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Fixing the model for the seasonal component: A new revision policy

María Novás*, Félix Aparicio-Pérez, Rafael López, Soledad Saldaña, David Salgado and Luis Sanguiao
National Statistics Institute of Spain (INE), Madrid, España

Abstract. One of the multiple decisions that statisticians have to face on the release of seasonal and calendar adjusted series, is the revision policy when new data are available. The INE used to apply the policy of *Partial Concurrent Adjustment: ARIMA Parameters* in JDemetra+, but huge revisions from the beginning of the series were occasionally observed. Analyzing this issue deeply, we realized that revisions were due to two main reasons: model changes because of lack of admissible decomposition, and especially, changes in the autoregressive roots assignment. In this paper, we present the new revision policy applied at the INE, which may be considered a compromise between the *Partial Concurrent Adjustment: ARIMA Parameters* policy and the *Partial Concurrent Adjustment: Fixed Model*, both implemented in JDemetra+. This new policy avoids model changes by: (i) fixing the last estimated model with admissible decomposition when a model change is triggered and (ii) adjusting root assignment parameters to make sure autoregressive roots remain in the same component. In doing so, we improve the estimation of the model parameters with the new data, while avoiding big revisions, as shown in the examples.

Keywords: Seasonal adjustment, revision policy, partial concurrent adjustment, ARIMA parameters, canonical decomposition

1. Introduction

There are two main widely used methodologies for seasonal adjustment: the model based approach (see [1,2]) and the fixed filters approach (see [3,4]). Both methodologies are officially used (and recommended) by Eurostat and by the European Central Bank. This paper refers only to the former methodology as it does not make any sense in the latter. Note that the first step in the signal extraction approach is to obtain an autoregressive integrated moving average (ARIMA) model for the complete series, so it is sometimes called the ARIMA-model based seasonal adjustment method.

TRAMO-SEATS (that stands for Time Series Regression with ARIMA Noise, Missing Observations and Outliers-Signal Extraction in ARIMA Time Series) is a program following the ARIMA-model based approach, and it consists of two steps. In the first step, the reg-ARIMA model that fits best the series is adjusted. In the second step, the ARIMA model is decomposed into several ARIMA models, one for each of the unobserved components (Trend-cycle, Seasonal, Transitory and Irregular, see [5]). The unobserved components are then estimated using the Wiener-Kolmogorov filter, which has the property of being the MMSE (Minimum Mean Squared Error) estimator. This filter is symmetric and centered, convergent in B (backward operator) and in F (forward operator). Unless the model for the observed series is a pure AR model, the filter will extend from $-\infty$ to $+\infty$. The convergence of the filter guarantees that it can be approximated by a finite 2-sided filter (In practice, the approximated filter uses a window of width between 3 and 5 years). Assuming that the length of the series is much bigger than the width of the window, the estimator for the central observations of the series can be considered final. But, for time points close to the beginning or the end of the series, the filter cannot be realized, and the preliminary estimator arises, in which the same filter is applied to the time series extended with forecasts and backcasts (note that in doing so, the filter weights change, since the backcasts and forecasts are actually a function of the observed time series). In

*Corresponding author: María Novás, National Statistics Institute of Spain (INE) Avda. Manoteras, 52 28050 Madrid, España. Tel.: +91 583 9341; E-mail: maria.novas.filgueira@ine.es.

other words, near the beginning and the end of the series a non-symmetric filter is used instead of the optimal Wiener-Kolmogorov filter. When a new observation becomes available, it replaces the first forecasted value and the filters give new estimates of the unobserved components (see [2,6]). These new estimates are called revisions, and they can be substantial.

JDemetra+ (see [7]) is an open source, platform independent, extensible software for seasonal adjustment (SA) and other related time series problems developed by the National Bank of Belgium in cooperation with the Deutsche Bundesbank and Eurostat. JDemetra+ implements the concepts and algorithms used in the two leading SA programs: TRAMO-SEATS and X-12ARIMA/X-13ARIMA-SEATS. These methods have been re-engineered using an object-oriented approach that enables easier handling, extensions and modifications.

