UNITED NATIONS
INDUSTRIAL DEVELOPMENT ORGANIZATION

SUSTAINABLE DEVELOPMENT GOALS

Methodological document

Seasonal Adjustment

Edition 2024

Progress by innovation with reliable industrial statistics

Methodological document

Seasonal Adjustment

Edition 2024

UNIDO Statistics

UNITED NATIONS
INDUSTRIAL DEVELOPMENT ORGANIZATION

Acknowledgements

The present report was prepared by Nina Goltsch, statistician at the United Nations Industrial Development Organization (UNIDO). The document template and technical design were developed by Martin Haitzmann. The author would like to thank Fernando Cantu-Bazaldua, Martin Haitzmann, Jürgen Muth and other staff members of UNIDO's Division of Capacity Development, Industrial Policy Advice and Statistics for their valuable feedback and suggestions.

The production of this fully-reproducible report relied on open-source software, such as git, LaTeX, R and R Studio. UNIDO Statistics extends its gratitude to all contributors of these open source projects.
The full report is available online at https://stat.unido.org.

Original: ENGLISH.

Contents

List of Figures

List of Tables

Abbreviations

AO additive outlier
AR autoregressive
ARIMA autoregressive integrated moving average

COVID-19 coronavirus disease

EU European Union
Eurostat Statistical Office of the European Union

I_t Irregular component of a time series
IIP index of industrial production
IMA integrated moving averages
IRIIP International Recommendations for the Index of Industrial Production
ISIC International Standard Industrial Classification of All Economic Activities *(see glossary)*

LS level shift

MA moving average

NSO national statistical offices

regARIMA regression model with ARIMA errors

S_t Seasonal and calendar effects
SEATS Signal Extraction in ARIMA Time Series
SO seasonal outlier

T_t Trend component of a time series
TC temporary change
TRAMO Time series Regression with ARIMA noise, Missing values and Outliers

UNIDO United Nations Industrial Development Organization

1 Introduction

Short-term and sub-annual indicators are essential for detecting a business cycle's turning points as early as possible. This allows planners, decision makers and the business community at large to detect possible changes in the economy in order to take appropriate and timely policy measures. However, these statistics are often influenced by seasonal as well as calendar effects (e.g. moving holidays or the number of working days), which can mask relevant short- and long-term movements of the time series and prevent a clear understanding of economic phenomena. In this way, the seasonally-adjusted results do not show "regular" and repeating events, thus revealing the "news" contained in the time series [1, p.102].

The main reasons for relying on seasonal adjustment in UNIDO Statistics are:

- providing more reliable short-term forecasts;
- comparing data from different countries;
- comparing growth rates with the previous period;
- revealing real movements and turning points of industrial activities.

UNIDO Statistics has published seasonally-adjusted quarterly data [2] and a corresponding quarterly report on World Manufacturing Production [3] since 2011. Furthermore, UNIDO Statistics started publishing seasonally-adjusted monthly data [4] in the beginning of 2020. Additional methodological information regarding the compilation of an index of industrial production (IIP) can be accessed through the respective methodological document [5].

This document presents a summary of the main methodological aspects of the seasonal adjustment calculated by UNIDO for sub-annual series, such as the IIP or manufacturing trade. It serves as a background for the analysis of these figures, as presented in UNIDO databases and related statistical publications.

2 Theory of seasonal adjustment

2.1 Time series and its components

A time series is a set of statistics, collected at regular intervals, e.g. quarterly or monthly IIP or monthly merchandise trade data. Usually, the intent is to describe and summarize the data, apply a model and detect a (possible) discernible pattern with the objective of short-term modelling as a base for policy making. Time series data diverges from other data due to its time dependence and correlation, so that many statistical methods are not applicable because of the common assumption of independence.

An economic time series records the direction and turning points of economic activities. In such cases, data undergo regular and fairly predictable changes over time, recurring every calendar year (so-called periodic fluctuations, such as Christmas). These regular patterns are called seasonality.

One way to describe a time series is to decompose the series into its components:

- Seasonal and calendar effects (S_t): Cyclical fluctuations related to the calendar (including moving holidays and working day effects).

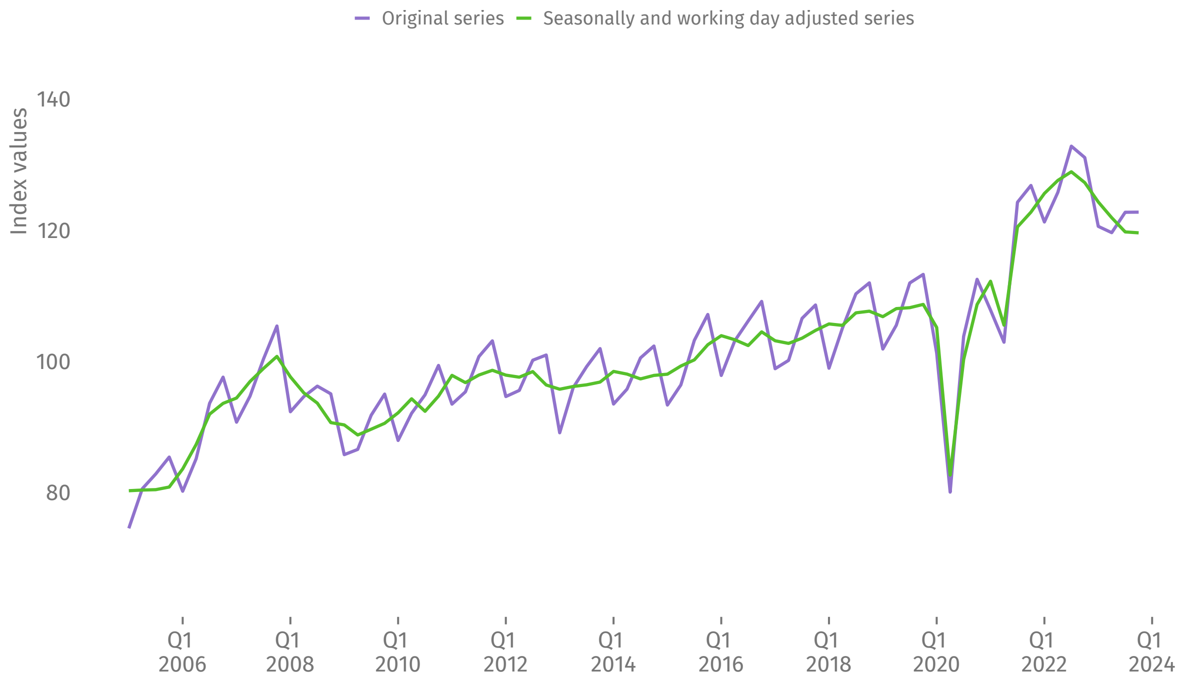

Figure 2.1 | Comparison of the seasonally-adjusted and unadjusted IIP of Colombia
Source: [2]
Note: Data used to create this figure can be accessed at the UNIDO Statistics portal.

