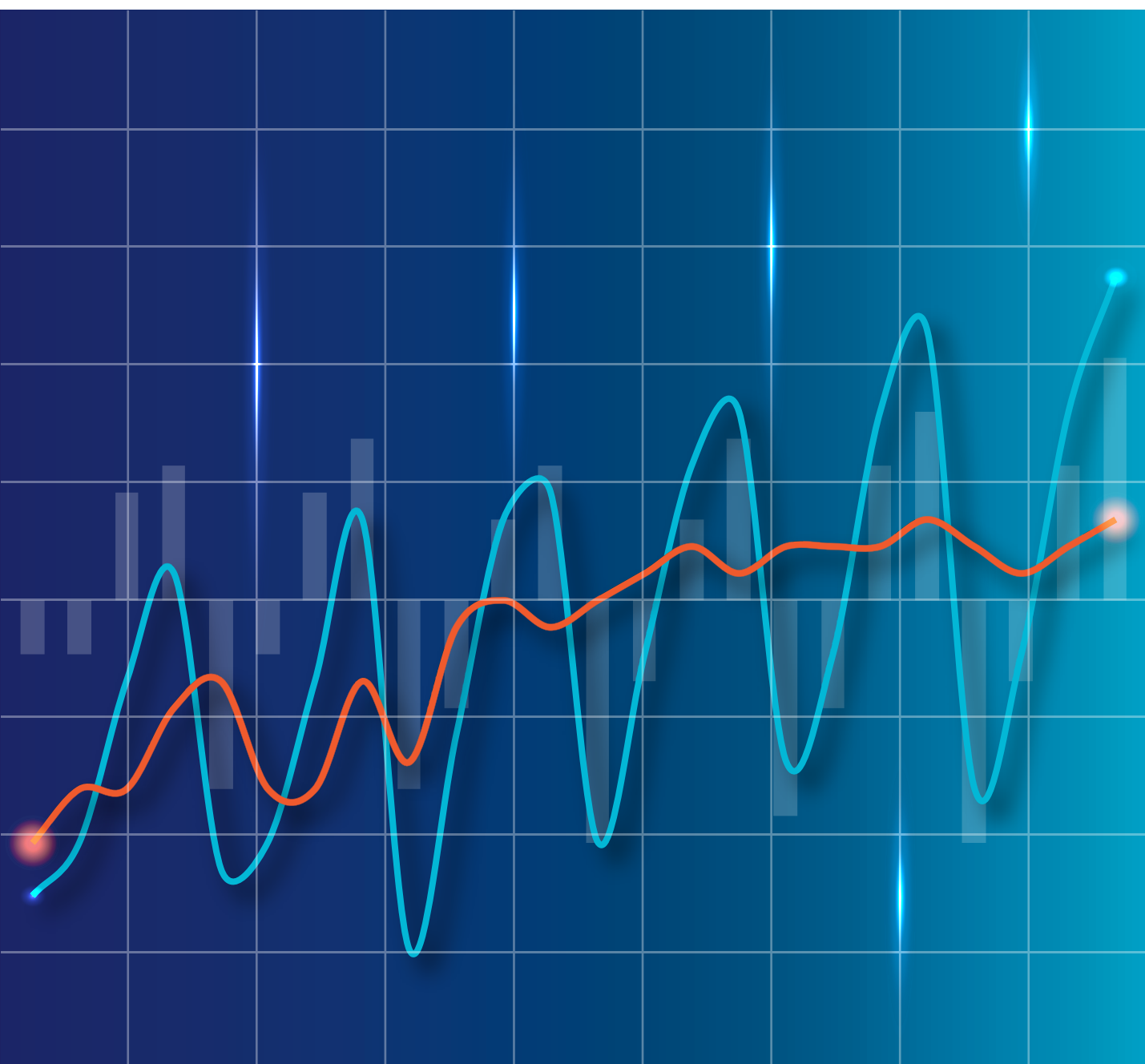UNECE

Practical Guide to Seasonal Adjustment with JDemetra+

From source series to user communication

UNITED NATIONS

PRACTICAL GUIDE TO

SEASONAL ADJUSTMENT

WITH

JDEMETRA+

FROM SOURCE SERIES TO USER COMMUNICATION

UNITED NATIONS

Geneva, 2020

Preface

To assess the economic development and make informed decisions on economic policy, relevant and timely economic statistics must be available to users. However, since many economic phenomena such as production, income and employment are influenced by seasonal factors, simply relying on the original, unadjusted statistical series may not provide a clear picture of the development.

Seasonally adjusted time series provide a more transparent and comparable measure of socioeconomic developments over time and enable the monitoring and detection of cyclical movements and turning points. This is achieved by identifying and removing the seasonal pattern to reveal the underlying development. Seasonal adjustment makes it easier to draw comparisons over time and to interpret the development in the series. It allows time series with different seasonal patterns to be compared between different industries or countries. It also provides more meaningful and insightful month on month or quarter on quarter comparisons of time series.

This Guide introduces seasonal adjustment and gives practical guidance to national statistical offices in producing seasonal adjusted monthly or quarterly time series covering all steps in the production process, from the evaluation of the original data series to the dissemination and communication of the seasonally adjusted series. The Guide can be used in introducing new staff to seasonal adjustment, in training courses or as a complement to other material on seasonal adjustments.

The Guide is based on the use of *JDemetra+* which is an open source software for seasonal adjustment. JDemetra+ is developed by the National Bank of Belgium in cooperation with Deutsche Bundesbank and Eurostat in accordance with the guidelines of the European Statistical System (ESS). JDemetra+ offers the possibility to perform seasonal adjustment by use of internationally recommended methods, TRAMO/SEATS and X-13-ARIMA-SEATS, and is officially recommended to members of the ESS and the European System of Central Banks for seasonal and calendar adjustment of official statistics.

The Guide is an update of the *Practical Guide to Seasonal Adjustment with Demetra+* (UNECE, 2012). This Guide has been updated to support the new version of the software, JDemetra+, and give guidance on the use of the new and improved features of JDemetra+. The Guide refers to JDemetra+ version 2.1.0 but may also be used for later versions of the software.

The Guide is targeted to countries of Eastern Europe, Caucasus and Central Asia but may also be found useful by other countries.

Acknowledgments

Contents

1 Introduction

This introduction outlines briefly the purpose of the Guide and gives a general overview of what is understood by seasonal, calendar and irregular effects in sub-annual (monthly or quarterly) time series and why it is necessary to adjust for these effects to derive time series that allow comparisons over time and enable a coherent interpretation of the developments in the series. JDemetra+ is introduced followed by a short description of the four main steps of seasonal adjustment: preparation of data, seasonal adjustment, analysis of the results and user communication. Lastly, an overview of the chapters of the Guide is provided.

1.1   The purpose of the Guide

The aim of this Guide is to provide information and practical guidance to statistical offices on how to undertake seasonal adjustment of time series by using JDemetra+ Version 2.1.0 or later versions.

It provides background information on methods applied in JDemetra+ and gives practical guidance to compilers of short-term statistics that need to produce seasonal adjusted time series, covering all steps in the production process, from the evaluation of the original data series to the dissemination and communication of the seasonally adjusted series. It offers guidance on how to interpret quality diagnostics produced as part of the process of seasonal adjustment and practical tips on using the software. It highlights the user-friendly and flexible features of JDemetra+. The Guide can also be used for training of staff in statistical offices on how to perform seasonal adjustment. The Guide is targeted to countries of Eastern Europe, Caucasus and Central Asia but it may also be useful in a wider context.

1.2   Seasonal, calendar and irregular effects

Many short-term time series, e.g. monthly or quarterly data series, may be influenced by seasonal, calendar or irregular effects.

Seasonal effects are associated with regular periodic changes in time series that repeat itself from calendar year to calendar year. Seasonal effects may be caused by many different reasons, including climate and weather conditions, traditions and cultural or administrative habits. For instance, economic activity in terms of production and employment in some sectors of the economy will be influenced by the season of the year, e.g. the agriculture and fishing and tourism. In many countries retail sales peak in the run up to Christmas. Similarly, there may be a tradition for summer sales that impact on the values and volume of sales. Administrative and legal habits may also be linked to the time of the year and cause seasonal effects, including for instance quarterly provisional tax payments or periodic invoicing.

Calendar effects usually include both *working day effects* and *trading day effects*. Working day effects are such changes that can be attributed to the number of working days in a given month (or quarter). The number of working days changes from month to month and is influenced by fixed holidays and moving holidays, such as e.g. Easter and Ramadan, as well as the occurrence of leap years (Eurostat, 2015). Trading day effects are changes than can be attributed to working days when the level of activity depends on the day of the week. For example, sales may be higher on Fridays than on Tuesdays (Findley & Soukup, Detection and Modeling of Trading Day Effects, 2000). The full calendar effect therefore includes both the effects of the number of working days and their distribution on weekdays.

Calendar effects that are reoccurring at regular intervals, i.e. the lengths of the months and Easter falling most often in April, can be considered seasonal effects. Hence, to the extent that calendar effects are seasonal there is an overlap between these two types of effects.

Irregular effects are changes in time series which are neither systematic nor predictable. Irregular effects can be caused by unusual weather conditions that may influence the level of economic activity, for example natural disasters, social unrest or strikes. Irregular effects are transitory and not recurring regularly.

1.3   Adjusting for seasonal, calendar and irregular effects

Monthly and quarterly statistics are used for a variety of purposes. One important purpose of economic short-term statistics is to measure the development in economic activity such as production, income and employment. However, since the development in many economic time series may be influenced by seasonal, calendar and irregular effects, relying only on the raw, unadjusted statistical series may not give a clear picture.

As an example of a seasonal effect, consider an increase in agricultural production by 10% from July to August 2019. Taken alone, this reflects an increase in agricultural production and may be interpreted as showing a positive development in production. However, if in previous years production on average went up 15% from July to August, the 10% increase in 2019 could be interpreted as a poor development in agricultural production, compared to the "normal" development from July to August.

Calendar effects, mainly through their influence on the number of working days, are also likely to influence many short-term economic time series. For instance, there were 22 weekdays in March 2018 and 21 weekdays in March 2019. The fewer weekdays would tend to have a negative impact on production, for example, so part of the year on year change from March 2018 to March 2019 can be explained by the fewer number of weekdays. Simply comparing the raw data would mask the impact of the number of weekdays.

Holidays and their distribution on weekdays also play a role. For example, in October 2018, two of the four holidays of Eid al-Adha fell on weekdays, the other two fell on a weekend (non-working days). In October 2019, all four Eid al-Adha holidays fell on weekdays. Hence, there were fewer working days in October 2019 than in October the year before, which could be expected to have a negative impact on the value of the time series when comparing October 2019 with October 2018. The different number of working days in October 2019 and October 2018 would also affect comparisons over the previous month and have a different impact on the monthly changes from September to October in the two years. Another example would be 1 January in countries where this is a holiday. In 2018 it fell on a weekday, while in 2017 it fell on a weekend, which reduced the number of working days in January from 2017 to 2018. Taken alone, this could be expected to reduce the value of economic time series that are influenced by the number of working days, e.g. production. As in the previous example, this effect would also affect comparisons with previous month.

Irregular effects may influence the development of economic and other short-term series in different ways. Unusual weather conditions, for instance may give rise to unusual production in certain sectors of the economy. Strikes may influence the number of working days and thus have an impact on production and employment.

Adjusting short-term time series for seasonal, calendar and irregular effects makes it possible to compare the months or quarters of the year with each other and to draw conclusions about the underlying development in the series. Seasonally adjusted time series provide clearer and more comparable measures of the development and enable more timely and reliable detection of turning points. Seasonal adjustment makes it easier to make comparisons over time and to interpret the development in the series. It allows time series with different seasonal patterns to be compared between different industries and among countries.

Calculation and dissemination of time series adjusted for seasonal, calendar and irregular effects is in line with recommended international good practice. This practice is well established and adopted widely in the USA (BEA, 2019), Canada (Statistics Canada, 2019), in OECD member countries (OECD, 2019) and in EU member countries.

Some short-term economic time series do not display seasonal or calendar effects and it is important that these series are not seasonally adjusted. In other instances, for example the consumer price index, common practice is to omit seasonal adjustment even though many of the prices series are seasonal. However, many socioeconomic short-term series, e.g. production, income and employment, do display

seasonal effects and seasonally adjusting such series adds considerable value by providing clearer and more coherent insights into the development over time.

Sub-annual time series may be produced and disseminated in five different ways (Eurostat, 2014a)**:**

1. Original (unadjusted) data
2. Calendar adjusted data
3. Seasonally adjusted data
4. Seasonal and calendar adjusted data
5. Seasonal, calendar and irregular effects adjusted (trend-cycle) data

Based on various statistical analyses of the original time series the statistician can assess if series are influenced by calendar, seasonal or irregular effects. These types of analysis are the first step in the process of seasonal adjustment and are usually integrated in the software used for seasonal adjustment, including JDemetra+.

If it is not possible to identify any of the seasonal effects in the original time series, the original data should be published without any seasonal adjustment.

Calendar adjusted time series are estimated by removing the calendar effects from the original series. Calendar adjusted time series can be used when comparing with the same month/quarter of the previous year in the case where the original series has seasonality.

Seasonally adjusted time series are estimated by removing seasonal effects from the original series. Seasonally adjusted time series can be used in comparison with the previous month/quarter in the case where the original series has calendar effect. Otherwise, seasonal adjusted time series can also be used in comparison with the previous month/quarter.

Seasonal and calendar adjusted time series can be obtained by removing both effects from the original data. Seasonally and calendar adjusted time series can be used in comparison with the previous month/quarter and the same month/quarter of the previous year.

Finally, *trend-cycle* time series can be obtained by removing seasonal, calendar and irregular effects from the original data. Trend-cycle time series should be used in comparison with the previous month/quarter and the same month/quarter of the previous year. Data on volatility such as industrial production and foreign trade; trend-cycle time series are becoming more easily interpretable for the users. Canada, OECD, EUROSTAT and some member countries have started to produce such data (DESTATIS (2019), Statistics Canada (2015), OECD (2007)). However, the statistical institutions of developing countries have not been published this type of time series, yet.

1.4 Seasonal adjustment with JDemetra+

The literature provides many methods that can be used to adjust for seasonal and calendar effects in time series. However, *TRAMO/SEATS* (Maravall & Caporello, Program TSW. Revised manual. Version May 2004, 2004) and *X-13-ARIMA-SEATS* (Sax & Eddelbuettel, 2018) methods are widely used by national statistical offices and international organizations.

Seasonal adjustment includes either statistical (econometric) modelling or smoothing of data with filters (moving averages) to separate seasonal effects and reveal the underlying development. The X-13-ARIMA-SEATs method, developed by the US Census Bureau, is a semi-parametric approach based on moving averages. The major disadvantage of this approach is that it uses similar types of filters for different types of time series. TRAMO/SEATS is a parametric method based on econometric model estimation developed by the Central Bank of Spain. The advantage of this approach is the use of data-specific filters. Both TRAMO/SEATS and X-13-ARIMA-SEATS are in continuous development. Each method has its strengths and weaknesses and there is no international consensus on which of the methods in general should be the preferred one.

While TRAMO/SEATS and X-13-ARIMA-SEATS differ in the methods used for identifying the seasonal variation they will often in practice give very similar results. The pre-adjustment part which may be defined as the part for identifying the non-seasonal effects is almost the same in the two methods.

JDemetra+ is a flexible tool with a user-friendly graphical interface that helps the statisticians through the various steps of seasonal adjustment. It is developed by the National Bank of Belgium in cooperation with Deutsche Bundesbank and Eurostat for use in official statistics (Eurostat, 2018a). JDemetra+ is programmed in Java® by Oracle®. JDemetra offers up-to-date versions of leading seasonal adjustment algorithms programmed in Java, which enables maintenance of the tool, integration of the libraries in the IT environment and reuse of the modules and algorithms for other purposes. JDemetra+ includes a set of open Java libraries that can be used to deal with time series related issues including seasonal adjustment processing of large-scale datasets, use of non-standard seasonal adjustment methods, development of advanced research modules, temporal disaggregation, benchmarking and business cycle analysis. Since 2019, there exists also an R interface for JDemetra+, called RJDemetra[1].

The JDemetra+ software and additional documentation and guidance are available on the Eurostat website[2] and on the github[3] page, which also provides a quick start guide. For further support, there is the possibility to contact the online ESS Seasonal Adjustment Helpdesk[4] and to interact directly with the developers via twitter[5].

JDemetra+ facilitates seasonal adjustment with both TRAMO/SEATS and X-13-ARIMA-SEATS. It provides several pre-defined *Routines for Seasonal Adjustment* (RSA) based on TRAMO/SEATS or X-13-ARIMA-SEATS, where the statistician must decide which one to use. JDemetra+ offers easy comparisons of the two methods and common presentation tools for both. While different RSAs generally produce very similar results, the quality diagnostics provided by JDemetra+ are essential for confirming and refining the results of the process. JDemetra+ facilitates one-time seasonal adjustment (single-processing) and batch analysis for mass production (multi-processing) and is thus suitable to apply for regular production of seasonal adjusted time series in statistical offices.

For presentation purposes and to keep things simple, the *Guide* focuses on using TRAMO/SEATS. This does not imply any preference between the two methods, both of which are internationally recommended and common in use in statistical offices.

The process of seasonal adjustment in JDemetra+ follows the steps outlined in the "*ESS Guidelines on Seasonal Adjustment*" (Eurostat, 2015). Further information about both the methods applied are available from *the JDemetra+ User Manual* (Grudkowska, JDemetra+ User Guide, 2015).

The Guide divides the process of performing seasonal adjustment into the following four steps:

1. Preparation of data
2. Seasonal adjustment
3. Analysis of the results
4. User communication

Each of the steps consists of several routines or intermediate steps. The main steps and the intermediate steps are shown in Table 1.1 and briefly described below.

1.4.1   Preparation of data

In the first step source data is prepared into a suitable format that can be imported into JDemetra+ where the original (unadjusted) time series is checked and prepared for seasonal adjustment. The raw data is checked in terms of accuracy, length of time series, time consistency and any other issues that

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[1] https://cran.r-project.org/web/packages/RJDemetra/index.html

[2] https://ec.europa.eu/eurostat/cros/content/software-jdemetra_en

[3] https://github.com/lmmurb/TestWiki/wiki/JDemetra--2.2-Quick-Start

[4] https://ec.europa.eu/eurostat/cros/content/ess-seasonal-adjustment-helpdesk_en

[5] https://twitter.com/jdemetraplus

might affect the seasonal adjustment process and/or the quality of the seasonally adjusted series. Visual analysis tools help to identify irregular effects, missing values, volatility, presence of trends, seasonality and breaks in the series. Many economic time series are influenced by calendar effects. JDemetra+ also offers the possibility to include national calendars with information about working days and holidays which can be incorporated in the seasonal adjustment process.

