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Experiences and Perspectives

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Seasonal Adjustment Procedures
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FOREWARD

This volume is a collection of papers discussed in the Committee on statistical instruments for short-term analysis, chaired by Prof. Domenico Piccolo, which has developed the SARA project: Seasonal Adjustment Research Appraisal[1]. The idea of considering the issue of seasonal adjustment (and on statisical techniques for treating short-term data that Statistical Institutes should adopt) dates back to 1996, and it was carried out in early 1997, few weeks after my appointment as Central Director for Institutions and Business Statistics.

Istat's proposal to conduct a new research project on this issue came in the wake of a long debate involving the scientific and academic world as well as public and private institutions dealing with statistical analysis for short-term data. Two important achievements marked this process: the DESEC project (1982-1985) and the three-year research of the Sis-Istat working group on "Short-term economic analysis" (1993-1995), which was completed with the meeting held on December 11-12, 1995. The outcome has been recently published in a volume of Istat Annals.

One of the key problems discussed has been the identification and removal of the seasonal component of time series, which represents one of the most outstanding aspects of short-term analysis and of the choice of the tools to carry out an adequate short-term appraisal of the economic situation. The above mentioned projects had adopted innovations in statistical methodology, in economic theories and information technology. For example, on completion of the DESEC project, Italian Institutions were recommended the adoption of the X11-ARIMA procedure, though the awareness of the advantages of model-based approach was spreading. In fact, its application was limited because user-friendly automated procedures were lacking.

In the early '90s TRAMO-SEATS (A. Maravall and V. Gomez) was an implementation of the model-based approach, while the new version of the X11-ARIMA, called X12-ARIMA, was based on an update of the filter-based approach, though adopting some typical concepts of the model-based approach. This is the scenario in which the Sis-Istat working group on "Short-term economic analysis" underlined the need of a synthesis between the two approaches, though model-based procedures seemed the key that official statistics should use in the field of seasonal adjustment.

In this context Istat established a scientific committee to work out suggestions and strategies to be used in the seasonal adjustment of Istat time series. Prof.

[1] Committee members: Simona Andreano, Fabio Bacchini, Giancarlo Bruno, Sergio Calliari, Mara Cammarrota, Anna Ciammola, Daniela Collesi, Marcella Corduas, Anna Di Filippo, Dario Focarelli, Pietro Gennari, Enrico Giovannini, Maurizio Maravalle, Aride Mazzali, Roberto Monducci, Alessandro Pallara, Carmine Pappalardo, Domenico Piccolo, Federico Polidoro, Mauro Politi, Tommaso Proietti, Alessandra Righi, Giovanni Savio, Alberto Sorce.

Domenico Piccolo was the chairman of the Committee and experts from the academic and scientific world were invited, as well as representatives from Istat, the Bank of Italy and other public and private bodies dealing with this issue.

Some key research fields were immediately specified and the Committee was divided into nine sub-committees to perform the following tasks: comparison of procedures, preliminary treatment of time series, identification of models underlying the time series, treatment of changing seasonality, assessment of diagnostics and revisions, experimenting with TRAMO-SEATS, experimenting with X12-ARIMA, software engineering, evaluation of needs resulting from EU regulations.

The sub-committees worked in 1997 and, at the beginning of 1998, on the basis of the progress made, a more detailed comparison between X12-ARIMA and TRAMO-SEATS was made. Thus, it was possible to develop a wider experimentation including some of the issues examined by the sub-committees. The Committee worked on the experimentation in the first half of 1998. Then it was thought that an international meeting would have been an event in which the Committee's results could have been discussed in a larger arena with Italian and foreign experts. The meeting was held at Istat on June 9-10, 1998, and the papers are published in this volume.

The debate was fruitful, even because foreign experts were ready to discuss their procedures. The results showed clearly the greater consistency of the model based approach to the problem of seasonal adjustment. Therefore, the Committee suggested the adoption of the TRAMO-SEATS procedure for the seasonal adjustment of Istat time series.

Istat has adopted this procedure since 1999. It was even decided to use it for the seasonal adjustment of short term indicators which had not been adjusted yet. These decisions were made to improve the quality of short term economic information in Italy, thus better meeting the needs of economic operators and scientific experts. Moreover, the Institute modified its organization, so that researchers in this field will remain in contact with structures similar to statistical institutes, such as Eurostat and other universities.

At the end of the work of the Committee, I thank, and on Istat's behalf, the Committee members and the institutions that supported us with their experts.

Special thanks goes to Mario Faliva (Catholic University of Milan), G. C. Tiao (Chicago University), Andrew Harvey (London University), Raoul Depoutot (Eurostat) who enthusiastically accepted to take part in the meeting and to David Findley (Bureau of Census of Washington) and Agustin Maravall (Bank of Spain), for their continuous contacts with the Committee during the progress of work and for their participation in the meeting, where they presented the results achieved with their procedures applied to a set of data prepared by the Committee.

Lastly, my personal and Istat's thanks to Domenico Piccolo, who chaired the scientific Committee, leading his activity with passion and experience. He offered his valued and generous contribution to the Italian scientific community and to the National statistical system.

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Central Director of Institutions
and Business Statistics, Istat

SEASONAL ADJUSTMENT RESEARCH APPRAISAL (SARA): FINAL STATISTICAL RECOMMENDATIONS OF THE SCIENTIFIC COMMITTEE

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1. Introduction

The SARA Project has been promoted by Istat during 1997-98 and has involved about thirty researchers from various Institutions: Universities (Roma "La Sapienza", Napoli Federico II, L'Aquila, Perugia, Verona), financial and research Institutions (Bank of Italy, Comit, Csream) and Istat itself. This research activity has been realized with the technical support of Istat and the generoııs cooperation of many academicians.

The main objective of the Project was to suggest a convenient seasonal adjustment procedure to the Italian Institutions which could be applied routinely on several thousands of economic, demographic and social time series, observed at different frequencies (quarterly or monthly). At the same time, the project intended to stimulate discussions, ideas, proposals and experiences about the analysis of the current economic conditions and, specially, of the main official business-cycle indicators.

In the past, other national research projects on seasonal adjustment were performed. We recall Giusti's Committee (1978-79), DESEC Project (1982-85), Sis-Istat Research Group (1992-95), which are the proof of a continuous interest of both public and academic Institutions towards the topic. This constant effort of Italian statisticians, motivated by the increasing need for updating the statistical procedures, produced several methodological and experimental results in the area.

One of the main issue, which has characterized the SARA Project as well as my previous experience, is the focus on the operative aspects of the proposals supported by a rigorous formal background. This concept has been a fundamental issue for the work done during this year. The methodological investigation and the empirical

We acknowledge the financial support of CNR, Murst and University projects in which the Author is involved

analyses were restricted exclusively to the main and recent procedures which could be included, with minor modifications, into the routine analyses of an official Institution (such as Istat) and extended to the other public and private operators.

2. General Features for a Seasonal Adjustment Procedure

A seasonal adjustment procedure should be able to produce unobservable components of a time series, which are accurate and stable, possibly by using full automatic options. The results should be presented with extensive comments to help interpretations. Hopefully, the underlying methodology should be understandable for a large number of users. The related software should be easy to implement and ready-to-use.

Obviously, most of the previous requirements are opposite and not attainable. Thus, an adequate procedure must balance these needs: the search for a perfect decomposition (which is theoretically impossible) and the requirements of the daily production of seasonally adjusted data in a statistical agency.

These objectives are not easy to achieve. There are statistical problems involved, but also some general constraints to take into account. For instance, we must consider the attitude of producers and users not to leave current seasonal adjustment procedures, the presence of adequate computational tools, the capability of a new proposal to be adapted to different environments, the presence in the output of sufficient information to help non-expert users to interpret and evaluate the quality of results, etc.

At present, Istat produces monthly some thousands of seasonally adjusted time series using X-11-ARIMA, following the main recommendations of the DESEC Project. A part from some isolated cases, no model-based adjusted series are published. Instead, as we already pointed out in the final remarks of the DESEC Project, the international Institutions are moving towards integrated procedures where the model-based approach is more applied than in the past.

Eurostat will soon request an increasing number of adjusted economic and demographic time series, concerning main indicators at several level of aggregation. Moreover, in some offices at Eurostat a model-based procedure is already working on a routine basis. Thus, a compelling need for Istat is to update the present procedure harmonizing its choices to those of many other European statistical agencies and, above all, gaining full support from Eurostat.

The general features of a seasonal adjustment procedure, that makes simple and immediate the interpretation of results to non-specialized users, can be summarized as follows:

1. It relies on well recognized statistical foundations.
2. It is fast and accurate.
3. It is able to handle extreme situations.
4. It provides good easy diagnostics and understandable outputs.
5. It has a good selection of default options.
6. It has a wide and clear documentation.
7. It is provided with a continuous software updating and assistance.

According to these general guidelines, the SARA Project considered the main statistical procedures currently in use in the majority of international and national statistical agencies, that is X-12-ARIMA and TRAMO-SEATS. The Project examined the related methodological issues and made an extensive empirical experience. The scientific contributions produced during this period adequately support the conclusions reported in this article. However, it is important to refer to them for specific issues and to find the statistical justifications of the general principles that we illustrate here.

Firstly, we wish to make explicit some assumptions that we adopted in the research and that, in the current literature, are often hidden or mixed with theoretical and empirical considerations. Since we believe that those assumptions influence in several ways the examination of the results and the final recommendations, we will make them clear at the beginning of the discussion.

• One should distinguish a *statistical procedure* (= a consistent set of sequential steps finalized to identify unobservable components in a time series) from a *statistical method* (= a tool, based on statistical theory, which reaches a specific objective by an optimization criterion).

In the seasonal adjustment context, statistical methods can still be improved and developed. However, the main statistical procedures available are well defined and, in the next future, we expect that they will resemble each other in a larger extent.

• Any seasonal adjustment procedure leads to a subjective solution depending on:

i) statistical foundations;
ii) restrictions imposed by data and their frequency;
iii) practical implementation requirements.

Thus, nobody can state, on an objective base, that a certain procedure must be adopted.

• The number of contributions relying on both methodological and empirical studies is so large that it is useless to develop a new general procedure without having considered, firstly, its formal implications. Similarly, it is pointless to perform extended experiments without taking into account methodological constraints and previous studies. Consistency with the definition of "procedures" and "methods" suggests to devote research and experience to "local" improvements which can effectively be added and tested in the current procedures. In fact, the statistical results in this area are so self-evident that it is surprising to find still people and agencies which use asymmetric filters, inefficient treatments of missing values, inaccurate and sub-optimal forecasts, deterministic trends for stochastic behavior, and so on.

• The best method (if this term has a common meaning for most of the users) should be implemented into an *effective* procedure. The problem we need to solve is complex. We do not need to provide a tool to a professional statistician to find the unobserved structure of a small number of time series. Instead, we need to implement a set of operational steps capable to achieve this objective many times, always in a convincing manner and in a simple way so that users can understand and use the results.

• Empirical experiences on a large number of real time series, which adopt a carpentry of indices in order to choose between procedures, are of pedagogical interest. Those studies should be encouraged before introducing a new procedure in a statistical agency. However, they do not provide any additional information to discriminate among procedures. This happens for many reasons:

i) each decomposition method is optimal with respect to certain properties. Thus, these theoretical findings can not be overcome by empirical experience;

ii) a procedure includes necessarily few steps (intervention analysis, preliminary transformations, missing values strategies, etc.) that are not primarily related to the decomposition problem, but that have a strong impact on the final results. Thus, the final comparison is a mixture of composite effects, some of them depending on the specific time series;

iii) the mechanism generating a time series could change in time. Then, a method can become more or less efficient, from an empirical point of view, depending on occasional circumstances.

• Any decomposition method includes a forecasting model (implicitly or explicitly) in order to reach an efficient evaluation of initial and final data. Thus, the performance of the procedure on current data (which are the most important information for short-term decisions) depends heavily on the correct choice of the forecasting method.

One of the main conclusion of the earlier discussion is that the knowledge of the stochastic generating process is fundamental for seasonal adjustment and represents the key issue for understanding the data. In this perspective, *ARIMA modeling is not an addition to the knowledge of the dynamics of a series but is the essential tool for both the decomposition and forecasting analyses.*

3. Results and Experiences of the SARA Project

The Committee has performed an empirical study on X-12-ARIMA and TRAMO-SEATS procedures using a representative set of economic time series chosen by Istat and related to the production and price indices, import and export series, data from economic expectation surveys, etc.

Then, the Committee has discussed the statistical criteria for the comparison of both the procedure and has pointed out the real problems concerning the choice and the implementation of a procedure for the decomposition of a large number of time series on a routinely basis.

In this respect, the Committee has not reached a definite and conclusive answer in favor of one of the two major competing procedures. However, several considerations, that we will explicit, induce us to *suggest Istat to move towards a model-based procedure, conditionally to some improvements in the actual software and to the establishment of a minimal task force of Istat researchers that should investigate the current issues of the seasonal adjustment problems within the harmonized framework developed by the European agencies.*

The papers produced by the researchers involved in the SARA Project represent a complete documentation of the different point of views on the procedures which emerged during the work. Difficulties in reaching a definite conclusion are again a proof of the intrinsic problems concerning unobservable components estimation and of the contrasting option between abstract modeling and operational needs.

However, a clear trend is slowly but unanimously coming out from researchers and users of seasonal adjustment procedures: a data-based procedure should be model-based. The model should be built efficiently within the procedure itself. In such a way, the formal aspects of the statistical analysis and the fidelity to the observed series are preserved.

In the following, we motivate the main implications of these choices.

◇ The search for unobserved classical components (trend-cycle, seasonality, noise) is meaningful if the observed time series has been generated by integrating a Gaussian stochastic process. Thus, *only the realization of a Gaussian ARIMA model, with no deterministic components, could be the input for a seasonal adjustment procedure based on a linear symmetric filters.*

The immediate consequence of this approach is the prominence of the preliminary treatments in both procedures. They look for the best transformations of the data and/or treatments of specific deterministic effects. The objective is to remove those components and submit as input to the decomposition procedure a genuine ARIMA realization. This fact simplifies filter identification, improving forecastability and statistical decomposition. In fact, it is quite evident that X-12-ARIMA and TRAMO-SEATS are substantially equivalent with respect to the initial steps that are performed, in both procedures, using the more recent statistical methods.

◇ The Committee experienced X-12-ARIMA and TRAMO-SEATS on a large number of economic time series. Although most of the results are rather similar in term of statistical implications, it is worth to emphasize the different impact from the point of view of the user:

i) X-12-ARIMA procedure is sufficiently stable to "local" modification since the central filters are based on the essential and recurrent features representing the majority of real economic time series;

ii) TRAMO-SEATS procedure should be applied by a standard user with "minor" modifications to the default options. In a model-based approach, significant alterations of the options can cause substantial modifications of the output that a non-expert user may not recognize.

Since these considerations lead to the usual balance between statistical efficiency and robustness, it is important to recognize that, in our experience, *both the procedures were efficient and robust* in most of the examined cases.

In atypical situations, a model-based approach is often preferable because is able to insert the specific features of the data in the model. However, to be honest, an experienced X-12-ARIMA analyst can cope with any data problem by choosing conveniently the options (among the increased number available) and identifying an ad hoc model.

4. ARIMA Modeling and Seasonal Adjustment Procedures

It is well known that, for linear Gaussian processes, there are mean-square optimal linear filters designed to extract well defined components which belong to the class of ARIMA models. Thus, it is extremely important to fit the "best" ARIMA models to the (transformed) time series.

In fact, both procedures rely on ARIMA models but with different purposes.

• The X-12-ARIMA procedure chooses a filter which implies a *fixed ARIMA model for central data.*

• The TRAMO-SEATS procedure chooses a filter implied by a *data-dependent ARIMA model.*

The procedures, however, often reach similar results in terms of decomposition. To justify the reasons of such empirical findings, we introduce the notion of *exchangeable ARIMA models.*

Given an observed time series, we are unable to detect the unique stochastic process which has generated that realization. Instead, it is well known that we can go through an iterative identification-estimation-testing cycle to build a convenient ARIMA model which is fully specified by a finite number of parameters. Since, we never reach the true model for a time series, it would be more correct to refer to the set of ARIMA model which are statistically coherent for the same data according to a fixed accuracy criterion. With respect to this criterion, the models in the set are completely exchangeable for the observed time series. There are no scientific or objective reasons to select one element belonging to that set a part from the convenience to use a decomposable structure, a simple or a convincing forecasting model. That justifies the strong similarity between the procedures:

• with reference to the TRAMO-SEATS procedure, previous considerations explain why starting from different ARIMA models the procedure applies the same filter by canceling out "similar" factors;

• with reference to the X-12-ARIMA procedure, they explain why a fixed ARIMA procedure is able to capture the essential features of the data by modifying the filter length.

These issues concern with the statistical aspects of ARIMA modeling. But in a seasonal adjustment, modeling is a part of a complex mechanism where a *fixed-filters* procedure becomes quite similar to a *data-dependent-filters* procedure.

• For the X-12-ARIMA procedure, data-dependent options modify fixed filters characteristics in order to satisfy some optimality criteria.

• For the TRAMO-SEATS procedure, data-dependent models determine filters directly related to the essential features of the series.

The problem of optimality of the filter is transformed in the problem of evaluating the "closeness" between the ARIMA model optimal for the data and the ARIMA model implied (or chosen) by the procedure. A criterion to measure such a feature is the AR-metric. This helps to discriminate among alternative decomposition filters since it compares their forecasting coefficients.

Given a threshold (chosen in function of the size of the data, the flexibility of the procedure, etc.), we will prefer the procedure whose distance to the data optimal model is less than the threshold. The suggestion would help in confirming the usefulness of X-12-ARIMA procedure and in discriminating among similar model-based decomposition filters. These criteria are not fully implemented in the current procedures but are well recognized in the statistical agencies and deserve general attention since they are simple, statistically based and consistent with the decomposition objectives.

From the point of view of modeling, the X-12-ARIMA is successful on most time series mainly for the great flexibility of the options and for the shape of the related implied linear filters. On the other side, the model-based approach implemented in TRAMO-SEATS relies on the direct statistical analysis of the data. In such a way it generates the best linear filters for the series and includes inferential results for the estimated components.

In this respect, the methodological dilemma:

i) we set a model for the data and for the observed components, allowing to the options the possibility to fit adequately to the series;

ii) we let the data produce the model and the filters for the components, should be solved in favor of the second approach, that is a model-based decomposition procedure.

The Committee strongly supports the TRAMO-SEATS procedure since it is a theoretically based approach with a wide and well experienced practice, it has an accurate implementation via efficient algorithms and includes confidence intervals for the components. However, it would agree to adopt it as a current procedure for Istat conditional to some modifications. That restricts, at the present, an immediate and simple implementation of the current version of the TRAMO-SEATS procedure.

5. Some Suggestions for the Implementation of the Procedures

The procedures examined by Committee would require some improvement of the current practice of seasonal adjustment. In some case, these modifications are essential for an effective implementation. Now, we examine these suggestions and critical issues for each procedure separately, adding, at the end, some remarks which are common for both of them.

☐ The X-12-ARIMA procedure should improve the graphical output including an high quality graphics within a wide available environment. This is fundamental for single users and statistical agencies who need to check very quickly the quality of the seasonally adjusted series. Most of the diagnostics could and should be re-formulated in a graphical environment.

The X-12-ARIMA procedure should include the evaluation of the AR-distance between the ARIMA model implied by the observed time series and the ARIMA model implied by the adopted filter. Such distance provides a measure of the feasibility of the procedure and, in the opinion of the Committee, will confirm, in many cases, the substantial robustness of the procedure. Statistical inference for such distance have been proposed and extensive evaluations are in progress.

☐ The TRAMO-SEATS procedure shows some weakness in the choice of the initial data transformation. It tends to over-estimate of the logarithmic transformation, also without a real need. The pre-test should be made robust and more efficient. Since choosing a preliminary transformation modifies the type of the implied decomposition, this step should be improved in short time.

The TRAMO-SEATS procedure fits the Airline model to a number of time series that seems too large compared to the ad-hoc modeling. When this happens there are no statistical reasons to prefer a model-based approach with respect to the X-12-ARIMA procedure. Thus, if a model-based procedure wishes to claim a statistical superiority, it needs to confirm its real flexibility in modeling decomposition. On the other side, if most of the economic series behave according to the Airline-mechanism, than there are no pragmatic reasons to leave a previous, simple and more experienced procedure. This point includes philosophical aspects of modeling and practical issues in the statistical testing which are not stressed enough by those who support the model-based approach. However, they represent critical issues for adopting the TRAMO-SEATS procedure.

The TRAMO-SEATS procedure output is still research-oriented. Instead, statistical agencies and users need a very simple user-oriented output, with few information which can lead "non-expert" people to correct decisions.

The TRAMO-SEATS procedure is the final product of years of high level individual research which is continuously updated. At present, it needs to become a commercial product. It should be updated regularly and interfaced with other main software procedures which usually are in use in large Institutions, such as Istat. Regular assistance and software maintenance should be provided.

Finally, we wish to draw the attention on the fact that a simple four-window graph showing series, kernel histogram, estimated global autocorrelation and smoothed spectrum is so revealing that should be always requested as a standard output of preliminary analysis for the observed series! Still now none of the two procedures seems to accept this simple and revealing indication.

6. Concluding Remarks

The previous discussion and moreover the technical papers prepared by the SARA Scientific Committee suggest some final considerations and recommendations. They propose to Istat a definite choice which is conditional to some internal and external requirements.

The Committee suggests:

i) to move towards a model-based procedure as TRAMO-SEATS, although the current software needs some improvements in the analysis and presentation as well as in the manual accompanying the software and in the organization of regular maintenance and assistance;

ii) to establish at Istat a task force of researchers for regular updating of the approach, for modeling purposes, for the additional software implementation, for the harmonization and comparison of the internal seasonal adjustment strategies with the European counterparts;

iii) to save the great experience in terms of analysis and interpretation arising from the use of procedures with pre-determined filters since they still provide a benchmark for most of economic and social time series. If possible, for a short time both procedures (X-12-ARIMA and TRAMO-SEATS) should be applied to a selected subset of time series for dynamic comparisons in order to improve the experience of users.

Finally, the Committee suggests to inform adequately public opinion and mass-media about the non-technical aspects implied by the introduction of a new seasonal adjustment procedure at Istat.

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The Results of SARA Committee
(Seasonal Adjustment Research Appraisal)

FIRST PART

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PROBLEMS OF PRELIMINARY ANALYSIS IN SEASONAL ADJUSTMENT OF TIME SERIES

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Introduction

The whole procedure of seasonal adjustment of time series states that, before the real adjustment of the seasonal component, a stage of so-called "pre-adjustment" has to be adopted. This stage is divided into two parts:

1) outlier detection and correction;
2) adjustment for the calendar influence on the variables represented as time series (trading day).

1. Outlier

The outliers of a time series are those extreme values caused by historic events relating neither to the trend nor to the seasonal component of the time series. For example, an outlier can be demonstrated by a marked fall of the index of industrial production caused by a slowing down of a company's production output located in an area in which an unexpected strong snow fall made the circulation of people and goods difficult.

The detection and removal of outliers is important because it prevents the negative influence of the latter on the estimate of the components of time series and particularly the seasonal component. Moreover the detection of outliers allows:

1) to reflect more on the nature of the time series and on the trend of the phenomenon that it describes, and
2) to facilitate the definition of a forecast model and to improve its forecasting capacities.

It should be stressed that the outlier treatment is an a priori procedure improving the estimate of seasonal fluctuations in order to arrive at a seasonally adjusted series which still contains the whole initial information. That is, the leaps observed in the original series must be observed also in the seasonally adjusted series.

In accordance with the outlier definition of Chen, Liu and Hudak (1990), there are three main categories of outliers:

1) Additive outlier (AO) is an event that affects the series only sporadically and is caused by unusual events such as strikes or bad weather conditions. In this case the time series shows an extreme value distant from the contiguous values;
2) Transitory change outlier (TC) is caused, for example, by interventions of economic policy which influence the economic process described by the time series. In this case the original series shows a high growth (or fall) for a certain period in which the values are maintained and then decrease more or less slowly at the end of the intervention of economic policy that caused the jump in the series;
3) Level shift outlier (LS) is an event that affects a series at a determined time and after such become permanent: the graph of the time series shows a marked step. An example of level shift outlier is given by the qualitative innovation in the productive process of a product that causes a growth to an upper level which then becomes permanent.

In figure 1 is an example of an additive outlier (AO). The industrial production of chocolate is a typical seasonal phenomenon. During the last four months of the year there is a high level of production since this is the period before Christmas. In November 1994 there was a flood in the Italian region Piedmont, where some large confectionery producing companies are situated, and for this reason the production of chocolate in Italy fell suddenly and strongly and after one month grew again.

Fig. 1 – Index of industrial production - Production of chocolate

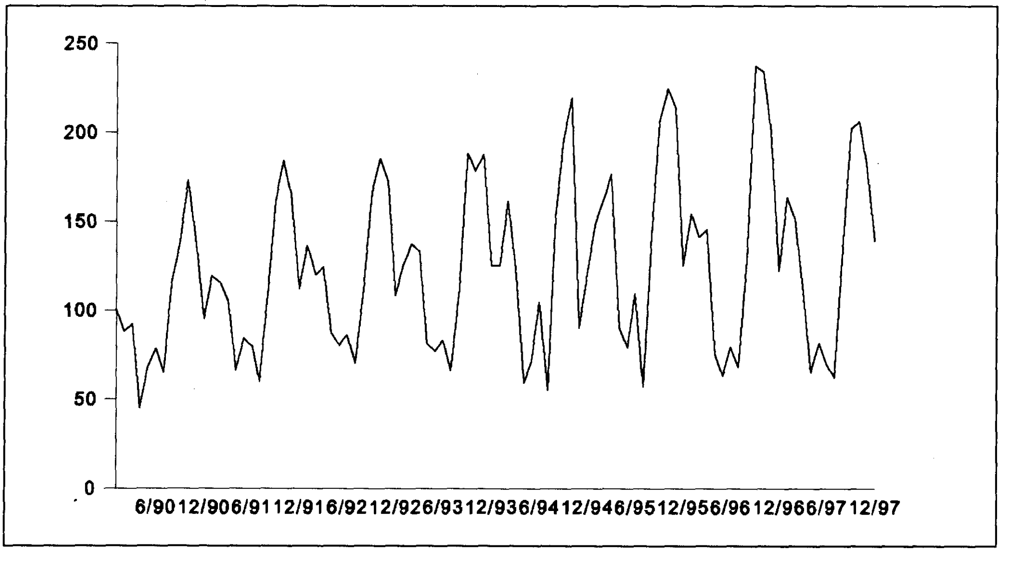


Figure 2 shows the index of industrial production of cattle slaughtering. At the end of 1995 the so-called "mad cow syndrome" occurred and during that period the consumption of meat fell considerably. The consequence of this was a decrease in the activity of cattle slaughtering from February 1996 to July 1996. The change of the level of the time series (TC) was temporary and it modified the trend of constant light growth.

Figure 3 shows the index of mining of lignite. Since 1994 the level of the index has undergone a considerable decrease because this material has been superseded by others qualitatively more profitable. In the time series a step can be observed (LS) and the low level reached remains constant for the subsequent period.

Fig. 2 – Index of industrial production - Cattle slaughtering

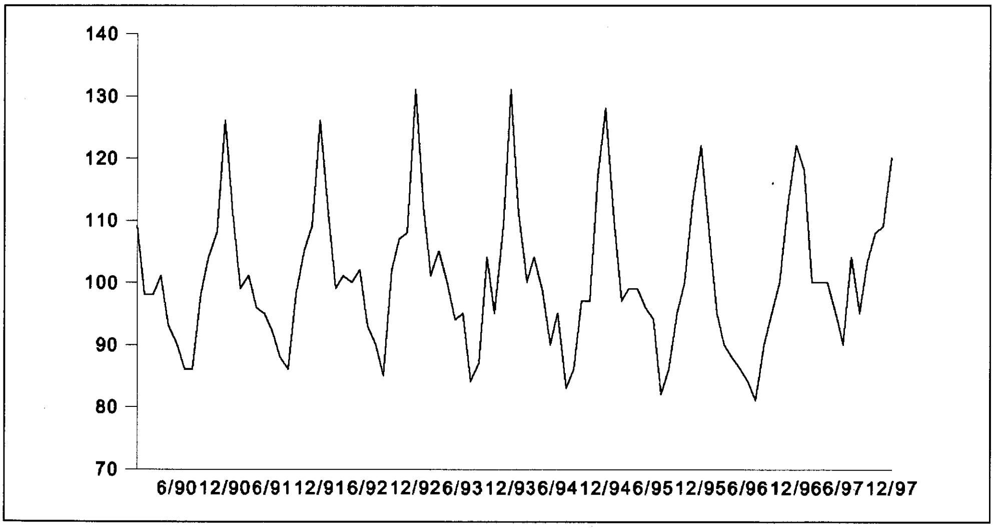
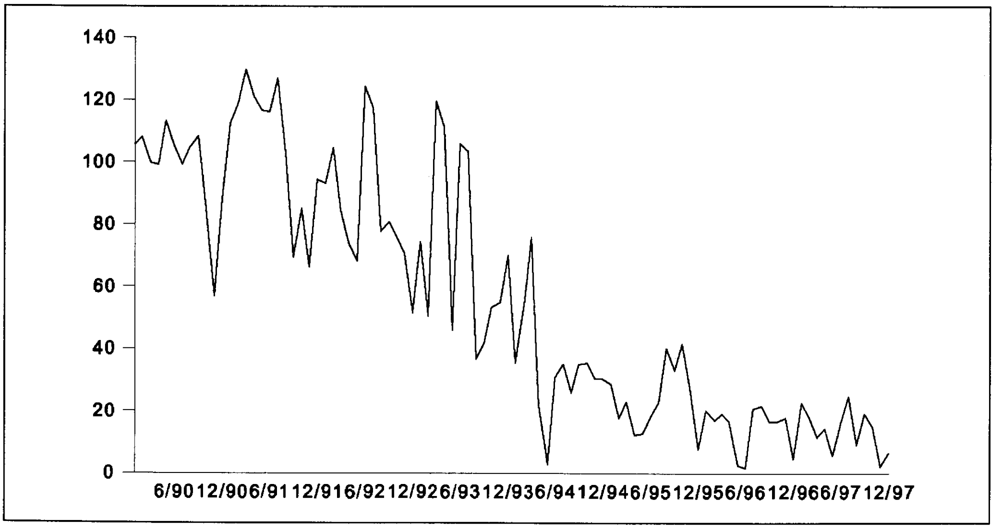


Fig. 3 – Index of industrial production - Mining of lignite



The detection and correction of an outlier can be expressed as the solution of the following equation

$$Y_t - y_t = a\; b(H)\; F_t(T)$$

where Y_t is the value of the observed series at time t

y_t is the value of the corrected series at time t

a is the amplitude of the outlier

$F_t(T)$ is a function such that is 1 for $t=T$ and 0 for $t \ldots T$

$b(H)$ is a determined lag.

The unknown quantities to be estimated in the equation are T, the period in which the outlier is detected, the type of $b(H)$, its function and its amplitude a.

For detecting and correcting time series outliers, regression techniques such as those proposed by Chen and Liu (1993) or by Chang, Tiao and Chen (1988) can be applied. The detection of outliers should also be used for making considerations regarding the trend of the phenomenon described by the time series. That is, it can be suggested that the results of this pre-adjustment should be verified by an expert of the variable to be analysed.

Moreover, it is preferable that the treatment of outliers should be made at the highest possible level of disaggregation, because the aggregate series could represent synthesis of different trends of the elementary series that compensate each other.

Both the methods of seasonal adjustment TRAMO-SEATS (Maravall and Gomez, 1996) and X-12-ARIMA (Findley, Monsell, Bell, Otto and Chen, 1998) include in their calculation routines several options that satisfactorily solve the problem of detection and correction of the different outliers.

2. Trading Day

Monthly and quarterly time series are influenced also by calendar effects (Trading Day effects). When values referring to different periods are to be compared it is important to consider how many public holidays there were (there are also moving holidays like Eastern), what is the frequency of the different days of the week and what is the length of the different months. To make an adjustment to consider all these aspects involves making a standardization, which facilitates homogeneous comparisons and thus leads to the adjustment of the seasonal component.

The so-called "proportional" calculation method for the trading day effects consists in multiplying the raw data of a given month by a coefficient equal to the ratio between the number of working days of a reference month (generally the average of the base year) and the number of the working days of the month. This method can be refined considering the type of production cycle:

- continuous when the plants run non-stop throughout the year (steel, electricity etc.),
- discontinuous (for the majority of the industries) when the activity of the plants run only in a part of the week (Istat, 1996).

The proportional method gives a proxy of the trading day effects valid only in the case in which the capacity utilization of the plants is the highest, that is one day more means a proportional increase in production. However, when the capacity utilisation of the plants is lower the method produces an overcorrecting of the raw data and provides biased data to be than seasonal adjusted.

Better results for correcting trading day effects can be obtained by methods based on regression. There are two main possibilities: regression on the irregular component and regression on the original series.

The regressors can be six (one for each working day and one for the week-end and holidays), or only one (for the distinction into working day or week-end plus holiday). The first possibility bring a risk of multicollinearity, that is sometimes Monday could have a negative influence on industrial production.

These two methods, TRAMO-SEATS and X-12-ARIMA, include several options to adjust the trading day effects: i.e. correction for February of Leap Year, removal of the different length of the months effects, test for verifying if there is a trading day effect, the possibility to choose the number of days contiguous to Eastern (generally eight) in which the variable to be seasonally adjusted is influenced and correction for the Labour Day and Thanksgiving/Christmas holidays.

However, there is something missing in these two methods that could be implemented, namely the availability of a test to ascertain the more convenient number of regressors. This test could be very useful to avoid repeating several trials to find the option leading to the best results.

For testing the correction of trading day effects it is also possible to use spectral analysis on the outlier cleaned irregular component (Cleveland and Devlin, 1980).

There is however an inherent flaw in the correction made by regression methods in that there are problems for considering the "moving holidays", i.e. holidays that occur during normal working days. In these cases the results of the correction could be biased. The program TRAMO-SEATS offers the possibility to add, in an external file, the information regarding the holidays to be deducted by the number of working days if they do not occur on Saturday and Sunday (case of one regressor), or if they do not occur on Sunday (case of six regressors). On the other hand, the program X-12-ARIMA considers only the options concerning Eastern, Labour Day and Thanksgiving/Christmas Days.

Three other problems should also be taken into account:

1) the holiday calendar varies sometimes from country to country and can also vary in a country between the different Regions;
2) there is also the so-called "bridge effect" which occurs when companies have the possibility to shut down (considering, for example, industrial production companies) also during the days contiguous to the holidays occurring on one day between Mondays and Fridays. It is supposed that these companies work also in these days when the economic trend is positive and shut down when the demand is low. Of course, the decision to close is related to the single policies of the different firms;
3) Saturday could also be a working day.

It is clear that each of these aspects has an influence on the trading day effect and that if there was more information available relating to the consistency of these "special effects" the quality of the correction could be improved.

An attempt to consider these aspects can be made by estimating the real working days companies worked (Politi, 1993). Istat leads a monthly inquiry into industrial production that also includes information about the number of days actually worked monthly by each company. This information gives a measure of the intensity of the production and could be used to improve the correction of trading day effects leading to regressions with better results.

The table below illustrates the results of some seasonal adjustments: the TRAMO-SEATS program was used (included in an Excel Macro written by Bjorn Fischer for Eurostat) on the series of industrial production for Italy, total industry (IPIGENGT), consumer goods (IPICONGT), capital goods (IPIINVGT) and intermediate goods (IPIINTGT).

It is possible to see that, by using automatic procedures (RSA=4 or RSA=6) there are several outliers and the results of the diagnostic tests are not satisfactory, since the data of August are often detected as outliers. However, the trading day correction made using only one regressor leads to better results. This can be ameliorated using a "non automatic" choice of the parameters and particularly using an additive model. This applies for both series of the total industry (IPIGENGT) and the index of consumer goods (IPICONGT); nearly all outliers disappear and the correction of trading day can be better achieved by using only one regressor.

3. Conclusions

With regard to the treatment of outliers both the seasonal adjustment methods TRAMO-SEATS and X-12-ARIMA lead to good results for the detection and removal, but it is necessary to stress that on the outliers placed at the end of the time series, these values are the most difficult to be detected and therefore can negatively influence the procedures of seasonal adjustment. For this reason they have to be tested taking their economic sense also into consideration.

With regard to the correction of trading day effects, only TRAMO-SEATS offers a significant option, i.e. the possibility to consider the "moving holidays" that influence the calendar. Both methods could be implemented by including a test for deciding the number of regressors to be used.

With regard to the procedures of pre-adjustment it appears to be unsuitable to use the completely automatic option. However, considering the large amount of time series that a Statistical Agency has to seasonally adjust, it is necessary, at least once at the beginning of the year, that the different options should be tested to detect the possible changes.

The possibility to include this information, when available, in the calculation routines, on the real working days, could surely improve the results of the seasonal adjustment methods.

Series	Model	Ljung-Box	Box-Pierce	Normality	Decomposition model	Easter corr.	Trading day	Outliers
RSA=4 (test initial transformation, correction AO, LS ad TC, automatic estimate of model, test Eastern effects, test trading day using 1 regressor)								
IPIGENGT	(0,1,1)(0,1,1)	33,96	12,53	0,8547	MULT.	YES	YES	AO(8 1984), AO(8 1995),
IPICONGT	(0,1,1)(0,1,1)	27,29	12,01	8,905	MULT.		YES	TC(8 1984),
IPIINVGT	(0,1,1)(0,1,1)	14,56	4,79	5,7	MULT.		YES	AO(8 1992), AO(8 1995), AO(8 1984), AO(8 1988), TC(1 1987),
IPIINTGT	(0,1,1)(0,1,1)	25,03	4,63	4,28E-02	MULT.	YES	YES	AO(8 1984), AO(8 1995), TC(12 1994), AO(8 1990),
RSA=4 (test initial transformation, correction AO, LS and TC, automatic estimate of model, test Eastern effects, test trading day using 6 regressors)								
IPIGENGT	(0,1,1)(0,1,1)	41	14,22	6,079	MULT.	YES	YES	AO(8 1984),
IPICONGT	(3,1,1)(0,1,1)	100,8	31,75	1,221	MULT.			No Outliers
IPIINVGT	(0,1,1)(0,1,1)	19,54	4,72	19,4	MULT.		YES	AO(8 1992), AO(8 1995), AO(8 1984),
IPIINTGT	(0,1,1)(0,1,1)	25,82	5,12	0,1175	MULT.	YES	YES	AO(8 1984), AO(8 1995), TC(12 1994) , AO(8 1990),
Additive model, correction of Eastern effects, correction of trading day using 1 regressor								
IPIGENGT	(0,1,1)(0,1,1)	30,75	6,75	0,301	ADD.	YES	YES	No Outliers
IPICONGT	(0,1,1)(0,1,1)	23,32	4,45	0,281	ADD.	YES	YES	No Outliers
IPIINVGT	(0,1,1)(0,1,1)	20,13	0,84	3,058	ADD.	YES	YES	TC(11 1995) ,
IPIINTGT	(0,1,1)(0,1,1)	37,23	9,2	1,177	ADD.	YES	YES	No Outliers
Additive model, correction of Eastern effects, correction of trading day using 6 regressors								
IPIGENGT	(0,1,1)(0,1,1)	35,56	8,31	0,13	ADD.	YES	YES	No Outliers
IPICONGT	(0,1,1)(0,1,1)	27,54	5,63	0,1866	ADD.	YES	YES	No Outliers
IPIINVGT	(0,1,1)(0,1,1)	16,56	0,71	2,205	ADD.	YES	YES	No Outliers
IPIINTGT	(0,1,1)(0,1,1)	40,06	10,23	1,047	ADD.	YES	YES	No Outliers

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SEASONAL ADJUSTMENT OF INDUSTRIAL PRODUCTION ORDER AND TURNOVER TIME SERIES BY TRAMO-SEATS AND X-12-ARIMA

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1. Introduction

To solve the problem of seasonal adjustment of economic time series, we can use one of the many methods and procedures that the statistical research has built mainly during the last decades. Neverthless, two procedures are particularly appealing for their logical basis and for the richness of their options: they are TRAMO-SEATS (due to Maravall A., Gomez, 1994) and X-12-ARIMA of the Bureau of Census.

In this paper we experiment the above mentioned procedures on time series concerning indices of industrial production, orders and turnover[1]. The main objective is to show the results and to compare the seasonal adjusted time series.

We anticipate that the comparison is not an easy task because of the differences in theoretical basis of the procedures and also in the input and output options.

As it is well know the procedure TRAMO-SEATS is a *model- based* one. It means that the linear filters for the estimation of the unobservable seasonal trend and irregular noise components are univocally deduced from the fitted invertible ARIMA model. Under the assumption of normality of the noise as well as under some restrictions on the component models, the procedure yields the canonical decomposition. The canonical decomposition maximizes the variance of the noise making the seasonal and trend components as deterministic as possible, remaining consistent with the information in the observable series (Hillmer et al., 1982).

The effectiveness of the decomposition depends on the fitted ARIMA model, so the linearization of the series done by TRAMO is of crucial importance. The linearization involving tranformation and removal from the series of some deterministic components such as outliers and calendar effects, homogenizes the series and makes

[1] We would like to thank Istat for providing us with the used economic time series and for supporting the research.

more easy its representation by linear models. TRAMO-SEATS furthermore replaces the eventually not decomposable ARIMA model with the best approximated decomposable one (Piccolo D., 1984).

The X-12-ARIMA seasonal adjustment procedure is an enhanced version of the X-11 Variant of the Census Method II (Shiskin, Young & Musgrave, 1967) and of the X-11-ARIMA/88 (Dagum E., 1988). The procedure includes a variety of new tools to overcome adjustment problems but it still retains its feature of *ad hoc* decomposition.

The new RegARIMA models are built for estimating various trading day effects and holiday effects and to extend the series with forecasts and backcasts in order to improve the seasonal adjustments of the most recent and earliest data.The components neverthless are estimated by moving averages unrelated to the seasonal ARIMA model of the series.

In sections 2 and 3 we report the results obtained by the two procedures. In section 4 we propose some tools to compare adjusted time series. Section 5 concludes the article. Appendix displays all the graphical representations.

2. The Seasonal ARIMA Models

We considered the following montlhy seasonal series:

A. *Turnover index* (1985.01 – 1996.12)

1. IFACONGN = turnover general index – national consumption goods
2. IFAINVGN = turnover general index – national investment goods
3. IFAINVGT = turnover general index – total –investment goods
4. IFAGENGE = turnover index – foreign

B. *Order index:*

1. ICOGENGT = general index of the orders consistency – total (1985.01-1996.12)
2. IORGENGT = general index of orders – total (1991.01 – 1996.12)

C. *Industrial production index* (1981.01 – 1996.12)

1. IPIGENGT = general index
2. IPIINVGT = industrial production index – investment goods
3. IPICONGT= industrial production index – consumption goods
4. IPIINTGT= industrial production index – intermediate goods
5. IPIODMGT= industrial production index – means of transport
6. IPIODJGT= industrial production index – metal products and manufacture
7. IPIODAGT= industrial production index –foodstuffs, beverages and tobacco
8. IPIODBGT= industrial production index – textiles and clothing

Seasonal adjustment has been performed either by TRAMO-SEATS or X-12-ARIMA using prevalently default input options, the only exceptions being the experimentation of RSA=4, RSA=6, RSA=8 by TRAMO-SEATS and the experimentation by X-12-ARIMA of an additive or multiplicative model with or without log transformation.

Table 1 reports some results of the linearization, identification and estimation obtained by the procedures. The meaning of heading columns is as follow:

- SERIE = processed time series

- PROC = procedure TRAMO-SEATS (TS) or X-12-ARIMA (X12) ;
- OPT = options: RSA=8, RSA=6, RSA=4; A= Additive model, M= Multiplicative model,
- LOG = log transformation (Y)
- TD = trading- day effect (Y)
- EA = easter effect (Y)
- OUT = number and type of outliers (AO= additive outlier, LS = level Shift, TC = transitory change, IO= innovative outlier)
- MODEL = the fitted seasonal ARIMA model (eventually the approximated ones*)
- LB= Ljung –Box text for residuals.

Table 1 shows only a small portion of the output of the programs. The procedures provide total and partial autocorrelation functions, many test on residuals, spectral density functions. The goodness of fit is quite always satisfactory. Only IPIGENGT shows a value of the Ljung-Box test greater than the critical one ($\chi^2_{\alpha=.05;v=22}$ =33.924). Furthermore X-12-ARIMA can't find in its model set a model for the series IPIINTGT.

The programs also identify and estimate too many outliers for IPIODMGT and IPIODBGT so their models seem less reliable.

Tab. 1 – Model identification by TRAMO-SEATS and X-12-ARIMA

SERIES	PROC.	OPT.	LOG.	TD	EA	OUT	MODEL	L.B. TEST v= 22
IFACONGN	TS	RSA=8	Y	Y	-	1 AO	(011)(011)	19.20
	X12	M	Y	Y	-	-	(011)(011)	18.89
IFAINVGN	TS	RSA=8	Y	-	-	2 AO; 1 LS	(210)(011)	21.41
	X12	M	Y	Y	Y	2 AO	(011)(011)	30.13
IFAINVGT	TS	RSA=8	Y	Y	-	-	(011)(011)	28.36
	X12	M	Y	Y	Y	1 AO	(011)(011)	20.94
IFAGENGE	TS	RSA=8	Y	Y	Y	-	(011)(011)	19.93
	X12	M	Y	Y	Y	-	(011)(011)	25.07
ICOGENGT	TS	RSA=8	Y	-	-	-	(110)(011); (011)(011)*	32.67
	X12	A	-	-	-	-	(022)(011)	25.45
IPIINVGT	TS	RSA=6	Y	-	-	4 AO	(210)(011)	30.97
	X12	A	-	Y	Y	-	(011)(011)	16.59
IPIGENGT	TS	RSA=6	Y	Y	Y	2 AO	(011)(011)	38.31*
	X12	A	-	Y	Y	-	(212)(011)	26.75
IPICONGT	TS	RSA=8	Y	Y	Y	1 TC	(011)(011)	29.73
	X12	M	Y	Y	Y	1 AO	(011)(011)	27.61
IPIINTGT	TS	RSA=4	Y	-	-	3 AO; 1 TC	(011)(011)	26.04
	X12	A	-	-	-	-	-	-
IPIODMGT	TS	RSA=4	Y	Y	-	9 AO; 1 LS;1 TC	(110)(011)	13.90
	X12	M	Y	Y	-	9 AO	(011)(011)	17.14
IORGENGT	TS	RSA=4	Y	Y	-	1 AO; 1 TC	(311)(011)	23.75
	X12	A	-	Y	-	1 AO	(011)(011)	27.80
IPIODJGT	TS	RSA=4	Y	Y	-	1 AO	(200)(011)	23.29
	X12	M	Y	Y	-	2 AO	(011)(011)	12.26
IPIODAGT	TS	RSA=4	-	Y	Y	1 LS	(100)(011)	17.93
	X12	M	Y	Y	-	-	(011)(011)	22.29
IPIODBGT	TS	RSA=4	Y	Y	-	5 AO	(011)(011)	26.32
	X12	A	-	Y	-	-	(011)(011)	26.91

3. Seasonal Adjustment by TRAMO-SEATS and X-12-ARIMA

The trend-cycle, seasonal and noise components are unobservable, so they have to be estimated by a decomposition algorithm using the observed time series $y^T=(y_1, y_2, .. \; y_t \ldots y_T)$ and assuming a compositional rule (additive or multiplicative).

The procedure TRAMO-SEATS using the finite realization y^T provides the linearized series, identifies and estimates an invertible ARIMA model and, under the assumption of normality, defines MMSE estimator of the component i, that is x_{it}, by conditional expectation (Maravall A., 1994):

$$x_{it|T} = E(x_{it} | \, y^T).$$

When t<T, conditional expectation provides the estimator of past component; when t=T the concurrent estimator; when t>T the (t-T) steps ahead forecast and when $T \rightarrow \infty$ the final estimator $\hat{x}_{it}$.

The conditional expectations E(.|.) admit the representation as Wiener-Kolmogorov (WK) filters. WK filters are centred on t, symmetric of infinite extension and stable even if the starting ARIMA model is not stationary. That is due to the invertibility of the moving average component in the ARIMA model. Components estimation is made on processing the observed series extended by forecasts and backasts, by WK filters. We can put the components forecast error in the form:

$$e_{it|T} = (x_{it} - \hat{x}_{it}) + (\hat{x}_{it} - x_{it|T}) = d_{it} + d_{it|T} \; ;$$

d_{it} is the error in the final estimator; $d_{it|T}$ the revision error in the preliminary estimator. The errors are indipendent.

The output of the procedure TRAMO-SEATS displays:

- ARIMA models,
- component autocorrelation functions,
- component pseudo-innovations,
- standard errors of final estimators,
- revisions in the concurrent estimators,
- component forecast,
- final component estimates,
- component standard errors.

Coherently with the model-based approach, these items make up a rigorous description of the model-based decomposition. Unfortunately no synthetic indicator of the goodness of the adjustment is proposed.

Table 2 shows some useful figures to appreciate the decompositions. More informations can be obtained from the graphical representations in the Appendix. In Tab. 2 the trend and seasonal component estimators, the maximally smoothed components in the canonical decomposition, show a very small variability, so that the estimates are reliable.

The X-12-ARIMA is a versatile seasonal adjustment program that seeks adjustments with properties appropriate for the analysis being undertaken. The X-12-

ARIMA performs seasonal adjustment by linear moving-average filters. Preliminarly to decomposition the program fits a RegARIMA model useful for calendar and outliers estimation and for forecast and backcast. The program also tests the presence of stable and moving seasonality. After the adjustment the program verifies the presence of residual seasonality in the adjusted component.

The procedure gives great importance to components stability analysis because such a property involves the validity of the estimates. Traditional diagnostics provide a set of 11 statistics M1-M11 and a summary statistic Q that are defined in such a way that values larger than 1.0 suggest that the adjustment is unacceptable. Q is a weighted average of M1-M11. Sliding- spans analyses (Findley, 1990) provides new kind of evidence on the stability.

Table 3 presents some tests that show us the validity of all the performed decompositions. Furthermore the graphs in the Appendix from fig. 1 a, b, c, d, to fig. 14 a, b, c, d give us more information[2].

Tab. 2 – Standard Errors of trend and seasonal final estimators and 95% confidence intervals concerning final and concurrent seasonal estimators

SERIES	S.E. FINAL ESTIMATOR		95% CONFIDENCE INTERVAL FINAL SEASONALITY ESTIMATOR		95% CONFIDENCE INTERVAL CONCURRENT ESTIMATOR	
	Trend	Seasonality	Lower Lim	Upper Lim.	Lower Lim	Upper Lim.
IFACONGN	.00675	.00948	98.16	101.9	97.49	102.6
IFAINVGN	.01251	.01607	96.90	103.2	95.76	104.4
IFAINVGT	.01396	.01407	97.28	102.8	96.14	104.0
IFAGENGE	.01255	.01098	97.87	102.2	96.98	103.1
ICOGENGT	.00553	.00464	99.09	100.9	98.71	101.3
IPIINVGT	.01233	.01570	96.97	103.1	95.87	104.3
IPIGENGT	.00809	.00795	98.45	101.6	97.85	102.2
IPICONGT	.00784	.01109	97.85	102.2	97.11	103.0
IPIINTGT	.00767	.00679	98.68	101.3	98.13	101.9
IORGENGT	.00893	.01030	97.99	102.0	97.06	103.0
IPIODMGT	.01657	.01323	97.44	102.6	96.38	103.8
IPIODJGT	.01856	.01788	96.54	103.6	95.24	105.0
IPIODAGT	.05119	.01107	97.83	102.2	97.19	102.9
IPODBGT	.01295	.01118	97.83	102.2	96.99	103.1

4. Comparisons between Adjusted Time Series

Let y_t the observed time series, let $y^A{}_{1t}$ and $y^A{}_{2t}$ the time series seasonally adjusted respectively by TRAMO-SEATS and by X-12-ARIMA. Then we intend to investigate the differences between $y^A{}_{1t}$ and $y^A{}_{2t}$.

To start we have reprocessed all the adjusted series by TRAMO-SEATS and by X12-ARIMA. No evidence of stable or moving residual seasonality is anywhere detected.

We have also computed the correlation coefficient r on the adjusted time series finding values very close to one with the exception of the series IPIODBGT (Tab. 4).

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[2] We thank Zuccolotto Paola for her help in the graphic section.

These results, combined with the evidence of graphical analysis, indicate a great similarity between adjusted time series so that it seems natural the following question: are some relevant informations the user needs for its decisions also shared by the couple (y^A_{1t}, y^A_{2t})?

To answer the question, we consider two points of view:

1. the discordances in sign of the relative variations between adjusted time series,
2. the stochastic structure of the adjusted time series.

With reference to the first point we define the relative variations of the adjusted series as:

$$\Delta y^A_{1t} = (y^A_{1t} - y^A_{1t-1}) / y^A_{1t-1}$$

$$\Delta y^A_{2t} = (y^A_{2t} - y^A_{2t-1}) / y^A_{2t-1}$$

The indicator δ_t of a discordance at time t is :

$$\delta_t = \begin{cases} 1 \; \textit{if} & \textit{sign}\,(\Delta y^A_{1t}) \neq \textit{sign}\,(\Delta y^A_{2t}) \\ 0 & \textit{otherwise} \end{cases}$$

so, the number of discordances is $d = \sum_{t=1}^{T-1} \delta_t$ and the rate of discordance is

$$D = d/(T-1)$$

Tab. 3 – Seasonal Adjustment by X-12-ARIMA (A=Accepted)

SERIES	F -TEST STABLE SEASONALITY	M1-M11 TEST	Q- TEST	REVISION ERROR CONC-FINALE: AVERAGE (1993-1996)
IFACONGN	0.43	0.25 A	0.28 A	0.63
IFAINVGN	0.64	0.23 A	0.26 A	1.15
IFAINVGT	0.61	0.18 A	0.20 A	1.11
IFAGENGE	0.15	0.21 A	0.23 A	0.60
ICOGENGT	0.09	0.31 A	0.34 A	0.24
IPIINVGT	0.15	0.33 A	0.37 A	0.94
IPIGENGT	0.13	0.68 A	0.75 A	0.66
IPICONGT	0.27	0.47 A	0.52 A	0.58
IPIINTGT	0.11	0.57 A	0.63 A	0.68
IPIODMGT	5.73	0.22 A	0.24 A	0.89
IORGENGT	0.56	0.17 A	0.18 A	
IPIODJGT	0.94	0.31 A	0.35 A	0.39
IPIODAGT	0.35	0.66 A	0.72 A	0.66
IPIODBGT	4.33	0.47 A	0.52 A	0.75

Table 4 shows the number and the rate of discordances for each couple of adjusted series and couple of trend. The rate of discordance is very high in many cases so that informations provided by adjusted series are substantially different. The rate of discordance between trends on the contrary is considerably lower. So, from the point of view of the relative variations, trend component seems preferable to the seasonal adjusted one. To verify the second point we use the variable $D_t = y^A_{1t} - y^A_{2t}$

When the adjusted series have the same linear structure, the difference series is a white noise (WN), when the structures are different D_t is autocorrelated. The discrepancy between the stochastic structures causes an irregular pattern of the autocorrelation function of D_t.

We found the following evidences (Tab. 5):

- D_t is always stationary in mean,
- the autocorrelation function is frequently significant, expecially at the first seasonal lag (k=12),
- in some cases the autocorrelation function seems not convergent.

We are not able to explain the autocorrelation functions of D_t where may be present nonlinear effects produced by seasonal adjustments (Ghysels E., et al., 1995), anyway we must conclude that series adjusted by different procedures show different structures.

Tab. 4 – Comparisons between adjusted time series: correlation coefficients (r) number of discordances (d) and rate of discordance (D) in trends and adjusted series

SERIES	r	ADJUSTED d	ADJUSTED D	TREND d	TREND D
IFACONGN	0.999	5	.035	1	.0069
IFAINVGN	0.994	33	.23	10	.0699
IFAINVGT	0.999	15	.10	1	.0069
IFAGENGE	0.999	4	.028	3	.0209
ICOGENGT	0.999	0	0	4	.0279
IPIINVGT	0.938	45	.23	8	.0418
IPIGENGT	0.988	22	.11	4	.0209
IPICONGT	0.993	12	.063	4	.0209
IPIINTGT	0.973	52	.28	11	.0576
IORGENGT	0.983	13	.18	5	.0704
IPIODMGT	0.995	5	.026	19	.0995
IPIODJGT	0.983	16	.084	16	.0838
IPIODAGT	0.994	11	.057	11	.0576
IPIODBGT	0.756	25	.13	6	.0314

Tab. 5 – Average and autocorrelations coefficients of time series D_t

SERIES	AVERAGE	r_1	r_{12}	r_{24}	r_{36}	CONVERGENCE
IFACONGN	.0999	.129	.475	.222	-.035	Y
IFAINVGN	.0888	-.233	.182	-.067	-.154	Y
IFAINVGT	.1109	-.090	.352	. 140	.113	Y
IFAGENGE	.0919	-.032	.263	.260	.083	Y
ICOGENGT	.9959	.220	.233	.145	.046	Y
IPIINVGT	-.0623	-.347	.309	-.355	-.600	N
IPIGENGT	.0840	-.027	.426	-.183	-.387	Y
IPICONGT	.114	.032	.589	.276	.066	Y
IPIINTGT	.0761	-.329	.273	-.298	-.378	N
IORGENGT	.1788	.076	.467	.006	-.148	Y
IPIODAGT	.0245	-.096	.307	.172	-.006	Y
IPODBGT	.4742	-.026	.477	.005	-.049	Y
IPODJGT	-.0076	-.001	.498	.297	.139	Y
IPIODMGT	.2489	-.076	.794	.624	.493	N

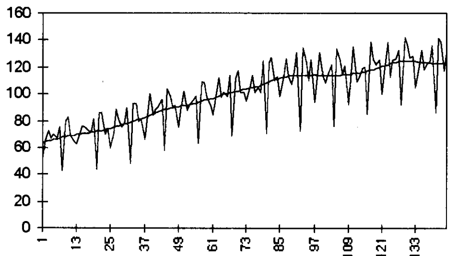
3. Conclusions

The performed experimentation allows the following conclusions:

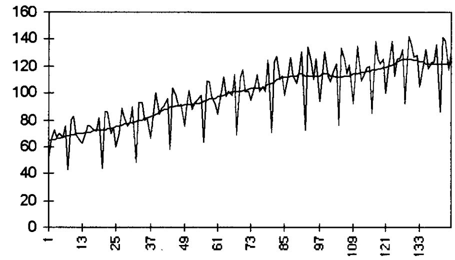
1. Both the procedure TRAMO-SEATS and X12-ARIMA work very well and appear equivalent in their capacity of removing seasonality.
2. In spite of the similarity displayed by graphical representations and some statistical indices, the stochastic structure of the series adjusted by the considered procedures are very different so that the user can't remain indifferent in choosing its seasonal adjustment method.

APPENDIX

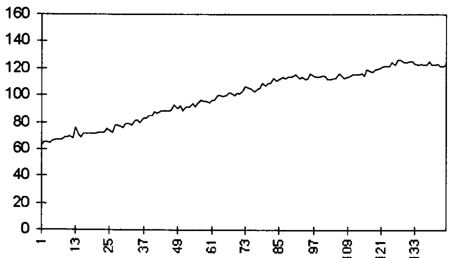
Fig. 1 – IFACONGN



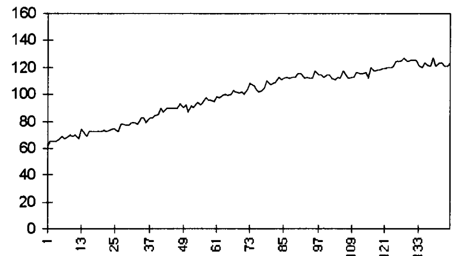
(a) Original series and trend estimated by TRAMO-SEATS



(c) Original series and trend estimated by X12-ARIMA

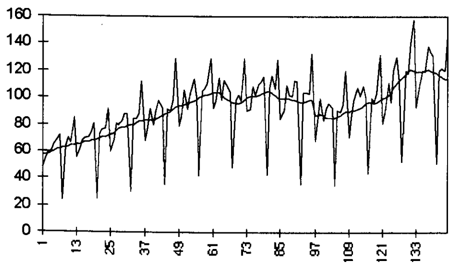


(b) Adjusted time series by TRAMO-SEATS

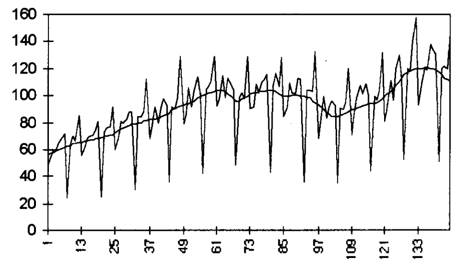


(d) Adjusted time series by X12-ARIMA

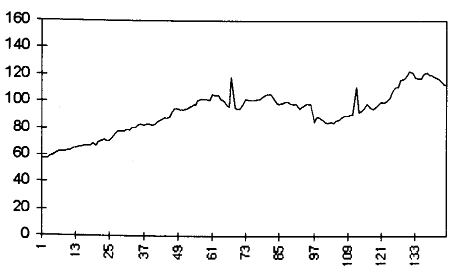
Fig. 2 – IFAINVGN



(a) Original series and trend estimated by TRAMO-SEATS



(c) Original series and trend estimated by X12-ARIMA



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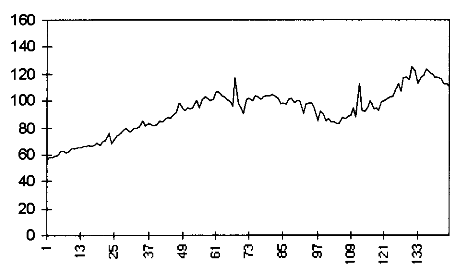

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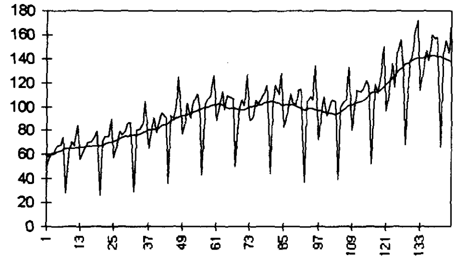
Fig. 3 – IFAINVGT



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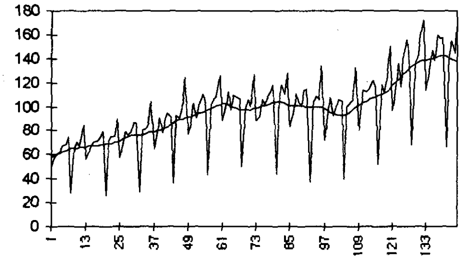
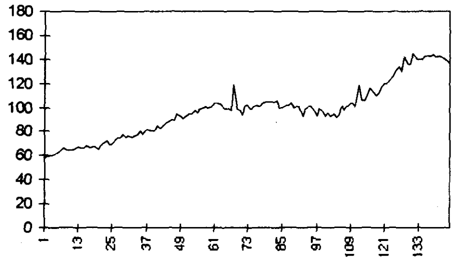


(c) Original series and trend estimated by X12-ARIMA



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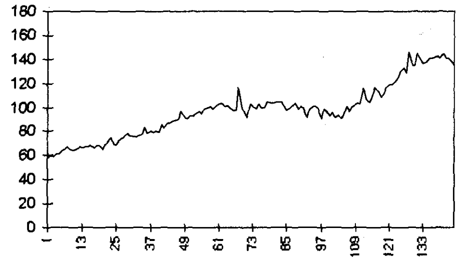

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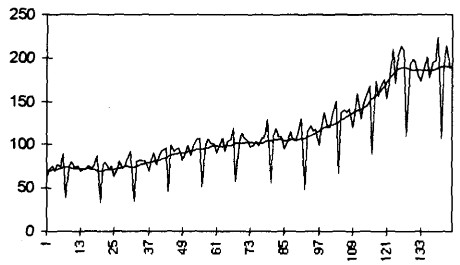
Fig. 4 – IFAGENGE



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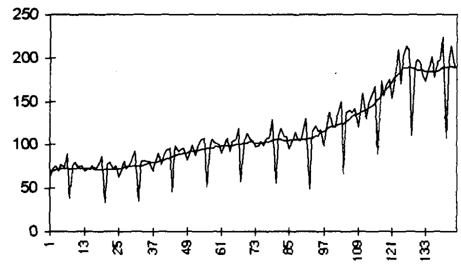
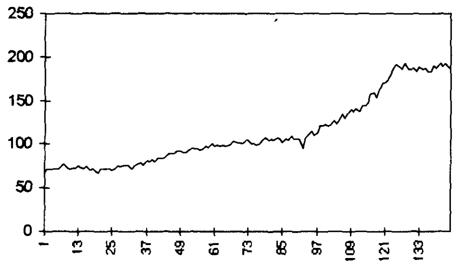


(c) Original series and trend estimated by X12-ARIMA



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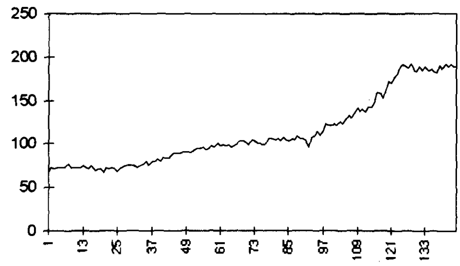

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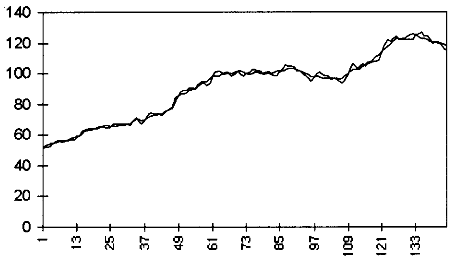
Fig. 5 – ICOGENGT



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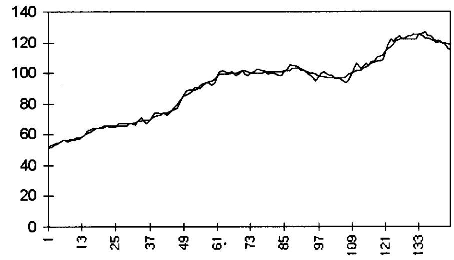

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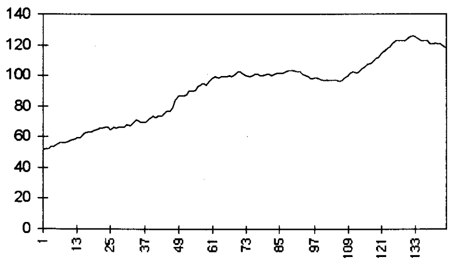

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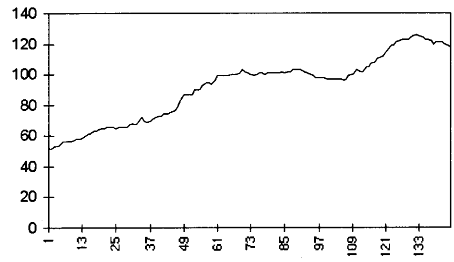
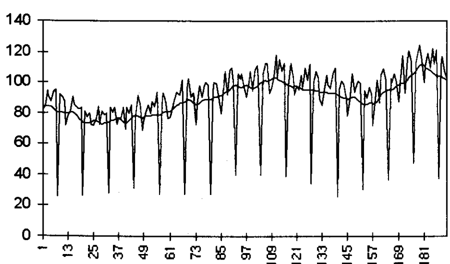
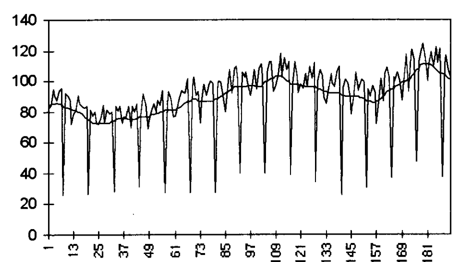


(d) Adjusted time series by X12-ARIMA

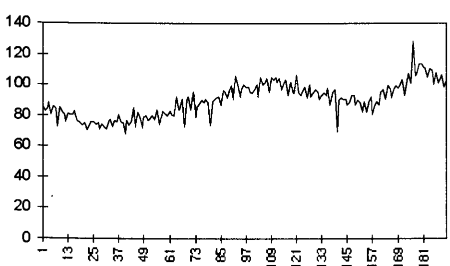
Fig. 6 – IPIINVGT



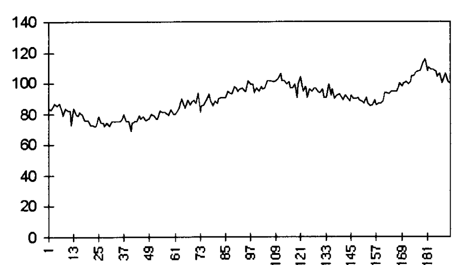
(a) Original series and trend estimated by TRAMO-SEATS



(c) Original series and trend estimated by X12-ARIMA

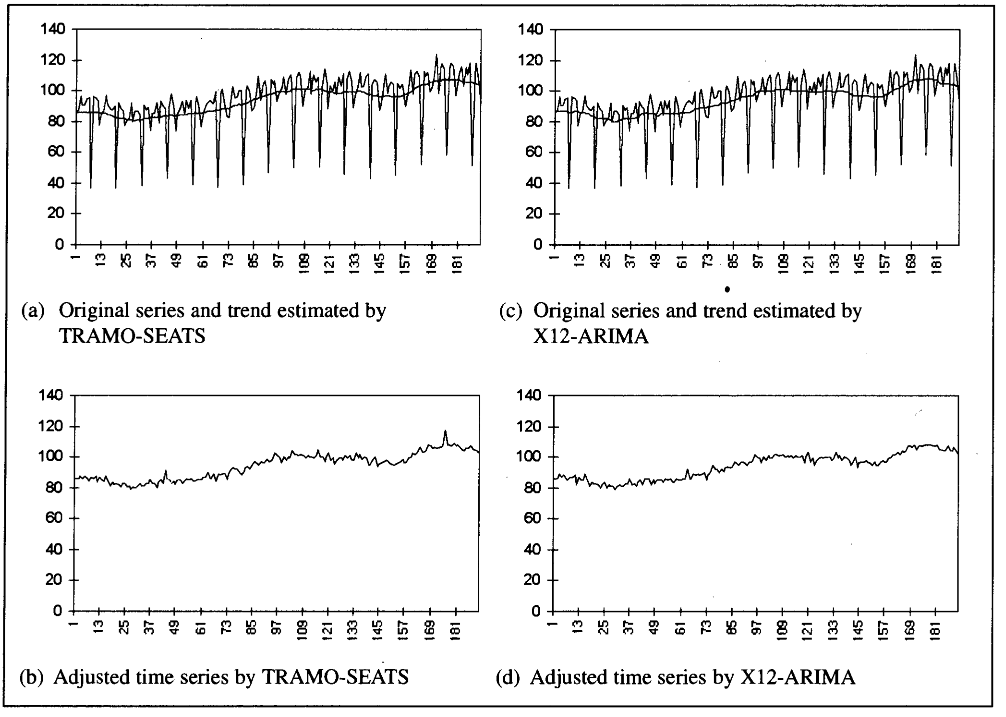


(b) Adjusted time series by TRAMO-SEATS



(d) Adjusted time series by X12-ARIMA

Fig. 7 – IPIGENGT



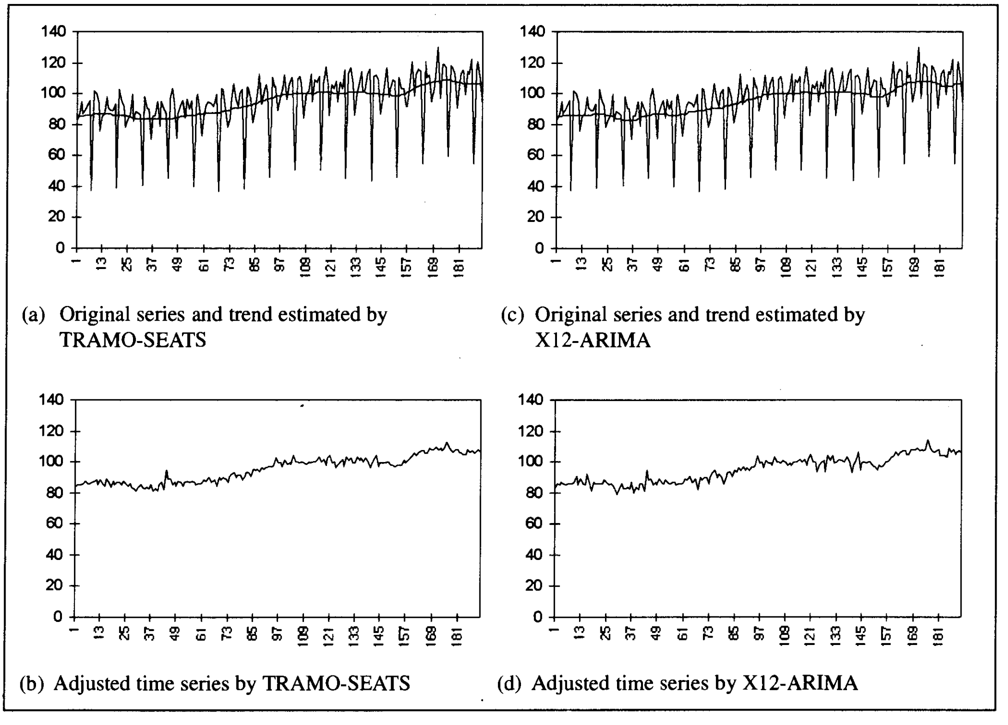
(a) Original series and trend estimated by TRAMO-SEATS

(c) Original series and trend estimated by X12-ARIMA

(b) Adjusted time series by TRAMO-SEATS

(d) Adjusted time series by X12-ARIMA

Fig. 8 – IPICONGT



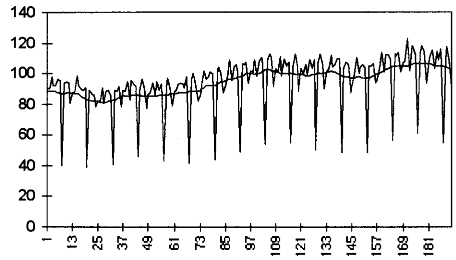
(a) Original series and trend estimated by TRAMO-SEATS

(c) Original series and trend estimated by X12-ARIMA

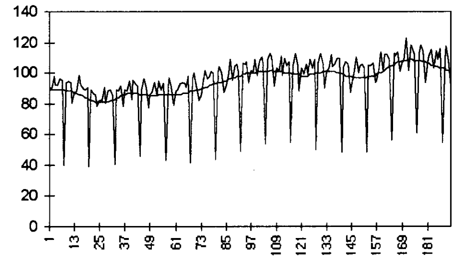
(b) Adjusted time series by TRAMO-SEATS

(d) Adjusted time series by X12-ARIMA

Fig. 9 – IPIINTGT



(a) Original series and trend estimated by TRAMO-SEATS



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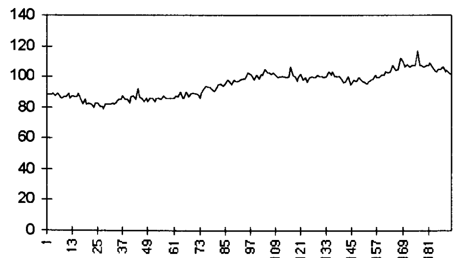

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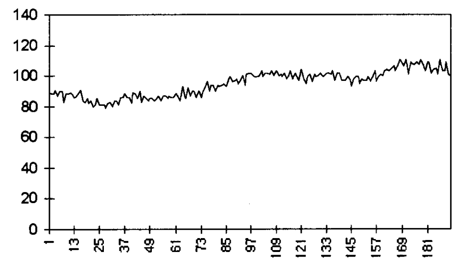

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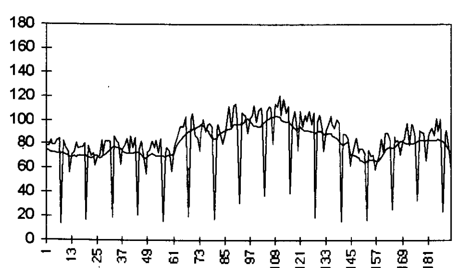
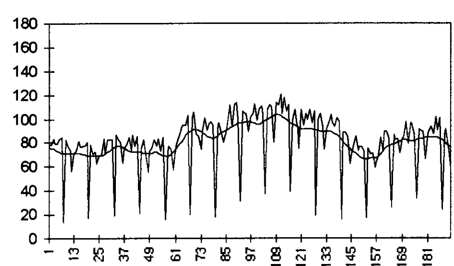
Fig. 10 – IPIODMGT



(a) Original series and trend estimated by TRAMO-SEATS



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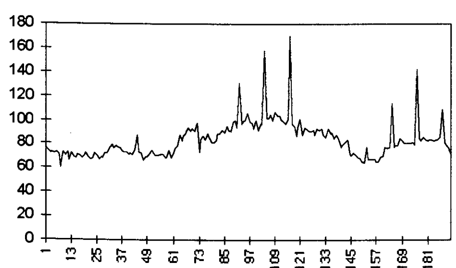

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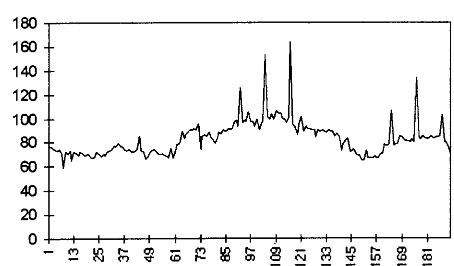

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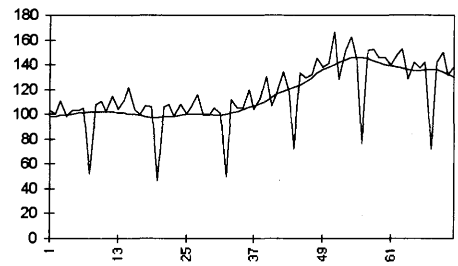
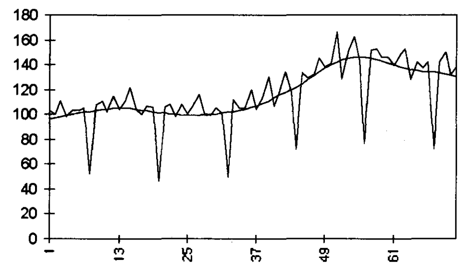
Fig. 11 – IORGENGT



(a) Original series and trend estimated by TRAMO-SEATS



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(b) Adjusted time series by TRAMO-SEATS

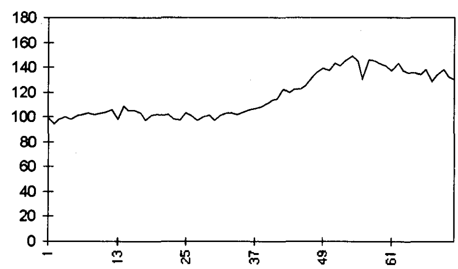

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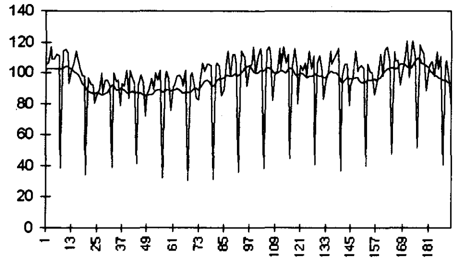
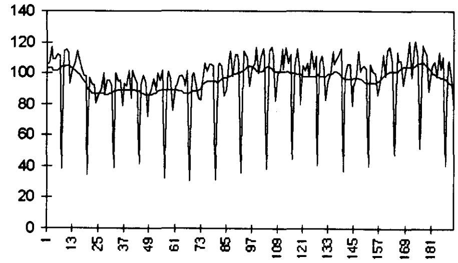
Fig. 12 – IPIODJGT



(a) Original series and trend estimated by TRAMO-SEATS



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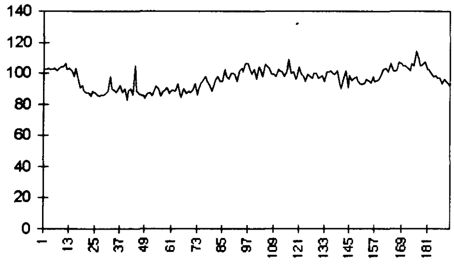

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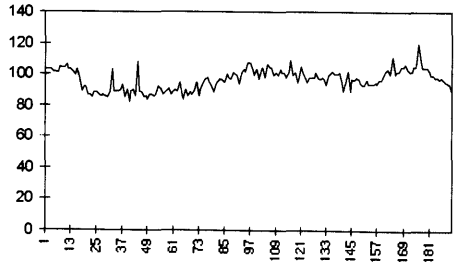

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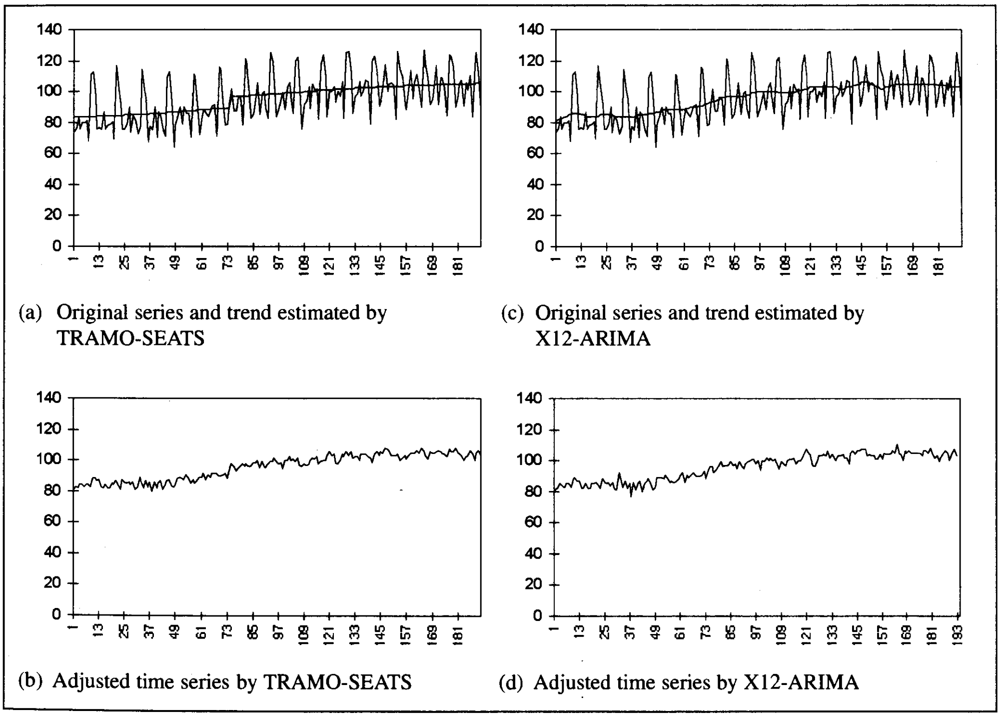
Fig. 13 – IPIODAGT



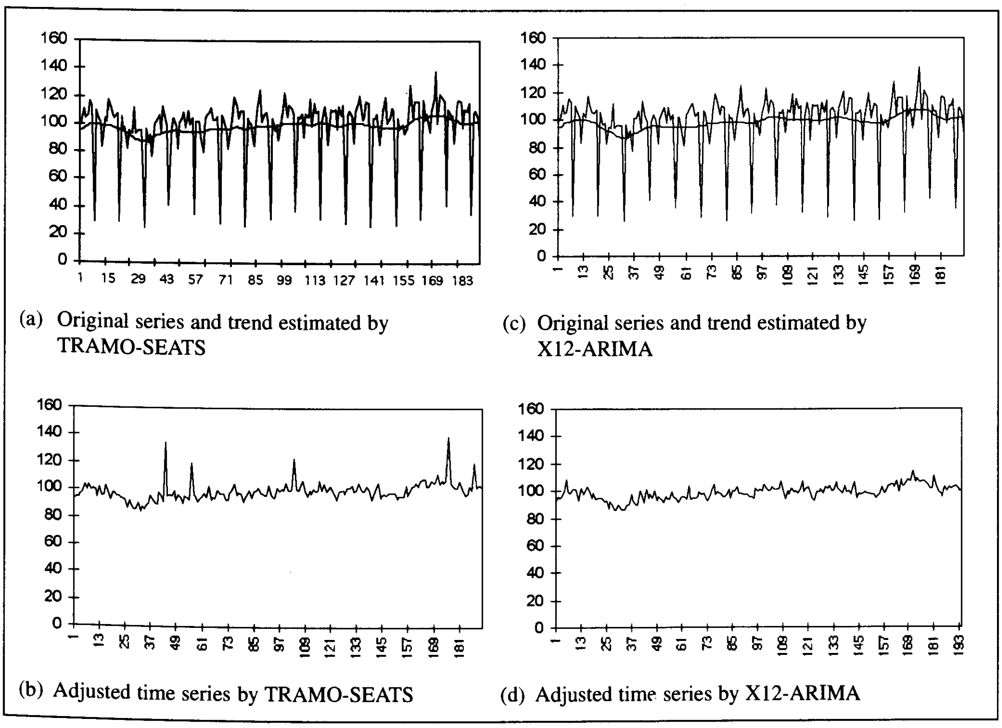
(a) Original series and trend estimated by TRAMO-SEATS

(c) Original series and trend estimated by X12-ARIMA

(b) Adjusted time series by TRAMO-SEATS

(d) Adjusted time series by X12-ARIMA

Fig. 14 – IPIODBGT



(a) Original series and trend estimated by TRAMO-SEATS

(c) Original series and trend estimated by X12-ARIMA

(b) Adjusted time series by TRAMO-SEATS

(d) Adjusted time series by X12-ARIMA

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SEASONAL ADJUSTMENT OF ITALIAN INDUSTRIAL PRODUCTION SERIES: MORE EVIDENCE FROM THE EMPIRICAL COMPARISON BETWEEN TRAMO-SEATS AND X-12-ARIMA

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1. Introduction

The definition of a criterion to evaluate performances of seasonal adjusted procedure seems to be an hopeless task (Planas, 1997a, Bell and Hillmer, 1984). Keeping these considerations in mind, following Fisher (1995) I referred to a list of criteria used in empirical comparisons. They could be divided referring to the Time domain or to the Frequency domain. Considering the first group we have three further main groups: 1) retrospective (idempotency, orthogonality between the seasonal component and the seasonal adjusted series; absence of autocorrelation in the residual); 2) prospective (annual total of the seasonal adjusted series and the original series; variability of the seasonal figures, detection of turning points); 3) forecast.

Following this classification Mazzali's works focused on correlation between the methods, autocorrelation in the residuals and detection of turning points. Expanding his results, at first I concentrated my attention on the pre-adjustment factors looking at the difference in estimation of outliers and trading days, secondly I looked at an important empirical criteria of comparison in the time domain: idempotency. Particularly for the trading days estimation in TRAMO-SEATS I proposed a comparison between the results coming from 2 different used regression.

I presented the description for the data in section 2. In section 3 I described the results of empirical comparison and in section 4 the conclusion.

2. Data description

The series used in this paper, regarding Italian industrial production data set consist in 4 aggregated series (general index and its three main industrial groupings) and 4 disaggregated at the industry level (Food, Textiles, Metals and Transport). The sample period

The opinions expressed are the author's and do not involve Istat spans from January 1981 to December 1996, for a total of 192 monthly observation.

All series (figure 1-8, graph a) are characterised , in level, by a low value of August. Particularity August is also reinforced, observing the variance (figures 1-8, graph b) of each month of the yearly growth rates (normalized for the total variance): for all the series except food industry, the variance in August is three times the total variance.

TRAMO-SEATS (version may 98) was applied using the Excel interface developed at Eurostat and X-12-ARIMA (X-12) (version 0.2)[1] was used both in the dos version than in the Graphical extension developed in SAS by U.S. Bureau of Census[2].

3. Empirical comparison between TRAMO-SEATS and X-12-ARIMA

3.1 Analysis of the Difference between TS and X-12 in the Estimation of Seasonal Adjusted Series and Trend Series

Computing the difference between TS and X-12 estimation of SA series (figure 1c-8c) and Trend series (figure 1d-8d) we note that, on average:

i) For aggregate series and for Transport series, SA values of August estimated by TS are always greater than the value estimated by X-12; for the other series do not seems to be regularity in the difference;

ii) The trend value for all series except Consumption and Food, for all month, is higher in TS respect to X-12.

From the difference on SA series seems that TS is more adaptable to capture seasonal effects in August. This empirical evidence could be related to the Planas' results (Planas, 1997c). It found that even when the default X-11 filter and the signal extraction filter can be very close, "some difference can still be found which are mainly due to the property of X-11 default adjusted filter to displays gains higher than 1 at some frequency between the seasonal harmonic. As a consequence short-terms movements in the series are amplified in the adjustment movements."

Moreover, application of TS to the series of difference in the SA estimation exhibits slight evidence for the difference in the two methods (table 1).

Table 1 – Results of TS application to the series of difference in SA estimation (*)[3]

Series	Model	Ljung-Box	Box-Pierce	Normality	Model
Ipigengt	(0,0,2)(0,1,1)	35.8	**14.4**	3.8	ADDITIVE
Ipicongt	(0,0,0)(1,0,0)	**44.5**	3.1	3.6	ADDITIVE
Ipiintgt	(2,0,1)(0,1,1)	**65.2**	1.6	2.8	ADDITIVE
Ipiinvgt	(0,0,1)(0,0,0)	36.7	5.4	**22.8**	ADDITIVE
Ipi0dagt	(0,0,1)(1,0,0)	33.3	0.8	1.8	ADDITIVE
Ipi0dbgt	(2,1,1)(0,1,1)	**63.7**	3.6	0.3	ADDITIVE
Ipi0djgt	(0,1,1)(0,1,1)	25.3	0.9	**12.1**	ADDITIVE
Ipi0dmgt	(0,1,1)(0,0,0)	31.4	4.4	3.0	ADDITIVE

(*) In bold the value significant at 5%

[1] I use TRAMO-SEATS with the default parameter RSA=4 and X12 with the multiplicative decomposition.

[2] An interface with Sas has been developed for the 2 methods at Insee (see Attal and Lariday, 1998a and 1998b).

[3] For the identifications of the series see Mazzali's paper.

3.2 Estimation of Outliers

Both TS than X-12 include an automatic method for identified outliers (Findley et al. 1998, Gomez and Maravall, 1997, Planas 1997b). In TS it is possible to identify 3 types of outliers: additive outlier (AO), Level shift (LS) and temporary change (TC); X-12 do not consider TC.

Except these differences the algorithms are very closed to the two procedure. Referring to TS (Gomez and Maravall, 1997, Planas, 1997b), the algorithms could be presented in the following way. Suppose to fit a model for the original series y_t and observe the residuals e_t. Denoting $I_{t0}(t)$ a dummy variable such that $I_{t0}(t) = 1$ if $t=_{t0}$, 0 otherwise, then 3 outliers are defined by:

- AO: $e_t = a_t + w_A I_{t0}(t)$
- TC: $e_t = a_t + w_T/(1-(\eta B) I_{t0}(t)$
- LS: $e_t = a_t + w_L/(1-B)\ I_{t0}(t)$

The methodology for Outliers detection, identification and estimation can be summarised as follows:

- A model is fitted to the series, and the residuals e_t are obtained;
- For every residual, estimator of w_A, w_T, w_L, are computed together with their variance;
- Compute the t-values: when the t-value of one or some w's at some time t exceeds a critical value C, then an outlier at time t has been detected;
- To identify which type of outlier is deal with, a comparison between the different t-values obtained is performed: the chosen outlier pattern is the one related to the greatest significativity.

In TS the default critical value is related to the size (NZ) of the sample (for NZ (50, VA=3; for 50 < NZ (≤250, VA=3.5; for 250 < NZ (≤500, VA = 3.8; for NZ > 500, VA=4). In X-12 the default critical value is 3.8 but the printed output shows also months whose AO and LS regressors are closed to the critical values.

From empirical results[4], collected in table 2, it is possible to note that the 2 methods identify a large number of common outliers. Particularly, in 2 cases X-12 identifies outliers different form those estimated by TS. However, for the Series ipi0dbgt l'AO(8,1996) it is also detected by Tramo when it is runned with the options RSA=4. In the case of series ipi0dmgt X-12 and TS are only different in the identification of the outlier type for January 1987. In all other cases, TS identify a large number of outliers. This evidence is partially related to the different level in the settings of the critical value. Infact, using the same value for the threshold, it reduces the number of Outliers present only in TS but also in this case, the linearisation set forth by TS is stronger.

3.3 Estimation of Trading Days

Both procedures include an estimation of the trading-day effects (Findley et al., 1998, Gomez and Maravall, 1997, Planas, 1997b) in the preadjustment.

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[4] To compare the 2 methods I use, for TS, option RSA=6 that include 6 regressor for the estimation of trading-days.

Table 2 – Outlier detection in TS (RSA=6) and X-12(*)

Series	TS	TS and X12	X12
Ipigengt		AO(8,1984) **AO(8,1995)**	
Ipicongt	TC(8,1984)		
Ipiintgt	AO(8,1984) AO(8,1995) **A0(8,1990) TC(12,1992)**		
Ipiinvgt	**AO(8,1984) AO(8,1988) TC(1,1987)**	AO(8,1992) AO(8,1995)	
Ipi0dagt	LS(3,1987)		
Ipi0dbgt		AO(8,1984) AO(8,1985) AO(8,1989) AO(8,1995)	AO(8,1996)
Ipi0djgt	**LS(6,1982) TC(8,1995)**	AO(8,1983) AO(8,1984)	
Ipi0dmgt	LS(1,1987) AO(8,1981) **AO(8,1996)**	AO(8,1990) AO(8,1989) AO(8,1995) AO(8,1988) AO(8,1994) **AO(8,1984)**	AO(1,1987)

(*) In bold outliers that are not present setting VA=3.8 instead of 3.5

The procedure used in both methods for the estimation is based on the idea to build 7 dummy variable (one by day) X_{1t}, ..., X_{7t} such that X1t is the number of Mondays in month t, ..., X_{it} the number of i-th day of the week. In practice, the coefficient of the X_{it} tend to be highly correlated, and a reparametrization is needed. In one way, introducing the average daily activity and the length of month t, we defined a model with six dummy variables plus a length of month adjustment variable. In TS there is also the possibility of considering a more parsimonious modelling of the trading day effect by using one variable instead of six. In this case, the days of the week are first divided into two categories: working days and no-working days. Then, the variable is defined as (no. of(M, T, W, Th, F) - (no. of(Sat, Sun) x 5/2).

Empirical evidence shows that there are no differences in the estimation of trading days: for all series: both methods identified a trading-days correction.

Moreover, for TS I compared the effects on decomposition process induced by a different regression for trading-days estimation. In the first case, parameter RSA=4, includes only 1 regressor; in the second case, parameter RSA=6 includes six regressors.

The results collected in tables 3-4 shows that in 3 cases (ipiinvgt, ipi0djgt, ipi0dmgt) change in the regression used for trading days estimation induce a change in the model estimate.

Table 3 – TS estimation of type of model and trading day, option RSA=4 and RSA=6

Series	Model		Trading days	
	RSA4	RSA6	RSA4	RSA6
Ipigengt	(0,1,1)(0,1,1)	(0,1,1)(0,1,1)	YES	YES
Ipicongt	(0,1,1)(0,1,1)	(0,1,1)(0,1,1)		YES
Ipiintgt	(0,1,1)(0,1,1)	(0,1,1)(0,1,1)	YES	YES
Ipinvgt	(0,1,1)(0,1,1)	(2,1,0)(0,1,1)	YES	YES
Ipi0dagt	(1,0,0)(0,1,1)	(1,0,0)(0,1,1)	YES	YES
Ipi0dbgt	(0,1,1)(0,1,1)	(0,1,1)(0,1,1)	YES	YES
Ipi0djgt	(2,0,0)(0,1,1)	(0,1,1)(0,1,1)	YES	YES
Ipi0dmgt	(1,1,0)(0,1,1)	(0,1,1)(0,1,1)	YES	YES

3.4 Idempotency

Idempotency is always seen as one of the most desiderable criteria for a seasonal-adjustment method (Fisher 1995, Maravall 1998). Using the seasonal adjusted series as original series, I looked at the results obtained performing the seasonal adjusted method. Both methods seem to performe quite well (table 4-5).

Table 4 – TRAMO-SEATS estimation of the seasonal adjusted series(*)

Series	Model	Ljung-Box	Box-Pierce	Normality	Decomposition model
Ipigengt	(0,1,1)(0,0,0)	**40.5**	**14.2**	2.2	MULTIPLICATIVE
Ipicongt	(0,1,1)(0,0,0)	39.7	**17.6**	0.9	MULTIPLICATIVE
Ipiintgt	(0,1,1)(0,1,1)	35.9	**11.2**	1.1	MULTIPLICATIVE
Ipiinvgt	(0,1,1)(0,0,0)	26.0	**9.5**	1.2	MULTIPLICATIVE
Ipi0dagt	(1,1,1)(0,1,1)	35.5	6.7	5.9	ADDITIVE
Ipi0dbgt	(0,1,1)(0,0,0)	36.6	**12.3**	0.3	MULTIPLICATIVE
Ipi0djgt	(0,1,1)(0,0,0)	27.5	**11.1**	0.1	ADDITIVE
Ipi0dmgt	(0,1,1)(1,0,0)	23.7	7.0	1.5	MULTIPLICATIVE

(*) in bold the value significant at 5%

Table 5 – Value of M7 and Q statistics for the seasonal adjusted series

Series	M7	Q
Ipigengt	3.0	1.4
ipicongt	2.6	2.0
ipiintgt	2.7	1.7
ipiinvgt	3.0	1.9
ipi0dagt	2.8	2.0
ipi0dbgt	3.0	2.3
ipi0djgt	3.0	1.6
ipi0dmgt	3.0	1.3

TRAMO-SEATS do not identify any seasonal adjusted series in 6 cases. In the other 2 cases the seasonal factors are not very different from 0: for ipi0dagt they span from –0.0447 to 0.0851(it was selected an additive model); for ipiintgt the span from 99.988 to 100.026 (it was selected a multiplicative model).

For X12, as suggested by Fyndley and al. (1998) I looked at the diagnostics Q and M[5]. In all cases M7 and Q statistics suggest to reject the seasonal adjustment.

4. Conclusion

The empirical comparison of both methods confirms results of Mazzali's paper.

[5] As point out in chapter 3 values larger than 1.0 for Q and M7 are interpreted as indications that the seasonal adjustment should be rejected.

Particularly, both TS then X-12 have a good performance in terms of idempotency criteria.

Some differences still remains. Looking at the comparison of outliers and the results of comparison between seasonal adjusted series, it is possible to argue for a much strong linearization operated by TS.

Moreover, it is important to stress that in some cases, the different estimation for the preadjustment factors could induce different models estimation.

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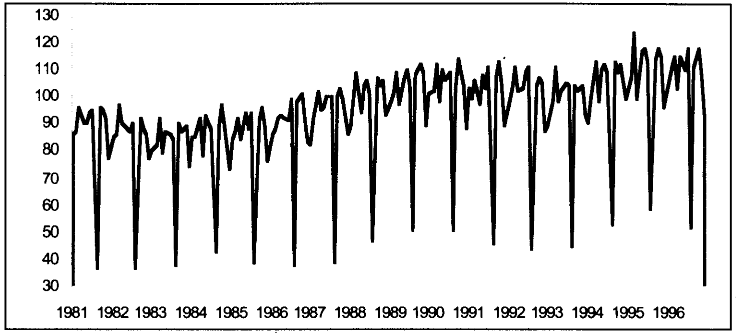
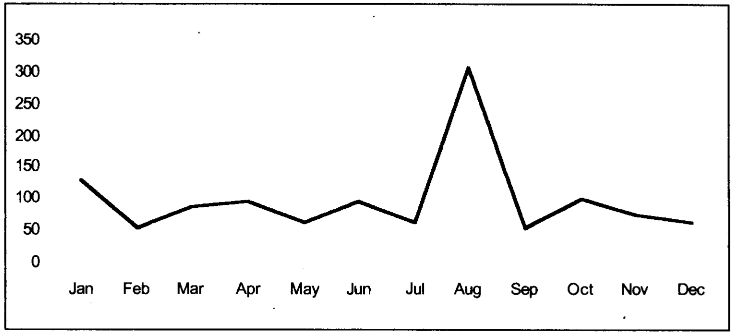
FIGURES

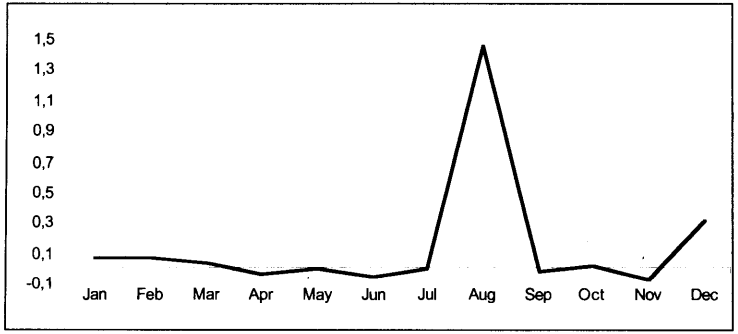
Figure 1 – Index of industrial production, Total - Jan. 81 - Dec. 96



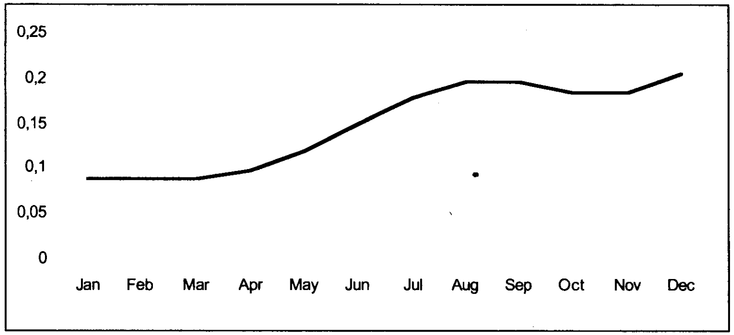
(a) Original series



(b) Seasonal differences (log): Variance

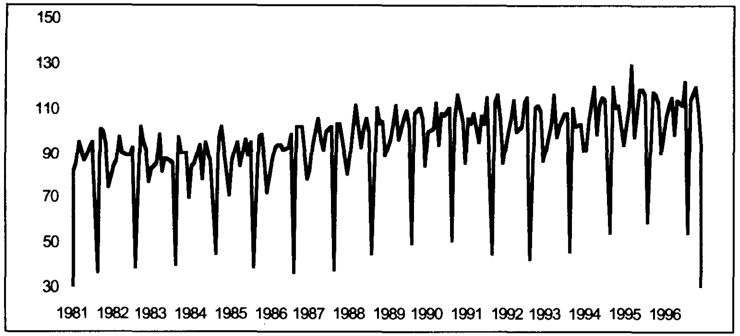


(c) Difference (mean) TS and X-12 estimation: SA series

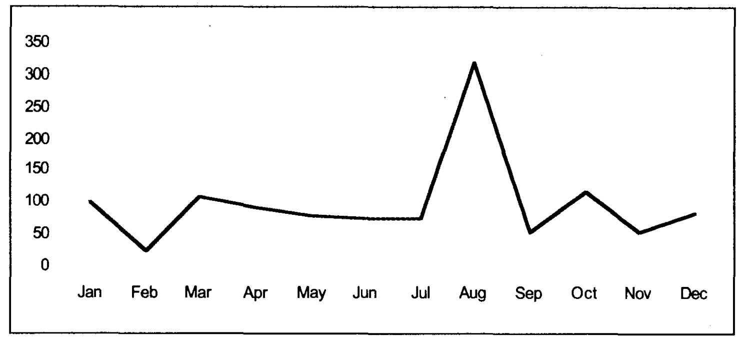


(d) Difference (mean) TS and X-12 estimation: Trend series

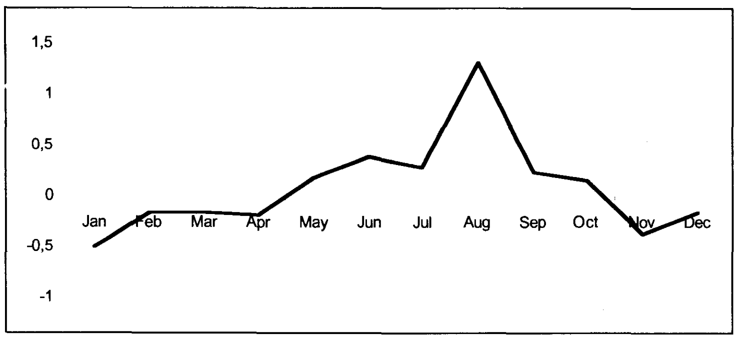
Figure 2 – Index of industrial production, Consumption - Jan. 81 - Dec. 96



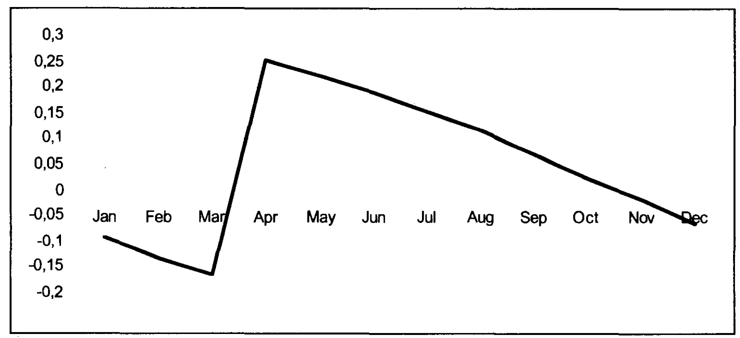
(a) Original series



(b) Seasonal differences (log): Variance

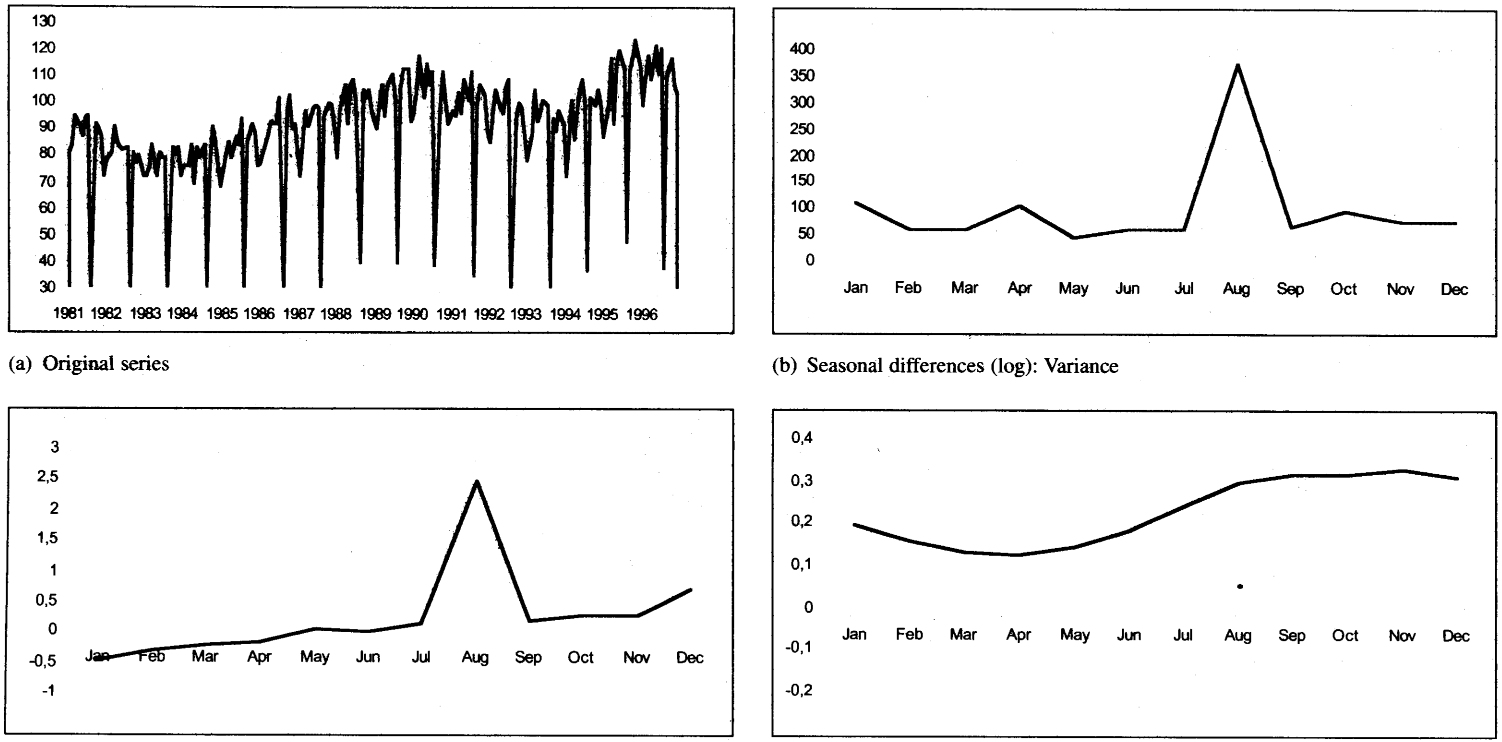


(c) Difference (mean) TS and X-12 estimation: SA series



(d) Difference (mean) TS and X-12 estimation: Trend series

Figure 3 – Index of industrial production, Consumption - Jan. 81 - Dec. 96



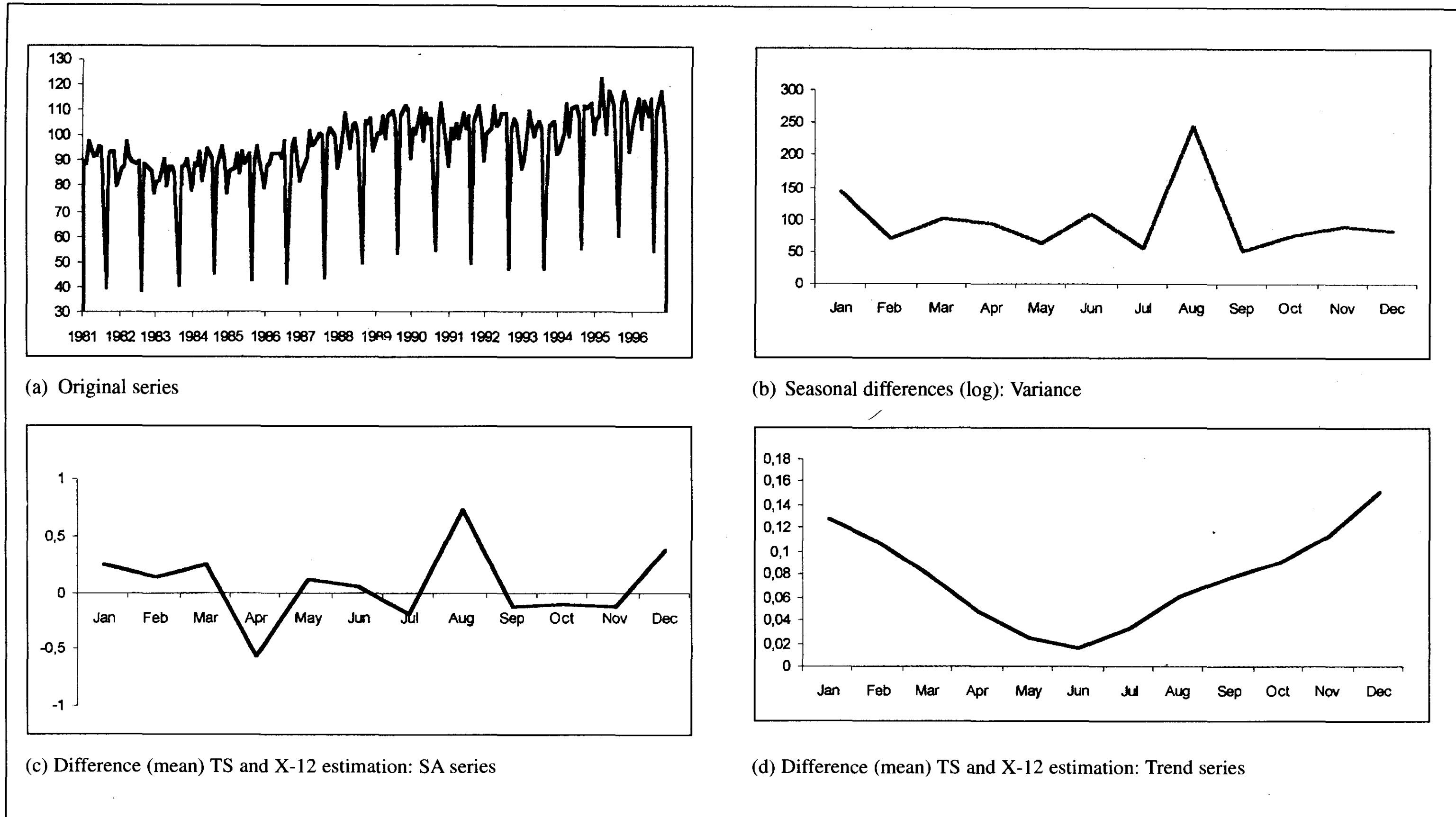
(a) Original series

(b) Seasonal differences (log): Variance

(c) Difference (mean) TS and X-12 estimation: SA series

(d) Difference (mean) TS and X-12 estimation: Trend series

Figure 4 – Index of industrial production, Intermediate goods - Jan. 81 - Dec. 96



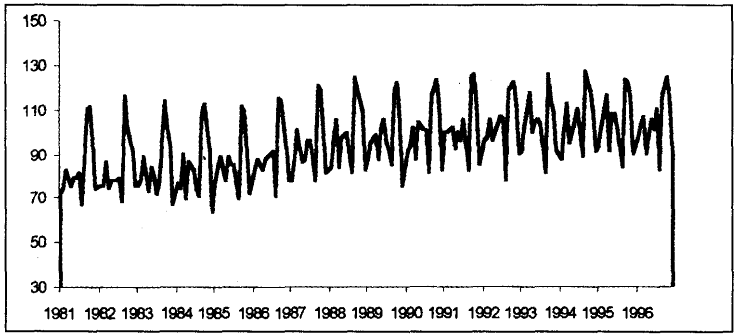
(a) Original series

(b) Seasonal differences (log): Variance

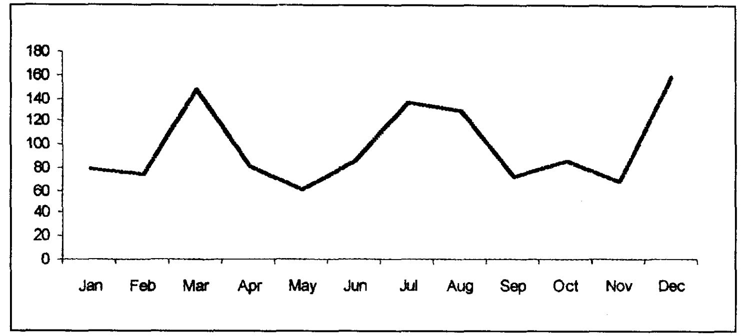
(c) Difference (mean) TS and X-12 estimation: SA series

(d) Difference (mean) TS and X-12 estimation: Trend series

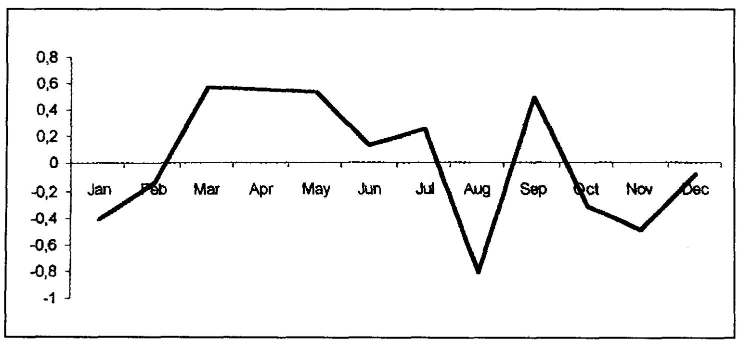
Figure 5 – Index of industrial production, Food - Jan. 81 - Dec. 96



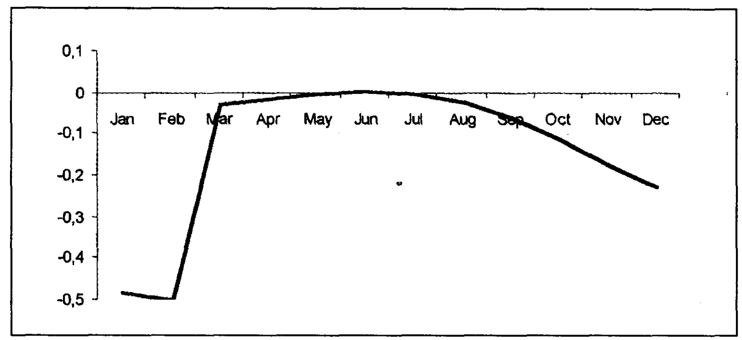
(a) Original series



(b) Seasonal differences (log): Variance

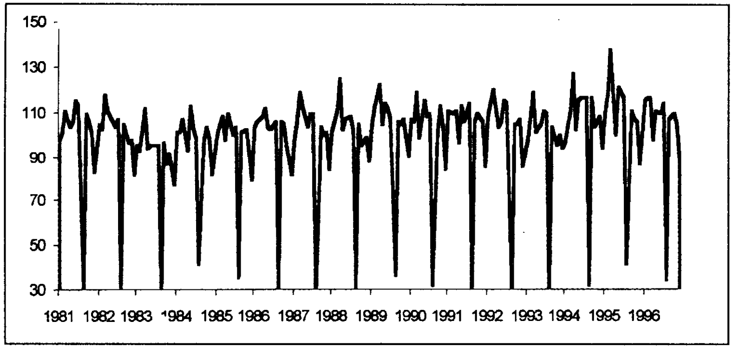


(c) Difference (mean) TS and X-12 estimation: SA series

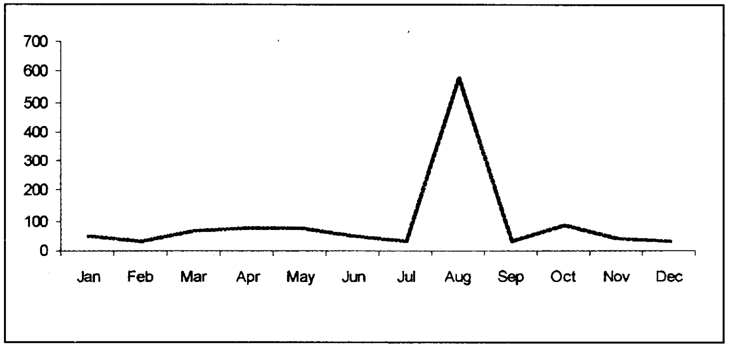


(d) Difference (mean) TS and X-12 estimation: Trend series

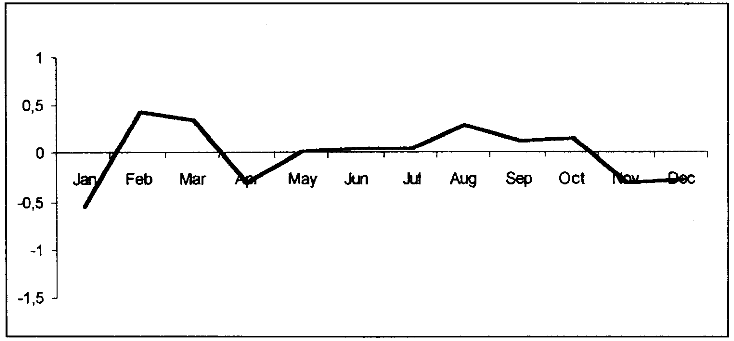
Figure 6 – Index of industrial production, Textiles - Jan. 81 - Dec. 96



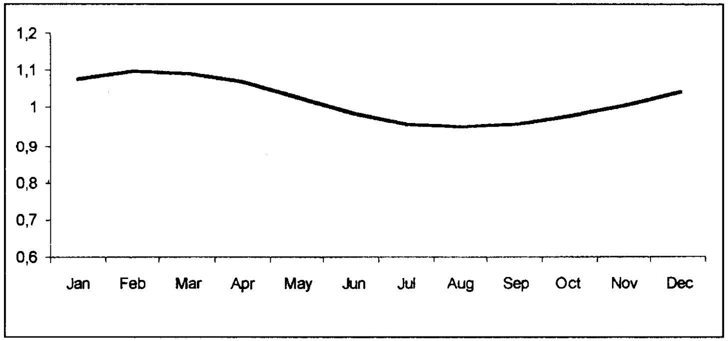
(a) Original series



(b) Seasonal differences (log): Variance

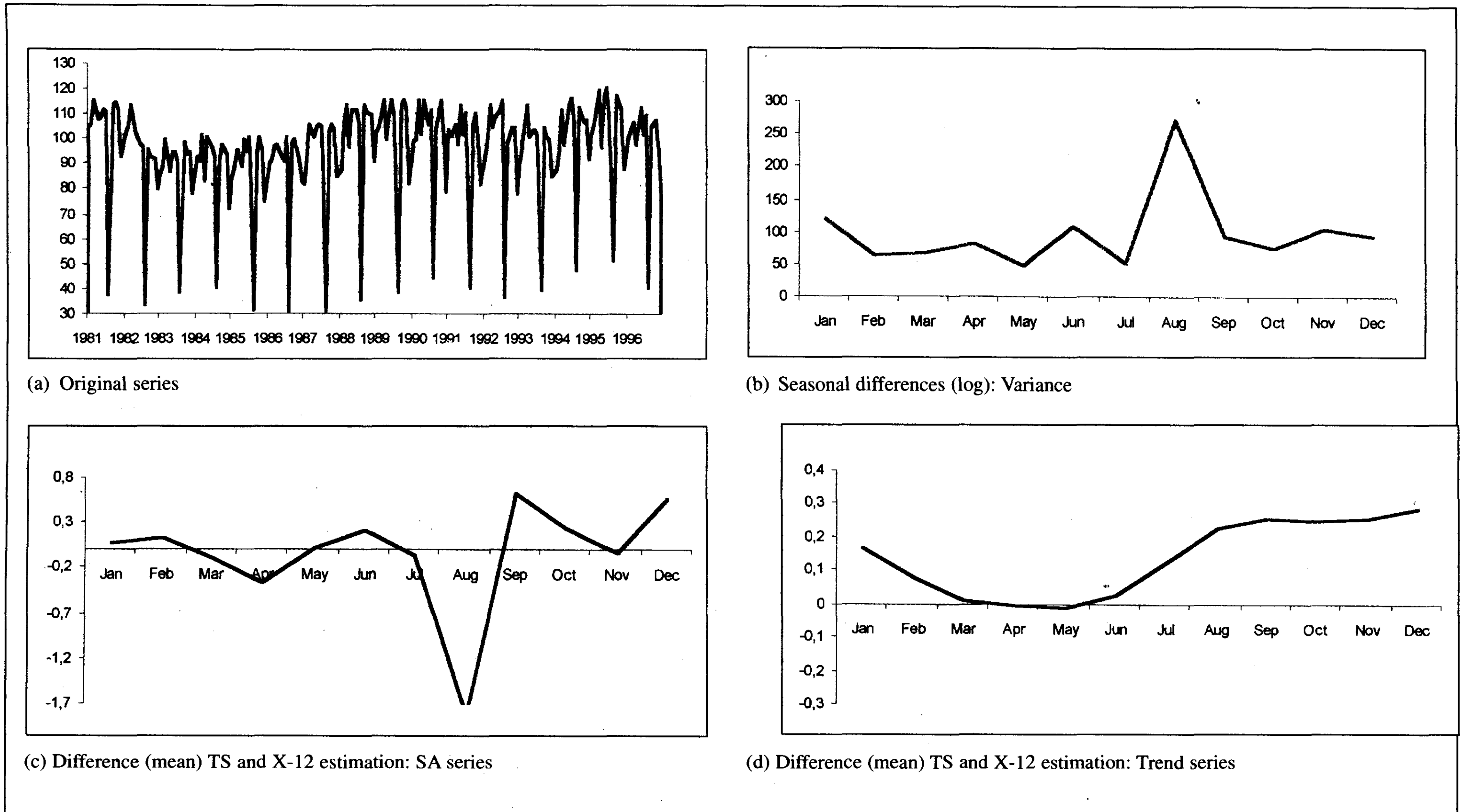


(c) Difference (mean) TS and X-12 estimation: SA series



(d) Difference (mean) TS and X-12 estimation: Trend series

Figure 7 – Index of industrial production, Metals - Jan.81 - Dec. 96



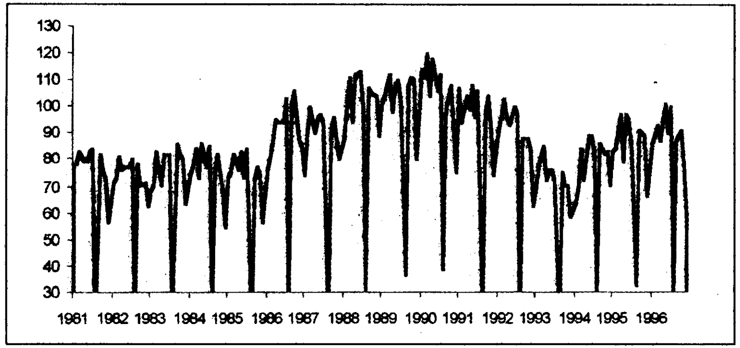
(a) Original series

(b) Seasonal differences (log): Variance

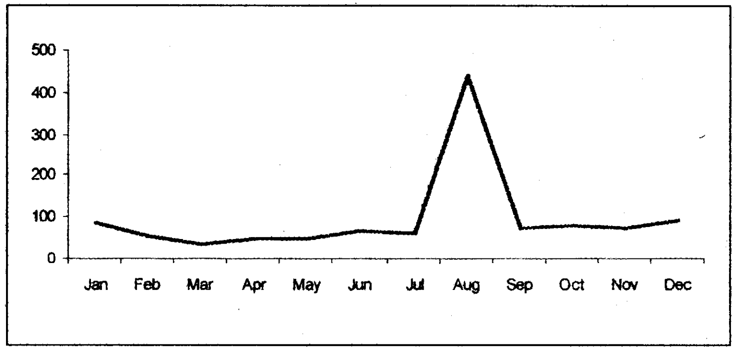
(c) Difference (mean) TS and X-12 estimation: SA series

(d) Difference (mean) TS and X-12 estimation: Trend series

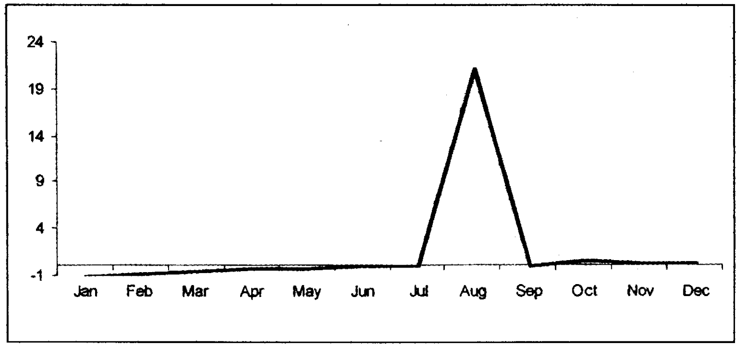
Figure 8 – Index of industrial production, Transport - Jan. 81 - Dec. 96



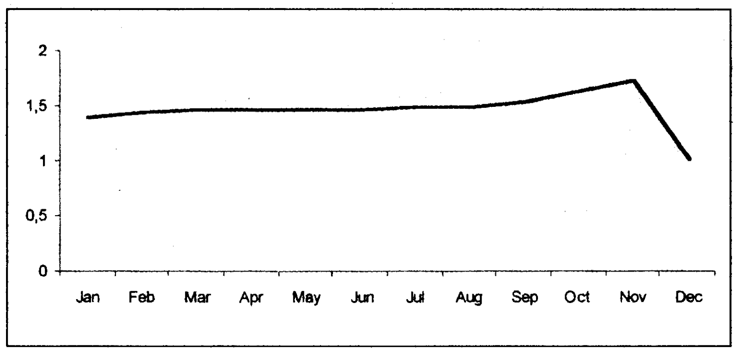
(a) Original series



(b) Seasonal differences (log): Variance



(c) Difference (mean) TS and X-12 estimation: SA series



(d) Difference (mean) TS and X-12 estimation: Trend series

THE SEASONAL ADJUSTMENT OF THE INDEXES OF INDUSTRIAL TURNOVER AND NEW ORDERS

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Istat, Italian National Institute of Statistics

1. Introduction

The recent debate on seasonal adjustment of a large number of economic time series by official statistical agencies has focused essentially on assessing advantages and limitations of two procedures, X-12-ARIMA from Bureau of Census (Findley *et al.*, 1998) and TRAMO-SEATS by Gomez and Maravall (1996), which are the most current developments of two quite different approach to the general problem of estimating unobserved components – trend-cycle, seasonal and irregular – in time series.

