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THE ANALYSIS OF SEASONALITY IN ECONOMIC STATISTICS: A SURVEY OF RECENT DEVELOPMENTS*

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This article describes the EUROSTAT *activities in the field of seasonal adjustment and trend extraction in economic time series. They follow a working program which has been set up during 1995. The attention focuses on X12*-REGARIMA *(X12 in short), a last update of the X11-family from the Bureau of the Census (see Findley and al., 1996), and on* SEATS-TRAMO *(see Gomez and Maravall, 1996) which implements the* ARIMA*-model-based approach to decompose time series. Three main directions are currently followed: evaluation and comparison of these two methods, construction of a software embodying and interfacing X12 and* SEATS-TRAMO*, and training in applied time series analysis. The preliminary results which have been obtained on the difficult task of comparing both methods are discussed and the design of the software in construction is presented.*

Keywords: Seasonal adjustment, signal extraction, X-11, unobserved components, ARIMA Models, Wiener-Kolmogorov filter.

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1. INTRODUCTION

One of the main tasks of the Statistical Office of the European Community consists in providing deciders with information about the economy of the Member States. This information is subject to a statistical treatment in order to meet the requirements of analysts and commentators. Typically, short-term analysis and the monitoring of the economy are conducted on the basis of seasonally adjusted series. Sometimes, when seasonally adjusted figures display too much erraticity, the attention is reported to a smoother signal such as the trend. Accordingly, EUROSTAT proceeds to seasonal adjustment and to trend extraction before publishing economic time series (see EUROSTAT 1997a).

Several methods for seasonal adjustment and trend extraction are available. Broadly speaking, they may be classified into three main groups: regression methods, empirical filtering and signal extraction. With the first one, the patterns of interest are represented as deterministic functions of time (see for example Hylleberg, 1986). It is perhaps the earliest model-based approach to seasonal adjustment and trend extraction, and was in use in EUROSTAT until recently with the software Dainties (see Fischer, 1995). The second group performs ad hoc application of moving average filters. The filters in use are said *empirical* because they do not depend on the statistical properties of the series under analysis: they are pre-existing filters and it is up to the user to select the most adequate one given the series under analysis. This is the principle implemented in the softwares of the X11-family (see Shiskin and al., 1967), which are very widely spread in public data-analysis agencies. The last approach, seasonal adjustment by signal extraction, has been developed by Burman (1980), Hillmer and Tiao (1982), among others (for a general presentation, see Maravall, 1993b). It is based on optimal filtering, the optimal filter being derived from a time series model of the ARIMA-type which describes the behaviour of the series while the components are explicitly specified. It is generally known as the ARIMA-Model-Based (AMB) approach to unobserved components analysis.

The comparison of the different approaches has been subject of a large debate in the statistical literature; see Bell and Hillmer, 1984. Yet the debate was oriented towards the search of an optimal criterion for evaluating seasonal adjustment procedures and with this perspective no definitive conclusion could be reached. Consequently, the evaluation of the relative performances of the different approaches is still an open question. Furthermore, EUROSTAT is confronted every day with the problem of choosing the method ensuring the highest quality data.

A glance at the situation in national statistical institutes of the European Union shows that practitioners favour ad hoc filtering through the general use of softwares of the X11 family (EUROSTAT 1997d). Two noticeable exceptions, however, are Bank of Italy and Bank of Spain, which have adopted AMB procedures (Bank of Italy, 1997, and Bank of Spain, 1993). The situation is opposite on the side of academic research where model-based approaches prevail; see for example the references in Maravall, 1993b. The dichotomy between the applied importance of X11 and variants of, and the attention that academics devote to model-based methods to decompose economic time series, heightens the need of a rigorous assessment of the different approaches.