JDemetra+ enables the implementation of the methodology proposed in [8]. JDemetra+ has been officially recommended, as of 2 February 2015, to the members of the ESS and the European System of Central Banks as software for seasonal and calendar adjustment in official statistics.

The revisions of seasonal adjusted data take place for two main reasons. First due to the availability of new observations in the observed time series, and second because of a better estimate/identification of the seasonal pattern. The former is unavoidable, but only causes revisions near the time points where the data set changes, often near the end of the time series (in most cases we just get one more observation at the end of the series). Regarding the latter, a different estimate of the seasonal pattern produces small revisions from the beginning of the series, because of the small changes in the estimated coefficients in the Wiener-Kolmogorov filter. However, a different model for the seasonal pattern results in a completely different Wiener-Kolmogorov filter, even if the model for the observed series is preserved, leading to big differences from the beginning of the series. The challenge is to find a balance between the need for the best possible seasonally adjusted data, specially at the end of the series, and the need to avoid revisions that may later be reversed (see chapter 4 in [8]).

The INE started publishing Seasonal and Calendar adjusted series for Short Term Statistics in 2003,[1] using TRAMO and SEATS. In 2018 the INE migrated to JDemetra+ (version 2.2.0), maintaining the TRAMO and SEATS method.

The first revision policy applied is based on two principles:

1. Identify the proper model (ARIMA model, calendar regressors and outliers) once a year (Using the time series with observations expanding until December in the previous year).
2. Re-estimate all coefficients every time new data become available (monthly or quarterly).

This revision policy is implemented in JDemetra+ under the name *Partial Concurrent Adjustment: ARIMA Parameters*. This policy has the advantage of incorporating the new information when it becomes available. But at the same time, it has the disadvantage of producing big revisions from the beginning of the series, when the re-estimation of all coefficients is applied from one month or quarter to the following, as shown in Section 4.

2. Canonical decomposition

The TRAMO-SEATS method is considered a model based signal extraction method (MBSE), based on ARIMA models. TRAMO is a program for estimation and forecasting of ARIMA models with regression variables, missing observations and outlier detection. From the ARIMA model obtained by TRAMO, SEATS derives appropriate models for the unobserved components (Trend-cycle, Seasonal, Transitory and Irregular, see [9]).

We consider the regression-ARIMA model:

$$y_t = W_t\beta + x_t \tag{1}$$

where y_t is the observed series, W_t is the matrix with the regression variables in columns, β is a vector of coefficients and x_t follows a possibly nonstationary (NS) ARIMA model.

The ARIMA model for x_t can be written in the form

$$\phi(B)\delta(B)x_t = \theta(B)a_t \tag{2}$$

where a_t is white noise with variance σ_a^2, $\phi(B)$ denotes the stationary autoregressive (AR) polynomial in B, $\delta(B)$ denotes the nonstationary autoregressive polynomial containing the unit roots, and $\theta(B)$ is the invertible Moving Average (MA) polynomial in B.

We now provide a brief introduction to the canonical decomposition to better understand the new policy adopted.

[1] Exceptions to this rule have been the Quarterly National Accounts and the Harmonised Labour Cost Index, where the seasonally adjusted data had been disseminated before.

SEATS decomposes a series that follows model Eq. (4) into several components: the Trend-cycle, Seasonal, Transitory and Irregular (see [2,9]). The decomposition can be multiplicative or additive. In the following we consider the additive decomposition, because the multiplicative one can be expressed as an additive scheme taking logs.

Let x_t be the sum of four uncorrelated unobserved components (UC).

$$x_t = p_t + s_t + c_t + u_t \tag{3}$$

(where p, s, c and u are the Trend-cycle, Seasonal, Transitory and Irregular components, respectively). The decomposition is obtained from the identity:

$$\frac{\theta(B)}{\phi(B)\delta(B)}a_t = \frac{\theta_p(B)}{\phi_p(B)\delta_p(B)}a_{pt} + \frac{\theta_s(B)}{\phi_s(B)\delta_s(B)}a_{st} + \frac{\theta_c(B)}{\phi_c(B)}a_{ct} + u_t \tag{4}$$

The decomposition assumes orthogonal components, and each component has an ARIMA model.

