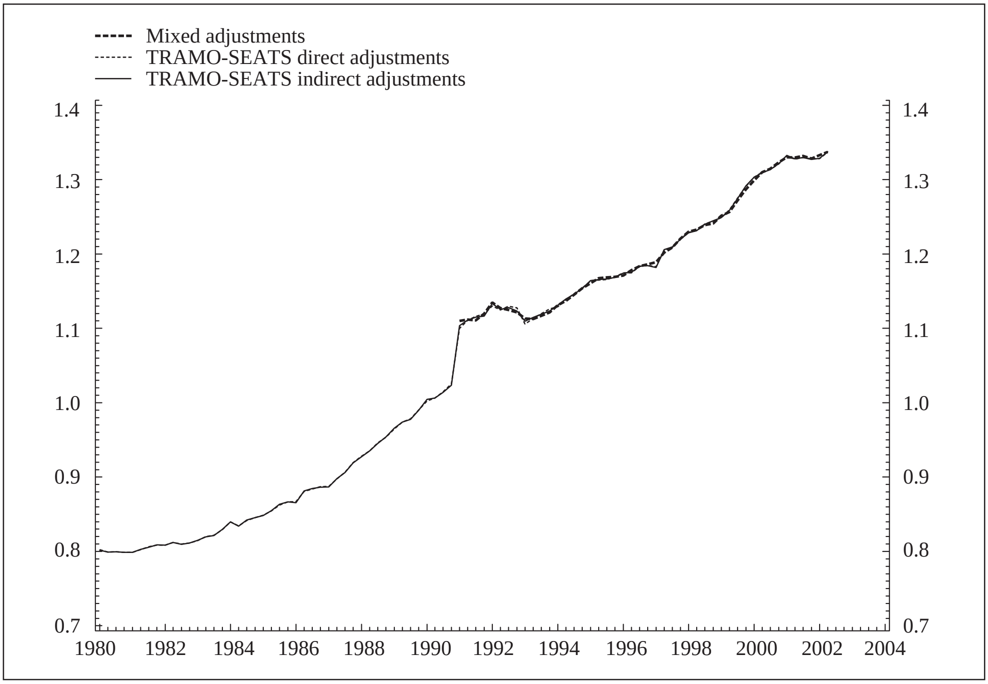



Figure 1 presents the mixed adjustment and the TRAMO-SEATS direct and indirect seasonally adjusted series. It is very difficult to detect a real difference between the three series (and it will be the same with the X-12-ARIMA estimates). This similarity is confirmed by the numerical indicators displayed in Table 2. The mean absolute percentage difference between two estimates is quite small: less than 0.1% between direct and indirect, and close to 0.2% between the mixed and the other estimates.

Table 2: Absolute percentage deviation indicators (GDP geographical aggregation)

| Indicator | Ind. T-S | vs Dir. X-12 | Best | Ind. T-S | vs Mixed X-12 | Dir. T-S | vs Mixed X-12 |
|---|---|---|---|---|---|---|---|
| Mean APD (SA) | 0.068 | 0.067 | X12ar | 0.180 | 0.168 | 0.214 | 0.207 |
| Max APD (SA) | 0.395 | 0.414 | Seats | 0.587 | 0.652 | 0.924 | 0.804 |
| Mean APD (SA), Last 3 years | 0.029 | 0.070 | Seats | 0.169 | 0.154 | 0.161 | 0.214 |
| Max APD (SA), Last 3 years | 0.051 | 0.316 | Seats | 0.350 | 0.399 | 0.323 | 0.446 |
| Mean APD (TC) | 0.060 | 0.109 | Seats | 0.132 | 0.184 | 0.173 | 0.150 |
| Max APD (TC) | 0.809 | 1.378 | Seats | 0.598 | 1.924 | 0.863 | 0.599 |
| Mean APD (TC), Last 3 years | 0.018 | 0.053 | Seats | 0.111 | 0.147 | 0.121 | 0.195 |
| Max APD (TC), Last 3 years | 0.045 | 0.133 | Seats | 0.257 | 0.251 | 0.269 | 0.368 |
| Mean APD (S) | 0.076 | 0.067 | X12ar | 0.165 | 0.168 | 0.214 | 0.207 |
| Max APD (S) | 0.443 | 0.415 | X12ar | 0.611 | 0.656 | 0.933 | 0.811 |
| Mean APD (S), Last 3 years | 0.033 | 0.070 | Seats | 0.149 | 0.154 | 0.161 | 0.214 |
| Max APD (S), Last 3 years | 0.098 | 0.317 | Seats | 0.342 | 0.397 | 0.324 | 0.444 |

Figure 2: Growth rates of mixed, TRAMO-SEATS direct and indirect adjustments: GDP geographical aggregation

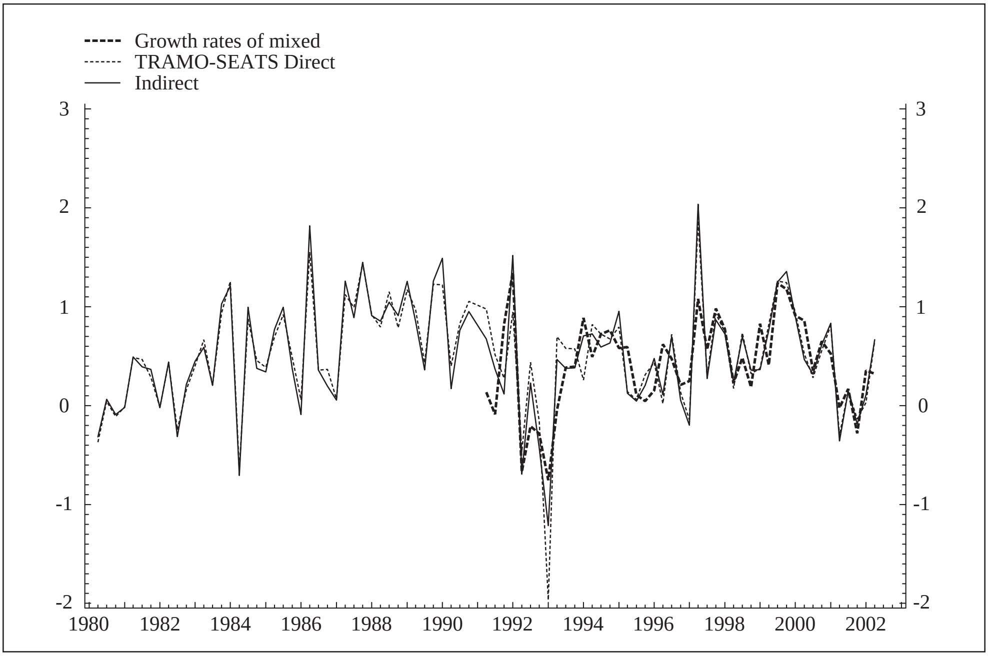



Figure 3: Growth rates of mixed, X-12-ARIMA direct and indirect adjustments: GDP geographical aggregation

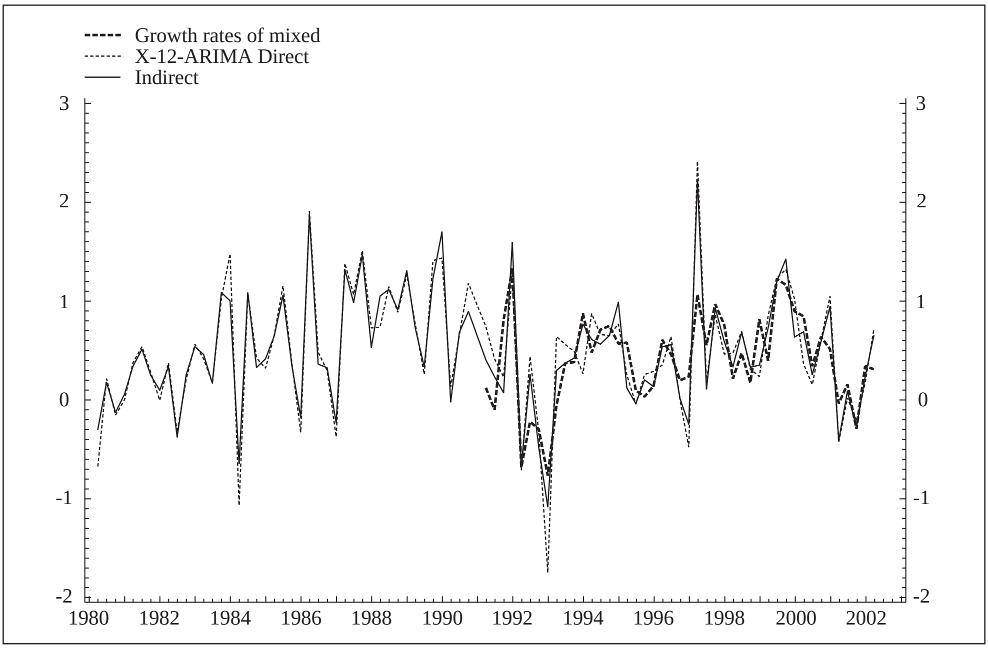


Figure 4: Relative differences of mixed aggregate versus direct and indirect adjustments: GDP geographical aggregation. TRAMO-SEATS

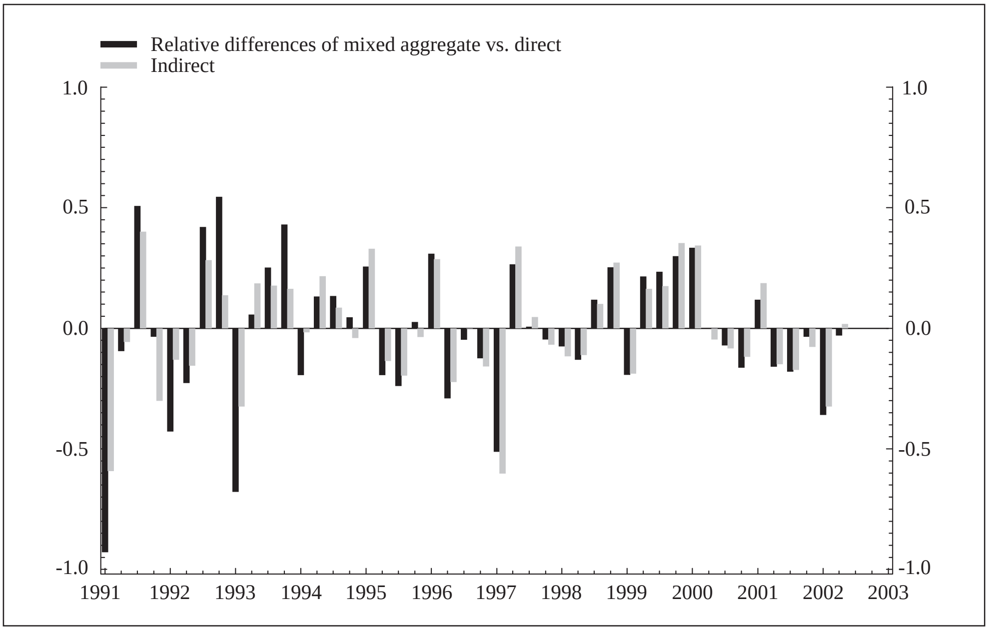



Figure 5: Relative differences of mixed aggregate versus direct and indirect adjustments: GDP geographical aggregation. X-12-ARIMA

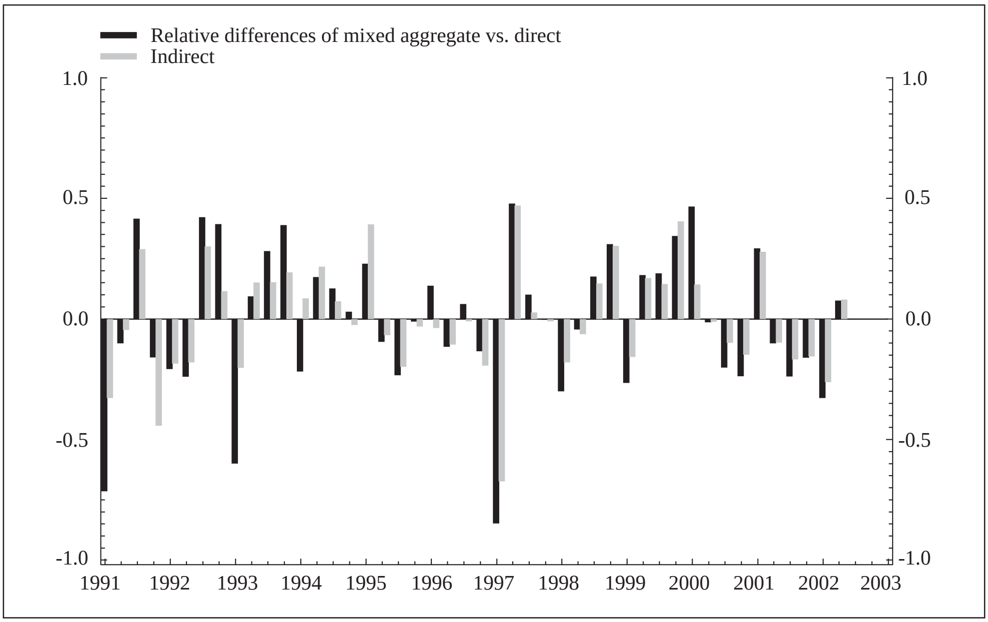


Table 3: Differences in growth rates between the three approaches: GDP geographical aggregation

| Indicator | Dir. vs Ind. | | Mixed vs Ind. | | Mixed vs Dir. | |
|---|---|---|---|---|---|---|
| | T-S | X-12 | T-S | X-12 | T-S | X-12 |
| Mean | -0.001 | -0.005 | -0.013 | -0.009 | -0.020 | -0.013 |
| Minimum | -0.729 | -0.511 | -0.925 | -1.131 | -0.853 | -1.311 |
| Maximum | 0.304 | 0.538 | 0.686 | 0.686 | 1.158 | 0.689 |
| Variance | 0.027 | 0.023 | 0.104 | 0.098 | 0.151 | 0.149 |
| Range | 1.033 | 1.049 | 1.611 | 1.817 | 2.011 | 1.999 |

The growth rates, which are in this case of greater interest, are displayed in Figures 2 and 3. Finally, Figures 4 and 5 show the relative difference of the mixed benchmark series with respect to the direct and indirect seasonal adjusted series obtained with TRAMO-SEATS and X-12-ARIMA.

The key elements emerging from this set of pictures can be synthesized as follows:

- direct and indirect adjusted series have a very similar behaviour, regardless to the software used (X-12-ARIMA or TRAMO-SEATS);
- 1993Q1 and 1997Q1 appear to be very special quarters where direct and indirect estimates show a much more important decrease in the GDP than mixed approach;
- the X-12-ARIMA estimates are slightly closer to the mixed estimate than those obtained with TRAMO-SEATS. This is certainly a direct consequence of the use of the Census filter in the large majority of Member States.

To complete this comparison, Table 3 presents some descriptive statistics on the differences between growth rates of the various approaches. Differences close to zero with little variance indicate a good agreement between the different estimates. This is the case as all average differences are very small. One must note that, as far as variances and ranges are concerned, the indirect approaches are closer to the mixed approach than the direct approaches; the X-12-ARIMA indirect estimate gets the best results.

### *4.3 Concordance analysis of growth rates*

Short-term analysts are mainly interested in the evolution of macroeconomic aggregates and therefore in growth rates of seasonally adjusted data. It is important that different seasonal adjusted data do not provide users with inconsistent messages.

Tables 4 and 5 detail the cases of discrepancies in sign between the various aggregates and with their sub-components, according to the adjustment approach.

Direct and indirect estimates only disagree, i.e. give an opposite evolution of the indicator, in two cases out of 89 for TRAMO-SEATS (1982Q1 and 1986Q1) and in one case for X-12-Arima (1995Q3). This leads to high concordance rates between the two approaches, namely 97.75% for TRAMO-SEATS and 98.88% for X-12-ARIMA. Furthermore, one should notice that these discrepancies concern growth rates close to zero.

The discrepancies are more numerous in the comparison with the mixed approach even if the global concordance rate remains good. 1991Q3 and 1993Q2 are strong inconsistencies for any software and approach. In these cases, the mixed series slightly decreases (-0.064% and -0.010%) when direct and indirect approach increase. The other inconsistencies concern smaller growth rates. The highest number of inconsistencies is given by a direct approach using X-12-ARIMA.

Table 4: Inconsistencies in growth rates between the three approaches: GDP geographical aggregation

| Direct vs Indirect | | | | | |
|---|---|---|---|---|---|
| TRAMO-SEATS | | | X-12-ARIMA | | |
| Date | Direct | Indirect | Date | Direct | Indirect |
| 1982Q1 | 0.007 | -0.023 | 1995Q3 | -0.043 | 0.046 |
| 1986Q1 | 0.034 | -0.072 | | | |
| **Mixed vs Direct** | | | | | |
| TRAMO-SEATS | | | X-12-ARIMA | | |
| Date | Mixed | Direct | Date | Mixed | Direct |
| 1991Q3 | -0.064 | 0.516 | 1991Q3 | -0.064 | 0.342 |
| 1992Q3 | -0.18 | 0.44 | 1992Q3 | -0.18 | 0.336 |
| 1993Q2 | -0.01 | 0.692 | 1993Q2 | -0.01 | 0.569 |
| 1997Q1 | 0.298 | -0.104 | 1995Q3 | 0.17 | -0.043 |
| | | | 1997Q1 | 0.298 | -0.391 |
| **Mixed vs Indirect** | | | | | |
| TRAMO-SEATS | | | X-12-ARIMA | | |
| Date | Mixed | Indirect | Date | Mixed | Indirect |
| 1991Q3 | -0.064 | 0.383 | 1991Q3 | -0.064 | 0.249 |
| 1992Q3 | -0.18 | 0.23 | 1992Q3 | -0.18 | 0.267 |
| 1993Q2 | -0.01 | 0.465 | 1993Q2 | -0.01 | 0.331 |
| 1997Q1 | 0.298 | -0.169 | 1997Q1 | 0.298 | -0.193 |

The inconsistencies between the evolution of an aggregate and the majority of its components are presented, for the different approaches and programs, in Table 5.

Table 6 presents the concordance rates between the various approaches, a statistic that summarizes the previous elements. The results are quite similar for the two programs: the concordance rate is very high between the direct and the indirect approaches, slightly lower in the other cases.

Table 5: Inconsistencies in growth rates between aggregate and components: GDP geographical aggregation

*(If weights is greater than 0.5 (less than 0.5), the main part of the national GDP increases (decreases)).*

| Direct or Indirect, TRAMO-SEATS | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Date | Direct | Indirect | Weights | BE | DE | ES | FR | IT | FI | NL |
| 1981 Q1 | -0.107 | -0.079 | 0.614 | -0.56 | 0.09 | -0.13 | 0.11 | -0.47 | 1.02 | -0.53 |
| 1981 Q4 | 0.263 | 0.312 | 0.471 | -0.07 | -0.27 | -0.06 | 1.16 | 0.52 | 1.29 | -0.27 |
| 1982 Q1 | 0.007 | -0.023 | 0.613 | 0.14 | -0.60 | 0.60 | 0.16 | 0.35 | 0.41 | -0.02 |
| 1983 Q3 | 0.282 | 0.212 | 0.412 | 0.71 | -0.20 | 0.03 | -0.16 | 1.31 | 0.83 | 0.41 |
| 1986 Q1 | 0.034 | -0.072 | 0.426 | -0.21 | -0.33 | 0.44 | 0.07 | -0.26 | -0.38 | 0.69 |
| 1990 Q2 | 0.406 | 0.195 | 0.486 | -0.79 | 0.46 | 1.09 | -0.12 | -0.05 | -0.96 | 0.69 |
| 1995 Q3 | 0.125 | 0.071 | 0.363 | 0.01 | -0.17 | 0.57 | -0.02 | 0.24 | -0.12 | 0.79 |
| Direct or Indirect, X-12-Arima | | | | | | | | | | |
| Date | Direct | Indirect | Weights | BE | DE | ES | FR | IT | FI | NL |
| 1980 Q4 | 0.085 | 0.157 | 0.343 | -0.24 | -0.55 | 0.80 | -0.38 | 0.70 | -0.83 | 4.07 |
| 1981 Q1 | -0.094 | -0.116 | 0.660 | 0.02 | 0.19 | -0.57 | 0.45 | -0.46 | 1.10 | -2.67 |
| 1983 Q3 | 0.314 | 0.270 | 0.321 | 0.72 | -0.21 | -0.08 | -0.00 | 1.07 | 0.72 | 1.55 |
| 1987 Q1 | -0.310 | -0.238 | 0.618 | 0.93 | -1.97 | 2.19 | 0.39 | 0.42 | 0.53 | -0.46 |
| 1990 Q2 | 0.090 | 0.018 | 0.162 | -0.45 | -0.08 | 1.24 | -0.13 | -0.11 | -1.02 | 0.39 |
| 1995 Q3 | -0.043 | 0.046 | 0.616 | 0.66 | -0.38 | 0.08 | 0.16 | 0.24 | 0.22 | 1.12 |
| 1996 Q4 | 0.059 | 0.050 | 0.221 | 0.63 | -0.02 | 0.56 | -0.27 | -0.04 | 1.06 | 0.44 |
| Mixed Approach | | | | | | | | | | |
| Date | Mixed | | Weights | BE | DE | ES | FR | IT | FI | NL |
| 1991 Q3 | -0.064 | | 0.598 | 0.53 | -0.69 | 0.37 | 0.18 | 0.63 | -1.29 | 0.32 |
| 2001 Q3 | 0.146 | | 0.358 | -0.03 | -0.19 | 1.01 | 0.40 | -0.02 | 1.34 | -0.10 |

Table 6: Concordance rates (in %): GDP geographical aggregation

| | TRAMO-SEATS | X-12-ARIMA |
|---|---|---|
| Direct and Indirect | 97.75 | 98.88 |
| Direct and Components | 93.26 | 92.13 |
| Indirect and Components | 93.26 | 93.26 |
| Mixed and Direct | 91.11 | 88.89 |
| Mixed and Indirect | 91.11 | 91.11 |
| Mixed and Components | 95.56 | |

### 4.4 Quality measures of seasonal adjustments

A comparison between the various adjustments can be also made with respect to the so-called quality measures proposed by X-12-ARIMA and here extended, where possible, to TRAMO-SEATS estimates and to the mixed approach. The results are presented in Table 7.

The M and Q statistics are commonly analyzed by statisticians in order to have a synthetic view of the performance of their adjustment: a value greater than one, for any of these statistics, indicates a possible problem in the seasonal adjustment. Table 7 does not shown significant differences among the approaches. The only case where none of the M statistics exceed the critical value is the direct adjustment with TRAMO-SEATS.

All the other approaches seem to present some problems concerning the M7 statistics, measuring wether the seasonal pattern in the series tends to remain constant over time or not. Furthermore the level of M4 for the indirect approach using X-12-ARIMA shows how the irregular component displays some residual autocorrelation.

Table 7: Quality measures: GDP geographical aggregation

| | TRAMO-SEATS | | X-12-ARIMA | | Mixed |
|---|---|---|---|---|---|
| Indicator | Direct | Indirect | Direct | Indirect | adjustment |
| M1* | 0.028 | 0.039 | 0.036 | 0.070 | 0.012 |
| M2* | 0.034 | 0.051 | 0.068 | 0.105 | 0.031 |
| M3* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| M4 | 0.131 | 0.131 | 0.261 | 1.045 | 0.692 |
| M5 | 0.200 | 0.200 | 0.200 | 0.200 | 0.200 |
| M7* | 0.769 | 2.035 | 1.828 | 2.108 | 0.856 |
| M8 | 0.571 | 0.567 | 0.246 | 0.531 | 1.691 |
| M9 | 0.174 | 0.173 | 0.156 | 0.124 | 0.188 |
| M10 | 0.525 | 0.466 | 0.139 | 0.404 | 1.531 |
| M11 | 0.444 | 0.263 | 0.139 | 0.387 | 1.279 |
| Q | 0.298 | 0.544 | 0.469 | 0.646 | 0.533 |

### 4.5 Roughness measures

Roughness measures are presented in Table 8 and refer to the seasonally adjusted series, the trend-cycle and the seasonal component. The smoothness of seasonally adjusted data is often considered as one of the most important criteria from the users point of view. Nevertheless, it must be stressed, as mentioned in Section 4, that this criterion has to be used carefully: the irregular component is an integral part of the series and it seems quite strange to prefer the series that presents the smallest irregular!

A first very simple conclusion we can draw from this table is that there is no clear evidence in favor of one of the approaches:

- the mixed approach gives, on the whole period, the smoother seasonally adjusted series and the smoother trend;
- X-12-ARIMA gets better results with the direct approach (in 9 cases out of 12) and on the opposite, for TRAMO-SEATS the indirect adjustment gives better results in all the cases;
- as far as the smoothness of the seasonal component is concerned, X-12-ARIMA gives the best results and the mixed approach the worse.

Table 8: Roughness measures: GDP geographical aggregation

| | TRAMO-SEATS Direct | TRAMO-SEATS Indirect | X-12-ARIMA Direct | X-12-ARIMA Indirect | Mixed approach | SEATS | X-12 |
|---|---|---|---|---|---|---|---|
| R1 (SA) | 11415.1 | 11868.9 | 12274.3 | 12222.7 | 8025.2 | D | I |
| R1 (SA), Last 3 years | 7038.7 | 7128.3 | 7776.6 | 7229.3 | 7167.2 | D | I |
| R2 (SA) | 0.245 | 0.271 | 0.289 | 0.289 | 0.106 | D | I |
| R2 (SA), Last 3 years | 0.112 | 0.117 | 0.136 | 0.132 | 0.083 | D | I |
| R3 (SA) | 0.178 | 0.216 | 0.250 | 0.310 | 0.106 | D | D |
| R3 (SA), Last 3 years | 0.137 | 0.142 | 0.154 | 0.145 | 0.083 | D | I |
| Mar (TC, 1) | 10948.9 | 11303.7 | 11221.9 | 9800.7 | 7420.9 | D | I |
| Mar (TC, 1), Last 3 years | 8317.1 | 8395.4 | 9236.2 | 8913.5 | 8766.3 | D | I |
| Mar (TC, 2) | 11195.8 | 12089.6 | 11497.4 | 6332.2 | 3219.7 | D | I |
| Mar (TC, 2), Last 3 years | 2373.8 | 2573.9 | 4063.9 | 3380.4 | 2596.1 | D | I |
| Mar (S) | 0.018 | 0.019 | 0.009 | 0.017 | 0.051 | D | D |
| Mar (S), Last 3 years | 0.017 | 0.018 | 0.005 | 0.014 | 0.052 | D | D |

### *4.6 Revision analysis*

Users prefer to deal with seasonally adjusted time series which are revised as few as possible. Non revised seasonally adjusted figures could be obtain with purely asymmetric filters (with the DAINTIES method for example) but with a possible serious counterpart: a phase shift in turning point detection.

Table 9 presents the revisions of direct and indirect estimates obtained with the two softwares. It is important to note that this revision analysis concentrates on revisions induced by the seasonal adjustment process:

- for the simulations, the ARIMA model and the decomposition model have been fixed;
- revisions of raw data which occur regularly, as new information became available have not been taken into account.

The results are very clear and speak in favour of the indirect approach, both for TRAMO-SEATS and for X-12-ARIMA.

Table 9: Absolute revisions (mean and standard deviation in %) and sliding spans analysis: GDP geographical aggregation

| Indicator | TRAMO-SEATS Direct | TRAMO-SEATS Indirect | X-12-ARIMA Direct | X-12-ARIMA Indirect | Direct vs Indirect SEATS | Direct vs Indirect X-12 |
|---|---|---|---|---|---|---|
| Mean AR 1 qtr | 0.126 | 0.088 | 0.083 | 0.062 | I | I |
| Mean AR 2 qtrs | 0.152 | 0.127 | 0.109 | 0.074 | I | I |
| Mean AR 3 qtrs | 0.165 | 0.126 | 0.117 | 0.075 | I | I |
| Mean AR 4 qtrs | 0.214 | 0.134 | 0.161 | 0.111 | I | I |
| Mean AR 5 qtrs | 0.226 | 0.122 | 0.149 | 0.099 | I | I |
| Std AR 1 qtr | 0.119 | 0.062 | 0.077 | 0.048 | I | I |
| Std AR 2 qtrs | 0.104 | 0.069 | 0.109 | 0.057 | I | I |
| Std AR 3 qtrs | 0.125 | 0.072 | 0.117 | 0.058 | I | I |
| Std AR 4 qtrs | 0.112 | 0.069 | 0.103 | 0.055 | I | I |
| Std AR 5 qtrs | 0.162 | 0.069 | 0.109 | 0.054 | I | I |
| Sliding Spans | | | | | | |
| A(%) | 0.000 | 0.000 | 0.000 | 0.000 | = | = |
| MM(%) | 1.266 | 1.266 | 0.000 | 0.000 | = | = |

The Sliding-Spans analysis does not reveal any stability problem for the various estimates which are therefore equivalent from this point of view.

It is also useful to point out that in the case of indirect approach we are working with some linear combination of possibly different filters so that it is difficult to talk about the "revision properties of the filter" in this specific case. The situation is much more clear in the case of the direct approach, where a unique filter is applied.

### *4.7 Analysis of the residuals*

The various estimated irregular components, even if they contain possible outliers, are supposed to present no specific structure and are often modelled as $N(0,\sigma^2)$ i.i.d processes. These estimates have been analysed with TRAMO and X-12-ARIMA. TRAMO provides us with an automatic identication of multiplicative seasonal Arima model $(p, d, q) * (P, D, Q)$ and with the associated whiteness tests to assess the absence of any significative autocorrelation structure. X-12-ARIMA permits us to test for the presence of residual seasonality.

Table 10 presents the results of this analysis. The estimated ARIMA models on the irregular components suggest the presence of residual seasonality for all the approaches, even if the spectrum-based test from X-12-ARIMA does not show this effect. The direct approach using TRAMO-SEATS gives an autocorrelated irregular component, as shown by the columns "pljung" and "dw" in Table 10.

Outliers have been detected only for the indirect approach using X-12-ARIMA: two additive outliers and a level shift. Furthermore a residual trading day and Easter effect has been detected for TRAMO-SEATS (both approaches) and a residual Easter effect for X-12-ARIMA, direct approach.

The results appear quite satisfactory even if some improvements in the specication seems to be needed in order to remove some undesirable effects such as the residual trading day and Easter effects.

Table 10: Analysis of the irregular components: GDP geographical aggregation

| Series | Model | pljung | dw | pnorm | ls | tc | ao | trad | east | Season? |
|---|---|---|---|---|---|---|---|---|---|---|
| SEATS Indirect | (0,0,1)(0,1,1) | 0.708 | 2.147 | 0.563 | 0 | 0 | 0 | Y | Y | N |
| X-12 Indirect | (1,0,1)(1,0,0) | 0.925 | 2.046 | 0.000 | 0 | 1 | 2 | N | N | N |
| SEATS Direct | (0,1,1)(0,1,1) | 0.050 | 2.705 | 0.515 | 0 | 0 | 0 | Y | Y | N |
| X-12 Direct | (0,0,1)(0,1,1) | 0.930 | 1.986 | 0.000 | 0 | 0 | 0 | N | Y | N |

## 5 Gross domestic product, aggregation by sector

In this application, we consider that the Euro-zone GDP at constant prices can also be seen as the sum of the gross value added of the six main branches in the NACE Rev. 1 classification and of a “Taxes minus FISIM” component. The direct vs indirect analysis performed in this Section is conditioned to the adoption of a direct approach for the geographical aggregation.

### *5.1 The data*

The seven components we have considered in this application are:
1. Agriculture, hunting, forestry and shing;
2. Total industry, excluding construction;
3. Construction;
4. Wholesale and retail trade;
5. Financial Intermediation;
6. Public administration;
7. Taxes minus FISIM.

The raw Member State series for each branch were summed up to obtain a “pseudo” Euro-zone aggregate for the considered branch. The same operation was done with seasonally adjusted data to obtain the corresponding mixed aggregate. Because of data availability, the exercise takes into account six countries only – Belgium, Germany, Spain, Finland, France and Italy – and the data range from 1980Q1 to 2002Q2 (90 observations). These countries represent more than 86% of the Euro-zone GDP. In this simulation the Netherlands is excluded because the breakdown by sector is available just for a shorter period.

### *5.2 A first comparison between seasonally adjusted series*

Figure 6 presents the mixed adjustment and the TRAMO-SEATS direct and indirect seasonally adjusted series. It is, like for the geographical aggregation case, very difficult to detect a real difference between the three series (and it will be the same with the X-12-ARIMA estimates). This similarity is confirmed by the numerical indicators displayed in Table 11. The mean absolute percentage difference between two estimates is very small, and smaller than for the geographical aggregation case: less than 0.1% between direct and indirect, and close to 0.2% between the mixed and the other estimates. The direct versus indirect problem is therefore not very important.

Figure 6: Mixed, TRAMO-SEATS direct and indirect adjustments: GDP aggregation by sector
*(millions)*

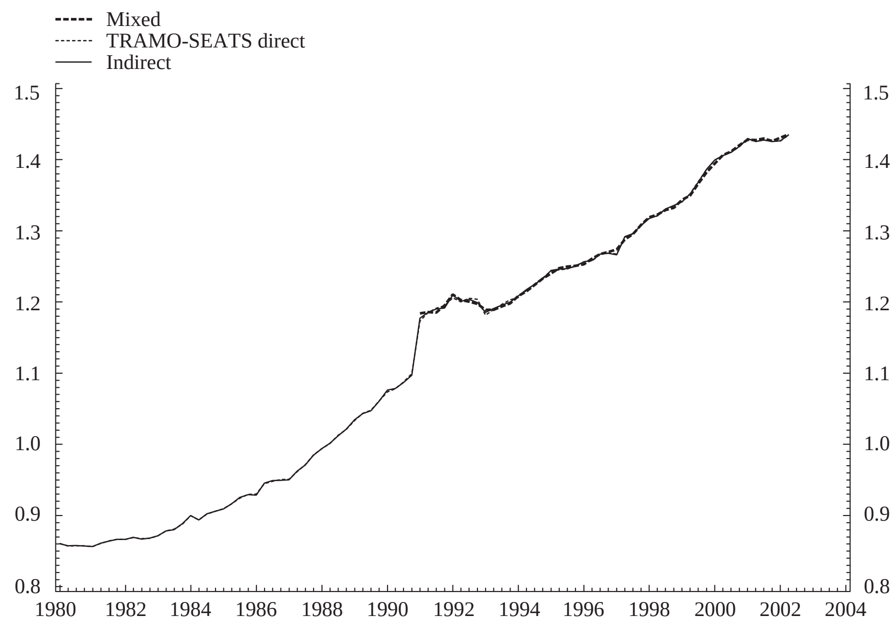



Table 11: Absolute percentage deviation indicators (GDP aggregation by sector)

| Indicator | Ind. vs Dir. T-S | Ind. vs Dir. X-12 | Best | Ind. vs Mixed T-S | Ind. vs Mixed X-12 | Dir. vs Mixed T-S | Dir. vs Mixed X-12 |
|---|---|---|---|---|---|---|---|
| Mean APD (SA) | 0.042 | 0.041 | X12ar | 0.170 | 0.178 | 0.147 | 0.179 |
| Max APD (SA) | 0.231 | 0.209 | X12ar | 0.841 | 0.988 | 0.712 | 1.001 |
| Mean APD (SA), Last 3 years | 0.025 | 0.057 | Seats | 0.108 | 0.157 | 0.105 | 0.174 |
| Max APD (SA), Last 3 years | 0.077 | 0.161 | Seats | 0.395 | 0.582 | 0.411 | 0.685 |
| Mean APD (TC) | 0.059 | 0.100 | Seats | 0.165 | 0.176 | 0.124 | 0.126 |
| Max APD (TC) | 0.443 | 1.873 | Seats | 0.632 | 1.774 | 0.611 | 0.693 |
| Mean APD (TC), Last 3 years | 0.030 | 0.063 | Seats | 0.064 | 0.081 | 0.063 | 0.057 |
| Max APD (TC), Last 3 years | 0.055 | 0.157 | Seats | 0.203 | 0.162 | 0.198 | 0.164 |
| Mean APD (S) | 0.399 | 0.240 | X12ar | 0.491 | 0.332 | 0.147 | 0.178 |
| Max APD (S) | 1.467 | 0.973 | X12ar | 2.195 | 1.656 | 0.718 | 0.731 |
| Mean APD (S), Last 3 years | 0.449 | 0.245 | X12ar | 0.529 | 0.370 | 0.105 | 0.185 |
| Max APD (S), Last 3 years | 1.293 | 0.826 | X12ar | 1.495 | 1.240 | 0.409 | 0.633 |

Figure 7: Growth rates of mixed and TRAMO-SEATS direct and indirect adjustments: GDP aggregation by sector

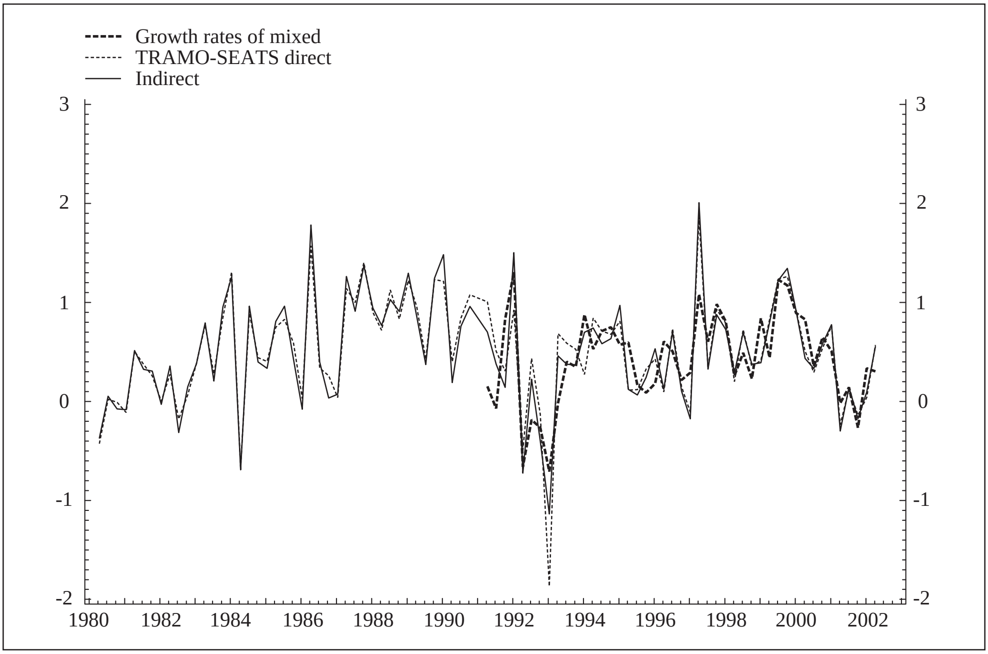



Figure 8: Growth rates of mixed and X-12-ARIMA direct and indirect adjustments: GDP aggregation by sector

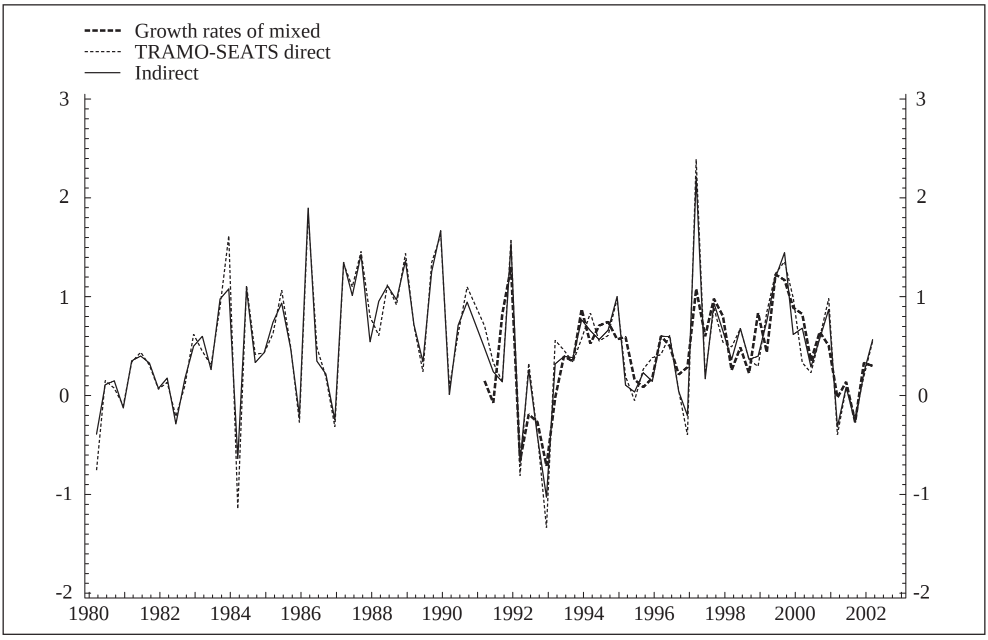


Figure 9: Relative differences of mixed aggregate versus direct and indirect adjustments: GDP aggregation by sector. TRAMO-SEATS

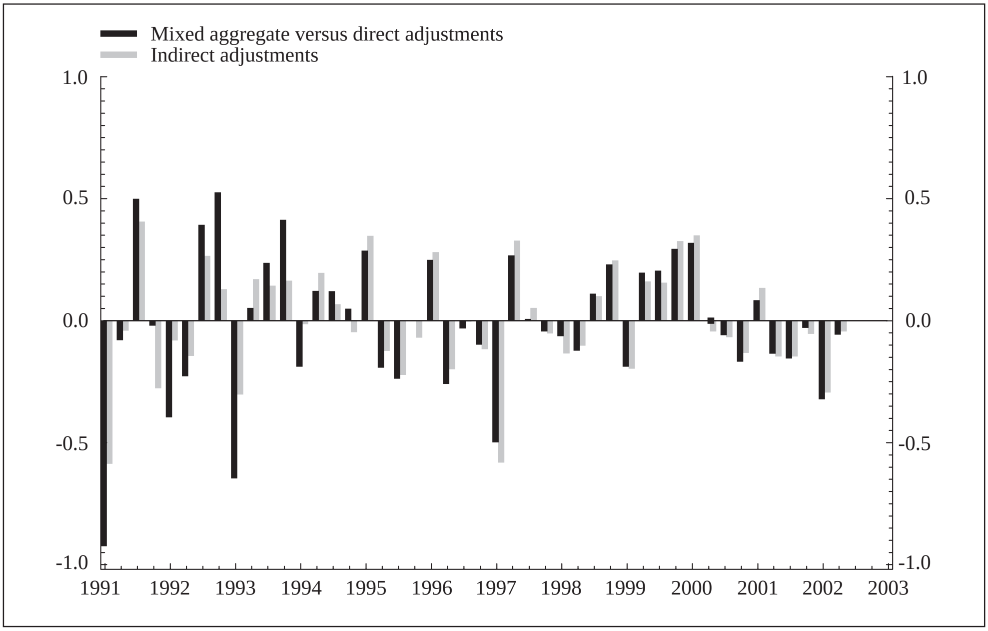



Figure 10: Relative differences of mixed aggregate versus direct and indirect adjustments: GDP aggregation by sector. X-12-ARIMA

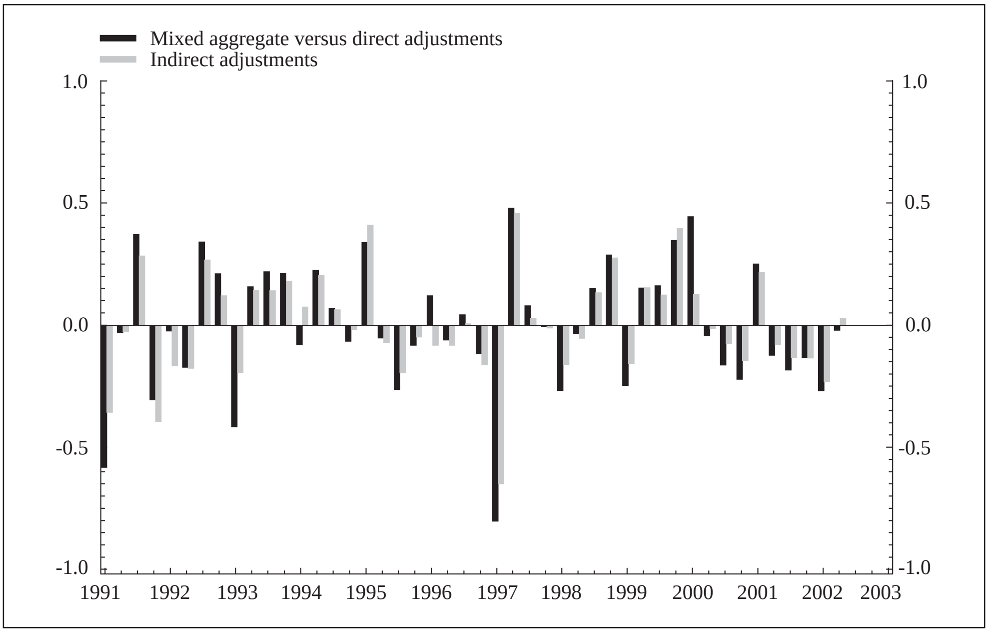


Table 12: Differences in growth rates between the three approaches: GDP aggregation by sector

| Indicator | Dir. vs Ind. | | Mixed vs Ind. | | Mixed vs Dir. | |
|---|---|---|---|---|---|---|
| | T-S | X-12 | T-S | X-12 | T-S | X-12 |
| Mean | 0.000 | 0.000 | -0.006 | -0.002 | -0.004 | -0.001 |
| Minimum | -0.221 | -0.332 | -0.745 | -0.960 | -0.626 | -1.002 |
| Maximum | 0.391 | 0.245 | 0.673 | 1.049 | 0.759 | 1.313 |
| Variance | 0.009 | 0.008 | 0.081 | 0.127 | 0.062 | 0.145 |
| Range | 0.611 | 0.577 | 1.418 | 2.009 | 1.385 | 2.315 |

The growth rates are displayed in Figures 7 and 8. Finally, Figures 9 and 10 show the relative difference of the mixed benchmark series with respect to the direct and indirect seasonal adjusted series obtained with TRAMO-SEATS and X-12-ARIMA.