Table 1.1 **The process of seasonal adjustment with JDemetra+**

Main Steps	Intermediate Steps
Preparation of data	Open JDemetra+
	Prepare source data
	Import data
	Check original series
	Prepare calendars
Seasonal adjustment	Select an approach (updating as calendar)
	Define specification and regressors
	Seasonally adjust
	Benchmarking
Analysis of the results	Visual check
	Quality diagnostics
	Refine and readjust
	Export data
User communication	Reports
	Documentation
	Supporting users

1.4.2 Seasonal adjustment

In the second step, the statistician must choose how to treat calendar and irregular effects. It is recommended to adjust for calendar effects because this improves the quality of the seasonal adjustment. The statistician can decide whether to use TRAMO/SEATS or X-13-ARIMA-SEATS for the seasonal adjustment of the time series. In addition, it is possible to use the "benchmarking" option depending on whether it is required that the annual totals of the data should be the same before and after seasonal adjustment.

1.4.3 Analysis of results

In the third step the seasonally adjusted series are analysed through visual validation and statistical diagnostics to assess the quality of the adjustment and the statistical model used. JDemetra+ provides statistical diagnostics that facilitate refinement and readjustment of the seasonally adjusted series. Transparency about methods and practices increases the usefulness of seasonally adjusted data and helps building trust and confidence in the adjusted series. After thorough examination of the raw data and the results, the decisions made during the adjustment must be documented for future use. Lists of national holidays and events that have caused outliers are also useful when documenting the seasonal adjustment process.

1.4.4 User communication

The purpose of adjusting for seasonal and calendar effects is to provide users with sub-annual (monthly or quarterly) time series that reflect the underlying development, allow meaningful comparison with the

previous month or quarter and give timelier information about changes in economic activity. JDemetra+ offers a summary of quality diagnostics that can be used in the documentation of the seasonally adjusted series. In addition, statistical offices will need to prepare documentation for the publication of the series, including providing suitable summary information and explanations of the series and therefore, helping users to make correct interpretation and use of the statistical news.

1.5 Overview of the Guide

The Guide divides the process of seasonal adjustment into four main steps: preparation of data, seasonal adjustment, analysis of the results and communication with users. For each step the Guide provides detailed instructions on how to apply JDemetra+ (version 2.1.0) and gives practical recommendations and examples. The four main steps are dealt with in four separate chapters briefly described below.

Chapter 2 Preparation of data

Chapter 2 in Section 2.2 discusses the quality and the length of the original time series required for seasonal adjustment. Section 2.3 presents the breakdown of an original time series into three components: the trend-cycle, the seasonal and the irregular components and gives advice on how to treat calendar effects and outliers as part of the seasonal adjustment. Section 2.4 provides practical and concrete guidance on how to prepare time series in suitable format to be used by JDemetra+.

Chapter 3 Seasonal adjustment

After the preparation of data, Chapter 3 explains the steps involved in the seasonal adjustment of time series. Section 3.2 discusses how the user defines specific calendar effects in JDemetra+, since it is critical to use user-defined calendar regressors to obtain high quality seasonal adjusted time series. Section 3.3 describes how to initiate the seasonal adjustment in JDemetra+. Then, the same section explains the various seasonal adjustment options, including the "benchmarking" option which is available with the new version of JDemetra+. If there is a single time series to be seasonally adjusted, the reader should follow Section 3.4. If there are more than one time series to be seasonally adjusted, Section 3.5 should be followed.

Chapter 4 Analysis of the results

Chapter 4 presents several quality assurance tools. Section 4.2 points out which criteria can be used to measure the performance of the seasonal adjustment for a single time series. There are a lot of aspects of analysis of single processing results. Section 4.2 is also important for understanding the topics covered by Section 3.5 which presents a more general point of view for analysing the multi-processing results. It is hard to analyse the results of multi-processing without understanding the results of single processing. Finally, Section 4.4 presents the options for getting outputs from the seasonal adjustment process i.e. seasonal adjusted series.

Chapter 5 User communication

Chapter 5 discusses the final step of producing seasonally adjusted time series in terms of documentation and dissemination of data. In Section 5.2, the chapter gives advice on both internal and external documentation and on establishing a policy for seasonal adjustment to guide work. It also discusses issues related to revisions of seasonal adjusted series. Finally, in Section 5.3, the chapter gives advice on communication with users, including examples of how to both disseminate seasonally adjusted series and provide explanations that help users to make correct interpretation and use of the statistics.

Annex: Establishing best practices

This annex suggests concrete steps and recommendations for statistical office for establishing best practices and building capacity in seasonal adjustment of short-term statistics.

Glossary

The glossary provides definitions and explanations of key terms and concepts in relation to seasonal adjustment. The definitions are mainly drawn from existing international recommendations.

2 Preparation of data

2.1 Introduction

The first phase of the seasonal adjustment process includes a careful review of the raw (original) data series: are data series of sufficient length and quality available, are there breaks in the series that needs to be considered and perhaps corrected for. The chapter provides brief recommendations on the required length and quality of the original series. It presents the decomposition of the original data time series into its trend-cycle, seasonal and irregular components. Seasonal adjustment means to correctly identify and estimate the seasonal component in the original data and removing this to obtain the seasonally adjusted series. The chapter also discusses calendar effects and the treatment of outliers. The chapter ends with explaining how to prepare data in the correct format for seasonal adjustment with JDemetra+.

2.2 Length and quality of original time series

Seasonal adjustment of sub annual data, usually monthly or quarterly observations, requires that time series of suitable quality and length are available.

The length of the original time series is crucial for the quality of the seasonal adjustment and observations for each period, i.e. every month or quarter, for several years must be available. For monthly series, observations for at least three years (36 months) should be available. For quarterly data, the series should be at least four years long (16 quarters). The number of years of original data corresponds to the number of samples for estimating the seasonal component.

In general, the quality of seasonal adjustment will increase with longer time series of original data; often five or seven years are recommended. However, very long time series do not necessarily lead to higher quality seasonal adjustment. The idea is to find the seasonal pattern from the part of the series that most accurately reflects the overall seasonality. To decide if the original time series should be shortened the series must be examined for data breaks due to e.g. structural changes or changes in data sources or compilation methods. Based on this, the period of observations that should enter the seasonal adjustment can be decided upon.

Users of statistics appreciate long time series. If there are breaks in the original time series, only a shorter seasonally adjusted series may be released while the longer historical series may be released with quality warnings. Another option is to provide two or more separate time series, one for the latest period and others for earlier periods, compiled with different methods or definitions.

The quality of the original time series affects the quality of the seasonal adjustment. It is therefore necessary to assess the quality of the original series, in particular to which extent it is coherent over time.

Changes in past observations may influence the seasonal pattern of the original time series and hence change the seasonal component that is estimated and thereby the seasonally adjusted series. The original time series, therefore, should be carefully reviewed. Outliers that are detected may be correct, caused by unusual circumstances. If so, they should remain in the data set. If an outlier turns out to be an error, it should be replaced by the correct value or by suitable imputation.

Changes in definitions, data sources, coverage, classification or compilation methods may influence the time series. In such cases it may be necessary to adjust the original time series to ensure consistency and enable comparison over time and between countries.

International guidelines and classifications support the production of time series. For instance, the *Methodology of short-term business statistics – Interpretation and Guidelines* (Eurostat, 2006) provides guidance for many monthly and quarterly statistics. Specific guidelines are also available, e.g. the *International Recommendations for the Index of Industrial Production* (UN, 2013).

Time series that have been produced by chain-linking[6], such as for instance may be the case for quarterly series of the national accounts, need special attention. Series may be chain-linked by different methods: by use of an annual overlap, a monthly or quarterly overlap or the over-the-year-approach, in which information from the same period (month or quarter) of the previous year is used. The different methods cause different types of breaks in the time series and will therefore also have an impact on the seasonal adjustment.

The *Final Report and Recommendations of Eurostat/ECD Task Force on seasonal Adjustment of Quarterly National Accounts* (Eurostat & ECB, 2002) concludes that the over-the-year approach has a larger effect on the seasonality of the series and does not recommended this approach. The other two methods are found to result in undistorted developments within the calendar year. For quarterly national accounts the report recommends annual-overlaps, which is widely used by statistical offices. The report also suggests performing seasonal adjustment after chain-linking of the original series to avoid the risk of artificial seasonality. Statistical offices are to choose the most appropriate method for their statistics. Also, in Chapter 5 of their document, the UN (2013) provide practical instructions on chain-linking.

Another challenge is data sets that include a total and its components where the components must add up to the total. If the total and its components are all individually seasonally adjusted (so-called *direct seasonal adjustment*) the sum of the seasonally adjusted components series may differ from the seasonally adjusted total. Hence, the seasonal adjustment of the series leads to lack of additivity. The other possibility (so-called *indirect seasonal adjustment*) is to seasonal adjust the component series and derive the total as the sum of the seasonally adjusted component series. Up to now, only mixed evidence has been provided on the superiority of either direct or indirect seasonal adjustment (Eurostat, 2015). The statistical office must decide whether to apply direct or indirect seasonal adjustment depending on an analysis of the time series and user needs.

2.3   Components of time series

An observable time series can be divided into three separate components that can be modeled and forecasted: a trend-cycle component, a seasonal component and an irregular component. The components are illustrated in Figure 2.1.

The *trend-cycle component* includes both long-term and medium-term developments. The trend reflects the long-term evolution over several decades, i.e. structural changes and is often the result of population growth, technological change and general economic development. The cycle component, on the other hand, represents the relatively smooth movement around the long-term trend from expansion to recession.

The *seasonal component* refers to those fluctuations observed during the year which repeat on a regular basis from one year to another. The timing, direction, and magnitude tend to be stable from year to year. The seasonal component may also include calendar effects that display a seasonal pattern, for instance the length of the months.

The *irregular component* captures the remaining short-term fluctuations in the series which are neither systematic nor predictable. It is assumed to include only white noise. The irregular component is the remaining component after the seasonal and trend-cycle components have been removed from the original data. For some data series, SEATS will identify and estimate a *transitory component*. While the irregular component is defined as white noise, the transitory component identifies and removes short-term (transitory) variation other than that, which would otherwise influence the estimation of the seasonal component. Once the components are estimated, the irregular and transitory component can be put together. For simplification, they will be discussed together.

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[6] Chain-linking refers to the practice where series are linked or spliced together by use of an overlap period to produce a continues time series that allows new weighting information to be introduced in the overlap period.

Figure 2.1 **Components of the Gross Domestic Product of Kazakhstan**

Original Series

Trend Component

Seasonal Component

Irregular Component
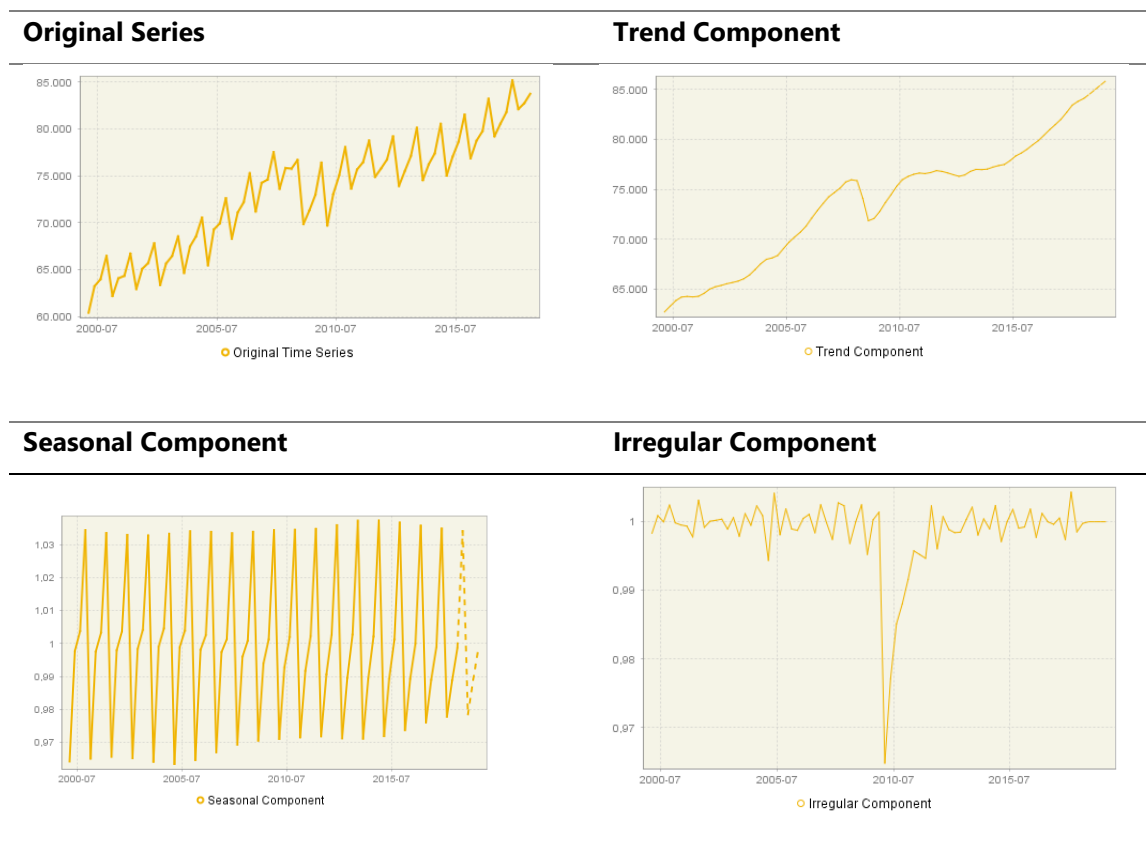
The decomposition assumes that the components of the series behave independently of each other. The two main types of decomposition are "additive" and "multiplicative". TRAMO and Reg-ARIMA automatically identify the most suitable model based on the TRAMO procedure.

The additive decomposition means that the time series is made up by the sum of its independent components:

(2.1) $X_t = TC_t + S_t + I_t$ (Additive model)

In equation (2.1) X_t is the observed value of the time series at time t. S_t is the seasonal component, TC_t the trend-cycle component and I_t the irregular component. The difference between the trend-cycle and the seasonal component is that the seasonal one occurs at regular annual intervals, while the trend-cycle reflects the combination of the long-term development (the trend) and the cyclical movements around the trend. In an additive decomposition, as illustrated in Figure 2.2, the magnitude of seasonal effects does not change as the level of the trend-cycle changes. Also, any series with zero or negative values are additive.

The multiplicative decomposition in equation (2.2) implies that, as the trend of the series increases, the magnitude of the seasonal fluctuations also increases (Figure 2.2). For a multiplicative decomposition, the original time series is the product of its components:

(2.2) $X_t = TC_t \times S_t \times I_t$ (Multiplicative model)

Most economic time series exhibit a multiplicative relation between the components. If the magnitude of the seasonal effects increases when the level of the series increases and vice versa, and if the series has no negative values, a multiplicative decomposition can be applied.

The seasonally adjusted series is, thus, the result of removing the seasonal component (including calendar effects) from the original data. At the same time, the seasonally adjusted series is a combination of the trend-cycle and the irregular component.

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Figure 2.2 **Additive and multiplicative decomposition**

Additive approach	Multiplicative approach
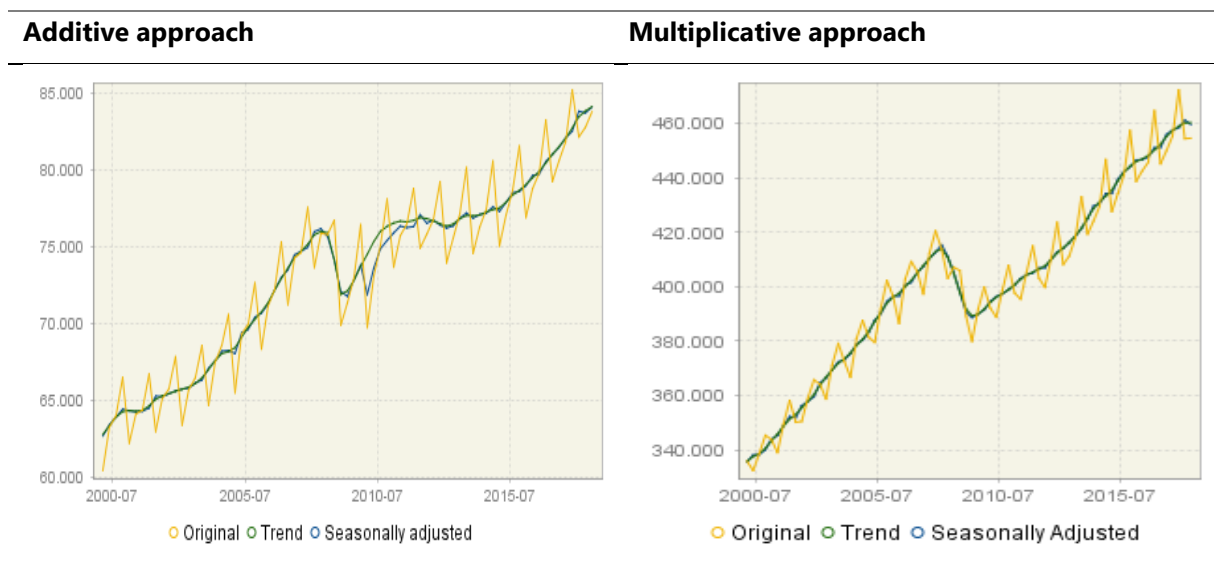
2.3.1   Calendar effects

In the above decomposition the original time series is made up of a seasonal, a trend-cycle and an irregular component. However, the original time series may also be subject to calendar effects, i.e. effects related to the number of working days and trading days. Calendar effects that are reoccurring at regular intervals, e.g. the lengths of the months, can be considered seasonal effects. Other calendar effects such as caused by moving holidays (Easter and Ramadan) or leap year are not seasonal.

Calendar effects may influence the level of activity in a month or quarter and should be removed before the seasonal adjustment. Adjusting for calendar effects aims to obtain monthly or quarterly time series whose values are not influenced by the number of working days and trading days effects in the individual periods (Eurostat, 2015). Removing these effects will improve the quality of the seasonal adjustment.

JDemetra+ facilitates removing of calendar effects before carrying out the seasonal adjustment of the series. Since the number and the distribution of working days and holidays varies from country to country this includes the use of information about national working days and holidays.

2.3.2   Outliers

Many time series contain one or more extreme values that deviate from the normal or expected development by a large margin. In the following, such extreme values are termed *outliers*.

Many outliers in a time series may make it difficult to identify a seasonal model and tend to reduce the quality of the seasonal adjustment. The statistician therefore must consider the number of outliers relative to the length of the series and regularly review the regression model that is used for outliers in JDemetra+.

It is useful to distinguish between four types of outliers, which are illustrated in Figure 2.3. An additive outlier is a single point jump in the time series; a transitory change is a point jump followed by a smooth return to the original path, and a level shift is a more permanent change in the level of the series. Lastly, a seasonal outlier/break refers to an abrupt change in the seasonal pattern.

An additive outlier is a single extreme observation. It may be caused by random effects, strikes or bad weather. A pre-announced price rise could cause an additive outlier by increasing the sales dramatically before the price change. Additive outliers need to be identified since the seasonal adjustment is based on moving averages, and is, therefore, sensitive to extreme values.