- Trend (T_t): Long-term movements at the level of the series, including cyclical fluctuations longer than a year (such as business cycles).
- Irregular (I_t): (Short-term) unpredictable or other random fluctuations (such as strikes or unusual weather situations).

2.1.1 Seasonal and calendar effects

Seasonal and calendar effects in economic time series make it difficult to determine whether the changes are in fact an essential improvement or decline in the level of activity, or whether they are part of regular variations. The example in Figure 2.1 shows the original as well as seasonally-adjusted IIP of Colombia. The calendar-related and regular movements of the original data are excluded in the seasonally-adjusted data.

The possible causes of seasonal effects can be classified into three groups:

- natural factors;
- administrative or legal rhythms; or
- social/cultural/religious traditions (e.g. fixed holidays or vacations timing).

Other calendar-related effects are usually included in the seasonal effects, although they are sometimes considered as separate components of time series. Moving holidays and the varying number of holidays of different countries (such as Easter holidays, Ramadan or the Chinese New Year) need to be included in the model. Another calendar-related effect refers to the leap year, where another (trading or weekend)

Table 2.1 | Example of trading days effect

	M	T	W	T	F	S	S
	1	2	3	4	5	6	7
	8	9	10	11	12	13	14
January 2024	15	16	17	18	19	20	21
	22	23	24	25	26	27	28
	29	30	31				
				1	2	3	4
	5	6	7	8	9	10	11
February 2024	12	13	14	15	16	17	18
	19	20	21	22	23	24	25
	26	27	28	29			

day is added every four years. Working day adjustment assumes a difference between working and non-working days. Most financial time series are influenced by this effect. On the other hand, the trading days effect influences many real industrial activities and refers not only to the difference between working and non-working days, but also to the varying levels of economic activity between the different working days. In the example of Table 2.1, the number of Fridays and weekend days are equal between January and February 2024; however, the number of other week days are different in the two months. This can have a significant influence on economic time series, considering the varying impacts of the different working/trading days. Therefore, trading day adjustment involves six regression variables for modeling these impacts, starting with Sunday.

2.1.2 Trend, irregular and other effects

The trend component (including cycles, also known as the trend-cycle component) is a reasonably smooth time series which denotes the long-term movement and direction of a time series. The underlying direction of time series can be interpreted based on trends, with no influence of volatility, which may distort and mislead the understanding of short-term movements. This component could be regarded as the representation of the underlying level of the time series.

The irregular or residual component is the time series' unpredictable component, which will remain after excluding the seasonal (including calendar-related effects) and trend-cycle components from the original series. It captures the remaining unsystematic or unpredictable short-term fluctuations in terms of timing, impact as well as duration and includes errors of measurement and unusual events. The major causes of irregular effects include unseasonable (unexpected) natural disasters, strikes and other shocks, as well as sampling and non-sampling errors.

2.1.3 Composition of a time series

If we call Z_t the IIP of a country at time t, the idea behind seasonal adjustment is to create separate models for all the time series' components and combine them either additively:

$$Z_t = S_t + T_t + I_t$$

where the seasonally-adjusted series is derived as:

$$SA_t = Z_t - S_t = T_t + I_t$$

or multiplicatively:

$$Z_t = S_t \times T_t \times I_t$$

where

$$SA_t = \frac{Z_t}{S_t} = T_t \times I_t$$

Seasonally-adjusted (SA) time series only contain the irregular I_t and the trend T_t components. The additive decomposition model assumes independent behavior of the components of time series. In other words, the amount of seasonal and irregular variations does not change if the level of the trend rises or falls. The observed time series in the additive model is considered to be the sum of the three independent components.

The multiplicative decomposition model is suitable for time series in which the magnitude of seasonal variation depends on changes in the components' trends. The degree of seasonal variation increases as the level of the components' trends rises. In the multiplicative model, the original time series is expressed as the product of trend T_t, seasonal S_t and irregular I_t components.

2.1.4 Outliers

Outliers are extreme observations that deviate from the trend and fall outside the expected range of typical time series patterns. These abnormal values may occur, for instance, as a result of new policies, new types of taxes, extreme natural events or a closure of a significant manufacturer. These outliers contain valuable information about unusual events. They are an important part of the data and will remain visible in seasonally-adjusted time series. However, outliers need to be identified to avoid distorting the estimation of the seasonal component.

The three most frequent outliers (see Figure 2.2) are additive outliers, temporary changes* and level shifts. An additive outlier (AO) affects a single observation. After this disruption, the series returns to its normal path as if nothing happened. The AO may be caused by a random effect, such as a strike or a short-term shock in the system. For instance, a pre-announced price rise could drastically increase sales before the price change is even introduced. Temporary changes (TCs) are spikes that take several periods to disappear gradually. An example are deviations from average monthly weather conditions. If the weather changes drastically, energy consumption may rise or fall and only return to normal levels gradually. A level shift (LS) refers to a more permanent change in the time series' level, often as a result of changes in economic behavior, social traditions or legislation. A LS changes the level of the time series, but does not modify seasonal behavior. It may also occur due to changes in concepts and definitions of the survey population or compilation methods, which should normally be avoided to preserve the comparability of the series.

Additionally, there are other types of outliers (see Figure 2.3), such as seasonal outliers (SO), temporary level shifts or ramp effects. In contrast to the outlier types covered before, they are not detected automatically within standard seasonal adjustment procedures (see section 2.2.2), but they can be manually identified by the data producer. A SO is determined by a sudden drop or rise occurring in the

* Also referenced as transitory changes.