The main conclusions we can draw from this set of pictures are the following:

- direct and indirect adjusted series have a very similar behaviour, regardless to the software (X-12-ARIMA or TRAMO-SEATS);
- 1993Q1 appears to be a very special date where direct and indirect estimates show a much more important decrease in the GDP than mixed approach;
- the X-12-ARIMA estimates are closer to the mixed estimate than those obtained with TRAMO-SEATS. This is certainly a direct consequence of the use of the Census filter in the large majority of Member States.

Table 12 statistics confirm the good agreement between the different estimates: all average differences are very small. One must notice that the direct approaches are closer to the mixed approach than the indirect ones.

### *5.3 Concordance analysis of growth rates*

Tables 13 and 14 detail the cases of discrepancies in sign of the growth rates obtained from the various adjustment approaches.

Direct and indirect estimates only disagree, e.g. give an opposite indication of the evolution of the indicator, in two cases out of 89 observations. But these discrepancies concern growth rates close to zero.

The discrepancies are more numerous when comparing with the mixed approach. X-12-ARIMA performs worse than TRAMO-SEATS. 1991Q3 is a strong inconsistency for any software and approach: the mixed series slightly decreases (-0.1%) when direct and indirect approaches increase (around 0.4%). The number of large discrepancies (i.e. higher than 0.5 percentage points) differs according to the approach: one for TRAMO-SEATS/direct, three for X-12-ARIMA/direct, three for TRAMO-SEATS/indirect and four for X-12-ARIMA/indirect.

The inconsistencies between the evolution of an aggregate and the majority of its components are presented, for the different approaches and programs, in Table 14.

TRAMO-SEATS presents six inconsistencies for the direct estimate and four for the indirect one. X-12-ARIMA presents five inconsistencies for the direct estimate and three for the indirect one. The mixed approach presents two inconsistencies in 1992Q3 and 1995Q4.

Table 13: Inconsistencies in growth rates between the three approaches: GDP aggregation by sector

| TRAMO-SEATS | | | X-12-ARIMA | | |
|---|---|---|---|---|---|
| Direct vs Indirect | | | | | |
| Date | Direct | Indirect | Date | Direct | Indirect |
| 1992 Q2 | 0.073 | -0.046 | 1992 Q3 | 0.023 | -0.035 |
| 1992 Q3 | 0.068 | -0.003 | 1996 Q4 | -0.055 | 0.007 |
| Mixed vs Direct | | | | | |
| Date | Mixed | Direct | Date | Mixed | Direct |
| 1991 Q3 | -0.089 | 0.484 | 1991 Q3 | -0.089 | 0.343 |
| 1993 Q2 | -0.047 | 0.347 | 1991 Q4 | 0.82 | -0.021 |
| 1996 Q1 | 0.153 | -0.064 | 1992 Q2 | -0.671 | 0.33 |
| | | | 1993 Q2 | -0.047 | 0.318 |
| | | | 1996 Q1 | 0.153 | -0.59 |
| | | | 2000 Q1 | 0.91 | -0.403 |
| Mixed vs Indirect | | | | | |
| Date | Mixed | Indirect | Date | Mixed | Indirect |
| 1991 Q3 | -0.089 | 0.586 | 1991 Q3 | -0.089 | 0.437 |
| 1992 Q2 | -0.671 | 0.073 | 1991 Q4 | 0.82 | -0.077 |
| 1992 Q3 | -0.208 | 0.068 | 1992 Q2 | -0.671 | 0.289 |
| 1993 Q2 | -0.047 | 0.491 | 1992 Q3 | -0.208 | 0.023 |
| 1996 Q1 | 0.153 | -0.155 | 1993 Q2 | -0.047 | 0.244 |
| | | | 1996 Q1 | 0.153 | -0.603 |
| | | | 1996 Q4 | 0.209 | -0.055 |
| | | | 2000 Q1 | 0.91 | -0.139 |

Table 14: Inconsistencies in growth rates between aggregate and components: GDP aggregation by sector

*(If weights is greater than 0.5 (less than 0.5), the main part of the national GDP increases (decreases))*

| Direct or Indirect, TRAMO-SEATS | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Date | Direct | Indirect | Weights | AGRI | IND | CONS | RETA | FINAN | PUBL | TAXES | FISIM |
| 1984Q4 | 0.206 | 0.328 | 0.333 | -2.22 | 1.08 | -0.67 | -0.04 | 0.85 | 0.07 | -0.04 | 0.45 |
| 1992Q2 | -0.046 | 0.073 | 0.667 | 0.77 | -0.41 | 0.15 | -0.12 | 0.53 | 0.23 | 0.06 | 0.26 |
| 1992Q3 | -0.003 | 0.068 | 0.833 | 1.00 | -1.36 | 0.34 | -0.16 | 0.55 | 0.85 | 0.62 | -0.21 |
| 1992Q4 | -0.390 | -0.220 | 0.667 | -0.52 | -2.28 | 0.31 | -0.06 | 0.36 | 0.01 | 2.04 | -0.35 |
| 1995Q4 | 0.139 | 0.159 | 0.333 | 2.95 | -0.23 | -0.80 | -0.25 | 0.85 | 0.60 | -0.58 | 0.84 |
| 1996Q4 | 0.065 | 0.016 | 0.333 | -1.86 | -0.50 | -0.92 | 0.52 | 0.76 | 0.11 | -0.62 | 0.58 |
| Direct or Indirect, X-12-ARIMA | | | | | | | | | | | |
| Date | Direct | Indirect | Weights | AGRI | IND | CONS | RETA | FINAN | PUBL | TAXES | FISIM |
| 1984Q4 | 0.246 | 0.274 | 0.167 | -1.16 | 0.98 | -0.95 | -0.22 | 0.96 | -0.02 | -0.12 | 0.55 |
| 1988Q1 | 0.296 | 0.234 | 0.333 | -1.48 | 0.92 | -0.01 | 0.58 | -0.28 | -0.13 | 0.44 | 0.21 |
| 1992Q3 | -0.035 | 0.023 | 0.667 | 1.42 | -1.45 | -1.02 | -0.25 | 0.81 | 0.98 | 0.44 | -0.12 |
| 1995Q4 | 0.126 | 0.113 | 0.333 | 2.55 | -0.45 | -0.95 | -0.35 | 0.84 | 0.71 | -0.35 | 0.95 |
| 1996Q4 | 0.007 | -0.055 | 0.333 | -1.67 | -0.63 | -1.57 | 0.45 | 0.62 | 0.15 | -0.37 | 0.56 |
| 2001Q2 | -0.021 | -0.067 | 0.667 | -1.17 | -0.89 | 0.11 | 0.05 | 0.46 | 0.27 | 0.18 | 1.13 |
| Mixed Approach | | | | | | | | | | | |
| Date | Mixed | | Weights | AGRI | IND | CONS | RETA | FINAN | PUBL | TAXES | FISIM |
| 1992Q3 | -0.208 | | 0.667 | 1.65 | -1.75 | -1.00 | -0.60 | 0.56 | 0.65 | 0.52 | -0.40 |
| 1995Q4 | 0.047 | | 0.333 | 2.13 | -0.35 | -0.76 | -0.36 | 0.82 | 0.57 | -0.97 | 0.77 |

Table 15 presents the concordance rates between the various approaches, a statistic that summarizes the previous elements. The concordance rate of the direct/indirect approaches with respect to the mixed one are higher for TRAMO-SEATS than for X-12-ARIMA. They are all satisfactory except for the concordance between the mixed approach and the indirect approach using X-12-ARIMA.

Table 15: Concordance rates: GDP aggregation by sector

*(in %)*

| | Tramo-Seats | X-12-Arima |
|---|---|---|
| Direct and Indirect | 97.75 | 97.75 |
| Direct and Components | 93.26 | 93.26 |
| Indirect and Components | 95.51 | 95.51 |
| Mixed and Direct | 93.33 | 86.67 |
| Mixed and Indirect | 88.89 | 82.22 |
| Mixed and Components | 95.56 | |

Table 16: Quality measures

| Indicator | TRAMO-SEATS | | X-12-ARIMA | | Mixed |
|---|---|---|---|---|---|
| | Direct | Indirect | Direct | Indirect | adjustment |
| M1* | 0.015 | 0.023 | 0.027 | 0.076 | 0.015 |
| M2* | 0.016 | 0.025 | 0.033 | 0.107 | 0.034 |
| M3* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| M4 | 0.751 | 0.555 | 0.849 | 1.045 | 0.969 |
| M5 | 0.200 | 0.200 | 0.200 | 0.200 | 0.200 |
| M7* | 2.256 | 2.158 | 2.523 | 3.344 | 0.105 |
| M8 | 0.485 | 3.087 | 0.397 | 1.918 | 1.338 |
| M9 | 0.183 | 0.219 | 0.204 | 0.171 | 0.143 |
| M10 | 0.408 | 2.710 | 0.363 | 1.621 | 1.045 |
| M11 | 0.345 | 1.937 | 0.363 | 1.288 | 0.624 |
| Q | 0.631 | 0.968 | 0.691 | 1.031 | 0.327 |

### *5.4 Quality measures of seasonal adjustments*

The M and Q-statistics results are presented in Table 16. All the approaches present some problems concerning the M7 statistics, so the seasonal pattern in the series is not constant over the sample period. Furthermore the indirect approaches present high values of M8, M10 and M11, indicating that large variations in the magnitude of the seasonal component are recorded, especially in the last three years of the series. The high value of M4 for the indirect adjustment using X-12-ARIMA suggests the presence of autocorrelation in the residuals, a result which is also confirmed by Table 19.

### *5.5 Roughness measures*

Roughness measures are presented in Table 17 and refer to the seasonally adjusted series, to the trend-cycle and to the seasonal component.

A first very simple conclusion we can draw from this table is that, once more, there is no clear evidence in favor of one of the approaches. In particular, we may notice how:

- in general the indirect approaches seem to give smoother seasonally adjusted series, following the R1 and R2 statistics, even if R3 gives the opposite results. For TRAMO-SEATS we get to the opposite conclusion if we consider only the last three years of the sample;
- the indirect approaches give also the smoother Trend-Cycles, even if for X-12-ARIMA the direct approach seems preferrable when considering only the last three years;
- the direct approaches provide the smoother seasonal factors.

Anyway the differences between direct and indirect are too small to be considered as relevant, especially for TRAMO-SEATs.

Table 17: Roughness measures: GDP aggregation by sector

| | TRAMO-SEATS | | X-12-ARIMA | | Mixed | | |
|---|---|---|---|---|---|---|---|
| | Direct | Indirect | Direct | Indirect | approach | SEATS | X-12 |
| R1 (SA) | 11278.1 | 11060.7 | 11816.8 | 11749.4 | 7479.3 | I | I |
| R1 (SA), Last 3 years | 6468.5 | 6573.4 | 8163.3 | 7891.3 | 6827.6 | D | I |
| R2 (SA) | 0.283 | 0.270 | 0.308 | 0.306 | 0.111 | I | I |
| R2 (SA), Last 3 years | 0.129 | 0.134 | 0.220 | 0.197 | 0.091 | D | I |
| R3 (SA) | 0.124 | 0.156 | 0.181 | 0.323 | 0.111 | D | D |
| R3 (SA), Last 3 years | 0.120 | 0.128 | 0.227 | 0.214 | 0.091 | D | I |
| Mar (TC, 1) | 10854.4 | 10508.9 | 11103.4 | 9281.7 | 6861.6 | I | I |
| Mar (TC, 1), Last 3 years | 7923.0 | 7852.7 | 8211.8 | 8236.1 | 8203.4 | I | D |
| Mar (TC, 2) | 11906.1 | 10877.6 | 12326.3 | 6031.0 | 3107.3 | I | I |
| Mar (TC, 2), Last 3 years | 2149.2 | 2084.3 | 2327.6 | 2796.5 | 2444.8 | I | D |
| Mar (S) | 0.015 | 0.079 | 0.011 | 0.051 | 0.062 | D | D |
| Mar (S), Last 3 years | 0.013 | 0.071 | 0.009 | 0.043 | 0.044 | D | D |

### *5.6 Revision analysis*

Table 18 presents the revisions of direct and indirect estimates obtained with the two programs. Both for TRAMO-SEATS and for X-12-ARIMA the indirect approach performs better both in terms of mean and variance of the revisions, even if the difference between the two approaches is smaller for TRAMO-SEATS than for X-12-ARIMA.

The Sliding-Spans analysis reveals a small problem of instability for the direct approach using TRAMO-SEATS (3.7% of dates have unstable adjustments) and for both approaches using X-12-ARIMA (3.7% of dates have unstable month-to-month percent changes).

Table 18: Absolute revisions (mean and standard deviation in %) and sliding spans analysis: GDP aggregation by sector

| Indicator | TRAMO-SEATS | | X-12-ARIMA | | Direct vs Indirect | |
|---|---|---|---|---|---|---|
| | Direct | Indirect | Direct | Indirect | SEATS | X-12 |
| Mean AR 1 qtr | 0.157 | 0.129 | 0.170 | 0.131 | I | I |
| Mean AR 2 qtrs | 0.157 | 0.131 | 0.189 | 0.135 | I | I |
| Mean AR 3 qtrs | 0.160 | 0.134 | 0.204 | 0.136 | I | I |
| Mean AR 4 qtrs | 0.156 | 0.130 | 0.187 | 0.127 | I | I |
| Mean AR 5 qtrs | 0.158 | 0.137 | 0.198 | 0.144 | I | I |
| Std AR 1 qtr | 0.090 | 0.082 | 0.110 | 0.075 | I | I |
| Std AR 2 qtrs | 0.097 | 0.085 | 0.119 | 0.072 | I | I |
| Std AR 3 qtrs | 0.091 | 0.081 | 0.105 | 0.064 | I | I |
| Std AR 4 qtrs | 0.096 | 0.086 | 0.153 | 0.105 | I | I |
| Std AR 5 qtrs | 0.089 | 0.084 | 0.146 | 0.098 | I | I |
| Sliding Spans | | | | | | |
| A (%) | 3.659 | 1.220 | 0.000 | 0.000 | = | = |
| MM (%) | 1.236 | 1.236 | 3.704 | 3.704 | = | = |

### 5.7 Analysis of the residuals

The various irregular component estimates have been analysed with TRAMO and X-12-ARIMA. Table 19 presents the results of this analysis:

- no residual seasonality is detected on the irregular components, and just for the direct approach using TRAMO-SEATS the estimated ARIMA model contains a non-zero seasonal moving average term;
- all the estimates of the irregular component present residual Easter and trading day effects;
- for what regards outliers, TRAMO identifies just one transitory change for the indirect approach using TRAMO-SEATS.

Table 19: Analysis of the Irregular Components: GDP aggregation by sector

| Series | Model | pljung | dw | pnorm | ls | tc | ao | trad | east | Season? |
|---|---|---|---|---|---|---|---|---|---|---|
| SEATS Indirect | (1,0,0)(0,0,0) | 0.527 | 2.009 | 0.042 | 0 | 1 | 0 | Y | Y | N |
| X-12 Indirect | (0,0,1)(0,0,0) | 0.382 | 2.552 | 0.000 | 0 | 0 | 0 | Y | Y | N |
| SEATS Direct | (3,0,0)(0,0,1) | 0.196 | 1.935 | 0.631 | 0 | 0 | 0 | Y | Y | N |
| X-12 Direct | (0,0,1)(0,0,0) | 0.535 | 2.038 | 0.000 | 0 | 0 | 0 | Y | Y | N |

## 6 Conclusion

The comparison presented in this paper shows some interesting results. The first one is that the figures currently published by Eurostat using the mixed indirect approach are quite different with respect to those obtained by using either the direct or the indirect approaches, independently of the seasonal adjustment program. This can be viewed as a consequence of the different seasonal adjustment policies and options adopted by Member States to compile their aggregates. Moreover the mixed seasonal adjustment appears to be the less satisfactory in terms of the different quality measures that have been analysed in this paper.

On the basis of these considerations, we may conclude that the seasonal adjustment strategy currently used by Eurostat in the field of Quarterly National Accounts needs to be amended in order to supply users with higher quality and more transparent results.

The second result is that there are no evident and significant differences between the direct and the indirect approach, both using TRAMO-SEATS and X-12-ARIMA. In some cases the proposed quality measures seem to privilege the direct approach, in other cases the indirect. Moreover for the same group of criteria, like for roughness measures for example, the subjective appreciation can lead to prefer one approach to the other or *vice versa*.

These elements apply both to the geographical and to the sectoral aggregation. Even if the definition of a general Eurostat strategy to compute seasonal adjusted QNA figures is outside the scope of this paper, a reasonable seasonal adjustment strategy emerging from the results can be synthesised as follows:

- use of a direct approach on each aggregate for the geographical aggregation;
- use of the indirect approach for the sectoral aggregation.

The indirect seasonal adjusted may be less useful for the geographical aggregation because it would be impossible for Eurostat to publish different seasonal adjusted figures with respect to those published by Member States. Under this constraint, the additivity of the seasonal adjusted data that one would obtain by using an indirect approach cannot be used in practice. Considering also the similarity of the results obtained with the direct/indirect methods, it seems then natural to prefer the direct approach since it is easier to implement in practice.

The use of the indirect approach for sectoral aggregation could be replaced by the use of a direct approach with redistribution of discrepancies in the case of sectoral aggregation. Nevertheless this alternative solution is only feasible under the condition that the discrepancy between the sum of the seasonally adjusted components and the seasonally adjusted aggregate series are small. The results presented in the paper suggest, anyway, that this condition is fulfilled.

## References

[1] Blake, A., Kapetanios, G., Weale, M. (2000), *A Common European Business Cycle*, Working Paper, Eurostat.

[2] Dagum, E.B. (1979), On the Seasonal Adjustment of economic Time Series Aggregates: A Case Study of the Unemployment Rate, *Counting the Labor Force, National Commion Employment and Unemployment Statistics, Appendix*, 2, 317-344, Washington.

[3] European Central Bank (2000), *Seasonal Adjustment of Monetary Aggregates and HICP for the Euro Area*, Working Paper.

[4] Eurostat (2000), *Eurostat Recommandations Concerning Seasonal Adjustment Policy*, Report of the Internal Task Force on Seasonal Adjustment.

[5] Findley, D. F., Monsell, B. C., Bell, W. R., Otto, M. C. and Chen, B. (1998), New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program, *Journal of Business and Economic Statistics*, 16, 127-177.

[6] Geweke, J. (1976), The Temporal and Sectoral Aggregation of Seasonally Adjusted Time Series, *Proceedings of the Conference on the Seasonal Analysis of Economic Time Series*, Economic Research Report ER-1, Arnold Zellner Editor, Washington.

[7] Gómez, V. (2000), *Revision-based Test for Direct versus Indirect Seasonal Adjustment of Aggregated Series*, Working Paper, Ministerio de Economia y Hacienda, Madrid.

[8] Gómez, V. and Maravall, A. (1999), *Application of* TRAMO-SEATS*: Examples 2 and 4*, Bundesbank Seminar, Unpublished manuscript.

[9] Gómez, V. and Maravall, A. (1997), *Programs* TRAMO *and* SEATS*: Instructions for the User, Beta version*, Banco de España.

[10] Hood, C. C., Ashley, J. D. and Findley, D. F. (2000), *An Empirical Evaluation of the Performance of* TRAMO-SEATS *on Simulated Series*, Working Paper, US Bureau of Census, Washington.

[11] Ladiray, D., Quenneville, B. (2001), *Seasonal Adjustment with the X-11 Method*, Lecture Notes in Statistics, Springer-Verlag, New York.

[12] Lothian, J. and Morry, M. (1977), *The Problem of Aggregation; Direct or Indirect*, Working Paper, Time Series Research and Analysis Division, *Statistics Canada*, Ottawa ON, Canada.

[13] Pfefferman, D., Salama, E. and Ben-Tuvia, S. (1984), *On the Aggregation of Series: A New Look at an Old Problem*, Working Paper, Bureau of Statistics, Jerusalem, Israel.

[14] Planas, C., Campolongo, F. (2000), *The Seasonal Adjustment of Contemporaneously Aggregated Series*, Working Paper, Joint Research Centre of European Commission, Ispra, Italy.

[15] Scott, S., Zadrozny, P. (1999), Aggregation and Model-based Methods in Seasonal Adjustment of Labor Force Series, *Journal of Business and Economic Statistics*, 156-161.

[16] Scott, S. (1984), A Case Study of Direct and Indirect Seasonal Adjustment of Aggregate Series, *Journal of Business and Economic Statistics*, 686-691.

[17] U.S. Census Bureau (2001), *X-12*-ARIMA *Reference Manual, Version 0.2.8*, Washington DC, U.S. Bureau of the Census.

# 4

# Criteria to determine the optimal revision policy: a case study based on euro zone monetary aggregates data

Laurent Maurin

## Introduction

Seasonal factors are only estimate, so are seasonally adjusted (SA) data. At the extremities of a time series, the symmetric filters used to produce SA data in the cases of X12 and SEATS require forecasting. Hence, each time a new observation is added, the substitution of the actual value for the previous forecasted one and the production of new forecasts lead to a variation in the SA data, not only for the last previous one. Moreover, original data and in the case of SEATS, the model, can be revised too.

This implies the need to define a revision policy in the context of recurrent publications of SA data. The revision policy is defined as the process used to update the estimates of the published SA data. In consequence, the frequency of revisions is only determined by the revision policy of SA data. But the intensity of the revisions depends also on the quality of the forecasts used to extend the series at the end of the sample. As it seems plausible that the quality of forecasts increases with the frequency of updates of the underlying model, there is a trade-off between the cost of revisions and the quality of data published.

The interest of the study presented here arises from this trade-off. This trade-off might be contingent to the time series, as they behave differently. So the problem is contemplated from an empirical point of view, using Euro-aggregated monetary statistics. The two main methods are considered: X12 and SEATS. To concentrate only on seasonal filters, they are applied to the same time series, the one adjusted for outliers and calendar effects obtained by TRAMO.

The paper is made of three sections. The first section presents the methodology tested at the Banque de France, and some interesting preliminary results[1]. The second section presents the relation between the underlying ARIMA model used to forecast the time series and the resulting SA data. The third section compares the revisions implied by twenty different revision policies. The paper ends with some concluding remarks.

## 1. Methodological aspects

The study is carried on the eight aggregated monetary statistics which have been calculated backward by the ECB, since the beginning of 1981.[2] These series are seasonally adjusted by the ECB using a methodology described in ECB (2000a) and ECB (2000b).
The methodological framework developed at the Banque de France differs from the ECB-method on several topics (see Lacroix, 2002). They are presented in the first paragraph, whereas the second paragraph comments some results.

---

[1] As it isn't the core of the paper, this section is developped to the extent that it allows a better understanding of the results provided below.

[2] These time series are: currency in circulation, overnight deposits, deposits with agreed maturity and redeemable at notice, market instruments, M1, M2, M3, and loans to the private sector (which starts later).

### 1.1 Preliminary options retained at the Banque de France

The seasonal adjustment is made on the net flows, F. The initial value of the stock, $E_{t_0}^{SA}$, is obtained from direct seasonal adjustment of the stock series. Then, SA stocks are reconstructed by summing SA flows, $F^{SA}$, and corrections, $C^{SA}$, up to the present date :

$$E_t^{SA} = E_{t_0}^{SA} + \sum_{p=t_0+1}^{t} (F_p^{SA} + C_p^{SA}) \tag{1}$$

Using Spectral analysis and white noise tests, a previous study has shown that the corrections have no seasonal patterns (see Maurin, 2002). So the calculus of SA stocks involves only the calculus of the SA flows.

Considering the methodology used (Eq. 1), in all the cases, the seasonal model is constrained to be additive. This is not embarrassing since at some date, the flows are negative.

- The indirect method is used to adjust aggregates, "bottom to top".[3] But, as the interest is to calculate indicators that are meaningful from a monetary policy point of view, the study is not made at the most disaggregated level.
- TRAMO is used to calculate the corrected original series. Moreover, an investigation is carried about the economic or statistical justification of the outlier. The adjustment is made using the two main methods: X12 and SEATS, on the same time series, corrected for outliers and other deterministic effects (trading days, Easter effects...).
- DEMETRA 2.0 (April 2001), a Windows based interface for DOS versions of X12 and TRAMO-SEATS, is used to estimate SA data. Then Sas macros are developed to construct SA stocks, monthly SA growth rates, annualised three and six months growth rates, and analyse results.

### 1.2 Some results obtained with TRAMO

After much calculus done with TRAMO, it is difficult to obtain a low degree of differentiation and a few numbers of corrections. Using the automated research, one can obtain puzzling results: sometimes, one level shift is reverted a few months after. So, the results of automated research are not taken into account. Instead, we use the standard exploratory methods for Arima models on a case by case basis.[4]

After inspection of the graphs of the flows, it appears that some series have a changing dynamic pattern at the beginning of the nineteen. Particularly for market instruments, a clear breakdown emerges at the beginning of 1993 (see Figures 1 and 2). At the same date, European economies faced some turmoil's, in the following of the German reunification and the two Exchange Rate Mechanism crisis. Euro zone economies slowed down, and entered a quick economic recession, whereas interest rate moved a lot following the beginning of a credit crunch.[5] Though the breakdown is not so evident for all the series, we choose to impose the same breakdown for all.

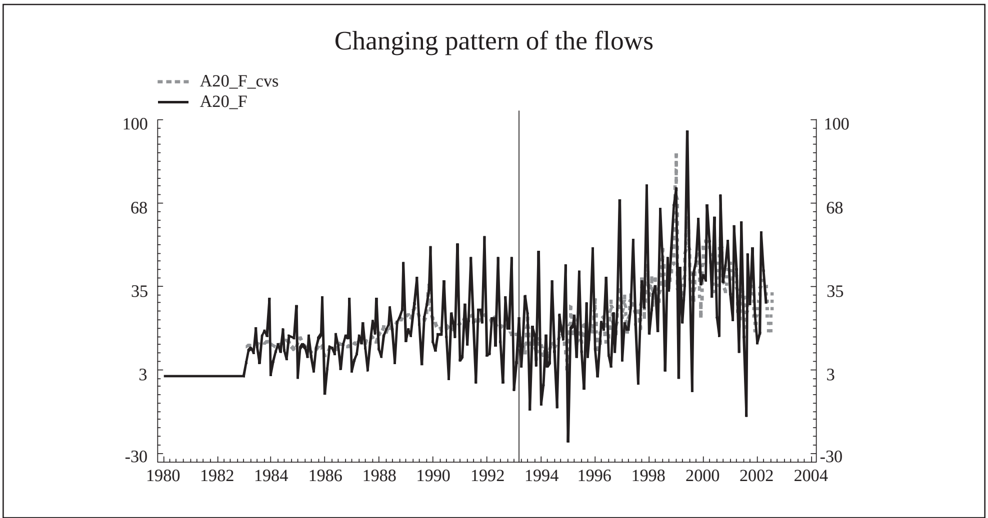
---

[3] As SA aggregates are in fact obtained both indirectly and directly, the statistical tretaments made would enable to compare the two methods, but it is not the scope of the paper.

[4] As the identified Arima and the preliminary corrections are interdependent, it is difficult to validate a model with 1 or 2 differenciations on the flows, when the corrections include temporary changes or level shifts. In the original spirit of the paper of Perron (1989), the alternative for a time serie is between break-stationary or non-stationary.

[5] Stability tests will be used to study more deeply the hypothesis of a breakdown in the time series.

Figure 1: A20, loans to private sector
*(EUR billions)*




For all the time series, considering two periods to make seasonal adjustment, the results are more convincing. First, forecast errors are weaker when the Arima model is identified and estimated on two separated periods. Second, after calculus done by TRAMO, the identified Sarima doesn't need any differenciation on the non-seasonal part. On each period, for all series, the Arima process is based on the level of the annual difference in the flows, and doesn't require any other differentiation.

Figure 2: LT3, market instruments
*(EUR billions)*

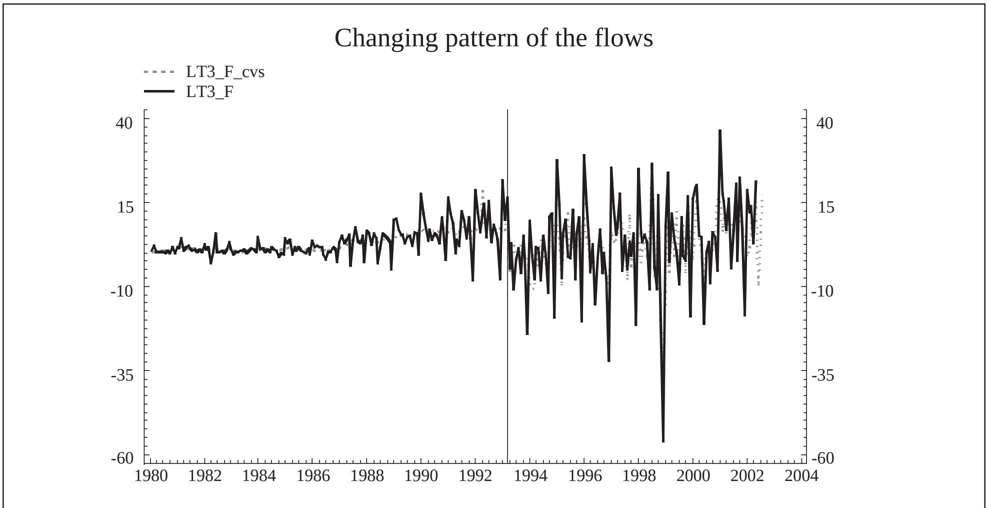


Table 1: Results obtained using TRAMO on the flows 1)

| | Mean correction | Calendar Effects | Easter Effect | Outliers | Arima model |
|---|---|---|---|---|---|
| L10<br>Currency in circulation | Yes | TD<br>LY | Yes | AO DEC1999, AO JAN 2000<br>TC SEP2001 | (003) (011) |
| L2A<br>Other short term deposits | | | | AO JAN2000 | (300) (011) |
| A20<br>Private loans | Yes | | | AO JAN1999, LS MAY2001 | (000) (011) |
| LT3<br>Market instruments | Yes | | Yes | AO JAN2001, AO JAN1999<br>AO DEC1998 | (000) (011) |
| L21<br>Overnight deposits | | TD<br>LY | | AO JAN1999, AO JAN2000<br>TC SEP2001 | (000) (011) |
| M10<br>Narrow mon. aggr. | | TD<br>LY | | AO JAN1999, AO JAN2000 | (000) (011) |
| M20<br>Intermediary mon. aggr. | | WD | | AO JAN1999, AO FEB1999 | (000) (011) |
| M30<br>Broad mon. aggr. | Yes | WD | | AO JAN1999 | (000) (011) |

1) WD is for Working Days, TD is for Trading Days, LY is for Leap Year, AO is for Additive Outlier, TC for Transitory Change and LS for Level Shift.

So, waiting the results of the stability tests that are available in order to study the hypothesis of a breakdown in the time series, we can’t conclude. As the aim of the present study is not to publish SA data, but to study revision policy by simulating updates, we impose a breakdown in March 1993. The results obtained using TRAMO are presented below, in the Table 1.
Three majors source of outliers appear:
– The introduction of the Euro currency inside the Euro area, which explains the transitory change at the end of 2001 in L10 and conversely in L21).
– The end of national moneys, in January 1999, which explains the additive outliers in M10, M20, M30, and LT3.
– The fear of the millennium bug or the extraordinary new year, which explains the additive outliers in December 1999 and January 2000.

As the original time series are corrected by TRAMO independently of the filter used to calculate SA data, X12 is used on the corrected time series imposing no corrections for calendar and outlier effects in the Regarima part. In many cases, statistical tests reject the series retained by TRAMO on the whole period and accepted on shorter period because forecast errors over last year exceeds 15% between December 98 and December 2000. This leads us to consider that selected Sarima model performs poorly in explaining recent monetary dynamics and that criteria used to validate Arima model in Regarima are harder to comply with.

### 1.3 *Preliminary descriptive analysis (SEATS)*

- Using non-parametric estimations, spectrums of SA data doesn't point to any residual seasonality since there isn't any peaks at seasonal frequencies.
- Differences between SA stocks evaluated directly, by summing SA flows, and those evaluated indirectly, by aggregating SA stocks, are weak, below 0.5 %.
- Compared to SA data published by the ECB, the SA data calculated using the methodology described above show less variability.[6]

## 2. The nature of revisions

Only one source of revision is studied in this section. The one that comes from the substitution of observed data to the data previously forecasted. This is the only source on which one can study theoretical variance of revisions, assuming fixed and known coefficients in the Sarima model used.
Consider a time series, $y_t$, made of two components, a seasonal one $s_t$, and a non seasonal one $n_t$:[7]

$$y_t = s_t + n_t \tag{2}$$

Using SEATS or X-12, the estimated seasonal component is constructed by applying a symmetric filter, Θ, to the original time series, $y_t$. Moreover this filter is supposed to be time invariant: this hypothesis is certainly true for SEATS. For X-12, it neglects the dependency induced by automatic corrections for outliers.

$$\hat{s}_t = W(B)y_t \qquad \textit{where } W \textit{ is symetric}$$
$$W(B) = W_p B^p + \ldots + W_1 B + W_0 + W_1 F + \ldots + W_p F^p \tag{3}$$

To simplify further, assume $y_t$ is stationary, and apply the Wold decomposition. Then $y_t$ can be expressed as an infinite moving average process:

$$y_t = \psi(B)\varepsilon_t \qquad \textit{where } \varepsilon_t \textit{ is iid} \tag{4}$$

Using (3) into (2), one founds:

$$\hat{s}_t = W(B)\psi(B)\varepsilon_t = \chi(B) = \sum_{j=-\infty}^{-1} \chi_j B^j + \chi_0 + \sum_{j=1}^{\infty} \chi_j F^j \tag{5}$$

Hence, as $E_t[\varepsilon_{t+1}] = 0$, $E_{t+p}[\varepsilon_{t+h}] = \varepsilon_{t+h}$ if $h < p + 1$ and 0 if $h > p$, the estimate at the period (t+h) of the seasonal component, s, in t is calculated using (4):

$$E_{t+h}[s_t] = \hat{s}_{t/t+h} = E_{t+h}\left[\left(\sum_{j=-\infty}^{-1} \chi_j B^j + \chi_0 + \sum_{j=1}^{\infty} \chi_j F^j\right)\varepsilon_t\right] = \left(\sum_{j=-\infty}^{-1} \chi_j B^j + \chi_0 + \sum_{j=1}^{h} \chi_j F^j\right)\varepsilon_t = \chi^h(B)\varepsilon_t \tag{6}$$

[6] Thought that is not a criteria to evaluate the quality of seasonal adjustment, the volatility of the SA figures is less important than the volatility of the ECB adjusted figures, which are based on the whole period.

[7] Deterministic effects have been filtered from the series (using TRAMO for example), so that expectation of both components is zero.

Using (5), one can express the variation in the estimated seasonal component, between the estimation for t made h periods ahead and the estimation made (h-1) periods ahead, $REV_{t,t+h}$:

$$REV_{t,h} = \hat{s}_{t,t+h} - \hat{s}_{t,t+h-1} = \chi_h \varepsilon_{t+h} \tag{7}$$

More generally, one can express the difference between the first estimate of the seasonal component and the one made h periods ahead as a moving sum of the successive innovations:

$$REV0_{t,h} = \hat{s}_{t,t+h} - \hat{s}_{t,t} = \sum_{i=1}^{h} \chi_i \varepsilon_{t+i} \tag{8}$$

According to this analysis, one can study revision process using forecast errors statistics. Moreover, one can calculate the theoretical variance of revisions and compare it to its estimate, which takes into account all the effects (change in the model or in its coefficients, non-linearity of the filter (X12), substitution of the actual data to the forecasted ones and updates of forecasted values).

## 3. Simulating and comparing twenty revision policies

SA data can be updated each year, each half-year, each quarter, or each month. Considering SEATS, there are three kinds of update: the identification of the Arima model, the estimation of the coefficients, and the forecasts. Considering X12, another possibility not considered here is provided by the partial parameterisation of the filters used (trend and seasonal filter). This parameterisation is let free to move automatically according to X12; the filter is not blocked. On the same way, SEATS parameters are managed automatically and aren't modified. Combining these possibilities (on the frequency and on the process updated), one obtains twenty revision sequences (see Table 2).[8] These sequences are simulated in the analysis below.[9]

This study is made by incrementing the sample during two years, on a period that starts in December 1999 and ends in December 2001. The time series used is corrected for calendar and deterministic effects (these effects are estimated on the whole sample available, as described above). Month after month, a new observation is added, and depending on the revision sequence studied, new seasonal adjusted data are obtained.

Assume that the final SA data is calculated using the entire time span, up to August 2002. For each date between December 1999 and December 2001, the difference between SA data obtained for differing expiry date and the final SA data are revisions, and can be assimilated to forecast errors, so that we can evaluate the different methods using empirical criteria.

Then two criteria are considered in order to evaluate the relative merits of our twenty revision policies: What is the quality of the first estimation of SA data? And what is the speed of convergence toward the final value? To answer these questions, many indicators are calculated to compare the twenty time series obtained for SA data for each expiry date.

The time series that is seasonally adjusted is the flow. But, once SA data are estimated, SA stocks are built and month on month seasonally adjusted growth rate is calculated. As it is the prominent variable for short term monitoring of monetary policy, the revision policies will be

[8] One must consider the fact that identification must be less frequent than estimation that must be less frequent than updating the forecast.

[9] Due to a bug in Demetra 2.0, it isn't possible to obtain forecasted seasonal components using X12. Hence, results for policies 4, 8-9-10, and 15-16-17-18-19-20 are not available.

Table 2: Description of the twenty sequences used: update frequency[1)]

| Sequency | Identification | Estimation | Forecast |
|---|---|---|---|
| 1 | month | month | month |
| 2 | quarter | month | month |
| 3 | quarter | quarter | month |
| 4 | quarter | quarter | quarter |
| 5 | half-year | month | month |
| 6 | half-year | quarter | month |
| 7 | half-year | half-year | month |
| 8 | half-year | quarter | quarter |
| 9 | half-year | half-year | quarter |
| 10 | half-year | half-year | half-year |
| 11 | year | month | month |
| 12 | year | quarter | month |
| 13 | year | half-year | month |
| 14 | year | year | month |
| 15 | year | quarter | quarter |
| 16 | year | half-year | quarter |
| 17 | year | year | quarter |
| 18 | year | half-year | half-year |
| 19 | year | year | half-year |
| 20 | year | year | year |

1) Annual in December, half-year in December and June, Quarter in December, March, June and September.

evaluated according to it. Hence, revisions are considered in absolute terms, not relatively to the final value. They are shown in basis points.

### *3.1 The statistics calculated*

Firstly, for each expiry date (December 98 to December 2000), and each sequence, the following statistics are calculated. Hence, for each time series, one obtains fourteen tables. Secondly, statistics according to different expiry dates are aggregated.

In the presentation of statistics $x_{i,k}$ is the SA data: i refers to the expiry date, the time on which the SA data is calculated, and k refers to the date of the publication ($k \geq i$). i ranges from 1 to 25 (December 1998 to December 2000).

### Statistics on revision

Let $R_{i,k}$ refers to the revision for the SA data concerning the date i, the difference between the publication made at the date k and the previous one:

$$r_{i,k} = x_{i,k} - x_{i,k-1}$$

– **Total Absolute Revision, TAR:**
This simple statistic gives an indication about the information contained in the first publication of the SA data. It calculates the total amount of revision between the first publication, $x_{i,i}$ and the last one, $x_{i,T}$, evaluated using all the data up to August 2002.

$$TAR_i = \left| x_{i,i} - x_{i,T} \right|$$

– **MEDian Absolute Revision, MEDAR:**

$$MEDAR_i = Me\left\{ \left| r_{i,i+1} \right|, \ldots, \left| r_{i,25} \right| \right\}$$

– **Mean Absolute Revision, MAR:**

$$MAR_i = \frac{1}{25-i} \sum_{k=i+1}^{25} \left| r_{i,k} \right|$$

– **Root of Mean Square Revision, RMSR:**

$$RMSR_i = \sqrt{\frac{1}{25-i} \sum_{k=i+1}^{25} r_{i,k}{}^2}$$

All these statistics have the same unity. In the following tables, they are expressed in point basis. Although these statistics are comparable, MEDAR is the most robust since it depends less on extreme values. Compared to MAR, in RMSR, the importance of strong (weak) revisions is diminished.

**Statistics on convergence**

Let Sh represent the share of the k$^{th}$ revision:

$$Sh_{i,k} = \frac{r_{i,k}{}^2}{\sum_{j=i+1}^{25} r_{i,j}{}^2}$$

One can presume that Sh decreases monotonically, as important revisions are expected for preliminary figures. Comparing revision policies, an interesting insight is obtained by considering the speed of convergence. For that purpose, two families of criteria can be used:

– **Using the cumulative share square revision: d50, d75, d90**

$$F_{i,k} = \sum_{j=i+1}^{k} Sh_{i,k}$$

F is the cumulative share square revision, the share of the total square revisions already realised since the first publication. Using F, one can calculate the delay (in months from the first publication) since which 50%, 75% and 90% of the cumulative square revisions have been made (d50, d75, d90). Interval between each delay provides an information about the rate of convergence.

– **Mean Convergence, MC:**

$$MC_i = \sqrt{\frac{1}{25-(i+1)} \sum_{j=i+2}^{25} Sh_{i,j}^2}$$

This statistics allows to distinguish between sequences that lead to many weak revisions (MC is low) and whose that lead to a few strong revision.

– **Smoothness of Convergence, SC:**

$$SC_i = \sqrt{\frac{1}{25-(i+1)} \sum_{j=i+2}^{25} \left(Sh_{i,j} - \bar{S}h_{i,j}\right)^2}$$

This statistic is the standard deviation of the share of revision. The higher is this statistic, steeper is the share convergence curve, and so the fastest is the convergence toward the final SA data.