A *transitory change* marks a sudden shift (jump) in the time series followed by a return to the previous level of the series. Transitory changes could occur due to deviations from average monthly weather

conditions. If in winter the weather suddenly becomes colder than usual, the energy consumption would probably go up. When the weather gradually returns to the average level the consumption should settle back to normal.

Figure 2.3 **The most common type of outliers**
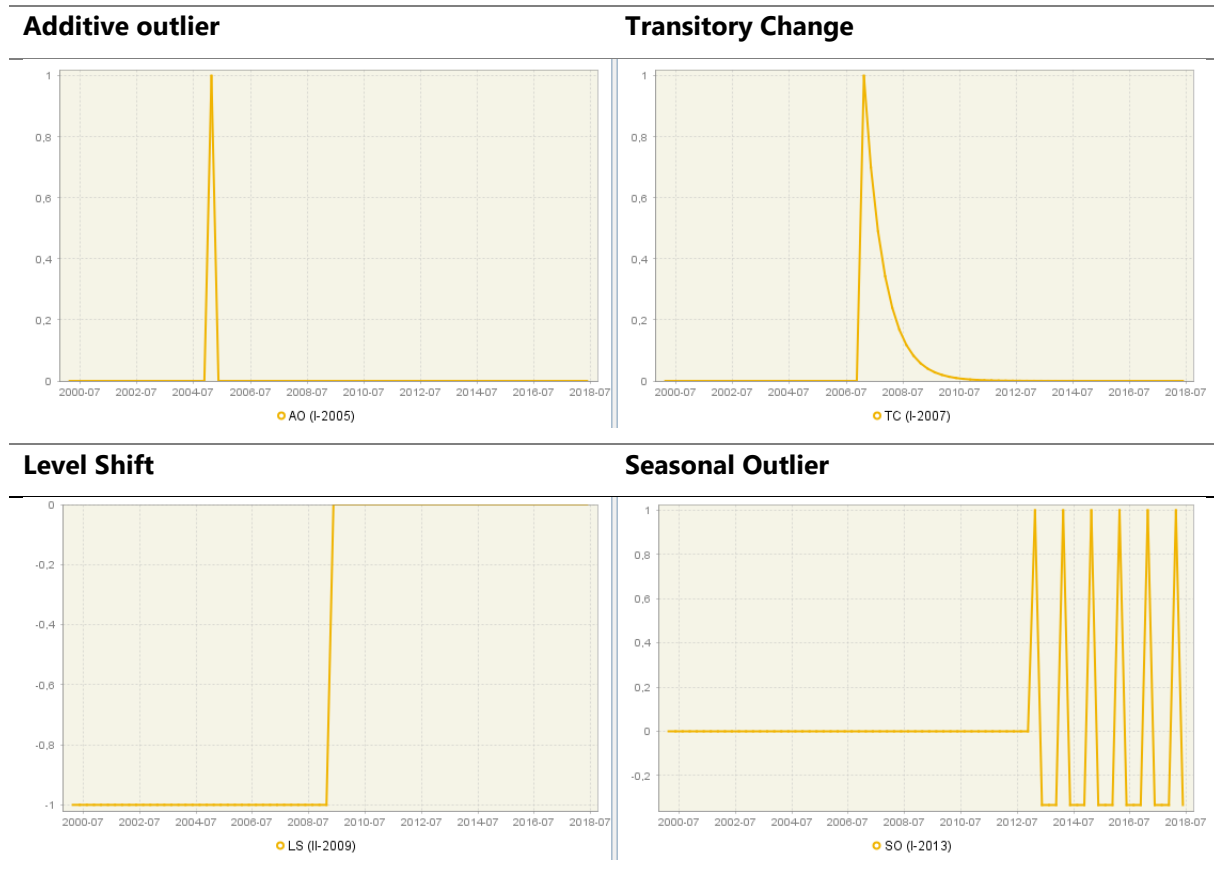
A *level shift* refers to a permanent change in the level of the series. Sometimes a change in concepts and definitions or compilation methods of a survey may cause this kind of shift. But statisticians should try to maintain the comparability of the series if a level shift results from a methodological change. Level shifts often occur because of changed economic behavior, new legislation or changed social traditions. For example, if the salaries increase for some profession, the level of that time series becomes permanently higher, but the seasonal pattern does not change. Level shifts need to be identified so that they do not prevent the optimal identification of the seasonal component.

A *seasonal outlier* or a *seasonal break* is a permanent change in the seasonal pattern of the series. In this case, the level shift has a peak in a specific month/quarter of the remaining time series with the condition of a non-zero-mean. Thus, it will also influence the trend. This type of outlier can occur due to a permanent change in the size of the seasonal effect for a specific month/quarter of the remaining time series. Seasonal outliers should be permanently removed from a seasonally adjusted series.

To ensure the optimal identification of the components of an unadjusted series, outliers are removed from a series prior to the actual seasonal adjustment process taking place. However, since the outliers include information about specific, unusual events, such as strikes, they are generally re-introduced as part of the final seasonally adjusted data, and therefore they remain observable after seasonal adjustment. The exception is with seasonal outliers, as these should not be evident in the seasonally adjusted data.

Outliers in the latest month or quarter are difficult to identify. Before additional observations become available, it is not possible to distinguish a level shift from an additive outlier since there is no information about how the level of the series will behave. Knowing the series and having external information of the

event in question would help define the type of outlier. It would be good to conduct a continuous analysis to identify reasons for outliers, where possible, and to document the explanations for them.

Missing observations could also interrupt the series. Series with too many missing values will cause estimation problems in the adjustment. Thus, statisticians should use appropriate statistical methods to replace missing data.

2.3.3   Extreme events

The effects on time series by extreme events often manifest as one of the four above explained types of outliers or combinations of them. Extreme events may be national or international developments that have a big impact on the activity of the society, such as e.g. the 2007-2008 financial crisis or the COVID-19 crisis or natural catastrophes.

While the reason for the outlier may be clear, the question of the nature of the outlier, its duration and impact on the trend-cycle cannot be answered without additional observations. In practice it is recommended to treat such an outlier as an additive outlier at first (unless an effect to the trend-cycle is expected). When enough observations are available, the type of the outlier can be changed into a transitory change or a level shift, depending on which is more suitable. A change in the outlier type can render a revision necessary and can also change the identification of turning points in the trend-cycle. The outlier will still be visible in the seasonally adjusted time series, as it will be captured by the irregular component. At the initial stage, it is not recommended to assume a seasonal outlier, unless the outlier is expected to reappear on a regular basis (Eurostat, 2015).

As with other outliers, additional information can be helpful to determine the type of the outlier and its duration and impact on the trend-cycle. In such exceptional situation, it might be helpful to increase the frequency of the observations (i.e. from quarterly to monthly) to better identify any turning point in the trend-cycle. Another option is to model the outlier using additional external regressors. Furthermore, for clear communication, users need to be warned about higher uncertainties regarding the seasonally adjusted series and the possibility of revisions (Eurostat, 2020).

2.4   Preparation of time series

JDemetra+ software has some specific requirements for the format of the input data. The software supports several input formats and file types, but the files need to follow a certain structure. Additionally, JDemetra+ supports the repeated seasonal adjustment of the same source data with an in-built tool. It allows for the reading of revised and new figures from the (updated) original file.

2.4.1   Opening JDemetra+

The JDemetra+ software and additional documentation and guidance is available from the Eurostat website[7]. It should be noted that this Guide is written for version 2.1.0. Once installed, JDemetra+ can be started by double-clicking on the JDemetra+ shortcut on the desktop. The JDemetra+ User Manual (Grudkowska, 2015) and related user documentation contain detailed instructions for using the software.

The view of JDemetra+ consists of different panels and tabs (Figure 2.4):

- *Providers* tab (left panel - left) provides some connecting methods to upload the time series.
- *Workspace* tab (left panel - centre) gives access to information used or generated in the workflow.
- The empty panel on the right may contain several windows created by JDemetra+. As it also displays the analyses, it will be called the *Results* panel in this *Guide*.

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[7] https://ec.europa.eu/eurostat/cros/content/software-jdemetra_en

Figure 2.4 **JDemetra+ at a first glance**
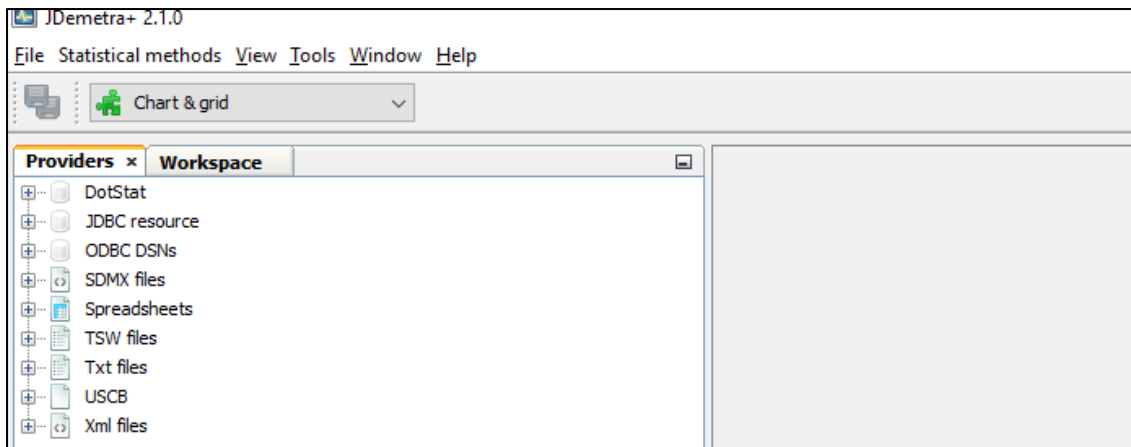
The user can move, resize and close panels as needed. Time series can easily be dragged and dropped between panels. The user can re-open closed panels through the main menu command: ***Window***. JDemetra+ remembers the chosen setup for later use.

2.4.2 Preparing source data

JDemetra+ provides an easy process for importing data from several types of files. It offers several simple solutions, such as the drag and drop facility or the clipboard. The various alternatives for dynamic (will be explained later) data uploads include:

- Files with "***.xls/.xlsx***" extensions of Microsoft® Excel® (consisting of spreadsheets) and text files with "***.txt/.csv/.tsv***" extensions.
- Files from the X-13 software provided by the U.S. Census Bureau (USCB) and from the TRAMO/SEATS for Windows (TSW) software provided by Bank of Spain.
- Files in Statistical Data and Metadata eXchange (SDMX) or Xperimental Markup Language (XML) format.
- Files in generic database drivers i.e. Oracle® Database Connection (ODBC) or Java® Database Connection.

The data files mentioned above have specific data storage rules and are connected to JDemetra+ by their own specific rules. For further details, see Grudkowska (2015). There is also the facility to import pre-defined data via web-services in XML format to JDemetra+. To perform this, a plug-in called "DotStat" is required (Charles, 2016). But this topic is beyond the scope of this Guide.

A commonly used file format to store the data is Microsoft® Excel®. For this reason, this format is used in the following example of how to prepare input data for JDemetra+.

As a start, the source file, including the data to be seasonally adjusted, needs to be prepared. The data series used in this example are obtained from the UNECE Statistical database[8]. The selected data set contains quarterly gross domestic product (GDP) at average prices of 2010 in national currency by country (ISIC Rev. 3.1) for 52 countries. The starting date is not the same for all countries. The initial format of the data is shown in the upper part of Figure 2.5.

The user can arrange the set of time series either vertically or horizontally. Then, the transposed and re-formatted data in terms of date (column A), as illustrated in the lower part of Figure 2.5.[9]

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[8] www.unece.org/stats

[9] The prepared file can be downloaded at https://www.unece.org/index.php?id=53959

Figure 2.5 **Shape of the Excel file to be used as input for JDemetra+**

Before

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	GDP: Output Approach, in National Currency, by Activity, Measurement, Country and Quarter																				
2																					
3				2000Q1	2000Q2	2000Q3	2000Q4	2001Q1	2001Q2	2001Q3	2001Q4	2002Q1	2002Q2	2002Q3	2002Q4	2003Q1	2003Q2	2003Q3	2003Q4	2004Q1	2004Q2
4	GDP	Millions of NCU	Albania																		
5			Armenia	198125	335941	530230	544511	222867	349007	602279	589100	241671	387879	666951	699501	271728	454341	770564	778810	292974	502135
6			Austria	60400	63232	63975	66462	62185	64069	64338	66697	62940	65079	65708	67811	63368	65653	66441	68538	64656	67470
7			Azerbaijan					2367	2765	3435	3211	2540	3008	3764	3578	2778	3277	4163	3986	3036	3603
8			Belarus																		
9			Belgium	75476	78498	75399	81553	76876	79495	75792	81285	77242	80826	77443	83519	78258	81177	77740	84326	80464	84232
10			Bosnia and Herzegovina																		
11			Bulgaria	10306	10960	13210	13265	10654	11331	13742	13815	11236	12044	14557	14648	11856	12662	15098	15575	12423	13564
12			Canada	333654	346225	356970	357268	343097	353249	356135	362252	349030	364828	367905	373969	358608	371764	373990	378549	363818	381191
13			Croatia	59905	63947	68469	64849	61804	66928	70775	66542	65503	70453	75106	68964	69537	75132	78789	72196	72638	77614
14			Cyprus	3325	3612	3533	3514	3411	3666	3754	3706	3568	3819	3822	3870	3687	3841	3950	3996	3870	4032
15			Czechia	672694	724662	741405	761164	699155	747350	757570	780202	707637	756326	776473	793156	728945	782379	807468	824100	761771	820685
16			Denmark	406046	418756	413159	439257	410884	421474	418611	440054	411412	428665	419750	439082	416295	423951	418403	446887	423388	438713
17			Estonia	2456	2758	2653	2796	2632	2921	2833	2950	2718	3108	3053	3147	2976	3301	3261	3380	3281	3410
18			Finland	37458	39319	39231	42081	38719	40678	40237	42536	38800	41675	40807	43613	39232	42249	42016	44686	41005	43708
19			France	435991	440882	430612	454425	446641	450138	438902	461181	449855	456559	445673	465179	456102	456184	448382	471561	466746	473252
20			Georgia									2765	3346	3679	4063	3016	3563				
21			Germany	577611	587286	597671	596058	591221	596703	606701	604186	584319	597606	613216	603605	582126	589737	608056	601670	591479	599219
22			Greece	44076	45589	50105	50132	46753	47760	52052	51182	47839	50597	54039	53030	50671	53517	56748	56476	54143	56212
23			Hungary	5075711	5517896	5706633	5983954	5284056	5753098	5923508	6179357	5516579	6008194	6203481	6459594	5679057	6242329	6455595	6741763	5950214	6572127
24			Iceland	305058	312829	339418	330570	312091	332368	343038	350590	317077	333222	348822	348080	345608	335363	350815	345972	363882	360341
25			Ireland	30235	31251	32367	32819	32547	33248	33310	34305	34311	34974	35422	36611	35024	35921	35726	38822	37640	38961
26			Israel	152544	158988	166992	163363	161658	159969	161886	157314	157969	160341	161397	160114	159889	160561	166015	160399	166408	166839
27			Italy	374017	392058	380772	408704	386818	401364	385805	409130	382074	401753	390024	413202	384548	401062	389847	413998	388698	409907

After

	A	B	C	D	E	F	G	H	I	J	K	L	M
1		Albania	Armenia	Austria	Azerbaijar	Belarus	Belgium	Bosnia and	Bulgaria	Canada	Croatia	Cyprus	Czechia
2	1.1.2000	..	198125	60400	..	..	75476	..	10306	333654	59905	3325	672694
3	1.4.2000	..	335941	63232	..	..	78498	..	10960	346225	63947	3612	724662
4	1.7.2000	..	530230	63975	..	..	75399	..	13210	356970	68469	3533	741405
5	1.10.2000	..	544511	66462	..	..	81553	..	13265	357268	64849	3514	761164
6	1.1.2001	..	222867	62185	2367	..	76876	..	10654	343097	61804	3411	699155
7	1.4.2001	..	349007	64069	2765	..	79495	..	11331	353249	66928	3666	747350
8	1.7.2001	..	602279	64338	3435	..	75792	..	13742	356135	70775	3754	757570
9	1.10.2001	..	589100	66697	3211	..	81285	..	13815	362252	66542	3706	780202
10	1.1.2002	..	241671	62940	2540	..	77242	..	11236	349030	65503	3568	707637
11	1.4.2002	..	387879	65079	3008	..	80826	..	12044	364828	70453	3819	756326
12	1.7.2002	..	666951	65708	3764	..	77443	..	14557	367905	75106	3822	776473
13	1.10.2002	..	699501	67811	3578	..	83519	..	14648	373969	68964	3870	793156
14	1.1.2003	..	271728	63368	2778	..	78258	..	11856	358608	69537	3687	728945

Table 2.1 shows the number of observations and start and end dates of the series in the examples. The number of observations differ among the countries but all the series in the dataset are suitable for seasonal adjustment since they meet the minimum length criteria for time series.

To be processed in JDemetra+, the spreadsheet must meet the following criteria:

- Dates in the first column must be in a format recognized by Excel (e.g. "*ddmmyyy*"). Monthly data entries can be the first days of each month, such as "1.1.2000, 1.2.2000" (dd.mm.yyyy). Quarterly data can be specified by the dates of the first day of the quarter, such as "1.1.2000, 1.4.2000, 1.7.2000" (dd.mm.yyyy). There must be three months intervals between the dates.
- The first row contains the names of the variables.
- Time series data comes in the number format.
- Top-left cell [A1] is empty.
- Missing values to be estimated are manually set to -99999. JDemetra+ uses the "Additive Outlier Approach" (Gómez, Maravall, & Pena, 1999) for the estimation of missing observations.

A transposed table, following the same layout with variable names in the first column and dates in the first row, is also accepted by JDemetra+.

