The effects of seasonal adjustment methods in nonparametric trend-cycle prediction

Estela Bee Dagum* Silvia Bianconcini†

Abstract
In a previous study, Dagum and Bianconcini (2014) have shown that using local time-varying bandwidth parameters in asymmetric nonparametric trend-cycle filters reduces significantly revisions and turning point detection respect to the Musgrave (1964) standard approach. The authors observed that the best choice of local time-varying bandwidth is the one obtained by minimizing the distance between the gain functions of the asymmetric and the symmetric filter to which it must converge. The purpose of this study is to evaluate the effects of the seasonal adjustment method when the real time trend is predicted with such nonparametric filters. The seasonal adjustments are made with the X12ARIMA and TRAMO-SEATS on a large sample of series.

Key Words: Asymmetric filters, turning point detection, reproducing kernel Hilbert space, X12ARIMA, TRAMO-SEATS.

1. Introduction

The basic approach to the analysis of current economic conditions, known as recession and recovery analysis, is that of assessing the real time trend-cycle of major economic indicators (leading, coincident and lagging) using percentage changes, based on seasonally adjusted units calculated for months and quarters in chronological sequence. The main goal is to evaluate the behavior of the economic indicators during incomplete phases by comparing current contractions or expansions with corresponding phases in the past. This is done by measuring changes of single time series (mostly seasonally adjusted) from their standing at cyclical turning points with past changes over a series of increasing spans. It should be noticed that this is different than business cycle studies where cyclical fluctuations are measured around a long term trend to estimate complete business cycles. The real time trend corresponds to an incomplete business cycle and its prediction is done by means of either univariate parametric models or nonparametric techniques.

In recent years, statistical agencies have shown an interest in providing trend-cycle or smoothed seasonally adjusted graphs to facilitate recession and recovery analysis. Among other reasons, this interest originated from the recent crisis and major economic and financial changes of global nature which have introduced more variability in the data. Consequently, it has become difficult to determine the direction of the short term trend (or trend-cycle) by looking at month to month (quarter to quarter) changes of seasonally adjusted values, particularly to assess the upcoming of a true turning point.

Seasonal adjustment means the removal of seasonal variations in the original series jointly with trading day variations and moving holiday effects. The main reason for seasonal adjustment is the need of standardizing socioeconomic series because seasonality affects them with different timing and intensity. Hence, the seasonally adjusted data reflect variations due to only the remaining components, namely trend-cycle and irregulars. The information given by seasonally adjusted series has always played a crucial role in the analysis of current economic conditions and provides the basis for decision making and forecasting, being of major importance around cyclical turning points.

*Department of Statistical Sciences, University of Bologna. Via Belle Arti, 41 - 40126 Bologna, Italy
†Department of Statistical Sciences, University of Bologna. Via Belle Arti, 41 - 40126 Bologna, Italy

Seasonal methods can be classified as deterministic or stochastic depending on the assumptions made concerning how seasonality evolves through time. Deterministic methods assume that the seasonal pattern can be predicted with no error or with variance of the prediction error null. On the contrary, stochastic methods assume that seasonality can be represented by a stochastic process, that is a process governed by a probability law and, consequently, the variance of the prediction error is not null. The best known seasonal adjustment methods belong to the following types:

(a) regression methods which assume global or local simple functions of time,

(b) stochastic model-based methods which assume simple AutoRegressive Integrated Moving Average (ARIMA) models, and

(c) moving average methods which are based on linear filtering and hence do not have explicit parametric models.

Only methods (a), which assume global simple functions for each component, are deterministic; the others are considered stochastic. Moving averages and ARIMA Model-Based (AMB) methods, particularly being the X12ARIMA and TRAMO-SEATS respectively, are those applied mostly by statistical agencies to produce officially seasonally adjusted series.

In a previous study, Dagum and Bianconcini (2014) have shown that using local time-varying bandwidth parameters in asymmetric nonparametric trend-cycle filters reduces significantly revisions and turning point detection respect to the Musgrave (1964) standard approach applied by X12ARIMA. The authors observed that the best choice of local time-varying bandwidth is the one obtained by minimizing the distance between the gain functions of the asymmetric and the symmetric filter to which it must converge. Because the series to which these trend-cycle filters are applied are seasonally adjusted, we want to analyze the extent to which different seasonal adjustment methods could influence the final results. The seasonal adjustments of officially published series are made either with the X12ARIMA or TRAMO-SEATS, hence we used both on a large sample of real life series which are mainly used to identify and predict true macroeconomic turning points.

