The Choice of Time Interval in Seasonal Adjustment: A Heuristic Approach

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Abstract

A typical problem of the seasonal adjustment procedures arises when the series to be adjusted is subject to structural breaks. In fact, using the full span of the series can result in a biased estimation of the "true" seasonal adjusted series, with unclear evidence showed by the usual diagnostic tests. In these cases the researcher has to decide where to cut-off the observed series to obtain a homogeneous span; this is generally performed by a simple visual inspection studies of the graph of the series and/or using a-priori information about the occurrence of the break. In this paper we propose a statistical criterion based on a distance measure between filters, evaluating its performance with Monte Carlo experiments.

JEL Classification: C32.

Key words: Linear filters, Structural break, Distance.

1 Introduction[1]

The growing use of seasonal adjustment methods by agencies producing official statistics has lead to a more careful evaluation of the test statistics made available by seasonal adjustment procedures. Among the most used procedures we can distinguish between *ad-hoc* methods (such as X-11, X12-RegARIMA, see Dagum, 1988 and Findley *et al.*, 1998) and model-based methods (such as TRAMO-SEATS, see Gómez and Maravall, 1996). Both the procedures are based on the application of linear filters, even though many other elements (e.g. outlier correction) can make seasonal adjustment an essentially non-linear transformation (Ghysels et al., 1996). While X-12-RegARIMA is basically a nonparametric approach, the application of TRAMO-SEATS needs a considerable effort in order to assess the fitting of the ARIMA model representation for

[1] A preliminary version of this paper was presented at the XL scientific meeting of the Italian statistical society, Florence, 26-28 April 2000 and circulated as ISAE working paper No. 21/2001 with the title "The Choice of Time Interval in Seasonal Adjustment: Characterization and Tools"

the observed series. This is an important objective, considering the influence of the model in the estimation of the seasonal component.

In this paper we concentrate on a particular aspect of the model estimation: the best choice of the length of the series which is to be modelled. In fact in the seasonal adjustment context there is a trade-off between the need for a long time series in order to better estimate the ARIMA model and the implied seasonal factors, and the necessity to avoid modelling a time series containing a structural break, *i.e.* a series whose data generating process is changing over time. The problem of structural breaks in the general regression model is quite known and there is a considerable number of tests to detect such occurrences; for example, the classical Chow (1960) test for the simple case of one structural break at a known time, the Andrews (1993) test for structural change at an unknown point and the Andrews and Ploberger (1994) test for $h > 1$ structural changes.

However, in the seasonal adjustment context, neither the occurrence of a break always implies a bad performance of the usual tests statistics on estimated residuals, nor it is always implied by them. Ghysels and Perron (1993) note that the X-11 routine is not invariant with respect to breaking trends and level shifts and Ghysels and Perron (1996) show that the power and the size of their structural change test can be affected by the filtering of the X-11 procedure. In a model-based context, Planas (1998) noted that the problems caused by the presence of nonlinearities can be by-passed using intervention variables; in fact, in many simulation experiments the results of the typical specification tests conducted on the estimated residuals are consistent with a good fitting and the hypotheses of normal, independent, identically distributed disturbances. Nevertheless, in the same paper it is showed that the threshold models (that are particular structural change models) often presents residual autocorrelation; in addition, the eventual persistent nonlinearity is generally found in the irregular component, which is a part of the seasonal adjusted series. In other words, the structural changes in the observed series can affect the outcome of the seasonal adjustment procedure, probably depending on the size of the change and on its type.

In addition, when the main objective of the model is seasonal adjustment, one might not be interested at all in the occurrence of a break, unless it causes a major bias in the estimate of the seasonally adjusted series.

This is why we propose here a measure based on the concept of distance between seasonal filters as a way to assess the existence and the relevance of a break in a time series in the context of the seasonal adjustment problem. The method is heuristic, being based on the observation of the distance pattern, and provides a useful help for the choice of the most convenient time interval; moreover, as we will show in an application with real data, it can be supported by a statistical test, using bootstrap to derive the distribution of the distance.