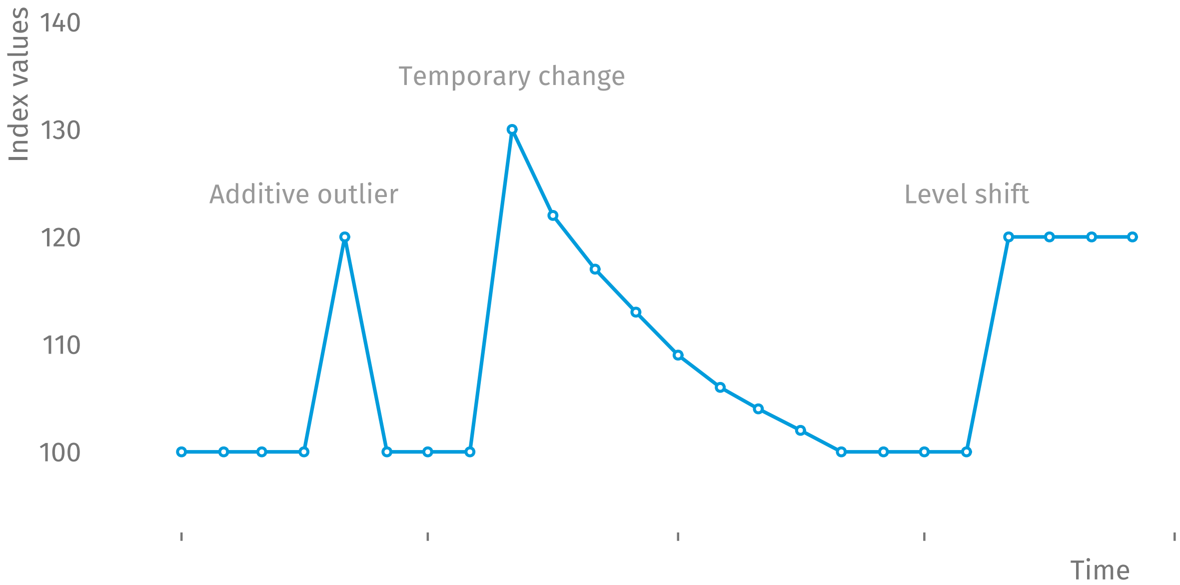

Figure 2.2 | Examples of outliers by type

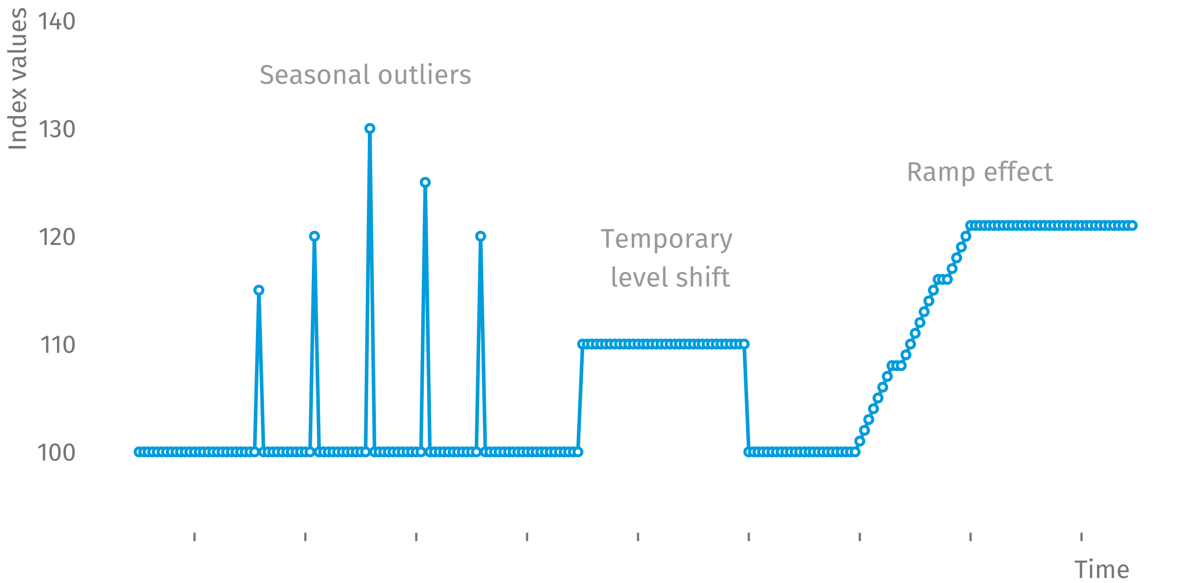

Figure 2.3 | Other forms of outliers

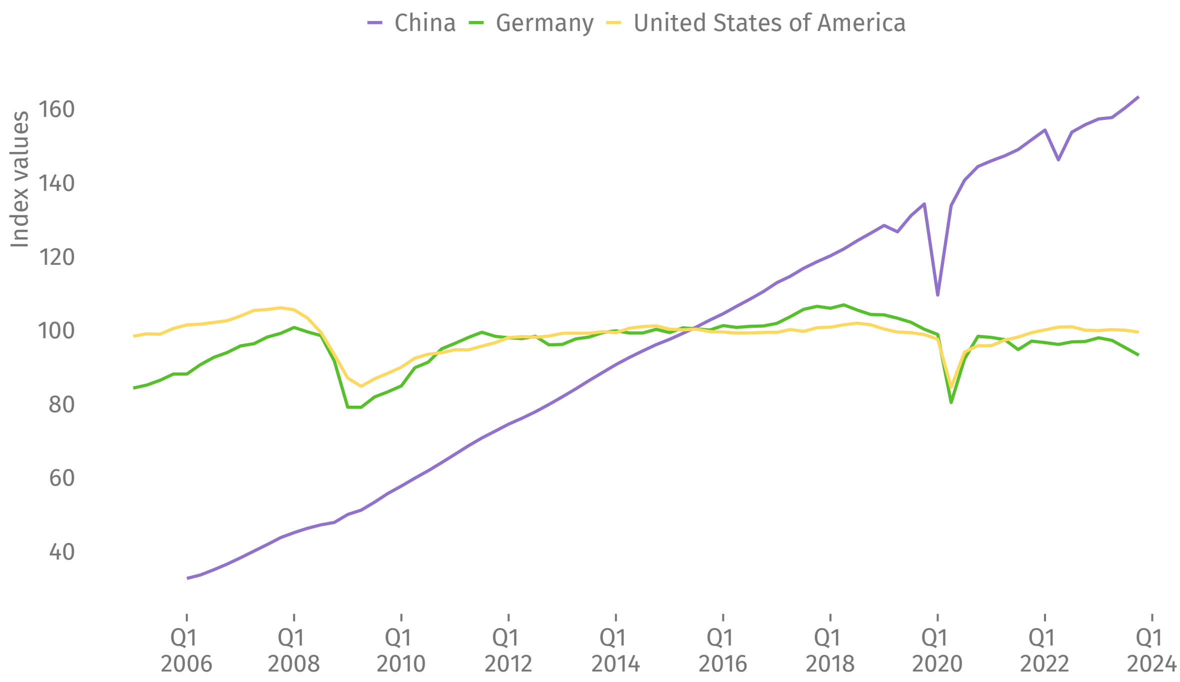

Figure 2.4 | Seasonally-adjusted IIP for China, Germany and the United States of America
Source: [2]
Note: Data used to create this figure can be accessed at the UNIDO Statistics portal.

same period regularly, but with a different magnitude every year. This can be explained, for example, by different weather situations, such as summer periods cooler or hotter than the average. Temporary level shifts, on the other hand, relate to a shift in the data but, unlike a LS, only for a limited time, after which the series returns to its preceding level. This might be caused by an economic crisis in the specific region. Ramp effects indicate a linear increase or decrease of the level of a series during a certain period, with the same trigger as a LS.