The paper is structured as follows: Section 2 provides an overview of the X12ARIMA and TRAMO-SEATS procedures. Section 3 presents and discusses the nonparametric filters developed by Dagum and Bianconcini (2014) whose properties are analyzed as function of the seasonal adjustment method applied to the original data. Section 4 analyzes the size of the revisions of the filters when applied on seasonally adjusted series with outliers either replaced or not, and deals with their time lag in detecting true turning points. Finally, Section 5 gives the conclusions.

2. An overview of TRAMO-SEATS and X12ARIMA

TRAMO-SEATS and X12ARIMA are two different methods for seasonal adjustment. TRAMO (Time series Regression with ARIMA noise, Missing observations, and Outliers) and SEATS (Signal Extraction in ARIMA Time Series) are linked programs developed by Agustin Maravall and Victor Gomez in 1997 to seasonally adjust time series using ARIMA model-based signal extraction techniques. SEATS uses signal extraction with filters derived from an ARIMA-type model that describes the behavior of the series. This method extended the works done by Burman (1980) and Hillmer and Tiao (1982). See also Maravall (1993) and Gomez and Maravall (1997).

X12ARIMA is one of the Census Bureau's latest program in the X11 line of seasonal adjustment programs. X12ARIMA uses signal-to-noise ratios to choose between a fixed set of moving-average filters, often called X11-type filters. X12ARIMA is based on the well-known X11 program (Shiskin, Young, and Musgrave, 1967) and Statistics Canada's X11ARIMA and X11ARIMA/88 (Dagum, 1988). Major improvements in X12ARIMA over X11ARIMA/88 are discussed in Findley et al. (1998), mainly consisting in the identification and estimation of several types of ARIMA models and new seasonal adjustment diagnostic tools.

A more detailed description of the two procedures is provided in the following.

2.1 X12ARIMA

X12ARIMA is characterized by the RegARIMA modeling routine, the enhanced X11 filtering procedure, and various diagnostic tools. The RegARIMA modeling routine fulfills the role of prior adjustment and forecast extension of the time series. That is, it first estimates some deterministic effects, such as calendar effects and outliers using predefined built-in options or user-defined regressors, and it removes them from the observed series. An appropriate ARIMA model is identified for the preadjusted series in order to extend it with forecasts. Then, this extended preadjusted series is decomposed into the unobserved components of the series using moving averages, also accounting for the presence of extreme values, as follows:

1. a preliminary estimate of the trend-cycle is obtained using a centered thirteen (five) term weighted moving average of the monthly (quarterly) original series ;

2. this trend-cycle series is removed from the original one to give an initial estimate of the seasonal and irregular components, often called SI ratios;

3. initial preliminary seasonal factors are estimated from these initial SI ratios by applying weighted seasonal moving averages for each month over several years, separately;

4. an initial estimate of the irregular component is obtained by removing the initial preliminary seasonal factors from the initial SI ratios;

5. extreme values are identified and (temporarily) adjusted to replace the initial SI ratios with the modified ones;

6. step 3 and 4 are repeated on the modified SI ratios, initial seasonal factors are derived by normalizing the initial preliminary seasonal factors;

7. an initial estimate of the seasonally adjusted series is obtained by removing the initial seasonal factors from the original series;

8. a revised trend-cycle estimate is obtained by applying Henderson moving averages to the initial seasonally adjusted series;

9. steps 2 to 8 are again repeated twice to produce the final estimates of the trend-cycle, seasonal, and irregular components.

Various diagnostics and quality control statistics are computed, tabulated, and graphed in order to assess the seasonal adjustment results. If they are acceptable based upon the diagnostics and quality measures, then the process is terminated. If this is not the case, the above steps have to be repeated to search for a more satisfactory seasonal adjustment of the series. The procedure is summarized in the LHS of Figure 1.