The X-12-ARIMA new seasonal adjustment program represents a significant improvement in the long-standing tradition of using linear, *ad hoc*, filters to remove seasonality from an observed series, which have been used extensively by statistical agencies and financial institutions after the release of the Census Bureau's X11 program (Shiskin *et al.*, 1967). The X11 method consists basically of a set of (symmetric) moving averages applied to the series to estimate its seasonal component and hence obtain the seasonally adjusted (SA) series. The filters are called empirical because they do not depend on the statistical properties of the series under analysis. With respect to the X11 method and its successors, X-12-ARIMA introduces additional diagnostics and a fairly complete set of tools for automatic outlier treatment and modeling of trading days and other calendar effects, as well as new seasonal adjustment and trend filters options, which intend to overcome some limitations of the filters incorporated in previous releases of the program. TRAMO-SEATS is a seasonal adjustment procedure which has refined and incorporated in a fully developed software program the so-called ARIMA model-based (AMB) approach to decomposition of time series which has first been proposed at the end of seventies

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(Burman, 1980, Hillmer and Tiao, 1982). In AMB approach, an observed time series is assumed to consist of two or more independent unobserved components, whose stochastic properties are known. Then, there exist optimal filters to separate the components and estimation can be obtained, imposing some restrictions on their stochastic structures. Indeed, under the assumptions that the components are stationary, orthogonal and that an admissible decomposition exists, the optimal filter is given by the *ratio* of the component spectrum to the series spectrum and it is such that it yields an estimate of the components that minimizes Mean Squared Error (the *canonical* decomposition).

Comparing different seasonal adjustment methods has traditionally been considered a controversial issue. Bell and Hillmer (1984) discuss the main approaches that have been used to evaluate adjustments, concluding that many proposed criteria are of little value. They then suggest that seasonal adjustment methods should be evaluated based on whether they are consistent with an adequate model for the observed data, a recommendation that leaves many problems unresolved. A proper criterion for evaluating seasonal adjustments should be based on a comparison between the estimation and the underlying theoretical estimator, which is only possible in the AMB approach. Recently, Depoutot and Planas (1998), extending an early result by Cleveland and Tiao (1976) on default X11 filter, propose to give a model-based interpretation of empirical filters, based on a distance measure between linear filters, which could be useful for studying the properties of the theoretical estimator associated to X11 seasonal adjustment. Nevertheless, the methods based on fixed filters cannot solve satisfactorily the problem of choosing a filter that implies a reasonable model for the components.

It is then difficult to find optimal criteria for comparing seasonal adjustment methods using different approach. A plausible solution consists in carrying out empirical comparisons to check whether the performances of different methods change significantly in presence of time series with particular features, for example either series with unstable components or series exhibiting strong variations at regular interval over the observed time span. This is, e.g., the approach followed by Fischer (1995), who compared six methods, performing an experiment on eighty economic series. For empirical comparison he chooses several prospective and retrospective criteria, in time as well as frequency domain, concluding that TRAMO-SEATS seems preferable because it combines the advantages of a firmly established theoretical approach with the capacity to model adequately most of the time series analyzed.

This paper performs a limited experiment on seasonal adjustment of six Italian indicator series on industrial turnover and new orders with X-12-ARIMA and TRAMO-SEATS. These series are analyzed in another paper appearing in this volume (Mazzali, 2000), focusing essentially on examining the differences between the SA series resulting from the application of the two procedures. The differences in the latter paper are studied in terms of: *i)* discordance in the sign of the monthly relative variation in the SA series obtained with the two methods and *ii)* the stochastic structure of the series resulting from subtracting out one SA series from the other. In this paper the attention is instead concentrated on analyzing the differences between the two procedures in regard to: *a)* average monthly differences between the SA adjusted series and *b)* verifying idempotency of SA series, i.e. the property that a seasonal-adjustment procedure applied to the SA series that it has produced should leave the SA series unchanged. To this end the paper is organized as follows. In section 2, after a description of the series analyzed, the outcome of the application of the two methods is presented. The results are illustrated following the operational sequence of the two procedures: preadjustments — including testing for Trading days and Easter effect and outlier detection — and automatic model identification for the series (sec. 2.1), diagnostic checking of the models fitted by TRAMO-SEATS (sec. 2.2) and X-12-ARIMA (sec. 2.3). Section 3 is devoted to the comparison of the results of the two procedures according to the criteria selected. Finally, section 4 contains some concluding remarks, outlining the main findings of the experiment.

2. The Time Series Analyzed: Seasonal Adjustment with X-12-ARIMA and TRAMO-SEATS

In this paper the following monthly series are analyzed:

1. Index of Industrial Turnover – Foreign markets (IFAGENGE);
2. Index of Industrial Turnover – Investment Goods - Domestic market (IFAINVGN);
3. Index of Industrial Turnover – Investment Goods - Total market (IFAINVGT);
4. Index of Industrial Turnover – Consumption Goods - Domestic market (IFACONGN);
5. Index of new orders - Total market (IORGENGT);
6. Stock of Orders - index - Total market (ICOGENGT).

The time span is Jan. 1985 through Dec. 1996 for the four turnover and the stock of orders series, while the new orders indicator series spans from Jan. 1991 through Dec. 1996, for a total 84 observations. The graphs of original series are presented in the first display dedicated to each series at the end of the paper. Visual inspection suggests that five out of the six series analyzed are strongly seasonal while, not surprisingly, the stock series (ICOGENGT, Fig.6a) is quite smooth. The turnover series, such as many Italian series of industrial production, show very low August values, because of the shutdown of factories in this month for summer vacations. The trough in the series occurring in August is presumably the main reason for both procedures favoring multiplicative adjustment.

2.1 Some General Remarks on the Results of the Seasonal Adjustment Using the Two Procedures

The main results of the automatic model identification using default options, with the parameter estimates and their standard error, are displayed in Tab.1. For three of the series (IFAGENGE, IFAINVGT, IFACONGN) the two procedures select the same ARIMA model (the *airline*), resulting in very similar parameter estimates. As for the other three series, with the two procedures yielding different models, there seem to be some indications for inadequate model identification, as it will be discussed shortly later on, in a more detailed illustration of the results of the application of each procedure.

Tab.1 – Automatic model identification with TRAMO-SEATS (TS) and X-12-ARIMA (X12)

Series		Log	ARIMA model	Parameter estimates (std error)	Notes
IFAGENGE	TS	yes	airline	θ_1 = - .3869 (.084), θ_{12} = - .638 (.086)	Using shorter (6 days) Easter affecting period yields signif. East. effect
	X12	yes	airline	θ_1 = - .3929 (.08), θ_{12} = - .6814 (.079)	
IFAINVGN	TS	yes	(2,1,0)(0,1,1)	ϕ_1 = .777 (.077), ϕ_2 = .504 (.08) θ_{12} = -.623 (.09)	
	X12	yes	airline	θ_1 = - .376 (.081), θ_{12} = - .5423 (.079)	
IFAINVGT	TS	yes	airline	θ_1 = - .432 (.084), θ_{12} = - .512 (.089)	
	X12	yes	airline	θ_1 = - .4615 (.077), θ_{12} = - .5847 (.079)	
IFACONGN	TS	yes	airline	θ_1 = - .659 (.067), θ_{12} = - .378 (.09)	
	X12	yes	airline	θ_1 = - .6483 (.064), θ_{12} = - .44 (.078)	
IORGENGT	TS	yes	(3,1,1)(0,1,1)	ϕ_1 = - .21 (.244), ϕ_2 = - .128 (.161), ϕ_3 = - .429 (.141) θ_1 = - .576 (.24), θ_{12} = - .657 (.22)	With RSA=6 get a different model [(2,2,1)(0,1,1)] with TD not significant.
	X12	yes	airline	θ_1 = - .17 (.122), θ_{12} = - .6962 (.117)	
ICOGENGT	TS	yes	airline	θ_1 = .2105 (.0831), θ_{12} = - .7471 (.061)	TRAMO estimates a diff. model [(1,1,0)(0,1,1)] that involves not admiss. decomp.
	X12	no	(0,2,2)(0,1,1)	θ_1 = - .622 (.084), θ_2 = - .183 (.084), θ_{12} = - .6692 (.067)	

Testing for possible trading day (TD) effects, X-12-ARIMA yields significant TD effects for all-but-one (ICOGENGT) series, while TRAMO introduces a correction for trading days in three of the turnover series (IFAGENGE, IFAINVGT, IFACONGN) and the IORGENGT series. In the latter case, however, significance is obtained using only one parameter in the specification of TD effect. Surprisingly, using same default option for duration of Easter affecting period (8 days), TRAMO never identifies a significant Easter effect, while X-12-ARIMA introduces a correction for Easter in three series (IFAGENGE, IFAINVGN, IFAINVGT). After reducing the length of Easter affecting period to 6 days, TRAMO identifies a significant Easter effect for the series IFAGENGE. Automatic outlier treatment with the two procedures results in a few observations selected as irregular in each series, such as showed in Tab.2.

Tab.2 – Outlier detection*

Series	Both TRAMO and X12	Only TRAMO	X12 - critical. value $|t|$ >3.25
IFAGENGE		AO (8/92)	AO (7/93)
IFAINVGN	AO (8/90), AO (4/94)	LS (1/93)	AO (12/91)
IFAINVGT	AO (8/90)	AO (4/94)	AO (7/93), AO (7/94)
IFACONGN		AO (1/86)	
IORGENGT	AO (8/94)	TC (2/92)	
ICOGENGT		LS (12/88)	

*AO (additive outlier), LS (level shift), TC (temporary change)

TRAMO and X-12-ARIMA use broadly the same method for detecting outliers [cf. Chang, Tiao and Chen (1988) and Chen and Liu (1993)]. The procedure is based on a significance test of the estimated coefficients of the regression of the residuals of a model fitted to the series on each type of outlier. Increasing the critical value decreases the sensitivity of the outlier detection routine, possibly decreasing the number of observations treated as outliers – default critical value differs in the two programs (TRAMO uses $|t|>3.5$ while X12 sets $|t|>3.8$). However, the set of automatically identified outliers can change if the ARIMA model fitted to the original series is changed and depending on the set of other regression effects introduced in the preadjustments (e.g., Easter effect). This issue is confirmed to some extent examining the results of automatic outlier detection for the series analyzed in this paper. This problem deserves further attention. Indeed, an important step of the analysis is trying to give an economic interpretation of irregular observations, in order to guard against detecting spurious outliers, due to, e.g., non-linearity in the data not accounted for in the modelling process.

2.2 *Seasonal Adjustment Using TRAMO-SEATS*

TRAMO-SEATS has been applied in a fully automatic way, using the parameter RSA. In this case the program tests for the log/level specification – for all the series analyzed the test selects a multiplicative decomposition –, makes a pre-test for the presence of Trading Day (TD) and Easter effects and performs automatic model identification and detection and correction of three types of outliers: additive outliers, level shift and transitory changes. The results of the procedure have been examined using three different value of RSA(4, 6 and 8). The three situations differ only for the number of parameters used for the Trading day effect specification.[1] For the series analyzed, the results obtained using the three different options are broadly the same, with one remarkable difference for the series of new orders indicator

[1] For RSA=4 TRAMO uses a one parameter specification (working-non working days) for TD effect ; RSA=6 implies 6 parameters (one for each working day), while RSA=8 uses same specification as RSA=6, adding a length-of-month correction factor.

(IORGENGT). Therefore, apart from the series IORGENGT, the results which are examined hereafter have generally been obtained using RSA=6. In the case of the series IORGENGT, with RSA=4, TS selects a model with a significant TD effect. However, the estimates of the autoregressive (AR) parameter at lag 1 and 2 have very large standard error, a circumstance that casts some doubts on the stability of the model identified. On the other hand, setting RSA=6 or 8 will end up with a $(2,2,1)(0,1,1)_{12}$ model, with an estimates of the AR parameter at lag 1 very close to 1 (0.96). Nevertheless, diagnostics based on the residuals (cf. Tab.3) are broadly satisfactory with both the models selected, with the exception of an indication for the presence of significant residual autocorrelation (Ljung-Box test) in the second model fitted. The reduced extension of the series involves that TRAMO during automatic model identification, after attempting to estimate ARIMA models for the linearized series using polynomials of gradually lower order, eventually results in using the default model. On the whole, there is the impression that the decomposition for this series is of poor quality.

Tab.3 – Diagnostic checking *

Series	Model	Ljung Box (LB)	LB - sq. res.	Box-Pierce	Normality
IFAGENGE	airline	26.44	29.81	1.66	1.332
IFAINVGN	(2,1,0)(0,1,1)	21.41	26.54	3.33	1.047
IFAINVGT	airline	28.36	30.17^{+}	6.5	9.78^{++}
IFACONGN	airline	19.2	17.00	0.69	1.638
IORGENGT 1)	(3,1,1)(0,1,1)	23.75	17.41	4.88	0.7509
2)	(2,2,1)(0,1,1)	35.16^{++}	23.08	6.9	
		0.5705			
ICOGENGT	airline	32.67^{+}	31.17^{+}	5.63	2.943

* Value significant at: 5% ($^{++}$), 10% ($^{+}$)

Concerning the other series, in four out of five cases the ARIMA model identified is a $(0,1,1)(0,1,1)_{12}$, i.e. the *airline*, while for the series IFAINVGN the model selected is a $(2,1,0)(0,1,1)_{12}$. Indeed, it is suggested [cf. Findley et al. (1998)] that model $(2,1,0)(0,1,1)_{12}$ can approximate the airline model, as long as the nonseasonal MA parameter of the latter model is not large (say, <.4). However, parameter estimates (Tab. 1) and diagnostics on the residuals from the model selected (Tab.3) do not suggest model inadequacy or overparametrization, with the exception of an indication of nonlinearity, such as resulting from a value of the Ljung-Box statistic for the squared residuals higher than the value computed for the residuals.

Turning to the four series whose decomposition is based on the airline model, three series (IFAGENGE, IFACONGN, IFAINVGT) achieve satisfactory results, apart for a violation of the normality test of the residuals of the model fitted to IFAINVGT and some indication of nonlinearity when comparing Ljung-Box test for the residuals and the squared residuals of the series IFAGENGE and IFAINVGT (Tab.3). Conversely, in the case of the stock of order series (ICOGENGT) it is rather questionable the need for a multiplicative decomposition, because of the smoothness of the series, cf. Fig. 6a. Pre-processing of the series with TRAMO results in a non-admissible decomposition (negative spectrum) and SEATS replaces the model identified from TRAMO with the airline model, in order to achieve an admissible one. The estimated seasonal factors span over a very small range (between 98.6 and 103.3) and all indicators of the result of the decomposition (e.g. standard error of the final estimator, confidence interval for final seasonal estimator) suggest that the decomposition yields a weak signal. This impression is reinforced from the observation of the graphical display of the results of the decomposition, that can be examined in the appendix of Mazzali (2000), where the estimated trend and SA series for all the series analyzed in this paper are graphed. The graphs in Fig. 5a and Fig. 5b of that paper show that estimated trend and SA series are quite regular and almost indistinguishable from the original series. Indeed, this is an example where adopting a multiplicative decomposition, after that automatic test for log/level specification has selected log-transformation of the original data, does not appear entirely appropriate. Additive decomposition has then been examined for this series, resulting in a $(2,2,1)(0,1,1)_{12}$ model, with TD and Easter effects not significant and the same outlier identified (LS, 12/88) as with multiplicative model. However, estimates of the AR parameters are very small ($\phi_1 = -.0257$, $\phi_2 = .167$), with large standard error. Although diagnostic checking (autocorrelation of the residuals, residual seasonality, normality) suggests an acceptable fit, on the whole the model selected seems to undergo overparametrization and overdifferencing, which leads to consider the additive decomposition not a viable alternative for this series.

2.3 Seasonal Adjustment Using X-12-ARIMA

Methods of seasonal adjustment based on *ad hoc* filters lack the rigorous theoretical foundations of AMB methods. However, X-12-ARIMA include a large set of diagnostic tools to check, at least qualitatively, the result of the procedure. It is then possible to trace a kind of automatic application of X-12 that parallels automatic application of TRAMO-SEATS. X-12 incorporates, for example, a modeling subprogram, called RegARIMA, for prior adjustments for various effects as well as a sort of automatic model identification, which is in the same operational relationship with the core procedure as it is TRAMO with respect to seats. Indeed, X12 does not have a pre-test for the log/level specification, so the results for both the additive and the multiplicative decomposition have to be compared and the selection of one model between the two is not always simple. In this experiment a multiplicative decomposition appeared to be the most reasonable solution for five series, while for the last one both the model identified (one for the level and one for the logs) are not entirely satisfactory.

Automatic model identification in X-12-ARIMA consists of searching for an acceptable ARIMA model among a default set, represented by five models with non-seasonal orders (0,1,1), (0,1,2), (2,1,0), (0,2,2) and (2,1,2) and always a seasonal order of (0,1,1). In order to be acceptable a model has to meet three requirements: *i)* it must have a Ljung-Box statistic that does not reject at the 5% level the hypothesis that the model residuals are uncorrelated, *ii)* it must have an average percentage standard error in h-step ahead (within-sample) forecasts over the last 36 months which is less than 15% and *iii)* it must satisfy a criterion based on the moving average coefficients that protect against overdifferencing. The model selected for five series is the airline with multiplicative decomposition (cf. Tab.1, partly reproduced in Tab. 4). However, for two series (IFAINVGN, IORGENGT), setting a less conservative threshold for the p-value of Ljung-Box *portmanteau* test (≈10%, say), would involve rejection of the airline model. The F-test and Kruskal-Wallis test identify the presence of stable seasonality, while the test for the presence of moving seasonality is always rejected at five percent.

Tab. 4 – Model checking and stability diagnostics

Series	Model	Ljung Box (p-value)	F-test for mov.seas. (p-value)	Q statistic (M1 - M11)
IFAGENGE	airline	.277	.77	.24
IFAINVGN	airline	.105	.615	.24
IFAINVGT	airline	.526	.765	.22
IFACONGN	airline	.652	.316	.28
IORGENGT	airline	.072	.931	.18
ICOGENGT 1)	(0,2,2)(0,1,1)	.223	<.01	.45
2)	(2,1,0)(0,1,1)	.061	.148	.34

To assess the adjustment, X-12-ARIMA (and most of its ascendant versions) has a set of statistics pertaining to the estimated trend-cycle, seasonal and irregular components (the M1-M11 and Q statistics) which, although they cannot be given a formal statistical interpretation, yet can be looked at for a qualitative appraisal of the results of the decomposition. For the five series for which the model identified is the airline, the M1-M11 diagnostics are all rather good and their weighted average (Q statistic, cf. Tab. 4) has always a low value, indicating good quality (with 1 being the cut-off point for the test).

Conversely, examination of spectral plots reveals visually significant residual trading day peaks in the first differences of the SA series (IFAINVGT, IORGENGT) and in the final irregular component (IFAINVGN). All of these series had previously been adjusted for trading-day effect.

A new diagnostic tool included in X-12-ARIMA for assessing the stability of seasonal adjustments are the sliding spans (Findley et al., 1990). The sliding spans provide summary statistics for the different outcomes obtained running the program on up to four overlapping intervals of the series. For each month in common to at least two of the subspans, the difference between the largest and smallest adjustments obtained from different spans are analyzed, together with the estimates of month-to-month changes and of other statistics. A summary of the most significant results of the sliding spans analysis is showed in Tab.5. The program has not performed a sliding spans analysis for two of the six series: for IORGENGT the data span of the series (Jan. 1991 through Dec. 1996) was too short for the program to accomplish the analysis, while for the series ICOGENGT the program warns that the range of seasonal factors is too low for summary sliding spans measures to be reliable, therefore not printing out any statistics of sliding span analysis. This confirms somewhat the comment on the significance of the decomposition of this series proposed after running TRAMO-SEATS. The table displays the number of months (and the percentage thereupon) flagged as unstable in some of the relevant statistics of the sliding span analysis, including most of the times an indication of the month with multiple occurrence of unstable estimates. Although the percentage of unstable months do not exceed in all-but-one case the empirical limits recommended by the program, still there is some evidence of instability in short-term variation for some of the SA series (IFAINVGN, IFAINVGT).

Tab.5 – Sliding spans - months flagged as unstable

Series	Seasonal factors	Final SA series	Month-to-month changes in final SA series	Year to year changes in final SA series
IFAGENGE	2 (1.9 %)	5 (4.6 %) (3 Aug.)	14 (13.1 %) (3 Apr.)	2 (2.1 %)
IFAINVGN	8 (7.4 %) (3 Aug.)	10 (9.3 %) (4 Aug.; 3 Apr.)	30 (28%) (5 Aug., Apr.; 4 Jul.)	13 (13.5 %)** (4 Apr.; 3 Mar.)
IFAINVGT	4 (3.7 %) (3 Aug.)	7 (6.5 %) (3 Aug.)	22 (20.6 %) (3 Jun., Aug., Sep., Nov., Dec.)	1 (1.0 %)
IFACONGN	0	1 (0.9%)	2 (1.9%)	0

** Percentage observed beyond recommended limits

Turning now to the examination of the results for the series ICOGENGT, Tab. 4 shows the outcome of the procedure with both the additive and the multiplicative decomposition. None of the two models identified appear for some reason completely satisfactory. For the additive model the moving seasonality test suggests the presence of moving seasonality at the one percent level, while the model selected after log-transforming the original series $[(2,1,0)(0,1,1)_{12}]$ would be rejected using a less conservative significance level of the Ljung-Box test. Although the Q test suggests good quality of the adjustment, in both cases the M4 test has a value greater than 1, indicating the presence of significant autocorrelation in the final irregulars, which can be interpreted as an evidence of incorrect model specification. It is suggested [Lothian and Morry, (1976)] that in such cases a trading-day effect should have been specified for the series.

A final comment on the outcome of the seasonal adjustment with X12 is about the diagnostic for the presence of calendar-month heteroschedasticity, such as indicated by the moving seasonality ratio. The moving seasonality ratio is measured by the ratio between the average monthly differences in the irregulars (obtained as ratio between the detrended series and the seasonal factors) and the average monthly differences in the detrended series. A low value for some month is an indication of highly variable seasonal movement. The turnover and the new-order series show very low August value of the moving seasonality ratio, which could be afforded shortening the length of the seasonal filter, although the special pattern of the series in August will still involve, even with this change, large revisions in the August adjustment. Findley *et al.* (1998) suggest that a plausible solution to reduce volatility of series having quite small values in the same month each year (relative to the other months) is using the pseudo-additive adjustment. However, with pseudo-additive adjustment it is not clear how to deal with calendar and other regression effects, so this option for seasonal adjustment with X12-ARIMA has not been explored in this paper.

3. Comparing the Results of the Two methods

Although various criteria have been proposed for evaluating seasonal adjustment methods based either on their theoretical properties or their empirical performances, it is very difficult to find appropriate standards for comparison of different methods. Bell and Hillmer (1984) review several criteria, suggesting for example that criteria based on optimal properties of the (generally unknown) components in the spectral domain (e.g., coherence between original and adjusted series, with peaks removed at the seasonal frequencies without affecting the spectral density at other frequencies) could be misleading, since the estimated components may behave very differently from the true components, even in the case that the statistical model of the components is known. They also argue that a measure of the magnitude of revisions is of little or no value for evaluating seasonal adjustment methods, because the amount of revisions is affected by the choice of the model for the components, which should depend on information in the data. Therefore a criterion based on the stability of the SA series can only be useful to evaluate the quality of seasonal adjustment in the case of methods based on fixed filters, such as those of the X11 family, that give the same final adjustments, while it is inappropriate in AMB approach, using filters depending on the amount and the features of the observed time series and resulting in different final adjustments. They then suggest [Bell and Hillmer (1984), p.310] that a proper "criterion for evaluating a method of seasonal adjustment" is that it "should be consistent with an adequate model for the observed data", warning, however, that "the application of the criterion depends on arbitrary judgements regarding the adequacy of the fitted model" for the observed series and the implied models for the unobserved components.

The two procedures yield the same ARIMA model (the "airline") for three of the series analyzed. Graphical comparison of the resulting SA series (IFAGENGE, Fig. 1b, IFAINVGT, Fig. 3b and IFACONGN, Fig.4b) shows that the two methods achieve very similar results with these series. In two other cases (IFAINVGN, Fig. 2b and IORGENGT, Fig. 5b) SA series obtained with TS exhibit a slightly more regular pattern (see also Fig. 2 and Fig. 11 of Mazzali, 2000). As for the series ICOGENGT, the two SA series (Fig. 6b) have a very similar pattern, broadly reproducing the smoothness of the original series. As mentioned earlier, for this series the component extracted through the seasonal filter is rather small with both the procedures. However, visual inspection of the results of the seasonal adjustment leaves the impression that in this case the SA series includes a cyclical component that should properly accounted for in the decomposition.

Furthermore, examination of average monthly differences between the two SA series (cf. Figg.1c-6c) suggest that the two procedures, while showing some systematic features – SA series with TS are, e.g., on average higher than the series adjusted with X-12-ARIMA in the first three months and in December, with few exceptions – generally lead to quite similar results. In this case, it is then difficult to conclude which procedure is preferable after comparing the SA series resulting from the model fitted to the observed series.

A desirable property of a seasonal adjustment method is idempotency, that is when applying the procedure for a second time to the SA series that has been obtained after the first run it should leave the series unchanged. Both the methods produce SA series that generally do not show any seasonal feature. When applied to the SA series TS identifies a seasonal component only for one series (IFACONGN). However, diagnostic checking suggests poor fitting of the ARIMA model identified (an "airline" with additive decomposition): the residuals exhibit significant autocorrelation (Ljung-Box test) as well as — somewhat surprisingly — significant residual seasonality, as indicated from autocorrelations at seasonal lags (Pierce test). The estimated seasonal MA root is near the unit boundary (-0.933), indicating an almost deterministic seasonality. The outcome of the application of X-12-ARIMA to the SA series, although showing no evidence of identifiable seasonality, is somewhat more disturbing. A model containing a seasonal component is identified for three SA series. However, in two cases (IFAGENGE, IFAINVGT) the estimated seasonality is deterministic (unit seasonal MA root). The other series exhibiting seasonality in SA series is IFACONGN, such as it was the case when using TS. Indeed, diagnostic checking (*F*-test and Kruskal-Wallis test) always lead to rejection of the hypothesis of the presence of either stable or moving seasonality, while the M7 and Q statistics for assessment of the seasonal adjustment are beyond the empirical cut-off value, indicating poor quality of the adjustment. For the series IFAINVGT and IORGENGT spectral plots of the resulting SA series still display visually significant residual trading day peaks.

Fig. 1d - Fig. 6d at the end of the paper compare the seasonality estimated in the SA series by both methods. While TS estimates no seasonal component in four series, the seasonality in SA series resulting from the application of X-12-ARIMA, although not large, is nevertheless a nuisance.

Concluding Remarks

This paper has proposed an assessment of the main properties of the currently most popular methods for seasonal adjustment, namely TRAMO-SEATS and X-12-ARIMA. Attention has been essentially focused on automatic use of the procedures, in view of routine application to a large number of series. Based on the findings of the limited empirical comparison carried out, the series adjusted with TS exhibit a very good idempotency property while, although the results with the two programs are quite similar, seasonal component estimated by TS shows, for some series, a more regular pattern. On the other hand, some instability in the outlier identification step suggests that both procedures have the unpleasant feature of exhibiting a strong interaction between preadjustment of the series and automatic model identification.

Theoretical properties of an approach based on global stochastic models, like TS, make it preferable with respect to an approach based on *ad hoc* filters, because: *i)* the filter is selected based on known assumptions on the stochastic properties of the series, *ii)* the estimated components minimizes a well-defined criterion and *iii)* a set of statistical tests for model checking is incorporated. As mentioned earlier, the new program X-12-ARIMA offers some new options for the filters and a large set of tools for examining and improving the quality of the seasonal adjustment, and these, as remarked by Maravall (1998), "represent a move toward a 'model-based' (MB) approach". Nevertheless, most of the diagnostics included in X-12-ARIMA are based on empirical measurements and not on statistical tests of the adequacy of a model for the data. On the other hand, the MB approach depends crucially on the selection of a satisfactory model for the observed series. TRAMO-SEATS offers a wide variety of options for model fitting and a large selection of diagnostics involving well-defined criteria for model checking. Indeed, this flexibility is achieved trading occasionally some instability in the results of the adjustment (more outliers, uncertainty of Trading day effect, no parsimony).

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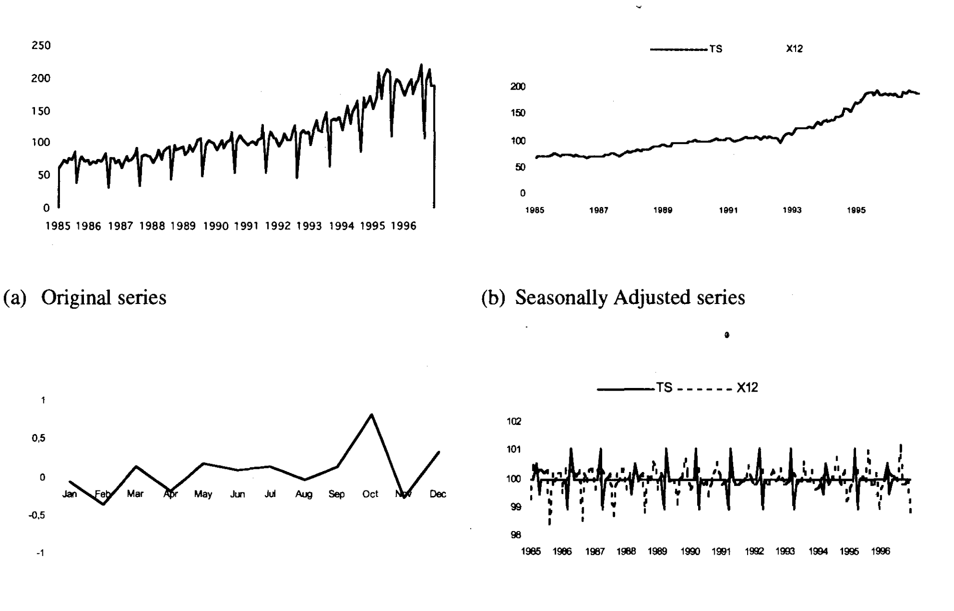
Figure 1 – Index of Industrial Turnover - Foreign markets (IFAGENGE)



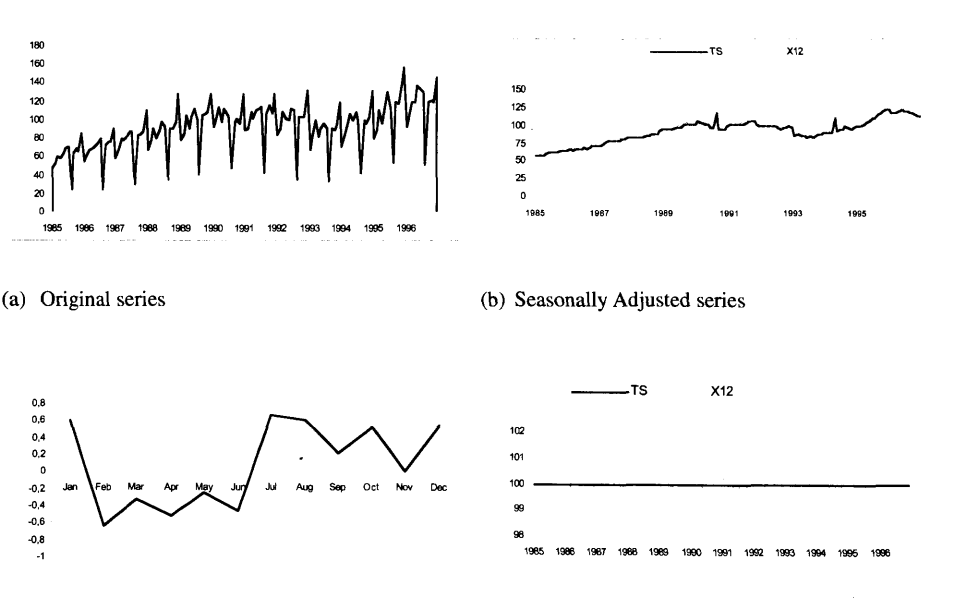
(a) Original series

(b) Seasonally Adjusted series

(c) Difference (mean) TS and X-12 estimation: SA series

(d) Seasonality in SA series: seasonal component

Figure 2 – Index of Industrial Turnover - Investment Goods, Domestic market (IFAINVGN)



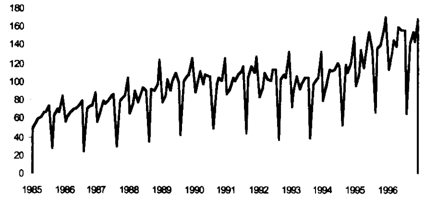
(a) Original series

(b) Seasonally Adjusted series

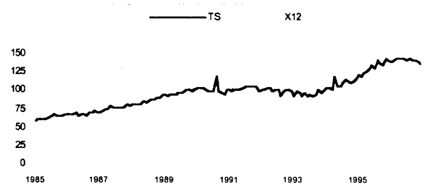
(c) Difference (mean) TS and X-12 estimation: SA series

(d) Seasonality in SA series: seasonal component

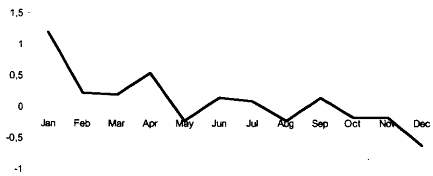
Figure 3 – Index of Industrial Turnover - Investment Goods, Total (IFAINVGT)



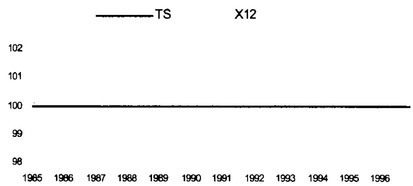
(a) Original series



(b) Seasonally Adjusted series

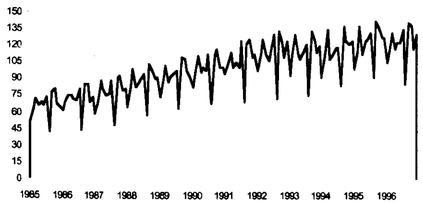


(c) Difference (mean) TS and X-12 estimation: SA series

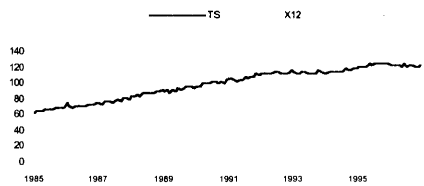


(d) Seasonality in SA series: seasonal component

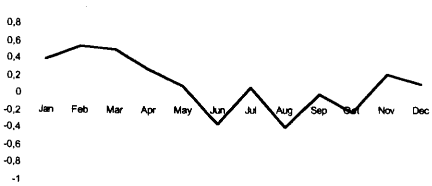
Figure 4 – Index of Industrial Turnover - Consumption Goods, Domestic market (IFACONGN)



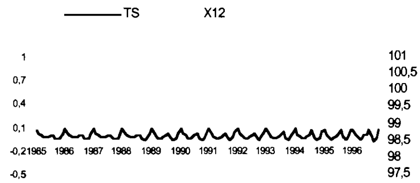
(a) Original series



(b) Seasonally Adjusted series

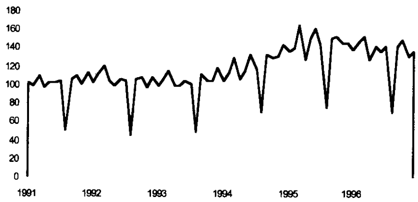


(c) Difference (mean) TS and X-12 estimation: SA series

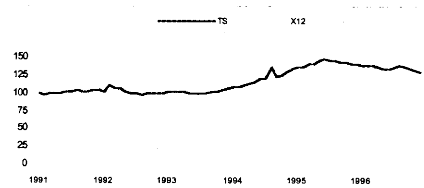


(d) Seasonality in SA series: seasonal component

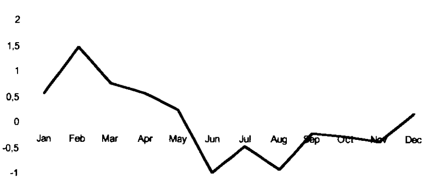
Figure 5 – Index of new orders - Total (IORGENGT)



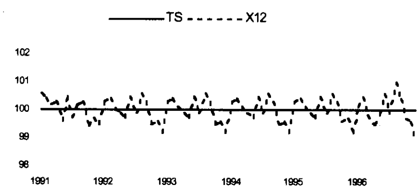
(a) Original series



(b) Seasonally Adjusted series

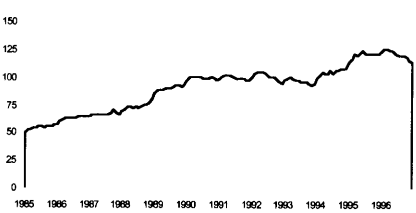


(c) Difference (mean) TS and X-12 estimation: SA series

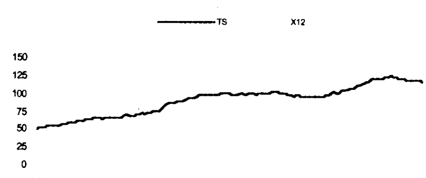


(d) Seasonality in SA series: seasonal component

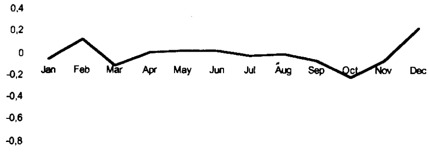
Figure 6 – Stock of orders - Total market (ICOGENGT)



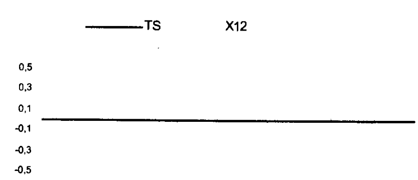
(a) Original series



(b) Seasonally Adjusted series



(c) Difference (mean) TS and X-12 estimation: SA series



(d) Seasonality in SA series: seasonal component

SEASONAL ADJUSTMENT OF ITALIAN PRICE INDEX SERIES

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1. Introduction

The aim of this work is to examine price index series and to identify unobserved components (trend, seasonality, cycle and irregular) by applying TRAMO-SEATS (Maravall and Gomez, 1991) and X-12-ARIMA (Bureau of the Census, 1997) procedures. Since this paper is to be included in a vaster research project aimed at implementing these programs on a wide range of Italian economic series, our principal purpose is to use default options and automatic identification of ARIMA models to draw the above components. In other words the assumption of our experiments is that these procedures have to be used by institutions which cannot carry out detailed analyses on each series: in fact they have to deal with a large number of series and meet the demands of the users quickly.

This study is organized as follows: the second paragraph describes the price index series; the third paragraph stresses the role of ARIMA models in time series decomposition; the fourth paragraph briefly presents the results yielded by applying the two procedures; the last paragraph contains conclusions.

2. Price index series. Preliminary analysis

Seasonal behavior in the price index series is explained by the fact that companies review prices in particular times of the year. Moreover for consumer price series, a spurious seasonal component is linked to how prices are collected: prices of some items (rents, durable goods and services) are collected every three months and left unchanged otherwise (Banca d'Italia, Bollettino Economico n. 30, 1998). This is an important aspect in the seasonally adjustment of these series and Cubadda and Sabbatini (1997) take it into account in analyzing the Italian cost-of-living index. In their work they conclude that the seasonal component for this series has essentially a deterministic nature.

The following series are examined:

- consumer price indices: PCOALTGP (food excluding tobacco), PCOBENGP (food – total), PCOGNTGP (total excluding tobacco), PCONALGP (non food) and PCOSERGP (services – total);
- wholesale price indices: PINGENGP (total);
- producer price indices: PPICONGP (consumer goods), PPIGENGP (total), PPIINTGP (intermediate goods) and PPIINVGP (investment goods).

Consumer and wholesale prices are available for the period going from January 1989 to December 1996 for a total of 96 observations while the sample of producer prices extends from January 1981 to December 1996 for a total of 192 observations. For the latter first differences and sample autocorrelations lead to exclude the period 1981.1 - 1985.12 that shows a very accentuated seasonal behavior. If the first 60 observations are removed, data become more homogeneous, seasonal effects on the autocorrelations are reduced and identification of ARIMA models becomes easier. Moreover seasonality in the raw series is completely hidden by trend and emerges only after first differencing.

As regards the instantaneous data transformations graphs of the raw series and of their first differences do not suggest logarithmic transformation. These graphs are plotted in appendix (figures 1, 2, ..., 10). Despite this all the producer price series are transformed according to the pretest for the level-versus-log specification of TRAMO-SEATS, while in X-12-ARIMA only the series PPICONGP is transformed. However logarithmic transformation, thus a multiplicative (log-additive) model of decomposition, is imposed on the producer price indices in order to facilitate data comparison[1].

Before identifying ARIMA models it would be advisable to exclude irregularities produced by changes in the base year and in indirect taxes, i.e. changes in VAT rates, whose effects take place over several months. This is performed by the Bank of Italy which computes indices without changes in VAT rates and seasonally adjusts these modified series. In this study for the above reasons only automatic treatment of outliers (additive outliers AO, temporary changes TC and level shifts LS, excluding innovational outliers IO) is implemented.

3. Building of ARIMA Models

Building of ARIMA models for price index time series is rather difficult due to a weak seasonality and to the length of the period analyzed. If these indicators are compared with other economic series (production, turnover, foreign trade, national accounts), they show some peculiarities that clearly appear through graphics and sample autocorrelations. Since ARIMA models play an important role in the decomposition of the series, both within the ARIMA model-based approach and within the empirical or "ad hoc" methods for forecasting purposes, it is important to check

[1] Logarithmic transformation is analyzed in the work of Ciammola and Maravalle (1998).

whether the ARIMA models are able to take in the price index features.

To this end we thought it was interesting to compare the models of many Italian economic indicators by using a map built through a multidimensional scaling (MDS). Here the purpose of MDS is to construct a map of the locations of ARIMA models from data that specify the dissimilarities (distances) between pairs of objects, i.e. between pairs of models[2]. By considering the nature of the data analyzed we choose the metric classical MDS whose fundamental equation is:

$$T = D^2 + E$$

where T is a linear transformation of the dissimilarities, matrix D^2 has elements that are squares of the Euclidean distances and E is the error (residual) matrix. Measures of fit, i.e. Young's S-stress, Kruscal's stress measurement and the squared correlation coefficient between the data and the Euclidean distances, indicate that the two-dimensional Euclidean model describes the dissimilarities among ARIMA models perfectly.

Figure 11 contains the map of the models. It shows the models built on the prices series and marked by the labels x72, ..., x76, x79, x82, x84, ...,x86, the models identified for the quarterly data of the national accounts labeled sc1, sc2, ..., sc41 and the models for the other series analyzed (industrial production, turnover and foreign trade): the first and the second group of models branch off from the group including the models of different typologies of economic indicators and forming a crowed nucleus. Therefore the map shows how ARIMA models are able to "embody" the information embedded in the data. This is an important result especially for the consequent implications: from a methodological point of view this "ability" makes the ARIMA model-based approach of the procedure SEATS preferable to the empirical approach of the procedure X-12-ARIMA. However there are some doubts about this presumed superiority of the model-based method. Firstly SEATS does not allow to decompose models whose autoregressive (AR) and moving average (MA) polynomials have orders $p>3$ and $q>3$: as experience shows, these constraints are admissible for the AR polynomials but not so for the MA polynomials. Secondly some models do not accept an admissible decomposition because irregular component may have pseudo-spectra with negative values. When SEATS fails to decompose a time series and thus an ARIMA model, it automatically approximates that model with a decomposable one, but the model approximation cannot always be justified by the "principle of exchangeability" (Piccolo, 1995).

As we have outlined above, model specification for the price series presents some difficulties: the sample autocorrelations of the differenced series $(1 - B)X_t$ are quite small and they slowly die out at seasonal lags (12, 24 and 36). So three different strategies to model these series are considered:

1. applying a seasonal difference $(1 - B^{12})$;
2. estimating an autoregressive seasonal polynomial which allows a parsimonious parameterization in some cases, but it has roots near the unit circle, so that a seasonal differencing may be preferable;

[2] The software SCA is used to model time series and the software SPSS is used to construct the map. For some series adjustment for trading day effects is needed and logarithmic transformation is applied for $|\lambda| \leq .2$, where λ is the parameter of the Box-Cox transformation.

3. fitting a harmonic model (linear combination of sinus and cosines waves) to remove a supposed deterministic seasonality and therefore building an ARIMA model without seasonal components on the residuals.

In appendix table 1 shows these models built through SCA, whereas table 2 contains the model automatically identified by TRAMO-SEATS implementing the routine *RSA* and by X-12-ARIMA through the procedure *automdl*[3]. The results often show that the seasonal MA polynomial has root near the unit circle and it is nearly cancelled out by the seasonal difference. This yields in two cases: when the seasonal component has deterministic nature, so SEATS is able to extract an extremely stable stochastic seasonality and when there is overdifferencing so that SEATS extracts a spurious seasonal component, as it happened within simulation experiments to generate series from models without seasonal AR and MA polynomials.

4. Empirical Results

This paragraph briefly presents the performances of the SEATS and the X-12-ARIMA procedures for seasonal adjustment (see tables 3 and 4 and figures 1, ..., 10). As we stated, an additive decomposition is implemented on consumer and wholesale prices while on producer price indices a multiplicative (log-additive) model is applied.

Divergent results are produced by the two seasonal adjustment procedures in the following series:

1. PCOSERGP (figure 5) for which the X-12-ARIMA estimated an almost deterministic seasonal component while seasonality extracted by the SEATS program shows an evolutionary behavior;
2. PINGENGP (figure 6) for which SEATS estimated a nearly deterministic seasonal component. It is important to underline that the X-12-ARIMA diagnostic supplies enough elements to reject decomposition: the quality of seasonal adjustment is poor, as the M1 to M11 statistics and the Q value show; the F tests for stable and moving seasonality produce the following message: "identifiable seasonality probably not present"; moreover the use of a deterministic seasonal model is suggested by the test for the inclusion of 11 seasonal dummies;
3. PPIGENGP (figure 8) for which seasonal factor extracted by SEATS and that one estimated by X-11 show accentuated differences in the first part of the sample: however this does not effect the monthly growth rates and the autocorrelations computed on the first difference of the seasonally adjusted series;
4. PPINTGP (figure 9) for which SEATS does not extract a seasonal component while X-12-ARIMA estimates an evolutionary seasonal component even if the F tests produce the message "identifiable seasonality not present".

The last situation allows us to make two observations. Firstly since the model-based approach uses filters derived directly from the ARIMA model built on the series and not "ad hoc" filters, SEATS is able to use the information embedded in the data; secondly the results give an idea of the ability of X-12-ARIMA to show

[3] We provided to modify the file *x12a.mdl*.

clearly all the elements necessary for evaluating the reliability of the decomposition.

Peculiarities of price index series and especially the weak seasonality produce an interesting result: the correlation coefficients between the monthly growth rates of the seasonally adjusted series estimated by the two programs take on almost unitary values, notwithstanding methodological and empirical divergences in the seasonal adjustment approaches. In fact these values go from .94 to .98 except for the series PCOSERGP[4].

A final consideration on the quality of the decomposition performed by SEATS. We compared theoretical components, theoretical estimators and estimates and for the series with unreliable decompositions we estimated different models from those automatically identified. This did not produce noteworthy effects except for occasional smoother monthly growth rates of trend components, but without visible consequences on monthly growth rates of seasonally adjusted series and on their turning points.

5. Conclusions

Price index series have particular characteristics in comparison with other economic indicators: this makes difficult to build ARIMA models and for some of them this leads to partly divergent results implementing the two procedures. However because of the rather weak seasonality of these series the two approaches or different models in the same program do not bring visibly different results in terms of growth rates computed on the seasonally adjusted series and of their turning points. This is confirmed by a marked correlation between series seasonally adjusted using both TRAMO-SEATS and X-12-ARIMA. In conclusion notwithstanding the methodological differences at the basis of the two decomposition procedures, the divergences are not so evident from an operative point of view. This final consideration derives from the specific cases analyzed in this study and it cannot be extended to other economic indicators.

[4] Correlation coefficients are not computed on seasonally adjusted data, but on their monthly growth rates.

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APPENDIX

- Tables
- Figures

Tables

Table 1 – ARIMA models (SCA)

SERIES	LOG.	CONST.	MODEL	OUTLIERS	Q(24)	RES. VAR.
PCOALTGP	NO	YES	(1,1,0)(0,0,1)	AO(14)	25	0.044
PCOBENGP	NO	YES NO	(0,1,3)(1,0,0) (1,1,1)(0,1,1)	TC*(20,74,91)*	18.5 22.4	0.1351 0.1545
PCOGNTGP	NO	YES NO	(1,0,1)(0,0,0)* (0,1,2)(0,1,1)		29.6 27.9	0.1224 0.1387
PCONALGP	NO	YES NO	(0,1,0)(1,0,0) (0,1,1)(0,1,1)	TC(20,74) *AO(91)*	19.9 20.8	0.1821 0.2194
PCOSERGP	NO	YES NO	(0,1,4)(1,0,0) (0,1,4)(0,1,1)	AO(36)	22.8 22.7	0.1571 0.146
PINGENGP	NO	YES	(0,1,1)(0,0,0)	AO(20,23)	20.3	0.562
PPICONGP	NO	YES YES	(0,0,4)(0,0,0)* (0,1,0)(1,0,0)	TC(105,111),LS(124) TC(111),LS(125)	22.7 24.3	0.0157 0.0268
PPINGENGP	NO	YES	(2,1,0)(1,0,0)	AO(56,61),TC(110)	18.8	0.0361
PPIINTGP	NO	YES	(2,1,0)(0,0,0)	AO(13,61)	12.4	0.0972
PPIINVGP	NO	YES NO	(0,1,0)(1,0,0) (0,1,0)(0,1,1)	AO(37,49),TC(23,109) LS(61,112)	22.2 20.6	0.0304 0.0407

* Model identified after using a harmonic model to remove the seasonality

Table 2 – ARIMA models (TRAMO-SEATS and X-12-ARIMA)

SERIES	1. TRAMO 2. SEATS 3. X-12	LOG.	CONST.	MODEL	OUTLIERS	N.T.[1]	Q(24) Q(21)	Q(24)SR [2]	QS	QSSR
PCOALTGP	1.	NO	NO	(1,1,0)(0,1,1)	AO(14)	0.18	23.01			
	2.					0.82	28.61	20.89	3.89	0.51
	3.			(1,1,0)(0,1,1)	LS(14)		17.94			
PCOBENGP	1.	NO	NO	(0,1,2)(0,1,1)[3]		1.27	17.9			
	2.					0.46	21.35	19.87	5.03	0.05
	3.			(1,1,0)(0,1,1)			28.31			
PCOGNTGP	1.	NO	NO	(1,1,0)(0,1,1)[3]		1.65	31.48			
	2.					0.67	33.75	15.79	3.71	0.61
	3.			(0,1,2)(0,1,1)			25.73			
PCONALGP	1.	NO	NO	(0,1,1)(0,1,1)	LS(20)	1.14	20.73			
	2.					1.52	18.7	24.19	1.18	0.6
	3.			(0,1,1)(0,1,1)			19.43			
PCOSERGP	1.	NO	NO	(0,1,0)(0,1,1)	TC(25)	26.96	25.22			
	2.					23.26	27.6	13.45	0.91	0.43
	3.			(0,1,1)(0,1,1)			28.31			
PINGENGP	1.	NO	NO	(0,1,1)(0,1,1)	LS(20),AO(35,22)	8.95	28.37			
	2.						19.34	42.37	11.14	5.371.62
	3.			(0,1,1)(0,1,1)	LS(20),AO(22)		22.46			
PPICONGP	1.	SI	NO	(0,1,1)(0,1,1)	LS(111)	1.95	33.14			
	2.					0.7	37.34	17.56	8.09	2.55
	3.			(2,1,0)(0,1,1)			32.23			
PPIGENGP	1.	SI	NO	(1,1,1)(0,1,1)	TC(25),LS(56)	5.9	30.42			
	2.						34.02	37.62	1.9	13.21
	3.			(1,1,0)(0,1,1)	TC(61),LS(13,56)	1.3	42.36[4]			
PPIINTGP	1.	SI	SI	(2,1,0)(0,0,0)	TC(1,61),LS(13)	15.69	14.16			
	2.					22.27	12.23	20	0.55	2.15
	3.		NO	(1,1,0)(0,1,1)	TC(1)		39.89[4]			
PPIINVGP	1.	SI	NO	(0,1,0)(0,1,1)	LS(61,13,23,112)	2.27	20.89			
	2.					2.55	19.34	19.49	0.65	5.31
	3.			(0,1,1)(0,1,1)	LS(13,61)		26.28[4]			

[1] Normality test on residuals.- [2] Q statistic is computed on squared residuals. - [3] Model with non admissible decomposition. - [4] Q(24).

Table 3 – M and Q statistics of X-12-ARIMA

SERIES	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	Q
PCOALTGP	.040	.029	.000	.158	.000	.402	1.1064	1.398	1.241	1.499	1.445	.55
PCOGNTGP	.018	.064	.000	.411	.000	.563	.588	1.173	1.091	1.518	1.461	.53
PCONALGP	.49	.117	.000	.063	.000	.846	1.283	2.208	1.967	2.832	2.683	.95
PCOSERGP	.019	.068	.000	.032	.000	.387	.458	.641	.482	.750	.674	.29
PINGENGP	.153	.052	.000	.727	.000	.797	1.175	2.248	2.026	3	3	1.04
PPICONGP	.062	.116	.000	.376	.000	.075	.501	.785	.462	.904	.812	.33
PPIGENGP	.45	.019	.000	.376	.000	.806	.970	2.153	1.33	3	2.964	.77
PPIINTGP	.074	.016	.000	.457	.000	.445	1.303	1.815	1.218	2.449	2.365	.87
PPIINVGP	.038	.094	.000	.208	.000	.149	.341	.616	.380	.648	.6	.23

Table 4 - Results of SEATS

SERIES	RESIDUAL VARIANCE	VARIANCE OF SEASONAL INNOVATION	IRREGULAR VARIANCE[1]	TREND VARIANCES[1] 1. INNOVATION 2. F.E.E[2] 3. R.C.E[3]	SEAS. ADJ. VARIANCES[1] 1. INNOVATION 2. F.E.E[2] 3. R.C.E[3]
PCOALTGP	.0334	.0319	.0656	1. .2818 2. .310 3. .333	1. .7581 2. .283 3. .296
PCOBENGP	.0252	.0309	.1091	1. .2809 2. .199 3. .195	1. .7479 2. .156 3. .162
PCOGNTGP	.0213	.0130	.1548	1. .2655 2. .163 3. .141	1. .8320 2. .097 3. .099
PCONALGP	.0461	.0451	.1133	1. .2416 2. .209 3. .217	1. .6958 2. .172 3. .182
PCOSERGP	.0291	.0668	.1526	1. .1516 2. .187 3. .218	1. .6229 2. .160 3. .175
PINGENGP	.3814	.9817	.0462	1. .6018 2. .054 3. .024	1. .9817 2. .019 3. .016
PPICONGP	.3039E-5	.001	.1888	1. .2926 2. .126 3. .075	1. .9531 2. .028 3. .028
PPIGENGP	.7135E-5	.0662	.0769	1. .1801 2. .28 3. .38	1. .6039 2. .264 3. .326
PPIINTGP	.1387E-4	.0122 (CYCLE)	.1053	1. .2206 2. .061 3. .050	1. - 2. - 3. -
PPIINVGP	.4615E-5	.0450	.1682	1. .1687 2. .181 3. .195	1. .6868 2. .140 3. .149

[1] Variances in units of residual variance.
[2] Final estimation error.
[3] Revision in concurrent estimator.

Figures

Figure 1 – Consumer price index (Food excluding tobacco)

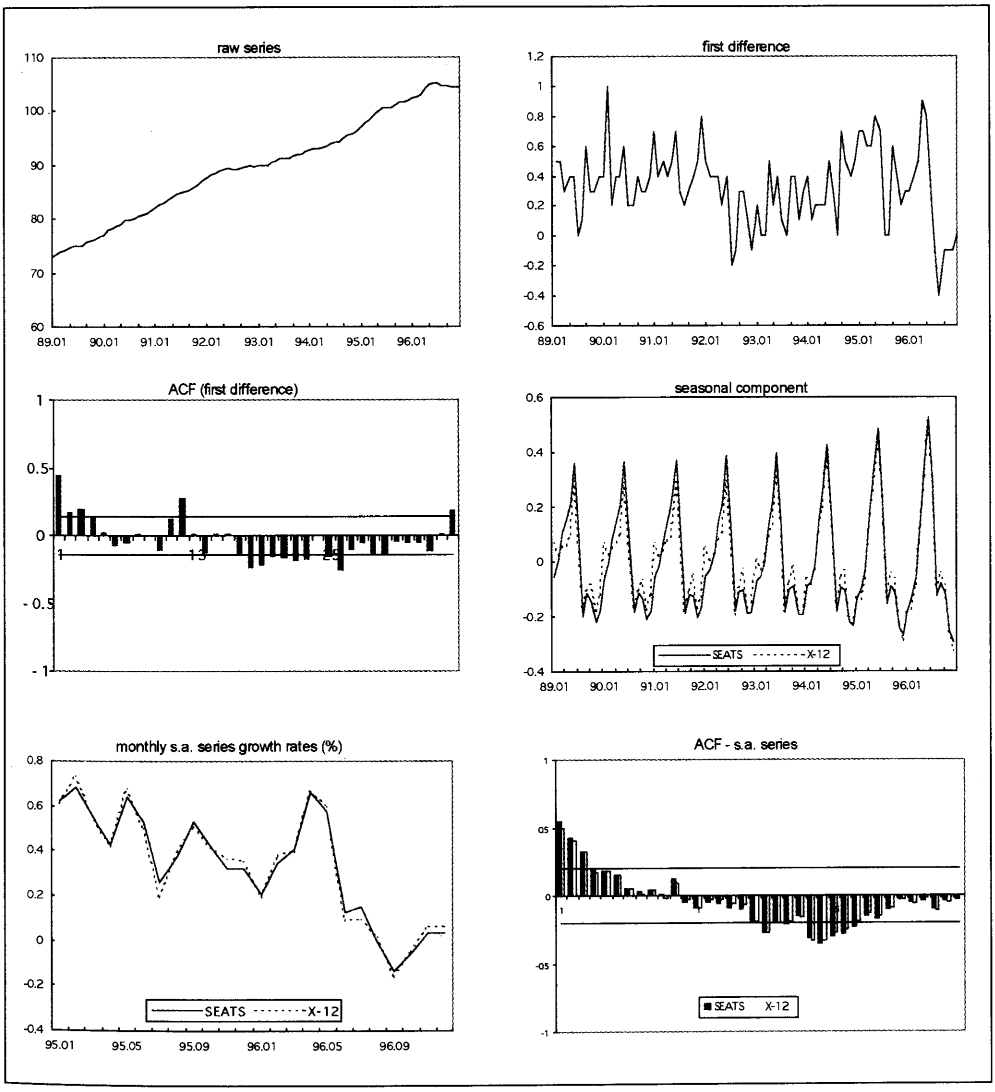


Figure 2 – Consumer price index (Food total)

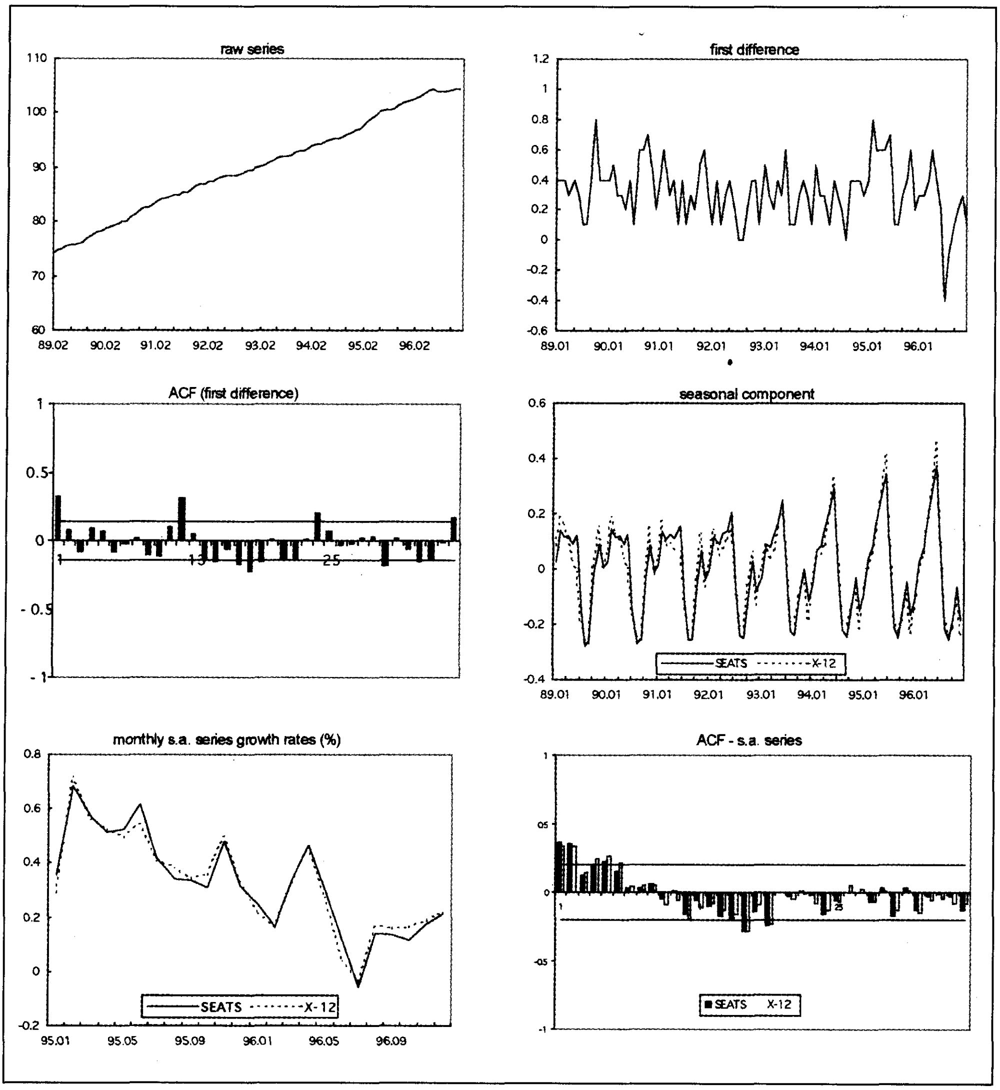


Figure 3 – Consumer price index (Food excluding tobacco)

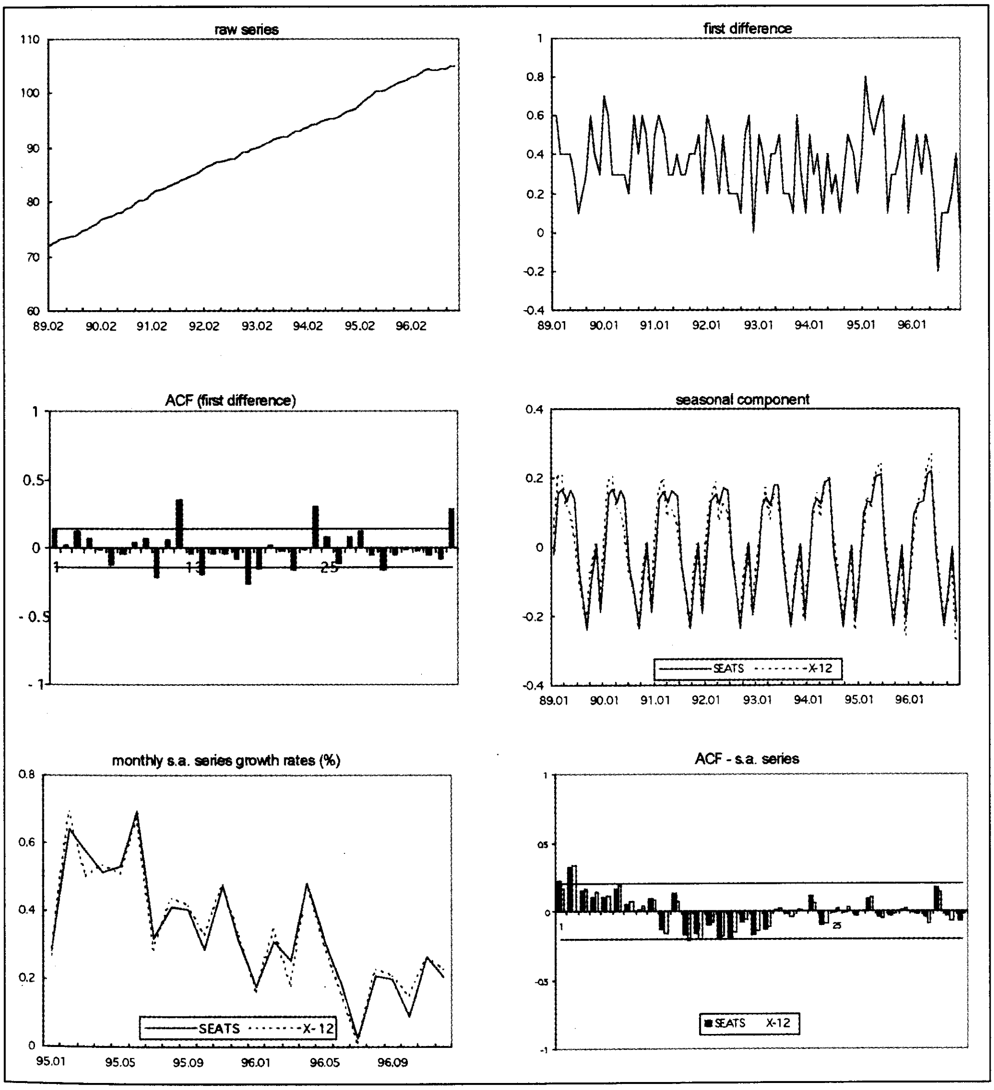


Figure 4 – Consumer price index (Non food)

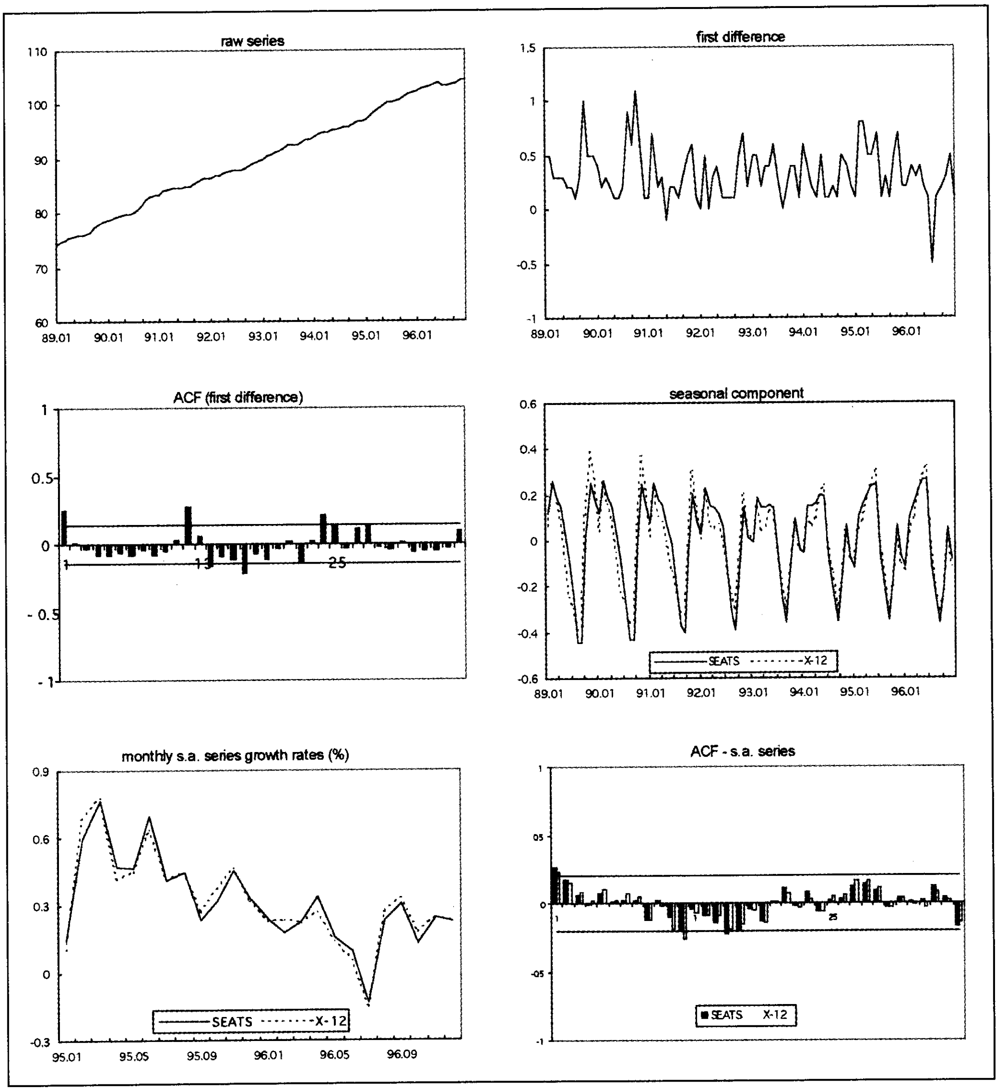


Figure 5 – Consumer price index (Services total)

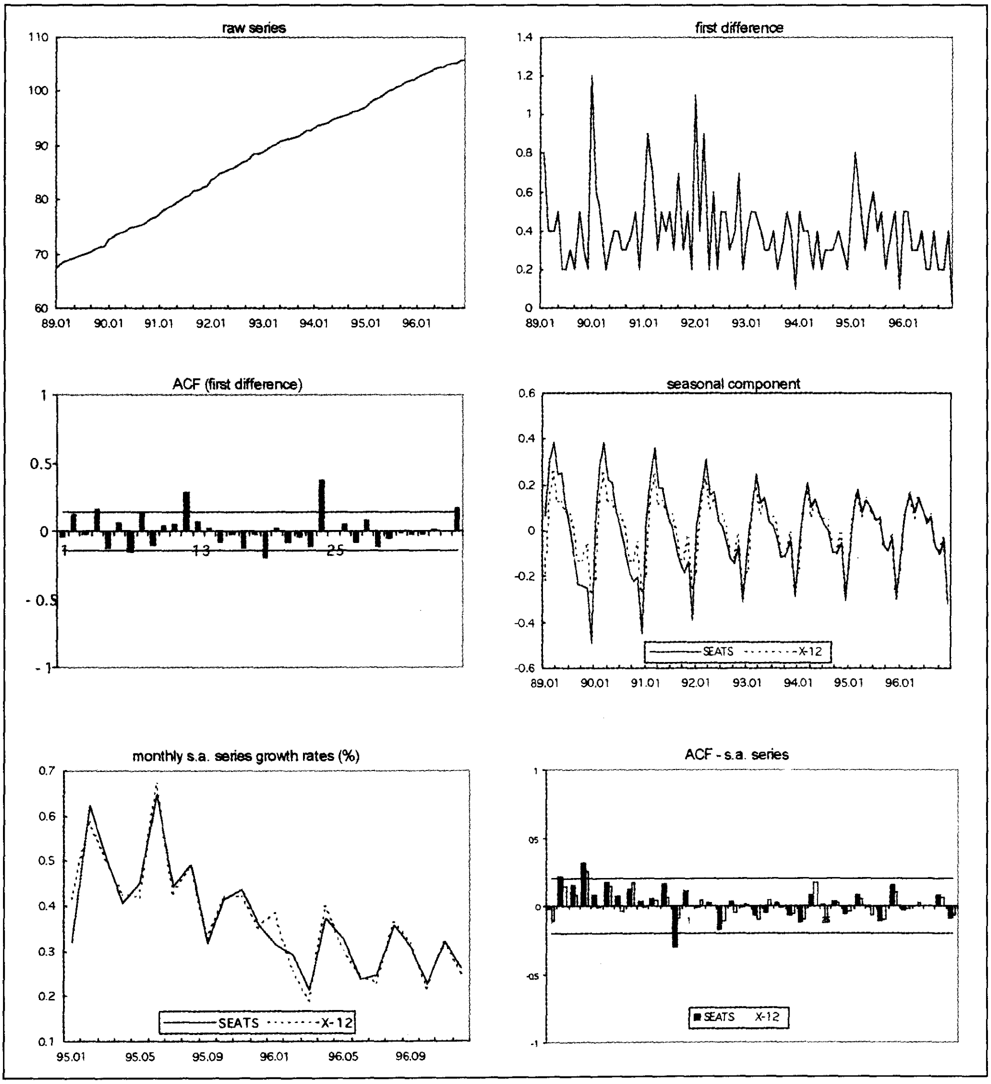


Figure 6 – Wholesale price index (Total)

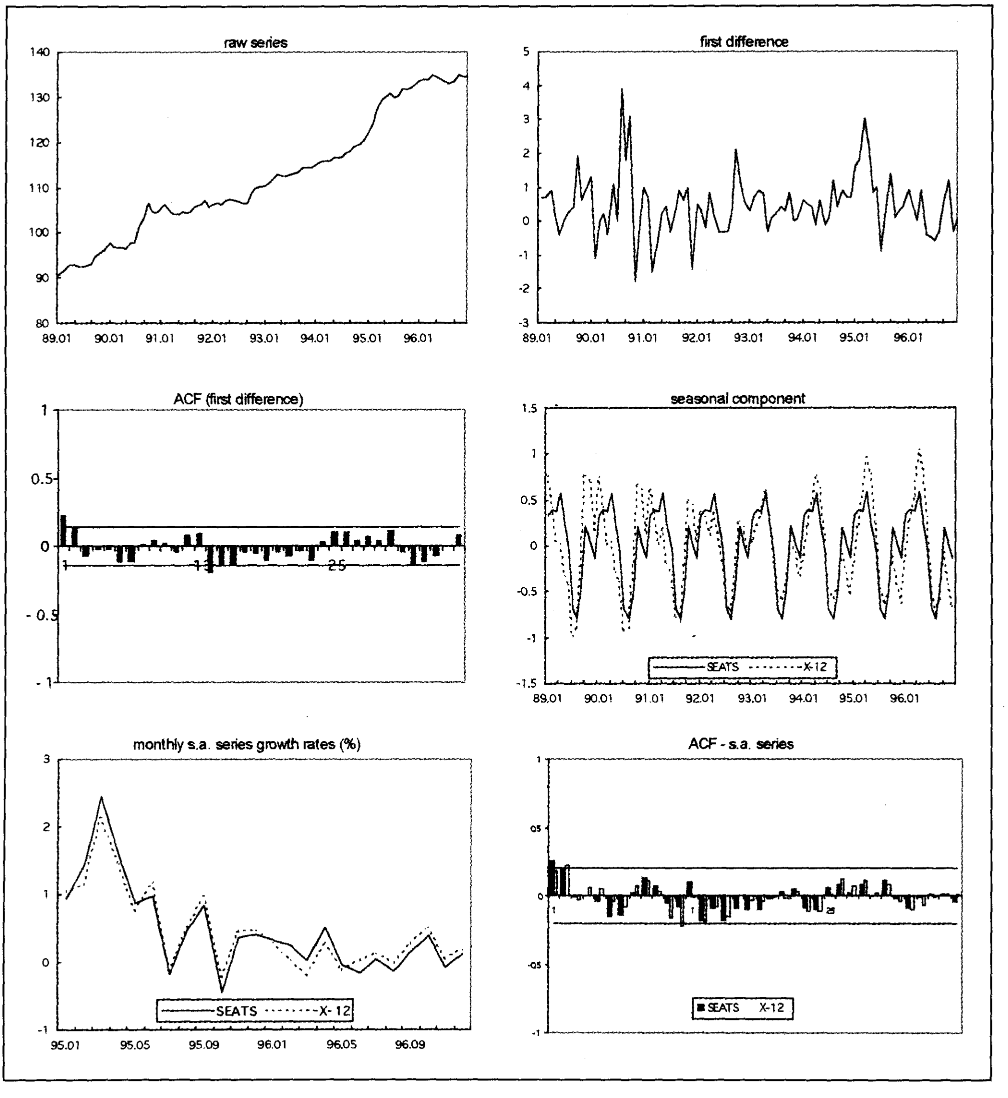


Figure 7 – Producer price index (Consumer goods)

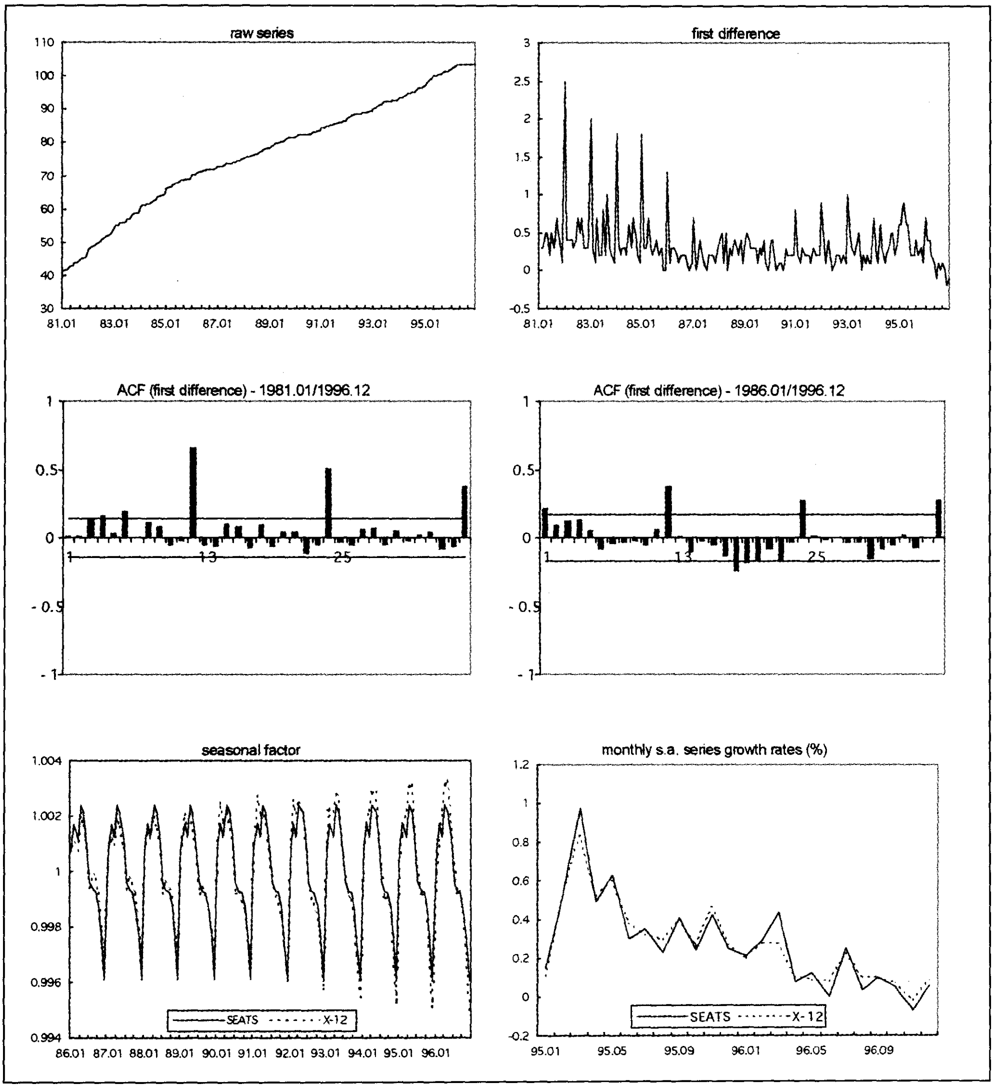


Figure 8 – Producer price index (Total)

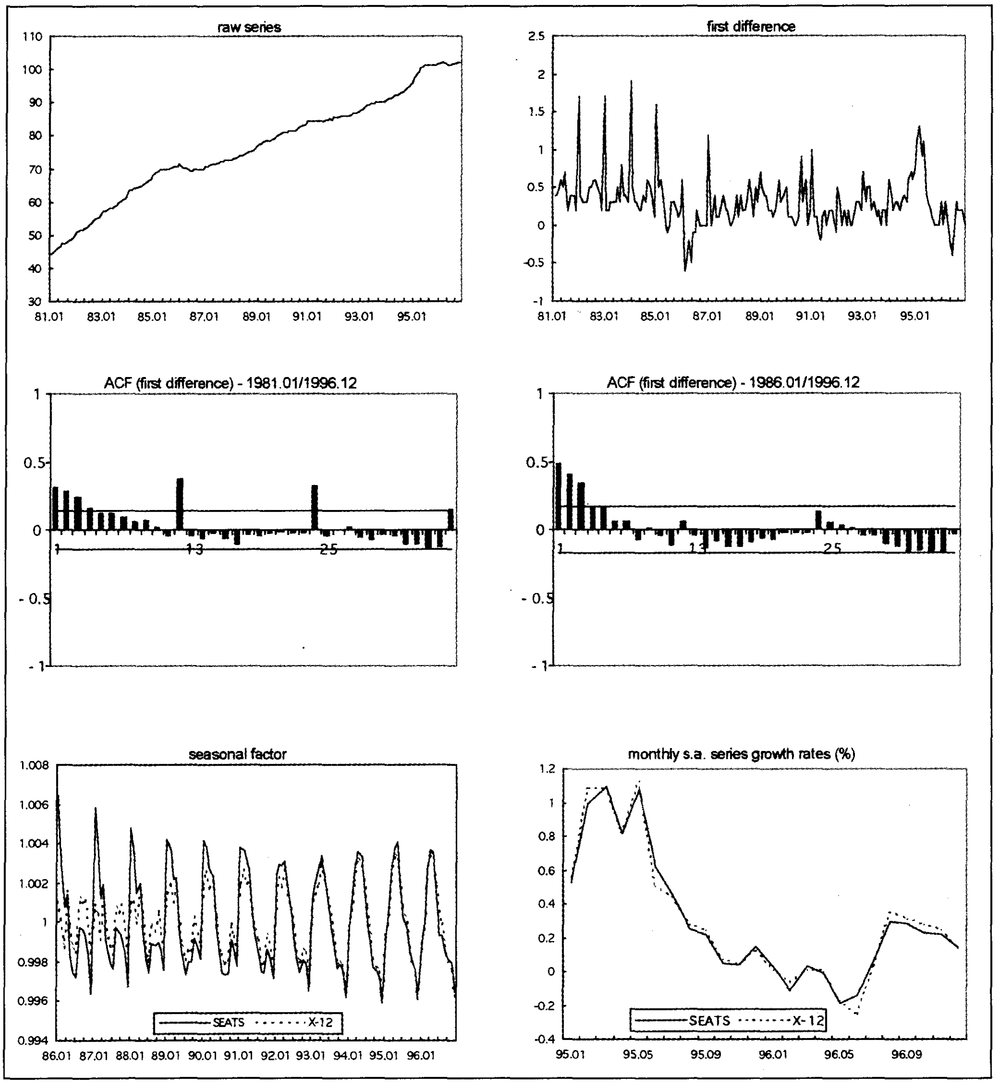


Figure 9 – Producer price index (Intermediate goods)

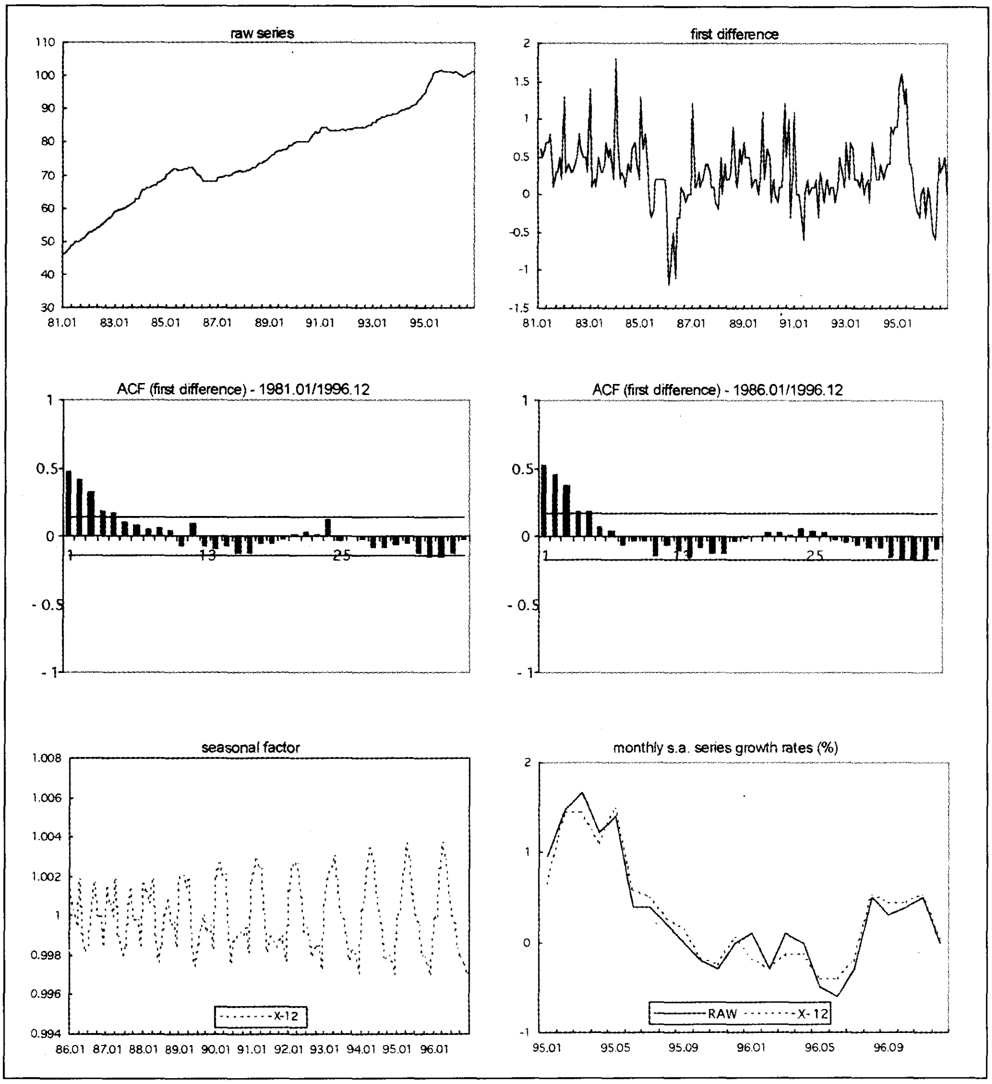


Figure 10 – Producer price index (Investment goods)

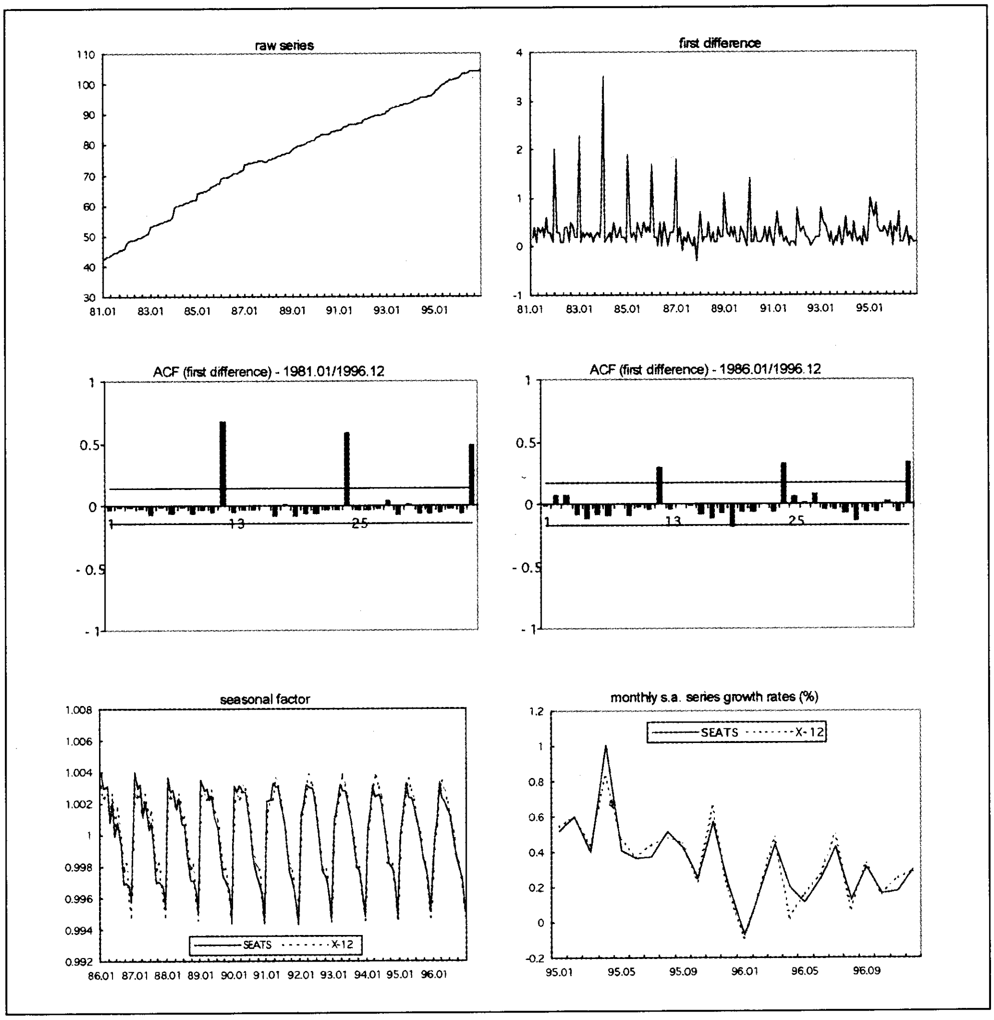
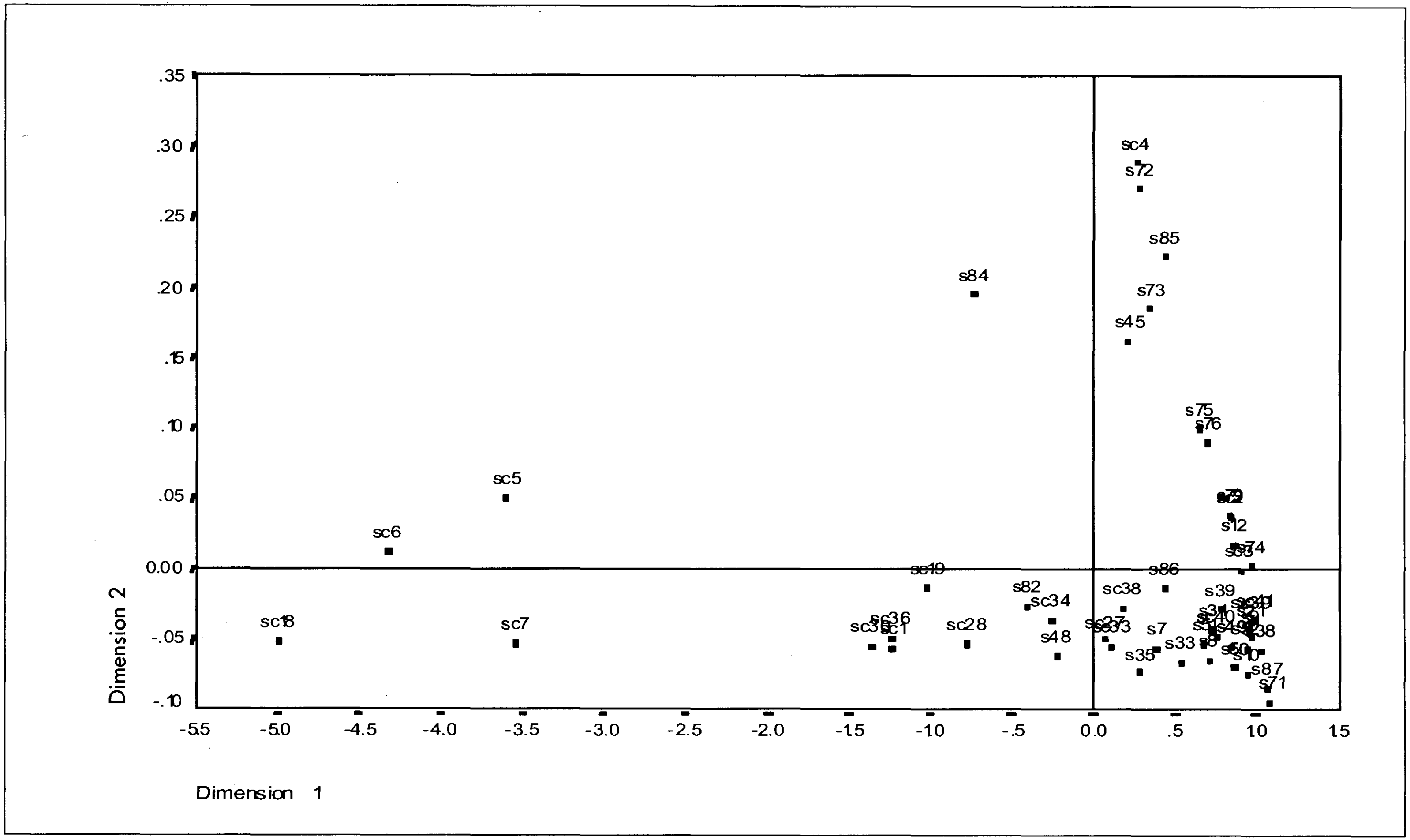


Figure 11 – Map of ARIMA models



SEASONAL ADJUSTMENT OF FOREIGN TRADE SERIES

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1. Introduction

In this paper the performance of the seasonal adjustment of some relevant Italian foreign trade series is sketched. In more detail, the series of quantity and value index concerning exports and imports are considered in this exercise, as well as the series of trade flows referring to mechanical products (Table 1). All the series come from a monthly inquiry and the reference period retained for seasonal adjustment is January 1986 - October 1996.

Table 1 – Codes of the series analysed

Code	Definition
CITGENGV	Imports - value index (1980=100)
CETGENGV	Exports - value index (1980=100)
CITGENGQ	Imports - quantity index (1980=100)
CETGENGQ	Exports - quantity index (1980=100)
CIT006GC	Imports of mechanical goods - values
CET006GC	Exports of mechanical goods - values

Seasonal adjustment has been performed by means of the procedures TRAMO-SEATS and X-12-ARIMA (from now on X12 and TS). Both the procedures are characterised by a great deal of flexibility, allowing the user to set the value of many options, so as quite different results can be obtained even by running the same procedure on the same series. In this exercise we chose to apply X12 and TS in the most automatic way, setting the option parameters always at their default values (Bureau of Census, 1997; Gómez et al., 1997).

The comparison of the results stemming from the two procedures is a quite difficult task (Fischer, 1995), given their different theoretical background and the non-observable character of the seasonal component. In the next paragraphs we will then limit ourselves to describe the output of the two procedures applied to foreign trade series and to calculate some indicators aimed at constituting a first comparison criteria between TS and X12.

2. The Procedure TRAMO-SEATS

The results of the procedure TS depend in a fundamental way from the selection of the Arima representation of the series to be decomposed. The procedure allows the user to automatically identify such a model and to estimate it; in addition TS can identify and estimate also some regression effects, such as calendar ones, outliers, etc. .

Routine application of TS is made easier with the use of the option RSA (routine seasonal adjustment) which can take values from 1 to 8. The different values set the different ways in which the adjustment is executed. In our case we adopted the value 8. This means that the procedure tests for the log/level specification, automatically identifies an ARIMA model representing the series, tests the need of regression variables such as trading days correction, Easter, length of month effect. In addition, a routine for the identification and estimation of several type of outliers is applied: it identifies and removes the effects of additive outliers (AO), level shifts (LS) and temporary changes (TC).

For all the series considered the procedure TS applied the log transformation and, consequently, a multiplicative decomposition (Table 2). In five of the six series the model identified has been the so called "Airline" model, that is a $(0\ 1\ 1)(0\ 1\ 1)_{12}$, which is the default model. The "Airline" model has many attractive features that make it suitable for seasonal adjustment; it has only three parameters but it can deal with quite a great deal of flexibility with series which show very different patterns. In addition, the values taken by its parameters MA(1) and MA(12) are easy to interpret: the closer they are to assume value 1, the more deterministic will be the pattern, respectively, of the trend and the seasonal component. Only in the case of the export value index TS identified a different model.

Table 2 – Procedure TRAMO-SEATS. RSA = 8

Series	Model	TD	E	Outliers	LB	LBq	JB	Add./Mult.
CITGENGV	(0 1 1)(0 1 1)	X	X	TC(88 1), AO(92 8)	**41,7**	27,4	0,3	M
CETGENGV	(2 1 0)(0 1 0)			AO(87 3), LS(87 7), AO(88 1)	10,4	26,7	1,4	M
CITGENGQ	(0 1 1)(0 1 1)	X	X	LS(92 12)	31,3	**38,3**	**8,1**	M
CETGENGQ	(0 1 1)(0 1 1)				23,2	15,5	0,8	M
CIT006GC	(0 1 1)(0 1 1)	X		AO(88 1), AO(91 3) AO(93 1), LS(96 1)	27,9	22,2	**15,2**	M
CET006GC	(0 1 1)(0 1 1)			AO(87 3), AO(88 1)	22,1	13,0	3,3	M

Bold: values significant at 5%.

For the three series referring to imports the trading days correction was found to be significant. In two of them also the Easter effect was detected. These calendar effects were not detected in the export series. In the end, several outliers were found.

Concerning the diagnostic of the estimated residuals, in one out of six cases there is a significant autocorrelation (Liung-Box test, LB) and in two they display departure from normality distribution (Jarque-Bera test, JB) (Greene, 1993). In one case there is a significant autocorrelation of the squared residuals (Liung-Box test, LBQ), which can be a signal of possible nonlinearities in the series (Planas, 1997). All these cases were found in the import series.

The procedure TS was repeated using the value 4 for the parameter RSA (Table 3); in this case TS considers just one regressor to represent the trading days effect, reducing the possible collinearity among the variables. The results are somewhat different: in all cases an "Airline" model has been identified, with trading days correction. Some differences arise also in the outlier identification. In what follows we will refer to the results obtained running the procedure in the more general way, that is considering the value of the RSA option set to the value 8.

Table 3 – Procedure TRAMO-SEATS. RSA = 4

Series	Model	TD	E	Outliers	LB	LBq	JB	Add./Mult.
CITGENGV	(0 1 1)(0 1 1)	X		LS(86 3), TC(88 1), AO(91 3), AO(92 8)	**35.1**	**42.1**	0.23	M
CETGENGV	(0 1 1)(0 1 1)	X			20.1	20.6	1.27	M
CITGENGQ	(0 1 1)(0 1 1)	X			26.2	**35.5**	1.90	M
CETGENGQ	(0 1 1)(0 1 1)	X			20.9	22.2	0.02	M
CIT006GC	(0 1 1)(0 1 1)	X		AO(88 1), AO(91 3), AO(93 1), LS(96 1)	22.7	19.4	**9.93**	M
CET006GC	(0 1 1)(0 1 1)	X		AO(86 8), AO(87 3), AO(88 1)	14.8	19.6	0.33	M

Bold: values significant at 5%.

3. The Procedure X-12-ARIMA

X-12-ARIMA constitutes the evolution of the X-11-Arima procedure. The most relevant changes do not concern the core of the seasonal adjustment routine, but the preceding and the following steps, which are the pre-treatment and the diagnostic checking (Findley et al., 1998). In the first step an ARIMA model is identified to extend the original series, so as to reduce the use of asymmetric filters; during this step it is possible also in X12 to identify and estimate various effects (trading days, Easter effects, outliers) which can be removed from the series before seasonal adjustment is performed.

X12 procedure does not allow the user to do at the same time both automatic ARIMA model identification and transformation choice. Because of this reason were considered both the results coming from a log transformation (and a multiplicative decomposition), as well as those coming from considering the levels and an additive decomposition. In both these cases automatic model identification has been performed, as well as automatic outlier identification and estimation (additive outliers and level shift). The choice of the moving averages for the estimation of the final seasonal component and of the Henderson average for the estimation of the final trend have been let to the program too.

Concerning the log/level specification, in four cases the BIC criterion favours the log transformation, in one case (CETGENGQ) the level of the series. In the remaining one (CIT006GC) this criterion cannot be applied because for the log transformed series no ARIMA model has been identified; imposing the "Airline" model, the BIC criterion favours the log specification (Table 4). If we look at the seasonally adjusted series, the log specification and the multiplicative decomposition give the best results for all the series (considering the synthetic test Q of adequacy of the seasonal adjustment; for a critical approach concerning this indicator see Findley et al., 1990; Battipaglia et al., 1994). For this reason the results in what follows will refer to the log transformed series and to the multiplicative decomposition.

Table 4 – Procedure X12-Reg ARIMA

Series lev	log	Model	TD	E	Outlier	Forec. err. % (last 3 years)	LB	LBq	JB	BIC
CITGENGV	log	(2 1 0)(0 1 1)	X	X	AO(92 8)	10,56	32.3	17.4	**6.10**	984.0
CITGENGV	lev	(2 1 0)(0 1 1)	X	X		11,95	**35.6**	31.2	0.53	1005.5
CETGENGV	log	(0 1 1)(0 1 1)				8,96	26.5	21.5	2.48	1085.0
CETGENGV	lev	(0 1 1)(0 1 1)	X			7,94	20.3	36.1	0.78	1110.9
CITGENGQ	log	(0 1 1)(0 1 1)	X	X	LS(92 12)	7,33	24.5	25.4	2.62	822.2
CITGENGQ	lev	(0 1 1)(0 1 1)	X	X	LS(92 12)	7,16	**36.8**	27.4	**6.43**	829.8
CETGENGQ	log	(0 1 1)(0 1 1)				7,86	25.5	16.1	0.69	896.5
CETGENGQ	lev	(0 1 1)(0 1 1)				7,45	22.6	22.3	0.40	888.3
CIT006GC	log	(0 1 1)(0 1 1)*	X	X	AO(88 1), AO(91 3), AO(93 1)	16,23	32.1	26.1	**13.4**	3335.1
CIT006GC	lev	(0 1 1)(0 1 1)	X	X	AO(88 1), AO(91 3), AO(93 1)	11,36	33.6	**37.1**	**6.29**	3338.5
CET006GC	log	(0 1 1)(0 1 1)			AO(86 8), AO(87 3), AO(88 1)	10,56	33.3	23.9	4.53	3407.3
CET006GC	lev	(0 1 1)(0 1 1)			LS(95 1)	5,20	23.7	22.0	4.64	3421.6

** No model was selected by the automatic procedure. "Airline" was imposed to calculate the remaining values of the tables.*

As already mentioned, the pre-adjustment step did not succeeded in identifying a suitable ARIMA model for the series concerning import values of mechanical products; this was the case because all the models provided for by the procedure get a forecasting error higher than 15% in the last three years; the consequences of this fact will be examined in the paragraph concerning this series.

4. Comparison of the Seasonally Adjusted Series

Imports Value Index

The series stemming from the procedure X12 does not show any particular problem. It is forecasted by means of an ARIMA model $(2\ 1\ 0)(0\ 1\ 1)_{12}$, and it is corrected for trading days and Easter effects. The quality of the seasonal adjustment is confirmed also by the smoothness of the resulting series (although this characteristics is not a straightforward indicator of the goodness of the adjustment): the index MCD (months for cyclical dominance) (Zani, 1982) indicates that a moving average of order three is sufficient for the cyclical component changes to prevail on the irregular ones (Table 5). This represents the smallest MCD value among the series adjusted with X12.

The value of the synthetic statistics Q is quite low too (0,22) and none of its component indicators takes on a value larger than 1 (which is the threshold over which a seasonal adjustment is traditionally considered unreliable). The adjusted series does not show any residual seasonality, neither it shows peaks in the spectrum frequencies associated with the trading days component.

Table 5 – Main results

	Q	Resid. seas.	Resid. TD	MCD	Standard dev. growth rate seas. adjusted series	Correlation seas.comp. /sa series	Seasonal correlation irregular component (CS)
CITGENGV - X12	0,22			3	0,0417	0,012	4,88
CITGENGV - TS				2	0,0368	0,001	3,09
CETGENGV - X12	0,40		X	4	0,0609	0,017	1,12
CETGENGV - TS		X	X	2	0,0365	0,022	0,07
CITGENGQ - X12	0,26	X		4	0,0378	0,019	0,39
CITGENGQ - TS		X		3	0,0306	-0,005	0,87
CETGENGQ -X12	0,58	X	X	8	0,0620	0,015	1,06
CETGENGQ - TS		X	X	7	0,0461	0,024	2,86
CIT006GC - X12	0,50		X	5	0,0894	0,002	4,53
CIT006GC - TS		X		3	0,0553	0,001	1,06
CET006GC -X12	0,46		X	4	0,0585	-0,006	3,04
CET006GC - TS			X	5	0,0640	0,007	3,45

In TS the model identified is an "Airline" one, with trading days correction. One more outlier is identified in comparison with the results coming from X12. Moreover, the Liung-Box test shows the presence of significant autocorrelation in the residuals. Residual seasonality has been tested using the series adjusted by TS as an input for X12 procedure and checking the F statistics; no evidence of residual seasonality has been detected.

The irregular components, derived from both procedures, do not show significant correlation at the seasonal lags, as measured by the following statistics (Planas, 1997):

$$CS = T(T+2)[r^2(12)/(T-12)- r^2(24)/(T-24)]$$

Where *r(i)* stands for the i-th lag autocorrelation coefficient. This statistics is distributed, under the null hypothesis of no significant correlation at lags 12 and 24, as a $\chi^2(2)$. The correlation between the seasonal component and the adjusted series is very close to zero, thus both the procedures seem to respect the criteria of orthogonality between the different components (den Butter et al., 1991)

The series adjusted with the two methods are very similar (Figure 1). This is confirmed also by considering their growth rate (approximated by the first differences of the log of series): in fact, the correlation between the latter is very high (0.95). However, the growth rate of the series adjusted by X12 shows a larger variability, as measured by the standard deviation. Also, the MCD index is smaller for the series adjusted by TS.

In the case of the trend the series produced by X12 is slightly smoother, as showed also in figure 1; however there are no differences in the detection of the turning points.

Exports Value Index

The procedure X12 forecasts this series with an "airline" model, obtaining a satisfactory seasonal adjustment (Q=0.40). Nevertheless, the spectrum of the first differences of the adjusted series shows significant peaks at trading days frequencies. On the other hand, TS does not estimate the default model; instead, it identifies an Arima (2 1 0)(0 1 1)$_{12}$ model. Moreover, more outliers than in X12 are identified, in particular at the beginning of the series. Also in this case the spectrum of the first differenced adjusted series shows significant peak at the trading days frequencies: this was detected by X12 procedure run on TS seasonal adjusted series. The same run showed also some residual seasonality in the series treated by TS.

The presence in the model identified by TS of a cyclical component has probably allowed to pick up the effects of a trading days component, not identified as a separate regression effect. Anyway, it has determined the choice of a seasonal component which has absorbed much of the noise of the series, so as the resulting adjusted series is much smoother than the corresponding X12 one, considering both the growth rates variance and the MCD index. The larger variability of the X12 series is clear also by a visual inspection (Figure 2). An analogous behaviour characterises the trend series.

Exports and Imports Quantity Index

Import quantity index shows a pattern similar to the one described for the corresponding value index. In this case too, the results of the two procedures are quite similar: both of them identify an "airline" model, with a level shift in December 1992. The resulting seasonally adjusted series are consequently very close. Their growth rates show in fact a high correlation coefficient (0.93). Anyway, their periodogram (Figure 3) shows a larger variability of the series adjusted by X12, confirmed by the measures given in table 5. Also, the trend estimated by X12 is less smooth.

The test F performed by the procedure X12 shows the presence of residual moving seasonality in both the adjusted series.

Export quantity index is characterised by a strong irregular component, which determines a poor result, in terms of smoothness, with both the procedures: the MCD index takes the value of 8 with X12 and 7 with TS. In both cases there are signs of residual seasonality in the adjusted series, as well as residual trading days effects. In fact, both the procedures identify an "airline" model with no trading days correction. In addition, both of them exclude the presence of significant outliers. The series obtained are quite similar (growth rates correlation is 0.93), although TS output shows less variability.

Mechanical Sector

For export series concerning mechanical products both procedures identify an "airline" model. This is the only case in which TS identifies less outliers than X12. In both the seasonally adjusted series residual trading days effects are detected. In this case the output of X12 shows a smaller variability than that of TS, both considering the MCD index and the standard deviation of the growth rates. Also, the closeness of the two adjusted series is not as high as in the previous case: the correlation coefficient between the growth rates is in fact 0.72. The trend series are slightly closer, but the one produced by X12 is more volatile.

Concerning imports, X12 does not identify an ARIMA model, because the forecasting error of all the models were found to be more than 15% in the last three years, which is the default threshold value for a model to be accepted. As a consequence, the series adjusted by X12 performed worse than that that stemming from TS, because no correction was made for calendar effects and outliers. On the other hand, TS identified an "airline" model, calendar effects and four outliers. In this case too, the correlation between the growth rate of the two adjusted series is not as high as for other series (0.77).

In another trial we imposed to X12 the estimation of the "airline" model; in that case the program identifies also calendar effects and three outliers. The resulting seasonal adjusted series is much more stable, showing a corresponding improvement of the Q synthetic statistics, determined in particular by the lower variance attributable to the irregular movements of the seasonally adjusted series. Moreover, the MCD index diminishes from a value of 5 to 4, and there is a strong decrease of the standard deviation of the growth rates (Table 6).

Table 6 – Procedure X12 applied to the imports of mechanical goods - comparison between the decomposition done using a forecasting model and not

Series	Model	TD	E	Outliers	Q	MCD	Standard dev. growth rate seas. adjusted series
CIT006GC	none				0,50	5	0,0894
CIT006GC	(0 1 1)(0 1 1)	X	X	AO(88 1), AO(91 3), AO(93 1)	0,28	4	0,0657

Revisions

An indicator of convergence of the revisions towards the final values of seasonally adjusted series (trend) has been calculated. The benchmark considered is the "final" estimate of the seasonally adjusted series (trend) referring to the period January 1991 - December 1993, as estimated using the series ending in October 1996. With respect to the "final" series, root mean squared error of concurrent estimates, 1 lag estimates, etc. has been calculated and graphed (Figures 7 and 8). In particular, if one indicates the estimate of the seasonally adjusted series at time t obtained at time t+k as $x_{t,t+k}$, with k≥0, and the final estimate of the seasonally adjusted series at time t as $x_{t,F}$, the following indicator has been calculated:

$$rev\ (k) = \sqrt{\frac{\sum_{t=1}^{n} (x_{t,t+k} - x_{1,F})^2}{n}} \qquad \forall\, k = 1,2...,34$$

with n=36. Figures 7 and 8 show this indicator plotted against k.

The convergence of the estimates of X12 is faster only for imports values and quantity index; by the way, these are the series for which the Q statistics takes the lowest values, thus confirming a good quality of the adjustment. An analogous path is followed by the corresponding trend series.

Obviously, the revision pattern cannot give a decisive answer for the evaluation of the results of the two procedures, mostly because such results are heavily influenced by the effects of the different outliers detected.

With reference to the last point it is interesting to compare the results for the exports quantity index, a series for which no outliers are identified by both procedures. In this case TS shows a faster convergence; moreover, both the procedures show a significant improvement every time a complete year is added to the series to be adjusted. Another interesting case is that of the series CETGENGV which is much smoother when adjusted with TS. Nevertheless, even after 30 periods, it shows a significant discrepancy with respect to the final estimate (more than 1%). This is due manly to the instability of the Arima model identified, which changed repeatedly during the period considered.

Conclusions

The series analysed are characterised by the presence of an important, but rather stable in time, seasonal component, which is extracted in a quite satisfactory way by the two procedures. Moreover, in many cases a trading days component is identified. Nevertheless, X12 identified such a component only for the series concerning imports, while it detected significant trading days effect in the spectrum of the irregulars of export series. TS detected trading days effects in all the series when the value of RSA option was set at 4, while they were detected only in import series when RSA=8. In this last occurrence X12 found significant peaks in the spectrum of the export series adjusted by TS. It seems therefore useful to dispose of the diagnostic of X12 that, although in an informal way, shows the presence of residual calendar effects in the adjusted series.

In both the procedures the model selection represents a fundamental step, in so far it is needed to correctly identify calendar effects as well as outliers. In the one case where it was not possible, in the set of series here concerned, the results obtained were quite poor.

In the end , referring to the properties of the seasonally adjusted series, in five cases the series obtained by X12 was more volatile than the one stemming from TS. This larger volatility is not so clear in the case of the trend. Convergence towards final estimate of the seasonal adjusted series was in four out of six cases faster in TS; nevertheless the instability in the model selection (in our case the series CETGENGV) can represent a problem in the routine use of the last procedure.