In the next section the tools used in this paper to derive the proposed procedure are briefly described. In section 3 this procedure is evaluated with some Monte Carlo experiments. Section 4 illustrates an application to a real case. Some final remarks follow.

2 Tools of analysis

Different spans of a time series can be generated from different processes. In practice, this fact can arise for various causes; for example, a change in the survey method or an exogenous shock (the oil shocks are typical examples of this last case, known in econometric literature as structural change). In the seasonal adjustment case we are interested in choosing the longest homogeneous span of data. A series generated by a certain process until the time t and by a different one thereafter would probably need different seasonal extraction filters in the two sub-periods. Given that interest in seasonal adjusted series normally refers to the last period, the main purpose is not the detection of the precise location of the structural break; instead, it is the choice of the longest period which provides a seasonal adjusted series as similar as possible to the true unobserved one. The aim of this section is to provide some tools able to help detecting the cutting-off time interval. In particular, the concept of linear filters and the formalization of a distance measure between filters will be briefly recalled.

2.1 Linear Filters and Model-Based Approach

If we consider a process x_t, a frequently applied transformation is the following:

$$y_t = A(L)x_t = \sum_{j=-r}^{s} a_j x_{t-j}. \tag{1}$$

The operation illustrated in (1) is referred as the application to x_t of a *linear time invariant filter*, represented by the lag polynomial $A(L)$, where L is the lag operator. The main features of the application of such a filter are better understood if we resort to the frequency domain representation. In fact, taking the Fourier transform of the filter (1), that is considering $L = e^{-i\omega}$, with ω representing a frequency expressed in radians, we get the *frequency response function* of the filter:

$$\Gamma(\omega) = \sum_{j=-r}^{s} a_j e^{-i\omega j} \tag{2}$$

which describes the way a sinusoid of frequency ω is transferred from the input process x_t to the output y_t.

The function defined in (2) is, in general, complex-valued. It can then be expressed in polar form:

$$\Gamma(\omega) = \gamma(\omega) e^{-i\phi(\omega)}. \tag{3}$$

Equation (3) makes clear that the effect of the application of a linear filter can be split in two parts. The first is expressed by the function $\gamma(\omega)$, which is termed the *gain* of the filter, and determines the extent with which each periodic component of frequency ω is multiplied by the filter itself. The second effect is due to the term $\phi(\omega)$, which is known as the *phase shift*, and produces a shift in time of the input process. In order to avoid the presence of the phase shift it is sufficient that the filter is symmetric, that is $a_j = a_{-j}$. In this case the action of the filter is completely specified by the gain and, denoting the spectrum of the process x_t and y_t, respectively, as $g_x(\omega)$ and $g_y(\omega)$, the following relation holds:

$$g_y(\omega) = \gamma(\omega)^2 g_x(\omega).$$

Therefore, an ideal seasonal adjustment filter would have a squared gain of zero around seasonal frequencies and unit gain at all the others, so as to annihilate seasonal movements while leaving unchanged the rest of the series. The search for such a filter has been the traditional way to deal with seasonality, adopted by so called *ad-hoc* filters like X-11.

An alternative is represented by the *model based* approach; in particular here we concentrate on the *ARIMA model based* approach (Burman, 1980), upon which TRAMO-SEATS is constructed. In this case an ARIMA model fits the series which is to be seasonally adjusted, and ARIMA models for the unobserved components (trend, seasonal, irregular) are derived, according to some identification assumptions (Maravall, 1995). Optimal estimators (in a mean square sense) of the unobserved components can then be constructed by means of linear filters, which have the advantage to adapt themselves to the stochastic features of the components to be estimated. In TRAMO-SEATS, the Wiener-Kolmogorov filter is used. Consequently, some of the key features of the components depend on the estimated filters.