When identifying outliers, it needs to be considered that different outlier types may impact different components of the time series. For instance, a LS is related to the trend-cycle component, whereas an AO or a TC are assimilated to the irregular component. Figure 2.4 visualizes IIP data for China, Germany and the United States, with a focus on the 2008 financial crisis and the COVID-19 pandemic in 2020. While the recovery after the disruptions of 2008 took longer, which influenced the model as a TC, the impact of the pandemic was modeled as an AO due to the quick recovery of the economies. In general, real-time modelling of extreme situations is very difficult and would mostly require LSs or TCs depending on the current economic situation and its prospects.

2.2 Seasonal adjustment methodologies

2.2.1 Types of seasonal adjustment approaches

There are two types of seasonal adjustment approaches:

- model-based approach;
- filter-based approach

The model-based approach specifies explicit statistical models of the trend, seasonal and irregular components and derives the different observations in accordance to these models. Examples of model-based methods include TRAMO[†]/SEATS[‡] and STAMP [6]. As TRAMO/SEATS is the chosen method for seasonal adjustment in UNIDO Statistics, it is described in greater detail below.

The filter-based approach, on the other hand, is based on the 'ratio to moving average' procedure and applies a set of fixed filters (moving averages (MAs)) to decompose the time series into a trend, seasonal and irregular component. Typically, symmetric linear filters are applied to the middle of the series and asymmetric ones to the beginning and end of the series. The main procedure usually consists of the following steps:

1. Estimate the trend by a MA;
2. Remove the trend, leaving the seasonal and irregular components;
3. Estimate the seasonal component using MAs to smooth out the irregular components.

Examples of filter-based methods are X11-ARIMA [7] or X12-ARIMA [8] (using regARIMA models for forecasts, backcasts and pre-adjustments).

2.2.2 TRAMO/SEATS

TRAMO and SEATS were developed by Victor Gómez and Agustín Maravall [9] at the Bank of Spain. The two programs are used by different statistical agencies, including Eurostat and the European Central Bank. TRAMO and SEATS are parametric methods and provide a fully model-based method for forecasting and signal extraction in univariate time series. TRAMO estimates, forecasts and interpolates regARIMA models[§], including missing observations and several outlier types. Additionally, it linearizes the original series by removing all calendar-related effects and outliers among others. SEATS, on the other hand, uses the results of TRAMO and decomposes the time series into different components. Due to their model-based features, they are powerful tools for a detailed analysis of time series. The two algorithms are briefly described below, but detailed information can be found, for example, in [10] or [11].

[†] Time series Regression with ARIMA noise, Missing values and Outliers (TRAMO)
[‡] Signal Extraction in ARIMA Time Series (SEATS)
[§] Regression models with autoregressive integrated moving average (ARIMA) errors

2.2.2.1 regARIMA models in TRAMO

Let *z* represent an original time series

$$z = (z_{t_1}, z_{t_2}, ..., z_{t_m}) \tag{2.1}$$

where $1 = t_1 < t_2 < ... < t_m = T$ are the time points. Missing observations are included and a log-transformation of the original observations might be used to improve the characteristics of the data. The regARIMA model can be derived as

$$z_t = y_t'\beta + x_t \tag{2.2}$$

where $y_t' = (y_{1_t}, ..., y_{n_t})$ is a vector with *n* regression variables (related to outliers, calendar effects or other user-defined variables) and $\beta = (\beta_1, ..., \beta_n)'$ is the vector of corresponding regression coefficients. The variable x_t represents the stochastic component, whereas $y_t'\beta$ represents the deterministic one. x_t follows the (possibly non-stationary) ARIMA process

$$\phi(B)\delta(B)x_t = \theta(B)a_t, \quad a_t \underset{\text{iid}}{\sim} N(0, V_a) \tag{2.3}$$

where *B* is the backshift operator, such that $B^j x_t = x_{t-j}$. $\delta(B)$ is a non-stationary autoregressive (AR) polynomial containing regular and seasonal differences, $\phi(B)$ is a stationary AR polynomial in B and $\theta(B)$ is an invertible MA polynomial in *B*. a_t refers to the white noise error (with a zero mean and constant variance) and can be interpreted as the forecasting error of x_t. In other words, it's the "fundamental innovation" at time *t* and cannot be predicted from previous observations.

TRAMO assumes the following multiplicative structure:

$$\delta(B) = (1 - B)^d(1 - B^s)^{d_s} = \nabla^d\nabla_s^{d_s} \tag{2.4}$$

where *s* denotes the number of observations per year in TRAMO and ∇ and ∇_s are the regular and seasonal differences; and

$$\phi(B) = \phi_p(B)\Phi_{p_s}(B^s) = (1 + \phi_1 B + ... + \phi_p B^p)(1 + \Phi_1 B^s + ... + \Phi_p B^{ps}) \tag{2.5}$$

$$\theta(B) = \theta_q(B)\Theta_{q_s}(B^s) = (1 + \theta_1 B + ... + \theta_p B^q)(1 + \Theta_1 B^s + ... + \Theta_p B^{qs}) \tag{2.6}$$

where p is the number of regular AR terms (less than or equal to 3), p_s the number of seasonal AR terms (less than or equal to 1), q the number of regular MA terms (less than or equal to 3) and q_s the number of seasonal MA terms (less than or equal to 1). d is the regular differencing order and d_s the seasonal differencing order.

The regression variables (calendar variables as well as intervention variables and outliers) can be manually defined or generated automatically through the seasonal adjustment software. Intervention variables reflect the dynamic patterns generated by dummy variables (and sequences thereof) aimed at capturing a priori known special events (such as strikes or price devaluations). Outliers are simple forms of intervention variables and atypical observations that distort the normality assumption for residuals. Identifying the above-mentioned outlier types (see section 2.1.4) is crucial, because regARIMA models are based on MAs and therefore sensitive to extreme values. Additive outliers, temporary changes and level shifts are considered automatically.