Figures

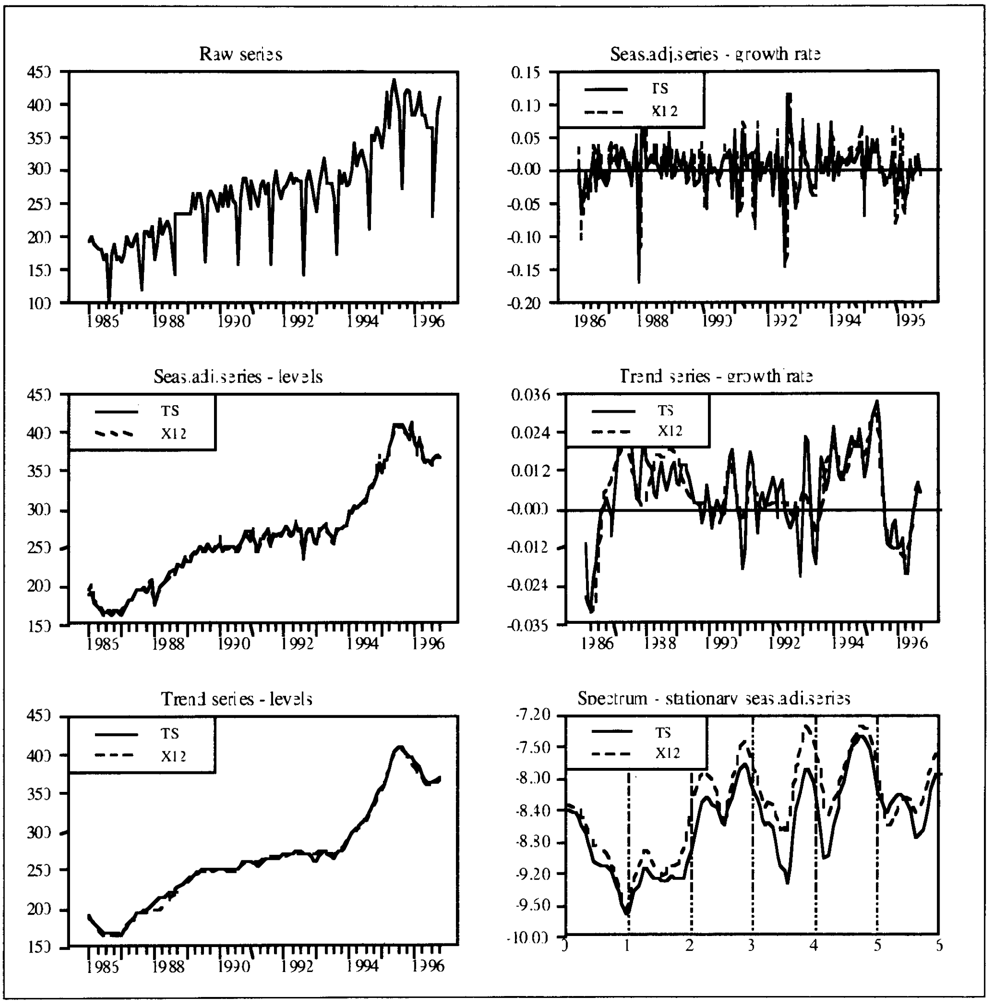

Figure 1 – Results of the adjustment of series CITGENGV

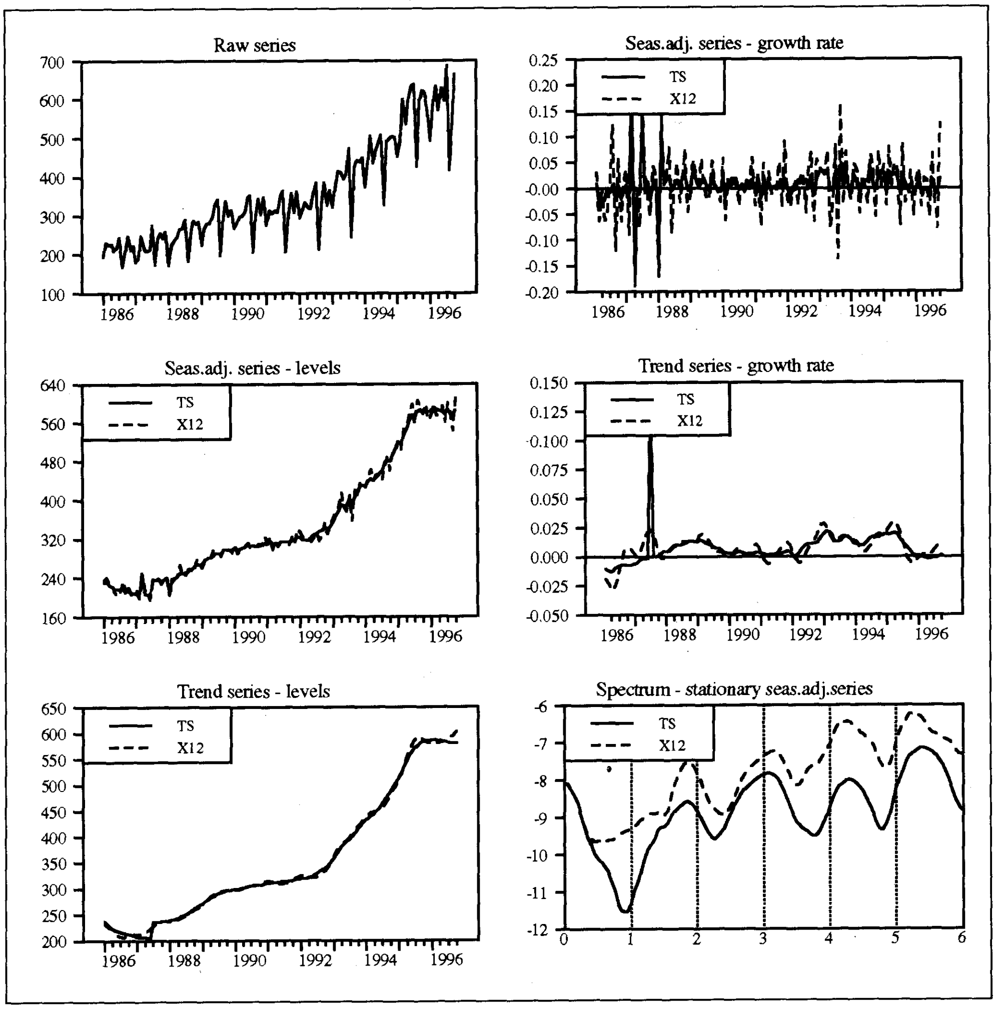

Figure 2 – Results of the adjustment of series CETGENGV

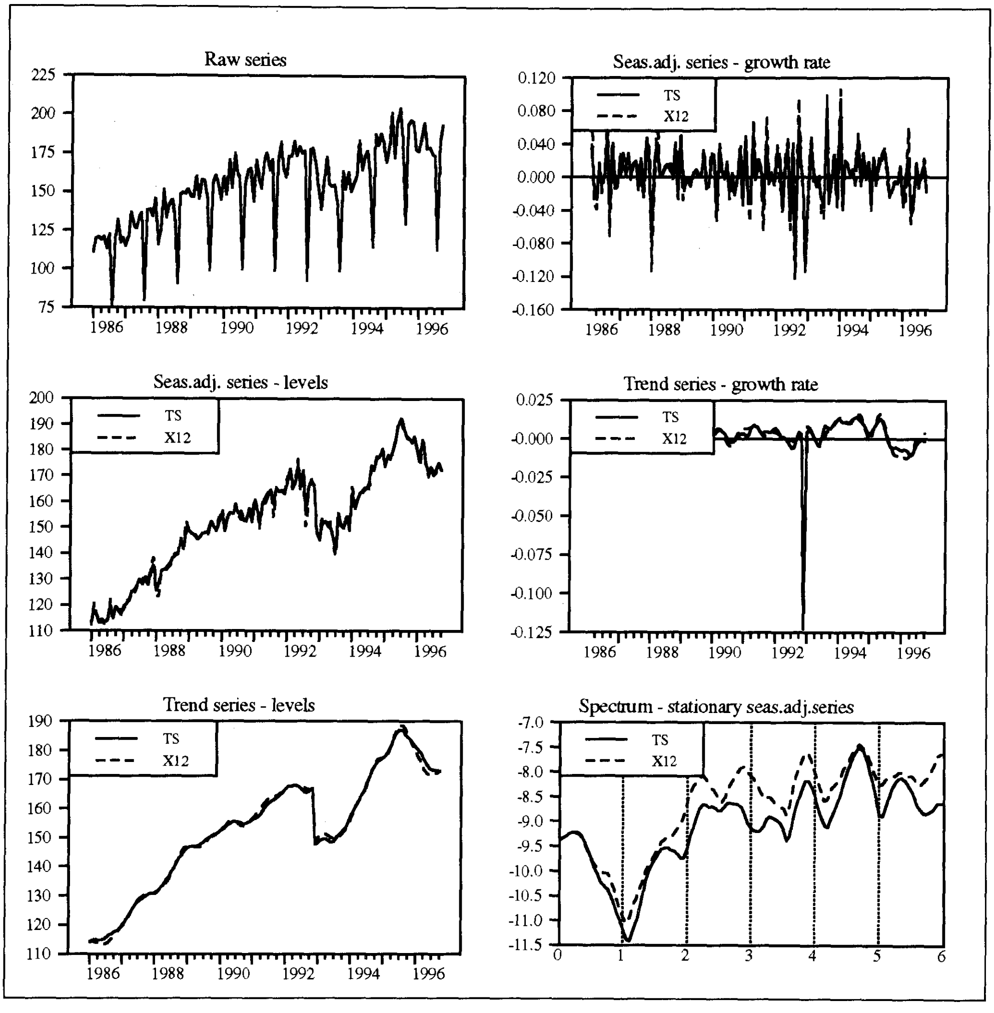

Figure 3 – Results of the adjustment of series CITGENQ

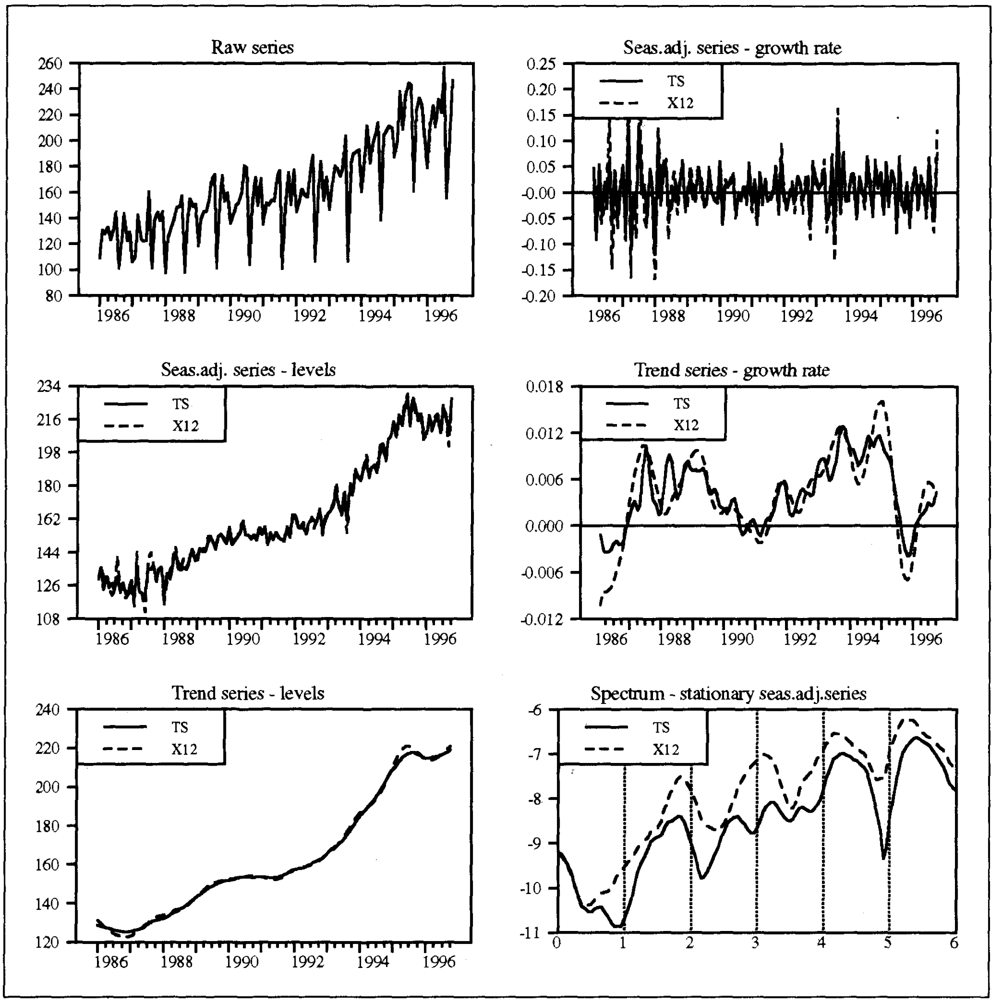

Figure 4 – Results of the adjustment of series CITGENQ

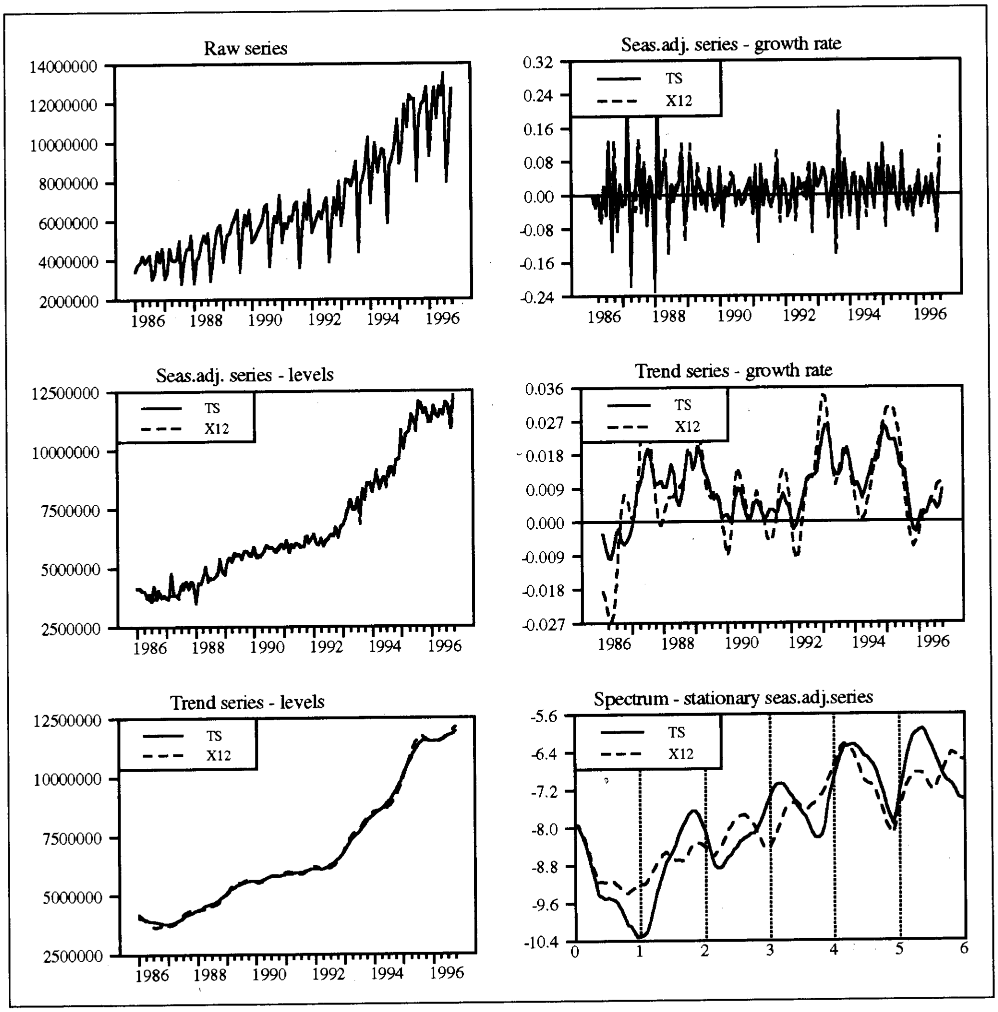

Figure 6 – Results of the adjustment of series CET006GC

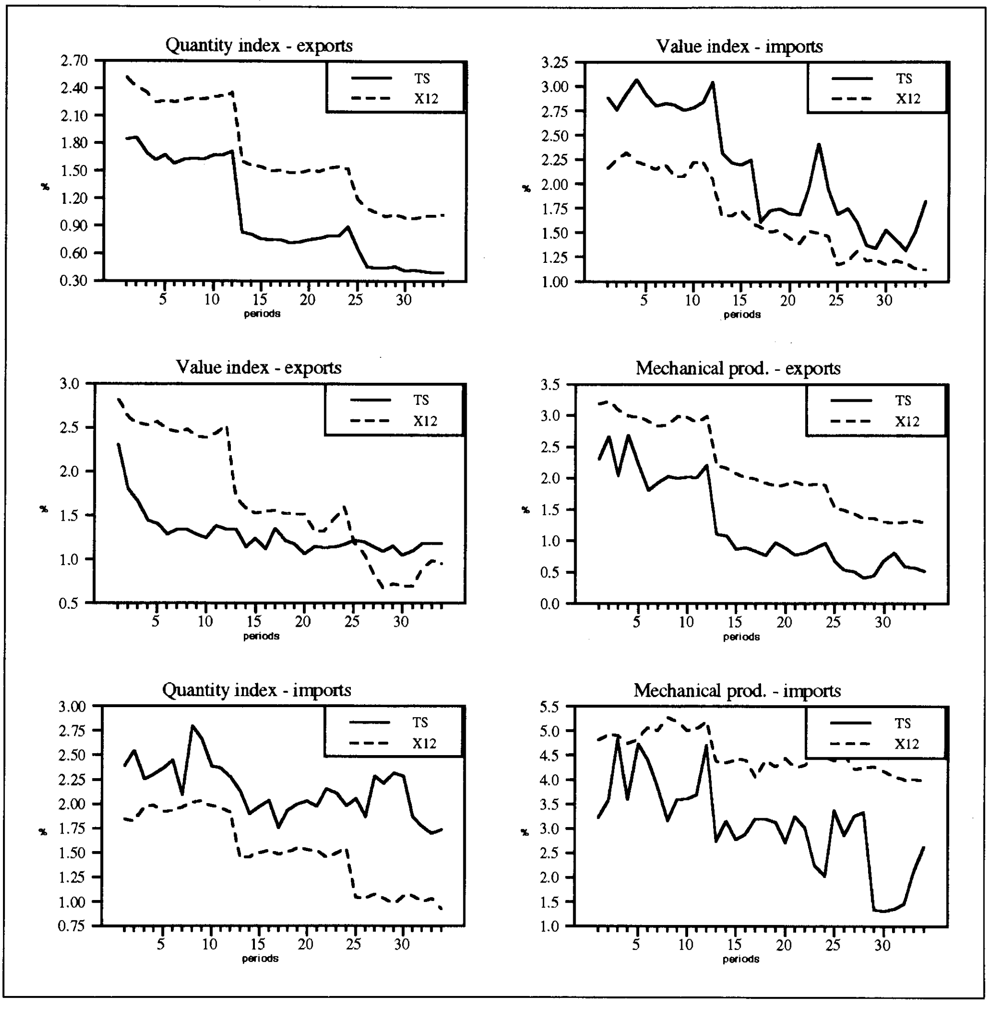

Figure 7 – Convergence of the preliminary estimates of seasonally adjusted series

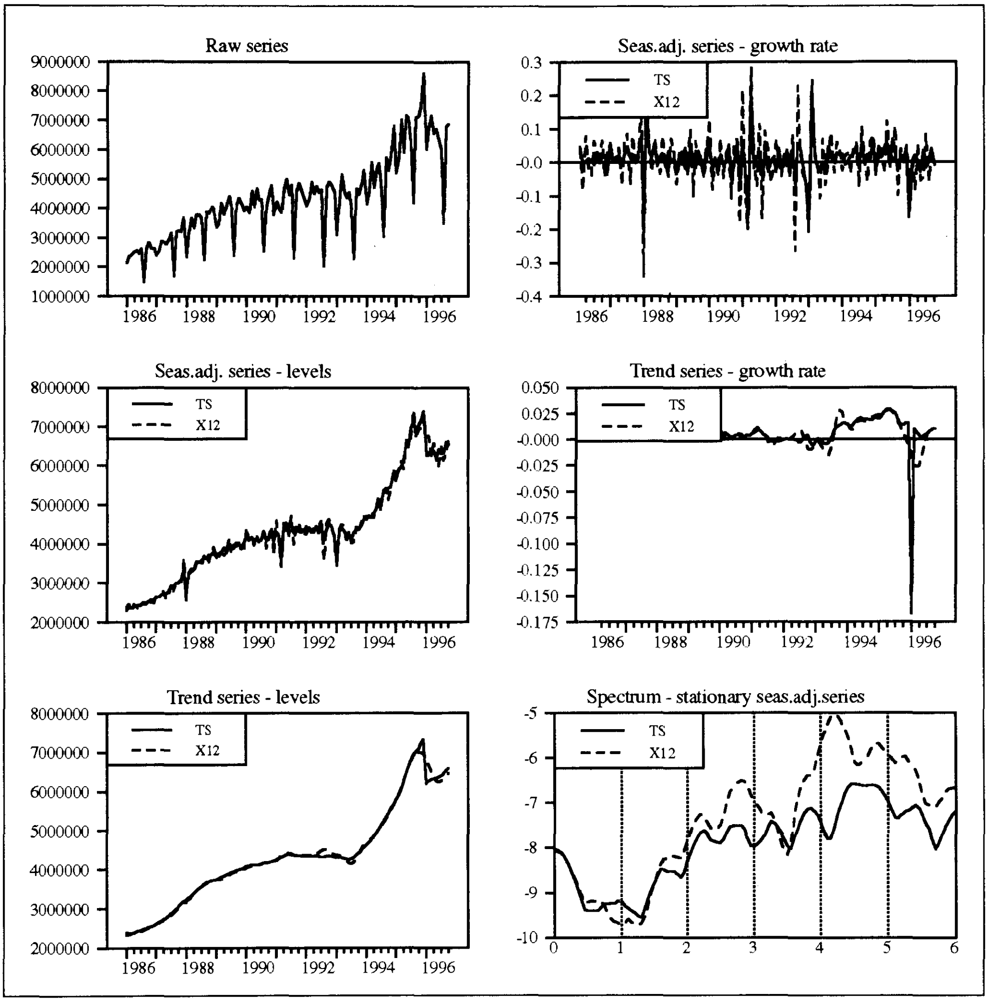

Figure 5 – Results of the adjustment of series CIT006GC

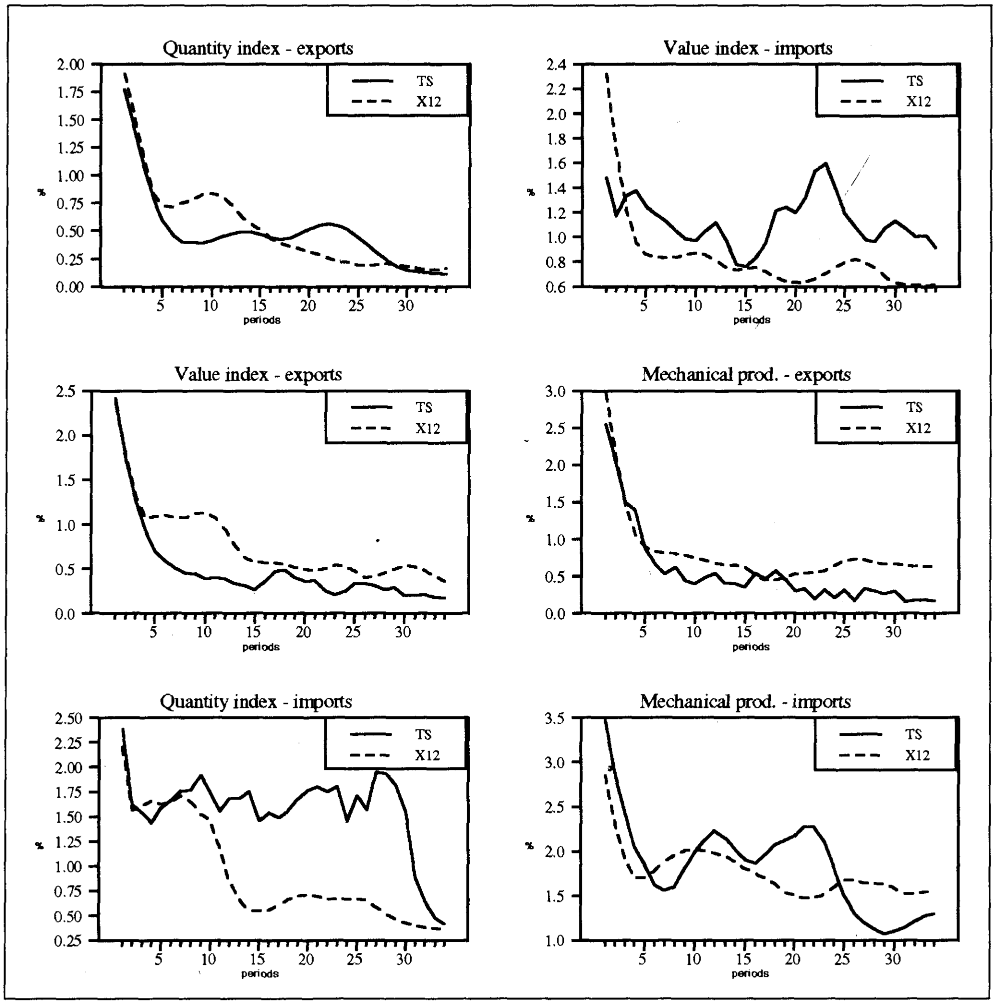

Figure 8 – Convergence of the preliminary estimates of trend series

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REVISIONS IN SEASONAL ADJUSTMENT TECHNIQUES

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1. Introduction

Seasonal adjustment methods often imply revisions in adjusted series when new observations become available. As the revisions induced by the adjusting procedures are statistical in nature, in that they depend on the use of moving average filters, an important criterion to consider in choosing among different seasonal adjustment techniques is the minimization of the revision[1]. The importance of this criterion is enforced by the consideration that revisions are often concentrated in the final part of the series, which is the most relevant for short-term macroeconomic decisions and policy analyses[2].

As the revision patterns caused by different methods depend on a number of factors - data generation process, parameter estimates, filter used, ... - their comparison is theoretically impracticable. Therefore, we investigate this matter using an empirical approach, that is by simulating the revision patterns which should occur using different seasonal adjustment techniques.

The competitive methods considered here are X-12-ARIMA and TRAMO-SEATS described in Bureau of the Census (1997) and in Gómez and Maravall (1997) respectively.

The comparison has been conducted on a number of Italian economic time series covering, in most cases, the sample 1970-1996. The data are monthly and refer to a wide spectrum of economic phenomena: industrial production, external trade, turnover, orders, prices, and employment.

The paper is structured as follows. In Section 2 we show the reasons why an empirical comparison *via* simulations is necessary to compare the behaviour of dif-

We gratefully acknowledge the members of the S.A.R.A. Commission, Raoul Depotout, Augustin Maravall and Andrew Harvey for their comments and suggestions on earlier drafts of this paper.

[1] Other important criteria, such as the comparison of the diagnostics, the robustness and the easiness of implementation of the methods, the speed of estimation, the quality of forecasts and, in general, the type of approach used, are nor considered here (see Fisher (1995)).

[2] The literature dealing with the theme of revisions in seasonal adjustment procedures includes, amongst others, Pierce (1980), Dagum (1982) and Maravall (1986).

ferent seasonal adjustment methods. Section 3 describes the plan of the experiment and the data used. The results of the analyses are reported in Section 4. Section 5 concludes.

2. Seasonal Adjustment and Revisions

Suppose we want to decompose the time series x_t in a seasonal component s_t and in a residual, nonseasonal component n_t:

$$x_t = s_t + n_t. \tag{1}$$

We indicate with $\nu_s(B) = \ldots + \nu_{-1}B + \nu_0 + \nu_1 F + \ldots$ the filter used for the final estimate of s_t:

$$s_t = \nu_s(B)\, x_t. \tag{2}$$

If x_t is stationary, we have the Wold representation:

$$x_t = a_t + \psi_1 a_{t-1} + \ldots = \psi(B)\, a_t, \tag{3}$$

where a_t is a Gaussian white-noise error term. Therefore, the final estimator of the seasonal component is:

$$\hat{s}_t = \nu_s(B)\psi(B)a_t = \xi_s(B)a_t, \tag{4}$$

with $\xi_s(B) = \ldots + \xi_{s-1}B + \xi_{s0} + \xi_{s1}F + \ldots$.

A preliminary estimate of s_t at time $t + k$, denoted by $\hat{s}_{t|t+k}$ is the expectation $\hat{s}_t$ of given the information available at time $t + k$, that is:

$$\begin{aligned} \hat{s}_{t|t+k} &= E_{t+k}\left[\xi_s(B)a_t\right] = \\ &= E_{t+k}\left[\ldots + \xi_{s-1}B + \xi_{s0} + \xi_{s1}F + \ldots + \right. \\ &\quad \left. + \xi_{sk}F^k + \xi_{sk+1}F^{k+1} + \ldots\right] a_t = \\ &= \left[\ldots + \xi_{s-1}B + \xi_{s0} + \xi_{s1}F + \ldots + \xi_{sk}F^k\right] a_t = \\ &= \xi_s^k(B)a_t, \end{aligned} \tag{5}$$

where the filter $\xi_s^k(B)$ is the same as the filter $\xi_s(B)$ truncated in F^k.

The revision in the preliminary estimate of s_t in $t + k$ is given by:

$$R_k = \hat{s}_t - \hat{s}_{t|t+k} = \sum_{i=k+1}^{\infty} \xi_{si} a_{t+i}. \tag{6}$$

The updating in the preliminary estimate after adding one observation is:

$$r_k = \hat{s}_{t|t+k+1} - \hat{s}_{t|t+k} = \xi_{sk+1} a_{t+k+1}. \tag{7}$$

From (6) and (7) it is possible to see that:

- the revisions follow an MA scheme;
- different forecasts and different filters imply different revision patterns;
- a new, different estimation of the parameters modifies the polynomial $\psi(B)$ and consequently $\xi(B)$. Further, in the model-based approach, a new filter $\nu_s(B)$ is obtained;
- when new observations are added, the identification of the model may change thus originating a new estimate of the polynomial $\psi(B)$.

These results justify an empirical comparison of the revision patterns of the two programs, X-12-ARIMA and TRAMO-SEATS, *via* a simulation study.

3. Simulation Design and Data Used

The experimental design has been similar to the one adopted by Dossé and Planas (1996) in comparing the revision patterns of French import and export series. We have removed the last three years of each series and thereafter have performed seasonal adjustments adding each time a new observation until the end of the sample has been reached. Therefore, for every monthly series we have obtained 36 successive vintages from which we have calculated r_k and R_k as described above.

The estimators obtained after adding the 36^{th} observation are considered as final and yield the final series $\hat{s}_t$.

The comparison of the revision patterns derived from X-12-ARIMA and TRAMO-SEATS has been made on the basis of three revision indices:

1. Mean squared revisions

$$MSR = \frac{1}{36} \frac{\sum_{k=0}^{T} r_k^2}{\hat{s}_{t|t+36}};$$

2. Smoothness of revisions

$$SR = \frac{\sum_{k=0}^{T-1} (r_{k+1} - r_k)^2}{\hat{s}^2_{t|t+36}};$$

3. Convergence of revisions.

The first criterion compares two adjacent estimates of the seasonal component, the second concentrates on two successive revisions of $\hat{s}_t$. The two measures have been standardized with the final estimator of the seasonal component $\hat{s}_{t|t+36}$ in order to obtain comparable results from the two methods used. Following the last criterion, we have counted the number of periods after which the revisions are less than the .5% of the final estimate of the seasonal component.

The formula above have been computed for each time t in the truncated sample of the series. However, in most cases we have concentrated on the 12 observations immediately before the truncated sample.

We have used two different approaches in dealing with the forecasting model and its parameters. In the first approach, the model and the parameters are free to vary each time a new observation is added. In the second approach, the model is fixed and the parameters are free to vary during the experiment. The model used is that chosen by X-12-ARIMA and TRAMO-SEATS in correspondence with the first observation, that is at time $T-36$.

Table 1 – Series analysed in the simulations

Series	Sample
Index of value of imports	1980.1-1996.10
Index of value of exports	1980.1-1996.10
Index of volume of imports	1980.1-1996.10
Index of volume of exports	1980.1-1996.10
Value of imports - engineering products	1982.1-1996.10
Value of exports - engineering products	1982.1-1996.10
Turnover index - foreign (total)	1985.1-1996.12
Turnover index - national (consumer goods)	1985.1-1996.12
Turnover index - national (investment goods)	1985.1-1996.12
Turnover index - total (investment goods)	1985.1-1996.12
Stock of orders - total	1985.1-1996.1
Level of orders - total	1991.1-1996.12
Industrial production index - total	1981.1-1996.12
Industrial production index - consumer goods	1981.1-1996.12
Industrial production index - investment goods	1981.1-1996.12
Industrial production index - intermediate goods	1981.1-1996.12
Employees - industry, gross CIG (labour force survey)	1989.1-1996.11
Consumer prices - food and beverages excluding tobacco	1989.1-1996.12
Consumer prices - food (total)	1989.1-1996.12
Consumer prices - total excluding tobacco	1989.1-1996.12
Consumer prices - non food (total)	1989.1-1996.12
Consumer prices - services (total)	1989.1-1996.12
Wholesale prices - total	1989.1-1996.12
Producer prices - consumer goods	1981.1-1996.12
Producer prices - total	1981.1-1996.12
Producer prices - intermediate goods	1981.1-1996.12
Producer prices - investment goods	1981.1-1996.12
Retail sales - food (major outlets)	1991.1-1996.11
Industrial production index - food, beverages and tobacco	1981.1-1997.2
Industrial production index - textiles and clothing	1981.1-1997.2
Industrial production index - metallic prod. and manuf. of by-products	1981.1-1997.2
Industrial production index - machinery	1981.1-1997.2

The data used in the experiment are described in Table 1, where we report the description of the series and the sample covered. The data-base is constituted by 32 monthly time series covering a wide spectrum of high-frequency observed phenomena of the Italian economy. The source of all the data analysed is Istat. The series are part of a larger data-set chosen by the S.A.R.A. Commission as a basis for its researches on seasonal adjustment techniques.

4. Empirical Results

The results of our analysis are reported in Figures 1-6, where we represent the values obtained for the three indices discussed above using X-12-ARIMA (horizontal axis) and TRAMO-SEATS (vertical axis). The comparison of the number of points at the left and at the right of the bisector gives an indication about the program which performs better in terms of (reducing) the revision errors. Each point refers to the revision occurred in a particular time *t* for a given time series[3].

When both the model and the parameters are free, we have a total of 348 points (12 months x 29 series[4]). The revisions yielded by the two programs are roughly of the same order of magnitude and there is no a clear predominance of one program on the other. In fact, TRAMO-SEATS performs better in terms of smoothness (*SR* criterion), while X-12-ARIMA gives better results when considering the *MSR* and the convergence criteria. However, one could easily notice that for the smoothness and the convergence criteria the differences in the results are statistically insignificant for the two programs and, in effect, standard tests on the relative frequencies of the experiments (e.g. they are not significantly different from .5) give marginal significant levels of .107 and .388 respectively for the smoothness and the convergence criteria, whilst for the *MSR* the value is .017. However, the regression lines reported in the graphs indicate that the weight associated to the revisions induced by X-12-ARIMA is greater than the one obtained for TRAMO-SEATS.

A different situation arises when the model is fixed and the parameters are free to vary within the sample period. It is importantly to notice that this situation closely resembles the practice usually followed by National Statistical Institutes which consists in maintaining the best ARMA model chosen by data for a certain period letting the parameters be free to change as new data are added.

In this case, TRAMO-SEATS performs better in terms of *MSR* and convergence but it is overcome by X-12-ARIMA considering the *SR* criterion (see Figures 4-6). Under this hypothesis, the tests on relative frequencies lead us to decidedly reject the null hypothesis of an equal number of successes for the two programs[5].

Two further results are worth noting. First, the size of the revisions is smaller in the case of fixed model/free parameters. Second, the regression line indicates that also under this hypothesis the weights of extreme values are greater for the program X-12-ARIMA.

Two important questions arise: a) for each series, are the points casually or systematically located in the graphs?; b) are there any systematic differences in the revisions' time profiles induced by the two procedures?

The graphs 7-10 report the results of the *MSR* criterion for some series under the two hypotheses considered in the experiment: model and parameters free (graphs 7-8) and model fixed/parameters free (graphs 9-10). Each series is represented by 12 points, one for each month of the sample from *T*–37 to *T*–48. The evidence suggests

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[3] Few extreme points have been eliminated from the graphs to render the remaining points less concentrated in the origin of the axes.

[4] Three series have been excluded in the experiments. In fact, the series of retail sales and of the level of orders contain too few observations, while for the series of wholesale prices TRAMO-SEATS has not been able to detect a seasonal component.

[5] The marginal significance level obtained for the test is .000 for all the convergence criteria considered.

that in both cases the points for each series do not tend to be positioned casually over the two areas identified by the bisector, but are often located in the same area of the graph. This should confirm what emerged from section 2. In fact, a number of factors may play an important role in choosing the best program to use: most of these are closely linked to the stochastic characteristics and representation of the series under analysis, and they can well vary from a time series to another.

The graphs in Figure 11 show the revision patterns induced by X-12-ARIMA (solid line) and TRAMO-SEATS (dotted line) when the model is fixed and the parameters are free. The revisions generated by X-12-ARIMA are usually greater in the final part of the sample, while those associated to TRAMO-SEATS, though less pronounced, are more persistent overall the whole sample considered in the analyses.

5. Conclusions

Some conclusions arise from the results obtained. They could be summarised as follows:

- the revisions yielded by the two programs are roughly similar and there is not a clear predominance of one program on the other;
- the results may vary depending on the choice of the revision policy (free model/free parameters or fixed model/free parameters);
- for about 45% of the cases, the number of new observations needed to obtain a convergence of the revision pattern is nearly the same with the two competitive programs. Further, independently of the program considered, there is a non negligible number of points for which revisions are still relevant after adding two complete years of new observations;
- there is a general tendency of the results to depend on the series considered in the experiment;
- TRAMO-SEATS often guarantees a greater stability of the estimates in the final part of the series, which is the most scrutinized for political economy purposes;
- the greater stability of X-12-ARIMA in the initial part of the series well adapts to the revision policy frequently followed by National Statistical Institutes consisting in maintaining artificially fixed the initial sample of the data.

The results here obtained closely resemble those reported in Dossé and Planas (1996) where, however, a better performance of TRAMO-SEATS program is obtained.

Obviously, as in every experiment, our outcomes may closely depend on the simulation design (series used, sample covered, indices of revision considered, length of the revision period, ...). The same applies for the program options, though we have tried to apply them as automatically as possible.

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APPENDIX

– Figures

Figure 1 – Model and parameters free. Mean squared revisions obtained with X-12-ARIMA and TRAMO-SEATS

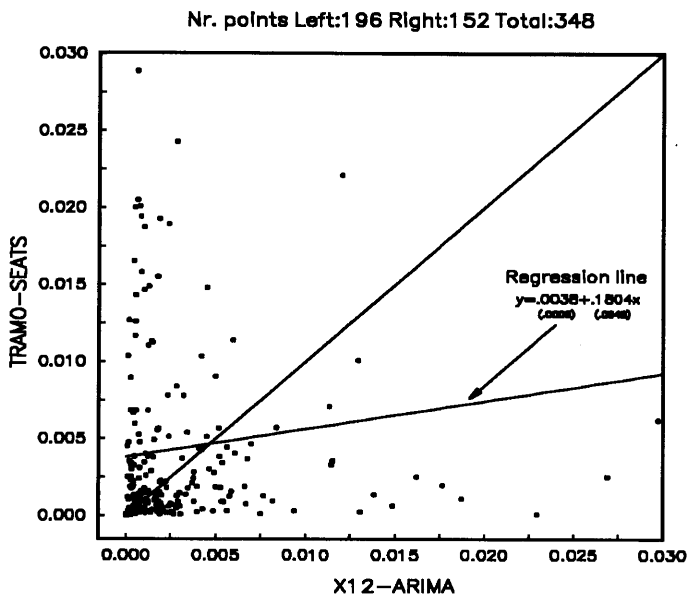


Figure 2 – Model and parameters free. Smoothness of revisions obtained with X-12-ARIMA and TRAMO-SEATS

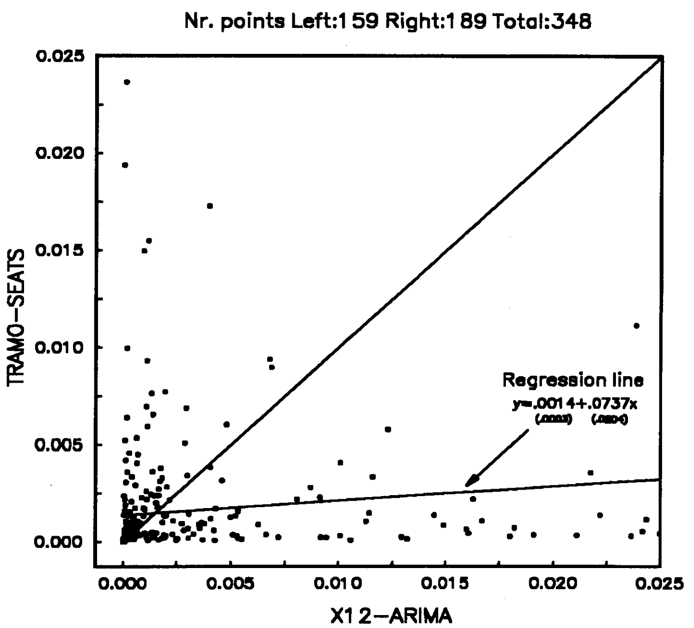


Figure 3 – Model and parameters free. Convergence of revisions obtained with X-12-ARIMA and TRAMO-SEATS

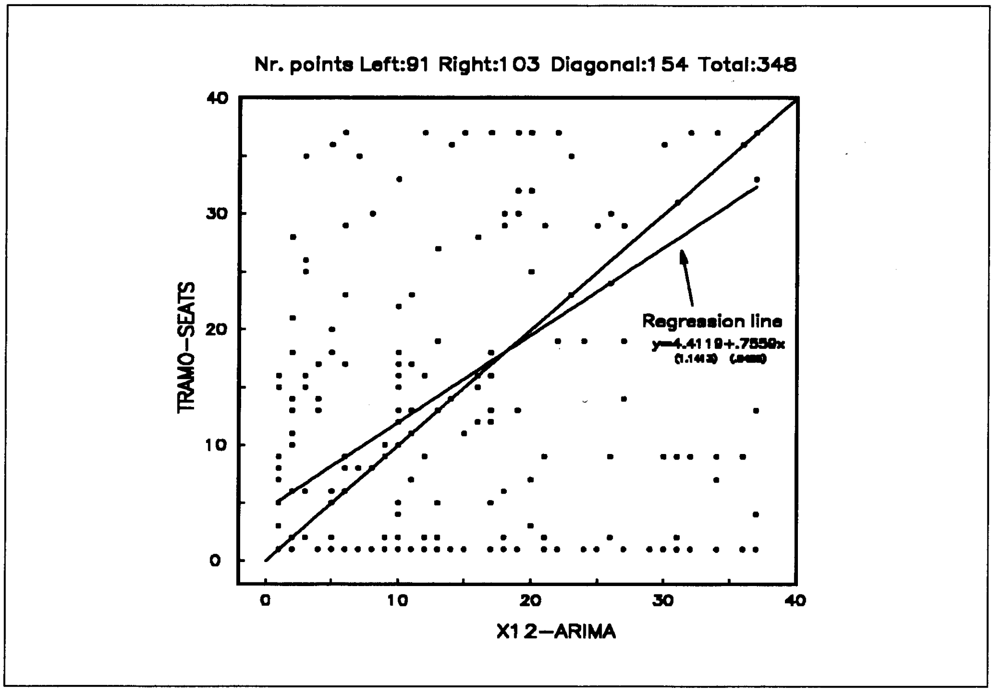


Figure 4 – Model fixed and parameters free. Mean squared revisions obtained with X-12-ARIMA and TRAMO-SEATS

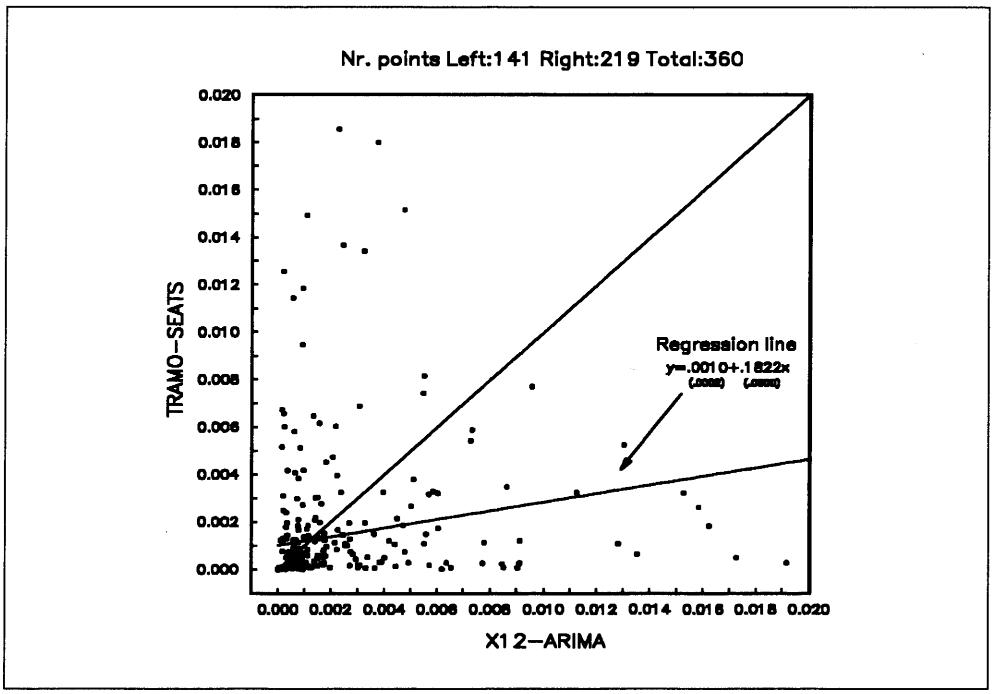


Figure 5 – Model fixed and parameters free. Smoothness of revisions obtained with X-12-ARIMA and TRADE-SEATS

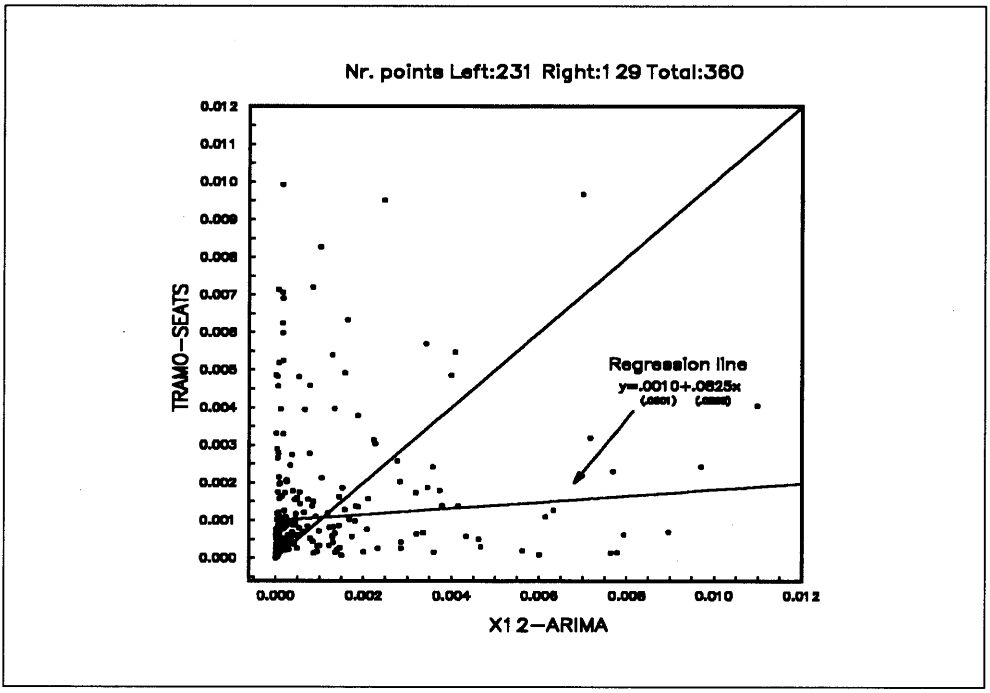


Figure 6 – Model fixed and parameters free. Convergence of revisions obtained with X-12-ARIMA and TRADE-SEATS

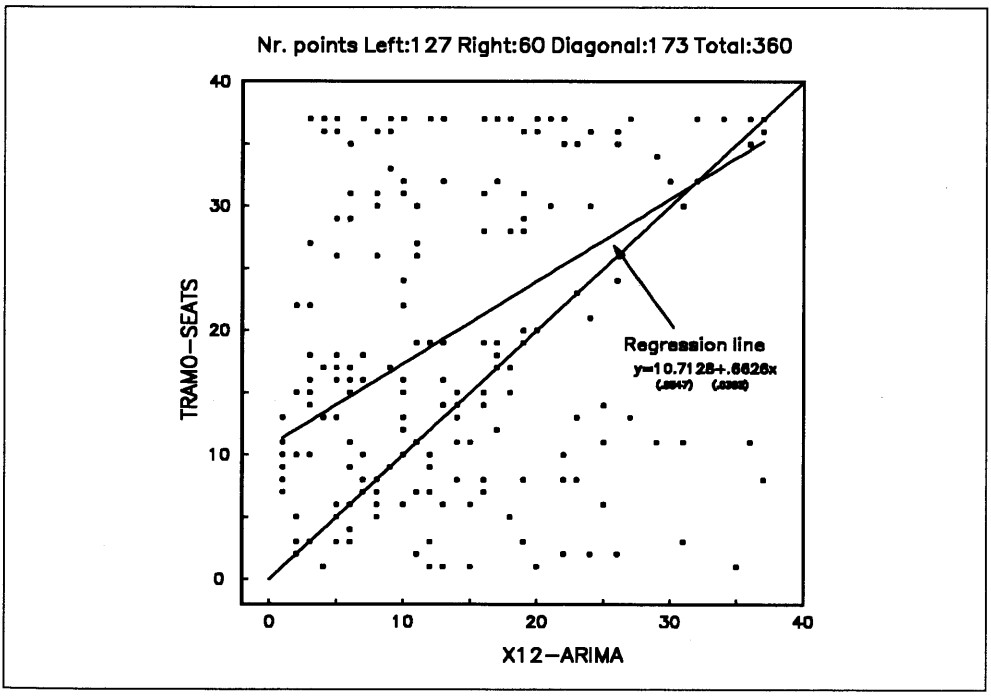
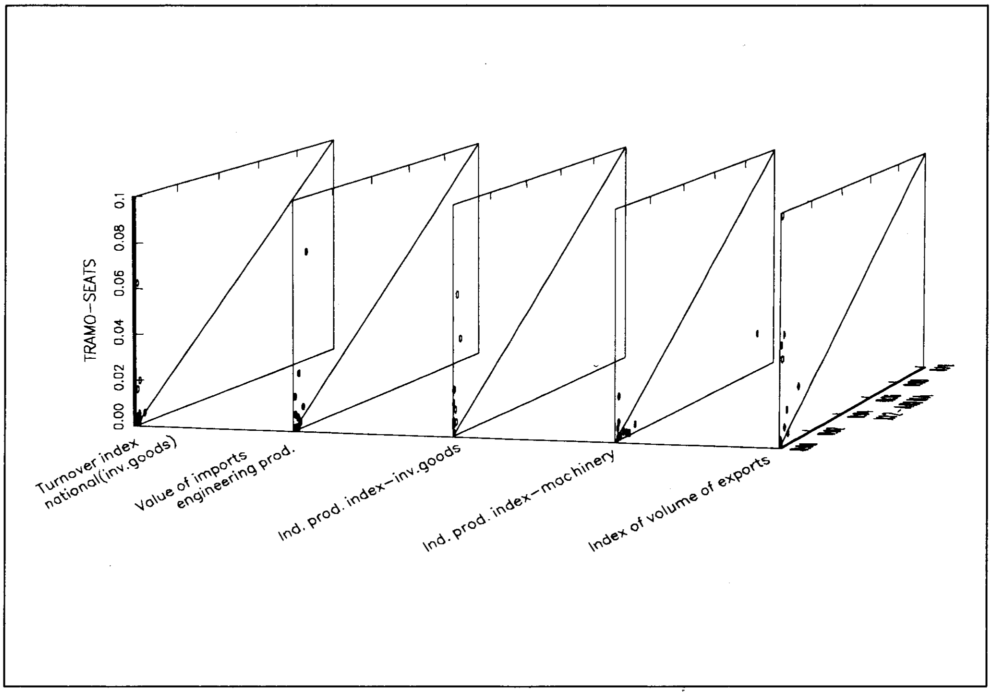


Figure 7– Model and parameters free. Mean squared revisions for some series obtained with X-12-ARIMA and TRAMO- SEATS



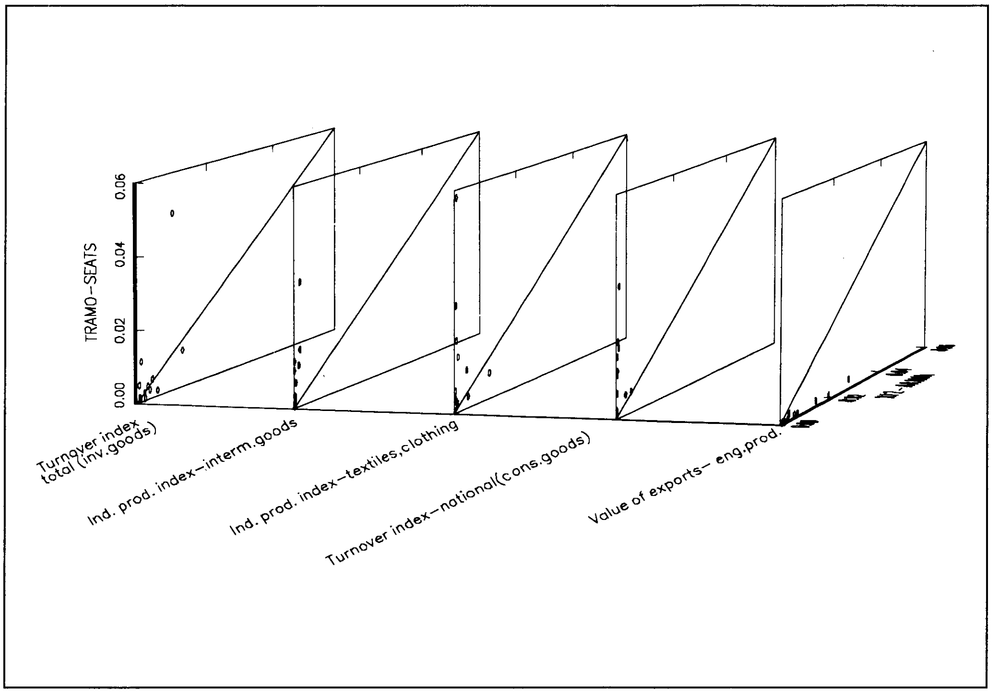
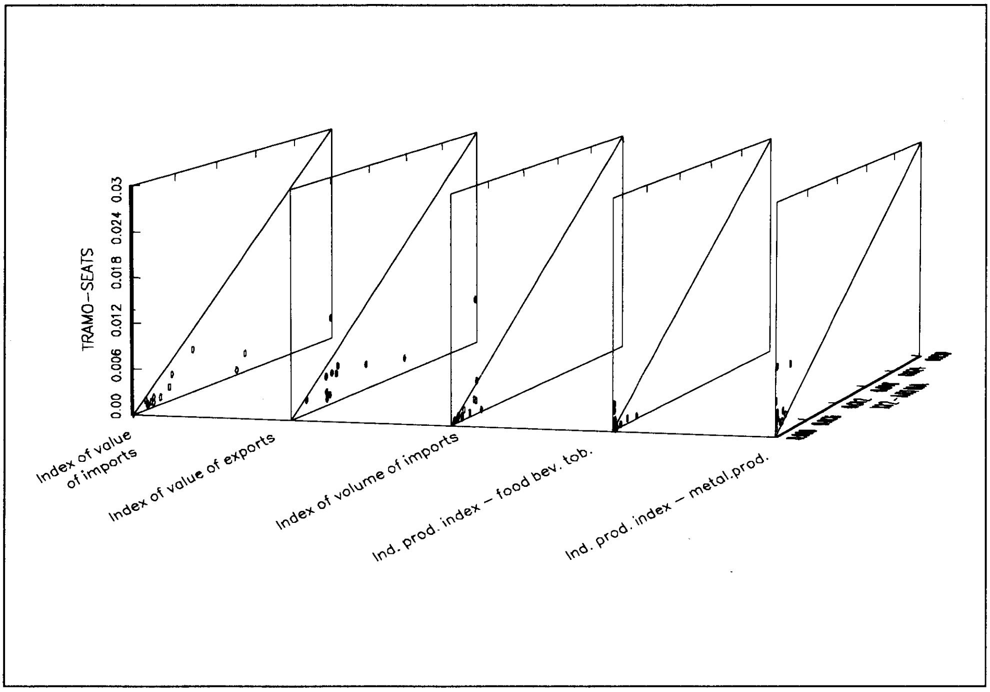


Figure 8 – Model and parameters free. Mean squared revisions for some series obtained with X-12-ARIMA and TRAMO- SEATS



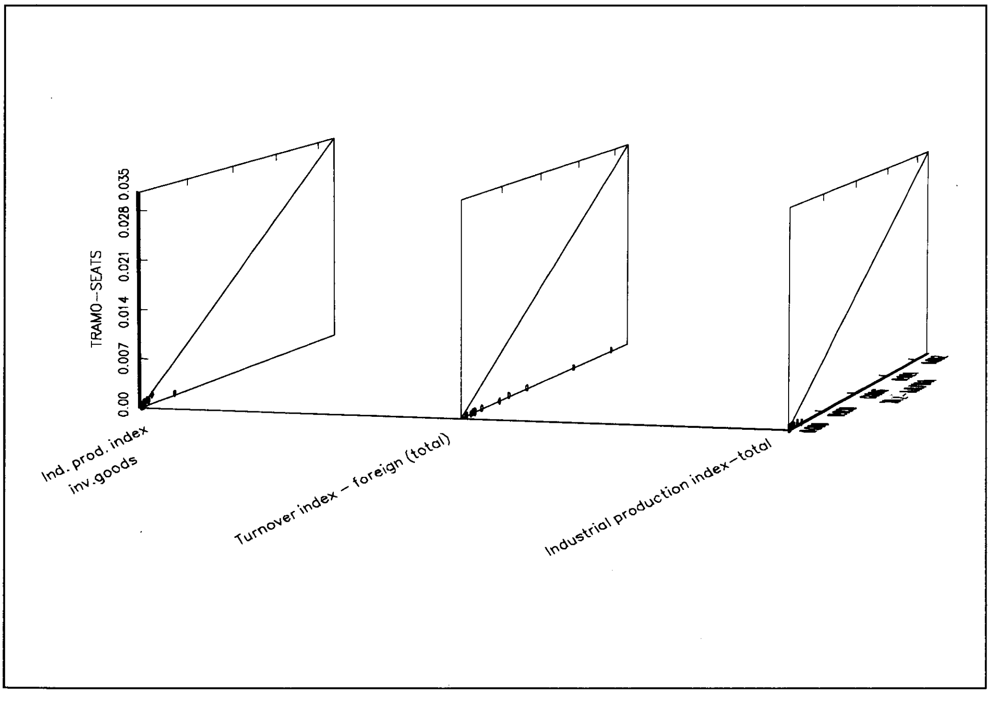
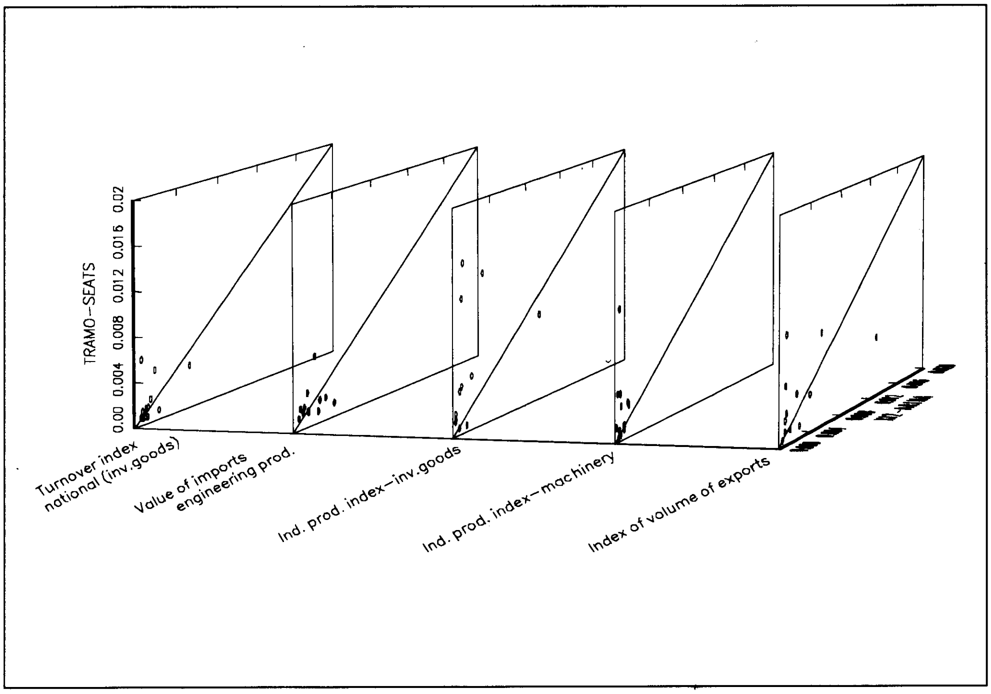


Figure 9 – Model fixed and parametres free. Mean squared revisions for some series obtained with X-12-ARIMA and TRAMO-SEATS



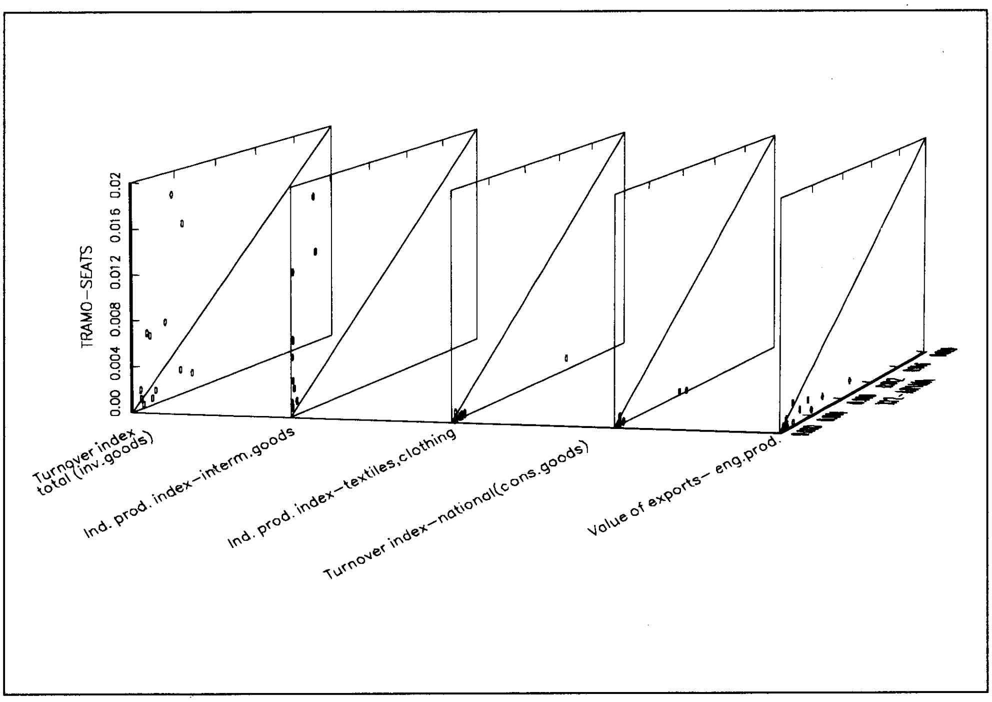
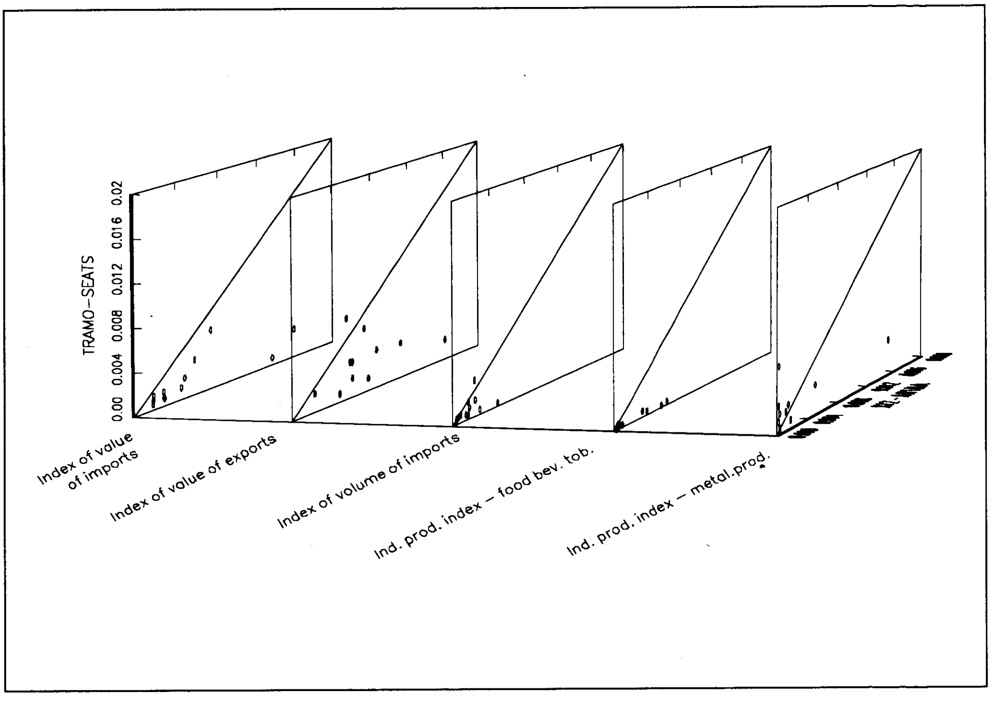


Figure 10 – Model fixed and parametres free. Mean squared revisions for some series obtained with X-12-ARIMA and TRAMO-SEATS



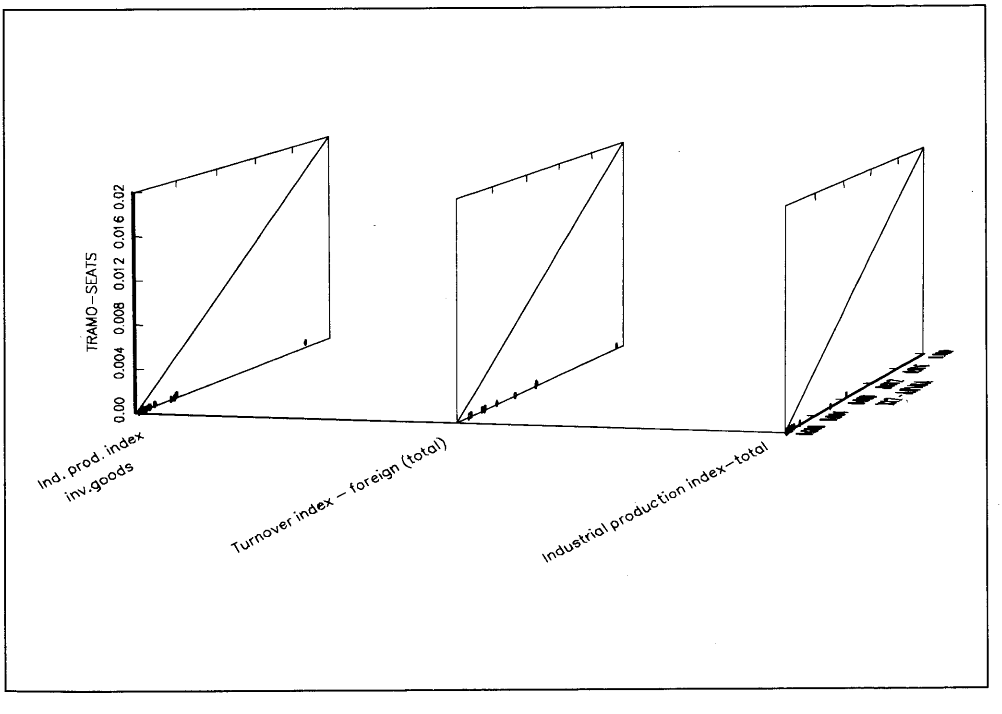
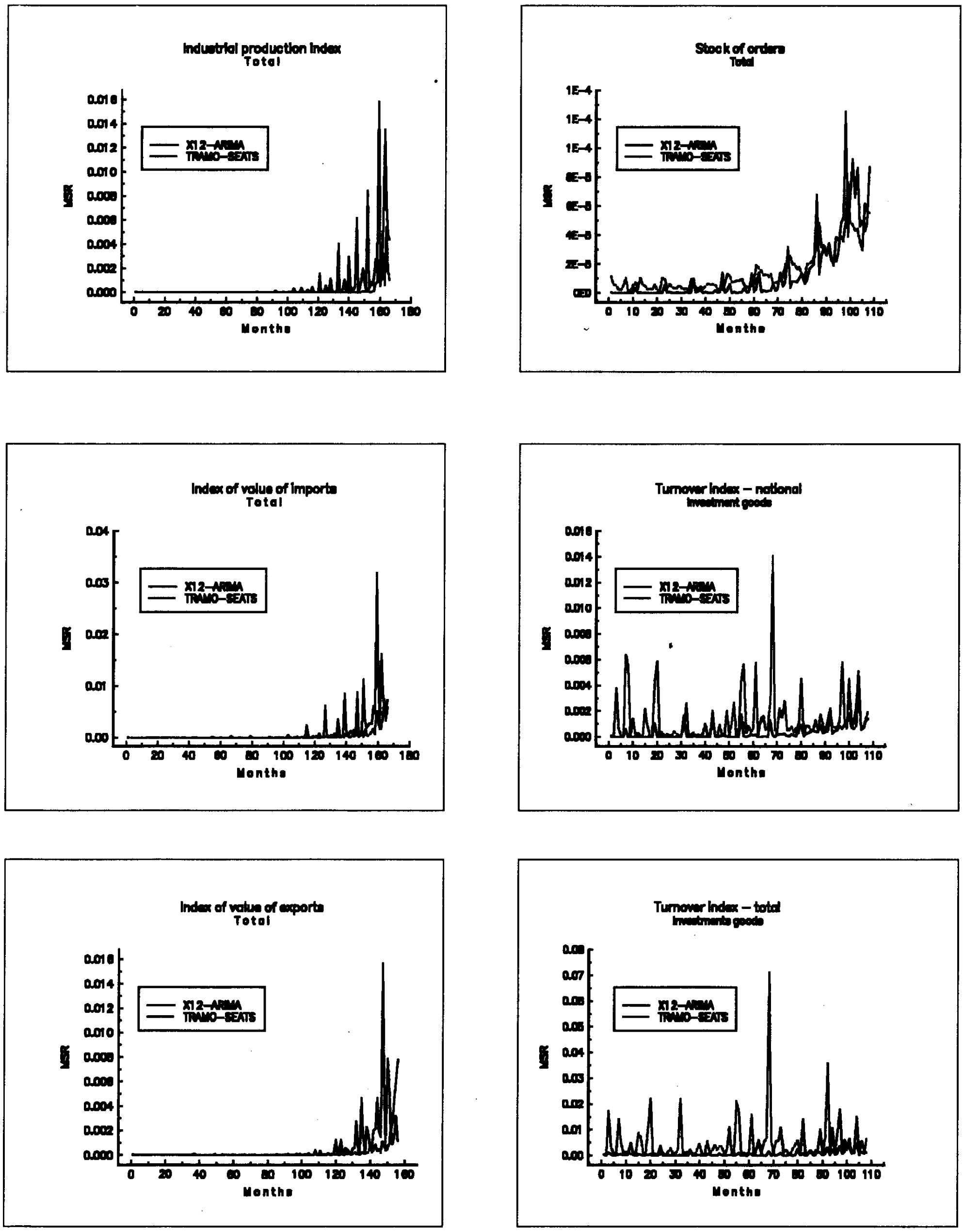


Figure 11 – Model fixed and parametres free. Mean squared revisions for some series with TRAMO-SEATS and X-12-ARIMA



SEASONAL ADJUSTMENT PROGRAM DIAGNOSTIC: COMPARISON OF X-12-ARIMA AND TRAMO-SEATS

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1. Introduction

The seasonal adjustment procedures, X-12-ARIMA and TRAMO-SEATS (*TRAMO*, Time Series Regression with ARIMA Noise, Missing Observations and Outliers; *SEATS* Signal Extraction in ARIMA Time Series), involve moving average filters. The difference between the two procedures mainly is due to the filters used. In the case of X-12-ARIMA, the filter is empirical, as it does not depend on the statistical properties of the series under analysis. Whereas, the ARIMA-model-based signal extraction method, as implemented in the program SEATS, uses the information obtained from the modelisation of the series to estimate the components.

Apart from this major difference, this document gives a brief summary of the *diagnostic* performed by the two programs.

Diagnostic is first considered as a *general diagnostic*, that is the set of the capabilities and methods of the two programs provided for the prior adjustments of the models, before the seasonal adjustment is performed. The prior adjustment is performed by RegARIMA in X-12-ARIMA and by TRAMO in TRAMO-SEATS and consists of the methods used to detect, for example, outliers or missing values or trading day effects.

As regards a more *specific diagnostic*, that is the indicators of the effectiveness of the modelling and seasonal adjustment options chosen, they are considered in two different steps:

- diagnostic checking of the model, that is residual analysis (provided by RegARIMA and TRAMO);
- diagnostic routines that can be used to obtain indicators on the effectiveness of the seasonal adjustment options. These routines are presented in the final analysis of X-12-ARIMA and TRAMO-SEATS.

The paper is structured as follows: section 2 describes the *general diagnostic* making a comparison between RegARIMA and TRAMO; section 3 and 4 briefly discuss significant diagnostic capabilities with regard to *diagnostic checking* and *seasonal adjustment diagnostic* for the two programs. In each of these sections a summary table is given showing the different features performed by X-12-ARIMA and TRAMO-SEATS.

2. General Diagnostic: Comparison of RegARIMA and TRAMO

The two seasonal adjustment procedures present a pre-program: the pre-program for X-12-ARIMA is called RegARIMA, whereas TRAMO is the pre-program for TRAMO-SEATS.

A general diagnostic can be analysed considering the main tasks of these pre-programs. They can mainly:

- detect and correct for different types of outliers;
- estimate a calendar component or any type of regression parameters and check for the evidence of this component;
- automatically estimate ARIMA models.

2.1 Outliers Treatment

The different types of data irregularities that can be considered in the context of seasonal adjustment are:

- *Additive Outliers* (AO), which catches a single point jump in the data;
- *Temporary Change* (TC), which catches a single point jump followed by a smooth return to the original path;
- *Level Shift* (LS), which catches a permanent change in the level of the series.

If we consider a series Y_t and a fitted model, the residuals can be obtained as:

$$e_t = pY_t.$$

Denoting $l_{t_0}(t)$ the dummy variable such that $l_{t0}(t) = 1$ if $t = t_0$ and 0 otherwise, then the different outliers can be defined according to:

$$\text{AO: } e_t = a_t + w_A l_{t_0}$$

$$\text{TC: } e_t = a_t + w_T \frac{1}{(1-\partial B) l_{t_0}} \qquad |\partial| < 1$$

$$\text{LS: } e_t = a_t + w_L \frac{1}{(1-B) l_{t_0}}.$$

Chang, Tiao e Chen (1988) and other authors developed the methodology for outlier detection, identification and estimation according to the following steps:

1) the residuals e_t are obtained from a fitted model;
2) for every residual, estimators of w_A, w_T, w_L are obtained with their *t-value*;
3) we say that an outlier t_0 has been detected when the *t-value* of one w exceeds a critical value;
4) in order to identify the type of outlier, the different *t-value* for the same t_0 of the w_A, w_T, w_L are compared. The chosen outlier pattern is the one related with the greatest significativity.

In TRAMO an automatic detection and correction procedure is performed; the three above mentioned outliers and a fourth type of outlier (*Innovation Outlier*, IO) are considered. The procedure consists of:

a) as above, the outliers found are removed from the series;
b) the model parameters are then re-estimated and a) is performed again until no more outliers are encountered.

After correcting for the outliers found in the first round, the program performs a new automatic model identification, followed by a new search for outliers, if the model has been changed. If the second round does not provide a satisfactory model, a third round is carried out.

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

A notable feature of this algorithm is that all calculations are based on linear regression techniques, which reduces computational time.

In RegARIMA an automatic methodology detects outliers *AO, TC, LS* or any combination of the three using the specified model. After outliers have been identified, the appropriate regression variables are incorporated into the model as "automatically identified outliers" and the model is re-estimated. This procedure is repeated until no additional outliers are found.

Two estimation procedure are available with the program RegARIMA:

a) *addone method:* the program calculated *t-values* for each type of outlier specified (AO, TC and/or LS) at all time points for which outlier detection is being performed. If the maximum absolute outlier *t-value* exceeds the critical value, then an outlier has been detected and the appropriate regression variable is added to the model. The program then estimates the new model, that is the old model with detected outliers added, and looks for an additional outlier. This process is repeated until no additional outliers are found;

b) *addall method:* this method follows the same general steps as the *addone method*, except that on each outlier detection step, the addall method adds to the model all outliers with absolute *t-values* exceeding the critical value.

All the significant outliers in step a) are put as regressors. The multiple regression is performed, after what the outliers which come out as insignificant are removed. If outliers are suspected at specific known time points, then they may be included in the model by adding the appropriate AO, TC or LS regression variables to the model in the regression spec.

Also a *ramp effect* would be available in RegARIMA, but the user has to enter the specification of this effect, which allows for a linear increase or decrease in the level of a series over a specified time frame.

2.2 Missing Observations

Missing observations can be treated in TRAMO in two different but equivalent ways:

- *skipping approach*;
- *additive outliers approach.*

The first one is an extension to nonstationary models of the skipping approach of Jones (1980) and is described in Gomez and Maravall (1994). Interpolation of missing value is made by a simplified fixed point smoother and yields identical results to Kohn and Ansley (1986).

If the missing observations are treated as additive outliers, the missing data are first replaced by tentative values, which come from the sum of the two adjacent observations. Then, for ARIMA model identification of the differenced series, the program estimates all regression parameters, included those of the missing observations. In this way the missing observations are implicitly estimated as the difference between the tentative value and the estimated regression parameter of the additive outliers.

In RegARIMA no missing observation treatment is performed.

2.3 Trading Day and Easter Effects

Trading day effects occur when a series is affected by the differing day-of-the-week compositions of the same calendar month in different years; for instance, business activity varies over the different days of week and considering the case of monthly or yearly series, the business activity is affected to the number of Mondays, Tuesdays, ... and Sundays contained in a given month or in a given year.

A correction for this trading day effects may thus be needed. Trading day effects can be modelled with 7 dummy variables (one by day) X_{1t}, ..., X_{7t}, since:

X_{1t} is the number of Mondays in month t;
X_{2t} is the number of Tuesdays in month t;
..;
X_{7t} is the number of Sundays in month t,

and then to regress the series, Y_t is regressed on the X_{it} so as to obtain:

$Y_t = b_1X_{1t} + \dots + b_7X_{7t} + Z_t$.

In practice, the b's coefficients tend to be highly correlated, and so a reparametrization is needed. This may be done in two different ways:

- parametrization with 6 dummy variables:
  (no. of Mondays) - (no. of Sundays),
  ...,
  (no. of Saturdays) - (no. of Sundays)
  (Bell, Hillmer, 1983);
- an adjustment which involves only one regressor:
  (no. of Mondays, Tuesdays,....., Fridays) - 5/2 (no. of Saturdays, Sundays).

This is motivated by the idea that the pattern for the working days on one hand and for Saturdays and Sundays on the other are similar.

Table 1 – General diagnostic for X-12-ARIMA and TRAMO-SEATS

Method	X-12 ARIMA	TRAMO-SEATS
Outliers	OUTLIER handle three types of outliers: AO - Additive Outliers LS - Level Shifts TC - Temporary Changes and Temporary ramps.	IATIP handle four types of outliers: AO - Additive Outliers LS - Level Shifts TC - Temporary Changes IO - Innovations Outliers.
Missing observations	No missing observation treatment is performed.	INTERP treats missing values in two different ways: skipping approach additive outliers approach.
Trading day effects	REGRESSION performs a parametrization with 6 dummy variables or with only one regressors. Also leap-year effects are considered.	ITRAD performs a parametrization with 6 dummy variables or with only one regressors.
Easter effects	REGRESSION provides an Easter effects correction.	IEAST provides an Easter effects correction.
Model identification	AUTOMDL make a selection in a set of 5 models, but the users can introduce himself other models.	AMI searches for regular polynomials up to order 3 and for seasonal polynomials up to order 2.

X-12-ARIMA provides the two approaches. If the series is transformed (Box-Cox o logistic transformation) then leap-year effects are removed by prior adjustment: the series is divided before transformation by a set of factors lp_t where $lp_t = 28,25/29$ if t is a leap year February, $lp_t = 28,25/28$ if t is a non-leap year February, and $lp_t = 1,00$ otherwise.

If the series is not transformed, then the leap-year regression variable is included in the model. Its value, denoted by LP_t , is given by $LP_t = 29 - 28,25$ if t is a leap year February, $LP_t = 28 - 28,25$ if t is a non-leap year February, and $LP_t = 0,00$ otherwise. In both cases the six regression variables: (no. of Mondays) - (no. of Sundays), ..., (no. of Saturdays) - (no. of Sundays), are also included in the model.

TRAMO contains a facility to pretest the possible presence of trading day and Easter effects; the pretest are made with regressions using the default model for the noise and, if the model is subsequently changed, the test is redone. In automatic model identification if the model is changed, both tests are then redone.

Also in TRAMO, trading day effects can be estimated in two different ways:

- trading day correction (6 variables);
- working day correction:
  (no. of Mondays, Tuesdays,....., Fridays) - 5/2 (no. of Saturdays, Sundays).

In both cases the length of month adjustment can be considered:
(no. total days in month) - (365,25)/12.

Business activity also varies around some special days in the year, like Christmas or Easter, when the sales increase. While the effect of Christmas on activity is always caught by the month of December, the effect of Easter may concern either March or April, according to the year. The date of Easter implies some instabilities on the seasonal patterns related to the months of March and April. So Easter effect requires a special statistical treatment. The increase in the purchases related to Easter affects a period of *n-days* before and ends the Saturdays before Easter. In order to represent this effect a dummy variable is created. This variable denotes, for a given month t, the proportion of the affected time period that falls in month t.

2.4 Model Identification

In TRAMO an automatic model identification procedure is available. The program searches first the order of differentiation for the regular and the seasonal part of the series through the fitting of a sequence of possibly multiplicative AR(1) and ARMA(1, 1) with mean. Then, ARMA with or without seasonal part are selected and fitted, the final choice depending on the BIC criterion.

The program searches for regular polynomials up to order 3 and for seasonal polynomials up to order 2; so the most complicated model which could be examined by the procedure is $(3, 2, 3)\ (1, 1, 1)_s$.

RegARIMA presents an automatic model selection procedure similar to the one used by X11-Arima/88 (see Dagum, 1988); in this case the user has to introduce himself which types of models have to be fitted to the time series and can change the thresholds of the selection criteria.

The default setting for the automatic model selection procedure classify a model as acceptable if:

1) the absolute average percentage error of the extrapolated values within the last three years of data is less than 15%;
2) the *p-value* associated with the fitted model's Ljung-Box Q-statistic, testing the uncorrelatedness of the model's residuals, is greater than 5%;
3) there are no signs of overdifferencing.

The most complicated model within the default list is $(2, 1, 2)\ (0, 1, 1)_s$.

3. Diagnostic Checking

Diagnostic checking of a model is performed through various analysis of the residuals from model estimation, the objective being to check if the true residuals appear to be white noise. For example, changes in the variance over time would suggest that a modification of the initial transformation of the data is necessary.

Both X-12-ARIMA and TRAMO-SEATS, in order to check for autocorrelation, produce ACFs and PACFs of the residuals with standard errors. But, a more formal test could be useful to discern the remaining residual autocorrelation.

X-12-ARIMA produces the Ljung-Box Q-statistic (Ljung, Box, 1978), together with some basic descriptive statistics of the residuals and a histogram of the standardised residuals.

The Ljung-Box Q-statistic tests the significance of the first *m* autocorrelations:

$$Q_m = T\,(T+2) \sum_{i=1}^{m} r^2\,(i)\ /\ (T - i).$$

The choice of *m* is arbitrary; for example for monthly series, one may consider m = 24. Given that the *r(.)'s* estimates are independent, when r(.)'s are computed from ARMA residuals, the Q-statistics should be distributed as a χ^2 with (m-p-q) degrees of freedom.

The Q-statistic may also be modified so as to consider specifically seasonal lags. For example, for a monthly series, the significance of the autocorrelations of the residuals at lags 12 and 24 may be tested using the Pierce statistic:

$$Q_s = T\,(T+2)\,[r^2\,(12)\ /\ (T-12) + r^2\,(24)\ /\ (T-24)]\ .$$

Pierce (1978) showed that Q_s can be roughly approximated by a χ^2_2 distribution. The Pierce Q-statistic is provided by TRAMO-SEATS program.

Moreover, TRAMO-SEATS checks the linearity assumption with the Q-statistics. In fact, Maravall (1983) showed that if a series Y_t is linear, then the lag-k autocorrelation is such that:

$$r_k(Y^2_t) = [r_k(Y_t)^2\,]\ .$$

Further, McLeod and Li (1983) proved that $Q_m(a_t)$ and $Q_m(a^2_t)$ have the same distribution. So, computing the Q-statistics for both the residuals and the squared residuals, an increase in the Q-value for squared residuals is an indication of nonlinearity. Similarly, a test for nonlinearity at seasonal lags may be performed by comparing $Q_s(a_t)$ and $Q_s(a^2_t)$.

In order to test the residual normality, TRAMO-SEATS provides the skewness and kurtosis tests.

Table 2 – Diagnostic checking: comparison of X-12-ARIMA and TRAMO-SEATS

X-12-ARIMA	TRAMO-SEATS
ACF	ACF
PACF	PACF
Q statistics of Ljung-Box	Q statistics of Ljung-Box and Pierce
	Q-value for squared residuals
	Residual normality tests

4. Seasonal Adjustment Diagnostics

4.1 Seasonal Adjustment Diagnostics in X-12-ARIMA

The diagnostic for seasonal adjustment in X-12-ARIMA presents a lot of indicators. First of all the F-tests for seasonality are provided in order to detect the presence of stable seasonality and moving seasonality from indirect adjustment.

Eleven quality control statistics from indirect adjustment, (M1, M2, ..., M11), are then performed. These monitoring statistics show:

- the relative contribution of the irregular component over the three months span (M1);
- the relative contribution of the irregular component to the stationary portion of the variance (M2);
- the amount of month to month change in the irregular component as compared to the amount of month to month change in the trend-cycle (M3);
- the amount of autocorrelation in the irregular component as described by the average duration of run (M4);
- the number of months the change in the trend-cycle takes to surpass the amount of change in the irregular (M5);
- the amount of year to year change in the irregular component as compared to the amount of year to year change in the seasonal (M6);
- the amount of moving seasonality present relative to the amount of stable seasonality (M7);
- the size of the fluctuations in the seasonal component throughout the whole series (M8);
- the average linear movement in the seasonal component throughout the whole series (M9);
- same as M8, calculated for recent years only (M10);
- same as M9, calculated for recent years only (M11).

An overall index of the acceptability of the seasonal adjustment is calculated through a weighted average of M1-M11 statistics. Moreover, Q-statistic computed without the M2 quality control statistic is presented. For Q-value greater than 1, the seasonal adjustment is unacceptable.

The above mentioned diagnostics are presented in X11, but in X-12-ARIMA some important seasonal adjustment diagnostics are added: spectrum estimates for the presence of seasonal and trading day effects and the sliding spans (Findley et al., 1990) and revision history diagnostics of the stability of seasonal adjustment. The sliding spans and revisions histories have the significant advantage over M1-M11 of being directly interpretable, whereas M1-M11 are indirect measures, in some cases very indirect, of data features known to be troublesome for the X11 methodology.

4.1.1 Sliding Spans

The sliding spans diagnostics display and provide summary statistics for the different outcomes obtained by running the program on up to four overlapping sub-spans of the series.

The sliding spans diagnostics are described in detail and compared with other quality diagnostics in the article Findley, Monsell, Shulman and Pugh (1990) and Findley and Monsell (1986). Other comparisons can be found in Battipaglia and Focarelli (1994) where simulation experiments are performed; the conclusion in this article is that stability statistics from sliding spans were significantly more correlated with adjustment accuracy than the Q-statistic of X-11 ARIMA.

These diagnostics analyse the difference between the largest and the smallest adjustments of the month's datum obtained from the different spans.

They also analyse the largest and smallest estimates of month-to-month changes and of other statistics of interest.

To obtain sliding spans for a given series, an initial span is selected and its length depends on the seasonal adjustment filters being used. A second span is obtained from this one by deleting the earliest year of data and appending the one following the last year in the span. A third span is obtained from the second in this manner, and a fourth one from the third, data permitting. This is done in such a way that the last span contains the most recent data.

For series whose seasonally adjusted values are all positive, the two most important sliding spans statistics are *A(%)* and *MM(%)*. For a month *t* that is common to at least two of the subspans, one of which is the *k-th* span, let A_t denotes its seasonally adjusted value obtained from the complete series, and let $A_t(k)$ denotes the adjusted value obtained when the seasonal adjustment procedure being considered is applied only to data in the *k-th* span. The seasonal adjustment A_t is called unstable if:

$$A_t^{\max} = \frac{\max_k A_t(k) - \min_k A_t(k)}{\min_k A_t(k)} > 0.03 \ .$$

Further, for months *t* such that both *t* and *t-1* belong to at least two spans, the "seasonally adjusted month-to-month percent change" MM_t (k) is called unstable if:

$$MM_t^{\max} = \max_k MM_t(k) - \min_k MM_t(k) > 0.03$$

where

$$MM_t(k) = \frac{A_t(k) - A_{t-1}(k)}{A_{t-1}(k)} 100.$$

The month t is considered having an unreliable seasonal factor if:

$$S_t^{\max} = \frac{\max_k S_t(k) - \min_k S_t(k)}{\min_k S_t(k)} > 0.03 \qquad ,$$

where S_t (k) denotes the seasonal factor estimated from span k for month t.

There is a similarly defined statistic, YY(%), for year-to-year percent changes in the seasonally adjusted data:

$$YY_t^{\max} = \max_k YY_t(k) - \min_k YY_t(k) > 0.03 \,,$$

where

$$YY_t(k) = \frac{A_t(k) - A_{t-12}(k)}{A_{t-12}(k)} \,.$$

$YY_t(k)$ denotes the year-to-year percentage change in the adjusted value from span k for month t.

Table 3 – Seasonal adjustment diagnostics: comparison of X-12-ARIMA and TRAMO-SEATS

X-12 ARIMA	TRAMO-SEATS
F-tests for seasonality	Comparison of variances for the
Quality control statistics (M1, ..., M11)	component, the estimator and the estimate
Spectrum estimates	Revision error
Sliding spans	
Revision histories	

4.1.2 History

The second type of stability diagnostic in X-12-ARIMA considers the revisions associated with continuos seasonal adjustment over a period of years. The basic revision calculated by the program is the difference between the earliest adjustment of a month's datum, obtained when that month is the final one in the series, and a later adjustment based on all future data available at the time of the diagnostic analysis. Similar revisions are obtained for month-to-month changes, trend estimates and trend changes. Sets of these revisions are called *revision histories.*

These revisions can suggest how many years of forecasts to use in forecast extension of the series and how they indicate whether the (final) Henderson trend estimates are stable.

We consider the unadjusted time series Y_t, $1 \le t \le N$; for any of these months t, and any integer u in the interval $t \le u \le N$, let $A_{t/u}$ denote the seasonally adjusted value for time t obtained with these options when only the data Y_t, $1 \le t \le u$, are used. For a given t, as u increases these adjustments converge to a final adjusted value. When the *3 x m* seasonal filter is used, convergence is usually effectively reached in about 1+m/2 years. The adjustment $A_{t/t}$ obtained from data through time t is called *concurrent* adjustment, while $A_{t/N}$ is the *most recent* adjustment. In the case of a multiplicative decomposition, the revision from the concurrent to the most recent adjustment for month t is calculated by the program as a percentage of the concurrent adjustment:

$$R^A_{t/N} = 100 \; \frac{A_{t/N} - A_{t/t}}{A_{t/t}}.$$

For given N_0 and N_1 with $N_0 < N_1$, the sequence $R^A_{t/N}$, $N_0 \le t \le N_1$, is called a *revision history* of the seasonal adjustment from time N_0 to time N_1.

Period-to-period percent changes are often as important as the seasonal adjustment:

$$\Delta^{\%} A_{t/u} = 100 \; \frac{A_{t/u} - A_{t-1/u}}{A_{t-1/u}}.$$

The program can produce revision histories for them:

$$R^{\Delta^{\%}A}_{t/N} = \Delta^{\%} A_{t/N} - \Delta^{\%} A_{t/t}, \; N_0 \le t \le N_1 \cdot$$

The program also calculates the analogous quantities for final Henderson trends $T_{t/u}$ and for their period-to-period percent change $\Delta^{\%}T_{t/u}$. These histories are denoted $R^T_{t/N}$ e $R^{\Delta\%T}_{t/N}$, $N_0 \le t \le N_1$:

$$R^T_{t/N} = 100 \; \frac{T_{t/N} - T_{t/t}}{T_{t/t}}$$

$$R^{\Delta\%T}_{t/N} = \Delta^{\%}T_{t/N} - \Delta^{\%}T_{t/t}$$

where

$$\Delta^{\%} T_{t/u} = 100 \; \frac{T_{t/u} - T_{t-1/u}}{T_{t-1/u}}.$$

4.1.3 Spectrum Estimates

In order to detect seasonal effects we can use spectrum estimates. Because seasonal and calendar effects are approximately periodic, it is natural to use spectrum estimation to detect their presence. The period that defines seasonal effects is one year. Thus, in monthly series, seasonal effects can be discovered through the existence of prominent spectrum peaks at any of the frequencies K/12 cycles per month, $1 \le K \le 6$. In quarterly series the relevant frequencies are 1/4 and 1/2 cycles per quarter.

Whenever seasonal adjustment is done, X-12-ARIMA automatically estimates two spectra:

- the spectrum of the first differences of the adjusted series;
- the spectrum of the final irregular component adjusted for extreme values.

The program compares the spectral amplitude at the seasonal and trading day frequencies noted above with the amplitudes at the next both lower and higher frequencies plotted. If these neighbouring amplitudes are smaller by a margin that depends on the range of all spectrum amplitudes, then plots of the estimated spectra are automatically printed, together with a warning message that gives the number of "visually significant" peaks found at seasonal or trading day frequencies.

4.2 Seasonal Adjustment Diagnostics in TRAMO-SEATS

The ARIMA model based signal extraction method (as implemented in the program Seats) uses the information obtained from the modelisation of the series to estimate the components and so the theoretical estimator is calculated for each component. The performance evaluation of the seasonal adjustment procedure made in TRAMO-SEATS program can be evaluated with the comparison of final estimate and theoretical estimator. Maravall and Gomez (1992) suggest to compare the autocorrelation functions at lags 1 and 12 and the related variances.

The output of SEATS shows for each component the autocorrelation functions at lags from 1 to 12 for the component, the estimator and the estimate; the related variances are also presented. For all components it should happen that:

- *Var (Component) > Var (Estimator)*

and

- *Var (Estimator) close to Var (Estimate).*

Moreover, for evaluating the seasonal adjustment procedure, the different errors have to be compared. The output of TRAMO provides an error analysis containing the autocorrelation functions for the final estimation error, the revision in concurrent estimator and the total estimation error with the related variances, together with the standard error of revisions and final estimator for each component.

The *revision error* is due to the difference from the final estimator and *concurrent estimator*, that is the estimator of component for the last observed period. In fact, the moving average methods apply a two-sided filter, that is the estimator of the signal for period *t* depends on observations posterior to *t;* the two-sided filter will always produce revisions in the estimator, since, for example, the estimator of s_t at time *t* (the concurrent estimator) cannot use observations for T > t, given that the are not available yet. The arrival of new observations will induce revisions in a preliminary estimator until, once the filter has converged, the final estimator is obtained. But the final estimator of an unobserved component also contains an error which is orthogonal to the revision. So, for a preliminary estimator, the estimation error is equal to the revision plus the final estimation error.

5. Concluding Remarks

The analysis conducted in this paper shows the diagnostic capabilities of the two seasonal adjustment programs, X-12-ARIMA and TRAMO-SEATS.

As regard the general diagnostic, that is the set of the capabilities and methods of the two programs provided for the prior adjustments of the models, before the seasonal adjustment is performed, TRAMO seems to be a more complete pre-program since it detects missing observations, while in X-12-ARIMA no missing observations treatment is performed (see Table 1). As regard diagnostic checking of the model, that is the residual analysis, Tramo is no doubt to prefer (see Table 2). On the other hand, X-12-ARIMA offers many indicators to assess the quality of seasonal adjustments (see Table 3).

As far as indicators of the quality of seasonal adjustments are concerned, it has to stress, however, that the choice is related to the different way in which the filters are constructed. In fact, with model-based procedure the assumptions on the components are clearly defined and the statistical properties of estimators are obtained directly; whereas with automatic procedure it is difficult to define them, so that the evaluation refers to the properties of the results.

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NONLINEARITIES AND ASYMMETRIES IN ISTAT TIME SERIES

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1. Introduction

The empirical modelling of economic time series is dominated by methods that assume linearity of the underlying dynamic economic system. The main argument in favour of linearity and the reason for its original adoption is its simplicity and its good approximation of many dynamic processes.

In recent years, however, there has been a growing interest in testing for nonlinearity in economic data, but much disagreement and controversy has arisen about the available results. There seems to be little agreement about the existence of nonlinearity in economic data, with some researchers continuing to insist that linearity remains a good assumption for all economic time series, despite the fact that economic theory provides little support for the assumption of linearity.

It would appear that the controversies must be produced by the nature of the tests themselves. In fact inferences varied across tests for the same data, and within tests for different sample sizes and various methods of aggregation of the data; robustness of inferences in this area of research seemed to be low. It has been argued that it is this robustness problem that accounts for the controversies surrounding empirical claims of nonlinearity in economic.

This consideration enforced the idea that linearity must be verified conducting different tests on the series. In fact, none of the tests available in literature completely dominates the others, because some tests may have higher power against certain alternatives than other tests, without any of the tests necessarily having higher power against all alternatives. If this is the case, each of the tests may have its own comparative advantages, and there may even be gain from using more than one of the tests in a sequence designed to narrow down the alternatives.

Therefore, to investigate the presence of linearity in our Istat data set and to overcome the stated disadvantages, we have conducted various tests of linearity. Some of them are general tests against nonlinearity whereas others have been designed with a specific nonlinear alternative in mind. By this way we expect to be able to recognize the different nonlinearity dynamics.

The paper is organized as follows. The tests applied to the series are presented in section 2. Section 3 summarizes the main results of the analysis of the linearity for the data set.

2. Nonlinearity tests

We use seven inference methods to test for stochastic nonlinearity. We chose those tests as a result of their high repute among tests for nonlinearity. The tests McLeod-Li, Keeenan, $\gamma_{21}(k)$ and $\gamma_{31}(k)$ are all methods for testing for general nonlinear dynamics. The tests ARCH, BL and STAR are applied in their LM version and are tests against specific nonlinear alternatives.

Although the McLeod-Li and the Keenan tests are proposed in literature as tests to verify general nonlinearity, they show high power against some particular nonlinear models: the bilinear and the ARCH in the first case, the asymmetric exponential model in the second. In particular Saikkonen and Luukkonen (1988) show that the Keenan test is equivalent to an LM test with an EAR model as alternative hypothesis.

McLeod-Li test

Historically, one of the first nonlinear tests presented in literature is a portmanteau test considered by McLeod and Li (1983) based on the autocorrelations of squared residual from a linear fit. It is analogous to the well known Box-Pierce statistic used to test the adequacy of an ARMA model. The McLeod-Li test statistic is defined by

$$T_n = n(n+2)\sum_{i=1}^{M} \frac{\hat{\rho}_i}{n-i}$$

where ρ_i are the autocorrelations at lag i of the squared residuals. T_n is distributed as a χ^2_M.

Keenan test

Nonlinear processes can be expressed as Volterra series, as a generalization of the Taylor expansion in the linear context. The Keenan test (1985) is obtained to test linearity against a second order Volterra expansion, namely

$$X_t = \mu + \sum_{i=-\infty}^{\infty} \theta_i \varepsilon_{t-i} + \sum_{i,j=-\infty}^{\infty} \lambda_{ij} \varepsilon_{t-i} \varepsilon_{t-j}$$

and tests for the presence of no multiplicative terms. There is a striking ressemblance of this to the framework of Tukey's one degree of freedom test for non-additivity.

The Keenans test statistic is based on the use of auxiliary regressions: first X_t on $(1, X_t, ..., X_{t-M})$ and than the estimated $\hat{X}_t^2$ on $(1, X_t, ..., X_{t-M})$. The test has a $F_{1,n-2M-2}$ distribution.

Reversibility tests

If the probabilistic structure of a time series going forward in time is identical to that in reverse time, the series is time reversible. Under the assumption of Gaussian residuals, Weiss (1975) shows that a linear model is reversible and vice-versa. Referring on the concept of reversibility, two tests of linearity are constructed: $\gamma_{21}(k)$ and $\gamma_{31}(k)$ of Ramsey and Rothman (1996) and Andreano and Savio (1998) respectively. The test statistics are

$$\hat{\gamma}_{21}(k) = \hat{B}_{21}(k) - \hat{B}_{12}(k)$$

$$\hat{\gamma}_{31}(k) = \hat{B}_{31}(k) - \hat{B}_{13}(k)$$

where $\hat{B}_{i1}(k)$ and $\hat{B}_{i1}(k)$ are method of moments estimators of the bicovariances $E(X^i_t X_{t-k})$ and $E(X_t X^i_{t-k})$, for i = 2, 3. By construction the $\gamma_{21}(k)$ and $\gamma_{31}(k)$ tests have no power against nonlinear processes as ARCH and GARCH. Simulation have shown that the two reversibility tests behave differently for increasing k, when the underlying model is a threshold model or a bilinear one. In the first case $\gamma_{i1}(k)$ is significant only for $k = 1$; on the contrary, for a bilinear model the power of the tests decreases slowly. However, the $\gamma_{21}(k)$ test shows higher power against asymmetric processes.

LM test for ARCH, BL and STAR models

A popular linearity test against a fully specified nonlinear alternative is the Lagrange Multiplier (LM) test. It has the advantage that the estimation of the nonlinear model is not necessary. An early proponent of these tests in time series analysis has been Pagan (1978). Later contributors include Engle (1982) who has developed such a test against an autoregressive conditionally heteroskedastic (ARCH) model:

$$\varepsilon_t \sim N(0,h_t) \qquad h_t = \sigma^2 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2$$

The null hypothesis of linearity is $H_0: \alpha_i = 0,\ i = 1,...,p$. The LM test statistic against an ARCH model, is equivalent to TR^2 from the auxiliary regression

$$\varepsilon_t^2 = \sigma^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + e_t$$

where e_t is an artificial error term. TR^2 is distributed as a χ^2_p.

In the analysis of nonlinear time series models, particular attention has been paid to bilinear (BL) and smooth transition autoregressive models (STAR), whose theoretical properties and applicability in practical problems have been considered in a number of papers and books:

$$BL: \quad X_t = \mu + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{j=1}^{m} \sum_{h=1}^{k} \beta_{jh} \varepsilon_{t-j} X_{t-h} + \varepsilon_t$$

$$STAR: \quad X_t = \mu + \sum_{i=1}^{p} \alpha_{1i} X_{t-i} + F(X_{t-d}) \sum_{i=1}^{p} \alpha_{2i} X_{t-i} + \varepsilon_t$$

Saikkonen and Luukkonen (1988) have considered an LM test against a bilinear alternative, while Teräsvirta (1994) against a STAR model. Both tests can be performed using an auxiliary regression. In particular, the LM-BL may be calculated from the auxiliary regression of $\hat{\varepsilon}_t$ on a constant, X_{t-i} (i = 1,...,p) and $\hat{\varepsilon}_t X_{t-j}$ (i = 1,...,m, j = 1,...,k). TR^2 from this regression is distributed as a χ^2_{mk}.

The STAR test can be conducted under the hypothesis that the regime shift occurs for a change in the level (S_1) or in the coefficients (S_3). Both tests can be given as TR^2, where the auxiliary regressions are $\hat{\varepsilon}_t$ on $(1, X_{t-i}, X_{t-i}X_{t-j}; i,j = 1,\ldots,p)$ and $\hat{\varepsilon}_t$ on $(1, X_{t-i}, X_{t-i}X_{t-j}, X^3_{t-i}, i,j = 1,\ldots,p)$ respectively. S_1 is distributed as a $\chi^2_{p(p+1)/2}$ and S_3 as a $\chi^2_{p+[p(p+1)/2)]}$.

3. Empirical results

The following table is a summary of the results of the tests discussed above on the series of our data set.

As has been emphasized by many authors, in conducting such tests it is important that the series being investigated are serially uncorrelated. We thus fit ARMA(p,q) models to each series, differenced before with a ∇^1 or ∇^{12} operator to assure the stationarity, which is verified by ADF tests. Some tests of whiteness (e.g. Ljung-Box and Bera-Jarque) are conducted to verify the adequacy of the estimated models. We do not report these results to save space.

If the null of linearity is accepted we report L in the table, if the null is rejected NL. For the $\gamma_{21}(k)$ and $\gamma_{31}(k)$ tests we show in some cases an upper A or B, if there is clear evidence of asymmetric nonlinearity as STAR models or of leptocurtic dynamic as bilinear models.

It is immediately clear that only four series do not exhibit any form of nonlinearity (Ifainvgn, Ifainvgt, Iorgengt and Pconalgp). On the contrary none of the series considered reject the hypothesis of linearity in all the tests. The Pingengp series refuses linearity in six of the seven tests. However, the nonlinearity of Pingengp, as that of Pcoaltgp and Citgengv, is expressed in a general form and is impossible to distinguish between an asymmetric or a leptocurtic behaviour. On the contrary, although for the series Ipiintgt, Cit006gc and Pcosergp only four tests refuse linearity, there is a great coherence between them in identifying an asymmetric pattern in the first and second case, and a bilinear dynamic in the third case.

Table 1 – Results of the linearity tests

	McL.-Li	Keenan	$\gamma_{21}(k)$	$\gamma_{31}(k)$	STAR	ARCH	BL
Ifagenge	L	L	L	NL	L | NL	L	L
Ifacongn	L	L	L	L	L | L	L	NL
Ifainvgn	L	L	L	L	L | L	L	L
Ifainvgt	L	L	L	L	L | L	L	L
Icogengt	L	NL	NL	NL	NL | NL	L	L
Iorgengt	L	L	L	L	L | L	L	L
Ipigengt	NL	L	L	NL	L | L	L	L
Ipicongt	NL	L	L	L	L | L	L	L
Ipiinvgt	L	L	L	NL	L | L	L	NL
Ipiintgt	L	L	NL	NL	L |NL	L	L
Pcobengp	L	L	L	NL	L | L	L	L
Pingengp	L	NL	NL	NL	NL | NL	NL	NL
Ppigengp	L	NL	L	NL	NL | NL	L	NL
Pconalgp	L	L	L	L	L | L	L	L
Ppicongp	NL	L	L	NL	NL | NL	L	NL
Ppintgp	NL	NL	L	L	NL | NL	L	NL
Ppinvgp	NL	NL	L	NL	L | NL	L	L
Lgoltogi	NL	L	L	NL	NL | NL	NL	L
Svgaligi	NL	L	L	L	NL | NL	L	L
Citgengv	NL	NL	NL	L	NL | L	NL	NL
Cetgengc	NL	L	L	L	NL | NL	L	NL
Citgengq	NL	L	NL	L	NL | NL	L	L
Cetgengq	NL	L	L	L	NL | NL	L	NL
Cit006gc	L	L	NL	NL	NL | NL	L	L
Cet006gc	L	L	L	NL	L | L	NL	L
Pcoaltgp	L	NL	NL	NL	NL | NL	L	NL
Pcogntgp	L	L	L	L	L | L	L	NL
Pcosergp	L	L	NL	NL	NL | L	L	NL
Ipi0dagt	NL	L	L	L	L | L	L	L
Ipi0dbgt	NL	L	L	NL	L | L	L	NL
Ipidjgt	L	L	L	NL	L | L	NL	NL
Ipi0dmgt	NL	L	NL	NL	L | NL	L	L

Summering up, the series show more asymmetric nonlinearities (18 on 32 series) than bilinearities (14 on 32), whilst ARCH nonlinearities do not seem to be recurrent in our data set.

The turnover and the industrial production index series are globally more linear than the prices and the external trade series, except Icogengt and Ipi0dmgt, which seem to be asymmetric.

Nonlinearity is at most present in the price indices series. Ppigengp, Ppicongp, Ppintgp, in addition to those presented above, refuse linearity in at least four of the seven tests. This result seems to contradict usual economic analysis; however these series present some kinds of structural breaks due to the introduction of new classification system and standards. This may be interpreted as a presence of asymmetry and extreme values.

Changes in classification and in the data collection system are also present in the external trade series; therefore, it is not easy to assert if the identified nonlinearity is proper of the dynamic of the series or due to these technical problems.

The observed presence of nonlinearities in the analyzed time series makes the continued reliance on linear models questionable. The recourse to a diagnostic nonlinearity analysis should therefore be preliminary to all future modelling time series analysis.

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THE SEASONAL ADJUSTMENT OF SISTAN TIME SERIES: A COMPARISON OF TRAMO-SEATS AND X-12-ARIMA

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1. Introduction

This paper discusses some of the issues raised by the seasonal adjustment of a set of representative time series produced by statistical agencies belonging to the Italian National Statistical System (*Sistema Statistico Nazionale, Sistan*). The criteria that guided the choice of the set are twofold: the relevance of the information provided about the state of the economy and the non standard nature of the adjustment, due to the peculiar seasonal behaviour. The exercise is carried out with the objective of evaluating the performance of two seasonal adjustment procedures, X-12-ARIMA and TRAMO-SEATS.

In particular, we focus on three case studies. The first concerns a group of qualitative indicators produced by Isco (Istituto Nazionale per lo Studio della Congiuntura), an organisation belonging to Sistan, usually in the form of balances. Their interest lies in the nature of the seasonal fluctuations, which are stationary; as a matter of fact, the seasonality that is observed in the aggregate series is residual, due to the inability of the respondents to filter out all seasonal movements. Therefore, these indicators provide a useful test for judging the flexibility of the two approaches to seasonal adjustment.

The second deals with industrial turnover indices. Due to the tremendous drop of economic activity connected to the contemporaneous shutdown of factories for summer holidays, the treatment of August is rather troublesome: standard multiplicative or log-additive adjustment tend to point out this particular season as outlying or highly "unstable". The pseudo-additive decomposition implemented in X-12-ARIMA can sometimes handle this feature properly.

The third case study concerns price indices. The issue here is whether the seasonal fluctuations can be identified at all, due to the level of aggregation of the series available to the SARA project and to their length.

The paper is divided into three main sections, each devoted to a case study in the same order as outlined above. In a final section (section 5) we draw some conclusions.

2. Seasonality in Qualitative Business Survey Indicators

An important set of indicators on current economic conditions arise from the monthly business survey conducted by Isco (*Istituto Nazionale per lo Studio della Congiuntura*) for the Italian manufacturing sector. Their relevance stems from the fact that they provide timely information on economic variables that are either difficult to measure, such as expectations or capacity utilisation, or whose measurement on a quantitative scale is more expensive and time consuming (turnover and production in volume).

The data collected are mostly categorical or ordinal and timeliness is achieved by a suitable survey design. Survey questions are kept to a minimum and bear on the direction of the trend in an economic variable, as perceived by the respondent. For instance, with respect to orders, the respondents is asked whether they are above normal, normal, or below normal, abstracting from seasonal fluctuations. The individual data are finally aggregated into a single time series subtracting the percentage of responses falling in the below normal category from the percentage of the above normal. These differences are called balances.

Now, although the respondent is explicltly asked to abstract from seasonal movement in forming his/her judgement, a well known common feature of business survey indicators is the presence of seasonality. This evidence has been advocated in support of the notion that seasonal fluctuations are not independent of the trend-cycle, which implies that economic time series are not decomposable (Franses, 1996).

The seasonal dynamics in the business survey indicators reflect the seasonality in the underlying quantitative indicators (orders, turnover and industrial production) as far as the location of seasonal peaks and troughs within the year is concerned; however, seasonality is weaker (less persistent) and evolves more rapidly.

Of the six series considered for the project SARA we shall concentrate on the quarterly series BCUGENGT (Industrial capacity utilisation rates - Total) available for the period 1986.1-1996.4, and on the monthly series BDIGENGS (domestic orders and demand - Total) available in the form of balances for the period 1986.1-1996.12. The latter is displayed in figure 1 along with its spectral density in decibels ($10 \log_{10} f(\lambda)$), which shows distinctive peaks at the seasonal frequencies. This is a reflection of the puzzling phenomenon described above. Another feature is that on average balances are negative (pessimism is more frequent than optimism).

Graphical inspection tells that seasonality has little persistence, and is characterised by a trough in August that is coincident with that occurring for turnover and production. As a matter of fact, seasonality arises somewhat spuriously from the respondent inability to filter out seasonal factors completely; nevertheless, the respondents apply a seasonal adjustment filter that, however imperfect, produces a series whose seasonality is markedly different from that characterising quantitative indicators: namely, we do not observe the persistent behaviour induced by seasonal unit roots. This descriptive evidence can be supported by formal tests, such as the Canova - Hansen (1995) test.

The automatic model selection procedure implemented in the programme TRAMO, which is based on consistent least square estimation of the autoregressive parameters, see Tiao e Tsay (1983) e Tsay (1984), leads instead to the identification of an ARIMA(0,2,2) x $(0,1,1)_{12}$ model. Since the same holds for the remaining series in the ISCO dataset, it can be concluded that, when the adjustment is made routinely, the automatic model identification is biased towards selecting representations implying more unit roots than are present in the data (the *Airline* transformation is selected most often).

If all the orders of integration are constrained to zero, by means of the options IDIF=2, D=0, BD=0, the programme automatically chooses a (2,0,0) x $(0,0,1)_{12}$, model for which the sum of the autoregressive coefficients is close to one and significant residual autocorrelation is present. Actually, an adequate model for the series is the following:

$$\underset{}{(1-}\underset{(.08)}{.70\,L}-\underset{(.09)}{.42\,L^2}+\underset{(.04)}{.22\,L^6})(1-\underset{(.07)}{.55\,L^{12}})y_t=-\underset{(7.05)}{18.22}+\varepsilon_t$$

with σ^2=15.6970; the Ljung-Box statistic with 12 and 24 autocorrelations are not significant (6.85 and 13.33, respectively).

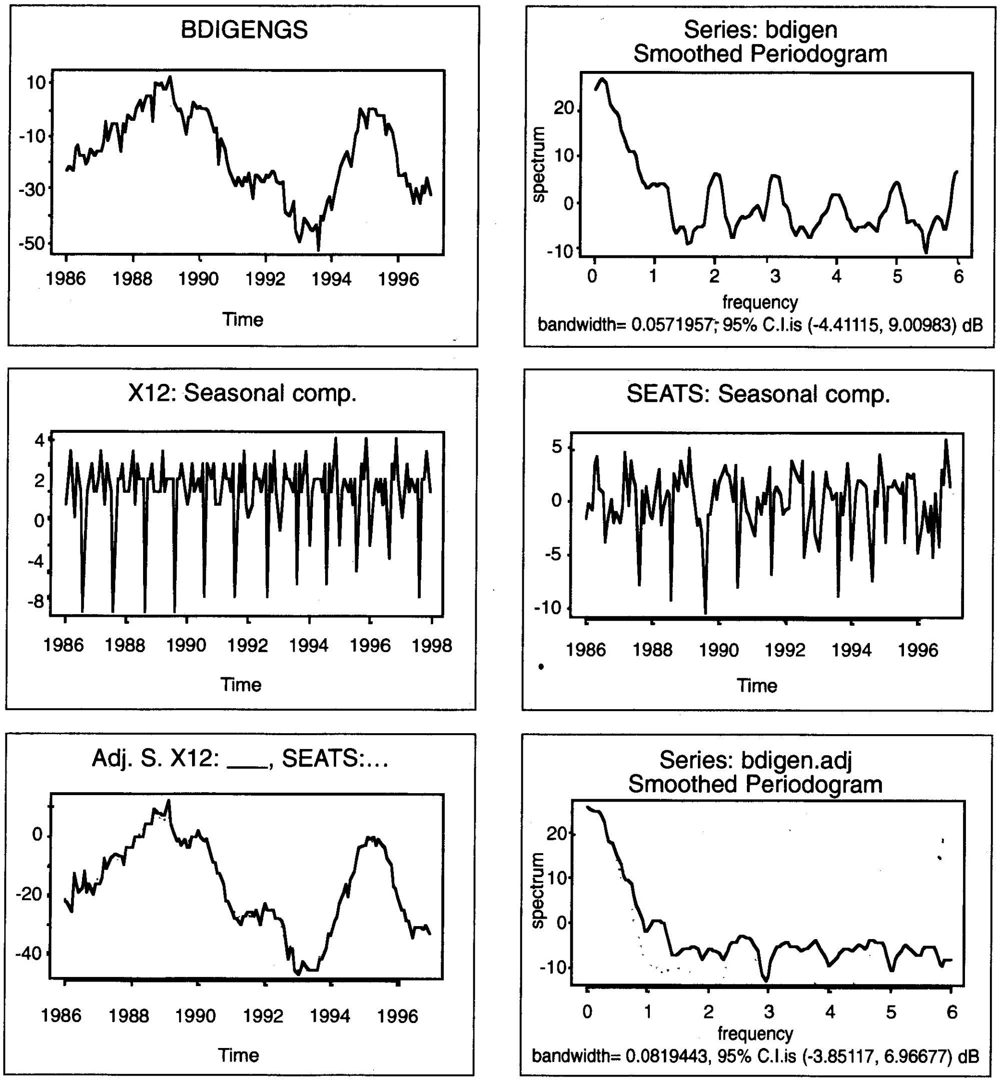
Unfortunately, this model does not belong to the class of models that are decomposable by SEATS, which constraints to 3 the maximum order of the autoregressive component. Hence, in the sequel we present the adjustment provided by a model that is the closest substitute in the class of decomposable models, with orders (3,1,0)x$(1,0,0)_{12}$ and acceptable diagnostics, although residual correlation is still present at lag 4. The estimated seasonal AR coefficient is .57, underlying a model of stationary seasonality.

X-12-ARIMA has been applied with the following specifications:

```
series{title = "ISCO - Liv. Ordini e Dom. dall'Interno"
  start = 1986.1 period= 12 name= "BDIGENGS"
  file = "c:\sara\bdigengs.dat"}
regression{variables=(const td)}
arima{model=(3,1,0)(1,0,0)}
check{ }
estimate{ }
outlier{ }
x11{mode=add seasonalma=msr save=(d10 d11 d12)}
```

The seasonal components estimated by the two procedures are plotted in the central panels of figure 1: it can easily be noticed that the seasonal pattern extracted by X-12-ARIMA is much more stable than its TRAMO-SEATS counterpart. The seasonally adjusted (SA) series obtained from the two procedures are plotted in the bottom left hand panel of figure 1; on the right their spectral density is graphed. The evidence produced by this plots is that the SA series produced by TRAMO-SEATS is smoother and that X-12 is prone to the risk of overadjustment, as the dips in the spectral density are more pronounced.

Figure 1 – BDIGENGS balances of orders and internal demand. Total industry.



Similar considerations arise with respect to the quarterly index of capacity utilisation (BCUGENGT). As the range of the series is (0,100), it should be analysed on a logit scale, by the transformation: $z_t = \ln[y_t/(100-y_t)]$; however, since its values are well removed from the extremes, the logarithmic transformation is suitable.

Now, if the choice of the order of differentiation is left to the procedure (RSA$\geq$ 3), TRAMO-SEATS selects an ARIMA(0,1,0)x(0,1,1)$_4$. If we impose stationarity both AIC and BIC lead to the model with orders (3,0,0)x(1,0,0)$_4$, such that the AR(3) polynomial has a root with modulus .6 at the frequency π, and a pair of complex conjugate roots with modulus .7 and phase .3, corresponding to a period of 21 quarters, which account for the cyclical behaviour of the series. Nevertheless, the model is not decomposable, so TRAMO-SEATS automatically proceeds to pick up a close substitute, achieving a decomposition into a stationary autoregressive trend plus stationary seasonality plus irregular by an ARIMA(2,0,1)x$(1,0,0)_4$ model, such that the nonseasonal AR roots are a pair of complex conjugates.

3. Industrial Turnover

Similarly to the industrial production series discussed in another paper by the same author in this volume, industrial turnover index series are characterised, although to a lesser extent, by the August phenomenon: the seasonal trough, connected to the dramatic drop in economic activity caused by the contemporaneous closing of factories for summer holidays, is highly unstable. As a result, for these series, and particularly for those concerning investment goods, the multiplicative (default) adjustment performed by X-12-ARIMA suffers from severe limitations that are highlighted by sliding-spans diagnostics. As a matter of fact, the rigidity of the default adjustment leads to flag August as outlying or highly unstable and leads to the alternation of periods in which the August value is underadjusted to periods in which it is overadjusted.

A more satisfactory adjustment can sometimes be achieved by the pseudo-additive decomposition (see Findley et al., 1998):

$$y_t = T_t\,(S_t + I_t - 1)$$

where T_t, S_t, I_t are respecively the pseudo trend, seasonal and irregular components. The adjusted series is obtained subtracting the level-dependent component $T_t\,(S_t - 1)$ from the series, where S_t are factors that average to unity over the seasonal period. This implies that when $S_t \cong 0$ the seasonally adjusted series is determined by adding an estimate of T_t, computed as described in Appendix A of the quoted paper, to y_t. Unfortunately, it is not clear how to deal with regression effects, such as outliers and calendar components, so in the sequel we shall work on series already adjusted for these effects at a preliminary stage.

In the following we will also try to show that the log-additive adjustment performed by TRAMO-SEATS is preferable to the default X-12-ARIMA.

3.1 Industrial Turnover Index for Investment Goods, Total (IFAINVGT)

The first series we consider is the total index for investment goods (IFAINVGT), available for the sample period 1985.1-1996.12. The plot of the series, displayed in the first panel of figure 2, reveals the presence of an upward trend, a cyclical downturn in 1991, and strong seasonal variation, mostly attributable to August.

The plot of the 12 yearly series associated to each month (panel 2 from left to right), and that of the relative means and variances of the logarithmic seasonal differences (panel 3), indicate that the behaviour of the series in August is somewhat different from that of the remaining months and that yearly growth rates are seasonally heteroscedastic (in particular, their variance is three times above the average). Due to the very low August value, as argued by Findley et al. (1998), the pseudo-additive adjustment could yield more stable results.

Let us first consider the multiplicative X-12-Arima adjustment: the procedure identifies August 1990 as an additive outlier and corrects for trading days and Easter effects. The RegARIMA model estimated for the extrapolation of the series is the following:

$$\begin{aligned} &\Delta\Delta_{12}(\ln y_t - C_t) = (1-.46L)(1-.58L^{12})\varepsilon_t, \quad \varepsilon_t \sim WN(0,.0019) \\ &C_t = -.0049\ TD_1 + .0148\ TD_2 + .0063\ TD_3 + .0219.TD_4 + .0010\ TD_5 \\ &\qquad -.0182\ TD_6 - .0307\ EASTER + .1801.AO_{1990.8} \end{aligned} \tag{1}$$

The F_S, F_M and KW test statistics signal the presence of identifiable seasonality and is not significant at the 5% level; the M_1-M_{11} diagnostics are all within the acceptance range and no residual seasonality is detected. *Visually significant* peaks are present at the trading days frequencies for the first order differences of the seasonally adjusted series. Sliding-spans diagnostics, summarised below, hint that the adjustment of the August values could be critical:

```
Percentage of months flagged as unstable.
Seasonal Factors 4 out of 108 (3.7%)
  August: 3 (AMPD= 2.8)
Final Seasonally Adjusted Series: 7 out of 108 (6.5%)
  August: 3 (AMPD= 2.8)
Month-to-Month Changes in SA Series: 22 out of 107 (20.6%)
```

Although these percentages do not cross the empirical thresholds reported in Findley et al. (1990), the month to month changes in the seasonally adjusted series vary according to the span of the series under consideration.