2.2 Distance between Filters

A useful tool to compare two ARIMA models is represented by the idea of distance between models. This concept was introduced by Piccolo (1990), who considered the class of ARIMA invertible processes to define the metrics:

$$d = \left[\sum_{k=1}^{\infty} (\pi_{1k} - \pi_{2k})^2 \right]^{1/2}$$

where $\pi_j(B) = (1 + \pi_{j1}B + \pi_{j2}B^2 + \ldots)$ is the AR expansion of the $j-th$ $(j = 1, 2)$ ARIMA model. This metrics was used in a seasonal adjustment context by Otranto and Triacca (2002) to compare direct and indirect seasonal adjustment within the framework of model-based procedures.

An alternative measure of distance has been recently described by Depoutot and Planas (1998) and Planas and Depoutot (2002), who propose a direct comparison of the filters. Dealing with seasonal adjustment, this last concept seems more natural with respect to Piccolo's distance. In fact, if a model-based approach is adopted, linear filters are explicitly considered; if an *ad hoc* method is used (like X-11), the filter adopted has not necessarily a model-based interpretation, making unapplicable Piccolo's distance. Depoutot and Planas use the filter distance to compare the empirical filters of X-11 and the Wiener-Kolmogorov filters derived by the ARIMA model-based approach.

To define this distance let x_t a seasonal time series, that is decomposed in the nonseasonal part n_t and the seasonal component s_t:

$$x_t = n_t + s_t.$$

Let $f_1(B)$ and $f_2(B)$ be two filters with length, respectively, r_1 and r_2, which extract two alternative seasonal adjusted series. The spectrum of each estimator can be expressed as:

$$g_j(\omega) = \left| f_j \left(e^{-i\omega} \right) \right|^2 g_x(\omega) \qquad j = 1, 2 \tag{4}$$

where

$$f_j \left(e^{-i\omega} \right) = \sum_{k=-r_j}^{r_j} f_{jk} e^{-ik\omega},$$

$g_x(\omega)$ represents the spectrum of the observed series, and $\left| f_j \left(e^{-i\omega} \right) \right|$ is the gain of the filter of the $j-th$ estimator. From equation (4) it is clear that the two filters produce the same estimator if they have the same gain. From this consideration, the distance proposed by Depoutot and Planas has the following form:

$$d(f_1, f_2) = \frac{1}{\pi} \int_0^{\pi} \left| f_1 \left(e^{-i\omega} \right) - f_2 \left(e^{-i\omega} \right) \right|^2 d\omega.$$

Considering symmetric filters, the distance measure, developed in terms of Fourier analysis, can be defined as:

$$d(f_1, f_2) = (f_{10} - f_{20})^2 + 2 \sum_{k=1}^{r} (f_{1k} - f_{2k})^2 \tag{5}$$

with $r = \max(r_1, r_2)$.

3 The distance based procedure

The proposed procedure consists of estimating an ARIMA model on the full series and then making one year reduction of the period considered, re-estimating the ARIMA model. The distance measure between the seasonal filter obtained using the full series and that obtained from the reduced series is then evaluated at each step.

The key feature of the distance is its possible link with the Root Mean Squared Error (RMSE) which affects the estimation of the seasonally adjusted series. This can be evaluated only with a simulation exercise; in fact, while the distance proposed can be calculated also in a real context, the RMSE is in general not available, given the nature of the seasonally adjusted series, which is an unobserved component.

For this distance a distribution is not provided, but it will be shown that its dynamic is sufficiently clear and different in the case the break exists. Bacchini *et al.* (2001) suggest the use of bootstrap to derive the distribution of (5) under the null of zero distance; we will apply this method in section 4, studying a real situation, to support the heuristic graphical evidence.