Table 2.1 **Basic properties of the example dataset**

| Name of Country	Number of observations	Start	End
Albania	37	31.3.2009	31.3.2018
Armenia	60	31.3.2000	31.12.2014
Austria	73	31.3.2000	31.3.2018
Azerbaijan	69	31.3.2001	31.3.2018
Belarus	36	31.3.2009	31.12.2017
Belgium	73	31.3.2000	31.3.2018
Bosnia &Herzegovina	40	31.3.2008	31.12.2017
Bulgaria	73	31.3.2000	31.3.2018
Canada	73	31.3.2000	31.3.2018
Croatia	73	31.3.2000	31.3.2018
Cyprus	73	31.3.2000	31.3.2018
Czechia	73	31.3.2000	31.3.2018
Denmark	73	31.3.2000	31.3.2018
Estonia	73	31.3.2000	31.3.2018
Finland	73	31.3.2000	31.3.2018
France	73	31.3.2000	31.3.2018
Georgia	60	31.3.2003	31.12.2017
Germany	73	31.3.2000	31.3.2018
Greece	73	31.3.2000	31.3.2018
Hungary	73	31.3.2000	31.3.2018
Iceland	73	31.3.2000	31.3.2018
Ireland	73	31.3.2000	31.3.2018
Israel	72	31.3.2000	31.12.2017
Italy	73	31.3.2000	31.3.2018
Kazakhstan	72	31.3.2000	31.12.2017
Kyrgyzstan	33	31.3.2010	31.3.2018
Latvia	73	31.3.2000	31.3.2018
Lithuania	73	31.3.2000	31.3.2018
Luxembourg	73	31.3.2000	31.3.2018
Malta	73	31.3.2000	31.3.2018
Moldova, Republic of	72	31.3.2000	31.12.2017
Montenegro	-	-	-
Netherlands	73	31.3.2000	31.3.2018
North Macedonia	71	31.3.2000	30.9.2017
Norway	73	31.3.2000	31.3.2018
Poland	73	31.3.2000	31.3.2018
Portugal	73	31.3.2000	31.3.2018
Romania	73	31.3.2000	31.3.2018
Russian Federation	56	31.3.2000	31.12.2013
Serbia	73	31.3.2000	31.3.2018
Slovakia	73	31.3.2000	31.3.2018
Slovenia	73	31.3.2000	31.3.2018
Spain	73	31.3.2000	31.3.2018
Sweden	73	31.3.2000	31.3.2018
Switzerland	73	31.3.2000	31.3.2018
Tajikistan	-	-	-
Turkey	71	31.3.2000	30.9.2017
Turkmenistan	-	-	-
Ukraine	32	31.3.2010	31.12.2017
United Kingdom	73	31.3.2000	31.3.2018
Uzbekistan	-	-	-

2.4.3 Importing data

Once the source (Excel) file satisfies the necessary conditions, the file can be imported into JDemetra+. There exist several alternative ways to import data.

The direct way to import data to JDemetra+ is through the *Providers* tab *(*Figure 2.6*)*. Calling data using *Providers* also allows for dynamic data updating. More precisely, when the user needs to rerun an existing seasonal adjustment with fresh data, the updated dataset can be dynamically refreshed (re-read) from the file. JDemetra+ then automatically updates the seasonal adjustment results for the latest data.

The indirect way to import data to JDemetra+ is by copy and pasting the data from the source file (that meets the conditions) to the *Grid/List* panel JDemetra+ (Figure 2.7). This way is only recommended for one-time seasonal adjustment of data and quick analyses, but not for producing official statistics in a formal production process.

Figure 2.6 **Importing data to JDemetra+ by reading an Excel file**
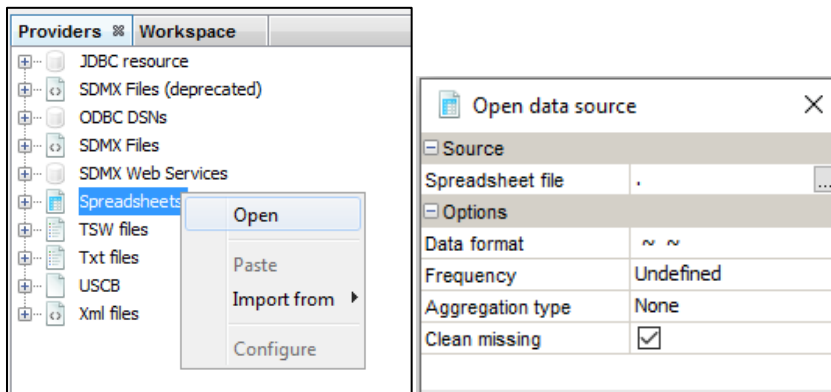
Direct way: Loading file

- Right-click on **Spreadsheet** in the *Providers* tab and select **Open** (Figure 2.6, left).
- Select source file by clicking **"…"** right to **Spreadsheet file** under **Source** (Figure 2.6, right).
- Chose the desired source file from a local folder (Excel).

Once imported, right-click on the source file in the **Providers** tab, allows for some operations as: **edit, close** or **rename** of the file. The file can be located using the **Show in Folder** *option*.

Figure 2.7 **A short-cut to load data to JDemetra+**
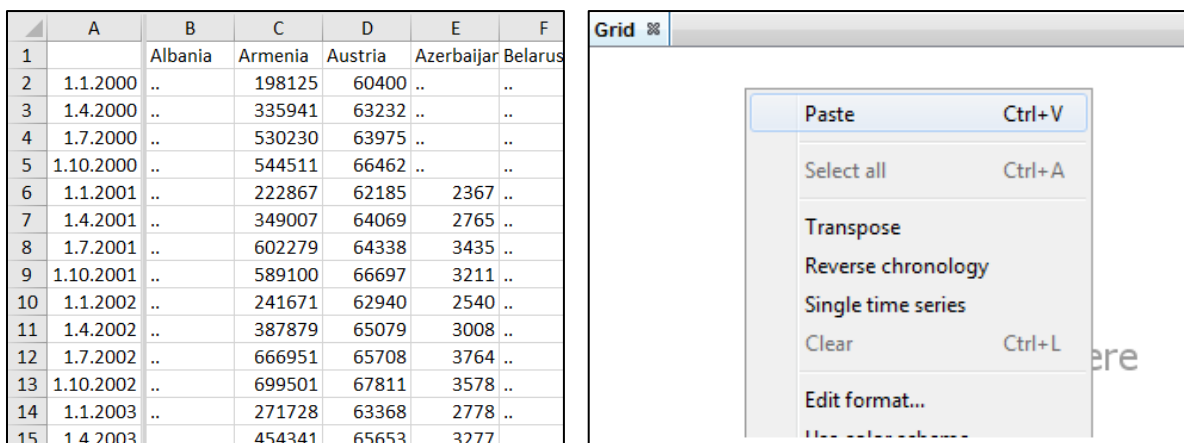
Indirect way: Copy and paste

- Select all time-series data including the column containing the dates and the row containing the titles of the data in the source file and copy it (right-click or Ctrl+c).
- Switch to JDemetra+ and click on **Tools → Container→ Grid,** right-click on the open Grid panel and **Paste** (or Ctrl+v).

With this indirect method, dynamic updates are not possible since the data are not linked to the source file. On the other hand, it is the quickest way for looking at data and for one-time seasonal adjustment processes.

2.4.4 Checking the original series

"Original series" refers to the underlying time series before seasonal adjustment. It can also be called a raw series. As mentioned earlier in this chapter, it is important to check/analyse the original series before starting the seasonal adjustment process. The quality of the seasonal adjustment highly depends on the quality of the underlying data. Properties that need to be considered are the length, and the existence of: a visible trend, visible seasonality, any visible outliers and missing observations.

Visual analysis of the original time series is helpful to see the general picture before seasonal adjustment, and JDemetra+ provides several useful tools for this purpose. The visual analysis may help to confirm the suitability of the original time series for seasonal adjustment, but also to identify possible weaknesses of the original time series. Good knowledge of the original time series certainly helps during the process of seasonal adjustment and for interpreting the results.

Visual analysis can further help to identify possible outliers, the presence of the trend or seasonality and the breaks in the trend or in the seasonality. This type of information will increase the robustness of the seasonal adjustment of the series. Good documentation of the properties of the raw data helps to share information with colleagues and users.

For seasonal adjustment, the original time series must be at least three years long for monthly series and four years for quarterly series. The quality of seasonal adjustment (in terms of the determination of seasonality and calendar effects) is likely to be higher with more than seven years of data (Statistics Canada, 2015).
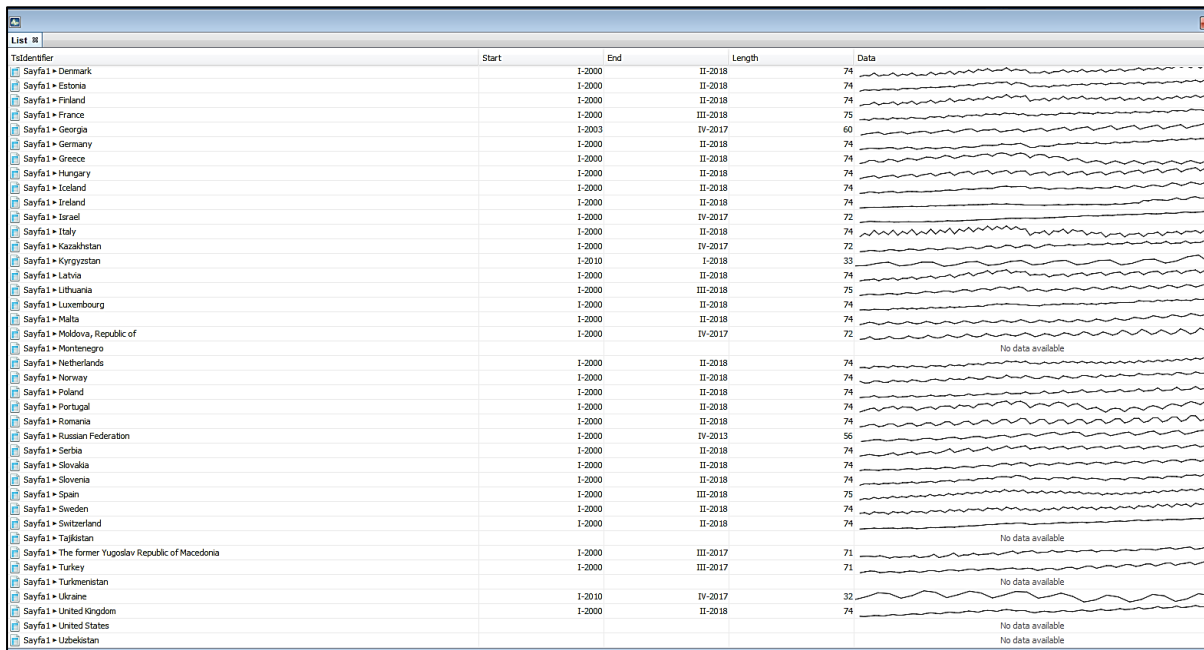
On the other hand, very long series may not be ideal either, as they may not be consistent over time. The historical data may not reflect the seasonal pattern of the current data. For statistical offices, it can be hard to find too long time-series though, due to the changes in the classification or production method of the data. Therefore, no upper limit will be considered for the length of data to be seasonally adjusted.

Seasonal adjustment can be applied for time series of stock variables as well as for those of flow variables. One should be aware that the interpretation of seasonality and calendar effects in seasonally adjusted stock time series is different from the case of flow time series.

In JDemetra+, the main properties of the time series can be accessed via the menu item **Tools → Container → List**. The empty **List** panel appears and the sheet in question can be visualized via drag and drop from **Providers** to **List**. The data will then be visualized as in Figure 2.8.
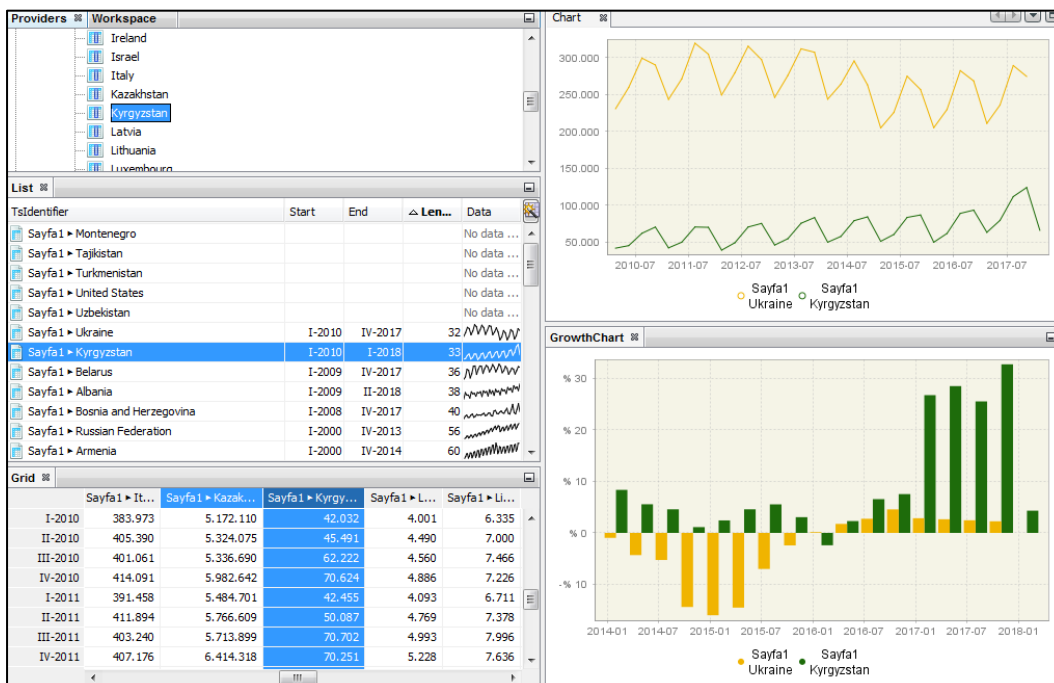
Figure 2.8 **List view of time series**

TsIdentifier	Start	End	Length	Data
Sayfa1 ▸ Denmark	I-2000	II-2018	74	
Sayfa1 ▸ Estonia	I-2000	II-2018	74	
Sayfa1 ▸ Finland	I-2000	II-2018	74	
Sayfa1 ▸ France	I-2000	III-2018	75	
Sayfa1 ▸ Georgia	I-2003	IV-2017	60	
Sayfa1 ▸ Germany	I-2000	II-2018	74	
Sayfa1 ▸ Greece	I-2000	II-2018	74	
Sayfa1 ▸ Hungary	I-2000	II-2018	74	
Sayfa1 ▸ Iceland	I-2000	II-2018	74	
Sayfa1 ▸ Ireland	I-2000	II-2018	74	
Sayfa1 ▸ Israel	I-2000	IV-2017	72	
Sayfa1 ▸ Italy	I-2000	II-2018	74	
Sayfa1 ▸ Kazakhstan	I-2000	IV-2017	72	
Sayfa1 ▸ Kyrgyzstan	I-2010	I-2018	33	
Sayfa1 ▸ Latvia	I-2000	II-2018	74	
Sayfa1 ▸ Lithuania	I-2000	III-2018	75	
Sayfa1 ▸ Luxembourg	I-2000	II-2018	74	
Sayfa1 ▸ Malta	I-2000	II-2018	74	
Sayfa1 ▸ Moldova, Republic of	I-2000	IV-2017	72	
Sayfa1 ▸ Montenegro				No data available
Sayfa1 ▸ Netherlands	I-2000	II-2018	74	
Sayfa1 ▸ Norway	I-2000	II-2018	74	
Sayfa1 ▸ Poland	I-2000	II-2018	74	
Sayfa1 ▸ Portugal	I-2000	II-2018	74	
Sayfa1 ▸ Romania	I-2000	II-2018	74	
Sayfa1 ▸ Russian Federation	I-2000	IV-2013	56	
Sayfa1 ▸ Serbia	I-2000	II-2018	74	
Sayfa1 ▸ Slovakia	I-2000	II-2018	74	
Sayfa1 ▸ Slovenia	I-2000	II-2018	74	
Sayfa1 ▸ Spain	I-2000	III-2018	75	
Sayfa1 ▸ Sweden	I-2000	II-2018	74	
Sayfa1 ▸ Switzerland	I-2000	II-2018	74	
Sayfa1 ▸ Tajikistan				No data available
Sayfa1 ▸ The former Yugoslav Republic of Macedonia	I-2000	III-2017	71	
Sayfa1 ▸ Turkey	I-2000	III-2017	71	
Sayfa1 ▸ Turkmenistan				No data available
Sayfa1 ▸ Ukraine	I-2010	IV-2017	32	
Sayfa1 ▸ United Kingdom	I-2000	II-2018	74	
Sayfa1 ▸ United States				No data available
Sayfa1 ▸ Uzbekistan				No data available

Our example consists of quarterly time series for fifty-two countries. In *List,* the start and end dates of the series, the number of observations, and a small line graph displaying the shape the series can be seen. When there are no data for a country, which is the case for some countries in the example, the warning "No data available" appears. For all other countries in the example, the time series consists of enough observations (32 - 75 observations per country).

Figure 2.9 **Chart & Growth Chart Tools**

	Sayfa1 ▸ It...	Sayfa1 ▸ Kazak...	Sayfa1 ▸ Kyrgy...	Sayfa1 ▸ L...	Sayfa1 ▸ Li...
I-2010	383.973	5.172.110	42.032	4.001	6.335
II-2010	405.390	5.324.075	45.491	4.490	7.000
III-2010	401.061	5.336.690	62.222	4.560	7.466
IV-2010	414.091	5.982.642	70.624	4.886	7.226
I-2011	391.458	5.484.701	42.455	4.093	6.711
II-2011	411.894	5.766.609	50.087	4.769	7.378
III-2011	403.240	5.713.899	70.702	4.993	7.996
IV-2011	407.176	6.414.318	70.251	5.228	7.636

List (Figure 2.9):

TsIdentifier	Start	End	Len...	Data
Sayfa1 ▸ Montenegro				No data ...
Sayfa1 ▸ Tajikistan				No data ...
Sayfa1 ▸ Turkmenistan				No data ...
Sayfa1 ▸ United States				No data ...
Sayfa1 ▸ Uzbekistan				No data ...
Sayfa1 ▸ Ukraine	I-2010	IV-2017	32	
Sayfa1 ▸ Kyrgyzstan	I-2010	I-2018	33	
Sayfa1 ▸ Belarus	I-2009	IV-2017	36	
Sayfa1 ▸ Albania	I-2009	II-2018	38	
Sayfa1 ▸ Bosnia and Herzegovina	I-2008	IV-2017	40	
Sayfa1 ▸ Russian Federation	I-2000	IV-2013	56	
Sayfa1 ▸ Armenia	I-2000	IV-2014	60	

Good starting points for any visual analysis are the **Tools→Container→Chart** or **GrowthChart** options. Further visual tools can be found under **Tools→Spectral Analysis**. All these containers become active by drag and drop of data from *Providers, List* or *Grid*. Figure 2.9 illustrates *Providers*, *List*, *Grid*, *Chart* and *GrowthChart* for some countries from the example.

The top right of Figure 2.9 shows the **Chart**. The existence of seasonality and trend patterns can already be identified from this example. The bottom right part shows the **GrowthChart**, displaying quarterly year-on-year growth rates. The type of growth rates can be changed to quarterly quarter-on-quarter growth rates by right-clicking on the graph and selecting **Kind → Previous period.** The existence and the reversal (yellow columns) of a trend can be confirmed from this chart.

Chart also provides the possibility to look at data divided into years, each year being represented by a different colour. With this type of graph, the level differences between months/quarters can be quickly identified. These differences represent a significant seasonality in the data. The option is selected in **Chart** by right-clicking on the graph and selecting **Split into yearly components** (Figure 2.10).

