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Abstract

The past few years have been marked by the occurrence of many unexpected events that have had many social and economic repercussions, with the COVID-19 pandemic and rising tensions in energy commodity markets standing out above the others. This period of great uncertainty has also had a considerable effect on the production of official economic statistics, undermining the goodness and the predictive capacity of short-term stochastic models. In this condition of extreme unpredictability, there is a need for a strategy of monitoring and reviewing the seasonal adjustment models and anomalous observations, especially over the period 2020-2023. In this work several intervention strategies were defined and tested, focusing over series that manifested a distinct break in their dynamic. Temporary level shifts, included with their lagged versions, have proven to be a particularly useful tool. The outcomes reveal that the policies we considered are effective, and the TRAMO-SEATS procedure manages to be helpful in both ordinary and extraordinary conditions. The whole data analysis has been conducted with JDemetra+ that is a complete and flexible tool in performing several statistical estimates and tests.

Keywords: Seasonal adjustment, structural breaks, outlier detection, intervention variables, JDemetra+.

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1 Introduction

The significant events that took place between 2020 and 2023 heavily impacted the time series data collected by governmental institutions, necessitating interventions on the seasonal adjustment models [1, 2]. Statistical offices carry out seasonal adjustment using the TRAMO-SEATS method [3, 4] or the procedures derived from the X-11-ARIMA methodology [5, 6, 7]. As the decomposition routines of these methods are based on the assumption of stochasticity of the input time series, both methodologies incorporate a pre-treatment step aimed at removing deterministic effects from the time series. In this pre-treatment stage it possible to specify parameters and regressors respectively for a model called TRAMO or RegARIMA. As Gomez and Maravall say [3] the pre-treatment can also be seen as a routine "that polishes a contaminated ARIMA series". "That is, for a given time series, it interpolates the missing observations, identifies outliers and removes their effect, estimates Trading Day and Easter Effect, etc., produces a linear purely stochastic process (i.e., the Arima model)". The selection of RegARIMA specifications is crucial for seasonal adjustment in the case of 2020-2023 economic time series characterized by the influence of many unpredictable and impactful events. For this purpose, in this work, we evaluated the use of the automatic model identification (AMI) method of the software JDemetra+ [8, 9, 10, 11, 12], both independently and in conjunction with external user-defined regressors. In this work we use the TRAMO-SEATS, but the approach we adopt is also suitable for the procedures derived from the X11 software, given that the algorithm implementation for RegARIMA follows the TRAMO logic. Because of this, from now on we will use the terms "TRAMO model" and "RegARIMA" as synonyms. TRAMO-SEATS, together with X13-ARIMA-SEATS is implemented in the software JDemetra+, promoted by Eurostat and officially recommended to scholars and practitioners who are members of the ESS (European Statistical System) and users of the European Central Bank system. This software, in its graphical user interface version, is the main tool employed to carry out the analyses presented in this writing. In section 2, we select and condense the theory necessary to understand the parts of the TRAMO-SEATS procedure we rely on the most, with particular focus on the TRAMO part. Section 3 discusses outliers and intervention variables applicable to linearizing time series data. In section 4 we introduce the algorithm for automatic model identification in the presence of outliers, as implemented in JDemetra+. In Section 5 we present the results of applying three different strategies on two time series that are particularly affected by historical events, which have breaks that need extraordinary intervention. The last section summarizes the results of the work. Finally, an appendix was included, in which we list general recommendations for a user facing a full model revision in an extraordinary historical phase, also giving operational guidance regarding the software JDemetra+.

2 The TRAMO-SEATS methodology

TRAMO-SEATS is a model-based seasonal adjustment method composed of two linked programs: TRAMO and SEATS. TRAMO (Time Series Regression with ARIMA Noise, Missing Observations, and Outliers) executes estimation, forecasting and interpolation of regression models with missing observations and ARIMA errors, in presence of various types of outliers. SEATS (Signal Extraction in ARIMA Time Series) performs an ARIMA-based decomposition into unobserved components [13], each representing the impact of certain types of phenomena on a time series (X_t). These components, the meaning of which is effectively summarized in the JDemetra+ Reference Manual, are:

1. the trend-cycle (T_t) that captures long-term and medium-term behavior (trend) and the smooth, almost periodic movement along them (cycle);
2. the seasonal component (S_t) exhibiting intra-year variations, monthly or quarterly, that recur more or less regularly year after year;
3. the irregular component (U_t) combining all somewhat erratic fluctuations not addressed by the preceding components.

TRAMO-SEATS organizes the components into an additive model $X_t = T_t + S_t + U_t$ or a log additive model $\log(X_t) = \log(T_t) + \log(S_t) + \log(U_t)$, which is subject to the decomposition, is assumed to be a collection of random variables, i.e. a realization of stochastic, covariance-stationary process. However, this is not guaranteed in the overwhelming majority of the time series, which do not have a constant mean due to a trend and to seasonal movements. The variance of these time series may vary in time and usually deterministic effects such as outliers, calendar and regression effects are present. Because of this, time series must undergo a pre-processing step, referred to as preadjustment or linearization, performed with the TRAMO model: the constant variance is usually achieved through taking the logarithmic transformation (i.e. choosing a log additive model for the components) and correcting for the deterministic effects, while the mean is made stationary through regular and seasonal differencing. Our discussion will primarily focus on the TRAMO model, as it presents potential for refining seasonal adjustments in light of the uncertainty of recent years. The TRAMO model is expressed as follows:

$$z_t = y_t'\boldsymbol{\beta} + x_t$$

where z_t is the original time series, x_t is the so called 'linearized series', $y_t\boldsymbol{\beta}$ are the deterministic effects, made by the n regression variables $y_t = (y_{1t}, \ldots, y_{nt})$ and their coefficients $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_\mathrm{n})$. For the following discussion, it is useful to expand the deterministic effects into their components, as follows:

$$y_t'\boldsymbol{\beta} = C_t'\eta + \sum_{j=1}^{k} \alpha_j \lambda_j(B) I_t(t_j) + w_t'\boldsymbol{\gamma}$$

where $C_t'\eta$ are the calendar effects, namely the number of working days, the moving holidays, and leap years, $\alpha_j \lambda_j(B)\, I_t(t_j)$ are the outliers' effects, and $w_t'\boldsymbol{\gamma}$ are the ad-hoc regressors' effects. Regarding calendar effects and ad-hoc regressors, C_t' and w_t' are the regressors (respectively m- and r-dimensional), while η and $\boldsymbol{\gamma}$ are their coefficients. The outliers' effects and parameters are discussed in sections 3 and 4.3.

The linearized series x_t (with mean μ), follows the general ARIMA (p, d, q) (P, D, Q)$_s$ process

$$\varphi(B)\delta(B)(x_t - \mu) = \theta(B)\xi_t$$

where $\varphi(B) = \varphi_p(B)\Phi_P(B^s)$ is a stationary autoregressive (AR) polynomial, $\theta(B) = \theta_q(B)\Theta_Q(B^s)$ is an invertible moving average (MA) polynomial, $\delta(B) = \Delta^d \Delta_s^D$ is a filtering structure, and ξ_t is white noise. Considering s observations per year (frequency of the time series) and defining the backshift operator B, such that $B^k x_t = x_{t-k}$, both the autoregressive and moving average polynomials are made by a regular and a seasonal component, respectively

$$\varphi_p(B) = (1 - \varphi_1 B - \cdots - \varphi_p B^p),$$

$$\Phi_P(B^s) = (1 - \Phi_1 B^s - \cdots - \Phi_P B^{Ps})$$

for the AR, and

$$\theta_q(B) = (1 - \theta_1 B - \cdots - \theta_q B^q),$$

$$\Theta_Q(B^s) = (1 - \Theta_1 B^s - \cdots - \Theta_Q B^{Qs})$$

for the MA. The same applies to the differencing filter, where

$$\Delta^d = (1 - B)^d \quad \text{and} \quad \Delta_s^D = (1 - B^s)^D$$

are respectively the regular and seasonal components.