3.1 The Monte Carlo Design

To evaluate the performance of this procedure and to explain its operative usefulness, we perform a Monte Carlo experiment. We have generated 500 monthly series of length 20 years, following the ARIMA(0,1,1)(0,1,1) model (so called *Airline model*):

$$y_t = \frac{(1+\theta_1 B)\left(1+\theta_{12}B^{12}\right)w_t}{(1-B)\left(1-B^{12}\right)} \qquad w_t \sim IIN(0,\sigma^2), \tag{6}$$

for various combinations of the parameters θ_1 and θ_{12}. If we consider the observed series composed by the sum of the non seasonal part n_t and the seasonal component s_t, the canonical decomposition performed by TRAMO-SEATS is:

$$n_t = \frac{\left(1+\theta_1^n B+\theta_2^n B^2\right)w_t^n}{(1-B)^2} \qquad w_t^n \sim IIN(0,\sigma_n^2), \tag{7}$$

$$s_t = \frac{\left(1+\theta_1^s B+\theta_2^s B^2+\ldots\theta_{11}^s B^{11}\right)w_t^s}{\left(1+B+B^2+\ldots B^{11}\right)} \qquad w_t^s \sim IIN(0,\sigma_s^2), \tag{8}$$

with parameters derived by θ_1, θ_{12} and σ. To obtain the simulated series, the components (7) and (8) have been generated separately and then aggregated so as to be consistent with the desired combination of θ_1, θ_{12} and σ in (6). For example, generating a series from (7) with coefficients

$$\theta_1^n = -1.5645, \quad \theta_2^n = 0.5809, \quad \sigma_n^2 = 0.65986,$$

and a series from (8) with coefficients

$$\begin{aligned}
\theta_1^s &= 0.9061, \quad \theta_2^s = 0.6817, \quad \theta_3^s = 0.4064, \quad \theta_4^s = 0.1306, \quad \theta_5^s = -0.1142, \\
\theta_6^s &= -0.3096, \quad \theta_7^s = -0.4482, \quad \theta_8^s = -0.5306, \quad \theta_9^s = -0.5654, \\
\theta_{10}^s &= -0.5709, \quad \theta_{11}^s = -0.5859, \quad \sigma_s^2 = 0.65786,
\end{aligned}$$

and summing up them, is equivalent to generate a series from (6) with coefficients

$$\theta_1 = -0.6, \quad \theta_{12} = -0.6, \quad \sigma^2 = 1,$$

with the advantage that the unobserved components are known.

The choice of the airline model is justified by the empirical experience; in fact it fits in a very good way many real series. For example, Fischer and Planas (2000) found that the 55.6% of more than 13000 monthly economic series was well described by the airline model.

In the same way we have generated series from another usual model, the ARIMA (1,1,0)(0,1,1):

$$y_t = \frac{\left(1+\theta_{12}B^{12}\right)w_t}{(1-B)\left(1-B^{12}\right)(1+\phi_1 B)} \qquad w_t \sim IIN(0,\sigma^2), \tag{9}$$

for various combinations of the parameters ϕ_1 and θ_{12}.

Generating these series we have considered cases without break (series prefixed with NB in Table 1) and cases with breaks of various size, located in the middle of the series (series prefixed with B); the arrow indicates the change in the parameters.

We have calculated the distance following this scheme:

1) seasonal adjust the series;

Table 1: Parameters of the simulated series

Series	Parameters
NB1	$\theta_1 = -0.90; \quad \theta_{12} = -0.95$
NB2	$\theta_1 = -0.90; \quad \theta_{12} = -0.60$
NB3	$\theta_1 = -0.90; \quad \theta_{12} = -0.30$
NB4	$\theta_1 = -0.60; \quad \theta_{12} = -0.60$
NB5	$\theta_1 = -0.30; \quad \theta_{12} = -0.60$
NB6	$\theta_1 = -0.60; \quad \theta_{12} = -0.30$
NB7	$\theta_1 = -0.30; \quad \theta_{12} = -0.30$
B1	$\theta_1 = -0.90; \quad \theta_{12} = 0.00 \Rightarrow -0.95$
B2	$\theta_1 = -0.90; \quad \theta_{12} = 0.00 \Rightarrow -0.60$
B3	$\theta_1 = -0.90; \quad \theta_{12} = -0.90 \Rightarrow -0.30$
B4	$\theta_1 = -0.30 \Rightarrow -0.95; \quad \theta_{12} = -0.90$
B5	$\theta_1 = -0.30 \Rightarrow -0.60; \quad \theta_{12} = -0.90$
B6	$\theta_1 = -0.30 \Rightarrow 0.00; \quad \theta_{12} = -0.90$
B7	$\theta_1 = -0.90; \quad \theta_{12} = -0.30 \Rightarrow -0.95$
B8	$\theta_1 = -0.90; \quad \theta_{12} = -0.30 \Rightarrow -0.60$
B9	$\theta_1 = -0.90; \quad \theta_{12} = -0.30 \Rightarrow 0.00$
B10	$\phi_1 = 0.30 \Rightarrow 0.60; \quad \theta_{12} = -0.90$
B11	$\phi_1 = 0.30 \Rightarrow 0.90; \quad \theta_{12} = -0.90$
B12	$\phi_1 = 0.90; \quad \theta_{12} = -0.60 \Rightarrow 0.90$
B13	$\phi_1 = 0.90; \quad \theta_{12} = -0.30 \Rightarrow 0.90$