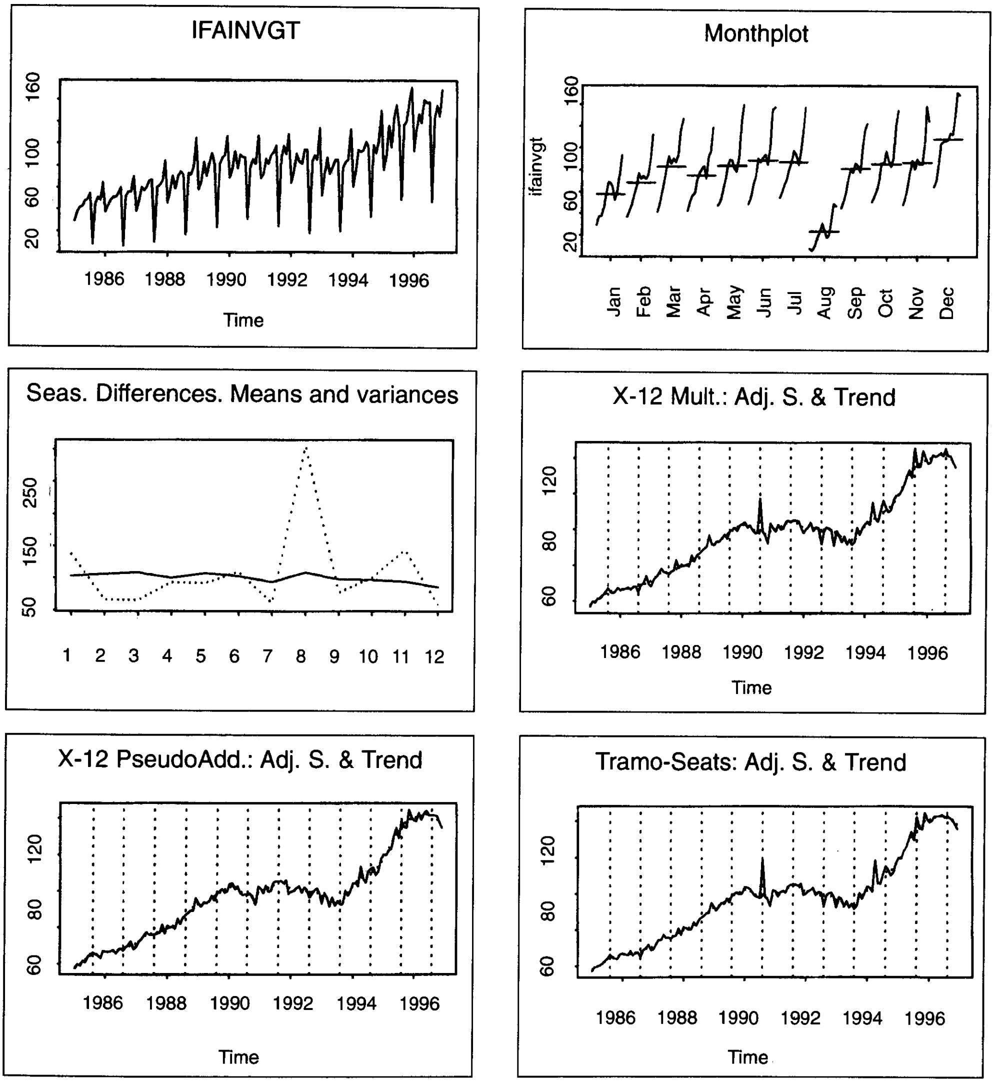
If the additive decomposition is considered, the situation is even worse as far as these diagnostics are concerned:

```
Percentage of months flagged as unstable.
Final Seasonally Adjusted Series: 14 out of 108 (13.0%)
  August: 7 (AMPD= 5.0)
Month-to-Month Changes in SA Series: 31 out of 107 (29.0%)
  August: 8 (AMPD= 5.6)
  September: 7 (AMPD= 5.6)
```

The pseudo-additive decomposition has been applied to the series B1, obtained as an output of the preliminary adjustment for outliers and calendar components, performed according to the estimated model (1). There is now a substantial improvement in the sliding spans diagnostics:

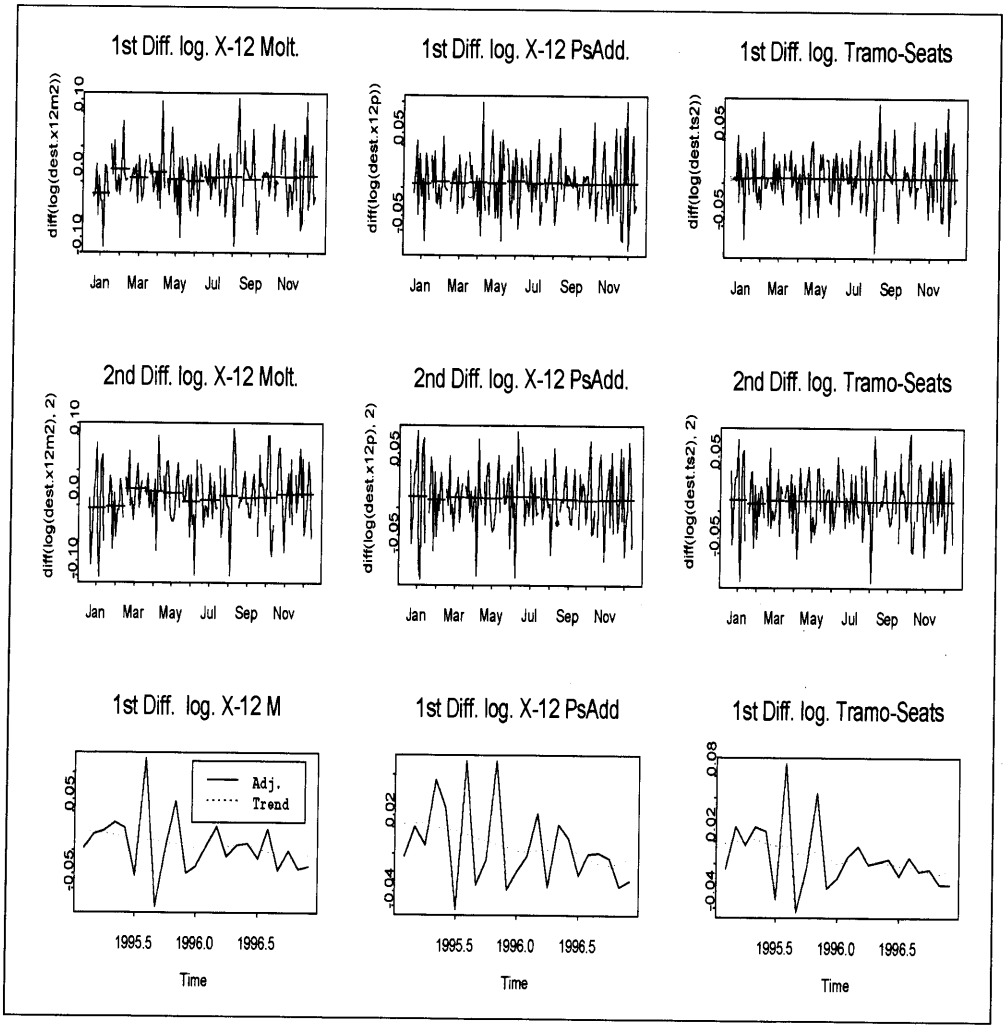
```
Percentage of months flagged as unstable.
Seasonal Factors: 3 out of 108 (2.8%)
  August: 3 (AMPD= 3.0)
Month-to-Month Changes in SA Series: 8 out of 107 (7.5%)
```

Figure 2 – Index of turnover, Investment Goods (IFAINVGT). Original Series (1). Monthplot (2). Relative means and variances of the logaritmic seasonal differences, $\Delta_{12} \ln y_t$ (3). Seasonally adjusted series, X-12-ARIMA, multiplicative mode (4). Seasonally adjusted series, X-12-ARIMA, pseudo-additive mode (5). Seasonally adjusted series, TRAMO-SEATS, log-additive decomposition (6). The vertical dotted lines correspond to Augusts.



We now proceed to compare the SA series obtained from default X-12-ARIMA default, X-12-ARIMA pseudo-additive and TRAMO-SEATS (using the specifications: LAM=-1, INIC=2, IDIF=3, ITRAD=-7, IEAST=1, IATIP=1, AIO=2, SEATS=2). The latter selects the *Airline* model and identifies two additive outliers: August 1990 and April 1994. The SA series are presented in the last three panels of figure 2 along with the trend. It should be noticed that the pseudo-additive SA series is smoother that its multiplicative and TRAMO-SEATS counterpart and that no sharp peak or trough is associated with August. In order to make the comparison fair

Figure 3 – Index of turnover, Investment Goods (IFAINVGT). Comparison among the seasonally adjusted series. Monthplot of Δ ln y_t^{SA}, X-12 multiplicative (1). Monthplot of Δ ln y_t^{SA}, X-12 pseudo-additive (2). Monthplot of Δ ln y_t^{SA}, TRAMO-SEATS (3). Monthplot of Δ ln y_t^{SA}, X-12 multiplicative (4). Monthplot of Δ ln y_t^{SA}, X-12 pseudo-additive (5). Monthplot of Δ ln y_t^{SA}, TRAMO-SEATS (6). Δ ln y_t^{SA}, 1994.1-1996.12, X-12 multiplicative (7). Δ ln y_t^{SA}, 1994.1-1996.12, X-12 pseudo-additive (8). Δ ln y_t^{SA}, 1994.1-1996.12, TRAMO-SEATS (9).



we have to filter out the effect of the additive outlier occurring in August 1990, since the pseudo additive adjustment was carried out on a series already corrected for its effect.

As a second step we look at the month to month changes in the SA series and at the yearly growth rates and search for systematic features. In the upper half of figure 3 the series Δln y_t^{SA} and Δln y_t^{SA} are displayed separately for each month; it is apparent that the result are sensitive to the seasonal adjustment method and that we have to introduce some criteria in order to choose among the three. A sensible one is that the SA series and its transformations, such as first and second differences, ought to be aperiodic, i.e. do not possess seasonal variation in their moments.

Note that the variance of and are often proposed as a measure of the quality of the adjustment relating to smoothness; there is a difference here, since we look for hidden periodicities in the seasonally adjusted series.

Now, as the figure 3 shows, the mean of the month to month and yearly relative changes of the X-12 multiplicative SA series vary with the month. In particular, growth rates tend to be higher in march. This feature is much alleviated in the pseudo-additive adjustment and as far as TRAMO-SEATS is concerned, the monthly means are practically identical.

The presence of a seasonal drift in the SA series can be stated more formally by a test of H_0:$\mu_j = \mu$ within the models:

$$\varphi(L)\Delta \ln y_t^{SA} = \sum_{j=1}^{12} \mu_j D_{jt} + \theta(L)\varepsilon_t,$$

$$\varphi(L)\Delta^2 \ln y_t^{SA} = \sum_{j=1}^{12} \mu_j D_{jt} + \theta(L)\varepsilon_t,$$

where D_{jt} =1 in month j and 0 elsewhere. The test is easily implemented in RegArima and is never significant (for the X-12 multiplicative case its p-value is .16). Hence, the variation in the drift according to the month is not significant, even though it can be appreciated visually.

3.2 Industrial Turnover Index for Investment Goods, Exports (IFAGENGE)

The considerations made in the previous subsection are strengthened for this series (IFAGENGE), which is available for the same period. Sliding-span diagnostics indicate the inadequacy of the multiplicative adjustment, due to a very high variability of the monthly changes of the SA series.

No outliers are identified by RegARIMA (whereas TRAMO-SEATS flags two additive outliers corresponding to August 1985 and 1990); the F_s, F_M and *KW* test statistics signal the presence of identifiable seasonality and F_M is not significant at the 5% level. Moreover, no residual seasonality is detected. Nevertheless, the adjustment is rather problematic with respect to August since, on the one hand, the corresponding values are heavily downweighted or are assigned zero weight in the computation of the seasonal factors, and, on the other, the adjustment is highly unstable, as can be seen from the following table:

```
Percentage of months flagged as unstable.
Seasonal Factors: 12 out of 108 (11.1%)
August: 8 (AMPD= 5.3)

Final Seasonally Adjusted Series: 16 out of 108 (14.8%)
August: 8 (AMPD= 5.3)

Month-to-Month Changes in SA Series: 43 out of 107 (40.2%)
August: 8 (AMPD = 5.0)
September: 6 (AMPD = 4.8)
```

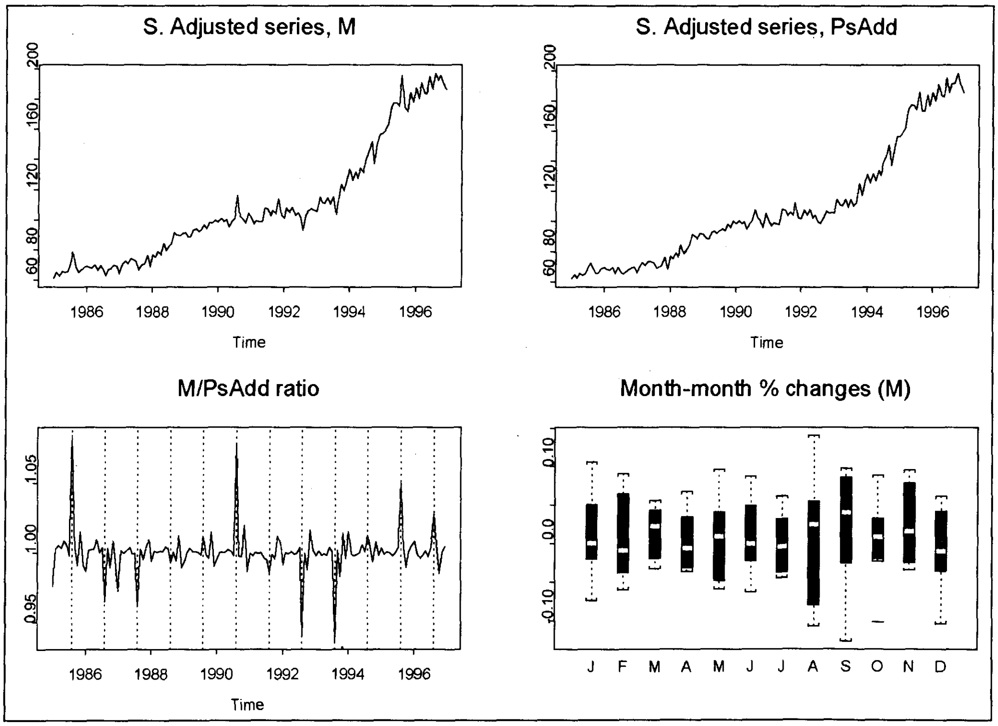
The unstable seasonal factors are concentrated in August and in the years 1988-1993; the same considerations arise with reference to the month to month changes, for which of course the instability spreads also to September.

Instability is dramatically reduced if one considers the pseudo-additive adjustment: for instance, the percentage of unstable month to month changes drops to 11%, a value well below the empirical threshold suggested by the proponents (40%).

Figure 4 compares the seasonal components arising from the two alternative decompositions; the third panel plots the ratio between the SA multiplicative series and the pseudo-additive one: the spikes that are observed in correspondance to August are expression of the over/underadjustment made by the multiplicative option. In relative terms the gaps between the two series can reach up to ± 5%. Essentially the latter extracts a very regular seasonal. The forth panel is a box-plot of $\Delta \ln y_t^{SA}$ for the multiplicative model separately for each month, and is indicative of seasonal variation in the moments.

We may conclude that the pseudo-additive decomposition yields a seasonally adjusted series with better properties and that varying the model August ceases to be anomalous.

Figure 4 – Index of turnover, Investment Goods, Exports (IFAINVGE). Comparison between the seasonally adjusted series obtained by X-12-ARIMA multiplicative and pseudo-additive. Seasonally adjusted series, X-12 multiplicative (1). Seasonally adjusted series, X-12 pseudo-additive (2). Ratio between the multiplicative and pseudo additive SA series (3). Box-plot of $\Delta \ln y_t^{SA}$, X-12 multiplicative, by month (4).



4. Seasonality in Price Indices

In a recent contribution, Cubadda and Sabbatini (1997) have tackled the issue of seasonality in the italian consumer price index for employees (*Indice dei prezzi al consumo per le famiglie di operai e impiegati*). Their conclusion is that seasonality is by and large deterministic, and is partly an artefact of the statistical data generating process: as a matter of fact, some items, accounting for a 20% of the consumption expenditures, are surveyed only at quarterly intervals, in a specified month of the quarter; for the months in which no measurement is taken, the missing value is replaced by the last quotation observed.

This practice is implicitly based on the assumption that prices are a random walk process, so that their best linear predictor is the last observation available. However, once new information becomes available the best linear predictor is the interpolating line between two consecutive observations. Actually, this second stage is not carried out in the computation of the index, and the missing values are replaced brutally by their best linear predictor conditional on the past, under the random walk hypothesis.

Therefore, even though the item is non seasonal, the statistical DGP induce jumps in coincidence with the month of the quarter in which a new measurement takes place. So, if prices are monotonically increasing or decreasing, the price index will display a spurious seasonal cycle at the frequency $\pi/3$ (4 cycles per year).

Now, as long as the seasonal behaviour in prices can be ascribed to this data registration mechanism, the underlying problem is one of temporal disaggregation and in particular of interpolating monthly values from a quarterly series, rather than a problem of seasonal adjustment. In fact, the latter would distort the genuine information provided by the observed data by replacing them with an artificial trend plus irregular component.

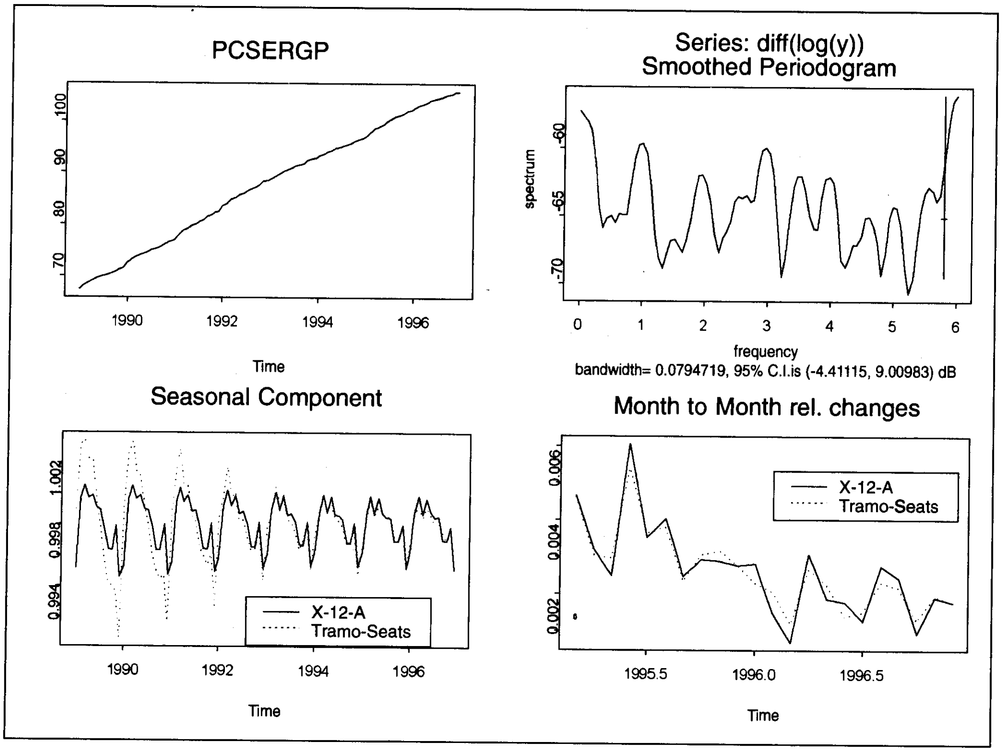
It must also be recalled that Istat has implemented strategies that minimise the role of seasonal fluctuations in the indices, in particular by the definition of composite goods such as groceries, which gathers all the variety available on the market in the survey period.

To characterise the seasonal properties of price index series properly, a disaggregated analysis should be carried out: aggregation with non seasonal items leads to produce evidence for deterministic representations, with the side effect of hiding the evolutive nature of this component, at the risk of over/underadjusting in particular sample periods. Unfortunately, the SARA project could only consider aggregated series, and we shall limit ourselves to some consideration on the following series: PCOSERGP (Consumer price index, Services), PINGENGP (Wholesale price index, Total), for the period 1989.1-1996.12; PPIGENGP (Production price index, Total) for which are available 192 monthly observations from January 1981 to December 1996.

4.1 Consumer Price Index, Services (PCOSERGP)

This series is plotted in figure 5. TRAMO-SEATS (with parameters LAM=0, INIC=3, IDIF=3, IATIP=1, AIO=2, SEATS=2) adjusts the series by decomposing the model.

Figure 5 – Consumer price index, Total (PCOSERGP). Original series (1). Spectral density of Δ ln y_t in decibels (10 $\log_{10}$ f(λ)) estimated by a Daniel window (2). Seasonal components estimated by X-12-ARIMA and TRAMO-SEATS (3). Monthly growth rates of the SA series (4).



$$\Delta\Delta_{12} \ln y_t = -.00045 + (1 - .41L^{12})\varepsilon_t$$

A temporary level change is identified in January 1991. This model is used for the extrapolation of the series in the default X-12-Arima procedure; the MA parameter estimate produced by RegARIMA is closer to the non invertibility region (Θ_{12} =0.76), and two level shifts are identified corresponding to January 1990 and January 1992. It is interesting to notice that this shifts coincide with the rebasing of the index and that the estimate of the MA parameter, acconting for the evolution of the seasonal component, is sensitive to interventions. It would be interesting to investigate if the base change has affected also other components, namely the seasonal pattern: no automatic testing of seasonal breaks is possible in either procedures, although one could exploit the of TRAMO and RegARIMA features to implement a suitable test.

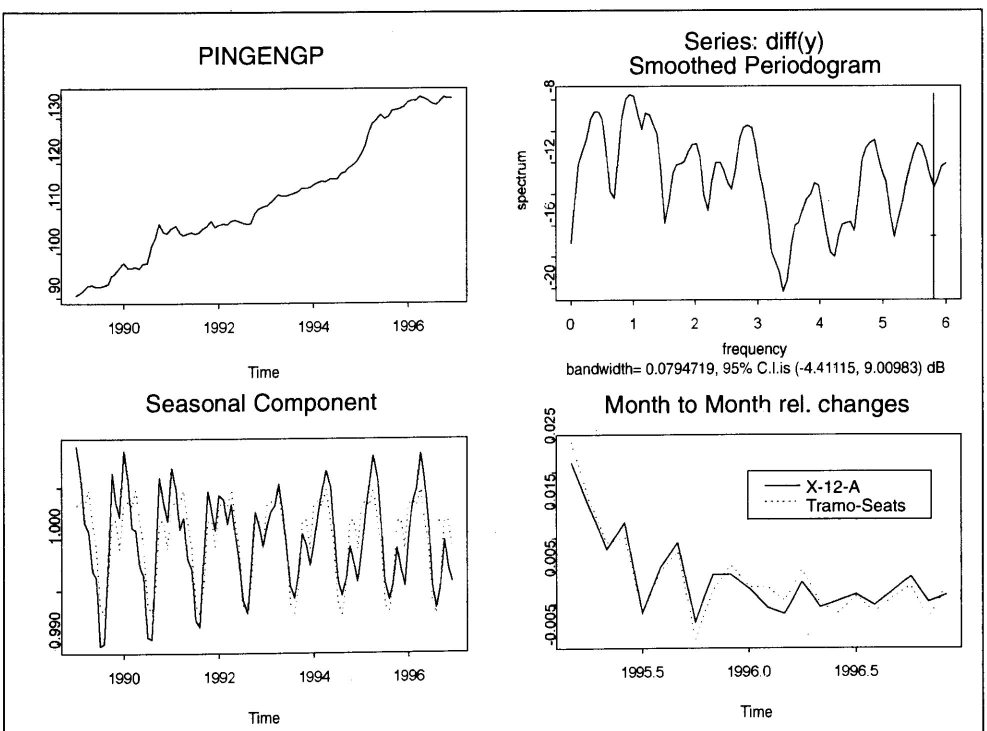
Going back to X-12, the ANOVA based statistics for stable and moving seasonality are all significant and seasonality is identifiable: F_s=21.5, F_M=5.3 and KW=67.4. Residual seasonality is detected only for the month to month changes of the SA series, whose estimated autoregressive spectrum displays "visually sigificant" peaks at the seasonal frequncies, which contradicts the results of the ANOVA test F_s for residual seasonality.

The comparison between the seasonal components is made in figure 5. The one extracted by X-12 is nearly deterministic; in order to render it more evolutive we tried to set the parameter `seasonalma=s3x3`, without achieving different results. The component estimated by TRAMO-SEATS has higher amplitude at the beginning of the sample period and later it settles down to a pattern overlapping with that produced by X-12. Further investigation is needed to see whether this evolution is related to the changes occurred in the composition of the index, which took place at discrete times in the interval considered. The last panel aims at appreciating the impact of the two procedures on the monthly inflation rates computed on the SA series: although TRAMO-SEATS gives rise to smoother inflation rates, the differences are not relevant, as should be expected since at the end of the sample period the two procedures extract the same seasonal components.

4.2 Wholesales Price Index, Total (PINGENGP)

The presence of seasonality in this series, presented in figure 6, is difficult to detect by the usual identification tools: for instance the autocorrelation functions of $\Delta \ln y_t$ and $\Delta \ln y_t$ do not present significant values at seasonal lags, and the partial auto-

Figure 6 – Wholesales price index, Total (PINGENGP). Original series (1). Spectral density of Δ ln y_t in decibels (10 $\log_{10}$ f(λ)) estimated by a Daniel window (2). Seasonal components estimated by X-12-ARIMA and TRAMO-SEATS (3). Monthly growth rates of the SA series (4).



correlation function of $\Delta \ln y_t$ is significant only at lags 1 and 14. Nevertheless, the test for the inclusion of seasonal dummies, conducted by RegARIMA, is significant.

Automatic model identification in TRAMO-SEATS leads to the Airline model

$$\Delta\Delta_{12} \ln y_t = (1+.29L)(1-.98L^{12})\varepsilon_t$$

with quasi cancellation of Δ_{12}. It comes therefore as no surprise that the seasonal component extracted is deterministic. A level shift in august 1990 and an additive outlier in October 1990 are identified.

Automatic model selection in RegARIMA leads to the exclusion of all the models listed in the metafile `x12a.mdl`, as all are affected by ovedifferencing. For the extension of the series has been employed the Airline model anyway and the procedure identifies the same outliers.

As a consequence of the values taken by the ANOVA test for stable and moving seasonality (F_s=4.5, F_M=2.0 and KW=40.2), the message "identifiable seasonality probably not present" is produced. Moreover, the M_7-M_{11} statistics pertaining to the quality of the adjustment and concerning the variability of the seasonal component, are outside the admissible range (M_7 is the amount of moving seasonality present relative to the amount of stable seasonality; M_8 concerns the size of the fluctuations in the seasonal component throughout the whole series; M_9 the average linear movement in the seasonal component throughout the whole series; M_{10} and M_{11} are the same as M_8 and M_9, but are computed using the last three years of observations).

Figure 6 indicates that, oppositely from the previous case, the seasonal component extracted by X-12-ARIMA is more evolutive than its TRAMO-SEATS counterpart; however, as the range of the seasonal factors is very limited, the monthly inflation rate, presented in the last panel, does not show systematic differences.

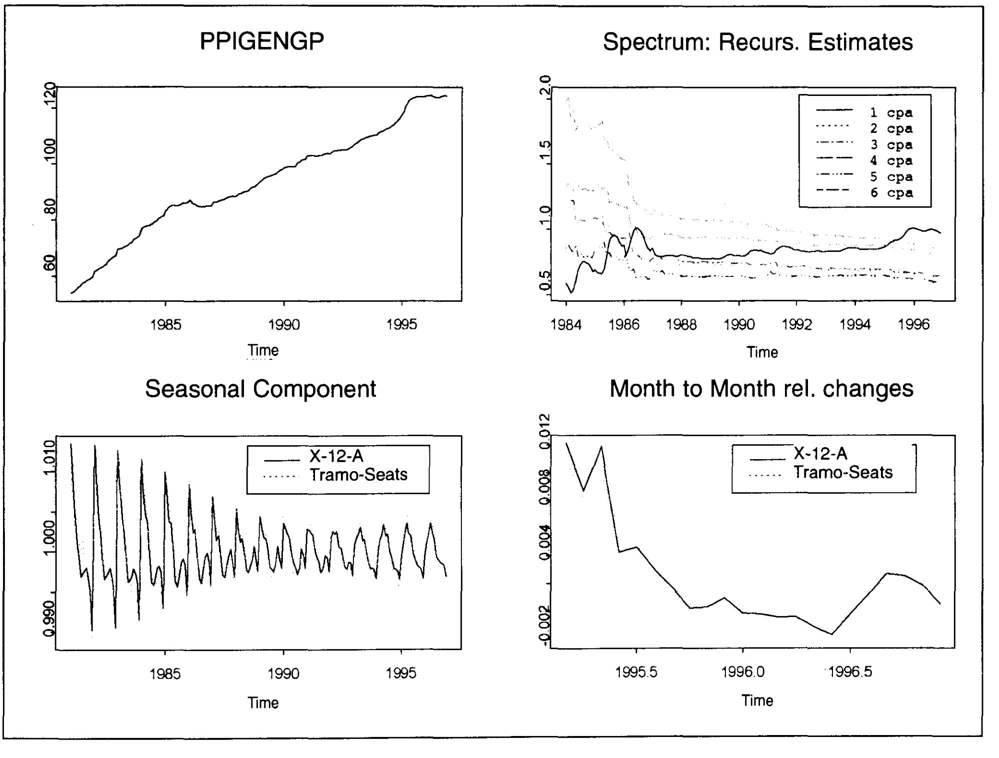
4.3 Production Price Index, Total (PPIGENGP)

The seasonal fluctuations in this series, displayed in figure 7, are characterised by a systematic tendency to reduce their amplitude during the first years of the sample period. The second panel of figure 7, which presents the recursive spectrum of at the seasonal frequencies, estimated by a Bartlett window using 12 autocorrelations, testifies the evolutionary character of the seasonal dynamics. At the end of the sample period they settle down to a pattern such that the fundamental frequency prevail over the harmonics, whose role lessens over time.

As far as TRAMO-SEATS is concerned, different results are obtained according to as to whether one uses the automatic model identification procedure built in the programme (in which case the ARIMA $(2,1,0)\times(1,0,0)_{12}$ model is selected; this is not decomposable, so SEATS approximates this model by an ARIMA $(1,2,1)\times(1,0,0)_{12}$) or the *Airline* (default) model. In the second case the seasonal component is very close to the default X-12-ARIMA, as illustrated in the third panel of figure 7. For the latter, seasonality is identifiable and the ANOVA test for the moving seasonality is significant at the 5% level. The quality of the adjustment is unsatisfactory with respect to M_8, M_{10}, and M_{11}.

A glance at the monthly inflation rates in the last panel of figure 7 indicates that the SA series not differ significantly. As for the PCOSERGP case, it remains to be seen whether the evolution of the seasonal component is related to the composition effects due to the change of the basis of the index.

Figure 7 – Production price index, Total (PPIGENGP). Original series (1). Recursive estimate of the spectrum of $\Delta \ln y_t$ at the seasonal frequencies (cpa: cycles per annum) estimated by a Barlett window (2). Seasonal components estimated by X-12-Arima and TRAMO-SEATS (3). Monthly growth rates of the SA series (4).



5. Conclusions

The objective of this paper was not that of selecting the optımal seasonal adjustment method for the series produced by the organisations belonging to Sistan; rather we aimed at pointing out some issue arising as a consequence of the peculiar features those series display.

As for the Isco data set, due to its ad hoc nature, the X-12 filter is prone to overadjustment. A model based approach is more effective here, in that it provides a solution tailored for the series under investigation, capable of extracting a stationary seasonal pattern. However, if the adjustment is made routinely in TRAMO-SEATS, the automatic model identification is biased towards selecting representations implying the more seasonal unit roots than are present in the data.

Furthermore, the limitations on the class of ARIMA models which are decomposable often impose to perform the adjustment by a suboptimal model. This is inconvenient and may lead to TRAMO-SEATS to converge towards an *ad hoc* seasonal adjustment method.

Under these circumstances the automatism of the procedure should be carefully avoided, by a direct specification of the model by the user. The constraints on the orders of the AR and MA polynomial could be somewhat restrictive.

The second set of series we have investigated concerns industrial turnover; for these series the default adjustment of both procedures can prove inadequate to account for the behaviour of the series in August. We have argued that the pseudo-additive decomposition implemented in X-12 can handle the August phenomenon, but this option is still experimental and does not lend itself to the treatment of calendar and intervention effects.

The identification of seasonality in price index series is made problematic by contemporaneous aggregation, the length of the series available and other data recording practices for items surveyed quarterly. The first two factors tend to favour deterministic representations; moreover, the seasonal components has very low amplitude. When the span of the data available is relatively large, interesting dynamics arise, as illustrated with reference to the PPIGENGP series. This analysis confirm a recent study by Corduas e Piccolo (1997) with respect to consumer price indices spatially disaggregated at the provincial level, who find seasonality *weak and moving*. Further investigation is needed to establish if the changes in the seasonal pattern are due to the rebasing of the indices.

The question that arises is whether we should forget at all about seasonal adjustment in the analysis of inflation: recent orientations at other institutions, such as the Bank of Italy, seem to suggests that there is a real need for seasonally adjusted inflation measures. The proper action is perhaps that of seasonally adjusting the disaggregated series for genuinely seasonal items and interpolating the monthly missing values of the items surveyed only quarterly.

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THE SARA PROJECT: THE SEASONAL ADJUSTMENT PROCEDURES-COMPUTING ASPECTS

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1. Introduction

The mode of interfacing the programs built for specific uses has changed over the years. Initially, the first packages contained in the input source(input channels) of reading the data as well as the output data results in a print file or saved on mass storage devices.

It is mostly during the first years of 70s that one can found the first steps of interfacing the software applications which were packed in the same environment of the main program; through a standard interface of the same environment, the necessary data are processed by the program and the results are sent back by the application to the host environment.

Such configuration considers the host program running as a " function ", i.e. a tool activated during the application execution through a command that coincides with the name of the written function. This environment contains an interface which implements the functionality rules of the host environment and the compilation of source program by means of scientific language, such as Fortran, Pascal, etc.

Based on such hypothesis, some emerging problems might be the following:

- the absence of the source program of the specialised program;
- a source program with a lot of code lines;
- a source program written in language non compatible with the host environment;
- a lot of parameters to be tuned;
- difficulties while reading the code;
- output differences due to the compilation program of various developers;
- different system routines vis à vis to the original version;
- part of the code rewritten from the author of the method of calculation because of lack of routines of support supplied from scientific bookstores available, for purpose;

The authors of some scientific packages, like SAS, Speakeasy, Gauss, have accepted the contributions written by the developers on the concerned specialised applications. Generally the applications to add to the principal system were modified in order to receive the necessary data for the calculation through the software environment. The storage of the output was done by the use of standard procedures.

The increase of difficulty of integration of such contributions has developed a different methodology. Through an interface of connection, the application is fed by the data input saved on mass storage; by doing so, the program is able to load the data input, to process the information, and to save back the results on mass storage. These results are promptly red by the interface of communication that makes them available to the principal processing environment. The advantages are evident:

- it's not necessary to re-write parts of the code of the application;
- the compiler's incompatibility with respect to the version and the type of generation, doesn't exist any more;
- the problems related to the understanding of the applied methodology has been removed;
- the problems deriving from the different modes of mapping memory among the applied environments has been avoided;
- the updating process of the versions became more efficient by checking on the structure of the input and the output;
- It's not necessary to have the versions of the compilers for the specialised application.

During the last years, the wide use of electronic sheets running under graphic environments using a proper language of elaboration (i.e. Visual Basic, Visual C++, Delphi, etc.) made possible to record the necessary information in a friendly environment. By means of some code lines displayed by icons it make running the applications in an intuitive and simple way. Then the result of the elaboration is stored in the same environment, increasing the opportunity of running in a recursively and efficient way.

The advantages of this methodology are as following:

- it's necessary to know only the structure of input and output of the application;
- the problem of the rewriting of the specific application doesn't exists any more;
- there are no problems related to the version of software needed to build the program compatible with the environment of development;
- due to the fact that the same environment is performed to all necessary tools, the problem of data input storage and the relative results has been avoided;
- the same environment disposes the additional tools needed for further processing.

1.1 The management of the error

If the environment of the application is developed internally(in house), there is no doubt that the management of the error has been resolved from the author during the building of the application. In the most of cases, through an appropriate dialogue window the error code is showed followed by a brief explanation; the error code gives a full explanation thanks to the operational help on line within the application.

In the case of a specialised application, as generally happens, it becomes difficult to manage the error when it is not foreseen by the program developer. In the cases when the application is included in the processing environment, it is quite easy to deal with the lack of error management; when the application is interfaced with the input and output channels, the problem remains open(not resolved) because it is not possible to modify the program unless the whole revision of the source code by recompiling a new program.

1.2 Application interfaced during the trial

In the framework of SARA project two environments are made available to the researchers for their own elaboration: an environment workstation running under the IBM operating system UNIX AIX and a personal computer environment running under Windows operating system.

There have been developed two applications with regard to data management: X-12- ARIMA and TRAMO-SEATS, since the other software dealing with the input and output management were developed in house.

2. X-12 -ARIMA

X-12- ARIMA has been copied, by telematic network, from the site of the Bureau of the Census in Washington. The application is available as an executable program running under personal computer, or as program running under UNIX. In addition to that, there is available a source program written in Fortran language with the purpose to create its own executable programs under other operating systems. The whole documentation is available on the site of Internet ftp.census.gov under the directory pub/ts/x12a. It can be saved in its proper work-station through a communication program like FTP (by opening the login as " anonymous ").

The programs of the seasonal adjustment make use of the X-11 method as explained by the authors Shishkin, Young and Musgrave (1967) and Dagum (1988). The program responds to all the performances the programs X-11 and X-11-ARIMA have. The seasonal moving average, their trend and the adjusted calendar with the weekday holidays are available as well.

The programs developed for the seasonal adjustment are further strengthened by following options that include:

- the " sliding span " diagnostic procedures, illustrated by Findley, Monsell, Shulman and Plugh (1990);
- the ability to carry out the historical revision of a seasonal adjustment;
- a new filter of Henderson that allows the user to choose every even number for the length of the filter of Henderson;
- new options for the filters of seasonally;
- many options for the search of new " outliers " for the irregular components of the seasonal adjustment;
- a factors table of the " trading day " for the type of day;
- a pseudo-additive mode for the seasonal adjustment.

The program of construction of the model of X-12- ARIMA is built based on the cyclic economic time series. To this purpose, a lot of categories of default regressions are available, including trend constants over all the average, fixed seasonal effects, effects related to "trading-days", the vacations, the impulse effects (additive outliers), the levels of glide, the changes of temporary outliers and the ramps type effects. The types of regressions can be easily chosen by the users and included in the model. The program is built based on specific necessary capacities towards ARIMA modelling, without meaning it as a statistical package for general use. In particular the X-12-ARIMA should be together performed with an other graphic software able to produce graphic of high resolution of the time series.

The input data (the time series) which must be modelled or adjusted of the seasonality using X-12-ARIMA they have to be quantitative and not binary or categorical. The observations have to be equally spaced in the time, and the null values are not allowed. X-12-ARIMA has only univariate models of the time series, and it doesn't measure, for instance, the existing relations among groups of time temporary series.

X-12-ARIMA uses the standard notation (p d q)(P D Q)s for the seasonal models ARIMA. The part (p d q) it is respectively reported to the orders of the operators of the part autoregressive (AR), differential, and moving average (MA) for the non seasonal component. The part (P D Q)s is reported to the seasonal part of the orders autoregressive, differential, and moving averages. The inedx "s" points out the seasonal period, s=12 for instance points out a monthly frequency of the data. It's possible to use a great variability in the structure of the operators; it's possible specify null values in the delays of the operator AR and MA and it's possible to fix its values.

For the construction of a model RegARIMA the specification is necessary for both variables of the regression to be introduced in the model and the type of models ARIMA (ex. he orders of (p d q)(P D Q)s). The specification of the variable for the regression depends on the user knowledge over the series to be used. The identification of the model ARIMA for the errors of regression follows a procedure based on the examination of the examples of functions of autocorrelation and partial autocorrelation produced by X-12-ARIMA. Once specified the model RegARIMA, the method evaluates the parameters with the method of the maximum likelihood using an iterative algorithm of the minimum generalised squares. The process of diagnostic involves the examination of the residuals built with the calculated model. X-12-ARIMA produces quite a lot of standard statistics on the residuals and supplies sophisticated methods for the estimation of the outliers and levels of glide. Finally it is possible to have a forecast of the time series and the diagnostic on the forecast.

X-12-ARIMA possesses a procedure of automatic selection for the estimation of the model and an option using the AIC in order to determine if it is possible to introduce the " trading day " in a particular time series. It is moreover possible to evaluate the calculated historical part and the estimated part for the comparison of the results of the various chosen models.

2.1 The structure of the input

To apply X-12-ARIMA to a time series, it is essential to create an input file, called file of specifications. This file (in ASCII format) contains the list of specifications or specs that the X-12-ARIMA reads for obtaining the necessary information on the time series, the model to use, the analysis to be performed, and the desired output; the extension of this file is .spc.

2.2 The output

Generally the output file has the extension .out. The individual specifications compete to form the structure of the output. The save issue is used for creating some files for further analyses (for example the storage of a time series of the residuals to be used in the graph programs).

2.3 The errors of input

The errors of input are recorded with appropriate messages. These messages of errors are saved in a file whose name has as extension .err. Initially the X-12-ARIMA reads the whole file spec, bringing all the errors that it finds. In this way the user can correct all the errors with an only simulation. The program stops if a serious error is noticed. Errors of attention don't stop the program but only inform and ask the user to verify attentively both the input and the output in order to obtain the expected results.

2.4 The flags

The flags are used for getting other forms of input and output. The following table provides a list of the flags available that can be displayed in different order on command bar.

-i FILENAME	FILENAME (without extension) it is lines of input
-o FILENAME	FILENAME (without extension) used for all the files produced during the execution of programme
-m FILENAME	FILENAME (without extension) for the input metafile
-d FILENAME	FILENAME (without extensicn) for the data metafile
-g DIRNAME	The DIRECTORY where the metafile and the files are stored for the graphic application
-n	The number of printed tables
-w	The width format (132 characters) for the lines of output
-p	No pagination is used in the output file
-s	The diagnostic is stored in a file
-c	It's performed the sum of every part of a composite adjustment, but the estimation of the model or seasonal adjustment is given only in total
-v file1	As far as concern the errors, it performs only the control of the input

X-12-ARIMA produces a great number of outputs; while usually it convenes to compress the output at only few tables. To facilitate this operation, the flag -n specifies that, by default, no table will be produced without the user specification. A program to be downloaded from the Internet is available under the site ft.census.gov . It reads the diagnostic of the seasonal adjustment and it produces a re-examination of the same diagnostic; this program is written based on programmed icons (see Griswold and Griswold, 1997).

2.5 The limitations of the program

X-12-ARIMA contains limits on the maximum length of the time series, the maximum number of variables for the regression in a model, etc. These limits are set to a value that in first approximation they are sufficiently great for the majority of the applications, without being so great to cause storage problems or to slow down in a significant manner the execution of the program. These limits can be modified upon the request, but the Fortran source code has to be recompiled and re-linked in a meaning that the changes take effect. The following table shows the details of the parameters that can be subject of modification by the user:

Variable	Limit value	Parameters description
POBS	600	Maximum lenght of series in input. The number pobs+pfcst is the maximum lenght of the series of input defined by user for the variable regression. The additional value pfcst is permitted for values for necessary values is allowed for the process of forecast
PYRS	60	Maximum number of years in the forecast in the historical component
PFCST	60	Maximum period of forecast
PB	48	Maximum number of variable of regression in a model (comprising variables default and specified for the regression from the user, plus every variable of the regression produced by the automatic disco very of an outliers)
PUREG	20	Maximun number of variables for the regression defined by user
PORDER	24	Maximum number of lag corresponding to every parameter AR or MA
PDFLG	3	Maximum number of differences in every factor ARIMA (not seasonal or seasonal).

2.6 Modeling capabilities of RegARIMA

During the building of a model RegARIMA, is recommended to examine with a graphic program at high resolution the course of the time series over the time. Such graph can supply information for the seasonal courses, the potential outliers, the stochastic non-stationarity, etc. It can be generated additional graphics to examine the effects of the possible transformations on the time series, or to apply many differential operators to the series. Since X-12-ARIMA doesn't dispose the capability to provide graphic at high quality and resolution, it is essential to use other products built for this purpose.

It could be problems during the phase of model estimation. The user can provide the values of AR and MA rates that are used for the estimation with the method of the maximum likelihood. It is an operation not recommended to be performed. The initial choice of the system is value equal to 0,1 for the parameters of MA and AR. This choice seems to be adequate in the majority of cases. The substitution of the initial data, in general it doesn't accelerate the estimation process, except the case when the difference between true values and those provided is very close, for example during the re-estimation of the model with a time series extended. The purpose of supplying the initial values consists when the model has a difficult convergence. When the estimation procedure doesn't converge, other resolving means are available. If the program reaches the maximum number of iterations, it is possible to restart with the last calculated values. If the convergence were not reached, it would be better to estimate the model under the condition of conditioned likelihood and by using the estimated values with the condition of exact maximum likelihood. The model doesn't often converge because of its level of complication, or it is less conditioned. In this case it would be better to examine the obtained results using a simplified model.

Other existing problems on the estimation of the parameters of selected model that might be are: the reversibility of the operator MA, the stationarity of the operator AR, the erasing of the factors AR and MA and the over-differentiation.

2.7 The file of specification and his syntax

The principal input to X-12-ARIMA is represented by a special file called file of specification. This file contains a whole of specific or specs that furnish varied information to X-12-ARIMA about the data and the options desired for the varied specific of analysis and the form of output, the form of the model for the time series, etc. The different specifics are:

Series	It is required for furnishing the data of the temporary series, the date of departure, the frequency, the title, the arc of time for the respect, etc.
Composite	It specific that an adjustment is used directed and indirect of a series compsta
Transform	It specific a transformation
X11	It specific the option seasonal adjustment, included the type of adjustment, the filters of seasonality and trend, options of adjustment for the holiday days and the " tradings days " and some diagnostic ones on the adjustment
X11regression	It specific irregular options of regression, including what regression compo nents is used and what types of values of extreme of adjustments will be made for strengthening the regression on the irregular components
Identify	It produce total and partial autocorrelation for specified orders of differential of the data with regressive effects removed for the identification of the model ARIMA
Regression	It specify the variable of regression to form the part of regression of the model regARIMA, and to determine the effects of the regression removed by identify specs.
Arima	It specify the part ARIMA of the model regARIMA
Automdl	It specify the type of automatic procedure of the model
Estimate	It query the respect or the method of likelihood for the model specified by the specific ones of regression and arima, and it specifies the options of the esti mation
Outlier	It specify the automatic search of the outliers additive and/or the level of skid used in the respect of the model
Check	It produce statistics used in the respect of the model
Forecast	It specify that it is wanted a forecast with the estimated model
Slidingspans	It specify that it is wanted to get an analysis of the state of glide on the stability of the seasonal adjustments
History	It is wanted the calculation of a historical record of the revisions of the adjustments seasonal and/or the statistics on the quality of the model regARIMA

Every specific is defined by his name and it is followed by parenthesis bracket containing the arguments and their values. The arguments and their values take the form argument=value, and if necessity is had to introduce multiple values, then the form is argument=val1,val2,val3...,valn.

3. The programs TRAMO and SEATS

TRAMO (Time series Regression with Arima noise, Missing Observations and outliers) and SEATS (Signal Extraction in Arima Time Series) are programs written in code Fortran according to the theories developed in the search econometric of Victor Gomez and Agustin Maravall.

Both the programs, together with the manual of instructions, are available at the Bank of Spain to the following address of Internet: http://www.bde.es.

TRAMO is a program developed for the respect and forecast of econometric models, even if they contain errors of not stazionarity (Arima) and with any sequence of values missing. The program interpolates these values, it identifies and straps quite a lot types of outliers, respect particular courses like the trading days and the easters. It possesses an automatic procedure for the identification of the model and the correction of the outlier.

The program has been thought and realized for completing the following operations:

- estimation of the parameters of the model through the maximum likelihood (least square conditional/unconditional);
- estimation of numerous types of outliers with correction;
- compute the better forecast for the time series together with their MSE;
- compute the better interpolation for the lacking variable and their associated MSE;
- it's possible the automatic identification of the model and the outliers.

The program has been written in language Fortran v.77 and it overcomes the barrier of the limit of the memory of 640k using the addressing to 32-bit. It requires at least 4M of memory ram and 4M of memory of mass. The errors of execution are brought in the lines report.bug, and the program continues however his own execution. To the moment TRAMO, as pure SEATS, have been compiled for a maximum number of 600 observations for time series, and obviously with a new compilation this limit can easily be old.

SEATS is a program developed for the components' respect observed not in a time series following the criterion of the models said ARIMAs. The trend, the seasonal irregularity, the cyclical components and the forecast are esteemed with extraction of the signal applying the techniques of the models Arima. The standard errors of the respect and the forecast are esteemed with the structure of the esteemed model.

The two programs are built in such way by to be used together for the analysis of few time series, or for automatic applications performed to a big number of time series. In the case of respect of the seasonal adjustment Tramo pre-adjust the series that must be adjusted from SEATS.

3.1 The management of the memory

Both the programs are linked with the kernel MK (Microway Dos Extender Kernel) that the extended memory makes available. The MK is compatible with the manager of the expanded memory (EMM) and these programs stick to a standard interface, the VCPI (Virtual Control Program Interface) to which the MK also sticks. MK is not compatible only if it is specified in the activation of the memory the option NOEMS.

3.2 the parameters of input

❒ Control of the output through the parameter out;
❒ Model Arima: the options:

Mq	Number of observations within a for year
Lam	1 it means any transformation of the data, =0 only logarithmic transformation
Imean	0 any correction with the average, =1 correction with the average
D	Number of non seasonal differences
Bd	Number of seasonal differences
P	Number of terms non seasonal autoregressive
Bp	Number of terms seasonal autoregressive
Q	Number of terms of moving averages not seasonal
Bq	Number of terms of moving averages seasonal
Th	Q initial terms of estimate of the parameters of moving averages regular
Bth	Bth initial terms of estimate of the parameters of moving averages seasonal
Phi	P initial terms of estimate of the parameters of averages seasonal
Bphi	P initial terms of estimate of the parameters of moving averages seasonal
Jpr(i)	1 the parameter i in the polynomial of estimate of the regualar autoregressive is fixed, 0 are not fixed
Jps(i)	1 the parameter i in the polynomial of estimate of the seasonal autoregressive is fixed, 0 are not fixed
Jqr(i)	1 the parameter I into polynomial of estimate of the part moving average regular is fixed, 0 are not fixed
Jqs(i)	1 the parameter I into polynomial of estimate of the part moving average seasonal is fixed, 0 are not fixed

- Minimun number of observations: the least number is fixed by mq in a particular model, and from the particular required options; for default, if m points out the least number of observations, for mq >= 12 then m = 36, for mq <12, then m = max(12,4 X mq).

3.3 The initial tests for the specification log-level

In order to obtain this test, the parameter is LAM that can have the values of =0 for the log, =1 for the level, = -1 for both, the value of default=0.

Automatic identification of the model.

Inic	=0 are not effected the automatic identification of the model, =2 the pro gram looks for regular polynomials up to the 2 order, and for seasonal polynomials up to the 1 order, =3 the program looks for regular polyno mials up to the 3 order, and for seasonal polynomials up to the 1 order, =4 the program looks for regular polynomials up to the 3 order, and for seaso nal polynomials up to the 2 order
Idif	=0 are not effected the automatic identification =1 used for the automatic identification,; the program seeks for regular differences up to the 2 order and for seasonal differences up to the 1 order, used with Inic>1 therefore the it programs it is stopped, =2 used for the automatic identification; the program seeks for regular differences up to the D order and for seasonal differences up to the BD order, used with Inic>1 therefore the program is stopped, =3 used for the automatic identification; same behaviors of
Idi	f=1, but the program is not stopped and continues the elaboration with the identification of model Arma for differential series, used with Inic>1, =4 same behavior of Idif=1, and besides the program looks for complex un tary roots, =5 same behavior of Idif=3 and besides the program seeks for complex unitary roots
Ub1	Ub1 if a root of the estimation of "AR(2) X ARs(1) + average" in the first cycle of automatic identification of the differential polynomial it is greter than Ub1, the form is set equal to the unity
Ub2	If a root of the estimation of "ARMA(1,1) X ARMAs(1) + average" in the second cycle of automatic identification of the differential polynomial it is greater than Ub2, the form is set equal to the unity
Cancel	If the difference in absolute value of a root of a model AR and MA in the second step of automatic identification of the differential polynomial is smaller than cancel, the two roots are set to zero
Pcr	=a the level of significant of the test of Ljung-Box used in the identification of the model
Ifal	=0 normal procedure, =1 if in the first simulation the model of default is satisfactory the trial it is stopped

3.4 The parameters of the estimation

Incon	=0 estimate with the method of the maximum likelihood, =1 estimate with the method of the least squares not conditioned
Init	=0 estimate of the unknown parameters and the values of departure are fixed by the program, =1 the values of departure are fixed by the user, =2 no estimation
Ifilt	=1 filter with square root, =2 application of the algorithm of Morf, Sidhu and Kailath, =3 filter of Kalman, =4 filter of the least squares conditioned
Idensc	=1 the denominator of the sum of the squares of the residues is that of Ansley and Newbold, =0 the denominator is set equal to the number of the non initial observations
Tol	Criteria of convergence of the method of Gauss-Marquardt
Iconce	=1 ó2 and the parameters of the regression are assembled out of likeli hood =0 only ó2
Ubp	If in the respects of a model AR and MA the root of an AR it is great of Ubp, this it is fixed equal to 1
M	Print the autocorrelations and partial autocorrelations
Iqm	The Autocorrelation used in the estimation of Q
Iroot	=1 are calculated the roots of the polynomials of AR and MA, =0 are not furnished, =2 are calculated the roots and those of MA they are set equal to 1 if their value in form is great of Ubp.
Igrbar	Print out of the graph of the autocorrelations
Tsig	It's excluded the value of t

3.5 The parameters of the forecast

Nback	Number of observations to be esteemed in forecast from the end of the
Npred	Number of values to be esteemed
Logn	Levels obtained as exponents of the logarithmic curve

Missing observations.

Interp	=0 any interpolation, =1 interpolation with the method skipping, =2 inter polation as they were additive outliers
Icdet	Correction in the determinant

3.6 The parameters of the outliers

va	determination of the outliers
latip	estimation of the four types of the outliers (Me, AO, LS, TC) and his automatic correction
imvx	method of automatic estimation of the outliers
pc	Percentage with which VA is reduced
deltatc	work only on the outliers type TC
istdv	Estimation of the residual variance in the determination of the outliers
aio	Correction of the outliers

The input begins with the time series to model, and don't have to be more than 250 observations every, followed anymore by a whole parameters of control for the model a list of instructions for the variable of regression.

4. The graphic interface

It's developed an user interface in Excel environment that contains both the data of the time series, and, in visual form through icons, the commands to perform the simulations. Once performed, the programs TRAMO and SEATS, the output is captured, always from Excel, and visualized in the cells, furnishing a friendly and efficient visualization of the whole trial. At such moment an application for X-12-ARIMA doesn't result to have been done, but it could be a positive realization and of breadth use, also for the comfortable characteristic of Excel to be able to automatically format the output making the presentation of his own results immediate.

The Results of SARA Committee
(Seasonal Adjustment Research Appraisal)

SECOND PART

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A FILTER-BASED METHOD FOR TREND-CYCLE ESTIMATION: THE THEORETIC FRAMEWORK OF TEXAMF/2 PROCEDURE

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Section 1 - The Symmetric-Filter Approach to Trend-Cycle Detection

1.1 The Time-Domain Reference Model

A wide range of economic time series may be adequately represented by the following model:

$$\left.\begin{aligned} x_t &= p_t + s_t^{(ev)} + \eta_t \\ p_t &= f_t + c_t \end{aligned}\right\} \qquad (1)$$

where:

x_t is the observed time series;
p_t is the so-called trend-cyclic component;
f_t is the trend component;
c_t is the cyclic component;
$s_t^{(ev)}$ is the (evolutive) seasonal component;
η_t is the random disturbance term.

The trend, cycle and seasonality make up the latent signal of the observed series, while the random disturbance corresponds to the noise. The assumption that the components at stake have finite average power[1] is supported by real world experience and it is actually the key which bridges time-domain and frequency-domain analysis.

[1] The *average power* of a signal z_t is defined by the limit:

$$\lim_{T \to \infty} \frac{1}{2T+1} \sum_{t=-T}^{T} z_t^2$$

Even if the *true* trend, cycle and seasonality are not known, it is always possible to reach operational definitions of these components.

More precisely, since the notion of trend tallies with the long-run regular behaviour of the phenomenon under analysis, the distinctive features of this component are either monotonicity or unimodality within the observed time span.

The cyclical component mirrors the medium term economic fluctuations. Its distinctive feature is a fairly irregular oscillation mode, with period swinging over a time-span of a few years and with amplitude possibly changing over the time. On the basis of empirical evidence, the fluctuation period can be conveniently fixed between two and a half and eight years.

The seasonal component corresponds to the shorter fluctuations associated with climatic and conventional seasons. It has an essentially periodic behaviour on year basis and it usually exhibits an evolutive pattern.

As far as the evolutive mechanism of seasonality is concerned a reasonable conjecture turns out to be that longer period components affect the amplitude swings of the shorter period ones, by an amplitude-modulation-like process, namely:

$$s_t^{(ev)} = m_t s_t \tag{2}$$

with m_t mirroring the trend-cicle dynamics, according to a specification such as:

$$m_t = 1 + \alpha p_t \tag{3}$$

where α is a scalar factor and s_t denotes the underlying constant-amplitude seasonal pattern.

The disturbance term represents the outcome of unexplainable events of all sorts, whose overall influence is expected to be negligible on average even if appreciable on variance. We can actually identify the irregular component with a realization of a zero-mean, possibly heteroscedastic, stochastic process, namely a (mildly) coloured noise.

1.2 The Frequency-Domain Reference Model

Let us assume to have a record of N successive observations on x_t taken at equally spaced time intervals $t = 1, 2, \ldots, N$[2]. Let us further assume that there is an even number T of observations for each year, e.g. $T = 4$ for quarterly data and $T = 12$ for monthly data.

On such bases, the notion of trend comes out to encompass every movement lasting enough, namely any wave of period over $2N$, or otherwise stated, the trend spans over the (low) frequency band:

$$|\omega| < \frac{\pi}{N} \tag{4}$$

[2] With this assumption the Nyquist frequency is equal to π and the reference frequency domain is $-\pi < \omega \leq \pi$.

On the support of empirical evidence the cyclic component c_t may be assumed as composed by fairly irregular swings, whose periods run roughly from two and a half to eight years, which entails a frequency-domain localization onto the wavebands:

$$\frac{\pi}{4T} < |\omega| < \frac{4\pi}{5T} \tag{5}$$

Hence the trend-cycle components p_t turns out to be harmonizable over the frequency range:

$$|\omega| < \frac{4\pi}{5T} \tag{6}$$

according to a Fourier-integral expansion of the form:

$$p_t = \int_{|\omega| < \frac{4\pi}{5T}} e^{j\omega t} dY(\omega) \tag{7}$$

where $Y(\omega)$ is a function of bounded variation in an appropriate sense.

On the argument that the constant-amplitude seasonal component s_t is strictly periodic on a yearly basis and it is consequently marked by the harmonic frequencies:

$$\omega_k = \frac{2\pi}{T} k, \quad k = \pm 1, \pm 2, \ldots, \pm \frac{T}{2} \tag{8}$$

and on the basis of the asserted evolutive mechanism, the evolutive seasonality $s_t^{(ev)}$ scatters about the ranges:

$$-\pi < \omega < -\frac{6}{5T}\pi, \ \frac{6}{5T}\pi < \omega \le \pi \tag{9}$$

of the frequency axis, according to a Fourier-integral expansion of the form:

$$s_t^{(ev)} = \int_{-\pi < \omega \le -\frac{6}{5T}\pi} e^{j\omega t} dY(\omega) + \int_{\frac{6}{5T}\pi < \omega \le \pi} e^{j\omega t} dY(\omega) \tag{10}$$

Assuming harmonizability, the disturbance term η_t has a Fourier-integral expansion too, i.e.:

$$\eta_t = \int_{-\pi}^{\pi} e^{j\omega t} dH(\omega) \tag{11}$$

where H (ω) represents a continuum of zero-mean, bounded-variation-autocovariance random variables, widespread over the whole frequency domain.

1.3 The Filter Design for Optimal Estimation of Mid-range Values

In the light of the arguments developed so far, the issue of evaluating the trend-cycle of an observed series turns out to be equivalent to the problem of finding an operator which allows frequencies in the range (6) to pass while blocking those in the ranges (9).

Looking at trend-cycle estimation from this standpoint leads to a filter-oriented approach to the problem, namely to look for a low-pass filter with cut-off frequency ω_c in the hollow waveband:

$$\frac{4}{5T}\pi < \omega < \frac{6}{5T}\pi \tag{12}$$

between the component of interest and the nuisance one.

The natural choice falls into the class of linear time-invariant discrete-time operators[3] known as moving averages.

A moving average $\mathcal{M}$ is a transformation of the form:

$$\mathcal{M}(x_t) = \sum_{-L \leq h \leq M} a_h \, x_{t-h} \tag{13}$$

which depends on the sequence of weights a_h, known as impulse response. Impulse response and transfer function (see footnote 3) form a Fourier-transform pair, so that if the former is even:

$$a_h = a_{-h}, \; h = 1, 2, \ldots, L \equiv M \tag{14}$$

- i.e. the moving average is symmetric -, the latter is a real and even function given by:

$$\lambda\,(\omega) = a_o + 2 \cdot \sum_{h=1}^{L} a_h \cos\,(\omega h) \tag{15}$$

[3] The importance of such operators is due to the fact that (complex) exponentials act as eigenfuncions of these filters, since:

$$\mathcal{M}\,(e^{j\omega t}) = \lambda\,(\omega) \cdot e^{j\omega t} \tag{o}$$

where $\lambda\,(\omega)$ is the so-called transfer function, which plays a crucial role in system analysis. Actually, should the harmonizable function:

$$z_t = \int_{-\pi}^{\pi} e^{j\omega t} dZ\,(\omega)$$

be the input of filter $\mathcal{M}$, then the filter response ζ_t would take the form:

$$\mathcal{M}\,(z_t) \equiv \zeta_t = \int_{-\pi}^{\pi} e^{j\omega t}\, \lambda\,(\omega)\, dZ\,(\omega) \tag{oo}$$

A moving average should fulfill a set of basic requirements in order to meet the target of detecting the trend-cycle component from an economic time series correctly (cf. Faliva, 1994).

Focusing on the transfer function, such requirements can be stated as follows:

i) $$\lambda\,(o) = 1,\quad \lambda'\,(o) = 0,\quad \lambda''\,(o) \leq 0 \tag{16}$$

$$|\,1 - \lambda\,(\omega)\,| < \varepsilon,\ \textit{were } \varepsilon \textit{ is ``small'' and } |\,\omega\,| < \frac{4\pi}{5T} \tag{17}$$

i.e., the filter should act like an identity operator ($\mathscr{I}$) for low-frequency components and introduce no significant loss all over the trend-cycle waveband;

ii) $$\lambda\left(\tfrac{2\pi}{T}k\right) = 0,\ \lambda'\left(\tfrac{2\pi}{T}\,k\right) = 0,\ \lambda''\left(\tfrac{2\pi}{T}\,k\right) \geq 0,\ k = F1,\dots,F\tfrac{T}{2} \tag{18}$$

$$|\,\lambda\,(\omega)\,| < \varepsilon,\ \textit{were } \varepsilon \textit{ is ``small'' and } \frac{6}{5T}\,\pi < |\,\omega\,| \leq \pi \tag{19}$$

i.e., the filter should act like an annihilating operator at the seasonal frequencies and sharply cut any wave falling into the side-bands of the evolutive seasonality;

iii) $$\lambda\,(\omega) = \lambda^*\,(\omega) = \lambda\,(-\,\omega) \tag{20}$$

i.e., the filter should act as a zero-delay transducer.

Specification parsimony, aiming at pushing the moving-average length downward, is a complementary target indeed.

A mathematical programming approach to a filter choice lined up with the foregoing criteria proves convenient.

In this connection, the objective function can be conveniently defined as a combination of passband loss and rejectionband residual gain, with $\frac{\pi}{T}$ as a cut-off frequency and penalty weights in the proportion two to one, according to the formula:

$$g\,(a_o, a_h;\,\omega) = 2\cdot\int_0^{\pi/T}\left|1-\lambda(\omega)\right|\cdot d\omega + \frac{1}{T-1}\cdot\int_{\pi/T}^{\pi}\left|\lambda(\omega)\right|\cdot d\omega \tag{21}$$

while the opportunity set is shaped out by the side conditions (16), (18), (20).

Parametrically, on the data recording rate (T) and the moving-average length

(2L + 1), the optimization problem at stake can be formally stated as follows:

$$\begin{cases} \min\limits_{a_o, a_h} g(a_o, a_h; \omega) \\ \text{subject to} \\ \lambda(\omega) = \lambda^*(\omega) = \lambda(-\omega), \\ \lambda(o) = 1, \\ \lambda''(o) \leq 0 \\ \lambda\left(\frac{2\pi}{T}k\right) = 0, \quad k = 1, 2, \ldots, \frac{T}{2} \\ \lambda'\left(\frac{2\pi}{T}k\right) = 0, \\ \lambda''\left(\frac{2\pi}{T}k\right) \geq 0 \end{cases} \tag{22}$$

The solution corresponding to $T = 4$ and $L = 5$, which realizes the best compromise between parameter parsimony and low-pass performances[4] for trend-cycle estimation from quarterly data, plays a central role in the foregoing analysis. The impulse response of the resulting 11-term symmetric moving average is given by:

$$\begin{cases} a_0 = \frac{5}{16}, \\ a_{-1} = a_1 = \frac{15}{64}, \\ a_{-2} = a_2 = \frac{1}{8}, \\ a_{-3} = a_3 = \frac{5}{128}, \\ a_{-4} = a_4 = -\frac{1}{32}, \\ a_{-5} = a_5 = -\frac{3}{128}. \end{cases} \tag{23}$$

[4] Since all the constrains of the optimization problem (22) turn out to be binding at the solution point, the resulting low-pass filter is maximally flat at both zero and Nyquist frequencies.

and the corresponding transfer function can be written in closed form as follows:

$$\lambda(\omega) = \frac{1}{2T^2} \cdot \left[\frac{\sin(\frac{T}{2}\omega)}{\sin(\frac{\omega}{2})} \right]^2 \cdot \left[1 + \cos(\frac{T}{4}\omega) \right] \cdot \left[4 - 3 \cdot \cos(\frac{T}{4}\omega) \right] \text{ (24)} \tag{24}$$

in terms of the data recording rate T.

Looking at (24) as a function of the discrete parameter T, it is possible to conceive a whole family of $(3T - 1)$-long low-pass filters. Eventually, this leads – in particular for monthly data, i.e. for $T = 12$ – to pick out a well-behaved 35-term symmetric moving average, whose impulse response is given by:

$$\begin{cases} a_0 = \frac{120}{1152}, & a_{-1} = a_1 = \frac{110}{1152}, \\ a_{-2} = a_2 = \frac{100}{1152}, & a_{-3} = a_3 = \frac{90}{1152}, \\ a_{-4} = a_4 = \frac{76}{1152}, & a_{-5} = a_5 = \frac{62}{1152}, \\ a_{-6} = a_6 = \frac{48}{1152}, & a_{-7} = a_7 = \frac{37}{1152}, \\ a_{-8} = a_8 = \frac{26}{1152}, & a_{-9} = a_9 = \frac{15}{1152}, \\ a_{-10} = a_{10} = \frac{6}{1152}, & a_{-11} = a_{11} = -\frac{3}{1152}, \\ a_{-12} = a_{12} = -\frac{12}{1152}, & a_{-13} = a_{13} = -\frac{11}{1152}, \\ a_{-14} = a_{14} = -\frac{10}{1152}, & a_{-15} = a_{15} = -\frac{9}{1152}, \\ a_{-16} = a_{16} = -\frac{6}{1152}, & a_{-17} = a_{17} = -\frac{3}{1152}. \end{cases} \tag{25}$$

Now, let us pass a time series of the type specified in sections 1.1 and 1.2 through a moving-average belonging to the class (24) above. According to the design characteristics of the filters at stake, it follows that:

$$\mathcal{M}(x_t) = \mathcal{M}(p_t + s_t^{ev} + \eta_t) = \mathcal{M}(p_t) + \mathcal{M}(s_t^{ev}) + \mathcal{M}(\eta_t) = p_t + \mu_t \tag{26}$$

where

$$\mu_t = (\mathcal{M} - \mathcal{I})(p_t) + \alpha \cdot \mathcal{M}(p_t s_t) + \mathcal{M}(\eta_t) \tag{27}$$

represents a twofold nuisance term – as it depends on the filter amplitude-distortion (cf. first two addends of the right-hand side of (27)) on the one hand, and on the low-frequency noise thickening on the other – whose overall effect can be considered nearly negligible inasmuch as the feasible filter factually mirrors the transfer-function behaviour of an ideal filter and the filtered noise component causes only faint discrepancies.

On the basis of these arguments, we can refer to $\mathcal{M}(x_t)$ as an estimator of p_t, and accordingly write:

$$\hat{p}_t = \mathcal{M}(x_t) \tag{28}$$

Making use, as we actually do, of symmetric moving-averages of length $3T - 1$ and dealing with an input series of N observations spanning the time period $1 \leq t \leq N$, the filtering process above provides feasible estimates of the latent trend-cycle component only to the extent of the mid-range period

$$\frac{3}{2}T \leq t \leq \mathrm{N} + 1 - \frac{3}{2}T. \tag{29}$$

In order to evaluate the missing estimates at the front and tail-end of the series a more sophisticated procedure is needed. The issue will be dealt with in section 2.

Section 2 - The Retrieval Algorithm of Trend-Cycle Extreme Values

2.1 Sampling the Series

Let us define a sampler $\mathcal{S}_\vartheta$ as a linear – although not time-invariant – operator which acts as an identity operator on the input series y_t for $t = t_o - \vartheta - iT$, where $i \in Z$, and t_o connotes the conventional present, whereas it acts as an annihilating operator otherwise.

The time-span T elapsing between the selected data is the sampling period, and the index ϑ marks, with respect to t_o, the origin of the sampling process.

The sampling operator can be written as a sequence of equidistant unit pulses[5], distance T apart, namely:

$$\mathcal{S}_\vartheta = \sum_{i \in z} \delta_{t - t_o + \vartheta + iT} \tag{1}$$

which entails an input-output relationship of the form:

$$\mathcal{S}_\vartheta\, y_t = \sum_{i \in z} y_{t_o - \vartheta - iT} \cdot \delta_{t - t_o + \vartheta + iT} \tag{2}$$

which in turn leads – provided the input series is harmonizable, i.e. $y_t = \int_{-\pi}^{\pi} e^{j\omega t}\, dY(\omega)$ – to a harmonic expansion for the output of the form:

$$\mathcal{S}_\vartheta\, y_t = \int_{-\pi}^{\pi} e^{j\omega t}\, d\tilde{Y}_\vartheta(\omega) \tag{3}$$

where

$$d\tilde{Y}_\vartheta(\omega) = \frac{1}{T} \cdot \sum_{-\frac{T}{2}+1} e^{j\frac{2\pi}{T}\vartheta h} \cdot dY\left(\omega - \frac{2\pi}{T} h\right) \tag{4}$$

is periodic of period T.

Indeed, the spectrum of the output turns out to be simply the average of shifted copies (images) of the spectrum of a base-band corresponding to $|\omega| < \frac{\pi}{T}$.

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[5] The unit pulse δ_t is defined as follows:

$$\delta_t = \begin{cases} 1 & \text{for } t = 0 \\ 0 & \text{otherwise} \end{cases}$$

2.2 Low-Frequency Interpolating and Forward-Looking Operators

A symmetric moving-average is called an (ordinary) interpolating filter if its impulse response a_h meets the following requirements:

$$a_h = \begin{cases} 1 & \text{for } h = 0, \\ 0 & \text{for } h = iT, i \in Z. \end{cases} \tag{5}$$

Should the moving-average length not exceed 4T – 3 and its impulse response a_h satisfy an extra constraint such as:

$$a_{T-k} = 0, \quad \textit{for at least} \quad k = 1, \tag{6}$$

the operator qualifies as a forward-looking interpolating filter.

Since the response characteristics of the interpolating filters we are interested in should mirror those of the low-pass filter used for mid-range estimation of the trend-cycle component, the design criteria of the former should tally with those of the latter.

For $T = 4$, i.e. for quarterly data, well-suited solutions to problem for ordinary and forward-looking interpolating filters, are given by the following 11-term and 13-term symmetric moving-averages with impulse responses g_h ($|h| \leq 5$) and γ_k ($|k| \leq 6$), respectively:

$$\left. \begin{array}{ll} g_0 = 1, & g_{-1} = g_1 = \frac{17}{16}, \\ g_{-2} = g_2 = \frac{1}{2}, & g_{-3} = g_3 = \frac{3}{32}, \\ g_{-4} = g_4 = 0, & g_{-5} = g_5 = -\frac{5}{32}, \end{array} \right\} \tag{7}$$

$$\left. \begin{array}{ll} \gamma_0 = 1, & \gamma_{-1} = \gamma_1 = \frac{5}{4}, \\ \gamma_{-2} = \gamma_2 = \frac{13}{32}, & \gamma_{-3} = \gamma_3 = 0, \\ \gamma_{-4} = \gamma_4 = 0, & \gamma_{-5} = \gamma_5 = -\frac{1}{4}, \\ \gamma_{-6} = \gamma_6 = \frac{3}{32} & \end{array} \right\} \tag{8}$$

which satisfy the side condintions[6] (see footnote 4):

[6] As it can be easily verified, should we divide by T the transfer functions, as well as the impulse responses of the interpolating filters at stake, we would get two families of well-behaved low-pass filters with characteristics comparable to those of the class (24) of Section 1.3.

$$\begin{cases} \lambda''(o) = 0 \\ \lambda\left(\frac{\pi}{2}\right) = \lambda(\pi) = 0 \\ \lambda'\left(\frac{\pi}{2}\right) = 0 \end{cases} \tag{9}$$

After some computations, the following closed-form expressions – parametric on T – can be obtained for the transfer functions of the ordinary and forward-looking interpolating filters at stake, respectively

$$\lambda_g(\omega) = \frac{1}{4T} \cdot \left[\frac{\sin(\frac{T}{2}\omega)}{\sin(\frac{\omega}{2})} \right]^2 \cdot \left[-1 + 10 \cdot \cos\left(\frac{T}{4}\omega\right) - 5 \cdot \cos\left(\frac{T}{2}\omega\right) \right] \tag{10}$$

$$\lambda_\gamma(\omega) = \frac{1}{4T} \cdot \left[\frac{\sin(\frac{T}{2}\omega)}{\sin(\frac{\omega}{2})} \right]^2 \cdot \left[-4 + 19 \cdot \cos\left(\frac{T}{4}\omega\right) + \right.$$
$$\left. - 14 \cdot \cos\left(\frac{T}{2}\omega\right) + 3 \cdot \cos\left(\frac{3T}{4}\omega\right) \right] \tag{11}$$

Indeed, looking at (10) and at (11) as functions of the discrete parameter T, two whole families of ordinary and forward-looking interpolator filters, respectively, turn out to be implicitly defined. Hence, by focusing on monthly time series in particular – i.e., by setting $T = 12$ in formulas (10) and (11) above –, we eventually arrive at identifying the pair of symmetric moving average:

$$\left.\begin{array}{ll} g_0 = 1 & g_{-1} = g_1 = \frac{49}{48} \\ g_{-2} = g_2 = \frac{25}{24} & g_{-3} = g_3 = \frac{51}{48} \\ g_{-4} = g_4 = \frac{7}{8} & g_{-5} = g_5 = \frac{11}{16} \\ g_{-6} = g_6 = \frac{1}{2} & g_{-7} = g_7 = \frac{35}{96} \\ g_{-8} = g_8 = \frac{11}{48} & g_{-9} = g_9 = \frac{3}{32} \\ g_{-10} = g_{10} = \frac{1}{16} & g_{-11} = g_{11} = \frac{1}{32} \\ g_{-12} = g_{12} = 0 & g_{-13} = g_{13} = -\frac{5}{96} \\ g_{-14} = g_{14} = -\frac{5}{48} & g_{-15} = g_{15} = -\frac{5}{32} \\ g_{-16} = g_{16} = -\frac{5}{48} & g_{-17} = g_{17} = -\frac{5}{96} \end{array}\right\} \qquad (12)$$

$$\left.\begin{array}{lll} \gamma_0 = 1 & \gamma_{-1} = \gamma_1 = \frac{13}{12} & \gamma_{-2} = \gamma_2 = \frac{7}{6} \\ \gamma_{-3} = \gamma_3 = \frac{5}{4} & \gamma_{-4} = \gamma_4 = \frac{31}{32} & \gamma_{-5} = \gamma_5 = \frac{11}{16} \\ \gamma_{-6} = \gamma_6 = \frac{13}{32} & \gamma_{-7} = \gamma_7 = \frac{13}{48} & \gamma_{-8} = \gamma_8 = \frac{13}{96} \\ \gamma_{-9} = \gamma_9 = 0 & \gamma_{-10} = \gamma_{10} = 0 & \gamma_{-11} = \gamma_{11} = 0 \\ \gamma_{-12} = \gamma_{12} = 0 & \gamma_{-13} = \gamma_{13} = -\frac{1}{12} & \gamma_{-14} = \gamma_{14} = -\frac{1}{6} \\ \gamma_{-15} = \gamma_{15} = -\frac{1}{4} & \gamma_{-16} = \gamma_{16} = -\frac{13}{96} & \gamma_{-17} = \gamma_{17} = -\frac{1}{48} \\ \gamma_{-18} = \gamma_{18} = \frac{3}{32} & \gamma_{-19} = \gamma_{19} = \frac{1}{16} & \gamma_{-20} = \gamma_{20} = \frac{1}{32} \end{array}\right\} \qquad (13)$$

where the former – 35-term long – acts as a well-behaved ordinary interpolating filter while the latter – 41-term long – acts as a well-behaved forward-looking (three-steps ahead) interpolating filter for monthly data.

2.3 The Desampling Procedure and the Estimation of Trend-Cycle Extreme Values

Cascading a sampler $\mathcal{S}_\vartheta$ with a low-pass interpolating filter J we obtain a composite system whose input-output relationship can be expressed as:

$$y_{t,\vartheta} = J\mathcal{S}_\vartheta(y_t) = \sum_{i \in Z} y_{t_o-\vartheta-iT} \cdot \sum_{h=-L}^{L} a_h\, \delta_{t-t_o+\vartheta+iT-h} \tag{14}$$

and whose output reproduces exactly the input levels at the sampling points $t = t_o - \vartheta - iT$, $i \in Z$, and performs a low-frequency (i.e. smooth) interpolation of the sampled values elsewhere[7].

The frequency-domain counterpart of the operation turns into a shrinkage of the spectrum of the signal onto the baseband $|\omega| \leq \frac{\pi}{T}$, by cancelling out unnecessary images beyond the cut-off frequency $\omega_c = \frac{\pi}{T}$.

A few remarkable properties of the composite operators $J\mathcal{S}_\vartheta$'s are worth mentioning:

i) let z_t be periodic of period T – e.g., such as s_t of Section 1.1 – then the following proposition holds:

$J\mathcal{S}_\vartheta z_t$ is a constant, say ζ_ϑ, depending on the index ϑ[8] ;

ii) Let z_t be as above and y_t be arbitrary, then the following equality holds:

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[7] Should the sampled serie $\mathcal{S}(y_t)$ run from $t = \tau_l$ to $t = \tau_\mu$, should $\frac{T}{4}$ be an integer and the filter J belong to either of the classes (10) and (11) of Section 2.1, the composite system $J\mathcal{S}$ turns out to provide with feasible estimates of the interpolating pattern of $\mathcal{S}(y_t)$ for:

$$t = \sum_{j \in A} \delta_{t-j} + \sum_{j \in B} \delta_{t-j} + \sum_{j \in C} \delta_{t-j}$$

where $A = [\tau_l - \Psi, \tau_l]$, $B = [\tau_l + \frac{T}{2} + \Psi, \tau_u - \frac{T}{2} - \Psi]$, and $C = [\tau_u, \tau_u + \Psi]$, with:

$$\Psi = \begin{cases} o, & \text{for ordinary interpolating filters;} \\ \frac{T}{4} & \text{for } (\frac{T}{4}\text{- steps ahead) forward looking interpolating filters.} \end{cases}$$

The missing elements can be retrieved by a pluristage procedure based on the same operators. For instance, the interpolated values for:

$$\tau_u + 1 - \frac{T}{2} \leq t \leq \tau_u - \frac{T}{4}$$

result from;

$$J_{ord}\{\mathcal{S}_{\frac{3}{4}T}[J_{ord}\,\mathcal{S}(y_t)] + \delta_{t-\tau_u+\frac{T}{4}}\,[J_{fl}\,\mathcal{S}(y_t)]\}$$

where J_{ord} anf J_{fl} represent ordinary and forward-looking interpolating filters, respectively.

[8] Should z_t equal s_t, the ζ_ϑ's represent a set of T seasonal coefficients which balance each other out, i.e.:

$$\sum_{0 \leq \vartheta \leq T-1} \zeta_\vartheta = 0$$

$$J\mathcal{S}_\vartheta\,(z_t y_t) = \zeta_\vartheta \cdot J\mathcal{S}_\vartheta\,(y_t) \tag{15}$$

iii) Let w_t be band-limited – e.g., such as p_t of Section 1.2 – and J^* be an ideal low-pass interpolating filter with cut-off frequency outside the reference band of w_t, then following relationship holds:

$$J^*\mathcal{S}_\vartheta w_t = w_t \tag{16}$$

iv) Should a feasible filter J, either of the class (10) or of the class (11) of Section 2.2 above, be used in place of an ideal low-pass operator in the desampling procedure, the aforementioned result still holds, though in a weaker form, namely with an *almost equal* replacing the *equal sign* between the left and right-hand sides of (16). That is:

$$J^*\mathcal{S}_\vartheta w_t \approx w_t \tag{17}$$

While bearing in mind the foregoing arguments, let x_t be a time series of the type specified in Sections 1.1 and 1.2, then the following result is easily esablished:

$$\begin{aligned} x_{t,\vartheta} &= J\mathcal{S}_\vartheta(x_t) = J\mathcal{S}_\vartheta(p_t + s_t^{ev} + \eta_t) = \\ &= J\mathcal{S}_\vartheta(p_t) + J\mathcal{S}_\vartheta(s_t^{ev}) + J\mathcal{S}_\vartheta(\eta_t) = \\ &= \zeta_\vartheta + (1 + \alpha\zeta_\vartheta) \cdot p_t + v_{t,\vartheta} \end{aligned} \tag{18}$$

where:

$$v_{t,\vartheta} = (1 + \alpha\zeta_\vartheta) \cdot (J - J^*)\ \mathcal{S}_\vartheta\ (p_t) + J\mathcal{S}_\vartheta\ (\eta_t) \tag{19}$$

represents a composite nuisance term, which brings on only faint discrepancies inasmuch as the feasible filter performances do not significantly differ from those of an ideal filter J^* and the noise component variance is not too high.
Moreover, by averaging out with respect to ϑ, we get (cf. footnote 8):

$$\frac{1}{T}\sum_{0\le\vartheta\le T-1} x_{t,\vartheta} = \frac{1}{T}\sum_{0\le\vartheta\le T-1} J\,\mathcal{S}_\vartheta\,(x_t) = p_t + \bar{v}_t \tag{20}$$

where:

$$\bar{v}_t = \frac{1}{T}\sum_{0\le\vartheta\le T-1}(J - J^*)\ \mathcal{S}_\vartheta\,(p_t) + \frac{1}{T}\sum_{0\le\vartheta\le T-1} J\,\mathcal{S}_\vartheta\,(\eta_t) \tag{21}$$

is an arithmetic mean of nuisance terms – namely the $v_{t,\vartheta}$'s in (18) –, and, as such, it should be considered nearly negligible *a fortiori*.

Hence, we can draw the conclusion that $\frac{1}{T}\sum_{0\le\vartheta\le T-1} x_{t,\vartheta}$ provides a feasible estimator of p_t – once the interpolated values for ϑ running from O to $T-1$ are given – and accordingly write:

$$\tilde{p}_t = \frac{1}{T} \sum_{0 \le \vartheta \le T-1} x_{t,\vartheta} \tag{22}$$

It can be shown (see, e.g., Faliva, 1984, for a hint on the issue) that the estimator (22) of p_t – with $x_{t,\vartheta}$ as in (18) above – tallies with the mid-range estimator (28) of Section 1.3, inasmuch as the transfer function behaviour of the virtual low-pass filter $\frac{1}{T} J$ (cf. footnote 6) actually mirrors that of the low-pass moving averages $\mathcal{M}$ of class (24) of Section 1.3.

The very advantage inherent to such an approach to trend-cycle estimation rests on its operativness beyond the mid-range extent, thus putting forward an effective tool to retrieve the missing values at the front and tail-end of the reference series.

Operationally, the algorithm[9] requires a recursive application of the sampling-desampling procedure at stake, making use of either ordinary or forward-looking filters whenever necessary, in order to figure out all the interpolated values (cf. footnote 7) needed to look at (22) as an estimation formula.

This retrieval process eventually leads to update[10] the estimated pattern of the latent trend-cycle components by a set of linear transformation of the latest years' data, which can be put in matrix notation as follows:

$$\hat{p}_{m.r.} = \frac{1}{T} A_T \cdot x_{L.y.} \tag{23}$$

where:

$\hat{p}_{m.r.} = \left[\hat{p}_N, \hat{p}_{N-1}, \ldots, \hat{p}_{N+2-\frac{3}{2}T}\right]'$,

is the vector of the estimates of the $\frac{3}{2}T - 1$ *most recent* (i.e., beyond the mid-range, forwards) values of p_t;

$x_{L.y.} = [x_N, x_{N-1}, \ldots, x_{N-k_T+1}]'$

is the vector of the *latest years'* data, in particular $k_4 = 12$ and $k_{12} = 48$;

A_T is a $(\frac{3}{2}T - 1) \times k_T$ coefficient matrix, whose elements turn out to depend on the impulse responses of the interpolating filters used for the desampling procedure.

The A_T's matrices for quarterly and monthly series are given respectively by the 5×12 and 17×48 arrays displayed, in partitioned form, here below:

$$\underset{(5,\,12)}{A_4} = [Q_1, Q_2, Q_3]$$

[9] The whole estimation process of latent components has been implemented in Rats and Speakeasy: the relevant application programme - TEXAMF/2 (acronym for *T*rend-cycle *E*xtraction Applying the *M*ethod of *F*ilters, release no. 2) - is avaialable on request by the authors.

[10] Reference is made here to trend-cycle estimation of most recent data. Similar arguments - reversing the time arrow - apply for the retrieval of the tail-end values.

where:

$$\underset{(5,4)}{Q_1} = \begin{bmatrix} 1.000000 & 1.250000 & 1.539063 & 1.798828 \\ .6718750 & 1.000000 & 1.250000 & 1.539063 \\ .5000000 & .6718750 & 1.000000 & 1.250000 \\ .0937500 & .5000000 & .6718750 & 1.000000 \\ .0000000 & .0937500 & .5000000 & .6718750 \end{bmatrix}$$

$$\underset{(5,4)}{Q_2} = \begin{bmatrix} .0000000 & -.2500000 & -.5781250 & -.8476563 \\ .4062500 & .0000000 & -.2500000 & -.5781250 \\ .5000000 & .4062500 & .0000000 & -.2500000 \\ 1.062500 & .5000000 & .4062500 & .0000000 \\ 1.000000 & 1.062500 & .5000000 & .4062500 \end{bmatrix}$$

$$\underset{(5,4)}{Q_3} = \begin{bmatrix} .0000000 & .0000000 & .0390625 & .0488281 \\ -.0781250 & .0000000 & .0000000 & .0390625 \\ .0000000 & -.0781250 & .0000000 & .0000000 \\ -.1562500 & .0000000 & -.0781250 & .0000000 \\ .0000000 & -.1562500 & .0000000 & -.0781250 \end{bmatrix}$$

$$\underset{(17,48)}{A_{12}} = [M_1, M_2, M_3, M_4]$$

where:

$\underset{(17,\ 12)}{M_1} =$

1.000000	1.083333	1.166667	1.250000	1.346354	1.442708	1.539062	1.625651	1.712240	1.798828	1.892741	1.986654
.9036457	1.000000	1.083333	1.166667	1.250000	1.346354	1.442708	1.539062	1.625651	1.712240	1.798828	1.892741
.7766384	.9036457	1.000000	1.083333	1.166667	1.250000	1.346354	1.442708	1.539062	1.625651	1.712240	1.798828
.6718749	.7766384	.9036457	1.000000	1.083333	1.166667	1.250000	1.346354	1.442708	1.539062	1.625651	1.712240
.5201823	.6718749	.7766384	.9036457	1.000000	1.083333	1.166667	1.250000	1.346354	1.442708	1.539062	1.625651
.3684896	.5201823	.6718749	.7766384	.9036457	1.000000	1.083333	1.166667	1.250000	1.346354	1.442708	1.539062
.5000000	.3684896	.5201823	.6718749	.7766384	.9036457	1.000000	1.083333	1.166667	1.250000	1.346354	1.442708
.3645833	.5000000	.3684896	.5201823	.6718749	.7766384	.9036457	1.000000	1.083333	1.166667	1.250000	1.346354
.2291667	.3645833	.5000000	.3684896	.5201823	.6718749	.7766384	.9036457	1.000000	1.083333	1.166667	1.250000
.0937500	.2291667	.3645833	.5000000	.3684896	.5201823	.6718749	.7766384	.9036457	1.000000	1.083333	1.166667
.0625000	.0937500	.2291667	.3645833	.5000000	.3684896	.5201823	.6718749	.7766384	.9036457	1.000000	1.083333
.0312500	.0625000	.0937500	.2291667	.3645833	.5000000	.3684896	.5201823	.6718749	.7766384	.9036457	1.000000
.0000000	.0312500	.0625000	.0937500	.2291667	.3645833	.5000000	.3684896	.5201823	.6718749	.7766384	.9036457
-.0520833	.0000000	.0312500	.0625000	.0937500	.2291667	.3645833	.5000000	.3684896	.5201823	.6718749	.7766384
-.1041667	-.0520833	.0000000	.0312500	.0625000	.0937500	.2291667	.3645833	.5000000	.3684896	.5201823	.6718749
-.1562500	-.1041667	-.0520833	.0000000	.0312500	.0625000	.0937500	.2291667	.3645833	.5000000	.3684896	.5201823
-.1041667	-.1562500	-.1041667	-.0520833	.0000000	.0312500	.0625000	.0937500	.2291667	.3645833	.5000000	.3684896

$$
\underset{(17,\,12)}{M_2} = \begin{bmatrix}
.0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 & -.5781250 & -.6679687 & -.7578125 & -.8476562 & -.9521484 & -1.056641 \\
.1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 & -.5781250 & -.6679687 & -.7578125 & -.8476562 & -.9521484 \\
.2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 & -.5781250 & -.6679687 & -.7578125 & -.8476562 \\
.4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 & -.5781250 & -.6679687 & -.7578125 \\
.6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 & -.5781250 & -.6679687 \\
.8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 & -.5781250 \\
.5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 & -.4687500 \\
.6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 & -.3593750 \\
.8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 & -.2500000 \\
1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 & -.1666667 \\
1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 & -.0833333 \\
1.020833 & 1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 & .0000000 \\
1.000000 & 1.020833 & 1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 & .1093750 \\
1.020833 & 1.000000 & 1.020833 & 1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 & .2827691 \\
1.041667 & 1.020833 & 1.000000 & 1.020833 & 1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 & .4062499 \\
1.062500 & 1.041667 & 1.020833 & 1.000000 & 1.020833 & 1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302 & .6344401 \\
.8750000 & 1.062500 & 1.041667 & 1.020833 & 1.000000 & 1.020833 & 1.041667 & 1.062500 & .8750000 & .6875000 & .5000000 & .8626302
\end{bmatrix}
$$

M_3 = (17, 12)

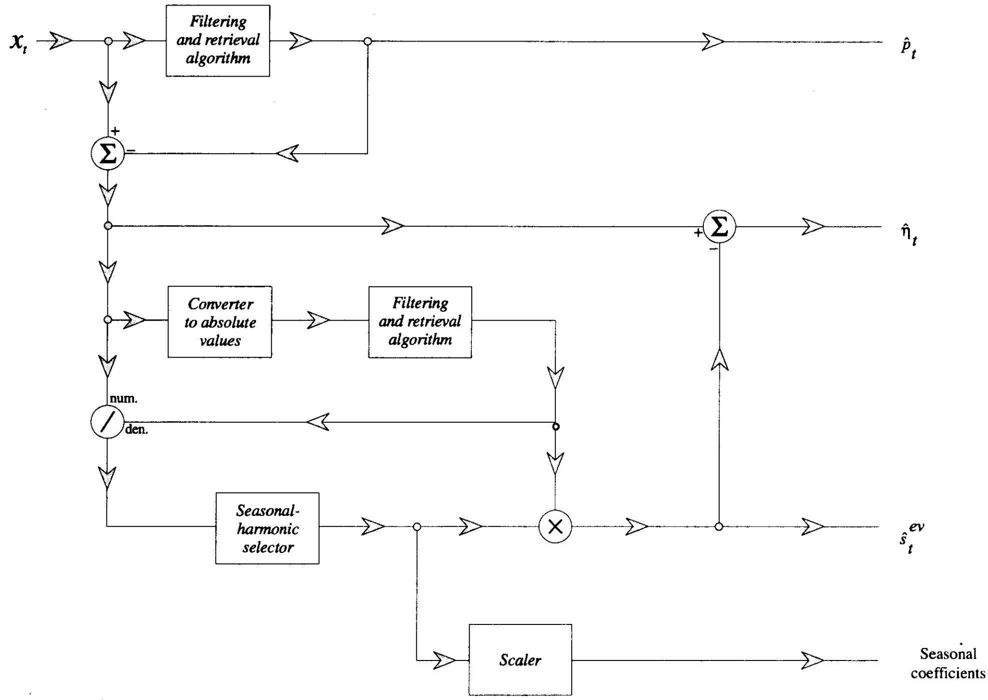
.0000000	.0000000	.0000000	.0000000	.01302083	.0260416	.0390625	.04231771	.0455729	.0488281	.0594075	.0699869
-.0130208	.0000000	.0000000	.0000000	.0000000	.0130208	.0260416	.03906250	.0423177	.0455729	.0488281	.0594075
-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000	.0130208	.02604166	.03906250	.0423177	.04557291	.0488281
-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000	.01302083	.02604166	.03906250	.04231771	.0455729
-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000	.01302083	.02604166	.03906250	.0423177
-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000	.01302083	.02604166	.0390625
.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000	.01302083	.02604166
-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000	.01302083
-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000	.0000000
-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000	.0000000
-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000	.0000000
-.0520833	-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208	.0000000
.0000000	-.0520833	-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202	-.0130208
.0312500	.0000000	-.05208332	-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249	-.0621202
.0625000	.0312500	.0000000	-.0520833	-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604	-.0781249
.0937500	.0625000	.0312500	.0000000	-.0520833	-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958	-.1627604
.2291667	.0937500	.0625000	.0312500	.0000000	-.0520833	-.1041667	-.1562500	-.1041667	-.0520833	.0000000	-.2473958

$\underset{(17\times12)}{M_4} =$

.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0027127	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0000000	.0027127	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0081380	.0000000	.0027127	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0162760	.0081380	.0000000	.0027127	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0000000	.0162760	.0081380	.0000000	.0027127	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0000000	.0000000	.0162760	.0081380	.0000000	.0027127	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000
.0000000	.0000000	.0000000	.0162760	.0081380	.0000000	.0027127	.0000000	.0000000	.0000000	.0000000	.0000000
.0000000	.0000000	.0000000	.0000000	.0162760	.0081380	.0000000	.0027127	.0000000	.0000000	.0000000	.0000000
.0000000	.0000000	.0000000	.0000000	.0000000	.0162760	.0081380	.0000000	.0027127	.0000000	.0000000	.0000000
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0162760	.0081380	.0000000	.0027127	.0000000	.0000000
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0162760	.0081380	.0000000	.0027127	.0000000
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0162760	.0081380	.0000000	.0027127
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0162760	.0081380	.0000000
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0162760	.0081380
.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0000000	.0162760

Addendum

Once the trend-cycle component has been detected, an effective procedure leading to identify the other latent components of interest can be easily set up along the lines traced by Faliva (1978, 1996), as sketched out in the block-diagram below (cf. footnote 9).



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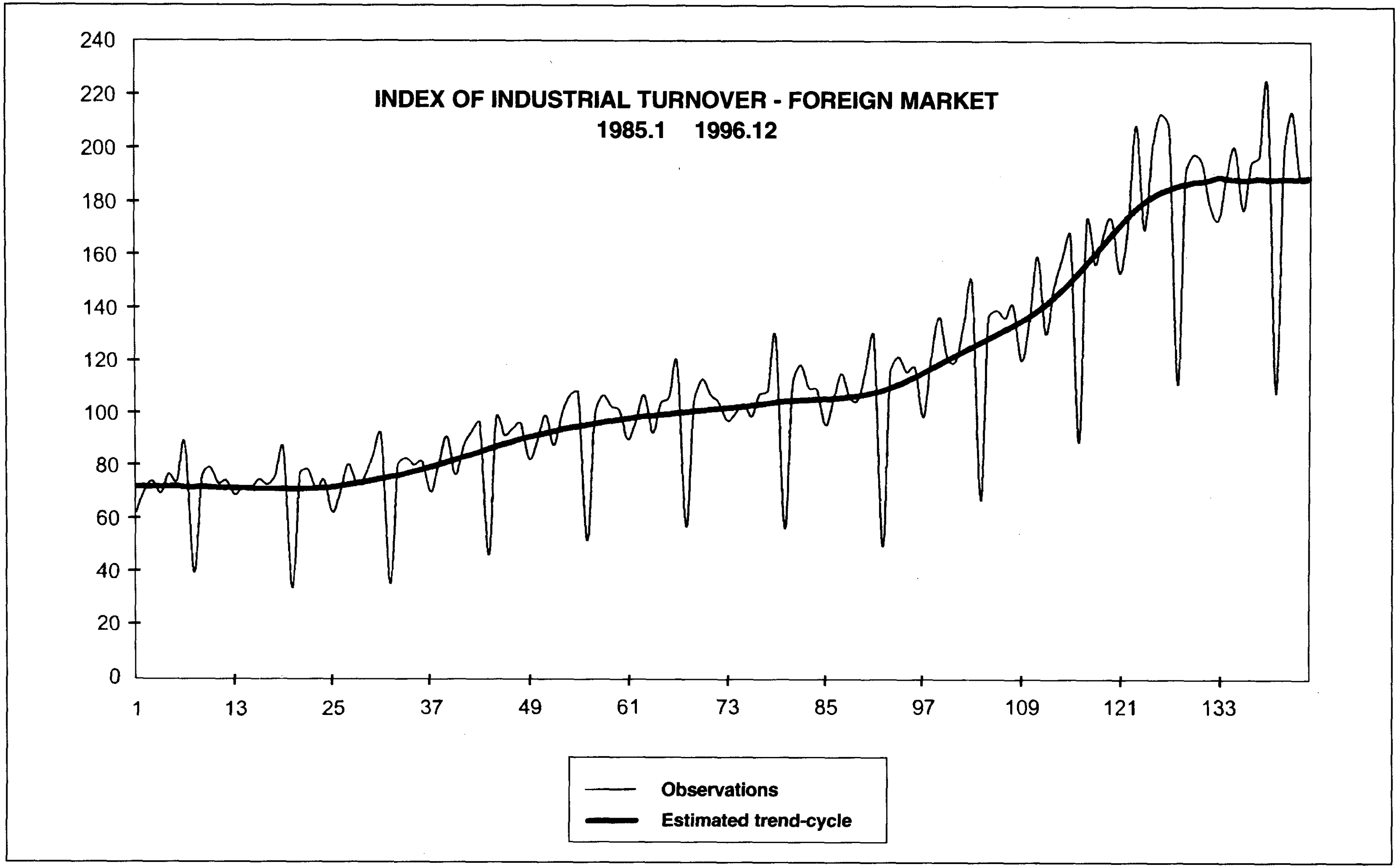
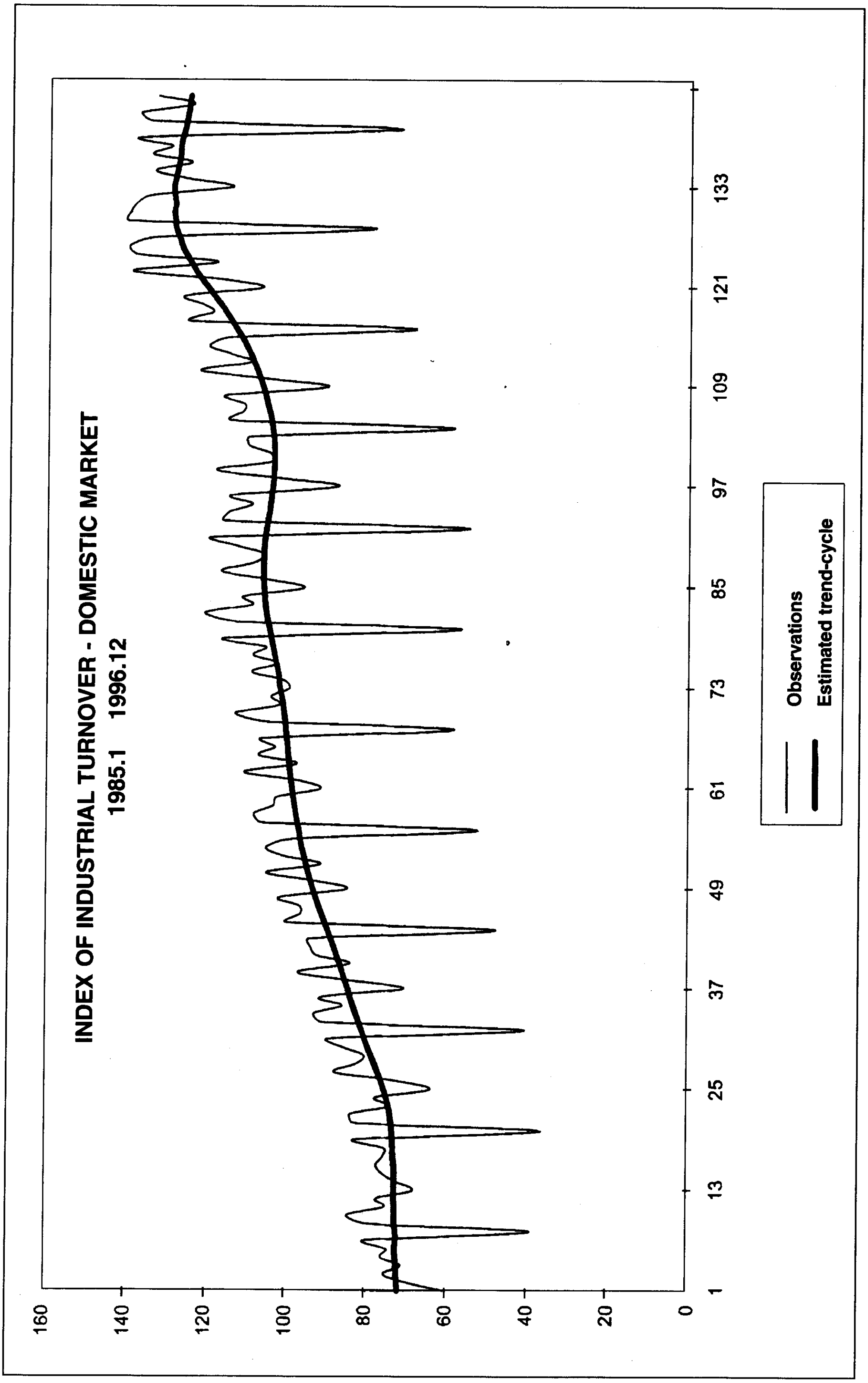
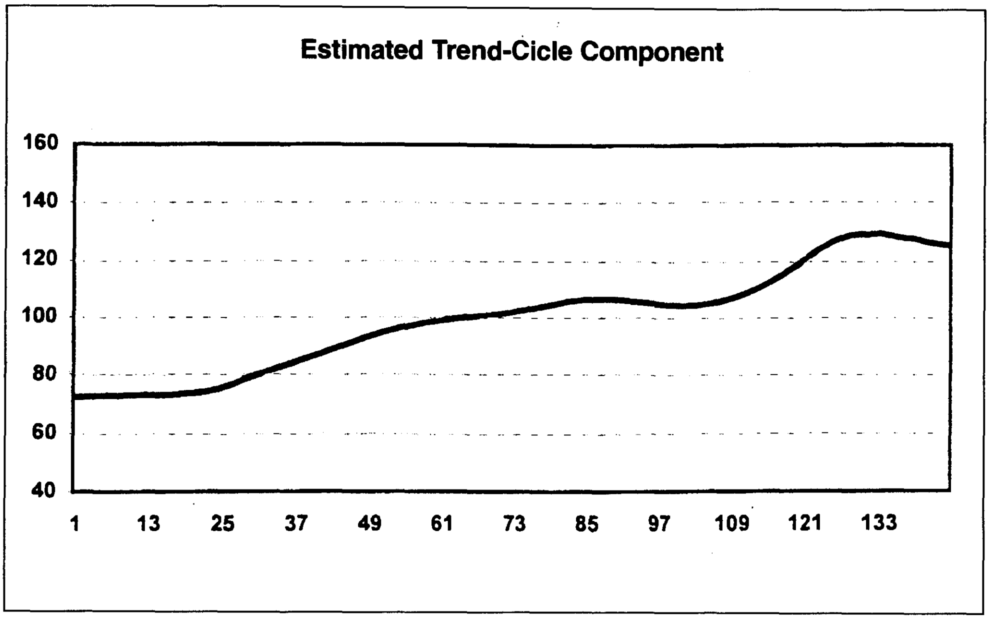
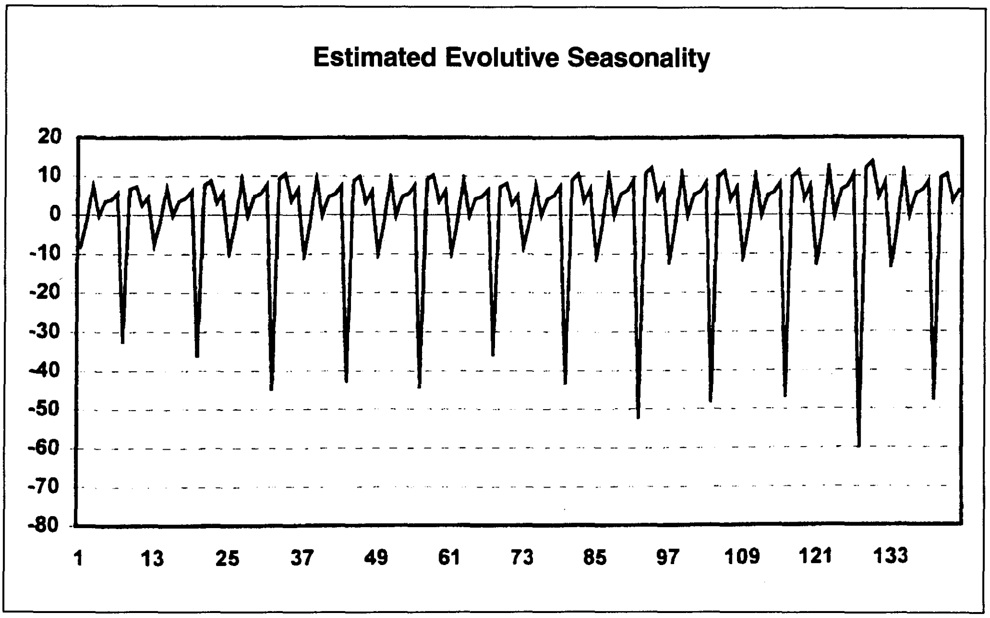
APPEDIX

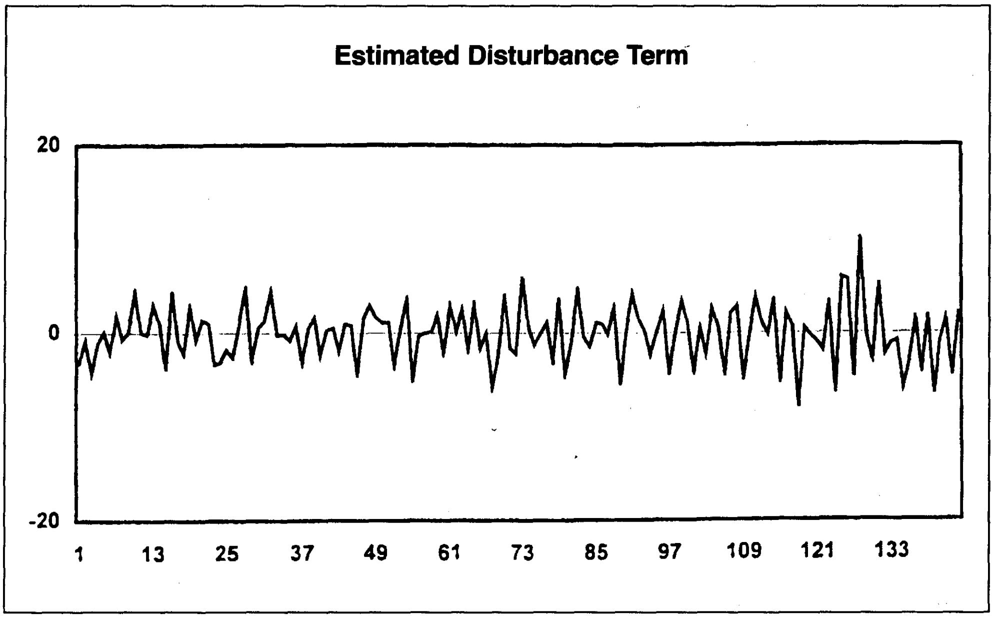
Some empirical evidence of the performance of the TEXAMF/2 procedure

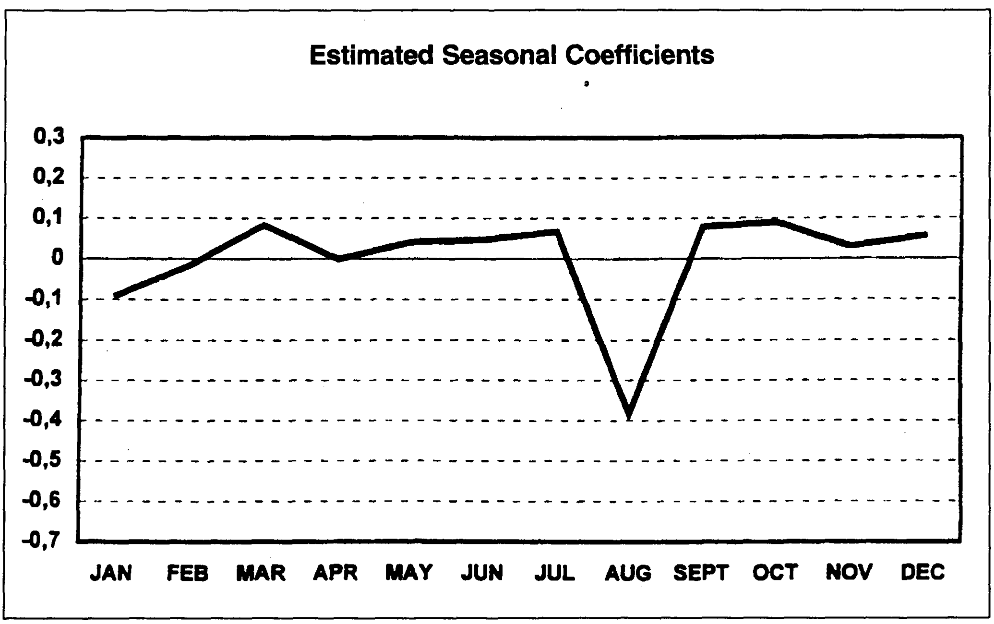

INDEX OF INDUSTRIAL TURNOVER - FOREIGN MARKET
1985.1 1996.12
240
220
200
180
160
140
120
100
80
60
40
20
0
1
13
25
37
49
61
73
85
97
109
121
133
Observations
Estimated trend-cycle

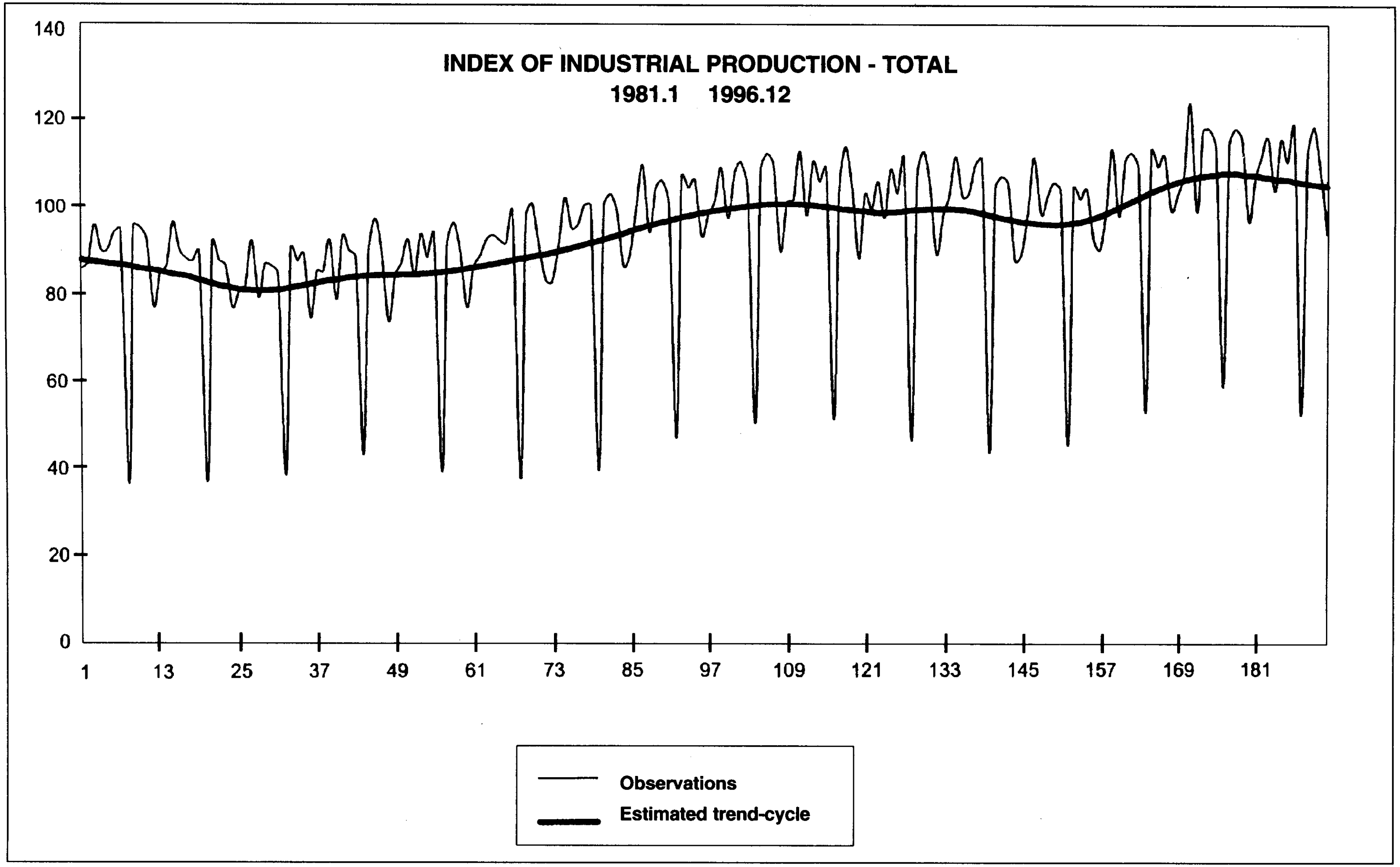

INDEX OF INDUSTRIAL TURNOVER - DOMESTIC MARKET
1985.1 1996.12
0
20
40
60
80
100
120
140
160
1
13
25
37
49
61
73
85
97
109
121
133
Observations
Estimated trend-cycle

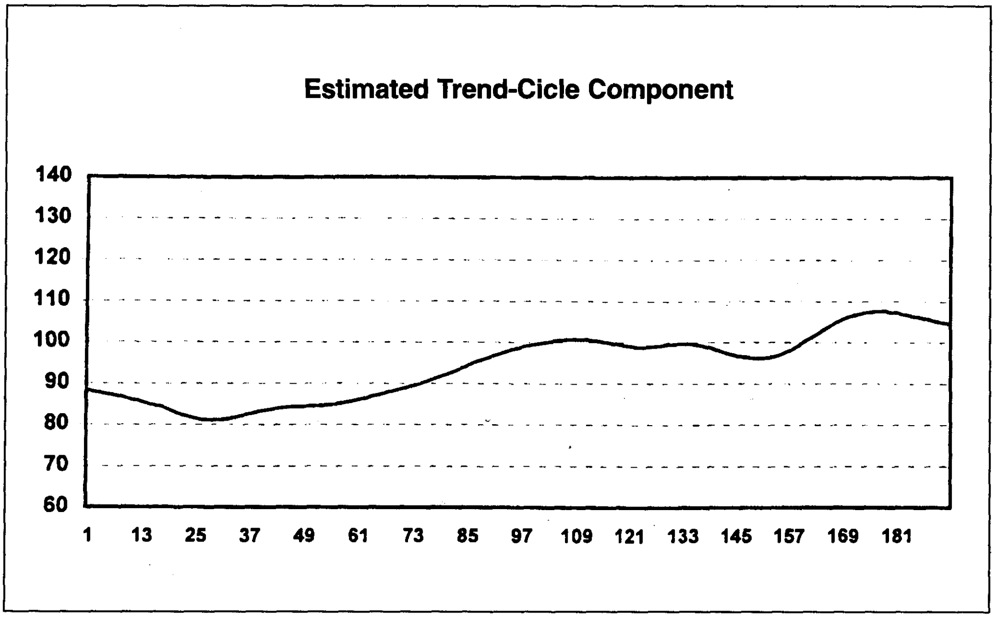

Estimated Trend-Cicle Component
160
140
120
100
80
60
40
1
13
25
37
49
61
73
85
97
109
121
133

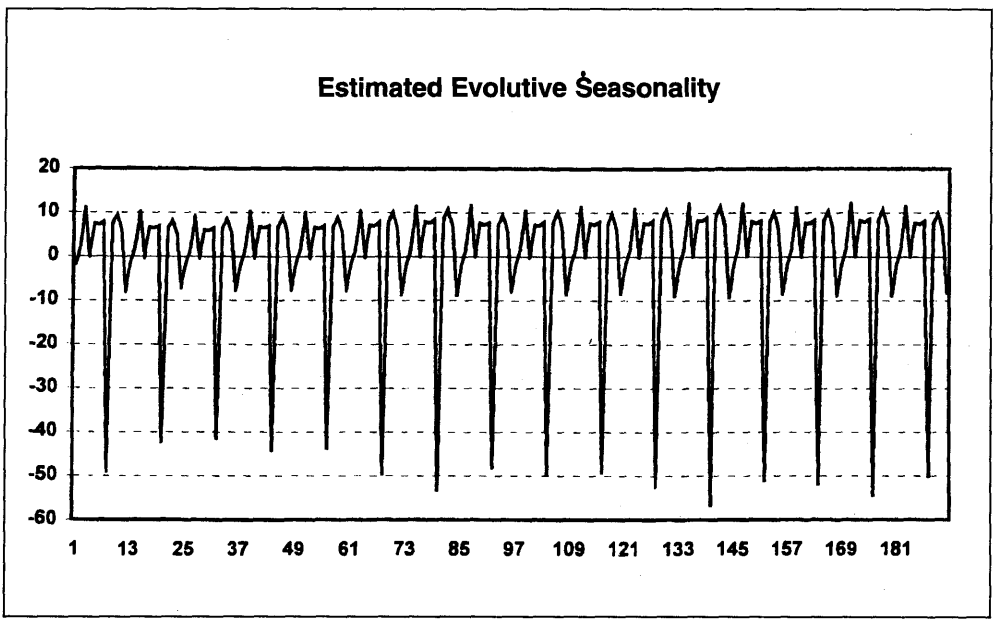

Estimated Evolutive Seasonality
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
1
13
25
37
49
61
73
85
97
109
121
133

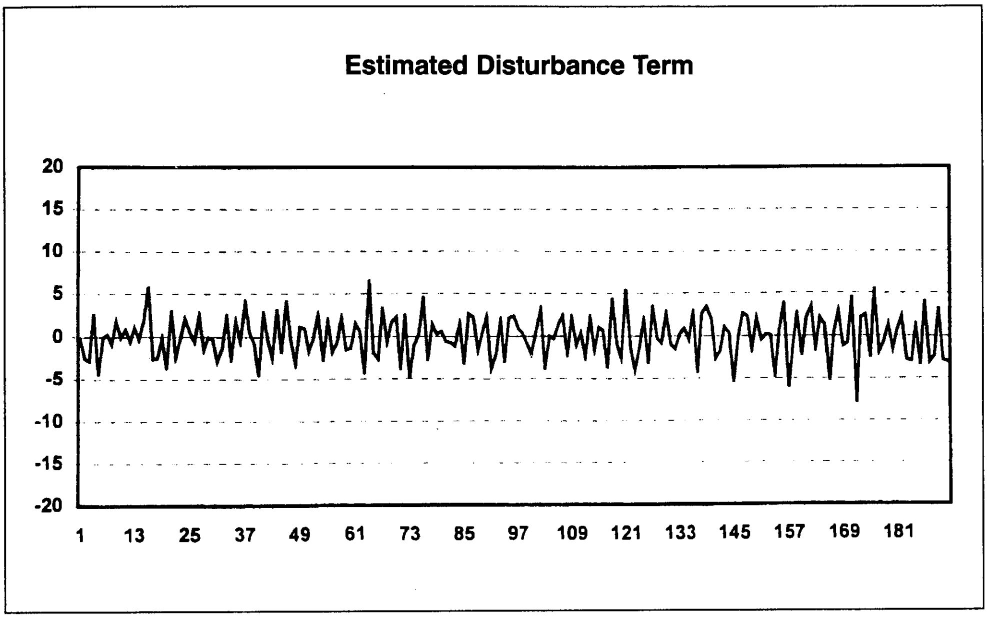

Estimated Disturbance Term
20
0
-20
1
13
25
37
49
61
73
85
97
109
121
133

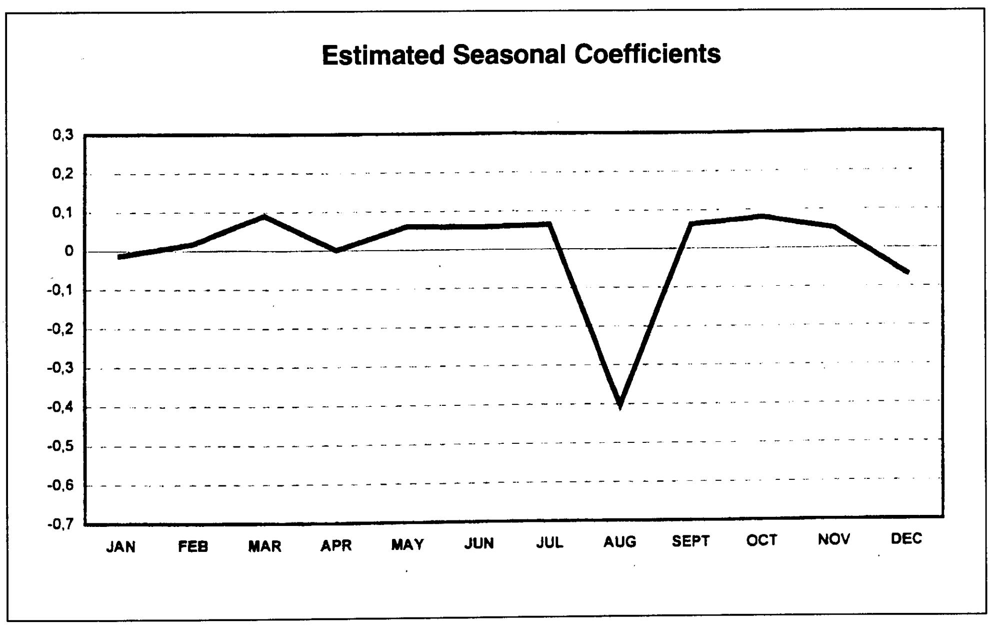

Estimated Seasonal Coefficients
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
-0,5
-0,6
-0,7
JAN
FEB
MAR
APR
MAY
JUN
JUL
AUG
SEPT
OCT
NOV
DEC