After estimating the TRAMO model, as described in section 4, the linearized series $\mathrm{x_t}$ is used as an input for the decomposition carried on in SEATS. SEATS decomposes the linearized series (and the ARIMA model) into trend-cycle, seasonal and irregular components, provides forecasts for these components and finally adds back the deterministic effects (that have been previously removed in the linearization process), producing the final components. The computation of the components' estimators is made by applying the Burman algorithm, that approximates the Wiener-Kolmogorov (WK) filter (which is infinite) in a way that it can be applied to the finite series, extended by forecasts and backcasts. The forecasting and the backcasting are made through the ARIMA model previously estimated by TRAMO, with the aim to make the Burman's algorithm applicable at the beginning and at the end of the time series. The procedure is based on the so called "canonical decomposition", namely the decomposition among the admissible ones that maximizes the variance of the irregular component. This decomposition is computed in the frequency domain and involves the allocation of the variance to T_t, S_t or U_t, starting from the assignment of the roots of the AR polynomial among the components according to their module and phase (complex argument).

Although SEATS implements the seasonal adjustment procedure effectively, it is evident that during times of uncertainty and exogenous shocks such as those under consideration, the proper selection of the TRAMO model, upon which SEATS relies, is crucial. In fact, if an outlier effect is not adequately modeled, it could be absorbed into the seasonal component, thereby spreading its influence across the entire time series and leading to revisions. The Handbook on Seasonal Adjustment [14] states that no matter if the effect of an outlier is assigned to the irregular or to the trend component, as long as it has an economic explanation; the important thing is that it is not included in the seasonal. The Handbook also states that the use of external information can be really helpful to reduce revisions. Given that external information is not always available and considering the importance of the preprocessing phase, TRAMO-SEATS incorporates procedures for ARIMA automatic model identification (AMI) and outlier detection, both of which are discussed in section 4.

3 Outliers detection and intervention variables

In recent years, the economy and social life have been profoundly affected by the overlapping of numerous unpredictable events. From a statistical perspective, these disruptions can introduce non-stationarity and non-linearity into the linear framework of ARIMA models and the Box-Jenkins methodology. Correctly identifying such atypical observations (outliers) is crucial, as failure to detect them or incorrect identification can introduce significant bias into the overall configuration of the TRAMO-RegARIMA model and its estimated parameters (see Chapter 7 of The Handbook on Seasonal Adjustment). Specifically, the consequences may include:

1. distortions in the calendar correction component;

2. biased estimation of the ARIMA model parameters for the linearized series;

3. poor specification of the ARIMA model in the automatic model identification (AMI) procedure used in JDemetra+;

4. significant bias in the estimation of the seasonal component;

5. compromised predictive performance, particularly when outliers occur near the end of the sample [15].

The presence of outliers in a time series induces a departure from normality as they weigh down the tails of the frequency distribution. The identification and treatment of outliers is part of the linearization phase of time series, and most importantly, in identifying the correct model. The use of exogenous regressors to model the outliers is crucial for achieving the linearized time series and Gaussian residuals. A linearized time series, which is completely described by its own past and not by other (exogenous) variables, is a necessary (though not sufficient) condition for identifying the most appropriate model.

Remembering the definition of RegARIMA configuration:

$$y_t'\boldsymbol{\beta} = C_t'\eta + \sum_{j=1}^{k} \alpha_j \lambda_j(B) I_t(t_j) + w_t'\gamma + x_t$$

the outliers are parameterized through an unknown parameter α_j, a parameter $\lambda_j(B)$ defining the conformation of the dummy variable, and an *Indicator function* for the presence-absence of the phenomenon. Considering E as the set of time points where the outlier effect is active, we have:

$$I_t(t_j) = \begin{cases} 1, & \text{if } t_j \in E \\ 0, & \text{if } t_j \notin E \end{cases}$$

Let us make a brief presentation of the tools that may be adopted to represent shocks. The simplest and most typical intervention tool is the *Additive Outlier* (AO), which uses the value 1 in the presence of a single specific anomalous observation and 0 in the absence. The effect of this dummy variable is obviously temporary and acts on the irregular component:

$$\lambda_j(B) = 1$$

which results in the regression variable:

$$AO(t, t_1) = \begin{cases} 1, & \text{if } t = t_1 \\ 0, & \text{if } t \neq t_1 \end{cases}$$

The *Temporary change* is a variable that models series level changes with limited duration. The magnitude of the temporary regime is defined by a transition parameter δ, and we have:

$$\lambda_j(B) = \frac{1}{1-\delta B}$$

which results in the regression variable:

$$TC(t,t_1) = \begin{cases} 0, & \text{if } t < t_1 \\ \delta^{(t-t_1)}, & \text{if } t \geq t_1 \end{cases}$$

where δ is the rate of decay for the transitory change outlier (with $0 < \delta < 1$).

A *Level shift* intervenes on the level of the series permanently from a certain observation onward, strongly influencing the trend-cycle component. To be consistent with the coding adopted by JD+, we use the values -1 and 0 for the two stochastic regimes. In terms of B, we have:

$$\lambda_j(B) = \frac{1}{1-B}$$

which results in the regression variable:

$$LS(t,t_1) = \begin{cases} -1, & \text{if } t < t_1 \\ 0, & \text{if } t \geq t_1 \end{cases}$$

Where the level change in the series is not immediate, but a transition period is identified, it is advisable to use a *Ramp effect*:

$$RP(t,t_1,t_2) = \begin{cases} -1, & \text{if } t \leq t_1 \\ \frac{(t-t_1)}{(t_2-t_1)} - 1, & \text{if } t_1 < t < t_2 \\ 0, & \text{if } t \geq t_2 \end{cases}$$

The extraordinary nature of the events that have occurred in recent years consequently warrants extraordinary interventions, especially where outlier identification procedures identify a large cluster of anomalous observations or structural breaks (i.e. a sequence of AO and TC). In these cases, the user is allowed to try the insertion in the RegARIMA model of particular regressors, which can be a mixture of simpler and more typical dummies, or a noncontiguous sequence of zeros and ones. A typical behavior, caused by the restrictions imposed during the pandemic period, has been noted in some time series: a collapse in the value of the series in the first quarter of 2020 (March-April), a slight recovery due to the reopening of country borders (and a less heavy restrictions regime), followed again by new restrictions. These series showed, at the turn of 2021-2022, a return to around the pre-Covid values, on a dynamic path of the first regime. Following these events, into the seasonal adjustment procedure, specific intervention variables can be introduced, which are a mix of simpler and more typical dummies (i.e. AO or TC), or a contiguous, or noncontiguous, sequence of zeros and ones.