By default, TRAMO performs pre-tests for the log/level transformation of the series as well as for the possible presence of calendar effects. The process is followed by an automatic model identification along with automatic outlier detection and correction (see below), an estimation of the regARIMA model using the exact maximum likelihood method, missing values interpolation and the forecasting of time series data.

The algorithm of the automatic model identification iterates between the following two stages to identify the best model:

1. Automatic outlier detection and correction. This procedure is based on Tsay (1986) [12] and Chen and Liu (1993) [13] with some modifications. First, it assumes that a proper ARIMA model has been correctly identified for the series and uses this model to detect and correct the series for outlier effects. This method uses some form of "one by one" as well as a joint outlier detection.
2. Automatic model identification. This consists of two steps. First, the differencing orders for the ARIMA model (polynomial $\delta(B)$) are automatically obtained. Second, it preforms the automatic identification of an ARMA model, i.e. $\phi_p(B)$, $\Phi_{p_s}(B^s)$, $\theta_q(B)$ and $\Theta_{q_s}(B^s)$, for the differenced series, and corrects for outliers and other regression effects, if any. For seasonal series, the default model in Stage 1 is the so-called "airline model" [14], provided by the equation:

$$\nabla\nabla_s x_t = (1 + \theta B)(1 + \theta B^s)a_t, \tag{2.7}$$

   i.e. the IMA $(0, 1, 1)(0, 1, 1)_s$ model, which is very flexible. It encompasses many other models and is often applied in practice. For non-seasonal series, the default model is provided by the equation

$$\nabla x_t = (1 + \theta B)a_t + \mu, \tag{2.8}$$

   i.e. the IMA (1,1) plus the mean model. Identification of the ARIMA model is performed based on the time series corrected for outliers and regression effects.

2.2.2.2 SEATS

SEATS uses the results of TRAMO for the decomposition of the series. This includes the original series z_t, the stochastic component x_t, i.e. the original series without the deterministic effects, the ARIMA model of x_t and all deterministic effects. A basic assumption of SEATS is that the stochastic component x_t follows the ARIMA model indicated in (2.3).

SEATS replaces the TRAMO procedure of the automatic model identification with a faster, but rougher version. It starts directly by fitting the default model and tries other possible models, if the default is inappropriate. The ARIMA model can be expressed as

$$z_t = \delta(B)x_t \tag{2.9}$$

and represents the linearized time series. As already mentioned, the stochastic time series x_t can be predicted with a certain error with observations of the past. This model can also be expressed as

$$\phi(B)(z_t - \mu_z) = \theta(B)a_t, \tag{2.10}$$

where μ_z is the mean of z_t and in practice it is an estimated regression parameter.

x_t is assumed to be centered around its mean and the expression for the model is the general ARIMA $(p, d, q)(p_s, d_s, q_s)_s$ model:

$$\phi_p(B)\Phi_{p_s}(B^s)\nabla^d\nabla_s^{d_s}x_t = \theta_q(B)\Theta_{q_s}(B^s)a_t, \tag{2.11}$$

which can be put in the more concise form:

$$\Phi(B)x_t = \theta(B)a_t, \tag{2.12}$$

where $\Phi(B) = \phi(B)\delta(B)$ represents the complete AR polynomial with all unit roots.

As already described in section 2.1.3, there is an additive or multiplicative decomposition. For seasonal series, the polynomials typically follow a "multiplicative" structure. The results of the decomposition process of a differenced series consists of the S_t, T_t and I_t components. Additionally, SEATS filters the transitory component, if existent, which is a stationary (with a zero mean) seasonally-adjusted time series, without trends or white noise.

When using the additive model, it results to

$$x_t = \sum_i x_{it}, \tag{2.13}$$

where x_{it} represents a specific component of a time series.

The program assumes orthogonal components, which are all following the ARIMA model:

$$\Phi_i(B)x_{it} = \theta_i(B)a_{it}, \tag{2.14}$$

where $\Phi_i(B) = \phi_i(B)\delta_i(B)$ and x_{it} is the i-th unobserved component.

It is essential, that no white noise can be extracted from the components (so-called canonical property), aside from the irregular component.

3 Calculation of seasonal adjustment

3.1 Adjusting with JDemetra+ Software

The JDemetra+ project/software [15] started as an extension of the active role played by Eurostat in the promotion, development and maintenance of a statistical analysis software solution for seasonal adjustment. The Seasonal Adjustment Steering Group (SASG) has been promoting the development of freely available JDemetra+ solutions for seasonal adjustment to be used within European statistical systems for several years. The development of the JDemetra+ software has been outsourced to the Department of Statistics of the National Bank of Belgium (NBB), and, for the time being, NBB remains the sole developer of JDemetra+.

JDemetra+ is a family of modules on seasonal adjustment, which are based on the two leading algorithms in that domain, TRAMO/SEATS and X-13-ARIMA-SEATS (in short, X-13; [16]). The literature does not propose a method selection criteria between TRAMO/SEATS and X-13. TRAMO/SEATS (see section 2.2.2) is a parametric method and has a model-based facility to extract the underlying components. Therefore, the results of TRAMO/SEATS can be statistically explored. X-13, on the other hand, was developed by the United States Census Bureau and is a filter-based method, where in a first phase the regARIMA-model is estimated and afterwards the common X-11 method (using MAs) together with SEATS is used for seasonal adjustment. Statistical evaluation is provided by the last phase, including diagnostics for measuring the reliability of the results.

The comparison of the two methods is often difficult as their diagnostics focus on different aspects and their outputs take different forms. JDemetra+ provides a variety of graphical presentation and analysis tools for a better comparison of different methods. A number of procedures for both methods has been included in JDemetra+, following an object-oriented approach. This could imply minor discrepancies in comparison to the original program in diagnostics or peripheral information, which should not, however, alter the general information provided by the algorithms. In any case, the original program's main results (i.e. the seasonally-adjusted series) should not be affected by this solution.

Since 2017, UNIDO Statistics performs seasonal adjustment using the TRAMO/SEATS method in the JDemetra+ software [15] mainly due to the following reasons:

- easy-to-interpret statistical tests;
- accurate automatic outlier detection and correction as well as automatic model identification;
- low probability of finding spurious seasonality; and,
- a simple and easy-to-use interface.

The latest version of JDemetra+ 2.2.4 (released on 31 January 2023) [15] can be easily downloaded and is compatible with the latest Microsoft Office software. Detailed information on JDemetra+ can be found in the reference manual [17] or in the documentation [18].