INDEX OF INDUSTRIAL PRODUCTION - TOTAL
1981.1 1996.12
140
120
100
80
60
40
20
0
1
13
25
37
49
61
73
85
97
109
121
133
145
157
169
181
Observations
Estimated trend-cycle


Estimated Trend-Cicle Component
140
130
120
110
100
90
80
70
60
1 13 25 37 49 61 73 85 97 109 121 133 145 157 169 181


Estimated Evolutive Seasonality
20
10
0
-10
-20
-30
-40
-50
-60
1 13 25 37 49 61 73 85 97 109 121 133 145 157 169 181


Estimated Disturbance Term
20
15
10
5
0
-5
-10
-15
-20
1
13
25
37
49
61
73
85
97
109
121
133
145
157
169
181


Estimated Seasonal Coefficients
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
-0,5
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-0,7
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MAR
APR
MAY
JUN
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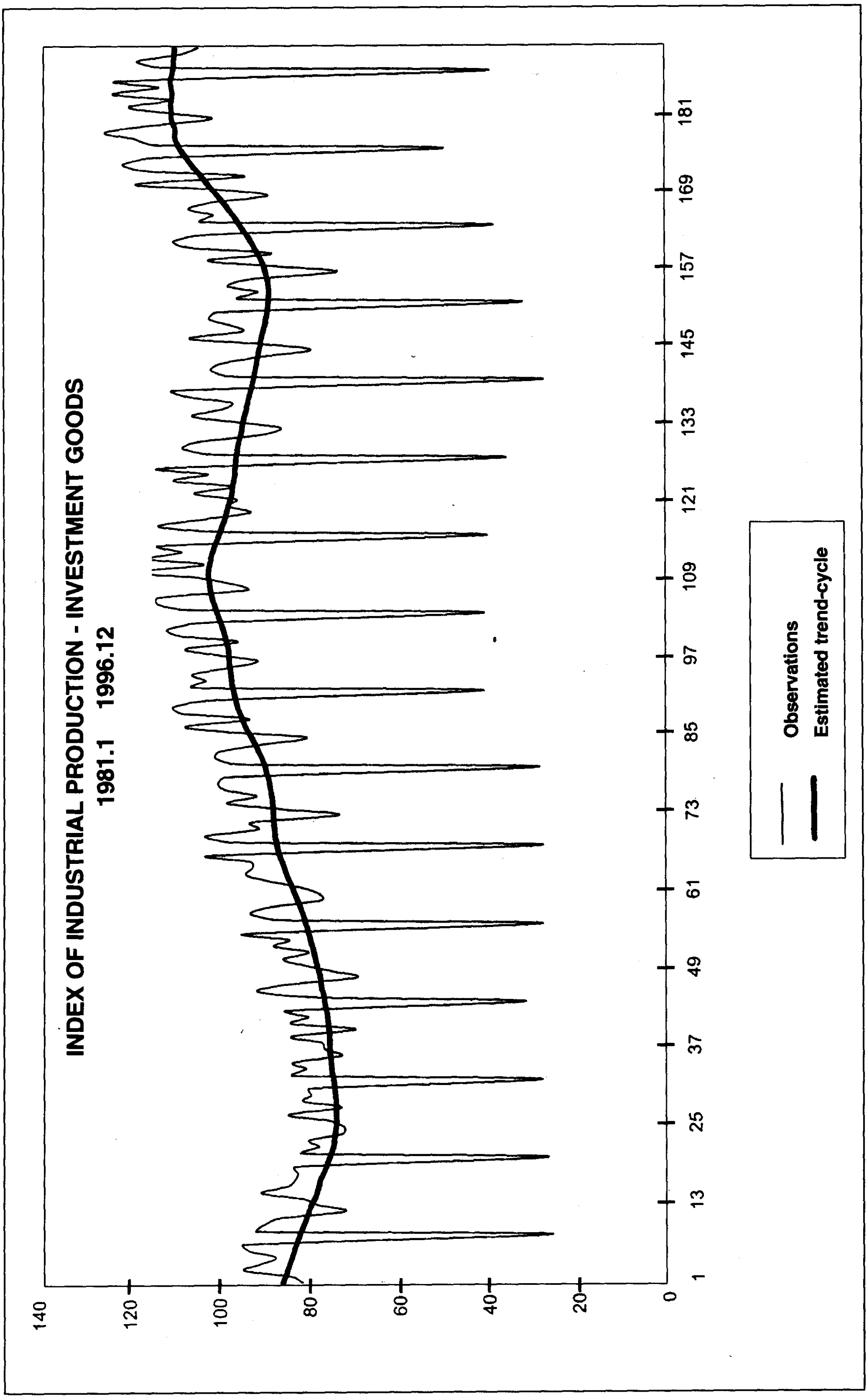
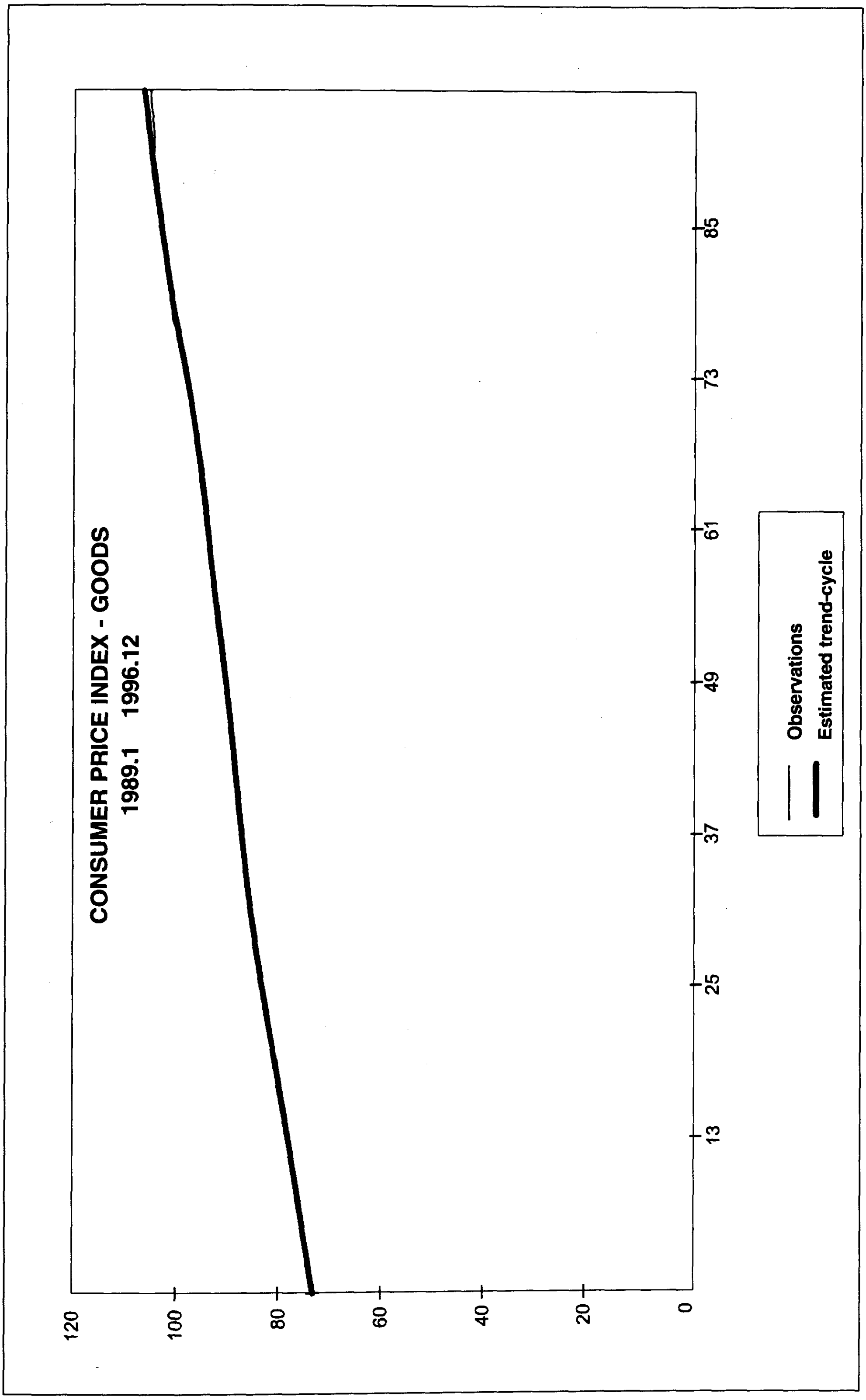
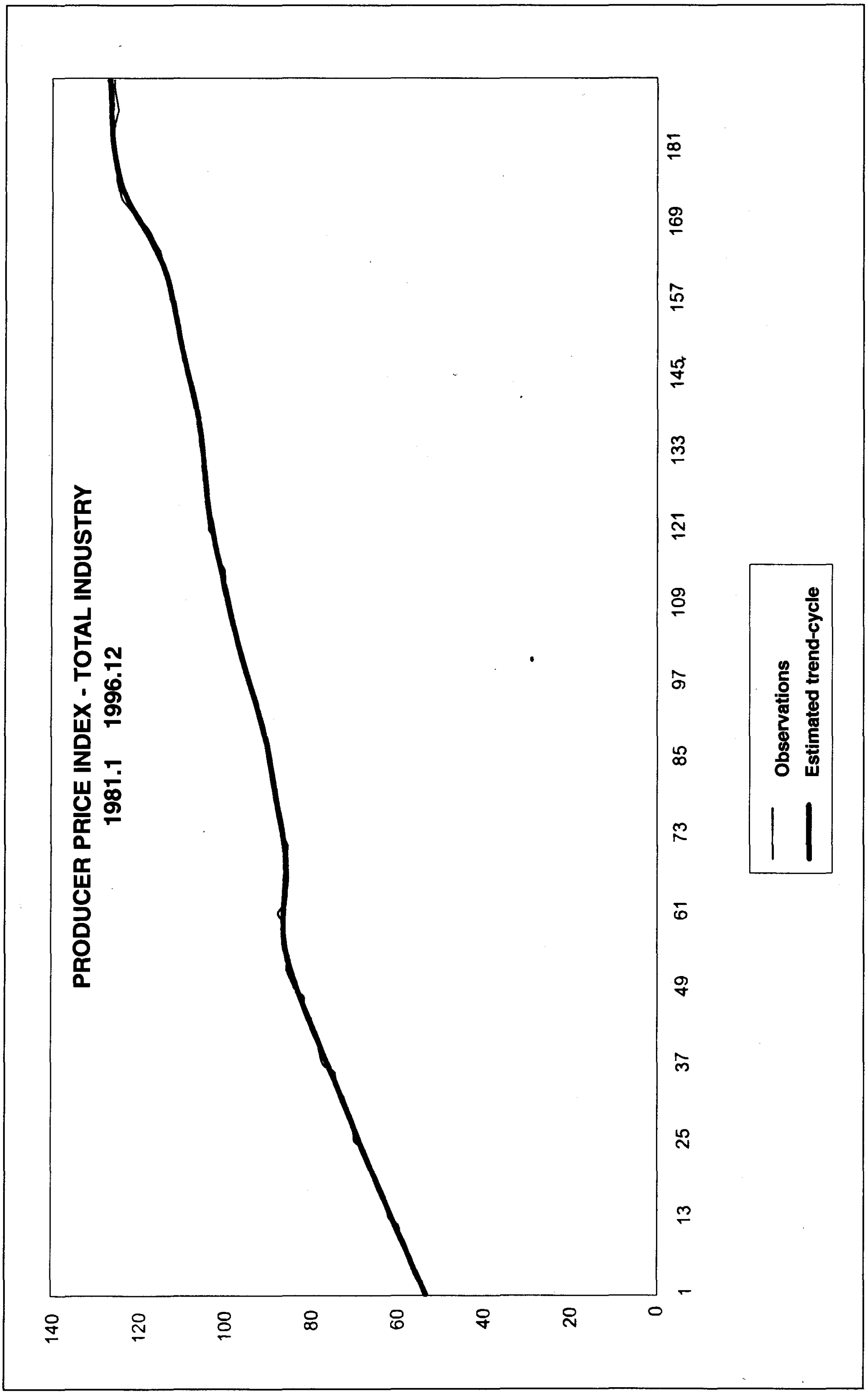
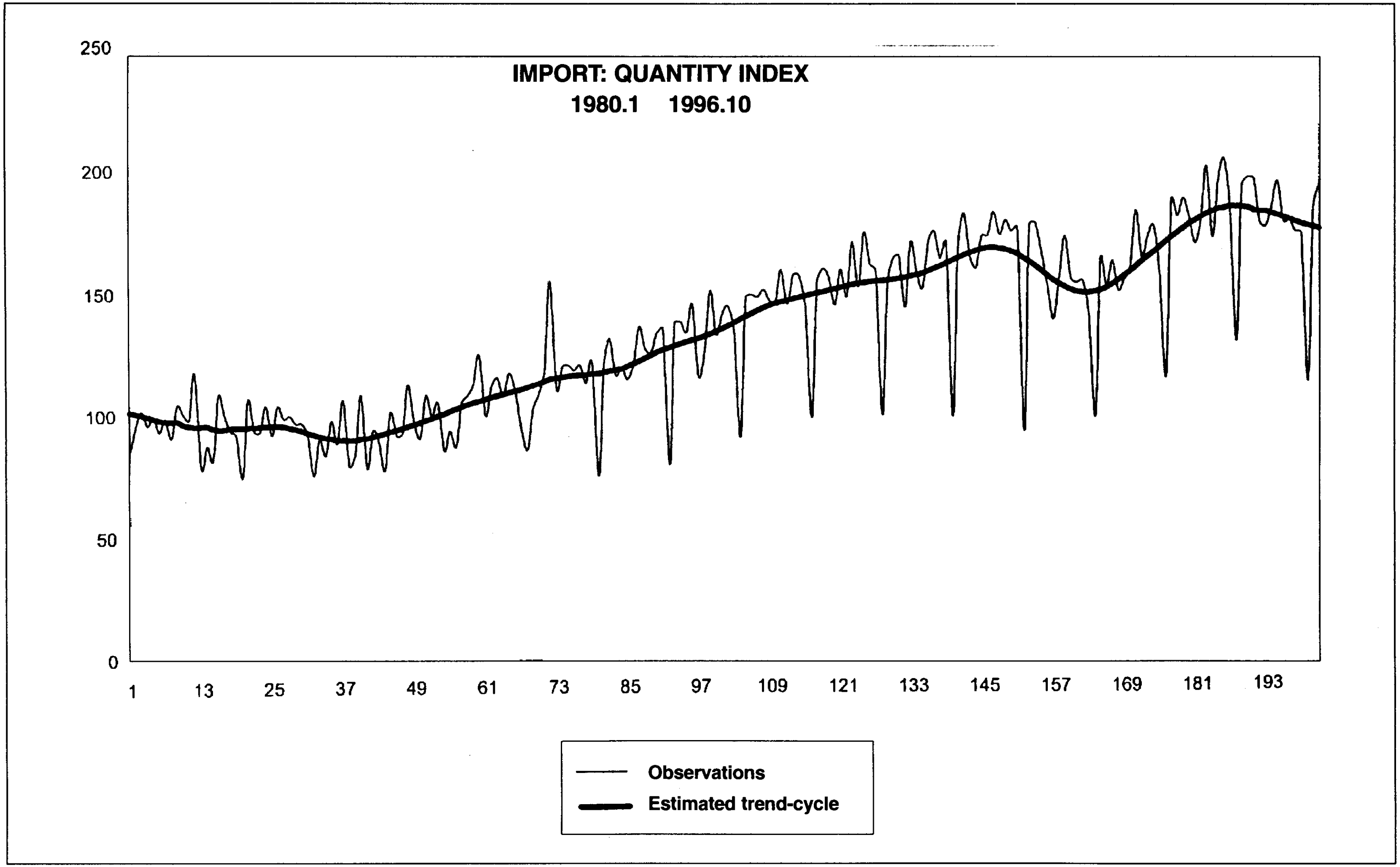
SEPT
OCT
NOV
DEC

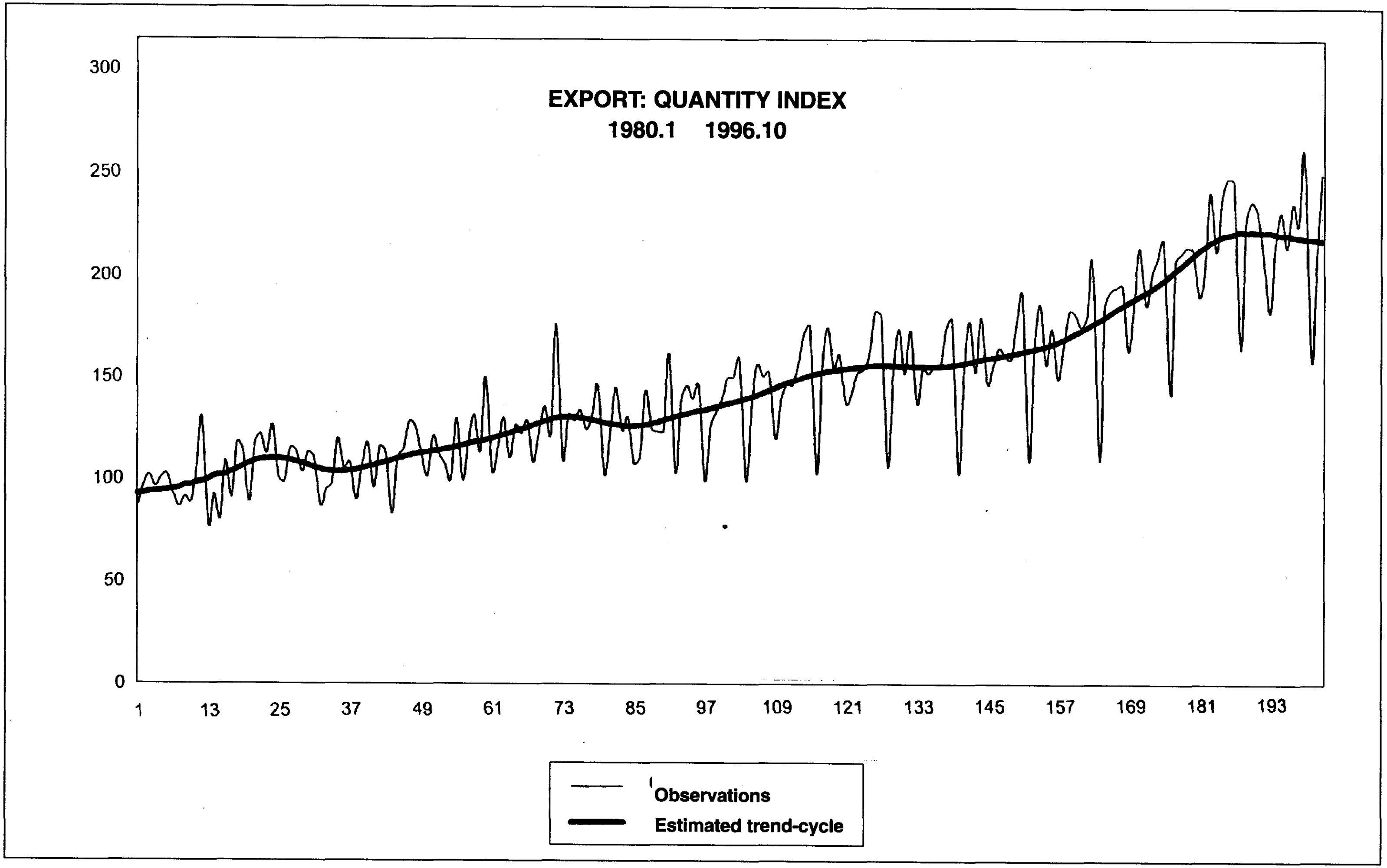

INDEX OF INDUSTRIAL PRODUCTION - INVESTMENT GOODS
1981.1 1996.12
Observations
Estimated trend-cycle
0
20
40
60
80
100
120
140
1
13
25
37
49
61
73
85
97
109
121
133
145
157
169
181

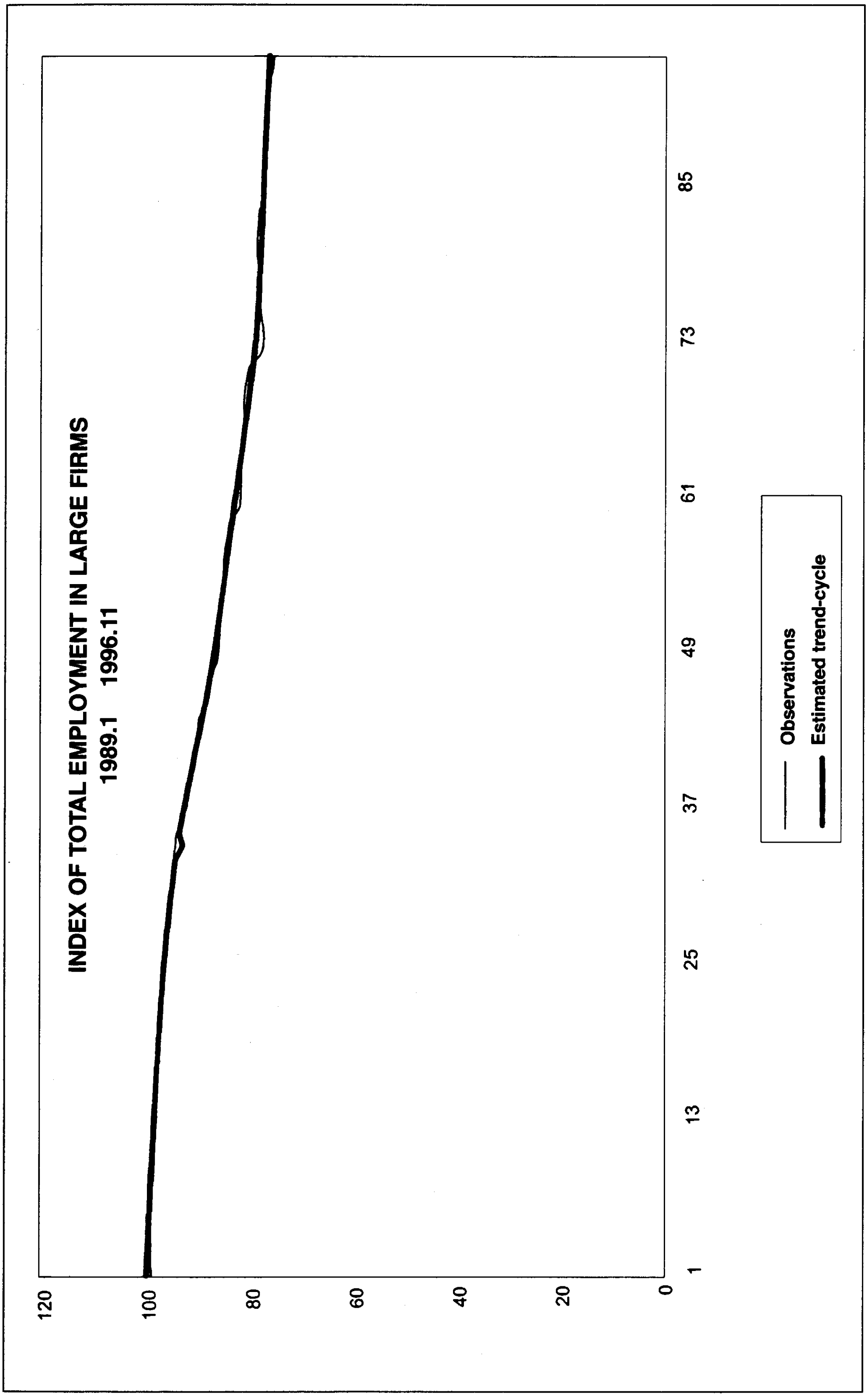

CONSUMER PRICE INDEX - GOODS
1989.1 1996.12
120
100
80
60
40
20
0
13
25
37
49
61
73
85
Observations
Estimated trend-cycle

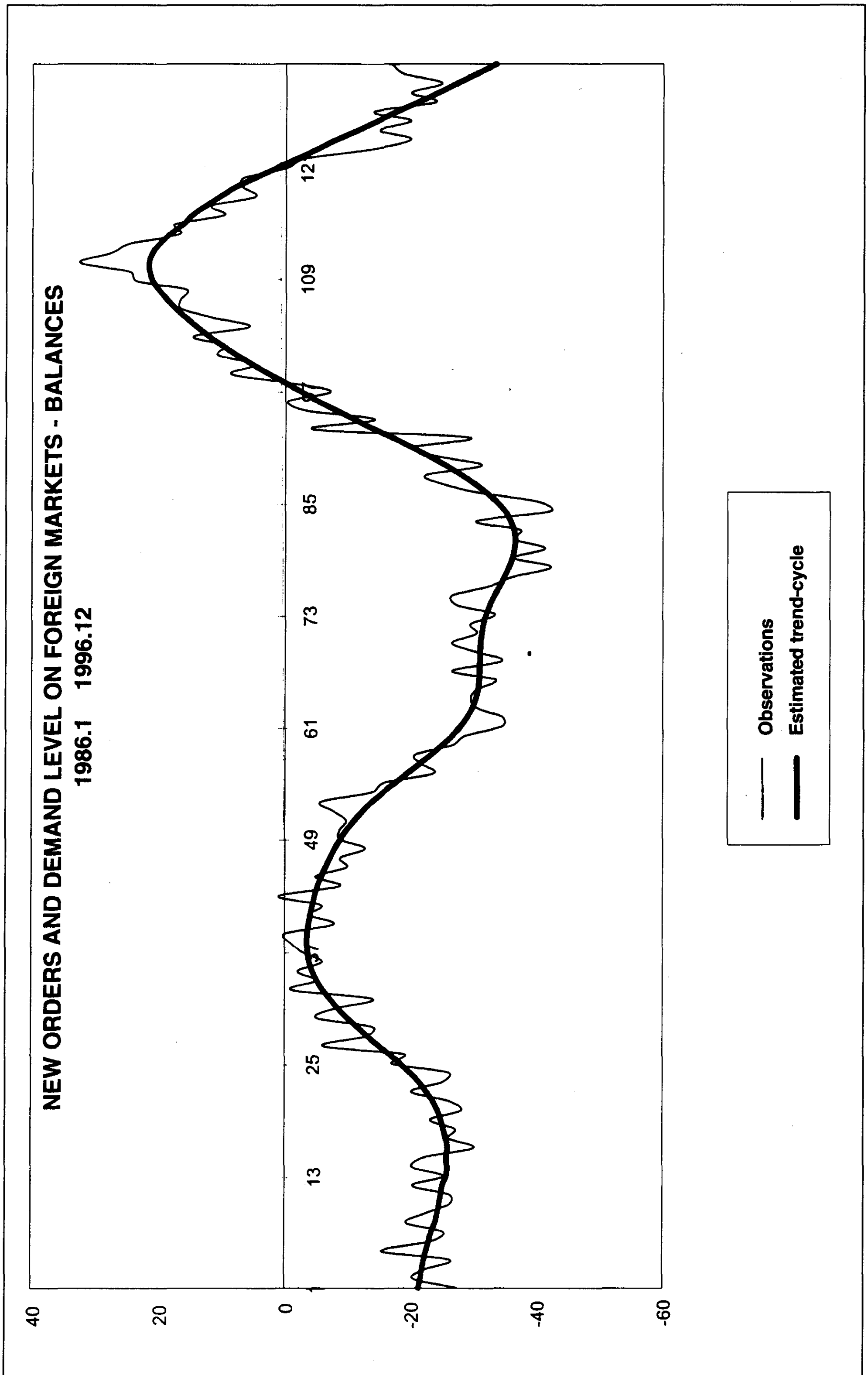


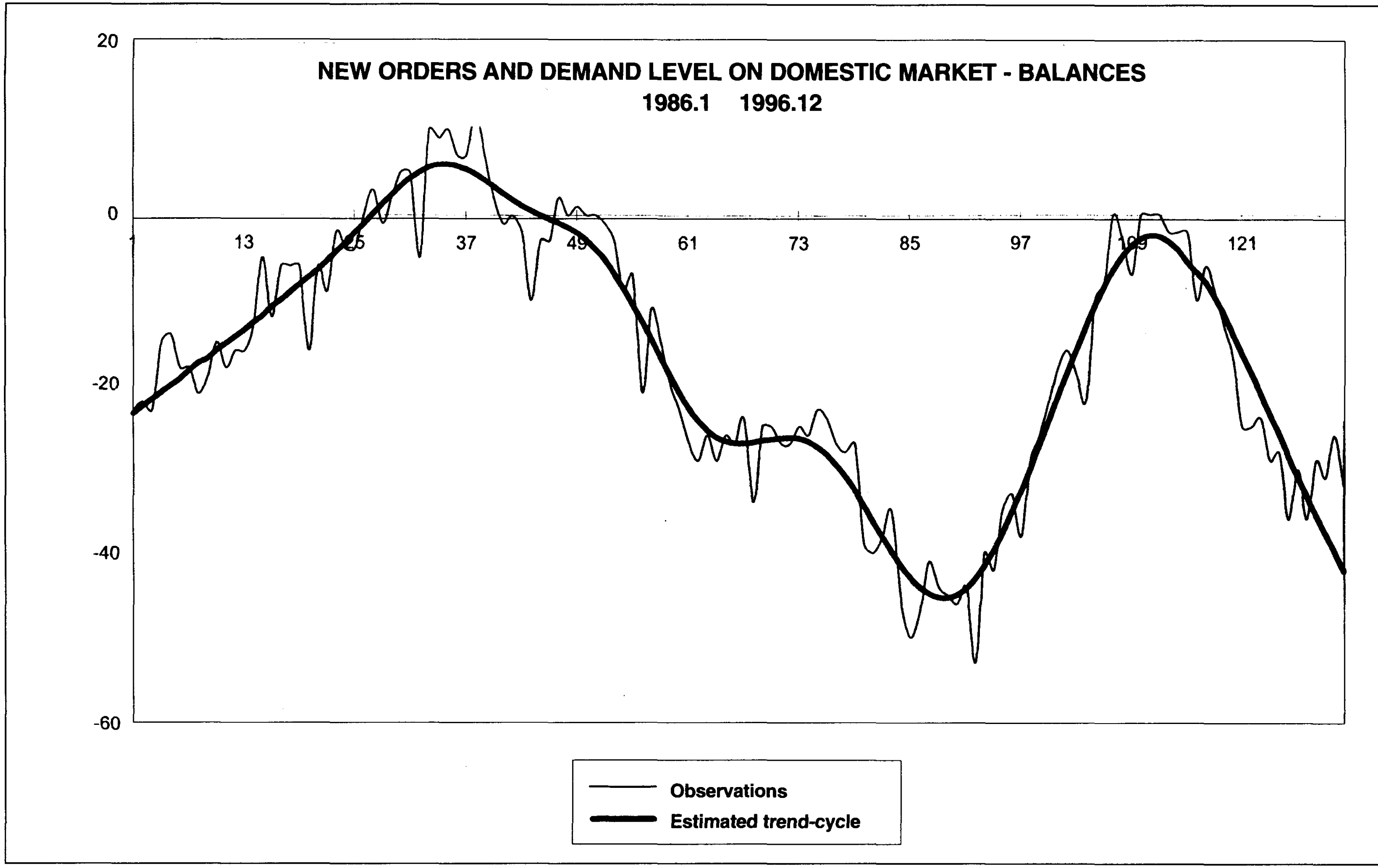
PRODUCER PRICE INDEX - TOTAL INDUSTRY
1981.1 1996.12
140
120
100
80
60
40
20
0
1
13
25
37
49
61
73
85
97
109
121
133
145
157
169
181
Observations
Estimated trend-cycle


IMPORT: QUANTITY INDEX
1980.1 1996.10
250
200
150
100
50
0
1
13
25
37
49
61
73
85
97
109
121
133
145
157
169
181
193
Observations
Estimated trend-cycle


EXPORT: QUANTITY INDEX
1980.1 1996.10
300
250
200
150
100
50
0
1
13
25
37
49
61
73
85
97
109
121
133
145
157
169
181
193
Observations
Estimated trend-cycle


INDEX OF TOTAL EMPLOYMENT IN LARGE FIRMS
1989.1 1996.11
Observations
Estimated trend-cycle
0
20
40
60
80
100
120
1
13
25
37
49
61
73
85


NEW ORDERS AND DEMAND LEVEL ON FOREIGN MARKETS - BALANCES
1986.1 1996.12
40
20
0
-20
-40
-60
13
25
49
61
73
85
109
Observations
Estimated trend-cycle


NEW ORDERS AND DEMAND LEVEL ON DOMESTIC MARKET - BALANCES
1986.1 1996.12
20
0
-20
-40
-60
1
13
25
37
49
61
73
85
97
109
121
Observations
Estimated trend-cycle

TIME SERIES DECOMPOSITION AND SEASONAL ADJUSTMENT

George C. Tiao

University of Chicago, U.S.A.

1. Introduction

Economic time series often exhibit a strong seasonal behavior. It is a common practice to remove the seasonal pattern from the data, as this may make it easier to study the 'underlying' trend movement. In this report, we present a brief discussion of two approaches to seasonal adjustment of economic time series: an empirically developed filtering method used by the U. S. Bureau of the Census, Findley et al (1998); and an ARIMA-model-based canonical decomposition method, Hillmer and Tiao (1982) and Maravall (1995). For a discussion of issues in seasonal adjustment, see Bell and Hillmer (1984).

2. The Bureau of the Census Method

Conceptually, an observable time series D_t can be written as the sum

$$Z_t = D_t + R_t, \qquad (1)$$

where D_t represents the aggregate of deterministic components including trading day effect, holiday effect, interventions, outliers and other special effects, and R_t represents the aggregate of random components such as trend cycle movement, evolving seasonal patterns, and irregular noise. The deterministic components can be modeled via linear and nonlinear regressions. The random term R_t is typically expressed as the sum of a stochastic seasonal component S_t, a stochastic trend component T_t , and a noise component N_t:

$$R_t = S_t + T_t + N_t, \qquad (2)$$

The key problem is to estimate the seasonal component S_t and subtract it from the data to get the "seasonally adjusted" series.

The additive X-11 version of the census procedure, Shiskin et al (1967), employs specific symmetric moving filters of the form

$$x_t = MZ_t,$$
$$M = \delta_0 + \delta_1 (B + F) + ... + \delta_k(B^k + F^k), \tag{3}$$

where B is the backward shift operator such that $BZ_t = Z_{t-1}$ and $F = B^{-1}$ is the forward shift operator, to estimate the S_t, T_t, and N_t components,

$$\hat{S}_t = M^{(S)}Z_t,\ \hat{T}_t = M^{(T)}Z_t,\ \hat{N}_t = Z_t - \hat{S}_t - \hat{T}_t \tag{4}$$

This method has been used widely by government and industry and found to produce sensible result. Details of $(M^{(S)}, M^{(T)})$ can be found in Findley et al (1998).

3. A Model for the X-11 Procedure

The strength and weakness of the X-11 procedure lies in its use of roughly the same filters for most series. Such a procedure seemingly has the advantage of uniform interpretation of the seasonal and trend components of most series. On the other hand, if we believe that observed phenomena are generated according to the physical mechanisms of the problem, then we could certainly be misled by the results of the procedure when no checks on its adequacy are performed. Such checks would, however, be difficult to make unless one had some ideas as to the underlying stochastic mechanisms for which the X-11 method would be appropriate. In Cleveland and Tiao (1976), an unobserved component model of the following form is postulated:

$$Z_t = S_t + T_t + N_t \tag{5}$$

where

$$(1-B)^2 T_t = (1 - \eta_1 B - \eta_2 B^2) b_t$$
$$(1 - B^{12}) S_t = (1 - \delta_1 B^{12} - \delta_2 B^{24}) c_t$$

(b_t, c_t, N_t) independent Gaussian noise with variances $(\sigma_b^2, \sigma_c^2, \sigma_N^2)$.

They have found that, for the specific choice of parameter values

$$(\eta_1 = -.49, \eta_2 = .49); \quad (\delta_1 = -.64, \delta_2 = -.83)$$
$$\frac{\sigma_c^2}{\sigma_b^2} = 1.3; \quad \frac{\sigma_N^2}{\sigma_b^2} = 14.4 \tag{6}$$

the conditional expectations of S_t and T_t are very close to the census filters, i. e.

$$\tilde{T}_t = E(T_t|Z) \cong \hat{T}_t \text{ and } \tilde{S}_t = E(S_t|Z) \cong \hat{S}_t \tag{7}$$

where Z represents the entire series $\{Z_t\}$. Thus, we have an unobserved component model for approximating the X-11 filters. From this unobserved component model, the overall (or reduced form) model for Z_t is, approximately,

$$\begin{aligned}(1-B)(1-B^{12})Z_t &= (1-.34B+.14B^2+.14B^3+.14B^4+.14B^5+.13B^6+.13B^7 \\ &\quad +.12B^8+.11B^9+.09B^{10}+.08B^{11}-.42B^{12}+.23B^{13})a_t\,,\end{aligned} \tag{8}$$

where a_t is Gaussian white noise with variance σ_a^2,
which is 'close' to the model for the famous 'airline data' of Box and Jenkins (1970). The implication of this result is that a series obeying the above overall model or at least of the form

$$(1-B)(1-B^{12})Z_t = \theta(B)a_t, \tag{9}$$

where $\theta(B)$ is a polynomial in B, may be adequately analyzed using the census X-11 procedure. On the other hand, if the overall model of a series $\{Z_t\}$ is found to be vastly different from (9), then the appropriateness of the census decomposition procedure will be in doubt. Thus, the reduced form model in (8), which can be built and identified from the data, provides a useful partial check of the appropriateness of the X-11 procedure.

4. A Model Based Approach, Identification and Canonical Decomposition

In contrast to employing empirically developed fixed filters (with options) to estimate the seasonal and trend components, a model based approach specifies the stochastic structure of the observable time series and its unobserved seasonal, trend and other components. These unobserved components are then estimated in the context of the model specified. Such a model based approach for seasonal adjustment has the following features:

- all the assumptions about the model are made explicit,
- inferences about the components can be readily deduced,
- appropriateness of the assumptions can be at least partially checked.

On the other hand, like many unobserved component models proposed in the literature, see e.g. the state space or structural models proposed by Harvey (1989), this formulation runs immediately into the problem of 'identification'. This is because only the overall (reduced form) model can be identified from the data and there can be more than one choice of component models leading to the same overall model.

To illustrate the nature of the problem, consider the simpler case of a two-component model, Tiao and Hillmer (1978),

$$Z_t = T_t + N_t \tag{10}$$

where N_t is Gaussian white noise independent of T_t. Let $f_x(\omega)$, $0 \leq \omega \leq \pi$, be the spectrum of the process $\{x_t\}$. Clearly,

$$f_z(\omega) = f_T(\omega) + \sigma_N^2. \tag{11}$$

If the models of T_t and N_t are known, we can deduce the corresponding overall model for Z_t. On the other hand, if only the overall model for Z_t is known, any choice of σ_N^2 in the range

$$0 \leq \sigma_N^2 \leq \bar{\sigma}_N^2 \tag{12}$$

where $\bar{\sigma}_N^2 = \min_\omega f_z(\omega)$ gives an acceptable decomposition, and this is because

$$f_T(\omega) = f_z(\omega) - \sigma_N^2 \geq 0. \tag{13}$$

The decomposition $Z_t = \bar{T}_t + \bar{N}_t$ corresponding to the coice

$$\bar{\sigma}_N^2, \text{ and } f_{\bar{T}}(\omega) = f_z(\omega) - \bar{\sigma}_N^2 \tag{14}$$

is called the *canonical decomposition.*

As an example, consider the monthly inflation rate of U.S. CPI from Jan. 1964 to Dec. 1972 shown in Figure 1 (Box, Hillmer and Tiao, 1978). The overall model is found to be

$$\begin{aligned}(1 - B)Z_t &= (1 - \theta B)a_t \\ \theta = .84; &\quad \sigma_a^2 = .0019\end{aligned} \tag{15}$$

This implies that the model for T_t must be of the form

$$(1 - B)T_t = (1 - \eta B)b_t \tag{16}$$

and

$$(1 - \theta B)(1 - \theta F)\sigma_a^2 = (1 - \eta B)(1 - \eta F)\sigma_b^2 + (1 - B)(1 - F)\sigma_N^2. \tag{17}$$

Any choice of $(\eta, \sigma_b^2, \sigma_N^2)$ satisfying (17) is an acceptable decomposition. The estimate of T_t is

$$\tilde{T}_t = \left\{1 - \alpha \frac{(1-B)(1-F)}{(1-\theta B)(1-\theta F)}\right\} Z_t, \alpha = \frac{\sigma_N^2}{\sigma_a^2}. \tag{18}$$

The canonical decomposition corresponds to

$$\bar{\sigma}_N^2 = \frac{(1+\theta)^2}{4}\sigma_a^2, \quad \eta = -1, \quad \bar{\sigma}_b^2 = \frac{(1-\theta)^2}{4}\sigma_a^2, \quad \bar{\alpha} = \frac{(1+\theta)^2}{4} = .846 \tag{19}$$

Figure 1 shows the original data Z_t corresponding to $\sigma^2_{N}= 0$, the estimated trend component $\tilde{T}_t$ and noise component $\tilde{N}_t = Z_t - \tilde{T}_t$ for various values of α and η. Also shown are the weights in estimating T_t. We can make the following observations: Given the overall model,

- the canonical decomposition yields the most deterministic trend component;
- it attributes the largest possible variance to the noise component;
- the popular choice in the econometrics literature, $\eta = 0$, gives an estimated trend component very close to that from the canonical decomposition;
- all other trend estimates from acceptable decompositions are of equal claim; and
- thus for this data set the trend component is clearly not 'robust' over the entire range of acceptable decompositions.

This model-based approach has been extended in Hillmer and Tiao (1982) to an additive seasonal, trend, and noise decomposition,

$$
\begin{aligned}
&Z_t = S_t + T_t + N_t \\
&(1 - B)^d T_t = \eta(B) b_t, \quad U(B)S_t = \delta(B) c_t \qquad (20) \\
&U(B) = 1 + B + \cdots B^{s-1},
\end{aligned}
$$

where s is the period and $\eta(B)$ and $\delta(B)$ are polynomials in B, consistent with an overall model for Z_t of the form

$$(1 - B)^d U(B) Z_t = \theta(B) a_t \qquad (21)$$

It is shown that canonical decomposition yields the most 'deterministic' evolving stochastic seasonal and trend components. See the examples in Hillmer, Bell and Tiao (1983) and in the next section.

5. The X-12-ARIMA and the TRAMO/SEATS Programs

We now turn to a brief discussion of the X-12-ARIMA and the TRAMO/SEATS seasonal decomposition programs with two illustrative examples. Generally speaking, these two programs have many similarities:

- each consists of two main parts: a regression-ARIMA modeling program and a decomposition program;
- the regression-ARIMA features are very close, both taking into account trading day, holiday, interventions and other special effects, and employing an iterative outlier and level shift detection procedure of the kind proposed in Chang, Tiao and Chen(1988);
- the two decomposition programs are built on different foundations: X-12 retains the structure of the X-11-ARIMA, Dagum (1980), essentially an empirically developed fixed filter procedure, while SEATS is a model based procedure closely related to canonical decomposition;

- for many economic time series, the decomposition results from these two programs are again very close. This is not too surprising since the X-11 procedure and the 'airline model' are closely related.

For illustration, we consider two examples.

The monthly air-passenger-miles data (Jan. 1960 - Dec. 1977)

This data set was considered in Chen et al (1990), and is shown in Figure 2(a). We have first used the automatic modeling capability of the SCA software, X-12-ARIMA and TRAMO to model the data and to detect outliers, temporary changes and level shifts. All three programs arrive at the 'airline model'

$$(1-B)(1-B^{12})Z_t = (1-\theta B)(1-\Theta B^{12})a_t \tag{22}$$

and obtain essentially the same estimation and detection results. See Table 1. For this example, the effect of outliers is appreciable. Figure 2(b) and 2(c) show, respectively, the residual series $\hat{a}_t$, before and after adjustment of the outlier effects. Turning now to seasonal adjustment, Figure 3(a) gives the seasonally adjusted series from X-12-ARIMA, and Figure 3(b) presents the corresponding series from SEATS. We see that for this example, the two procedures are in close agreement.

Table 1 – Estimation Results for the Monthly Logged Air-passenger-miles Data (Jan. 1960– Dec. 1977)

Parameter	SCA	X-12-ARIMA	TRAMO
$\hat{\theta}$	.509(.062)*	.486(.061)	.414(.064)
$\hat{\Theta}$	.496(.060)	.411(.062)	.435(.066)
$\hat{\sigma}_a$	.0332	.0288	.0329
Outlier	**SCA**	**X-12-ARIMA**	**TRAMO**
1961.Feb(14)		-.154(.022) AO	-.153(.024) AO
1962.Jul(31)	-.097(.026) TC	-.092(.022) TC	
1966.Jul(79)	-.388(.027) TC	-.389(.023) TC	-.388(.026) TC
1966.Aug(80)	-.119(.029) TC	-.119(.024) TC	-.119(.027) TC
1966.Sep(81)	.266(.027) TC	.267(.023) TC	.266(.026) TC
1967.Mar(87)	.094(.025) AO	.096(.021) AO	.100(.023) AO
1970.Jan(121)	.312(.025) LS	.313(.021) LS	.313(.025) LS
1970.Apr(124)	-.102(.025) AO	-.102(.021) AO	-.100(.023) AO
1970.Oct(130)	-.090(.025) LS	-.089(.021) LS	
1975.Apr(184)	-.087(.025) AO	-.086(.021) AO	

* standard error of estimates

The monthly logged index of industrial turnover-foreign market (Jan. 1985 - Dec. 1996)

This data set was provided by the Istat, and is shown in Figure 4(a). For automatic modeling and outlier detection, X-12-ARIMA does not specify a model, and

TRAMO produces results that are somewhat different from those of SCA. The model covering both cases is

$$(1-\phi_1 B-\phi_2 B^2)(1-\Phi B^{12})(1-B)(1-B^{12})Z_t=(1-\Theta B^{12})a_t, \qquad (23)$$

and the detailed estimation results are given in Table 2 (where we have used the TRAMO model for X-12-ARIMA). The effect of outliers is not as pronounced as in the previous example, but still noticeable as can be seen from Figures 4(b) and 4(c). For seasonally adjusted series, Figure 5(a) gives the results from X-12-ARIMA and Figure 5(b), that from SEATS. Although the overall estimation results from the two approaches are nearly identical, canonical decomposition does produce a much smoother seasonally adjusted series.

Table 2 – Estimation Results for the Monthly Logged Index of Industrial Turnover – Foreign Market (Jan. 1985 – Dec. 1996)

Parameter	SCA	TRAMO	X-12-ARIMA
$\hat{\phi}_1$	-.725(.074)*	-.801(.073)	-.801(.071)
$\hat{\phi}_2$	-.564(.078)	-.560(.077)	-.560(.072)
$\hat{\Phi}$	-.196(.090)	N/A	N/A
$\hat{\Theta}$	N/A	.654(.085)	.657(.071)
$\hat{\sigma}_a$	.0442	.0492	.0485
Outlier	**SCA**	**TRAMO**	**X-12-ARIMA**
1988.Aug(44)	.165(.044) IO		
1992.Aug(92)	-.172(.029) AO	-.179(.038) AO	-.179(.037) AO
1993.Feb(98)	.095(.026) TC		
1995.Sep(129)	-.156(.044) O		

* standard error of estimates

6. Forecasting Unobserved Trend and Seasonal Components

Before concluding this report, it is of interest to discuss briefly the problem of predicting future values of the unobserved components. This is often mentioned as a goal of seasonal adjustment. As stated earlier, an advantage of the model based approach is that one can readily make inferences about the unobserved components from the data in the context of the specified model.

Consider first the simple case

$$Z_t = T_t + N_t \qquad (24)$$
$$(1-B)Z_t=(1-\theta B)a_t$$

discussed earlier. We see in (18) that the estimate $\tilde{T}_t$ of T_t depends on the variance ratio α.

Suppose we have available data through time t_0, i.e. $Z = (Z_{t_0}, Z_{t_0-1}, Z_{t_0-2}, \ldots)$, Then, it is readily seen that

$$\tilde{T}_{t_0} = Z_{t_0} - \alpha a_{t_0} \qquad (25)$$

which is the estimate of the current 'signal' T_{t_0}. For predicting future values of T_t, we have that

$$\tilde{T}_{t_0+\lambda} = \hat{Z}_{t_0}(\lambda) = \hat{Z}_{to}(\lambda),\ \lambda = 1,2,3... \tag{26}$$

where $\hat{Z}_{t_0}(\lambda)$ is the usual λ-step ahead forecast of the observation $Z_{t_0+\lambda}$ made at time t_0, independent of α. Thus, the point forecast of $T_{t_0+\lambda}$ is the same as the forecast of the future observation $Z_{t_0} + \lambda$, irrespective of the value of α. Thus, while the component T_t is not identifiable, the forecast is the same for all α. Also, for this model forecasts for all future periods are the same. It should be noted that the variance of the prediction error, $T_{t_0+\lambda} - \tilde{T}_{t_0+\lambda}$, will of course, depend on α.

Consider next the case

$$\begin{aligned} (1-B^s)Z_t &= (1-\Theta B^s)a_t \\ Z_t &= S_t + T_t + N_t \end{aligned} \tag{27}$$

it is readily seen that

$$\begin{aligned} \tilde{T}_{t_0+\lambda} &= [\hat{Z}_{t_0}(1) + ... + \hat{Z}_{t_0}(s)]/s \\ \tilde{S}_{t_0+\lambda} &= \hat{Z}_{t_0}(\lambda) - [\hat{Z}_{t_0}(1) + ... + \hat{Z}_{t_0}(s)]/s \end{aligned} \tag{28}$$

which is a natural decomposition of the forecasting function $\hat{Z}_{t_0}(\lambda)$ for the overall model of Z_t.

We see from these two examples that, if the goal of the decomposition is to forecast future values of the unobserved components, we can simply decompose the forecast function for the overall model to get the optimum point forecasts. This is a feature that seems to merit further investigation. See Box, Pierce and Newbold (1987).

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APPENDIX

– Figures

Figure 1 – Some possible decompositions into Trends and Noise: consumer price index example

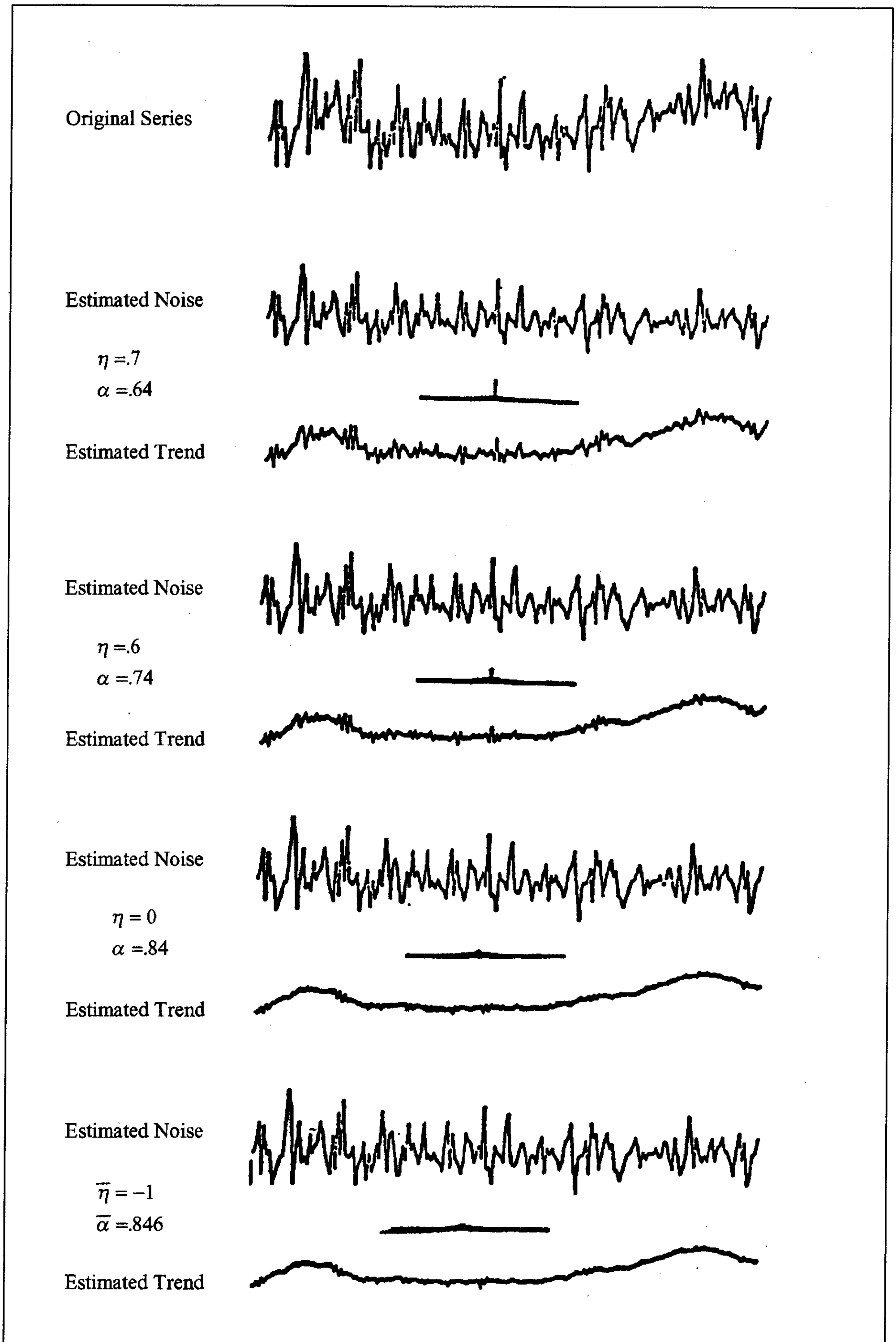
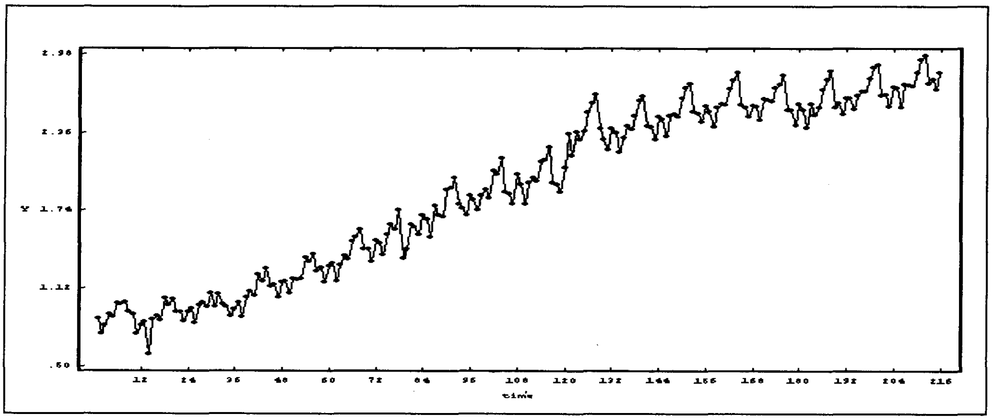
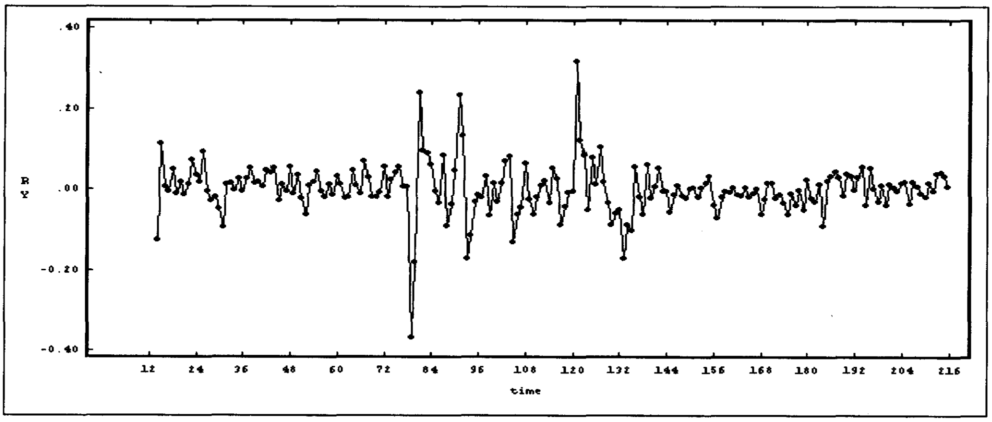


Figure 2.
(a) The Monthly Air-Passenger-Miles Data (Jan. 1960- Dec. 1977)



(b) Residuals Before Outlier Adjustment



(c) Residuals After Outlier Adjustment

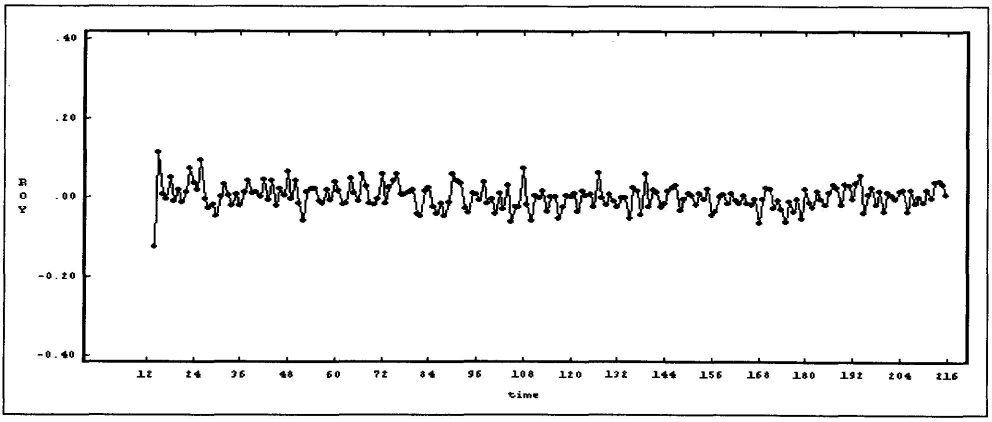
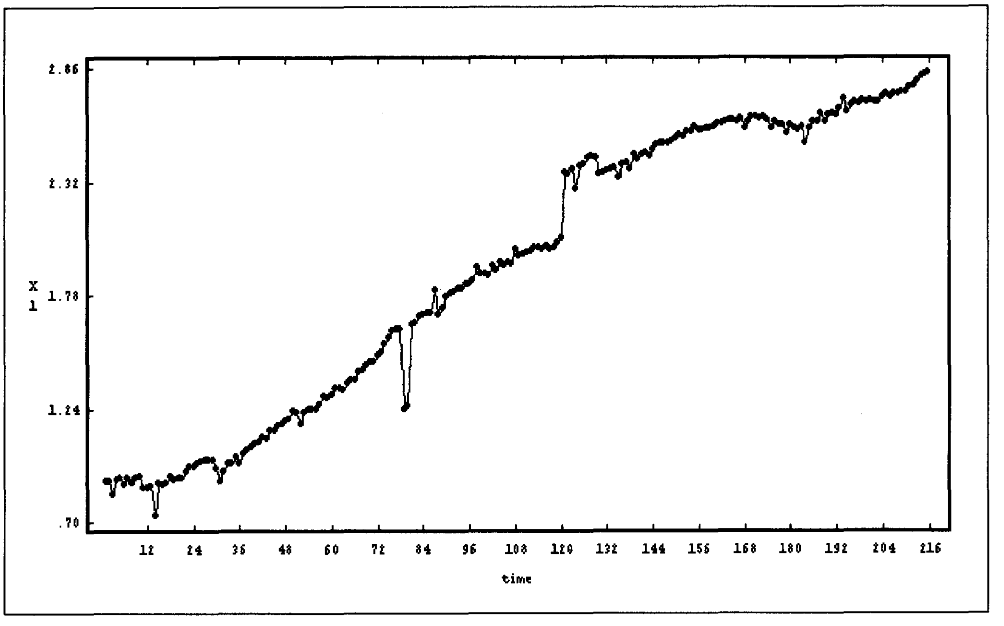


Figure 3 – Trend Estimates for the Air-Passenger-Miles Data
(a) X-12-ARIMA



(b) SEATS

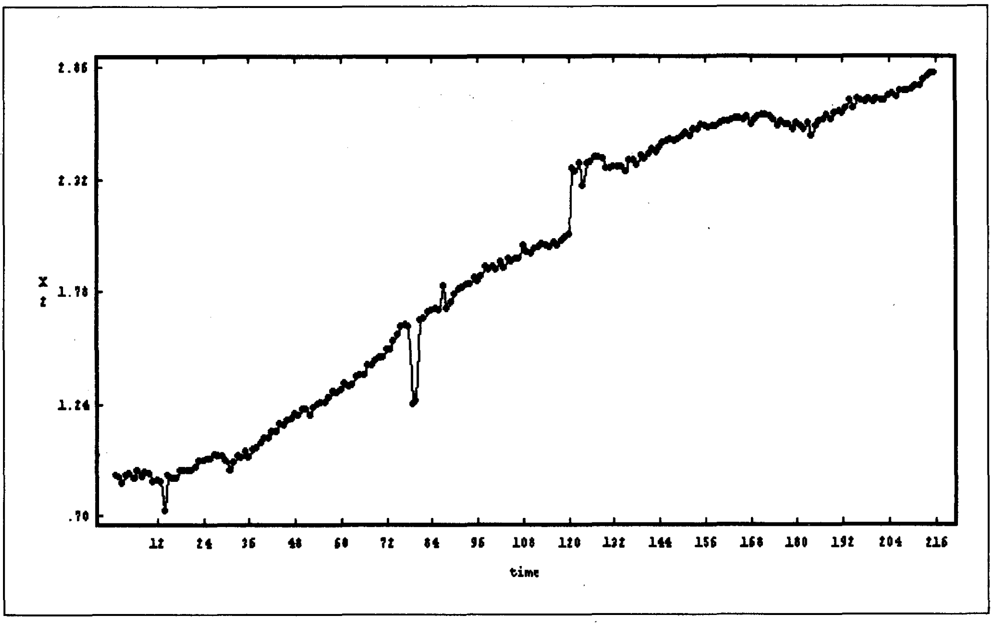
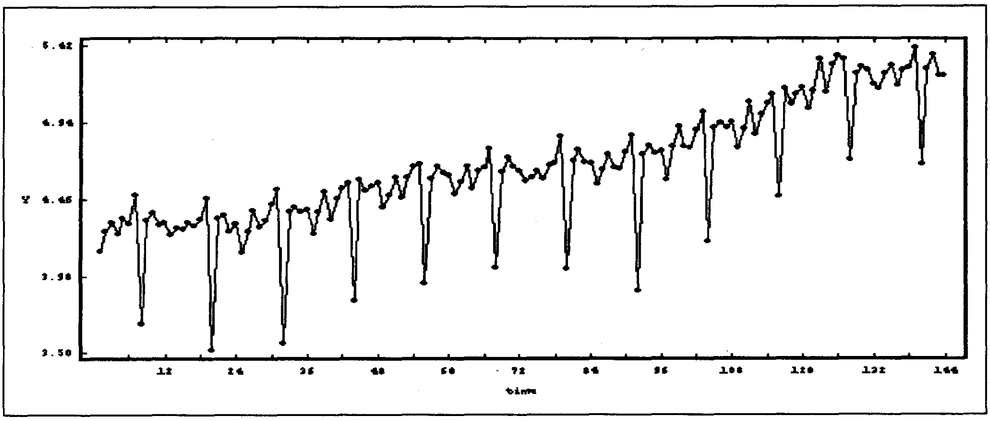
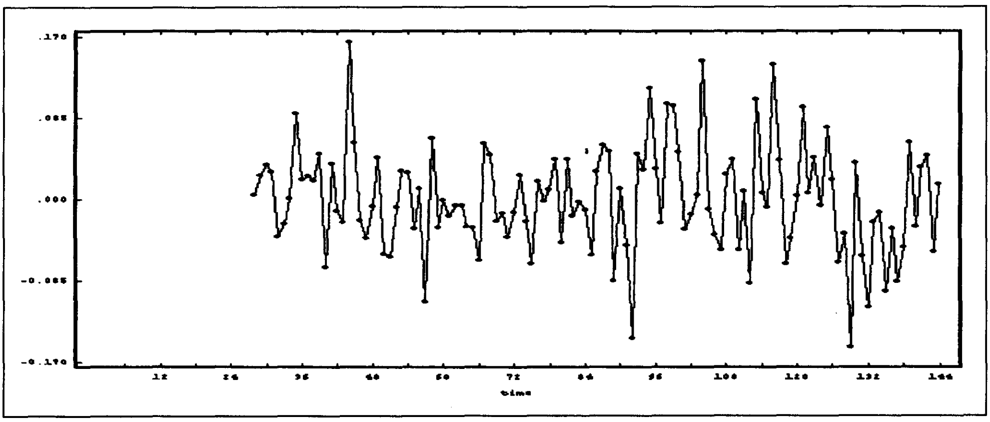


Figure 4.
(a) The Monthly Logged Index of Industrial Turnover – Foreign Market (Jan. 1985 – Dec. 1996)



(b) Residuals Before Outlier Adjustment



(c) Residuals After Outlier Adjustment

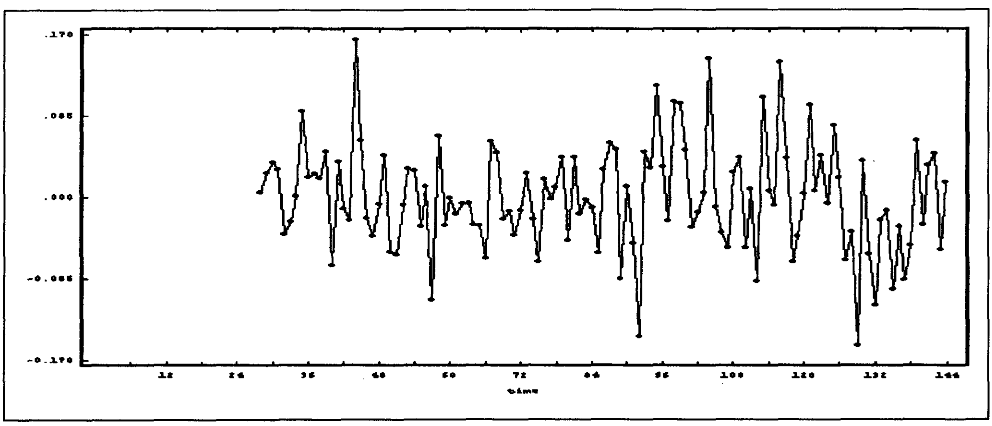
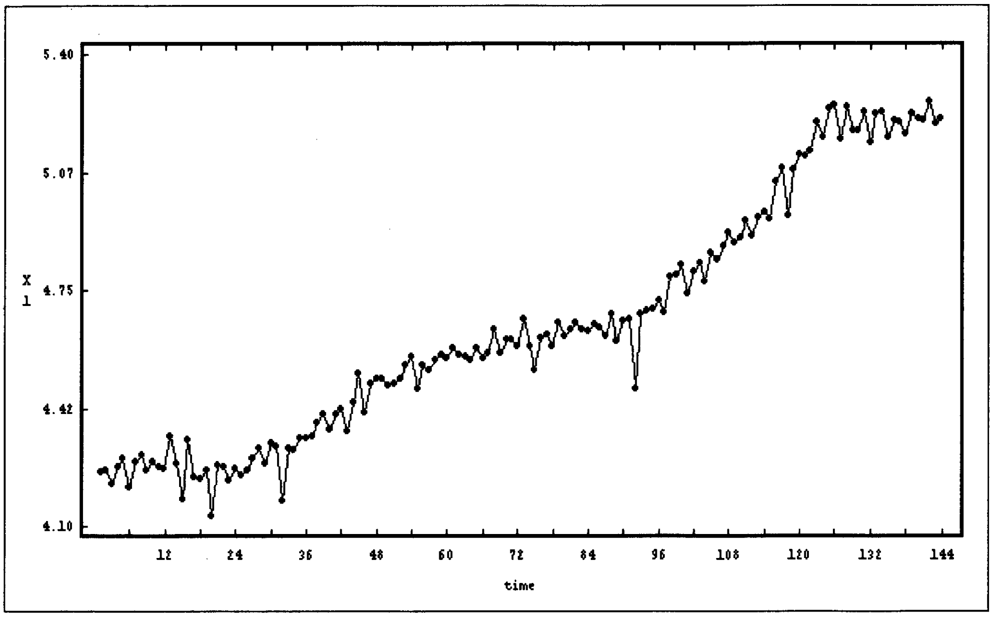
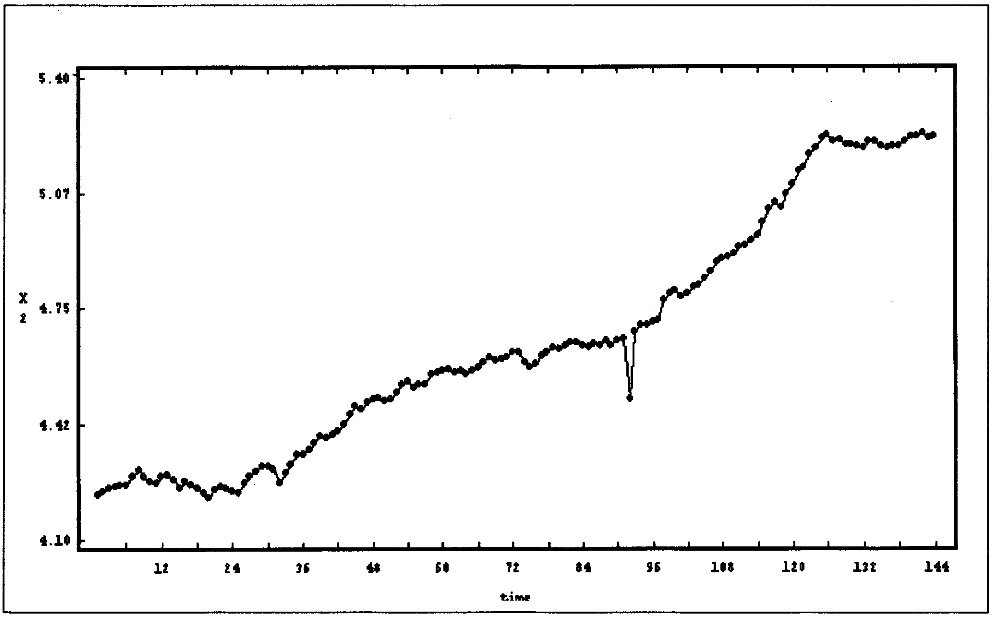


Figure 5 – Trend Estimates for the Industrial Turnover Index
(a) X-12-ARIMA



(b) SEATS



X-12-ARIMA AND ITS APPLICATION TO SOME ITALIAN INDICATOR SERIES

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1. Introduction and Overview

X-12-ARIMA is the Census Bureau's new seasonal adjustment program. It belongs to the methodological lineage of the Census Bureau's X-11 program (Shiskin, 1967) and Statistics Canada's X-11-ARIMA and X-11-ARIMA/88 (Dagum, 1988) programs. These methods estimate seasonality mainly by applying moving average filters to a possibly modified version of the input series. The modifications might include adjustments for extreme values, trading day effects, or holiday effects also estimated by the program. The filters are chosen from a fixed set of filters, partially or—in X-11-ARIMA/88 and X-12-ARIMA, possibly completely—automatically, on the basis of certain signal-to-noise ratios. See also U.S. Bureau of the Census (1998).

The major improvements of X-12-ARIMA fall into four general categories: 1) new modeling capabilities using regARIMA models—regression models with ARIMA errors—for estimating other calendar or disturbance effects with built-in or user-defined regressors; 2) new diagnostics for modeling, model selection, adjustment stability, and for the quality of indirect as well as direct seasonal adjustment; 3) additional capabilities to make it easier to adjust large numbers of series and determine which have problematic adjustments; and 4) a new user interface. The article by Findley, Monsell, Bell, Otto, and Chen (1998) gives a detailed overview.

At times, we will compare the results from X-12-ARIMA to results from the programs TRAMO (Time series Regression with ARIMA noise, Missing observations, and Outliers) and SEATS (Signal Extraction in ARIMA Time Series) by Gomez and Maravall (1997a, 1997b). These are linked programs for seasonally adjusting time series using ARIMA-model-based signal extraction techniques.

We begin by discussing the diagnostics used in this article to judge the quality of the X-12-ARIMA adjustment. We will then present some results from the default runs of both X-12-ARIMA and TRAMO/SEATS. Then we will discuss some of the options in X-12-ARIMA that helped us deal with the problems we found in the series. We will contrast the available diagnostics and the available options in X-12-ARIMA with the diagnostics and options available in TRAMO/SEATS.

2. Methods

2.1 Running X-12-ARIMA

In a situation in which the number of series being adjusted is small enough that there is time to give individual attention to each series, our basic procedure for running X-12-ARIMA is the following:

Step 1. Graph the series.
Step 2. Run the program in default mode on an appropriate span of the series determined by Step 1.
Step 3. Assess the adjustment and model obtained from Step 2 using available diagnostics from the program and graphs to look for deficiencies.
Step 4. Correct problems, when necessary and possible, using the available options.

We do not do Step 4 for all series, only for series with adjustment problems that are found in Step 3.

Specifically, for the 11 Italian indicator series, the steps involved the following:

Step 1. Graph the Series

Before we ran either X-12-ARIMA or TRAMO/SEATS, we graphed the series to look for visible problems with the series. Such problems can include abrupt changes in the seasonal pattern or obvious outliers. Changes in the seasonal pattern that occur sufficiently far back in the past can be avoided simply by advancing the starting date of the data used for adjustment or for modeling. Also, it is often clear from the graph that multiplicative adjustment is (or is not) appropriate, in which case a logarithmic transformation should (or should not) be used for modeling. (If, for example, there are zero or negative values, the log transform and multiplicative adjustment are not possible.)

Step 2. Run in Default Mode

For the 11 series considered in the paper, about which we had no information, we had X-12-ARIMA do a single run to

- test if the log transformation should be used and a multiplicative adjustment performed;
- search for additive outliers, level shifts, and temporary change outliers;

- search for an acceptable ARIMA model among those found in x12a.mdl (the default model file):
  - (0 1 1)(0 1 1)
  - (0 1 2)(0 1 1)
  - (2 1 0)(0 1 1)
  - (0 2 2)(0 1 1)
  - (2 1 2)(0 1 1)

- test for possible trading day effects (using six regression variables to get a coefficient for all seven days of the week, after a length of month correction for February);
- test for possible Easter effects (over the periods beginning one, eight, and 15 days before Easter and ending the day before Easter. If we had had more information about the Easter effect in Italy, we might have had the program test a different interval, say the six days before Easter);
- run the default seasonal adjustment procedure (which uses the automatic seasonal filter selection procedure of X-11-ARIMA/88);
- if the series is long enough, calculate a stability diagnostic, either sliding spans or a history of revisions. (The sliding spans might not be easy to interpret if the seasonal adjustment mode is additive or the seasonal factors are small.)

An example .spc file for such a run is:

```
series{
  name="PPI"
  start=1981.1
  period=12
  file="ppigengp.dat"
  title="Producer Price Index (Default Run)"
}
transform{function=auto}
regression{aictest=(td easter)}
automdl{savelog=amd}
estimate{ }
check{print=all}
outlier{types=all}
forecast{maxlead=24  print=none}
x11{savelog= (m7 q2 fd8 msf) }
history{estimates= (sadj sadjchng) print=all}
```

Step 3. Assess the Adjustment

X-12-ARIMA diagnostics include the following:

- spectral plots (Cleveland and Devlin, 1980) to reveal residual seasonal or trading day effects,

- the M and Q statistics (Lothian and Morry, 1972) to indicate properties of the adjustment that are often associated with adjustments of poor quality, and
- two kinds of stability diagnostics
  - sliding spans (Findley, Monsell, Shulman, and Pugh, 1990)
  - and revision histories (Findley, Monsell, Bell, Otto, and Chen, 1998).

The most basic analysis of X-12-ARIMA runs consists of looking at the M statistics and their summary Q statistic and noting warning messages produced by the program regarding residual trading day and seasonal peaks in the seasonally adjusted series or the irregular.

Important graphical diagnostics can be obtained from X-12-Graph (Hood, 1998), a companion graphics package for X-12-ARIMA. Using X-12-Graph, we can produce graphs of the original series with the seasonally adjusted series and the trend, graphs of the seasonal factors by month, and, if the series is long enough, graphs of the revisions of the initial (concurrent) adjustments for the last few years.

For the indicator series, using X-12-Graph, we also looked at seasonal factor by calendar month graphs (to look for excessive movements of the seasonal factors), plots of revisions to the level and month-to-month changes, and SI ratio plots (Cleveland and Terpenning, 1982). The SI ratio plots show, for each calendar month and all years, the detrended series (SI ratios and replacement values for extreme SI ratios) and the seasonal factors. As we will illustrate below, unusually large numbers of replacement values for a specific calendar month is an indicator of calendar-month-specific heteroskedasticity, the situation in which some calendar months have more statistical variability than the other calendar months, as measured by the calendar month variances of the irregular series.

Step 4. Correct Problems

We followed these interlocked steps to correct problems:

a. Review the choice of transformation.
b. Review the ARIMA model selection and decide on a provisional model.
c. Review choices concerning trading day (TD) and Easter effect adjustment.
d. Review choices of outliers.
e. Select a "final" model.
f. Review X-11 options.

Details of these six steps are given below.

Step 4a. Review the Choice for Transformation

In X-12-ARIMA, if the series values are all positive and *transform=auto* is used in the *transform* spec, the series is log transformed unless, for an indicated model, the AIC of model fit to the untransformed data is smaller by at least 2.0 than the AIC obtained from fitting the model to the log transformed data. Since we did not specify a model with the *arima* (and *regression)* specs, the program uses the first model in *x12a.mdl*, by default, the airline model.

Step 4b. Review the ARIMA model selection and select a preliminary model

In some cases, the automatic identification procedure in X-12-ARIMA rejects all of the candidate models as being inadequate for the purpose of forecast extension. In this case it chooses a designated model, by default, the airline model, to provide regARIMA estimation of regression coefficients or selection of regressors, but not forecasts. We looked for messages in the *automdl* output (or the *.log* file) to find series for which no forecasting model was identified. For these series, we looked at model diagnostics to help us seek a better model. Sometimes, these diagnostics also suggest that the model selected for forecasting by *automdl* can be improved. For example, the values of some of the selected model's coefficients can be insignificant, or they can suggest a cancellation of AR and MA factors to simplify the model. Alternatively, the autocorrelation graphs, the suite of P-values for the Box-Ljung Q's, or the spectrum of the model's residuals can suggest that it is necessary to change the model from the one selected.

Step 4c. Review choices for trading day and Easter effects

X-12-ARIMA prints out warnings if there are residual trading day peaks in the spectra either of the model residuals, the adjusted series, or the irregular series. Sometimes trading day peaks are found, even after trading day adjustment has been done, or after the *aictest* in *regression* rejects the trading day regression model tested. We then consider alternative trading day models or reducing the number of regressors in the tested model by fixing the values of very insignificant coefficients at zero. We also use AIC histories and forecast error history diagnostics to compare various choices of TD and Easter regressors when there is some doubt about the choice.

Step 4d. Review choices of outliers

We look at the list in the *.out* file of rejected outlier regressors whose t-statistics have magnitudes that are rather large even though they are below the critical value chosen. This can help us identify a need to lower the critical value. We also look for series with too many outliers, indicating a problem with the model or the critical value we used.

Step 4e. Select a final model

Once we complete Steps 4a-4d, we run the program again with the new model. If no unfavorable diagnostics occur, we accept the model. Otherwise we repeat Steps 4a-4e, possibly fitting the models to a data span with a different starting date, until good diagnostics are obtained or no further improvements seem possible.

Step 4f. Review X-11 options

The X-11 diagnostics we examine include the F statistics for stable seasonality and moving seasonality (associated with Table D8) and the M and Q statistics found in Table F3. To look for calendar-month heteroskedasticity, one can look at the X-11 values identified as extreme in Table C17 and at the SI ratios graphs to determine if there was a need to change the sigma limits used to identify X-11 extreme values. Alternatively, one can use the *calendarsigma=all* option of the *x11* spec to produce sample standard deviations for the irregulars of each calendar month.

2.2 Running TRAMO/SEATS

For the TRAMO/SEATS runs, we used the same data spans chosen for the adjustment by X-12-ARIMA. The results we present for TRAMO/SEATS will be from default runs, although we will make a comment about results obtained from option choices kindly provided to us by Agustin Maravall after the ISTAT conference for which this paper was prepared.

TRAMO/SEATS has an option, called RSA, for "routine treatment of perhaps a very large number of series." (Gomez and Maravall, 1997a) We used the RSA parameter set equal to six. This allows TRAMO/SEATS to

- test for a possible log transformation,
- search for additive outliers, level shifts, and temporary change outliers
- search for an ARIMA model with
  - regular differences up to and including order 2,
  - seasonal differences up to and including order 1,
  - regular polynomials up to and including order 3, and
  - seasonal polynomials up to and including order 1.
- replace the model in SEATS when the model chosen by TRAMO does not have an admissible decomposition
- test for possible trading day effects (using six regression variables to get a coefficient for all seven days of the week)
- test for possible Easter effects (for six days before Easter)

3. Results for the Indicator Series

By visual inspection, we found that the eleven series exhibit three different categories of seasonal movements: three series are very smooth, six are strongly seasonal, and two give the visual impression of being erratically seasonal, perhaps because of large movements in their trends. In the tables that follow, the series are grouped by these three categories.

3.1 Finding a good data span for modeling or adjustment

For six of the eleven series, we shortened the span of data used for the adjustment. For four series, this was decision based on a change of seasonal pattern seen in the graph of the original series. In the case of the two erratically seasonal series, omitting the first year of data for modeling gave much better Box-Ljung Q-statistics. For the four strongly seasonal series whose movements are dominated by large troughs in August, as part of our visual inspection, we also looked at graphs of the series obtained by replacing August values with the averages of the neighboring July and September values. In this way, we obtained a graph in which the movements of all months had a similar size.

The example below shows a series with a change in the seasonal pattern beginning in January 1986. For seasonal adjustment, we used only the data span beginning in January1986.

Figure 1 – Graph of Original Series with a Change in the Seasonal Pattern

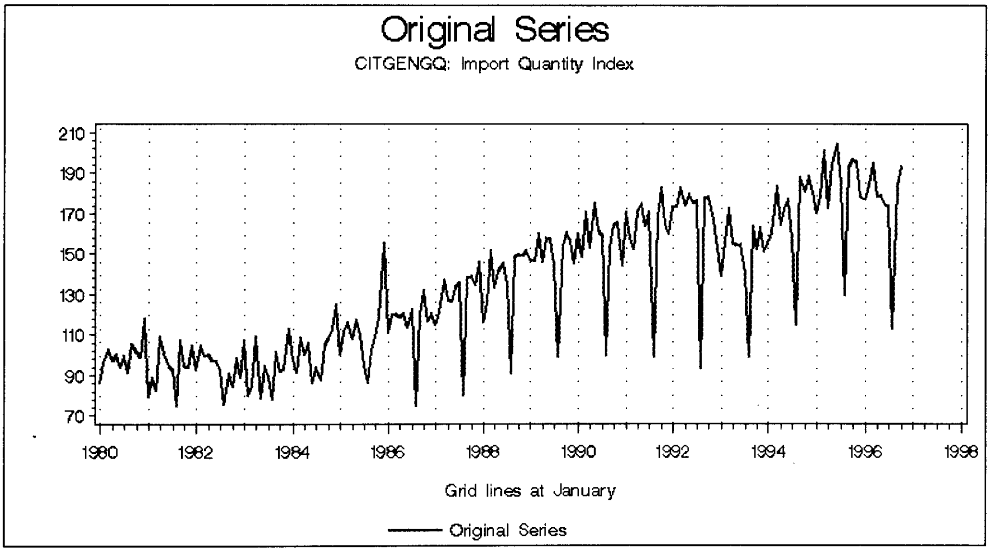


Table 1 below lists all eleven series with both the starting date for each series as it was given to us and the starting date we used for the *span* or *modelspan* option in the *series* spec.

3.2 Running in default

In X-12-ARIMA's default transformation selection scheme, the log transformation is chosen (multiplicative adjustment instead of additive adustment) unless AIC for specified regARIMA model fit to the untransformed data is smaller by at least 2.0 than the AIC for the same model fit to the log-transformed data. Because we did not specify a model, the program used the airline model, the first model in the default model list file (*x12a.mdl*). For some series for which the choice of the transformation seemed ambiguous, we also looked at the AIC and forecast error history statistics for both transformation possibilities.

Table 1 – Series Names and Original and Chosen Starting Dates

Name	Original Starting Date	Chosen Starting Date
Smooth series		
LGOLTOGI: Index of Total Employment in Large Firms	1989	1989
PCOBENGP: Consumer Price Index, Goods	1989	1989
PPIGENGP: Producer Price Index, Total Industry	1981	1981
Strongly seasonal series		
CETGENGQ: Export Quantity Index	1980	1986
CITGENGQ: Import Quantity Index	1980	1986
IFAGENGE: Index of Industrial Turnover, Foreign	1985	1985
IFAGENGN: Index of Industrial Turnover, Domestic	1985	1985
IPIGENGT: Index of Industrial Production, Total	1981	1983
IPIINVGT: Index of Industrial Production, Investment Goods	1981	1983
Erratically seasonal series		
BDEGENGS: Balances of New Orders on Foreign Markets	1986	1987
BDIGENGS: Balances of New Orders on Domestic Markets	1986	1987

For two series (CETGENGQ and CITGENGQ) the choice of transformation differed from our visual impression, so we also looked at the AIC and forecast error history diagnostics. This enabled us to investigate the consistency of the AIC choice, and whether log transformation resulted in better out-of-sample forecasts than no transformation. For both series we chose no transformation. Table 2 shows the transformation choices of X-12-ARIMA and TRAMO.

Table 2 – Transformation Choices of X-12-ARIMA and TRAMO

Name	X-12-ARIMA	TRAMO
Smooth series		
LGOLTOGI: Index of Total Employment in Large Firms	Add	Add
PCOBENGP: Consumer Price Index, Goods	Add	Add
PPIGENGP: Producer Price Index, Total Industry	Add	Log
Strongly seasonal series		
CETGENGQ: Export Quantity Index	Add	Log
CITGENGQ: Import Quantity Index	Add	Log
IFAGENGE: Index of Industrial Turnover, Foreign	Log	Log
IFAGENGN: Index of Industrial Turnover, Domestic	Log	Log
IPIGENGT: Index of Industrial Production, Total	Add	Log
IPIINVGT: Index of Industrial Production, Investment Goods	Add	Log
Erratically seasonal series		
BDEGENGS: Balances of New Orders on Foreign Markets	Add	Add
BDIGENGS: Balances of New Orders on Domestic Markets	Add	Add

Table 3 shows the results of automatic model, regressor, and outlier selections. Table 4 shows the final regARIMA models.

Table 3 – Automatic RegARIMA Modeling Selections

Name	Model selected by *automdl*	Regressors chosen by *aictest* and *outlier*
Smooth series		
LGOLTOGI: Index of Total Employment in Large Firms	airline	
PCOBENGP: Consumer Price Index, Goods	(1 1 0)(0 1 1)	
PPIGENGP: Producer Price Index, Total Industry	(2 1 0)(0 1 1)	TD, tc1991.1
Strongly seasonal series		
CETGENGQ: Export Quantity Index	airline	Easter[15]
CITGENGQ: Import Quantity Index	(2 1 0)(0 1 1)	TD, Easter[8], ls1992.12
IFAGENGE: Index of Industrial Turnover, Foreign	airline	TD, Easter[1], ao1992.8
IFAGENGN: Index of Industrial Turnover, Domestic	airline	TD, Easter[8]
IPIGENGT: Index of Industrial Production, Total	airline	TD, Easter[1]
IPIINVGT: Index of Industrial Production, Investment Goods	airline	TD, Easter[8]
Erratically seasonal series		
BDEGENGS: Balances of New Orders on Foreign Markets	airline *	ls1993.9 ls1996.3
BDIGENGS: Balances of New Orders on Domestic Markets	airline *	

* The airline model was used as the default model for regression coefficient estimation. No model was chosen for producing forecasts by *automdl* because of large average absolute percent forecast error in the last three years. (The values of this statistic were distorted by near-zero data, but there are also problematic movements, see Fig. 13)

Table 4 – Final RegARIMA Models

Name	ARIMA Model	Regression Variables
Smooth series		
LGOLTOGI: Index of Total Employment in Large Firms	(1 1 0)(0 1 1)	
PCOBENGP: Consumer Price Index, Goods	(0 1 2)(0 1 1)	
PPIGENGP: Producer Price Index, Total Industry	(2 1 0)	seasonal, Tdstock[31], tc1991.1
Strongly seasonal series		
CETGENGQ: Export Quantity Index	Airline	Tdstock[31], ao1987.3, 1s1987.7 ao1998.1, ao1993.8, ls1995.12
CITGENGQ: Import Quantity Index	Airline	TD, Easter[8], ls1992.12
Strongly seasonal series		
IFAGENGE: Index of Industrial Turnover, Foreign	Airline	TD, Easter[8], ao1992.8
IFAGENGN: Index of Industrial Turnover, Domestic	Airline	TD, Easter[8]
IPIGENGT: Index of Industrial Production, Total	(0 1 1)(1 0 0)	Seasonal, Tdstock[31], Easter[1]
IPIINVGT: Index of Industrial Production, Investment Goods	Airline	TD, Easter[8]
Erratically seasonal series		
BDEGENGS: Balances of New Orders on Foreign Markets	Airline	ls1993.9 ls1996.3
BDIGENGS: Balances of New Orders on Domestic Markets	(4 1 0)(0 1 1)	

3.3 X-12-ARIMA options to improve the adjustments

Problem: Residual Trading Day Peaks in the Spectrum Plots after Trading Day Adjustment
Solution: Stock Trading Day Option

When run in default mode both with X-12-ARIMA and with TRAMO/SEATS, the Export Quantity Index (CETGENGQ) had residual trading day effects in the regression residuals, seasonally-adjusted series, and the irregulars as indicated by the spectra of these series. In default mode, we asked both programs to test for possible trading day effects using six regression variables to obtain coefficients for the seven days of the week. In both X-12-ARIMA and TRAMO/SEATS, the AIC preferred the model with no trading day. (Most, but not all, of the day-of-week coefficients were statistically insignificant.)

Note: The TRAMO/SEATS output gave us no indication that there was a problem with the adjustment. We calculated spectral plots of the TRAMO/SEATS adjustments and irregulars by inputting these series into X-12-ARIMA. (Using only a series spec in the *.spc* file, one can obtain the spectrum of the input series, together with warning messages about visually significant trading day and seasonal peaks in the spectrum.)

By trying all of the types of trading day models of X-12-ARIMA, we found the end-of-month stock trading day model, tdstock[31], gave the best spectrum results (and also the lowest AIC value if we fixed some negligible coefficient values to be zero). Figures 2 and 3 below show the spectrum plot of the irregular series from X-12-ARIMA with no trading day adjustment (Figure 2) and with a stock trading day adjustment (Figure 3).

Figure 2 – Spectrum of the Seasonally-Adjusted Series from X-12-ARIMA for CETGENGQ with No Trading Day Variables

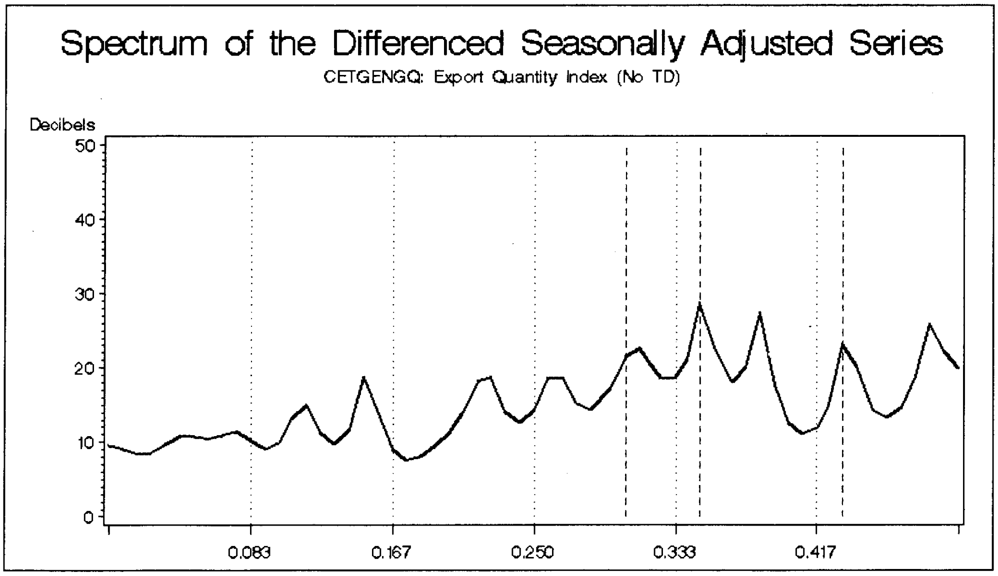
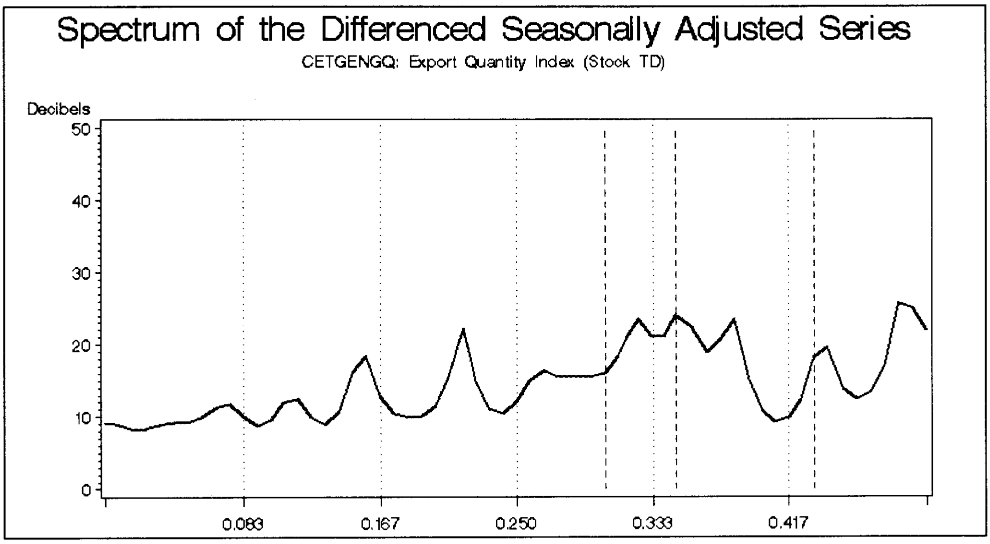


Figure 3 – Spectrum of the Seasonally-Adjusted Series from X-12-ARIMA for CETGENGQ with Stock Trading Day Variables



We used the forecast error histories available via X-12-ARIMA's *history* spec to obtain differences of the accumulating sums of squared forecast errors between the pairs of competing models at forecast leads 1 and 12. We then used X-12-Graph to produce graphs of these accumulating differences. In the graphs below, the direction of the accumulating differences is predominantly downward, especially at lead 12. Thus the forecast errors are persistently smaller for the first model, the regARIMA with Stock TD. Therefore, we prefer the Stock TD adjustment over all other trading day options, including no adjustment. Of course, a model designed by a knowledgeable user could be better.

Figure 4 – Stock TD Versus No TD for CETGENGQ

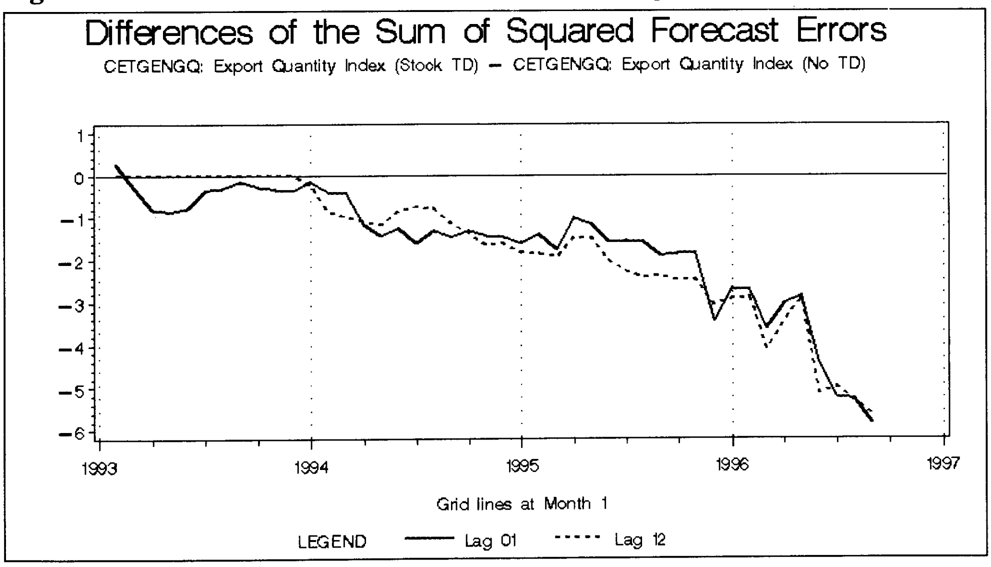


Figure 5 – Stock TD Versus Flow TD for CETGENGQ

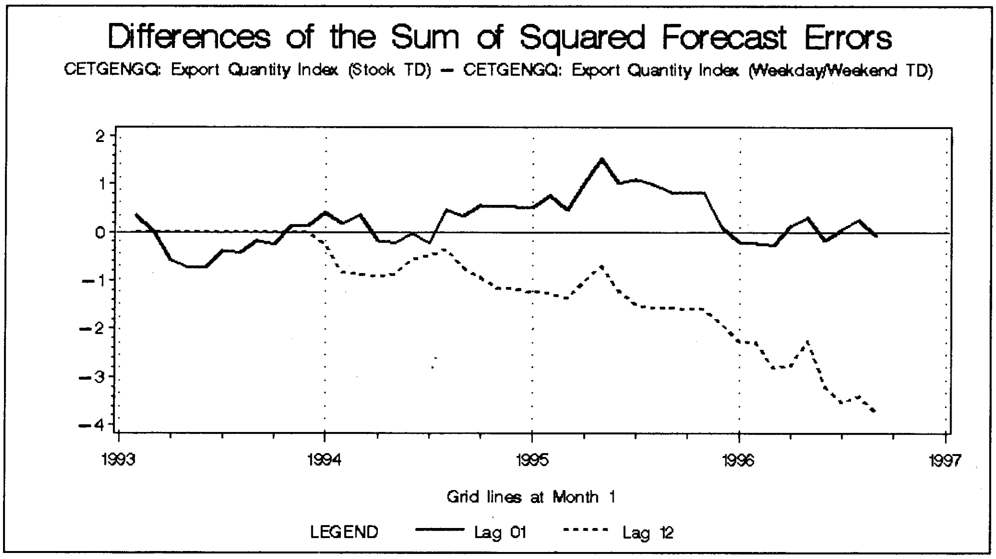
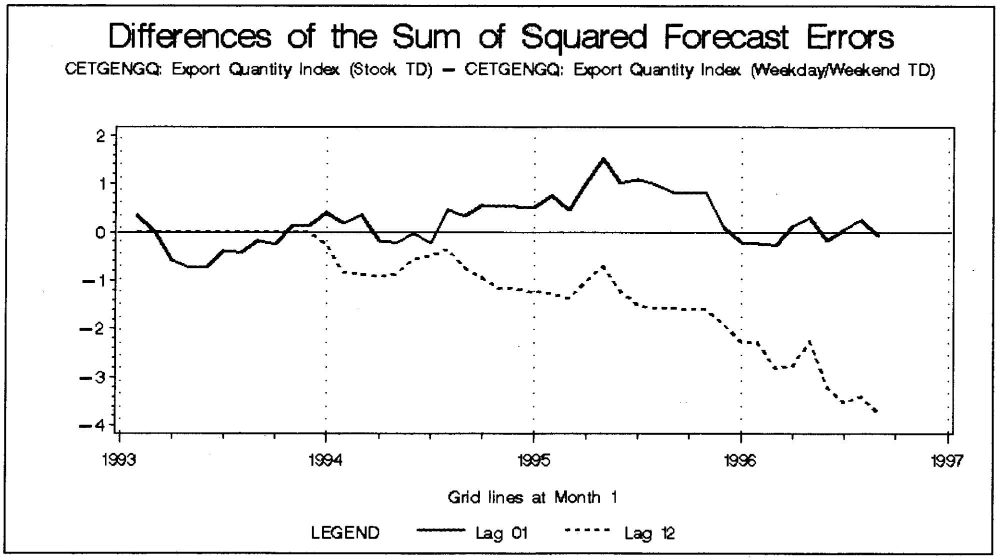


Figure 6 – Stock TD Versus Weekday/Weekend TD for CETGENGQ



Besides eliminating the residual trading day effect in the seasonal adjustment and giving us smaller forecast errors, the adjustment for stock trading day effects also gave us a smoother seasonal adjustment and smaller revisions.

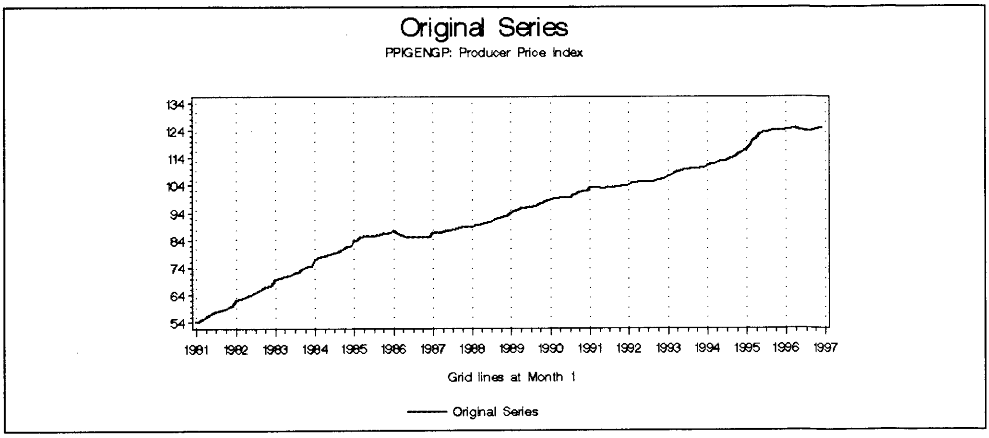
Given a choice between the one-coefficient weekday/weekend trading day model and no trading day model, TRAMO chose the trading day model. TRAMO/SEATS does not have a stock trading day variable.

Problem: Evidence of Heteroskedasticity
Solution: Calendar Sigma and Different Seasonal Moving Average Filters Lengths

For several of the series, we found there was a calendar month with more statistical variability than the other calendar months. We will give two quite different examples of such series: one very smooth series, the Producer Price Index for Total Industry (PPIGENGP); and one very seasonal series, the Index of Industrial Turnover of Domestic Markets (IFAGENGN).

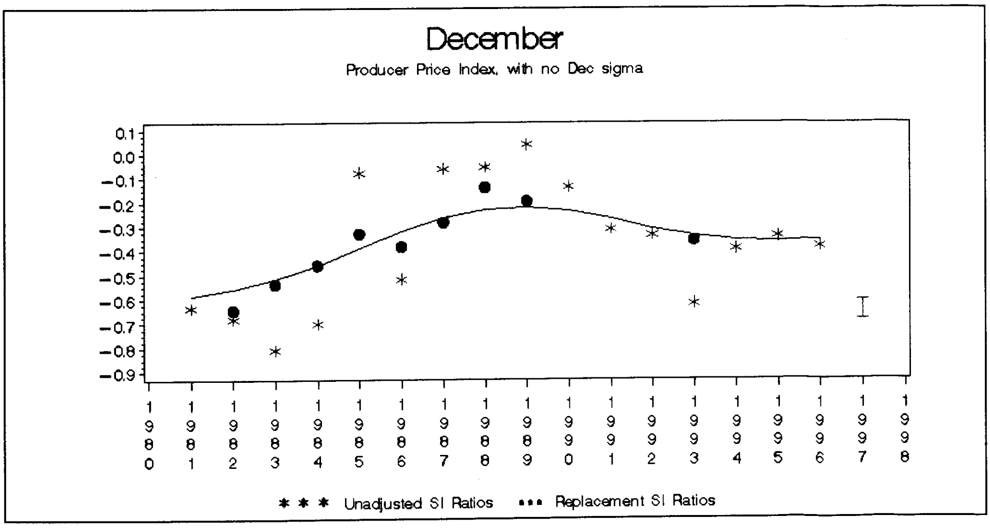
Example 1 – Large number of replacement values in December

Figure 7 – The Producer Price Index for Total Industry (PPIGENGP)



For every adjustment, we looked at the SI Ratios graphs. SI Ratio graphs show the relationship between the detrended series (SI ratios) and the seasonal factors. The replacement values of the SI ratios show the effect of the extreme value adjustment procedure in X-12-ARIMA. For PPIGENGP, we noticed a large number of replacement values for December.

Figure 8 – SI Ratio Graph for December for PPIGENGP



Setting *calendarsigma=all* in the *x11* spec produces a table of standard deviations for each month at the bottom of Table C17. For PPIGENGP, the variance for the Decembers is much higher than for the other months.

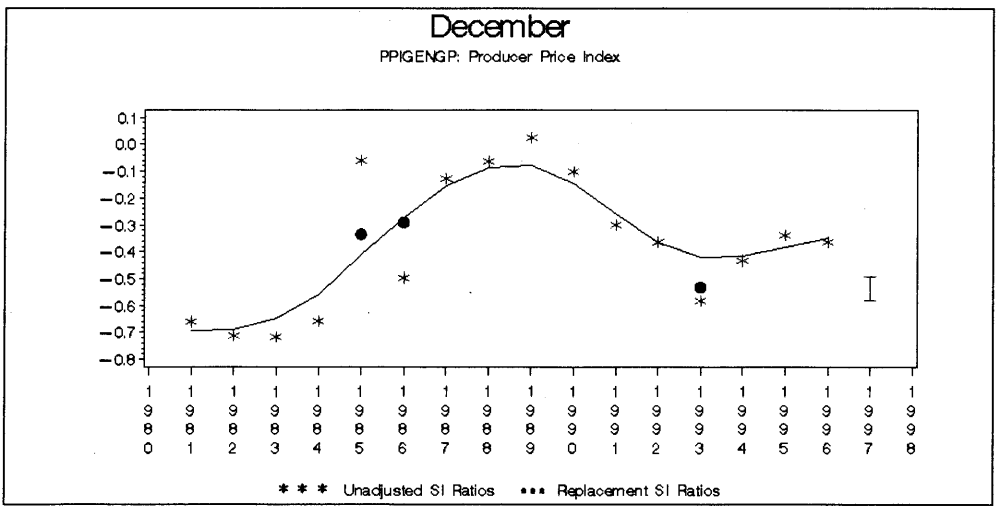
```
C 17  Final weights for irregular component
 From  1981.Jan to 1996.Dec
 Observations          192
 Lower sigma limit    1.5
 Upper sigma limit    2.5
-----------------------------------------------------------------
         Jan       Feb       Mar       Apr       May       Jun
         Jul       Aug       Sep       Oct       Nov       Dec
-----------------------------------------------------------------
 S.D.   8.72      6.01      4.57      5.55      7.83      5.66
        7.86      6.96      5.92      7.04      6.46     10.16
```

So that fewer Decembers are thrown out as outliers, we can change the sigma limits for December only. We do this with *calendersigma=select* option in conjunction with the *sigmavec* option.

```
x11{
  mode=add
  calendarsigma=select
  sigmavec=dec}
```

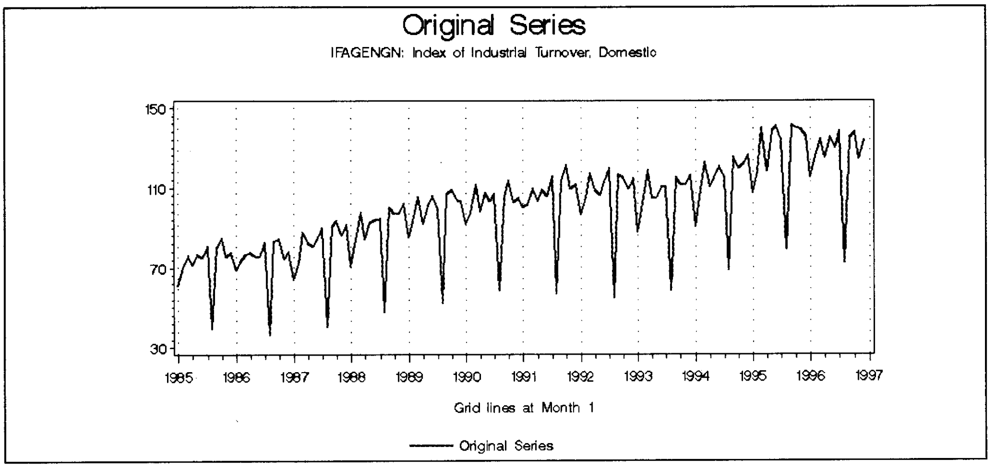
Now fewer December SI's receive extreme value adjustments. As a result, the seasonal factors estimated for Decembers show more movement and the adjustment around the year 1990 is smaller.

Figure 9 – SI Ratio Graph for December with Calendar Sigma for PPIGENGP



Example 2 – Large revisions of August and September adjustments

Figure 10 – The Index of Industrial Turnover for Domestic Markets (IFAGENGN)



First of all, we noticed for this series that the August value of moving seasonality ratios found in Table D9A was very low. A low value is frequently an indication of highly variable seasonal movements that are best estimated with a short seasonal filter.

D 9.A Moving seasonality ratio

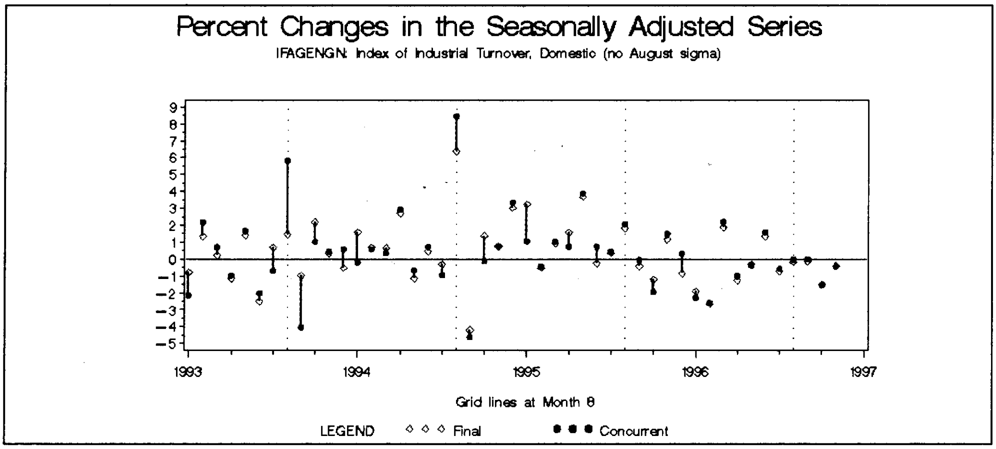
	Jan	Feb	Mar	Apr	May	Jun
I	1.446	0.910	1.424	1.087	1.217	1.222
S	0.310	0.180	0.220	0.182	0.144	0.186
RATIO	4.666	5.061	6.476	5.979	8.480	6.567
	Jul	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
I	1.088	0.907	1.144	0.889	1.267	0.681
S	0.147	0.983	0.166	0.307	0.212	0.274
RATIO	7.407	0.924	6.903	2.897	5.983	2.487

Therefore we shortened the seasonal-moving-average filter from 3x5 to 3x3 for the month of August as shown in the following *x11* spec.

```
x11{
   seasonalma=(s3x5  s3x5  s3x5  s3x5  s3x5  s3x5
               s3x5  s3x3  s3x5  s3x5  s3x5  s3x5)
}
```

However, even with this change, there are very large revisions in the August adjustment. The initial and last adjustment for each date is graphed below. The vertical dotted lines mark the August dates.

Figure 11 – Revisions from Initial to Full-Series Adjustment for IFAGENGN with No Calendar Sigma Option



We then looked for heteroskedasticity by using the *calendarsigma=all* option in the *x11* spec. The standard deviations for August were the highest among all months.

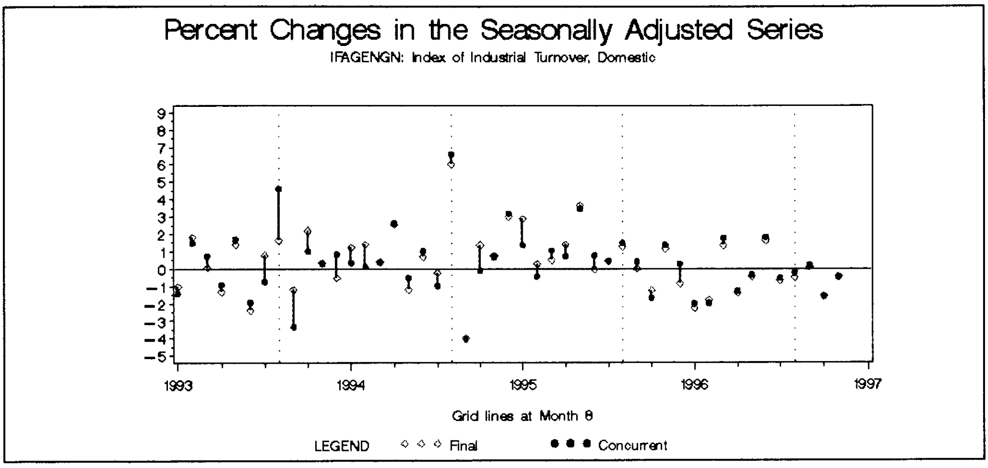
```
C 17  Final weights for irregular component
 From   1985.Jan to 1996.Dec
 Observations          144
 Lower sigma limit    1.5
 Upper sigma limit    2.5
```

	Jan	Feb	Mar	Apr	May	Jun
	Jul	Aug	Sep	Oct	Nov	Dec
S.D.	1.3	1.0	0.8	1.0	0.7	0.7
	0.9	1.4	0.8	0.5	1.0	0.9

Then we tried the *calendarsigma=select* option for August, which provides a sigma value for August separate from the sigma value used for detecting extreme values in the other months.

```
x11{
  calendarsigma=select
  sigmavec=aug
  seasonalma=(s3x5  s3x5   s3x5   s3x5   s3x5   s3x5
              s3x5  s3x3   s3x5   s3x5   s3x5   s3x5)
}
```

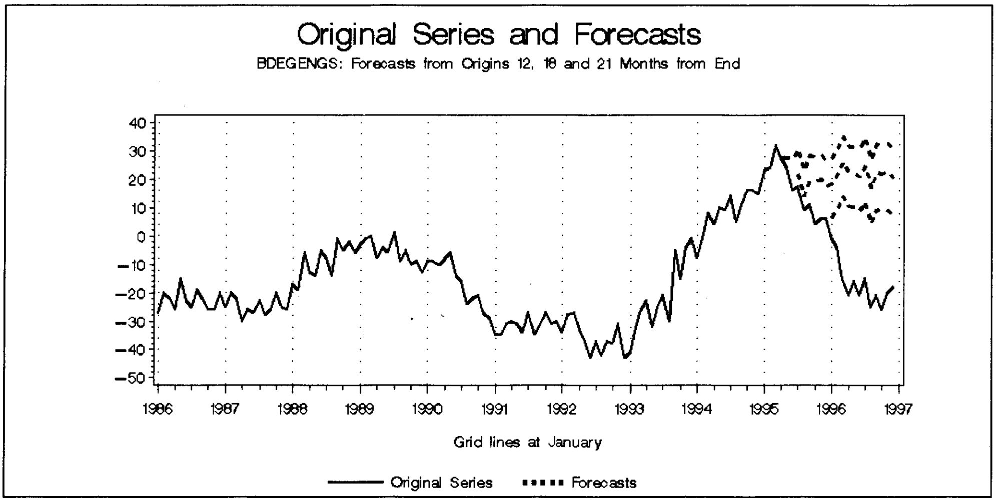
Figure 12 – Revisions from Initial to Full-Series Adjustment for IFAGENGN with Separate Sigma Values for August



<u>Problem: Identifying Series that are Difficult to Adjust</u>
<u>Solution: Quality-Control Diagnostics</u>

The M8, M10, and M11 diagnostics of X-12-ARIMA suggest that the series BDEGENGS could be a problematic series to adjust because the seasonal pattern might be changing too rapidly, especially in the last three years. The diagnostics in TRAMO/SEATS give no evidence of a problem, but the graph of the series shows a large upward and downward movement late in the series that a regARIMA model might not be able to capture. That is, the model used for model-based seasonal adjustment with SEATS may fit the data badly. To investigate this, we looked at forecasts from the regARIMA model with parameters estimated from the full series starting from various forecast origins in the last three years. The series and three sets of forecasts, from origins 12, 18, and 21 months from the end of the series, are shown in Figure 13. The forecasts are poor, indicating some inadequacy of the model. The situation with BDIGENGS was similar.

Figure 13 – Original Series and With-In Sample Forecasts for (BDEGENGS): Balances of New Orders on Foreign Markets



3.4 Non-default adjustments of TRAMO/SEATS

TRAMO/SEATS users often lower the critical value for outlier detection to improve the diagnostics for normality of the residuals found in TRAMO/SEATS (a Chi-square test, skewness, kurtosis, Ljung-Box Q statistics for the residuals and the squared residuals). For the 11 indicator series, when the option files provided to us by Agustin Maravall had significantly more outliers specified than the default run found, the resulting SEATS adjustments usually had some much larger revisions of initial estimates than either the default adjustment or the X-12-ARIMA adjustment. Thus the practice of adding outlier variables to improve normality diagnostics is problematic with a program, like TRAMO/SEATS in its present form, that cannot provide information about observable consequences for revisons, information that the history diagnostic of X-12-ARIMA makes easily available.

3.5 Direct versus indirect adjustments and adjustments of large numbers of series

Unlike X-12-ARIMA, TRAMO/SEATS does not have any diagnostics to provide information about the quality of indirect adjustments for a series that is a composite of other series that are seasonally adjusted. It also does not have a log file that can capture the diagnostics from adjusting many series in a compact way.

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AN APPLICATION OF TRAMO AND SEATS

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1. Description of the Programs

1.1 Program TRAMO

TRAMO ("Time Series **R**egression with ARIMA Noise, **M**issing Observations and **O**utliers") is a program that performs estimation, forecasting, and interpolation in regression models with missing observations and ARIMA errors, in the presence of possibly several types of outliers. The ARIMA model can be identified automatically (no restriction is imposed on the location of the missing observations in the series).

Given the vector of observations:

$$z = (z_{t_1}, \ldots, z_{t_M}) \tag{1}$$

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

$$z_t = y_t' \beta + v_t, \tag{2}$$

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

$$\phi (B)\, \delta (B)\, v_t = \theta (B)\, a_t \tag{3}$$

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

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

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

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

The program:

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

The basic methodology followed is described in Gómez and Maravall (1994), Gómez and Maravall (1992), Gómez (1997), and Gómez, Maravall and Peña (1999).

Estimation of the regression parameters (including intervention variables and outliers, and the missing observations among the initial values of the series), plus the ARIMA model parameters, can be made by concentrating the former out of the likelihood, or by joint estimation. Several algorithms are available for computing the likelihood or more precisely, the nonlinear sum of squares to be minimized. When the differenced series can be used, the algorithm of Morf, Sidhu and Kailath (1974), with a simplification similar to that of Mélard, (1984), is employed. This simplification extends to multiplicative seasonal moving average models, a case discussed, but not implemented, in Mélard. For the nondifferenced series, it is possible to use the ordinary Kalman filter (default option), or its square root version (see Anderson and Moore, 1979). The latter is adequate when numerical difficulties arise; however it is markedly slower.

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

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

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

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

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

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

If some outlier has been detected, the series is corrected by its effect and the ARMA model parameters are re-estimated. Then, a multiple regression is performed using the Kalman filter and the QR algorithm. If there are outliers whose absolute *t*-values are greater than the critical level *C*, the one with the greatest absolute *t*-value is selected and the algorithm goes on to the estimation of the ARMA model parameters to iterate. Otherwise, the algorithm stops. A notable feature of this algorithm is that all calculations are based on linear regression techniques, which reduces computational time. The four types of outliers considered are additive outlier, innovational outlier, level shift, and transitory change.

The program also contains a facility to pretest for the log-level specification and, if appropriate, for the possible presence of Trading Day and Easter effects; it further performs an automatic model identification of the ARIMA model. This is done in two steps. The first one yields the nonstationary polynomial $\delta(B)$ of model (3). This is done by iterating on a sequence of AR and ARMA(1,1) models (with mean), which have a multiplicative structure when the data is seasonal. The procedure is based on results of Tiao and Tsay (1983, Theor. 3.2 and 4.1), and Tsay (1984, Corol. 2.1). Regular and seasonal differences are obtained, up to a maximum order of $\nabla^2 \nabla_s$.

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

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

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

Finally, the program combines the facilities for automatic detection and correction of outliers and automatic ARIMA model identification just described in an efficient way, so that it performs automatic model identification of a nonstationary series in the presence of outliers when some observations may be missing.