We define the *Temporary level shift* as that dummy variable that helps to parametrize a temporary structural break, of a short-to-medium period, between two stochastic regimes:

$$TLS(t, t_1, t_2) = \begin{cases} -1, & \text{if } t \le t_1 \\ 0, & \text{if } t_1 < t < t_2 \\ -1, & \text{if } t \ge t_2 \end{cases}$$

The same applies in the case that the series break is not immediate, but slower: in this occasion, we define a *ramp with a transitory effect*:

$$TRP(t, t_1, t_2) = \begin{cases} -1, & \text{if } t \le t_1 \\ \frac{(t-t_1)}{(t_2-t_1)} - 1, & \text{if } t_1 < t < t_2 \\ -1, & \text{if } t \ge t_2 \end{cases}$$

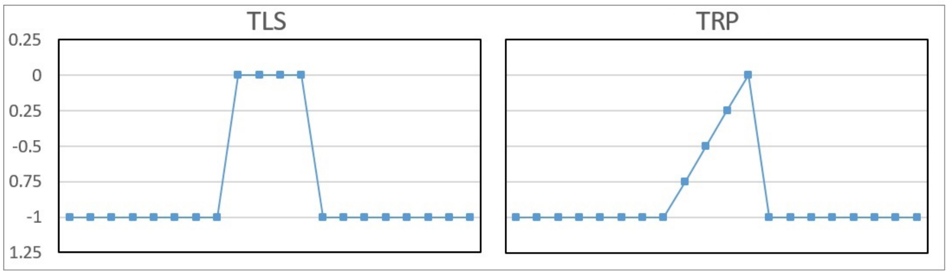

Figure 1: Shape of Temporary Level Shift and Temporary Ramp

JDemetra+ allows users to insert Temporary Level Shifts (TLS), Temporary Ramps (TR), and other custom "user-defined variables" through external files. It is also possible to input the delayed version of these variables. User-defined regression variables must be associated with a specific component, ensuring that effects that should be linked to another component are not included. Therefore, the following rules must be respected:

1. variables associated with the trend component must not include a seasonal pattern;

2. variables associated with the seasonal component should have a zero mean to exclude both trend and level components;

3. variables associated with the irregular component should have zero mean to exclude both seasonal patterns and trend components.

Considering that the shocks during the period of 2020-2023 are not seasonal and it is challenging to design a variable with a zero mean to assign to the irregular component, we will use user-defined variables assigned to the trend.

A particular type of outlier is the *Seasonal Outlier* (SO), which reflects a change in the typical seasonal pattern at a particular time point (t_1), while maintaining the overall level of the series by distributing a counterbalancing change across the remaining periods within the season. It is modeled by the regression variable:

$$SO(t, t_1, s) = \begin{cases} 0, & \text{if } t < t_1 \\ 1, & \text{if } t \geq t_1, \text{ and } t \text{ is in the same month/quarter as } t_1 \\ \frac{-1}{(s-1)}, & \text{otherwise} \end{cases}$$

where s is the frequency of the time series (12 for a monthly time series, 4 for a quarterly one).

Some other particular shape variables have been theorized and are specifiable analytically thanks to the custom "intervention variables" option in the seasonal adjustment software [16]. These variables are defined, for times t between t_1 and t_2, as:

$$\lambda_j(B) = \frac{1}{(1 - \delta B)(1 - \delta_s B^s)}$$

where the tunable parameters δ and seasonal δ_s range between 0 and 1. If the seasonal delta is set to 0, the effect of the intervention is attributed to the trend-cycle; otherwise, it affects the seasonal component. With this formula, all the previous outliers are obtainable. For example, with $\delta = 0$ and $\delta_s = 0$, we get temporary level shifts between t_1 and t_2. Another complex shape obtainable with intervention variables is the quadratic ramp, used by Foley [17] for the seasonal adjustment of some Irish time series during the Covid-19 period.

The expression *intervention variable* is used in the rest of this work in a general sense, and it can be mapped to both the JDemetra+ intervention variables (specified analytically, as described in this section) and user-defined variables (defined externally by the user, specifying their values for each time).

It should be noted that there are specific differences between dummy variables and intervention variables. The outliers, which are not identifiable a priori, are necessary to linearize the series that must be decomposed with filters later, and to remove spurious effects on the Autocorrelation Function and bias on model parameters and forecasts. Instead, the intervention variables are justified in their use by the possession of information about the

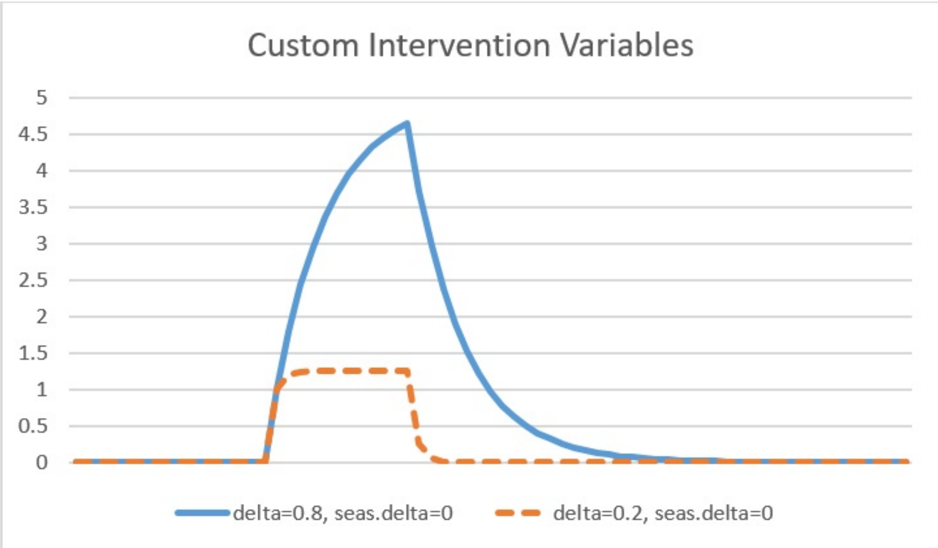

Figure 2: Some shapes of Intervention Variables

Outlier	Component effect	Effect duration
Additive outlier AO	Irregular component	Temporary effect
Temporary change TC	Irregular component	Temporary effect
Level shift LS	Trend-Cycle component	Permanent effect
Seasonal outlier SO	Seasonal component	Permanent effect
Ramp RA	Trend-Cycle component	Permanent effect
Temporary Level Shift TLS	Trend-Cycle component	Temporary effect
Temporary Ramp TRA	Trend-Cycle component	Temporary effect

Table 1: Taxonomy of outliers and features

events that occurred, and thus, although they are a mixture of basic dummies, there are different motivations for their inclusion in regression models, sometimes sacrificing even their statistical significance.

4 Automatic model identification and outlier detection

The automation of model selection and outlier identification was introduced in TRAMO-SEATS as a response to the need for objectivity and robustness in modeling. These procedures allow the analysts to reduce modeling time and to have a starting setting for their work. The specifications found by the automatic algorithm can already be explanatory of some of the time series dynamics and are also optimized on some important parameters for identifying a good model. Although these procedures are well-established, the guidelines on seasonal adjustment still suggest a subsequent intervention by the analyst, who must guarantee that the modeling is motivated by the socio-economic scenario it aims to represent.

JDemetra+ implements the same algorithm for automatic model identification in the presence of outliers as the program TRAMO-SEATS by Gomez and Maravall. This procedure also tests for the log level specification, trading days, and Easter effects. To explain this important procedure for our work, we share its description taken from the paper "Automatic modelling methods for univariate time series" [18] in section 4.4. Before presenting the full algorithm, we briefly outline the sub-procedures on which it relies, including the methods for determining the regular and seasonal differencing orders for an ARIMA model, and the procedure for automatic model identification, outlier detection, and correction. All of these methods were proposed by Gomez as an improved version of the procedure by Chen and Liu [19]. From now on, when we talk about the Chen-Liu procedure, we will refer to Gomez's improved version.

4.1 Obtaining the differencing orders

The procedure for determining the differencing orders, d and D, for an ARIMA model follows these steps:

1. Estimate an AR(2)(1) model;
2. Perform unit root tests to identify the number of unit roots. A root is considered unitary if its modulus falls within a customizable threshold, typically set between 0.97 and 1;
3. Apply the differencing orders given by the number of unit roots found in the previous step to an ARMA (1,1) (1,1) model to remove the identified unit roots;
4. Repeat the process if new unit roots emerge, halting when no additional unit roots are found;
5. Use the residuals from the final estimated model to determine whether a mean should be specified.