2) calculate the RMSE of the seasonal adjusted series with respect the true seasonal adjusted series;

3) calculate the distance (5) between the filter of the seasonal adjusted series with the full information (20 years) and the filter of the actual seasonal adjusted series (in the first step we compare the same series of 20 years so that the distance is 0);

4) cut-off one year of the aggregate series and start again from step 1 until a series of 6 years remains.

3.2 The Results of the Simulation Experiment

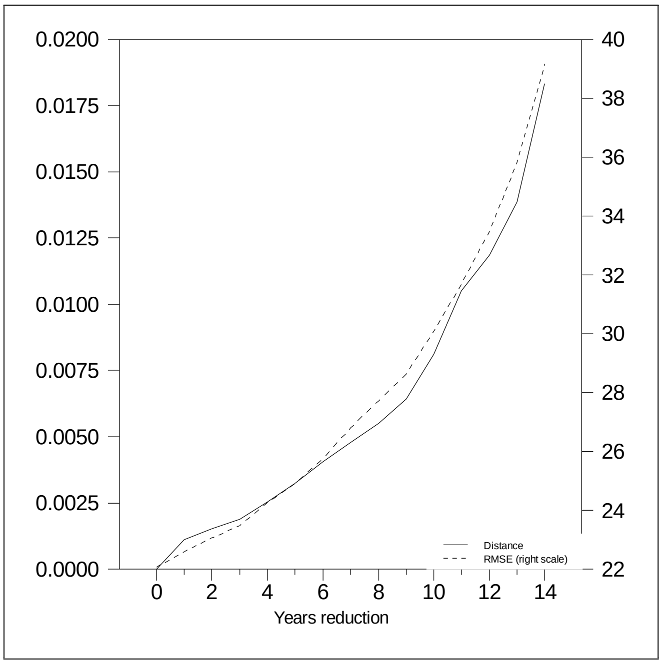
In this sub-section we try to resume the main results of the previous simulation exercise.

The first thing to evaluate is the behavior of the RMSE, which is the variable we are main interested in. Table 2 shows the averages of the RMSE of the estimated seasonally adjusted series using the full span of data and using just the first ten years. In the case of the series which do not have a break, the reduction of the span of data leads to an increase in the RMSE. This is something expected, given the increasing precision in the estimated model one can get from a longer span of data. What is less obvious is the fact that also in some cases where a break is present, nevertheless the RMSE decreases using a longer span of data. This is always the case, in particular, when the break occurs in the θ_1 parameter (series B4-B6). In the other cases, the occurrence of a break determines an increase or a stabilization of the RMSE. The next step is to understand if the behavior of the RMSE is well tracked by the distance measure, which is the