During 1995, EUROSTAT set up a program for investigating issues related to seasonal adjustment. The first step was an internal study comparing 6 different packages (see Fischer, 1995). It has led to the decision of concentrating the attention on X12-REGARIMA (X12 in short), a last update of the X11-family from the Bureau of the Census (see Findley and al., 1996), and on SEATS-TRAMO (see Gomez and Maravall, 1996) which implements the AMB approach to decompose time series. In brief, both programs are based on the following scheme: REGARIMA and TRAMO are respectively in charge of removing some deterministic effects like for example outliers and calendar effects, and of identifying and estimating linear stochastic models of the ARIMA-type for the remaining part of the series. It is that stochastic part which is then decomposed into seasonal, trend plus noise by X12 and by SEATS. The program X12 uses the forecasts made available by REGARIMA to extend the series before applying the adjustment filters and the trend filters. These filters were already present in X11, so X12 still embodies the X11 decomposition filters. On the other hand, SEATS uses the model identified and estimated by TRAMO to derive the optimal filters for estimating the different components. Details of the two decomposition procedures are given in sections 2 and 3.

The EUROSTAT activities in seasonal adjustment are currently developed in three main directions: evaluation and comparison of these two approaches, construction of a software embodying and interfacing X12 and SEATS-TRAMO, and training in applied time series analysis. The first one is mainly a research project, and it has given rise to a number of papers. Section 4 presents some of the main results which have been obtained, while section 5 gives an overview of the software project.

2. X11 LINEAR SEASONAL ADJUSTMENT FILTERS

We first present the principle of linear filtering. Writing B the backshift operator such that for a time series x_t, $Bx_t = x_{t-1}$, a linear time invariant filter can be expressed as:

$$a(B) = \sum_{k=-m}^{r} a_k B^k, \tag{2.1}$$

where the weights a_i are real, do not depend on time, and satisfy $\sum a_i = 1$ and $\sum a_i^2 < \infty$. The moving average filters most often employed share the property of being linear and, for observations not too close to both ends of the sample, symmetric. Such filters are considered since they induce no phase shift in the filtered series (see Priestley, 1981). Hence $m = r$, and assuming that $a(B)$ is a seasonal filter the seasonal component estimator will be written as:

$$
\begin{aligned}
\hat{s}_t &= \left[a_0 + \sum_{k=1}^{r} a_k (B^k + B^{-k})\right] x_t \\
&= a(B) x_t \qquad (2.2)
\end{aligned}
$$

while the nonseasonal part of the series will be obtained as :

$$\hat{n}_t = [1 - a(B)] x_t$$

so that the additive relationship $x_t = \hat{s}_t + \hat{n}_t$ holds. If needed, the nonseasonal part of the series can be further decomposed into a trend plus an irregular component.

Given that an unobserved component like seasonality is built so as to catch the movements of a series at some specific frequencies, it is convenient to draw the interpretation of linear filters in the frequency domain. Let w denote frequency measured in radians, $w \in [0, \pi]$, then the frequency response function of $a(B)$ is given by:

$$a(w) = a(e^{-iw}) = a_0 + 2 \sum_{k=1}^{r} a_k \cos kw. \qquad (2.3)$$

The squared gain of a filter defined by $\mid a(w) \mid^2$ relates the spectrum of the input series $g_x(w)$ to the spectrum of the component estimator $g_{\hat{s}}(w)$ through the general expression:

$$g_{\hat{s}}(w) = \mid a(w) \mid^2 g_x(w).$$

The squared gain controls the extent in which a movement of particular amplitude at a frequency w is delivered to the output series. For example, a zero-gain in $[w_1, w_2]$ corresponding to a response function vanishing in this band will make the output series free of movements in this range of frequencies. This is the principle adopted in empirical linear filtering as performed in X11 (which, we recall, is still embodied in X12). Actually, the decomposition of time series in X11 may also be multiplicative, but the linear filters can be seen as approximation of the multiplicative approach; see Young (1968). Dealing with linear filters eases the interpretation at the cost of missing some nonlinearities, which according to Young are in general not important.