2.2 TRAMO-SEATS

TRAMO-SEATS is an ARIMA Model-Based (AMB) seasonal adjustment method, that consists of two programs, TRAMO and SEATS, which are structured to be used together for seasonal adjustment. To be specific:

> TRAMO is a program for estimation, forecasting, and interpolation of regression models with possibly non-stationary ARIMA errors and any sequence of missing values. It consists of the following steps:
>
> 1. automatic detection of several types of outliers, and, if necessary, estimation of other regression variables, such as calendar effects;
> 2. automatic identification of an ARIMA model;
> 3. then, TRAMO removes all the estimated components (trading-days, moving holidays, outliers) from the original series and passes the linearized series to SEATS, where the actual component decomposition is performed.
>
> SEATS is a program to decompose the series into its unobserved components (namely, the trend-cycle, seasonal, irregular, and transitory ones) following an AMB method. It uses filters derived from an ARIMA model that captures the particular structure of the time series under consideration to tailor seasonal and trend filters to the series. In details,
>
> 1. first, the spectral density function of the estimated model is decomposed into those of the unobserved components with the use of the canonical decomposition, which maximizes the variance of the irregulars;
> 2. the parameters of the trend-cycle and seasonal components are estimated based on Minimum Mean Squared Error (MMSE) criterion and using Wiener-Kolmogorov (WK) filters;
> 3. the detected outliers and some special effects are finally reintroduced into the components.

As in the case of X12ARIMA, diagnostic checking and analyses of the decomposition accuracy and adequacy are performed using graphical, descriptive, nonparametric, and parametric measures included in the output of the program. The procedure is summarized in the RHS of Figure 1.

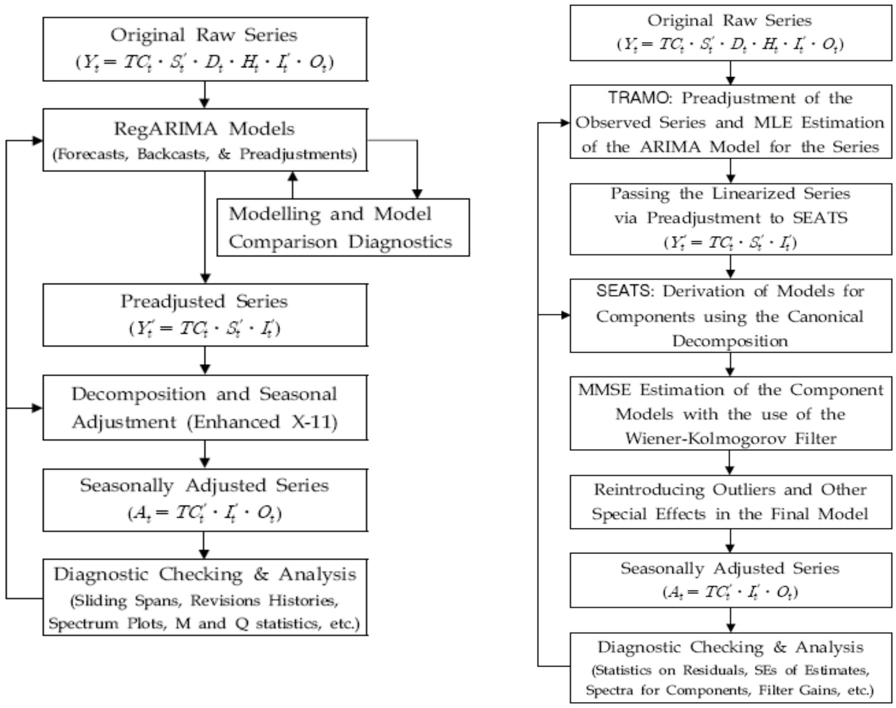
3. Trend-cycle prediction in Reproducing Kernel Hilbert Space (RKHS)

Due to major economic and financial changes of global nature, seasonally adjusted data, produced using either X12ARIMA or TRAMO-SEATS methods, are not smooth enough to be able to provide a clear signal of the short-term trend. Hence, further smoothing is required, but the main objections for trend-cycle estimation are :

(a) the size of the revisions of the most recent values (generally much larger than for the corresponding seasonally adjusted estimates);

(b) the time lag in detecting true turning points;

Figure 1: X12ARIMA (*left*) and TRAMO-SEATS (*right*) procedures.