### Aggregation of criteria along months observed

To concentrate the available information, criteria are aggregated along the twelve first observations (so that for each sequence used, the number of revisions saved is greater than twelve). Considering the nature of the statistics, each statistics is weighted by the number of revisions on which it is calculated, excepted the TAR.

For the twenty sequences, results are provided in the tables 3 to 8, each table considering a time series.[10] TAR, MAR, RMSR are expressed in basis points. d75 and d90 are expressed in months since the first publication. MC and SC are percentages and so belong to [0,1]. Concerning d90 or d75, in the case where in almost one of the twelve aggregated maturity date, the corresponding share is not reached in December 2000, the result, which would be meaningless, is not reported.

### *3.2 The results*

Many results can be drawn from the statistics calculated.

### Considering the tables 3 to 9:

– Surprisingly in some cases, the weakest original error (TAR) is not provided by the total revision policy activated each month, the sequence 1 (see Table 4, 6, 7 and 8). This result can be explained by the fact that sometimes the identified change during a short period before coming back to the previous one, so that ex post, this change isn't justified (see below). It can then be interpreted as an artefact of sampling variation. In these cases, a less frequent activation of the identification process provides better results (sequences 11 to 14).

[10] For convenience, thought calculus are available, two series have been excluded: L10, currency in circulation (taking into accout the recent turmoils) and L2A, other short terms deposits.

This seems to imply that re-identifying the model each year is the best policy.

– Compare sequences 2 to 3, 5 to 7 and 11 to 14, when the coefficients are refreshed at differing frequencies, whereas forecasts are produced each months. Then, it appears that the re-estimation of the coefficients doesn't seem to induce a major improvement in the revision process, be it considered relatively to the amount or the speed, when SEATS is used.
– In all the cases, the better results appear to be provided by policy 11 to 14, identification each year, and forecasting each month:
For A20, the optimal policy appears to be 13 or 14 (estimation each half-year or year).
For L21, the optimal policy appears to be 14 (estimation each year).
For LT3, the optimal policy appears to be 13 (estimation each half year).
For M10 and M20, the optimal policy appears to be 11 (estimation each month).
For M30, the optimal policy appears to be 14 (estimation each half year).
– The tables show clearly the trade-off between the speed in the revision process and the amount of revision. For each series, independently of the statistic chosen to represent the amount of revision (TAR, MAR or RMSR) and of the statistics chosen to approach convergence (MC or SC), a clear increasing relation appears. Hence strong revision are associated with faster convergence in absolute term.
– Considering d75 and d90, the convergence process appears to be slow, since in many cases, 75% of the revisions are not made within a year.
– The use of projected seasonal components is associated with a strong increase in the TAR (total error revision), and in d75 and d90. In many cases, d75 is above 12.
– Fortunately, the better results are obtained on M30 and M10. For M30, the TAR belongs to 9-20 basis points.

### Considering the figures:

The figures 1 to 24 plot the successive estimations of SA month on month (mom) growth rate, since the first observation and up to December 2000. Hence, the X-axis represents the number of month since the first actual data was available. The horizontal dotted line plots the "final" value, estimated in August 2002. Figures 1 to 12 concern the month of December 1998, whereas figures 13 to 24 concern the month of March 1999.
Considering the general pattern of the graphs, one can make some remarks.

– For each series, the same scale is used on the two graphs representing SA mom growth rate. So one can see that differences between final value estimated by each method are rather weak (the strongest being 35 basis point for M10 in December 98). In all but one case (M30 in December 98), first estimates are similar too.
– In all the cases, the sequence used is the most reactive: each month, the underlying Arima model is re-identified, coefficients are estimated, and new forecasts are made. But in some cases, the convergence is not smooth. Comparing the results obtained by SEATS and by X12, one can see that there is no smoother method on the whole.
– Usually, a clear breakdown appears twelve or twenty-four months after the first estimate. Apart from that frequency, the re-estimation of the model doesn't lead to significant modifications. Conversely, the re-identification of the model leads to strong variations in SA data but it is often reverted within some months, since the identified model turns back to be the same. In fact, this is due to the process used to calculate SA data in the final study: excepted for the entire time series, for each expiry date, the Arima model identified is automatically accepted even if it doesn't fulfil statistical criteria based on residuals, as it is often the case with Regarima.

– Conveniently, the convergence speed depends on the series but more surprisingly, on the month too. It is slow in December, the month for which the seasonality is the strongest for many monetary statistics.[11]

## Concluding remarks

The study has provided some empirical tools for the choice of an "optimal" policy revision. First, as a whole, frequent updates of the identification of the Sarima model do not improve the quality of SA data. In all the cases, a change in the model must be carefully monitored. Second, systematic re-estimations of the coefficients are not always optimal, and in all the cases don't improve strongly the quality of the SA data. Finally, using projected coefficients is not a good policy. Hence, the only degree of freedom is the frequency of update for Sarima coefficients: room of manoeuvre is provided by the frequency of estimation.

This study has considered the rate of growth. By construction, its conclusions are dependent on SA stock and on SA flows, two sources of possible variations whom the effect on the rate of growth might be amplified. A further analysis should then jointly study revisions on SA stocks and flows. But it would be interesting too, to study the revisions on the annualised three-months SA rate of growth and six-months SA rate of growth, as it is possible that these SA rates of growth are more stable.

To conclude, in the present situation, though SA data provides a useful guide for monitoring short run movements in monetary statistics, we can note that, due to the variability of SA monthly rate of growth, its use for monetary policy purposes requires additional tools (e.g. trend-cycle analysis). Besides, the ECB doesn't comment monthly rate of growth in its press release.

## References

Dosse J., Planas C., (1996), Revisions in seasonal adjustment methods: an empirical comparison of X-12-ARIMA and SEATS, Eurostats Working Papers, September.

ECB, (2002), Seasonal Adjustment of Euro Area Monetary Aggregates, Status report on the main developments over the last 12 months, mimeo.

ECB, (2000a), Final Report of the ECB Task Force on Seasonal Adjustment, Money and Banking Statistics Division, General Economic and Financial Statistics Division, June 28th 2000.

ECB, (2000b), Long-Term Approach for Euro Area Monetary Aggregates, Task Force on Seasonal Adjustment, 0001/02.

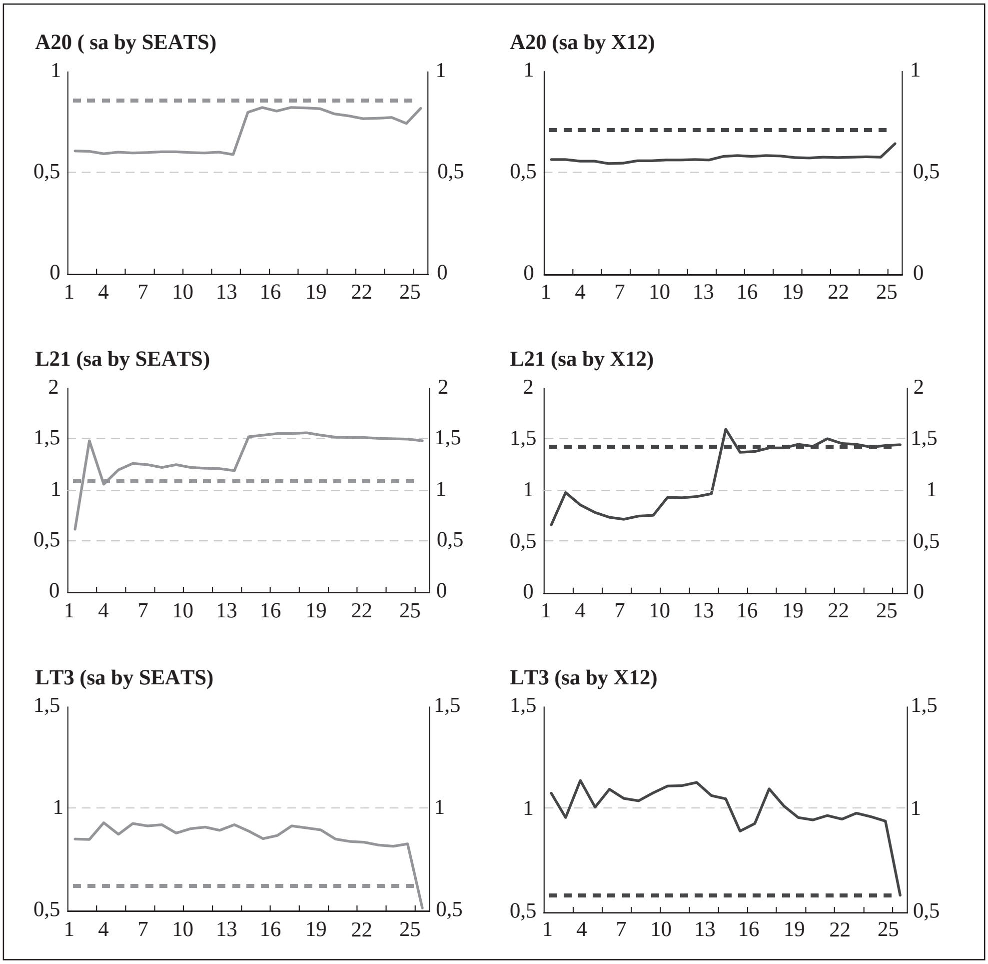
Lacroix R., (2002), Projet désaisonnalisation des agrégats monétaires, memo n° M02-059b, June 27th 2002.

Maurin L., (2002), Etude de la saisonnalité des corrections réalisées sur les agrégats monétaires français: M1, M2, M30, L2A et LTC), memo n° M02-061a, May 3th 2002.

[11] It should be interesting to correlate the convergence speed with the seasonal factor volatility for the twelve months of the year.

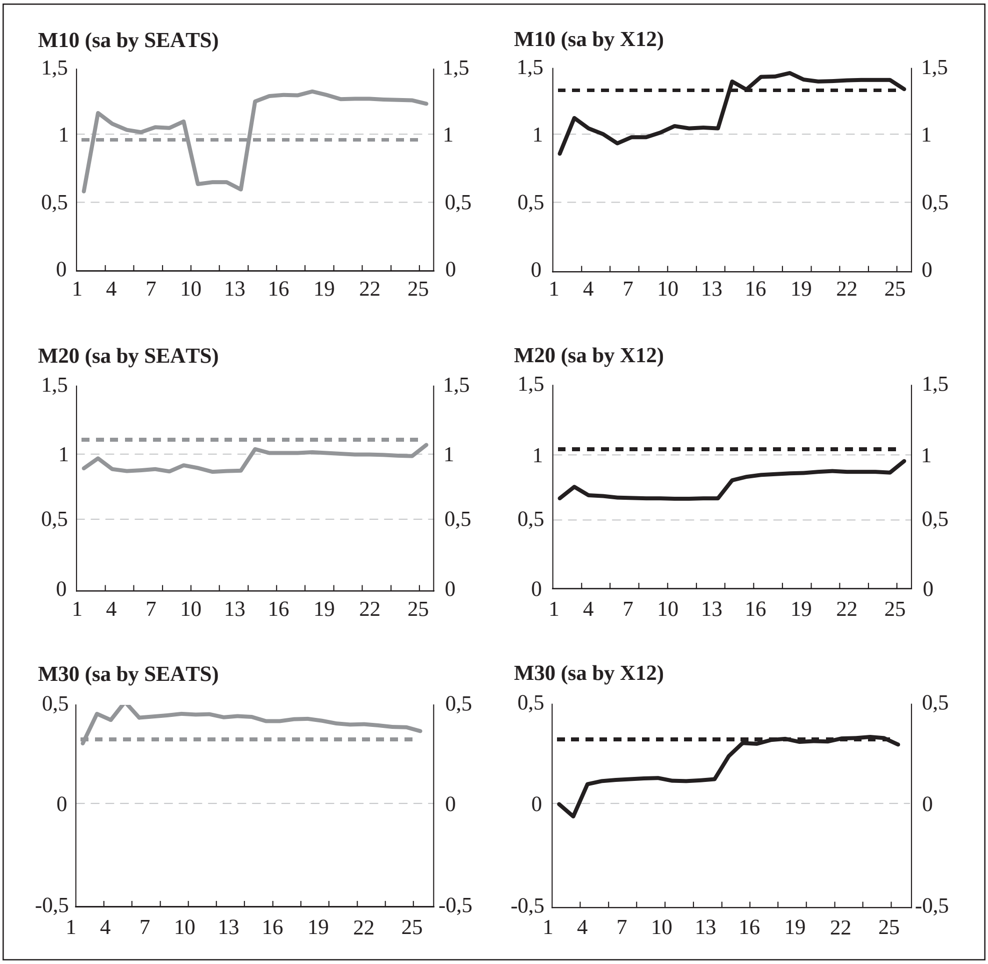
### Successive estimations in the SA month on month growth rate (FIG 1–12)

The case of December 1998
(thick dashed line represents the “final” value estimated in August 2002)



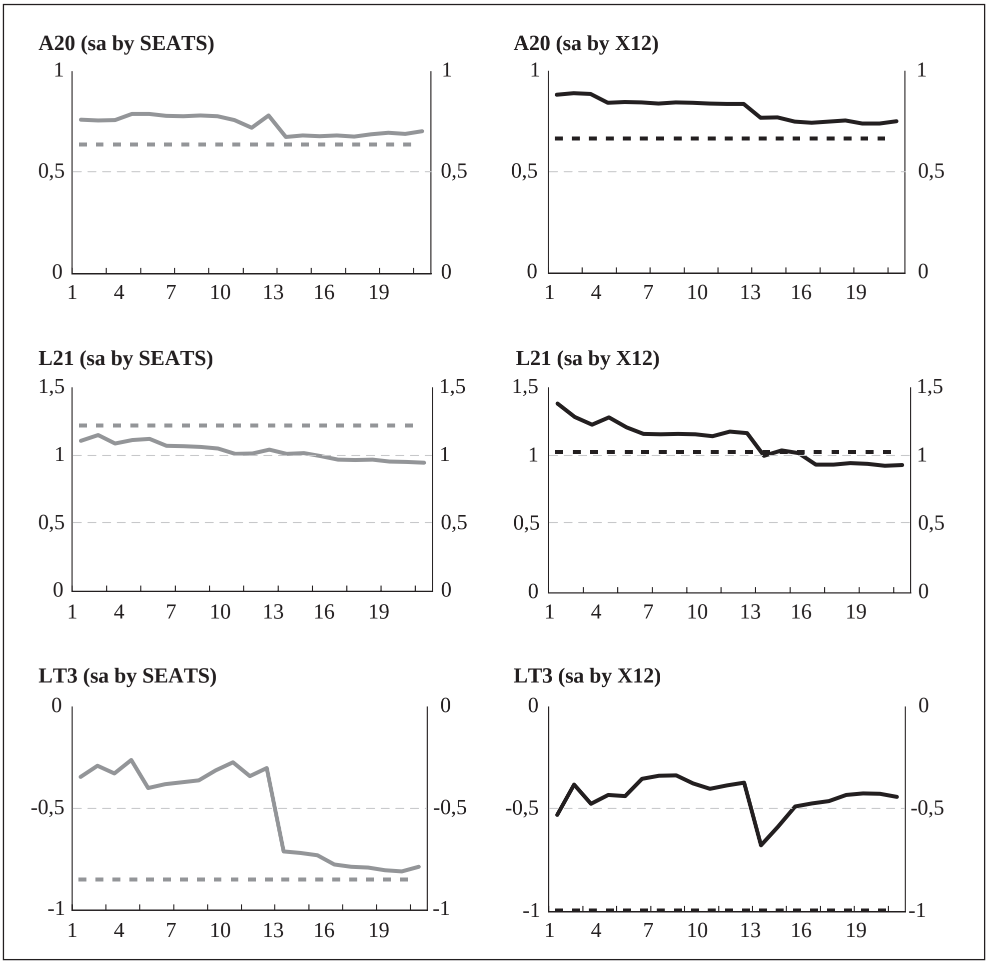
## Successive estimations in the SA month on month growth rate (FIG 1–12)

The case of December 1998
(thick dashed line represents the “final” value estimated in August 2002)



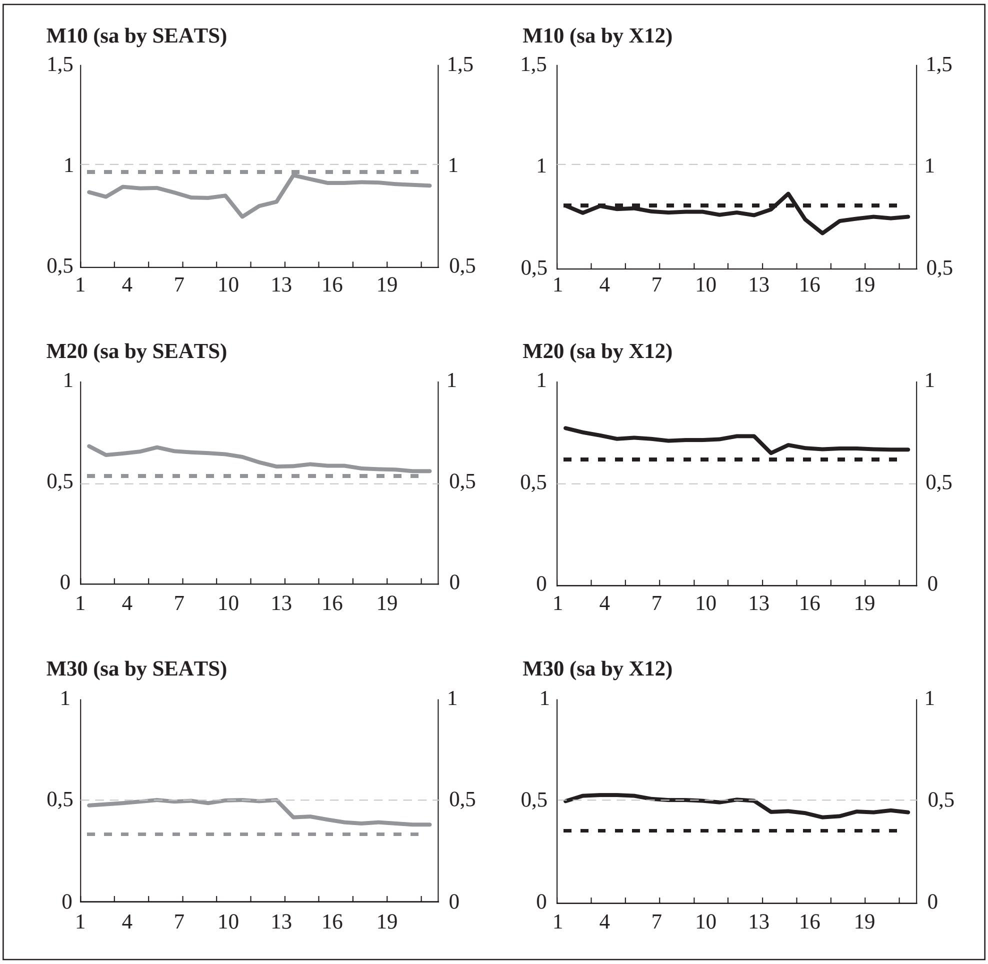
**Successive estimations in the SA month on month growth rate (FIG 13–24)**

The case of March 1999
(thick dashed line represents the "final" value estimated in August 2002)



**Successive estimations in the SA month on month growth rate (FIG 13–24)**

The case of March 1999
(thick dashed line represents the “final” value estimated in August 2002)



### Comparing the sequences

### Summary Tables 3 to 9

A20: Revisions on seasonal factors

| SEQ | Using SEATS TAR | MAR | RMSR | d75 | d90 | mc | sc | Using X12 TAR | MAR | RMSR | d75 | d90 | mc | sc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 8 | 4 | 9 | 12 | | 0,23 | 0,30 | 8 | 2 | 5 | | | 0,24 | 0,31 |
| 2 | 8 | 3 | 9 | 11 | | 0,25 | 0,35 | 8 | 5 | 11 | | | 0,18 | 0,21 |
| 3 | 8 | 3 | 8 | 10 | 13 | 0,26 | 0,37 | 8 | 3 | 7 | | | 0,20 | 0,24 |
| 4 | 10 | 4 | 11 | 12 | 13 | 0,25 | 0,33 | | | | | | | |
| 5 | 9 | 3 | 8 | 11 | | 0,25 | 0,34 | 8 | 3 | 8 | | | 0,25 | 0,33 |
| 6 | 9 | 3 | 8 | 11 | 12 | 0,26 | 0,37 | 8 | 4 | 9 | | | 0,20 | 0,26 |
| 7 | 8 | 3 | 9 | 11 | 12 | 0,26 | 0,37 | 8 | 3 | 8 | | | 0,20 | 0,23 |
| 8 | 11 | 3 | 10 | 10 | 12 | 0,29 | 0,40 | | | | | | | |
| 9 | 11 | 3 | 10 | 11 | | 0,28 | 0,39 | | | | | | | |
| 10 | 11 | 3 | 11 | | | 0,32 | 0,44 | | | | | | | |
| 11 | 10 | 4 | 11 | 9 | | 0,29 | 0,39 | 8 | 3 | 8 | | | 0,25 | 0,33 |
| 12 | 10 | 3 | 10 | 10 | 12 | 0,30 | 0,41 | 8 | 3 | 8 | | | 0,23 | 0,32 |
| 13 | 10 | 3 | 11 | 10 | 12 | 0,29 | 0,40 | 8 | 3 | 7 | | | 0,22 | 0,29 |
| 14 | 10 | 3 | 10 | 9 | | 0,30 | 0,42 | 8 | 2 | 6 | | | 0,22 | 0,26 |
| 15 | 11 | 3 | 11 | 9 | 11 | 0,30 | 0,42 | | | | | | | |
| 16 | 11 | 3 | 11 | 10 | 12 | 0,30 | 0,42 | | | | | | | |
| 17 | 11 | 4 | 12 | 12 | | 0,27 | 0,37 | | | | | | | |
| 18 | 11 | 3 | 11 | | | 0,32 | 0,44 | | | | | | | |
| 19 | 11 | 3 | 11 | | | 0,31 | 0,42 | | | | | | | |
| 20 | 12 | 3 | 12 | | | 0,34 | 0,42 | | | | | | | |

Results aggregated across time (Dec. 1998 to Nov. 1999)

L21: Revisions on seasonal factors

| SEQ | Using SEATS TAR | MAR | RMSR | d75 | d90 | mc | sc | Using X12 TAR | MAR | RMSR | d75 | d90 | mc | sc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 37 | 16 | 37 | 9 | 11 | 0,25 | 0,32 | 29 | 7 | 20 | 10 | 12 | 0,25 | 0,32 |
| 2 | 32 | 20 | 46 | 9 | 10 | 0,25 | 0,33 | 25 | 27 | 50 | | | 0,16 | 0,18 |
| 3 | 33 | 11 | 37 | 9 | 10 | 0,27 | 0,37 | 31 | 18 | 31 | 11 | | 0,17 | 0,20 |
| 4 | 43 | 14 | 55 | | | 0,30 | 0,39 | | | | | | | |
| 5 | 30 | 13 | 34 | 10 | 11 | 0,25 | 0,34 | 22 | 11 | 31 | | | 0,25 | 0,30 |
| 6 | 31 | 11 | 39 | 10 | 10 | 0,28 | 0,39 | 29 | 18 | 40 | | | 0,19 | 0,25 |
| 7 | 32 | 11 | 39 | 10 | 10 | 0,28 | 0,40 | 29 | 15 | 34 | 12 | | 0,20 | 0,22 |
| 8 | 42 | 13 | 45 | | | 0,29 | 0,40 | | | | | | | |
| 9 | 43 | 13 | 48 | | | 0,29 | 0,40 | | | | | | | |
| 10 | 42 | 12 | 47 | | | 0,33 | 0,47 | | | | | | | |
| 11 | 27 | 11 | 44 | 10 | 11 | 0,31 | 0,44 | 22 | 11 | 31 | | | 0,25 | 0,30 |
| 12 | 27 | 11 | 44 | 10 | 11 | 0,31 | 0,44 | 27 | 12 | 31 | | | 0,23 | 0,30 |
| 13 | 27 | 10 | 44 | 10 | 11 | 0,31 | 0,44 | 28 | 12 | 32 | | | 0,23 | 0,30 |
| 14 | 27 | 10 | 44 | 10 | 11 | 0,31 | 0,45 | 28 | 8 | 21 | | | 0,21 | 0,24 |
| 15 | 42 | 13 | 46 | | | 0,30 | 0,44 | | | | | | | |
| 16 | 42 | 12 | 46 | | | 0,30 | 0,44 | | | | | | | |
| 17 | 42 | 13 | 47 | | | 0,30 | 0,43 | | | | | | | |
| 18 | 42 | 12 | 47 | | | 0,33 | 0,47 | | | | | | | |
| 19 | 42 | 12 | 47 | | | 0,33 | 0,47 | | | | | | | |
| 20 | 43 | 12 | 56 | | | 0,35 | 0,47 | | | | | | | |

Results aggregated across time (Dec. 1998 to Nov. 1999)

## Summary Tables: comparing the sequences

LT3: Revisions on seasonal factors

| SEQ | Using SEATS | | | | | | | Using X12 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | TAR | MAR | RMSR | d75 | d90 | mc | sc | TAR | MAR | RMSR | d75 | d90 | mc | sc |
| 1 | 27 | 7 | 18 | | | 0,25 | 0,33 | 34 | 14 | 32 | | | 0,21 | 0,25 |
| 2 | 28 | 6 | 17 | | | 0,26 | 0,36 | 41 | 18 | 38 | | | 0,18 | 0,20 |
| 3 | 27 | 7 | 18 | | | 0,25 | 0,33 | 41 | 18 | 38 | | | 0,18 | 0,20 |
| 4 | 39 | 8 | 28 | | | 0,32 | 0,41 | | | | | | | |
| 5 | 30 | 5 | 16 | | | 0,26 | 0,35 | 40 | 12 | 31 | | | 0,22 | 0,25 |
| 6 | 28 | 7 | 19 | | | 0,25 | 0,33 | 37 | 15 | 36 | | | 0,19 | 0,21 |
| 7 | 27 | 6 | 18 | | | 0,25 | 0,33 | 40 | 12 | 31 | | | 0,22 | 0,25 |
| 8 | 42 | 6 | 27 | | | 0,36 | 0,47 | | | | | | | |
| 9 | 38 | 6 | 25 | | | 0,35 | 0,45 | | | | | | | |
| 10 | 37 | 5 | 27 | | | 0,36 | 0,48 | | | | | | | |
| 11 | 30 | 5 | 16 | | | 0,26 | 0,35 | 40 | 12 | 31 | | | 0,22 | 0,25 |
| 12 | 28 | 7 | 18 | | | 0,25 | 0,33 | 38 | 17 | 38 | | | 0,18 | 0,19 |
| 13 | 27 | 6 | 18 | | | 0,25 | 0,33 | 36 | 13 | 33 | | | 0,23 | 0,26 |
| 14 | 27 | 7 | 18 | | | 0,25 | 0,33 | 40 | 12 | 31 | | | 0,22 | 0,25 |
| 15 | 41 | 6 | 26 | | | 0,36 | 0,47 | | | | | | | |
| 16 | 38 | 6 | 25 | | | 0,35 | 0,45 | | | | | | | |
| 17 | 38 | 6 | 25 | | | 0,35 | 0,45 | | | | | | | |
| 18 | 37 | 5 | 27 | | | 0,36 | 0,48 | | | | | | | |
| 19 | 37 | 5 | 27 | | | 0,36 | 0,48 | | | | | | | |
| 20 | 36 | 5 | 27 | | | 0,36 | 0,47 | | | | | | | |

Results aggregated across time (Dec. 1998 to Nov. 1999)

M10: Revisions on seasonal factors

| SEQ | Using SEATS | | | | | | | Using X12 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | TAR | MAR | RMSR | d75 | d90 | mc | sc | TAR | MAR | RMSR | d75 | d90 | mc | sc |
| 1 | 54 | 19 | 48 | 10 | 11 | 0,23 | 0,30 | 18 | 6 | 18 | 12 | 13 | 0,23 | 0,28 |
| 2 | 31 | 23 | 63 | 9 | 10 | 0,24 | 0,33 | 16 | 31 | 58 | | | 0,17 | 0,20 |
| 3 | 31 | 23 | 63 | 9 | 10 | 0,24 | 0,33 | 18 | 9 | 21 | 12 | | 0,22 | 0,27 |
| 4 | 49 | 29 | 82 | | | 0,26 | 0,34 | | | | | | | |
| 5 | 30 | 16 | 50 | 9 | 11 | 0,27 | 0,37 | 16 | 13 | 38 | | | 0,24 | 0,30 |
| 6 | 33 | 29 | 64 | 8 | 10 | 0,23 | 0,30 | 18 | 19 | 43 | 13 | | 0,20 | 0,27 |
| 7 | 30 | 16 | 50 | 9 | 11 | 0,27 | 0,37 | 18 | 12 | 30 | 13 | | 0,21 | 0,25 |
| 8 | 49 | 20 | 63 | 8 | | 0,28 | 0,38 | | | | | | | |
| 9 | 49 | 20 | 63 | 8 | | 0,28 | 0,38 | | | | | | | |
| 10 | 43 | 11 | 40 | | | 0,33 | 0,45 | | | | | | | |
| 11 | 20 | 8 | 28 | 11 | | 0,30 | 0,42 | 16 | 13 | 38 | | | 0,24 | 0,30 |
| 12 | 27 | 37 | 69 | 9 | 10 | 0,20 | 0,23 | 17 | 13 | 35 | | | 0,22 | 0,29 |
| 13 | 26 | 14 | 43 | 10 | 11 | 0,26 | 0,36 | 16 | 12 | 33 | | | 0,23 | 0,29 |
| 14 | 20 | 8 | 28 | 11 | | 0,30 | 0,42 | 18 | 6 | 16 | 12 | | 0,24 | 0,31 |
| 15 | 43 | 11 | 39 | | | 0,31 | 0,43 | | | | | | | |
| 16 | 48 | 18 | 55 | 8 | | 0,28 | 0,38 | | | | | | | |
| 17 | 43 | 11 | 39 | | | 0,31 | 0,43 | | | | | | | |
| 18 | 43 | 11 | 40 | | | 0,33 | 0,45 | | | | | | | |
| 19 | 43 | 11 | 40 | | | 0,33 | 0,45 | | | | | | | |
| 20 | 45 | 10 | 48 | | | 0,35 | 0,46 | | | | | | | |

Results aggregated across time (Dec. 1998 to Nov. 1999)

## Summary Tables: comparing the sequences

M20: Revisions on seasonal factors

| SEQ | Using SEATS | | | | | | | Using X12 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | TAR | MAR | RMSR | d75 | d90 | mc | sc | TAR | MAR | RMSR | d75 | d90 | mc | sc |
| 1 | 19 | 6 | 13 | 10 | | 0,21 | 0,25 | 12 | 3 | 8 | 12 | | 0,26 | 0,33 |
| 2 | 12 | 6 | 16 | 8 | | 0,24 | 0,29 | 15 | 12 | 22 | 8 | | 0,19 | 0,21 |
| 3 | 13 | 6 | 17 | 8 | | 0,24 | 0,31 | 14 | 6 | 11 | | | 0,19 | 0,24 |
| 4 | 15 | 9 | 25 | | | 0,28 | 0,35 | | | | | | | |
| 5 | 12 | 5 | 16 | 7 | | 0,27 | 0,35 | 16 | 5 | 13 | 9 | | 0,24 | 0,29 |
| 6 | 12 | 5 | 16 | 7 | | 0,27 | 0,36 | 14 | 7 | 16 | 10 | | 0,22 | 0,29 |
| 7 | 12 | 5 | 16 | 8 | | 0,28 | 0,37 | 14 | 6 | 13 | 12 | | 0,21 | 0,27 |
| 8 | 14 | 6 | 19 | | | 0,30 | 0,40 | | | | | | | |
| 9 | 14 | 6 | 19 | | | 0,32 | 0,42 | | | | | | | |
| 10 | 12 | 5 | 17 | | | 0,30 | 0,43 | | | | | | | |
| 11 | 7 | 4 | 15 | 9 | | 0,29 | 0,38 | 16 | 5 | 13 | 9 | | 0,24 | 0,29 |
| 12 | 7 | 4 | 15 | 9 | | 0,28 | 0,39 | 15 | 5 | 13 | 10 | | 0,24 | 0,32 |
| 13 | 7 | 4 | 14 | 10 | | 0,28 | 0,39 | 16 | 5 | 14 | 10 | | 0,24 | 0,31 |
| 14 | 7 | 4 | 15 | 10 | | 0,28 | 0,39 | 14 | 4 | 9 | | | 0,23 | 0,30 |
| 15 | 13 | 5 | 16 | | | 0,27 | 0,38 | | | | | | | |
| 16 | 13 | 5 | 15 | | | 0,29 | 0,40 | | | | | | | |
| 17 | 13 | 6 | 17 | | | 0,24 | 0,34 | | | | | | | |
| 18 | 12 | 5 | 17 | | | 0,30 | 0,43 | | | | | | | |
| 19 | 12 | 5 | 16 | | | 0,29 | 0,41 | | | | | | | |
| 20 | 13 | 5 | 19 | | | 0,34 | 0,46 | | | | | | | |

Results aggregated across time (Dec. 1998 to Nov. 1999)

M30: Revisions on seasonal factors

| SEQ | Using SEATS | | | | | | | Using X12 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | TAR | MAR | RMSR | d75 | d90 | mc | sc | TAR | MAR | RMSR | d75 | d90 | mc | sc |
| 1 | 15 | 4 | 10 | 9 | 11 | 0,28 | 0,38 | 13 | 3 | 8 | 12 | 13 | 0,27 | 0,37 |
| 2 | 15 | 4 | 11 | 9 | 11 | 0,29 | 0,39 | 13 | 9 | 17 | 12 | | 0,17 | 0,19 |
| 3 | 11 | 4 | 13 | 9 | 9 | 0,29 | 0,40 | 13 | 4 | 9 | 13 | | 0,23 | 0,30 |
| 4 | 20 | 6 | 25 | 5 | | 0,32 | 0,41 | | | | | | | |
| 5 | 15 | 2 | 7 | 10 | 11 | 0,30 | 0,42 | 12 | 4 | 12 | | | 0,25 | 0,30 |
| 6 | 11 | 3 | 9 | 9 | 11 | 0,29 | 0,40 | 11 | 7 | 14 | 12 | | 0,19 | 0,25 |
| 7 | 10 | 3 | 9 | 9 | 12 | 0,29 | 0,42 | 13 | 4 | 11 | | | 0,22 | 0,25 |
| 8 | 13 | 4 | 16 | 7 | | 0,34 | 0,46 | | | | | | | |
| 9 | 13 | 4 | 14 | 7 | | 0,32 | 0,44 | | | | | | | |
| 10 | 13 | 4 | 16 | | | 0,35 | 0,49 | | | | | | | |
| 11 | 15 | 2 | 7 | 10 | 11 | 0,30 | 0,42 | 12 | 4 | 12 | | | 0,25 | 0,30 |
| 12 | 11 | 3 | 9 | 9 | 11 | 0,29 | 0,40 | 12 | 5 | 11 | | | 0,23 | 0,31 |
| 13 | 10 | 3 | 9 | 9 | 12 | 0,29 | 0,42 | 13 | 4 | 11 | 11 | | 0,24 | 0,33 |
| 14 | 9 | 3 | 9 | | | 0,28 | 0,40 | 13 | 3 | 8 | | | 0,25 | 0,32 |
| 15 | 13 | 4 | 16 | 7 | | 0,34 | 0,46 | | | | | | | |
| 16 | 13 | 4 | 14 | 7 | | 0,32 | 0,44 | | | | | | | |
| 17 | 11 | 6 | 15 | 9 | | 0,27 | 0,38 | | | | | | | |
| 18 | 13 | 4 | 16 | | | 0,35 | 0,49 | | | | | | | |
| 19 | 13 | 4 | 14 | | | 0,33 | 0,43 | | | | | | | |
| 20 | 11 | 3 | 16 | | | 0,35 | 0,45 | | | | | | | |

Results aggregated across time (Dec. 1998 to Nov. 1999)

5

# Direct versus indirect seasonal adjustment of UK monetary statistics: preliminary discussion

David Willoughby

## Historical background

The United Kingdom’s monetary statistics were traditionally analysed in a flow of funds context, with movements in the money stock being considered in conjunction with those in the “counterparts”, such as credit to the private sector, public sector, and external influences. For each period, transactions were assembled in the form of a matrix arranged by financial instrument and by economic sector. A flow in one cell of the matrix had to be offset by equal and opposite flows elsewhere, so that the matrix “balanced”. If the flow of funds matrix was to be adjusted by subtracting seasonal variations, then it was reasonable to expect that the adjusted matrix should continue to be balanced. It followed, therefore, that an essential property of the seasonal adjustment method was that it must produce a balanced set of seasonal adjustments for the matrix.

Before 1990, the seasonal adjustments were generated using a two-stage method. The first stage involved using conventional univariate procedures in the sense that they derived the seasonal adjustments for a series without reference to other series in the matrix, so that the resulting seasonal matrix for each period did not balance. The second stage involved amending the univariate adjustments so that they did balance. It was hoped that by exploiting the information inherent in the accounting relationship between the series, the balancing process would demonstrably improve the seasonal adjustments. In practice, however, the balanced seasonal adjustments were never entirely satisfactory. Although the univariate procedures generally produced plausible results, it proved to be difficult to allocate the large resulting imbalances across the series in an acceptable way. In some cases the balancing amendments proved to be so large that, when the balanced seasonal adjustments were applied, an apparently seasonal pattern remained, albeit of a different form to that present in the unadjusted series.

By the late 1980s, users of the seasonally adjusted monetary data began to question the growing complexity, and frequent changes, of the methodology. The judgement involved made the method very resource intensive, especially when applied to the roughly 650 series that were adjusted at the time. The bulk of the work had to be undertaken by specialists, which presented an obstacle to automation of the method. Automation was essential to allow current updating to be implemented at a reasonable cost. (Current updating had been recommended by an independent Working Party.) In 1989, therefore, the Bank of England decided to undertake a fundamental reform of its seasonal adjustment work, with the aim of producing a simplified one-stage procedure that would produce inherently balanced adjustments, with a minimal need for judgmental intervention.

The solution to the balancing problem was to apply a common, linear seasonal adjustment procedure to every cell in the flow of funds matrix. The procedure was linear in the sense that, at any particular point in the series, the seasonal adjustment was a weighted additive or linear combination of nearby observations. The package was developed within the Bank, and named General Linear Abstraction of Seasonality (GLAS). It was acknowledged that it could be seen as very restrictive to require that the seasonal adjustment procedure be linear, and to apply the same procedure, with fixed filtering properties, to every series in the matrix. On the other hand, the subjective nature of seasonality meant that, provided the common filter itself was well designed, the method would produce satisfactory results.

The linear properties of GLAS ruled out several options often provided by seasonal adjustment procedures, including:

- Adjustable smoothing
- Non-seasonal series
- Multiplicative seasonal models
- Automatic outlier modification
- Systematic identification and removal of calendar effects (for differing lengths of months, public holidays, etc.).

However, in the context of seasonally adjusting a flow of funds matrix, the cost was seen as tolerably small. Furthermore, in the case of dealing with outliers in the data, the manual approach that was used, which involved investigating the causes and locating the offsetting movement, was fully consistent with trying to understand the movements in the underlying data.

GLAS has performed well in terms of the remit it had been given, ie the balancing constraint, ease of use and resource efficiency. The pressure for change can be traced back to a workshop held at the Bank in March 2000, where there was general agreement that the Bank had fallen behind the mainstream in its approach. GLAS had been written to honour additivity, but the lack of diagnostics meant that users did not know the price they were paying for this feature. In addition to the views expressed at the workshop, at this time the policy use of the data had also changed, with the focus increasingly on the (by then monthly) sectoral breakdowns of broad money and credit. Although this move to a sectoral approach did not mean that the question of balancing had gone away, the lower profile of the counterparts to broad money certainly made the consideration of alternative approaches to seasonal adjustment more viable.

## Project to switch to X-12-ARIMA

Earlier reviews of seasonal adjustment methodology in the Bank of England have tended to get side-tracked by detailed comparisons of the outputs from various packages. Experience of other central banks and national statistical institutions identified X-12-ARIMA and TRAMO-SEATS as the most viable options to replace GLAS. We favoured X-12-ARIMA partly because it is the methodology used by the Office for National Statistics, which would mean that UK data were adjusted using consistent methodology. In addition, the work taking place to incorporate some of the modelling capabilities of TRAMO-SEATS into X-12-ARIMA, the excellent diagnostics of X-12-ARIMA, and the documentation and support provided by the US Census Bureau, would meet the aims of the Bank of England in moving to international best practice.

As noted above, a key feature of GLAS is that it generates seasonally adjusted data that obey the same accounting constraints as the unadjusted data. Consequently, the issue of direct versus indirect adjustment has not arisen, since both approaches generate the same outcome. So switching to X-12-ARIMA entails deciding whether to adopt a direct or indirect approach to the seasonal adjustment of the key monetary series. In the context of broad money and its components, the indirect approach would be where seasonally adjusted M4 was compiled as the sum of its seasonally adjusted components. (Indirect adjustment is generally considered better when the component series have distinct seasonal patterns, and direct adjustment when the component series have similar seasonal patterns.)

The ECB's paper of August 2000 set out the issues weighing on the question of direct versus indirect adjustment of M3. Although no clear "winner" could be found, the decision to use an indirect method of adjustment was, in part, based on the practical consideration of ensuring the addivity of the seasonally adjusted components to the seasonally adjusted aggregate.

The paper also noted that the issue of addivity had two dimensions, ie not only the components but also the balance sheet counterparts. The relatively short run of data means that the ECB has not yet had to address the issue of seasonal adjustment of the counterparts. But this is an issue for the Bank of England. And there is also a third dimension represented by the sectoral breakdowns of broad money and credit, where there is sufficient monthly data to be able to seasonally adjust, as well as longer runs of quarterly data.

The Bank of England's experience in using the sectoral breakdowns of broad money and credit was noted in the discussions leading up to the adoption of Regulation ECB/2001/13. The latter will furnish the ECB with similar data on a monthly basis to those which have been available to the Bank of England since 1997. In due course, when a sufficiently long run of these new sectoral data are available, the ECB is likely to face a similar question to that currently being addressed in the Bank, namely whether broad money and aggregate credit to the private sector should be seasonally adjusted directly, or indirectly as the sum of the seasonally adjusted sectoral components. Some preliminary results from the seasonal adjustment of the UK quarterly sectoral data using X-12-ARIMA are presented below.

## Preliminary results from the adjustment of sectoral data

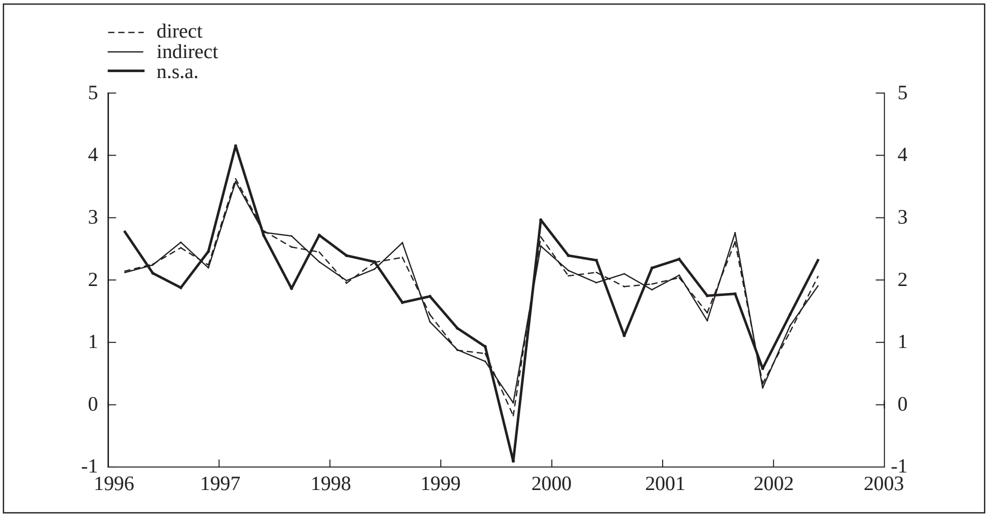
The preliminary analysis of the seasonal adjustment of the sectoral components of broad money and private sector credit have been carried out using the quarterly data which are available back to 1963. The series were prior adjusted for breaks, and then analysed with X-12-ARIMA using the standard options (multiplicative, automatic ARIMA modelling, one year's forecast appended, automatic scan for AO and LS outliers). To give an easy direct-indirect comparison, the composite spec was used; this automatically calculates the statistics for the indirect route and compares them with the direct analysis.