The linear filters in X11 can be seen as convolutions of moving averages. Details of the procedure can be found in Wallis (1974, 1982). According to the filter chosen at each step, a different outcome is obtained. For monthly series, standard options for seasonal moving average filters are 3×3, 3×3 followed by 3×5 (default), 3×9 and 3-term seasonal average filters. These are combined with a Henderson trend filter, whose standard length may be 9, 13, 23 terms. Graphics of the filters weights and squared gains can be found in numerous articles; the most complete may be Bell and Monsell (1992). For convenience, we reproduce the squared gains of the monthly seasonal adjustment filters. Namely, the default, 3×3, 3×9, and 3-term filters associated with a 13-term Henderson moving average are presented; the 3×5 is omitted since it does not differ very much to the default (see Bell and Monsell).

Figure 1. Squared Gain Functions of X11 Monthly Adjustment Filters

The graphics displayed in figure 1 illustrates how X11-filtering works in the frequency domain. The seasonal component is designed to capture the movements in the series which occur with a seasonal frequency. Thus the seasonal adjustment filters should annihilate the variability associated with the seasonal frequencies, and let the other unchanged. In agreement with that, the gain of the X11 adjustment filters presented on figure 1 displays that bandpass structure: they show a gain close to 0 around the seasonal frequencies and a gain close to one in the other regions. The width of the region where the gain is null is related to the stability of the seasonal movements which are supposed to be removed: for example, an unstable seasonal pattern yields large spectral peaks around the seasonal frequencies, and hence the range of frequencies where an adjustment filter should display a zero-gain must be sufficiently large to match them. Figure 1 shows that the 3-term seasonal filter would be adequate for a relatively unstable seasonality while the 3×9 filter corresponds to a relatively stable seasonality. Given the series under analysis, it is up to the user to select the filter which is believed to be the more appropriate. The X12 software helps in that task by delivering empirical measurement like irregular-to-seasonal ratio or cycle-to-irregular ratio (see Dagum, 1988) which are designed to indicate whether the seasonality is stable or not, or also whether the series presents a seasonal behaviour or not. However, for series displaying seasonal movements whose characteristics would be more accentuated than the two extreme patterns that the 3×9 and 3-term filters are able to accommodate, then respectively too much or not enough seasonality would be removed by simple application of these filters. This is an important feature of X11 that we shall discuss further in section 4.

3. ARIMA-MODEL-BASED SIGNAL EXTRACTION

The signal extraction approach to seasonal adjustment consists in estimating an unobserved seasonal component s_t having observation on a series x_t such that:

$$x_t = s_t + n_t,$$

where n_t represent the nonseasonal part of the series, independent of s_t. This problem can be solved using the so-called «Wiener-Kolmogorov» (WK) filter. The WK filter is also a linear moving average filter, but the main difference with ad hoc filters lies in the way that it is constructed: the WK filter is built so as to minimise the mean squared errors in the estimator. The component estimator corresponds to the linear projection of the unobserved component on the series; it gives the conditional expectation of the component.

Under the assumptions that the components are orthogonal and that an infinite realisation of the series is available, the WK filter $\nu_s(w)$ is given by the ratio of the component spectrum to the series spectrum (see Whittle, 1983). Let the seasonal spectrum and the series spectrum be denoted $g_s(w)$ and $g_x(w)$, respectively. Then, for stationary series,

$$\nu_s(w) = \frac{g_s(w)}{g_x(w)}, \tag{3.1}$$

and, using the Fourier Transform, the estimator of the seasonal component is:

$$\hat{s}_t = \nu_s(B) x_t. \tag{3.2}$$

It has been shown that the WK still yields consistent estimates when the series is nonstationary (see, for example, Pierce (1979) or Bell (1984)).

Cleveland and Tiao (1976) and Burman (1980) have suggested to use the signal extraction theory in conjunction with the specification of stochastic linear models of the ARIMA-type for the series and for the components. A simple reason for that is that the ARIMA models provide a very simple way to parametrize a spectrum (see Box and Jenkins, 1970). Typical models for the seasonal component are:

$$S(B)s_t = \theta_s(B)a_{st}$$

where $S(B) = 1 + B + \cdots + B^{m-1}$, m being the data-periodicity (e.g. 12 for monthly series), $\theta_s(B)$ a polynomial of order at most $m-1$, and a_{st} is an independent white noise variable normally distributed. Importantly, this specification let the sum of m consecutive seasonal movements be zero in expectation.