Figure 2.10 **Time series presentation types**
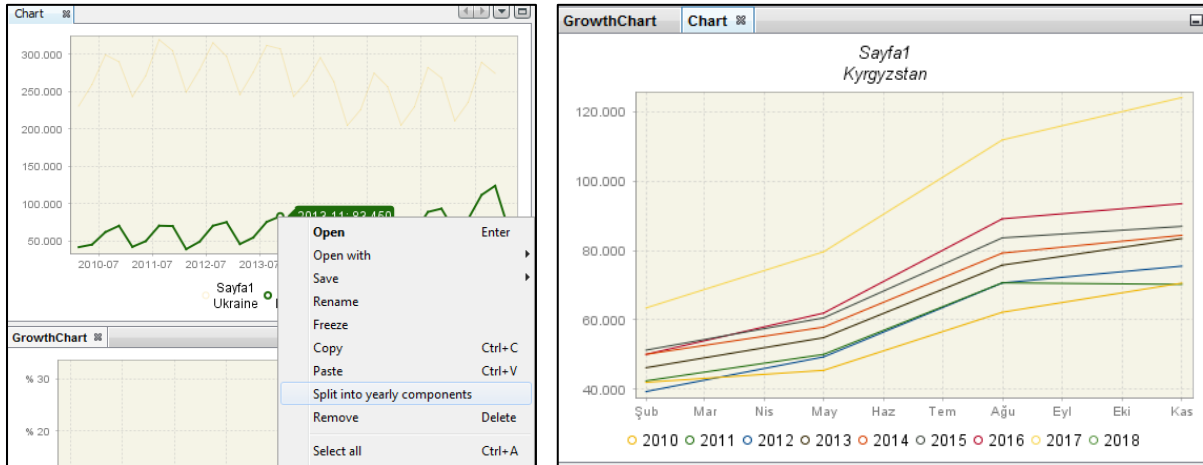
Three important graphical tools dealing with the spectral analysis of time series are the **Periodogram**, the **Auto-Regressive Spectrum** and the **Tukey Spectrum.** These are accessible in the menu **Tools→Spectral analysis**. In all three chart types, seasonal frequencies are marked as blue vertical lines, while the purple lines correspond to trading day frequencies. For a single series, a peak at one or more of these lines indicates the presence of seasonality or trading day effects. The **Periodogram** or **Auto-regressive Spectrum** does not require any lower limit for the number observations while **Tukey spectrum** requires over 40 observations for quarterly data and over 80 observations for monthly data. They detect periodic components in a time series.

A periodogram is one of mathematical tools for pointing out periodic movements in the time series which cannot be directly observed in the time series (Jenkins & Watts, 1968). The periodogram (Figure 2.11) displays a strong seasonal component, but it does not display any calendar component. The peak at the frequency $\pi/2$ (blue, i.e. it represents a year cycle) represents this. No peak is visible at calendar frequencies (purple). The interpretation of the frequency depends on the nature of the data (monthly/quarterly). A more thorough explanation of the spectral graphs can be found in Grudkowska (2015, Section 3.4.2).

The **Differencing** tool offers further visual analysis and provides information about the autocorrelation structure of the first differenced series together with its periodogram. This tool may be important to understand the differenced series in terms of the underlying movements. It can be accessed from the menu **Tools→Differencing**. Differencing is a common transformation to eliminate the trend in time series. Hence, the differenced series can be stationary meaning that mean, variance and distribution are constant over time. This makes the series easier to model.

Figure 2.11 **Periodogram example**
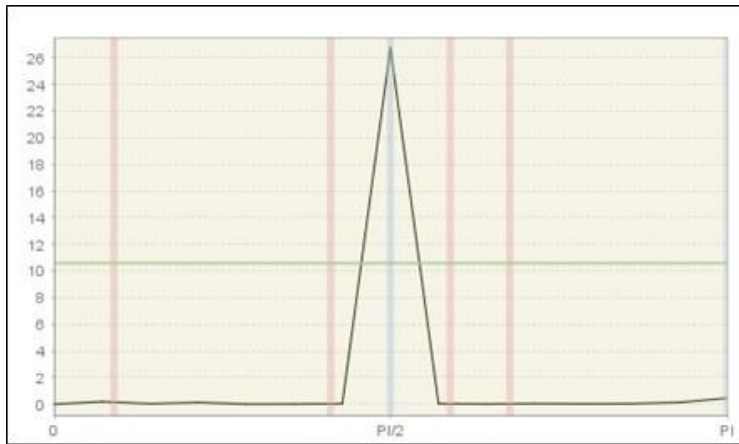
2.4.5   Preparing calendar regressors

Calendar effects, i.e. the effect of the varying number of holidays and working days influence most economic time series. The varying length of months, the number of different days appearing in a month, the composition of working and non-working days as well as different moving holidays may alter the level of activity described by a time series.

As an example of *moving holidays*, if the Easter holidays fall in March instead of April, the level of economic activity of these two months can change significantly. The movement of Easter can also influence quarterly series.

Calendar effects may be present in some time series, for example, the retail sales index, but not in all series. Quite often the pre-adjustment methods available in JDemetra+, TRAMO (modelling part of TRAMO/SEATS) and Reg-ARIMA (modelling part of X-13), detect a difference in working days and non-working days. With some series, they may find a *trading day effect*, meaning that different days show different levels of activity. For instance, depending on the branch, sales may be higher on Fridays than on Tuesdays.

Calendar regressors are the variables which contain the information about the relative importance of the holidays or weekends on weekdays in a month. It may also include information about the fixed or moving holidays for a country or a sector. The inclusion of regressors for these types of national days or holidays can improve the modelling of a time series. Using appropriate calendar regressors where necessary will ultimately increase the overall quality of the seasonal adjustment.

JDemetra+ provides some pre-defined regressors, i.e. *Working-days* and *Trading-days* variables, representing the relative superiority of working-days to the weekends in a month. JDemetra+ also provides a calendar tool to design more comprehensive calendar regressors. This tool may be used when it is necessary to model country specific national holidays. Creating country specific regressors can be time consuming. It is advisable to use official sources for the holidays and to make an external list containing the holiday's name, date, and explanations to provide greater transparency in the seasonal adjustment process.

To improve the seasonal adjustment, TRAMO, and Reg-ARIMA estimate and removes the calendar effects in the pre-adjustment process of the series. The pre-adjustment stage in JDemetra+ is based on the functions of TRAMO and Reg-ARIMA.

How to set up a new calendar regressor in JDemetra+ is explained in detail in Chapter 3.

3 Seasonal adjustment

3.1 Introduction

After the preparation of data presented in Chapter 2, this chapter presents the different steps in the seasonal adjustment using the QGDP as an example. First, a national calendar is defined followed by the explanation how to use the calendar in JDemetra+. Using national calendars improves the estimate of the calendar effects. Some special days are already available in JDemetra+, but others need to be manually created. After that, single processing is explained, i.e. how to seasonally adjust a single time series. In the last section of the chapter, multi-processing is introduced, consisting of instructions for performing seasonal adjustment of several time series simultaneously.

Currently, the most popular seasonal adjustment approaches are X-13 (Sax & Eddelbuettel, 2018) and TRAMO/SEATS (Maravall & Caporello, 2004). JDemetra+ provides statisticians with an interface for both methods.

In the econometric literature, the seasonally adjusted series, trend, and seasonal components are often called the "unobserved components", as they cannot be directly observed in a time series. Statisticians have developed several ways for estimating unobserved components. Historically, analysts often used a technique that consisted of drawing, by hand, the seasonally adjusted series based on the visual inspection of the original time series. The increasing use of computers enabled seasonal adjustment to be performed with more sophisticated mathematical techniques and with much greater efficiency.

One of the first mathematical methods for estimating the trend applies moving averages. In this method, each data point is formed by averaging the observations of a surrounding period (e.g. the value of Q2 could be the average of observations for Q1, Q2 and Q3). The trend-cycle is calculated based on the moving averages. After subtracting the estimated trend-cycle from the original series, the remaining series comprises the sum of seasonal and irregular components. This method, however, has some weaknesses. For example, it can be difficult to distinguish cyclical fluctuations from the seasonal effects. And outliers influence the estimation of the trend-cycle. The problem is also that the moving average over one year leads to a half-year time lag, as it is derived based on past observations. The end-point of the trend-cycle series is uncertain and new observations have a significant effect on the results.

Nonetheless, moving averages still form the basis of seasonal adjustment methods. Considering the weaknesses of moving averages, new methods using weighted averages were developed. As a result, in 1954, the United States Census Bureau introduced a new method, called Method I (Bell & Hillmer, 1984), for computer-assisted seasonal adjustment, which was followed by Method II. The later versions of this method were named X for experimental and called X-0, X-1, X-2… until the widely used X-11 model was introduced in the 1960s. The X-11 performs seasonal adjustment by carrying out several iterations to smoothen the series with moving averages.

The X-11 applies moving averages to arrive at the trend-cycle and seasonal component. The raw series is divided by the seasonal component to obtain the seasonally adjusted series in case of multiplicative decomposition. In case of an additive composition, the seasonal component is deducted from the raw series. This method still has many of the weaknesses of the simple moving averages. To overcome the time delay caused by the average of the previous year, one could either increase the weight of the uncertain last observations or stretch the time series at both ends by forecasting. The X-11-ARIMA method was developed to rectify this weakness.

The X-11-ARIMA, introduced by Statistics Canada, adds estimates at the beginning and at the end of the series before proceeding to seasonal adjustment. These estimates are done by forecasting and back casting using an ARIMA model. The forecasted ends of the series significantly decrease the size of revisions and the time lag of estimation. This improves the precision of the seasonal component. The "AR" of ARIMA comes from the word auto-regressive and means that the value is determined by its

correlation with the previous values of the series. The "MA" of ARIMA comes from the moving average part of the ARIMA model, and finally, the "I" means integrated.

The US Census Bureau developed the X-11-ARIMA further with the introduction of the X-12-ARIMA method (Findley, Monsell, Bell, Otto, & Chen, 1998). As well as applying the basic idea of its predecessor, X-12-ARIMA offers flexible tools for pre-adjustment (Reg-ARIMA) of a time series. It detects and corrects for calendar effects and outliers by means of a regression-ARIMA type model before identifying the seasonal component. X-12-ARIMA provides a comprehensive set of diagnostic tools important for checking the quality of the results (Medel, 2018).

The latest version of X-type approaches is the X-13-ARIMA-SEATS which is included in JDemetra+. For simplicity, it is called X-13 in the software and in the following. The X-13 has extensive capabilities for time series modelling and model selection using regression with ARIMA models. X-13 adopts both the SEATS procedure (Maravall & Caporello, 2004) and the X-11 procedure.

Another approach for seasonal adjustment is signal extraction, used in TRAMO/SEATS. This approach is based on describing the behaviour of the series and derives the different components of the series as captured by an ARIMA model. This leads to consistency between the ARIMA model obtained for the observed series and the models of the components (Gomez & Maravall, 1997). A comprehensive description of the software can be found in Gomez and Maravall (2000), and information on the latest facilities and interpretation of the SEATS results in Maravall, López-Pavón and Pérez-Cañete (2015).

In TRAMO/SEATS, the first part, TRAMO, is responsible for pre-adjustment. TRAMO refers to Time Series Regression with Arima Noise, Missing Observations and Outliers. It is a program for (often automatic) identification, estimation, forecasting and interpolation of Regression-ARIMA models. This model is used to extend the series with forecasts and to identify and estimate outliers, calendar and other effects with adequate regressors. The software can be used on its own for outlier detection or forecasting, for example, but it is mainly used for pre-adjustment before actual seasonal adjustment. TRAMO has many similarities with the pre-adjustment tool of the current X-13 since the latter uses the same Reg-ARIMA approach.

In the second step, TRAMO passes the series forward to SEATS which applies a filter to the extended series with any outliers and regression effects already removed. SEATS then estimates the seasonally adjusted series as well as the seasonal, trend-cycle and irregular component. SEATS is the abbreviation for Signal Extraction in ARIMA Time Series. It is a programme for decomposing a time series into its components, following an ARIMA-model-based method. The starting point for SEATS was a preliminary program built for seasonal adjustment at the Bank of England in 1982 (Gomez & Maravall, 1997).

The methods, X-13 and TRAMO/SEATS, have common features. They first perform pre-adjustment which adjusts for the working day effect and outliers by means of a regression model. Secondly, they identify and estimate the trend-cycle, seasonal and irregular components from the time series and sometimes also a transitory component. The two methods are very similar in the first part but differ in the adjustment step. The filter of X-13 is selected from a set of pre-designed filters, while SEATS follows a so-called ARIMA-model based decomposition. Furthermore, their outputs and quality diagnostics take different forms.

The combination of these two approaches in one seasonal adjustment tool is regarded as a promising way forward (Medel, 2018). JDemetra+ now brings these two methods closer to each other by offering them under the same interface. With JDemetra+ it is easy to compare the differences of the seasonally adjusted series between these methods.

3.2 Defining calendars

JDemetra+ provides an easy tool for creating calendar variables using the **Calendars** module. The calendar variables can include trading day (six variables + leap year effect) or working day (one variable + leap year effect) variables as well as country or sector-specific holidays. These holidays may occur at fixed or moving dates.

There are several options in JDemetra+ for designing the specific national calendar, including pre-defined options. If the national calendar includes one or more moving holidays that started or were abolished at some point of time, a validity period can be set for the holidays (**start** and **end** options). However, the validity periods should be used with caution. JDemetra+ includes long-term corrections on the trading day variables when national calendars are used, but the corrections do not consider the validity period, possibly leading to some seasonal effects in the variables. For more complex holidays, there is also the possibility to prepare the national calendar as an external user-defined variable, i.e. as a time series to be imported into JDemetra+.

In JDemetra+, TRAMO/SEATS and X-13 automatically create an appropriate trading day, working day, leap year and Easter variables depending on the chosen specifications. However, the user may need to change the automatic options for:

- Modifying the trading day, working day and leap year variables to match the national holidays that differ from the pre-specified options of JDemetra+.
- Chaining two calendars for two different time periods.
- Combining two or more calendar variables using proper weights.
- Importing user-regressors including holidays with changing frequency, duration, start and end dates.

JDemetra+ offers the following pre-defined regressors:

- Six variables to test for trading day effects: n{Monday} – n{Sunday}, n{Tuesday} – n{ Sunday},…, n{Saturday}–n{Sunday} where n means "the number of the day in a month".
- One variable to test the effect of weekdays versus weekend days: (N(*M, T, W, Th, F*)) - (N(*Sat, Sun*)×5/2).
- *Leap year* variable.
- *Easter* variable.

The leap year variable measures the effect of differences in the number of days in February, i.e. 28 or 29. This variable equals zero for all months except February. However, in February it takes the value of -0.25. if the month comprises 28 days that year and -0.75 for 29 days, i.e. a leap year.

TRAMO/SEATS assumes that the Easter effect lasts for six days. For X-13, the RSA5(c) specification tests for three different lengths of the Easter effect and selects the optimal length from 1, 8 or 15 days. The user may also define the duration. The variable includes a zero for all months different from March and April since Easter occurs in March or in April (Gomez & Maravall).

3.2.1   Creating a calendar

A new calendar can be created by right-clicking on **Calendars** under **Workspace→Utilities** and select **Add Calendar→National.** There are two more options under **Add Calendar** which are out of the scope of this Guide (Figure 3.1).

Figure 3.1 **Adding a national calendar**
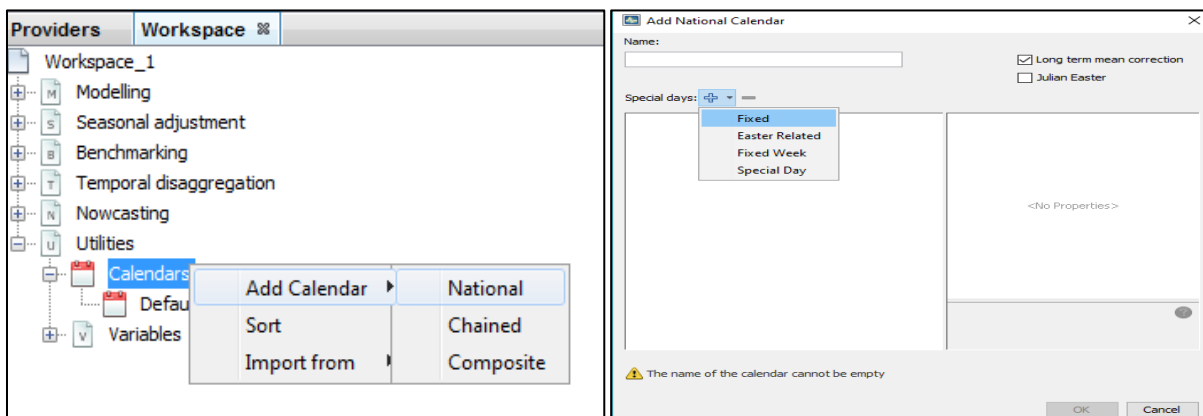
The **Add National Calendar** window appears which provides edit options for the national calendar (Figure 3.1, right). A new national holiday can be added by clicking the arrow near [+ ▾]. This opens a drop-down list with options: ***Fixed***, ***Easter Related***, ***Fixed Week***, and ***Special Day***. When all holidays are added to the national calendar, it can be saved by clicking ***OK.***

To demonstrate the different options and how to add national calendar to JDemetra+, this Guide will rely on the example of the national calendar of Belgium (Table 3.1).

Table 3.1 **List of holidays in Belgium**

Name of holidays	Date
New Year's Day	Special holiday in JDemetra+
Easter	Special holiday in JDemetra+
Easter Monday	Special holiday in JDemetra+
Mayday	Special holiday in JDemetra+
Ascension	Special holiday in JDemetra+
Pentecost	Special holiday in JDemetra+
Pentecost Monday (WhitMonday)	Special holiday in JDemetra+
National day	21st of July
Assumption of Mary	15th of August
All Saints	Special holiday in JDemetra+
Armistice Day	11th of November
Christmas	Special holiday in JDemetra+

3.2.2 Special days

JDemetra+ provides seventeen pre-specified holidays based on the most common European holidays. However, these holidays may vary between countries, so they need to be checked for the correct dates.

Figure 3.2 **Adding special days**
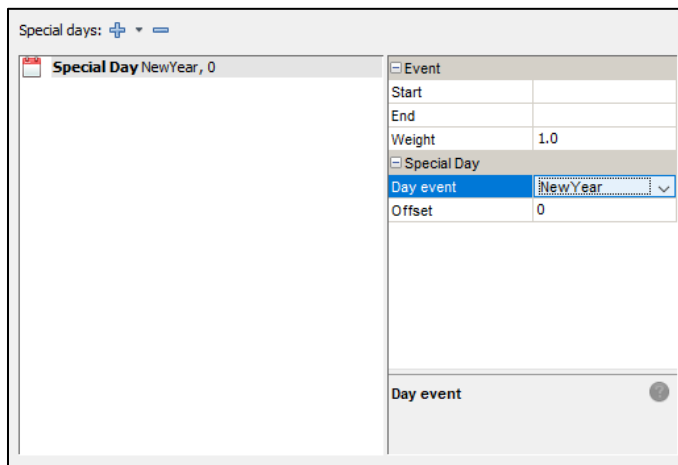
They can be added by clicking on [+ ▾] and then ***Special Day*** (Figure 3.2). Once a holiday from the list is added, its offset, the validity period (start&end) and its weight can be specified.

Nine holidays in the Belgian calendar are available as special days. *Pentecost* and *Whit Monday* are explained in the ***Easter related holidays*** section. The National day, Assumption of Mary and the Armistice Day are not included in the list of ***special days*** and need to be added as ***fixed days,*** if required.

Table 3.2 provides the definitions of the special days specified in JDemetra+.