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

1.2 Program SEATS

SEATS ("**S**ignal **E**xtraction in **A**rima **T**ime **S**eries") is a program that falls into the class of so-called Arima-model-based methods for decomposing a time series into its unobserved components (i.e., for extracting from a time series its different signals). The method was originally devised for seasonal adjustment of economic time series (i.e., removal of the seasonal signal), and the basic references are Cleveland and Tiao (1976), Box, Hillmer and Tiao (1978), Burman (1980), Hillmer and Tiao (1982), Bell and Hillmer (1984), and Maravall and Pierce (1987). An early related approach is contained in Piccolo and Vitale (1981). These approaches are closely related to each other and to the one followed in this program. In fact, parts of Seats developed from a program built by Burman for seasonal adjustment at the Bank of England.

The program may also start by fitting an ARIMA model to the series. In agreement with Tramo, the complete model can be written in detailed form as

$$\phi_p (B)\, \phi_P (B^s)\, \nabla^d\, \nabla_s^D\, x_t = \theta_q (B)\, \theta_Q (B^s)\, a_t + c, \qquad (4)$$

and, in concise form, as

$$\Phi (B)\, x_t = \theta\ (B)\, a_t + c \qquad (5)$$

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

The program decomposes a series that follows model (4) into several components. The decomposition can be multiplicative or additive. Since the former becomes the second by taking logs, we shall use in the discussion an additive model, such as

$$x_t = \sum_i x_{it}, \tag{6}$$

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

x_{pt} the *Trend* component,
x_{st} the *Seasonal* component,
x_{ct} the *Transitory* component,
x_{ut} the *Irregular* component.

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

The decomposition assumes orthogonal components, and each one will have in turn an ARIMA expression. In order to identify the components, we require that (except for the irregular one) they be clean of noise. This is called the "canonical" property, and implies that no additive white noise can be extracted from a component that is not the irregular one. The variance of the latter is, in this way, maximized, and, on the contrary, the trend, seasonal and transitory components are as stable as possible (compatible with the stochastic nature of the model). Although an arbitrary assumption, since any other admissible component can be expressed as the canonical one plus independent white-noise, it has some justification. (Moreover, the component estimates for any other admissible decomposition can be obtained from the canonical ones simply by removing a constant fraction of the irregular component estimate and adding it to the trend and/or seasonal ones).

The model that SEATS assumes is that of a linear time series with gaussian innovations. In general, SEATS is designed to be used with the companion program, TRAMO. In this case, SEATS uses the ARIMA model to filter the linearized series, obtains in this way new residuals, and produces a detailed diagnosis of them. The program proceeds then to decompose the ARIMA model. This is done in the frequency domain. The spectrum (or pseudospectrum) is partitioned into additive spectra, associated with the different components (these are determined, mostly, from the AR roots of the model). The canonical condition on the trend, seasonal, and transitory components identifies a unique decomposition, from which the ARIMA models for the components are obtained (including the component innovation variances).

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

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

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

$$d_{it} = x_{it} - \hat{x}_{it},$$

$$d_{it|T} = x_{it} - \hat{x}_{it|T},$$

$$r_{it|T} = \hat{x}_{it} - \hat{x}_{it|T},$$

denote the final estimation error, the preliminary estimation error, and the revision error in the preliminary estimator $\hat{x}_{it|T}$. The variances and autocorrelation functions for d_{it}, $d_{it|t}$, $r_{it|t}$ are displayed (the autocorrelations are useful to compute SE of linearized rates of growth of the component estimator). The program then shows how the variance of the revision error in the concurrent estimator $r_{it|t}$ decreases as more observations are added, and hence the time it takes in practice to converge to the final estimator. Similarly, the program computes the deterioration as the forecast moves away from the concurrent estimator and, in particular, what is the expected improvement in Root MSE associated with moving from a once-a-year to a concurrent seasonal adjustment practice. Finally, the SE of the estimators of the linearized rates of growth most closely watched by analysts are presented, for the concurrent estimator of the rate and its successive revisions, both for the trend and seasonally adjusted series. Further details can be found in Maravall (1988, 1995) and Maravall and Gómez (1992).

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

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

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

$$\nabla^2 x_{pt} = \theta_p (B)\, a_{pt},$$

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

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

Programs TRAMO and SEATS provide a fully model-based method for forecasting and signal extraction in univariate time series (the relation between them is somewhat similar to the one between the programs RegARIMA and X11 ARIMA that form the new method X12 ARIMA; see Findley et al, 1998). The procedure is flexible, yet robust and reliable. Due to the model-based features, it becomes a powerful tool for detailed analysis of important series in short-term policy making and monitoring. Yet TRAMO-SEATS can efficiently be used for routine application to a large number of series. For this routine-application case, fully automatic procedures are available. The standard procedure pretests for the log-level specification and, if appropriate, for the possible presence of Trading Day and Easter effects; it further performs an automatic model identification and outlier detection and correction procedure (for several types of outliers), interpolates the missing values if any, and decomposes the series net of the previous (deterministic) effects into a seasonal, trend, transitory, and irregular stochastic components (if the identified ARIMA model does not accept an admissible decomposition, it is automatically replaced by a decomposable approximation). Finally, the components (and forecasts thereof) estimated by SEATS are modified to reincorporate the deterministic effects that were removed by TRAMO.

2. The Application

2.1 The Series and Some General Comments on the Exercise

The SARA committee sent a set of eleven monthly italian series; they are listed in Table 1 (Appendix).

The number of observations vary between a minimum of 95 months (about 8 years) and a maximum of 202 (nearly 17 years). The 11 series can be classified into 5 groups. BDE and BDI are demand indicators; PCO and PPI are price indices; CIT and CET are foreign trade series; IPI, IPIIN, IFAE , and IFAN are industry related indicators; finally, LGOL is an employment index.

I understood that the purpose of the exercise was to decompose the series for the complete period, and hence took the sample size as fixed. It is a fact that a few of the series display some in-sample unstability associated with the early years of the sample, and for these series the results could improve by cutting the first years (this is true of the series CET and CIT and, to a lesser degree, PCO and PPI). But even in this case, the results are quite similar and the differences relatively minor. Further, besides their names and the period they span, nothing else was known *"a priori"* on any of the series.

Given that the most relevant audience of the Sara committee are likely to be data producing agencies and institutions, a very important criterion seemed to be the *Simplicity of the procedure*, reflected in a close to fully automatic functioning, where very few decisions have to be taken by the analyst on the individual series. We shall stick thus to mostly automatic procedures, where the only decisions allowed concern the specification of the trading day and easter effects, and the significance level for outlier detection. The results of this basically automatic procedure are, in all cases, acceptable. We shall see how, on occasion, they can be nevertheless improved.

A final comment: the present version of TRAMO contains a facility that provides the series of holidays for the different european countries. Since we have maintained the June 98 version of the program, the series of holidays have been added as a regression variable. One effect of including this variable is that, due to the correlation it displays with the easter variable, it decreases the significance of the easter effect.

2.2 The Procedure

To get a first general picture of the structure of the original series and, in particular, to assess whether trading day (TD), easter (EE) and holiday (HOL) effects should be included in the model, I run the 11 series with the input file

$$RSA = 4 \ , \ IREG = 1 \tag{I.1}$$

The regression variable was entered with IUSER = -1 and, given that it contains holidays, REGEFF = 2 (its effect are allocated to the seasonal component). For the rest of the paper, whenever the input file contains IREG = 1, the regression variable is entered in the same way.

Table 2 displays the results of the pre-test for TD and EE, as well as the t-value of the coefficient of the holiday variable when significant. It is seen that in no case easter effect appears to be significant, that trading day is moderately significant for the foreign trade series and that both trading day and holiday effects are significant for the industrial indicator series.

With these preliminary results concerning the presence or absence of special effects, I proceed now to discuss the results for the individual series. The point of the exercise is not to seek the "best possible" model, but to assess the performance of the automatic features. Thus in all 11 cases the automatic-option RSA-parameters are used. All will share the following characteristics:

- *Automatic test for the log/level specification;*
- *Automatic model identification.*

The ARIMA part of the model belongs to the general class

$$\phi_P(B)\,\phi^s_{BP}(B^{12})\,(\nabla^D \nabla^{BD}_{12} x_t - \mu) = \theta_Q(B)\,\theta^s_{BQ}(B^{12})\,a_t,$$

where $\phi_P(B)$, $\phi^s_{BP}(B^{12})$, $\theta_Q(B)$ and $\theta^s_{BQ}(B^{12})$ are the regular AR polynomial (of order P), the seasonal AR polynomial (of order BP), the regular MA polynomial (of order Q), and the seasonal MA polynomial (of order BQ), respectively. D and BD are the orders of the regular and seasonal differences, μ is the mean of the differenced series, and a_t is a white-noise innovation. Automatic model identification determines:

* whether $\mu = 0$,
* the values of P, BP, D, BD, Q, BQ.

- *Automatic outlier detection.* This is done jointly with automatic model identification. Three types of outliers are considered:

  * Additive outlier (AO),
  * Transitory change (TC),
  * Level shift (LS).

  AO represents a spike, TC is a spike that disappears (exponentially) over several periods, and LS is a step function.

- The model finally identified, consisting of:

  ARIMA model + Outliers + Special effects (TD, EE, and HOL, if present)

  is estimated by exact maximum likelihood, concentrating out of the likelihood the variance of a_t, σ^2_a, the mean, μ, and the regression variables (outliers plus special effects).

– The series is decomposed into a trend-cycle component, p_t, a seasonal component, s_t, an irregular component, u_t and, on occasion, a transitory component, c_t (when logs are used, the components are expressed as factors). Two years of forecasts are provided for the series and its components.

2.3 *The Selection of the Input Parameters; Some Basic Results*

Table 3 presents the input namelists considered for the 11 series; for 5 of them a reasonable alternative is provided. Table 4 displays the basic traits of the models identified. Table 5 exhibits the ARIMA model parameter estimates, Table 6 contains the outliers (date, type of outlier, and t-value), and Table 7 presents the residual root mean squared error (RMSE) and the Bayesian Information Criterion (BIC) for the 16 models.

Finally, Tables 8 and 9 display some basic diagnostics; Table 8 presents the results of tests for autocorrelation and normality of the residuals, and Table 9 shows the out-of-sample forecast F-test for each series when the last 12 and 18 observations are removed. These F-tests were carried out by fixing the models obtained for the shorter sample, estimated for the linearized series.

Starting with the demand indicators, for the series BDE the input namelist (I.1) indicated that the purely automatic procedure RSA = 3 seemed appropriate, and this is in fact the case, as evidenced by the first row of the Tables 4 to 9. For the series BDI, the same is true. RSA = 3 yields a satisfactory model. However, when used by SEATS, it does not accept an admissible decomposition. SEATS approximates the model by a decomposable one and the approximation amounts to a slight increase in the irregular component. The results would be clearly acceptable in any standardized automatic procedure (see the figures of SEATS). If manual intervention is allowed, one may be interested in replacing the nondecomposable model in a more careful manner, and proceed as follows. RSA = 3 yields the model

$$\nabla\nabla_{12}\, x_t = (1 - 0.248\, B + 0.105\, B^2 + 0.284\, B^3)\,(1 - 0.980\, B^{12})\, a_t,$$

The regular MA(3) polynomial factorizes into the product of the root (1 + 0.5375 B) and an MA(2) with a complex conjugate solution. The nonadmissibility of the model,as often happens, is due to the fact that the order of the total MA polynomial is larger than that of the total AR one (what Burman calls "top heavy" models). Moving towards a more balanced model (which tend to decompose better) it seems sensible to invert the MA(1), leaving a regular MA(2) specification. Estimation yields the model

$$(1 - 0.791\, B)\, \nabla\nabla_{12}\, x_t = (1 - 1.050\, B + 0.431\, B^2)\,(1 - 0.987\, B^{12})\, a_t\,,$$

which, as seen in the tables, gives very good results, slightly better than the pure automatic option. The AR(1) factor in this last model is assigned to the trend.

Moving to the employment in large firms series LGO, the absence of special effects again leads to the purely automatic procedure RSA = 3. Some problems with nonnormality are removed by lowering the threshold level for outlier detection to VA = 3.3. Unfortunately, the one-before-last observation is identified as an outlier, and this may produce unstability for the few next periods. Entering the parameter INT2 = -2, the one-before-last observation is flagged, but not corrected. No alternative model seems worth discussing.

The automatic procedure RSA = 3 works also well for the price series. For PCO the model identified by TRAMO performs very well but, as was the case with the series BDI, the model cannot be decomposed into an admissible decomposition. The approximation that SEATS provides is good, even better than for the BDI case. Still, as before, we may seek for an alternative model that can be decomposed. The model identified by Tramo is a $(0, 1, 2)\ (0, 1, 1)_{12}$ model, with the solution of the MA(2) again a pair of complex conjugate roots (which do not factorize). Reasoning as before, a sensible alternative is to invert the regular MA(2) and estimate a $(2, 1, 0)$ $(0, 1, 1)_{12}$ model. This yields the model

$$(1 - 0.276\ B - 0.232\ B^2)\ \nabla\nabla_{12}\, x_t = (1 - 0.737\ B^{12})\ a_t.$$

Since the MA (2) implies a minimum for ω close the middle of the $(0, \pi)$ frequency range, the AR(2) should imply a peak for $\omega = 0$ and a peak for $\omega = \pi$. This is indeed the case since the AR(2) factorises into $(1 - 0.639B)\ (1 + 0.364\ B)$. The alternative model does not improve the results, nor does it deteriorate them. It serves, however, to illustrate a feature of SEATS worth mentioning. The AR(2) root $(1 - 0.639\ B)$ is assigned to the trend, and the root $(1 + 0.364\ B)$, because its modulus is smaller than 0.5 (the default value of RMOD), is assigned to a "transitory component", c_t, which is found to follow the model

$$(1 + 0.364\ B)\ c_t = (1 - B)\ a_{ct}\ ,\ V(a_{ct}) = 0.0083\ V_a.$$

As the figures show, this transitory component is small and highly erratic. Its role is to remove erraticity from the trend-cycle and seasonal component, so as to improve their smoothness. For most practical purposes this transitory component can be added to the irregular component u_t.

For the series PPI, the results of the automatic procedure RSA = 3 are clearly improved by lowering VA to VA = 3.1. It may be worth mentioning that, in my experience, if something can be added to the fully automatic RSA parameter, the first thing to consider is outliers. If the series does not already contain a relative large number of outliers for the default value of VA (3.5 in all our cases), then it is worth looking for the next outlier (and perhaps ignore it). Very "*a grosso modo*", I would consider a large number of outliers something in the order of more than 3 outliers per 100 observations (LGO would be in the limit).

The rest of the series (foreign trade and industrial indicators) are all subject to TD effect. For most cases, the original specification RSA = 4 has been preserved, so that ITRAD = 1 and weekdays are classified into only 2 groups: working and non-working days.

For the quantity index of imports, CIT, the regression HOL is not significant. The input namelist RSA = 4, VA = 3.4 yields good results although, as Table 8 indicates, normality of the residuals is rejected, and this is due to a relatively high kurtosis. In general, kurtosis in the residuals and the associated nonnormality are not a serious problem. The estimators from SEATS are still optimal (see Bell, 1984). Point estimators of the components remain unchanged; what should change are the standard errors of the estimators computed by SEATS, which should be slightly increased.

EE is not detected as significant. A small search over the values of IDUR (the parameter that controls the number of days affected by easter) shows that IDUR = 4 is usually preferable to higher values for the italian series. In fact, forcing the EE variable with this value of IDUR yields a value of t = -2.2. Now all tests are passed, nonnormality has disappeared, and the RMSE (a_t) and BIC are slightly better. Therefore, for CIT we select the two input namelists in rows 8 and 9 of Table 3.

Concerning the quantity export index CET, a similar reasoning applies, except for the fact that normality of the residuals is in this case comfortably accepted. First, I consider the input namelist that uses RSA = 3, imposes TD (the t-value is 1.8), and uses VA = 3. The alternative input namelist also imposes IEAST = 1 IDUR = 4. Although the associated t-value is small (- 1.6), including it improves the overall results a bit. The two input namelists are given in rows 10 and 11 of Table 3. The model obtained with the alternative specification is given by

$$(1 - 0.630\,B - 0.265\,B^2)\,(\nabla_{12} \log x_t - 0.049) = (1 - 0.668\,B)\,(1 - 0.425\,B^{12})\,a_t.$$

The AR (2) polynomial factorises into the product of the root (1 - 0.918), which will be assigned to the trend, and the root (1 + 0.288 B). Because the modulus of this second root is smaller than 0.5, as was the case for the PCO alternative model, it will be assigned to a "transitory component", given by

$$(1 + 0.288\,B)\,c_t = (1 + B)\,a_{ct}\,,\; V(a_{ct}) = 0.0552\,V_a.$$

Although the component is now more important, the same comment made for the PCO case applies.

For the 4 industrial indicator series, TD effect is highly significant and HOL effect is also clearly significant. When EE is added, the results deteriorate. (The fact that EE is more significant than HOL for the foreign trade series, while the contrary is true for the industrial production series may have a very simple explanation. Different countries often share easter periods; holidays are more variable. For a particular country, the total number of holidays influences production more than the easter period). For the IPI series, the first input namelist is given by (I.1) with VA = 3.2 added. The second namelist changes RSA = 4 to RSA = 6, and uses thus a 6 variable specification for the TD variable (i.e., it assumes different effects for the 5 working days of the week). As Table 4 to 9 show, the results of the models are about equivalent. As for the index for investment goods, IPIIN, the original input namelist (RSA = 4, IREG = 1) provides results that are acceptable. Similarly to the case of the series CIT, the residuals of IPIIN cannot be accepted as normally distributed and, given that 5 outliers are identified with the default value of VA, I would be reluctant to lower this value. Although the residuals have a symmetric distribution, kurtosis is high. As was mentioned before, this feature does not invalidate point estimates and, considering the excellent out-of-sample performance of the model (Table 9), the input parameters are left unchanged.

One striking feature of the industrial production index series is the fact that the outliers are concentrated in the month of August. The two series share outliers for August 84, 92 and 95; IPI contains an additional outlier for August 87, and IPIIN for August 88. Except for one case, all outlier are AO; half of them positive, half of them negative.

Although 4 or 5 outliers in 200 observation is not an excessive number, the fact that 4 of the 16 months of August present in the sample are detected as outliers points towards the presence of some heteroscedasticity in the seasonal component. This fact has been pointed out by Proietti (1998), who deals with the problem using a state space approach. An alternative approach that appears to work well within the Tramo framework is the introduction of seasonal outliers (see Kaiser and Maravall, 1999). In any event, these are 2nd order improvements, with little effect on point estimators. The results of Tramo-Seats seem satisfactory, and this is strongly corroborated by the corresponding 6 F-tests for out-of-sample performance in Table 9.

If the industrial production indices are modelled in levels, not in logs, the trend-cycle becomes less smooth and the "august outlier" problem disappears. From the comparison of the full results, one could conclude that, for these two series, the levels are perhaps more appropriate to model than the logs. In fact, the next version of Tramo will include a modified log/level pretest, which will be, by default, slightly less favourable to the choice of the logs, and which will allow the user to enter his/her own preference. At present, given that I wish to stick to the automatic application, I choose the input namelists of rows 12, 13, and 14 of Table 3, bearing in mind that the drops in the month of August are particularly volatile (I wonder if this feature could not be perhaps related to the business cycle ...).

Finally, for the two industrial turnover series, the number of outliers is relatively small. For the series IFAN, the original input namelist (RSA = 4, IREG = 1) is kept. For the series IFAE RSA is changed from 4 to 6 because the results were clearly better; further VA is set to 3.2. The two input lists are in rows 15 and 16 of Table 3. The Q-statistics for the ACF of the residuals of IFAE (see Table 8) is slightly high. By lowering VA and increasing the outliers to 5, it becomes perfectly clean. The high value of Q, however, is caused by the single autocorrelation ρ_{13} = - 0.24, and hence of not much concern. Removing this autocorrelation at the cost of adding 3 outliers does not seem worth it.

These comments justify the 16 input namelists of Table 3. Besides the automatic features mentioned earlier (RSA = 3, 4, or 6), the only additional options that have been considered are:

* IEAST = 1 , IDUR = 4 in 2 cases;
* VA = a value between 3 and 3.5 for all cases;
* INT2 = – 2 in one case;
* IREG = 1 in the last 5 models.

In summary, the presence or absence of special effects can be determined (at least partly) automatically by looking at the results of the pretests with RSA = 4, as we did. Besides some possible modification (such as, in our case, to force on some occasion the inclusion of EE), the only action required from the user is to chose a value of VA between 3 and the default value 3.5.

When the series are going to be routinely treated, it should be emphasized that the input files of Table 3 provide only starting points. Once the models are identified (and, presumably, have passed the diagnostics), their structure should remain fixed for some time (perhaps a year, unless something very special happens). After this period of (say) a year, the models should be reidentified with the 12 new observations. Fixing the model for a period means:

* Fix μ, (p d q), (BP BD BQ) and the log/level transformation;
* Fix the type and position of outliers (through IUSER = 2);
* Fix the presence or absence of trading day, easter effect, and holidays;
* And, every month, reestimate the coefficients.

As seen in Dossé and Planas (1998), proceeding in this way provides an optimal mixture of flexibility and stability (for a more complete description of the procedure, see the appendix in Gómez and Maravall, 1998).

One final point: As mentioned earlier, the time span of the series was kept always equal to the one supplied by the SARA committee. This would be in line with routine application to data bases. When looking at an individual series, of course, one can always drop some first years if a change in regime is detected. Looking at the figures with the estimates of the components it is clear that this might well be the case for some of the series considered. In particular, both foreign trade series show a change in regime, whereby the first years contain a larger irregular component and smaller seasonal fluctuations. It may also apply to the two series of prices, where a change in the seasonal component is clearly appreciated.

2.4 *Summary of Model Identification*

From the previous tables, the following summary comments can be made:

1) Of the 11 series, 5 are modelled in levels, 6 in logs.
2) Of the 16 models considered, only one contains a mean.
3) Concerning the Arima model:
   * All 16 cases contain the multiplicative IMA $(1,1)_{12}$ seasonal structure.
   * Of the 16 models, 9 are of the Airline type (p = 0, d = 1, q = 1, bp = 0, bd = 1, bq = 1).
   * The model (regular) orders can be summarized as follows:

	P			D		Q			
	0	1	2	0	1	0	1	2	3
Number of models	11	3	2	1	15	2	11	2	1

* The average number of parameters is 2.3 parameters per model.

4) The average number of Outliers is 3 outliers per series. This is roughly equivalent to 1 outlier per 60 observations. Two of the 11 series contain no outlier, and the maximum number is 6 (for one of the largest series). As for the type of outliers, 60% are AO, 15% are TC, and 25% are LS.

   These results are quite in line with the large-scale results reported in Fischer and Planas (1998).

5) As for Trading Day effect, it affects moderately the foreign trade series (very moderately the exports one), and strongly the four industry indicators. Of the 9 models considered for theses series, 7 use the binary specification, and 2 use the 6-variable specification.

6) Easter effect is not significant for any of the series. The only ones for which it could be perhaps considered are the foreign trade series.

7) Holidays have a significant effect on all industry indicators, strongest for the case of the industrial production index.

8) As for diagnostics, the only noticeable problem is some evidence of nonnormality in the residuals for some of the series, which is mostly associated with kurtosis. This problem should have little effect on point estimators.

   On the positive side, what seems remarkable is that all 32 F-tests are passed comfortably (this is particularly true for the series modelled in logs). A further proof of the models stability is that the F-statistics is more clustered around 1 when 18 (instead of 12) observations are deleted from the sample.

9) Moving on to SEATS, two of the 16 models do not accept an admissible decomposition and Seats automatically approximates them with simpler models. The only two input files in Table 3 that do not contain the RSA parameter for automatic modelling correspond to additional alternatives to the nondecomposable models. Notice however that, when approximating a nondecomposable model, SEATS preserves the original forecasts, and the component forecasts are forced to satisfy the aggregation constraint.

2.5 Summary of the Model Decomposition

Let n_t, p_t, s_t, and u_t denote the SA series, the trend-cycle, the seasonal, and the irregular components, respectively. Concerning the output of SEATS the following comments may be helpful.

(1) Models for the components

What are called "numerator" and "denominator" in the output are the MA and AR polynomials in the model for the component, respectively. The variance of the innovation is expressed as a fraction of the variance (V_a) of the residual a_t.

Thus, for the BDE series, for example, the model for the trend-cycle is given by

$$\nabla^2 p_t = (1 + 0.006B - 0.994B^2)\, a_{pt},$$

with Var (a_{pt}) = 0.108 V_a. The MA polynomial contains the root B = -1, which implies a spectral zero for the π frequency, and the root B = 0.99, which nearly cancels out one of the unit AR root. Thus the model for the trend is, very approximately, equal to

$$\nabla p_t = (1 + B)\, a_{pt} + \mu$$

where μ is a constant.

The variance of the components innovations measure the degree of stochasticity of the component. In the BDE example, Var(a_{st}) = 0.0014 is very small, so that the component is very stable, and hence quite close to deterministic. The BDE series serves as an example of why, in the TRAMO-SEATS approach, the distinction deterministic-stochastic is not needed; the model will automatically capture and approximate very well deterministic seasonality. The variance of the SA series innovations, Var(a_{nt}) = 0.94 V_a shows that seasonal adjustment hardly affects the stochastic nature of the series. Further, Var(u_t) = 0.41 V_a means that the series contains a relatively important irregular component.

(2) Diagnostics and inference

The second order moments of the stationary transformation of the four components and their estimators are compared. First, the ACF of $\nabla^2 n_t$, $\nabla^2 p_t$, Ss_t and u_t, theoretically derived from the components models, is compared to the ACF of $\nabla^2\hat{n}_t$, $\nabla^2\hat{p}_t$, $S\hat{s}_t$, $\hat{u}_t$, derived also from the theoretical models implied for the MMSE estimators, and to the empirical ACF of the same transformation of the estimates actually obtained for the components. The comparison includes also the variances. Comparison of the component and the theoretical MMSE estimator shows the distortion induced by MMSE estimation. It should always be that the variance of the component is larger than that of the estimator. Comparison between the theoretical MMSE estimator and the empirical one provides elements for diagnosis. Both, theoretical and empirical estimator should be close, and large departures would indicate problems with the model specification (see, for example, Maravall, 1987).

A similar comparison is made for the crosscorrelation between the stationary transformation of the theoretical estimators and actual estimates. For example, for the BDE series it is seen that the estimators, and also the estimates, are practically uncorrelated.

Next, the variance of the components estimation error is presented, both for the estimation error of the final estimator and for the revision error in the concurrent estimator. The series BDE shows, for example, that the estimation error of the SA series is substantially smaller than that of the trend-cycle. Additional information on the revisions is provided: speed of convergence to the final estimator and duration of the revision period. For the BDE series example, it is seen that the first year revision in the trend-cycle is very large, and afterwards convergence proceeds slowly. Given that for this series the seasonal component is very stable and its estimation error is small, the gain from moving from a once-a-year adjustment to a concurrent one is minor: the root mean square error of the estimator is only reduced by 4%

Attention centres next on the estimator and forecast of the seasonal component. Considering the size of the estimation standard errors, for the BDE series it is seen that seasonality is highly significant and can be captured well even for preliminary estimators and forecasts.

Finally, the standard error of several growth measures is displayed (if the log transformation is used, the growth becomes the rate of growth). Growth is computed for the trend-cycle and the SA series. For the BDE series example, the monthly growth can be measured quite accurately and the 95% confidence intervals are in the order of ± 2.4 for the SA series, and ± 3.5 for the trend-cycle. Using the centered measure of annual growth (which uses 6 forecasts of the component), the trend outperforms both the SA series and the original series.

Concerning the figures, they are divided into 4 groups for each series. The first group comes from TRAMO and contains the original and linearized series, the residuals, and the series forecasts. The second group presents the components estimated by SEATS: seasonally adjusted series, trend-cycle, seasonal, and irregular components (the last two components are net of outliers and special effects). Proper assessment of the quality of a decomposition requires consideration of all components obtained: the irregular, in particular is obtained as a residual and hence will likely evidence problems in the estimation of the other components (if it were to display, for example, regular or seasonal features). The third group of figures presents the spectra of the components and the squared gain of the associated filter. The last group of figures shows the component forecasts. For two series (PPI and PCO) comparison of the levels of the original series, SA series, and trend is not informative. For these two cases, to assess the smoothing achieved by removing the seasonal component and the irregular the rates of growth are also compared.

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APPENDIX

- Tables
- Figures

Tables

Table 1 – Description of the series

Name	Meaning	Sample Period	No. of observation	Abbreviation
BDEGENGS	New orders and demand level on foreign markets. Balance.	1986/1 - 1996/12	132	BDE
BDIGENGS	New orders and demand level on domestic markets. Balance.	1986/1 - 1996/12	132	BDI
LGOLTOGI	Index of total employment in large firms.	1989/1 - 1996/11	95	LGO
PCOBENGP	Consumer price index. Goods.	1989/1 - 1996/12	96	PCO
PPIGENGP	Producer price index. Total Industry.	1981/1 - 1996/12	192	PPI
CITGENGQ	Imports. Quantity index.	1980/1 - 1996/10	202	CIT
CETGENGQ	Exports. Quantity index.	1980/1 - 1996/10	202	CET
IPIENGT	Industrial production index. Total.	1981/1 - 1996/12	192	IPI
IPIINVGT	Industrial production index. Investment goods.	1981/1 - 1996/12	192	IPIIN
IFAGENGE	Index of industrial turnover. Foreign market.	1985/1 - 1996/12	144	IFAE
IFAGENGN	Index of industrial turnover. Domestic market.	1985/1 - 1996/12	144	IFAN

Table 2 – Trading Day and Easter effect pretests; significance of holidays

Serie	Trading Day	Easter	Holiday(*)
BDE	No	No	No
BDI	No	No	No
LGOL	No	No	No
PCO	No	No	No
PPI	No	No	No
CIT	Yes	No	No
CET	Yes	No	No
IPI	Yes	No	-5.04
IPIIN	Yes	No	-5.15
IFAE	Yes	No	-2.16
IFAN	Yes	No	-2.56

(*) Since the holiday variable is entered as a regression, the t-values are reported ("NO" means | . | < 1.96).

Table 3 – Input Namelists

Series	Parameters
BDE	RSA = 3
BDI	RSA = 3
BDI2	P = 1, Q = 2, IMEAN = 0, IATIP = 1, LAM = 1
LGO	RSA = 3, VA = 3.3, INT2 = - 2
PCO	RSA = 3
PCO2	P = 2, Q = 0, IMEAN = 0, LAM = 1, IATIP = 1
PPI	RSA = 3, VA = 3.1
CIT	RSA = 4, VA = 3.4
CIT2	RSA = 3, ITRAD = 1, IEAST = 1, IDUR = 4
CET	RSA = 3, ITRAD = 1, VA = 3
CET2	RSA = 3, ITRAD = 1, IEAST = 1, IDUR = 4, VA = 3.3
IPI	RSA = 4, VA = 3.2, IREG = 1
IPI2	RSA = 6, VA = 3, IREG = 1
IPIIN	RSA = 4, IREG = 1
IFAE	RSA = 6, VA = 3.2, IREG = 1
IFAN	RSA = 4, IREG = 1

Table 4 – Identified Models

Series(*)	Number of observ.	Transfor-mation	Model	Outliers			Special effects		
				AO	TC	LS	TD(**)	EE	HOL(**)
BDE	132	Level	(***)	-	-	2	-	-	-
BDI	132	Level	$(0,1,3)\ (0,1,1)_{12}$	-	-	-	-	-	-
[BDI2	"	"	$(1,1,2)\ (0,1,1)_{12}$	-	-	-	-	-	-]
LGO	95	Level	$(1,1,0)\ (0,1,1)_{12}$	-	1	3	-	-	-
PCO	96	Level	$(0,1,2)\ (0,1,1)_{12}$	-	-	-	-	-	-
[PCO2	"	"	$(2,1,0)\ (0,1,1)_{12}$	-	-	-	-	-	-]
PPI	192	Level	$(1,1,1)\ (0,1,1)_{12}$	1	2	1	-	-	-
CIT	202	Log	(***)	3	1	1	5.9	-	-
[CIT2	"	"	(***)	4	1	1	6.1	-2.2	-]
CET	202	Log	(***)	3	-	1	1.8	-	-
[CET2	"	"	$(2,0,1)\ (0,1,1)_{12}$ with mean	2	2	-	1.5	-1.6	-]
IPI	192	Log	(***)	3	-	1	17.7	-	-6.0
[IPI2	"	"	(***)	4	-	1	6 var	-	-6.9]
IPIIN	192	Log	(***)	5	-	-	14.7	-	-5.2
IFAE	144	Log	(***)	2	-	-	6 var	-	-2.5
IFAN	144	Log	(***)	2	-	1	16.9	-	-2.6

(*) The rows in brackets represent reasonable alternatives.
(**) t-values are given, except when the TD effect has the 6 variable specification.
(***) Model is Airline model. For all cases $\mu = 0$.

Table 5 – ARIMA model parameter estimates

Series	ϕ_1	ϕ_2	θ_1	θ_2	θ_3	θ_{12}
BDE	-	-	-0.321	-	-	-0.931
BDI	-	-	-0.248	0.105	-0.284	-0.980
BDI2	-0.791	-	-1.050	0.431	-	-0.987
LGO	-0.674	-	-	-	-	-0.896
PCO	-	-	0.342	0.421	-	-0.811
PC02	-0.276	-0.232	-	-	-	-0.737
PPI	-0.848	-	-0.302	-	-	-0.494
CIT	-	-	-0.674	-	-	-0.502
CIT2	-	-	-0.665	-	-	-0.485
CET	-	-	-0.807	-	-	-0.539
CET2	-0.630	-0.265	-0.668	-	-	-0.425
IPI	-	-	-0.583	-	-	-0.598
IPI2	-	-	-0.541	-	-	-0.569
IPIIN	-	-	-0.544	-	-	-0.622
IFAE	-	-	-0.373	-	-	-0.564
IFAN	-	-	-0.393	-	-	-0.469

The parameters correspond to the polynomials
$(1 + \phi_1 B + \phi_2 B_2)$, $(1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)$, $(1 + \theta_{12} B^{12})$.

Table 6 – Outliers

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	TOTAL
BDE														9 LS 4.1			3 LS -3.9	2
BDI																		0
BDI2																		0
LGO													9 TC -7.8	12 LS -5.8	12 LS -7.4		1 LS 4.6	4
PCO																		0
PCO2																		0
PPI						12 TC 3.5			1 10 TC A0 -5.7 -3.2		8 LS 3.9							4
CIT			1 TC 3.7	1 4 6 AO AO LS 6.7 5.1 3.8		12 A0 4.4												5
CIT2		3 A0 -3.6	1 TC 3.5	1 4 5 AO AO LS 6.7 -4.9 3.9		12 AO 4.6												6
CET		4 LS 3.7	12 AO -3.1		6 AO -3.1	12 AO 3.4												4
CET2		3 9 AO TC -4.3 4.1			6 AO -3.6	12 TC 3.8												4
IPI					8 AO 4.9			8 AO -3.3					8 LS -3.4			8 AO 4.5		4
IPI2					8 AO 4.3		8 AO -3.4	8 AO -4.0					8 LS -3.5			8 AO 4.7		5
IPIIN					8 AO 4.5				8 AO 4.1				8 AO -6.6			8 12 AO AO 5.5 3.8		5
IFAE						8 AO 3.0							8 AO -6.6					2
IFAN								3 LS 4.1			8 AO 4.1	1 AO 3.9						3

First line: month of the year (1 for January, 12 for December) – Second line: type of outlier. – Third line: t-value.

Table 7 – Residual Root Mean Squared Error and Bayesian Information Criterion

Series	RMSE (a_t)	BIC
BDE	4.8367	3.28
BDI	3.5336	2.65
BDI2	3.4560	2.61
LGO	0.1503	-3.54
PCO	0.1587	-3.56
PC02	0.1647	-3.49
PPI	0.2577	-2.55
CIT	0.0697	-5.15
CIT2	0.0673	-5.17
CET	0.0761	-5.00
CET2	0.0717	-5.02
IPI	0.0244	-7.24
IPI2	0.0236	-7.17
IPIIN	0.0413	-6.16
IFAE	0.0362	-6.32
IFAN	0.0263	-7.07

Table 8 – Residual Diagnostics

Series	Q-test	N-test	Skewness (t-value)	Kurtosis (t-value)	Q_s-test
BDE	21.5	4.0	1.2	-1.5	3.3
BDI	16.1	0.8	-0.5	-1.0	4.1
BDI2	11.7	1.4	-0.9	-0.7	3.9
LGO	14.7	2.1	1.2	0.7	4.2
PCO	17.9	1.3	0.8	-0.8	5.0
PCO2	20.4	0.8	0.9	-0.1	3.7
PPI	24.4	4.0	0.6	1.8	0.2
CIT	23.3	8.3	-1.7	2.2	1.9
CIT2	32.4	3.2	-0.8	1.5	2.0
CET	31.4	0.3	0.0	-0.6	0.1
CET2	31.1	5.8	-2.3	0.5	3.6
IPI	25.7	4.9	2.1	0.1	5.5
IPI2	31.7	4.4	1.8	1.1	5.7
IPIIN	14.3	15.9	1.4	3.5	1.1
IFAE	33.6	4.5	2.0	0.6	0.9
IFAN	31.9	5.6	2.1	1.1	1.7
Approx. 95% critical values	34	6	± 2	± 2	6

Q-Test: Ljung-Box test for residual autocorrelation (with 24 lags).
Q_S-test: Pierce test for residual seasonality (with 2 seasonal lags).

Table 9 – Out-of-Sample Forecast F-Test

Series	Deleting 12 observ.	(Approx. 95% critical value)	Deleting 18 observ.	(Approx 95% critical value)
BDE	0.71	(1.85)	0.59	(1.73)
BDI	0.98	(1.85)	0.92	(1.73)
BDI2	1.04	(1.85)	0.97	(1.73)
LGO	1.89	(1.91)	1.52	(1.79)
PCO	1.48	(1.91)	1.26	(1.79)
PCO2	1.47	(1.91)	1.46	(1.79)
PPI	1.15	(1.80)	1.12	(1.67)
CIT	0.20	(1.78)	0.37	(1.65)
CIT2	0.20	(1.78)	0.39	(1.65)
CET	0.53	(1.78)	0.66	(1.65)
CET2	0.63	(1.78)	0.84	(1.65)
IPI	0.55	(1.80)	0.61	(1.67)
IPI2	0.52	(1.80)	0.60	(1.67)
IPIIN	0.29	(1.80)	0.53	(1.67)
IFAE	0.49	(1.83)	0.72	(1.71)
IFAN	0.62	(1.83)	0.74	(1.71)

Figures

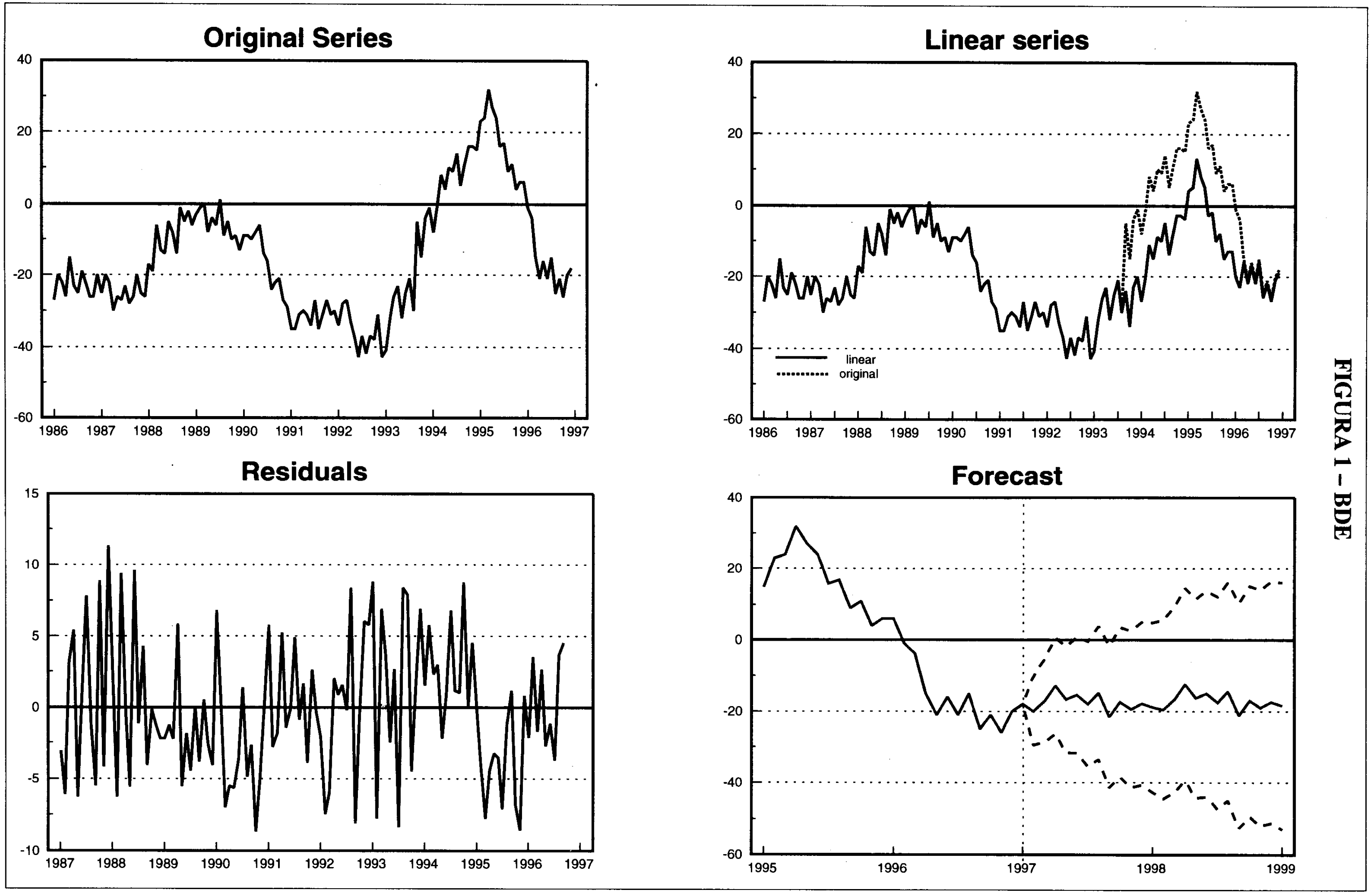


FIGURA 1 – BDE

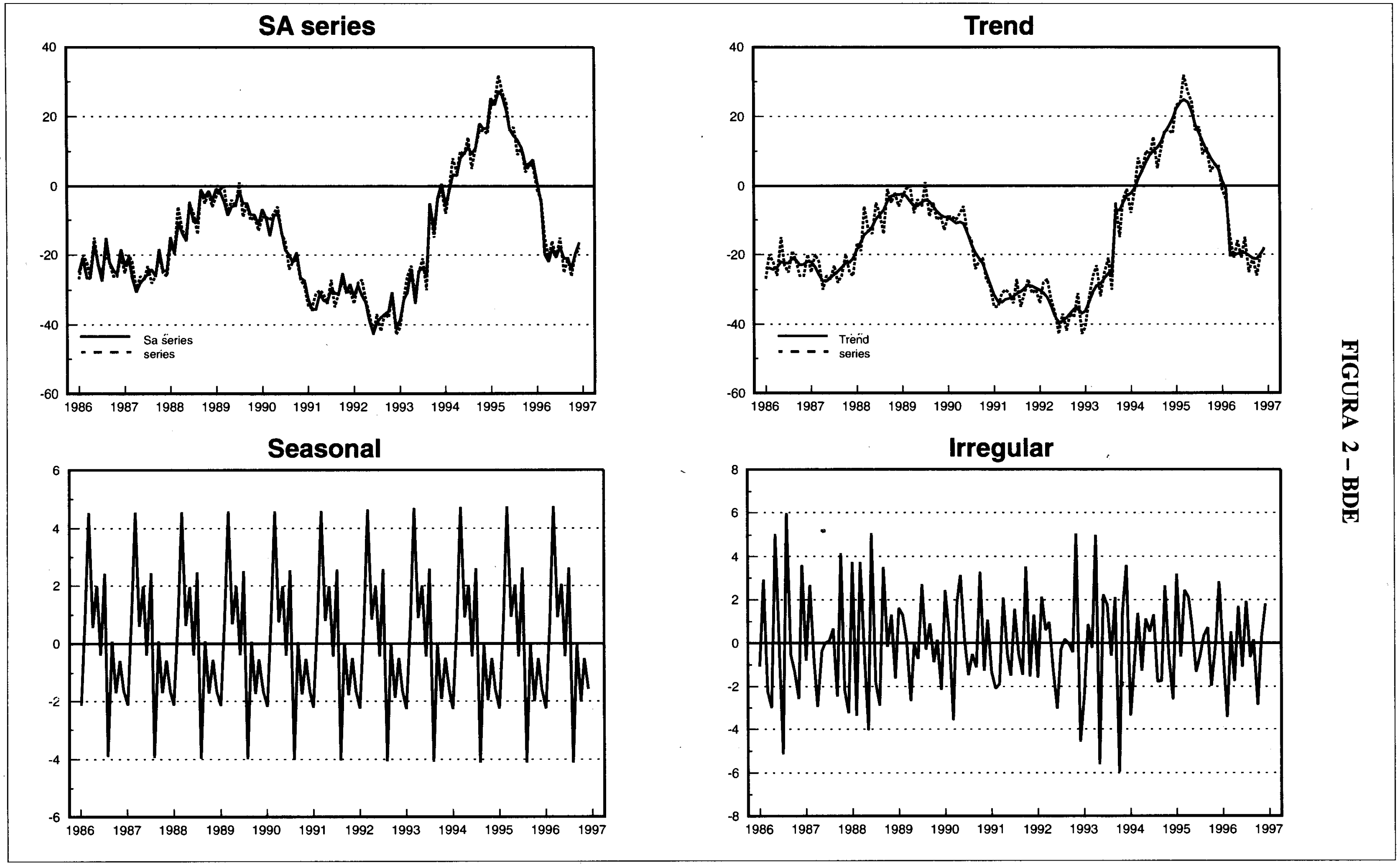

SA series
Sa series
series
Trend
Trend
series
Seasonal
Irregular
1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997

FIGURA 2 – BDE

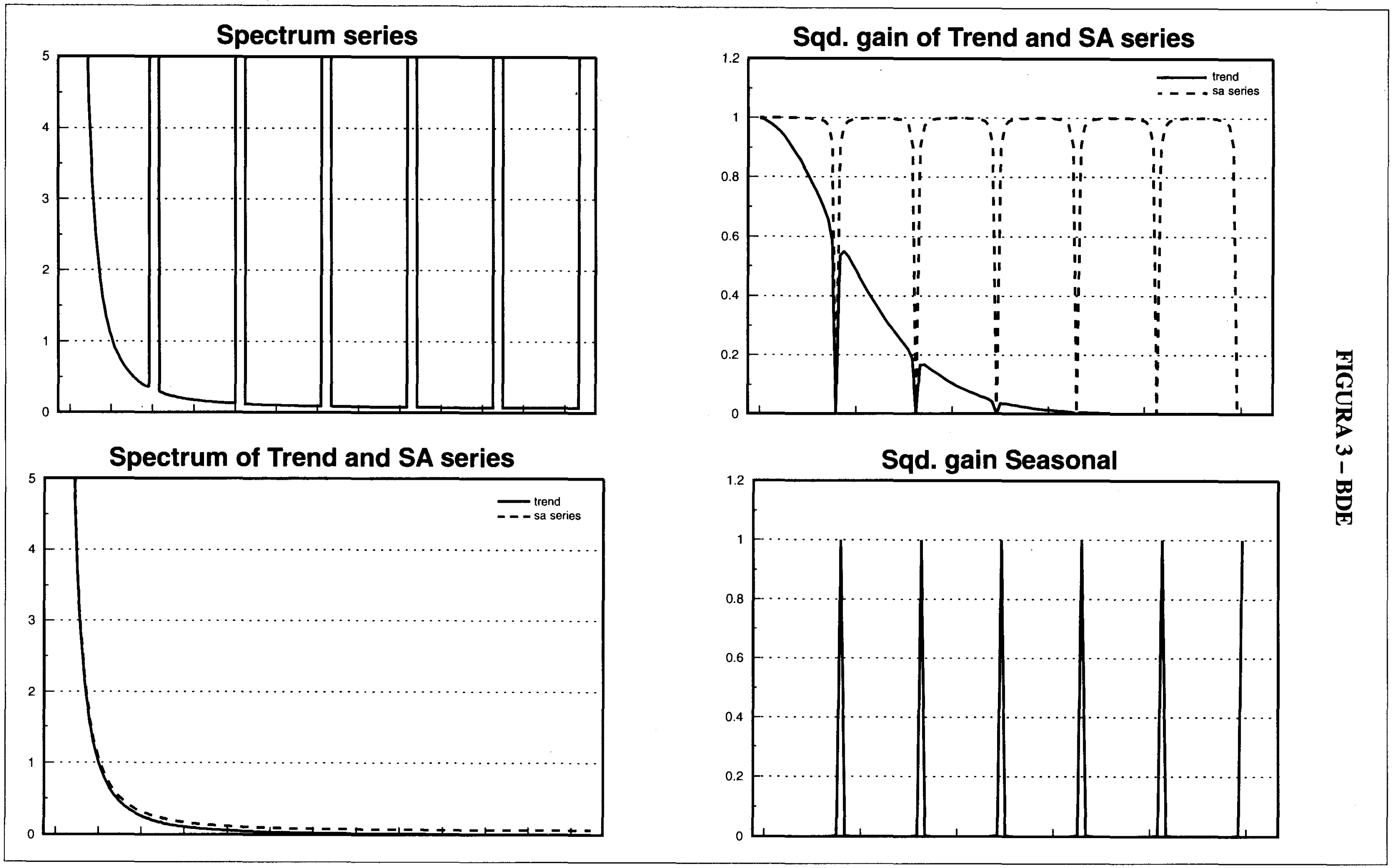
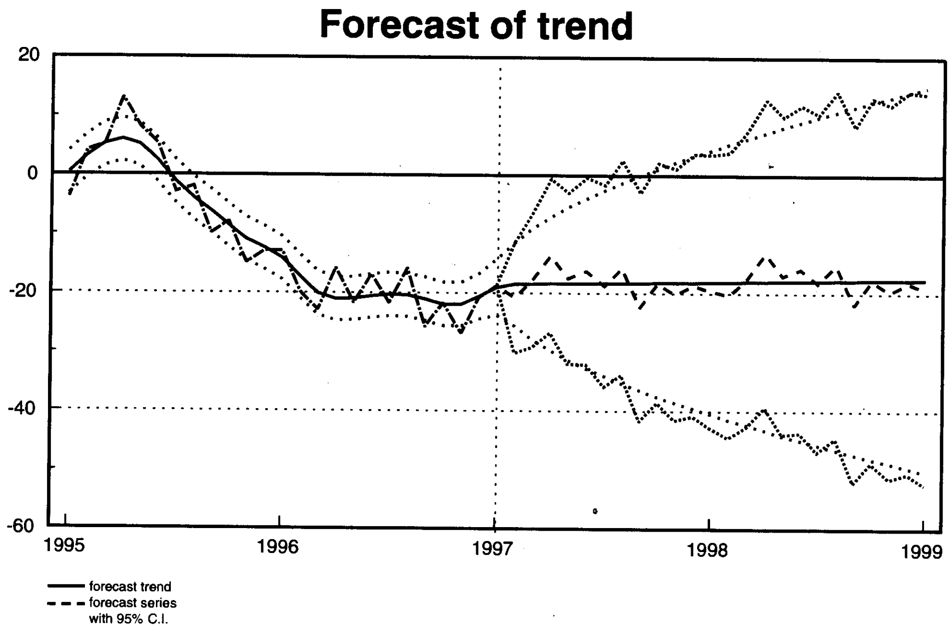

Spectrum series
5
4
3
2
1
0
Sqd. gain of Trend and SA series
1.2
1
0.8
0.6
0.4
0.2
0
trend
sa series
Spectrum of Trend and SA series
5
4
3
2
1
0
trend
sa series
Sqd. gain Seasonal
1.2
1
0.8
0.6
0.4
0.2
0

FIGURA 3 – BDE

FIGURA 4 – BDE


Forecast of trend
20
0
-20
-40
-60
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.

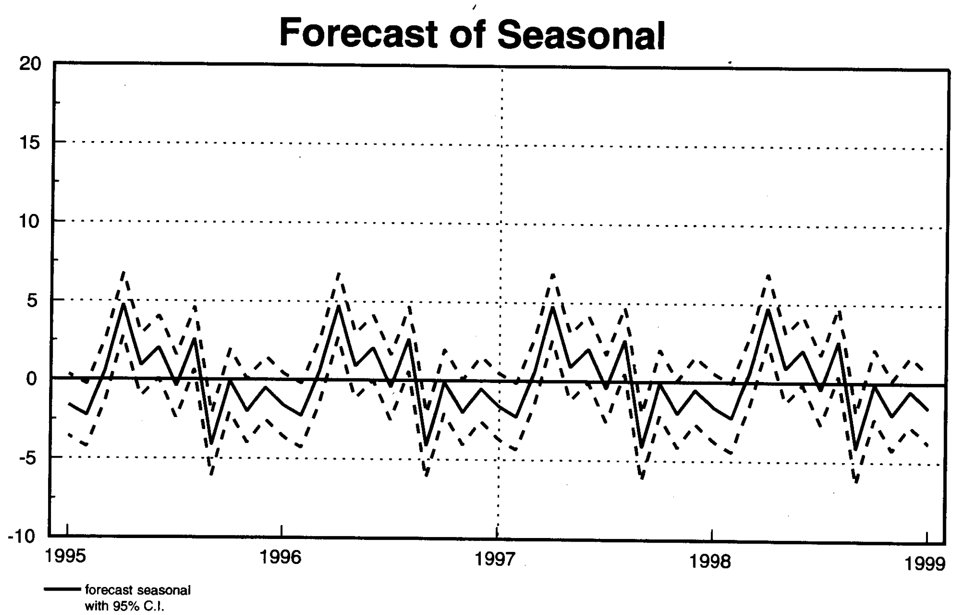
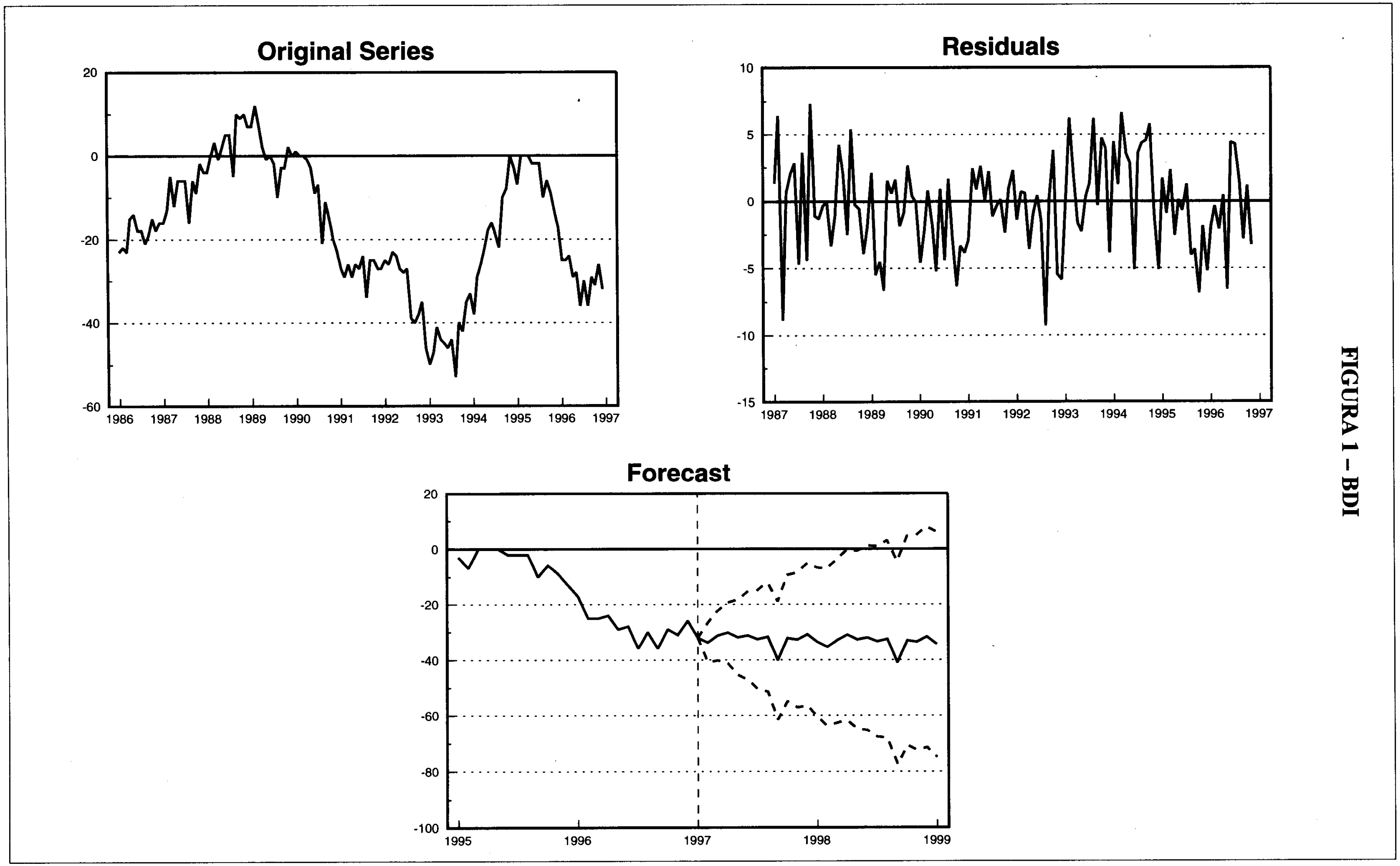

Forecast of Seasonal
20
15
10
5
0
-5
-10
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

FIGURA 1 – BDI


Original Series
20
0
-20
-40
-60
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
Residuals
10
5
0
-5
-10
-15
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
Forecast
20
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1995
1996
1997
1998
1999

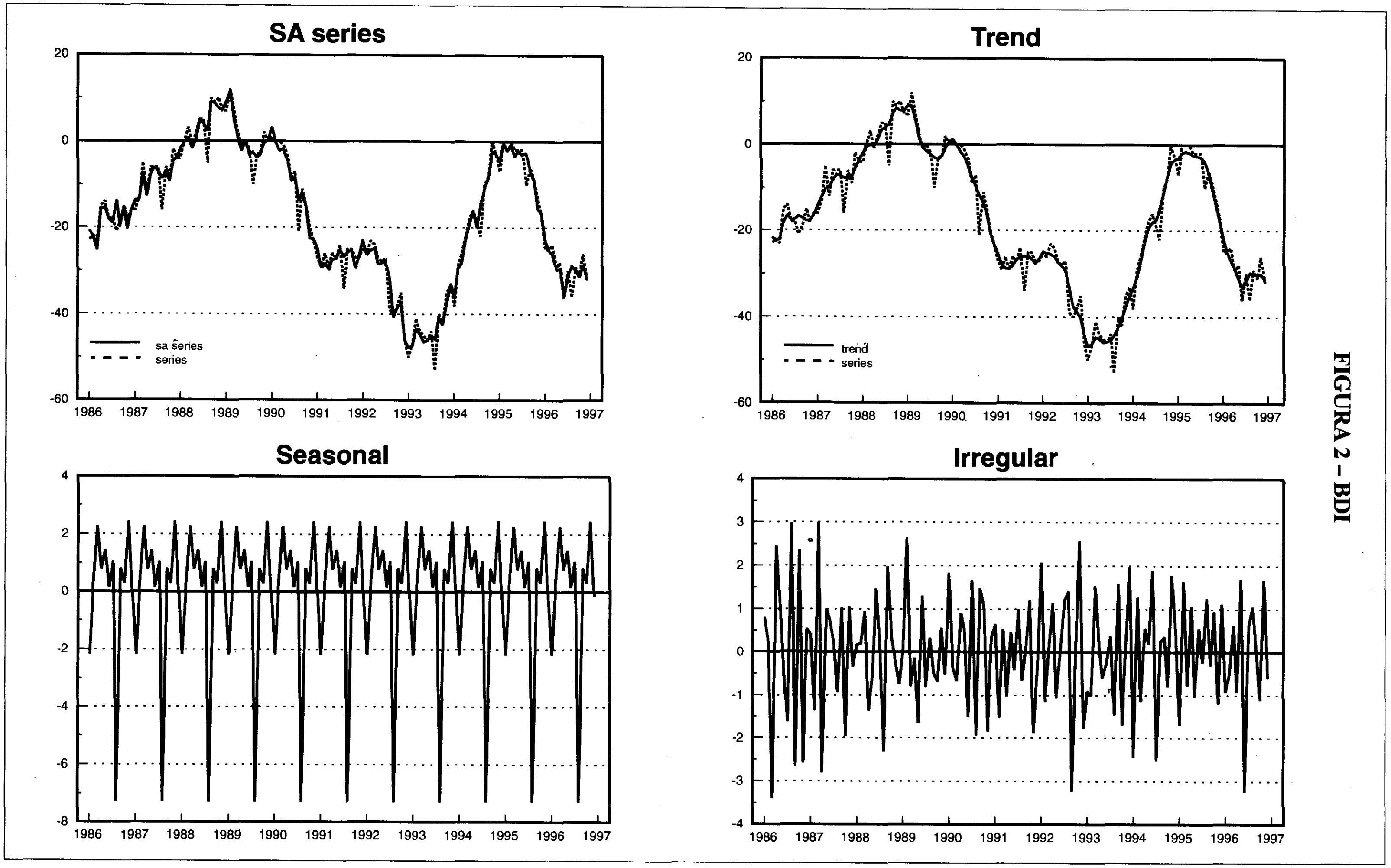

SA series
sa series
series
Trend
trend
series
Seasonal
Irregular
1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997

FIGURA 2 - BDI

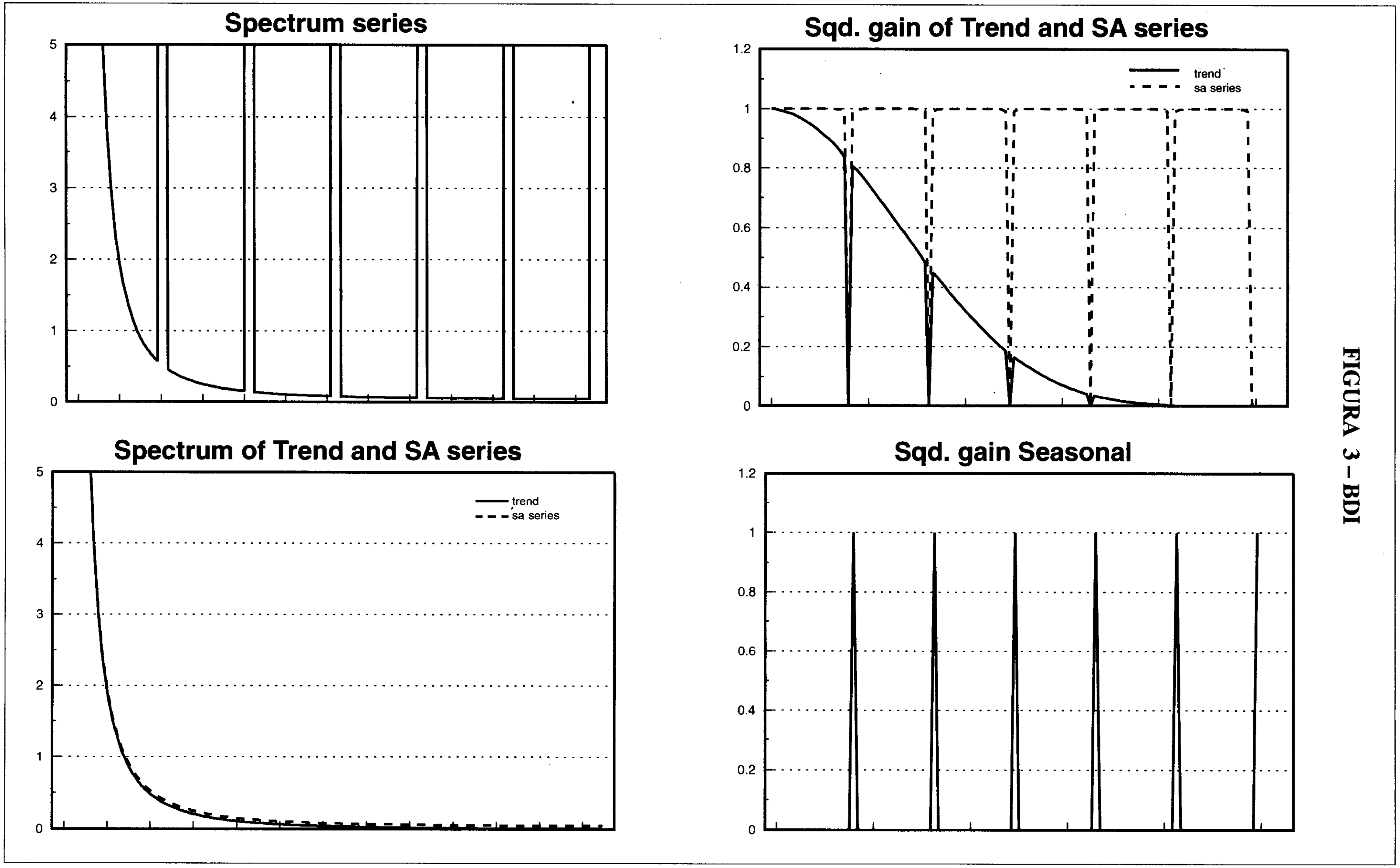
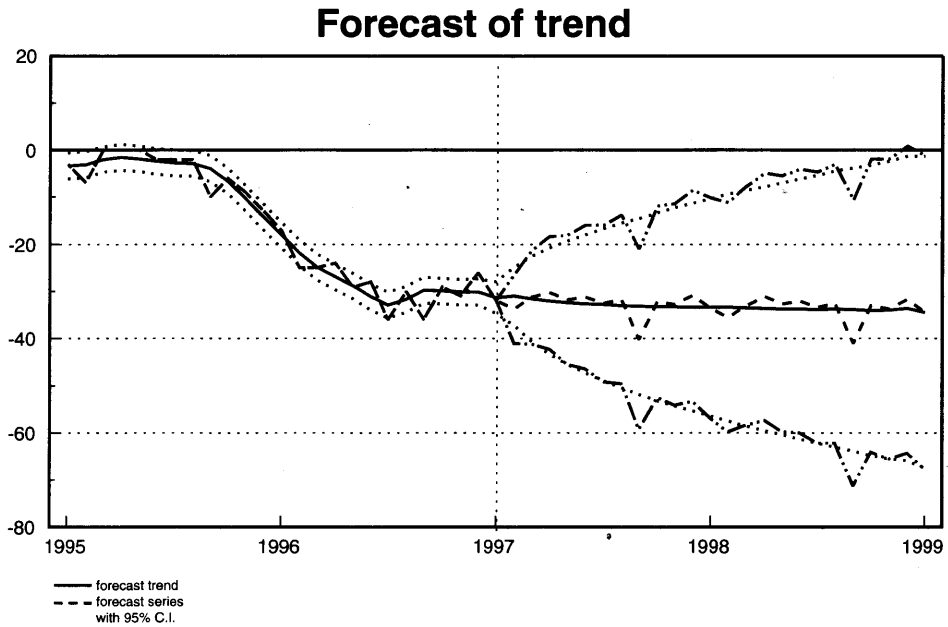

Spectrum series
Sqd. gain of Trend and SA series
trend
sa series
Spectrum of Trend and SA series
trend
sa series
Sqd. gain Seasonal

FIGURA 3 – BDI

FIGURA 4 – BDI


Forecast of trend
20
0
-20
-40
-60
-80
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.

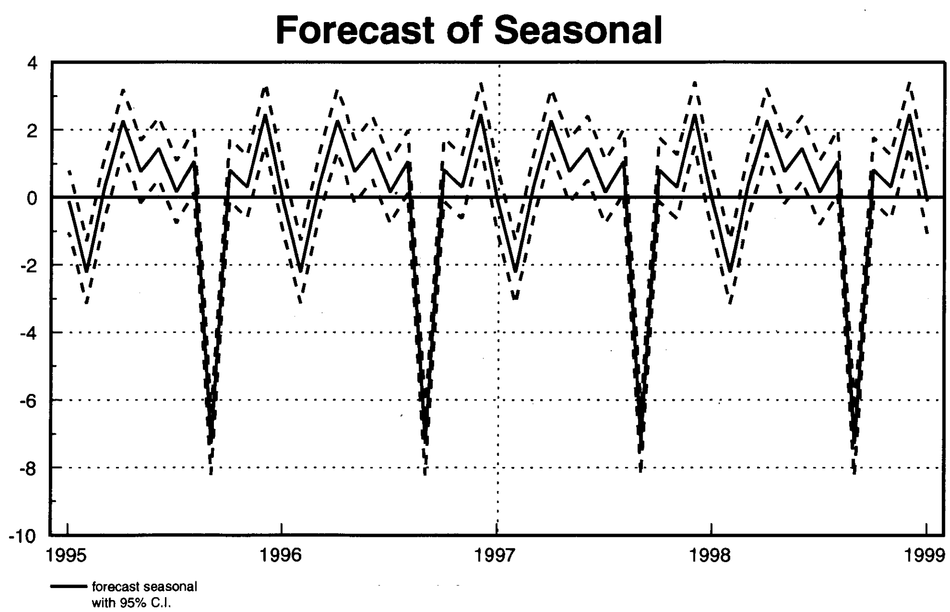
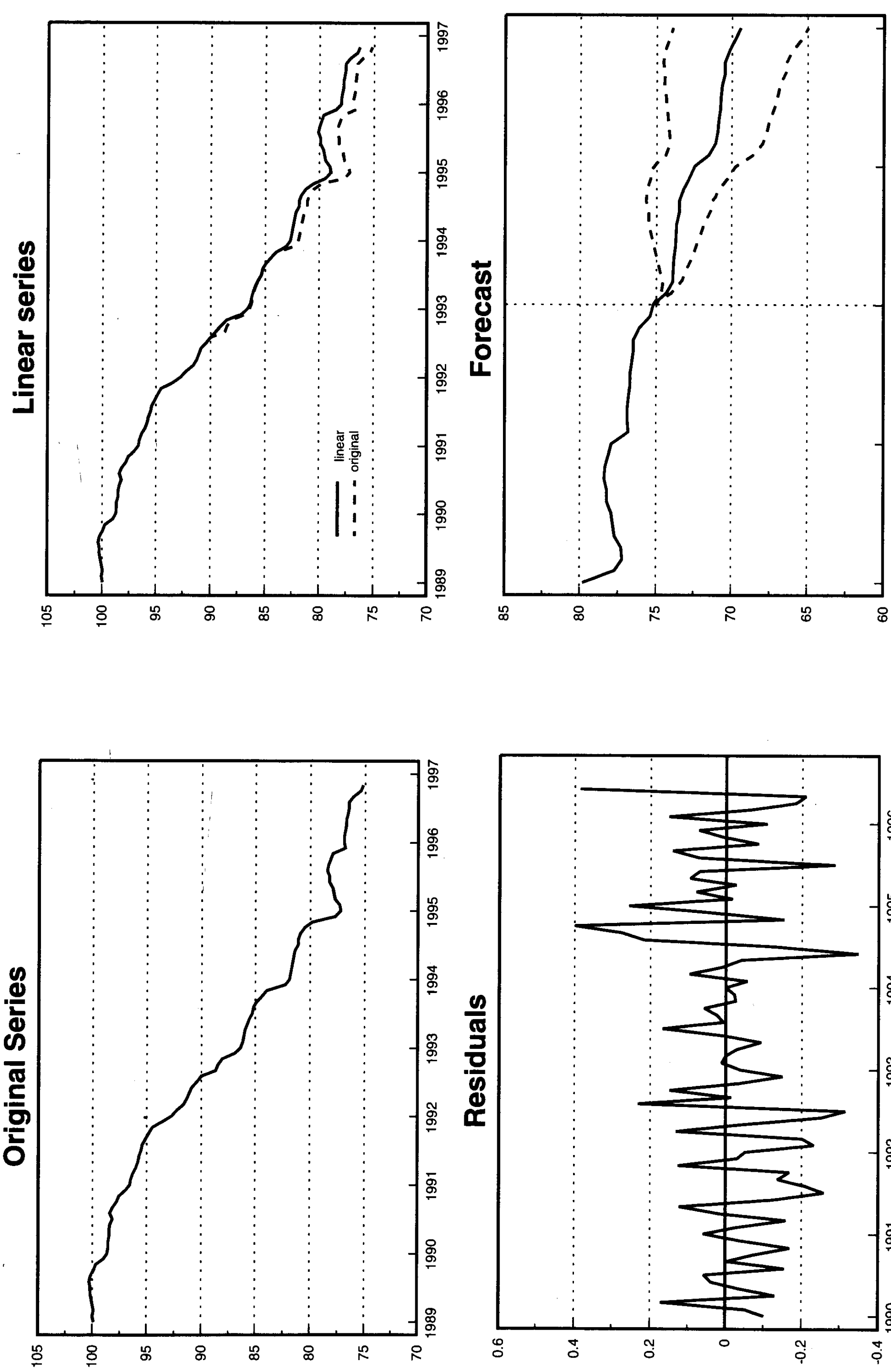

Forecast of Seasonal
4
2
0
-2
-4
-6
-8
-10
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

FIGURA 1 - LGO


Linear series
linear
original
Forecast
Original Series
Residuals

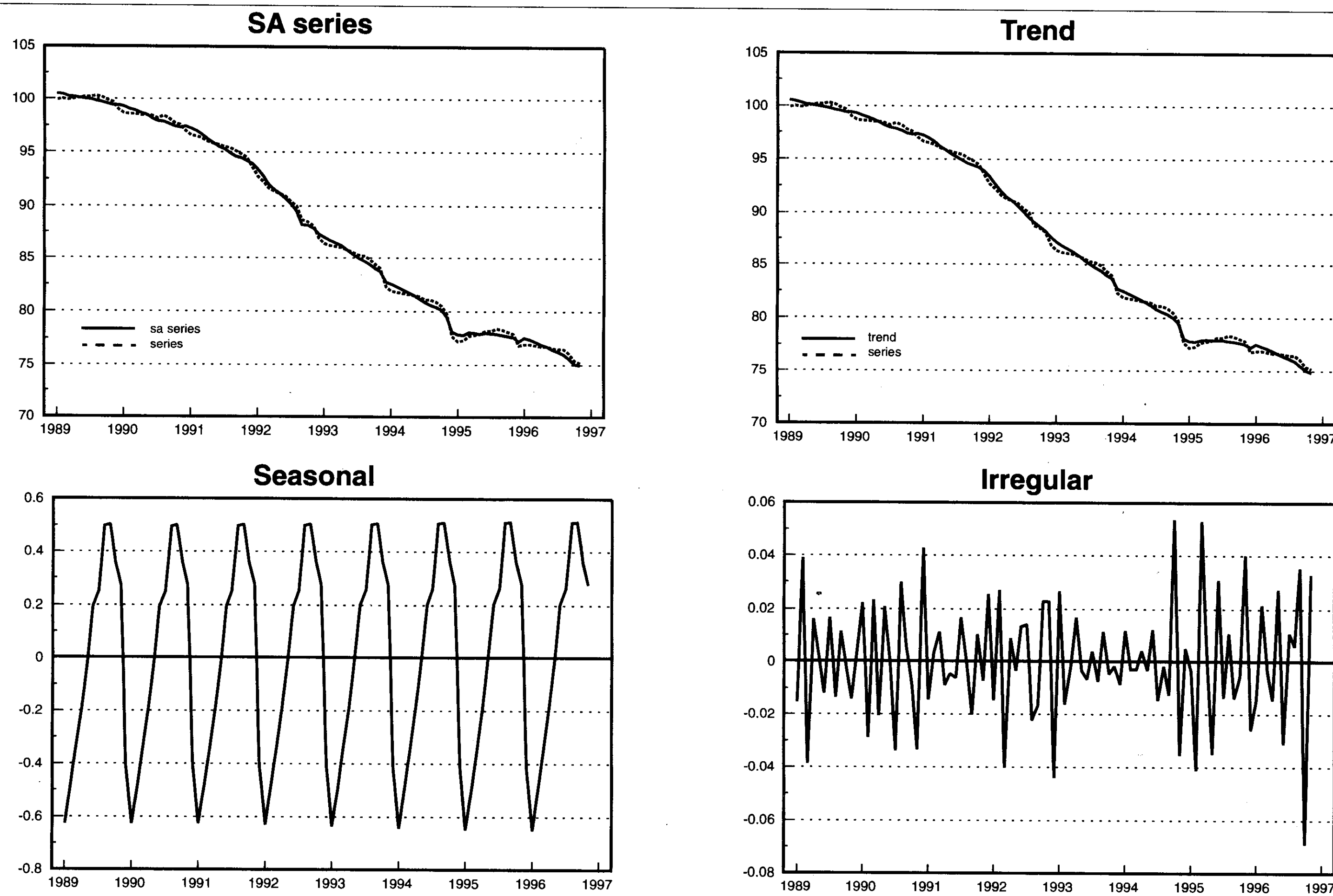

SA series
sa series
series
Trend
trend
series
Seasonal
Irregular
1989
1990
1991
1992
1993
1994
1995
1996
1997

FIGURA 2 - LGO

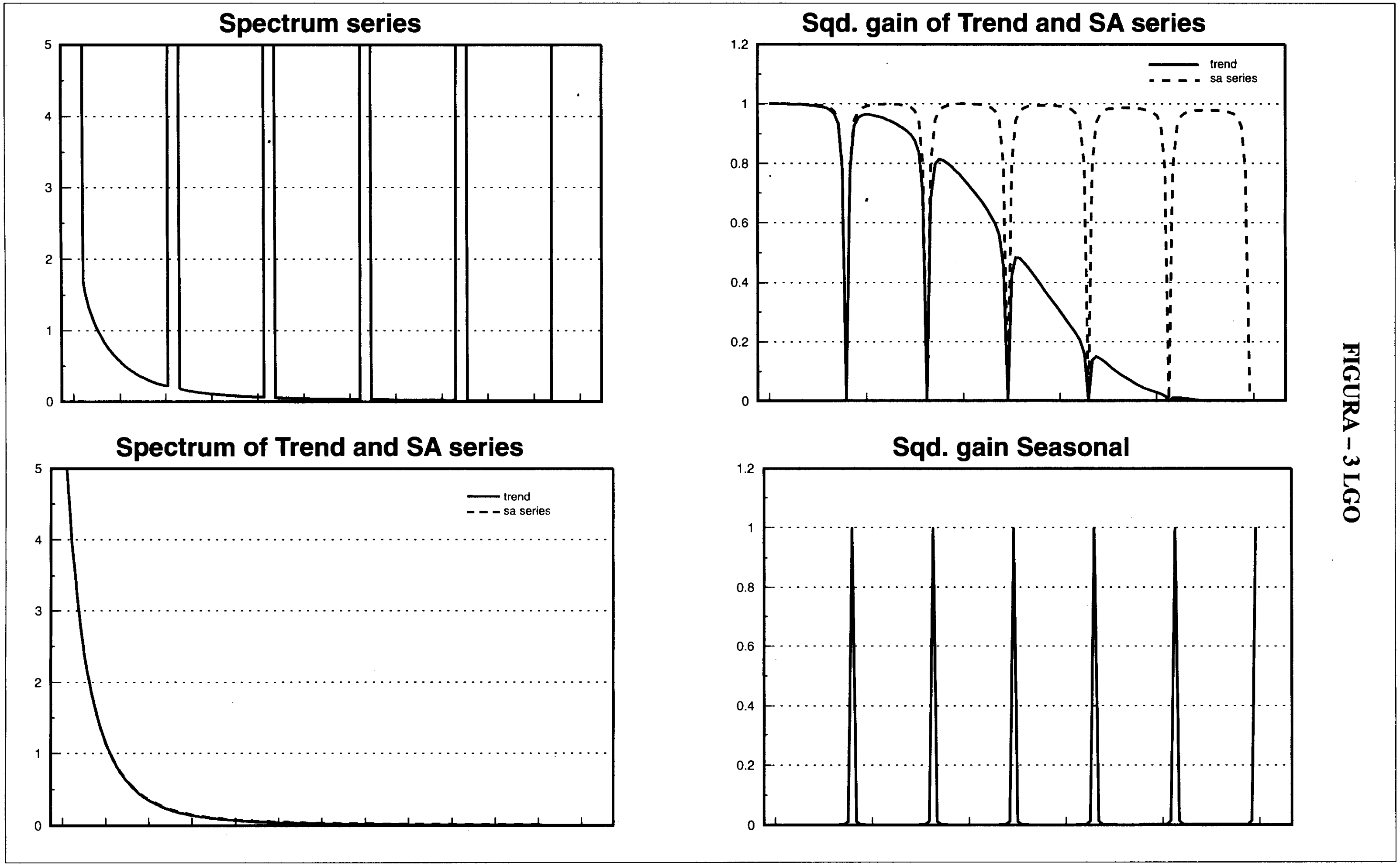
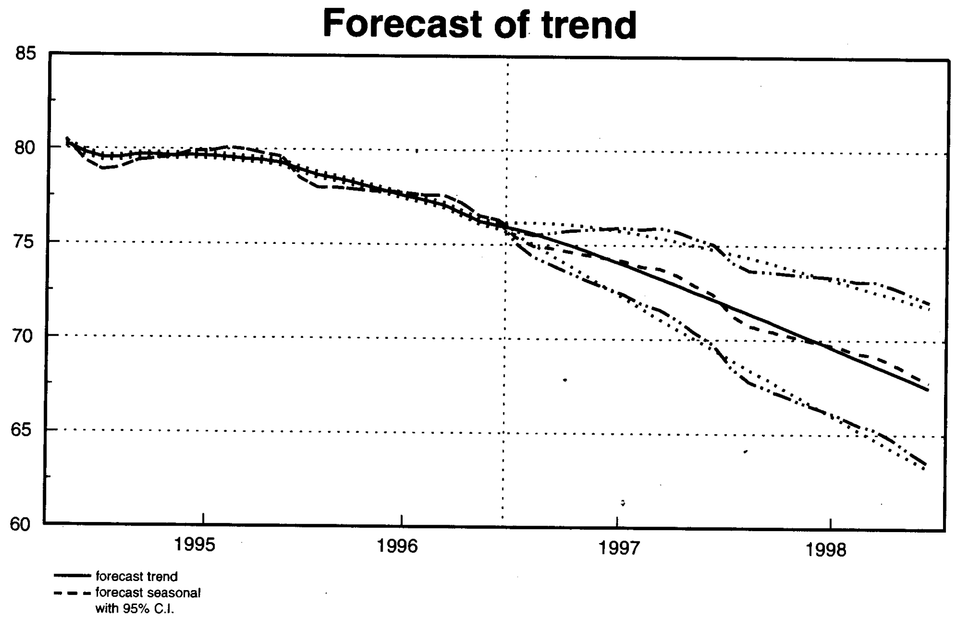
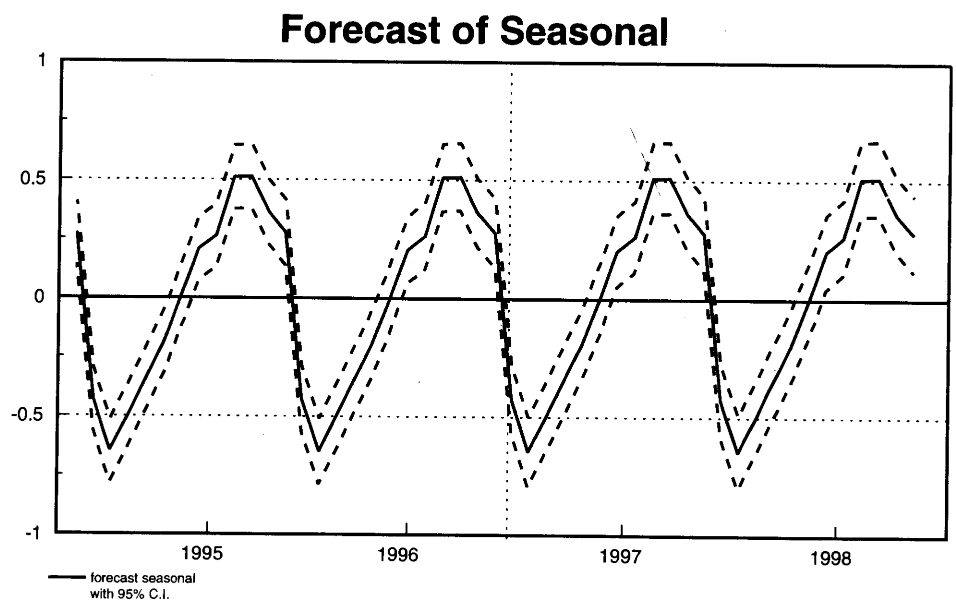

Spectrum series
Sqd. gain of Trend and SA series
trend
sa series
Spectrum of Trend and SA series
trend
sa series
Sqd. gain Seasonal
0
1
2
3
4
5
0
0.2
0.4
0.6
0.8
1
1.2

FIGURA – 3 LGO

FIGURA – 4 LGO


Forecast of trend
85
80
75
70
65
60
1995
1996
1997
1998
forecast trend
forecast seasonal
with 95% C.I.


Forecast of Seasonal
1
0.5
0
-0.5
-1
1995
1996
1997
1998
forecast seasonal
with 95% C.I.

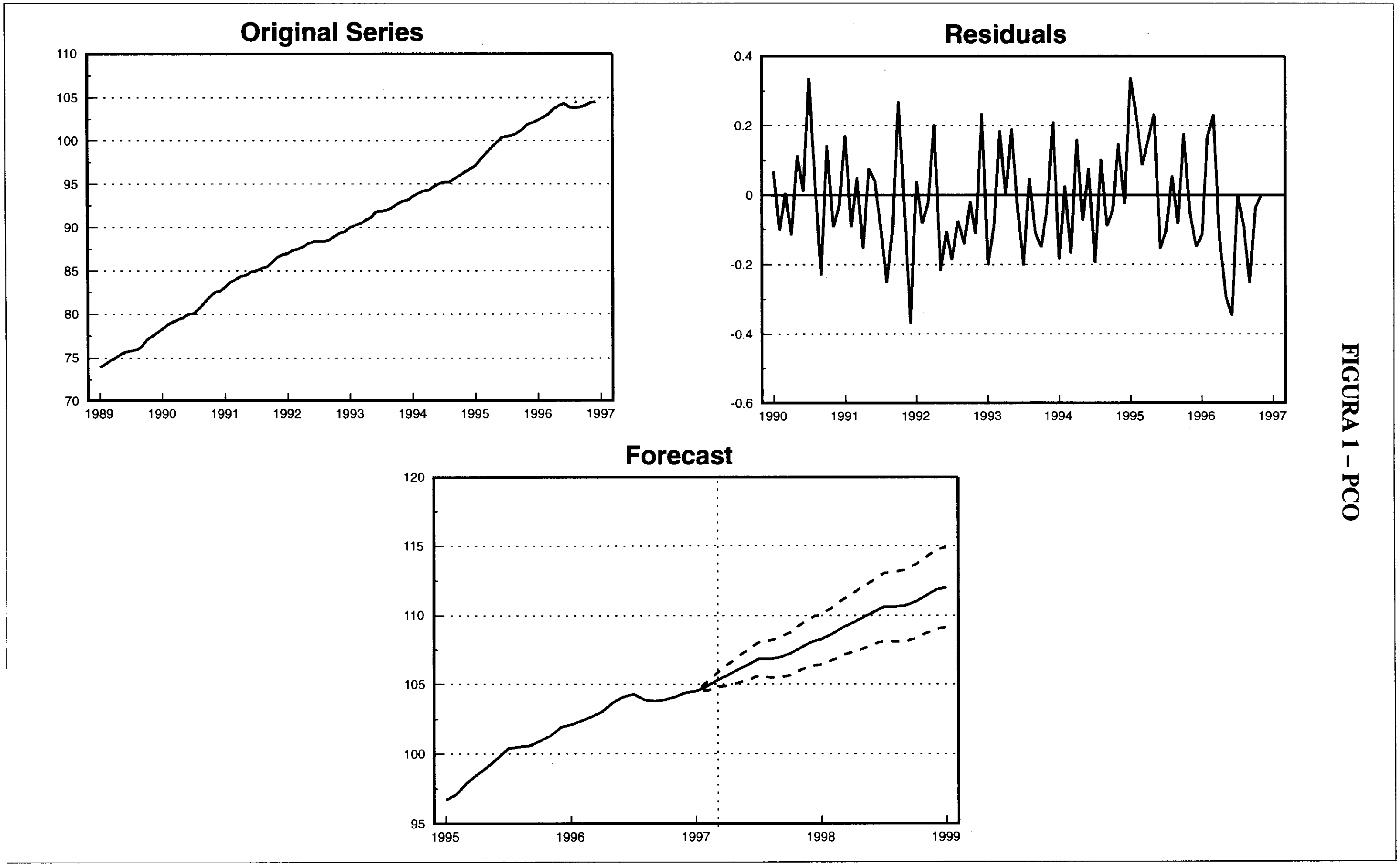

Original Series
110
105
100
95
90
85
80
75
70
1989
1990
1991
1992
1993
1994
1995
1996
1997
Residuals
0.4
0.2
0
-0.2
-0.4
-0.6
1990
1991
1992
1993
1994
1995
1996
1997
Forecast
120
115
110
105
100
95
1995
1996
1997
1998
1999

FIGURA 1 – PCO

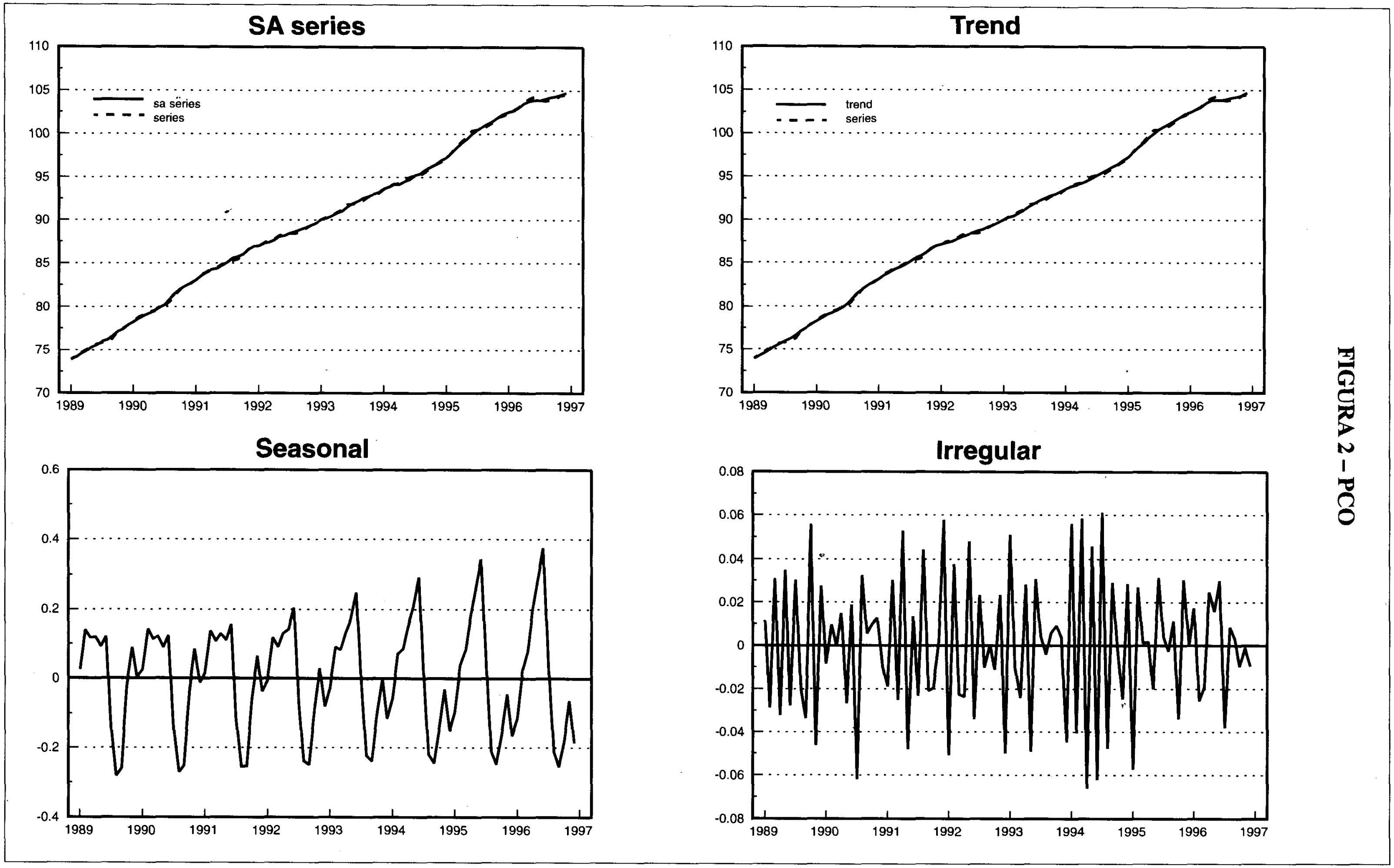

SA series
sa series
series
Trend
trend
series
Seasonal
Irregular
110
105
100
95
90
85
80
75
70
0.6
0.4
0.2
0
-0.2
-0.4
0.08
0.06
0.04
0.02
-0.02
-0.04
-0.06
-0.08
1989
1990
1991
1992
1993
1994
1995
1996
1997

FIGURA 2 - PCO

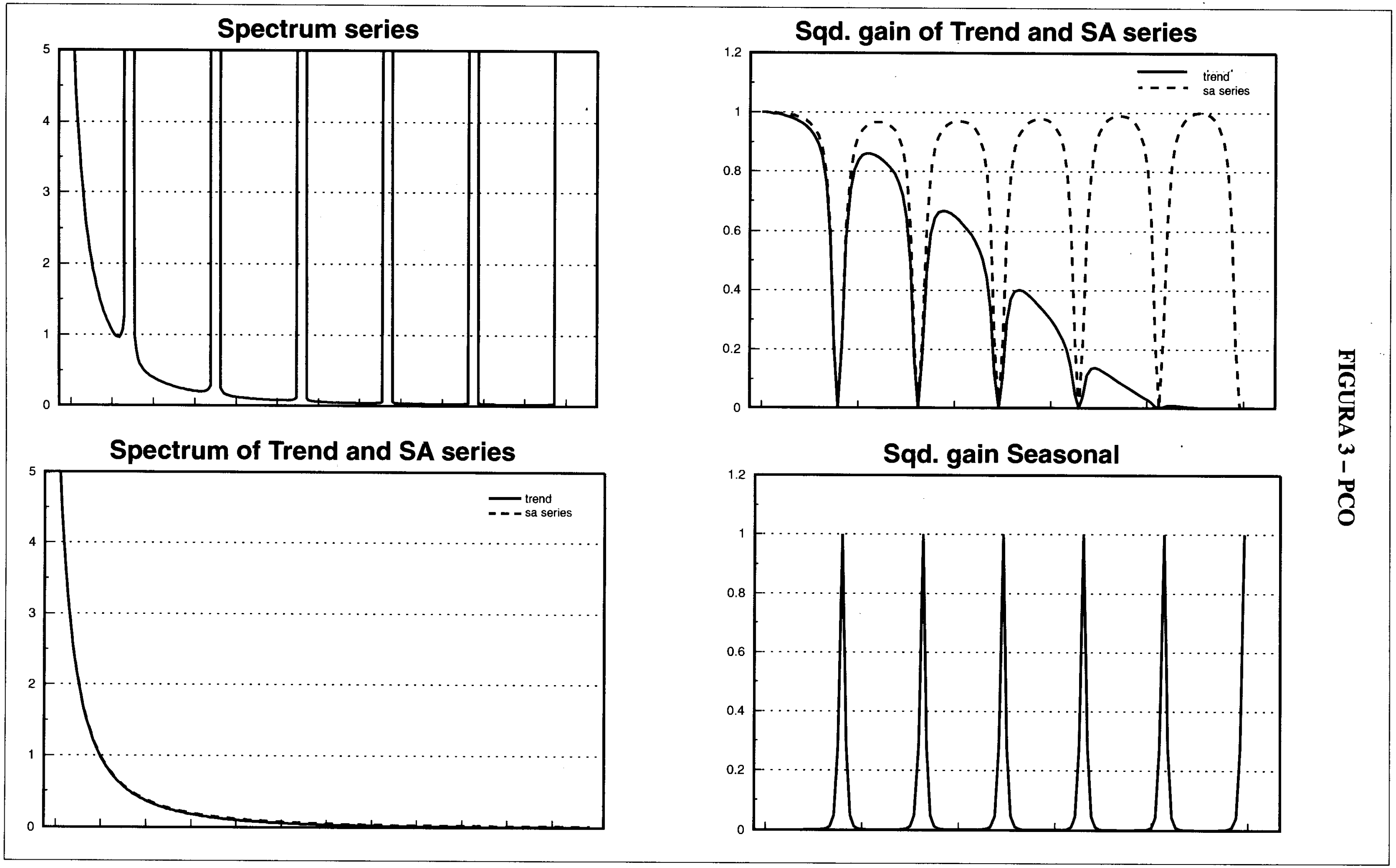

Spectrum series
5
4
3
2
1
0
Sqd. gain of Trend and SA series
1.2
1
0.8
0.6
0.4
0.2
0
trend
sa series
Spectrum of Trend and SA series
5
4
3
2
1
0
trend
sa series
Sqd. gain Seasonal
1.2
1
0.8
0.6
0.4
0.2
0

FIGURA 3 – PCO

FIGURA 4 – PCO

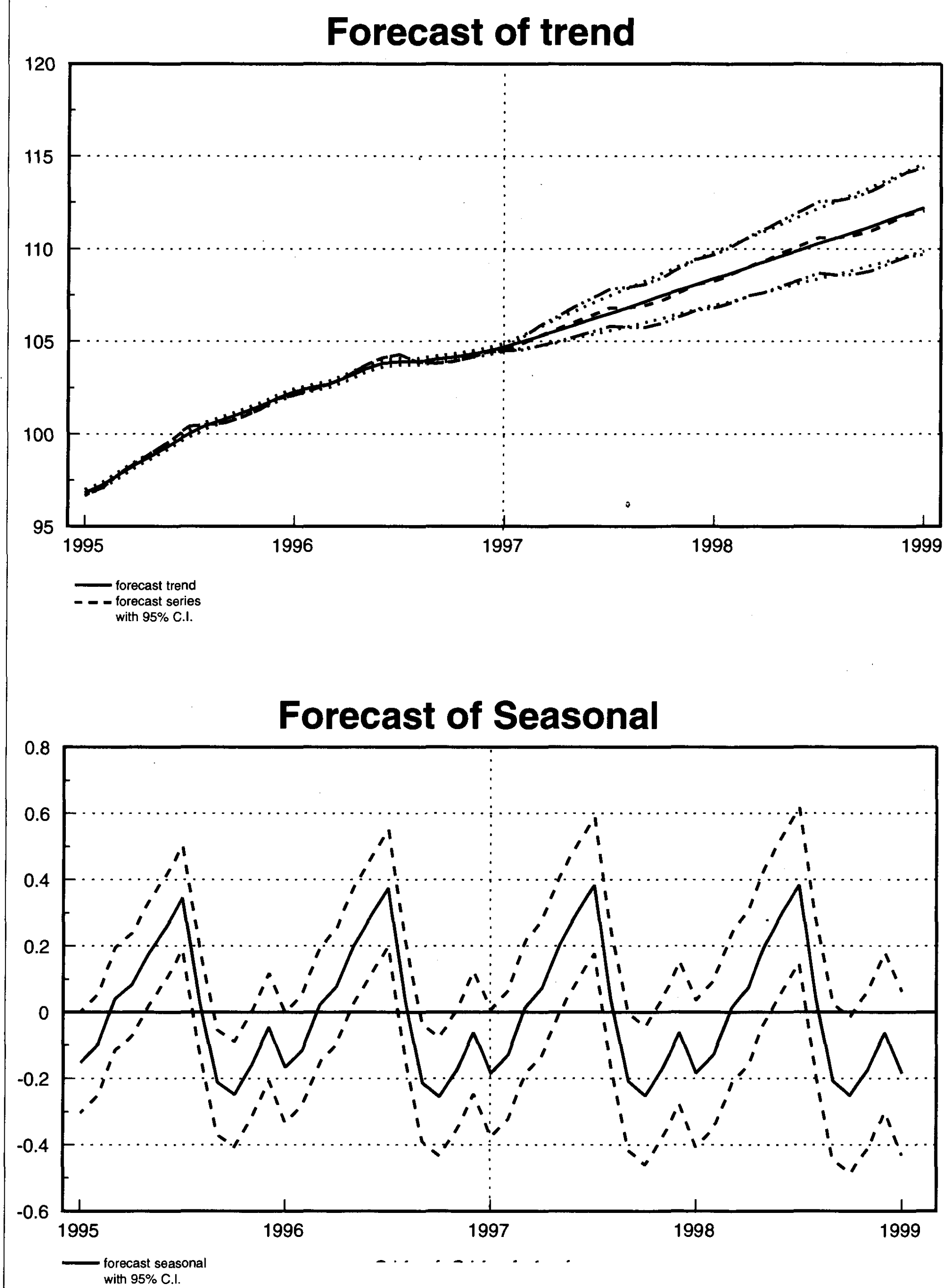
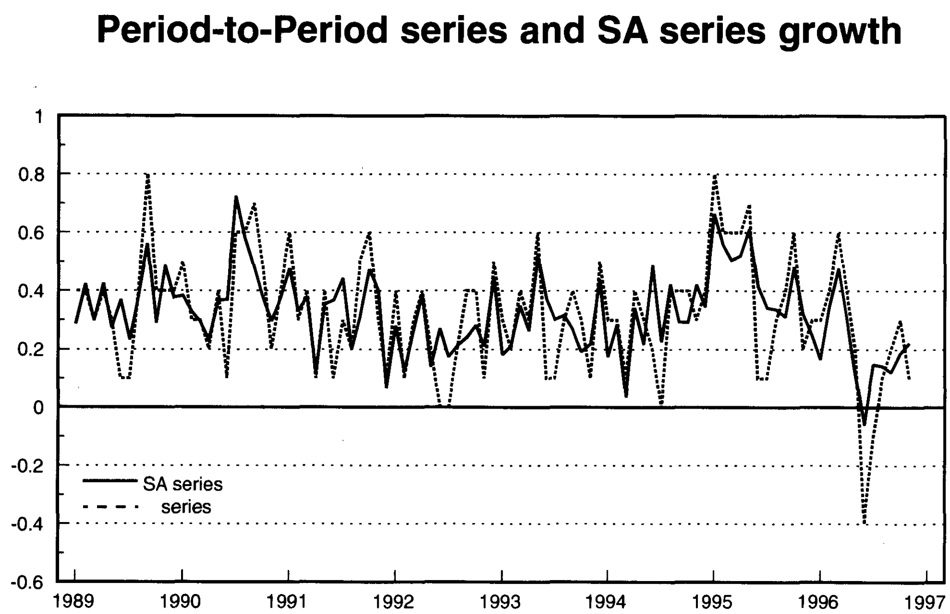

Forecast of trend
120
115
110
105
100
95
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.
Forecast of Seasonal
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

FIGURA 5 – PCO


Period-to-Period series and SA series growth
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
SA series
series
1989
1990
1991
1992
1993
1994
1995
1996
1997

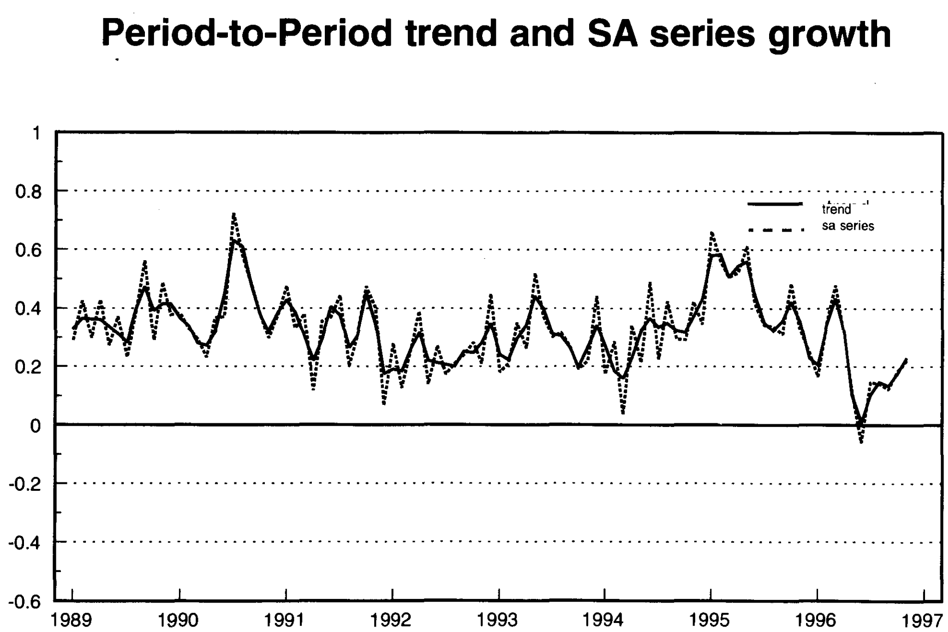
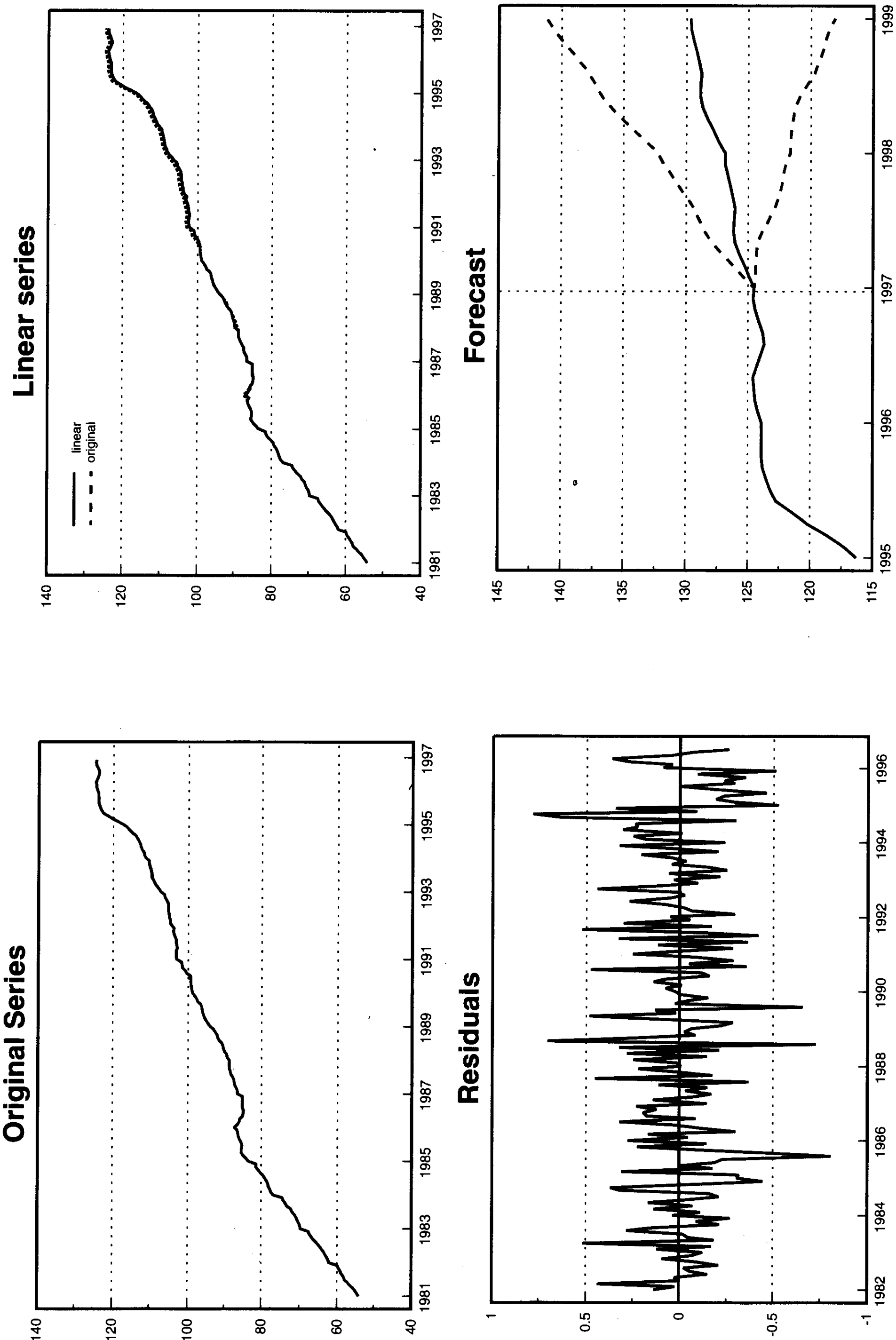

Period-to-Period trend and SA series growth
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
trend
sa series
1989
1990
1991
1992
1993
1994
1995
1996
1997

FIGURA 1 – PPI


Original Series
Linear series
linear
original
Residuals
Forecast

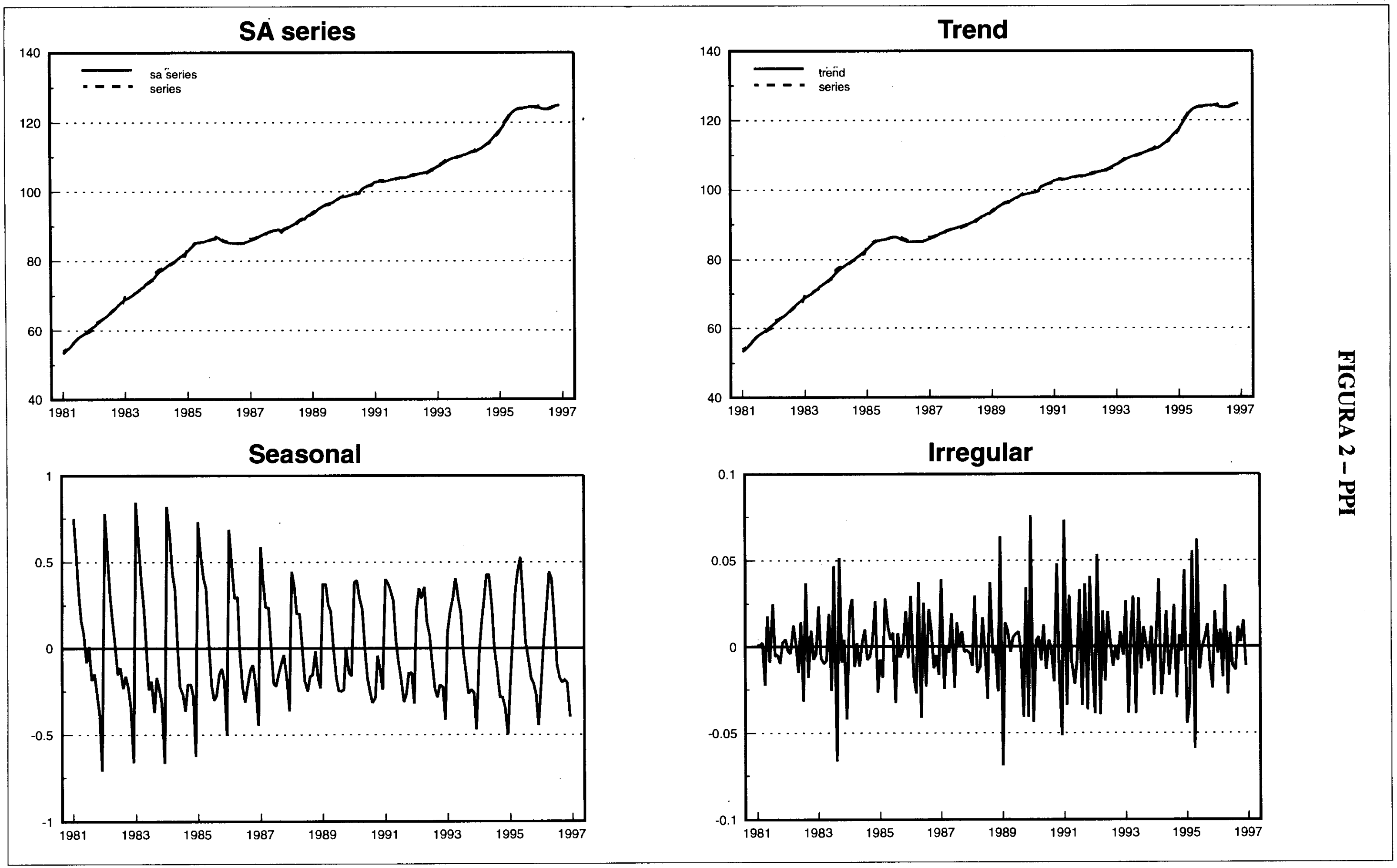

SA series
sa series
series
140
120
100
80
60
40
1981 1983 1985 1987 1989 1991 1993 1995 1997
Trend
trend
series
140
120
100
80
60
40
1981 1983 1985 1987 1989 1991 1993 1995 1997
Seasonal
1
0.5
0
-0.5
-1
1981 1983 1985 1987 1989 1991 1993 1995 1997
Irregular
0.1
0.05
0
-0.05
-0.1
1981 1983 1985 1987 1989 1991 1993 1995 1997

FIGURA 2 – PPI

FIGURA 3 – PPI

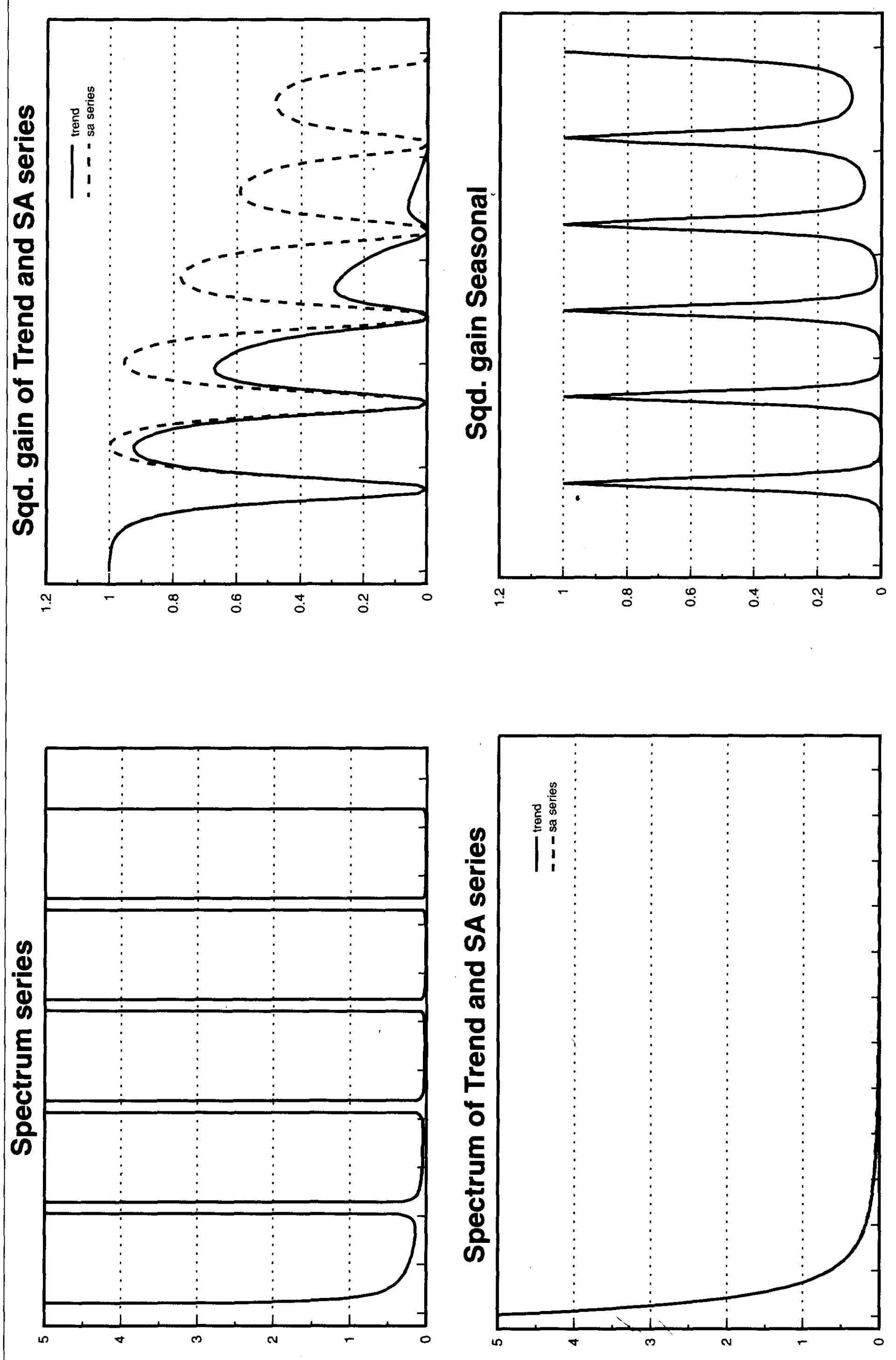
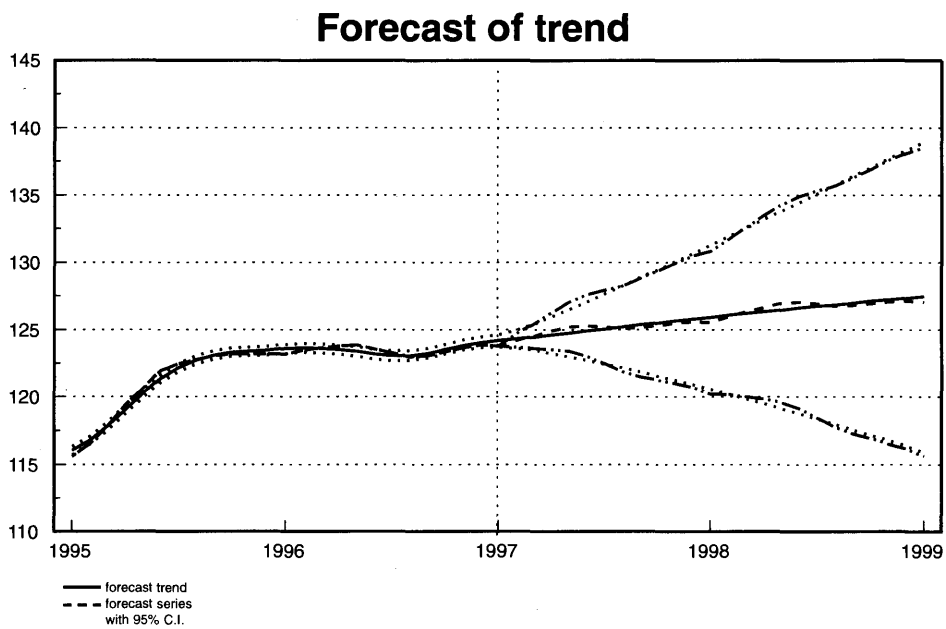

Sqd. gain of Trend and SA series
trend
sa series
Sqd. gain Seasonal
Spectrum series
Spectrum of Trend and SA series
trend
sa series

FIGURA 4 – PPI


Forecast of trend
145
140
135
130
125
120
115
110
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.