Looking first at broad money (M4) and its sectoral component series, "Automdl" found a model with little difficulty in each case, usually either (0 1 1)(0 1 1) or (0 1 2)(0 1 1), and the diagnostics were satisfactory. Usually no AO or LS outliers were found. All series had identifiable seasonality and a satisfactory Q statistic for overall adequacy of adjustment. All had some M statistics outside limits, usually M8, M10 or M11 indicating moving seasonality or M4 indicating autocorrelated irregulars.

The composite analysis showed satisfactory diagnostics for the indirect analysis. The Q value was exactly the same as for the direct (0.42), though a different M was outside the limits (M8 instead of M4). The "roughness statistics" which show which series is smoother indicate that direct is slightly smoother over the whole series but indirect over the last three years. It is confirmed that indirect has no residual seasonality, either over the whole series or the recent years. Chart 1 compares quarterly growth rates of M4 since 1996 derived from direct and indirect adjustment; non-seasonally-adjusted rates are also included.

Aggregate private sector credit (M4 lending) has also been analysed. This analysis had a few complications in the modelling, and there were more level shifts in the early years than

Chart 1: Comparison of quarterly M4 growth
*(percent)*




with M4, but nothing to give any concern about interpretation of the results. The comparison of direct and indirect via the X-12 M and Q statistics showed essentially the same result (Q=0.40 direct, Q=0.41 indirect, only M8 just outside limits in each case). Chart 2 compares the quarterly growth rates.

Chart 2: Comparison of quarterly M4 lending growth
*(percent)*

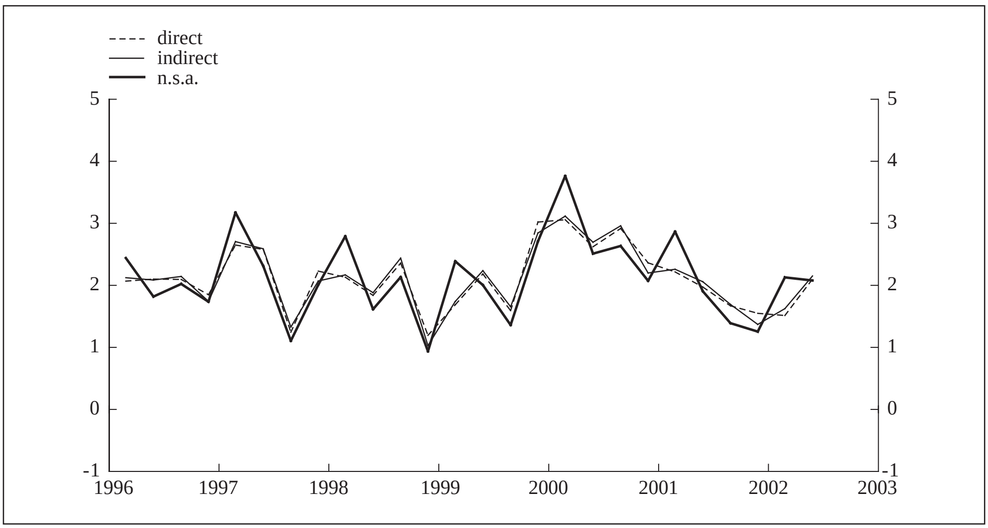
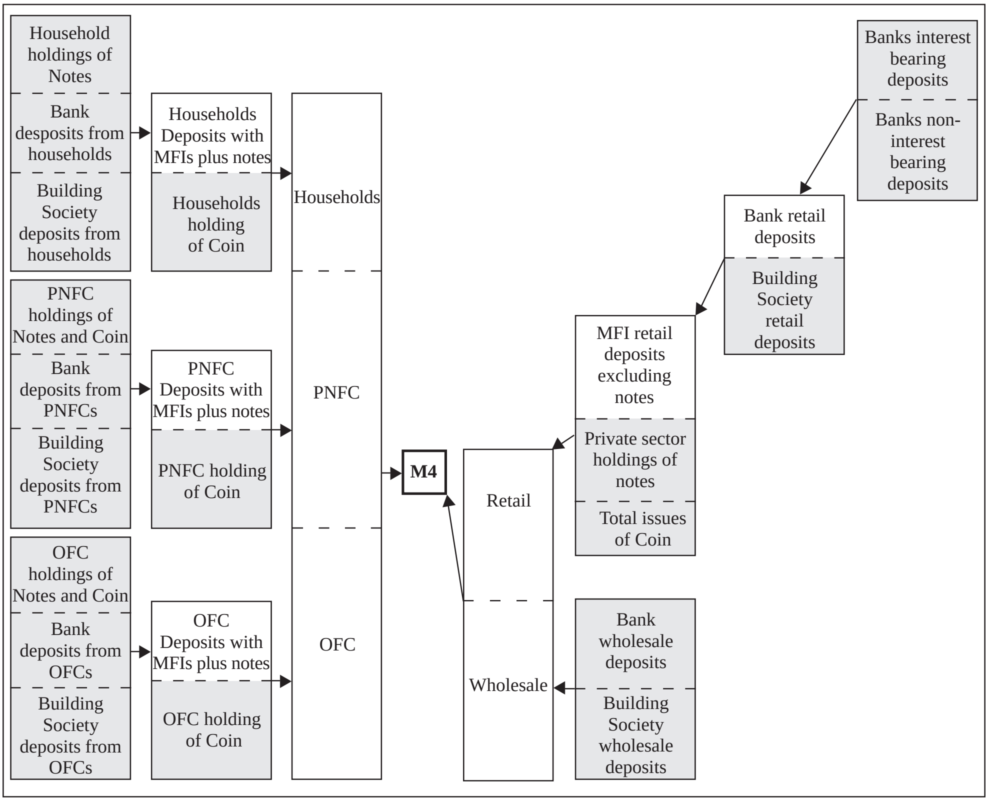


Chart 3: M4 coloured (greyed out) boxes currently seasonally adjusted

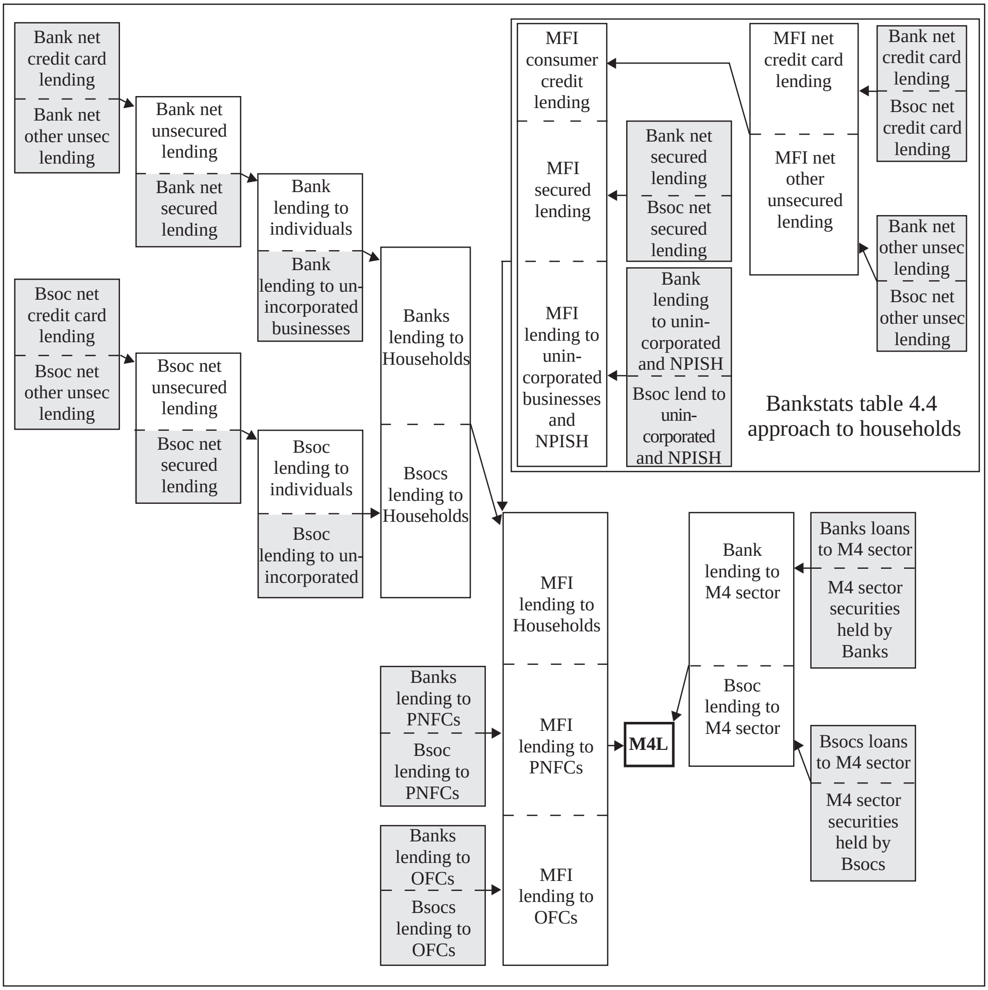



### Some qualifications

Although these preliminary results show little difference between the indirect and direct adjustment of broad money and private sector credit, there are some important qualifications. Firstly, even if M4 and M4 lending are seasonally adjusted indirectly as the sum of the seasonally adjusted sectoral component series, the issue of additivity still remains. This is because both aggregates can be broken down in alternative ways – see Charts 3 and 4. For example, in Chart 3, if M4 is seasonally adjusted indirectly as the sum of its sectoral components, it is unlikely that the sum of its retail and wholesale elements will produce the same result. Policy use of the data would dictate that the sectoral breakdown should take precedence, but the question of the lack of additivity remains as far as the retail/wholesale split is concerned.

The second qualification is that individual sector series have themselves been adjusted directly. It is possible that the quality of the seasonal adjustment could be improved if these sectoral series were themselves adjusted indirectly, by summing their seasonally adjusted components. If so, this might change the comparison between the direct/indirect adjustment of M4 and M4 lending.

Chart 4: M4 Lending coloured (greyed out) boxes currently seasonally adjusted




Third, and more significantly, in the case of at least one of the sectoral series (lending to the household sector – see Chart 4) many of the sub-component series are highly policy-sensitive and therefore require optimum seasonal adjustment. So even if the issue of direct versus indirect adjustment does not arise at the aggregate level (in the sense that the indirect adjustment of M4 and M4 lending is acceptable) there may still be problems lower down the pyramid.

# 6

# The seasonal adjustment of euro area monetary aggregates: direct versus indirect approach

Romana Peronaci

## 1 Introduction

The seasonal adjustment of euro area monetary aggregates, M1, M2 and M3 can be obtained indirectly through the aggregation of the main components previously seasonally adjusted or directly seasonally adjusting the aggregated series. The current procedure followed by the European Central Bank (ECB) for the derivation of the monetary aggregates M2 and M3 is based on the indirect seasonal adjustment. According to this, M2 is derived by aggregating the seasonally adjusted components M1 and the "Other short term deposits" (M2-M1), and M3 is finally obtained by adding to them the "Marketable instruments" (M3-M2).[1]

Empirical results show that the direct and the indirect seasonal adjustment of the same time series, produce same results only under very restrictive assumptions, that is when no trading day or outlier adjustment is made, when the seasonal decomposition is additive, and when no forecast is produced. However the discrepancies in the seasonally adjusted series obtained with the two methods might not be necessarily significant.

In this paper we compare the results obtained from the direct and the indirect seasonal adjustment of the monetary aggregates M2 and M3, using the X12-Arima diagnostics to evaluate the quality of the two seasonal adjustments and the differences between the two adjustments. The analysis is performed on the notional stocks[2] in order to ensure the additivity of the main components of the two aggregated series M2 and M3 as required by X12-Arima.

The work is organised as follows: Section 2 provides a description of the common criteria and diagnostics used to assess the quality of a seasonal adjustment and to compare seasonal adjustment results obtained with the alternative approaches. Section 3 reports the results of the direct and the indirect seasonal adjustment of M2 and M3 on the basis of these criteria. Section 4 reports the conclusions.

## 2 Seasonal adjustment: direct versus indirect approach

One of the recommendations of the ECB Task Force on Seasonal Adjustment held in 1999, was the use of the indirect approach for the seasonal adjustment of the euro area monetary aggregates. The choice was supported by practical considerations, by some criteria

[1] "Seasonal adjustment of monetary aggregates and HICP for the euro area", (August 2000), European Central Bank.

[2] The notional stocks are derived on the basis of the end-month stocks adjusted for the monthly changes not due to financial transactions. The ECB official seasonal adjustment of monetary aggregates is performed on the index of notional stocks (see details in ECB (2000)).

identifying the "preferred" characteristics of the seasonal adjustment, like the minimisation of revision errors and the out of sample forecast accuracy, and also by the conclusions of deeper investigations of the series concerned in terms of their seasonal and cyclical components and their relative importance within the aggregate series.

After three years since the implementation of seasonal adjustment procedures at the ECB, the need to re-assess the quality of the indirect adjustment versus the direct adjustment has arisen. Some empirical works have touched this aspect in the recent years, in particular with respect to the seasonal adjustment of euro area GDP (Astolfi, Ladiray and Mazzi (2001)), and euro area HICP (Cristadoro and Sabbatini (2000)). Other recent works developed statistical tests to compare the results obtained by the indirect and the direct approach and to assess which one performs better, as Planas and Campolongo (2000), Gomez (2000), Otranto and Triacca (2000). On the basis of these works a set of empirical criteria has been identified and is used here to evaluate the performance of the direct and indirect adjustment for the euro area monetary aggregates series M2 and M3. The criteria are described below.

### *a) Graphical analysis and sign concordance*

In principle the two approaches to derive seasonally adjusted (SA) series of the euro area monetary aggregates should lead to similar results, and the growth rates of the SA series should have the same sign. This is an essential aspect to be assessed in order to be able to deliver reliable statistical information to the users and to the public in general. In particular this is a critical issue for what concerns the seasonal adjustment of the euro area monetary aggregates, since these statistics are regularly used by the ECB to monitor the monetary situation of the euro area and to define its monetary policy.

For this purpose, a preliminary investigation of the results obtained with the direct and with the indirect approach is performed through the graphical analysis of the SA series obtained from the two approaches. In addition to this, the inspection of the SA annual growth rates series allows verification of whether the two approaches lead to a similar detection of turning points in the SA series. A further step concerns the consistency between the growth rates of the SA aggregated series and their adjusted components, which should evolve in the same direction. Hence, two statistics are used to assess the degree of consistency in the growth rates, which are calculated on the basis of the ratio of growth rate values, for the same observations, showing similar sign. The first statistics, C1, measures the percentage of concordance between the direct and indirect series and the second, C2, the percentage of concordance between the SA aggregate and the SA components.

### *b) Analysis of smoothness*

One of the aspects taken into consideration in the choice between direct and indirect seasonal adjustment is the roughness of the SA series. Dagum (1979) proposed two measures of roughness or lack of smoothness, of the SA series, that measure the size of their deviations from a smooth trend, and are based on the first difference filter and on the 13-term Henderson filter applied to the SA series.

The first measure is defined as:

$$R_1 = \frac{1}{N-1} \times \sum_{t=2}^{N} \left(A_t - A_{t-1}\right)^2 = \frac{1}{N-1} \times \sum_{t=2}^{N} \left(\nabla A_t\right)^2$$

where $\{A_t : 1 \leq t \leq N\}$ is the adjusted series and  is the length of the series.

The second measure is defined by:

$$R_2 = \frac{1}{N-1} \times \sum_{t=1}^{N} \left(A_t - H_{13} A_t\right)^2 = \frac{1}{N-1} \times \sum_{t=1}^{N} \left[(1 - H_{13}) A_t\right]^2$$

where $\{A_t : 1 \leq t \leq N\}$ is the adjusted series and $\{H_{13} A_t : 1 \leq t \leq N\}$ is the output from a 13-term Henderson filter that is applied to it.

### *c) Residual seasonality in the adjusted series*

Generally, the quality of a seasonal adjustment is assessed on the basis of any significant residual seasonality and calendar effects left in the SA series. The existence of residual seasonality in the SA series when this is obtained with the direct approach can result from an inadequate adjustment procedure, or from the existence of seasonality difficult to estimate in the original series. A SA series obtained indirectly by aggregating the SA components, might show residual seasonality when the seasonal and trading day effects present in the components series are not easily detectable and are not properly estimated, leaving residual effects in the adjusted series.

The existence of residual seasonality or trading day effects in the SA series and in the SA components is investigated here by means of the tests of residual seasonality proposed by X12-Arima and calculated on the SA series obtained with the direct and the indirect adjustment. Moreover, the analysis of the spectrum of the SA series allows detecting residual seasonality or residual trading day effects in the series (see Findley at al. (1998)).

### *d) Analysis of the irregular components*

As next step in the investigation of residual seasonality after the direct and the indirect adjustment approaches are applied, we analysed the irregular components of the SA series (i.e. the detrended seasonally adjusted series). The estimated residual components, which represent the irregular part of the series and are by definition white noise processes with zero expectation, non-correlated and of constant variance $\sigma^2$, should not present any residual seasonality and trading day effects.

Firstly, to assess the existence of seasonal or trading day effects in the residual component, the spectrum of the final irregular component for the direct and the indirect adjustment are investigated. Then a set of test statistics is calculated for the irregular components of the two aggregated series to test for their randomness and absence of first order autocorrelation.

### *e) Quality of seasonal adjustment*

X12-Arima computes a set of eleven indicators to assess the quality of the seasonal adjustment. These indicators are purely descriptive and based on empirical criteria (see Quenneville and Ladiray (2001)) and have not been derived in order to derive conclusions on the relative performance of the direct and indirect seasonal adjustments. However they can be calculated for the two approaches in order to verify whether these lead to significantly different results in terms of the quality of the adjustments (see J. Lothian and M. Morry (1978)).

### *f) Analysis of stability based on revision histories (1)*

A further aspect that is relevant for the production of a satisfactory seasonal adjustment concerns the amount and the size of revisions the SA data undergo, when they are recalculated as additional values for the raw series become available. Obviously, different causes can produce unstable seasonal adjustments, some of which are unavoidable, as the existence of moving seasonality in the raw series. However, the analysis of stability of the seasonal adjustment can also shed some light on the comparison between direct and indirect seasonal adjustment.

The analysis of revisions associated with continuous seasonal adjustment over a number of years is one of the stability diagnostics available in X12-Arima (see D. Findley et al. (1998)). The natural way to measure the size of revisions to SA data is the comparison between the earliest adjustment of a month’s datum, obtained when that month is the final month in the series (t), and a later adjustment based on all future data available at the time of the analysis (T). The formula below shows how the revision is calculated in the case of a multiplicative seasonal decomposition.

$$R_t = 100 \times \frac{A_{t|T} - A_{t|t}}{A_{t|t}}$$

where $\{A_{t|n} : n = 1,...,T\}$ is the SA series, $A_{t|t}$ is the “concurrent” adjustment and $A_{t|T}$ is the “final” adjustment of the month t observation, calculated at the end of the time series.

A revision history of the seasonal adjustment for a series $A_t$ is obtained calculating $R_t$ over a consecutive set of time points within the series. The analysis is applied here to both the direct and indirect seasonal adjustments to identify which approach leads to more stable results in terms of revisions of the adjusted data.

### *g) Analysis of stability based on the sliding spans (2)*

The second type of stability diagnostic available in X12-Arima is based on the comparison of the seasonal adjustment calculated on four overlapping sub-spans of the series (Findley at al. (1990), Findley at al. (1998)). For each month that is common to at least two sub-spans, the difference between the largest and the smallest seasonal adjustment obtained from the different spans for the reference month is analysed. Excessive variability among such estimates indicates unreliability.

The analysis is performed for the direct and for the indirect seasonal adjustment of M2 and M3 and the results obtained for the two approaches are compared on the basis of the following two statistics, to assess which one gives a more stable seasonal adjustment:

*Max percent difference for seasonal factors:* $S_t^{Max} = 100 \times \dfrac{\max_{k \in N_t} S_t(k) - \min_{k \in N_t} S_t(k)}{\min_{k \in N_t} S_t(k)}$;

where $S_t\,(k)$ is the seasonal factor estimated from span k for month t.

*Max difference for*
*monthly changes in SA series:* $MM_t^{Max} = \max_{k \in N_t} MM_t(k) - \min_{k \in N_t} MM_t(k)$;

where $MM_t(k) = 100 \times \dfrac{A_t(k) - A_{t-1}(k)}{A_{t-1}(k)}$ and $A_t\,(k)$ is the SA value from span k for month t.

## 3 The seasonal adjustment of euro area monetary aggregates

The direct and the indirect seasonal adjustment approaches are compared here on the basis of the results obtained for the seasonal adjustment of the euro area monetary aggregates M2 and M3. The euro area monetary aggregates M2 and M3 can be seasonally adjusted directly or indirectly as the sum of their SA components. In particular, M2 can be derived by aggregating the two components M1 and "other short term deposits" (M2-M1) previously seasonally adjusted, while M3 can be derived by the aggregation of seasonally adjusted M1, M2-M1 and "Marketable instruments" (M3-M2).

Both direct and indirect approaches to the seasonal adjustment of the aggregated series M2 and M3 were performed using X12-Arima[3] on the end-month notional stocks series. The two series are seasonally adjusted according to the multiplicative decomposition.

### *a) Graphical analysis and sign concordance*

Figure 1 reports the original series and the SA series according to the direct and the indirect approaches for M2 and M3 for the period Aug92-Aug02. Figures 2 and 3 show the annual growth rates of the SA series derived with the two approaches.

As emerges from the graphical analysis no significant differences between the series, derived with the two approaches, can be identified. For what concerns the divergence between the growth rates series, this is clearly not significant as shown in Figure 4, with a maximum discrepancy between the seasonally adjusted annual growth rates series obtained with the two methods of 9 basis points and 18 basis points for M2 and M3 respectively, as also shown in Table 1.

Table 1: Direct versus indirect approach: comparison between the SA annual growth rates series

| Series | Discrepancy between growth rates | | | C1 | C2 |
|---|---|---|---|---|---|
| | Average | Standard deviation | Max | | |
| **M2** | 0.0001 | 0.0223 | 0.095 | 100% | 100% |
| **M3** | -0.0001 | 0.0404 | 0.180 | 100% | 89.6% |

The annual growth rates derived on the basis of the direct and indirect SA series show full sign concordance (100%) for the whole period for M2 and M3, as indicated by the results of the statistics C1 (percentage of concordance between the direct and indirect SA series). As for the sign concordance between the growth rates of the SA components and the SA aggregate series measured by C2 (percentage of concordance between the SA series and the SA components), this is 100% for M2, while it is at around 90% for M3.

[3] X-12-ARIMA monthly seasonal adjustment Method, Release Version 0.2, U.S. Department of Commerce, Bureau of the Census.

Figure 1: Original series, direct and indirect seasonally adjusted series of M2 and M3
*(EUR billions)*

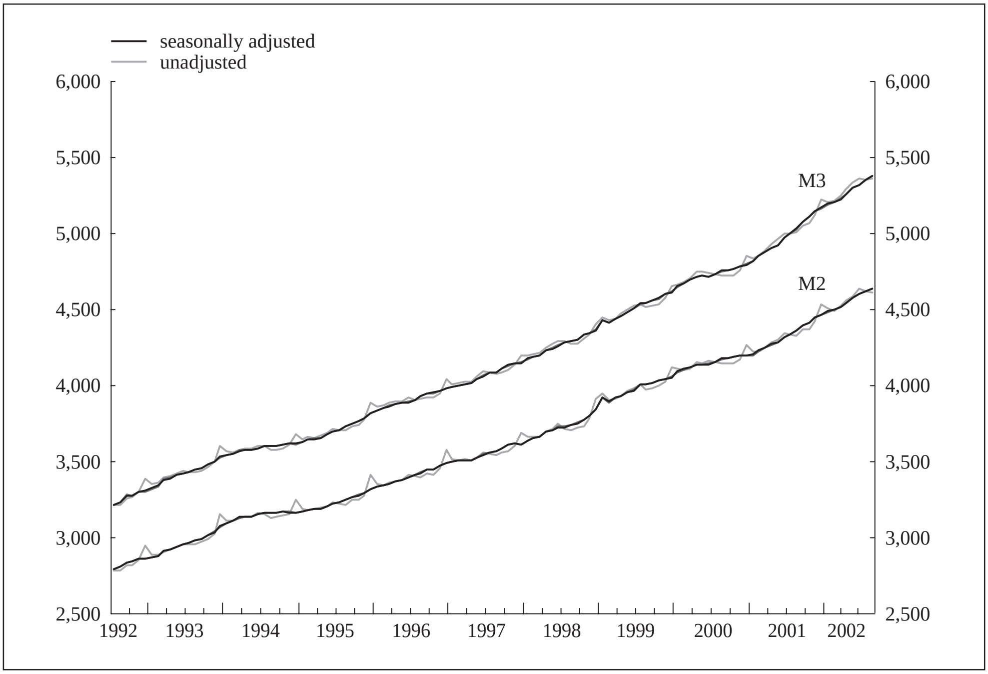



Figure 2: Annual growth rates of seasonally adjusted M2 obtained with the direct and indirect approaches
*(percentage)*

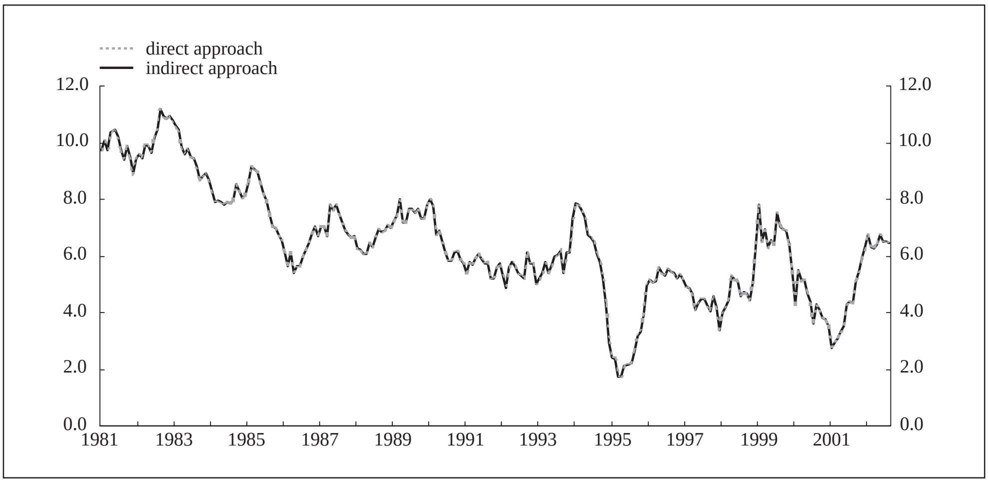


Figure 3: Annual growth rates of seasonally adjusted M3 obtained with the direct and indirect approaches
*(percentage)*


Figure 4: Difference in the annual growth rates of seasonally adjusted M2 and M3 obtained with the direct and indirect approaches (direct minus indirect adjustment)
*(percentage)*

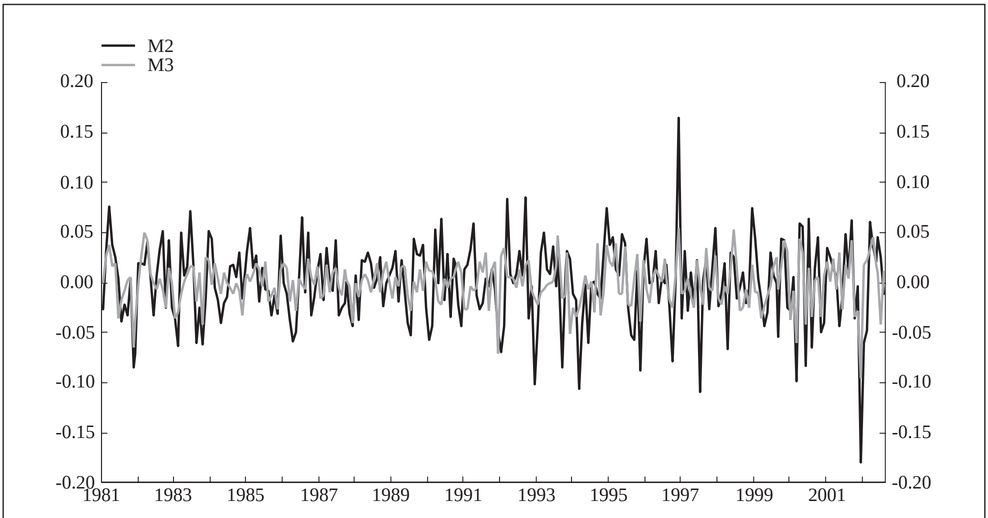


Table 2: Measures of roughness for seasonally adjusted series: direct versus indirect approach

| Series | Measures of roughness | Direct | | Indirect | | Percentage change[1)] | |
|---|---|---|---|---|---|---|---|
| | | Full series | Last 3 years | Full series | Last 3 years | Full series | Last 3 years |
| **M2** | **R1** | 15611.28 | 20132.42 | 15759.00 | 20247.25 | -0.953% | -0.570% |
| | **R2** | 0.002 | 0.001 | 0.002 | 0.001 | -1.952% | 0.533% |
| **M3** | **R1** | 18044.31 | 26019.28 | 18271.27 | 26249.83 | -1.258% | -0.886% |
| | **R2** | 0.002 | 0.001 | 0.002 | 0.001 | 5.096% | -8.192% |

Notes: The root mean square errors of the tests are reported here.
1) The percentage change values show the improvement in the smoothness of the SA series going from the indirect seasonal adjustment to the direct seasonal adjustment. A positive sign indicates that the indirect seasonal adjustment is smoother than the direct one.

### *b) Analysis of smoothness*

The smoothness of the SA series derived with the two approaches is assessed using the two tests presented in par. 2/b and calculated for the whole series and for the last three years only, the results of which are presented in Table 2. On the basis of the two measures R1 and R2 no clear conclusion can be derived on which is the best approach in terms of smoothness of the SA series. As regards to both M2 and M3, the results obtained on the full series and on the last three years for R1 indicate that the direct adjustment is smoother than the indirect one. On the other hand, R2 gives opposite messages when calculated on the whole series and on the last three years only, showing a smoother indirect adjustment for M2 when applied to the last three years only and a smoother indirect adjustment for M3 when calculated on the whole series.

### *c) Residual seasonality in the adjusted series and in the irregular components*

The spectrum is normally estimated by X12-Arima for the most recent period of data, since users are usually more concerned about recent data. However, in case of moving seasonality and trading day effect, the results of the spectrum inspection limited to the most recent years might be significantly different from those obtained on the whole series. For this reason, the spectrum is estimated first on the most recent eight years of data (as from September 1994 to August 2002) and then on the entire period available, for the two aggregates M2 and M3 and also for their main components M1, M2-M1 and M3-M2.

The results of the spectrum inspection are reported in Table 3. Concerning the comparison between the direct and indirect adjustment of M2 and M3, no residual seasonality or trading effects are found in the spectrum of the SA series and of the irregular components estimated for the whole period January 1980-August 2002 and for the most recent eight years period.

No residual seasonality is found for the component series M1, M2-M1 and M3-M2, for both the whole period of data and for the most recent eight years. However the spectrum does not give a clear indication on the residual trading day effects left in the irregular component of M1 and M3-M2.

Table 3: Spectrum analysis for seasonally adjusted series and irregular components

| Series | Residual effect | Direct | | Indirect | | Direct | | Indirect | |
|---|---|---|---|---|---|---|---|---|---|
| | | SA series | Irregular component | SA series | Irregular component | SA series | Irregular component | SA series | Irregular component |
| | | Sep. 1994 - Aug. 2002 | | | | Jan. 1980 - Aug. 2002 | | | |
| **M2** | Seasonality | NO | NO | NO | NO | NO | NO | NO | NO |
| **M2** | Trading day | NO | NO | NO | NO | NO | NO | NO | NO |
| **M1** | Seasonality | NO | NO | | | NO | NO | | |
| **M1** | Trading day | NO | ? | | | NO | ? | | |
| **M2-M1** | Seasonality | NO | NO | | | NO | NO | | |
| **M2-M1** | Trading day | NO | NO | | | NO | NO | | |
| **M3** | Seasonality | NO | NO | NO | NO | NO | NO | NO | NO |
| **M3** | Trading day | NO | NO | NO | NO | NO | NO | NO | NO |
| **M3-M2** | Seasonality | NO | NO | | | NO | NO | | |
| **M3-M2** | Trading day | NO | ? | | | NO | NO | | |

Notes: The spectrum are estimated by X12-Arima on the SA series modified for the extreme values identified by X11, and on the irregular component of the series modified for the extreme values identified by X11.

### *d) Further analysis of the irregular components*

A further step in the analysis of the irregular components is testing for the randomness and the absence of autocorrelation in these series. For this purpose, a set of test statistics is applied to the irregular components of M2 and M3, the results of which are reported in Table 4.

The results of this analysis support the randomness of the irregular components obtained from the two seasonal adjustment approaches, for both aggregates M2 and M3.

Table 4: Analysis of irregular components

| Test statistics | M2 | | M3 | |
|---|---|---|---|---|
| | Direct SA | Indirect SA | Direct SA | Indirect SA |
| Mean [1)] | 1 | 1 | 1 | 1 |
| Standard deviation | 0.00103 | 0.00127 | 0.00098 | 0.00125 |
| Skewness | 0.2766 | 0.1309 | 0.2008 | 0.1528 |
| Excess kurtosis | 0.0220 | -0.0160 | 0.0151 | 0.0382 |
| Asymptotic test [$\chi^2_{(2)}$] [2)] | 3.4749 [0.1760] | 0.77122 [0.6800] | 1.8297 [0.4006] | 1.0750 [0.5842] |
| Normality test [$\chi^2_{(2)}$] [2)] | 3.6419 [0.1619] | 0.81555 [0.6651] | 1.8883 [0.3890] | 1.1625 [0.5592] |
| DW [3)] | 2.498 | 1.899 | 2.408 | 1.946 |
| ADF [4)] | -21.15** | -15.59** | -20.17** | -15.96** |

Notes: ** indicates a level of significance of 1%, * a level of significance of 5%.
1) The mean of the irregular component obtained from the multiplicative adjustment in X12-Arima, is centered to 1 by construction.
2) The normality tests are a function of the skewness and excess kurtosis. In squared brackets is shown the probability of getting a number at least as large if the series has a normal distribution.
3) The Durbin Watson (DW) statistic is testing for whiteness against first order autocorrelation in the series. If the series is white noise, DW will be around 2, if the series is a random walk (integrated of first order) DW will be very small.
4) A significant result for the Augmented Dickey Fuller test (ADF) indicates that the null hypothesis of a unit root is rejected and the series is stationary. Critical values are derived from McKinnon (1991), two stars (**) indicate that the test is significant at the 1% level.

Table 5: Direct versus indirect approach: seasonal adjustment quality indicators

| Seasonal adjustment quality indicators | | Index | Notional | stocks | Index | Notional | stocks |
|---|---|---|---|---|---|---|---|
| | | M2 Direct | M2 Direct | M2 Indirect | M3 Direct | M3 Direct | M3 Indirect |
| Relative contribution of the irregular over three months span | $M_1$ | 0.034 | 0.034 | 0.074 | 0.031 | 0.030 | 0.064 |
| Relative contribution of the irregular component to the stationary portion of the variance | $M_2$ | 0.005 | 0.005 | 0.007 | 0.003 | 0.003 | 0.005 |
| Amount of month to month change in the irregular component as compared to the amount of month to month change in the trend-cycle | $M_3$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Amount of autocorrelation in the irregular as described by the average duration of run | $M_4$ | 0.560 | 0.560 | 0.784 | 0.952 | 0.840 | 1.400 |
| Number of months it takes the change in the trend-cycle to surpass the amount of change in the irregular | $M_5$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Amount of year to year change in the irregular as compared to the amount of year to year change in the seasonal | $M_6$ | 0.237 | 0.232 | 0.232 | 0.236 | 0.246 | 0.152 |
| Amount of moving seasonality present relative to the amount of stable seasonality | $M_7$ | 0.136 | 0.136 | 0.161 | 0.206 | 0.196 | 0.216 |
| Size of the fluctuations in the seasonal component throughout the whole series | $M_8$ | 0.455 | 0.454 | 1.428 | 0.498 | 0.489 | 1.562 |
| Average linear movement in the seasonal component throughout the whole series | $M_9$ | 0.199 | 0.199 | 0.209 | 0.300 | 0.291 | 0.291 |
| Same as 8, calculated for recent years only | $M_{10}$ | 0.529 | 0.529 | 1.076 | 0.612 | 0.615 | 1.047 |
| Same as 9, calculated for recent years only | $M_{11}$ | 0.492 | 0.493 | 0.680 | 0.592 | 0.597 | 0.696 |

Notes: These statistics vary between 0 and 3 and values below 1 are generally considered acceptable.

### *e) Quality assessment of seasonal adjustment*

The results of the eleven quality measures ($M_s$) available in X12-Arima for the direct and the indirect seasonal adjustment are reported in Table 5. The comparison between the performance of the direct and the indirect approach for M2 and M3 does not show significant differences in terms of quality of the adjustment, with only one exception. For the indirect adjustment of M2 and M3 the value of the statistics $M_8$ (1.428 and 1.562 respectively) are above the acceptance value of 1 and significantly bigger than the value obtained for the direct adjustment of M2 and M3 (0.454 and 0.489 respectively). However the statistics $M_8$ and $M_{10}$ for the indirect method give generally higher results than for the direct method, and they are considered crucial when they both show values above 1, as it is not the case here.

### *f) Analysis of stability using revisions histories*

The analysis of lagged revisions consents to assess the behaviour of the revisions to the seasonal estimates over time. This is performed with respect to the concurrent seasonal

Table 6: Direct versus indirect approach: analysis of absolute revisions to seasonally adjusted data *
*(percentages)*

| Additional observations | M2 direct | | M2 indirect | | M3 direct | | M3 indirect | |
|---|---|---|---|---|---|---|---|---|
| | Mean | *Standard deviation* | Mean | *Standard deviation* | Mean | *Standard deviation* | Mean | *Standard deviation* |
| A. With respect to concurrent seasonal adjustment | | | | | | | | |
| 1 extra month | 0.05 | *0.026* | 0.05 | *0.019* | 0.04 | *0.020* | 0.05 | *0.023* |
| 2 extra months | 0.06 | *0.017* | 0.06 | *0.023* | 0.06 | *0.026* | 0.06 | *0.022* |
| 3 extra months | 0.07 | *0.013* | 0.07 | *0.023* | 0.06 | *0.024* | 0.07 | *0.022* |
| 6 extra months | 0.08 | *0.024* | 0.09 | *0.036* | 0.08 | *0.040* | 0.09 | *0.041* |
| 12 extra months | 0.10 | *0.028* | 0.11 | *0.038* | 0.12 | *0.040* | 0.12 | *0.043* |
| Final estimate | 0.10 | *0.043* | 0.11 | *0.038* | **0.08** | *0.021* | **0.11** | *0.038* |
| B. With respect to final seasonal adjustment | | | | | | | | |
| 3 extra months | 0.06 | *0.028* | 0.07 | *0.027* | 0.04 | *0.012* | 0.07 | *0.023* |
| 6 extra months | 0.07 | *0.028* | 0.08 | *0.026* | 0.05 | *0.017* | 0.08 | *0.016* |
| 12 extra months | 0.07 | *0.033* | 0.08 | *0.035* | 0.06 | *0.024* | 0.09 | *0.040* |
| 18 extra months | **0.03** | *0.019* | 0.05 | *0.020* | **0.03** | *0.020* | 0.06 | *0.019* |
| 24 extra months | 0.02 | *0.027* | **0.03** | *0.027* | 0.02 | *0.016* | **0.04** | *0.025* |

* The size of revisions has been assessed over the 4-years-period from August 1999 to August 2002.
(1) The size of the revisions is evaluated comparing the SA data obtained according to the concurrent adjustment with those obtained adding 1, 2, 3, 6 and 12 extra observations [$R_t = 100 \times (A_{t/t+lag} - A_{t/t})/A_{t/t}$].
(2) The size of the revisions is evaluated comparing the SA data obtained according to the final adjustment with those obtained adding 1, 2, 3, 6 and 12 extra observations after the current observation [$R_t = 100 \times (A_{t/T} - A_{t/t+lag})/A_{t/t+lag}$].

adjustment (adjustment of observation t when this is the last observation available) and to the final seasonal adjustment (adjustment of month t calculated at the end of the time series). In order to evaluate the size of the revisions to the SA series when more observations are added at the end of the period, the concurrent estimates are compared to the estimates obtained when additional observations become available, while to evaluate how quickly an estimate converges to its final value, the final estimates are used as mean of comparison. Table 6 shows the results of the analysis with respect to the concurrent seasonal adjustment (panel A) and to the final seasonal adjustment (panel B).

For what concerns the size of the revisions to the SA data (Table 6 - A), no significant differences can be identified between the direct and the indirect seasonal adjustment for both M2 and M3, with the exception of the revisions between the concurrent and the final adjustment for M3, where the direct method seems to perform slightly better. When we look at how quickly an estimate converges to its final value (Table 6 - B) the direct adjustment shows a quicker convergence than the indirect adjustment for both M2 and M3.

Figure 6 and 7 show the concurrent and final adjustment for the direct and the indirect methods for M2 and M3 respectively. The differences between the revisions obtained with the two methods (abs [$R_t^{direct}$]- abs [$R_t^{indirect}$]) are also reported in the graphs with bars, where positive values indicate larger revisions for the direct method and negative values indicate larger revisions for the indirect method. The comparison between the concurrent and the final adjustment of M3 (Figure 7) obtained with the two methods indicates a slightly better performance of the direct adjustment against the indirect one, even though in most of the cases the discrepancies are quite small (below 5%). A similar result is obtained for M2 (Figure 6).