If the sum of the minima of the spectra of all the components is non-negative, the decomposition is said to be admissible. In this case, in order to identify the components, as much noise as possible will be extracted from each component, except for the irregular one where all the extracted noise is added. The decomposition so achieved is unique and it is called canonical.

Therefore, the components are determined from the factorization of the AR polynomial in the model for x_t.

Let the total AR polynomial $\phi(B)\delta(B)$ of the ARIMA model be factorized as

$$\varphi(B) = \phi(B)\delta(B) = \varphi_r(B)\varphi_s(B^s)\nabla^d\nabla_s^{d_s} \tag{5}$$

where in the TRAMO-SEATS method d_s can only be 0 or 1, $d < 3$, $\varphi_r(B)$ is the stationary regular polinomial in B, of order $p \leqslant 3$, and $\varphi_s(B^s)$ is the stationary seasonal polynomial in B^s, of order $\leqslant 1$. The allocation of the AR roots to the different unobserved components according to their associated frequency, $\phi(B)$ and $\delta(B)$ is as follows:

1. Non-stationary roots:
   - The roots of $\nabla^d = 0$ are assigned to the trend-cycle component.
   - Since $\nabla_s = \nabla S$, where $S = 1 + B + B^2 + \ldots + B^{s-1}$, the roots of $\nabla_s^{d_s}$ are divided into
     * The roots of $\nabla^{d_s} = 0$, that go to the trend-cycle.
     * The roots of $S^{d_s} = 0$, that go to the seasonal component.
2. Stationary roots: If $\varphi_r(B) = 1 + \phi_1 B + \phi_2 B^2 + \ldots + \phi_p B^p$ and $\varphi_s(B) = 1 + \phi_s B^s$ let $z = B^{-1}$ and consider the roots of the polynomials ($B^j = z^{-j}, j = 1, \ldots, p$).

   $$\varphi_r(z) = z^p + \phi_1 z^{p-1} + \phi_2 z^{p-2} + \ldots + \phi_p$$

   $$\varphi_s(z) = z^s + \phi_s$$

   2.1 Roots of $\varphi_r(z)$:

   2.1.1 Real positive roots:

   2.1.1.1 If modulus $\geqslant K$, it is assigned to the trend-cycle.

   2.1.1.2 If modulus $< K$, it is assigned to the transitory component.
   where K by default is 0.5 (input parameter RMOD in TRAMO-SEATS and *Trend boundary* in JDemetra+).

   2.1.2 Real negative roots:

   2.1.2.1 If $s \neq 1$ and modulus $\geqslant K_s$, it is assigned to the seasonal component.

   2.1.2.2 If $s \neq 1$ and modulus $< K_s$, it is assigned to the transitory component.

   2.1.2.3 If $s = 1$ (yearly time series), it is assigned to the transitory component.
   Where K_s = RMOD in TRAMO-SEATS or K_s = Seasonal Boundary = 0.8 in JDemetra+. If $\varphi(B)$ does not contain any other seasonal root then $K_s = 0.9$ (input parameter *Seas. boundary (unique)* in JDemetra+).

   2.1.3 Complex root: Let ω denote the frequency of the root and m its amplitude.

   2.1.3.1 If $\omega \in [$ a seasonal frequency $\pm\epsilon]$ (measured in degrees) and $m > K_s$, it is assigned to the seasonal component.

   2.1.3.2 Otherwise it is assigned to the transitory component.

   By default, $\epsilon = \frac{\pi}{90}$ rad (input parameter EPSPHI (seasonal tolerance) in TRAMO/SEATS and JDemetra+).

   2.2 Roots of $\varphi_s(z)$:
   - If $\phi_s < 0$, letting ϕ denote the real positive root of $(-\phi_s)^{1/s}$, the polynomial $\varphi_s(z)$ can be rewritten as $(z - \phi)(z^{s-1} + \phi z^{s-2} + \phi^2 z^{s-3} + \ldots + \phi^{s-1})$.