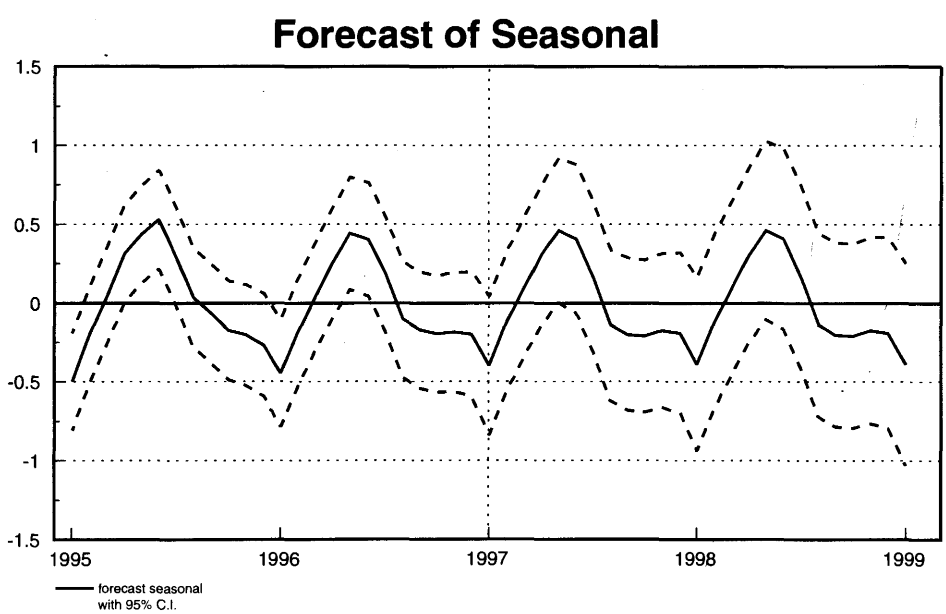
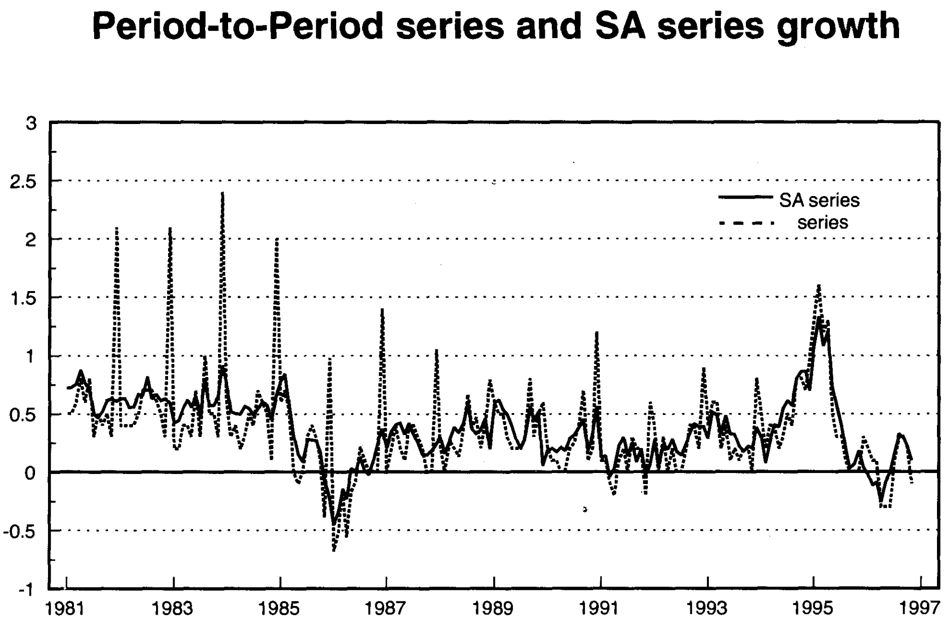
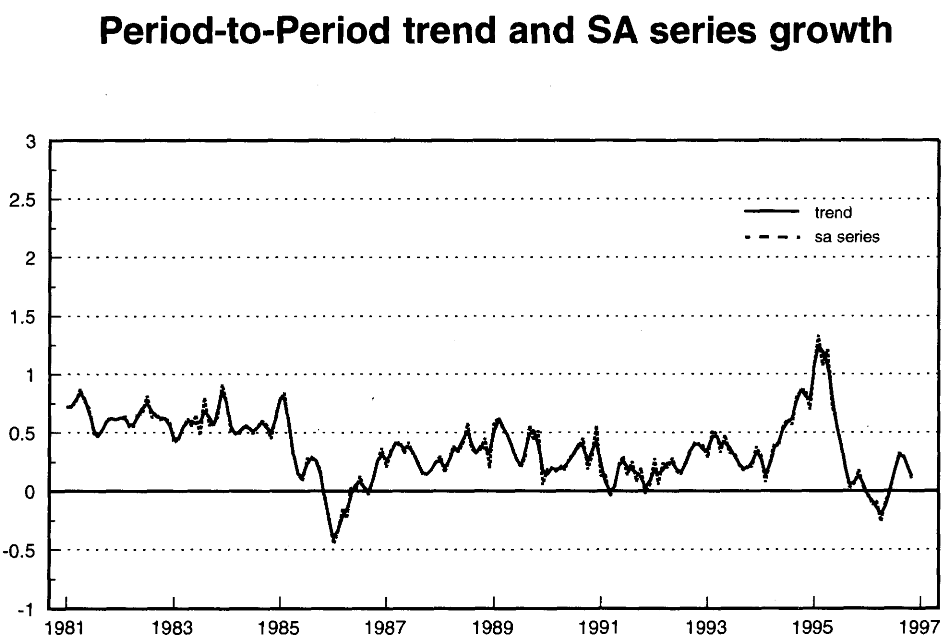

Forecast of Seasonal
1.5
1
0.5
0
-0.5
-1
-1.5
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

FIGURA 5 – PPI


Period-to-Period series and SA series growth
SA series
series
3
2.5
2
1.5
1
0.5
0
-0.5
-1
1981
1983
1985
1987
1989
1991
1993
1995
1997


Period-to-Period trend and SA series growth
trend
sa series
3
2.5
2
1.5
1
0.5
0
-0.5
-1
1981
1983
1985
1987
1989
1991
1993
1995
1997

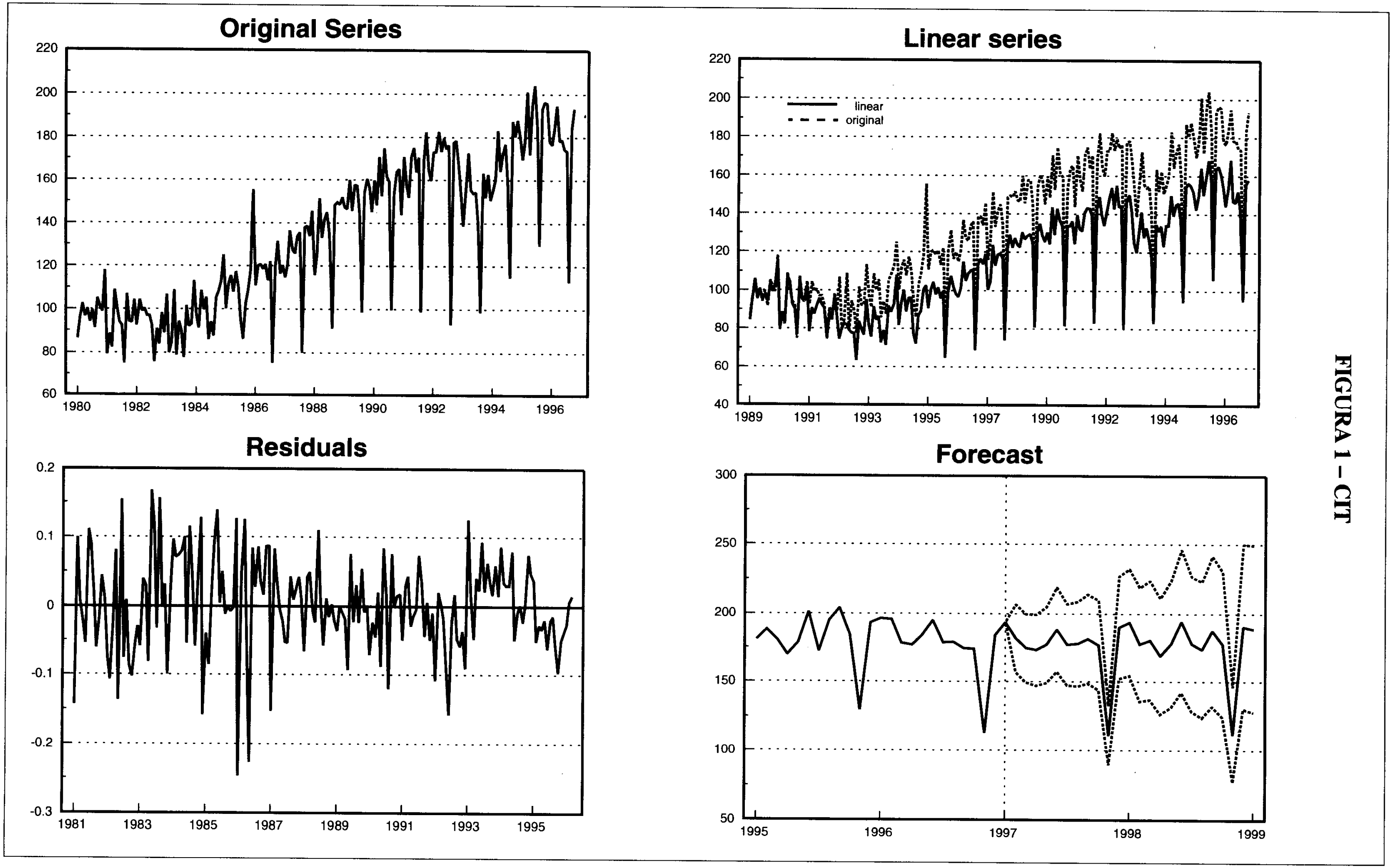

Original Series
220
200
180
160
140
120
100
80
60
1980
1982
1984
1986
1988
1990
1992
1994
1996
Linear series
linear
original
220
200
180
160
140
120
100
80
60
40
1989
1991
1993
1995
1997
1990
1992
1994
1996
Residuals
0.2
0.1
0
-0.1
-0.2
-0.3
1981
1983
1985
1987
1989
1991
1993
1995
Forecast
300
250
200
150
100
50
1995
1996
1997
1998
1999

FIGURA 1 – CIT

FIGURA 2 - CIT

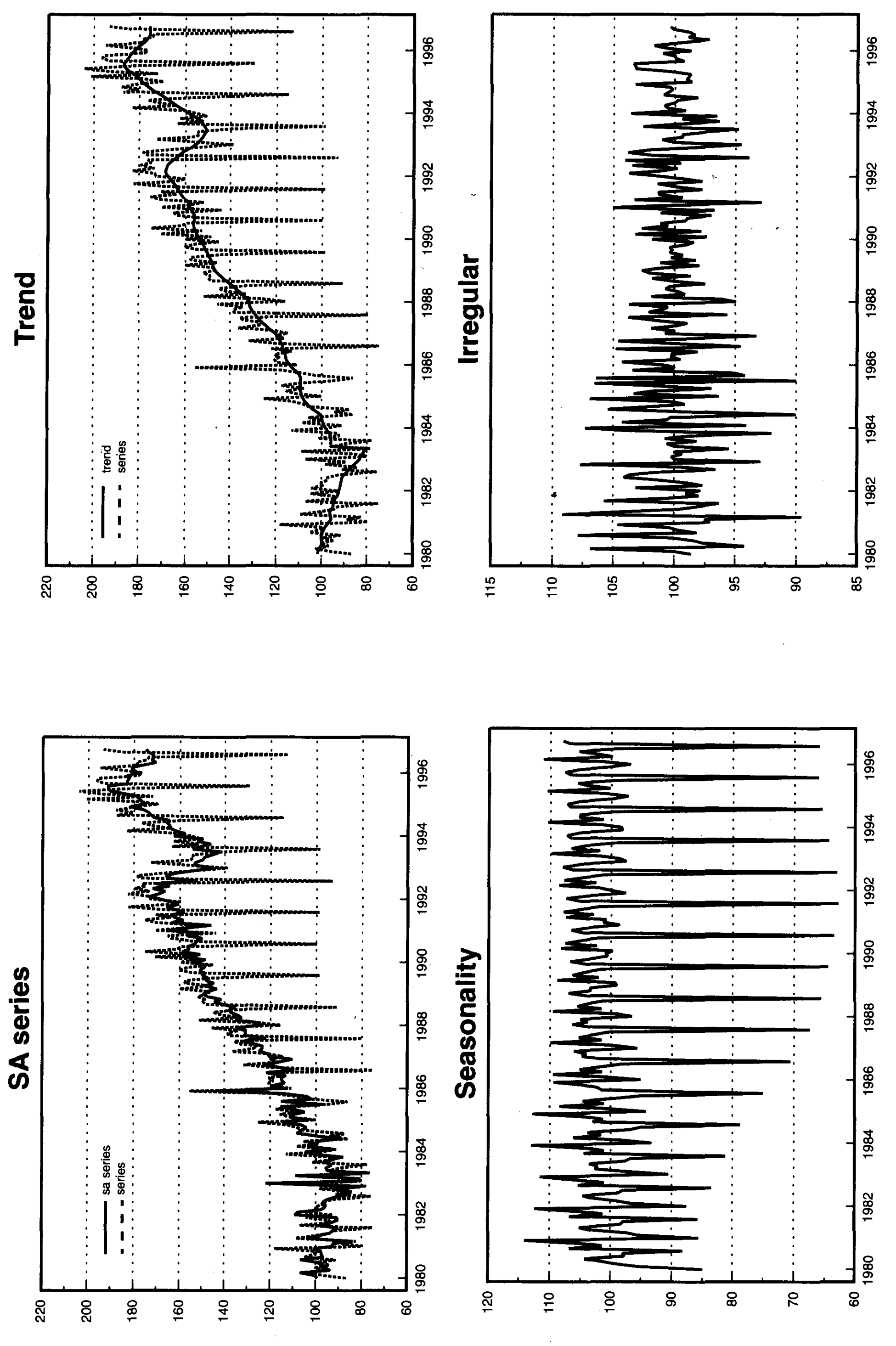

SA series
sa series
series
Trend
trend
series
Seasonality
Irregular

FIGURA 3 – CIT

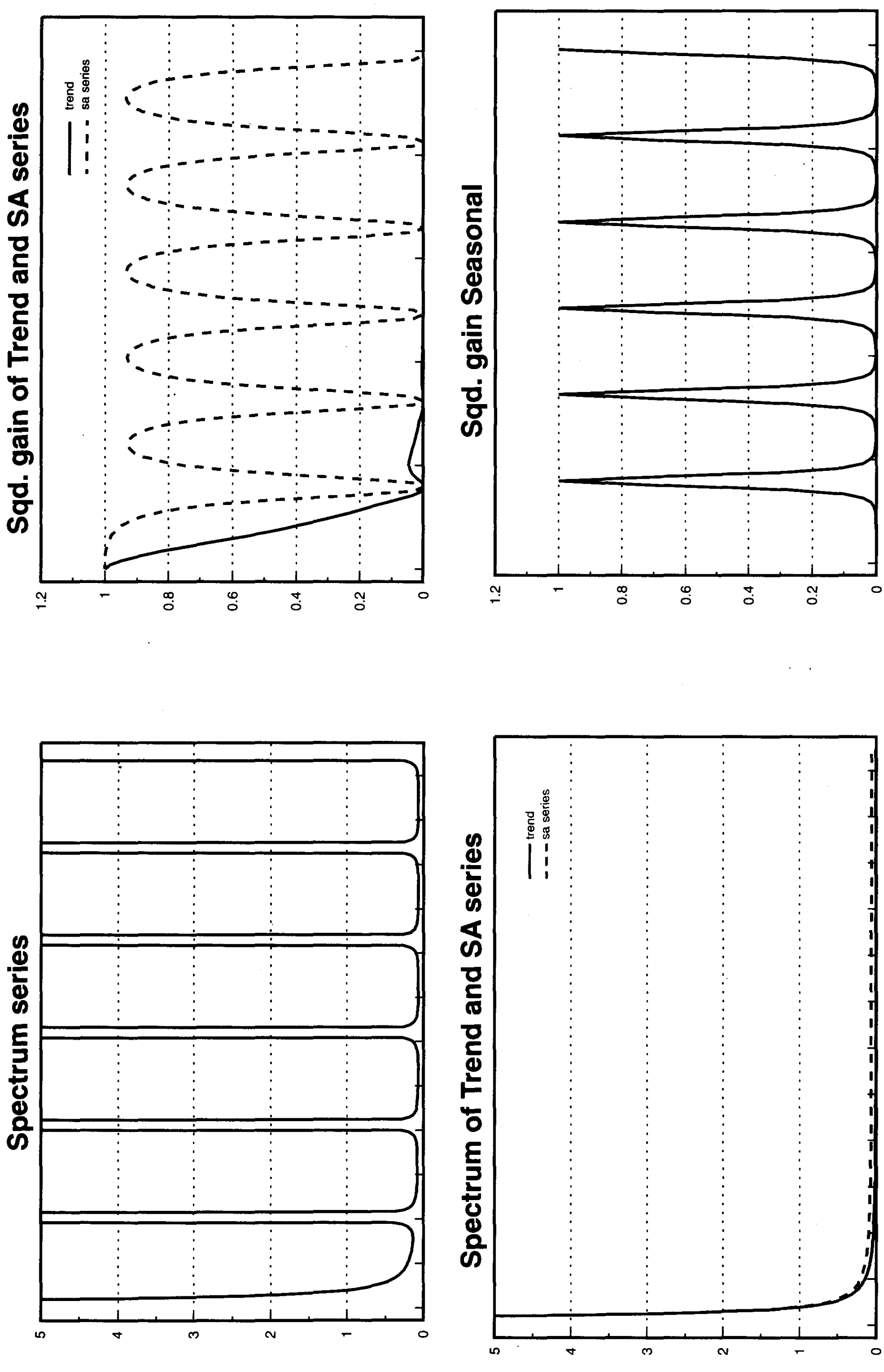
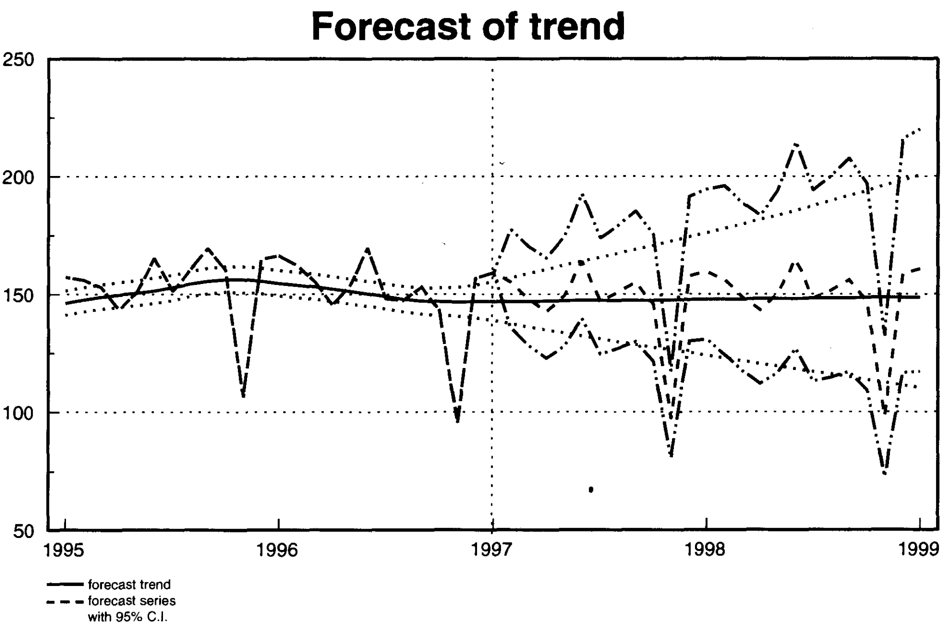
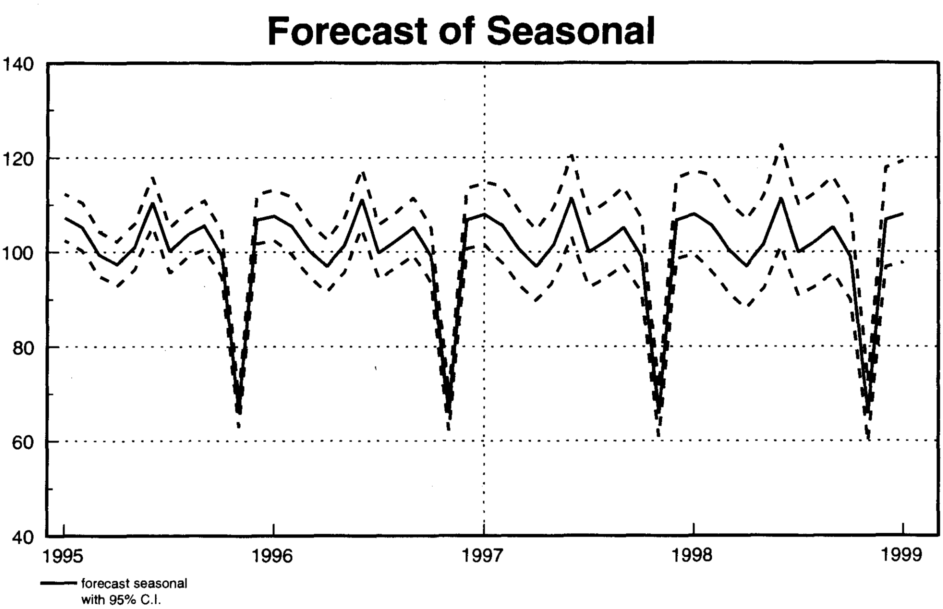

Sqd. gain of Trend and SA series
trend
sa series
1.2
1
0.8
0.6
0.4
0.2
0
Sqd. gain Seasonal
1.2
1
0.8
0.6
0.4
0.2
0
Spectrum series
5
4
3
2
1
0
Spectrum of Trend and SA series
trend
sa series
5
4
3
2
1
0

FIGURA 4 - CIT


Forecast of trend
250
200
150
100
50
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.


Forecast of Seasonal
140
120
100
80
60
40
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

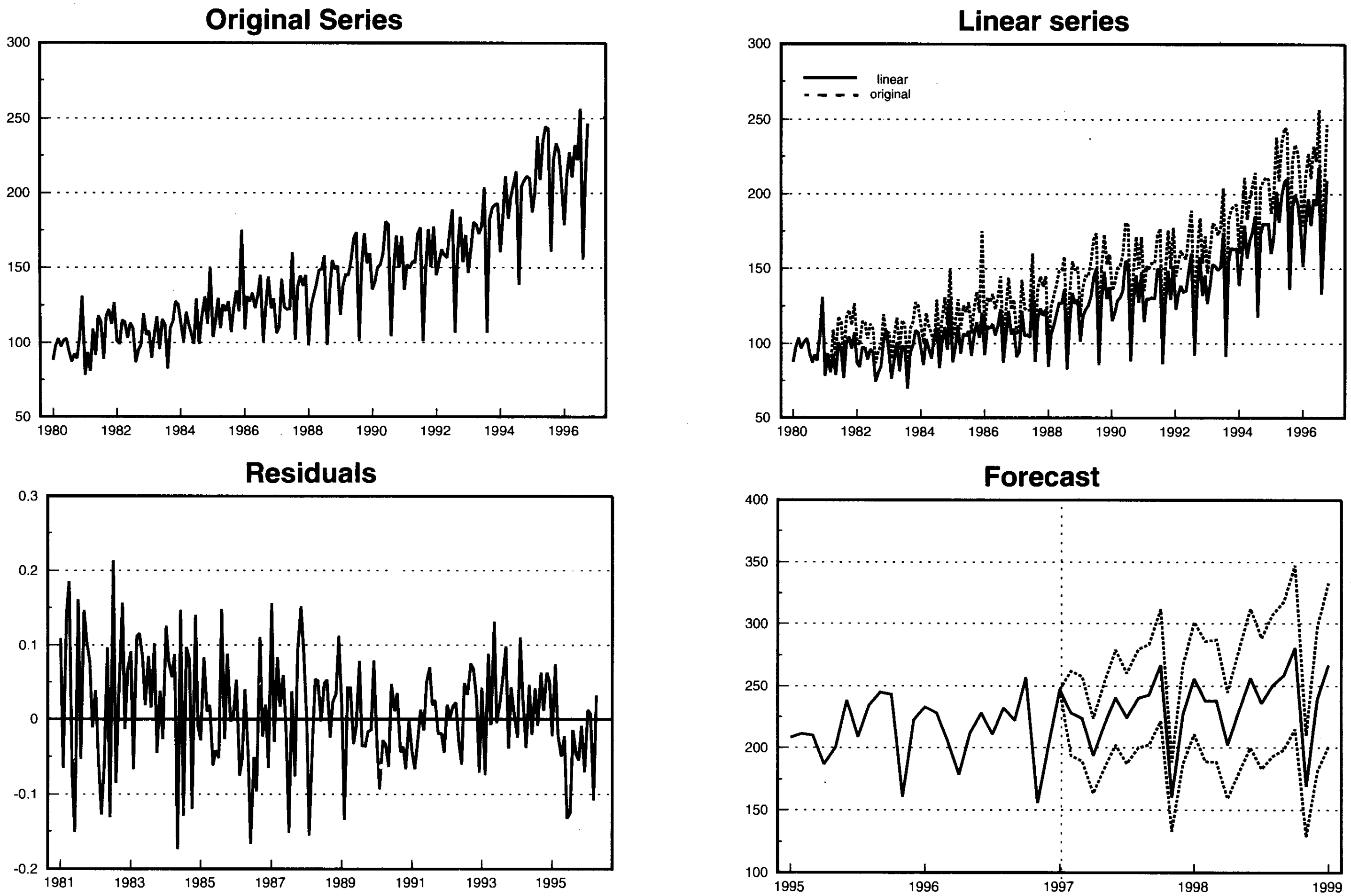

Original Series
300
250
200
150
100
50
1980
1982
1984
1986
1988
1990
1992
1994
1996
Linear series
linear
original
300
250
200
150
100
50
1980
1982
1984
1986
1988
1990
1992
1994
1996
Residuals
0.3
0.2
0.1
0
-0.1
-0.2
1981
1983
1985
1987
1989
1991
1993
1995
Forecast
400
350
300
250
200
150
100
1995
1996
1997
1998
1999

FIGURA 1 – CET

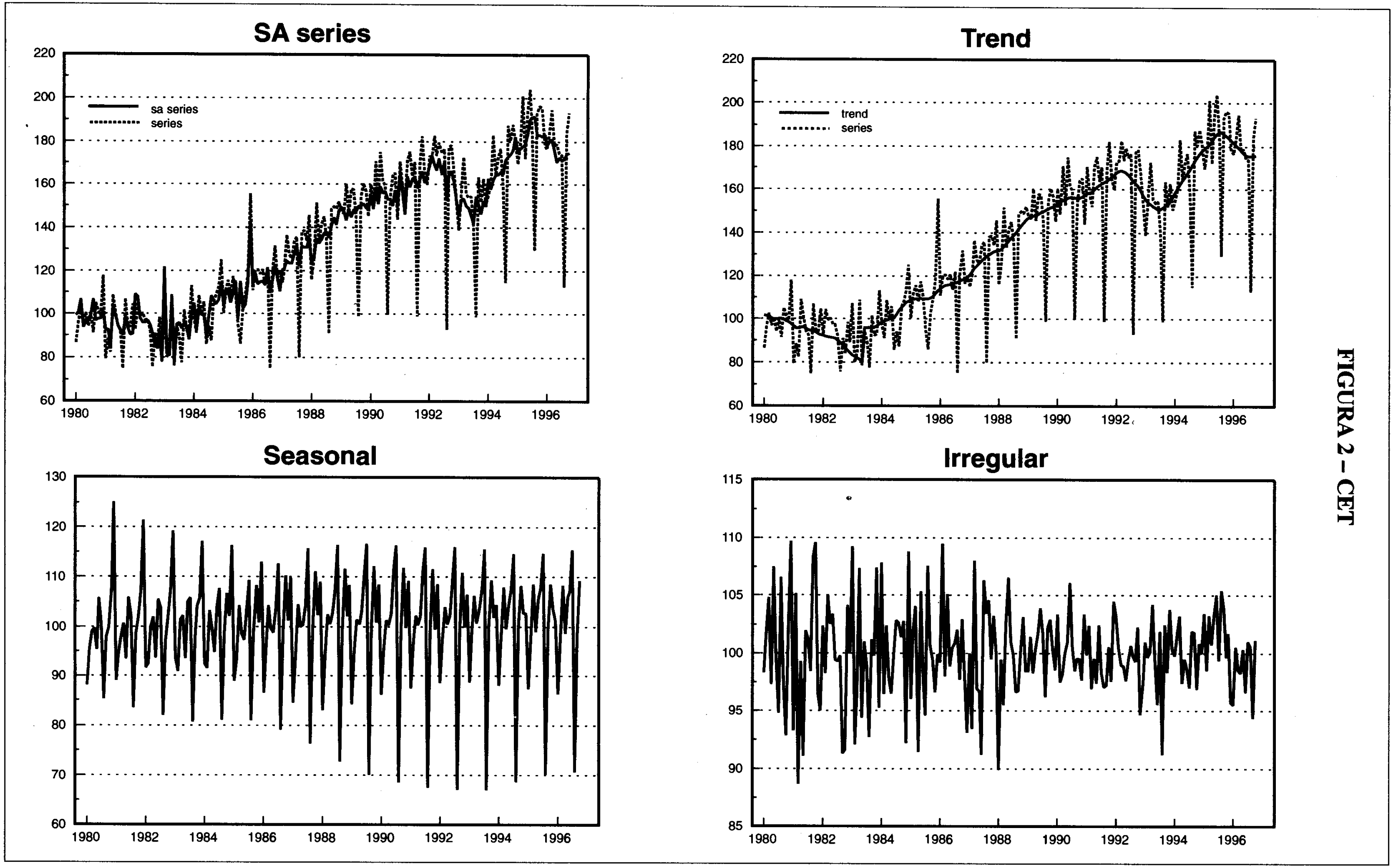

SA series
sa series
series
Trend
trend
series
Seasonal
Irregular
220
200
180
160
140
120
100
80
60
130
120
110
100
90
80
70
60
115
110
105
100
95
90
85
1980
1982
1984
1986
1988
1990
1992
1994
1996

FIGURA 2 – CET

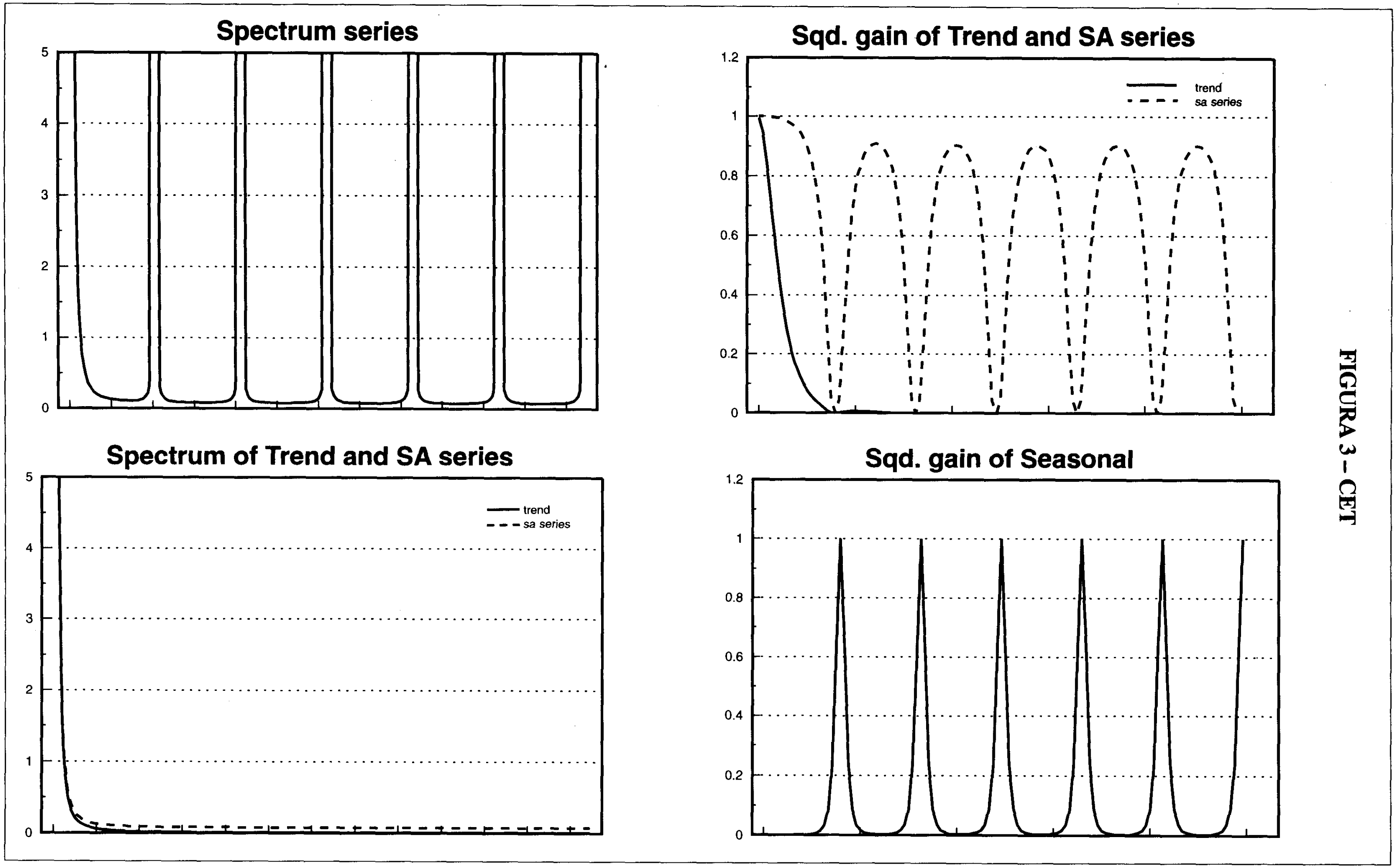
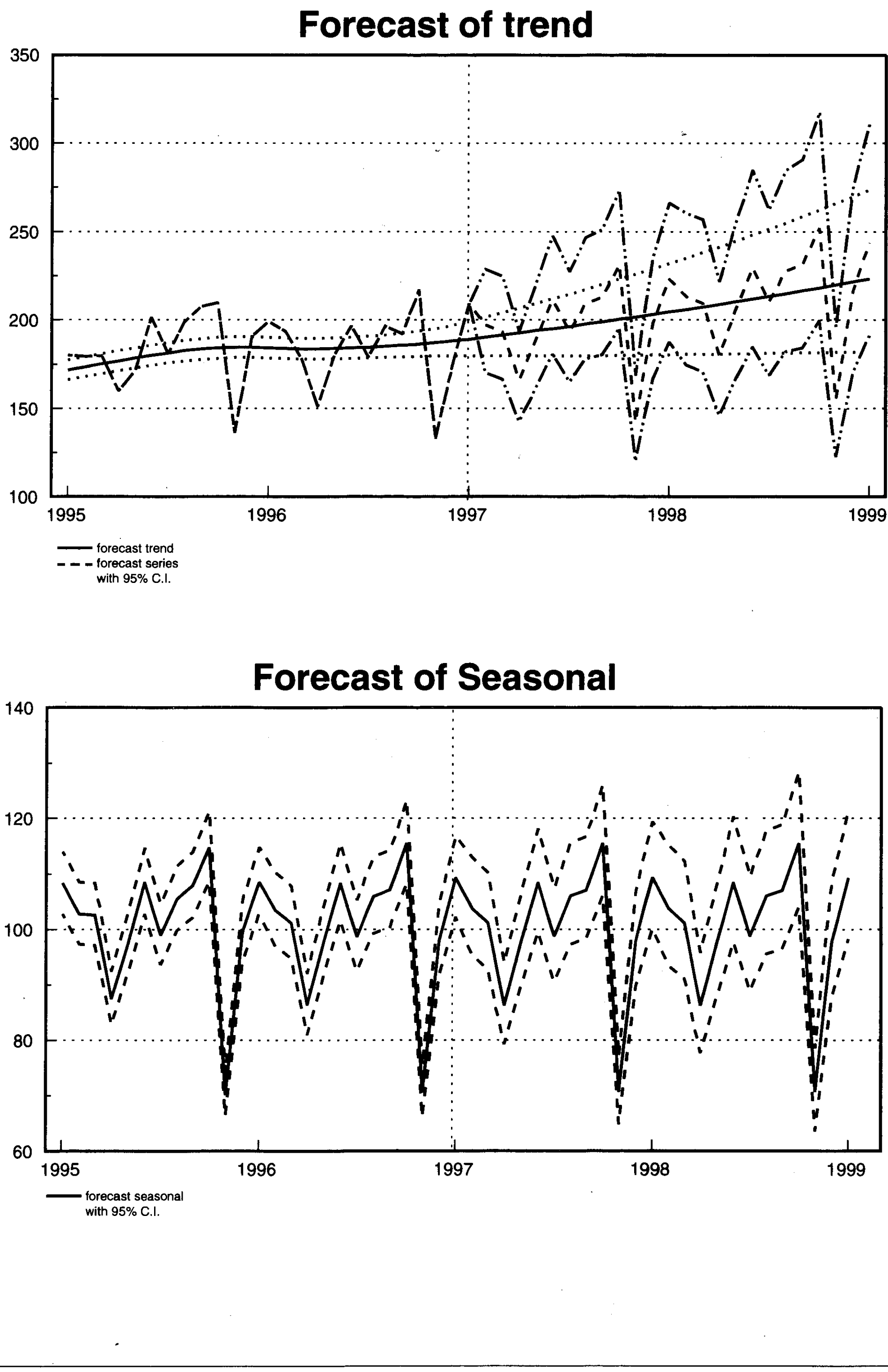

Spectrum series
5
4
3
2
1
0
Sqd. gain of Trend and SA series
1.2
1
0.8
0.6
0.4
0.2
0
trend
sa series
Spectrum of Trend and SA series
5
4
3
2
1
0
trend
sa series
Sqd. gain of Seasonal
1.2
1
0.8
0.6
0.4
0.2
0

FIGURA 3 – CET

FIGURA 4 – CET


Forecast of trend
350
300
250
200
150
100
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.
Forecast of Seasonal
140
120
100
80
60
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

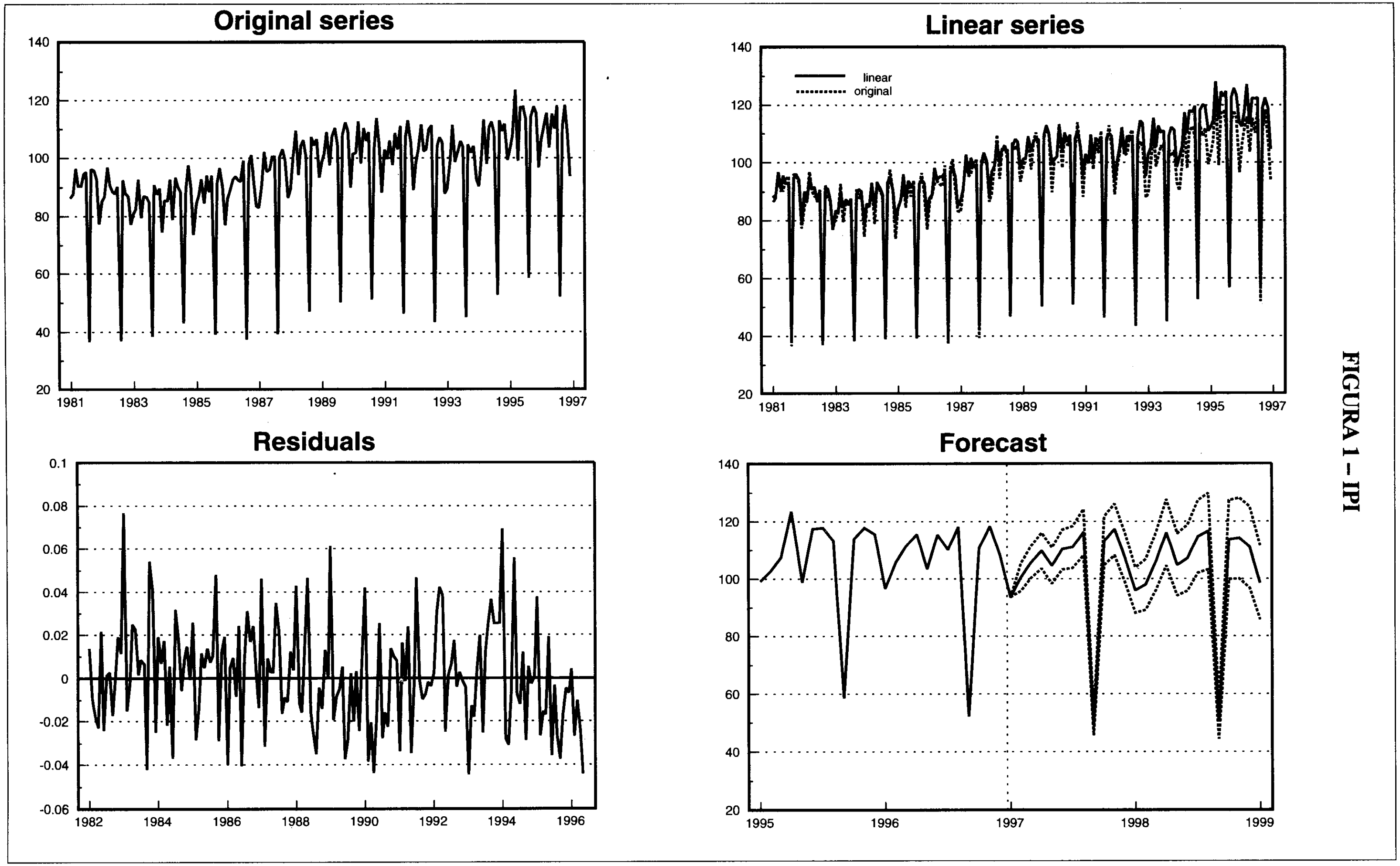

Original series
Linear series
linear
original
Residuals
Forecast

FIGURA 1 - IPI

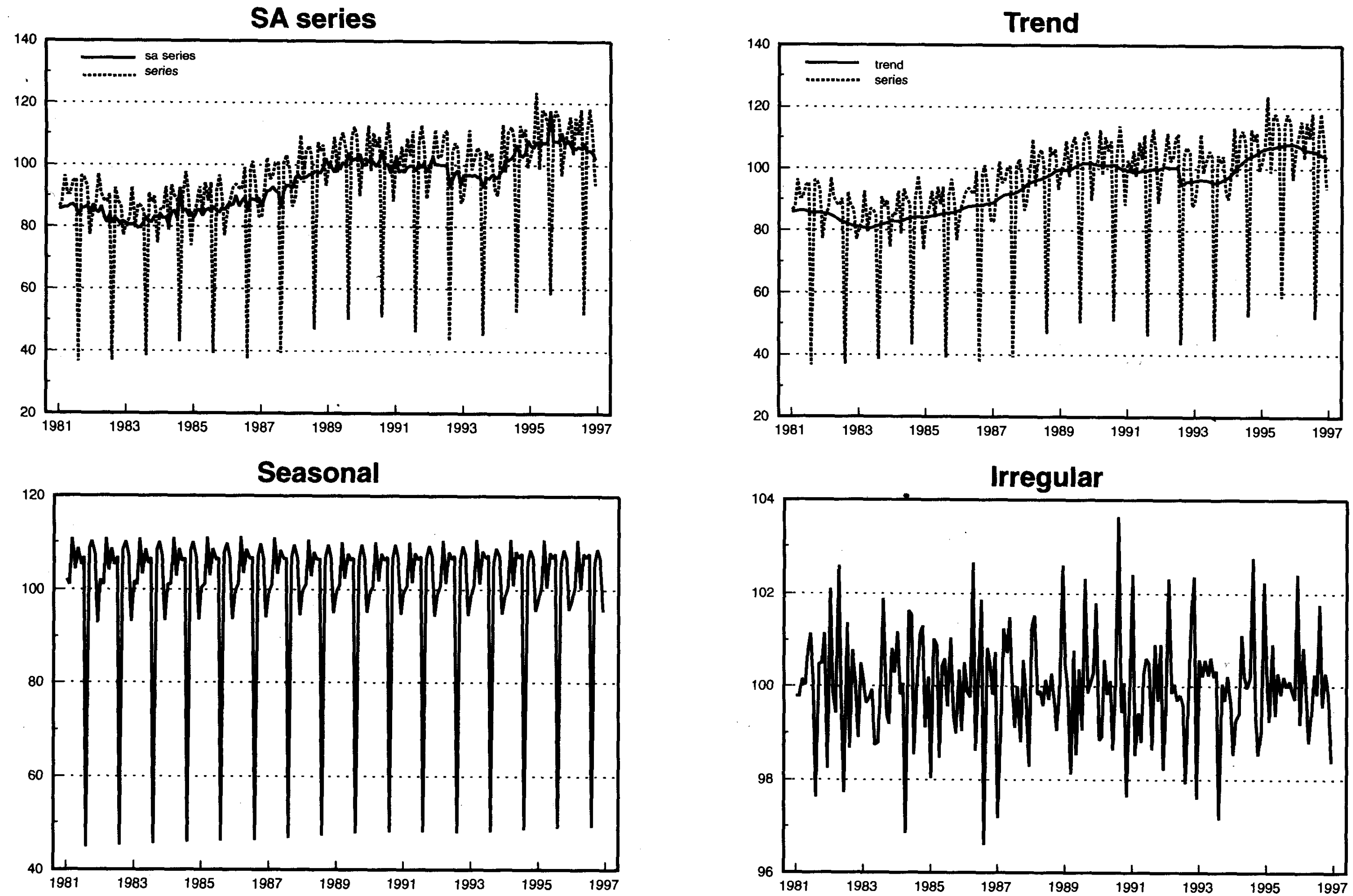

SA series
sa series
series
140
120
100
80
60
40
20
1981 1983 1985 1987 1989 1991 1993 1995 1997
Trend
trend
series
140
120
100
80
60
40
20
1981 1983 1985 1987 1989 1991 1993 1995 1997
Seasonal
120
100
80
60
40
1981 1983 1985 1987 1989 1991 1993 1995 1997
Irregular
104
102
100
98
96
1981 1983 1985 1987 1989 1991 1993 1995 1997

FIGURA 2 – IPI

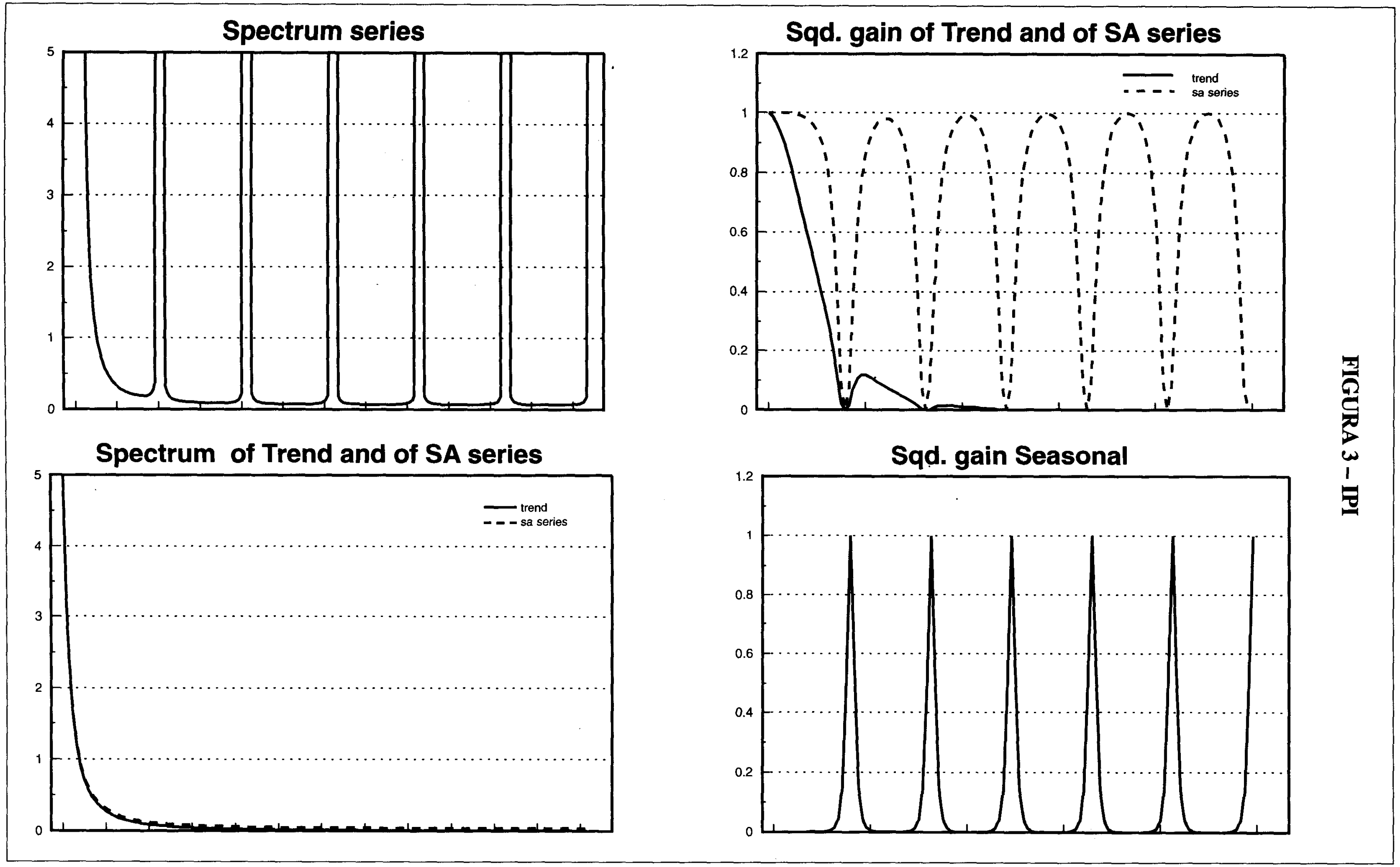
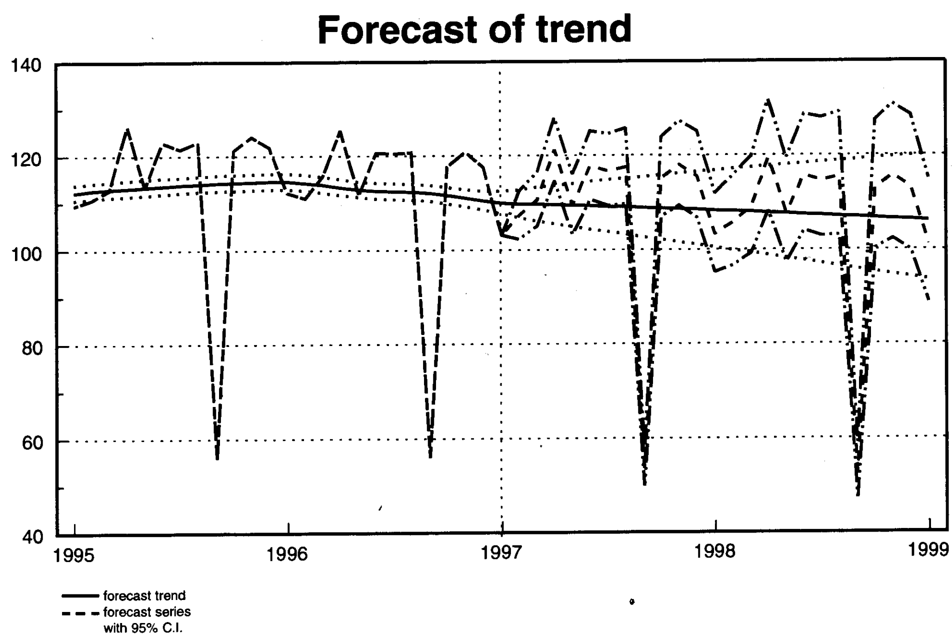
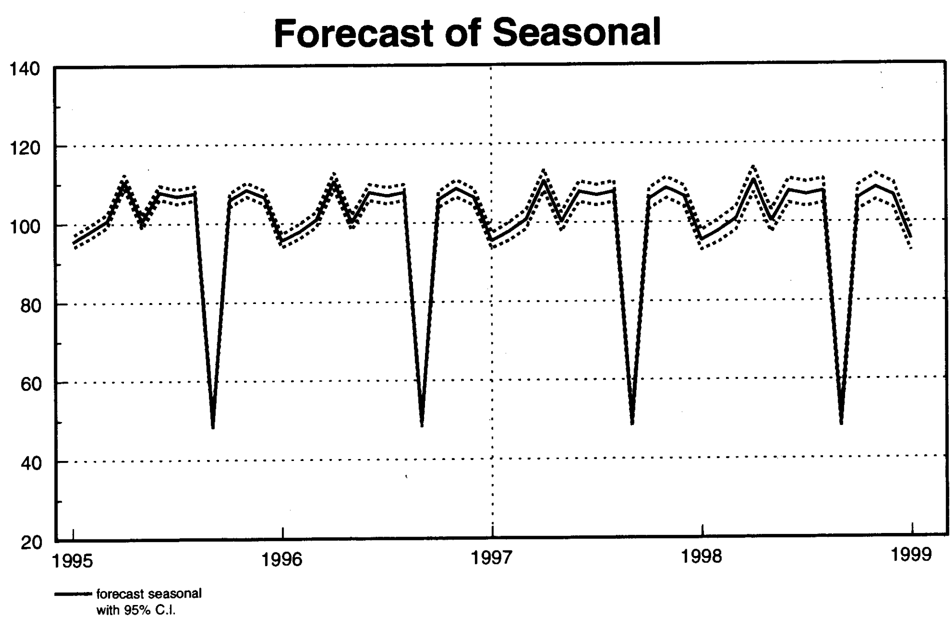

Spectrum series
Sqd. gain of Trend and of SA series
trend
sa series
Spectrum of Trend and of SA series
trend
sa series
Sqd. gain Seasonal

FIGURA 3 – IPI

FIGURA 4 – IPI


Forecast of trend
140
120
100
80
60
40
1995
1996
1997
1998
1999
forecast trend
forecast series
with 95% C.I.


Forecast of Seasonal
140
120
100
80
60
40
20
1995
1996
1997
1998
1999
forecast seasonal
with 95% C.I.

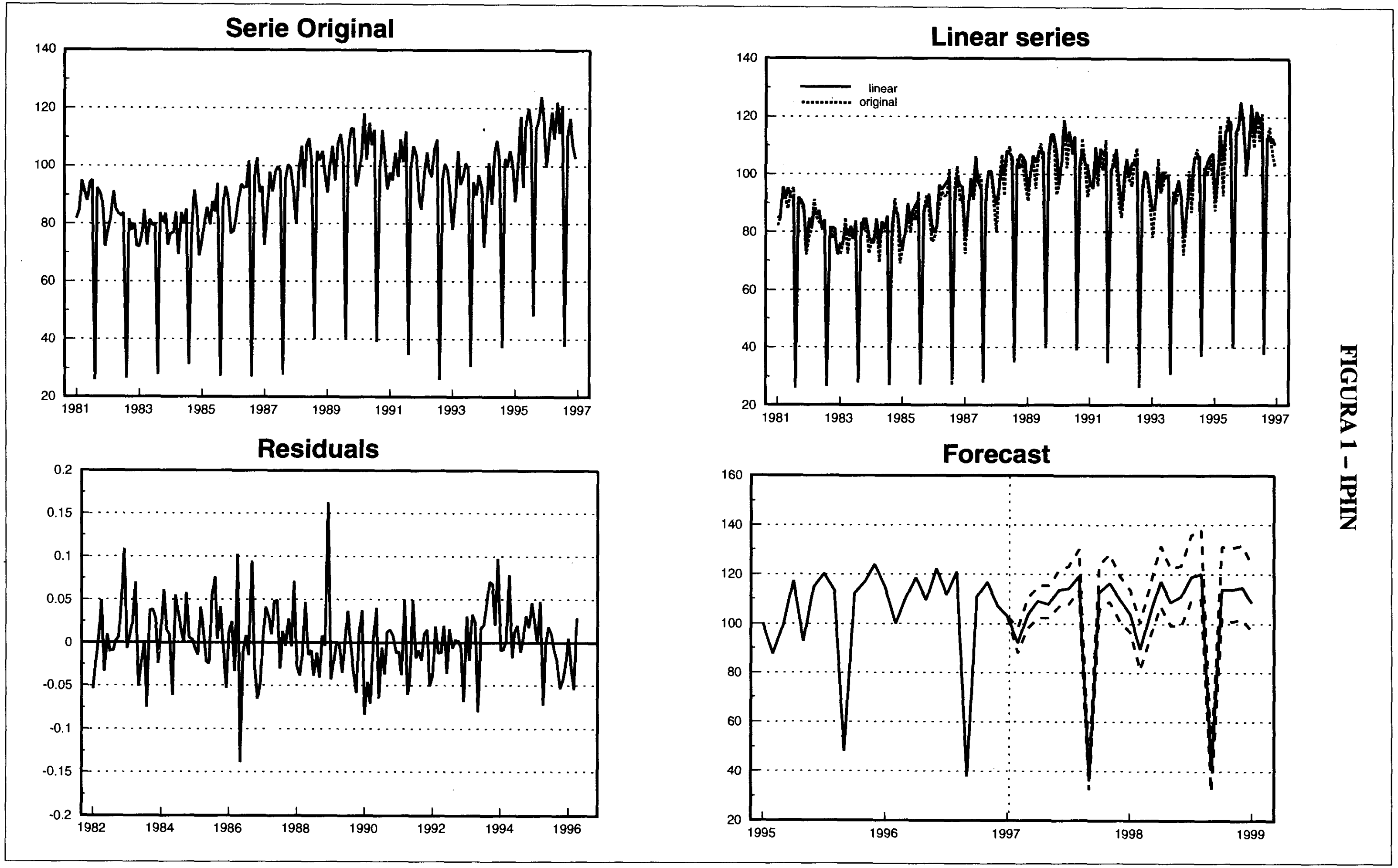


FIGURA 1 – IPIN

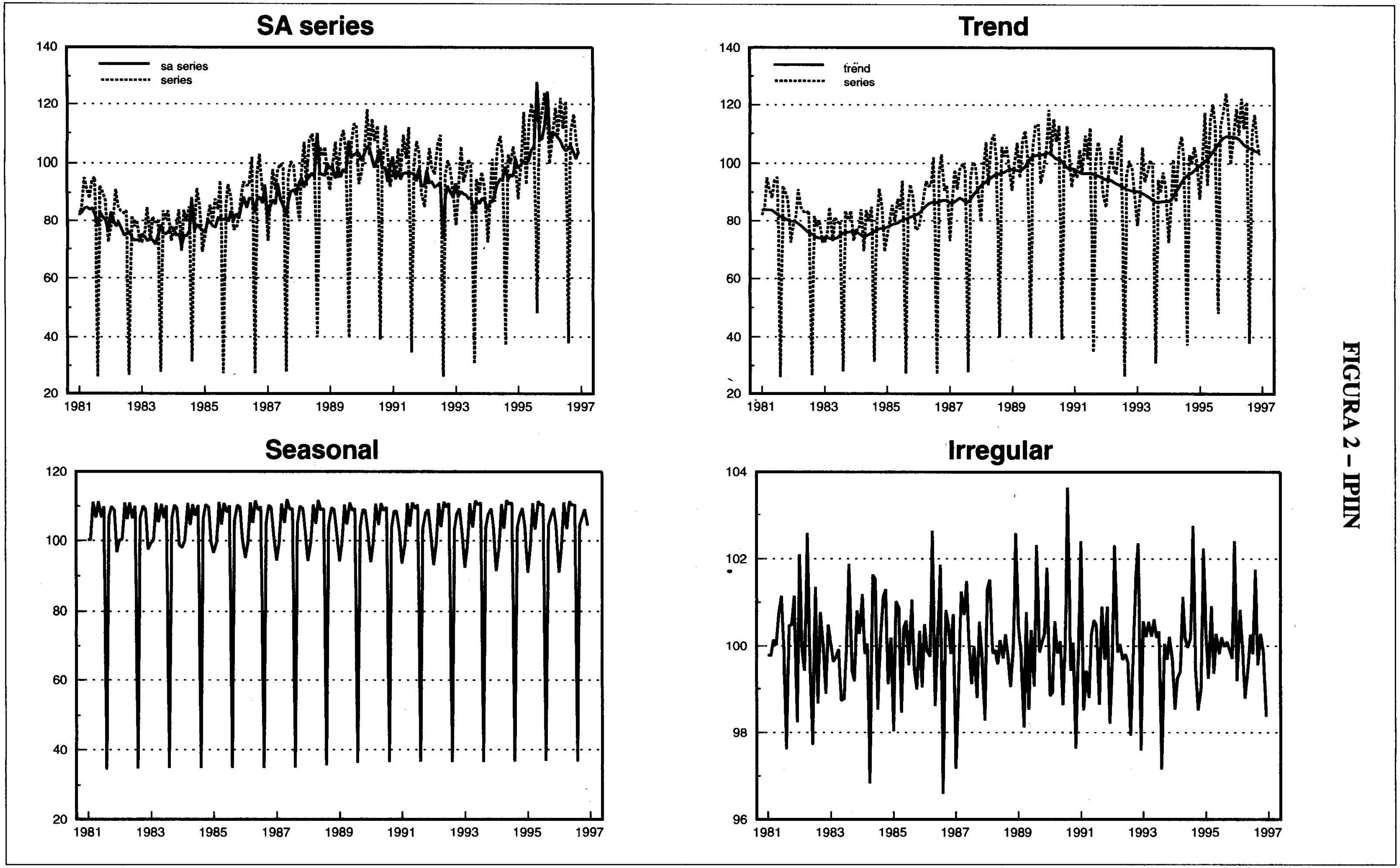


FIGURA 2 – IPIIN

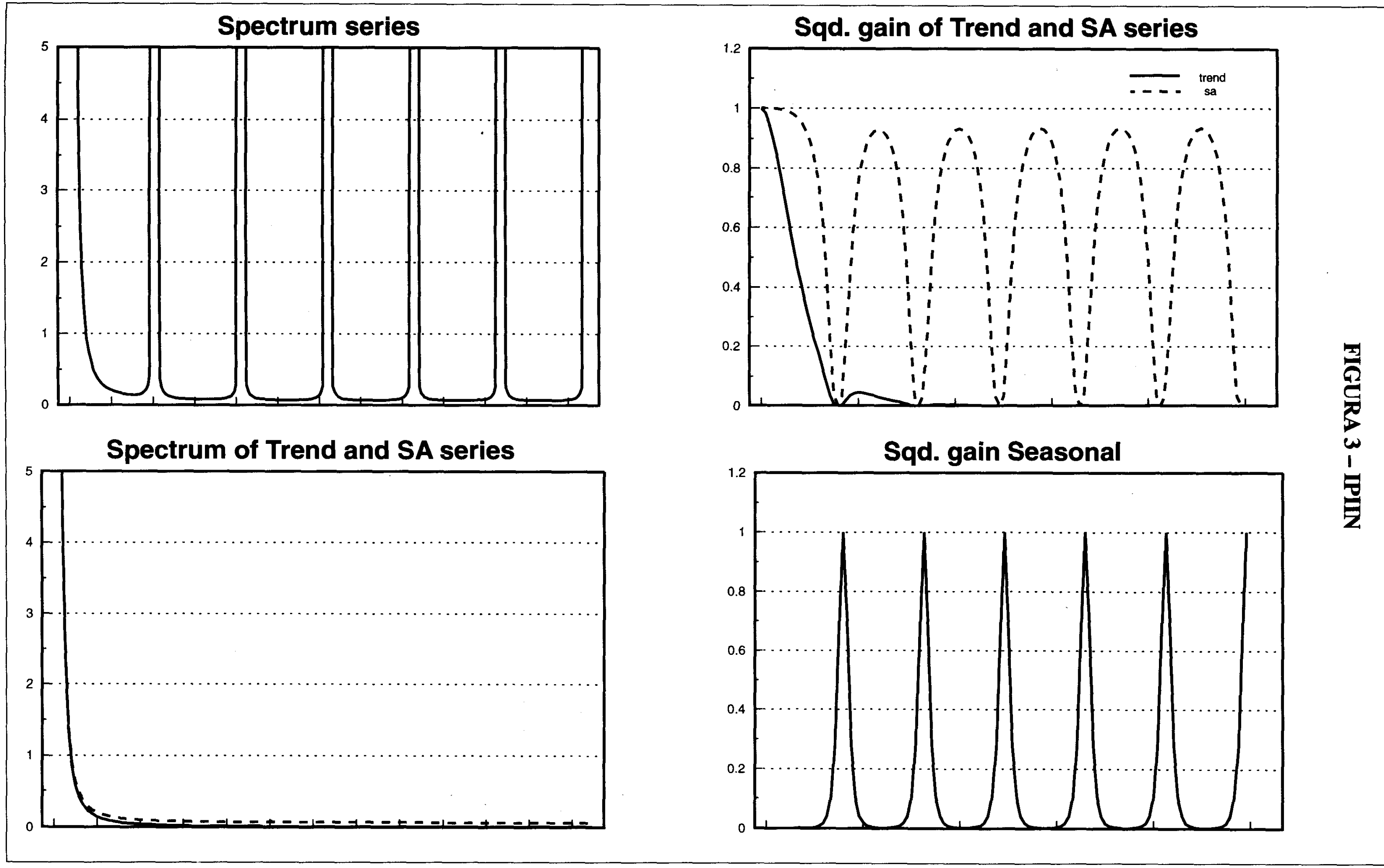
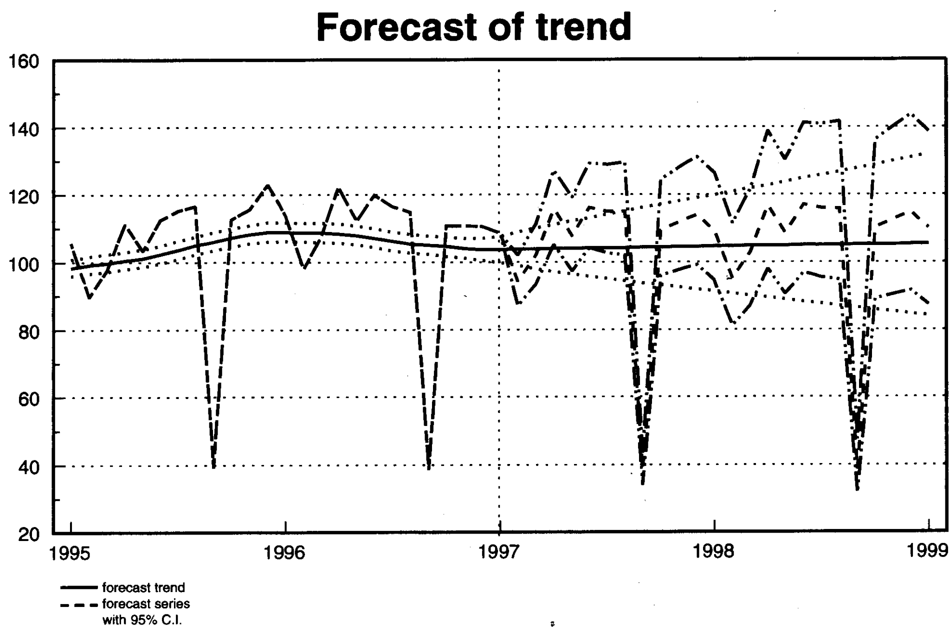
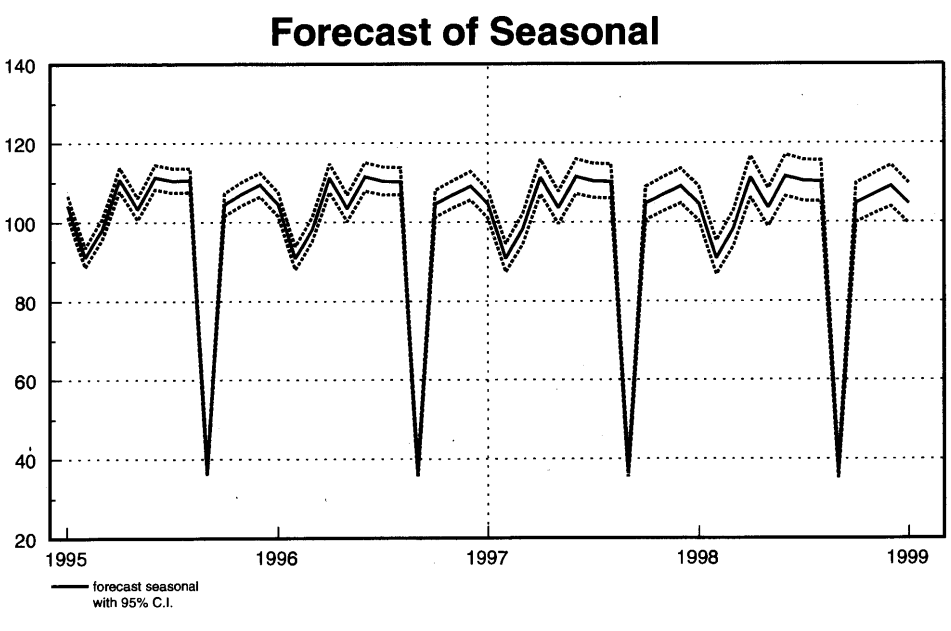


FIGURA 3 – IPIIN

FIGURA 4 – IPIIN





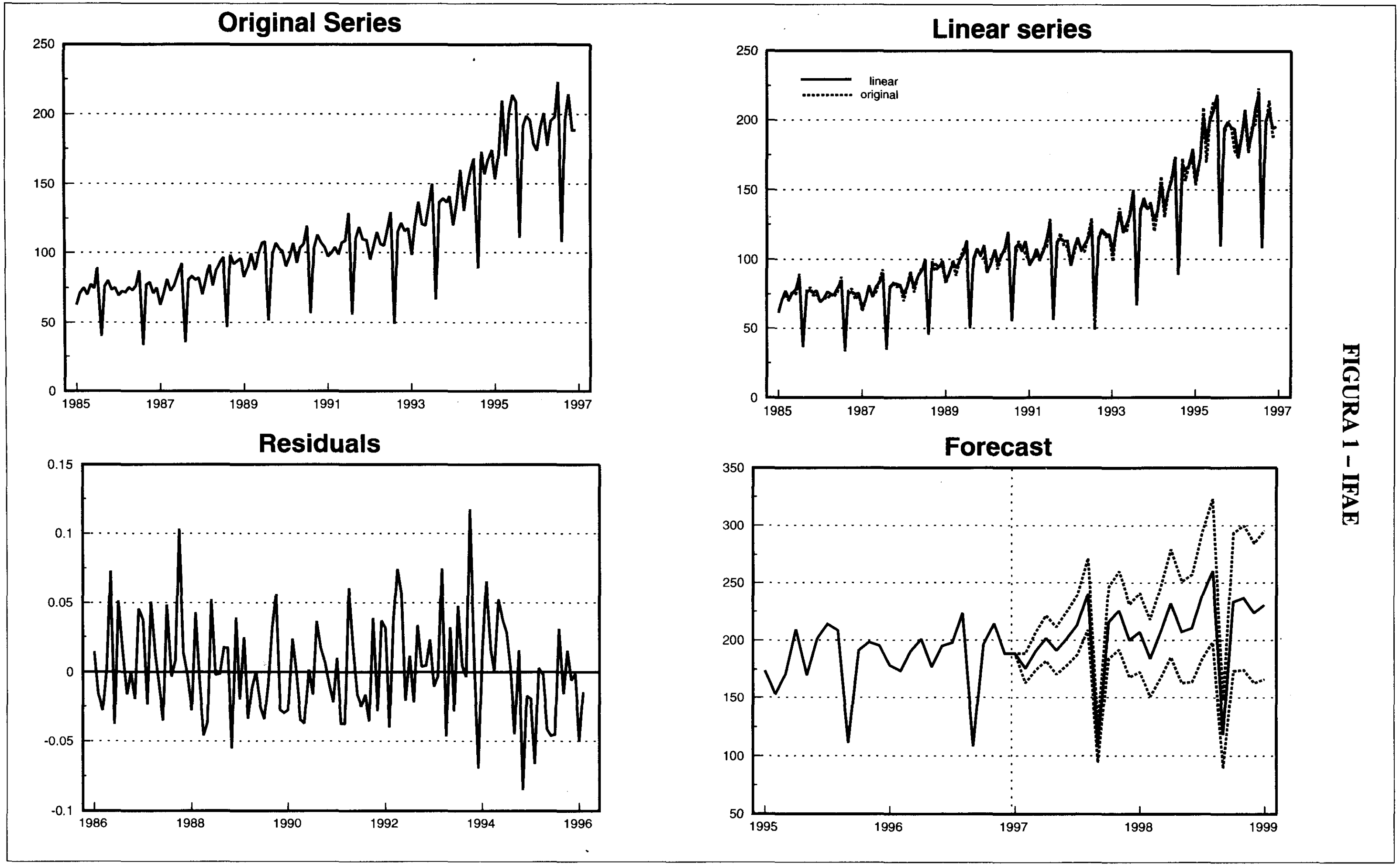
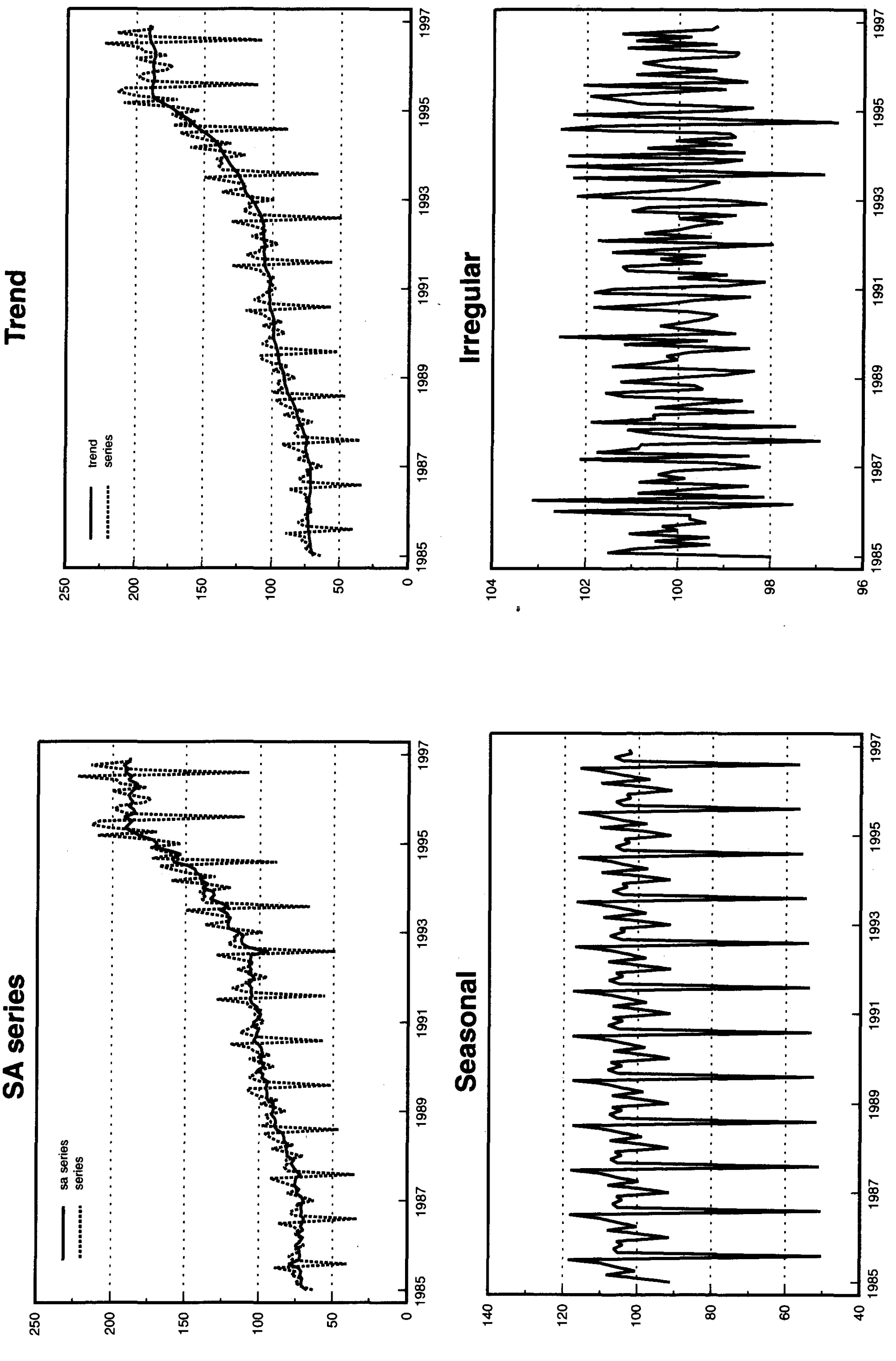


FIGURA 1 - IFAE

FIGURA 2 - IFAE



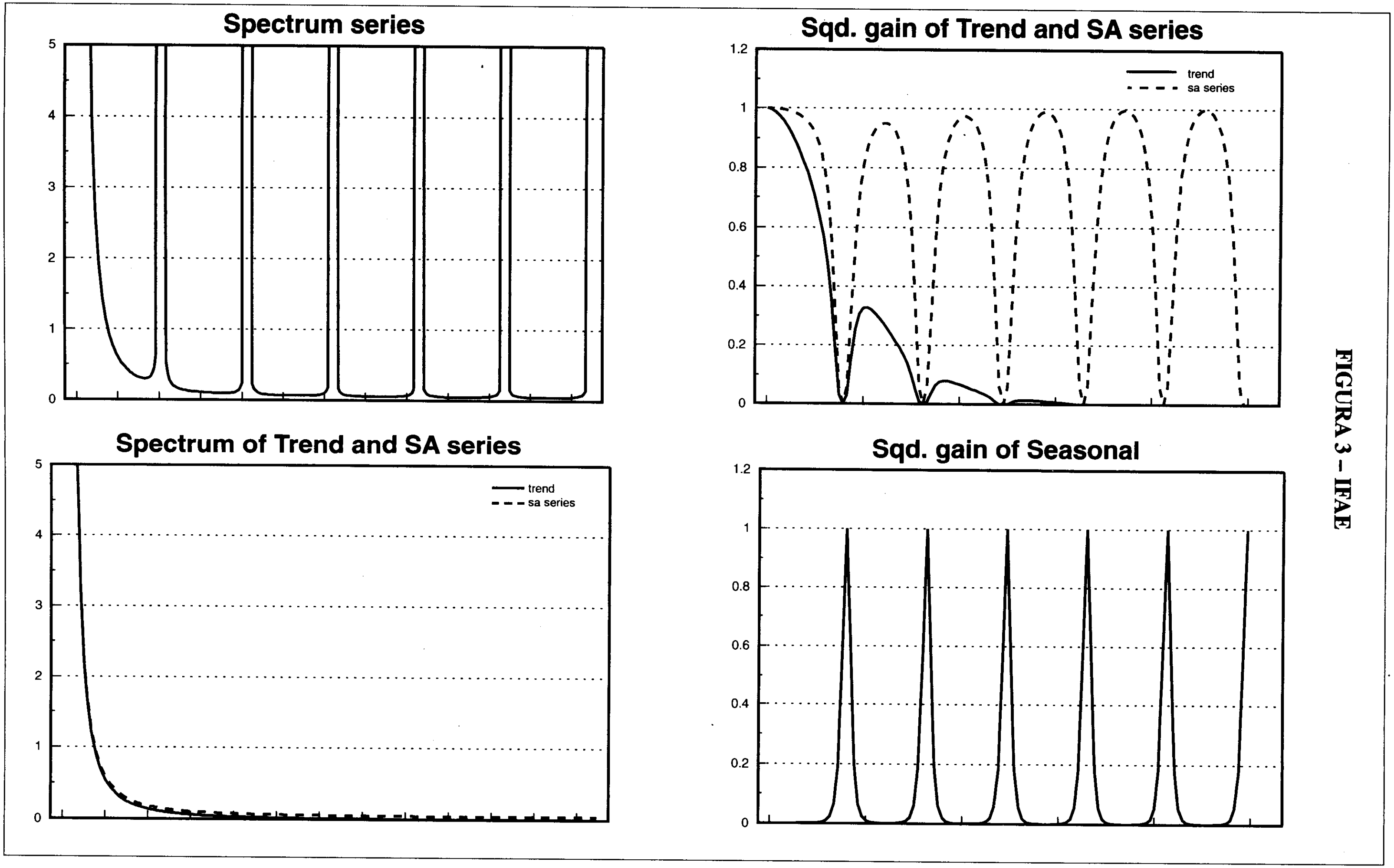
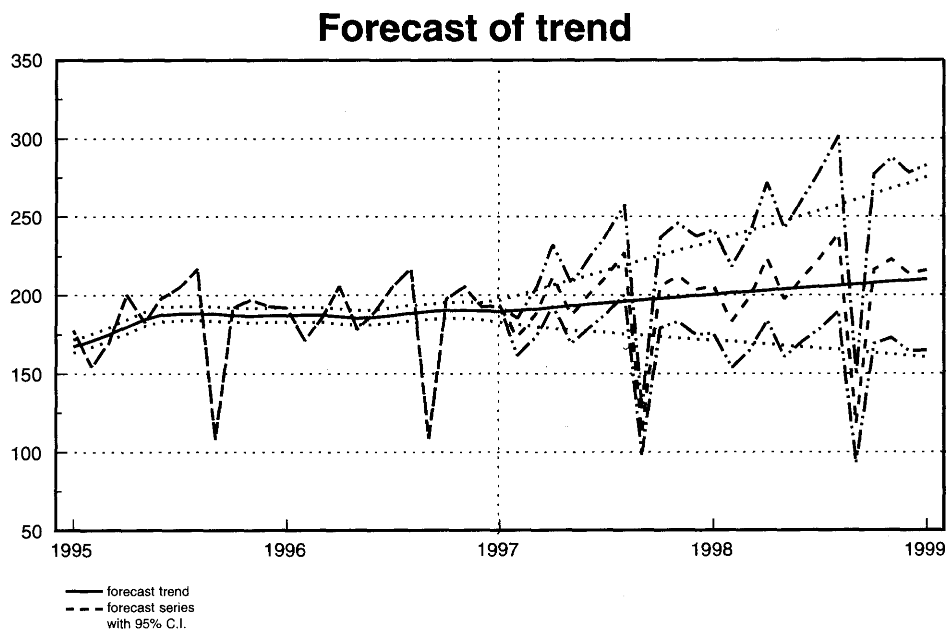


FIGURA 3 – IFAE

FIGURA 4 – IFAE



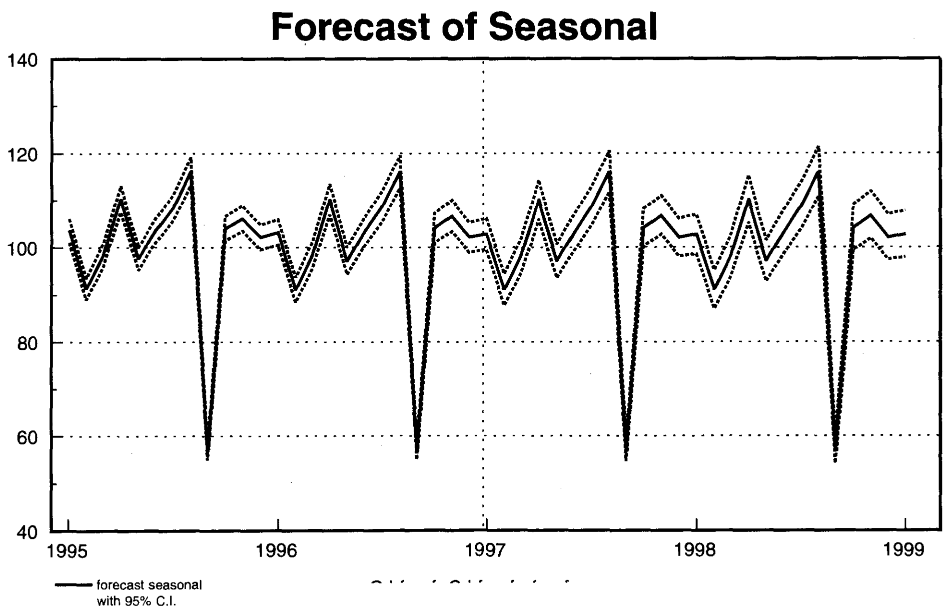
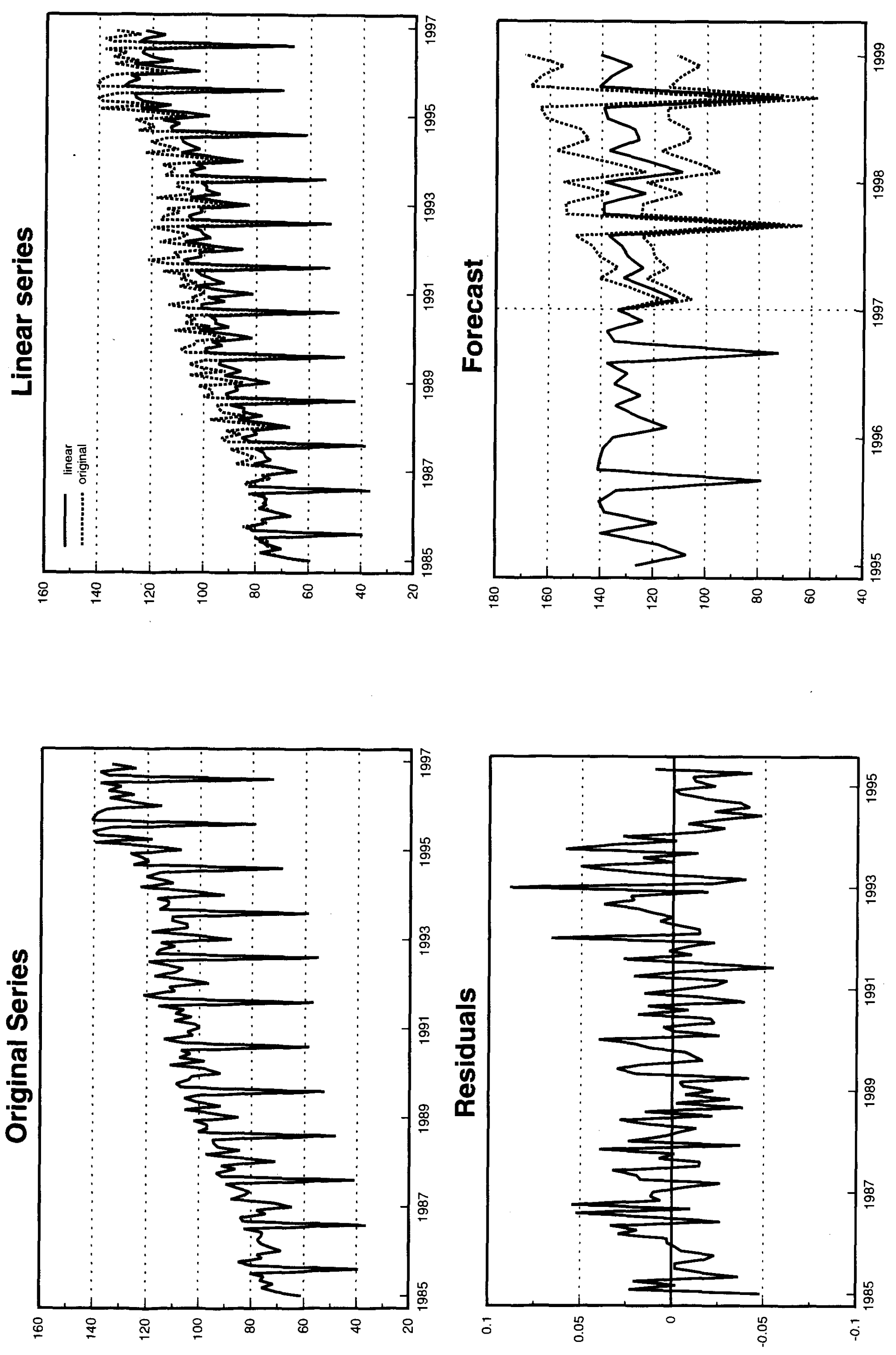


FIGURA 1 - IFAN



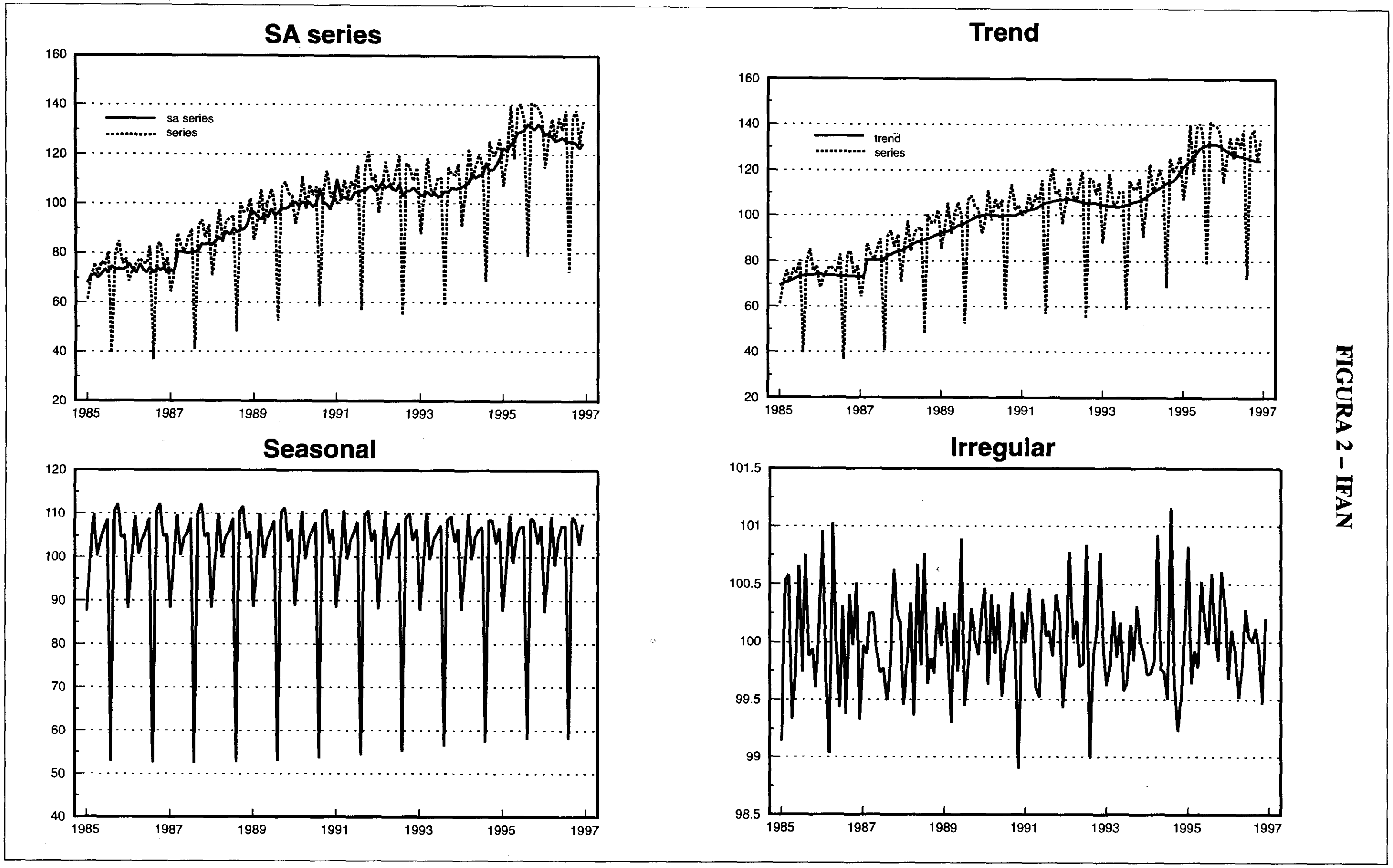


FIGURA 2 – IFAN

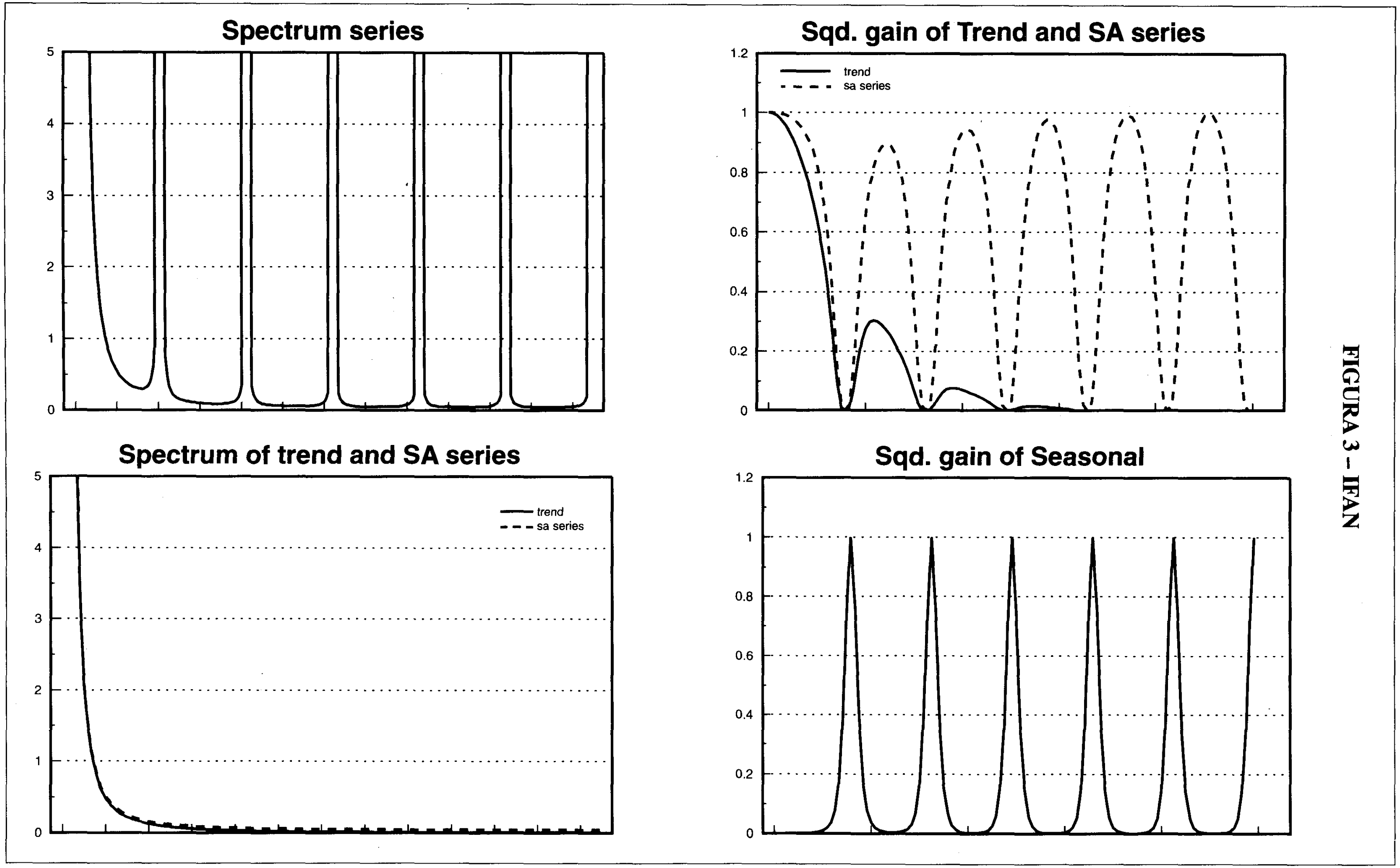
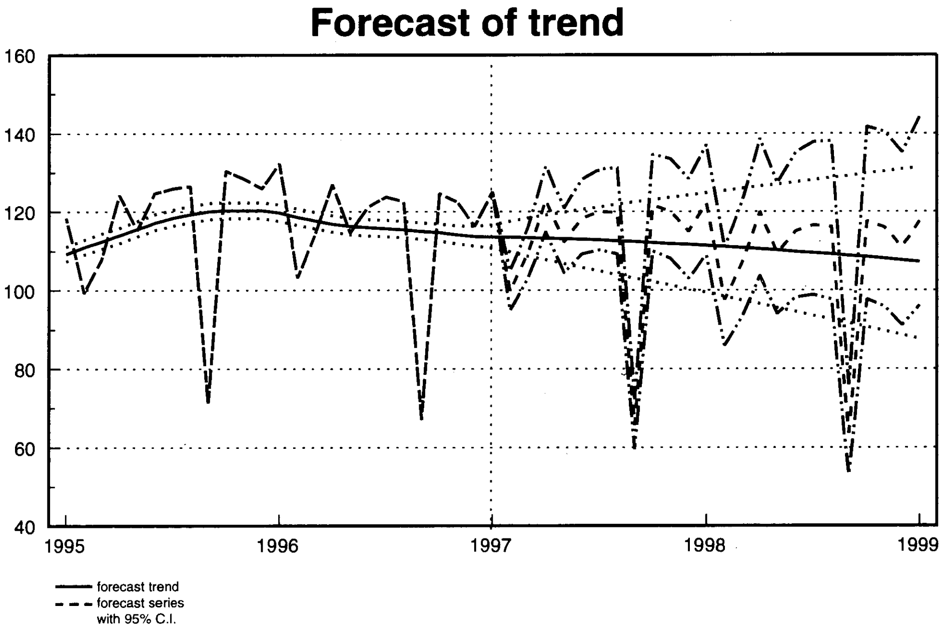
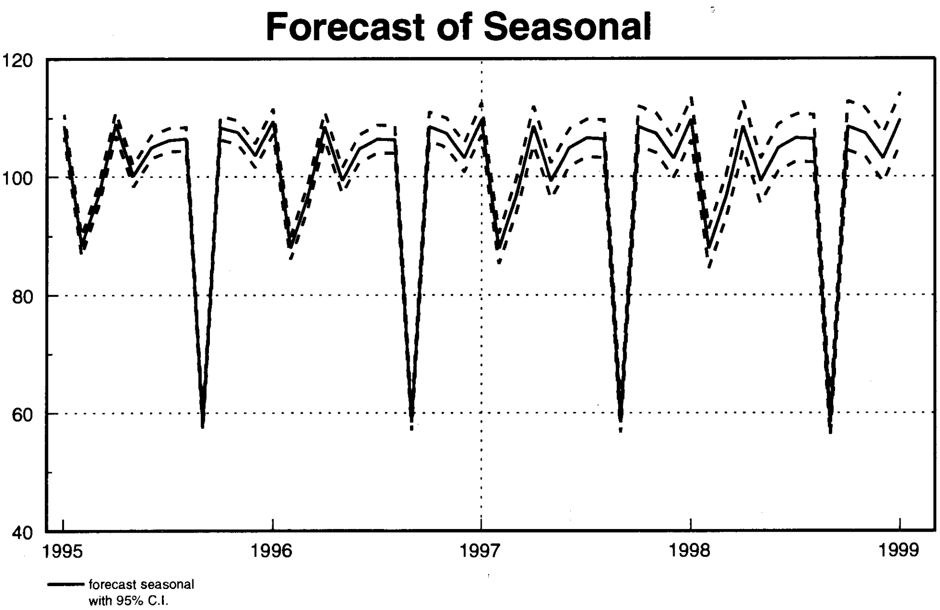


FIGURA 3 – IFAN

FIGURA 4 – IFAN





Round Table
Methodological and Practical Problems for a Choice of a Seasonal Adjustment Procedure

Relations and Interventions by: *Riccardo Cristadoro,*
Dario Focarelli and
Roberto Sabbatini
Andrew Harvey
Raoul Depoutot
Tommaso Proietti
Anna Ciammola and
Maurizio Maravalle

AN EMPIRICAL COMPARISON OF X12-ARIMA AND TRAMO-SEATS: WHAT CAN BE SAID FROM THE USER'S POINT OF VIEW?

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1. Introduction

From the point of view of the policy-maker the main aim of the statistical analysis of economic time series is to provide information which can facilitate the short-term monitoring of economic trends. Seasonally adjusted measures are therefore very helpful, as the short-term variability of economic time series often exhibits a seasonal pattern. It is only by removing this factor from the series considered that turning points can be promptly identified; they cannot readily be identified either by changes over the previous period calculated on the raw data (which are affected by seasonal factors) or by changes over the corresponding period of the previous year (which reveal turning points long after they have occurred, since they are affected by developments over the whole year).

The more general issue of the "harmonisation" of economic statistics across countries has become crucial today, in view of the need to analyse economic trends within the European union. This calls for a more careful assessment of the possible effects of different approaches to seasonal adjustment on the estimated components and therefore on the interpretation of the underlying economic phenomena. A homogeneous treatment of seasonality in time series within the European countries might help to avoid confusion and misleading interpretations of short-term changes in fundamental series attributable mainly to the use of different methods of seasonal adjustment.

In this paper we put ourselves in the shoes of an economist engaged in the short-term analysis of economic trends who is well grounded in the economic phenomena she is studying, but not necessarily a skilled or sophisticated statistician. It is nonetheless possible that she will decide to carry out the decomposition of economic time series into seasonal and non-seasonal components herself. In fact, an

The views expressed in this paper are those of the authors and do not involve the responsibility of the Bank of Italy important advantage of performing the statistical decomposition directly is that economists — especially when working within a research institution organised in specialised units — deal only with a limited number of time series referring to a specific economic field (e.g. inflation, industrial production and so on). Hence, specific information about the time series under study can be better exploited. The alternative of using seasonally adjusted series provided, for instance, by National Statistical Institutes has the advantage that the estimates are usually carried out by skilled statisticians. However, this advantage might be reduced if they have to deal with hundreds of series, in which case they might not be able to devote much time or attention to each series; moreover, the more limited knowledge of the phenomenon under study might lead to the sub-optimal use of the available information.

The solution of the trade-off between leaving an economist to perform the statistical decomposition of a time series, with the risk that he might not be particularly skilled, and leaving the job to a statistically sophisticated researcher, who might, instead, not make the best use of all the relevant economic information, largely depends on the degree of reliability of the results obtained when an unskilled user — unaware of statistical subtleties — works with seasonal adjustment routines that are designed to be "user friendly". In this paper, we compare the results obtained with X12-ARIMA and TRAMO-SEATS when these procedures are run by "skilled" and "unskilled" users on a set of economic time series. We do not analyse the two procedures from a purely methodological point of view, an issue which has been extensively studied in recent years, particularly within the Eurostat working group[1]. We judge each procedure on the basis of how user friendly it is and how good a guide one can find in the procedure's output to get results close to those obtained by skilled users. To this end we assessed how much help is provided by the manuals accompanying the software. The empirical analysis has been conducted on eleven Italian time series that differ in their economic content and statistical properties and that are generally regarded as key measures for short-term economic analysis.

The paper is organised as follows. The second section provides a brief overview of the main differences between X12 and TRAMO-SEATS in the treatment of seasonal variations. The third section illustrates the series used in this study and briefly describes their characteristics. In the fourth section we present the main results of the empirical analysis. Finally some conclusions are drawn and some open issues discussed.

2. A Description of the Alternative Seasonal Adjustment Methods

Many economic time series show a seasonal pattern — that is "systematic, although not necessarily regular, intra-year movements"[2] — which many economists tend to regard as "noise" that complicates the analysis of the more fundamental underlying economic forces. Accordingly, many methods have been developed over the years aimed at isolating the fundamental movements from those caused by

[1] See, among others, Planas (1997a), (1998) and Eurostat (1996).

[2] Hylleberg (1992), p. 4.

seasonal factors. There has been a long debate on the pros and cons of seasonally adjusting economic time series prior to econometric analysis[3] but, despite the many criticisms of the use of filtered series, it is common practice for statistical institutes to remove seasonality from time series and for economists to work with seasonally adjusted data.

Broadly speaking and restricting ourselves to linear symmetric filters[4], which are preferable to asymmetric ones since they do not induce phase shifts in the filtered series, the problem of seasonal adjustment can be stated as follows. Any time series can be thought of as being composed of two parts, a seasonal one and a non-seasonal one[5].

$$y_t = s_t + n_t$$

The seasonal component can be estimated by applying a "suitable" linear filter F (B) to the observed series:

$$\hat{s}_t = F(B)y_t$$

$$\hat{n}_t = [1-F(B)]y_t$$

and

$$F(\mathrm{B}) = \sum_{j=-m}^{m} \delta_j B^j \text{ , with}^5 \sum \delta^2_j < \infty$$

The weights δ_j are real and do not depend on time and where the backshift operator B is such that $B^j\, y_t = y_{t-j}$.

Seasonal variations appear in the spectrum of the series as peaks at seasonal frequencies ($\omega = 2\pi \frac{j}{12}$, with $j = 1, ..., 6$ for monthly series). To obtain a seasonally adjusted series one has to remove these peaks from the spectrum. The effect of a filter on a particular frequency interval of a series can be characterised by its squared gain. If $\Gamma(\omega)$ is the gain or, equivalently, the transfer function of the filter and $f(\omega)$ is the spectrum of the original series, then the spectrum of the seasonally adjusted component is given by:

$$f_n(\omega) = 1 - \Gamma(\omega)^2 f(\omega)$$

where

$$\Gamma(\omega) = F\left(e^{-i\omega}\right) = \sum_{j=-m}^{m} \delta_j e^{-ij\omega} \ .$$

[3] For a formal treatment, see Granger and Watson (1984), Wallis (1974), Planas (1998).

[4] To simplify the notation, we consider only additive decompositions.

[5] When the weights sum to unity we have a symmetric moving average filter.

Therefore the squared gain "represents the extent to which the contribution of the component of frequency ω to the total variance of the series is modified by the action of the filter"[6]. A zero gain on a particular frequency interval (say a seasonal frequency interval) removes all the variation associated with that interval from the filtered series, while a squared gain greater than one amplifies the variations at a given frequency. Approaches to seasonal adjustment can be distinguished according to the way in which the filter is constructed. The application of a symmetric filter to data close to the beginning or the end of the sample (i.e. in the intervals $[1;m-1]$ and $[T-m+1;T]$) requires the estimation of missing observations. Therefore, an important feature of seasonal adjustment methods is their use of backcasts and forecasts of the series to overcome this problem. Furthermore, this question lies at the heart of the problem of revisions in seasonal adjustment methods, since the reliability of backcasts, and especially of forecasts, directly influences the extent of the seasonal factor revisions.

The use of seasonal adjustment procedures on a wide scale has led to the development of computer routines that allow users, even with little training in econometrics, to decompose time series into a seasonal and a non-seasonal part. In this paper we focus on two software packages for decomposing time series: X12-ARIMA (Findley *et al.*, 1998, and Bureau of the Census, 1998) and TRAMO-SEATS (Gomez and Maravall, 1996). From a theoretical point of view, the comparison between the two methods has been subject to extensive debate, complicated by the fact that optimal properties for evaluating seasonally adjusted series do not exist, despite there being lots of generally desirable properties. It is worth remarking that these desirable properties may well differ from user to user; for instance, revisions, which are not particularly desirable from the point of view of the policy-maker, are, in a sense, optimal from a statistical point of view.

X12-ARIMA and TRAMO-SEATS are based on the same general scheme and they are better thought of as divided into two parts. The first module of the two programs — RegARIMA and TRAMO, respectively — is a complete and powerful routine based on ARIMA modelling. Its purpose is to select, for the data analysed, a suitable linear stochastic model in the ARIMA class following the Box-Jenkins three-stage methodology (identification, estimation and diagnostic checking) and to remove all the fixed effects that might bias the estimate of the seasonal component (trading days, Easter effects, outliers). RegARIMA selects a model from a limited set of choices, while TRAMO searches over a wider range of alternatives[7]. The basic reason is that the importance of the model identified in the first stage is much greater in TRAMO-SEATS, since it is used not only for the preadjustment, forecasting and backcasting of the original series, but also as a basis for the decomposition. At this stage there are no major differences between the two methods and empirical tests based on simulated series show that they tend to produce similar results[8].

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[6] Wallis (1974), p. 33.

[7] In automatic mode, TRAMO tries to identify the best model starting from the general model (3,2,3)(1,1,1) and considering nested alternatives. REGARIMA estimates a sequence of 5 models: (0,1,1)(0,1,1), (0,1,2)(0,1,1), (2,1,0)(0,1,1), (2,1,2)(0,1,1) and (0,2,2)(0,1,1). For a comparison of the two procedures based on an experimental design, see Planas (1997a).

[8] See Planas (1997a).

Whereas no major differences are found between RegARIMA and TRAMO, X12 and SEATS are based on very different methodological approaches. Filtering in SEATS is derived directly from the characteristics of the series. The process generating the observed data is thought of as the result of four underlying components that are not observed: a trend, a cycle, a seasonal part and an irregular part. The model estimated for the observed series is factorized into orthogonal linear stochastic processes and estimates of the various components are obtained by imposing appropriate identifying restrictions. In particular, SEATS performs the "canonical decomposition" of the series by maximising the variance of the irregular part. Consequently, the components are non-invertible and smoother than those obtained with other identifying assumptions. Since the filter is based on the stochastic properties of the series, it is able to represent a large number of time series with very different stochastic structures. It is also flexible enough to provide reasonable results when seasonality is fairly stable.

X12 relies on a set of *ad hoc* moving average filters where some degree of flexibility is given by the filter selection procedure (the length of the moving average), based on ratios of components to irregular. In any case the filter selected is largely independent of the stochastic structure of the series. Relying on predefined filters can lead to overadjustment and underadjustment problems, because seasonal variation is removed from the original series at all seasonal frequencies irrespective of its stochastic behavior. Moving average filters have been justified on the basis of a particular stochastic model for which they provide a good decomposition (Cleveland and Tiao, 1976). Slight movements away from this model do not affect the properties of the *ad hoc* filters, while more far-reaching changes in the stochastic nature of the process create problems. When a time series is actually well represented by the airline model, we can expect X12 to give results similar to those obtained using SEATS.

3. The data

Our purpose is to test the two seasonal adjustment methods on the "battle field", choosing series that are frequently used in economic analysis and that show very different cyclical and seasonal patterns. An important aspect of this kind of exercise is the possibility of simultaneously evaluating all the features of the two packages, including the pre-adjustment of the series, the model selection routines and the behaviour of the estimated components. In this respect we fully agree with Maravall (1997a, p. 32) when he argues that "the real test should involve a more systematic and complete comparison with well-defined alternative methods, based on a minimally meaningful set of real world series".

The eleven series considered in this study (Table 1) are key indicators of the Italian economy and concern different central aspects of its evolution.

Looking at the graphs, the levels of the quantity indices (namely, CETGENGQ, CITGENGQ, IFAGENGE, IFAGENGN, IPIGENGT, IPIINVGT and LGOLTOGI) clearly show seasonal peaks and troughs (Figures 1-2 and 5). First differences of the

Table 1 – Series considered in the empirical analysis

Series	Description	Range
BDEGENGS	New orders and demand level in foreign markets - balances	1986.1 - 1996.12
BDIGENGS	New orders and demand level in domestic market - balances	1986.1 - 1996.12
CETGENGQ	Export - quantity index	1980.1 - 1996.10
CITGENGQ	Import - quantity index	1980.1 - 1996.10
IFAGENGE	Index of industrial turnover in foreign markets	1985.1 - 1996.12
IFAGENGN	Index of industrial turnover in domestic market	1985.1 - 1996.12
IPIGENGT	Index of industrial production - total	1981.1 - 1996.12
IPIINVGT	Index of industrial production - investment goods	1981.1 - 1996.12
LGOLTOGI	Index of total employment in large firms	1989.1 - 1996.11
PCOBENGP	Consumer price index - goods	1989.1 - 1996.12
PPIGENGP	Producer price index - total industry	1981.1 - 1996.12

price series (PCOBENGP and PPIGENGP) still show some seasonal variation (Figure 3). Moreover, for the producer price index, visual inspection suggests that a change in the seasonal pattern took place around 1986, presumably owing to a change in the level of inflation as a result of the oil counter-shock. Finally, the two series of "balance statistics" from the Isae surveys on the manufacturing sector (BDEGENGS and BDIGENGS) exhibit rather peculiar characteristics (Figure 4). These data are obtained by subtracting the number of firms that expect a fall in orders and demand level from the number of those expecting a rise. In theory, the resulting "balance statistics" should not exhibit any seasonal pattern, since Isae explicitly asks firms to provide evaluations for both new orders and demand taking into account seasonal factors. In practice, however, their spectral densities show peaks at seasonal frequencies.

4. Comparison of Alternative Seasonal Adjustment Methods: Empirical Results

The purpose of our experiment is twofold. On the one hand, we want to check the performance of the two products when used by statistically unsophisticated researchers. Major differences in the results would imply that the automatic modelling and filtering procedures of the two software packages can produce adjusted series that could lead to alternative interpretations of short-term economic developments. On the other hand, we want to compare the results obtained by unskilled users with each package with those obtained by an expert statistician. We also checked whether the main test statistics reported in the output of the two programs can put "moderately" skilled users on the right track, enabling them to produce good approximations of the results obtained through the best use of the programs.

The comparison of the results obtained with X12 and TRAMO-SEATS was carried out as follows. We started by checking whether, in the preliminary stage, the two packages opted for the same data transformation (logs *versus* levels), fixed effects correction and ARIMA model identification. Differences at this stage have a bearing on the results obtained for the seasonal component estimated later. In particular, as mentioned previ-

Figure 1 – Indexes of Industrial Turnover

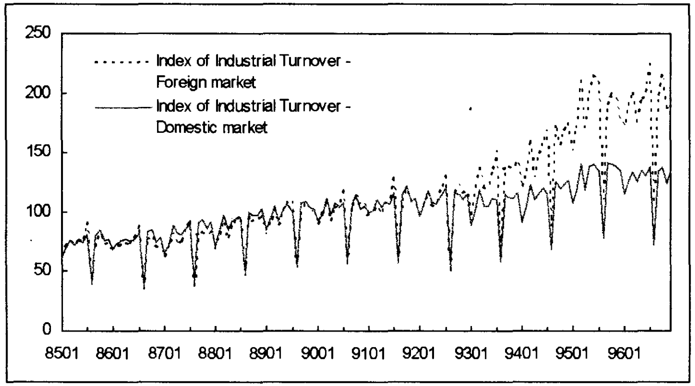


Figure 2 – Indexes of Industrial Production

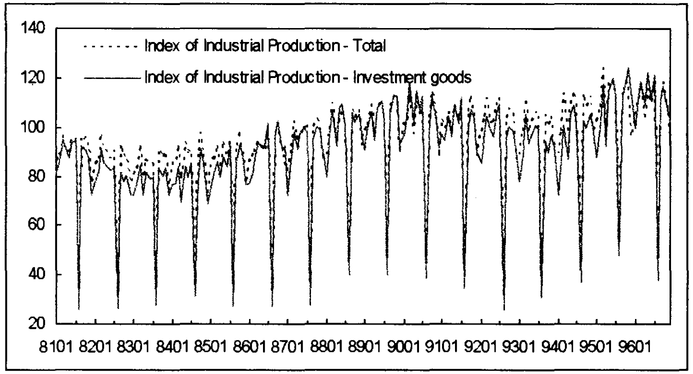


Figure 3 – Price Indexes

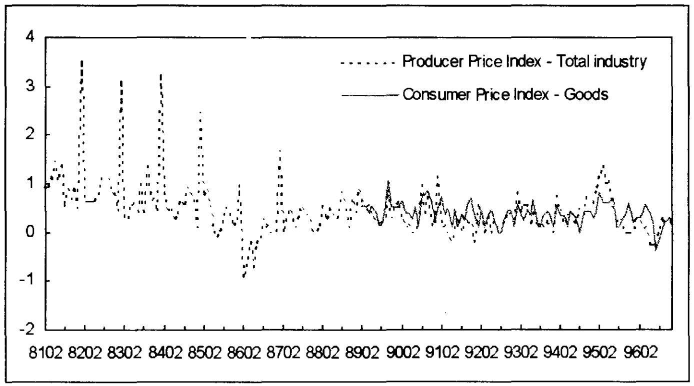


Figure 4 – New Orders and Demand Level

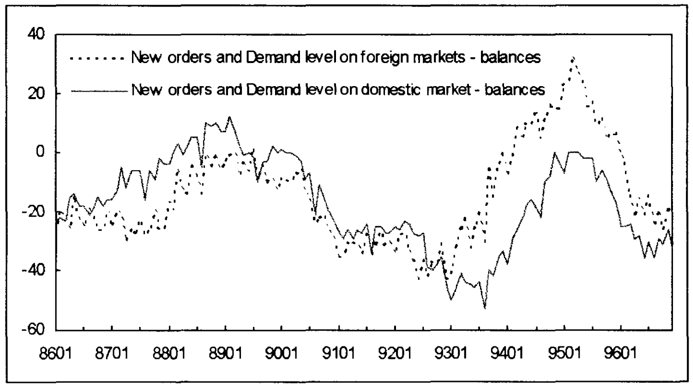
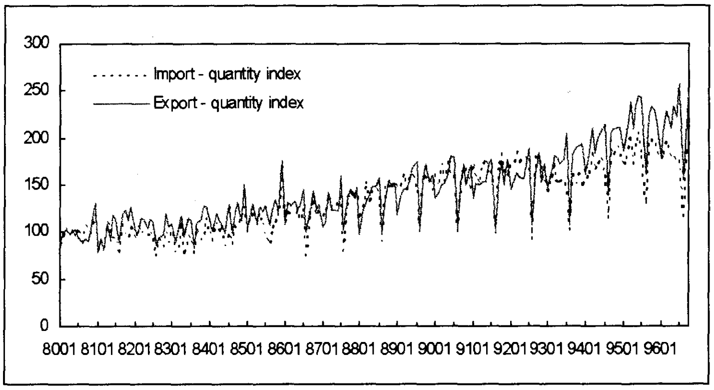


Figure 5: Import and Export



ously, the ARIMA model is the basis for backcasting and forecasting of the series in order to apply a symmetric seasonal filter; clearly different models imply different projections and therefore have an impact on the estimation of the seasonal component, independently of the identification method. The same holds for the detection of fixed effects. Subsequently, we analysed the estimates of the components obtained by SEATS and X12, focusing in particular on the trend-cycle and the seasonally adjusted component.

4.1 "Unskilled" Users

The statistically unsophisticated user conducted the analysis by setting the parameters of the two packages to enable the automatic identification routines.[9] This is what an unskilled user typically does when first running a procedure to estimate the seasonal component of a series[10]; it is also what skilled users have to do when dealing with a large number of data.

As a second step we imposed on X12 the model and data transformation obtained with the TRAMO-SEATS automatic model identification routine, so as to focus the comparison of the two packages on the components estimation part. Furthermore, in this way it was possible to proceed in X12 on the basis of a model even in the three cases in which RegARIMA could not find a suitable process for forecasting and backcasting the data.

The default ARIMA model in TRAMO is the airline; allowing automatic model search might lead to a different choice. In particular, for our 11 series, TRAMO chose the Airline model in 4 cases. This result is in line with the experiments conducted by Eurostat[11] based on 13,277 series, which showed that the airline model was adequate only in half of the situations. It follows that running TRAMO with its default options may be misleading[12]. Log-transformation was chosen for 6 time series; all the series were differentiated only once, and outliers were detected for

[9] TRAMO-SEATS was run setting the RSA parameter equal to 4, while X12-ARIMA was run with the AUTOMODL option.

[10] Maravall recommends such a strategy when using TRAMO-SEATS (Maravall, 1997a).

[11] See Eurostat, 1996.

[12] See also Maravall (1997a).

most of them. The number of outliers is small considering the time span of the sample, except in two cases (5 outliers each); more importantly, no outliers are detected towards the end of the sample (Table 2).

In 3 out of 11 cases RegARIMA was unable to find a suitable model for the data. In the remaining cases the airline was chosen 5 times (Table 3). While TRAMO did not detect Easter effects (EE), RegARIMA detected them for the index of industrial turnover in foreign markets (IFAGENGE). In 3 cases RegARIMA accepted the hypothesis of a trading day (TD) effect in the data. In all these cases TRAMO estimated a TD effect as well; in two additional ones such effects were detected by TRAMO but not by RegARIMA. Overall, RegARIMA detected a smaller number of outliers, which were the same as those found by TRAMO in half of the cases.

Table 2 – TRAMO - Automatic model identification (1)

Series	Starting dates	ARIMA model	Log transformation	Trading days	Easter	Outliers (2)		
BDEGENGS	1986.1	(0,1,3)*(0,1,1)	no	no	no	LS 1996.3		
BDIGENGS	1986.1	(0,1,3)*(0,1,1)	no	no	no	---		
CETGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	no	no	LS 1981.4	TC 985.12	
CITGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	yes	no	AO 1983.1	AO 1985.1	
IFAGENGE	1985.1	(2,1,1)*(0,1,1)	yes	yes	no	TC 1988.8	AO 1993.8	LS 1994.2
						LS 1995.8	AO 1995.10	
IFAGENGN	1985.1	(0,1,1)*(0,1,1)	yes	yes	no	LS 1987.3	AO 1991.1	
IPIGENGT	1981.1	(0,1,1)*(0,1,1)	yes	yes	no	AO 1984.8	AO 1995.8	
IPIINVGT	1981.1	(2,1,0)*(0,1,1)	yes	yes	no	TC 1987.1	AO 1988.8	AO 1992.8
						AO 1994.8	AO 1995.8	
LGOLTOGI	1989.1	(1,1,0)*(0,1,1)	no	no	no	TC 1992.9		
PCOBENGP	1989.1	(0,1,2)*(0,1,1)	no	no	no	---		
PPIGENGP	1981.1	(1,1,1)*(0,1,1)	no	no	no	TC1988.1		

(1) Parameter RSA is set equal to 4 (see Gomez and Maravall, 1996).
(2) Legend: LS = level shift; TC = transitory changes; AO = additive outliers.

Table 3 – RegARIMA - Automatic model identification (1)

Series	Starting dates	ARIMA model	Log transformation	Trading days	Easter	Outliers (2)		
BDEGENGS	1986.1	no model selected	no	no	no	---		
BDIGENGS	1986.1	no model selected	no	no	no	---		
CETGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	no	no	AO 1981.3		
CITGENGQ	1980.1	(2,1,2)*(0,1,1)	yes	yes	no	TC 1981.1	AO 1984.6	AO 1985.12
IFAGENGE	1985.1	(0,1,1)*(0,1,1)	yes	yes	yes	AO 1992.8		
IFAGENGN	1985.1	(0,1,1)*(0,1,1)	yes	no	no	LS 1987.3	AO 1991.1	
IPIGENGT	1981.1	no model selected	no	no	no	---		
IPIINVGT	1981.1	(0,1,1)*(0,1,1)	yes	yes	no	AO 1984.8	AO 1987.1	AO 1988.8
						AO 1992.8	AO 1995.8	
LGOLTOGI	1989.1	(0,1,1)*(0,1,1)	no	no	no	LS 1992.9		
PCOBENGP	1989.1	(0,1,2)*(0,1,1)	no	no	no	---		
PPIGENGP	1981.1	(2,1,0)*(0,1,1)	no	no	no	TC 1985.12	TC 1988.1	
						AO 1988.10	LS 1990.8	

(1) "AUTOMODL" option; 3x3 moving average used in section 1 of each iteration; 3x5 moving average in section 2 of iterations B and C; moving average for final seasonal factors chosen by global moving seasonality ratio (see Bureau of the Census, 1998; Findley *et al.*, 1998).
(2) Legend: LS = level shift; TC = transitory changes; AO = additive outliers.

In conclusion, some differences were found at this stage. In particular, only in

3 instances was the same model identified by the two procedures. It is not obvious, from a theoretical point of view, what impact these differences are likely to have on the estimated seasonal components. In fact, while SEATS decomposes the ARIMA model passed by TRAMO, X12 only uses the model passed by RegARIMA for backcasting and forecasting.

When we imposed on RegARIMA the ARIMA model and data transformation identified by TRAMO, the outliers detected were approximately the same. Furthermore, a trading day effect was detected by RegARIMA every time TRAMO detected it, whereas only RegARIMA found evidence of Easter effects in 4 cases (Table 4).

Table 4 – RegARIMA imposing the same model identified by TRAMO (automatic options) (1)

Series	Starting dates	ARIMA model	Log transformation	Trading days	Easter	Outliers (2)			
BDEGENGS	1986.1	(0,1,3)*(0,1,1)	no	no	no	LS1993.9	LS1996.3		
BDIGENGS	1986.1	(0,1,3)*(0,1,1)	no	no	no	---			
CETGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	no	no	TC1981.9	AO1984.6	TC1985.12	
CITGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	yes	yes	TC1982.12	AO1983.1	AO1983.5	AO1985.12
IFAGENGE	1985.1	(2,1,1)*(0,1,1)	yes	yes	yes	AO1992.8			
IFAGENGN	1985.1	(0,1,1)*(0,1,1)	yes	yes	yes	LS1987.3	AO1991.1		
IPIGENGT	1981.1	(0,1,1)*(0,1,1)	yes	yes	yes	AO1984.8	AO1995.8		
IPIINVGT	1981.1	(2,1,0)*(0,1,1)	yes	yes	no	TC1987.1	AO1992.8	AO1994.8	AO1995.8
LGOLTOGI	1989.1	(1,1,0)*(0,1,1)	no	no	no	TC1992.9			
PCOBENGP	1989.1	(0,1,2)*(0,1,1)	no	no	no	---			
PPIGENGP	1981.1	(1,1,1)*(0,1,1)	no	no	no	TC1988.1			

(1) Apart from the ARIMA model, same options as AUTOMODL are used; 3x3 moving average used in section 1 of each iteration; 3x5 moving average in section 2 of iterations B and C; moving average for final seasonal factors chosen by global moving seasonality ratio (see Bureau of the Census, 1998; Findley *et al.*, 1998).
(2) Legend: LS = level shift; TC = transitory changes; AO = additive outliers.

On the basis of this preliminary analysis the model selected by the automatic routines appears to give rise to differences. As already mentioned, RegARIMA, in automatic mode, compares five alternative ARIMA models (see footnote 8). The basic statistic for model selection is the absolute average prediction error over the last 3 years. When this statistic exceeds 15%, the model is rejected[13]. If this first test is passed, the package also produces the Ljung-Box test for autocorrelation in the estimated residuals and a test for overdifferencing, to check the goodness of fit of the selected model (Jain, 1989)[14].