3.2 Data handling and requirements

Before starting the seasonal adjustment process, a decision needs to be made regarding the direct or indirect approach. In the direct approach, each time series is adjusted, even if this time series is an aggregate of lower-level data. On the contrary, the indirect approach adjusts the lowest level of data and aggregates the time series after the adjustment process. If the main purpose is to preserve the relationship between data, the indirect approach is more appropriate. For time series that have very similar seasonal components, direct adjustment would suffice, noting that summing up the series together could reinforce the seasonal pattern while allowing the cancellation of some noise in the time series. UNIDO Statistics has adopted the indirect approach for country group aggregates to preserve the additive relationship between data. Aggregates with a presence of seasonality published by national statistical offices (NSOs) are seasonally-adjusted using the direct approach. For other aggregates at the country level created by UNIDO Statistics, a case-by-case study is used to determine the proper approach.

In seasonal adjustment methods, benchmarking entails a procedure in which the annual sums of seasonally-adjusted data are rendered equal to the annual sums of the non-seasonally-adjusted data. Even though this ensures consistency between seasonally-adjusted and raw data over the year, UNIDO Statistics does not implement this procedure, as it may degrade the quality of the seasonal adjustment and thus produce non-optimal results. Hence, careful consideration is needed when using annual data derived from quarterly data with filtered seasonality.

Seasonal adjustment at the country level is carried out by UNIDO Statistics only in case original data with a clear presence of seasonality are available from national sources. If no seasonality is present, the original data will be taken as seasonally-adjusted data. Occasionally, seasonal adjustment will be conducted in other special cases, such as now-casting. If necessary, measures to harmonize the data with international standards, such as the International Recommendations for the Index of Industrial Production (IRIIP) [1], are taken, while preserving the underlying message of nationally published figures. For example, if countries publish data based on a different or outdated classification scheme.

The data handling includes the following steps:

1. Collection of sub-annual data from national statistical sources, including seasonally-adjusted and unadjusted data;
2. In case only unadjusted data is available, seasonal adjustment is carried out, if needed;
3. Further data processing, such as chain linking or rebasing, if necessary;
4. Data storage and dissemination of the time series in appropriate databases.

JDemetra+ requires at least three years of data to compute a seasonally-adjusted time series and often more than four years of data to obtain an adequate adjustment and a more reliable forecast. Therefore, short time series or insufficient observations cause problems with the performance of seasonal adjustments and forecasts.

Within JDemetra+, the user has to choose between two options: TRAMO/SEATS and X13. As discussed earlier, UNIDO Statistics uses TRAMO/SEATS. The details of each available specification for TRAMO/SEATS are described in Table 3.1, where the RSAfull specification is the most comprehensive and the default for JDemetra+. With this option, the algorithm selects the best model, which accelerates the process by reducing manual intervention by the user. The results using RSAfull are often very reliable, but modification by the user is still possible.

As the seasonal adjustment process is very time consuming, UNIDO Statistics uses the RSAfull specification, whenever possible. In various cases, such as undetected seasonal outliers or a bad quality of the results, modifications are introduced manually; the major parameters for the modifications can be found in Table 3.2.

Table 3.1 | Available specification options in TRAMO/SEATS

Specification	Settings
RSA0	Use of default Airline model, producing models in levels.
RSA1	RSA3, but the default Airline model is always used.
RSA2	RSA4, but the default Airline model is always used.
RSA3	The software tests the log/level specification, interpolates missing observations (if any), performs automatic model identification and outlier detection. Three types of outliers are considered: additive outliers, temporary changes and level shifts. The level of significance is set by the program and depends on the length of the series. The full model is estimated by the exact maximum likelihood, and forecasts of the series up to a one-year horizon are computed. The model is decomposed and forecasts are obtained for each component (trend, seasonal, irregular and (possibly) transitory). If the model does not accept an admissible decomposition, it is replaced by a decomposable one.
RSA4	As RSA3, but a pre-test is carried out for the presence of trading day, leap year and Easter effects, with one parameter specification for trading days (working/non-working days).
RSA5	As RSA4, but the trading day specification uses six parameters (effect of all weekdays are pre-tested).
RSAfull	As RSA5, but the working day specification uses one parameter.

3.3 Revision policy

Revisions of seasonally-adjusted data are done for two main reasons. First, seasonally-adjusted data are modified due to a revision of the unadjusted (raw) data, attributed to additional or improved information (in terms of coverage or reliability). Second, revisions can also be made due to a better estimate of the seasonal pattern based on new information provided by new unadjusted data and due to the characteristics of the filters and procedures for removing seasonal and calendar components. Revisions are generally accepted if they are based on new information. In particular, the modelling of unpredictable and unstable events (such as the crisis due to COVID-19) is based on assumptions made on future developments, which make data revisions inevitable as soon as new data or information becomes available.

However, it needs to be considered that one additional observation could result in revisions of the entire series of seasonally-adjusted data. The challenge is to find a balance between the need for the best possible seasonal adjustment, especially towards the end of the time series, while avoiding unnecessary revisions that may later be reversed. Seasonally-adjusted data is aligned with the revision policy and the revision calendar for the unadjusted data.

JDemetra+ offers three types of workspace refreshment when new data becomes available:

- Current adjustment: Adjustment with fixed specification while user-defined regression variables can be updated (Partial concurrent - Fixed model in JDemetra+).

Table 3.2 | Explanation of manual modifications for seasonal adjustments

Reason	Modification	Description
Unstable time series (e.g. possible changes of methods)	Shortening the time span	To correct annual totals, auto-correlation and normality problems as well as 'zero' observations.
Residual seasonality	Imposing the default (Airline) model (0,1,1)(0,1,1)) (check 'Automatic' in 'ARIMA')	In rare cases, the ARIMA model defined by TRAMO cannot capture seasonality. The automatically selected ARIMA model may produce irregular components correlated with seasonal components. The Airline model is a good benchmark model in such cases and its flexibility may offer a solution.
Undetected trading days effects	Imposing trading days effect (change to 'Automatic' in 'REGRESSION')	Although the software pre-tests the presence of the trading days effect, it sometimes does not capture significant effects. The residual trading day graph can help, if the trading days effects should be imposed manually or not.
Definition error in main results	No trading day effect (change 'Option' in 'REGRESSION')	If the software's main results indicate 'definition' or 'seas-irr correlation' error, the trading days effect should be removed from the model.
Seasonal outliers	Include seasonal outliers (Pre-specified outliers in 'REGRESSION')	With seasonality at certain time intervals but not for the entire time series, the automatically identified model fails to capture seasonality. The model should be identified by the expert using seasonal outliers or intervention variables.
Undetected significant outliers	Decreasing the critical value (change in 'OUTLIERS' 'Use default critical value')	JDemetra+ defines a default critical value to detect outliers. The expert can change the value manually, if significant outliers are evident in the graphs.