(c) the presence of short cycles or ripples (9 or 10 month cycles) in the final trend-cycle curve when the symmetric filter is applied.

With the aim to overcome such limitations, Dagum and Bianconcini (2008, 2013, and 2014) have recently proposed nonparametric trend-cycle filters that reduces significantly revisions and turning point detection respect to the Musgrave (1964) filters which are applied by X12ARIMA.These authors rely on the assumption that the input series $\{y_t, t = 1, 2, ..., N\}$ is seasonally adjusted (where trading day variations and extreme values, if present, have been also removed), such that it can be decomposed into the sum of a systematic component (signal) g_t, that represents the trend and cycle usually estimated jointly, plus an erratic component u_t, called the noise, as follows

$$y_t = g_t + u_t. \tag{1}$$

The noise u_t is assumed to be either white noise, $WN(0, \sigma_u^2)$, or, more generally, a stationary and invertible AutoRegressive Moving Average (ARMA) process. On the other hand, the signal $g_t, t = 1, \cdots, T$, is assumed to be a smooth function of time that can be estimated as a weighted moving average as follows

$$\hat{g}_t = \sum_{j=-m}^{m} w_j y_{t+j} \qquad t = m+1, \cdots, N-m, \tag{2}$$

where $\{w_j, j = -m, \cdots, m\}$ are the weights applied to the $(2m+1)$ observations surrounding the target observation y_t. In the RKHS framework, the weights are derived from the following kernel function

$$K_4(t) = \sum_{i=0}^{3} P_i(t) P_i(0) f_0(t) \qquad t \in [-1, 1] \tag{3}$$

where $f_0(t) = \frac{15}{16}(1-t^2)^2, t \in [-1,1]$ is the biweight density function, and $P_i, i = 0,1,2,3$, are the corresponding orthonormal polynomials. In particular, the generic weight $w_j, j = -m, \cdots, m$, is given by

$$w_j = \left[\frac{\mu_4 - \mu_2 \left(\frac{j}{b}\right)^2}{S_0\mu_4 - S_2\mu_2} \right] \frac{1}{b} f_0\left(\frac{j}{b}\right) \tag{4}$$

where $\mu_r = \int_{-1}^{1} t^r f_0(t)dt$ are the moments of f_0, and $S_r = \sum_{j=-m}^{m} \frac{1}{b}\left(\frac{j}{b}\right)^r f_0\left(\frac{j}{b}\right)$ their discrete approximation that depends on the bandwidth parameter b whose choice is of fundamental importance to guarantee specific inferential properties to the trend-cycle estimator. It has to be selected to ensure that only $2m+1$ observations surrounding the target point will receive nonzero weight and to approximate, as close as possible, the continuous density function $f_0(t), t \in [-1,1]$, with the discrete one $f_0\left(\frac{j}{b}\right), j = -m, \cdots, m$, as well as the moments μ_r with S_r. Dagum and Bianconcini (2008 2014) have shown that the best choice is to use a time-invariant global bandwidth b equal to $m+1$, which gave excellent results.

At the end of the sample period, that is $t = N-(m+1), \cdots, N$, only $2m, \cdots, m+1$ observations are available, and time-varying asymmetric filters have to be considered. At the boundary, the effective domain of the kernel function K_4 is $[-1, q^*]$, where $q^* = q/b, q = 0, ..., m-1$, instead of $[-1,1]$ as for any interior point. This implies that the symmetry of the kernel is lost, and it does not integrate to unity on the asymmetric support ($\int_{-1}^{q^*} K_4(t)dt \neq 1$). Based on these considerations, Dagum and Bianconcini (2014) have suggested to derive the asymmetric weights by "cutting and normalizing" the symmetric kernel K_4, that means by omitting that part of the function lying between q^* and 1, and by normalizing it on [-1,q^*]. Hence, the corresponding asymmetric weights result

$$w_{q,j} = \left[\frac{\mu_4 - \mu_2 \left(\frac{j}{b_q}\right)^2}{S_0^q\mu_4 - S_2^q\mu_2} \right] \frac{1}{b_q} f_0\left(\frac{j}{b_q}\right) \tag{5}$$

$$j = -m, \cdots, q; q = 0, \cdots, m-1.$$

where $S_r^q = \sum_{j=-m}^{q} \frac{1}{b_q}\left(\frac{j}{b_q}\right)^r f_0\left(\frac{j}{b_q}\right)$ is the discrete approximation of $\mu_r^{q*} = \int_{-1}^{q*} t^r f_0(t)dt$ that are proportional to the moments of the truncated biweight density f_0 on the support $[-1, q^*]$.