In the time domain, the WK filter can be seen as the ratio of the component AutoCorrelation Generating Function (ACGF) to the series ACGF, which are straightforwardly available from the ARIMA modelling. Hence, the historical WK filter is symmetric, as the X11 central filters. It is also convergent, so it is valid for computing the estimators in the central periods of the samples. At the end of the sample, preliminary estimates are obtained by replacing unknown future observations with their forecasts.

In practice, the selection and estimation of an ARIMA model for the observed series is conducted using the well-known Box-Jenkins techniques, and the spectrum associated with that model is decomposed by partial fraction decomposition. However, the derivation of a model for the unobserved components is subject to an important identification problem. In general, when a time series admits a decomposition into unobservables, the number of admissible decompositions is infinite. In the ARIMA-model-based approach, the selection of a single one is operated by maximizing the irregular component variance (see Hillmer and Tiao 1982). This yields the canonical decomposition, where the canonical components display a zero in their spectra.

Looking at the WK filter in the frequency domain, it is easily seen that it displays a band pass structure similar to that of X11. From (3.1), and using $g_x(w) = g_n(w) + g_s(w)$, we have

$$\nu_s(w) = \frac{1}{1 + \frac{g_n(w)}{g_s(w)}}. \tag{3.3}$$

When the relative contribution of the seasonal component is large at a particular frequency w^*, we have $g_n(w^*)/g_s(w^*) \simeq 0$. In that case, most of the observed series spectrum is used for the signal estimation: the gain of the filter for this frequency will be close to one. Conversely, when the relative contribution is low at a particular frequency, the WK filter just ignores it for the signal estimation. For example, if the nonseasonal component embodies a nonstationary long term trend, then the spectrum of n_t is infinite in the low frequencies region, and we will have $g_n(w^*)/g_s(w^*) \to \infty$. It follows that $\nu_s(w^*) \simeq 0$, and the gain will be close to zero in this area: no low-frequencies variations are passed to the seasonal component. Given that both are moving averages, the band-pass interpretation of the X11 filters and of the WK filter is similar. The main difference is that the WK filter adapts itself to the stochastic properties of the series under analysis, while the X11 filters do not: they are ad hoc (see for example Maravall, 1993a).

4. AD HOC FILTERING AGAINST SIGNAL EXTRACTION: PRELIMINARY RESULTS

4.1. Methodology

The obvious way to perform a comparison is to define a criterion, to design a situation where to implement the different methods, and to evaluate the relative performances of the alternatives with respect to this criterion. Unfortunately, defining a criterion for evaluating seasonal adjustment procedures seems to be an hopeless task; mainly because, as noted in Bell and Hillmer (1984), «different methods produce different adjustments because they make different assumptions about the components and hence estimate different things». In the unobserved component analysis framework, the possibility of different assumptions does exist since in general the decompositions are not identified. Consequently, a direct comparison of the outputs of the different approaches is not informative. In this respect, the analysis being conducted at EUROSTAT follows another strategy, which simply consists in studying the theoretical properties of the different methods in order to point out their relative advantages and drawbacks.

Consider for example the case of regression methods. These typically specify the unobserved components as deterministic functions of time. Hence, by construction, the components are constrained to exactly reproduce their previous behaviour. Given that most of the economic time series are characterised by moving trends and by evolving seasonal patterns, this modelling has soon been found very restrictive and unsuited to many applied cases. Accordingly, regression methods have been gradually replaced by more flexible procedures, such as moving averages methods.

In a similar way, we concentrate on the properties of X11 filters and of AMB-signal extraction. Of course, for such a comparison to be conclusive, the investigations must be as deep and complete as possible. The applied relevance is put forward so as to inform the practitioners about some situation profiles where one approach can be superior to the other.