  * When $d_s = 1$, the AR root $(1 - \phi B)$ is assigned to the trend; the other (s-1) roots are assigned to the seasonal component.
  * If $d_s = 0$, the root is assigned to the seasonal component whenever $\phi_s < -0.2$ and/or the overall test for seasonality indicates presence of seasonality. Otherwise it is assigned to the transitory component.
- If $\phi_s > 0$, roots are assigned to the transitory component.

There are some exceptions to the previous rules (see [9]).

3. Revision policies

One of the multiple decisions that statisticians have to face on the release of seasonal and calendar adjusted series, is the revision policy when new data become available. There are different revision policies (see [8]) such as:

- Current adjustment: Based on the re-identification and re-estimation of the model, filters, outliers and regression parameters at appropriately set review periods.
- Concurrent adjustment: Based on the re-identification and re-estimation of the model, filters, outliers and regression parameters every time new data become available.

Both of these strategies have some drawbacks. In particular, under current adjustment, we are keeping the model until the next review despite the fact that according to the new evidence perhaps it is no longer acceptable. On the other hand, concurrent adjustment does completely review the model each time we have a new observation of the series. While this ensures that we have a well specified model at each step, it might also result in major revisions from the beginning of the series after each new observation becomes available. This is because re-identification might lead to a model change, thus changing the Wiener-Kolmogorov filter used to extract the seasonal component [10].

Therefore, in practice, the following policies are applied:

- *Partial concurrent adjustment*: The model, filters, outliers and calendar regressors are re-identified once a year and the respective parameters and factors are re-estimated every time new data become available. There are 6 different policies of this type implemented in JDemetra+ (see [11]):
  * *Fixed model*: The ARIMA model, outliers and other regression parameters are not re-identified and the values of all parameters are fixed. The transformation type remains unchanged.
  * *Estimate regression coefficients*: The ARIMA model, outliers and other regression parameters are not re-identified. The coefficients of the ARIMA model are fixed, other coefficients are re-estimated. The transformation type remains unchanged.
  * *Estimate regression coefficients and ARIMA parameters*: The ARIMA model, outliers and other regression parameters are not re-identified. All parameters in the RegARIMA model are re-estimated. The transformation type remains unchanged.
  * *Estimate regression coefficients and last outliers*: The ARIMA model, outliers (except for the outliers in the last year of the sample) and other regression parameters are not re-identified. All parameters in the RegARIMA model are re-estimated. The outliers in the last year of the sample are re-identified. The transformation type remains unchanged.
  * *Estimate regression coefficients and all outliers*: The ARIMA model and regression parameters, except for outliers) are not re-identified. All parameters of the RegARIMA model are re-estimated. All outliers are re-estimated. All outliers are re-identified. The transformation type remains unchanged.
  * *Estimate regression coefficients and ARIMA model*: Re-identification of the ARIMA model, outliers and regression variables, except for the calendar variables. The transformation type remains unchanged.
- *Controlled current adjustment*: Apply current adjustment, checking the results with the ones obtained by "partial concurrent adjustment", which is preferred if a significant difference exists.

So, taking into account all the advantages and disadvantages of the range of policies, the INE started applying *Partial concurrent adjustment: ARIMA parameters*, because this policy has the advantage of the incorporation of the new information when it becomes available, and also fulfills the requirement of presenting

Table 1
Monthly growth rates of the seasonally adjusted service sector turnover index

Period	Final date February	Final date March	March new policy
2000-02-01	−0.1	−0.4	−0.1
2000-03-01	−1.3	−3.6	−1.2
2000-04-01	2.8	6.3	2.6
2000-05-01	−0.6	−1.8	−0.5
2000-06-01	−1.2	−2.5	−1.2
2000-07-01	1.2	3.0	1.1
2000-08-01	0.3	−1.0	0.3
2000-09-01	2.1	3.5	2.0
2000-10-01	−0.2	−1.5	−0.1
2000-11-01	0.3	0.2	0.3
2000-12-01	0.9	3.2	0.9
2001-01-01	−1.9	−4.7	−1.9
2001-02-01	0.5	1.6	0.5
2001-03-01	1.0	2.8	1.0