Dagum and Bianconcini (2014) have analyzed in detail the statistical properties of these asymmetric filters as function of the bandwidth parameters $b_q, q = 0, \cdots, m-1$. They have shown, both theoretically and empirically, that filters based on local time-varying bandwidth parameters $b_q, q = 0, \cdots, m-1$, selected to minimize the distance between the gain functions of each asymmetric filter $\{w_{q,j}, j = 0, \cdots, q, q = 0, \cdots, m\}$ and the symmetric one $\{w_j, j = -m, \cdots, m\}$ have excellent properties. In particular, the last point trend-cycle filter reduces around a half the size of the total revisions as well as the time delay to detect a true turning point with respect to the Musgrave (1964) filter. The weight systems of these filters are given in Table 1 for the 13-term symmetric filter.

4. Empirical application

Since the RKHS trend-cycle estimators discussed in the previous Section are applied to seasonally adjusted data, we want to evaluate how their statistical properties are affected by

Table 1: 13-term symmetric and corresponding asymmetric filters

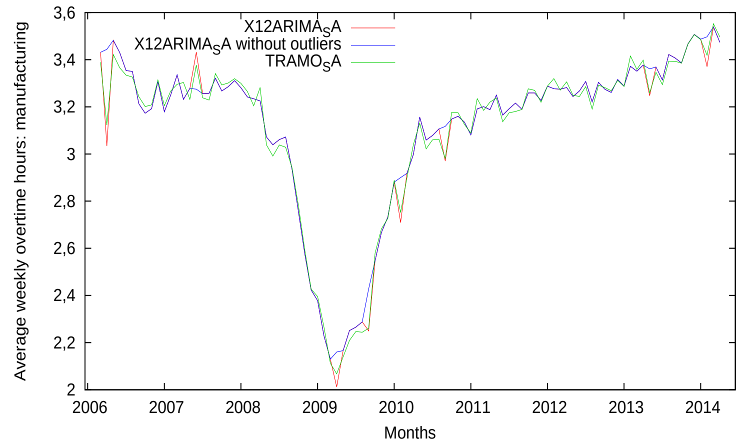
-0.020	-0.030	0.002	0.070	0.149	0.211	0.234	0.211	0.149	0.070	0.002	-0.030	-0.020
0.000	-0.019	-0.030	0.001	0.068	0.147	0.208	0.232	0.208	0.147	0.068	0.001	-0.030
0.000	0.000	-0.016	-0.0 30	-0.003	0.063	0.142	0.205	0.229	0.205	0.142	0.063	-0.003
0.000	0.000	0.000	-0.016	-0.030	-0.002	0.063	0.142	0.205	0.228	0.205	0.142	0.063
0.000	0.000	0.000	0.000	-0.026	-0.026	0.012	0.080	0.154	0.210	0.231	0.210	0.154
0.000	0.000	0.000	0.000	0.000	-0.020	0.014	0.065	0.122	0.175	0.211	0.224	0.211
0.000	0.000	0.000	0.000	0.000	0.000	0.027	0.069	0.114	0.157	0.193	0.216	0.224

the seasonal adjustment method used to produce the input data as well as by the presence of outliers. At this regard, in this Section, we analyze the behavior of the RKHS asymmetric filters in terms of size of revisions in the estimates as new observations are added to the series, time lag to detect true turning points, and number of unwanted ripples when they are applied on data seasonally adjusted using X12ARIMA, with outliers either replaced or not, and TRAMO-SEATS.