Table 3.2 **Definitions of the special holidays in JDemetra+**

Holidays	General Definitions
New Year	It is a fixed holiday which falls on the 1st of January.
Shrove Monday	It is a moving holiday which falls on the Monday before Ash Wednesday.
Shrove Tuesday	It is a moving holiday which is the preceding day of Ash Wednesday.
Ash Wednesday	It is a moving holiday which is occurring 46 days before Easter.
Easter	It is a moving holiday which varies between 22nd of March and 25th of April depending on offset time. It always falls on a Sunday.
Maundy Thursday	It is a moving holiday which falls on the Thursday before Easter. It is the fifth day of Holy Week and is preceded by Holy Wednesday and followed by Good Friday.
Good Friday	It is a moving holiday which refers to the Friday in Easter week.
Easter Monday	It is a moving holiday which is the day after Easter Sunday.
Ascension Day	It is a moving holiday which is celebrated on a Thursday, the 40th of the day from Easter day.
Pentecost	It is a moving holiday which is celebrated seven weeks (50 days) after Easter Sunday, Pentecost falls on the tenth day after Ascension Thursday.
Corpus Christi	It is a moving holiday which is two months after Maundy Thursday.
Whitmonday	It is a moving holiday which is celebrated the day after Pentecost.
May Day	It is a fixed holiday which falls on the 1st of May, and which is a spring festival and usually a public holiday.
Halloween	It is a fixed holiday which is observed on the 31st of October.
Assumption	It is a fixed holiday which is celebrated on the 15th of August.
All Saints Day	It is a fixed holiday which is celebrated on 1st of November by parts of Western Christianity, and on the first Sunday after Pentecost in Eastern Christianity.
Christmas	It is a fixed holiday which is observed on the 25th of December in many countries.

3.2.3   Fixed holidays

Countries usually have ***Fixed*** holidays in their national holiday calendar. These holidays occur on the same date each year. Therefore, it might be assumed that their effect will be captured by the seasonal component already. However, fixed holidays may occur on working days or during the weekend, which makes the seasonal component irregular. Hence, it is recommended to include fixed holidays in the calendar regressor variable in JDemetra+.

From the Belgian example, the National day, Assumption of Mary and Armistice Day are not included in the pre-specified holidays in JDemetra+. As they occur on fixed dates every year (Table 3.1) they can be added as fixed holidays. This is done by clicking on and then ***Fixed***. The respective specifications can then be entered as shown in Figure 3.3.

A specific design of a user-regressor may be needed in the case where a fixed or special holiday is moved to a trading day, usually a Monday, when it falls on the weekend. On the other hand, this type of holidays may be captured by the seasonal component and there may be no need to use any user-regressor. The decision depends on the type of the holiday.

Figure 3.3 **Fixed holidays in calendar module**

3.2.4 Easter related holidays

The duration and the exact timing of Easter and Easter related days (e.g. Pentecost and Whit Monday) may vary among countries. Moreover, the number of holidays before/after Easter may vary (offset day). Therefore, JDemetra+ provides an option called ***Easter related*** days for the user to design such a holiday (Figure 3.4). This is done by clicking on ⊞ ▾ and then ***Easter related***. The relationship between Easter and the related days is determined by ***offset***.

Figure 3.4 **Selecting Easter-related days**

As the Easter-related holidays may vary among the countries, for the example of the Belgian calendar, it is assumed that Pentecost and Whit Monday is not applicable under ***special days.*** These holidays occur as defined in Table 3.1.

Since the Pentecost holiday occurs 50 days after Easter the offset is set to 50. If it were to occur 50 days before Easter, the user would enter 50 with a minus (-) sign. For Whit Monday, the offset value will be 51 since the holiday is celebrated one day after Pentecost.

The resulting full holiday calendar for Belgium, used in this example, is illustrated in Figure 3.5. It includes seven pre-specified holidays, two Easter- related holidays and three fixed dates that repeat each year.

Figure 3.5 **The example holiday calendar for Belgium**

3.2.5 Fixed week

Some countries have holidays on a specific weekday of a specific week of a month. There is no such fixed week holiday in the example of the Belgian calendar, but an example is shown in Figure 3.6.

Figure 3.6 **Adding fixed week to calendar module**

3.2.6 Composite calendars and chained calendars

JDemetra+ provides an option to define a composite calendar. Sometimes it could be useful, e.g. for preparing a calendar for the aggregate industrial production index of the EU-countries. With this application, the user can combine the calendar variables previously created by defining appropriate weights for each calendar.

On rare occasions, the user of JDemetra+ may need to chain two different calendar variables. This request may arise for a holiday being removed after a certain date. Chained calendar variables can be created by selecting the calendars and a break date.

After selecting **Chained** or **Composite** calendar instead of **National** (see Figure 3.1), the desired calendars and their break date can be selected. The calendars to be used need to be created by the user first, as it was shown above for the example of Belgium.

3.2.7 Viewing calendar variables

JDemetra+ presents the calendar variable created for Belgium by **double clicking on the calendar** called "Belgium" under **Workspace→Utilities→Calendars**. Figure 3.7 displays the regressors. The upper-left panel, ***Properties***, displays the properties of the calendar variable. The upper-right panel presents the selected regressor graphically.

The ***Properties*** panel allows the user to access the frequency of the regressor, start date, length in years and variable type. The user can transform the regressor: the option ***None*** of the variable type leads to JDemetra+ applying only the leap year variable. The option ***Trading days*** refers to the six trading day variables and the leap year variable.

The last option ***Working days*** represents the calendar variable which models the difference of activity between the weekend and the weekdays and the leap year variable (Figure 3.7). The regressors generated can be copied to Excel by drag and drop.

Figure 3.7 **Viewing the calendar variables**
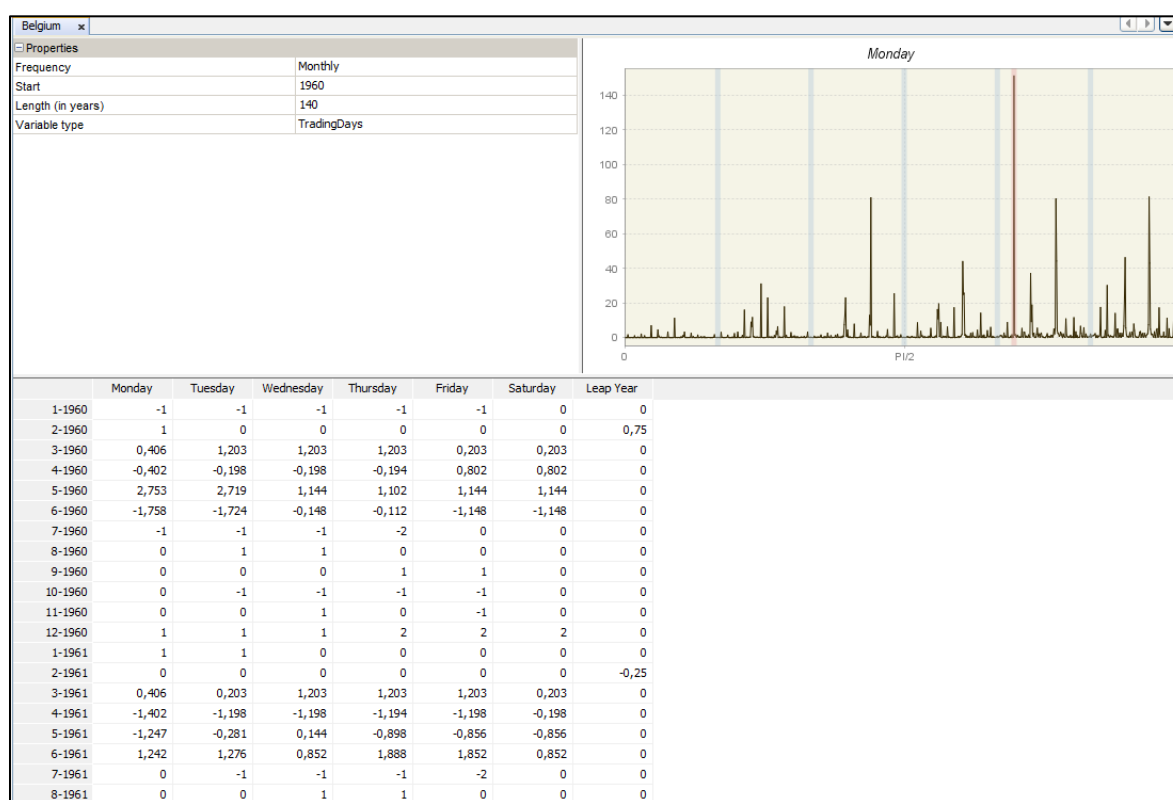
3.2.8 External user-defined variables

The user may want to add specific calendar variables by defining them outside of JDemetra+. Some moving holidays such as Ramadan or the Feast of Sacrifice may require using an external user-defined variable. To do this, the regressors can be prepared in Excel and imported then to JDemetra+ as a user-defined variable. This section shows how to create such an external variable. For reproduction, the file corresponding to the example in this section can be found on this publication's website[10].

First, the dates of Ramadan and the Feast of Sacrifice should be determined day-by-day for a specific length. In this example, the length covers the period from 1 January 1974 to 31 December 2023. Table 3.3 displays the design of the required Excel file. The columns from A to F represent the official holidays in Turkey. Saturdays and Sundays are also listed in the file to see when they coincide with the dates of Ramadan or the Feast of Sacrifice. For each moving holiday value 1 is given when it occurs on a specific

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[10] https://www.unece.org/index.php?id=53959

date. This is measured in two ways: first for each time the holiday occurs excluding Saturdays, Sundays and official holidays, and second, for each time the holiday occurs excluding Sundays and official holidays. This list is then constructed for the required period for which the regressor is needed. As shown in Table 3.4, the second step is to aggregate the results for each month.

Table 3.3 **Design of an Excel file for compiling an external calendar variable**

Date	Sacrifice	Ramadan	A New Year	B 23 April	C 1 May	D 19 May	E 30 August	F 29 October	Saturday	Sunday	G Sacrifice = 1; otherwise = 0 (Excl. Sat, Sun and official holidays)	H Sacrifice = 1; otherwise = 0 (Excl. Sun and official holidays)	J Ramadan = 1; otherwise = 0 (Excl. Sat, Sun and official holidays)	K Ramadan = 1; otherwise = 0 (Excl. Sun and official holidays)
1.1.1974	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2.1.1974	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3.1.1974	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4.1.1974	1	0	0	0	0	0	0	0	0	0	1	1	0	0
5.1.1974	1	0	0	0	0	0	0	0	1	0	0	1	0	0
6.1.1974	1	0	0	0	0	0	0	0	0	1	0	0	0	0
26.12.2023	0	0	0	0	0	0	0	0	1	0	0	0	0	0
27.12.2023	0	0	0	0	0	0	0	0	0	1	0	0	0	0
28.12.2023	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29.12.2023	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30.12.2023	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31.12.2023	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3.4 **Aggregated monthly values**

Date	Sacrifice Holidays (Excl. Sat, Sun and official holidays)	Ramadan Holidays (Excl. Sat, Sun and official holidays)	Sacrifice Holidays (Excl. Sun and official holidays)	Ramadan Holidays (Excl. Sun and official holidays)
1.1.1974	2	0	3	0
1.2.1974	0	0	0	0
1.3.1974	0	0	0	0
1.4.1974	0	0	0	0
1.5.1974	0	0	0	0
⋮	⋮	⋮	⋮	⋮
1.8.2023	0	0	0	0
1.9.2023	3	0	4	0
1.10.2023	0	0	0	0
1.11.2023	0	0	0	0
1.12.2023	0	0	0	0

The third step is to extract the variables from the averages of each month (Table 3.5). JDemetra+ assumes that a user-defined regressor is appropriately centred, i.e. the mean of each user-defined regressor is subtracted from the means for each calendar period. One must be careful with the centred regressor, as changes in the number of public holidays will influence the monthly average for the whole time span.

Table 3.5 **Feast of Sacrifice holiday variable**

Date	Sacrifice Holidays (Excl. Sat, Sun, and official holidays)	Average values for 1974-2015	Sacrifice Regressors (Excl. Sat. Sun. and official holidays)
1.2.1974	2	0.2381	1.7619
1.2.1974	0	0.2143	-0.2143
1.3.1974	0	0.2143	-0.2143
1.4.1974	0	0.1905	-0.1905
1.5.1974	0	0.1429	-0.1429
1.6.1974	0	0.2143	-0.2143
⋮	⋮	⋮	⋮
1.7.2023	0	0.2143	-0.2143
1.8.2023	0	0.2143	-0.2143
1.9.2023	3	0.2619	2.7381
1.10.2023	0	0.3333	-0.3333
1.11.2023	0	0.4048	-0.4048
1.12.2023	0	0.2857	-0.2857

The calendar variable should be centred, first, not to cause any level effect on the series. Second, the monthly average should be extracted from the calendar variable since the calendar variable may contain seasonality. The calendar variable should measure only calendar effects, not seasonality.

The average value for the regressor is calculated for each month. The user can directly deduct the sum of the Ramadan and Sacrifice holiday variables from the monthly average to obtain a total holiday variable.

Figure 3.8 **User-defined regressor in specification**
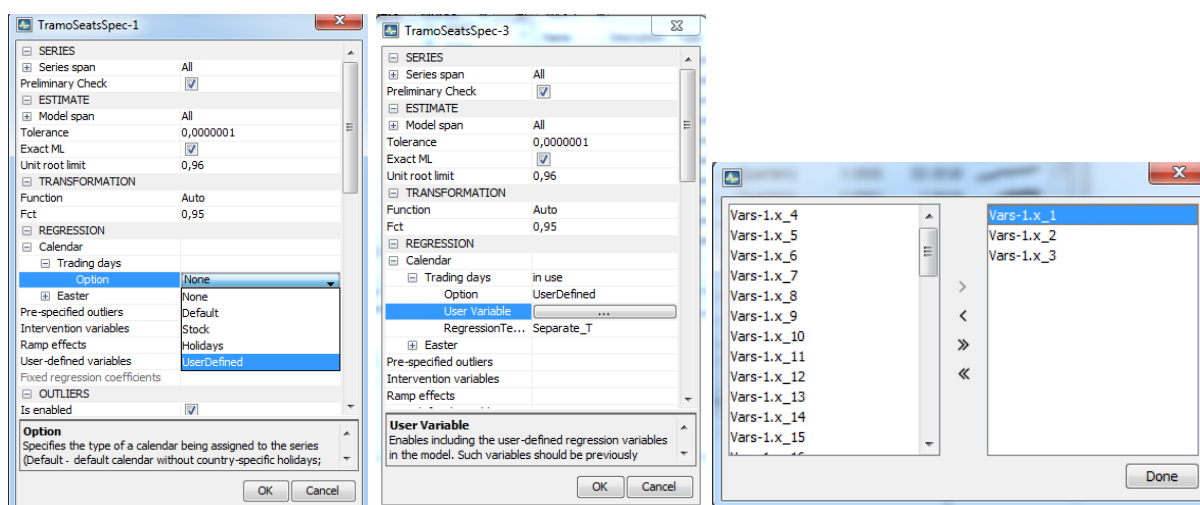
To import the user-defined calendar variables, they can be dragged and dropped into JDemetra+ to create a static variable or they can be directly read from an Excel file to create dynamic variables. For the first option, a new variable is created by selecting **New** after right-clicking on **Workspace/Utilities/-Variables**. After double clicking on the newly created **"Vars-1"**, the time series can be dragged and dropped from Excel or copied and pasted with **Ctrl-c** and **Ctrl-v**. To apply this imported regressor, the type of *specifications* for calendar effects needs to be changed to **UserDefined** (Figure 3.8). The *specifications* are further explained in the section on Specifications and user-regressors.

3.3 Initiate seasonal adjustment

The process of seasonal adjustment separates seasonal effects from a time series to reveal the underlying movements. In this process, first the structure of the components is identified, then the components are estimated. At the last step, the time series is decomposed into its components. The components are trend-cycle, seasonal and irregular component. Sometimes a transitory component may also be estimated. Once the components have been estimated, the irregular and the transitory components can be put together into a single component called irregular/transitory component. Depending on the series, the decomposition can be in the additive or the multiplicative form, which means the components either sum up or are multiplied to obtain the original time series.

JDemetra+ provides a comprehensive solution to perform seasonal adjustment for single or multiple time series. How to select the appropriate approach, what specifications exist, and how to choose or edit them is explained in the following sections.

3.3.1 Selecting approach

JDemetra+ refers to the processing of one time series at a time as **Single Analysis** and to the parallel processing of several time series as **Multi-Processing**. It provides several different processes for adjusting time series. Therefore, first the method needs to be selected from the methods: TRAMO/SEATS and X-13. It is also possible to perform seasonal adjustment with both methods to see the difference.

Both methods are officially recommended by Eurostat, ECB, OECD, IMF and others and produce similar but not identical results. The choice of the seasonal adjustment approach, either X-13 or TRAMO/SEATS, should be consistent in terms of continuity and the standardization of the production of the official statistics. More information on both methods can be found in Section 3.1

The first step in JDemetra+ is to decide whether to perform single- or multi-processing. The method can be selected from the menu **Statistical methods→Seasonal Adjustment** panel (Figure 3.9), where one can select **Single Analysis** and then the preferred method (upper part of Figure 3.9) or **Multi-Processing→New,** and then the method in the **Multi-Processing** panel (lower part of Figure 3.9).

Figure 3.9 **Method selection**
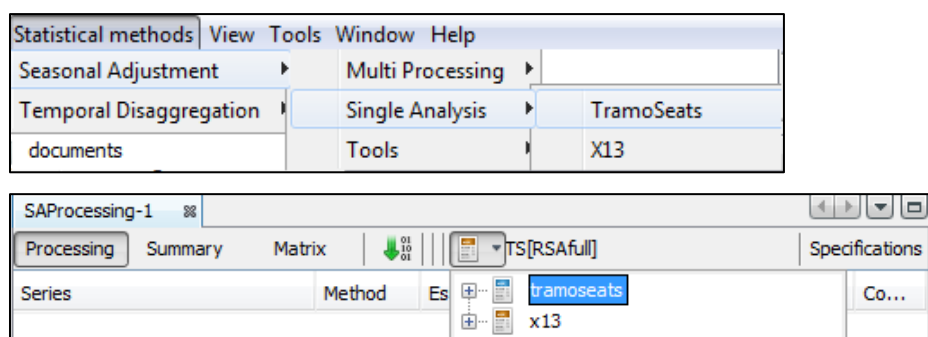
For simplicity, in this Guide the example method selected will be TRAMO/SEATS. It is also possible to replicate all applications and exercises with X-13. More instructions on X-13 can be found in the JDemetra+ User Manual.

3.3.2 Specifications and user-regressors

Seasonal adjustment implies a series of mathematical and statistical operations (outlier detection, model identification, decomposition etc.) and each of these operations can be specified in the software. This can be done under **Workspace→Seasonal Adjustment→Specification**. JDemetra+ provides seven pre-defined specifications for both TRAMO/SEATS and X-13 and uses some default specifications for each method (Figure 3.10). The options vary from the Airline model (**RSA0**) to more complex specifications (**RSAfull**). The specifications for TRAMO/SEATS and X-13 are presented in Table 3.6. The user can choose from these pre-set specifications or modify them if necessary, as explained later in this section.