Table 2
Decomposition

TRAMO model (2,1,0) (0,1,1)	TRAMO model (2,1,0) (0,1,1)
Polynomials Regular AR: 1,00000 + 0,660626B + 0.394167B^2 Seasonal MA: 1,00000 + 0,374738S Regular AR inverse roots argument = 2,1248, modulus = 0,6278, (seasonal frequency) argument = −2,1248, modulus = 0,6278, (seasonal frequency) (a) AR roots February	Polynomials Regular AR: 1,00000 + 0,675585B + 0.393497B^2 Seasonal MA: 1,00000 + 0,368697S Regular AR inverse roots argument = 2,1394, modulus = 0,6273, (td frequency) argument = −2,1394, modulus = 0,6273, (td frequency) (b) AR roots March

Table 3
Decomposition February

Model
`AR: 1.00000+0.660626B+0.394167B^2`
`D: 1.00000-B-B^12+B^13`
`MA: 1.00000-0.374738B^12`

Sa
`D: 1.00000-2.00000B+B^2`
`MA: 1.00000-1.32902B+0.375555B^2`
`Innovation variance: 0.29699`

Trend
`D: 1.00000-2.00000B+B^2`
`MA: 1.00000+0.0781882B-0.921812B^ 2`
`Innovation variance: 0.02630`

Seasonal
`AR: 1.00000+0.660626B+0.394167B^2`
`D: 1.00000+B+B^2+B^3+B^4+B^5+B^6+B^7+B^8+ B^9+B^10+B^11`
`MA: 1.00000+1.01074B+0.832934B^2+ 0.825810B^3+0.726687B^4+0.535348B^5+ 0.253180B^6-0.0967037B^7-0.446693B^8- 0.736845B^9-0.783615B^10-0.583549B^11- 0.494483B^12-0.201170B^13`
`Innovation variance: 0.21854`

Irregular `Innovation variance: 0.13578`

Table 4
Decomposition March

Model
`AR: 1.00000+0.675585B+0.393497B^2`
`D: 1.00000-B-B^12+B^13`
`MA: 1.00000-0.368697B^12`

Sa
`AR: 1.00000+0.675585B+0.393497B^2`
`D: 1.00000-2.00000B+B^2`
`MA: 1.00000-0.914552B-0.0131470B^2- 0.0304396B^3+0.0346963B^4`
`Innovation variance: 0.47221`

Trend
`D: 1.00000-2.00000B+B^2`
`MA: 1.00000+0.0794146B-0.920585B^2`
`Innovation variance: 0.02563`

Seasonal
`D: 1.00000+B+B^2+B^3+B^4+B^5+B^6+B^7+B^8+ B^9+B^10+B^11`
`MA: 1.00000+0.728242B+0.729443B^2+ 1.05674B^3+0.762173B^4+0.556685B^5+ 0.476614B^6+0.272224B^7+0.0655056B^8- 0.236786B^9-0.368317B^10-0.338703B^11`
`Innovation variance: 0.12293`

Transitory
`AR: 1.00000+0.675585B+0.393497B^2`
`MA: 1.00000-0.552735B-0.447265B^2`
`Innovation variance: 0.04454`

Irregular `Innovation variance: 0.11585`

comprehensible data to the users. This last advantage disappeared when we observed the effect of this policy on the huge revisions from the beginning of the series.

The INE started to analyze a new policy, which may be considered a compromise between the *Partial Concurrent Adjustment: ARIMA Parameters* policy and the *Partial Concurrent Adjustment: Fixed Model*. It can be summarized in the following principles:

1. Identify the proper model (ARIMA model, calendar regressors and outliers) once a year (In general, with data up to December of the previous year).
2. Re-estimate all coefficients every time new data become available (monthly or quarterly period) avoiding model changes, on the unobserved components, by:
   (a) Fixing the last estimation of the model with admissible decomposition when a model change is triggered.
   (b) Adjusting root assignment parameters to make sure autoregressive roots remain in the same component.