Table 2: Statistics on the simulated series

Series	Average RMSE (10-year)	Average RMSE (full series)	% Reduction(-)/ Increase(+) in the average RMSE	Distance
NB1	30.08	22.06	-26.7	0.008
NB2	39.27	36.65	-6.7	0.003
NB3	39.43	38.01	-3.6	0.001
NB4	35.50	32.92	-7.3	0.002
NB5	37.89	35.20	-7.1	0.002
NB6	36.42	34.73	-4.6	0.001
NB7	40.03	38.22	-4.5	0.001
B1	29.34	43.28	47.5	0.061
B2	38.65	39.34	1.8	0.022
B3	39.20	35.01	-10.7	0.008
B4	30.98	27.31	-11.8	0.012
B5	27.66	23.88	-13.7	0.008
B6	32.72	25.63	-21.7	0.007
B7	29.34	40.24	37.2	0.038
B8	38.66	38.92	0.7	0.008
B9	27.66	35.10	26.9	0.013
B10	34.90	37.47	7.4	0.059
B11	29.34	34.44	17.4	0.005
B12	29.40	29.45	0.2	0.010
B13	29.44	31.66	7.5	0.027

Figure 1: Evolution of the distance measure for series NB1



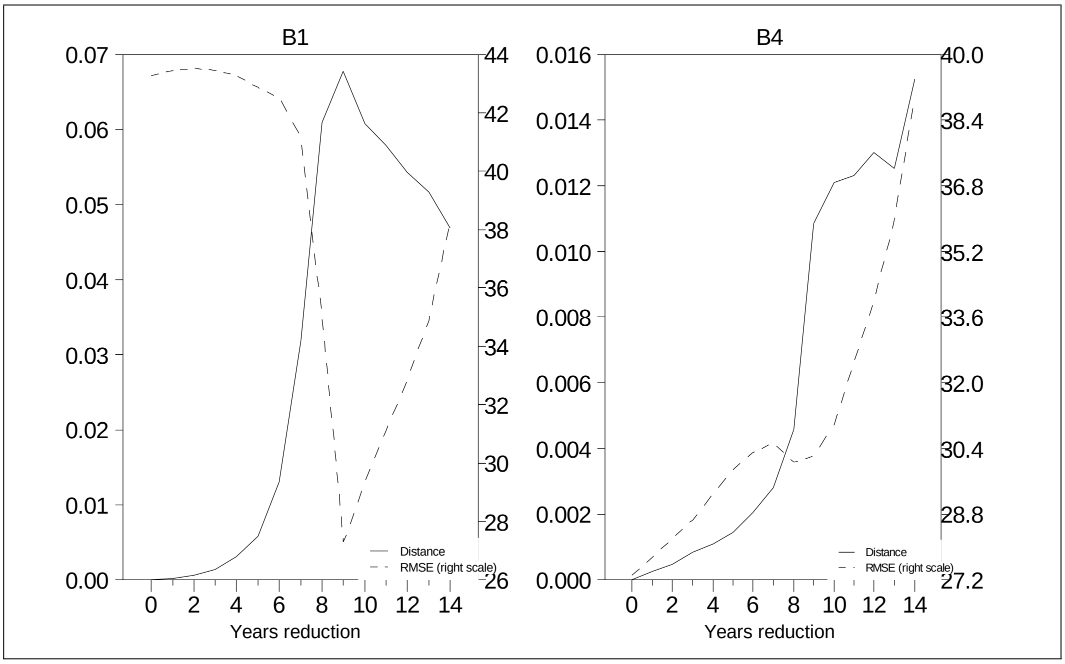
operational device that should allow us to detect the significance of a break in the context of seasonal adjustment. Using the simulated series are concerned, we see that there is a positive correlation (0.66) between the increase in the RMSE when using a longer span of data and the distance between filters. The latter, in particular, takes always a low value in the case of no break, less than, say, 0.01. The only significant departure from this pattern is showed by the series B11, which is characterized by a strong break in the ϕ_1 coefficient.

The previous analysis has showed a possible usefulness of the distance measure to help detecting a break in the DGP of the observed series. A way to use it in practical applications can be represented by the plot of the distance against the years reduction made. This would produce, in the case of no break, a monotonically increasing function as in Figure 1, consistent with the path of the RMSE.

This figure represents the typical shape of the distance measure when no break exists. The other NB series are not reported here, but they are all similar to the one reported. Only in the case of series NB3 the distance is a little noisier.