4.2 Automatic model identification

In Gomez's automatic model identification algorithm, the identification of an ARMA (p, q) model is realized through an optimized version of the Hannan and Rissanen's (HR) method [20] which chooses a model considering a penalty function based on BIC criterion. The optimized version of HR methodology was proposed by Gomez and originally implemented by the software TRAMO-SEATS. Gomez's version of HR is computationally faster than the original, thanks to a heuristic strategy that avoids computing the BIC for every combination of p, q, P, and Q. This strategy is also tailored to avoid the tendency of BIC to overparametrize, especially in the seasonal part, and to choose balanced models (i.e., with the same degrees for AR and MA parts). Given that this approach operates a reduction of the research space, although it has proven to be very satisfactory in practice [21, 22], users must always consider that models suitable for the data could be sacrificed in the name of the criteria that drives the heuristic.

HR is an algorithm to get an approximate estimation of the coefficients of an ARMA model by means of fast linear routines (OLS). TRAMO uses it everywhere (not only for ARMA identification). The identification of the ARMA model uses the BIC that is derived from HR.

4.3 Outlier detection

The article by Chen and Liu [19] shows that even if the model is properly specified, outliers may still lead to bias in parameter estimates, thus potentially impacting the effectiveness of outlier detection. This results in the identification of the so-called "spurious outliers". On the other hand, some other outliers may not be identified due to a "masking effect". A common workaround for these issues involves adopting procedures that iterate between parameter estimation and outlier detection to achieve a joint estimation of the two.

For outlier identification, Gomez's procedure presupposes the knowledge of the orders $(p,\ d,\ q)$ $(P,\ D,\ Q)$ of the ARIMA model and that desired regression effects are included.

To detect an outlier of a specific type $j \in \{\mathrm{AO}, \mathrm{TC}, \mathrm{LS}, \mathrm{SO}\}$ its estimator $\widehat{\alpha_j}(t) = (\hat{X}'\hat{X})^{-1}\hat{X}'\widehat{r^*}$ and statistic $\widehat{\tau_j}(t) = \left(\hat{X}'\hat{X}\right)^{1/2}\hat{X}'\widehat{\alpha}_j/\widehat{\sigma}$ must be computed, where $\widehat{r^*}$ are the residuals of the model including the outlier, $X = L^{-1}Y$ where L is the inverse of the Cholesky factor from $\mathrm{Var}(z_t)$.

Given a critical value C (typically around 3.5) the type of the outlier is chosen between a set of desired types $tp \subseteq \{\mathrm{AO}, \mathrm{TC}, \mathrm{LS}, \mathrm{SO}\}$ taking the type j for which the absolute value of the statistic is the highest (and greater than C). To sum up, the statistic for the outlier detected at time t is $\lambda_t = \max_j |\widehat{\tau_j}(t)|$ where $j \in tp$.

In the first step of the algorithm, outliers are identified iteratively one by one, modifying the parameters of the model after each outlier has been identified. When outlier detection no longer identifies any outliers, the procedure goes to the second step, wherein a multiple regression is estimated. The procedure then removes the outlier with the lowest t-value and restarts the iteration from the first step. The technique employed to include or discard outliers resembles stepwise regression used to choose the best regression equation. The difference between Gomez's and the original Chen-Liu procedures lies in this stepwise regression instead of a backward elimination approach, which results less robust.

4.4 Overall procedure

After introducing its main parts, we present the complete procedure for estimating the TRAMO model included in JDemetra+, derived from the TRAMO-SEATS software. The following algorithm is reported as it is described by Gomez and Maravall [18].

- *Preliminary* tests. If desired by the user, the procedure can test for the log-level specification, trading days, and Easter effects. Since trading days and Easter effects are modeled using regression variables, the first are tested with an F-test on their coefficients (since they could be 6 variables), while for the second a t-test is sufficient. These tests are performed using the default ARIMA (0,1,1) (0,1,1) model. The log-level specification is tested through the Box-Cox transformation.

- *Initialization.* If the user wants the series to be corrected for outliers, accept the model specified by the user (the default model is the airline model) and go to step 3. Otherwise, go to step 1. The critical value C for outlier detection can be either entered by the user or specified by the procedure. In this last case, the value of C is chosen depending on the length of the series. The critical value at this stage should not be low because we want to correct the series for the effects of the biggest outliers, which are the outliers that can distort most the automatic model identification procedure.

- *Step 1.* If the user has specified the differencing orders and whether there should be a mean in the model, go to step 2. Otherwise, the series is first corrected for all regression effects, if any. Then, using the corrected series, the differencing orders for the ARIMA model are automatically obtained and, also automatically, it is decided whether to specify a mean for the series or not. Go to step 2.

- *Step 2.* Perform automatic identification of an ARMA (p, q) model for the differenced series, corrected for all outliers and other regression effects, if any. If the user wants to test for trading days and Easter effects and any of these effects were specified in the preliminary tests, check whether the specified effects are significant for the new model. If the user wants to correct the series for outliers, go to step 3. Otherwise, stop.

- *Step 3.* Assuming the model is known, perform automatic detection and correction of outliers using C as the critical value. If a stop condition is not satisfied, perhaps decrease the critical value C and go to step 1. This cycle can be repeated several times until a satisfactory model is found. Usually, two iterations are enough.

In this work, we employ a critical value C=4: experience has taught us that this is a good value to detect outliers that remain significant over time, and especially for monthly series, it allows for more selectivity in identifying outliers.

5 Empirical Evidences

In this section, we present some applications on official data during the concurrent review phase of seasonally adjusted data. Our purpose is to test, on those time series that have undergone permanent or temporary structural breaks, the best strategy for modeling the extraordinary period from 2020 to 2023, also taking into account the historical events in Italy. Below is a brief chronology of the main measures decided in Italy to deal with the Covid-19 pandemic:

1. *January 31, 2020*: the Italian government declares a state of health emergency for six months following the first confirmed case of Covid-19 in the country;

2. *March 9, 2020*: the "phase 2" is announced, shutting down all non-essential activities;

3. *May 4, 2020*: the "phase 2" begins with the gradual reopening of economic activities;

4. *May 25, 2020*: "phase 3" begins with the reopening of bars, restaurants, stores, and gyms;

5. *November 3, 2020*: a night curfew is introduced in some regions of Italy to counter the spread of the virus;

6. *April 2021*: new rules are issued, providing further restrictions and closures to counter the third wave of Covid-19.

We considered three intervention scenarios on the estimates (concurrent revision policy), using the cleaned-up model for the period 2020-2023 as a comparison series:

1. in the first scenario, we apply the automatic integral estimation procedure of the RegARIMA model (Chen-Liu procedure, AMI – Automatic Model Identification);

2. in the second scenario, we consider the introduction of an extraordinary ad-hoc intervention variable (a TLS or a TRamp);
3. in the third scenario, we consider a mixture of intervention variables and typical outliers (AO, TC), following the guidance of the AMI procedure.

We selected two important official series (quarterly and monthly frequency) that show a clear break in the first quarter of 2020, coinciding with the spread of the pandemic and government interventions. All estimates, results, and graphs were carried out using JDemetra+ (GUI version 2.2.2) and the TRAMO-SEATS procedure. To measure the quality of seasonal adjustment, we chose tests for the independence and normality of residuals. Other metrics include relative differences and the root mean squared error (*rmse*) in the revision history of the seasonally adjusted series for the last two years.

The relative differences are computed as follows:

- For the additive decomposition:

$$R^A_{t|N} = A_{t|N} - A_{t|t}$$

- For the multiplicative decomposition:

$$R^A_{t|N} = 100 \times \frac{A_{t|N} - A_{t|t}}{A_{t|t}}$$

The *rmse* is also computed by comparing $A_{t|t}$ with $A_{t|N}$.