Figure 6: Revisions concurrent to final for the direct and indirect seasonal adjustment values of M2, and differences between the two approaches
*(percentage)*

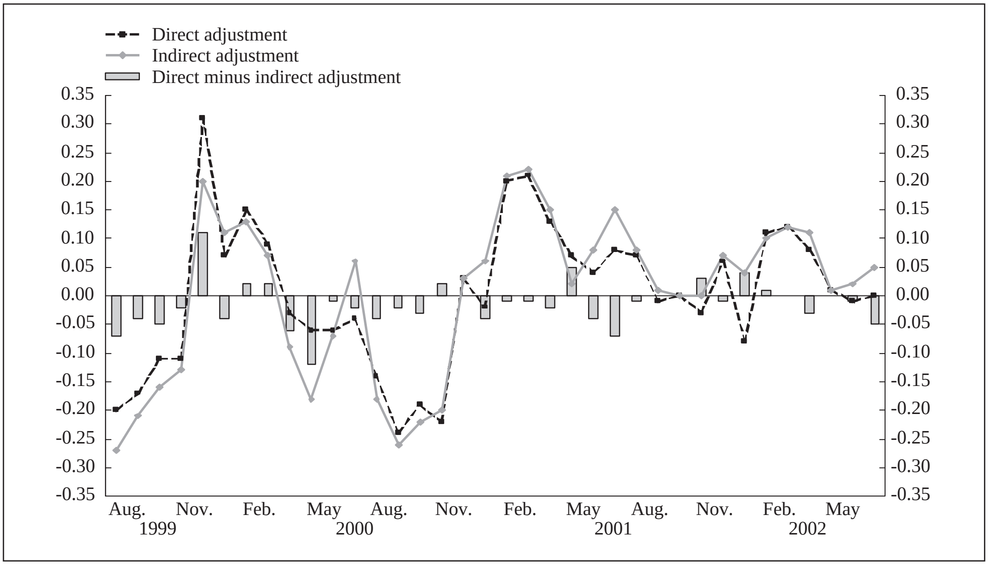
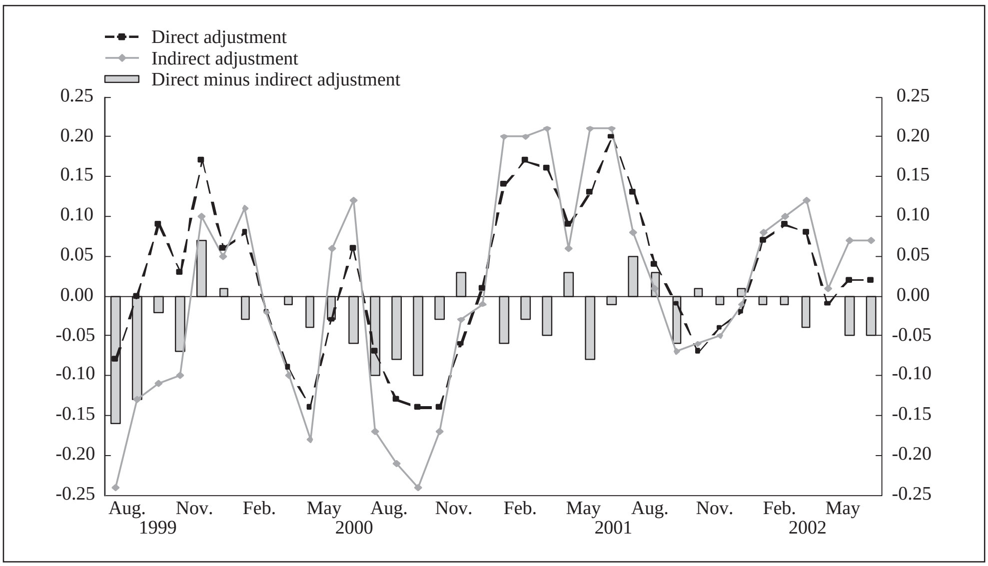



Figure 7: Revisions concurrent to final for the direct and indirect seasonal adjustment of M3, and differences between the two approaches
*(percentage)*



### g) *Analysis of stability using sliding spans*

Four spans of 8 years each have been considered in the analysis. The first span covers the period January 1991-August 1999, the second span the period January 1992-August 2000, the third span the period January 1993-August 2001 and the last one the period January 1994-August 2002. The analysis focuses on the comparison between the seasonal factors and the month-to-month changes in the SA series for all observations present in at least two spans, for the period August 1994-August 2001. X12-Arima computes summary statistics to indicate the percentage of seasonal factors and month-to-month changes in SA series for which a discrepancy larger than a fixed threshold is identified. When the seasonal factors are very close to 100 or their range is too small, as is the case for the SA M2 and M3 obtained with the direct and indirect approaches, these indicators are not reliable since the discrepancies identified are too small. For this reason those statistics are not reported here. However, a comparison between the seasonal factors and the-month-to-month changes in the SA series obtained from the different spans of data, for the direct and indirect adjustment, is performed and reported in Tables 7 and 8 and in Figures 8, 9, 10 and 11.

Table 7: Direct versus indirect approach: sliding spans analysis (1)

A. Monthly means of seasonal factors: difference across spans

| | Direct approach | | Indirect approach | |
|---|---|---|---|---|
| January 1991-August 2001 | Extreme seasonal factors | Average max differences | Extreme seasonal factors | Average max differences |
| **M2** | | 0.15 (st dev: 0.138) | | 0.14 (st dev: 0.095) |
| Highest seasonal factor [max diff across spans] | December [0.54] | | December [0.42] | |
| Lowest seasonal factor [max diff across spans] | October [0.10] | | October [0.08] | |
| **M3** | | 0.13 (st dev: 0.109) | | 0.13 (st dev: 0.084) |
| Highest seasonal factor [max diff across spans] | December [0.43] | | December [0.35] | |
| Lowest seasonal factor [max diff across spans] | October [0.10] | | October [0.11] | |

B. Maximum percent differences across spans

| | M2 | | M3 | |
|---|---|---|---|---|
| August 1994-August 2001 | Direct | Indirect | Direct | Indirect |
| **Seasonal factors** | | | | |
| Median | 0.14 | 0.36 | 0.11 | 0.33 |
| Max | 0.47 | 0.65 | 0.47 | 0.63 |
| Standard deviation | 0.21 | 0.54 | 0.16 | 0.50 |
| **Month to month changes in SA series** | | | | |
| Median | 0.80 | 0.65 | 0.58 | 0.57 |
| Max | 1.23 | 1.00 | 0.94 | 0.88 |
| Standard deviation | 1.18 | 0.97 | 0.86 | 0.84 |

First, we looked at the means of seasonal factors per month and at their discrepancies across the spans, calculated over the complete four spans of data. No significant differences are identified between the two approaches. The months of October and December are identified as having the lowest and the highest seasonal factors in all the data spans for both the direct and indirect seasonal adjustment of M2 and M3 (Table 7A). Moreover, the seasonal factors estimated with the direct method show slightly larger discrepancies as opposed to those estimated with the indirect method for these two extreme months.

Looking at the distribution of the largest discrepancies between the seasonal factors across the spans for the 7-years period August 1994-August 2001, an indication of larger discrepancies and higher variability is evident in the indirect approaches for both M2 and M3 (Table 7B), as also shown in Figure 8 and 9. However, this is not the case for the monthly percentage changes calculated for the SA series of M2 in the different spans of data, where the picture is the opposite, and the indirect approach is performing better in terms of discrepancies across the different spans (Figure 10). As for the monthly percentage changes calculated on the SA M3 series, no significant differences between the direct and the indirect approaches can be identified (Figure 11).

Finally, as shown in Table 8, the direct method performs better in terms of number of months of inconsistent estimates of the seasonal factors across the spans for the two series, M2 and M3. However, the indirect method gives more stable results in terms of monthly percentage changes across the spans for M2, while no differences are identified for M3.

Table 8: Direct versus indirect approach: sliding spans analysis (2)

| Comparison between spans | Direct approach | | | Indirect approach | | |
|---|---|---|---|---|---|---|
| | Number of months | Average | Standard dev | Number of months | Average | Standard dev |
| **Seasonal factors** | | | | | | |
| **M2** - Inconsistent estimates [1] | 12 out of 84 [14.3%] | | | 17 out of 84 [20.2%] | | |
| **M2** - Max % difference | | 0.14 | 0.089 | | 0.37 | 0.103 |
| **M3** - Inconsistent estimates [1] | 6 out of 84 [7.1%] | | | 15 out of 84 [18.9%] | | |
| **M3** - Max % difference | | 0.12 | 0.080 | | 0.33 | 0.094 |
| **Month to month changes in SA series** | | | | | | |
| **M2** - Sign inconsistency in monthly percentage changes [2] | 35 out of 84 [40.5%] | | | 30 out of 84 [35.7%] | | |
| **M2** - Max difference | | 0.74 | 0.280 | | 0.60 | 0.218 |
| **M3** - Sign inconsistency in monthly percentage changes [2] | 22 out of 84 [26.2%] | | | 23 out of 84 [27.4%] | | |
| **M3** - Max difference | | 0.54 | 0.224 | | 0.53 | 0.189 |

1) Seasonal factors estimates are considered inconsistent when some are below 100 and some above 100, indicating an increase and a decrease in the SA value for the same observation across the spans.
2) The monthly percentage changes calculated on the four spans show different signs.

Figure 8: Largest percentage differences between seasonal factors across spans and inconsistent estimates – direct and indirect seasonal adjustment of M2

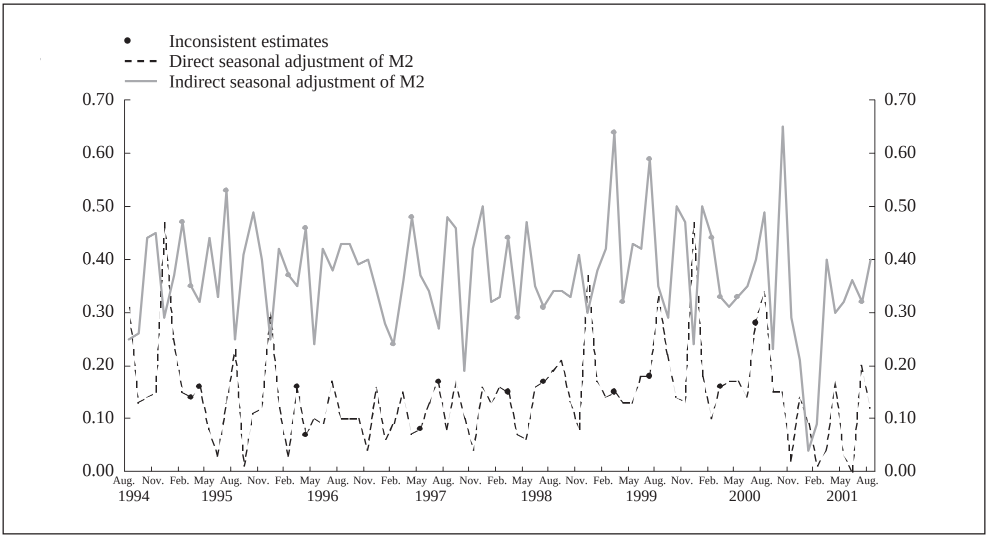



Figure 9: Largest percentage differences between seasonal factors across spans and inconsistent estimates – direct and indirect seasonal adjustment of M3

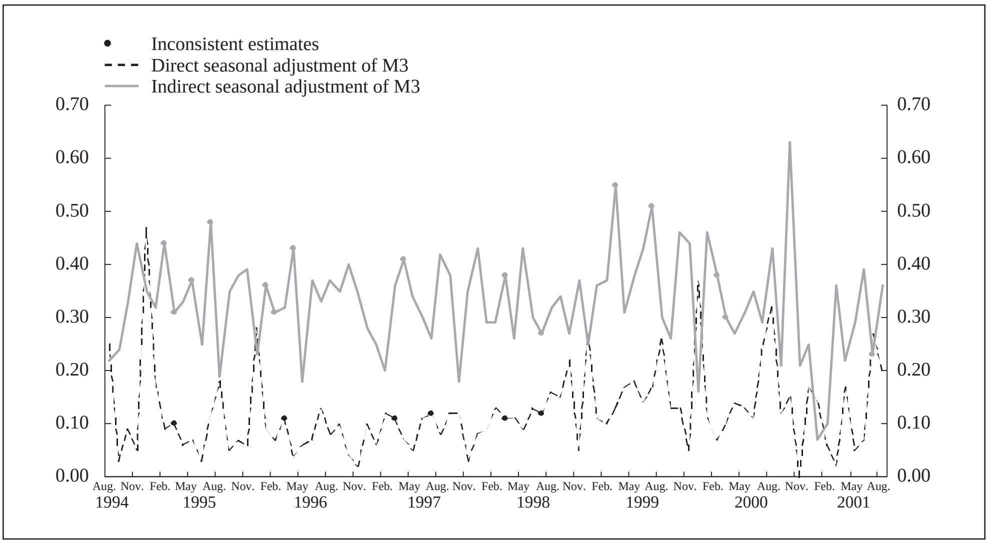


Figure 10: Largest differences between month to month changes across spans and sign inconsistencies – direct and indirect seasonal adjustment of M2
*(percentage)*

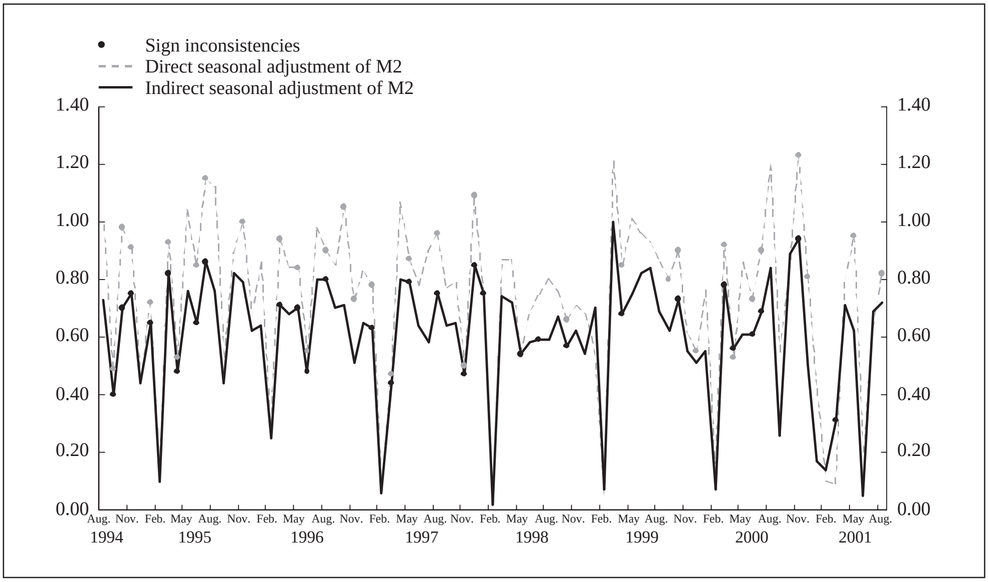
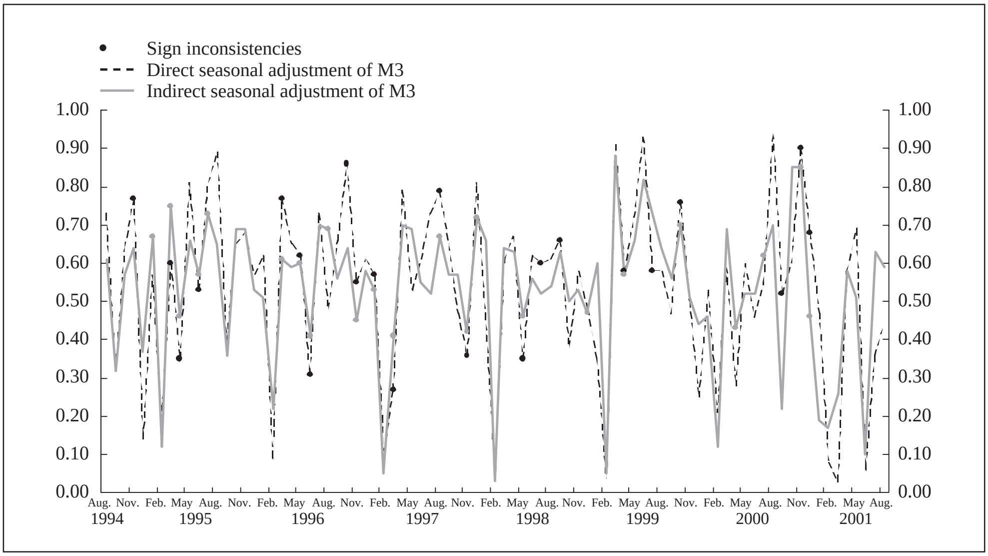



Figure 11: Largest differences between month to month changes across spans and sign inconsistencies – direct and indirect seasonal adjustment of M3
*(percentage)*



## 4 Conclusions

In this paper we compared the performance of the direct and the indirect seasonal adjustment of the euro area monetary aggregates series, in order to verify whether the original choice of indirect adjustment, is still supported by empirical evidence.

The two series M2 and M3 have been investigated using the X12-ARIMA diagnostics to evaluate the quality of the two alternative seasonal adjustment approaches, and also to identify any significant difference between the performances of the two adjustments.

The results obtained do not provide clear evidence of superior performance of any of the two approaches. In particular, in terms of graphical analysis no differences between the series adjusted with the two methods are identified with respect to both their levels and their annual growth rates. The two tests of smoothness of the SA series do not provide clear results, showing opposite messages when calculated on the full sample or on the most recent three years period. The quality of the direct and indirect adjustments does not differ significantly, both in terms of residual seasonality in the SA series and of the $M_s$ statistical indicators calculated by X12-ARIMA. The analysis of stability of the results of the seasonal adjustment when additional and more recent information are added to the series shows a quicker convergence of the estimates obtained with the direct adjustment to their final values for both M2 and M3. As for the size of the revisions to the SA figures when additional information becomes available, the direct adjustment performs slightly better than the indirect one even though the differences between them are quite small. Finally, the comparison between alternative seasonal estimates for the same observations, obtained on different spans of data, does not give a clear indication in favour of the direct or the indirect approach.

As a follow up of the work done here, the empirical analysis might be extended to the use of Seats, and then formal statistical tests might be developed and used to choose between the direct and the indirect adjustment.

To conclude, it is recognised the need to perform an accurate analysis on a regular basis of the discrepancies between the direct and the indirect seasonal adjustment also in view of the fact that the number of series seasonally adjusted by the ECB in the field on money and banking statistics will grow in the future, and the principles defined by the Seasonal Adjustment Task Force may not necessarily always represent the best choice.

## References


Astolfi, R., D. Ladiray, G. L. Mazzi, (2001), Seasonal adjustment of european aggregates: Direct versus indirect apporach, Eurostat, WP17/2001.

Cristadoro, R., R. Sabbatini, (2000), The seasonal adjustment of the harmonised index of consumer prices for the euro area: A comparison of direct and indirect methods. Banca d'Italia, Temi di Discussione n.371.

Dagum, E. B., (1979), On the seasonal adjustment of economic time series aggregates: A case study of the unemployment rate, *Counting the Labor Force*, *National Commission on Employment and Unemployment Statistics*, *Appendix*, 2: 317-344.

European Central Bank, Seasonal adjustment of monetary aggregates and HICP for the euro area, (August 2000).

Findley, D. F., B. C. Monsell, H. B. Shulman, and M. G. Pugh, (1990), Sliding Spans Diagnostics for Seasonal and Related Adjustments, Journal of the American Statistical Association, 85: 345-355.

Findley, D. F., B. C. Monsell, W. R. Bell, M. C. Otto, and B.-C. Chen, (1998), New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program, *Journal of Business and Economic Statistics*, 16: 127-176.

Gomez, V., (2000), Revision-based tests for direct versus indirect seasonal adjustment of aggregated series. Doc. Eurostat A4/SA/00/08.

Ladiray, D., B. Quenneville, (2001), *Seasonal adjustment with the X-11 method*, Lectures Notes in Statistics, Springer, New York.

Lothian, J., M. Morry, (1978), A set of quality control statistics for the X-11-Arima Seasonal Adjustment Method, Working paper 78-10-005, Methodology Branch, Statistics Canada, Ottawa ON, Canada.

Otranto, E., U. Triacca, (2000), A distance-based method for the choice of direct or indirect seasonal adjustment, WP presented at the seminar *L'applicazione delle nuove techniche di destagionalizzazione*, ISTAT.

Planas, C., F. Campolongo, (2000), The seasonal adjustment of contemporaneously aggregated series, Doc. EurostatA4/SA/00/06.

U.S. Census Bureau, (2002), *X-12-ARIMA Reference Manual*, *Version 0.2.9*, Washington, DC: U.S. Census Bureau.

# 7

# Monthly re-estimation of the parameters of a once-a-year fixed model: an assessment

Bravo Cabría, Soledad; García Esteban, Coral; Montesinos Afonso, Antonio[1]

## 1. Introduction

TRAMO/SEATS (T/S) is a powerful system for the univariate analysis of economic time-series. In the course of the development of its modelling and signal extraction functions, the system has been equipped with different utilities intended to help the expert in the complex and sometimes subjective task of identifying models and evaluating results. Among these utilities those of automatic modelling have reached such high levels of efficiency and reliability that increasingly more confidence is being placed in them to deal with an ever-wider range of indicators. Also, their output is frequently being incorporated directly into wider systems of macroeconomic modelling and forecasting.

While recognising the potential and reliability of TRAMO/SEATS, and specifically acknowledging that it has fulfilled one of the goals for which it was developed –namely to free the analyst from routine tasks –, and while also admitting that modelling and signal extraction has apparently become an easy and, at times, mundane task, it is worth remembering that its automatic functions have led to a degree of distancing between user and data and that they are not always used efficiently. This distancing is partly due to the great number of series treated in sequence, which makes it difficult to examine thoroughly the diagnoses produced by the system; moreover, the complexity of the mathematical instruments used calls for expert knowledge to interpret the diagnoses, which are in any event not presented in a user-friendly way.

Distancing from the data is in some way unavoidable in mass production processes. This is why the user should always be aware of the extent to which the system's results could be influenced by, for instance, the influential observations at the beginning or at the end of the sample period, the sample length or the model selection. In addition, results could also be affected by modelling practices and the options chosen regarding the revision of model and the parameters values, i.e. whether they are re-estimated or not each time data are updated.

The paper focuses on this last point; it will offer evidence, first, of how the presence of influential observations at the end of the sample period determines changes in the models and in the estimated parameters. Further, it will discuss the recommended practice in the use of T/S which, according to the authors, should be: *first, to identify the model once a year and, second, to fix the model orders and to re-estimate monthly the associated parameters*. In the case of conjuncture-related time series modelling, this practice is questioned by analysts who, on occasions, prefer to fix both the model and the parameters in order to evaluate the possible factors of change in the economic situation.

[1] Our thanks to Carmen Carretero for her contribution to the initial part of the work.

This paper reasserts the T/S recommended practice. The documentation presented will show the way T/S results, in terms of the predicted path of the original series and of the estimated SA and TC signals, may differ when each of the alternative options (fixed versus variable parameters values) is applied; It concludes that the recommended practice is a source of flexibility that helps the system to adjust to the latest data evolution. The next section is divided into three parts: the first initiates the debate; the second presents detailed graphic evidence; and the third and final part draws the conclusions.

The thrust and presentation of the paper is practical. It was produced to elicit discussion among experts on seasonal adjustment at the ECB seminar. Its main objective was to gather evidence of other experiences and to encourage the convergence of best practices in the treatment of data.

## 2. Models and parameters revision practice for univariate series

### *2.1 Possible options*

In our work we analyse in detail the macroeconomic aggregates of the CNTR (Spanish Quarterly National Accounts) and their related indicators, and the task of modelling and signal extraction of SA and TC data[2] has to achieve the twin objectives of producing information for the analysis of the present economic situation and for short-term prediction. SA data are also inputs for the macroeconomic modelling process. As a result of these twin objectives which the treatment of conjunctural indicators must fulfil, and due also to the extremely variable nature of some of those series, the definition of a single working procedure is not advisable. However, there should be a guide to summarise the best practices. In our institution, and excepting the macroeconomic aggregates of the CNTR, SA and TC series are based on univariate models identified and fixed once a year and their associated parameters are also estimated and fixed once a year. CNTR aggregates do not follow this practice. They rather undergo a slightly more complicated process of short-term forecasting with regression variables[3], and the general solution of treatment based on fixed models is less suitable insofar as its data are revised, sometimes significantly, whenever a new observation is added.

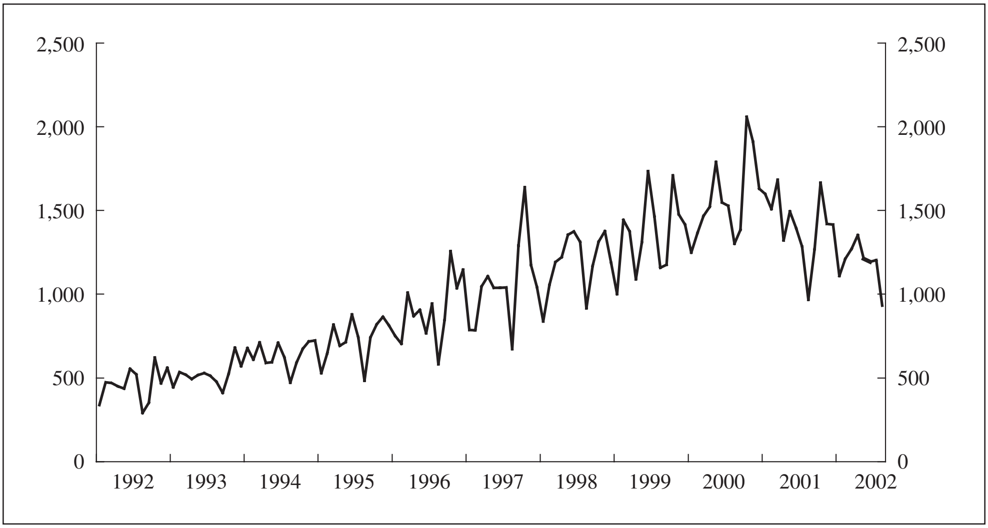
Even if the practice recommended by T/S experts is to fix the model but not the value of the parameters, which should be re-estimated each time new data are available, the practice of forecasting and signal extraction using fixed models and parameters values is preferred by conjunctural analysts. They stress the interest in evaluating forecasting errors, free from the influence of possible changes in the model or in the values of the coefficients, that are in turn influenced by the latest observations which may vary significantly in future data revisions. This discussion –fixed models and parameters as against fixed models and re-estimation of parameters –appears not to be relevant when the conditions determining the generation of data are stable; however, the opposite is clearly the case in situations of change. The recent slowdown besetting the economy, which has been reflected in several of the indicators analysed, offered an opportunity to confirm the validity of the argument.

---

2 In Spain, CNTR figures are also analysed in TC terms.

3 A kind of bridge model is used here. This is also the case of CPI.

Figure 1: XBCAR original data. LEVELS




The original series of real exports of capital goods (XBCAR) was submitted to re-estimation, coincidentally at a point in time immediately prior to the change in behaviour which, as shown in Figure 1, began in the final months of the year 2000.

At the end of 2000, when identifying the XBCAR series, the diagnoses of two competing models gave no conclusive evidence in favour of either. The two models were defined as being equally possible, and the one used up until that moment was retained; only its parameters were re-estimated.

Figure 2: XBCAR: residuals autoregressive model with fixed parameters

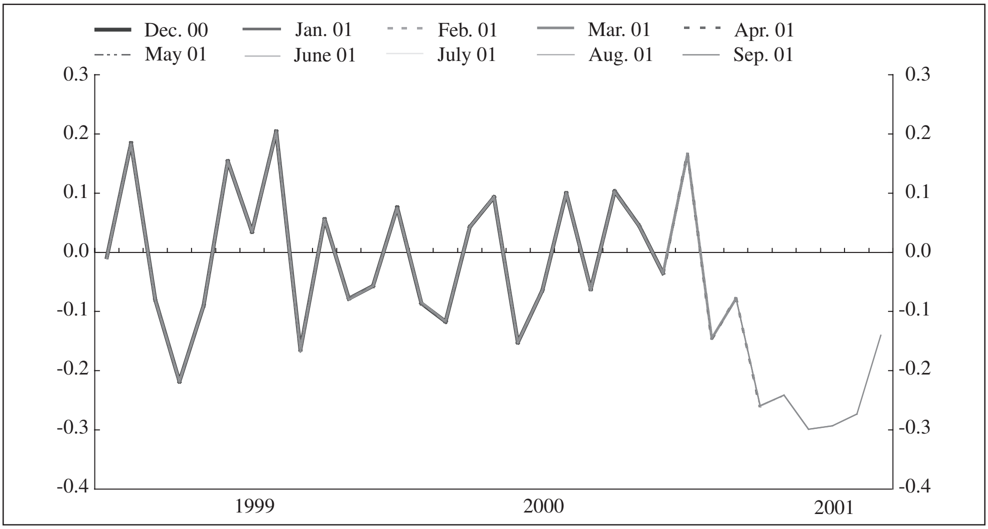
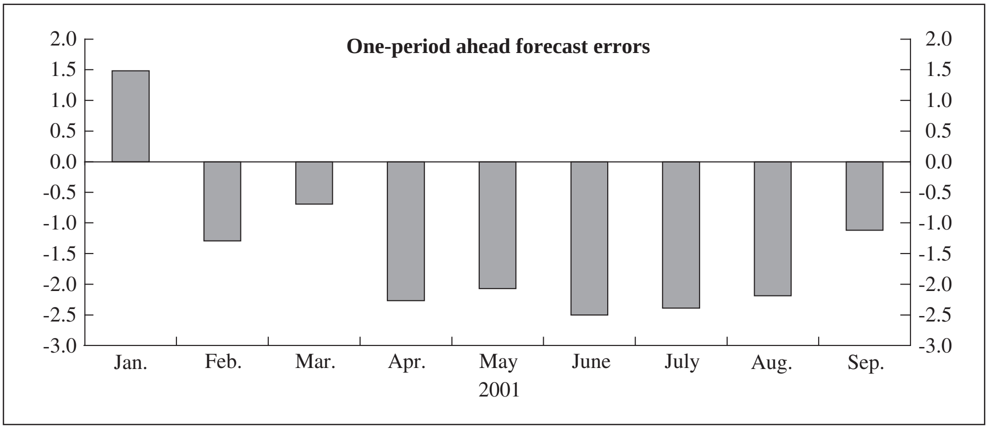


Figure 3: XBCAR: autoregressive model with fixed parameters
*(standard deviation)*




In the opening months of 2001 the model was seen to be producing a structure of non-random errors (see Figures 2 and 3). Since XBCAR is an important component of another indicator used to analyse changes in productive investment, which is in turn significant for forecasting GNP, it was necessary to analyse it carefully.

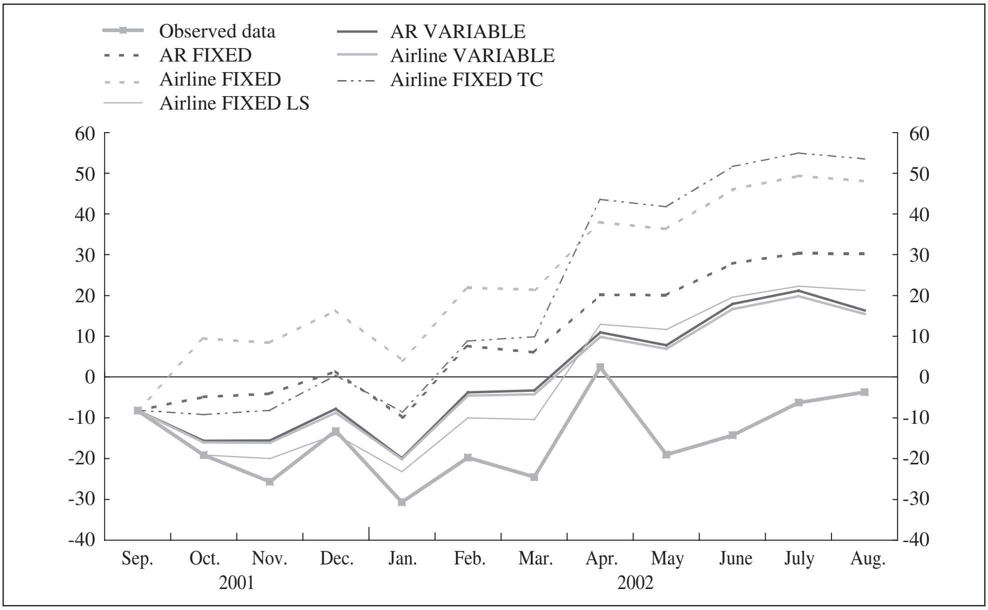
Influential observations were the cause of the error structure noted. The problem of how to treat them was posed by the fact that the observations were detected at the end of the sample period and there was no frame of reference to determine their cause. There might have been either a structural change, a sequence of outliers, or a temporary change.

In the course of the tests to analyse the problem, we went back to compare the results produced by the two initially identified models and we compared the output produced when XBCAR was processed with each model and with fixed or variable parameters.

The following subsection will show a sequence of the most interesting results of this exercise, which are summarised in Figure 4. It shows the predicted paths for XBCAR which, commencing September 2001, are obtained by modelling differently the influential observations detected at the end of the series. As no further information was available on their nature, all the solutions taken could have been equally reasonable. The figure also illustrates one of the points stressed in the introduction, namely that, in addition to the sensitivity of the results to influential observations at the end –or at the beginning –of the sample period, different modelling practice may also affect results.

In the next subsection we show graphically the extent to which the results derived from processing the series of real exports of capital goods (XBCAR) differ with alternative models and options of T/S. The results from XBCAR are contrasted with those from another series, the real exports of non-energy intermediate goods (XBINER), which also shows a slowdown in the last period of the sample, but not of the intensity observed in XBCAR. This latter case shows that the results from T/S are quite robust to the model or to the option selected; however, the case of XBCAR illustrates why the option of letting the parameters be re-estimated when a time series is updated should be the preferred one, mainly in the production environment, when batches of indicators are processed in sequence. In this case, the system gains in flexibility, parameter values adapt to last observations, and contribute to making predictions and signal paths adjust more quickly to potentially undetected changes in data generation processes.

Figure 4: XBCAR: forecast with origin in September 2001
*(Year-on-year rates of change; percent)*




## 2.2 *Results of the different options*

### *2.2.1 The case of XBCAR*

To begin with, the models initially identified for XBCAR were the following[4]:
[1] (2,1,3)(0,1,1)
[2] (0,1,1)(0,1,1)
Although model [1] is less *parsimonious*, it was the one initially chosen[5].

#### *2.2.1.1 The nature of influential observations at the end of the sample period*

When it was first noted that the structure of the errors in the model appeared not to be random, it was not clear to conjunctural analysts that the economic environment had changed. In this respect, the slow down of the XBCAR series was anticipating the evidence which the other indicators would later show. As Figure 5 depicts, the original series reflected a negative year-on-year rate of change, which the predicted path of both models [1] and [2] failed to anticipate.

[4] Appendix 1 summarises the results of the estimation and of the different tests of randomness produced by TRAMO/SEATS. Significantly, this series is especially difficult to model. Indeed, it is one of those which Maravall himself had classified as manic-depressive!

[5] Occasionally in the test, model [1] is referred to as the AR model whereas model [2] is called the air-line model.

Figure 5: XBCAR: observed data (up to September 2001) and predicted path
*(Year-on-year rates of change; percent)*

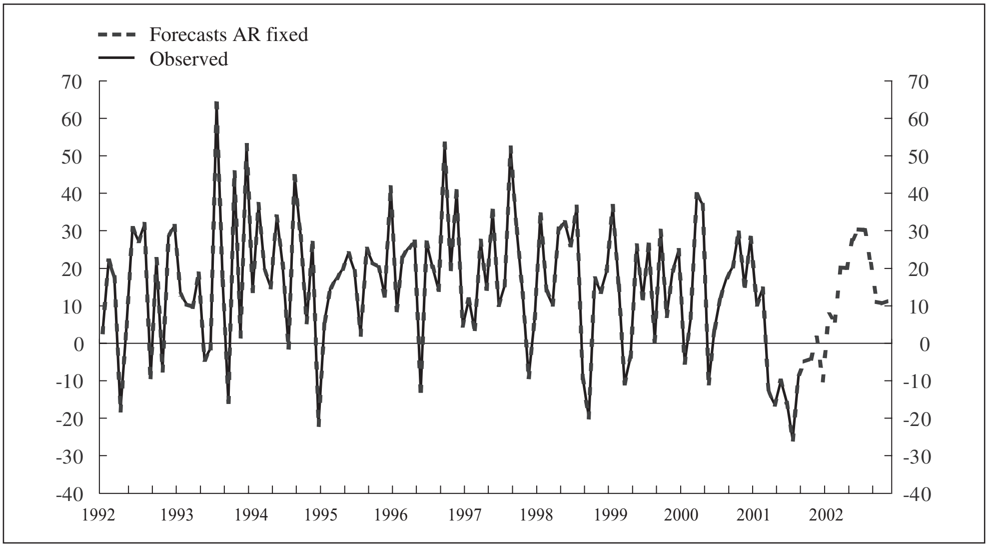



Figure 6 shows the year-on-year rate of change forecast one-period-ahead by either model [1] (central curve), or model [2] (upper curve) when the values of the parameters were fixed. Both paths differ significantly from the lower curve, which reproduces the observed year-on-year rate of change.

Figure 6: XBCAR: observed and forecast data with FIXED parameters
*(Year-on-year rates of change; percent)*

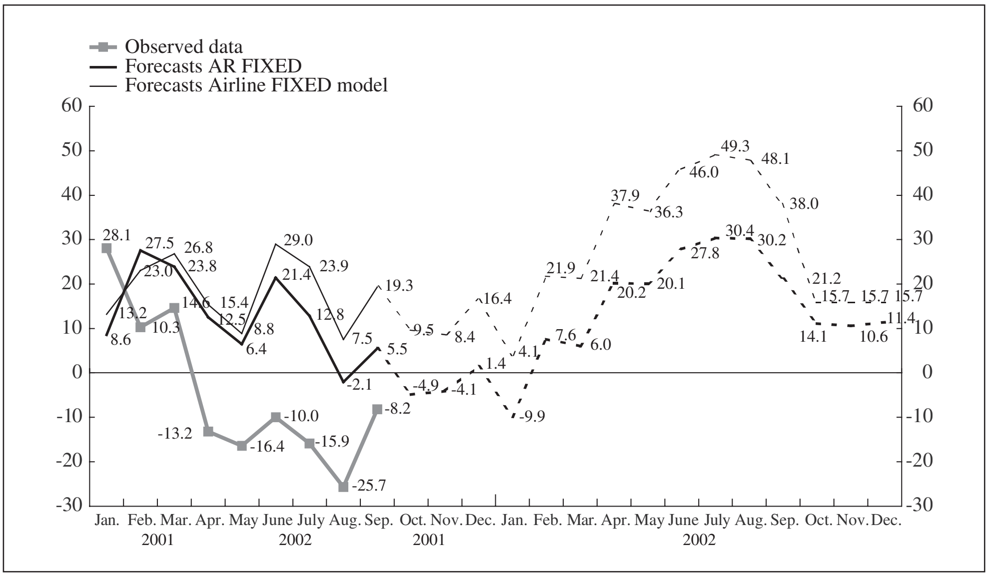
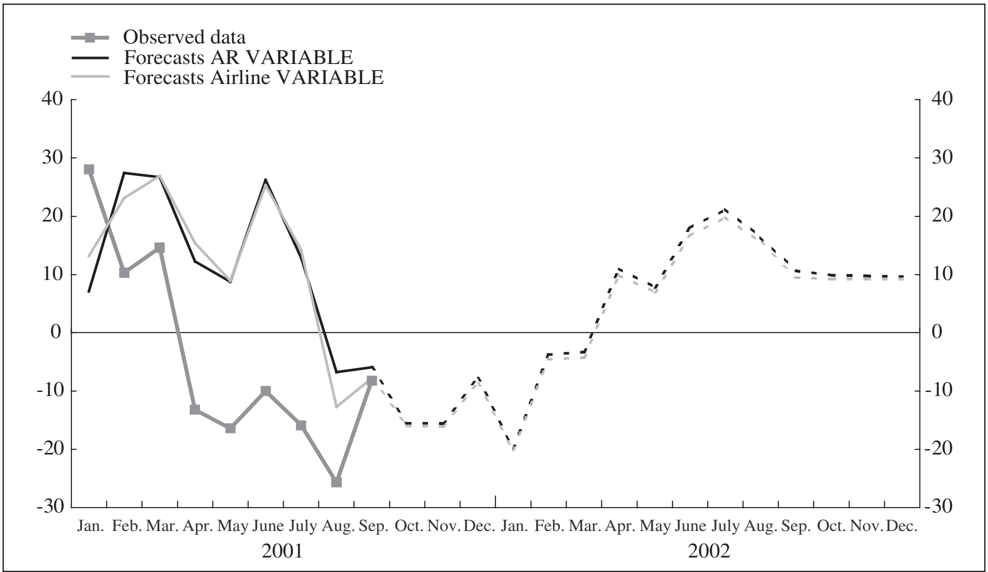


Figure 7: XBCAR: observed and forecast data with VARIABLE parameters
*(Year-on-year rates of change; percent)*




The above figure reveals that the forecasting functions of the two models hardly adjust; indeed, model [2] failed to do it. However, when the parameters of the models were estimated on an ongoing basis –i.e. parameter values were allowed to be re-estimated each time new data were observed –the predicted path adjusted, albeit slowly, and finally started to reveal the contractive behaviour of the series.

In terms of numbers, the forecast growth for January 2002 would have been 4.1% in the estimate of the airlines model with fixed parameters, -9.9% in the autoregressive model with fixed parameters, and -20% if these two models had been estimated with the variable parameters option. It should also be noted that the model selected influences the forecast path when the fixed parameter option is selected, whereas it hardly makes a difference when the variable parameter option is taken. In the option of variable parameter value, the change of the forecasting function reflect the change in the estimated value of the parameters which, in turn, reflect the influence of the latest sample observations.

Figure 8: XBCAR Parameters value

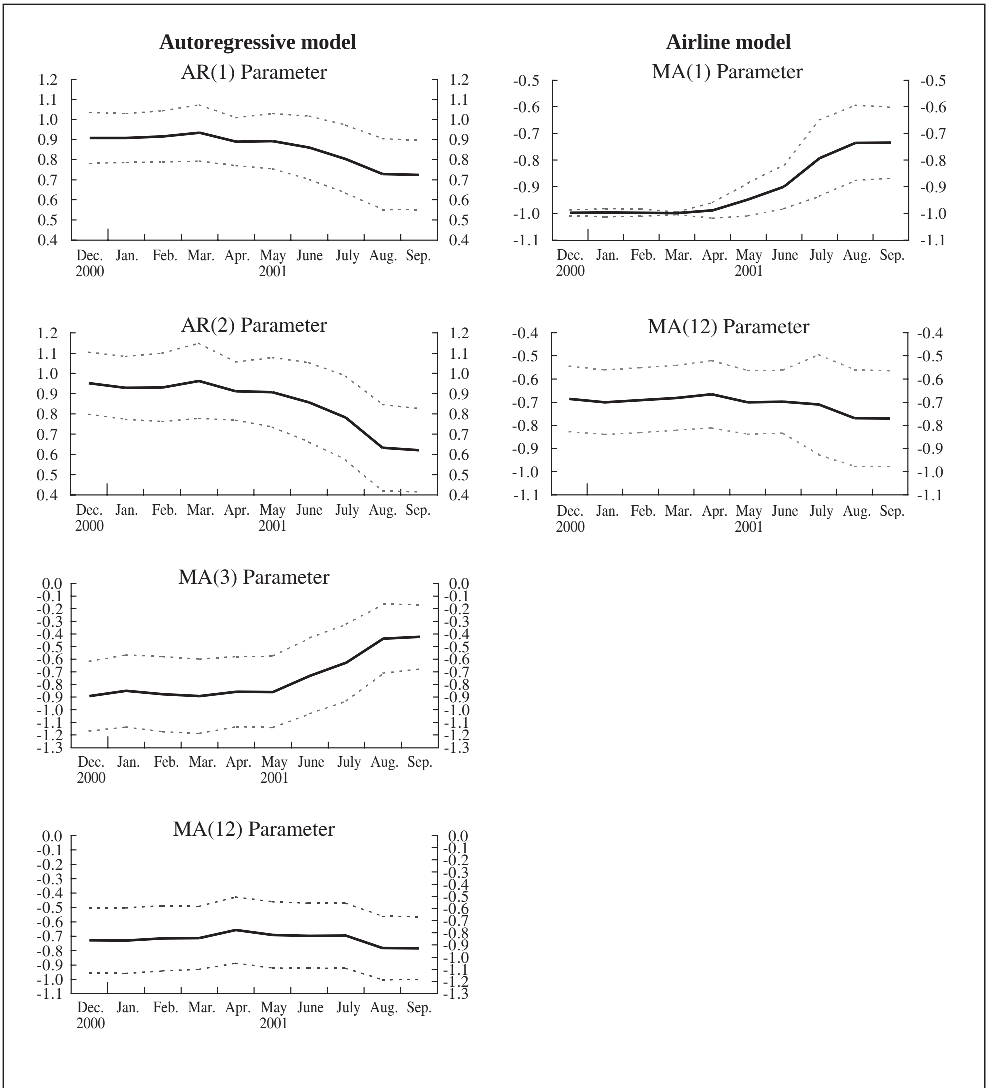



Figure 8 (right) shows the adjustment produced in the value of the parameters each time new observations are added to the sample period.