When considering the broken series, quite a different picture emerges. When the break causes, adding more data, a significant increase in the RMSE, the distance shows a concave form, with a rebound close to break point, mirroring the path of the RMSE. In the other cases, a discontinuity is evident in the graph. Only in four cases the graph does not show a departure from the shape of the no break case: series B5, B6, B8 and B11. In the first two cases the break does not create any problem in terms of RMSE of the seasonal adjusted data. In the third the effect is marginal; more difficult to explain is the last case, when

Figure 2: Distance pattern for two series with a break



a significant break occurs, but is not picked up by the distance. The graphs in Figure 2 show the pattern of the distance and of the RMSE for two series, one with a strong departure from the shape of the no break case, the other with a less strong departure.

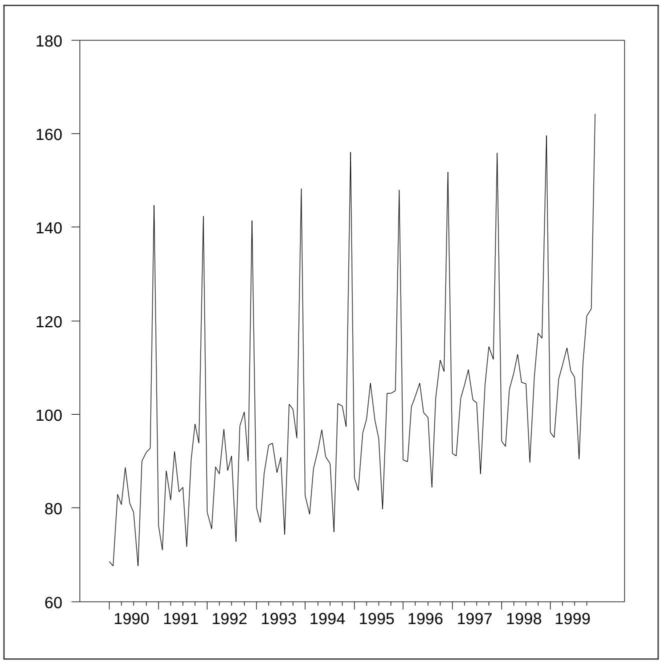
Finally, if we agree that the RMSE is the criterion to evaluate the effect of a structural break in the seasonal adjustment procedure, the distance (5) is a useful proxy of RMSE to decide to cut-off the series. If the distance function is approximately monotically increasing, the full observed series can be used for the seasonal adjustment procedure; if the distance function is a concave curve, the span corresponding to the turning point can be adopted as a good interval.

4 A study case: the retail sales in Italy

In Italy, from January 1996, a new survey on retail sales started, with a different methodology with respect to the previous one. This was caused essentially by new indications of the Short-Term Statistics Regulation, changes in the structure of the retail sales and the change of base in the construction of the index (from 1990 to 1995). The classification criteria, the weighting scheme, the sample size and its composition have been changed. The official substitution of the old series with the new series began in May 1997, and the data from January 1990 were reconstructed following the new methodology.

It is clear that this changes in the series can cause a structural break in the observed series; the graph in Figure 3 shows a change in the dynamics

Figure 3: Total retail sales (1990-99)



of the series in 1993; in fact the previous period presents a peak in March that disappears from 1993. In the same way, from 1994 the peak in July has disappeared. In addition the seasonality seems more regular after 1996. In this section we analyze with our methodology if these changes can affect the seasonal adjustment procedure; in particular we refer to the TRAMO-SEATS routine, adopting an airline model as the (6).

We have reduced the series year by year till the interval 1996-1999. In Table 3 the estimation of the moving average coefficients and the dynamics of the distance are reported. We can note a sudden change in the seasonal MA coefficient within the interval 1993-1999 and a change in the sign within the successive interval. The distance shows a clear break with effects on seasonal adjustment in 1994; the distance has an abrupt jump from 0.002 to 0.056. It is more evident then the simulation cases and it can be appreciated in Figure 4.