5.1 Expenditure by Non-Residents in Italy

Scenario 1: Automatic Model Identification

Summary

Estimation span: [I-1995 - IV-2023]
116 observations
No trading days effects
No easter effect
5 detected outliers
Final model

Likelihood statistics

Number of effective observations = 112

Number of estimated parameters = 8

Loglikelihood = -838.3426359552301
Standard error of the regression (ML estimate) = 430.4182028319966
AIC = 1692.6852719104602
AICC = 1694.0833301628875
BIC (corrected for length) = 12.424420781013001

ARIMA model

[(0,0,1)(0,1,0)]

	Coefficients	T-Stat	P[|T| > t]
Theta(1)	0,5351	6,49	0,0000

Regression model

Mean

	Coefficient	T-Stat	P[|T| > t]
mu	224,3795	3,40	0,0010

Outliers

	Coefficients	T-Stat	P[|T| > t]
TC (II-2020)	-8794,0336	-24,41	0,0000
TC (II-2021)	-5632,9812	-15,59	0,0000
TC (I-2020)	-2361,1279	-7,46	0,0000
LS (IV-2021)	2479,1561	7,94	0,0000
LS (III-2020)	-1600,4355	-5,14	0,0000

Analysis of the residuals

Summary

1. Normality of the residuals

	P-value
Mean	0,9942
Skewness	0,3790
Kurtosis	0,7066
Normality	0,5168

2. Independence of the residuals

	P-value
Ljung-Box(16)	0,8365
Box-Pierce(16)	0,8959
Ljung-Box on seasonality(2)	0,4747
Box-Pierce on seasonality(2)	1,0000

Durbin-Watson statistic: 2,0489

Relative differences (%)
mean = -0,5858
rmse = 9,1300

	2019	2020	2021	2022	2023
Q1		2,920	0,070	2,620	1,291
Q2		4,257	12,028	-1,532	0,408
Q3		-33,082	-0,679	-1,561	0,151
Q4	0,829	-3,751	6,255	0,402	

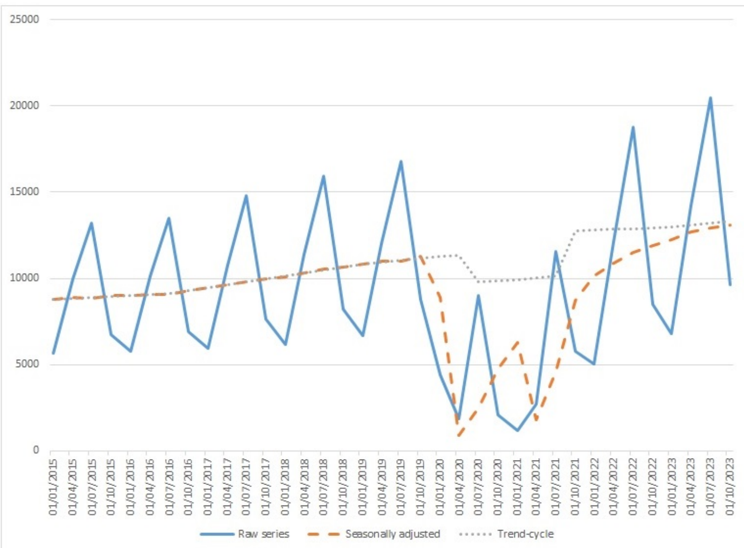

Figure 3: Raw Series, SA Series, and Trend in Chen-Liu Procedure (Scenario 1)

Scenario 2: Intervention Variable

Summary

Estimation span: [I-1995 - IV-2023]
116 observations
No trading days effects
No easter effect

Final model

Likelihood statistics
Number of effective observations = 112
Number of estimated parameters = 4

Loglikelihood = -919.0205742945475
Standard error of the regression (ML estimate) = 884.2716491644231
AIC = 1846.041148589095
AICC = 1846.4149803647958
BIC (corrected for length) = 13.695916984357854

ARIMA model
[(0,0,1)(0,1,0)]

	Coefficients	T-Stat	P[|T| > t]
Theta(1)	0,5809	7,45	0,0000

Regression model
User variables

	Coefficients	T-Stat	P[|T| > t]
TLS	-2860,0118	-6,36	0,0000
TLS [-1]	-3575,5481	-8,79	0,0000

Analysis of the residuals

Summary

1. Normality of the residuals

	P-value
Mean	0,1066
Skewness	0,0000
Kurtosis	0,0000
Normality	0,0000

2. Independence of the residuals

	P-value
Ljung-Box(16)	0,7297
Box-Pierce(16)	0,8025
Ljung-Box on seasonality(2)	1,0000
Box-Pierce on seasonality(2)	1,0000

Durbin-Watson statistic: 1,9811

Relative differences (%)
mean = 2,4665
rmse = 10,1908

	2019	2020	2021	2022	2023
Q1		-12,355	23,194	1,750	4,915
Q2		14,048	11,912	-12,112	2,077
Q3		5,514	10,067	-6,995	1,389
Q4	-5,107	-11,631	10,117	2,682	

Scenario 3: Mixed Strategy

Summary

Estimation span: [I-1995 - IV-2023]
116 observations
No trading days effects
No easter effect
3 detected outliers

Final model

Likelihood statistics

Number of effective observations = 112
Number of estimated parameters = 7

Loglikelihood = -845.5505318602216
Standard error of the regression (ML estimate) = 458.83034892742666
AIC = 1705.101063720443
AICC = 1706.1779867973662
BIC (corrected for length) = 12.510137788363888

ARIMA model

[(0,0,1)(0,1,0)]

	Coefficients	T-Stat	P[|T| > t]
Theta(1)	0,5936	7,59	0,0000

Regression model

Mean

	Coefficient	T-Stat	P[|T| > t]
mu	245,1299	3,46	0,0008

Outliers

	Coefficients	T-Stat	P[|T| > t]
TC (II-2020)	-8393,8438	-22,37	0,0000
AO (II-2021)	-5741,0915	-15,35	0,0000
AO (III-2021)	-3264,6948	-9,63	0,0000

User variables

	Coefficients	T-Stat	P[|T| > t]
TLS	-2095,7954	-8,69	0,0000

Analysis of the residuals

Summary

1. Normality of the residuals

	P-value
Mean	0,9945
Skewness	0,7598
Kurtosis	0,3965
Normality	0,3599

2. Independence of the residuals

	P-value
Ljung-Box(16)	0,6773
Box-Pierce(16)	0,7742
Ljung-Box on seasonality(2)	0,5047
Box-Pierce on seasonality(2)	1,0000

Durbin-Watson statistic: 2,0195

Relative differences (%)

mean = -2,5660
rmse = 10,2551

	2019	2020	2021	2022	2023
Q1		2,667	6,054	2,933	2,731
Q2		-32,559	-5,136	1,552	1,727
Q3		-11,804	-18,971	0,378	0,371
Q4	0,175	1,026	3,782	4,016	

Generally, the goal of these procedures is to minimize revisions in the corrected and seasonally adjusted series. However, in this extraordinary social and economic phase, revision might not be the best indicator of a model's effectiveness. We find that in this period of extraordinary events, updating parametric models and efficiently representing breaks in series is more crucial, especially when some national accounts data undergo an extraordinary revision of definitions and methodologies.

Let us comment on the results: In all three intervention strategies, JD+ releases a "good" encoding in the synthetic parameter summary, although difficulties arise in identifying the best model due to numerous and impactful outlier observations. The Chen-Liu procedure (Scenario 1) succeeds in identifying and representing the extraordinary period of 2020-2022 fairly well. However, the model identified by the information criterion is not parsimonious and lacks full statistical significance, despite strong cyclical signals at frequencies of 0.40 and 1.33, as seen in the periodogram and auto-regressive spectrum.

Several Seasonal-ARIMA models were tested, and the same pre-crisis model (0,0,1)(0,1,0) was selected to adhere to the "golden rule" of adopting parsimonious models. Diagnostics significantly improve over the previous model, which had compromised performance. The new model has good results for both the independence of the residuals and their Gaussian distribution. Five outliers were identified in 2020 and 2021, two of which are LS (2020 Q3 and 2021 Q4), clearly indicating a temporary structural break.

