SOME COMMENTS ON SEASONAL ADJUSTMENT *

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ABSTRACT

This paper discusses the practical usefulness of seasonally adjusted time series data. Aspects of seasonal adjustment are considered, and the relevance of adjusted data for economic modelling is examined. One recommendation which emerges from the discussion is that the adjusted data should be presented together with their estimated standard errors. Another is that it is perhaps better not to seasonally adjust at all.

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I. INTRODUCTION

It has become common practice to seasonally adjust quarterly or monthly observed macroeconomic time series, like GDP and unemployment. Key motivations for this practice are, first, that practitioners seem to want to compare the current observation with that in the previous month or quarter, and, second, that it is believed that seasonal effects are mainly caused by the weather and institutional issues, and hence that they are not of particular interest for economists. As many such series display seasonal fluctuations which do not seem to be constant over time, at least not for the typical time span considered in practice, there is a lively debate in the statistics and econometrics literature about which method is most useful for seasonal adjustment. Roughly speaking, there are two important methods. The first one concerns (variants

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of) the Census X-11 method, initiated by Shiskin and Eisenpress (1957), and the second one concerns (variants of) model-based methods, see for example Maravall (1995). Interestingly, it seems that with the recently developed Census X-12 method, the two approaches have come a fair bit closer together, see Findley et al. (1998).

In the last 10 years one could have witnessed a discussion on the relevance of seasonal adjustment and the analysis of seasonal data in the academic literature. After this decade, one can now oversee the battlefield, and the single foremost conclusion that can be drawn is that there are people who want to consider seasonally adjusted data, and there are those who do not. Advocates of the latter view are convinced that seasonal fluctuations are of interest to study in their own right, see Hylleberg (1986), Miron (1996), Franses (1996), and Ghysels and Osborn (2001), among others. Admittedly, a consequence of analyzing the raw data is that the econometric models tend to become a little more involved, but these days this should not be too much of a problem. At present it seems that the literature has come to a standstill, as the stands have been made concerning seasonal adjustment, and there does not seem much room for further discussion.

In the present paper, however, I would like to re-address the discussion again by not focusing on methods or models, but merely on the question of why one would want to seasonally adjust in the first place. Indeed, except for Macroeconomics, there is no economic discipline in which the data are seasonally adjusted prior to analysis. It is hard to imagine, for example, that there would be a mirror Dow Jones index, in which the returns have been corrected for day-of-the-week effects. Also, at the disaggregated level, one can expect that seasonality in sales or market shares is of particular interest to a manager, and seasonal adjustment would simply result in an uninteresting time series. In this paper I will argue that it is perhaps better if one simply does not seasonally adjust the data. There is ample evidence that seasonal adjustment destroys or changes key features of economic data, that it invalidates impulse-response analysis as the genuine innovations cannot be estimated, and also that the original data frequently cannot be obtained anymore. Additionally, I would like to make a plea for presenting the estimated standard errors of the seasonally adjusted data, if possible. Indeed, far too often one tends to forget that the adjusted data are just estimates.

The outline of this paper is as follows. In Section II, I give a brief discussion of the purpose of the analysis of macroeconomic data. In Section III, I give a (very) concise outline of the principles of seasonal adjustment. In Section IV, I review the properties of seasonally adjusted data, which one typically encounters in practice, and which are widely documented in the literature. Finally, in Section V, I conclude this paper with some personal statements.

II. THE ANALYSIS OF MACROECONOMIC DATA

Typical features of many seasonally observed macroeconomic time series are that they have a trend (usually upward-moving), pronounced seasonal variation, some form of nonlinearity and a few outliers. The outliers often correspond with changes in measurement systems or exogenous events like nation-wide strikes. Nonlinearity often appears as regime-switching behaviour, in the sense that recessions may require a different model than expansions. Hence, nonlinearity tends to get associated with the business cycle. Once the trend has been removed, for example by transforming the data to growth rates, seasonal variation can take account of up to 95 per cent of the total remaining variation in the data, see for example Miron (1996), among others.

As many practitioners tend to be interested in the trend and the business cycle, it may now be relevant to somehow take care of that seasonality. As indicated above, this can be done by incorporating some description of seasonality in an econometric model, or by applying statistical techniques to get rid of the intra-year fluctuations, one way or another.

Generally, the interest in analyzing macroeconomic data concerns the trend and the business cycle. First of all, one may want to generate out-of-sample forecasts for the next quarter or for more than one step ahead. A second issue concerns the search for common patterns. Such common features can imply a reduction of the number of model parameters, and may facilitate the analysis of dynamics and causal relationships. In case the data have stochastic trends, one usually resorts to well-known techniques for common trends analysis and cointegration, see for example Engle and Granger (1991). Finally, one may try to understand business cycle fluctuations, for example in the sense of examining which variables seem to be able to predict recessions. For this purpose one can use nonlinear models like the (smooth transition) threshold model and the Markov-switching model, see Granger and Teräsvirta (1993) and Franses and van Dijk (2000) for surveys.