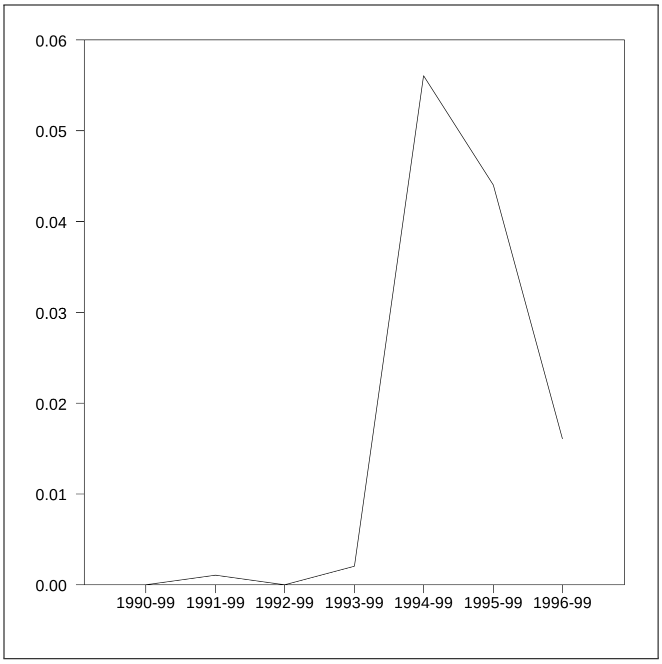
>From this analysis it seems clear that the structural break on the observed series can affect the seasonal adjustment, which needs a reduction of the time interval. Considering the reduction of the distance within the period 1996-99, it can be probably explained by the fact that the estimation of the model is not very reliable, due to the low number of observations. Probably, a good choice is the interval 1994-1999.

To support these considerations, we have calculated the distribution of the distance via bootstrap; in practice we have generated 1000 series of length 120 using the residuals derived from the first model (estimated on the full time series) and reduced progressively the series obtaining reduced spans like in Table 3. The 95th percentiles from the interval 1991-1999 to the interval 1996-1999

Table 3: Total Retail Sales: dynamics of the distance

Time interval	θ_1	θ_{12}	distance
1990-99	-0.78	-0.11	0.000
1991-99	-0.76	-0.12	0.001
1992-99	-0.76	-0.10	0.000
1993-99	-0.69	-0.01	0.002
1994-99	-0.90	0.03	0.056
1995-99	-0.91	0.01	0.044
1996-99	-0.34	0.03	0.016

Figure 4: Total retail sales: evolution of the distance



are respectively 0.004, 0.009, 0.015, 0.025, 0.037, 0.045. So, it is verified that the distance is significantly different by zero for the 1994-1999 and 1995-1999 spans with respect the full period.

5 Concluding remarks

In this paper we have illustrated a simple procedure to evaluate the more convenient time interval in order to apply an ARIMA model based seasonal adjustment procedure. The criterion is represented by a distance measure between filters which provides a useful indication for the presence of structural breaks affecting the estimation of the seasonal component; the choice is based on heuristic considerations. The Monte Carlo simulations demonstrate the performance of this approach; it is interesting to note that generally the chosen length is larger that the correct one, permitting the presence of a short data generated from a different process. The airline model was adopted in the Monte Carlo experiments given its wide use in modeling seasonal economic time series and because it represents the default model in TRAMO-SEATS. In addition, an ARIMA(1,1,0)(0,1,1) model has been considered.

The use of a distance measure and an heuristic procedure, bypassing the usual statistical tests to detect breakpoints, derives by practical considerations; very often the need of homogeneous spans is in contrast with the need of series sufficiently large. In other terms, this procedure avoids the choice of time intervals which provides models sufficiently stable for statistical analysis. The framework with wich this paper deals is that of seasonal adjustment, but the procedure can be extended to the other time series problems and considered as a general method to choice the time span.

Future work should study more in depth the properties of the proposed measure; moreover, the implementation of such a device as a formal statistical test deserves further investigation. In this paper, to derive the distribution of this statistics, we have used the usual bootstrap procedures, obtaining a good degree of coherence with the results derived by the empirical study of the distance dynamics.

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