The filters are applied to a sample of thirty series that cover various sectors, such as labour, imports, exports, housing, industrial production, inventories, and so on. The series have been observed on different time periods. As an example, Figure 2 illustrates the Seasonally Adjusted (SA) monthly series of Average Weekly Overtime Hours in Manufacturing (AWOHM) for the period March 2006 - April 2014. This series is provided monthly by the Bureau of Labor Statistics in the U.S. Department of Labor. These data are defined to include work time for which premium pay is received beyond straight time workday or workweek. Holiday hours are included only if premium wages are paid. Average weekly hours are a sensitive barometer of labor demand. Employers generally prefer to increase or decrease hours worked before hiring or laying off workers in response to movements in retail sales, corporate profits, manufacturer's orders, inventory sales ratios, or planned production schedules. This is particularly true when the changes in the demand for labor are small or are expected to be temporary.

The seasonal adjustment is done using the default options of the officially adopted X12ARIMA and TRAMO-SEATS methods. For the X12ARIMA, we have requested the SA series with and without outliers. It can be noticed that the seasonal adjusted series are very close one another, being the main difference presented by the SA series in which the outliers have been appropriately replaced. It is evident that AWOHM peaked at the middle of 2007, and underwent thenceforth a very steep decline up to June 2009.

Figure 2: Seasonally Adjusted (SA) monthly Average Weekly Overtime Hours in Manufacturing (AWOHM) series.



4.1 Reduction of revisions in real time trend-cycle estimates

The reduction of revisions in real time trend-cycle estimates is very important because they are preliminary and used to assess the current stage of the economy. Here, we study how the RKHS filters proposed by Dagum and Bianconcini (2014) respond to the seasonal adjustment of the data and to the replacement of the outliers. For the seasonally adjusted series considered in this study, the length of the filters is selected according to the I/C (noise to signal) ratio, as classically done in the X11- and X12ARIMA procedure. It ranges from 0.20 to 4.47, hence symmetric filters of 9-, 13-, and 23-term and corresponding asymmetric filters have been applied. The comparisons are based on the relative filter revisions between the final symmetric filter S and the last point asymmetric filter A, that is,

$$R_t = \frac{S_t - A_t}{S_t}, \quad t = 1, 2, ..., N. \tag{6}$$

For each series, we calculate the Mean Square Percentage Error (MSPE) and the Mean Absolute Percentage Error (MAPE) of the revisions corresponding to the filters derived following the RKHS methodology. Table 2 illustrates the mean, minimum and maximum values of MAPE and MSPE of the revisions induced by the RKHS filters when applied to SA data produced by X12ARIMA, with and without outliers, as well as by TRAMO-SEATS.

Table 2: Mean, minimum and maximum values of MSPE and MAPE of the revisions induced by RKHS filters applied on different SA series.

	X12ARIMA with outliers		X12ARIMA without outliers		TRAMO-SEATS	
	MAPE	MSPE	MAPE	MSPE	MAPE	MSPE
Mean	2.85	0.44	2.77	0.41	2.88	0.46
Min	0.17	0.00	0.17	0.00	0.18	0.00
Max	14.79	7.29	14.55	6.69	15.18	7.52

It can be noticed that, even if the differences are minimal, we obtain more accurate estimates when the filters are applied to SA data in which outliers have been appropriately replaced, and, in particular, when the seasonal adjustment of the series is performed using X12ARIMA procedure.

4.2 Turning point detection

It is important that the reduction of revisions in real time trend-cycle estimates is not achieved at the expense of increasing the time lag to detect true turning points. A turning point is generally defined to occur at time t if (*downturn*):

$$y_{t-k} \leq \cdots \leq y_{t-1} > y_t \geq y_{t+1} \geq \cdots \geq y_{t+m}$$

or (*upturn*)

$$y_{t-k} \geq \cdots \geq y_{t-1} < y_t \leq y_{t+1} \leq \cdots \leq y_{t+m}.$$

Following Zellner et al. (1991), we have chosen $k = 3$ and $m = 1$ given the smoothness of the trend-cycle data. For the considered RKHS estimator, the time lag to detect the true turning point is affected by the convergence path of its asymmetric filters $\{w_{q,j}, j = -m, \cdots, q; q = 0, \cdots, m-1\}$ to the symmetric one $\{w_j, j = -m, \cdots, m\}$.