### *2.2.1.2 SA and TC signal show different paths*

Not only do the predicted paths of the models change when the option of fixed or variable parameters is taken, but also, and accordingly, SA and TC data vary significantly. This point will show that the SA and TC signals change and, in this case, the differences arise both from the model and from the parameters option chosen.

Figure 9: XBCAR: seasonal adjusted data based on model [1] with fixed parameters
*(Year-on-year rates of change; percent)*

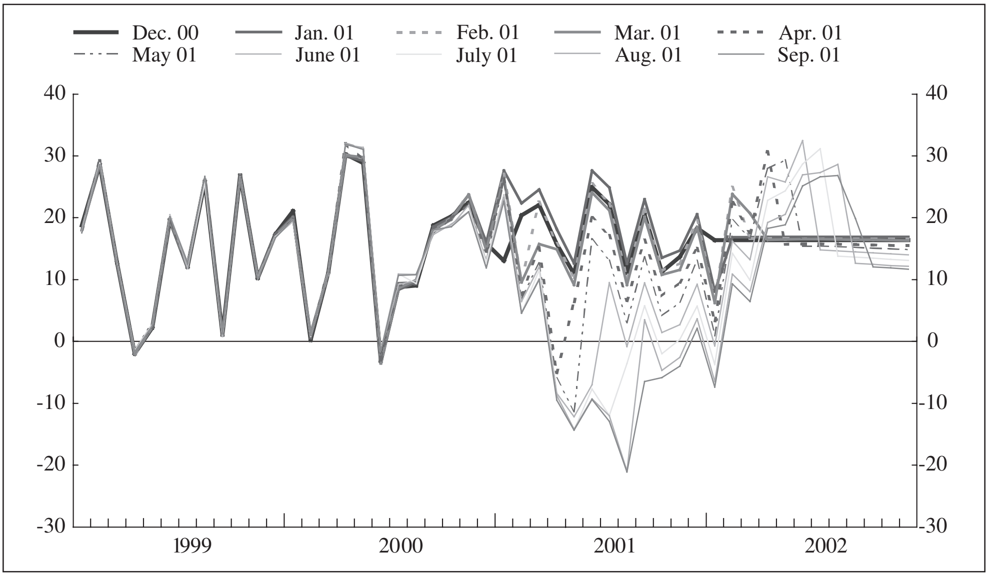



Figure 9 shows how seasonally-adjusted series adapt as new observations are added to the sample period.

Given that some of the most noteworthy features of this figure are clearer when the graph is produced with TC series, in the discussion that follows these series are presented:

Figure 10: XBCAR: trend data based on model [1] with fixed parameters
*(Year-on-year rates of change; percent)*

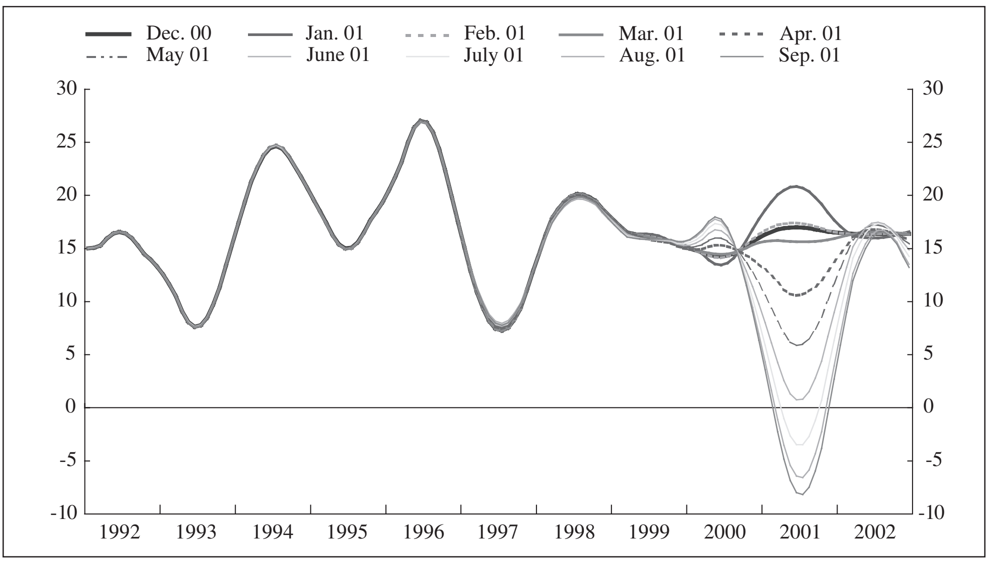


Figure 11: XBCAR: trend-cycle data based on the airline model (model [2]) with fixed parameters
*(Year-on-year rates of change; percent)*

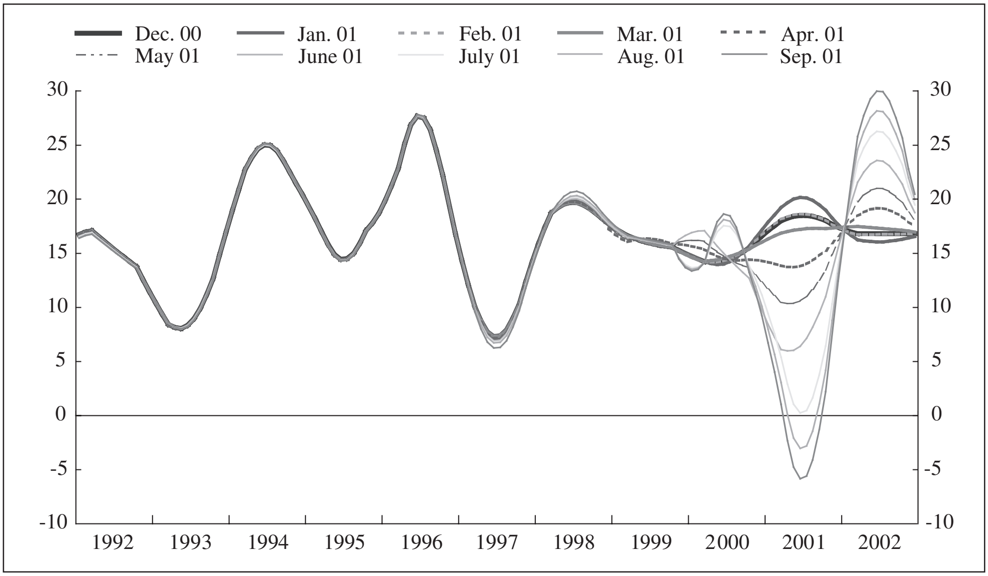


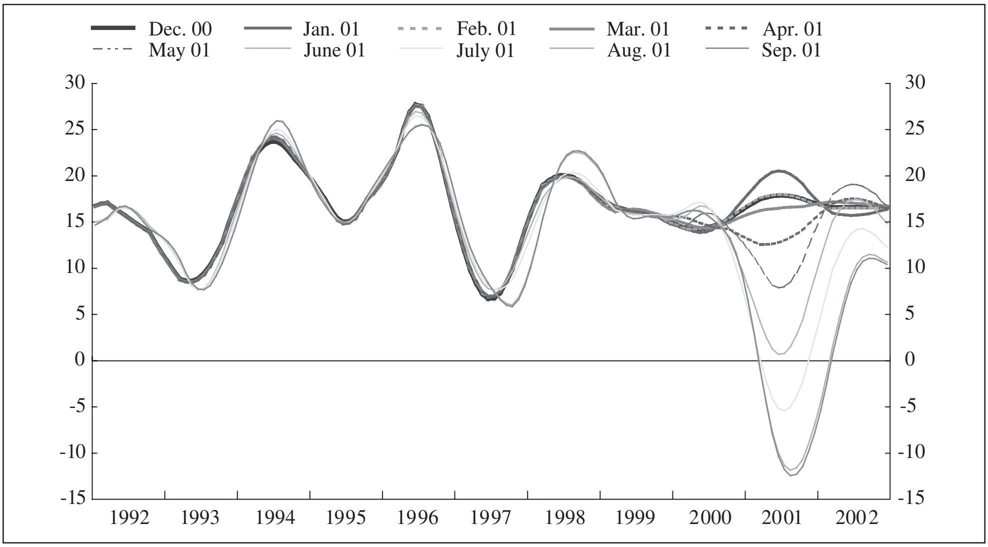

Figure 10 reproduces Figure 9 in TC terms. Here it is more clearly seen the way the estimated TC series adapt as new observations are added to the sample. The curves drawn have a different forecast origin, ranging from December 2000 (the start of the slowdown period) to September 2001 (the time when the more general contraction of the economy became clearly noticeable).

The figure also shows a correction of the long-term trend-cycle horizon as a response to the latest sample observations: the year-on-year rates forecast in the long-term trend drop by approximately 5 percentage points over the 10 months in which the model had been registering respective negative forecast errors.

When the same exercise is repeated with the airline model (model [2]) and fixed parameters, the SA and the TC signals differ from those shown above. Figure 11 illustrates these differences in TC terms; the long-term trend-cycle horizon hardly adapts in the same way as the predicted path of the original data did no adapt to lower observed growth rates. Here, the TC predicted values have to over-react to compensate for the drop in the current estimates.

Figure 12: XBCAR: trend-cycle data based on model [1] with the variable parameters option

*(Year-on-year rates of change; percent)*




With the option of variable parameters estimation, the trend-cycle horizon adapts more quickly, irrespective of the model chosen, and it corrected itself by more than 8 percentage points with each of the models. (See Figures 12 and 13)

Figure 13: XBCAR: trend-cycle data based on model [2] with the variable parameters option

*(Year-on-year rates of change; percent)*

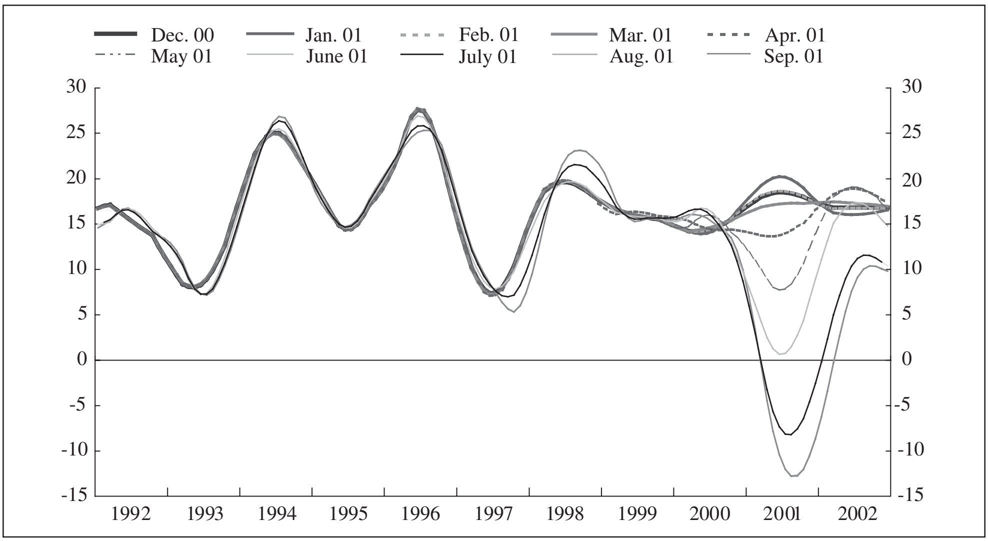
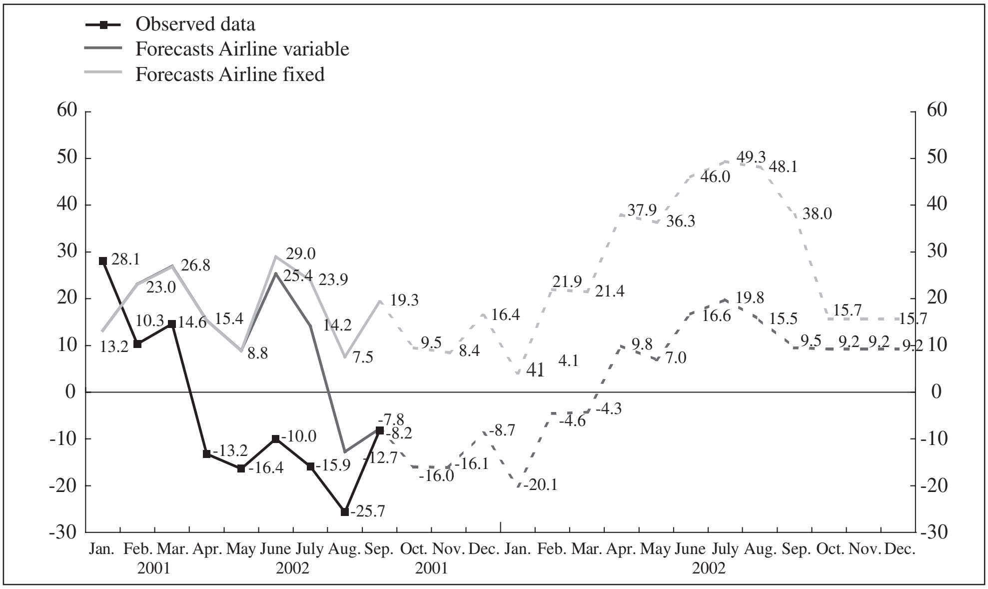
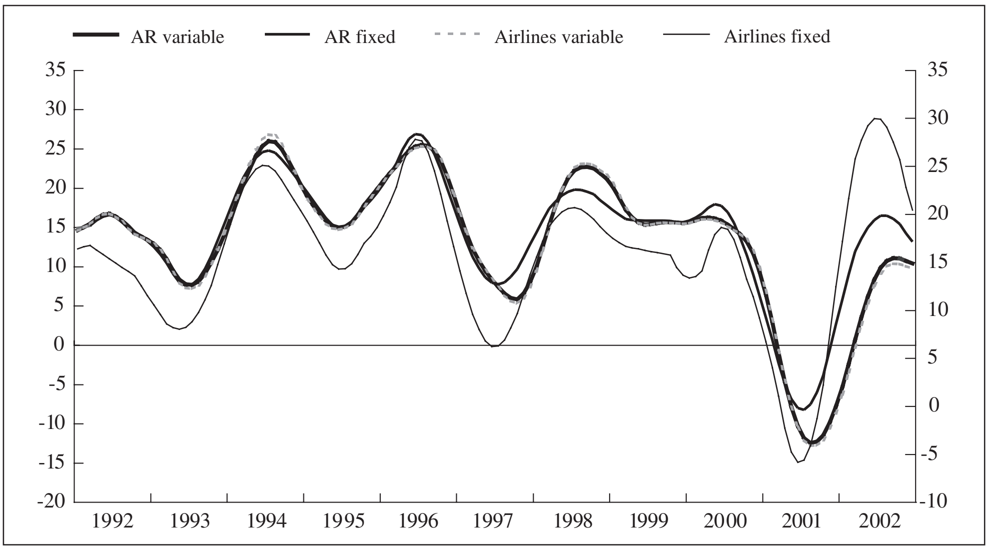


Figure 14: XBCAR: observed and forecast data based on the airline model (model [2])
*(Year-on-year rates of change; percent)*




The next two figures help to summarise results. They illustrate, in turn, how the option of the parameter estimates (fixed versus variable) influences the forecasts of the same model: specifically, Figure 14 compares the one-period-ahead forecast produced by the airline model with fixed (upper curve) and with variable parameters value (lower path). The second figure

Figure 15: XBCAR: trend-cycle data based on models [1] & [2]
*(Year-on-year rates of change; percent)*



(Figure 15) shows the extent to which the TC estimates (and consequently the SA) differ when the model changes and/or the option on the parameters changes.

Figure 15 also indicates clearly that the long-term trend-cycle horizon converges at a different rate. In addition, the correction of the long-term trend-cycle would have arisen differently if the T/S user, on observing the first forecast errors with a value greater than twice their standard deviation, had "intervened" in their outcome. The lack of perspective the user has when "influential observations" are at the end of the sample period gives rise to a whole range of possible treatments which, in any case, will have a direct influence on the predicted paths both in the original series and in the estimated signals. As mentioned, this paper does not illustrate the different interventions that were tested.

To sum up, the significant and early change in the growth pattern that the series of real exports of capital goods (XBCAR) started to show in mid-2000 was not clearly reflected in their univariate predicted values and, consequently, the transfer models that used XBCAR as an indicator fail to signal in advance a possible change in the path of the CNTR aggregate. One of the reasons for this misalignment between forecast and observed values was the way T/S was set up for the univariate modelling and signal extraction of the indicator, which, as a general practice, is processed with the option of fixed model and parameter value during a year. As said, this is the option preferred by most conjunctural analysts, but it causes data forecasts to hardly adapt to the behaviour of the most recent observations. In addition, signal estimates are more dependent on the model selected. This might not have been the case if parameter values had been allowed to adjust to the latest sample observations.

To conclude, we think it is important to stress that the uncertainty in the results of univariate estimation of time-series, which this paper seems to emphasize is due to notable changes in the behaviour of the latest series analysed. In other words, for most series with which we work, if the models are correctly "identified", the option of fixed or variable re-estimation of parameters has less influence. As an illustration of this, the next point presents the same type of graphs produced for the series of actual exports of non-energy intermediate goods (XBINER).

Figure 16: XBINER observed data up to September 2001

*(Year-on-year rates of change; percent)*

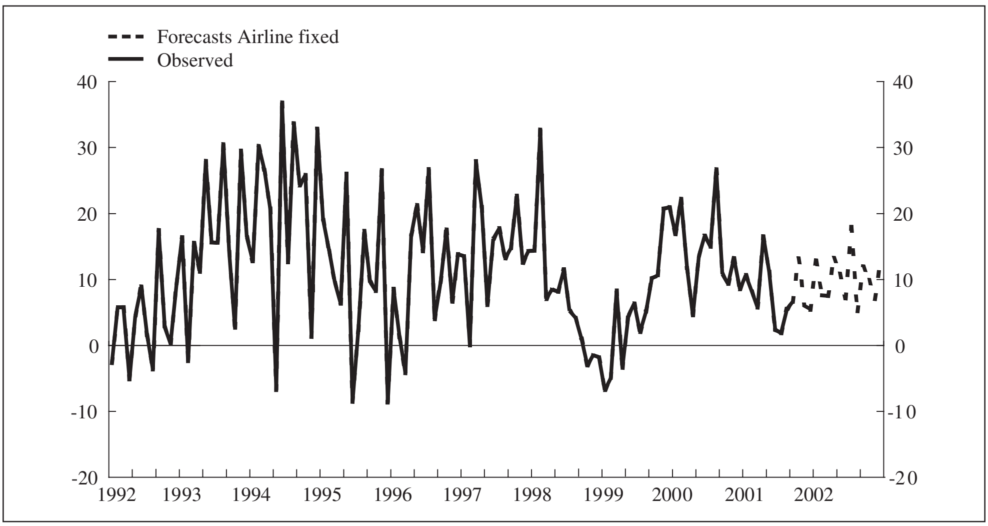


Figure 17: XBINER: residuals airline model with fixed parameters value

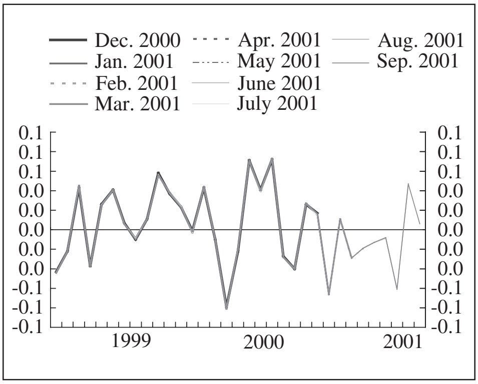
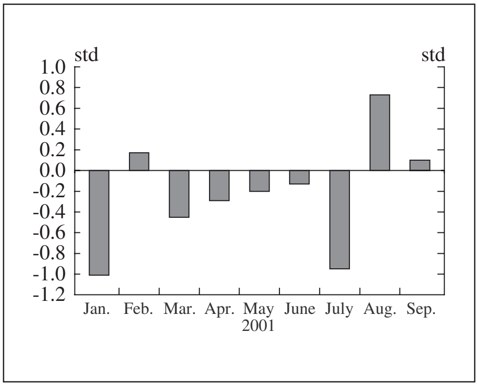



Figure 18: XBINER: one period ahead forecast errors. Airline model with parameters value fixed




### 2.2.2 *The case of XBINER*

The model identified for this time series is an Airlines model. No competing model was suitable.

As Figure 16 shows, the year-on-year rate of change also reflected a slowdown, although in this case it was less pronounced.

Although the residuals and one-period ahead error started to show a non-random structure, as Figures 17 and 18 illustrate, their size was small.

Consequently, the one-period-ahead predicted paths adjusted fairly quickly with both options of fixed or variable parameter values.

Consequently again, the signals SA and TC produced by the model with each option hardly differ.

The case illustrated represents the large number of series whose behaviour is free from special or unusual events affecting their course, and should be ‘intervened”in some way. For these series, T/S results are quite robust to different modelling practices.

Figure 19: XBINER: observed data and forecasts with fixed parameters
*(Year-on-year rates of change; percent)*

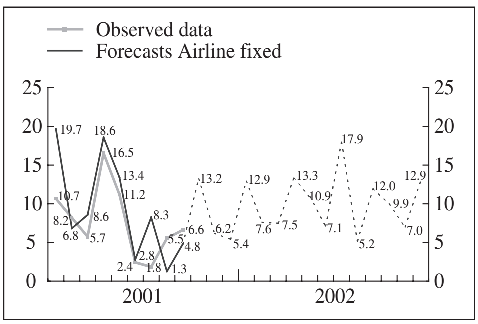



Figure 20: XBINER: observed data and forecasts with variable parameters values
*(Year-on-year rates of change; percent)*

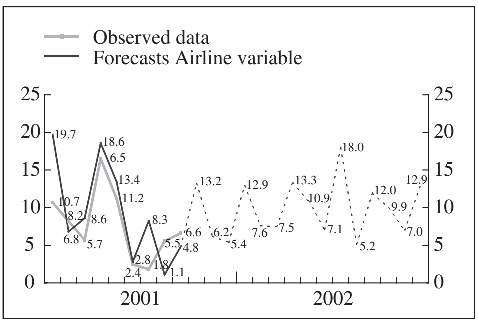


Figure 21: XBINER: trend-cycle data airlines model with fixed parameters value
*(Year-on-year rates of change; percent)*

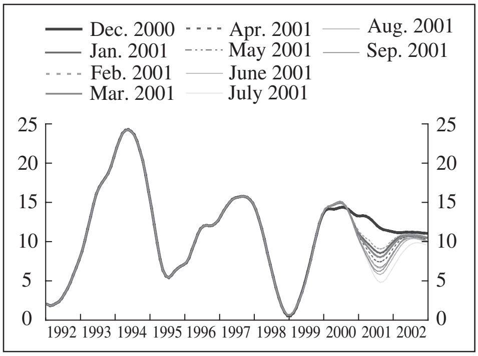
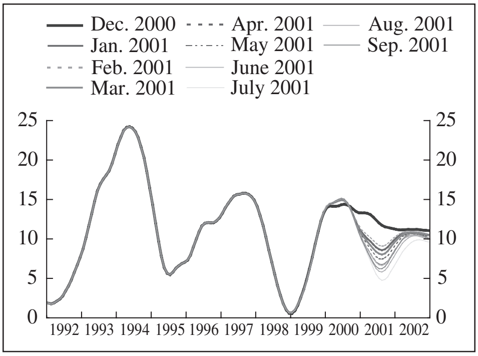



Figure 22: XBINER: trend-cycle data airlines model with variable parameters value
*(Year-on-year rates of change; percent)*




### *2.3 Conclusions*

As different users stress different requirements in the time-series with which they work, it is difficult to combine them into one single treatment. A solution adopted as a general practice for dealing with conjuncture analysis may not satisfy those responsible for short-term forecasting. This paper has documented the influence of the decision of re-estimation or not of parameters on the results of the processes of forecasting and signal extraction. And, at the same time, it has stressed yet again the importance of influential observations at the end of the sample period. They may have a determining influence on the estimated series studied, which are generally seasonally-adjusted or trend-cycle series.

The question we asked is how to control those influential observations in the production environment, when large number of series are processed sequentially and a detailed analysis of the input data and the system's output diagnostics is not feasible. Detection and treatment of influential observations is important; more so when the influential observations take place at the end of the sample period even though it is difficult to determine their nature and thus proper treatment. The exercise presented here illustrates that:

- Adding flexibility to the systems to allow the modelling process to adapt to the latest evolution of the series will reduce forecast errors. To allow the system to re-estimate models and/or parameters each time new data are available is an aspect of this flexibility that should be adopted, mainly in data production.
- The concurrent estimation of models and parameters may be suitable when the data of a series are revised each time new observations are added; otherwise, models should be fixed for a limited period.
- Once the model is fixed, the option fixed versus variable parameters values will influence results. If there is a significant change in the conditions determining the data, both the predicted paths of the original series and the signals may differ noticeably.
- The predicted paths of different, equally possible models may differ very little; however, the paths of the SA and TC signals may vary considerably.
- The evidence shown illustrate that the re-estimation of the parameters value in an ongoing basis should the option adopted in routine T/S practice.

## References

Gómez, V. and Maravall, A., (1996), Programs TRAMO and SEATS, *Working Paper 9628*. Banco de España.

Gómez, V. and Maravall, A., (2000a), Automatic Modeling Methods for Univariate Series, *Working Paper 9808*, Research Department, Banco de España.

Kaiser, R. and Maravall, A., (2000), Notes on time series analysis, Arima models & signal extraction, *Working Paper 0012*, Banco de España.

# Appendix 1

**ARIMA MODELS: actual exports of capital goods (XBCAR)**

**Estimated model: (2,1,3)(0,1,1)**

$$\Delta\Delta_{12}LXPCAR = \underset{(3.07)}{0.36145}\Delta\Delta_{12}ABR91 + \underset{(2.55)}{0.27417}\Delta\Delta_{12}AGO93 + \underset{(3.60)}{0.38458}\Delta\Delta_{12}ENE94 + \frac{\underset{(3.03)}{0.25535}}{(1-0.7L)}\Delta\Delta_{12}SEP97 +$$

$$+\left[\frac{\left(1-\underset{(-4,88)}{0.73267}L^{3}\right)\left(1-\underset{(-6.13)}{0.69688}L^{12}\right)}{\left(1+\underset{(10.93)}{0.85910}L+\underset{(8.75)}{0.85719}L^{2}\right)}\right]a_t$$

Estimation period: January 1991- June 2001

Total number of observations: 126

Number of effective observations: 109

BIC = -4.0046

Correlation between parameters: less than or equal to |0.829|

Residual mean = -0.034892 (-0.3134)

Standard deviation = 11.84903%

Normality test = 2.301 (CHI_squared (2))

Skewness = -0.3221 (se: 0.2346)

Kurtosis = 2.6971 (se: 0.4692)

Durbin-Watson = 1.8186

Box-Pierce-Ljung statistics: Q(24) = 9.11 (CHI_squared (22))

Test F (deleting 12 obs.): F(12.101) = 2.535

# Appendix 2

**ARIMA MODELS: Actual exports of capital goods (XBCAR)**

**Estimated model: Airline (0,1,1)(0,1,1)**

$$\Delta\Delta_{12}\text{LXPCAR} = \underset{(3.07)}{0.36015}\,\Delta\Delta_{12}\,\text{ABR91} + \underset{(2.86)}{0.30955}\Delta\Delta_{12}\,\text{AGO93} + \underset{(3.15)}{0.33825}\,\Delta\Delta_{12}\,ENE\,94 + \frac{\underset{(2.97)}{0.24837}}{(1-0.7L)}\Delta\Delta_{12}\,\text{SEP97} +$$

$$+\left[\frac{\left(1-\underset{(-21.82)}{0.90031}\,L\right)\left(1-\underset{(-10.27)}{0.69736}\,L^{12}\right)}{}\right]a_t$$

Estimation period: January 1991- June 2001

Total number of observations: 126

Number of effective observations: 109

BIC = -4.0645

Correlation between parameters: less than or equal to |0.122|

Residuals mean = -0.035007

(-0.112670)

Standard deviation = 11.87783%

Normality test = 1.870 (CHI_squared(2))

Skewness = -0.2955 (se: 0.2346)

Kurtosis = 2.7499 (se: 0.4692)

Durbin-Watson = 1.7595

Box-Pierce-Ljung statistics: Q(24) = 12.12 (CHI_squared(22))

Test F (deleting 12 obs.): F(12.101) = 2

# 8

# Seasonal adjustment quality reports

Stefano Nardelli

Since the approval of the report by the ECB Task Force on Seasonal Adjustment by the ESCB Statistics Committee in February 2000, progress has been made on the implementation of the report's recommendations.

An important tool developed at the ECB is the seasonal adjustment quality report. This data quality report has proved to be a useful instrument for supporting decisions on seasonal adjustment options and ensuring that proper documentation is available to data users. It combines statistical measures, tables and charts for unadjusted and adjusted series. Particular emphasis is put on revision analysis and stability checks on the options in use. This paper also gives examples of the practical use made of the information contained in the report.

The paper concludes by presenting a project currently under development, which aims to establish a common user interface for Census X-12 and TRAMO-SEATS. The information contained in the quality reports will be maintained and further developed in this project.

## 1. Overview of seasonal adjustment practices at the ECB

### *1.1 The ECB Task Force on Seasonal Adjustment*

In February 1999, the Statistics Committee of the ESCB agreed to set up a temporary Task Force on Seasonal Adjustment. Its main purpose was to prepare practical proposals for the seasonal adjustment of euro area monetary aggregates and the Harmonised Index of Consumer Prices (HICP). In addition, the Task Force was requested to make a general assessment of other seasonally adjusted macroeconomic statistics available for the euro area and to examine advantages and disadvantages of the two main seasonal adjustment software packages, X-12-REGARIMA and TRAMO-SEATS.

After seven months of work, the Task Force reached a general agreement on an array of important issues. The Task Force expressed a preference for the indirect adjustment of both M3 and the HICP via euro area components and for the use of projected factors instead of concurrent adjustment of the series. Both recommendations were formulated in such a way as to combine as much as possible statistical accuracy and internal user requirements. Additivity in headline monetary and consumer price indicators for the euro area and the limitation of (unnecessary) revisions to adjusted data were two rather important requirements.

With regard to software, both X-12-REGARIMA and TRAMO-SEATS were acknowledged as being high-quality tools for seasonal adjustment and a preference was expressed for their combined use in one seasonal adjustment tool. The motivation for this was based on the observation that both programs were valid from a statistical standpoint and that there was no evidence of significant and systematic differences in the results when the two packages were used in a consistent manner (or at least no differences exceeding the range of results that can normally be produced by each of the two programs).

Finally, the ECB stressed the importance of transparency and good documentation of any transformed data, especially those with a high level of technical input such as seasonally adjusted data. A detailed description of the general principles and methodologies of seasonal adjustment at the ECB was given in a comprehensive publication.[1] Moreover, to provide more details on the seasonal adjustment results, the ECB was invited to produce further information on revisions of raw data and on the methods and settings used. This information was supposed to be published with the results or to be made available to users upon request.

The recommendations of the Task Force were endorsed by the ESCB Statistics Committee in February 2000.

### *1.2 The creation of a production environment*

Following this phase, some work was done to develop a proper production environment to implement the recommendations and ensure a regular production of seasonally adjusted data.

The first issue to be addressed was the link between the seasonal adjustment software and data retrieval/storage. After considering the pros and cons of the few available tools, a choice was made to adopt a FAME/X-12 interface. This decision was intended as an interim measure to allow production to commence. Ways to allow a more integrated use of X-12-REGARIMA and TRAMO-SEATS are still being sought.

The second problem was the computation and (monthly) monitoring of projected seasonal factors. The current practice consists of a usually annual re-estimation of models and options for the computation of the most accurate projected factors to be used. In this phase, a parallel modelling exercise is carried out using both X-12-REGARIMA and TRAMO-SEATS in order to cross-check results. In addition to the standard diagnostics offered by the two programs, importance is not only given to statistical tests, but also to actual numerical results and descriptive statistics, since in most cases headline adjusted indicators are derived indirectly and no specific diagnostics are available. This process is often carried out outside the standard production environment, but the final choices (models and any options for the adjustment) are stored in special databases containing all options to be regularly used.

Every month, an adjustment round using X-12-REGARIMA with the stored options is performed and new results are checked against the ones that are stored and normally used. Generally, attention is focused on the stability of outliers and other regression variables, on the model robustness and on the changes in seasonal factors, including implied changes in month-on-month growth rates and coherence between adjusted aggregates and components. When necessary, some options (including model structure) may be changed or the factors updated before one year has elapsed. Changes are recorded in a file to keep track of the occurrence and frequency of the updates of seasonal factors.

To facilitate this task, the standard output is summarised in a set of tables referred to as the *seasonal adjustment quality report*, which is presented in detail in the second section of this paper.

### *1.3 Data production at the ECB*

After the initial set monetary aggregates and consumer price indices, in the course of the following three years seasonal adjustment at the ECB has been extended to other variables, including Balance of Payments series, short-term indicators, external trade unit values and volumes and car registration.

---

[1] See “Seasonal adjustment of monetary aggregates and HICP for the euro area”, European Central Bank, August 2000. The document can be downloaded from the ECB’s website (http://www.ecb.int).

In spite of the differing relevance of indicators, it is attempted to always follow the same general principles for all datasets that are regularly adjusted in order to ensure the consistency of the common ECB approach to seasonal adjustment.

## 2. The ECB's seasonal adjustment quality report

Following the recommendations of the ECB Task Force on Seasonal Adjustment, an analytical tool was developed to assess the quality of results: the *seasonal adjustment quality report*.

### *2.1 General structure*

The quality report was primarily intended to be an internal tool for use within the framework of the seasonal adjustment policy suggested by the ECB Task Force, but it also had to satisfy the need for transparency within the institution and vis-à-vis the outside world. In this respect, the report has to meet some general criteria, such as:

- *Simplicity*: the quality report must be a useful tool for statisticians involved in seasonal adjustment, but it must also be understandable to non-statisticians; descriptive measurements, charts and tables have therefore been favoured.
- *Flexibility*: the structure of the quality report is not fixed and can be modified according to the importance of indicators; some ad hoc tables can be added for specific needs.
- *Generality*: in the quality report, those indicators that can be simultaneously derived in X-12-REGARIMA and TRAMO-SEATS have been privileged as much as possible.

The quality report is not intended to replace the actual output produced by the seasonal adjustment software, which is still an important evaluation tool for thorough checks of (problematic) series and in the annual setting-up of options and estimation of projected factors. It has been developed to provide statisticians with a flexible and synthetic tool to focus on key statistical features.

Like the structure of the quality report, its content is not fixed and can be simplified or adapted to the specific importance of particular indicators. New indicators can be added if necessary or requested.

Some ad hoc indicators of the stability of models and some descriptive statistics on changes in projected seasonal factors have been inserted and are very useful in supporting decisions. Examples of practical use are given at the end of this section.

A limitation of the quality report is its format. It is currently available as a PDF file and can only be viewed or printed out, but its content cannot be altered or used for any further computations. Some proposals to increase its flexibility and content accessibility are currently under discussion and are presented in the third section.

Quality reports are regularly produced for almost all adjusted indicators and can be made available to users upon request.

The quality report is a tool tailored to the special nature of the work carried out at the ECB. It may not be effective for the adjustment of a massive set of series, to which other criteria should probably be applied (use of automatic decision criteria and rules for acceptance/ rejection, etc.).

### 2.2 Content of the quality report

The quality report is a combination of charts and tables, which are built using the standard output of the seasonal adjustment software and presented in a user-friendly manner (especially the charts).
A general description of the content is given below.

- Figures

a. *Time series and different components*
The figure shows original time series and seasonally adjusted series, and seasonal and irregular components. When a working-day adjustment is made, the linearised series is also displayed together with the trading-day factors. Seasonal and irregular components (and working-day factors when available) are shown on the same scale to allow an analysis of their different impact on and relevance for a time series.

b. *Concurrent adjustment vs. projected factors*
Original and concurrent seasonally adjusted time series are shown in the same figure. The concurrent seasonally adjusted series is also displayed against the seasonally adjusted series computed using projected factors.

c. *Figure of D8, D9 versus D10 concurrent and D10 with projected seasonal factors per month*
Twelve small figure display concurrent vs. projected seasonal factors by month. When X-12-REGARIMA is used, preliminary seasonal factors (D8) and replacement values (D9) are also shown.

d. *Comparison of direct and indirect seasonally adjusted series*
For important indicators, a figure showing the results of direct and indirect adjustment and a bar figure of growth rates computed for both series are produced. The figures are intended to provide some evidence on the accuracy of the adjustment (high discrepancies are normally interpreted as a sign of possible inaccuracies in the direct adjustment of the aggregates or of some components).

e. *Forecast error and revision page*
Forecasts often give indications of problematic months, inappropriate models (for example when important regressors are missing) or, more generally, data quality problems. The revision analysis of seasonal factors gives inter alia some indications of problematic outlier treatment and months with rapidly evolving seasonality.

- Tables

f. *Specification file used in the adjustment*
The table shows the set of options used in the adjustment (*only available for X-12-REGARIMA*).

g. *Parameters and coefficients*
This page contains all the parameters of the REGARIMA model, split into regression parameters, the parameters of the REGARIMA model and the innovation variance of the residuals. The stability of the parameters is checked by calculating the difference between the parameters estimated at times *t* and *t*-1. Small confidence intervals for each parameter are shown in the table. When seasonal factors need to be updated and there is evidence of instability in parameters/outliers for some series, a full re-estimation of options/models/ seasonal factors is performed.

h. *Tests and quality criteria for models and seasonal adjustment*
The table reports a variety of tests and quality criteria for the REGARIMA model (significant lags of the autocorrelation of the residuals, normality test for residuals,

Kurtosis, forecast errors) and some X-11 quality criteria for the seasonal adjustment (M1 to M11, Q statistics, MCD, I/S ratio, I/C ratio, etc.).

i. *Tables of original/transformed series*
A limited set of tables – similar to those generated by X-12-REGARIMA – are produced. The following tables are normally available: A1 (original series), B1 (linearised series), D8 (final unmodified S-I ratios), D9 (final replacement values for S-I ratios), D10 (final seasonal factors), D11 (final seasonally adjusted data) and D16 (combined adjustment factors, only if a working-day adjustment is performed). These basic tables may be extended to include TRAMO-SEATS results, with the exception of D8 and D9, which are specific to X-12-REGARIMA.

Additional indicators supplement some of these tables:

- in Table D8, the figures which are identified as outliers either in the REGARIMA modelling phase or on the basis of the X-11 definition, are marked in different colours;[2]
- in Table D10, seasonal factors for the current run and the forecast factors at the series end are reported; and
- Table D11 shows the effects on annual growth rates caused by the effects of an update of the seasonal factors on the seasonally adjusted results at the series end (this indicator is very useful for assessing the practical implications of an early update of seasonal factors).

According to the importance of indicators, other tables can be added to the basic set, such as revisions to raw data and adjusted series derived in different ways (direct compilation, indirect compilation via country components or via area-wide breakdowns, etc.).

### 2.3 Some practical examples

The harmonisation of national practices underway in many statistical domains – implying compliance with new regulations, and changes in methodologies and data sources, etc. – often adversely affects the stability of the seasonal pattern of area-wide aggregates. As a consequence, the adjustment of some series can suddenly become difficult to carry out. The quality reports have often proved to be a useful and efficient tool to spot critical situations, inaccuracies in results and, in many cases, indications of possible improvements.

A first recent example[3] comes from the seasonal adjustment of the consumer price index for industrial goods excluding energy, an important component of the euro area HICP (accounting for around 32% of the total index).

In order to comply with the HICP harmonised rules, starting from 2002 Italy and Spain take into account sale prices in the compilation of the HICP. In order not to bias the inflation rates for 2002, these countries also revised the data for 2001. Since January 2001, both national series have shown sharp seasonal drops, which have also affected the corresponding euro area series (Italy and Spain account for around 19.4% and 10.3% of the euro area series, respectively).

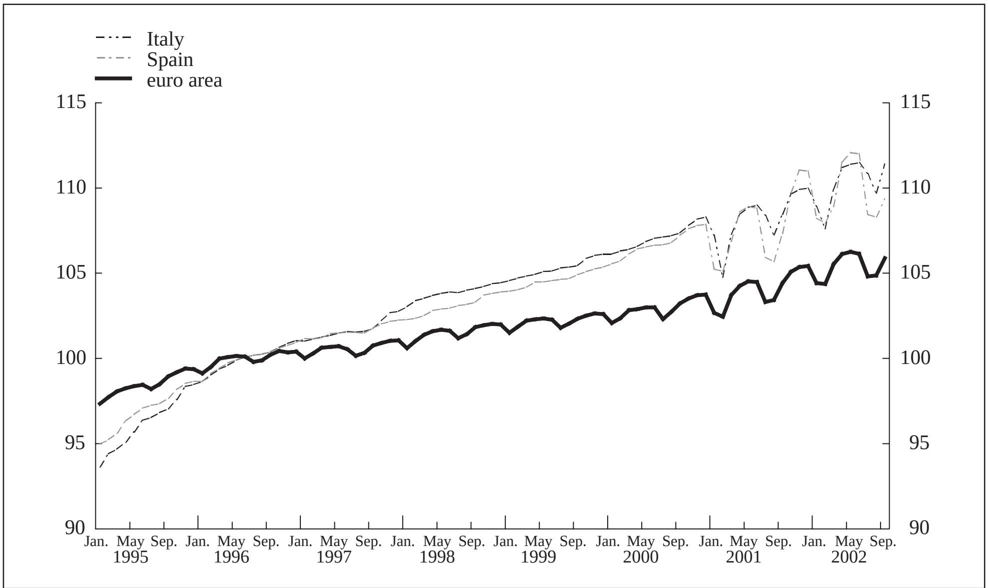
In spite of the seasonal break, a decision was made not to discontinue the compilation of a seasonally adjusted series for this component and, consequently, of an adjusted overall HICP for the euro area. Special efforts were made to produce the best possible factors and their period-to-period changes (including any other relevant options) have been closely monitored. In March 2002 new factors were computed for all series and the seasonal factors for this particular series were updated in April and October 2002.

---

[2] Since release 0.2.8 of X-12-REGARIMA, a similar table has been added to the standard output.

[3] The full quality report for this series is given in the annex.

Figure 1: HICP for industrial goods excluding energy




The series concurrently estimated actually showed a more regular behaviour and appeared to be less affected by changes in the seasonal pattern. Because the model structure (including outliers) did not show any instability, the update was limited to the seasonal factors (see Figure 2).