- Partial concurrent adjustment: Re-estimates respective parameters and factors each time new or revised observations become available (Partial concurrent - estimate regression coefficients, ARIMA parameters and others, depending on the chosen parameters in JDemetra+).
- Concurrent adjustment: Adjustment performed without any fixed specifications (Concurrent in JDemetra+).

During the production year, UNIDO Statistics uses a partial concurrent revision policy with a fixed model, whereas a full review of all seasonal adjustment parameters is carried out once a year, usually at the beginning of the year. This type of revision is preferred in order to take the new information into account, while minimizing the extent of revisions of the seasonal adjustment.

When revisions affect two or more years, the specification, such as outliers and regression parameters, have to be reidentified and re-estimated. It is usually acceptable to revise the last three to four years

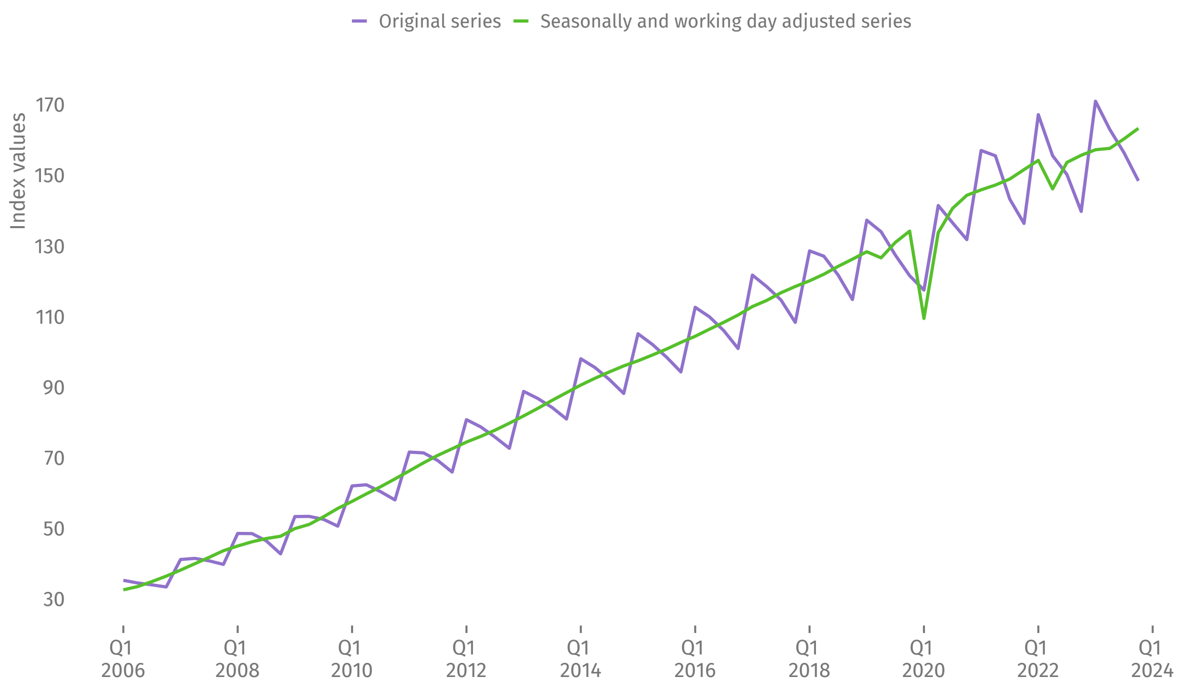

Figure 3.1 | Seasonally-adjusted and original IIP for China
Source: [2]
Note: Data used to create this figure can be accessed at the UNIDO Statistics portal.

Table 3.3 | IIP percentage changes compared to the previous period in China and Japan, selected quarters

	2008 Q4		2019 Q3		2020 Q1	
	China	**Japan**	**China**	**Japan**	**China**	**Japan**
Original	-7.9	-9.0	-4.9	1.8	-3.3	-2.7
SA	1.4	-9.7	3.5	-1.0	-18.4	-1.3

Source: [2]

of seasonally-adjusted data before the beginning of the revision period of the unadjusted data, while earlier data should remain unchanged.

3.4 Examples

The seasonally-adjusted and original IIP data for China and Japan are illustrated in Figure 3.1 and Figure 3.2, respectively. It is easy to identify the seasonal pattern of the original time series in both figures, even though the Japanese data appear more volatile. The gradual drops and rises in almost every year can be attributed to variations in demand, changes in working hours during the specific period or to the country's weather conditions, which affect productivity. Fluctuations due to exceptionally strong or weak seasonal influences as well as shocks will continue to be visible in the seasonally-adjusted series. For instance, the economic disruptions at the beginning of 2020 due to COVID-19 remain in both seasonally-adjusted time series. The 2008 financial crisis is also strongly visible in the case of Japan, while Chinese production was hardly affected. Other random disruptions and unusual movements understandable in economic terms (e.g. the consequences of economic policy, large scale orders or strikes) will also remain in the adjusted data.

Figure 3.2 | Seasonally-adjusted and original IIP for Japan
Source: [2]
Note: Data used to create this figure can be accessed at the UNIDO Statistics portal.

Examples of the differences in growth rate figures before and after performing seasonal adjustment are shown in Table 3.3. This provides a better picture of why seasonal adjustment is necessary and how it helps to reveal the real movements and turning points in industrial activity, which may be difficult or even impossible to identify due to seasonal movements. For instance, in the third quarter of 2019, the original data for Japan indicated a growth of 1.8 percent in manufacturing production compared to the previous quarter, while seasonally-adjusted data shows a decline of 1.0 percent. In the fourth quarter of 2008, China's original data recorded a drop of almost 8 per cent, but the seasonally-adjusted data grew by 1.4 per cent.

3.5 Data quality and costs

Seasonal adjustment is a time-consuming procedure, demanding significant computer and human resources. For example, more than 800 time series of IIPs of around 60 countries at the division (2-digit) level of the International Standard Industrial Classification of All Economic Activities (ISIC) are seasonally-adjusted by UNIDO Statistics for every quarterly data update. According to preliminary results, more than 90 percent of the available unadjusted time series had significant underlying seasonality and/or trading days effects.

UNIDO Statistics performs a seasonal adjustment exercise at the country level. This provides more precise results and prevents unknown constraints, which may emerge at the international level. Unsuitable or low-quality seasonal adjustment can generate misleading results and increase the probability of false signals. The presence of residual seasonality as well as over-smoothing, are concrete risks that can negatively affect the interpretation of seasonally adjusted data.