Testing a single intervention variable, such as a Temporary Level Shift (TLS, start 2020 Q1, end 2021 Q4), leads to interesting results. The selected model is similar to the first scenario, but diagnostics improve with a lag in the TLS, especially in terms of seasonally adjusted series fluctuations. This model with lagged TLS minimizes seasonal adjustment revisions during 2020-2021, but performance worsens outside this period.

	Chen-Liu	TLS	TLS+TLS_1	MIX
2019-01-01	-700.41	-269.84	-412.19	-763.61
2019-04-01	2152.17	1392.12	1721.78	2241.34
2019-07-01	-2220.96	-2474.54	-2104.01	-2279.04
2019-10-01	-2939.53	-2448.28	-2249.63	-2866.31
2020-01-01	-1779.35	-903.44	-590.31	-1757.91
2020-04-01	2217.51	1178.68	75.67	2471.98
2020-07-01	1759.44	1082.55	553.21	1305.23
2020-10-01	-2220.65	-1647.51	-754.18	-2296.83
2021-01-01	-3335.58	-2047.00	-1617.19	-3319.49
2021-04-01	1976.94	1071.24	-680.88	2328.07
2021-07-01	352.08	-609.88	-479.48	296.27
2021-10-01	-1660.12	-959.94	519.84	-1442.01
2022-01-01	-1616.54	-633.56	-199.96	-2093.47
2022-04-01	301.69	-616.98	-1227.52	157.25
2022-07-01	-1060.75	-1983.37	-1696.66	-1066.51
2022-10-01	58.98	1037.65	284.31	299.73

Table 2: Revision Error of SA Data in Several Scenarios (2019-2022)

In the third scenario, the mixed strategy provides the best results regarding diagnostics of the TRAMO model, with a more parsimonious model selected for both typical outliers and a temporary TLS without lags. The results indicate that automatic procedures work well but tend to include too many outliers. An intervention variable improves the fit during its period of application, but overall performance may suffer. The mixed strategy might be the right compromise, with TRAMO-SEATS and JD+ showing great adaptability to large volume shocks. The major difference between the scenarios lies in the use of variables (LS or ramps) that influence the trend component, which is important for statistical offices or academics interested in extracting and publishing cycle-trend series.

5.2 Nights Spent by Italian Citizens in Hotels and Similar Establishments

Scenario 1: Automatic Model Identification

Summary

Estimation span: [1-2000 - 11-2023]
287 observations
Trading days effects (1 variable)
Easter [6] detected
8 detected outliers

Final model

Likelihood statistics
Number of effective observations = 274
Number of estimated parameters = 15

Loglikelihood = -3965.380900236518
Standard error of the regression (ML estimate) = 457439.1057256462
AIC = 7960.761800473036
AICC = 7962.622265589314
BIC (corrected for length) = 26.353600271219427

Arima model
[(0,1,2)(1,1,1)]

	Coefficients	T-Stat	P[|T| > t]
Theta(1)	-0,5049	-8,73	0,0000
Theta(2)	-0,3722	-6,44	0,0000
BPhi(1)	-0,3823	-5,02	0,0000
BTheta(1)	-0,8697	-20,07	0,0000

Regression model
Working days

	Coefficients	T-Stat	P[|T| > t]
Week days	-37994,1874	-4,57	0,0000

Easter [6]

	Coefficients	T-Stat	P[|T| > t]
Easter [6]	318447,3425	3,38	0,0008

Outliers

	Coefficients	T-Stat	P[|T| > t]
LS (3-2020)	-5578703,9938	-13,93	0,0000
TC (6-2020)	-3416230,5421	-7,64	0,0000
TC (8-2020)	3908825,1820	8,49	0,0000
LS (7-2021)	4253104,1656	14,97	0,0000
AO (7-2023)	-2587679,5833	-6,20	0,0000
LS (7-2020)	3027512,4369	8,54	0,0000
LS (4-2020)	-2200404,8691	-4,91	0,0000
AO (8-2021)	1581657,2175	4,06	0,0001

Analysis of the residuals

Summary

1. Normality of the residuals

	P-value
Mean	0,8721
Skewness	0,2746
Kurtosis	0,0429
Normality	0,0647

2. Independence of the residuals

	P-value
Ljung-Box(24)	0,9112
Box-Pierce(24)	0,9312
Ljung-Box on seasonality(2)	0,9995
Box-Pierce on seasonality(2)	0,9996

Durbin-Watson statistic: 2,0101

Relative differences (%)
mean = -1,5424
rmse = 15,1476

	2019	2020	2021	2022	2023
January		0,487	7,251	-1,552	-1,064
February		0,232	3,099	0,713	-0,766
March		9,160	7,860	-0,021	-0,721
April		13,077	8,239	0,280	-0,171
May		-0,954	5,239	1,158	1,079
June		-101,743	0,707	1,357	1,714
July		-2,976	-1,370	1,010	-3,596
August		-0,983	-2,332	0,718	-0,009
September		-7,198	-2,339	1,793	-0,055
October		-6,711	-2,453	1,017	-0,086
November	-0,244	-1,850	-2,352	1,056	
December	-0,271	3,493	-2,591	-0,370	

Scenario 2: Intervention Variable

Summary

Estimation span: [1-2000 - 11-2023]
287 observations
Trading days effects (1 variable)
Easter [6] detected

Final model

Likelihood statistics
Number of effective observations = 275
Number of estimated parameters = 9

Loglikelihood = -4073.752489444529
Standard error of the regression (ML estimate) = 641809.7084448666
AIC = 8165.504978889058
AICC = 8166.184224172077
BIC (corrected for length) = 26.907491246275022

Arima model
[(2,0,0) (0,1,1)]

	Coefficients	T-Stat	P[|T| > t]
Phi(1)	-0,6503	-10,76	0,0000
Phi(2)	0,1692	2,79	0,0057
BTheta(1)	-0,7957	-19,04	0,0000

Regression model
Working days

	Coefficients	T-Stat	P[|T| > t]
Week days	-45806,8428	-5,09	0,0000

Easter [6]

	Coefficients	T-Stat	P[|T| > t]
Easter [6]	306234,0987	2,18	0,0301

User variables

	Coefficients	T-Stat	P[|T| > t]
TLS	4725953,9370	10,61	0,0000
TLS [-1]	1083598,0713	2,47	0,0141
TLS [-2]	-1149387,9090	-2,56	0,0109

Analysis of the residuals

Summary

1. Normality of the residuals

	P-value
Mean	0,9131
Skewness	0,0001
Kurtosis	0,0000
Normality	0,0000

2. Independence of the residuals

	P-value
Ljung-Box(24)	0,1067
Box-Pierce(24)	0,1476
Ljung-Box on seasonality(2)	0,4262
Box-Pierce on seasonality(2)	0,4450

Durbin-Watson statistic: 1,9874

Relative differences (%)
mean = -0,5813
rmse = 12,0433

	2019	2020	2021	2022	2023
January		1,757	-0,270	-1,506	-0,321
February		-3,741	4,142	0,009	-0,207
March		-42,197	1,610	-0,592	-0,473
April		-38,101	-0,081	-0,513	-0,121
May		-1,342	-0,453	0,442	-0,257
June		-39,537	-4,217	-0,290	-0,213
July		26,399	1,802	3,190	0,595
August		25,610	0,007	-1,100	-0,140
September		21,015	0,260	-0,040	0,037
October		14,091	-0,606	-0,184	-0,024
November	0,448	9,551	-0,337	-0,048	
December	1,224	-1,744	-1,282	-0,153	

Scenario 3: Mixed Strategy

Summary

Estimation span: [1-2000 - 11-2023]
287 observations
Trading days effects (1 variable)
Easter [6] detected
1 pre-specified outlier
5 detected outliers

Final model

Likelihood statistics
Number of effective observations = 274
Number of estimated parameters = 14