These three research issues can concern historical data, but one is usually really interested in how one should interpret this month's or quarter's observation. Hence, genuine interest lies in examining whether the current observation suggests that the trend has changed, or whether a shift from an expansion to a recession is to be expected. Naturally, in this setting one would not want that seasonally adjusted data have different trending and business cycle properties. Indeed, if seasonality is a nuisance that just adds some irrelevant noise to a time series, one should not want that removing it also removes part of the trend and business cycle. Before I turn to this issue in Section IV, I will first give a brief discussion of the basic principles of seasonal adjustment.

III. SOME PRINCIPLES OF SEASONAL ADJUSTMENT

The literature on seasonal adjustment methods has become pretty large, is growing every year, and is getting increasingly more complicated at a technical level. One really needs to have an advanced training in statistics and econometrics to be able to grasp the details of the various methods. In this section, I only discuss the main ideas underlying seasonal adjustment. Next, I provide some further personal thoughts on these ideas.

A. Principles

Consider a seasonally observed time series , where *t* runs from 1 to *n*. In practice one can be interested in the seasonally adjusted observation at time *n*. For this purpose, one can use all data up to and including this observation. The main purpose of seasonal adjustment is to separate the observed data into two components, a nonseasonal component and a seasonal component. These components are not observed, and hence have to be estimated from the data. This notion can be represented by

$$y_t = \hat{y}_t^{NS} + \hat{y}_T^{S}, \tag{1}$$

where $\hat{y}_t^{NS}$ denotes the estimated nonseasonal component, and $\hat{y}_t^{S}$ the estimated seasonal component. This decomposition assumes an additive relation. When this is not the case, one usually transforms such that it holds for the transformed data. For example, if the seasonal fluctuations are multiplicative with the trend, one can consider the natural logarithmic transformation.

Roughly speaking, there are two approaches to estimate the components in (1). The first originates from the work of Shiskin and Eisenpress (1957), and is usually coined the Census X-11 method. There is a new version of this method, which includes features of the second approach to be discussed below, but the main principle is still the same. The Census X-11 approach applies a sequence of two-sided moving average filters like

$$w_o + \sum_{i=1}^{m} w_i (L^i + L^{-i}), \tag{2}$$

where L is the familiar backward shift operator, and where the value of m and the weights w_i for $i = 0,1,..., m$ are to be set by the practitioner. This approach additionally contains a range of outlier removal methods, and corrections for tradingday and holiday effects.

An important by-product of the use of two-sided filter is that to adjust observation y_n , one needs the observations at time $n + 1, n + 2$ to $n + m$. As these are not yet observed at n, one may opt for using forecasted values, generated by an ARIMA type model and to treat these as genuine observations. Of course, this automatically implies that seasonally adjusted data may have to be revised after a while, especially if the newly observed realizations differ from those forecasts. On the other hand, one can also use one-sided filters for the last observations. Interesting surveys of this method are given in Bell and Hillmer (1984), Hylleberg (1986), and more recently in Findley et al. (1998).

The second approach involves the model-based methods. These assume that the seasonal component can be described by a certain model, like for example

$$(1 + L + L^2 + L^3) y_t^S = \varepsilon_t. \tag{3}$$

With an estimate of the variance of ε_t, and with suitable starting-values, one can estimate the seasonal component using Kalman-filtering techniques, see Harvey (1989), among others. Given $\hat{y}_t^S$, one can simply use (1) to get the estimated adjusted series.

B. A few remarks

Before I turn to a review of the empirically discovered properties of publicly available seasonally adjusted data in the next section, a few remarks can be made. The first and most important one is the recognition that seasonally adjusted data concern estimated values. This is something practitioners tend to forget, though should not. This tendency is caused by the fact that those who provide the seasonally adjusted data tend not to provide the associated standard errors. To my opinion this is misleading, as a correct statement would read for example like: this month's unemployment rate is 8.6, and after seasonal adjustment it is 8.4 plus or minus 0.3. To my knowledge, the Census X-11 method cannot generate standard errors, but for the model-based methods it should not be too difficult. In fact, Koopman and Franses (2001) propose a method which even allows for business cycle-dependent confidence intervals around seasonally adjusted data.

The second remark concerns the trivial but important notion that when only $\hat{y}_t^{NS}$ gets saved and $\hat{y}_t^S$ gets thrown away, as is usually done, one cannot reconstruct the original series y_t. Additionally, if the original series y_t can be described by an econometric time series model with innovations ε_t, it is unclear to what extent these innovations get assigned to either $\hat{y}_t^{NS}$, $\hat{y}_t^S$ or both. Hence, when one constructs an econometric time series model for the adjusted series $\hat{y}_t^{NS}$, the estimated innovations in this model are unlikely to be equal to the "true" innovations. This feature complicates so-called impulse-response analysis, which is a useful technique for analyzing the properties of models and variables.