Table 3.6 **Summary definitions of specifications presented in JDemetra+**

Method	Name	Trans-formation	Calendar Effect	Outlier detection	Modelling	Bench-marking
TRAMO/SEATS	RSA0	Level	None	None	Airline model with mean	None
TRAMO/SEATS	RSA1	Test for log/level	None	Automatic	Airline model with mean	None
TRAMO/SEATS	RSA2	Test for log/level	Test for working day and/or leap year and/or Easter	Automatic	Airline model with mean	None
TRAMO/SEATS	RSA3	Test for log/level	None	Automatic	Automatic Model Identification	None
TRAMO/SEATS	RSA4	Test for log/level	Test for working day and/or leap year and/or Easter	Automatic	Automatic Model Identification	None
TRAMO/SEATS	RSA5	Test for log/level	Test for trading day and/or leap year and/or Easter	Automatic	Automatic Model Identification	None
TRAMO/SEATS	RSAfull	Test for log/level	Test for trading day or working day and/or leap year and/or Easter	Automatic	Automatic Model Identification	None
X-13	X-11	Non-Applicable	Non-Applicable	Non-Applicable	Non-Applicable	None
X-13	RSA0	Level	None	None	Airline model with mean without mean	None
X-13	RSA1	Test for log/level	None	Automatic	Airline model with mean without mean	None
X-13	RSA2c	Test for log/level	Test for working day and/or leap year and/or Easter	Automatic	Airline model with mean without mean	None
X-13	RSA3	Test for log/level	None	Automatic	Automatic Model Identification	None
X-13	RSA4c	Test for log/level	Test for working day and/or leap year and/or Easter	Automatic	Automatic Model Identification	None
X-13	RSA5c	Test for log/level	Test for trading day and/or leap year and/or Easter	Automatic	Automatic Model Identification	None

The chosen specification defines whether TRAMO and Reg-ARIMA should test for the trading and working day effects as well as for the leap year effect etc. They run the tests and apply the regressors accordingly, if the effects are significant. If included in the specification, TRAMO and Reg-ARIMA will also test for the Easter effect, but not all moving holidays are tested for by default as these vary between countries.

Figure 3.10 **Specifications**
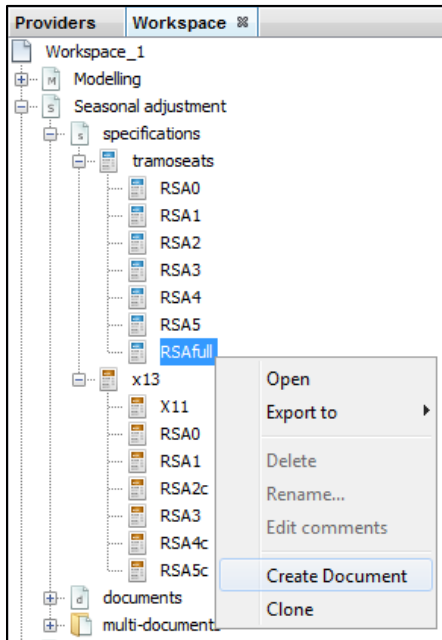
To start, the RSAfull specification in TRAMO/SEATS or RSA4c or RSA5c specifications of X-13 are suggested for time series with a significant calendar effect. The RSA3 specifications for both methods are a good benchmark for a time series without calendar effect.

While the specification RSA3 runs no test for calendar effect, the specifications RSA4 and RSA5 for TRAMO/SEATS run pre-tests and a decision for working-day/leap-year effect and trading-day/leap-year effect, respectively. Although it may be the case that the working-day effect is effective for the financial time series (i.e. monetary aggregates like M1, M2 or amount of deposits) and the trading-day effect is effective for real sector time series (i.e. the measurements of industrial production, construction or services sectors), this is not true in every case. The specification RSAfull for TRAMO/SEATS tests for all effects and selects the appropriate calendar effects according to their significance.

The specifications RSAfull and RSA4c/RSA5c for both TRAMO/SEATS and X-13 also test for the Easter holiday effect and leap-year effect. This implies that no creation of any additional regressor for these calendar effects is needed. If any additional calendar effect like a country-specific moving holiday should be part of the pre-adjustment process, the external regressor can be imported and selected in the specifications. If user defined specifications are used frequently, for example to include national calendar effects or exclude some types of outliers, the best solution is to define a specification and add it to the *Workspace*.

Figure 3.11 **The general structure of the specification dialogue box**
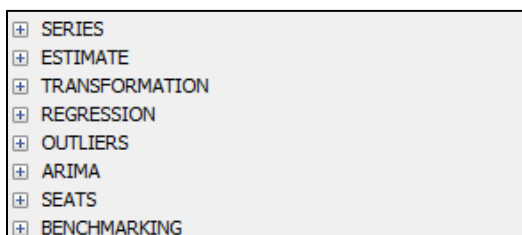
This can be done by right-clicking on **tramoseats** or **X-13** under **Workspace/Seasonal Adjustment/-specifications** and selecting **New**. The new specification will automatically appear in the *Workspace* panel. Double-click on it or right-click and **Open** opens a dialogue box where its properties can directly be specified (Figure 3.11).

Another approach to creating new tailored specifications is to **clone** and edit one of the default specifications. This is done by right-click on one of the default specifications under **Workspace/Seasonal Adjustment/specifications/tramoseats/** and selecting "**Clone**" (Figure 3.12). The newly cloned specification can be modified in the same way as if the specification is created from scratch. The structure of the specifications dialogue is explained on the following pages in detail.

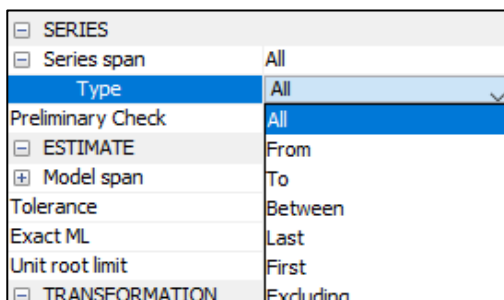Figure 3.12 **Steps for user-defined specification**
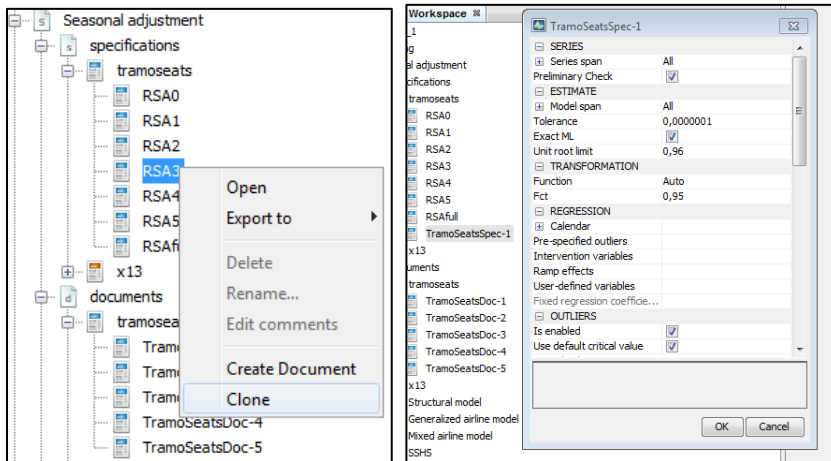
Saving the **Workspace** will include saving the new specifications. They can be recalled by reloading the **Workspace** and are then ready for use.

Series

The first part of the specification box is **SERIES,** which contains **Series span** and **Preliminary check**.

Figure 3.13 **"Series" part of the specification**

The user can set the span of the original time series to be analysed/seasonally adjusted by selecting one of several options such as From, To, Between, etc. When the **Preliminary check** option is checked, the quality of the input series is checked and highly problematic series, e.g. those with several identical observations and/or missing values above pre-specified threshold values, are excluded. When unchecked, the thresholds are ignored, and the process is performed when possible. The series are analysed over its full length when the selection type **All** is chosen (Figure 3.13).

Estimate

The next part is **ESTIMATE** which contains **Model Span**, **Tolerance, Exact ML** and **Unit root limit options.** In general, these options do not need to be changed or set to another value (Figure 3.14). However, the Model Span option can be used to limit the span of data to be used in determining the RegARIMA model. The RegARIMA model selected is then, however, applied to the whole series.

Figure 3.14 **"Estimate" part of the specification**

ESTIMATE	
⊞ Model span	All
Tolerance	0,0000001
Exact ML	☑
Unit root limit	0,96

Transformation

The **TRANSFORMATION** part includes *Function* and *Fct* (Figure 3.15). The options for *Function* are:

- **None**, no transformation of original time series.

- **Log,** taking the logarithm of the original time series.

- **Auto,** the program performs a test for selecting either the logarithmic or level specification. It then automatically chooses the transformation specification.

Fct controls the bias in the test. If *Fct* > 1, it favours levels, otherwise it favours logarithms.

Figure 3.15 **"Transformation" part of the specification**

TRANSFORMATION	
Function	Auto
Fct	0,95

TRANSFORMATION	
Function	Auto
Fct	None
REGRESSION	Auto
⊞ Calendar	Log

Regression

REGRESSION consists of five main divisions, *Calendar*, *Pre-specified outliers*, *Intervention variables*, *Ramp effects* and *User-defined variables* (Figure 3.16).

Figure 3.16 **"Regression" part of the specification**

REGRESSION	
⊟ Calendar	
⊟ Trading days	
automatic	Unused
Option	None
⊟ Easter	
Option	Unused
Julian	☐
Duration	6
Test	☐
Pre-specified outliers	
Intervention variables	
Ramp effects	
User-defined variables	

Calendar includes two separate parts; *Trading* **days** and *Easter*. *Option* is used to define the type of the calendar regressor such as **None**, **Default**, **Stock**, **Holidays** or **UserDefined**. **Automatic** is used to define the test type, e.g. **FTest** for multiple tests, **WaldTest** for a single test (Figure 3.17).

The **Default** option includes choosing a calendar type (*None*, *TradingDays* (6 regressors) or *WorkingDays* (1 regressor)) and leap year effect regressor. The test type of the regressors for the trading-day effect can be specified. When the F-test or t-Test are selected, JDemetra+ performs the test for trading-day variables. Otherwise, trading-day variables are used without prior testing. Day-of-week effects for stock variables can be described and measured under **Stock**. **Holidays** may be used when a user-defined calendar with country-specific holidays is used. **UserDefined** option is used for uploaded calendar variables. Finally, **None** means no calendar variables are used for the regression model.

Figure 3.17 **"Calendar" part of the specification**

Calendar effects can be added to the model manually (by setting the **automatic** parameter to **Unused**) or automatically, where the choice of the number of calendar variables is based on the **FTest** or **Waldtest**. In this example, **Option** is set as **Default** and **automatic** set as **Ftest** with a 1% Pftd value (Figure 3.18).

Figure 3.18 also displays the main properties of **Easter**. It is advised to use the *standard* option since both Easter and Easter Monday effects are generally taken into account in the user-defined regressors. If necessary, the length of this effect can be modified from the default length of six days (for TRAMO/SEATS) if the effect is likely to be different in the country or economic activity in question. The statistical t-test is performed for the Easter effect, if the box **Test** is checked. Otherwise, it is added to the model without prior testing.

Figure 3.18 **"Easter" part of the specification**

Pre-specified outliers and **Intervention effects** are not used at the beginning of the seasonal adjustment process. **Pre-specified outliers** are outliers known before adjustment. **Intervention variables** refer to known special events, such as strikes, political decisions etc. which influence the data. It enables not only the creation of outliers but allows more sophisticated interventions to match particular events. They may be needed in the case of problematic cases of seasonal adjustment.

The remaining two options namely **Ramp effects** and **User-defined** variables are beyond the scope of this basic seasonal adjustment treatment. **Ramp effect** means a linear increase or decrease in the level of a series that lasts for a certain period. They are more related to advanced time series analysis or seasonal adjustment.

Outliers

The next part is **OUTLIERS** (Figure 3.19). **Is enabled** means that automatic outlier detection and correction will be performed during the seasonal adjustment process, and this option is active for all default specifications. **Use default critical value** defines the threshold value for the detection of outliers. This is the most important fine-tuning parameter, affecting the quality of the seasonal adjustment process. The number of outliers decreases if this value increases, and vice versa. Using the default value is recommended in the initial seasonal adjustment process but modifying it may be usefull for problematic series.

However modifying the default values should be carried out with caution. Sometimes it may be useful to limit the **Detection span** of the automatic outlier detection, for instance, to reduce revisions. The next boxes allow the selection of the four main types of outliers: **additive** outliers (AO), **level shift** (LS), **Transitory change** (TC), and **Seasonal outlier** (SO). The remaining two options **EML estimation** and **TC rate** are not considered during the standard cases of seasonal adjustment presented in this Guide.

Figure 3.19 **"Outliers" part of the specification**

⊟ OUTLIERS	
Is enabled	☑
Use default critical value	☑
Critical value	3,5
⊞ Detection span	All
Additive	☑
Level shift	☑
Transitory change	☑
Seasonal outlier	☐
EML estimation	☐
TC rate	0,7

ARIMA and SEATS

ARIMA and **SEATS** are the core parts of the specifications when using the TRAMO/SEATS method. Usually, it is not necessary to modify their parameters. The only exception is under **ARIMA** the parameter **Automatic** which should be unchecked to apply the default ARIMA model. This is only needed in problematic cases of seasonal adjustment though. In the default case, set to **Automatic**, TRAMO/SEATS performs automatic model identification (Figure 3.20).

Figure 3.20 **"ARIMA" part of the specification**

| ⊟ ARIMA	
Automatic	☑
Accept Default	☐
Cancelation limit	0,05
Initial UR (Diff.)	0,97
Final UR (Diff.)	0,91
Arma limit	1
Reduce CV	0,12
LjungBox limit	0,95
Compare to default	☐
⊟ SEATS	
Approximation mode	Legacy
MA unit root boundary	0,95
Trend boundary	0,5
Seasonal tolerance	2
Seasonal boundary	0,8
Seas. boundary (unique)	0,8
Method	Burman

3.3.3 Benchmarking

For many types of economic indicators annual aggregates are compiled for comparison purposes etc. One may wish for the annual aggregates of the seasonally adjusted time series to be identical to the annual aggregates of the original time series. However, this is generally not the case due to the stochastic structure of the seasonal component which means the seasonality is not necessarily cancelled out during a year. JDemetra+ provides a **benchmarking** option. The Benchmarking option forces the annual sums of the seasonally adjusted data to match the annual sums of the raw or calendar adjusted data.

This option is activated by checking **Is enabled** in **BENCHMARKING** (Figure 3.21). ***Target*** specifies the target variable for the benchmarking procedure, which can be the *Original* series; or the *Calendar adjusted* series. When **Use forecasts** is checked, the benchmarking is also applied to the forecasts of the seasonally adjusted series and the target variable.

Rho is the value of the first auto-regressive (AR 1) parameter (set between 0 and 1) in the function used for benchmarking. **Lambda** is a parameter in that same function that relates to the weights in the regression equation; it is typically equals 0, 1/2 or 1.

Figure 3.21 **Benchmarking specification**
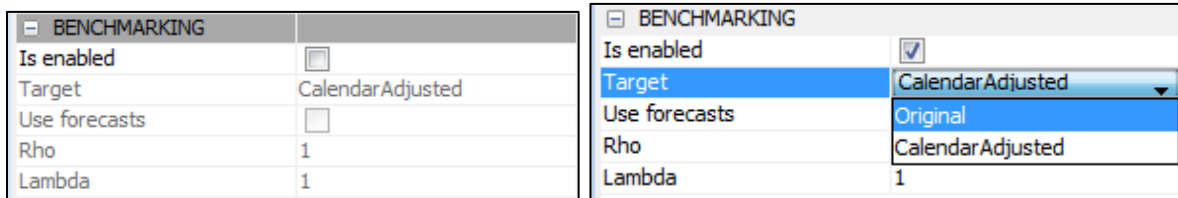
3.4 Single-processing

Once the specifications are decided on, there are two ways to initiate a single process seasonal adjustment. In the case of a default specification, like **RSAfull** for TRAMO/SEATS, being chosen, the user can initiate the process via the main menu, selecting ***Statistical Methods→Seasonal Adjustment→ Single Analysis→TramoSeats***. A new blank document is created under ***Workspace/Seasonal adjustment/documents***, where the time series to be seasonally adjusted can be dragged and dropped to.

To use a pre-modified specification, the second way to initiate the seasonal adjustment has to be applied. This is done by right-clicking on the chosen specification under ***Workspace→Seasonal Adjustment→ Specifications→tramoseats*** and selecting ***Create Document*** (Figure 3.22). Again, a new blank document is created, where the time series in question can be dragged and dropped to.