To determine the time lag of the estimator in detecting a true turning point we calculate the number of months it takes for the real time trend-cycle estimate to signal a turning point in the same position as in the final trend-cycle series. For the three SA series considered here, the average time delay in detecting true turning points calculated over the sample of series are shown in Table 3, together with the corresponding minimum and maximum values.

Table 3: Time delay in detecting true turning points for RKHS filters applied on seasonally adjusted series.

	X12ARIMA with outliers	X12ARIMA without outliers	TRAMO-SEATS
Mean	2.52	2.47	2.50
Min	1.00	1.17	1.25
Max	6.17	4.17	5.60

It can be noticed that the property of the filters in fast detecting true turning points is not strongly affected by the seasonal adjustment procedure used to produce the input data, as well as by the presence of outliers. A better performance, on average, is observed when outliers are removed from the SA series, and when the filters are applied on data seasonally adjusted using TRAMO-SEATS rather than X12ARIMA.

On the other hand, the presence of outliers strongly affects the performance of the symmetric filter in detecting false turning points or unwanted ripples, that is in producing short cycle or ripples (9 and 10 months cycles) in the final trend-cycle curve when the symmetric filter is applied. The presence of ripples in the final estimates of the trend-cycle leads to false turning points, that can make the filter unsuitable for monitoring current changes in the economy. Table 4 shows that this property of the filters is strongly dependent on the input data, that means on the seasonally adjustment procedure adopted.

Table 4: Unwanted ripples and true turning point detection based on RKHS filters applied on different seasonally adjusted series.

Number of unwanted ripples

	X12ARIMA with outliers	X12ARIMA without outliers	TRAMO-SEATS
Mean	11.96	9.64	11.89
Min	2.00	1.00	3.00
Max	24.00	22.00	24.00

Number of true turning points detected

	X12ARIMA with outliers	X12ARIMA without outliers	TRAMO-SEATS
Mean	7.00	7.21	6.93
Min	2.00	2.00	4.00
Max	12.00	11.00	12.00

It is evident that removing outliers in the SA series implies a reduction of almost 25% of the number of unwanted ripples, on average, respect to the case in which the filters are applied to SA series where the outliers are present, independently on the fact that the series has been adjusted using the X12ARIMA method or TRAMO-SEATS.

On the other hand, it is important to notice that, independently on the outliers replacement, when the symmetric filter is applied on data seasonally adjusted using TRAMO-SEATS it tends to miss some true turning points, being the average number of turning points detected smaller than in the case in which the filter is applied to X12ARIMA SA series.

5. Conclusions

This study deals with the problem of real time trend-cycle estimation approached by means of linear filters developed using the RKHS methodology. In previous works, Dagum and Bianconcini (2008, 2013, and 2014) have used the RKHS methodology to derive asymmetric linear filters having excellent statistical properties in terms of revisions and time delay to detect true turning points. The properties of these RKHS asymmetric filters strongly depend on bandwidth parameters. Dagum and Bianconcini (2014) have shown that using local time-varying bandwidth parameters in asymmetric nonparametric trend-cycle filters reduces significantly revisions and turning point detection respect to the Musgrave (1964) standard approach. The authors observed that the best choice of local time-varying bandwidth is the one obtained by minimizing the distance between the gain functions of the asymmetric and the symmetric filter to which it must converge.

In this study, we have evaluated the effects of the seasonal adjustment method when the real time trend is predicted with such nonparametric filters, being the latter applied on seasonally adjusted series. We have considered a sample of thirty important indicators of the US economy, whose original data have been seasonally adjusted using X12ARIMA, with outliers either replaced or not, and TRAMO-SEATS. These two procedures are the most widely used to produce officially seasonally adjusted data.

We have observed that the revisions reduce when the asymmetric filters are applied on seasonally adjusted series in which the outliers have been properly replaced. However, the main effect of outlier replacement is on detecting false turning points or unwanted ripples. The latter are short cycle (9 and 10 months cycles) in the final trend-cycle curve produced when the symmetric filter is applied. The presence of ripples in the final estimates of the trend-cycle leads to false turning points, that can make the filter unsuitable for monitoring current changes in the economy. It is evident that this property of the filters is strongly dependent on the input data, that means on the seasonally adjustment procedure adopted and particularly by the presence of outliers in the input series.

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