Table 5
Monthly growth rates

Period	Final date February	Final date March	March new policy	Period	Final date February	Final date March	March new policy
2000-02-01	−0.1	−0.4	−0.1	2015-02-01	−0.4	−1.0	−0.6
2000-03-01	−1.3	−3.6	−1.2	2015-03-01	0.8	−0.1	0.1
2000-04-01	2.8	6.3	2.6	2015-04-01	−0.5	0.6	−0.2
2000-05-01	−0.6	−1.8	−0.5	2015-05-01	0.1	−0.1	0.2
2000-06-01	−1.2	−2.5	−1.2	2015-06-01	−0.4	−1.1	−0.3
2000-07-01	1.2	3.0	1.1	2015-07-01	2.0	3.7	2.0
2000-08-01	0.3	−1.0	0.3	2015-08-01	0.6	−0.8	0.7
2000-09-01	2.1	3.5	2.0	2015-09-01	1.4	2.1	1.6
2000-10-01	−0.2	−1.5	−0.1	2015-10-01	0.7	1.9	0.8
2000-11-01	0.3	0.2	0.3	2015-11-01	−1.3	−3.0	−1.2
2000-12-01	0.9	3.2	0.9	2015-12-01	0.9	2.0	0.7
2001-01-01	−1.9	−4.7	−1.9	2016-01-01	0.4	0.8	0.9
2001-02-01	0.5	1.6	0.5	2016-02-01	0.8	1.6	1.3
2001-03-01	1.0	2.8	1.0	2016-03-01		2.9	1.7

(a) First periods monthly growth rates. Data from January 2000 to February 2016

(b) Final periods monthly growth rates. Data from January 2000 to March 2016

In this way, we still improve the estimation of the model parameters with the new data, while avoiding big revisions, as shown in the example of the next section.

4. Example: Services Sector Turnover Index

This is an example of the huge revisions from the beginning of the series, applying *Partial concurrent adjustment: ARIMA Parameters* policy, with the Services Sector Turnover Index. The series starts in January 2000 and ends in March 2016. The model selected at the beginning of 2016 is (2,1,0)*(0,1,1), with 4 calendar regressors (that account for the effects of working days with holidays, Easter working days, Easter holidays and leap year) and one additive outlier in August 2012.

In February 2016, the seasonal and calendar adjusted series was published applying the *Partial Concurrent Adjustment: ARIMA Parameters* policy. In March 2016, when the seasonal and calendar adjusted series was going to be published, we noticed huge revisions from the beginning of the series, as shown in Table 1.

The second column of the table shows the monthly growth rates of the seasonally adjusted series with data until February 2016, applying *Partial concurrent adjustment: ARIMA Parameters*. The third column shows the rates with data until March 2016, same policy, which are very different. And the last column shows the rates obtained applying our new policy, which are much more similar to those in the second column.

Our first thought was that the new March 2016 observation could be an outlier, which yielded a drastic change in the coefficients estimation of the ARIMA model between the two periods. But we quickly realized that the new observation was not an outlier, the observed value in March 2016 was 119.3203132 $\in$ [98.1, 123.8] (the 95% confidence interval for the forecast).

Later on, we understood clearly that the reason for this significant discrepancy was the different assignment of the complex AR roots to the unobserved components, as we have seen in Section 2.

On one hand, the complex AR roots in February are allocated to the seasonal component, because the argument is 121.74 degrees ($= 2.1248\frac{180}{\pi}$, converting from radians to degrees the argument in the left part of Table 2), higher than the seasonal frequency 120 by less than 2 degrees (default EPSPHI parameter).

On the other hand, the argument of the complex AR roots in March are allocated to the transitory component, because this time the argument is 122,58 degrees ($= 2.1394\frac{180}{\pi}$, converting from radians to degrees the argument in the right part of Table 2), higher than the seasonal frequency 120 by more than two degrees.