4.2. Series with Extreme Patterns

The main discrepancy between ad hoc filtering and AMB approach is that this last designs the signal extraction filter according to the stochastic properties of the series under analysis. In cases of series with extreme characteristics, the consequences of that discrepancy can be very apparent. Two cases of extreme patterns can be encountered in practice: series with a component displaying either a very unstable behaviour or a very stable, close-to-deterministic behaviour.

The first case is studied in Fiorentini and Planas (FP) (1997a), where it is pointed out that series embodying a very unstable pattern may be difficult to decompose with the AMB approach: typically, problems of nonadmissibility arise. The canonical requirement would identify a nonseasonal component with negative values in its spectrum, which is not acceptable. This problem does not arise with ad-hoc filtering since the components are never directly specified but are output of the filtering process. A simple solution available consists of decomposing an approximated model. An alternative developed by FP considers higher-order models for the seasonal component. This exact solution was then used as a basis for evaluating the performances of the approximate solution and for comparing them with the performances of ad-hoc filtering. The X11 filter considered was the 3×3 adjustment filter, the most adequate for unstable seasonality. An important finding of that study was that the range of filters available with X11 is too limited to be able to deal correctly with very unstable patterns. In the case of a series characterised by a very unstable seasonality, an underadjustment could clearly be seen: some seasonal fluctuations were still present in the X11 adjusted series.

The opposite case of close-to-deterministic patterns is analysed in Maravall and Planas (MP) (1997). Deterministic patterns cause problem to the AMB approach since optimal signal extraction cannot be performed in noninvertible models. Only an approximation to the optimal decomposition is available in SEATS. Ad hoc filtering, by construction, does not face any theoretical problem with noninvertible processes. MP were able to extend the WK filter to that case, and they evaluated the performance of the approximated solution and of X11-filtering. The attention focused on the 3x9 adjustment filter with a 23-term Henderson trend estimator. While the approximated solution was found to accommodate in a satisfactory way situations of close-to-deterministic patterns, the use of the 3×9 X11 filter was seen to be too much restrictive: an overestimation of the seasonality could be found. This overestimation was due to an inadequate separation between noise and seasonal movements.

4.3. Series with Common Patterns

Most of time series encountered in practice display more regular movements. For these cases, the default X11 filter and the optimal signal extraction filter can be very close. Yet, Planas (1997c) shows that some differences can still be found which are mainly due to the property of the X11 default adjustment filter to display gains higher than one at some frequency between the seasonal harmonics. As a consequence, short-term movements in the series are amplified in the adjustment process, and in the case of the French Total Industry Production (FTIP) series, an overestimation of the irregular could be seen. While the canonical decomposition is designed to maximise the irregular component variance, the irregular obtained from X11 in the FTIP series was subject to more volatility than the canonical one. This amplification of the short-term movements could then be seen in the month-to-month growth rate of the adjusted series.

4.4. About the Identification Problem

One of the main reason which invalidates direct comparison between the outputs of different seasonal adjustment procedures is that unobserved components are not identified. Every approach makes a different identifying assumption. This assumption is explicitly made in the AMB approach: according to the canonical requirement, a signal free of noise is selected among the admissible decompositions of a given observed series model. Further, the estimation accuracy is related to the unobserved components models specification. Maravall and Planas (1996) explored that dependence, and they show that a canonical decomposition always minimises the variance of the error in historical and in any preliminary estimator among the range of the admissible decompositions. On the contrary, they show that a canonical decomposition always maximizes the variance of revisions. It should be underlined that this result only concerns the range of admissible decompositions of a given model; it does not state that the revisions will be higher than the one obtained with any other method. MP also pointed out that in two-component decompositions they are two canonical decompositions, and that it may perfectly be the case that the other canonical decomposition minimises the revision variance.

4.5. About Preadjustment Procedures

As mentioned in introduction, both programs embody a preadjustment procedure which consists mainly in correcting for calendar effect and for outliers, and in identifying a stochastic linear model of the Arima-type for the series under analysis. Part of the comparisons focused thus on that stage (see EUROSTAT, 1996a). If REGARIMA and TRAMO implement basically the same method for calendar effect corrections and close procedures for outlier detection and identification, some discrepancies could be found in the automatic model identification process. But the major discrepancy which could be pointed out concerned the computing time: processing a set of 358 series with different options, TRAMO has been found to be at the minimum 3 times faster than Regarima.