The quality of the original data plays a key role for reliable and meaningful seasonally-adjusted data. For instance, series with too many zero values will cause estimation problems for JDemetra+ and the software may estimate negative values for those units or may simply send an error message.

Possible outlier values (see section 2.1.4) in the time series have to be identified and considered in the model to prevent future problems. Furthermore, changes in the time series patterns might lead to modifying the time span of data to be used for seasonal adjustment, as a more consistent pattern in the time series often improves the seasonal adjustment. Graphic illustrations of the original series as well as of year-by-year growth rates before and after running JDemetra+ are powerful tools for identifying adjustment quality issues.

4 Final considerations

UNIDO publishes seasonally-adjusted and original data in its databases, as well as periodic reports and infographics. These publications have the main objective of providing an overview of the current growth trends by country groups and other aggregates. In general, there are two sets of growth indicators:

- growth compared to the previous quarter, and
- growth compared to the same period of the previous year.

While the first set of growth indices represents more recent growth trends and allow to study short-term developments, the second set provides more stable estimates when analyzing a country's performance, as year-on-year comparisons help mitigate many undetected seasonal or calendar variations. The user should be aware that certain hidden seasonal or calendar patterns caused by a country's specific national holidays or other particularities might remain in the adjusted series when carrying out seasonal adjustment at the international level. Calculating the growth rate of a given period and comparing it to the same period of the previous year would be an implicit solution to avoid seasonality, but it could not be replaced by seasonal adjustment, since it does not remove all seasonal and calendar effects (e.g. moving holidays). Therefore, countries with no seasonal adjustment experience are encouraged to compile, maintain and update their national calendars or, as an alternative, to supply a list of past and future public holidays including information on compensation holidays.

A decision regarding a specific seasonal adjustment approach for each time series under review as well as the overall revision policy is made, with the aim of avoiding unnecessary data revisions. UNIDO Statistics publishes unadjusted and, in case of identifiable seasonality in the data, seasonally-adjusted data in its databases.

One common misconception is that seasonal adjustment hides outliers. Unusual or unpredictable events, such as the impacts of the COVID-19-pandemic in 2020, play an important role for modelling and analysing economic data. Seasonally-adjusted data referring to uncertain times might face bigger data revisions as new information can lead to rejecting or adapting assumptions made in previous periods.

Seasonally-adjusted data provide more readily interpretable measures of changes that occur in a given period and reflect real economic movements without misleading seasonal patterns. However, users of seasonally-adjusted data should be aware of the limitation of seasonal adjustment and consider the suitability of adjusted data for econometric modelling or other purposes.

References

[1] United Nations Statistical Commission. *International Recommendations for the Index of Industrial Production*. Available at https://unstats.un.org (accessed on Apr. 2024). New York, 2010 (cited on pages 1, 12).

[2] United Nations Industrial Development Organization (UNIDO). *Quarterly IIP Database*. Available at https://stat.unido.org (accessed on May 2024). Vienna, 2023 (cited on pages 1, 2, 6, 15, 16).

[3] United Nations Industrial Development Organization. *World Manufacturing Production - Quarterly Report*. Available at https://stat.unido.org (accessed on May 2024). Vienna (cited on page 1).

[4] United Nations Industrial Development Organization (UNIDO). *Monthly IIP Database*. Available at https://stat.unido.org (accessed on May 2024). Vienna, 2023 (cited on page 1).

[5] UNIDO Statistics. *World Manufacturing Production (Methodological Note)*. Available at https://stat.unido.org (accessed on May 2024). Vienna, 2020 (cited on page 1).

[6] Department of Statistical and LSE Mathematical Sciences. *Structural Time Series Analyser, Modeller and Predictor (STAMP 9.0)*. Available at https://stamp-software.com/ (accessed on Apr. 2024). 2021 (cited on page 7).

[7] Time Series Research and Statistics Canada Analysis Centre. *X-11-ARIMA version 2000*. Available at https://www.census.gov (accessed on Apr. 2024). 1999 (cited on page 7).

[8] U.S. Bureau of the Census. *New capabilities and methods of the X-12-ARIMA seasonal adjustment program*. Available at https://www.census.gov (accessed on Apr. 2024). 1998 (cited on page 7).

[9] Víctor Gómez and Agustín Maravall. *Programs TRAMO and SEATS Instructions for the user*. Available at https://www.bde.es (accessed on Apr. 2024). 1996 (cited on page 7).

[10] Agustín Maravall, Roberto López Pavón, and Domingo Pérez Cañete. *Reliability of the Tramo-Seats Automatic Identification of Regression-Arima Models*. Available at https://www.researchgate.net (accessed on Apr. 2024). 2013 (cited on page 7).

[11] Eurostat, European Commission. *Handbook on Seasonal Adjustment 2018 Edition*. Available at https://ec.europa.eu (accessed on Apr. 2024). 2018 (cited on page 7).

[12] Ruey Tsay. 'Time Series Model Specification in the Presence of Outliers'. In: *Journal of the American Statistical Association* 81 (1986), pp. 132–141 (cited on page 9).

[13] Chung Chen and Lon-Mu Liu. 'Joint Estimation of Model Parameters and Outlier Effects in Time Series'. In: *Journal of the American Statistical Association* 88 (1993), pp. 284–297 (cited on page 9).

[14] George E.P. Box and Gwilym M. Jenkins. *Time Series Analysis, Forecasting and Control*. HoldenDay, 1970 (cited on page 9).

[15] Deutsche Bundesbank National Bank of Belgium and Eurostat. *JDemetra+ (Version 2.2.4)*. Available at https://github.com (accessed on Apr. 2024). 2023 (cited on pages 10, 11).

[16] U.S. Bureau of the Census. *X-13-ARIMA SEATS*. Available at https://www.census.gov (accessed on Apr. 2024). 2023 (cited on page 11).

[17] Sylwia Grudkowska. *JDemetra+ Reference Manual Version 2.1*. Available at https://jdemetradocumentation.github.io (accessed on Apr. 2024). 2016 (cited on page 11).

[18] *Documentation of JDemetra+*. Available at https://jdemetradocumentation.github.io (accessed on Apr. 2024) (cited on page 11).

Vienna International Centre
Wagramerstr. 5, P.O. Box 300,
A-1400 Vienna, Austria
+43 1 26026-0
stat.unido.org
stat@unido.org

UNITED NATIONS
INDUSTRIAL DEVELOPMENT ORGANIZATION