This different assignment of the complex AR roots in the two periods, yields a different theoretical model for the components (see Tables 3 and 4). This leads to a change in the corresponding Wiener-Kolmogorov filter, with similar consequences to those of a model change.

So, it is difficult to explain to users, that the growth rates between one period and another change from the beginning of the series because of the argument of the inverse AR roots. After all, the seasonal tolerance parameter (EPSPHI) was by default 2, but it could be changed by the statistician.

The new policy applied at the INE, calculates the proper seasonal tolerance in each period, in order to maintain the assignment of the AR roots to the same component over a year, so preserving the theoretical model for the unobserved components.

In this example, it was considered that the complex AR roots were allocated to the seasonal component throughout the year, so the seasonal tolerance in March 2016 was fixed equal to 2.6. The results shown in Table 5 are the monthly growth rates of the seasonal and calendar adjusted series obtained with Seasonal Tolerance, EPSPHI = 2.6. This policy yields revisions in the final series, but not at the beginning (see Table 5).

Another case with a possible change in the theoretical model for the seasonal component, applying *Partial Concurrent Adjustment: ARIMA Parameters* policy happens when SEATS changes the model selected at the beginning of the year for the series because of a non admissible decomposition for a specific period. Our revision policy implemented checks if SEATS has changed the model, and if that is the case, the estimation of the coefficients of the model obtained in the more recent period (in the current year) with admissible decomposition is used instead of changing the model in the middle of the year. This is the same as applying the *Partial Concurrent Adjustment: Fixed Model* policy for a specific period.

5. Conclusions

Although we know that revisions are necessary in Seasonal Adjustment when new data become available, i.e., the adjustment reflects the new information, it is important to verify that these are reasonable.

If revisions in the final period, (and also in the two previous years), appear, this may be considered as reasonable. If, however, we observe huge revisions from the beginning of the series, this should always raise a red flag.

So, the new revision policy applied at the INE, which can be considered a compromise between the *Partial Concurrent Adjustment: ARIMA Parameters* policy and the *Partial Concurrent Adjustment: Fixed Model*, both implemented in JDemetra+, avoids model changes by: (i) fixing the last estimation of the model with admissible decomposition when a model change is triggered and (ii) adjusting root assignment parameters to make sure autoregressive roots remain in the same component. In this way, we still improve the estimation of the model parameters using the new data, while avoiding big revisions.

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References

[1] Burman JP. Seasonal adjustment by signal extraction. Journal of the Royal Statistical Society, Ser A. 1980; 143: 321-337.
[2] Maravall A, Gómez V. Seasonal adjustment and signal extraction in economic time series. Working Papers Banco de España. 1998; (9809).
[3] Shiskin J, Young A, Musgrave JC. The X-11 variant of the census method II seasonal adjustment program. Bureau of the Census Technical Paper. 1967; (15).
[4] Findley BF, Monsell BC, Bell WR, Chen B. New capabilities and methods of the X-12-ARIMA seasonal adjustment program. Journal of Business and Economic Statistics. 1998; 16: 127-177.
[5] Maravall A, Caporello G. Program TSW. Revised Reference Manual. Banco de España. 2004.
[6] Maravall A. Quality of seasonal adjustment in the model-based approach of tramo-seats. Banco de España. 2016.
[7] SACE. (Seasonal Adjustment Center of Excellence). JDemetra+ online documentation on Github. 2016-2019. Online available at: https://jdemetradocumentation.github.io/JDemetra-documentation/pages/reference-manual.
[8] EUROSTAT. ESS Guidelines on Seasonal Adjustment; 2015.
[9] Maravall A, Caporello G, Pérez D, López R. New features and modifications in tramo-seats. Banco de España. 2014.
[10] Hillmer SC, Tiao GC. An ARIMA-model-based approach to seasonal adjustment. Journal of the American Statistical Association. 1982; 77(277): 63-70.
[11] Grudkowska S. JDemetra+ User Guide, version 2.2; 2017.