A second example of the use of information contained in the quality report comes from new passenger car registrations. Data are received monthly from the European Automobile

Figure 2: Model parameters and stability tests

Parameters of the REGARIMA model
Regression parameters

| Group | Variable | Estimate | STDE | Stability check[1)] |
|---|---|---|---|---|
| LS2001. Mar | LS2001. Mar | 0.004498 | 0.000953 | [....X....] |

Parameters of stochastic model [Arima (0,1,1) (0,1,1)12]

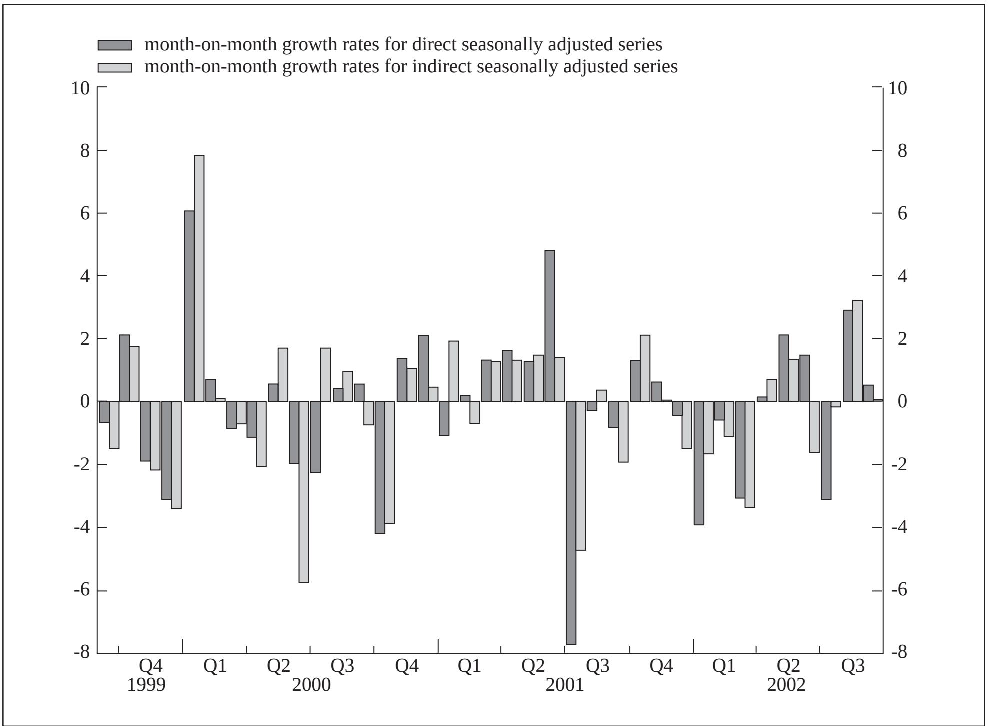
| OP. | Factor | Per. | LAG | Estimate | STDE | Stability check[1)] |
|---|---|---|---|---|---|---|
| MA | Nonseasonal | 01 | 01 | -0.368886 | 0.086868 | [....X....] |
| MA | Seasonal | 12 | 12 | 0.059232 | 0.094730 | [....X....] |

Innovation Variance

| Operator | Variance |
|---|---|
| mle | 0.00000109 |

1) The stability check shows the position of the concurrent point estimate within the 95% confidence interval of the estimates, when forecasting the factors.

Figure 3: New passenger car registrations – month-on-month growth rates for direct and indirect seasonally adjusted series




Manufacturers' Association, euro area aggregates are derived and all national and European aggregates are then working-day and seasonally adjusted. Owing to several irregularities in national series, the seasonally adjusted euro area series is directly calculated and published in the ECB Monthly Bulletin. A parallel indirectly adjusted series is also regularly compiled and maintained for testing purposes. This latter series is calculated by aggregating the seasonally adjusted series of the 12 euro area countries. A summary chart showing both adjusted series and month-on-month growth rates is a regular supplement to the quality report for the euro area series (see Figure 3).

Differences in the two series are normally rather limited, but occasionally they can be very large. In August 2001, the difference in growth rates is almost 4 percentage points. A closer look at national data indicated that this abnormal value was due to problems in the adjusted series for France. A change in the traditional commercial patterns (in the form of a premium granted between July and August 2001 for the purchase of new cars) induced a change in the number of new car registrations (especially in July and August) and, more generally, in the seasonal pattern of the series.

This phenomenon has only a marginal effect on the seasonal pattern of the euro area aggregate, for which the direct seasonal adjustment is still satisfactory, though the big difference in the two series persists.

## 3. Some ideas for the future

### *3.1 Considerations regarding quality criteria*

One of the main recent developments in seasonal adjustment tools is the planned fusion of X-12-REGARIMA and TRAMO-SEATS into one unique product. The ECB Task Force on Seasonal Adjustment already concluded that this initiative would be the best possible way to develop seasonal adjustment and it would certainly be beneficial to practical work. A positive side effect might be the establishment of a common set of quality indicators for seasonally adjusted results.

In a recent paper,[4] it is argued that it would be extremely difficult to develop common quality indicators given the different theoretical foundations of X-12-REGARIMA and TRAMO-SEATS. The first model produces output that contains essentially empirical or descriptive indicators, while the second mainly offers statistical criteria based on model assumptions.

Any attempt to achieve convergence between the two outputs is interesting in principle and should be generally supported. Efforts in this direction should, however, always be made in relation to the specific purposes of the adjustment and the particular conditions under which the adjustment is made. Of course, the modes for making seasonal adjustments are different, as are the needs in terms of statistical tools to assess the quality of results. In this respect, an important distinction should be made between *occasional* adjustment and *regular* adjustment.

The case of *occasional* adjustment includes situations where a new set of statistical indicators is analysed for a future regular production or the annual re-estimation exercise of individual options for seasonal adjustment (identification of ARIMA models and regression effects, derivation of projected factors, etc.). In these cases, the estimation is normally carried out outside the normal production environment to increase flexibility and to make use of detailed statistics that can be derived from the output of the adjustment software. In this phase, methodological considerations and individual preferences for either method normally prevail. Final decisions are made on the basis of individual judgement based on some (many) elements of the full evidence produced by the seasonal adjustment software. The general aim is to have a broad set of statistical indicators to identify the different statistical features of time series in order to enrich the analysis and make the right decision. In this respect, the fusion of the two IT programs may have several practical advantages by simplifying the working environment and automating input/output processes. A common output is definitely less urgent and of less interest, since practitioners may prefer to have at their disposal many statistical details to judge the adjustment and options to use in the regular production. Reducing the two outputs to a common denominator can even have negative effects.

In the case of *regular* (monthly or quarterly) adjustment, the perspective can be different. Very often the time between the receipt of raw data and the release of adjusted results is rather short (slightly more than an hour for highly sensitive indicators). Depending on the time available and the amount of series to be adjusted, the dependence on a limited set of key quality indicators is often the only possible solution. As in the ECB quality report, these indicators may be selected on the basis of both statistical relevance and empirical results (especially when seasonally adjusted series are expected to loosely meet some additivity requirements, such as accounting relationships, etc.). When the number of time series is very

[4] See Dominique Ladiray and Jean-Marc Museux, “Quality Report for Seasonal Adjustment: Some Ideas” (Eurostat Working Group on Seasonal Adjustment, 25-26 April 2002).

large, this aspect becomes even more important and the reliance on automatic rules for acceptance/rejection is often the only possible option. In this case, having a common (reduced) output is crucial to create common and shared concepts for the assessment of the quality of seasonally adjusted results. In these cases, a common and limited set of criteria can be beneficial.

However, even if the attempts to merge X-12-REGARIMA and TRAMO-SEATS were to prove successful, a common output would only cover part of the quality checks. Seasonal adjustment software is generally designed to ensure the best possible adjustment at a precise point in time. A descriptive analysis of the developments in raw and adjusted series results – including stability analysis or the monitoring of changes in projected factors – cannot be produced using the seasonal adjustment software alone, but rather by using a tool combining information from the data-storage environment with the seasonal adjustment software output.

### *3.2 Seasonal adjustment project under development at the ECB*

To satisfy the previously mentioned needs and to overcome the limitations of the current data production environment, a proposal for the development of an interface has been recently put forward, The objective is to facilitate the joint use of seasonal adjustment software (X-12-REGARIMA and TRAMO-SEATS) and enhance data retrieval/storage processes. In a first phase, the two programs would be accessed separately but through a common working environment, including a harmonised set of options for the seasonal adjustment.

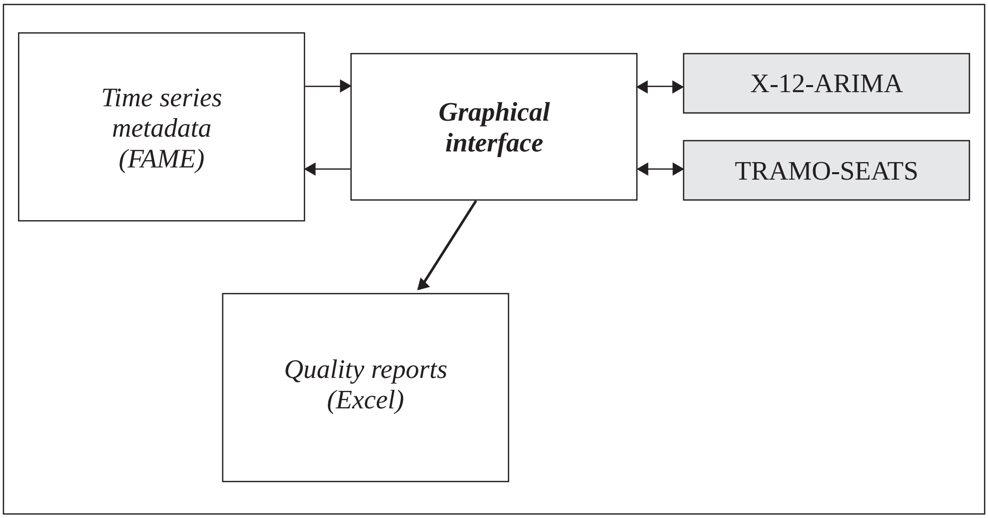
The interface would make it possible to seasonally adjust groups of series for regular production and/or individual time series for detailed analysis. Users will have the choice between expert adjustment (i.e. with options specified for any single time series) or standard adjustment (i.e. based on a set of predefined default parameters). Whenever options are common to both software packages (e.g. details on ARIMA or regression models used in the pre-adjustment phase), they will be specified through a set of common commands.

The interface will retrieve FAME time series, activate the necessary seasonal adjustment procedures and deliver the following types of results:

1. Transformed time series stored in FAME.
2. Individual Excel spreadsheets containing transformed time series and charts with a similar structure and content to the quality report (currently only available as individual PDF files).
3. Excel spreadsheets reporting a selected set of quality criteria to summarise the results of an adjustment round or to help focus on critical cases when a large-scale adjustment is made.

In this way, the quality reports will increase flexibility, enabling users to compute derived statistics or additional indicators. Their content will at first remain largely unchanged, but simplifications and/or additions will always be possible.

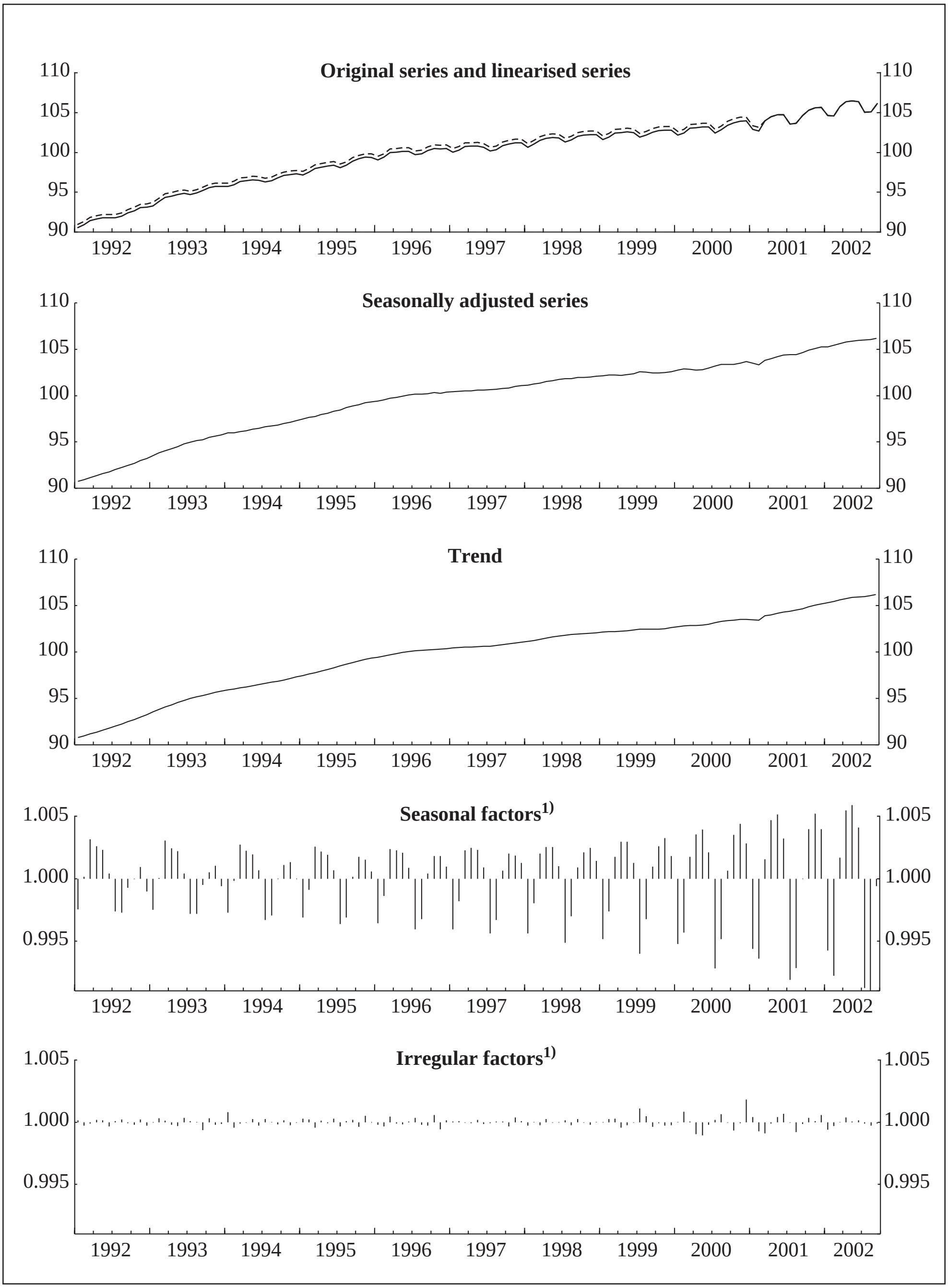
Figure 4: Functioning of the season adjustment interface




The interface is designed to be an open tool, which will allow the adaptation to changes in seasonal adjustment software (including the release of an integrated X-12-REGARIMA/ TRAMO-SEATS software package) and to possible changes in the database environment. The same concept also applies to the content of the quality reports.
The diagram above presents these concepts in simplified terms.

Annex: *An example of a seasonal adjustment quality report*
In the following pages, an example of complete seasonal adjustment quality report is shown. The report refers to the harmonised consumer price index for industrial goods excluding energy for the euro area. This series is an important component in the compilation of the seasonally adjusted total HICP, which is indirectly derived from the aggregation of this index and the following additional components: processed food, unprocessed food, services and energy (not adjusted).

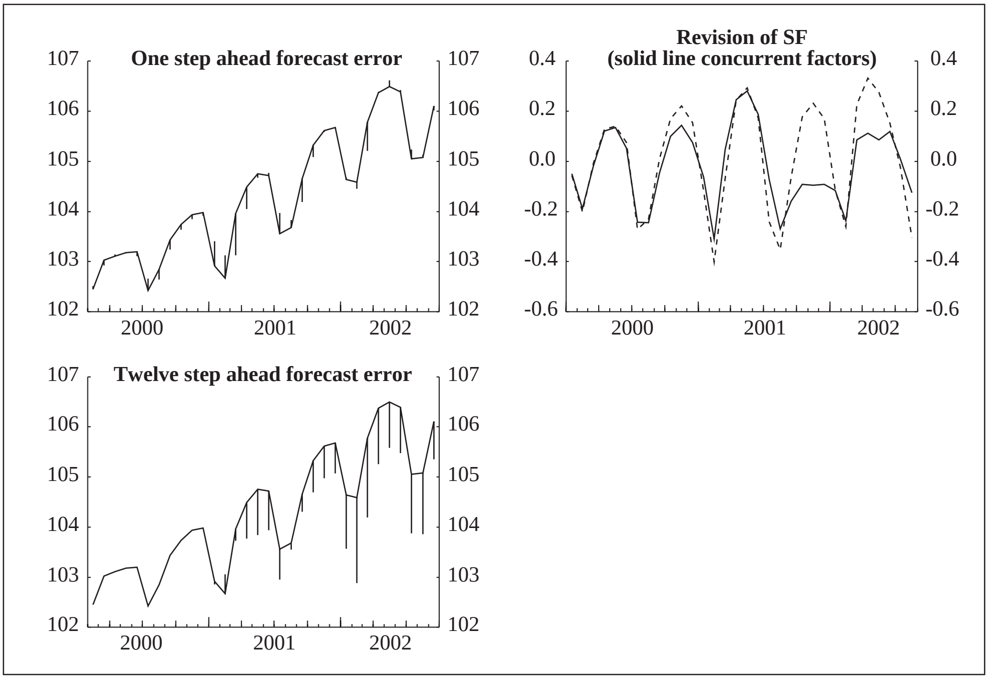
HICP for industrial goods excluding energy for the euro area




1) shown as deviation from one.

HICP for industrial goods excluding energy for the euro area

*(1-step and 12-step ahead forecast error plus revision of seasonal factors)*



SPECIFICATION FILE FOR icp.m.i2.n.igxe00.4.inx

```

#
# Specification set: ICP_I2_IGXE00
# Description:      Industrial goods (excl. energy) index for the euro area (MU-12)
#
SERIES
  {
  FILE   = "icp.m.i2.n.igxe00.4.inx.dat"
  FORMAT = DATEVALUE
  NAME   = "ICP.M.I2.N.IGXE00.4.INX"
  PERIOD = 12
  }
#
TRANSFORM
  {
  FUNCTION = LOG
  }
#
X11
  {
  APPENDFCST    = YES
  CALENDARSIGMA = ALL
  MODE          = MULT
  SAVE          = (TREND TRENDD7 UNMODSI REPLACSI SEASONAL SEASADJ IRREGULAR
                 ADJUSTFAC IRRWT ADJORIGINAL)
  SAVELOG       = (M1 M2 M3 M4 M5 M6 M7 M8 M9 M10 M11 Q Q2 MOVINGSEASRATIO
                 ICRATIO FSTABLEB1 FSTABLED8 MOVINGSEASF IDSEASONAL)
  SEASONALMA    = S3X1
  SIGMALIM      = (2.0,3.5)
  }
#
REGRESSION
  {
  AICTEST   = (USER)
  SAVE      = (LEVELSHIFT TEMPORARYCHANGE AOUTLIER)
  VARIABLES = (LS2001.Mar)
  }
#
ARIMA
  {
  MODEL =  (0,1,1)(0,1,1)12
  }
#
ESTIMATE
  {
  SAVE    = (RESIDUALS ESTIMATES ROOTS)
  SAVELOG = (AIC AICC BIC AVERAGEFCSTERR)
  }
#
OUTLIER
  {
  CRITICAL = 4.5
  TYPES    = ALL
  }
#
CHECK
  {
  SAVELOG = (NORMALITYTEST LJUNGBOXQ)
  }
#
HISTORY
  {
  ESTIMATES = (FCST SEASONAL)
  SAVE      = (FCSTHISTORY SFREVISIONS)
  SAVELOG   = (AVEABSREVCHNG AVEABSREVINDSA AVEABSREVTREND
              AVEABSREVTRENDCHNG AVEABSREVSF AVEABSREVSFPROJ)
  START     = 2000.Jan
  }
#
```

| One and twelve step ahead forecast error | | | Revision of seasonal factors (concurrent/forecast) | | |
|---|---|---|---|---|---|
| | 1-step | 12-step | | Concurrent | Projected |
| Feb. 2000 | -0.062 | -- | Jan. 2000 | -0.049 | -0.056 |
| Mar. | 0.101 | -- | Feb. | -0.188 | -0.200 |
| Apr. | -0.040 | -- | Mar. | -0.018 | -0.007 |
| May | 0.001 | -- | Apr. | 0.121 | 0.129 |
| June | 0.086 | -- | May | 0.135 | 0.141 |
| July | -0.231 | -- | June | 0.052 | 0.076 |
| Aug. | 0.200 | -- | July | -0.243 | -0.271 |
| Sep. | 0.188 | -- | Aug. | -0.244 | -0.231 |
| Oct. | 0.099 | -- | Sep. | -0.046 | 0.010 |
| Nov. | 0.095 | -- | Oct. | 0.099 | 0.170 |
| Dec. | 0.064 | -- | Nov. | 0.144 | 0.222 |
| Jan. 2001 | **-0.492** | 0.060 | Dec. | 0.076 | 0.155 |
| Feb. | -0.456 | -0.385 | Jan. 2001 | -0.061 | -0.117 |
| Mar. | **0.834** | 0.238 | Feb. | -0.310 | -0.402 |
| Apr. | 0.439 | 0.722 | Mar. | 0.048 | -0.068 |
| May | 0.079 | 0.909 | Apr. | 0.246 | 0.244 |
| June | -0.056 | 0.778 | May | 0.282 | 0.293 |
| July | -0.415 | 0.602 | June | 0.187 | 0.174 |
| Aug. | -0.152 | 0.132 | July | -0.073 | -0.240 |
| Sep. | **0.466** | 0.353 | Aug. | -0.269 | -0.352 |
| Oct. | 0.240 | 0.632 | Sep. | -0.159 | -0.062 |
| Nov. | 0.028 | 0.638 | Oct. | -0.091 | 0.177 |
| Dec. | 0.020 | 0.602 | Nov. | -0.095 | 0.232 |
| Jan. 2002 | -0.040 | 1.072 | Dec. | -0.092 | 0.171 |
| Feb. | 0.135 | 1.708 | Jan. 2002 | -0.117 | -0.114 |
| Mar. | **0.565** | 1.582 | Feb. | -0.238 | -0.260 |
| Apr. | -0.015 | 1.113 | Mar. | 0.085 | 0.226 |
| May | -0.118 | 0.920 | Apr. | 0.112 | 0.333 |
| June | -0.034 | 0.912 | May | 0.085 | 0.275 |
| July | -0.188 | 1.178 | June | 0.120 | 0.152 |
| Aug. | -0.051 | 1.220 | July | 0.009 | -0.025 |
| Sep. | 0.085 | 0.750 | Aug. | -0.126 | -0.304 |

HICP for industrial goods excluding energy for the euro area
*(Parameters of the regarima model)*

**Regression parameters**

| GROUP | VARIABLE | ESTIMATE | STDE | STABILITY CHECK (*) |
|---|---|---|---|---|
| LS2001.Mar | LS2001.Mar | 0.004498 | 0.000953 | ..[.....X.....].. |

PARAMETERS OF STOCHASTIC MODEL [ARIMA (0,1,1)(0,1,1)12]

| OP. | FACTOR | PER. | LAG | ESTIMATE | STDE | STABILITY CHECK (*) |
|---|---|---|---|---|---|---|
| MA | Nonseasonal | 01 | 01 | -0.368886 | 0.086868 | ..[.....X.....].. |
| MA | Seasonal | 12 | 12 | 0.059232 | 0.094730 | ..[....X......].. |

INNOVATION VARIANCE

| OPERATOR | VARIANCE |
|---|---|
| mle | 0.00000198 |

(*) The stability check shows the position of the concurrent point estimtate within the 95% confidence interval of the estimates, when forecasting the factors.

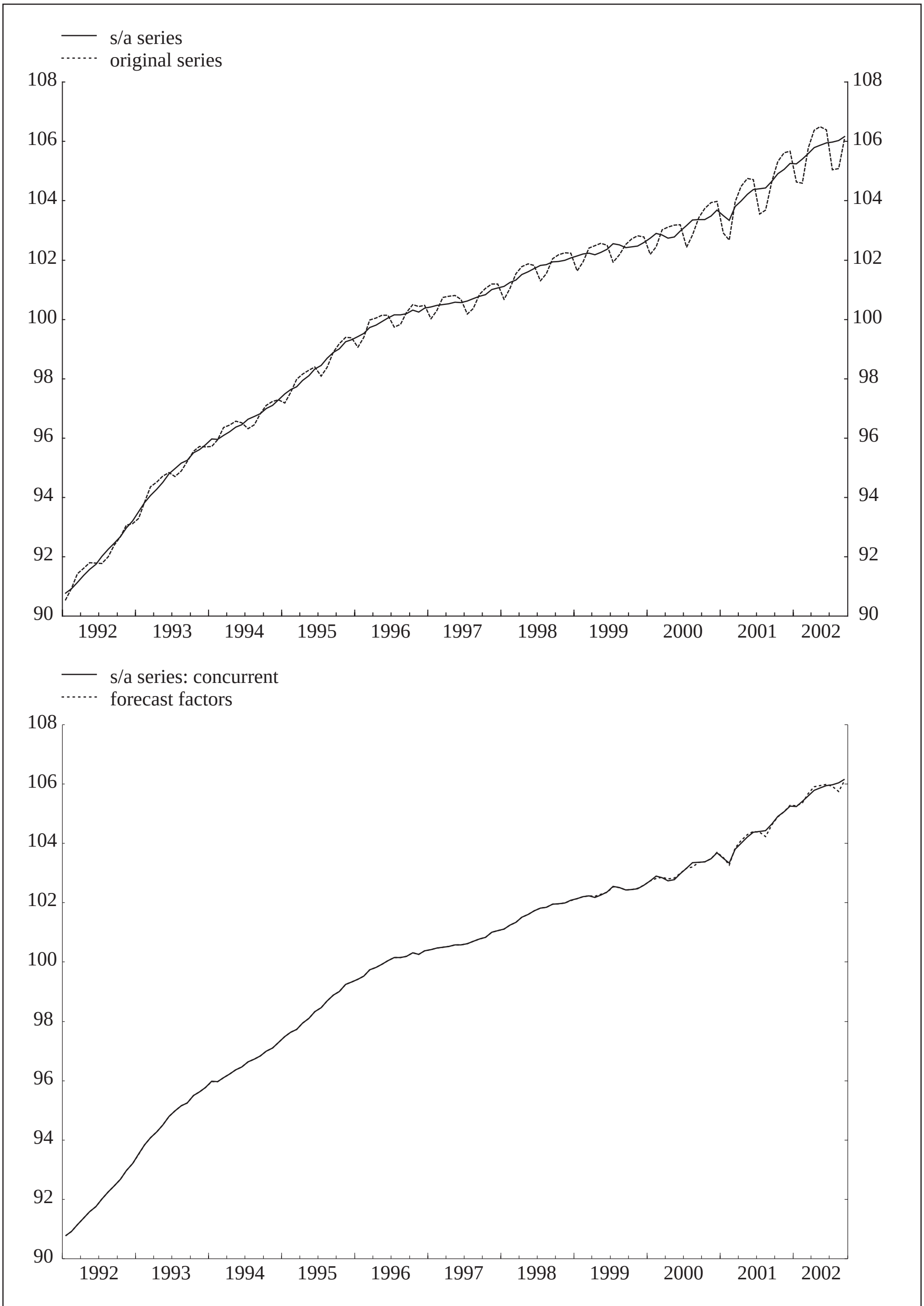
HICP for industrial goods excluding energy for the euro area
*(Quality criteria of X-11)*

| CRITERIA | PARAMETER VALUE |
|---|---|
| Average Absolute Percentage Error | within-sample forecasts |
| AAPE(Last year) | 0.52 |
| AAPE(Last-1 year) | 0.26 |
| AAPE(Last-2 year) | 0.16 |
| AAPE(Last 3 years) | 0.31 |
| AIC | -116.0806 |
| AICC | -115.7203 |
| BIC | -105.0663 |
| Summary of Significant Ljung-Box Q | |

| Lag | Q | DF | P |
|---|---|---|---|
| 6 | 16.445 | 4 | 0.002 |
| 7 | 18.044 | 5 | 0.003 |
| 8 | 29.511 | 6 | 0.000 |
| 9 | 29.517 | 7 | 0.000 |
| 10 | 30.530 | 8 | 0.000 |
| 11 | 31.675 | 9 | 0.000 |
| 12 | 31.686 | 10 | 0.000 |
| 13 | 31.744 | 11 | 0.001 |
| 14 | 35.903 | 12 | 0.000 |
| 15 | 37.201 | 13 | 0.000 |
| 16 | 37.314 | 14 | 0.001 |
| 17 | 38.322 | 15 | 0.001 |
| 18 | 43.330 | 16 | 0.000 |
| 19 | 48.277 | 17 | 0.000 |
| 20 | 48.277 | 18 | 0.000 |
| 21 | 49.579 | 19 | 0.000 |
| 22 | 49.769 | 20 | 0.000 |
| 23 | 49.819 | 21 | 0.000 |
| 24 | 50.839 | 22 | 0.000 |

| CRITERIA | PARAMETER VALUE |
|---|---|
| Geary's a statistic | 0.7424 (significant) |
| Kurtosis | 4.2768 |
| Moving seasonality ratio | 1.531 |
| I/C Ratio | 0.397 |
| Stable Seasonal F, B1 table | 26.133 |
| Stable Seasonal F, D8 table | 32.239 |
| Moving Seasonal F, D8 table | 12.695 |
| Identifiable seasonality | yes |
| M01 | 0.055 |
| M02 | 0.015 |
| M03 | 0.000 |
| M04 | 0.462 |
| M05 | 0.000 |
| M06 | 0.988 |
| M07 | 0.836 |
| M08 | 1.417 |
| M09 | 1.274 |
| M10 | 1.430 |
| M11 | 1.320 |
| Q | 0.548 |
| Q2 | 0.622 |
| AveAbsRev of Seasonal | 0.132 |
| AveAbsRev of Projected Seasonal | 0.184 |

HICP for industrial goods excluding energy for the euro area



## B1 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 90.957 | 91.349 | 91.842 | 92.027 | 92.209 | 92.206 | 92.183 | 92.417 | 92.803 | 93.096 | 93.486 | 93.536 | 92.343 |
| 1993 | 93.713 | 94.263 | 94.788 | 94.942 | 95.145 | 95.263 | 95.136 | 95.319 | 95.639 | 95.987 | 96.151 | 96.143 | 95.207 |
| 1994 | 96.148 | 96.381 | 96.794 | 96.870 | 97.001 | 96.957 | 96.747 | 96.883 | 97.267 | 97.541 | 97.678 | 97.733 | 97.000 |
| 1995 | 97.624 | 97.987 | 98.422 | 98.600 | 98.732 | 98.837 | 98.538 | 98.825 | 99.353 | 99.634 | 99.850 | 99.829 | 98.853 |
| 1996 | 99.512 | 99.843 | 100.427 | 100.494 | 100.591 | 100.588 | 100.197 | 100.284 | 100.686 | 100.956 | 100.891 | 100.933 | 100.450 |
| 1997 | 100.470 | 100.751 | 101.190 | 101.231 | 101.267 | 101.123 | 100.634 | 100.815 | 101.304 | 101.499 | 101.653 | 101.648 | 101.132 |
| 1998 | 101.123 | 101.500 | 101.996 | 102.236 | 102.328 | 102.283 | 101.757 | 102.001 | 102.502 | 102.639 | 102.709 | 102.688 | 102.147 |
| 1999 | 102.098 | 102.397 | 102.874 | 102.951 | 103.028 | 102.956 | 102.393 | 102.645 | 102.990 | 103.182 | 103.279 | 103.239 | 102.836 |
| 2000 | 102.660 | 102.914 | 103.490 | 103.572 | 103.646 | 103.663 | 102.889 | 103.308 | 103.899 | 104.206 | 104.408 | 104.451 | 103.592 |
| 2001 | 103.381 | 103.135 | 103.964 | 104.490 | 104.754 | 104.716 | 103.556 | 103.681 | 104.655 | 105.325 | 105.617 | 105.677 | 104.413 |
| 2002 | 104.638 | 104.588 | 105.778 | 106.371 | 106.498 | 106.387 | 105.050 | 105.082 | 106.107 | 106.793 | 107.083 | 107.142 | 105.960 |

## D8 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 99.788 | 99.999 | 100.310 | 100.284 | 100.255 | 100.017 | 99.749 | 99.745 | 99.900 | 99.955 | 100.107 | 99.872 | 99.998 |
| 1993 | 99.762 | 100.054 | 100.337 | 100.241 | 100.207 | 100.091 | 99.728 | 99.712 | **99.863** | 100.059 | 100.076 | 99.932 | 100.005 |
| 1994 | **99.823** | 99.955 | 100.267 | 100.218 | 100.214 | 100.033 | 99.692 | 99.713 | 99.990 | 100.141 | 100.127 | 100.010 | 100.015 |
| 1995 | 99.723 | 99.925 | 100.204 | 100.221 | 100.181 | 100.102 | 99.610 | 99.705 | 100.038 | 100.137 | 100.202 | 100.058 | 100.009 |
| 1996 | 99.626 | 99.837 | 100.290 | 100.218 | 100.187 | 100.085 | 99.621 | 99.655 | 100.021 | 100.251 | 100.134 | 100.113 | 100.003 |
| 1997 | 99.594 | 99.823 | 100.224 | 100.249 | 100.266 | 100.094 | 99.564 | 99.677 | 100.072 | 100.166 | 100.223 | 100.132 | 100.007 |
| 1998 | 99.530 | 99.804 | 100.179 | 100.287 | 100.260 | 100.116 | 99.515 | 99.681 | 100.107 | 100.188 | 100.209 | 100.141 | 100.001 |
| 1999 | 99.521 | 99.772 | 100.202 | 100.238 | 100.253 | 100.118 | **99.523** | 99.751 | 100.095 | 100.283 | 100.328 | 100.180 | 100.022 |
| 2000 | 99.487 | 99.632 | 100.142 | **100.211** | **100.253** | 100.181 | 99.309 | 99.599 | 100.081 | 100.308 | 100.458 | **100.491** | 100.013 |
| 2001 | 99.493 | 99.286 | *LS* **100.052** | *LS* 100.437 | *LS+1* 100.533 | 100.369 | 99.172 | 99.204 | 100.002 | 100.468 | 100.572 | 100.481 | 100.006 |
| 2002 | 99.359 | 99.171 | 100.155 | 100.589 | 100.614 | 100.442 | 99.112 | 99.055 | 99.908 | -- | -- | -- | -- |

Seasonal factors of concurrent run

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | 99.438 | 99.359 | 100.158 | 100.474 | 100.519 | 100.326 | 99.189 | 99.283 | 100.000 | 100.400 | 100.526 | 100.400 | 100.006 |
| 2002 | 99.424 | 99.222 | 100.172 | 100.551 | 100.593 | 100.413 | 99.123 | 99.101 | 99.943 | 100.436 | 100.560 | 100.485 | 100.002 |

Seasonal factors officially in use

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | 99.420 | 99.422 | 100.115 | 100.381 | 100.445 | 100.303 | 99.217 | 99.475 | 100.028 | 100.408 | 100.516 | 100.379 | 100.009 |
| 2002 | 99.399 | 99.262 | 100.090 | 100.438 | 100.523 | 100.371 | 99.179 | 99.368 | 99.991 | 100.453 | 100.556 | 100.464 | 100.008 |

## D9 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 1993 | -- | -- | -- | -- | -- | -- | -- | -- | 99.972 | -- | -- | -- | -- |
| 1994 | 99.741 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 1995 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 1996 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 1997 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 1998 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 1999 | -- | -- | -- | -- | -- | -- | 99.399 | -- | -- | -- | -- | -- | -- |
| 2000 | -- | -- | -- | 100.372 | 100.400 | -- | -- | -- | -- | -- | -- | 100.254 | -- |
| 2001 | -- | -- | 100.153 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |
| 2002 | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- | -- |

## D10 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 99.755 | 100.018 | 100.318 | 100.265 | 100.234 | 100.043 | 99.738 | 99.731 | 99.928 | 99.997 | 100.098 | 99.899 | 100.002 |
| 1993 | 99.751 | 100.008 | 100.309 | 100.248 | 100.224 | 100.043 | 99.718 | 99.721 | 99.954 | 100.054 | 100.107 | 99.942 | 100.007 |
| 1994 | 99.728 | 99.985 | 100.275 | 100.228 | 100.199 | 100.069 | 99.669 | 99.707 | 100.001 | 100.114 | 100.137 | 100.003 | 100.010 |
| 1995 | 99.691 | 99.912 | 100.260 | 100.222 | 100.194 | 100.070 | 99.637 | 99.690 | 100.018 | 100.178 | 100.155 | 100.060 | 100.007 |
| 1996 | 99.644 | 99.864 | 100.241 | 100.230 | 100.210 | 100.089 | 99.594 | 99.678 | 100.045 | 100.186 | 100.185 | 100.098 | 100.005 |
| 1997 | 99.597 | 99.822 | 100.231 | 100.249 | 100.235 | 100.094 | 99.563 | 99.670 | 100.068 | 100.204 | 100.190 | 100.128 | 100.004 |
| 1998 | 99.561 | 99.804 | 100.203 | 100.258 | 100.257 | 100.103 | 99.487 | 99.701 | 100.094 | 100.214 | 100.251 | 100.146 | 100.007 |
| 1999 | 99.516 | 99.738 | 100.177 | 100.300 | 100.300 | 100.129 | 99.398 | 99.676 | 100.101 | 100.265 | 100.330 | 100.183 | 100.009 |
| 2000 | 99.478 | 99.568 | 100.178 | 100.359 | 100.396 | 100.214 | 99.281 | 99.515 | 100.066 | 100.355 | 100.445 | 100.288 | 100.012 |
| 2001 | 99.438 | 99.359 | 100.158 | 100.474 | 100.519 | 100.326 | 99.189 | 99.283 | 100.000 | 100.400 | 100.526 | 100.400 | 100.006 |
| 2002 | 99.424 | 99.222 | 100.172 | 100.551 | 100.593 | 100.413 | 99.123 | 99.101 | 99.943 | 100.436 | 100.560 | 100.485 | 100.002 |

## D11 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 90.771 | 90.923 | 91.140 | 91.373 | 91.581 | 91.753 | 92.010 | 92.250 | 92.453 | 92.681 | 92.976 | 93.211 | 91.927 |
| 1993 | 93.525 | 93.832 | 94.072 | 94.281 | 94.507 | 94.794 | 94.976 | 95.157 | 95.254 | 95.505 | 95.617 | 95.767 | 94.774 |
| 1994 | 95.977 | 95.962 | 96.096 | 96.217 | 96.375 | 96.456 | 96.633 | 96.731 | 96.830 | 96.993 | 97.106 | 97.291 | 96.555 |
| 1995 | 97.487 | 97.633 | 97.726 | 97.940 | 98.099 | 98.325 | 98.454 | 98.687 | 98.889 | 99.010 | 99.248 | 99.322 | 98.402 |
| 1996 | 99.420 | 99.530 | 99.735 | 99.814 | 99.930 | 100.048 | 100.154 | 100.156 | 100.189 | 100.316 | 100.253 | 100.381 | 99.994 |
| 1997 | 100.424 | 100.478 | 100.504 | 100.526 | 100.576 | 100.574 | 100.621 | 100.695 | 100.781 | 100.838 | 101.006 | 101.063 | 100.674 |
| 1998 | 101.114 | 101.243 | 101.332 | 101.515 | 101.608 | 101.720 | 101.823 | 101.847 | 101.947 | 101.960 | 101.992 | 102.078 | 101.682 |
| 1999 | 102.134 | 102.205 | 102.231 | 102.183 | 102.259 | 102.362 | 102.551 | 102.517 | 102.424 | 102.448 | 102.476 | 102.588 | 102.365 |
| 2000 | 102.736 | 102.897 | 102.842 | 102.738 | 102.774 | 102.978 | 103.169 | 103.346 | 103.365 | 103.371 | 103.479 | 103.684 | 103.115 |
| 2001 | 103.499 | 103.334 | 103.800 | 103.996 | 104.214 | 104.376 | 104.403 | 104.430 | 104.656 | 104.905 | 105.064 | 105.255 | 104.328 |
| 2002 | 105.245 | 105.408 | 105.597 | 105.788 | 105.871 | 105.950 | 105.979 | 106.036 | 106.167 | -- | -- | -- | -- |

Seasonally adjusted series when using the official forecast seasonal/trading day factors

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | 103.518 | 103.269 | 103.844 | 104.093 | 104.290 | 104.400 | 104.373 | 104.229 | 104.627 | 104.897 | 105.074 | 105.278 | 104.324 |
| 2002 | 105.271 | 105.366 | 105.684 | 105.907 | 105.944 | 105.994 | 105.920 | 105.751 | 106.116 | -- | -- | -- | -- |

Month to month percentage variation concurrent run

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | -0.2 | -0.2 | 0.5 | 0.2 | 0.2 | 0.2 | 0.0 | 0.0 | 0.2 | 0.2 | 0.2 | 0.2 | 0.1 |
| 2002 | -0.0 | 0.2 | 0.2 | 0.2 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | -- | -- | -- | -- |

Month to month percentage variation when using the official forecast seasonal/trading day factors

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | -0.2 | -0.2 | 0.6 | 0.2 | 0.2 | 0.1 | -0.0 | -0.1 | 0.4 | 0.3 | 0.2 | 0.2 | 0.1 |
| 2002 | -0.0 | 0.1 | 0.3 | 0.2 | 0.0 | 0.0 | -0.1 | -0.2 | 0.3 | -- | -- | -- | -- |

## D12 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 90.757 | 90.947 | 91.149 | 91.356 | 91.567 | 91.785 | 92.003 | 92.228 | 92.460 | 92.700 | 92.956 | 93.237 | 91.929 |
| 1993 | 93.527 | 93.803 | 94.060 | 94.302 | 94.536 | 94.761 | 94.969 | 95.153 | 95.315 | 95.476 | 95.636 | 95.780 | 94.777 |
| 1994 | 95.898 | 96.003 | 96.107 | 96.220 | 96.350 | 96.484 | 96.608 | 96.728 | 96.847 | 96.978 | 97.130 | 97.296 | 96.554 |
| 1995 | 97.459 | 97.613 | 97.768 | 97.930 | 98.106 | 98.297 | 98.488 | 98.679 | 98.870 | 99.048 | 99.197 | 99.322 | 98.398 |
| 1996 | 99.441 | 99.563 | 99.691 | 99.825 | 99.946 | 100.042 | 100.119 | 100.177 | 100.218 | 100.259 | 100.309 | 100.366 | 99.996 |
| 1997 | 100.420 | 100.469 | 100.508 | 100.533 | 100.557 | 100.588 | 100.630 | 100.691 | 100.775 | 100.871 | 100.965 | 101.052 | 100.671 |
| 1998 | 101.140 | 101.239 | 101.356 | 101.489 | 101.613 | 101.719 | 101.806 | 101.871 | 101.922 | 101.965 | 102.014 | 102.076 | 101.684 |
| 1999 | 102.137 | 102.181 | 102.203 | 102.228 | 102.285 | 102.366 | 102.438 | 102.468 | 102.461 | 102.456 | 102.504 | 102.611 | 102.361 |
| 2000 | 102.732 | 102.811 | 102.835 | 102.838 | 102.882 | 102.999 | 103.151 | 103.280 | 103.370 | 103.438 | 103.486 | 103.494 | 103.110 |
| 2001 | 103.455 | 103.409 | 103.893 | 104.009 | 104.170 | 104.306 | 104.406 | 104.513 | 104.671 | 104.869 | 105.054 | 105.193 | 104.329 |
| 2002 | 105.308 | 105.439 | 105.594 | 105.748 | 105.867 | 105.935 | 105.989 | 106.063 | 106.178 | -- | -- | -- | -- |