In TRAMO the adequacy of the model is tested by a standard set of statistics based on estimated residuals. In particular, the output includes a test of normality and two tests of the Ljung-Box type for serial autocorrelation of the residuals and the squared residuals[15]. When run on our data, TRAMO identified a satisfactory

[13] For a critical remark on the use of this statistics, see Maravall (1997a).

[14] When a series is differenced too many times in order to reach stationarity, a unit root is induced in the MA part of the model, which becomes non invertible. Detection of this effect of overdifferencing is based on the roots of the MA polynomial.

model in most cases. Normality was rejected 3 times and the absence of serial autocorrelation (for both the residuals and the squared residuals) in four cases (Table 5).

The RegARIMA diagnostics, reported in Table 6, show that the models chosen exhibit satisfactory performances. In only three cases was the average prediction error greater than 15% so that no model was selected. For the remaining series overdifferencing is always rejected, average forecast errors are well below 15% and the only problem detected is residual autocorrelation for the import quantity index (CITGENGQ).

The next step was to compare the seasonal components estimated in the second stage using SEATS and X12. A rough assessment of the differences between the components is given by the correlations of their monthly growth rates. A high correlation in the seasonally adjusted series means that the differences in the seasonal component identified using the two methods are small, and vice-versa.

Table 5 – TRAMO-SEATS - Comparison between the main diagnostics referred to fully automatic options (RSA=4) and those selected by a "skilled" user (1)

Series	Normality (2)		Residuals Ljung-Box Q value (3)		Square residuals Ljung-Box Q value (3)		BTH (4)	
	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	Skilled"
BDEGENGS	2,59	unch.	0,82	0,82	0,41	0,41	-0,88	unch.
BDIGENGS	1,17	unch.	0,64	0,64	0,78	0,78	-0,98	unch.
CETGENGQ	1,16	0,92	0,03(*)	0,47	0,00 (*)	0,05	-0,56	-0,54
CITGENGQ	5,45	9,27 (*)	0,02 (*)	0,19	0,00 (*)	0,02 (*)	-0,59	-0,50
IFAGENGE	1,35	3,44	0,09	0,61	0,78	0,07	-0,62	-0,67
IFAGENGN	10,74 (*)	7,70 (*)	0,16	0,05	0,73	0,65	-0,56	-0,51
IPIGENGT	3,30	3,21	0,02 (*)	0,14	0,28	0,27	-0,66	-0,65
IPIINVGT	6,51 (*)	2,96	0,89	0,94	0,57	0,80	-0,60	-0,59
LGOLTOGI	3,10	unch.	0,90	0,90	0,00 (*)	0,00 (*)	-0,28	unch.
PCOBENGP	0,46	unch.	0,44	0,50	0,53	0,59	-0,81	unch.
PPIGENGP	51,48 (*)	2,36	0,63	0,17	0,64	0,01 (*)	-0,59	-0,41

(*) Null hypothesis is rejected at 5% confidence level.
(1) For a description of diagnostic checking included in TRAMO-SEATS, see Planas, 1997b.
(2) Bera-Jarque test for normality of residuals (null hypothesis is that residuals are normal; critical value equal to 6).
(3) P-values of the Ljung-Box portmanteau test for serial correlation of residuals:

$$Q = T(T+2)\sum_{k=1}^{H}(T-k)\tilde{\rho}_k^2$$

where T is the number of observations, H the order up to which autocorrelation in the residuals is tested and the sample autocorrelation. The test - under the null hypothesis of absence of autocorrelation - is distributed as a chi-square with degrees of freedom p and q being - respectively - the number of autoregressive and the number of moving average parameters estimated in the regular part of the ARIMA model. If the same test based on squared residuals fails, this is an indication that the linear approximation (selected ARIMA model) of the original series has not been able to capture the nonlinearity in data.
(4) Estimated seasonal MA parameter; a value close to -1 produces a stable seasonal component.

[15] A test for serial correlation at seasonal frequencies is also available, although it is not reported in the paper.

Table 6 – RegARIMA - Model selection diagnostics (1)

Series	Residuals Ljung-Box Q value		Overdifferencing		Predictive	
	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"
BDEGENGS	no model selected	0,090	no model selected	...	no model selected	62,15
BDIGENGS	no model selected	0,098	no model selected	...	no model selected	60,87
CETGENGQ	0,061	0,744	no	no	7,94	6,97
CITGENGQ	0,020 (*)	0,059	no	no	8,11	7,14
IFAGENGE	0,422	0,601	no	no	6,13	5,99
IFAGENGN	0,069	0,154	no	no	7,26	7,09
IPIGENGT	no model selected	0,448	no model selected	no	no model selected	3,17
IPIINVGT	0,820	0,697	no	no	8,38	9,29
LGOLTOGI	0,618	0,978	no	no	0,84	n.a.
PCOBENGP	0,419	0,419	no	no	0,66	n.a.
PPIGENGP	0,391	0,640	no	...	1,40	n.a.

(1) Diagnostics:
- the null hypothesis is that no serial correlation is present (24 lags; P-value is reported in the table);
- test for overdifferencing (see Jain, 1989);
- average percentage standard error in within-sample forecasts (last three years).

X12 gives eleven summary statistics (the so-called "M-statistics"), which provide an overall assessment of the quality of the decomposition performed. Their values range from 0 to 3; values less than 1 for all the statistics denote a "good" seasonal adjustment. Moreover, the program contains a weighted average of the Ms, namely the Q-statistic (Lothian and Morry, 1978). The quality of the decomposition is considered acceptable if Q is less than one. It is worth noting that the M-statistic with the highest weight in Q is M7, which indicates the amount of moving seasonality present, relative to the amount of stable seasonality: if it exceeds 1 seasonality is not "identifiable" by X12. It is possible to have Q less than 1 and M7 higher than 1; in such a situation "the user is strongly advised not to adjust the series" (Lothian and Morry, 1978, p.18), or to try different options. The claim is that such statistics are valuable since they are extremely "user friendly" and offer a sound basis for evaluating estimations.

By contrast, the quality of seasonal adjustment in SEATS depends largely on the adequacy of the model selected by TRAMO. When the estimation of unobserved components is performed by letting the automatic identification routines work, the correlations between the monthly growth rates of the series seasonally adjusted by the two packages are well above 0.9 except in two cases (Table 7). When the estimation of the seasonal component is performed by X12 on the basis of the model used by SEATS, the correlation between the monthly growth rates of the seasonally adjusted data is even higher, still exceeding 0.9 except for the index of industrial turnover in foreign markets.

Turning to the correlations between trends, these are almost always lower — in a few cases much lower — than those computed with respect to seasonally adjusted series. While in SEATS a unique decomposition is obtained by maximising the variance of the irregular component (canonical decomposition), in X12 the use of centred moving averages implies in general a smoother irregular component. It is worth noting that correlations between the trend components are on average greater when X12 is made to run with the model selected by TRAMO.

Table 7 – Correlation between monthly growth rates in the components estimated by X12 and TRAMO-SEATS

Series	Seasonal adjusted series			Trend-cycle series		
	Automatic options	Same ARIMA model imposed to X12 (1)	"Skilled"	Automatic options	Same ARIMA model imposed to X12 (1)	"Skilled"
BDEGENGS	0.959	0.949	0,849	0,686	0,969	0,832
BDIGENGS	0.937	0.939	0,933	0,891	0,888	0,896
CETGENGQ	0.973	0.973	0,544	0,255	0,255	0,810
CITGENGQ	0.959	0.991	0,294	0,424	0,485	0,727
IFAGENGE	0.761	0.761	0,709	0,397	0,397	0,845
IFAGENGN	0.955	0.955	0,827	0,986	0,986	0,467
IPIGENGT	0.653	0.957	0,600	0,831	0,896	0,765
IPIINVGT	0.982	0.982	0,372	0,257	0,638	0,795
LGOLTOGI	0.945	0.937	0,929	0,798	0,807	0,936
PCOBENGP	0.949	0.949	0,951	0,893	0,893	0,906
PPIGENGP	0.986	0.986	0,971	0,959	0,959	0,972
Mean Standard	0,914	0.944	0,725	0,671	0,743	0,814
Deviation	0,101	0.060	0,230	0,270	0,246	0,130

(1) Correlation with the TRAMO-SEATS series obtained with the automatic options.

4.2 "Skilled" users

In the second experiment skilled users came into action. We asked Agustìn Maravall and David Findley to run their programs on our series and send us the results (it would be hard to think of anyone more skilled than the two people who actually built the programs). The experiment was a bit unfair, as we did not tell them about the game we were playing. Hence, the results are likely to have been affected by the amount of time they were able to devote to the analysis[16].

Findley's results are rather different from those we got with the automatic routines. What is probably most striking is the number of changes that occurred in the preliminary analysis (Table 8). In 7 cases the starting dates of the series were changed, presumably as a consequence of visual inspection or some other informal evidence since the program does not provide any test to evaluate the best time span to estimate the seasonal component (the same holds true for TRAMO-SEATS). The models are different from those identified by the automatic options: they were changed in 6 cases, whereas in another 4 cases the airline model proved to perform properly. When RegARIMA failed to find a model for the series (3 cases), Findley imposed an ARIMA model without the seasonal part and hence considered the fixed seasonal effects (in the same cases Maravall chose the airline model). The decomposition was changed from multiplicative to additive in 3 cases. Finally, Findley also

[16] Findley apparently devoted more time to improve the quality of seasonal adjustment.

made important changes when dealing with TD and, in particular, with EE effects. The number of outliers was greatly reduced, from 17 detected in automatic mode to 6 accepted by Findley.

Table 8 – RegARIMA - Comparison between "skilled" and "unskilled" users with respect to the main options

Series	ARIMA model		Log transformation		Trading days		Easter		Holidays	
	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"
BDEGENGS	no model selected	(0,1,1)	no	no	no	no	no	no	no	no
BDIGENGS	no model selected	(0,1,1)	no	no	no	no	no	no	no	no
CETGENGQ	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	no	no	yes	no	yes.	no	yes
CITGENGQ	(2,1,2)*(0,1,1)	(0,1,1)*(0,1,1)	yes	no	yes	yes	no	yes	no	yes
IFAGENGE	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	yes	yes	yes	yes	yes	yes
IFAGENGN	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	no	yes	no	yes	yes	yes
IPIGENGT	no model selected	(0,1,1)*(1,0,0)	no	no	no	yes	no	yes	no	yes
IPIINVGT	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	no	yes	yes	no	yes	no	yes
LGOLTOGI	(0,1,1)*(0,1,1)	(0,1,2)*(0,1,1)	no	no	no	no	no	no	no	no
PCOBENGP	(0,1,2)*(0,1,1)	(0,1,2)*(0,1,1)	no	no	no	no	no	no	no	no
PPIGENGP	(2,1,0)*(0,1,1)	(2,1,0)	no	no	no	yes	no	no	no	yes

Turning to the empirical results, in general the changes introduced improved the diagnostics, though not in a dramatic way (Table 9). It is worth noting that, on the basis of the M-statistics and the Q summary statistics, a user would have accepted the estimates derived from the automatic options in most cases. In this respect, the refinements introduced by Findley seem to require a deeper knowledge of the procedure; the commonly used diagnostics, reported in our tables, might indeed be misleading in the cases considered here.

The other skilled user — that is to say Maravall — made only marginal changes with respect to the fully automatic options. The ARIMA model was changed only in 3 cases; the same log-transformations were used; only in two cases were further TD and EE effects introduced (Table 10). A larger number of outliers was detected as well. Overall, these changes tended to improve the diagnostics, although the basic estimates of the seasonal component were almost unaffected.

Table 9 – X12 - Comparison between the main diagnostics referred to fully automatic options (AUTOMODL) and those selected by a "skilled" user (1)

Series	Fkw (3)		Fm (4)		Test for the presence of identifiable seasonality (5)		M7 (6)		Q (7)	
	Default	"Skilled"	Default	"Skilled"	Default	"Skilled"	Default	"Skilled"	Default	"Skilled"
BDEGENGS	0,02	0,00	4,13 (*)	21,16	no	yes	1,180	0,824	0,85 (5)	0,75 (4)
BDIGENGS	0,00	0,00	74,68	79,28	yes	yes	0,527	0,490	0,40	0,38
CETGENGQ	0,00	0,00	99.55	32,55	yes	yes	0,321	0,189	0,82 (2)	0,28
CITGENGQ	0,00	0,00	88,30	28,26	yes	yes	0,080	0,278	0,18	0,53 (2)
IFAGENGE	0,00	0,00	33,38	34,90	yes	yes	0,357	0,081	0,72 (2)	0,16
IFAGENGN	0,00	0,00	49,45	6,49	yes	yes	0,068	0,083	0,19	0,19
IPIGENGT	0,00	0,00	99,97	0,09	yes	yes	0,082	0,086	0,68 (2)	0,29
IPIINVGT	0,00	0,00	52,82	0,07	yes	yes	0,081	0,117	0,32	0,29
LGOLTOGI	0,00	0,00	0,00 (*)	0,00 (*)	yes	yes	0,599	0,460	0,42	0,40 (1)
PCOBENGP	0,00	0,00	5,39	14,47	yes	yes	0,910	0,820	0,71 (4)	0,68 (4)
PPIGENGP	0,00	0,00	0,21 (*)	0,00 (*)	yes	yes	0,500	0,595	0,48	0,37

(1) P-values are reported in the Table, with the exception of the combined test for identifiable seasonality, where a qualitative statement is reported. For a complete description of the reported tests, see Dagum, 1988.
(2) Test for serial correlation of residuals (null hypothesis: no serial correlation - 24 lags; rejected at 5% confidence level).
(3) Kruskal-Wallis Chi Squared test (non-parametric test) for the presence of stable seasonality; start denotes that seasonality is not present at 1% confidence level.
(4) F-test for the presence of moving seasonality; start denotes that moving seasonality is present at the 5% confidence level.
(5) "Combined test"; "yes" means that identifiable seasonality is present.
(6) The amount of moving seasonality present relative to the amount of stable seasonality (M7 must be less than 1).
(7) Summary statistics (Q must be less than 1); in brackets is the number of the Ms' greater than 1.

Table 10 – TRAMO - Comparison between "skilled" and "unskilled" users with respect to the main options

Series	ARIMA model		Log transformation		Trading days		Easter	
	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"	Automatic	"Skilled"
BDEGENGS	(0,1,3)*(0,1,1) (1)	(0,1,3)*(0,1,1) (1)	no	no	no	no	no	no
BDIGENGS	(0,1,3)*(0,1,1) (1)	(0,1,3)*(0,1,1) (1)	no	no	no	no	no	no
CETGENGQ	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	no	yes	no	no
CITGENGQ	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	yes	yes	no	no
IFAGENGE	(2,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	yes	yes	no	no
IFAGENGN	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	yes	yes	no	no
IPIGENGT	(0,1,1)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	yes	yes	no	yes
IPIINVGT	(2,1,0)*(0,1,1)	(0,1,1)*(0,1,1)	yes	yes	yes	yes	no	yes
LGOLTOGI	(1,1,0)*(0,1,1)	(1,1,0)*(0,1,1)	no	no	no	no	no	no
PCOBENGP	(0,1,2)*(0,1,1)	(0,2,1)*(0,1,1)	no	no	no	no	no	no
PPIGENGP	(1,1,1)*(0,1,1)	(1,1,1)*(0,1,1)	no	no	no	no	no	no

(1) The decomposition is invalid (the spectrum of the irregular component takes negative values); the model is approximated ("airline" model in all the cases indicated).

Comparing the results obtained with the two procedures by skilled users, the main point seems to be that the correlations between the seasonally adjusted series are now much lower than those recorded using the automatic routines (Table 7). On the other hand, the correlations between the trend estimates are much less affected[17].

In the end we took a final step to assess the consistency of the two software packages. A desirable feature of any seasonal adjustment program is that there should be no remaining seasonal variations when it is applied to a series that has already been seasonally adjusted by the same procedure. This is known as the idempotency property (Maravall, 1997a). To check whether this property is satisfied with our data, we ran TRAMO-SEATS with automatic options on the data seasonally adjusted by the skilled and unskilled users. When the series produced by the unskilled user were fed into the program, no further adjustment was performed in 9 cases. In the remaining two cases there was further adjustment, but the diagnostic checking would have told even an unskilled user not to trust the output. The series adjusted by Maravall performed equally well with one exception: in the case of the index of industrial production for the whole manufacturing sector (IPIGENGT), the program detected seasonal variation and the diagnostic checking was satisfactory.

We also run TRAMO-SEATS on the series seasonally adjusted by X12. This is more a test to see whether the other program had removed all seasonality than a test for idempotency. In any case, and not surprisingly, the results were equally good. For none of the series seasonally adjusted with the AUTOMODL option did we find residual seasonal variation. Only one of the series adjusted by Findley was seasonally re-adjusted with statistics that would have led an unskilled user to accept the results.

[17] The results obtained by skilled and unskilled users with X12 give rise to estimated components that are less correlated than those obtained by skilled and unskilled users with SeATS.

5. What Did We Learn from this Experiment?

For our 11 time series the results obtained with TRAMO-SEATS and those obtained with X12-ARIMA are not dramatically different; to put it another way, they are not such as to lead an economist to different evaluations of the economic trends! Our general conclusion is that more effort should be devoted to enabling economists (who are typically not totally "unskilled", as assumed in this paper) to use the procedures considered here on their own, in order to exploit their deeper knowledge of the series studied.

A general point which arises from this analysis is that in both procedures there is room for skilled users to improve the quality of the statistical decomposition of a time series: therefore the idea that everybody can run the two procedures needs some qualification. In our opinion there is considerable scope for improvement in various directions, first of all through teaching and training. Turning to more specific issues, X12's more popular diagnostics — generally considered to be highly user friendly — might be insufficient, leading an unskilled user not to change the automatic options, whereas a skilled one would make major changes. In this respect the manual is not helpful, especially since it does not clarify, with suitable examples, how sliding spans and other newly introduced features should guide one in selecting the best seasonal filters. Diagnostic checking in TRAMO-SEATS, though less user friendly, is more powerful, in the sense that the available tests promptly indicate the need for changes in the basic specification. The range of tests is more limited compared with those printed in the output of X12. The TRAMO-SEATS reference manual should also be improved to allow users to learn from it.

In both approaches an automatic analysis of the results obtained with a different starting period is lacking. We wonder if it is possible to introduce such an automatic comparison, so as to free users from the cumbersome (and time consuming) job of trying different spans.

The analysis of revisions to the estimated components, a critical issue from the policy-maker's point of view, is lacking in both procedures. Particularly, revisions are not critical in general (as implicitly assumed in the available tests) but only in proximity of turning points; in such cases they can lead not only to different quantitative estimates, but also to different qualitative conclusions. Tests should be implemented around these turning points.

An important point concerns the so-called choice between a "direct" and an "indirect" method. This is particularly important in a European perspective, as one will typically be faced with the problem of deciding whether a seasonally adjusted aggregate measure should be computed directly from the country-aggregation of raw series or whether it would be more appropriate to aggregate 11 seasonally adjusted series directly. At present X12 has a built-in procedure to compare these two options, whereas TRAMO-SEATS does not.

Table 11 – Options selected by Maravall

Series	Starting dates	ARIMA model	Log transformation	Trading days	Easter	Outliers (1)						
BDEGENGS	1986.1	(0,1,1)*(0,1,1)	no	no	no	LS1996.3	LS1993.9					
BDIGENGS	1986.1	(0,1,1)*(0,1,1)	no	no	no	no						
CETGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	yes	no	LS1981.4	AO1985.12	AO1982.12	AO1984.6			
CITGENGQ	1980.1	(0,1,1)*(0,1,1)	yes	yes	no	AO1983.1	AO1985.12	TC1982.1	AO1983.4	LS1983.6		
IFAGENGE	1985.1	(0,1,1)*(0,1,1)	yes	yes	no	AO1993.8	TC1988.8	AO1987.8				
IFAGENGN	1985.1	(0,1,1)*(0,1,1)	yes	yes	no	LS1987.3	AO1991.1	AO1990.8				
IPIGENGT	1981.1	(0,1,1)*(0,1,1)	yes	yes	yes	AO1984.8	AO1995.8	AO1987.1	AO1990.8	TC1989.8	AO1984.4	
IPIINVGT	1981.1	(0,1,1)*(0,1,1)	yes	yes	yes	AO1992.8	AO1995.8	AO1984.8	AO1988.8	TC1987.1		
LGOLTOGI	1989.1	(1,1,0)*(0,1,1)	no	no	no	TC1992.9						
PCOBENGP	1989.1	(0,2,1)*(0,1,1)	no	no	no	no						
PPIGENGP	1981.1	(1,1,1)*(0,1,1)	no	no	no	TC1988.1	LS1990.8	TC1985.12	AO1988.10	TC1995.5	TC1991.1	LS1995.3

(1) Legend: LS = level shift; TC = transitory changes; AO = additive outliers

Table 12 – Options selected by Findley

Series	Starting dates	ARIMA model		Log transformation	Trading days	Easter	Outliers (1)		Moving average (lenght)	Holidays
BDEGENGS	1988,1	(0,1,1)	fix seas. effect	no	no	no	LS 1996.3	LS1993.9	s3x5	no
BDIGENGS	1988,1	(0,1,1)	fix seas. effect	no	no	no	no		s3x5	no
CETGENGQ	1986,1	(0,1,1)*(0,1,1)		no	yes	yes	no		s3x5	yes
CITGENGQ	1986,1	(0,1,1)*(0,1,1)		no	yes	yes	LS 1992.12		s3x5	yes
IFAGENGE	1985,1	(0,1,1)*(0,1,1)		yes	yes	yes	AO1992.8		s3x5, except august s3x3	yes
IFAGENGN	1985,1	(0,1,1)*(0,1,1)		yes	yes	yes	no		s3x5, except august s3x3	yes
IPIGENGT	1983,1	(0,1,1)*(1,0,0)	fix seas. effect	no	yes	yes	no		s3x5, except august s3x3	yes
IPIINVGT	1983,1	(0,1,1)*(0,1,1)		no	yes	yes	no		s3x5, except august s3x3	yes
LGOLTOGI	1989,1	(0,1,2)*(0,1,1)		add	no	no	TC 1992.9		s3x5	no
PCOBENGP	1989,1	(0,1,2)*(0,1,1)		add	no	no	no		s3x3, except mar apr aug sep s3x9	no
PPIGENGP	1987,1	(2,1,0)	fix seas. effect	add	yes	no	TC 1991.1		s3x5, except dec s3x3	yes

(1) Legend: LS = level shift; TC = transitory changes; AO = additive outliers

Table 13 – Correlations between monthly growth rates in the components estimated by "skilled" and "unskilled" users, respectively with reference to X12 and TRAMO-SEATS

Series	Seasonally adjusted series		Trend-cycle series	
	X12	TRAMO-SEATS	X12	TRAMO-SEATS
BDEGENGS	0,902	1,000	0,554	0,999
BDIGENGS	0,982	1,000	0,978	1,000
CETGENGQ	0,512	0,939	0,839	0,999
CITGENGQ	0,231	0,993	0,685	0,245
IFAGENGE	0,849	0,800	0,972	0,512
IFAGENGN	0,881	0,990	0,505	0,998
IPIGENGT	0,468	0,967	0,735	0,951
IPIINVGT	0,403	0,995	0,191	0,999
LGOLTOGI	0,989	1,000	0,852	1,000
PCOBENGP	0,982	1,000	0,995	1,000
PPIGENGP	0,968	0,985	0,974	0,985
Mean	0,742	0,970	0,753	0,881
Standard deviation	0,281	0,059	0,254	0,256

Table 14 – Violation of the property of idempotency *(with respect to TRAMO-SEATS estimates)* (1)

Series	TRAMO-SEATS		X12		
	Automatic (RSA=4)	Maravall (AUTOMODL)	the same model as TRAMO is imposed	Automatic	Findley
BDEGENGS	no	no	no	no	no
BDIGENGS	no	no	yes (no) (2)	no	no
CETGENGQ	no	no	no	no	no
CITGENGQ	yes (no) (2)	yes (no) (2)	yes (no) (2)	no	no
IFAGENGE	no	no	no	no	no
IFAGENGN	no	no	no	no	yes (no) (2)
IPIGENGT	no	**yes**	no	no	no
IPIINVGT	no	no	no	no	yes (no) (2)
LGOLTOGI	yes (no) (2)	no	no	no	no
PCOBENGP	no	no	no	no	no
PPIGENGP	no	no	no	no	**yes**

(1) The seasonal adjusted series are fed into TRAMO-SEATS in order to see whether residual seasonality can be detected.
(2) The procedure estimates a seasonal component; however, standard diagnostics leads not to accept the decomposition performed.

References

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SEASONAL ADJUSTMENT

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1. Introduction

Seasonal adjustment depends on a method of weighting the observations so as to decompose them into seasonal and nonseasonal components. A model-based procedure uses weights which are determined by the dynamic properties of the series.

The STAMP package is based on structural time series models (STMs). These models are set up in terms of components which have a direct interpretation, such as trend, cycle, seasonal and irregular; see Harvey (1989). Once a model has been estimated, the seasonal component is extracted by the Kalman filter smoother (KFS) to give the seasonally adjusted series. Given the model specification, the estimate of the seasonal component is the best estimate for all time periods, including the beginning and the end of the series. There is no need to extend the series by forecasting future observations since the KFS automatically uses the correct weights. Of course as more observations become available, the estimates of the seasonal component near what was the end of the series will change. This is a natural consequence of model-based seasonal adjustment. The estimates change every month (or quarter), but the decision as to how often the published seasonally adjusted figures are revised is a political one.

STAMP can produce graphs of the seasonal component and the seasonally adjusted series. It also produces a graph showing how each seasonal component has changed over time.

The structural approach to time series modelling and seasonal adjustment has been advocated by, amongst others, Akaike, Kitagawa, Gersch, and Young. Bayesian methods are discussed in the book by West and Harrison. A study of the practical implications of seasonally adjusting with STAMP can be found in a 1992 Bank of England report.

2. Model Fitting

The default in STAMP is the basic structural model (BSM). This model consists of a stochastic trend, stochastic seasonal and an irregular component. This model, which is very similar to the ARIMA airline model, is perfectly adequate for most series. It depends on three parameters (relative variances) which may be estimated by maximum likelihood (ML). A cycle may be included, but the evidence in Riani (1998) suggests that this has little effect on the estimates of the seasonal component. Thus the BSM is robust for the purposes of seasonal adjustment. The fact that the model specification is not too data dependent means that it is also relatively robust to outliers.

Although certain models like the BSM are often chosen on prior grounds, the standard diagnostics check that the fit is satisfactory.

When working with monthly data it is sometimes desirable to allow for calendar effects, such as trading days. This may be done by including appropriately formulated regressors in the model. The next version of STAMP, version 6, will allow this to be done automatically and will allow for such effects to evolve over time as in the work carried out at Statistics Canada by Dagum and Quenneville.

3. Outliers and Structural Breaks

STAMP allows for the detection of outliers and structural breaks by means of the auxiliary residuals; see Harvey and Koopman (1992). Distinguishing between outliers and breaks is important since the way in which they should be treated is entirely different.

The problem with an automatic outlier detection and removal procedure is that it may result in inappropriate action. For example, it may remove an observation when the problem stems from a break in the series. There is also the issue of what exactly constitutes an outlier. Clearly an untypical observation which results from some kind of measurement error is an outlier which should be removed (unless one can go back and correct the error). But suppose an outlier is a genuine observation caused, perhaps, by a strike or by unusually hot weather affecting a series on water consumption. Such an observation should not be removed. Of course there is the point that one may wish to ensure that the outlier does not affect estimates of model parameters adversely. The structural approach is less susceptible to such problems than the ARIMA approach. There is also the possibility of extending STMs so that some of the disturbances become heavy-tailed, hence making the model more robust; see Durbin and Koopman (1997).

When certain months are more liable to produce outliers than others, the irregular can be given a higher variances. Structural models can easily be extended to allow for such seasonal heteroscedasticity. Proietti (1998) fits models of this kind to Italian industrial production.

4. Weekly Observations

Some key series, for example the money supply, are available weekly in some countries. Weekly data introduces a number of new problems which cannot, in general, be handled by standard packages. However, the structural approach can be adapted to deal with such data. The paper by Harvey, Koopman and Riani (1997) shows how this was done for the UK money supply.

5. Survey Data

Some series, for example those on unemployment are obtained from surveys. The rotational pattern employed in the sample design means that serial correlation is introduced into the irregular term. This can be dealt with by constructing a suitable STM as discussed in Pfeffermann (1991) and Harvey and Chung (1998). Actually the aim of this second paper is to combine two measures of unemployment to produce an estimate of the underlying change in unemployment. Seasonality is included in the model, rather than seasonally adjusting first, and the STM approach gives a solution to what is a rather complex signal extraction problem.

6. Conclusion and Future Developments

The STAMP 5 package is an easy-to-use, menu-driven package which provides a means of analysing time series and seasonally adjusting in a way which is optimal given the model specification. It uses the same data-handling environment as the PC GIVE econometrics package.

The STAMP 6 package will include new features including the ability to handle missing observations and to construct trading day and calendar effects. In fact there will be a special seasonal adjustment dialog. Subsequent modifications will make it possible to handle features such as seasonal heteroscedasticity, and to go some way towards constructing models for weekly data by using time-varying splines. The program will operate in the latest windows environment in the same way as PC GIVE. Batch processing will be possible so that once a model has been set up, a large number of series can be automatically adjusted.

STMs can be extended to deal with non-standard problems, for example survey data. The SSFpack program, which operates in the OX environment and is available free on the internet (see Koopman, Doornik and Shephard), enables researchers to develop the appropriate software.

Finally it should be stressed that the STM framework enables statisticians to tackle a much wider range of issues than seasonal adjustment. There include estimation of underlying growth rates and interpolation of missing observations using related series.

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INTERVENTION

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In our view, the difference between X12 and TRAMO-SEATS is only limited to the differences between the seasonal decomposition parts of these programs, since TRAMO and RegARIMA are essentially equivalent. X-11 offers the combination of 4 filters for estimation of the trend and 4 filters for the estimation of the seasonal component. SEATS offers an infinity of filters, adapted to the profile of the decomposed series. More precisely, the set of possible filters is in bijection with R^{p+m+2} where p (resp.m) is the higher possible degree of the ARIMA that is fitted to the initial series. It can as well be shown that all X11 filters can be approximated as closely as desired by ARIMA model-based filters (see Depoutot and Planas, 1998), making of X11 filters a set of measure nil in the set of AMB filters.

Model-based methods are also to be retained, since they offer possibilities to solve pending problems, that cannot be tackled with ad-hoc filters like X11. We can quote the problem of changing patterns, sensitivity analysis of the model used to choose the filters, combination of sampling variance and seasonal adjustment variance, management of revisions (see Depoutot and Planas, 1998), multi-dimensionnal seasonal adjustment and aggregation, prevision of turning points, consequences of benchmarking of adjusted series on the yearly total of non-adjusted series, etc.

The new Windows 95/NT interface developed by Eurostat will incorporate both packages (X12 and TRAMO/SEATS), and make the comparison of seasonal adjustments by these package very easy (results will be provided on the same screen). Eurostat is about to issue as well recommendations for a Policy on Seasonal adjustment, for its internal use. This will be made public and could be useful to other statistical offices. In particular, the issue of comparability for seasonal adjusted series is raised, and of dependence from the chosen SA method.

Lastly, further analysis and methodological development is needed in general in the domain of Seasonal Adjustment, and the Eurostat team hopes that the starting co-operation with the US Census Bureau will continue, and that other academic teams will contribute to our work.

THE SEASONAL ADJUSTMENT OF THE ITALIAN INDUSTRIAL PRODUCTION SERIES

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1. Introduction

The seasonal behaviour of the Italian index of industrial production is somewhat atypical for most non food sectors, due to the seasonal trough occurring in August being very deep and well removed from the values of the remaining seasons; for instance, for the Total index the ratio between the August value and the March value of the same calendar year, corresponding to the seasonal peak, has an average of 0.42 over the period 1981-1996, corresponding to a seasonal drop in production of about 60%. This average goes down to .24 for Transportation Means, which implies that August production can reach down to just 1/4 of its seasonal peak value.

As will be shown in the next section, the multiplicative or log-additive decomposition leads to the systematic identification of August as outlying, which is a seasonal feature unexplained by the model. On the contrary, the additive decomposition poses no particular problems, in that no special feature is associated with August.

Therefore, the choice of the transformation turns out to be a relevant issue. In section 2 we show the consequences of adjusting the series via the multiplicative model; the spread-level regressions implemented in TRAMO-SEATS suggest the logarithmic transformation, at the cost of flagging August as outlying. Likelihood based inferences on the transformation parameter (implemented in X-12-ARIMA) suggests that the series should not be transformed. Actually, a deeper investigation. delayed until section 5, supports neither actions.

Assuming that the choice of the Box-Cox transformation parameter is restricted to the two values 0 and 1, the log-additive model needs to be amended in order to account for the August feature. This is achieved in section 3, where adjustment by a seasonally heteroscedastic (SH) model is presented. This is then compared to the additive adjustment performed by X-12-ARIMA and TRAMO-SEATS (section 4); the comparison shows that the seasonal component extracted by the SH model is more flexible in the short run and the corresponding seasonally adjusted series is smoother, as part of what is interpreted as noise by a linear-additive decomposition is, loosely speaking, attributed to the seasonal component.

In section 6 we use post sample predictive testing as a yardstick for assessing the performance of the SH model in comparison to a linear additive structural model. The conclusion is that two alternative representations of the data are plausible. A possible disadvantage of SH adjustment lies in the fact it requires a modelling effort that may be too time consuming for a statistical agency aiming at routine adjustment of a large number of series. In such case the strategy of presenting trends along with seasonally adjusted series is strongly advocated, a suggestion already made for Swedish production series by Wallgren and Wallgren (1990).

2. Seasonal Adjustment by TRAMO-SEATS and X-12-ARIMA: is August really Outlying?

In this section we present the main results of the application TRAMO-SEATS and X-12-ARIMA to the Industrial Production data set made available by Istat, consisting of 4 aggregate series and 16 series disaggregated at the industry level. The sample period spans from Jan. 1981 to Dec. 1996, for a total of 192 monthly observations.

TRAMO-SEATS was applied using the Excel interface developed at Eurostat. The set of options chosen includes automatic model selection, outlier detection, testing for calendar effects. By the option LAM = -1 the programme performs a preliminary test for level versus logarithm specification, based on the estimate of the slope coefficient in the trimmed range-mean regression; if it crosses a prespecified threshold, the log specification is chosen. If the evidence is unclear the airline model is estimated for both specifications and the one providing the smallest BIC is selected.

The main results are reported in table 1. The fourth column highlights that the multiplicative (M), i.e. log-additive, specification is selected in all but one occurrences. Furthermore, the automatic model identification procedure selects in most cases the *airline* model.

The evidence about the outlying observations automatically identified by the procedure is striking: August is more or less systematically flagged as outlying (AO). This is particularly evident for the series IPIODHGT, IPIODMGT and IPIODMGT. Due to aggregation the number of outlying observations detected by the procedure is much less for the first group of series.

The X-12-ARIMA procedure is initially applied choosing the multiplicative (default) decomposition; the results are summarised in table 2. The additive outliers identified by RegARIMA tend to coincide with TRAMO-SEATS; however, fewer *level shifts* are identified, and in general the linearisation set forth by TRAMO is much stronger.

Slidings span diagnostics have been introduced by Findley *et al.* (1990) as a mean

Table 1 - TRAMO-SEATS, Automatic model and outliers identification

Series	Descr.	Model	Dec.	Easter	Trading Days	Outliers
IPIGENGT	Total	(0,1,1)(0,1,1)	M	Y	Y	AO(8,1984), AO(8,1995)
IPICONGT	Consumpt.	(0,1,1)(0,1,1)	M	N	Y	TC(8,1984)
IPIINVGT	Investment	(0,1,1)(0,1,1)	M	N	Y	AO(8,1984), AO(8,1992), AO(8,1995)
IPIINTGT	Intermed.	(2,1,1)(0,1,1)	M	Y	Y	AO(8,1984), TC(8,1992), AO(8,1995)
IPI00CGT	Mining	(0,1,2)(0,1,1)	M	N	N	AO(2,1991)
IPI0DAGT	Food	(1,0,0)(0,1,1)	A	Y	Y	LS(3,1987)
IPI0DBGT	Textiles	(0,1,1)(0,1,1)	M	N	Y	AO(8,1984), AO(8,1985), AO(8,1989), AO(8,1995)
IPI0DCGT	Leather	(0,1,1)(0,1,1)	M	N	Y	AO(8,1991), TC(12,1992), AO(8,1994)
IPI0DDGT	Lumber	(0,1,1)(0,1,1)	M	N	Y	AO(4,1984), TC(8,1984), AO(8,1993)
IPI0DEGT	Paper	(0,1,1)(0,1,1)	M	Y	Y	TC(7,1982)
IPI0DFGT	Petroleum	(0,1,2)(0,1,1)	M	N	N	No Outliers
IPI0DGGT	Chemicals	(0,1,1)(0,1,1)	M	N	Y	AO(1,1985)
IPI0DHGT	Rubber	(0,1,1)(0,1,1)	M	N	Y	AO(8,1984), AO(8,1986), TC(12,1986), TC(8,1987), AO(8,1990), TC(12,1992), AO(8,1994), TC(12,1994), AO(8,1995)
IPI0DIGT	Stone	(0,1,1)(0,1,1)	M	N	Y	AO(1,1985), TC(1,1987), AO(12,1996), LS(12,1992) , TC(8,1995)
IPI0DJGT	Metals	(0,1,1)(0,1,1)	M	N	Y	AO(8,1983), LS(6,1982), AO(8,1984), TC(8,1995)
IPI0DKGT	Machinery	(0,1,1)(0,1,1)	M	N	Y	AO(8,1986)
IPI0DLGT	Elec.Mach.	(0,1,1)(0,1,1)	M	N	Y	AO(8,1981), AO(8,1986), AO(8,1987), AO(3,1989), AO(8,1990), AO(8,1995)
IPI0DMGT	Transport.	(0,1,1)(0,1,1)	M	N	Y	AO(8,1981), AO(8,1984), LS(1,1987), AO(8,1988), AO(8,1989), AO(8,1990), AO(8,1991), AO(8,1992), LS(12,1992), AO(8,1994), AO(8,1995)
IPI0DNGT	Other	(3,1,1)(0,1,1)	M	N	N	LS(4,1983), AO(8,1984), LS(11,1985), AO(8,1988), AO(8,1989), TC(2,1991), LS(11,1991), AO(8,1992), LS(12,1992), AO(8,1995),
IPI00EGT	Energy	(0,1,1)(0,1,1)	M	Y	N	TC(1,1985)

Table 2 - X-12-ARIMA, Multiplicative SA, automatic outliers identification and sliding spans diagnostics

Series	Descr.	Easter	Trading Days	Outliers	Sliding Spans Diagnostics			
					SF	TD	SA	MM
IPIGENGT	Total	Y	Y	AO(8,1984), AO(8,1995)	2.8 (3)	0.00	3.7 (4)	4.7 (2,3)
IPICONGT	Consumpt.	Y	Y	AO(8,1984)	6.5 (7)	0.00	6.5 (7)	16.8 (7,7)
IPIINVGT	Investm.	N	Y	AO(8,1992), AO(8,1995)	6.5 (1)	0.00	8.3 (1)	16.8 (0,0)
IPIINTGT	Interm.	Y	Y	No outliers	0.9 (1)	0.00	0.9 (1)	0.0 (0,0)
IPI00CGT	Mining	N	N	AO(2,1991)	0.9 (0)		0.9 (0)	3.7 (0,2)
IPI0DAGT	Food	Y	Y	No outliers	0.0 (0)	0.00	2.8 (0)	6.5 (2,1)
IPI0DBGT	Textiles	N	Y	AO(8,1984), AO(8,1985), AO(8,1989), AO(8,1995), AO(8,1996)	8.3 (5)	0.00	10.2 (5)	19.6 (5,4)
IPI0DCGT	Leather	N	Y	AO(8,1991), AO(8,1994)	10.2 (8)	0.00	10.2 (8)	25.2 (8,8)
IPI0DDGT	Lumber	N	Y	No outliers	13.9 (7)	0.00	13.0 (7)	26.2 (7,7)
IPI0DEGT	Paper	Y	Y	No outliers	1.9 (2)	0.00	1.9 (2)	3.7 (2,0)
IPI0DFGT	Petroleum	N	N	No outliers	6.5 (0)		6.5 (0)	20.6 (0,0)
IPI0DGGT	Chemicals	N	Y	AO(1,1985)	2.8 (3)	0.00	2.8 (3)	6.5 (3,4)
IPI0DHGT	Rubber	N	Y	AO(8,1984), AO(8,1986), AO(8,1987), AO(8,1990), AO(8,1994), AO(12,1994), AO(8,1995)	6.5 (5)	0.00	5.6 (5)	15.9 (6,5)
IPI0DIGT	Stone	N	Y	AO(1,1985), AO(1,1987), LS(12,1992), AO(12,1996)	2.8 (3)	0.00	3.7 (3)	6.5 (3,2)
IPI0DJGT	Metals	N	Y	AO(8,1983), AO(8,1984)	8.3 (7)	0.00	7.4 (7)	16.8 (7,7)
IPI0DKGT	Machinery	N	Y	AO(8,1995)	8.3 (8)	0.00	10.2 (8)	27.1 (8,8)
IPI0DLGT	Elec.Mach.	Y	Y	AO(8,1981), AO(8,1986), AO(8,1987), AO(8,1990), AO(8,1995)	10.2 (8)	3.00	12.0 (8)	25.2 (8,8)
IPI0DMGT	Transport.	N	Y	AO(8,1981), AO(8,1984), AO(1,1987), AO(8,1988), AO(8,1989), AO(8,1990), AO(8,1994), AO(8,1995), AO(8,1996)	13.9 (8)	3.00	20.0 (8)	42.1 (7,7)
IPI0DNGT	Other	N	N	AO(8,1984), AO(8,1988), AO(8,1989), AO(8,1992), AO(8,1995)	13.9 (7)	13.09	14.8 (7)	37.4 (6,7)
IPI00EGT	Energy	Y	N	AO(1,1985)	0.0 (0)	0.00	0.9 (0)	3.7 (0,0)

of assessing the stability and more generally the reliability of the adjustment, by looking at the relative changes in relevant output series, such as seasonal factors, the seasonally adjusted series and its monthly growth rates, when the procedure is applied to contiguous and partially overlapping spans. A span is a moving window of a fixed number of consecutive observations, depending on the length of the adjustment filter, that is obtained from the previous span by adding a year of observations and removing the first year.

Table 2 reports the percentage of months flagged as unstable, separately for the Seasonal Factors (SF), Trading Days, Seasonally Adjusted (SA) series, and the month to month (MM) percent changes in the SA series. In parenthesis are recorded the number of unstable August values, and for the monthly growth rates also the number of unstable September values. Even though only for the IPIODMGT these percentages cross the empirical thresholds suggested by the proponents, there is widespread evidence that the seasonal adjustment is unreliable, especially with respect to the August values. Also, in the course of the X-11 procedure, the August values are heavily downweighted when extracting the seasonal factors.

In conclusion, multiplicative and log-additive adjustment of the industrial production series raise a few concerns: in particular, there is strong evidence for misspecification, due to the failure to explain the seasonal behaviour of the series with respect to August.

How about additive adjustment? This option would be dismissed if one took for granted the evidence arising from a variety of spread-level regression test for the log transformation, such as that implemented by TRAMO-SEATS. More reliable likelihood based test, such as the AIC and BIC tests implemented in X-12-ARIMA by the spec transform{function=auto}, not reported for brevity, indicate that no transformation is preferable. This issue will be discussed further in section 5. As for now, we report the most important piece of evidence emerging from the application of the additive decomposition. For both TRAMO-SEATS and X-12-ARIMA the number of outlying observations is drastically reduced and what is more, August is no longer outlying; for instance, no outliers are found for IPIODMGT and IPIGENGT. Futhermore, the diagnostics are not at all a cause of concern. However, what needs to be anticipated is that the seasonal patterns are "surprisingly" stable, and that the noise component is highly variable, so that the seasonally adjusted series will differ significantly from the trend.

A subset of the IPIODMGT series is reported in the paper by Findley *et al.* (1998) as a case for which pseudo-additive adjustment is more reliable; this evidence is not stable, at least, since if we apply this adjustment to the full series we would end up with the following percentages of months flagged as unstable:

Seasonal Factors	18 out of 108 (16.7 %)
Month-to-Month Changes in SA Series	35 out of 107 (32.7 %)

with a high concentration of unstable values in August. Thus, this strategy does not represent a viable alternative (yet it would pose problems as far as the treatment of calendar and other regression effects is concerned[1]).

[1] The pseudo-additive adjustment above was performed on the series B1 outputted by the preliminary additive adjustment for calendar effects.

3. Seasonal Adjustment by a Structural Model with Seasonal Heteroscedasticity

In this section we are going to compare the performance of the additive and the log-additive decompositions within the structural time series framework. From the previous section it emerged that the log-additive decomposition needs to be amended so as to account for the fact that August is more variable than the other seasons. This calls for a seasonal model enhancing the flexibility of the seasonal pattern, which is straightforward to implement in the structural framework, which is particularly amenable for the problem at hand.

The basic structural model is specified as follows:

$$y_t = \mu_t + \gamma_t + \beta' \mathbf{x}_t + \varepsilon_t \tag{1}$$

where μ_t is the trend, γ_t the seasonal component, $\varepsilon_t \sim \mathrm{WN}(0,\sigma_\varepsilon^2)$ the irregular component and $\mathbf{x}_t$ is a K times 1 vector of regressors accounting for calendar effects: trading days (TD), Easter (E), length of month (LOM) and interventions (additive outliers - AO).

As usual, the trend is specified as a local linear component:

$$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t, & \eta_t &\sim WN(0, \sigma_\eta^2) \\ \beta_t &= \qquad\ \beta_{t-1} + \varsigma_t, & \varsigma_t, &\sim WN(0, \sigma_\varsigma^2) \end{aligned} \tag{2}$$

and $E(\eta_t\ \zeta_{t-j})=0$, $\forall j$; when $\sigma_\eta^2=0$ and $\sigma_\zeta^2>0$, the trend is an integrated random walk and is often referred to as a *smooth trend* (when this is imposed as a restriction, a smoothness prior representation is said to be imposed on μ_t; see Kitagawa and Gersh, 1984).

The seasonal component has the Harrison and Stevens (HS) representation:

$$\begin{aligned} \gamma_t &= \mathbf{e}_t' \delta_t \\ \delta_t &= \delta_{t-1} + \omega_t \end{aligned} \tag{3}$$

where ε_t is an s times 1 selection vector taking zero values and 1 in the j-th position corresponding to the j-th season and ω_t is a zero mean multivariate white noise with covariance matrix

$$\mathrm{Var}(\omega_t) = \sigma_\omega^2 \left(\mathbf{I}_s - \frac{1}{s}\, \mathbf{i}_s \mathbf{i}_s \right) \tag{4}$$

which enforces the constraint $\mathbf{i}_s$'Var(ω_t)=0', where $\mathbf{i}_s$ is a vector of 1's. This implies that $\mathbf{i}_s'\delta_t = \mathbf{i}_s'\delta_{t-1}$, which for $E(\mathbf{i}_s'\delta_0)=0$ implies $E[S(L)\, \gamma_t]=0$, for $S(L)=1+L+\ldots+L^{s-1}$. Moreover $S(L)\, \gamma_t \sim MA(s\text{-}2)$.

The HS seasonal model is very «close» to the trigonometric specification, although it is characterised by nicer properties (Proietti, 1997). Moreover, it lends itself to be extended so as to account for seasonal heteroscedasticity as in Proietti

(1998). This is achieved by setting the covariance matrix of the seasonal innovations as follows:

$$\mathrm{Var}(\omega_t) = \mathbf{D} - \frac{1}{\mathbf{i}_s'\mathbf{D}\mathbf{i}_s}\mathbf{D}\mathbf{i}_s\mathbf{i}_s'\mathbf{D} \quad (5)$$

where **D** is a diagonal matrix, $\mathbf{D} = \mathrm{diag}\{d_j, j=1...,s\}$. For the series at hand we specify $d_j = \sigma_\omega^2=0, j=1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12$, and $d_8 = \sigma_8^2$.

As far as the statistical treatment is concerned, under the further assumptions that ε_t, η_t, ζ_t, and ω_t, are mutually uncorrelated, model (1) is cast in the state space form and the Kalman filter is used for evaluation of the likelihood; in order to deal with the nonstationary elements in the state vector, the diffuse version of the filter proposed by DeJong (1991) can be used; related algorithms are available for smoothing. This approach is discussed at length in Harvey (1989). Interventions can be added to the state equations defining the components so as to model level shifts, temporary changes and breaks in seasonality.

Three different specifications of the basic structural model were estimated for the Total series (IPIGENGT) and for Transportation Means (IPIODMGT), 1981.1-1996.12. The first, labelled *HS Add*, is model (1) with no transformation on the response variable and Harrison-Stevens seasonality; the second (*HS Log*) is the same model applied to the log transformation and the last (*SH Log*) is model (1) for the log transformation and with seasonal heteroscedasticity. A smooth trend was imposed as a further specification for the IPIODMGT series (*SH SmPrior*) for later comparison (section 4).

The parameter estimates along with diagnostics and goodness of fit statistics are reported in table 3. As far as the log-additive specification is concerned, the evidence is in favour of the SH model: the LR test of

$$H_0\colon \sigma_8^2 = \sigma_\omega^2$$

is strongly rejected in both cases. Moreover, auxiliary residuals flag no additive outlier. However, the *AIC* reported in the last row, calculated on the original scale of the observations (see footnote below table 3), is minimum for the additive model.

We turn now to the comparison between the *HS Add* and the *SH Log* model with respect to the seasonal adjustment of the IPIODMGT series. The smoothed estimates of the seasonal component are presented in figure 3; for the logarithmic specifications, by properties of the lognormal distribution, they are obtained as $\exp[\tilde{\gamma}_{t|T} + .5MSE(\tilde{\gamma}_{t|T})]$. A noticeable feature is that the seasonal pattern extracted by the SH model is less stable, being characterised by higher flexibility. The first reaction, based on a simple graphical inspection, is that the pattern is more realistic, since it captures the behaviour of August. Correspondingly, the seasonally adjusted (SA) series is smoother and the trend is estimated with lower MSE.

4. Comparison with other SA Procedures; I(1) or I(2) Trends?

The structural model applied to the logarithms of the series for disaggregated

Table 3 - BSM parameter estimates and diagnostics

	IPIGENGT			IPIODMGT			
	HS Add	*HS log*	*SH log*	*HS Add*	*HS log*	*SH log*	*SH SmPrior*
σ_η^2	.0000000	.0000414	.0000000	5.69	.0010530	.0008810	.0000000
σ_ζ^2	.0127434	.0000006	.0000015	.0000000	.0000000	.0000000	.0000423
σ_ω^2	.0579636	.0000059	.0000066	.0000065	.0000181	.0001055	.0001107
σ_g^2	-	-	0.419017	-	-	155.68	62.12
σ_ε^2	2.29	.0003804	.0002773	0,463889	.0037287	.0004134	.0007813
TD_1	0.6197	0.0032	0.0048	1.3020	0.0099	0.0116	0.0099
TD_2	0.5573	0.0075	0.0067	0.8835	0.0088	0.0062	0.0088
TD_3	0.7062	0.0108*	0.0087*	11.490	0.0231*	0.0250*	0.0231*
TD_4	1.1850*	0.0121*	0.0114*	11.615	0.0556	0.0062	0.0056
TD_5	0.7003	0.0086	0.0070	0.5160	0.0088	0.0080	0.0082
TD_6	-2.3570*	-0.0263*	-0.0240*	-3.0513*	-0.0331*	-0.0334*	-0.0331
TD_7	-1.1411*	-0.0157*	-0.0146*	-1.9605*	-0.0225*	-0.0234*	-0.0225*
LOM	2.4381*	0.0255	0.0248*	3.3532	0.0345	0.0369	0.0345
Easter	-1.8706*	-0.0187	-0.0177*	-14.771	-0.0197	-0.0205	-0.0197
Likelihood	-168.8	580.9	594.8	-299.7	389.2	429.8	426.0
r_{12}	0.11	0.20*	0.08	0.16*	0.24*	-0.11	-0.16*
N_1	1.25	2.04	0.37	1.57	7.84*	6.25*	6.30*
N_2	0.20	3.81	0.02	5.02*	88.72*	34.64*	38.16
Q(12)	8.03	16.77	6.99	9.62	21.85*	10.46	11.14
Q(24)	38.46*	48.95*	40.26*	22.75	41.54*	25.34	26.5
R_s^2	0.75	0.75	-	0.23	0.56	-	-
AIC	345.06	581.04	551.06	607.04	896.08	817.06	823.02

NOTES: * significant at the 5% level.
All the diagnostics are computed on the generalised least squares residuals: r_{12} denotes the autocorrelation coefficient at lag 12; N_1 is a test for residual skewness based on the standardised third moment of the residuals about the mean (see Harvey, 1989, 5.4.2.); N_2 is a test for residual kurtosis and $N= N_1 +N_2$ is the Bowman and Shenton test for non-normality. $Q(12)$ and $Q(24)$ are the Ljung-Box statistic based on 12 and 24 residual autocorrelations, respectively. The goodness of fit statistic is $R_s^2 =1-SSE/SSDSM$, where $SSE=(T-d-k)\ pev$, *pev* is the prediction error variance, *d* is the number of nonstationary state components, *k* the number of explanatory variables, and *SSDSM* is the sum of squares of first differences around the seasonal means. As the *pev* cannot be computed for a time varying state space model, R_s^2 is not reported for the SH model. The Akaike Information Criterion is computed as $AIC = -2\ ln\ \Lambda^*+2\ n$, where *n* denotes the number of hyperparameters and Λ^* is the likelihood on the original scale of the observations: when the data are log-transformed, $\ln \Lambda^* = \ln \Lambda - \Sigma \ln y_t$

series produces estimates of the slope innovation variance, σ_η^2, equal to zero; furthermore the *t*-test for the fixed slope being equal to zero performed on the final state estimate $\tilde{\beta}_{T|T}$ is not significant, implying that the trend is a driftless RW. As a consequence, the trend extracted by the structural model is rougher than that extracted by TRAMO-SEATS which, being based on the decomposition of the airline model, has an I(2) representation.

A smoothness prior may be imposed as for IPIODMGT; the estimated parameters are reported in the last column of table 3 (*SH SmPrior*). A graphical comparison with the trend and seasonally adjusted series extracted by TRAMO-SEATS and X-12-ARIMA is made in figure 4. While TRAMO-SEATS and X-12-ARIMA perform very similarly, it is noticeable that the seasonally adjusted series obtained by the *SH SmPrior* model is much smoother and stands out as a very clear signal. As a matter of fact, some of the fluctuations that TRAMO-SEATS and X-12-ARIMA attribute to the noise component are embodied in the heteroscedastic seasonal component, which turns out to be more evolutive than its additive counterparts.

Furthermore, on comparison with figure 3 it can be seen that the smoothness prior restriction does not alter the SA series as it does with the trend component.

The monthplots of the SA series and its monthly growth rates in the bottom panel also show that the *SH SmPrior* decomposition is more well behaved. In particular, nothing peculiar is associated with August.

5. Box-Cox Transformation

The logarithmic transformation emphasises the role of August as a «strange» (outlying) month. In terms of the Box-Cox family of parametric transformations $z_t=\lambda^{-1}[y_t^{\lambda}-1]$, for $\lambda \geq 0$, and $z_t = \ln y_t$, for $\lambda = 0$, the more λ moves away from 1 in the negative direction, the more the distance is emphasised. Hence the insurgence of August as an outlying month, which motivated the introduction of the SH model. The latter yields a more noisy seasonal component and a more well behaved seasonal adjustment; nevertheless, on the basis of *AIC* the additive specification would be chosen.

So what is the right transformation? To answer this question we will consider the usual spread-level regression and added variable regression in a structural framework. We anticipate, however, that neither of the two is accepted and a square-root transformation should be in order for most of the series considered in this exercise.

We consider two kinds of spread-level regressions: first the series $z_t=\lambda^{-1}[y_t^{\lambda}-1]$, $\lambda \geq 0$, $z_t = \ln y_t$, $\lambda = 0$ is divided into n yearly non overlapping subsets consisting of $s = 12$ observations; then both the interdecile range and the standard deviation are regressed on the n yearly means of z_t. The slope estimates, b_λ are reported in the figures 1 and 2. On the basis of these plots one should select the value of λ for which $b_\lambda=0$, i.e. there is no spread-level relationship.

Both regressions lead to the same λ value that is half way between 0 (log transformation) and 1 (no transformation). Similar plots are obtained if the mean is replaced by the median. Hence, the evidence for the industrial production series analysed is that neither the original scale nor the logarithmic one is optimal.

The idea behind added variable test for transformation (Atkinson, 1980, ch. 6) is to consider the first order Taylor series expansion of $z_t(\lambda)$ about the known value λ_0 (0 or 1):

$$z_t(\lambda) = z_t(\lambda_0) + (\lambda - \lambda_0)w_t(\lambda_0)$$

with $w_t(\lambda_0) = \partial z_t(\lambda)/\partial\lambda|_{\lambda=\lambda_0}$. For instance, when $\lambda_0=0$, $w_t(\lambda_0) = \ln y_t\,(.5 \ln y_t - T^{-1}\Sigma \ln y_t)$. Then, if for some λ, $z_t(\lambda) = \mu_t + \gamma_t + \beta'\mathbf{x}_t + \varepsilon_t$, the approximate linear model is:

$$z_t(\lambda_0) = \mu_t + \gamma_t + \beta'\mathbf{x}_t + \delta\, w_t(\lambda_0) + \varepsilon_t, \tag{6}$$

with $\delta = \lambda_0 - \lambda$.

Thus, the test is performed including among the regressors the additional variable $w_t(\lambda_0)$. Significant regression denotes the need for a transformation and provides a preliminary estimate of the correct λ as

$$\hat{\lambda} = \lambda_0 - \hat{\delta}$$

For the state space model (6) the algebra of addition of explanatory variables is very simple (see Atkinson and Shephard, 1996, and Atkinson *et al.*, 1997), basically amounting to apply the same Kalman filter to the added variable and perform a GLS regression on the innovations.

The results, reported in table 4, agree in suggesting that the transformation parameter is approximately .6 for IPIGENGT and .5 for IPIODMGT, i.e. a square root transformation is in order.

Table 4 - Added Variable Tests for Transformation

$\lambda_0 = 1$	IPIGENGT	IPIODMGT
Coef. Est. ($\hat{\delta}$)	0.34	0.45
t - test	2.63	4.93
$\lambda_0 = 0$	IPIGENGT	IPIODMGT
Coef. Est. ($\hat{\delta}$)	-0.61	-0.49
t - test	-4.79	-5.90

6. Model Evaluation via Post-Sample Predictive Testing

Likelihood inference presented in section 3 is suggestive that the SH model does a good job in capturing the behaviour of August. Still we need to investigate whether this is due to overfitting, so that a spuriously good fit is obtained in the sample period. The evaluation of the performance outside the sample period can give some guidance over this issue. For this aim we restricted the estimation sample period to 1981.1-1994.12, leaving out the last 24 monthly observations (1995.1-1996.12) that are employed for predictive testing.

Post sample predictive testing is conducted on the one step ahead prediction errors (PE): $v_{T+j} = y_{T+j} - \hat{y}_{T+j|T+j-1}$, which are uncorrelated with variance $\sigma^2 f_{T+j}$, computed by the KF. The standardised PE are denoted by $\tilde{v}_{T+j}$, and under normality are NID(0,1). These are used to construct the *post-sample predictive failure test statistic*

$$\xi(l) = \sum_{j=1}^{l} \tilde{v}^2_{T+j}$$

which is asymptotically χ^2_l ,and the *CUSUM* t-test:

$$CUSUMt(l) = l^{-1/2} \sum_{j=1}^{l} \tilde{v}_{T+j}$$

Here l denotes the number of observations outside the estimation sample period ($l = 24$).

Other statistics for assessing model predictive performance, and for comparison with rival models, are based on the extrapolative residuals, $\nu_{T+j|T} = y_{T+j} - \hat{y}_{T+j|T}$, $j = 1,..., l$, where $\hat{y}_{T+j|T}$ denotes the j-steps ahead predicted value. The measures of forecast accuracy we will adopt are in the first place measures of bias such as mean prediction error (ME), that is the average of the $\nu_{T+j|T}\,\nu_{T+j|T}$'s, and the mean percent error (MPE), computed with respect to the relative errors $\nu_{T+j|T} / y_{T+j}$; further, we consider the root mean square error (RMSE), the mean absolute error (MAE) and the mean absolute percent error (MAPE).

When the data are log transformed, $\xi(l)$ and the *CUSUMt* are computed on the logarithmic scale, whereas the remaining measures are computed on the anti-log forecasts adjusted for bias.

According to the results reported in table 5, the *SH Log* model has the best predictive performance among the three models considered as far as the IPIGENGT series is considered, whereas the results are not really different for IPIODMGT, where the additive specification performs slightly better. For the former series both the post sample predictive failure and *CUSUMt* test statistics are significant for the *HS Add* model, whose multistep ahead predictions also suffer from serious downward bias.

Table 5 - Post sample predictive testing, 1995.1-1996.12

	IPIGENGT			IPIODMGT		
	HS Add	*HS Log*	*SH Log*	*HS Add*	*HS Log*	*SH Log*
$\xi(24)$	16.28	27.92	12.97	11.69	26.83	14.43
CUSUMt(24)	-2.37	-2.21	-1.01	-0.61	-0.50	-0.73
ME	9.53	-10.16	-1.15	0.09	-1.00	-1.08
MPE	-0.10	-0.10	-0.01	0.01	-0.00	-0.01
RMSE	11.65	12.65	2.95	3.76	4.26	4.18
RMSPE	0.13	0.12	0.03	0.07	0.08	0.07
MAE	9.58	10.44	2.29	2.85	3.04	2.90
MAPE	0.10	0.10	0.02	0.04	0.05	0.04

7. Conclusions

In this paper we have argued that for the italian industrial production series the traditional dichotomy between the logarithmic transformation and no transformation is non neutral in that it produces seasonal adjustments with strongly different characteristics. Actually the dichotomy is rather artificial for the data set analysed, being motivated by the need of keeping seasonal adjustment feasible; however, the evidence coming from both spread level plots and added variable tests for the Box-Cox transformation suggests that a square-root transformation is suitable.

This testifies a fundamental interaction among the components and implies that the seasonal fluctuations cannot be removed without introducing some further assumptions on their nature and removing also some information concerning other components, such as the trend-cycle, which is inconvenient.

Two suboptimal (with respect to the transformation parameter) representations have been compared on several grounds: likelihood inference, post sample predictive testing and the quality of the seasonal adjustment, the first being in favour of the additive adjustment (no transformation) and the remaining two going in favour of the log-additive adjustment by a model with seasonal heteroscedasticity. The latter was introduced to account for the peculiar behaviour of August.

Loosely speaking, the additive decomposition attributes to the noise part of the fluctuations that the alternative multiplicative model assigns to the seasonal component, thereby giving rise to a smoother seasonally adjusted series.

Due to the uncertainty surrounding the selection of an appropriate model, if the stategy of preferring the additive decomposition prevails on the grounds of its simplicity, which turns out as a big advantage in the routine adjustment of many time series, our suggestion is that this should be accompanied by the prudential strategy of producing trends, rather that seasonally adjusted series, which may be coloured by noise of an unknown nature, since it may be ascribed to our failure to capture the seasonal dynamics properly

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Figures

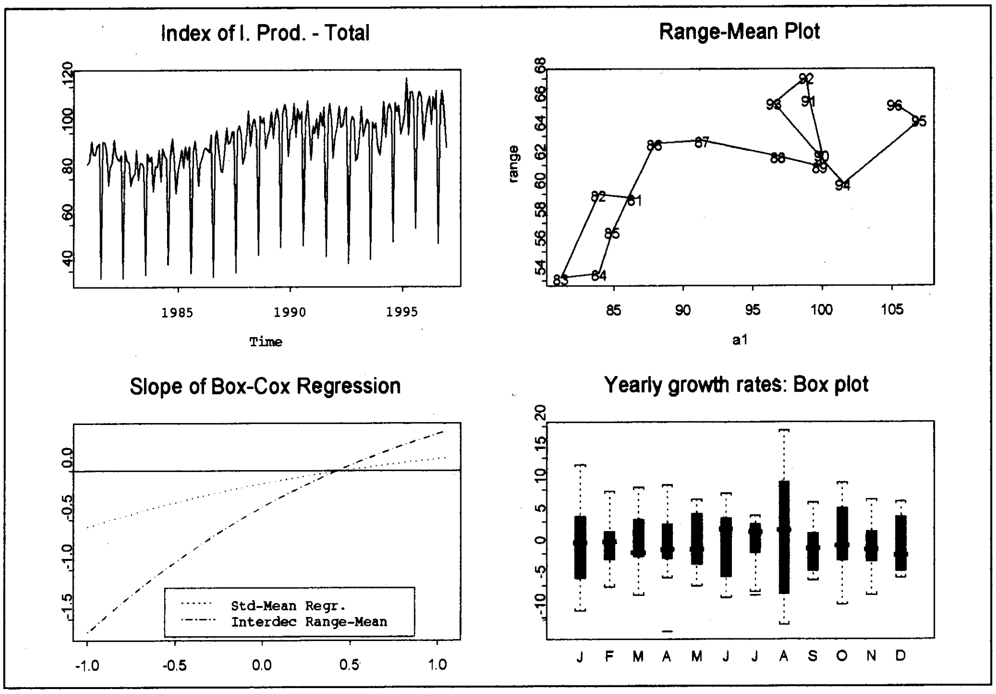

Figure 1 - Index of Industrial Production, Total, January 1981 - December 1996 (IPIGENGT)

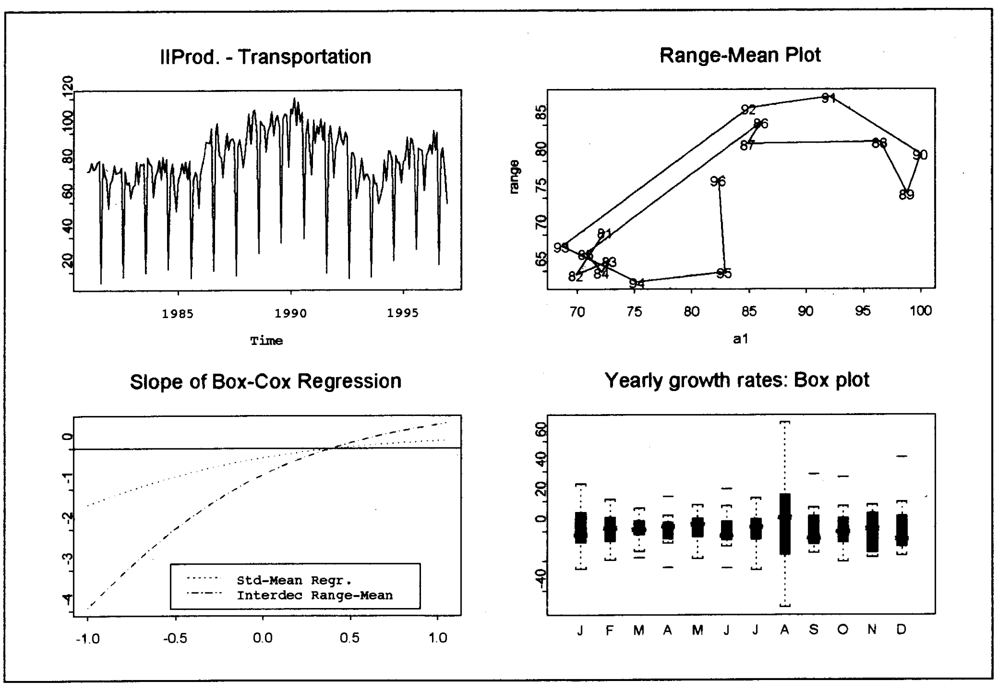

Figure 2 - Index of Industrial Production, Transportation, January 1981 - December 1996 (IPIGENGT).

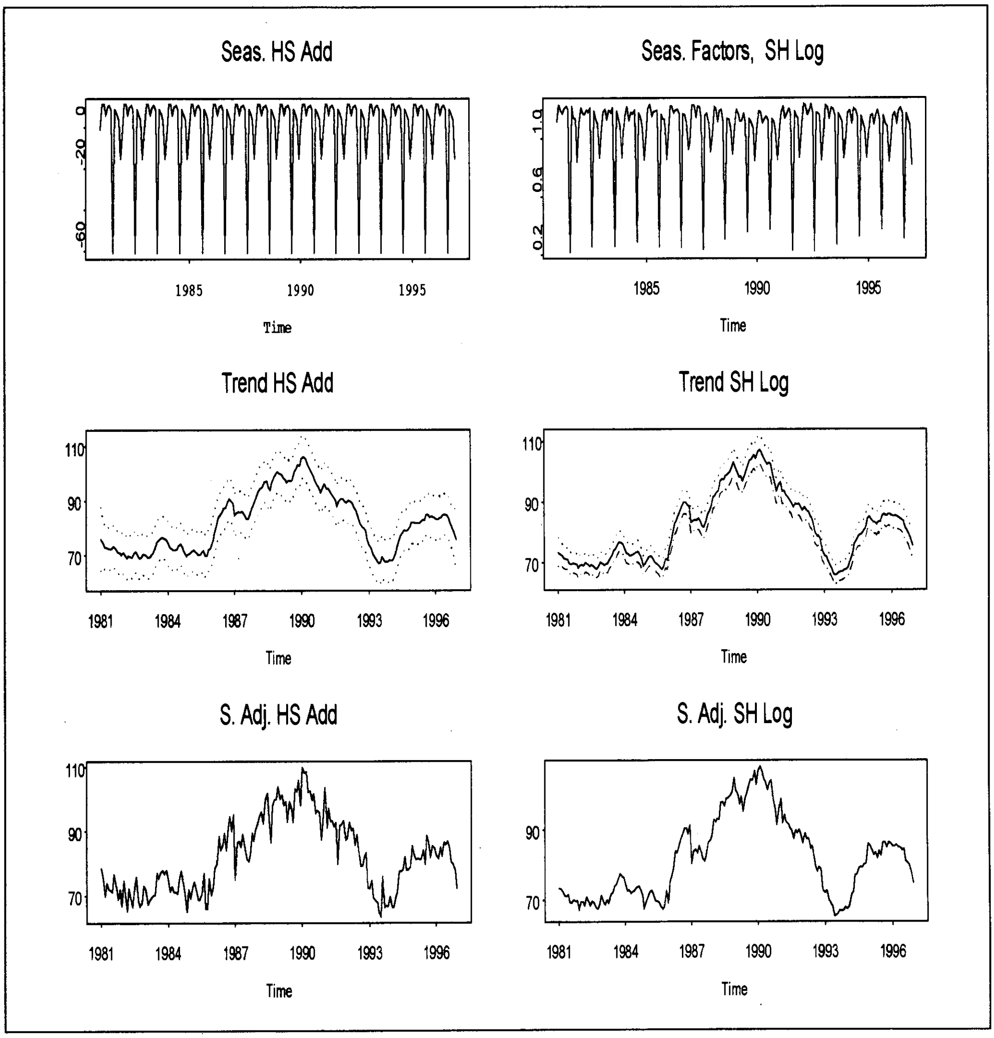

Figure 3 - Comparison of smoothed components from the HS Add and SH Log models, Index of Industrial Production, Transportation, Jan. 1981 - Dec. 1996 (IPIODMGT). The first row panel presents the seasonal components extracted by the HS Add and SH Log models, respectively; the second the smoothed estimates of the trend component, along with 95% confidence bands, and the third row panel the seasonally adjusted series.

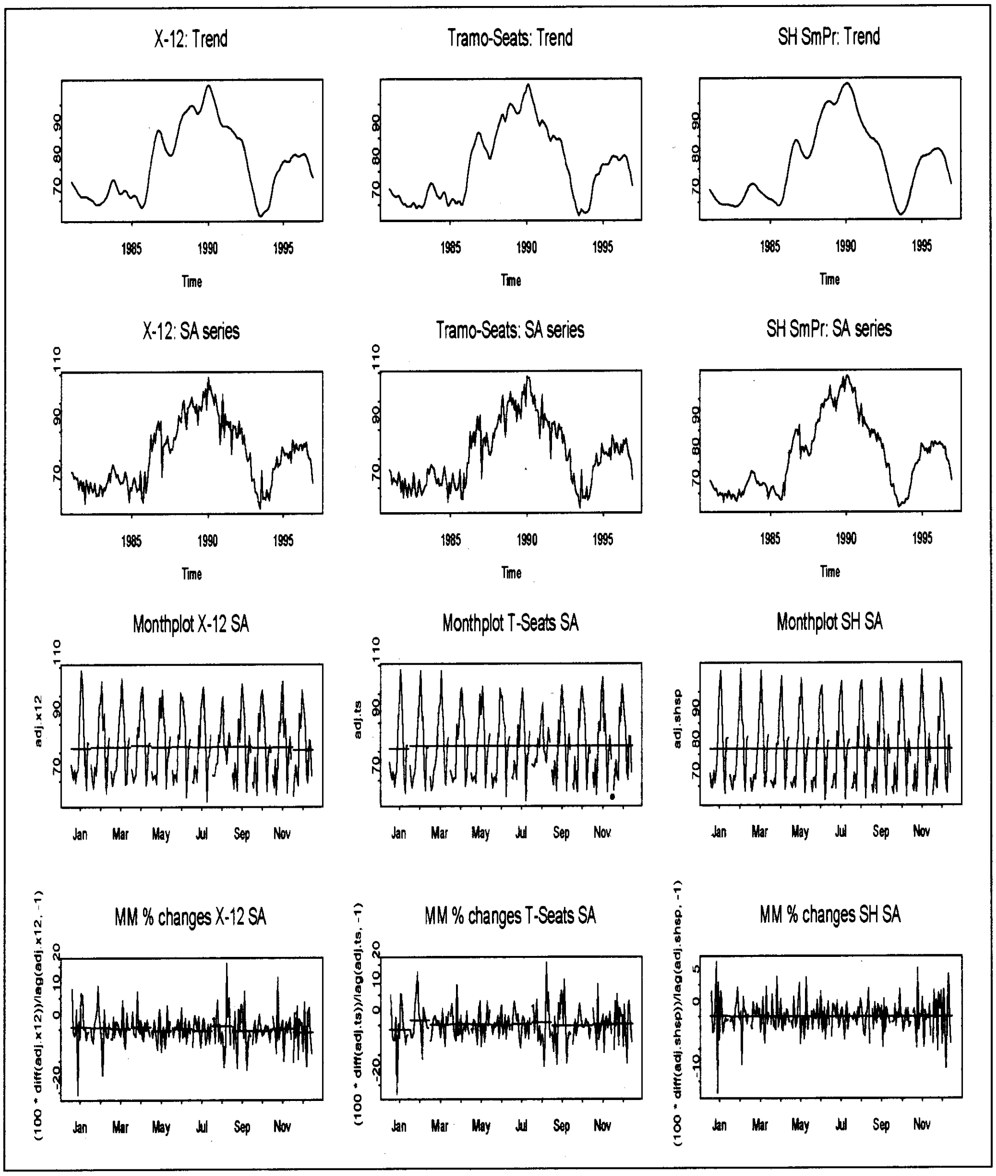

Figure 4 – Comparison of seasonal adjustment performed by X-12-ARIMA, TRAMO-SEATS, and the SH model with a smoothness prior imposed. Index of Industrial Production, Transportation, Jan. 1981 - Dec. 1996 (IPI0DMGT).

A CRITICAL ANALYSIS OF THE LOGARITHMIC TRANSFORMATION OF ECONOMIC TIME SERIES USING SIMULATION

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1. Introduction

The aim of this work is to verify the application of instantaneous data transformations relative to the procedure TRAMO-SEATS (T&S) and to evaluate some of the consequences. We know that the Box-Cox transformation[1] (1964) has been object of various evaluations through the years. After an initial positive reaction, studies on its implications and problems have gradually limited its application to the logarithmic transformation especially in the economic context. This happens even for time series having some observations more variable than others. In this circumstance a high λ value is considered more appropriate, in theory, even if it is better to analyse raw data (Piccolo, 1990).

In this study time series are simulated following the classical additive decomposition. Trend, seasonality and irregular component are first generated, then aggregated to obtain the final simulated series. This is decomposed by T&S and the effects of the logarithmic transformation are evaluated by comparing the SEATS components with the simulated ones. The simulation of series with some deterministic components does not reduce the ability of the seasonal adjustment procedure to identify the simulated components of the series.

This work is organized as follows: paragraph 2 briefly reviews why logarithmic transformation is applied and it describes the consequences of this transformation; paragraph 3 explains how the simulated series are generated; the last two paragraphs present the results and the conclusions.

[1] Let Xt be the original series, the class of transformations introduced by Box and Cox is:
$Z_t = [(X_t^{\lambda} - 1) / \lambda] I_{(\lambda \neq 0)}(\lambda) + (\ln X_t) I_{\{0\}}(\lambda)$

2. Logarithmic transformation

Instantaneous data transformation is applied for two main reasons: the first is that transformed series may become Gaussian and the second is that the transformation may eliminate nonstationarity in variance. For the latter logarithmic transformation should be used whenever standard deviation is a linear function of time (Granger and Newbold, 1977 and Wei, 1990), whereas normality is a more delicate topic and is requested for forecasting objectives. In fact if the data generating process is assumed to be Gaussian, the optimal least-squares forecast is a linear forecast, that is a linear combination of past observed values. Moreover any non linear instantaneous transformation of a Gaussian process X_t is always less forecastable than X_t (forecastability theorem, Granger and Newbold, 1976). There is no further completely convincing reason to transform time series data.

As regards the consequences of logarithmic transformation within the T&S procedure on Italian economic time series, we observed that this transformation proves to be pointless or bad for model specification and outliers when it is not necessary (see tables 1 and 2).

Other remarks concern seasonal adjustment. First of all the seasonally adjusted series of an aggregate can be equal to the sum of the seasonally adjusted sub-series only if raw data are used; secondly the geometric mean (the mean of the transformed data) underestimates the arithmetic mean, so when the period-to-period changes in the raw series are large, the level of the seasonally adjusted series and the level of the trend are underestimated.

A specific experience linked to the Italian industrial production index supports the previous observations. Since the main aim of seasonal adjustment of economic series is the estimate of the growth rates of the seasonally adjusted data, the analysis of the last two available years 1995 - 1996 shows that the use of the logarithmic transformation rather than raw data modifies the sign of the growth rates (see figure 1 in appendix). In other words 30% of monthly growth rates displays decreases instead of increases and vice versa. Considering the importance of the industrial production index in the economic analysis, in our opinion figure 1 can be seen as a serious warning for all "dogmatic users of the logarithmic transformation".

3. Simulation procedure

In our application fifty-four time series are simulated through a procedure which aims at making them as close as possible to real series. To this end the characteristics attributed to them are those of the Sistan series analyzed within the SARA project (Seasonal Adjustment Researches Appraisal) and indicated on table 4. Both a linear trend (LT) and a parabolic one (PT) are generated through the equations:

$$LT_t = k + a\,t$$
$$PT_t = a\,t^2 + b\,t + k \qquad \text{where } t=1,2,\ldots,180 \text{ and } a, b, k \text{ real scalars.}$$

A seasonal component is added to this trend and it is obtained in two steps:

1. extraction of the seasonal component from the Sistan series;
2. building of a new deterministic seasonal component by repeating the first 12 observations of the above components (step 1) fifteen times, so we cover the period of 15 years.

Finally irregular components, i.e. WN ~ $(0,\sigma_a^2)$, are generated through SCA software. Their variances have the same size of the variances of the irregular components extracted from the real series. The sum of trend, seasonality and irregular component turns the final simulated series named Ly or Py according to linear or parabolic trend. This series has "in common" with the real series y, where y is the numerical code of the series indicated on table 4. The seasonal component and approximately the variance of the irregular component (in appendix figures 2, ..., 5 show some simulated series).

In our opinion the use of deterministic components does not devaluate this experiment and its results. This is supported by various reasons. Firstly there are real series having some deterministic components. In other studies Pierce (1978) showed that the deterministic components, seasonality and trend, may coexist with stochastic components. In one of his examples concerning consumer price index only deterministic seasonality is extracted. More recently Cubadda and Sabbatini (1997) reached the same conclusion in their study on the Italian cost-of-living index. Secondly two drawbacks emerged in the simulation of time series with stochastic components[2]: the model identified on the simulated series does not always coincide with the model originally chosen and the pretest for level-versus-log specification gives different results according to the numbers of initial omitted observations. This is a factor of high instability which makes results unreliable. Thirdly, although the deterministic approach to seasonal adjustment (regressive or harmonic models) is elective from a methodological point of view, the T&S procedure is flexible and "sensitive" enough to the nature of components, as it follows a model-based method. In fact the ∇ and ∇_{12} differences and the moving average roots lying near the unit circle allow the extraction of extremely stable components[3]. Finally our aim is to build series as close as possible to "real" ones. Thus series with some deterministic components and patterns similar to real data are preferred to series with stochastic components but very different from the real data analyzed "every day, several times a day".

4. Results

The simulated series are treated with the program T&S using the routine RSA. This allows:

[2] The procedure followed to simulate series with stochastic components is very different from the procedure described above. Chosen an ARIMA model and a white noise with unit variance, the decomposition of such model is performed by SEATS yielding the models for the components that are then generated and summed to have the final series.

[3] In their paper, Battipaglia and Focarelli (1996) show that the performance of the X-11-ARIMA worsens exactly in this situation.

- automatic ARIMA model specification;
- pretest for the level-versus-log specification;
- automatic detection and correction of outliers (additive outliers AO, temporary changes TC and level shifts LS);
- pretest for Easter and trading day effects;
- treatment of missing observations;
- canonical decomposition.

The identified models together with the Ljung-Box test and the outliers are shown in table 5. What is remarkable first off is that approximately 52% of the series are subject to transformation; if these series are treated without logarithmic transformation, a different model is identified in 50% of cases (see table 6). Therefore we tried to highlight the impact of the logarithmic transformation by comparing growth rates of series adjusted for the seasonality through the multiplicative decomposition with the growth rates of those ones adjusted through the additive decomposition.

Then Theil's U coefficient is used as a synthetic indicator of the "ability" of the series seasonally adjusted through T&S with or without logarithmic to identify turning points of the simulated seasonally adjusted series (trend plus irregular). Figure 6 shows the U statistics for each of the twenty-seven series indicated in table 6: we have represented on the vertical axis the statistics calculated for seasonally adjusted series by using an additive decomposition and on the horizontal axis those computed for the seasonally adjusted series by using a multiplicative decomposition. The former range between 0 and 0.3, the latter have a much wider variation range.

Facts confirm that logarithmic transformation has "devastating" effects on seasonally adjusted series and on their growth rates since it provokes a different specification of the ARIMA models and it modifies the number of outliers detected. In other words official seasonally adjusted data and consequently patterns of economic indicators (industrial production, turnover, ...) depend on the competitive abilities of entrepreneurs and ... on the logarithmic transformation, too.

5. Conclusions

We experimented the T&S procedure within the SARA project and we realized that the level-versus-log specification favors logarithmic transformation with certain immediate consequences, e.g. on ARIMA model specification and outlier detection. The effects of an additive decomposition instead of a multiplicative one on seasonal adjustment were examined through time series simulation. The results of this experiment may be viewed as a warning for those analysts, especially economists, who use logarithmic transformation only because together with ∇ difference it allows to deal with period-to-period growth rates rather than raw data.

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APPENDIX

– Tables
– Figures

Table 1 - Results of TRAMO-SEATS on the industrial production series (LAM = -1)

Series[1]	Model	LB Test	Log	Outliers
IPIGENGT	(0,1,1)(0,1,1)	38.39	YES	AO(8 1984) AO(8 1995)
IPICONGT	(0,1,1)(0,1,1)	31.26	YES	TC(8 1984)
IPIINVGT	(0,1,1)(0,1,1)	19.77	YES	AO(8 1992) AO(8 1995) AO(8 1984)
IPIINTGT	(2,1,1)(0,1,1)	31.74	YES	AO(8 1995) AO(8 1984) TC(12 1992)
IPIGENCT	(0,1,1)(0,1,1)	36.74	YES	AO(8 1984) AO(8 1995) AO(12 1995) AO(1 1988)
IPICONCT	(0,1,1)(0,1,1)	37.12	NO	TC(8 1984) LS(3 1994) TC(3 1995) LS(1 1988)
IPIINVCT	(0,1,1)(0,1,1)	27.68	YES	AO(8 1992) AO(8 1995) AO(12 1995) AO(8 1984) AO(8 1988) AO(12 1986) AO(5 1987)
IPIINTCT	(0,1,1)(0,1,1)	24.31	YES	AO(8 1984) AO(8 1995) AO(8 1990) LS(1 1990) LS(5 1982) LS(8 1992) LS(4 1994)
IPI00CGT	(0,1,2)(0,1,1)	19.75	YES	AO(2 1991)
IPI0DAGT	(1,0,0)(0,1,1)	16.93	NO	LS(3 1987)
IPI0DBGT	(0,1,1)(0,1,1)	24.35	YES	AO(8 1984) AO(8 1985) AO(8 1995) AO(8 1989)
IPI0DCGT	(0,1,1)(0,1,1)	21.47	YES	AO(8 1994) TC(12 1992) AO(8 1991)
IPI0DDGT	(2,2,1)(0,1,1)	60.56	YES	AO(4 1984) AO(8 1984) AO(8 1993) LS(2 1985)
IPI0DEGT	(0,1,1)(0,1,1)	21.8	YES	TC(7 1982)
IPI0DFGT	(0,1,2)(0,1,1)	10.41	YES	
IPI0DGGT	(3,1,1)(0,1,1)	38.8	YES	
IPI0DHGT	(0,1,1)(0,1,1)	19.03	YES	AO(8 1984) AO(8 1990) AO(8 1986) TC(8 1987) TC(12 1994) AO(8 1995) AO(8 1994) TC(12 1986) TC(12 1992)
IPI0DIGT	(0,1,1)(0,1,1)	28.77	YES	AO(1 1985) TC(1 1987) AO(12 1996) LS(12 1992) TC(8 1995)
IPI0DJGT	(0,1,1)(0,1,1)	16.53	YES	AO(8 1984) AO(8 1983) TC(8 1995) LS(6 1982)
IPI0DKGT	(0,1,1)(0,1,1)	29.33	YES	AO(8 1986)
IPI0DLGT	(0,1,1)(0,1,1)	35.11	YES	AO(8 1995) AO(8 1987) AO(8 1990) AO(8 1981) AO(8 1986) AO(3 1989)
IPI0DMGT	(0,1,1)(0,1,1)	16.96	YES	AO(8 1990) AO(8 1989) AO(8 1995) AO(8 1988) AO(8 1994) LS(1 1987) AO(8 1981) AO(8 1984) AO(8 1992) AO(8 1991) LS(12 1992)
IPI0DNGT	(3,1,1)(0,1,1)	51.36	YES	AO(8 1992) AO(8 1984) AO(8 1995) AO(8 1988) AO(8 1989) LS(11 1991) TC(2 1991) LS(11 1985) LS(4 1983) LS(12 1992)
IPI00EGT	(0,1,1)(0,1,1)	20.93	YES	TC(1 1985)

Key: log = logarithm; LB = Ljung-Box test.

1. The description of the series is on table 3

Table 2 - Results of TRAMO-SEATS on the industrial production series (LAM = -1)

Series	Model	LB Test	Log	Outliers
IPIGENGT	(0,1,1)(0,1,1)	38.64	NO	
IPICONGT	(0,1,1)(0,1,1)	27.16	NO	
IPIINVGT	(0,1,1)(0,1,1)	16.42	NO	
IPIINTGT	(0,1,1)(0,1,1)	39.01	NO	
IPIGENCT	(0,1,1)(0,1,1)	37.86	NO	
IPICONCT	(0,1,1)(0,1,1)	37.12	NO	TC(8 1984) LS(3 1994) TC(3 1995) LS(1 1988)
IPIINVCT	(0,1,1)(0,1,1)	18.95	NO	AO(12 1995) AO(12 1986)
IPIINTCT	(0,1,1)(0,1,1)	39.22	NO	
IPI00CGT	(0,1,1)(0,1,1)	19.31	NO	AO(2 1991)
IPI0DAGT	(1,0,0)(0,1,1)	16.93	NO	LS(3 1987)
IPI0DBGT	(0,1,1)(0,1,1)	26.94	NO	
IPI0DCGT	(0,1,1)(0,1,1)	14.24	NO	
IPI0DDGT	(0,1,1)(0,1,1)	34.57	NO	AO(4 1984) LS(1 1985)
IPI0DEGT	(0,1,1)(0,1,1)	37.14	NO	TC(7 1982)
IPI0DFGT	(0,1,1)(0,1,1)	21.02	NO	
IPI0DGGT	(0,1,1)(0,1,1)	33.77	NO	AO(1 1985)
IPI0DHGT	(0,1,1)(0,1,1)	33.92	NO	TC(12 1994)
IPI0DIGT	(0,1,1)(0,1,1)	27.39	NO	AO(1 1985) LS(12 1994) TC(1 1987) LS(12 1993) AO(2 1991) AO(12 1981)
IPI0DJGT	(0,1,1)(0,1,1)	19.9	NO	
IPI0DKGT	(0,1,1)(0,1,1)	20.24	NO	TC(11 1995)
IPI0DLGT	(0,1,1)(0,1,1)	32.17	NO	
IPI0DMGT	(0,1,1)(0,1,1)	16.78	NO	AO(1 1987)
IPI0DNGT	(0,1,1)(0,1,1)	30.27	NO	
IPI00EGT	(0,1,1)(0,1,1)	10.37	NO	TC(1 1985)

Table 3 - Description of the industrial production series

Code	Description
IPIGENGT	industrial production index - total
IPICONGT	industrial production index - consumer goods
IPIINVGT	industrial production index - investment goods
IPIINTGT	industrial production index - intermediate goods
IPIGENCT	daily average prod. - total
IPICONCT	daily average prod. - consumer goods
IPIINVCT	daily average prod. - investment goods
IPIINTCT	daily average prod. - intermediate goods
IPI00CGT	industrial production index - mining
IPI0DAGT	industrial production index - food
IPI0DBGT	industrial production index - textiles
IPI0DCGT	industrial production index - leather
IPI0DDGT	industrial production index - lumber
IPI0DEGT	industrial production index - paper
IPI0DFGT	industrial production index - petroleum
IPI0DGGT	industrial production index - chemicals
IPI0DHGT	industrial production index - rubber
IPI0DIGT	industrial production index - stone
IPI0DJGT	industrial production index - metals
IPI0DKGT	industrial production index - machinery
IPI0DLGT	industrial production index - electrical machinery
IPI0DMGT	industrial production index - transportation
IPI0DNGT	industrial production index - other
IPI00EGT	industrial production index - energy

Table 4 - Description of the Sistan series

Num. code	Code	Description
7	CITGENGV	import - value index
8	CETGENGV	export - value index
9	CITGENGQ	import - quantity index
10	CETGENGQ	export - quantity index
31	IFAGENGE	turnover index - foreign market
33	IFAGENGT	turnover index - total
35	IFACONGN	turnover index - domestic market - consumer goods
38	IFAINVGN	turnover index - domestic market - investment goods
39	IFAINVGT	turnover index - total - investment goods
45	ICOGENGT	stock of orders - total
48	IORGENGT	level of orders - total
49	IPIGENGT	industrial production index - total
50	IPICONGT	industrial production index - consumer goods
51	IPIINVGT	industrial production index - investment goods
52	IPIINTGT	industrial production index - intermediate goods
71	LGHNTOGI	working hours per capita - total industry
72	PCOALTGP	consumer price index - food excluding tobacco
73	PCOBENGP	consumer price index - food - total
74	PCOGNTGP	consumer price index - total excluding tobacco
75	PCONALGP	consumer price index - non food
76	PCOSERGP	consumer price index - services - total
79	PINGENGP	wholesale price index - total
82	PPICONGP	producer price index - consumer goods
84	PPIGENGP	producer price index - total
85	PPIINTGP	producer price index - intermediate goods
86	PPIINVGP	producer price index - investment goods
87	SVGALIGI	retail sales (major outlets) - food

Table 5 - Results of TRAMO-SEATS on the simulated series (RSA = 8)

Series	Log	Outliers	TD	Model	LB
L7	NO	-	YES	(0,0,1)(0,1,1)	32.34
P7	YES	2	YES	(3,1,1)(0,1,1)	58.59
L8	YES	1	NO	(1,0,0)(0,1,0)	29.55
P8	YES	1	NO	(0,1,1)(0,1,1)	29.74
L9	YES	1	NO	(0,1,1)(0,1,1)	36.58
P9	YES	-	NO	(0,1,1)(0,1,1)	34.53
L10	NO	-	NO	(0,0,0)(0,1,1)	20.43
P10	YES	2	NO	(0,1,1)(0,1,1)	15.35
L31	YES	2	NO	(0,1,1)(0,1,1)	19.04
P31	YES	2	NO	(0,1,1)(0,1,1)	26.44
L33	NO	-	NO	(0,0,0)(0,1,1)	29.14
P33	YES	-	NO	(0,1,1)(0,1,1)	24.21
L35	NO	-	NO	(0,0,0)(0,1,1)	29.67
P35	YES	-	NO	(0,1,1)(0,1,1)	20.98
L38	YES	4	NO	(1,0,1)(0,1,1)	59.42
P38	YES	3	NO	(1,1,1)(0,1,1)	72.40
L39	NO	-	NO	(0,0,0)(0,1,1)	23.16
P39	YES	-	NO	(0,1,1)(0,1,1)	14.86
L45	NO	-	NO	(0,1,1)(0,1,1)	17.95
P45	NO	-	NO	(0,1,2)(0,1,1)	16.78
L48	NO	1	NO	(0,0,0)(0,1,1)	16.20
P48	YES	1	NO	(0,1,1)(0,1,0)	24.06
L49	NO	-	NO	(0,0,0)(0,1,1)	19.29
P49	NO	-	NO	(0,1,1)(0,1,1)	14.70
L50	YES	1	YES	(0,0,0)(0,1,1)	12.19
P50	NO	-	NO	(0,1,1)(0,1,1)	16.16
L51	NO	-	NO	(0,0,0)(0,1,1)	17.00
P51	NO	-	NO	(0,1,1)(0,1,1)	16.20
L52	YES	3	NO	(0,0,0)(0,1,1)	24.57
P52	NO	-	NO	(0,1,1)(0,1,1)	22.93
L71	YES	-	NO	(0,1,1)(0,1,1)	15.84
P71	NO	-	NO	(0,1,1)(0,1,1)	15.49
L72	NO	1	NO	(1,1,1)(0,1,1)	13.60
P72	YES	1	NO	(3,1,1)(0,1,1)	47.93
L73	NO	1	NO	(0,1,1)(0,1,1)	13.22
P73	YES	2	NO	(0,1,1)(0,1,1)	49.46
L74	NO	-	NO	(0,1,1)(0,1,1)	18.34
P74	YES	1	NO	(3,1,0)(0,1,1)	46.74
L75	NO	1	NO	(0,1,1)(0,1,1)	21.50
P75	YES	2	NO	(3,1,1)(0,1,1)	44.23
L76	NO	-	NO	(0,1,1)(0,1,1)	28.20
P76	YES	1	NO	(0,1,1)(0,1,1)	40.20
L79	NO	-	NO	(0,1,1)(0,1,1)	18.62
P79	YES	-	NO	(0,1,1)(0,1,1)	27.18
L82	NO	-	NO	(0,1,3)(0,1,1)	28.22
P82	NO	-	NO	(0,1,3)(0,1,1)	28.22
L84	NO	-	NO	(0,1,1)(0,1,1)	2.62
P84	YES	-	NO	(0,1,1)(0,1,1)	26.90
L85	NO	-	NO	(0,1,1)(0,0,1)	20.41
P85	YES	-	NO	(0,1,1)(0,1,1)	35.31
L86	NO	-	NO	(0,1,1)(0,1,1)	18.70
P86	YES	-	NO	(0,1,1)(0,1,1)	23.01
P87	NO	1	NO	(0,0,1)(0,1,1)	31.16
P87	YES	-	NO	(0,1,1)(0,1,1)	24.25

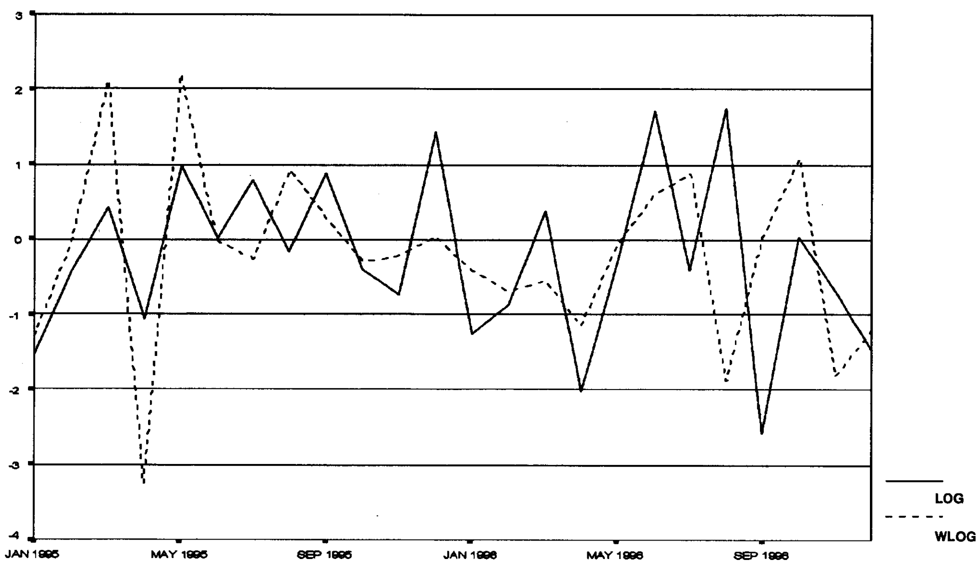
Key: log = logarithm; TD = trading-day; LB = Ljung-Box test.

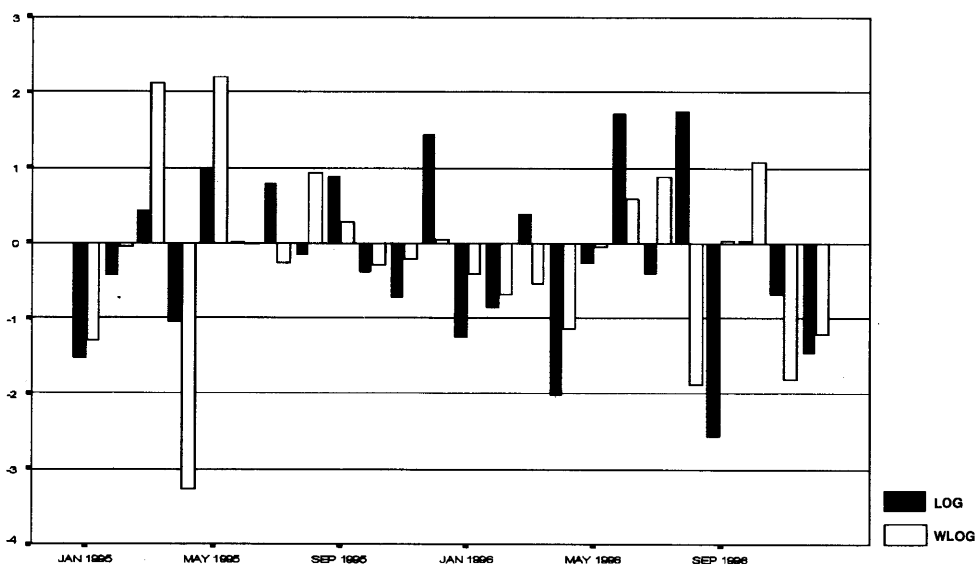
Table 6 - Results of TRAMO-SEATS on the simulated series (LAM = -1 and LAM = 1)

Series	Log	Outliers	TD	Model	LB
P7	YES	2	YES	(3,1,1)(0,1,1)	58.59
	NO	-	YES	(0,1,1)(0,1,1)	30.28
L8	YES	1	NO	(1,0,0)(0,1,0)	29.55
	NO	1	NO	(0,0,0)(0,1,1)	20.04
P8	YES	1	NO	(0,1,1)(0,1,1)	29.74
	NO	1	NO	(0,1,1)(0,1,1)	23.97
L9	YES	1	NO	(0,1,1)(0,1,1)	36.58
	NO	-	NO	(0,0,0)(0,1,1)	30.92
P9	YES	-	NO	(0,1,1)(0,1,1)	34.53
	NO	-	NO	(0,1,1)(0,1,1)	31.73
P10	YES	2	NO	(0,1,1)(0,1,1)	15.35
	NO	-	NO	(0,1,1)(0,1,1)	15.32
L31	YES	2	NO	(0,1,1)(0,1,1)	19.04
	NO	-	NO	(0,0,0)(0,1,1)	30.70
P31	YES	2	NO	(0,1,1)(0,1,1)	26.44
	NO	-	NO	(0,1,1)(0,1,1)	28.21
P33	YES	-	NO	(0,1,1)(0,1,1)	24.21
	NO	-	YES	(0,1,1)(0,1,1)	27.17
P35	YES	-	NO	(0,1,1)(0,1,1)	20.98
	NO	-	NO	(0,1,1)(0,1,1)	23.84
L38	YES	4	NO	(1,0,1)(0,1,1)	59.42
	NO	-	NO	(1,1,2)(0,1,1)	10.16
P38	YES	3	NO	(1,1,1)(0,1,1)	72.40
	NO	-	NO	(1,1,2)(0,1,1)	10.06
P39	YES	-	NO	(0,1,1)(0,1,1)	14.86
	NO	-	NO	(1,1,1)(0,1,1)	21.36
P48	YES	1	NO	(0,1,1)(0,1,0)	24.06
	NO	1	NO	(0,1,1)(0,1,1)	15.53

Series	Log	Outliers	TD	Model	LB
L50	YES	1	YES	(0,0,0)(0,1,1)	12.19
	NO	-	YES	(0,0,0)(0,1,1)	16.19
L52	YES	3	NO	(0,0,0)(0,1,1)	24.57
	NO	-	NO	(0,1,1)(0,1,1)	23.18
L71	YES	-	NO	(0,1,1)(0,1,1)	15.84
	NO	-	NO	(0,0,0)(0,1,1)	13.89
P72	YES	1	NO	(3,1,1)(0,1,1)	47.93
	NO	1	NO	(0,1,1)(0,1,1)	12.56
P73	YES	2	NO	(0,1,1)(0,1,1)	49.46
	NO	1	NO	(0,1,1)(0,1,1)	12.20
P74	YES	1	NO	(3,1,0)(0,1,1)	46.74
	NO	-	YES	(0,1,1)(0,1,1)	22.17
P75	YES	2	NO	(3,1,1)(0,1,1)	44.23
	NO	1	NO	(0,1,1)(0,1,1)	23.47
P76	YES	1	NO	(0,1,1)(0,1,1)	40.20
	NO	-	NO	(0,1,1)(0,1,1)	28.00
P79	YES	-	NO	(0,1,1)(0,1,1)	27.18
	NO	-	YES	(0,1,1)(0,1,1)	17.28
P82	YES	1	NO	(3,1,1)(0,1,1)	33.44
	NO	-	NO	(0,1,3)(0,1,1)	29.11
P84	YES	-	NO	(0,1,1)(0,1,1)	26.90
	NO	-	NO	(0,1,1)(0,1,1)	24.82
P85	YES	-	NO	(0,1,1)(0,1,1)	35.31
	NO	-	NO	(0,1,1)(0,1,1)	17.74
P86	YES	-	NO	(0,1,1)(0,1,1)	23.01
	NO	-	NO	(0,1,1)(0,1,1)	19.79
P87	YES	-	NO	(0,1,1)(0,1,1)	24.25
	NO	1	NO	(0,1,1)(0,1,1)	22.12

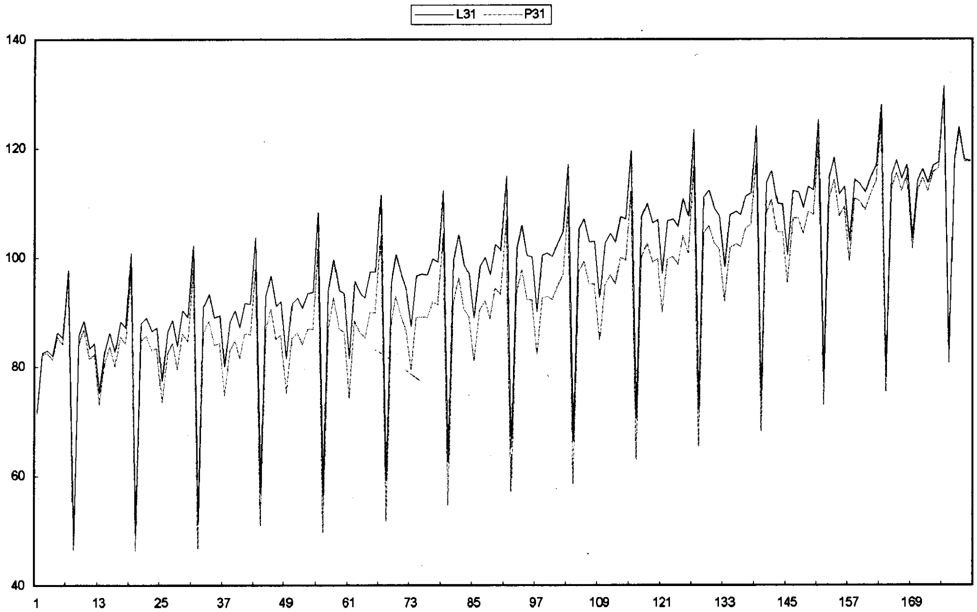
Figure 1 – Monthly growth % rates of the seasonally adjusted ipi (1995.1 - 1996.12)





Key: log = logarithm; wlog = without logarithm.

Figure 2 – Graphs of some simulated series



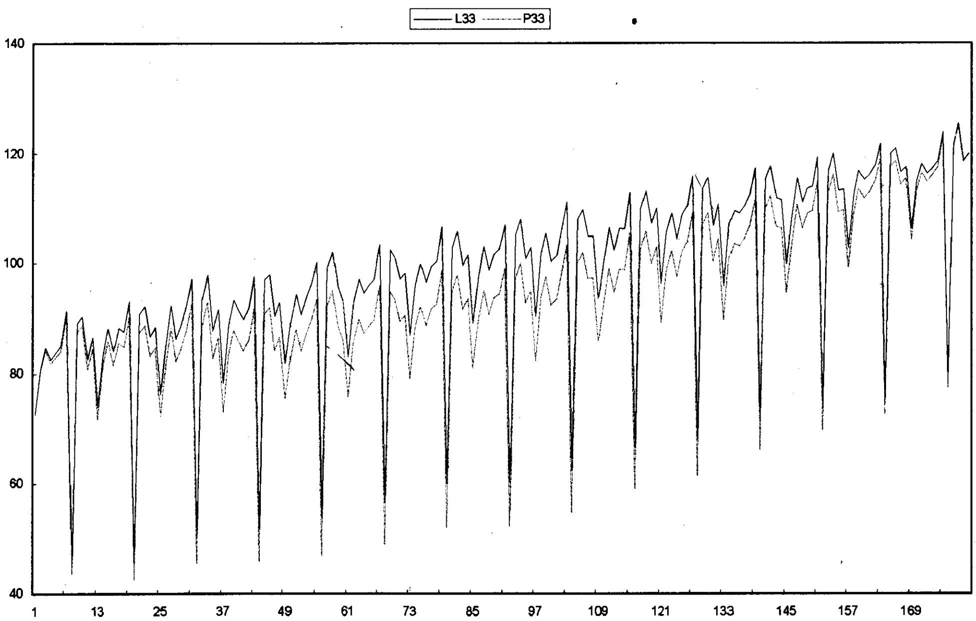


Figure 3 – Graphs of some simulated series

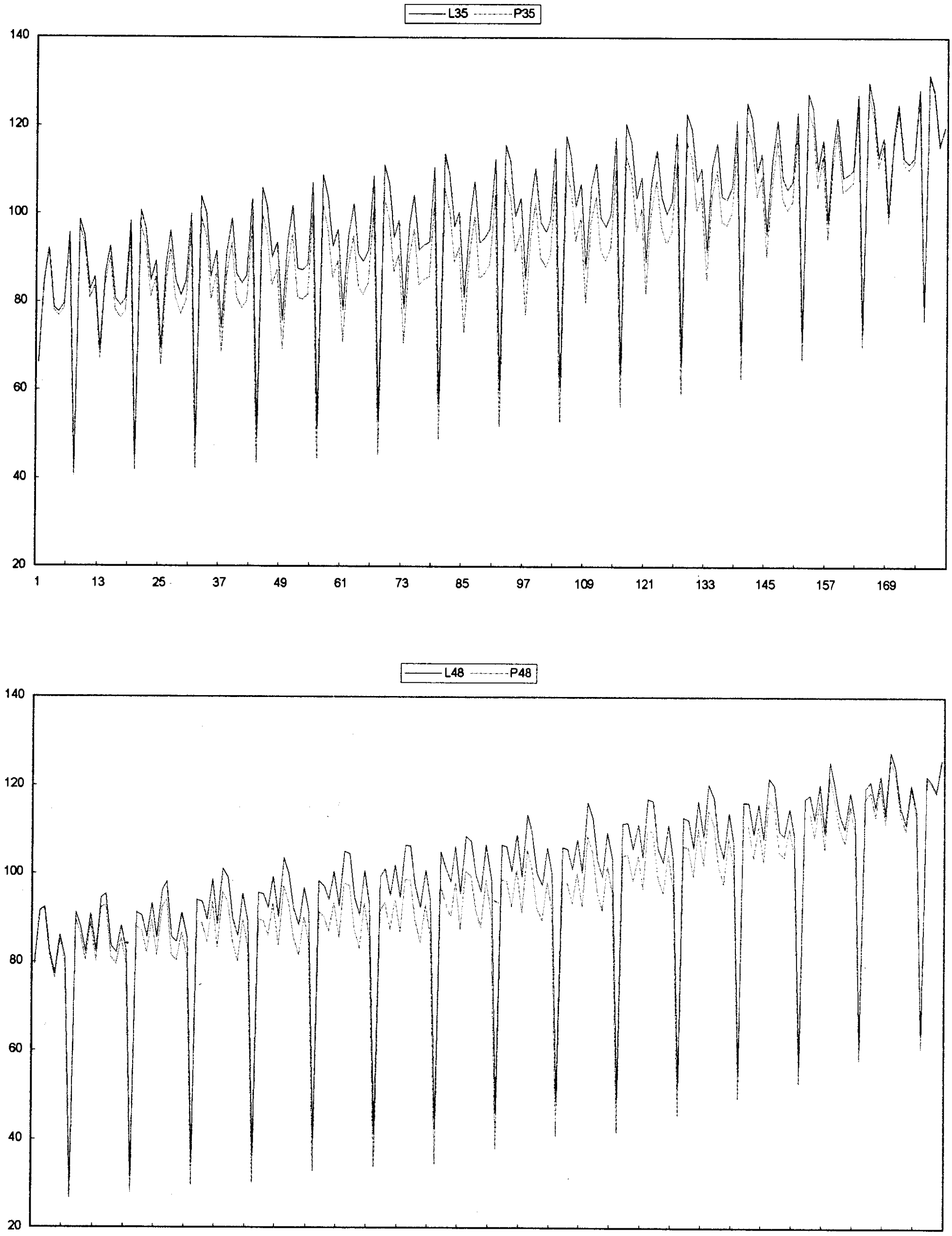
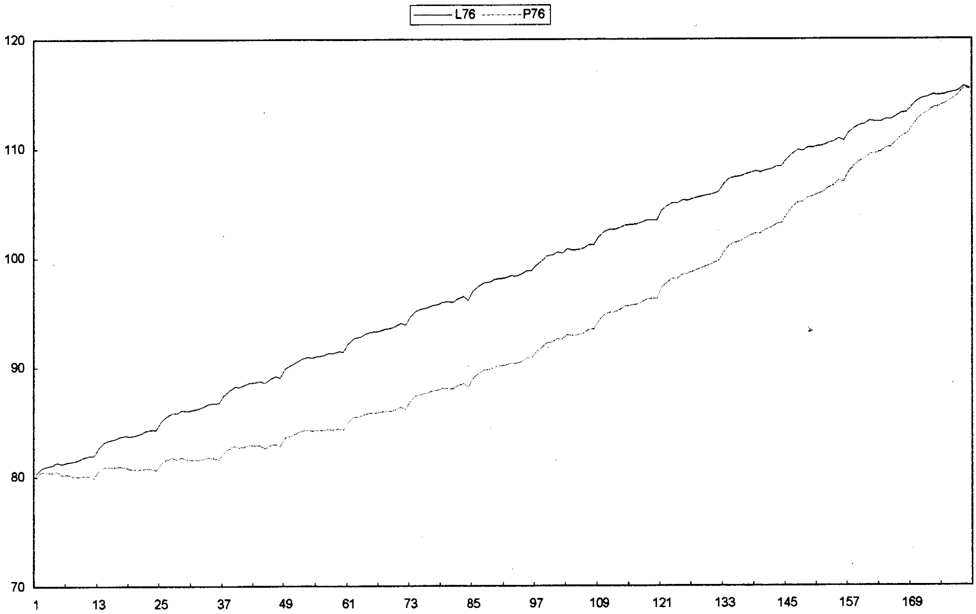


Figure 4 – Graphs of some simulated series



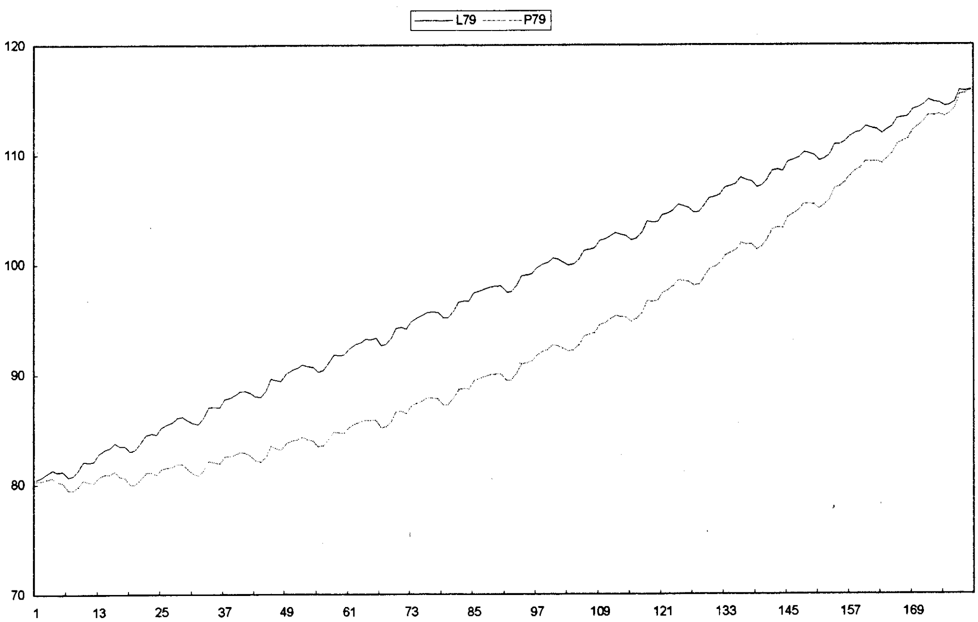
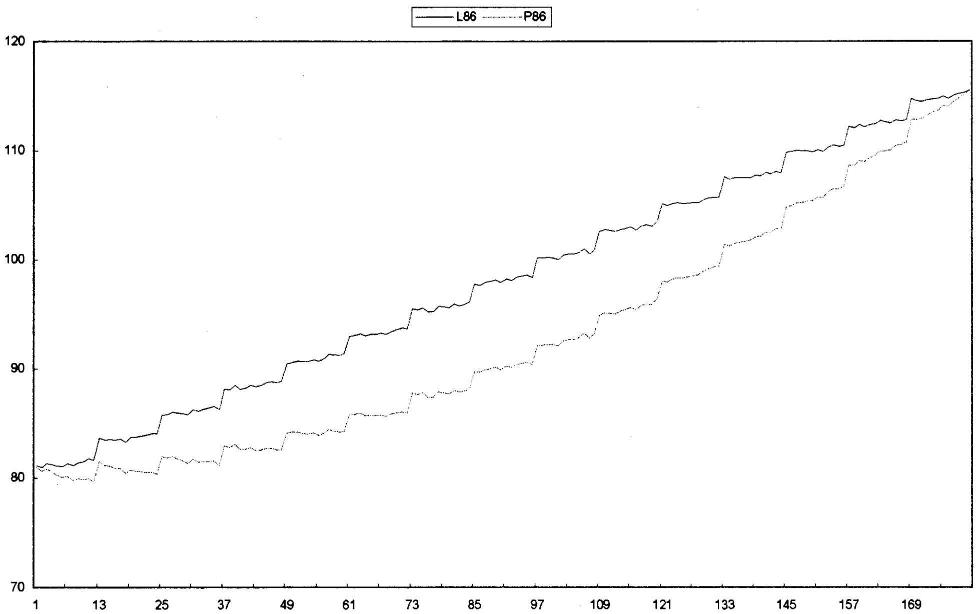


Figure 5 – Graphs of some simulated series



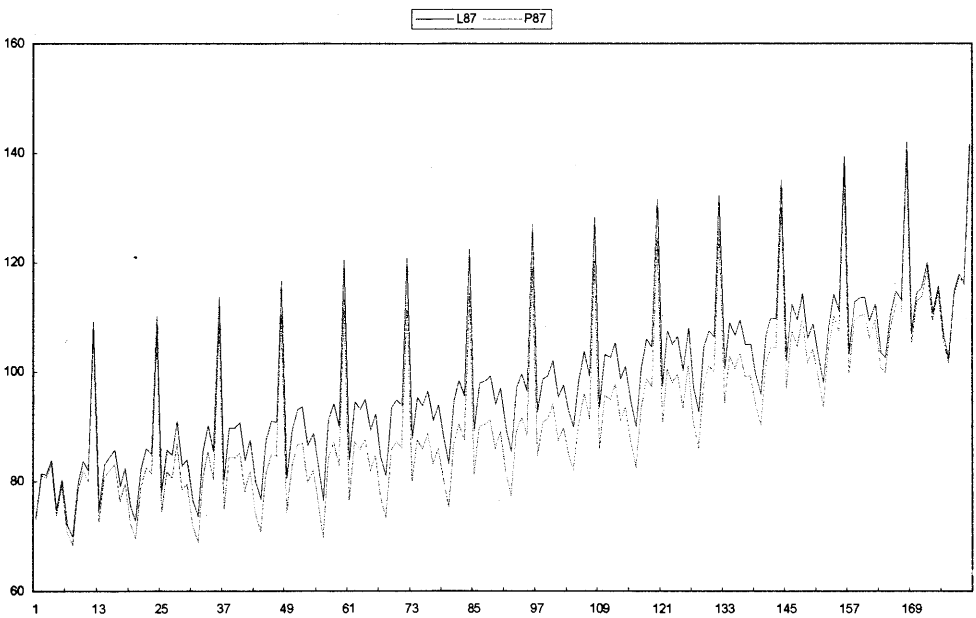
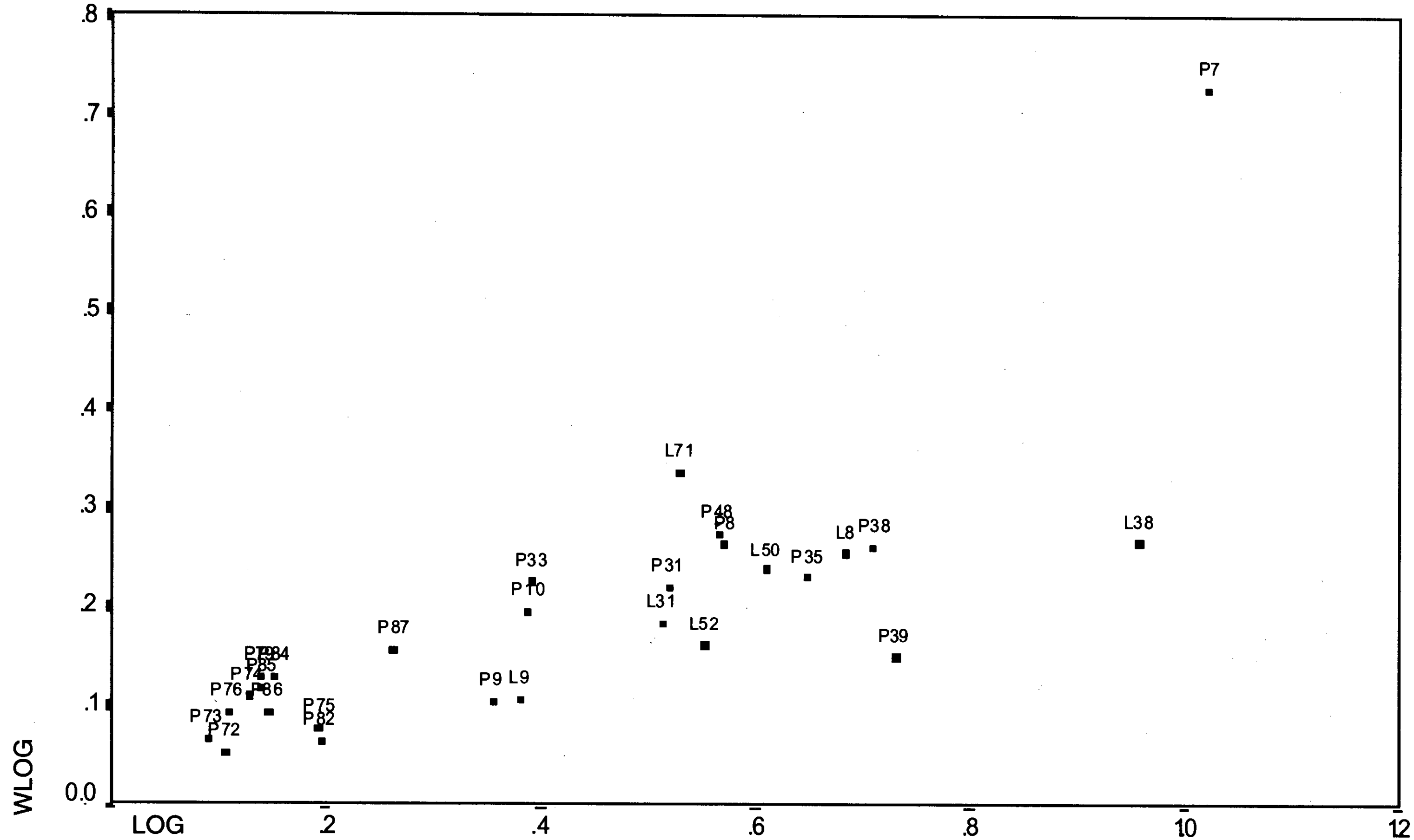


Figure 6 - Theil's U on the seasonally adjusted series through additive model (wlog) and multiplicative model (log)



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