Loglikelihood = -3964.2868385350957
Standard error of the regression (ML estimate) = 458674.899240557
AIC = 7956.5736770701915
AICC = 7958.195298691813
BIC (corrected for length) = 26.338510212162152

Arima model
[(1,1,1)(0,1,1)]

	Coefficients	T-Stat	P[|T| > t]
Phi(1)	-0,4172	-5,73	0,0000
Theta(1)	-0,9042	-25,66	0,0000
BTheta(1)	-0,6215	-12,37	0,0000

Regression model
Working days

	Coefficients	T-Stat	P[|T| > t]
Week days	-41651,9244	-5,96	0,0000

Easter [6]

	Coefficients	T-Stat	P[|T| > t]
Easter [6]	339920,8451	3,24	0,0013

Prespecified outliers

	Coefficients	T-Stat	P[|T| > t]
AO (2-2021)	1500214,8923	3,90	0,0001

Outliers

	Coefficients	T-Stat	P[|T| > t]
AO (6-2020)	-3967978,7793	-10,43	0,0000
TC (8-2020)	4261358,6086	9,53	0,0000
AO (7-2023)	-2444866,0259	-5,75	0,0000
TC (5-2021)	2933374,2220	7,09	0,0000
TC (9-2020)	2059027,3370	4,74	0,0000

User variables

	Coefficients	T-Stat	P[|T| > t]
TLS	5047950,4969	16,87	0,0000
TLS [-1]	1468150,1119	4,73	0,0000

Analysis of the residuals

Summary

1. Normality of the residuals

	P-value
Mean	0,9845
Skewness	0,5315
Kurtosis	0,0802
Normality	0,1174

2. Independence of the residuals

	P-value
Ljung-Box(24)	0,7087
Box-Pierce(24)	0,7569
Ljung-Box on seasonality(2)	0,4468
Box-Pierce on seasonality(2)	0,4655

Durbin-Watson statistic: 2,0080

Relative differences (%)
mean = -0,9654
rmse = 9,1090

	2019	2020	2021	2022	2023
January		1,074	6,739	-2,896	-0,566
February		-1,471	-1,899	-0,371	-0,531
March		-40,536	10,263	2,753	-0,199
April		12,590	5,201	2,532	0,034
May		7,249	1,760	2,143	0,430
June		-42,081	2,476	4,528	1,115
July		4,102	-2,199	1,028	-0,990
August		-1,480	-3,033	-1,038	-0,003
September		-3,064	-4,552	0,350	-0,011
October		-1,079	-4,480	0,258	-0,058
November	0,418	2,740	-2,474	0,314	
December	0,894	0,992	-3,271	-0,033	

This section focuses on monthly data, which show a significant number of outliers during 2020-2022. As depicted in Figure 4, the series exhibits distinct peaks during the summer months, particularly in August, and minor peaks in December and April corresponding with statutory holidays. During the Covid-19 pandemic, the series experiences a general decrease in its level, with minor peaks in December and April being smoothed out, especially the latter. The results of seasonal adjustment in the first and third scenarios are nearly identical, showing a clear smoothing of the minor peaks in spring and December, as well as a hidden negative peak in July 2020.

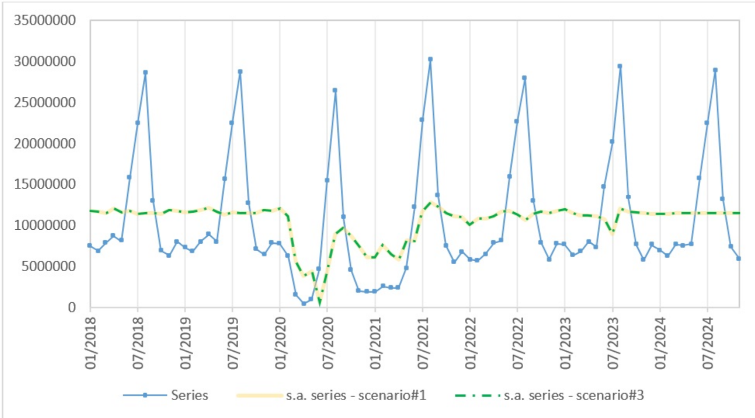

Figure 4: Original and Seasonally Adjusted Time Series

Monthly time series models are generally more complex than quarterly ones, as they involve more parameters, such as effects for Easter and trading days, which are absent in quarterly models. We explore the feasibility of incorporating external variables to reduce model complexity, given the higher granularity of monthly data. Our analysis reveals that simple user-defined variables, along with their lagged versions, can generate robust models for seasonal adjustment.

In evaluating the models, we prioritize achieving independence in the RegARIMA residuals and ensuring normality. If the residuals respect these assumptions, SEATS is likely to produce a good result.

In the first scenario (Chen-Liu procedure), the trend shows a deep depression from March to June 2020, during the “hard” lockdown, when activities were substantially closed. The crisis persisted with reduced intensity until July 2021. The seasonally adjusted series during this period is still influenced by irregular components, capturing variations due to restrictions and Covid-19 spread. Introducing a TLS with lagged versions in scenarios 2 and 3 alters the equilibrium between trend and irregular components. The third scenario, which includes outliers detected automatically with minimal intervention, yields the best diagnostics, with normal residuals and excellent independence.

The revision history table below shows that the third scenario outperforms the first. While the second scenario shows favorable results regarding mean relative differences and estimated parameters, its significant deviation from normality in the RegARIMA residuals renders it less reliable. Thus, user-defined variables and lagged versions, combined with outliers, reduce revisions and enhance the normality of the RegARIMA residuals.

	1st Scenario	*2nd Scenario*	*3rd Scenario*
Revision history: relative differences (%)			
mean	*-1,5424*	*-0,5813*	*-0,9654*
rmse	*15,1476*	*12,0433*	*9,1090*
RegARIMA residuls: p-values			
Normality	*0,065*	*0*	*0,117*
Independence	0,715	*0,107*	*0,709*
RegARIMA estimation			
Number of parameters	15	*9*	*14*

Table 3: TRAMO-SEATS diagnostics in the selected scenarios

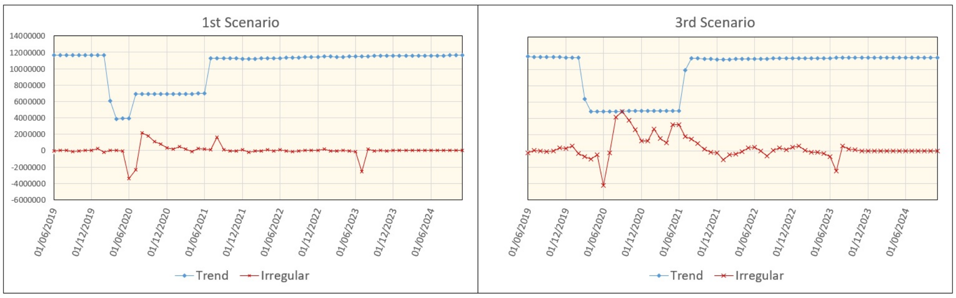

Figure 5: Focus on the trend and irregular components

Conclusion

The last few years are showing numerous signals of the entrance into an unstable historically transitional phase. National statistical offices have been challenged by the Covid-19 pandemic event and tensions in various strategic commodity markets. These events, which we can classify likely as *black swans*, have created considerable problems in estimating officially released short-term economic data. At some distance in time, we can make a more detached judgment and intervene with tools that econometric and statistical theory makes available to us, to try to represent strong shock phenomena, specifically in the methodologies of series decomposition and seasonal adjustment.