D13 HICP for industrial goods excluding energy for the euro area

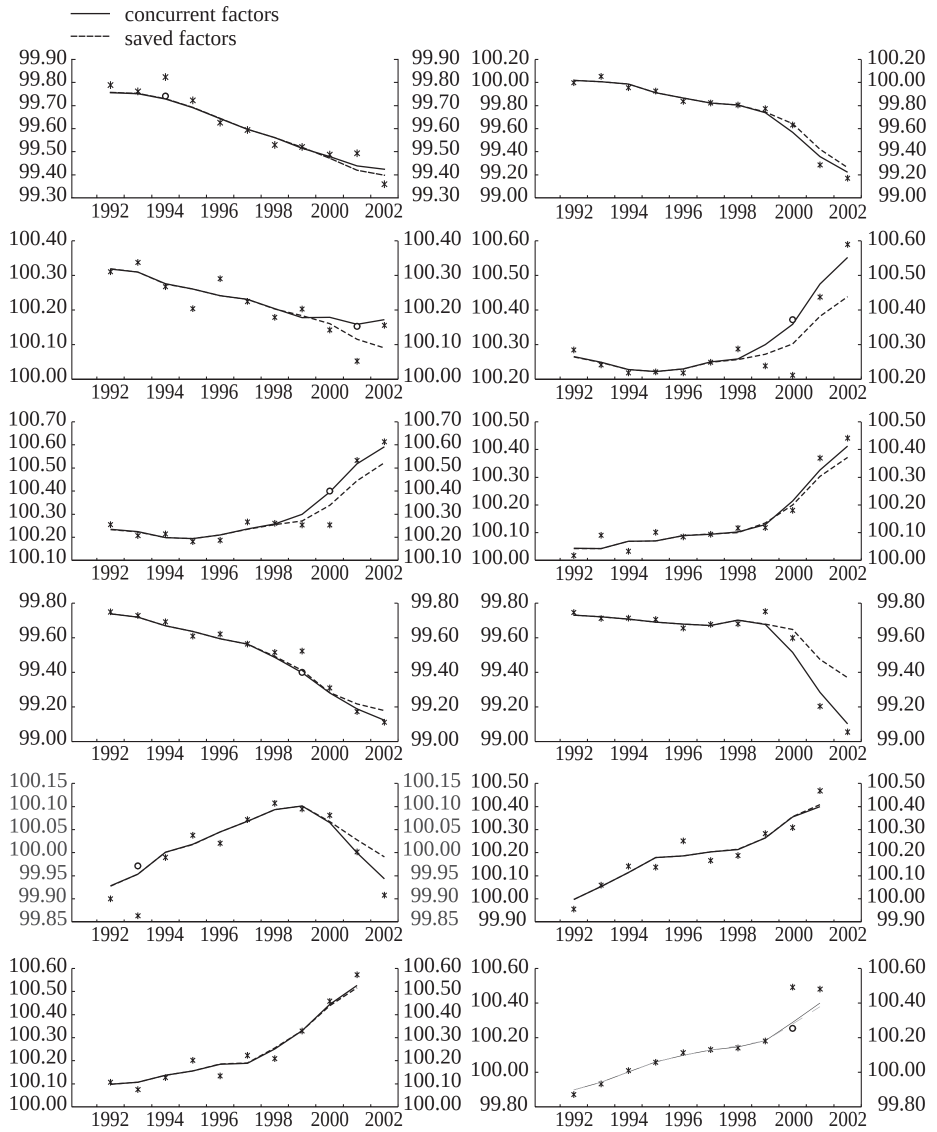
| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 100.015 | 99.973 | 99.990 | 100.018 | 100.015 | 99.966 | 100.008 | 100.023 | 99.992 | 99.979 | 100.021 | 99.971 | 99.998 |
| 1993 | 99.998 | 100.031 | 100.013 | 99.978 | 99.969 | 100.035 | 100.008 | 100.004 | 99.935 | 100.030 | 99.980 | 99.987 | 99.997 |
| 1994 | 100.082 | 99.958 | 99.988 | 99.996 | 100.025 | 99.971 | 100.026 | 100.004 | 99.982 | 100.015 | 99.975 | 99.995 | 100.001 |
| 1995 | 100.029 | 100.020 | 99.957 | 100.011 | 99.992 | 100.028 | 99.965 | 100.008 | 100.019 | 99.962 | 100.051 | 100.000 | 100.003 |
| 1996 | 99.979 | 99.967 | 100.044 | 99.990 | 99.984 | 100.006 | 100.036 | 99.979 | 99.971 | 100.057 | 99.943 | 100.015 | 99.998 |
| 1997 | 100.005 | 100.009 | 99.996 | 99.994 | 100.019 | 99.987 | 99.992 | 100.004 | 100.006 | 99.968 | 100.040 | 100.010 | 100.002 |
| 1998 | 99.974 | 100.004 | 99.976 | 100.026 | 99.995 | 100.000 | 100.017 | 99.977 | 100.025 | 99.995 | 99.978 | 100.002 | 99.997 |
| 1999 | 99.998 | 100.024 | 100.027 | 99.956 | 99.974 | 99.996 | 100.111 | 100.047 | 99.964 | 99.992 | 99.974 | 99.977 | 100.003 |
| 2000 | 100.004 | 100.083 | 100.007 | 99.904 | 99.895 | 99.980 | 100.017 | 100.064 | 99.996 | 99.935 | 99.993 | 100.184 | 100.005 |
| 2001 | 100.042 | 99.928 | 99.910 | 99.988 | 100.042 | 100.068 | 99.997 | 99.921 | 99.985 | 100.035 | 100.010 | 100.059 | 99.999 |
| 2002 | 99.940 | 99.971 | 100.003 | 100.037 | 100.004 | 100.014 | 99.990 | 99.974 | 99.989 | -- | -- | -- | -- |

D16 HICP for industrial goods excluding energy for the euro area

| | Jan. | Feb. | Mar. | Apr. | May | June | July | Aug. | Sep. | Oct. | Nov. | Dec. | AVGE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1992 | 99.755 | 100.018 | 100.318 | 100.265 | 100.234 | 100.043 | 99.738 | 99.731 | 99.928 | 99.997 | 100.098 | 99.899 | 100.002 |
| 1993 | 99.751 | 100.008 | 100.309 | 100.248 | 100.224 | 100.043 | 99.718 | 99.721 | 99.954 | 100.054 | 100.107 | 99.942 | 100.007 |
| 1994 | 99.728 | 99.985 | 100.275 | 100.228 | 100.199 | 100.069 | 99.669 | 99.707 | 100.001 | 100.114 | 100.137 | 100.003 | 100.010 |
| 1995 | 99.691 | 99.912 | 100.260 | 100.222 | 100.194 | 100.070 | 99.637 | 99.690 | 100.018 | 100.178 | 100.155 | 100.060 | 100.007 |
| 1996 | 99.644 | 99.864 | 100.241 | 100.230 | 100.210 | 100.089 | 99.594 | 99.678 | 100.045 | 100.186 | 100.185 | 100.098 | 100.005 |
| 1997 | 99.597 | 99.822 | 100.231 | 100.249 | 100.235 | 100.094 | 99.563 | 99.670 | 100.068 | 100.204 | 100.190 | 100.128 | 100.004 |
| 1998 | 99.561 | 99.804 | 100.203 | 100.258 | 100.257 | 100.103 | 99.487 | 99.701 | 100.094 | 100.214 | 100.251 | 100.146 | 100.007 |
| 1999 | 99.516 | 99.738 | 100.177 | 100.300 | 100.300 | 100.129 | 99.398 | 99.676 | 100.101 | 100.265 | 100.330 | 100.183 | 100.009 |
| 2000 | 99.478 | 99.568 | 100.178 | 100.359 | 100.396 | 100.214 | 99.281 | 99.515 | 100.066 | 100.355 | 100.445 | 100.288 | 100.012 |
| 2001 | 99.438 | 99.359 | 100.158 | 100.474 | 100.519 | 100.326 | 99.189 | 99.283 | 100.000 | 100.400 | 100.526 | 100.400 | 100.006 |
| 2002 | 99.424 | 99.222 | 100.172 | 100.551 | 100.593 | 100.413 | 99.123 | 99.101 | 99.943 | 100.436 | 100.560 | 100.485 | 100.002 |

HICP for industrial goods excluding energy for the euro area

D8 (*), D9 (o) versus D10



# 9

# The performance of X-12 in the seasonal adjustment of short time series

Antonio Matas Mir and Vitaliana Rondonotti

## 1. Introduction

The European Central Bank (ECB) currently produces seasonally adjusted data for euro area monetary aggregates and counterparts (8 series in total). These series cover a period of more than 20 years (with the exception for loans for which data is available as from January 1991). The approach used relies on multiplicative decomposition through X-12-ARIMA. For details see "Seasonal adjustment of monetary aggregates and HICP for the euro area", ECB (2000).

Seasonally and calendar adjusted data for further items of the consolidated balance sheet of the MFI sector are currently under development. At present, these series include only 5 years of data. Thus, there is an important need for studying from several perspectives the potential quality of such adjustments as compared to those already routinely produced by the ECB for the main monetary aggregates, which are based on historical series beginning in 1980.

This paper aims to make a contribution to such an assessment by means of the application of Monte Carlo simulation techniques[1]. For this purpose we will evaluate the performance of X-12-ARIMA using simulated economic time series of 5 years of data and compare the results to its performance on simulated time series with 15 years of additional historical data. The exercise considers different stochastic properties for the seasonal and trend components, the effect of different forecast/backcast extension options and the effect of outliers on the quality of the adjustment.

For the purpose of this evaluation, we will therefore restrict ourselves to the following:

- X-12-ARIMA (version 0.2.2), which is the method currently used at the ECB. The X-12-ARIMA seasonal adjustment program is based on the X-11 program (Shiskin, Young and Musgrave 1967) and Statistics Canada's X-11-ARIMA and X-11-ARIMA/88 (Dagum, 1988). For details of X-12-ARIMA see Findley, Monsell, Bell, Otto and Chen (1998) and U.S. Census Bureau (2002).
- Simulated time series with stochastic properties similar to the ones of a real monetary series currently seasonally adjusted by the ECB. In order to have a more complete set of the results, different values for the parameters of the models and the effect of different type of outliers will also be considered.
- Simulated time series of 5 years of data where no historical data is available (hereafter referred to as "short time series"), where 15 years of historical data are available (hereafter referred to as "long time series"), and where 7 years of data at each end of the time series are available.

[1] No similar study appears to have been conducted to date. Hood, Ashley and Findley (2000) examine the issue of the seasonal adjustment of short time series in a comparison between TRAMO/SEATS and X-12 ARIMA, although their approach is not based on parametric Monte Carlo simulation.

- Accuracy measures of the adjustment of the simulated series based primarily on how close the estimates of the monthly growth rates are to the "final" estimates, where by "final" estimates we indicate the seasonal adjustment for the simulated time series of 5 years of data obtained by making use of an additional 7 years of data at each end of the time series.

## 2. Methodology

Consider $x_t^f$ as being the result of seasonally adjusting the series $x_t$ for $t = 1,...,60$ (5 years of data) making use of data spanning from $t = -84$ to $t = 144$ (i.e. making use of 7 years of additional data at each end). Thus, $x_t^f$ represents what is usually referred to as "final adjustment", in the sense that consideration of additional data on $x_t$ for $t > 144$ or $t < -84$ should not fundamentally change the result of the adjustment.[2] Now consider $x_t^s$ as being the result of seasonally adjusting the series $x_t$ for $t = 1,...,60$ making use only of data from $t = 1$ to $t = 60$. Thus, this represents the situation in which the practitioner adjusts a sample of 5 years of data for which no observations are available before or after the series being adjusted. Finally, define $x_t^l$ as the result of adjusting the series $x_t$ for $t = 1,...,60$ making use of an historical time series spanning 15 years in the past from the initial observation to be adjusted, $t = 1$.

We aim at assessing the loss in adjustment quality in $x_t^s$ as compared to $x_t^l$ deriving from the fact that, being $x_t^s$ a series of only 5 years, there may not be enough information in the sample to obtain sufficiently accurate adjustments. In opposition, as $x_t^l$ utilises information spanning a total of 20 years of data, it is considered to be a good benchmark against which such quality may be assessed.

In order to do this, we will study for both cases, $x_t^l$ and $x_t^s$, the behaviour of the deviations from the "final" adjustment $x_t^f$ by means of Monte Carlo simulation techniques. Specifically, we draw replications from the following airline model

$$\Delta\Delta_{12}x_t = (1 - \theta L)\left(1 - \Theta L^{12}\right)a_t \qquad [1]$$

where $a_t \sim NID(0, \sigma_a^2)$

whose parameters have been chosen to match those estimated from the chain index of the euro area monetary aggregate other short term deposits.[3] We will refer throughout to this specific parameterisation as our "baseline model", as later on we will introduce some changes in the parameters for sensitivity analysis purposes. Then, for each replication, we obtain the adjustments $x_t^f$, $x_t^l$, and $x_t^s$ by making use of the relevant data spans as mentioned before.[4] For each replication we can compute the deviations of $x_t^l$ and $x_t^s$ from the "final adjustment". However, we have opted to focus instead on the behaviour of the monthly growth rate of the

---

[2] See, for instance, the discussion of the linear approximation to X-11 in Wallis (1974). Note that, strictly speaking, this applies to an adjustment making use exclusively of the X-11 filters with default options. Non-default seasonal filters, X-12 preadjustment and X-12 forecast options change the picture. However, since no preadjustment or forecast extension will be needed to determine $x_t^f$ in our simulations the issue can be ignored, and as for the possible change to non-default seasonal filters it should be expected that filter weights at lags or leads beyond 7 years should be very small.

[3] Specifically, the estimates for this series for the period January 80 – August 2002 are $\theta = -0.11$, $\Theta = 0.54$, $\sigma_a^2 = 1.2 \times 10^{-5}$. Starting values were chosen so that the seasonal pattern and long-run trend matched on average those of the empirical series.

[4] X-12 ARIMA has been run in each case with standard options with the following exceptions: for the computation of $x_t^f$ all preadjustment and forecast extension options are disabled (as they should not be invoked); for the computation of $x_t^s$ MAXBACK is set to 12 in the FORECAST spec. In the case of $x_t^s$ and, $x_t^l$, ARIMA model selection is left to X-12's automatic selection procedure.

series, a more relevant magnitude from the perspective of most economic analyses. Thus, we define the absolute deviations $\delta_t^l = \left| \dot{x}_t^l - \dot{x}_t^f \right|$ and $\delta_t^s = \left| \dot{x}_t^s - \dot{x}_t^f \right|$, where $\dot{x}_t^i$ stands for the monthly growth rate of the relevant seasonally adjusted series for $i = f,l$. By studying the properties of $\delta_t^l$ and $\delta_t^s$ and we may obtain important insights into the potential problems associated with the seasonal adjustment of short time series.[5]

## 3. Results for the baseline model

Figure 1 (a) plots the median across 1000 Monte Carlo replications of $\delta_t^l$ and $\delta_t^s$ for $t$ = 1,...,60. In order to facilitate the reader in assessing the practical importance of the magnitudes of $\delta_t^l$ and $\delta_t^s$, these are expressed in terms of the impact that such deviations would imply for the month-to-month growth rate expressed at annual rates.[6] As expected, the graph shows a larger discrepancy with respect to the final adjustment for the short time series across the whole time range.

Specifically, as it can be seen in Figure 1 (a), in the first and the second year of the sample, the adjustment using the short time series performs very poorly in comparison with the results for the long time series. Indeed, the discrepancy $\delta_t^s$ may be as large as 120 basis points (in median terms), compared to only 20 basis points for $\delta_t^l$. This is mainly due to the fact that in the case of the short time series, data have to be backcasted, while these data are available in the long time series. Furthermore, when using the short time series, complete application of the X-11 symmetric filters is not possible during the first years of data.

In contrast, in the last two years of data the magnitude of $\delta_t^l$ increases considerably and becomes closer to the magnitude of $\delta_t^s$. The rationale behind this is that, as one approaches the end of the time series, data have to be forecasted in both cases, long sample and short sample, and in neither case is the complete use of symmetric filters feasible.

Similar conclusions may be derived from a synthetic measure of the accuracy of the adjustment. We derive such measure as the mean absolute deviation (MAD) from the final adjustment. This is computed for the whole sample and then separately for its first and second halves. The relevant expected values as estimated from 1000 Monte Carlo replications are presented in Table 1. The mean absolute deviation (MAD) with respect to the final adjustment turns out to be larger by a factor (hereafter referred to as the “MAD ratio”) of 1.55 for the series using 5 years of data (T=60) compared to the long historical time series (T=240). This result is however compounded by a very large MAD ratio of 2.69 for the first half of the sample, and a relatively moderate value of 1.09 for the second half.

---

[5] From a more general perspective, our results will represent in fact a *lower bound* on the loss associated with adjustment using a small sample. Indeed, if one sees seasonal adjustment as a signal extraction problem, issues such as the additional uncertainty in the inference about the optimal seasonal adjustment filter would have to be taken into account. By restricting ourselves to X-12 ARIMA, these issues are side-stepped, as the X-12 filters have, to a great extent, fixed weights. For an approach to seasonal adjustment based on optimal signal extraction theory, see Gomez and Maravall (1996).

[6] Such annualisation is not totally invariant to the actual growth rate of the series, although differences are minor if one considers the range of plausible growth rates for a major monetary aggregate in the euro area. We have considered an annual growth rate of 5% to implement it.

Figure 1: Median absolute discrepancy with respect to final seasonal adjustment for short time series (T=60) and long time series (T=240)
*(Discrepancy expressed in terms of impact on annualised monthly growth rate)*

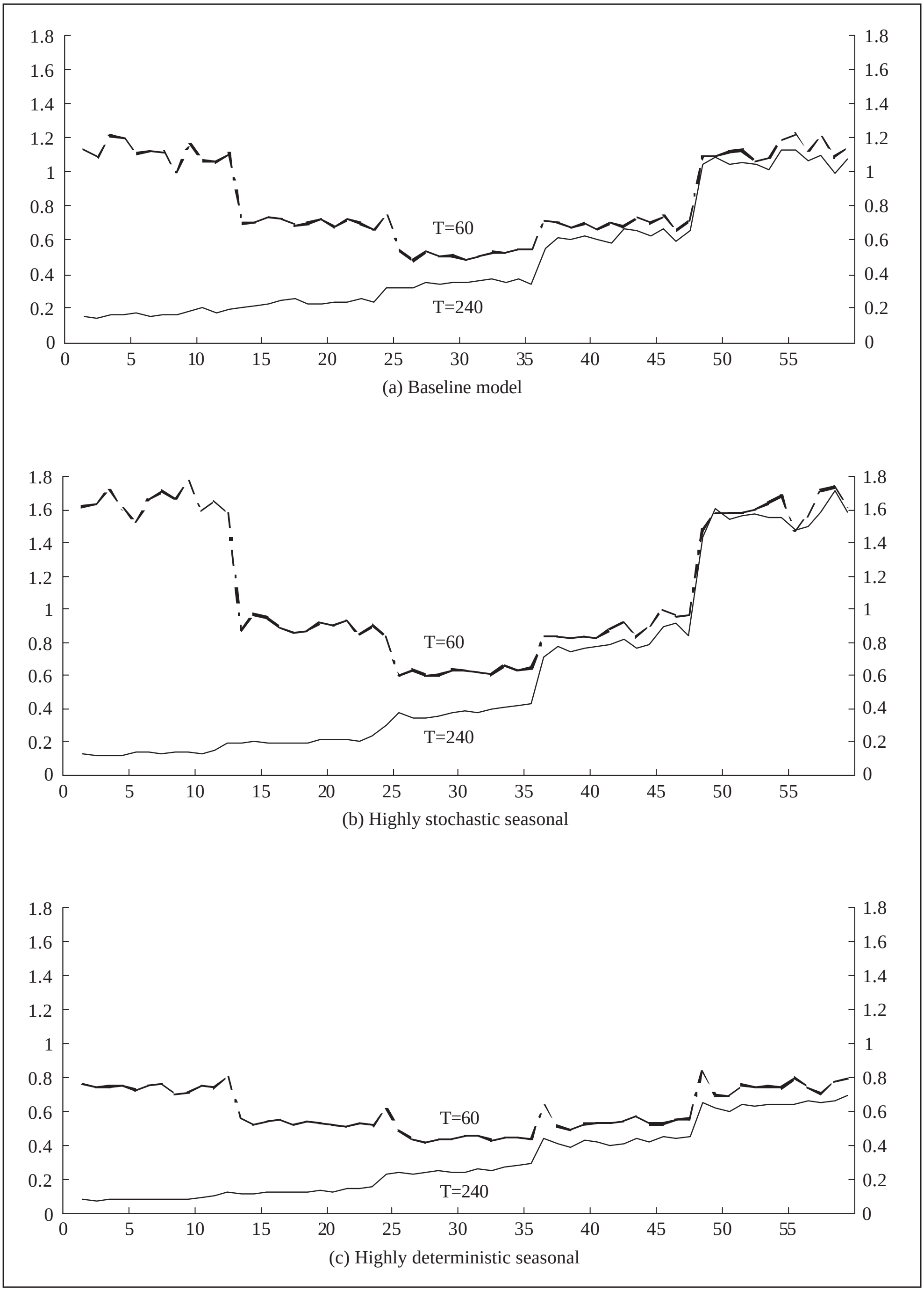


Table 1: Sensitivity to different time-series properties

| | All observations | | | t<=30 | | | t>30 | | |
|---|---|---|---|---|---|---|---|---|---|
| | (a) T=240 | (b) T=60 | Ratio (b/a) | (a) T=240 | (b) T=60 | Ratio (b/a) | (a) T=240 | (b) T=60 | Ratio (b/a) |
| Highly stochastic seasonal | 1.019 | 1.638 | 1.61 | 0.470 | 1.638 | 3.49 | 1.587 | 1.638 | 1.03 |
| **Baseline (Medium stochastic seasonal)** | **0.721** | **1.119** | **1.55** | **0.410** | **1.103** | **2.69** | **1.043** | **1.136** | **1.09** |
| Highly deterministic seasonal | 0.414 | 0.775 | 1.87 | 0.223 | 0.772 | 3.46 | 0.611 | 0.778 | 1.27 |
| **Baseline (Highly stochastic trend)** | **0.721** | **1.119** | **1.55** | **0.410** | **1.103** | **2.69** | **1.043** | **1.136** | **1.09** |
| Medium stochastic trend | 0.572 | 0.977 | 1.71 | 0.270 | 0.982 | 3.63 | 0.885 | 0.972 | 1.10 |
| Highly deterministic trend | 0.599 | 0.981 | 1.64 | 0.250 | 0.965 | 3.86 | 0.959 | 0.997 | 1.04 |

All figures represent the mean absolute deviation with respect to final seasonal adjustment and are expressed in terms of impact on percent annualised monthly growth rate.

## 4. Changing the nature of the seasonal cycle and the trend

In order to assess the impact of a different seasonal behaviour of the time series, our analysis needs now to consider setting different values of $\Theta$ in [1]. For instance, by setting $\Theta = 0$, a larger degree of variability in the seasonal pattern is introduced[7]. As it is shown in Figure 1(b), this results in a much larger magnitude for $\delta_t^s$ across the whole time range. In contrast, $\delta_t^l$ only increases to a similar degree in the last two years of data. Thus, the unavailability of long historical data coupled with the fact that backcasting becomes more difficult due to the high variability of the seasonal implies that the loss in quality dramatically increases for the short time series in the first half of the sample.

Next we consider a more stable seasonal pattern by setting $\Theta = 0.95$. The results of the Monte Carlo analysis for this parameterisation of the model are shown in Figure 1 (c). The most salient feature, apart from the reduction in the magnitude of both discrepancies $\delta_t^s$ and $\delta_t^l$, is that the superior behaviour of the adjustment using the long series is now also non-negligible even for the last two years of the sample. The reason behind this is that, with $\Theta = 0.95$, the seasonal pattern becomes more predictable, and hence more amenable to being easily extrapolated beyond the available data by means of forecasts. In such case, the advantages of having a better forecasting model (which should in principle be the case when using a long time series for estimation) increase, hence the larger difference between $\delta_t^s$ and $\delta_t^l$ towards the end of the sample as compared with previous cases. This shows up clearly in the MAD ratio (see Table 1), which for the second half of the sample goes up to 1.27 in the case of a highly deterministic seasonal from 1.09 observed when the seasonal is medium stochastic and 1.03 when it is highly stochastic.

The analysis has also considered the impact of a different stochastic nature of the trend. From the figures in Table 1 it is clear that, as the trend becomes more deterministic, the loss in the quality of the adjustment derived by using a short time series increases significantly in the first part of the sample. This is mainly due to the fact that the magnitude of $\delta_t^l$ reduces significantly with a more stable trend, whereas this is not so much the case for $\delta_t^s$ (possibly the backcasts used in the short time series do not benefit in excess from a more stable trend as

[7] In every instance in this study where the value of a parameter in [1] has been changed from our baseline model, the variance of the innovation $\sigma_a^2$ in the DGP has been suitably rescaled so that the unconditional variance of the stationary transformation of the series var($\Delta\Delta_{12}x_t$) = $\sigma_a^2\,(1+\theta^2+\Theta^2+\theta^2\Theta^2)$ remains invariant to the different specific parameterisations.

they do from a more stable seasonal). This implies an increase in the MAD ratio, for the first half of the sample, from 2.69 in the case of a highly stochastic trend to 3.86 when the trend becomes highly deterministic.

## 5. Changing the X-12 forecasting/backcasting options

Our analysis takes now into consideration different forecasting/backcasting options, in order to check whether our results are dependent in excess on the particular forecasting options chosen for our baseline model (default 12-month forecasts, 12-month backcasts for the short time series). We also aim at answering the question of whether it would be preferable to disable the backasting/forecasting extension in the case of the short time series due to a potential unfeasibility of deriving sensible forecasts from such a small sample.

As it can be inferred from the figures in Table 2, our previous conclusions in comparing short and long time series seem quite robust to changes in the number of observations that are forecasted/backcasted. At the same time, it is clear that backcasting 12 months, as opposed to

Table 2: Sensitivity to different X-12 forecasting/backcasting options

| | All observations | | | t<=30 | | | t>30 | | |
|---|---|---|---|---|---|---|---|---|---|
| | (a) T=240 | (b) T=60 | Ratio (b/a) | (a) T=240 | (b) T=60 | Ratio (b/a) | (a) T=240 | (b) T=60 | Ratio (b/a) |
| Maxlead. Maxback = 0 | 0.778 | 1.252 | 1.61 | 0.408 | 1.252 | 3.07 | 1.160 | 1.252 | 1.08 |
| **Baseline (Maxlead. Maxback = 12)** | **0.721** | **1.119** | **1.55** | **0.410** | **1.103** | **2.69** | **1.043** | **1.136** | **1.09** |
| Maxlead. Maxback = 24 | 0.651 | 1.055 | 1.62 | 0.352 | 1.052 | 2.99 | 0.959 | 1.058 | 1.10 |
| Maxlead. Maxback = 36 | 0.707 | 1.095 | 1.55 | 0.397 | 1.085 | 2.73 | 1.028 | 1.104 | 1.07 |

All figures represent the mean absolute deviation with respect to final seasonal adjustment and are expressed in terms of impact on percent annualised monthly growth rate.

complete reliance on the X-11 asymmetric filters at the beginning of the sample, does improve the results for the short time series, even notwithstanding the fact that the forecast model has to be estimated using only 5 years of data. However, the quality of the adjustment using 5 years of data does not substantially improve when moving to forecasts/backcasts longer that 12 months. Thus, the possible solution of widening the forecast/backcast period beyond 12 months as a way to alleviate the small sample problem, which practitioners may feel as intuitively plausible, does not seem worth pursuing in our case.[8]

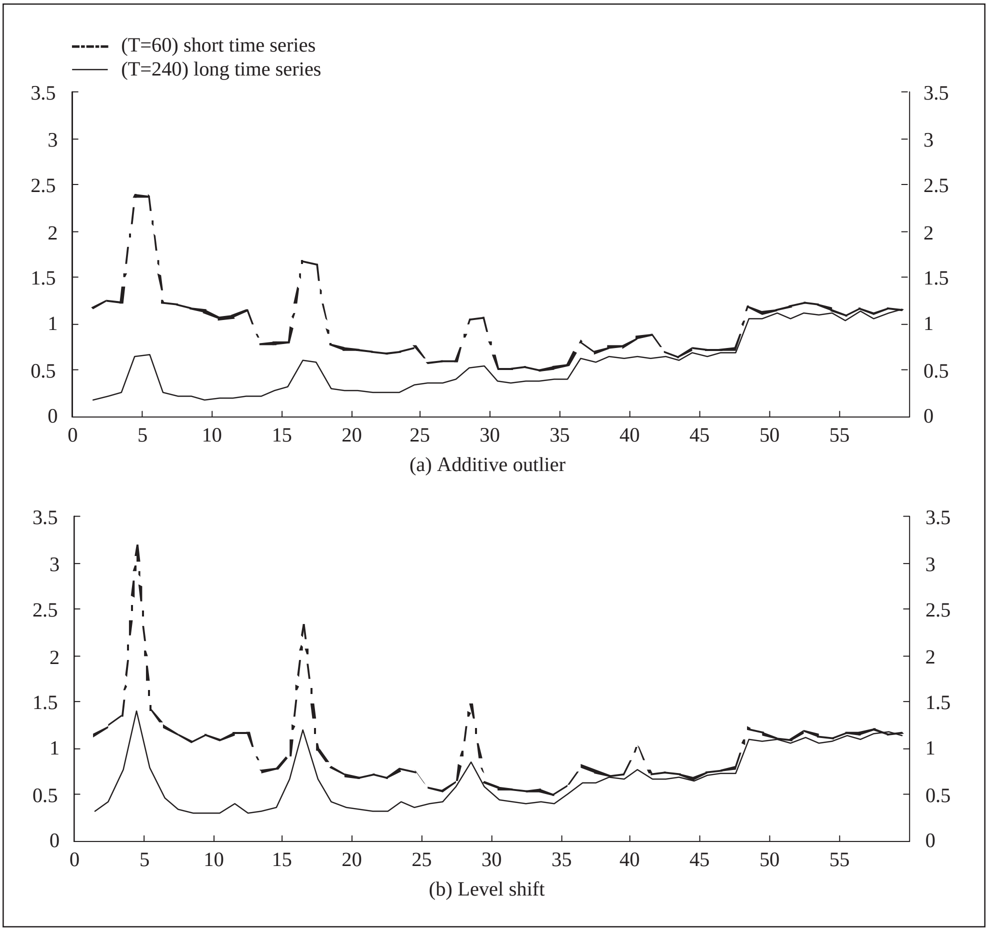
## 6. Robustness against outliers

An important feature of X-12 ARIMA compared with previous versions of the U.S. Census Bureau software for seasonal adjustment is the capability of the program to detect and control for the effect of several types of outlying observations by means of the well-known time-series techniques proposed by Chang and Tiao (1983) and Chang, Tiao and Chen (1988). In contrast, earlier versions of X-11 relied exclusively on an ad-hoc approach to controlling for outliers, with no connection with standard methods of statistical inference.

[8] Note that a different characterisation for the trend or seasonal components could change the picture; however, an extensive study of the effects of different forecasting options is not the main aim of this paper.

Figure 2: Effect of an outlier of size 1% for short time series and long time series located towards the start of the sample

*(Median discrepancy with respect to "clean" adjustment expressed as impact on annualised monthly growth rate)*




It is reasonable to anticipate that, in a small sample, such time-series tests for the detection of outliers may show enough lack of power to have an impact in the adjustments obtained when outliers are indeed a feature of the data. Thus, the aim of this section is to evaluate the potential loss of robustness against outliers of the seasonal adjustments produced by X-12 when adjusting short time series such as monthly series of only 5 years of data.[9] The benchmark for comparison shall again be the results obtained using instead time series including 15 years of additional past data.

[9] Note that the problem for a short time series is compounded by the following factors: diminished power in the detection of the outliers using the Chang *et al.* (1988) procedures; increased uncertainty in the determination of the type of outlier and the estimation of its size in the case that it is detected; and the effect of a switch to the ad-hoc outlier correction methodology utilised in X-11 in the case that the outlier is missed by the X-12 pre-adjustment.

The study considers two types of outliers contemplated in X-12, namely the Additive Outlier (AO) and the Level Shift (LS) outlier models[10] (see the "X-12-ARIMA Reference Manual", US Census Bureau, 1998, for details on their definition). To keep things manageable, we restrict ourselves to outliers that amount to a 1% increase in the level of the series $x_t^f$ at the time that they occur. We also consider three different positions for the outlier in the sample: shortly after the beginning, at the middle, and shortly before the end. The outliers are introduced in the replicated data from [1] before computing the adjustments for $x_t^l$ and $x_t^s$. In contrast, for the computation of $x_t^f$ the outlier is introduced after the seasonal adjustment has been derived from "clean" data. This is done so that $x_t^f$ may be thought of as an adjustment obtained in an ideal environment in which the impact of an outlier in the determination of the seasonal component of the series was nil.[11] Consequently, the discrepancies $\delta_t^s$ and $\delta_t^l$ defined earlier may be thought as deviations from this ideal outcome.

Figure 2 shows the results for the AO and LS cases when the outlier is located shortly after the start of the sample. In both cases, it is clear that the distortions are largely exacerbated in the case of the short time series. For instance, the immediate impact of an AO amounts to a median discrepancy of roughly 240 bp for the short time series, compared to only 65 bp for the long time series. This large discrepancy occurs again at around the seasonal lags from the time the outlier has occurred, and is still much more pronounced for the short time series, for which the distortion clearly shows a more prolonged effect in time (for instance, even two years after the outlier occurrence the effect on $\delta_t^s$ is still about twice as large as that for $\delta_t^l$).

For the case of a LS, a similar pattern can be observed, although the absolute magnitude of the distortion is larger for both time series lengths. In particular, the immediate impact on $\delta_t^s$ shoots up to 320 bp, with the same figure being 140 bp for $\delta_t^l$.

In contrast, when an outlier occurs towards the end of the sample (Figure 3), a different picture emerges. Indeed, while the behaviour of $\delta_t^s$ is symmetric with respect to the case of an outlier located at the beginning of sample, the distortion introduced by the extreme observation for the long time series approaches now that of the short time series. This is explained by the fact that data have to be forecasted at the end of the sample in both cases, and the possible improvement derived from the 15 years of additional data available for the long time series is marginal for data located near the end of the sample. However, for the case of the AO there still persists a small difference in favour of the long time series at around the peaks of the distortion introduced by the outlier.

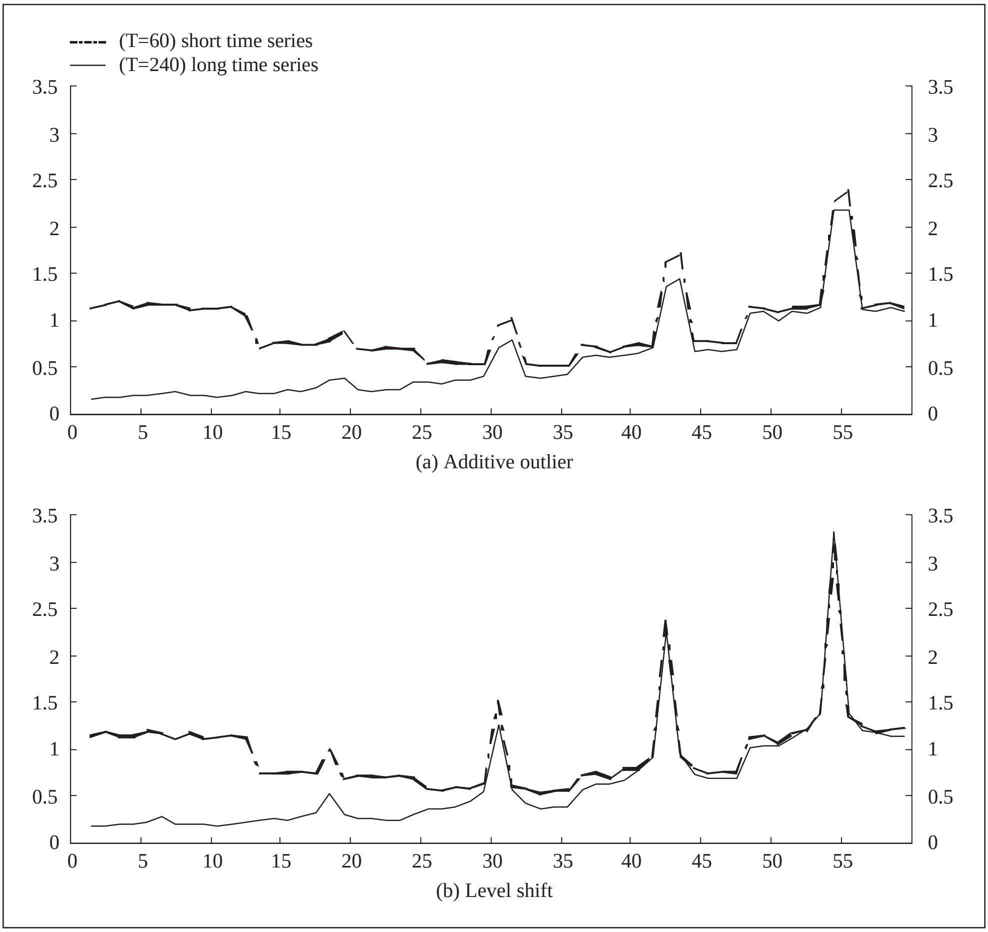
Finally, when an outlier occurs in the middle of the sample (Figure 4), its impact on the distortions seems roughly symmetric even for the long time series. This perhaps indicates that, with such location for the outlier, having additional historical data does not improve significantly the ability of X-12 to prevent such distortions at the beginning of the sample.

[10] The case of a transitory change was also considered, however results will not be presented as they turned out to be substantially similar to the LS or AO cases, depending on the rate of decay utilised.

[11] Note that if the outlier was introduced prior to the computation of $x_t^f$ by X-12, not even asymptotically could one obtain a 100% removal of the influence of the outlier from the adjustment.

Figure 3: Effect of an outlier of size 1% for short time series and long time series located towards the end of the sample

*(Median discrepancy with respect to "clean" adjustment expressed as impact on annualised monthly growth rate)*

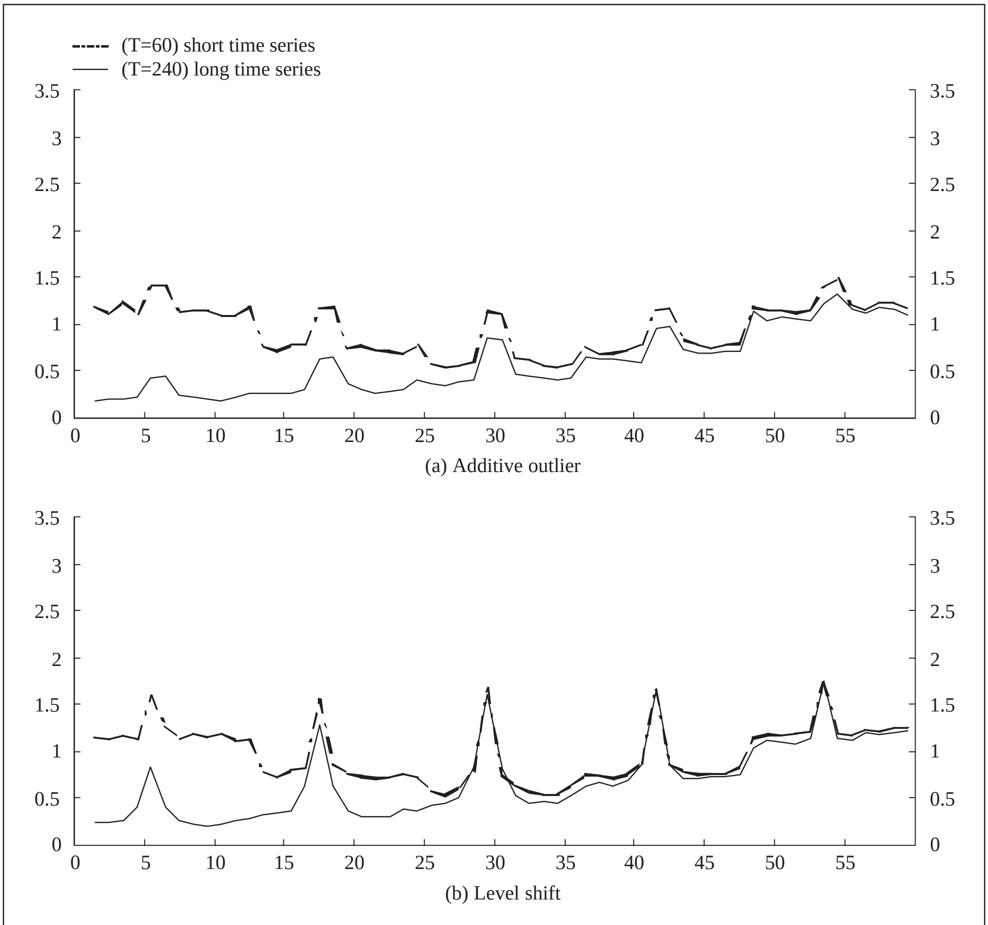



## 7. Summary and Conclusions

We compare the performance of X-12 in adjusting a short time series comprising only 5 years of monthly data (a "short time series") against a benchmark situation in which 15 additional years of historical data are available (a "long time series"). Our analysis concentrates on the effects on the monthly rate of growth as derived from seasonally adjusted data. By means of a Monte Carlo study we show that the adjustments obtained using short time series are seriously distorted for the first two years of the sample. These large distortions are specially exacerbated in the case of a highly variable seasonal pattern. In contrast, for the last two years of the sample the quality of the adjustments for the short time series may be regarded in most cases only slightly inferior to that obtained making use of a longer time series. An exception

Figure 4: Effect of an outlier of size 1% for short time series and long time series located at the middle of the sample

*(Median discrepancy with respect to "clean" adjustment expressed as impact on annualised monthly growth rate)*




is the case of a highly volatile seasonal component, for which a relevant improvement when using a longer series still persists.

We also examine the robustness against outliers, and find that when outliers occur near the beginning of a short time series the distortions introduced may be of a very large magnitude compared with the situation in which additional past data are available.

In sum, our results indicate that analysts should exert great caution when studying monthly developments from seasonally adjusted data derived from short time series. In particular, the benefits of using such adjustments for the purposes of econometric estimation should be questioned on the grounds that the effects of a serious errors-in-variables problem at both ends of the sample would be compounded with those already known to exist in conducting inference in small samples.

## References

Chang, I. and C. G. Tiao (1983), Estimation of Time Series Parameters in the Presence of Outliers, Technical Report 8, Statistics Research Center, University of Chicago.

Chang, I. , C. G. Tiao and C. Chen (1988), Estimation of Time Series Parameters in the Presence of Outliers, Technometrics, 30, 193-204.

Dagum, E. B. (1988), X-11-ARIMA/88 Seasonal Adjustment Method – Foundation and Users' Manual, Statistics Canada.

European Central Bank (2000), Seasonal adjustment of monetary aggregates and HICP for the euro area, ECB Other Publications, August 2000.

Findley, D., Monsell, B., Bell, W., Otto, M., and Chen, B. C. (1998), New Capabilities and Methods of the X-12-ARIMA Seasonal Adjustment Program (with discussion), Journal of Business and Economic Statistics, 16, 2, 127-176.

Gomez, V. and A. Maravall (1996), Programs TRAMO and SEATS, Instructions for the User (Beta Version: September 1996), Working Paper 9628, Bank of Spain.

Hood, C. C., J. D. Ashley and D. F. Findley (2000), An Empirical Evaluation of the Performance of TRAMO/SEATS on Simulated Time Series, ASA Proceedings, October 2000.

Shiskin, J., Young, A. H., and Musgrave, J. C. (1967), The X-11 Variant of the Census Method II seasonal Adjustment Program, Technical Paper No. 15, Bureau of Census, U.S. Department of Commerce.

U.S. Census Bureau (2002), X-12-ARIMA Reference Manual Version 0.2.10, Time Series Staff, Bureau of Census, Washington, D.C.

Wallis, K. F. (1974), Seasonal Adjustment and Relations Between Variables, Journal of the American Statistical Association, 69, 18-32.

# Seminar agenda

Seminar organisers: M. Manna (Chairman), R. Peronaci (Secretary)

*Opening speech*
S. Keuning (European Central Bank)

*Introduction to the seminar*
M. Manna (European Central Bank)

**Session 1**

*"Comparing direct and indirect seasonal adjustments of aggregate series"*
C. C. Hood (US Census Bureau)

*"A class of diagnostics in the ARIMA-model-based decomposition of a time series"*
A. Maravall (Banco de España)

**Session 2**

*"Seasonal adjustment of European aggregates: direct versus indirect approach"*
G. L. Mazzi (Eurostat)

*"Criteria to determine the optimal revision policy: a case study based on euro zone monetary aggregates data"*
L. Maurin (Banque de France)

**Session 3**

*"Direct versus indirect seasonal adjustment of UK monetary statistics"*
D. Willoughby (Bank of England)

*"The seasonal adjustment of euro area monetary aggregates: direct versus indirect approach"*
R. Peronaci (European Central Bank)

*"Monthly re-estimation of the parameters of a once-a-year fixed model: an assessment"*
S. Bravo (Banco de España)

**Session 4**

*"Seasonal adjustments quality reports"*
S. Nardelli (European Central Bank)

*"The performance of X-12 in the seasonal adjustment of short time series"*
A. Matas Mir, V. Rondonotti (European Central Bank)

*Concluding remarks*
M. Stubbe (European Central Bank)