Finally, the key assumption for seasonal adjustment is that the relation in (1) holds, after appropriate transformations. For some economic time series this is however not the case. For example, if the data can best be described by a so-called periodic time series model, where the parameters vary with the seasons, then one cannot separate out a seasonal component and reliably focus on the estimated nonseasonal component. There are no theoretical results about what exactly happens if one adjusts a periodic series, but some simulation and empirical results are available, see Franses (1996) and Ooms and Franses (1997). Generally it seems that the seasonally adjusted periodic data still display seasonality.

IV. PROPERTIES OF SEASONALLY ADJUSTED DATA

In the last 10 years many articles have appeared on modelling seasonally observed time series, in such journals as the *Journal of Business and Economic Statistics, Journal of Applied Econometrics, International Journal of Forecasting, Review of Economics and Statistics,* *Empirical Economics, Journal of Forecasting, Journal of Macroeconomics, European Economic Review, and the Journal of Econometrics*. There is no space here to review all these papers in detail, but many are referenced in Franses (1999). In this section I aim to review the main findings in these papers concerning the properties of seasonally adjusted data, where I should stress that these data almost always concern Census X-11 adjusted data.

Given the aim of seasonal adjustment, that is, to create time series which are more easy to analyze for trends and business cycles, it seems preferable that seasonally adjusted data (1) show no signs of seasonality, (2) do not have another trend property than the original data, and (3) do not have other nonlinear properties than these data. Unfortunately, there is ample evidence in the literature that most publicly available adjusted data do not have all of these properties. Indeed, it frequently occurs that $\hat{y}_t^{NS}$ can be modelled using a seasonal ARMA model, with highly significant parameters at seasonal lags in both the AR and MA parts of the model. The intuition for this empirical finding may be that two-sided filters as in (2) can be shown to assume quite a number of so-called seasonal unit roots. Empirical tests for seasonal unit roots in the original series however usually suggest a far smaller number of such roots. Hence, seasonal adjustment simply introduces seasonality in, say, the right-hand side (MA) part of the model. Furthermore, and as mentioned before, if the data seem to correspond with a periodic time series process, one can still fit a periodic time series model to the adjusted data. The intuition here is that linear moving average filters treat all observations as equal.

Now, would seasonal adjustment leave the trend property of the original data intact? Unfortunately not, as many studies indicate. The general finding is that the persistence of shocks is higher, which in formal test settings usually corresponds with more unit roots. In a multivariate framework this amounts to finding less evidence in favor of cointegration, that is, of the presence of stable long-run relationships, and thus more evidence of random walk type trends. The possible intuition of this result is that two-sided filters make genuine innovations to appear in $2m + 1$ adjusted observations, thereby creating a higher degree of persistence of shocks. Hence, seasonal adjustment incurs less long-run stability.

Finally, one would hope that seasonal adjustment does not affect business cycle fluctuations. Nonlinear data do not become linear after seasonal adjustment, but there is some evidence that otherwise linear data can display nonlinearity after seasonal adjustment, see Ghysels, Granger and Siklos (1996). Additionally, nonlinear models for the raw data seem to differ from those for the adjusted data. The structure of the nonlinear model does not necessarily change, it merely concerns the parameters in these models. Hence, one tends to find other recessions for adjusted data than for unadjusted data. A general finding is that the recessions for adjusted data last longer. The intuition for this result is that expansion data are used to adjust recession data and the other way round. Hence, regime switches get smoothed away, or at least, become less pronounced.

In sum, seasonally adjusted data may still display some seasonality, can have different trend properties than the original raw data have, and also can have different nonlinear properties. To my opinion this suggests that these data may not be useful for their very purpose.

V. CONCLUDING STATEMENTS

In the early days of developing seasonal adjustment methods there were not many computers, and the removal of seasonal fluctuations seemed to make life more easy. At present, however, we can observe that seasonal adjustment methods have become rather complicated, while on the other hand many econometric models have been developed which enable a proper analysis of unadjusted data. Examples of these models are the seasonal and periodic cointegration models, which allow for an analysis of trends and seasonality at the same time, and seasonal versions of Markov-switching and STAR models, which concern nonlinearity and seasonality.

Hence, there is in fact no need to consider seasonally adjusted data, at least not using the methods discussed in this paper. If one really wants to say something about this month's observation, the best approach seems to compare the observation y_n with $\hat{y}_n$, where $\hat{y}_n$ is the forecast of y_n generated from a properly specified econometric model for the original data based on the information up to and including n-1. This approach would provide information about to what extent the current observation is unexpected, which seems to provide truly relevant information.

Finally, if one really persists in the wish to use seasonally adjusted data according to data-filtering or model-based methods, I would think it is only fair that one also reports the estimated standard errors. Comparing the interval around the adjusted observation with the unadjusted observation would then provide useful information as to how useful the seasonally adjusted data really are.

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