In this work, we first presented the necessary theoretical references related to the TRAMO-SEATS seasonal adjustment method, the TRAMO /RegARIMA treatment model, the estimation algorithms, the automatic procedures for identifying the optimal seasonal ARIMA model in the presence of outliers, respectively. Then we list some possible intervention variables that could be appropriate to model the shocks occurred in recent years, with some hints on their parametrization. In addition, operational directions were discussed in a concurrent revision policy step, adopting the JDemetra+ tool. Finally, we selected some of the most problematic series to be treated and defined three intervention strategies: the first one concerns the Chen-Liu automatic procedure, and the second introduces the same automatic identification TRAMO model procedure, supplemented by a temporary intervention variable. The third scenario left greater degrees of freedom to the user, contemplating the choice of model, following indications received from outliers identified by Chen-Liu's procedure, supplementing them possibly with an ad-hoc binary intervention variable.

In the monthly time series we examined, where the Chen-Liu procedure struggles to ensure Gaussian residuals, integrating a Temporary Level Shift and its lagged version proves effective in rectifying the distribution of residuals. Moreover, it aids in reducing revisions without increasing the number of parameters. This strategy also demonstrates success in the quarterly time series example provided, serving as a viable alternative to the automatic procedure, which operates efficiently when used independently as well.

The selection of best strategy depends on a number of factors, especially which outputs are deemed most important by decision makers, and which metrics are selected to evaluate the goodness of those outputs. An important indication comes from the fact that the procedure works well even in critical situations, and that a versatile tool like JDemetra+ allows the user to get involved in various ways to calibrate the best representation of economic development. Finally, it must be emphasized how the JDemetra+ environment, the officially recommended software for ESS (European Statistical System) scholars and European Central Banks system, can show the user audience that it is not just a seasonal adjustment software, but represents a precious tool for a more complete and refined statistical analysis.

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Appendix

Seasonal adjustment revision strategy for 2020-2023 period with JDemetra+

The last four years have been marked by a concentration of events that exemplify a *black swan*, namely highly improbable events with severe and unpredictable consequences. Using the definitions of uncertainty proposed by David Hendry, we can classify these events between *instance unpredictability* and *intrinsic unpredictability* [23, 24]. The main uncertainty now is whether some effects, particularly in the health sector and industries related to tourism and trade, will become permanent, leading to a shift in economic and social structures, or if there will be a return to growth, though its timing and form remain unclear. In this context, regular monitoring and careful review of models and outlier detection are particularly important for the 2020–2023 period. To support this effort, the emergency guidelines issued by Eurostat in early 2020 [1, 25] recommend a minimal approach to handling outliers in the RegARIMA model, focusing mainly on additive outliers. The inclusion of numerous outliers, however, may conflict with the recommendations of the guidelines on seasonal adjustment [14]. Therefore, in this work, during the concurrent revision phase, we evaluate the possibility of grouping individual outliers into single outliers with a more prolonged effect. For this purpose, we outline below the steps we recommend for the concurrent revision of the models.
Before proceeding with any revision, we recommend the following steps:

1. perform a graphical inspection, looking for seasonal patterns and outliers;

2. in large-scale analyses with hundreds of series, it's best to focus efforts according to the importance of each series, both in terms of size and relevance. More attention should be given to series with higher values, such as those over 50 million euros, while less attention can be given to smaller ones.

We recommend performing the concurrent revision phase, in accordance with the stated objective, as follows:

1. upload the specifications adopted in previous revisions and make a first estimate without altering them. If any coefficients (calendar effects, outliers, ARIMA coefficients) are not significant, attempt to remove them and re-estimate the model;

2. if you are not satisfied with the result of the previous step, enable the detection of new outliers, also by reducing the critical value threshold,

while keeping the calendar effects and previously identified outliers fixed;

3. if this is not sufficient, iteratively perform new estimates, progressively removing constraints (fixed ARIMA model order, outliers and calendar effects). As a last resort, consider enabling the test for the log transformation of the data to assess whether improvements can be achieved by transforming or untransforming the data. Keep in mind that all of these operations may lead to significant revisions;

4. assess very carefully and whether LS has been present in the last observations and evaluate whether to keep it or change the type (test for any changes);

5. consider the direct inclusion of user defined or intervention variables for the period 2020-23, as an alternative to the automatic procedure for detecting outliers:

   (a) first, run AMI (outliers and ARIMA) to verify the structure of the outliers;

   (b) if a sequence of LS and TS outliers is present, test the temporary LS or ramp as a replacement.

The procedure can be considered completed if the following conditions are satisfied:

1. the synthetic parameter returns *Good* or at least *Acceptable* encoding;

2. the residual autocorrelation and seasonality tests are satisfactory;

3. there are no revisions of significant magnitude (not necessarily).

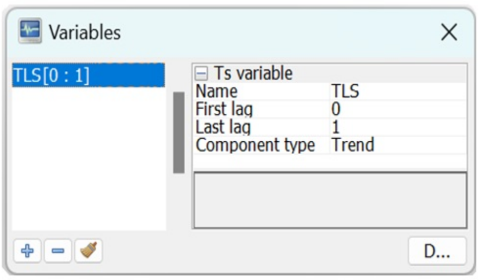

Figure 6: Screenshot of the panel for inserting intervention variables

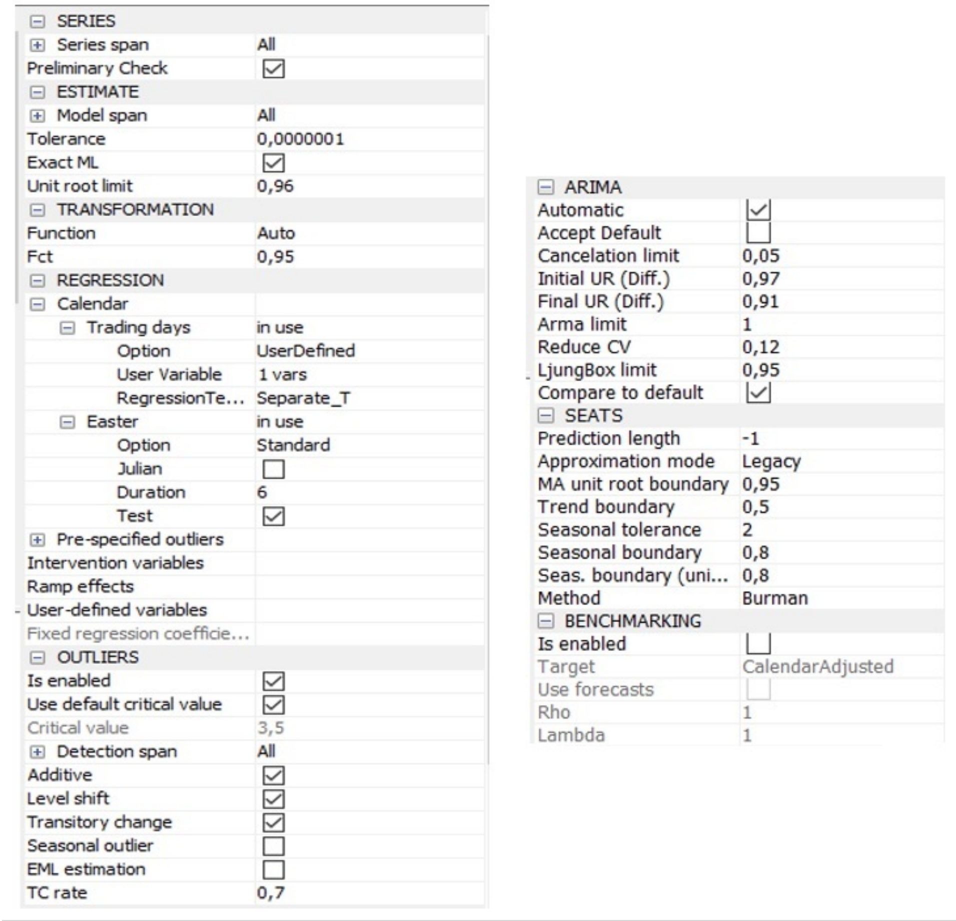

Figure 7: Example of Specification panel in JDemetra+, performing concurrent revision