Given that the AMB-signal extraction derives the optimal filter from a stochastic linear model of the ARIMA-type fitted to the series under analysis, the quality of the decomposition is related to the capability of the outlier removing procedure to linearize time series which present nonlinearities. Planas (1997a) investigated that point, and a major finding of this study is that, provided the nonlinearities do preserve the white noise property of the innovations on the observed series, then: (i) outlier removing is effectively able to linearize time series which present nonlinearities; (ii) the optimal estimator is stable with respect to nonlinear mispecifications; (iii) the nonlinearities are most often assigned to the irregular component.

5. DEVELOPMENT OF AN INTERFACE FOR SEASONAL ADJUSTMENT

In addition to the methodological work, EUROSTAT is currently supporting the development of a software for seasonal adjustment. This software will embody both X12 and TRAMO-SEATS and will provide users with a friendly interface to these two programs. The product is developed first for EUROSTAT internal needs, but it will be made available to the public on request.

Environment-specific interfaces are already available: GAUSS and EXCEL interfaces for SEATS-TRAMO and X12 have been built at EUROSTAT, while D.Ladiray and K.Attal, INSEE, France, has developed an interface for SAS environment. The product in construction will be more powerful, since it is aimed at covering all the main tasks of statistical production in official institutes. The main functions will be: seasonal adjustment and trend extraction in large-scale and in detailed analysis, forecasting in large-scale and automatic analysis of data-irregularities. Large-scale procedures will allow the fully automatic treatment of sets of thousands of series, and input/output direct access to databases like Fame will be offered.

The main computations include all the possibilities of X12 and SEATS-TRAMO: pre-adjustment by outlier removing and calendar effect corrections, automatic model identification, forecasts, seasonal adjustment and trend estimation, diagnostic checking and analysis of decomposition accuracy. Besides the fully menu-driven package which will mask the syntax of X12 and of SEATS-TRAMO, some assistance including fully automatic treatment of problematic series will be provided to the users. Graphs and tables will facilitate the reading of the outputs, the comparison between several results corresponding to different options, and also the comparison between X12 and SEATS-TRAMO in practical cases.

The main appeals of that software will lie first in the application of applied time series techniques to massive sets of series, and second in the explicit consideration of the needs of production units in statistical institutions. A full description of the specifications can be found in EUROSTAT (1997b), while the computational analysis of the project is detailed in EUROSTAT (1997c). A beta version is planned for January 1998. The software host environment will be Windows NT.

CONCLUSION

Regarding methodological studies, there are still a large number of issues to be investigated. If some empirical investigations on revisions in preliminary estimators obtained with empirical and optimal filtering have been conducted (see EUROSTAT 1996b), the problem of long-term revisions in the AMB approach remains of particular interest. Further, the seasonal adjustment of sets of time series subject to balancing constraints is still an open question. More generally, important issues are related to the multivariate extensions of AMB approach and to seasonal adjustment in nonlinear situations. The decomposition of series characterised by bilinear and by ARCH patterns have been analysed in Maravall (1983) and in Fiorentini and Maravall (1995). These patterns could be completed by other types of nonlinearities with the perspective of an automatic treatment of nonlinear patterns in massive analysis of time series. Finally, economists have shown a renewed interest in the seasonal movements of macroeconomic series. For example, Miron and Beaulieu (1996) discuss how some information relevant for the knowledge of business cycles can be found in the seasonal fluctuations. An interesting problem for time series analysts is thus the design of statistical tools helping economists in drawing conclusions about possible relationships between seasonal fluctuations and business cycles.

Besides methodological studies and software questions, a training program has been set up. During 1997, two sessions of Training for European Statisticians have been devoted to seasonal adjustment methods with Agustin Maravall, Bank of Spain, as course leader. Also, an internal course on applied time series analysis has taken place. This internal course is delivered by C. Planas on the basis of a textbook written for the occasion (see Planas 1997).

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