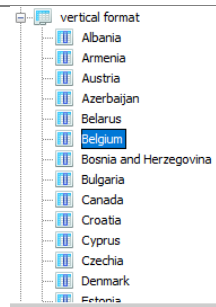Figure 3.22 **Creating a single processing document**
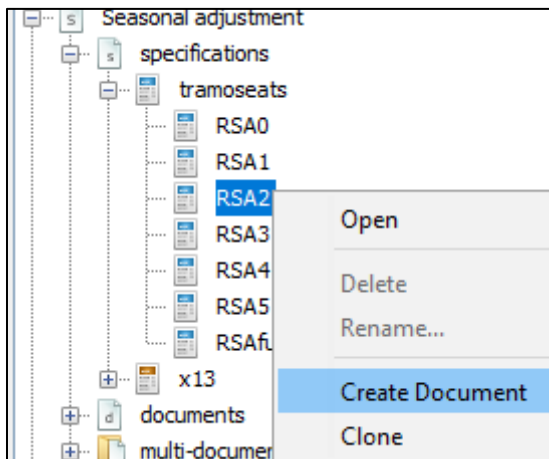
The whole procedure for single-processing is displayed and explained step-by-step, starting from the creation of a national calendar using the Belgium example in Figure 3.23 with the explanations in the following Table 3.7.
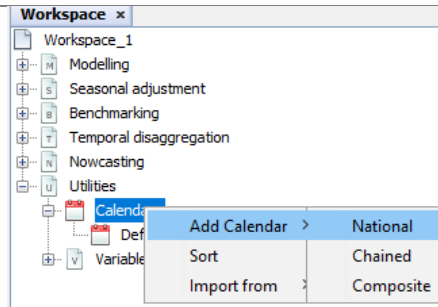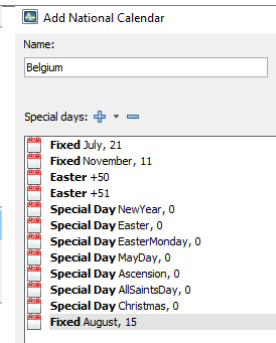
Figure 3.23 **Step-by-step single processing**

Step-1 Selecting time series	**Step-2 Adding a national calendar**	**Step-3 Composition of national holidays**

Step-4 Cloning a specification	**Step-5 Setting up a specification**	**Step-6 Creating a blank document**
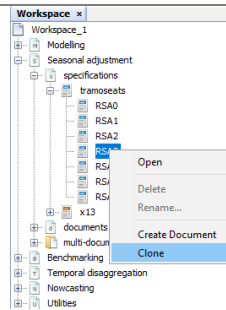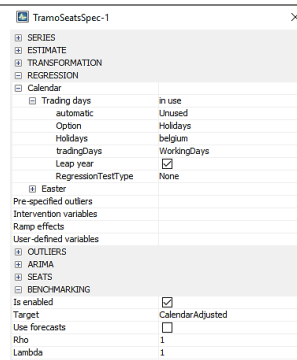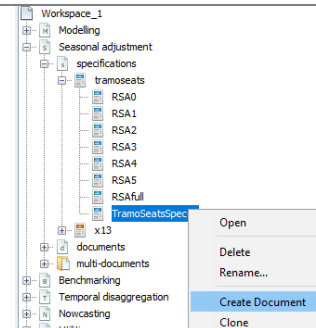
Step-7 View of a blank document	**Step-8 Dropping time series and getting results**	
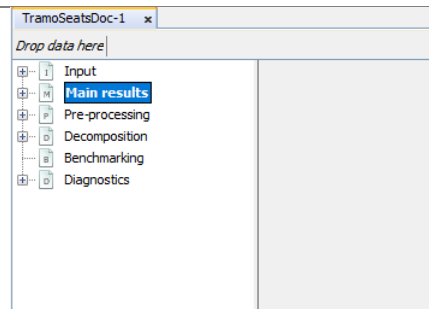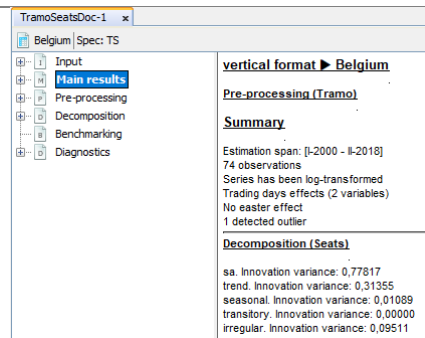
Table 3.7 **Explanation of the steps of a single processing**

| Steps	Explanation	Details
Step-1	The dataset explained in Chapter 1 is called by *Providers* and the time series of Belgium is identified.	
Step-2	A user-defined calendar is created.	
Step-3	All 11 Belgian calendar events are entered into calendar module.	Using the button "+" sign, one defines the type of the calendar effect depending on whether it is fixed, special day or other.
Step-4	A default specification is cloned as basis for user-defined specifications.	
Step-5	The *Regressor* and *Benchmarking* parts of the specification are modified.	REGRESSOR *Automatic* = "Unused", *Option* = "Holidays", *Holidays* = "belgium", *TradingDays* = "WorkingDays", *Leap year* = "True", *RegressionTestType* = "None" BENCHMARKING *Is enabled* = "True", *Target* = "CalendarAdjusted"
Step-6	The new seasonal adjustment document is created.	
Step-7	The blank document, ready for having the time series dragged and dropped on.	
Step-8	View of the results after performing the single process.	

3.5 Multi-processing

Via the multi-processing function, JDemetra+ can seasonally adjust a set of time series using different specifications and methods for each single time series.

To create a new multi-processing document, select **Statistical methods→Seasonal Adjustment→ Multi Processing→New** from the main menu (Figure 3.24, left). The new document *SAProcessing-1* is opened and the time series to be seasonally adjusted can be dragged and dropped on analogue to the single-processing (Figure 3.24, right)
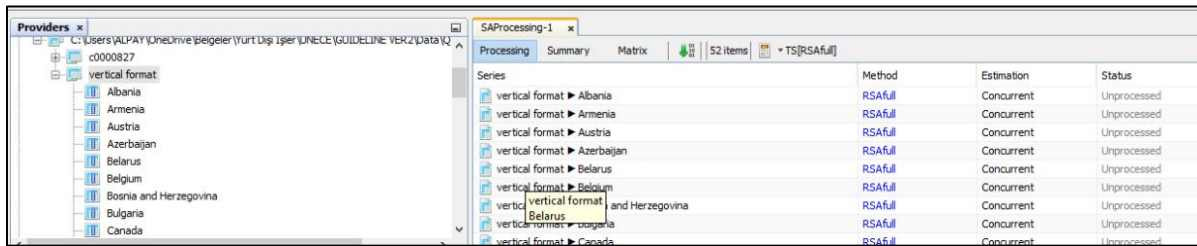
Figure 3.24 **Creation of multi-processing**
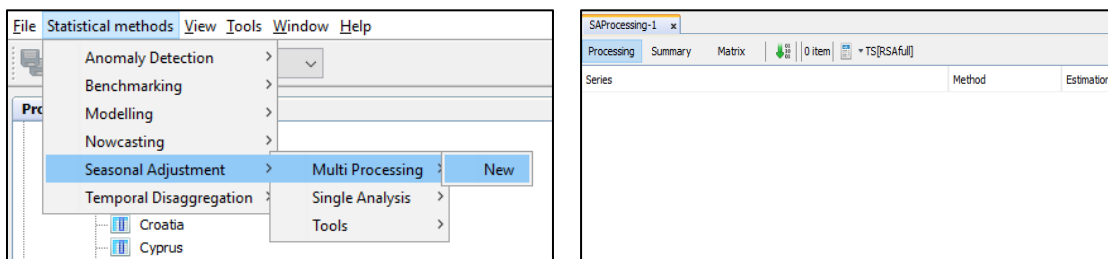
As a result, the chosen time series are listed in the *SAProcessing-1* (Figure 3.25). Here, the selected *Method*, type of *Estimation*, *Status* of time series and *Quality* of the adjustment are displayed for each time series. In the example, the method is *RSAfull* and the status is *Unprocessed* for all time series.

Figure 3.25 **A view of multi-processing**

After setting all specifications as desired, the seasonal adjustment is performed simultaneously by clicking on the green arrow ⬇ (Figure 3.26, left). The multi-processing document can be found under **Workspace/Seasonal adjustment/multi-documents** for future use (regular production of seasonally adjusted data), as displayed in Figure 3.26, right.

Figure 3.26 **Multi-processing in Workspace**
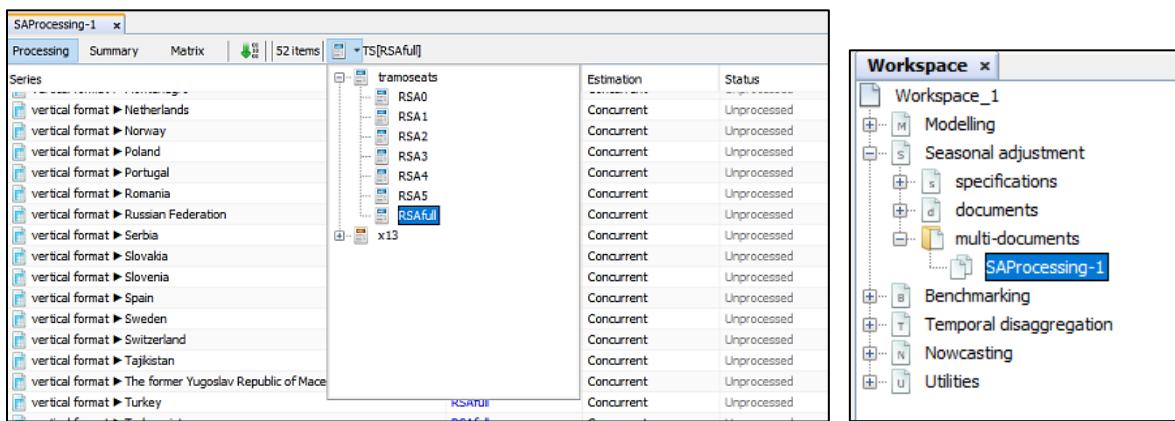
Another way to create a multi-processing is by right-clicking on **Workspace/Seasonal adjustment/-multi-documents** and selecting **New** (Figure 3.27).

Figure 3.27 **Creating a multi-processing**
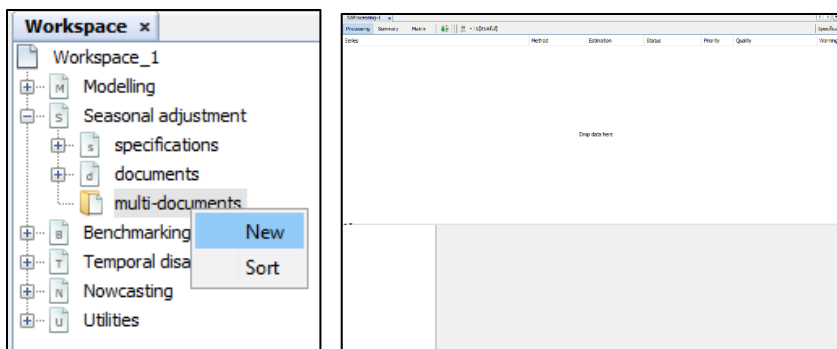
Multi-processing step-by-step

When performing **Multi-processing**, it is recommended to start with the default and most comprehensive specifications. These are **RSAfull** for TRAMO/SEATS and **RSA5c** for X-13. Then, the user may change the specification for each time series if necessary. There is also the possibility to change the default settings in the main menu under **Tools→Options**. Figure 3.28 displays the main steps to perform a multi-processing seasonal adjustment.

Figure 3.28 **Main steps for multi-processing**

Step-1 Creating a blank multi-processing document	Step-2 Dragging and dropping the set of time series into the blank area called "Drop data here"	Step-3 Pressing the green button and performing seasonal adjustment with the default specification
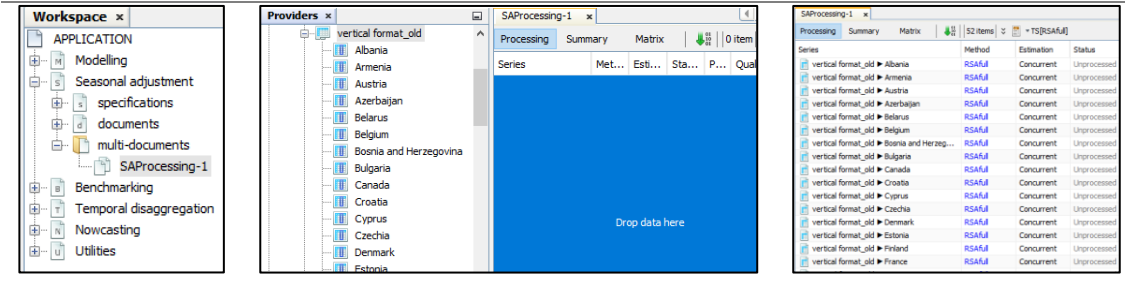
When modified specifications are required, such as including the Belgian calendar from the earlier example, some mid-steps between Step-2 and Step-3 need to be followed (Figure 3.29). In this example, the specification of the series *Belgium* is changed from **RSAfull** to the user-created **TS**.

Figure 3.29 **Setting specification for multi-processing**

Step-2a The initial situation of the Belgian series	Step-2b The *Choose active specification* dialogue window
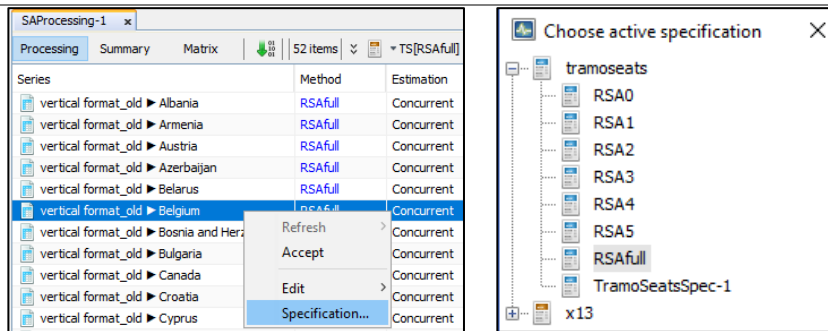
Step-2c Choosing the desired specification	Step-2d After changing the specifications for the Belgian series
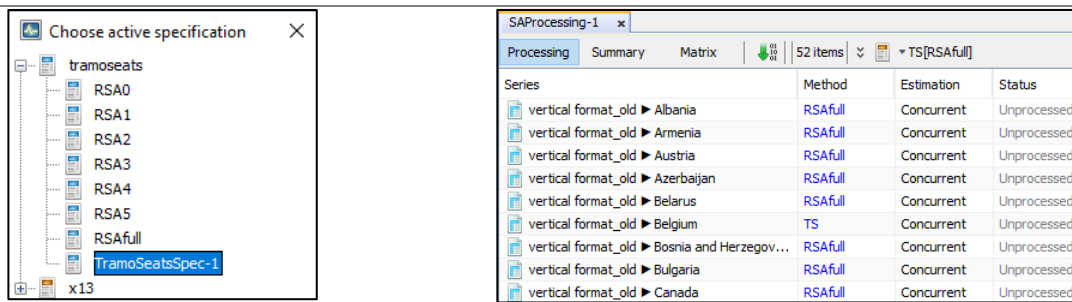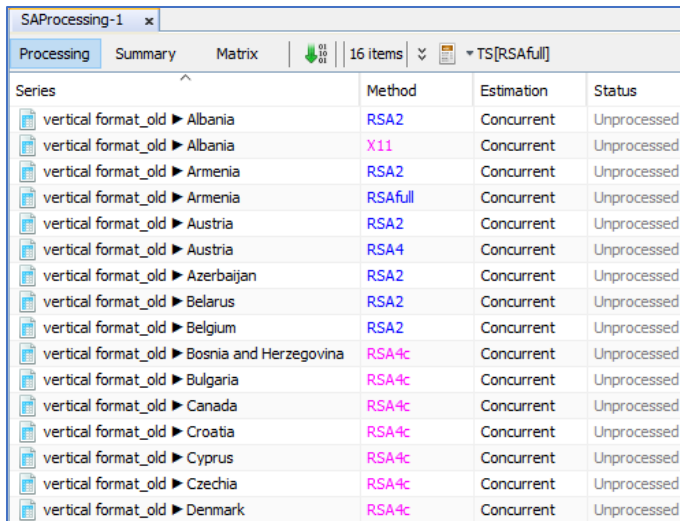
As visible from Step-2c (Figure 3.29), the method for seasonal adjustment may also be changed to X-13. Hence, using the multi-processing, even the same series may be seasonally adjusted using different methods or specifications. To do so, multiple copies of the same original series need to be created (copy+paste). This provides a good way to compare different methods and specifications at the same time. Figure 3.30 presents a more complex example of multi-processing in JDemetra+.

Figure 3.30 **Multiple specifications for multiple series in multi-processing**

The multi-processing is then finalized with Step-3 (Figure 3.28). Once the green button is pushed, the seasonal adjustment is performed, including the creation of the reports containing relevant statistical diagnostics. This step must be repeated if any specifications of the multi-processing have been changed.

4 Analysis of the results

4.1 Introduction

This chapter describes the third phase of the seasonal adjustment process which includes analyses of the quality of seasonal adjustment and fine-tuning the models if necessary. The main quality diagnostics presented by JDemetra+ are introduced and explained, in particular for TRAMO/SEATS. The aim is to help open the "black box" of the process of seasonal adjustment performed by the software, to support the achievement of robust seasonally adjusted data. Attention is paid to the following quality issues:

- Visual quality
- Statistical diagnostics
- The model (pre-processing)
- Model's residuals
- Components (decomposition)
- Benchmarking

Seasonality is not a solid and precise fact but is identified based on hypotheses about the underlying conditions and models. The purpose of quality diagnostics is to reveal any essential weaknesses in the results of the seasonal adjustment to prevent the use of misleading results, that are prone to large revisions and may provide false signals about the economy. The automatic procedure of TRAMO/SEATS and X-13 is quite reliable and, thus, useful for adjusting many series. Especially with a limited number of important series, it is of utmost importance to read the quality diagnostics well and with thorough consideration.

The output of JDemetra+ presents the statistical and mathematical properties of the identified model and components. It includes a wide range of quality diagnostics that reflect the different approaches of TRAMO/SEATS and X-13. However, they have also several common quality diagnostics. In addition to numeric diagnostic tests, JDemetra+ provides the user with a variety of readily available illustrative charts.

The smoothness of the seasonally adjusted series is not a quality measure. On the contrary, the irregular component is a part of the seasonally adjusted series. Ideally, the number of outliers would be relatively small, and they should not be unevenly distributed in the series. Modelling problems are more likely with a short time series which includes many outliers. Longer time series would be particularly helpful for identifying the seasonal pattern from a highly volatile time series. Nevertheless, high volatility may be a natural attribute of many time series from emerging economies or quickly evolving industries.

Careful assessment of the seasonally adjusted data includes analysis of the stability of the seasonal component. JDemetra+ reports the results of several quality diagnostics designed for this purpose. These include statistical tests and graphical diagnostics that depend on the chosen seasonal adjustment method. The M-statistics of X-13 are explained in Grudkowska (2015) and for instructions on the interpretation of the SEATS results see Maravall, López-Pavón and Pérez-Cañete (2015).

The residuals of the TRAMO process provide a useful tool for verifying whether the seasonal adjustment is satisfactory or not. In theory, the residuals should be random and not include any seasonality. On the other hand, JDemetra+ also provides a test for confirming that there is no residual seasonality in the seasonally adjusted data either. Seasonal adjustment should remove the seasonal component completely.

Benchmarking provides the equality of series of different frequencies between the adjusted series and calendar adjusted/original series. If the discrepancies between aggregates of original and adjusted series, which theoretically should be low, are too high, benchmarking is sometimes applied. However, benchmarking is generally not recommended as it may not produce the optimal seasonally adjusted series and may disrupt its stochastic structure.

The overall quality indicators displayed by JDemetra+ help draw attention to the most problematic series. Where the quality diagnostics question the validity of the results or indicate possible problems, modification of the specifications and re-adjustment of the series may be necessary. Modifying and fine-tuning seasonal adjustment specifications can be time consuming, therefore, sometimes it is pragmatic to manually intervene in only the most important time series.

The quality diagnostics indicate the features which are problematic for a standard seasonal adjustment process. For example, some highly non-linear series (with too many outliers) do not allow identification of a model with acceptable diagnostics, not even by shortening the series. A dominant irregular component or a large number of outliers could mask the seasonal component. In addition, inconsistent adjustments of overlapping time spans may be an indication of severely unstable seasonality. According to Eurostat (2015), these cases require consulting the literature, manuals, and experts to develop an adequate solution.

4.2   Single-processing

JDemetra+ provides comprehensive and detailed tests for analysing the quality of seasonal adjustment. The available tests vary between the chosen adjustment methods. The results of the seasonal adjustment and its tests are presented in the document created when performing seasonal adjustment as described in the previous chapter. These documents are found under **Workspace/Seasonal adjustment/documents** and then under the chosen method. The document consists of six main parts: **Input, Main Results, Pre-processing, Decomposition, Benchmarking,** and **Diagnostics**. For the adjustment method X-13, the decomposition part is called **Decomposition (X11)**.

4.2.1   Main Results

The **Main results** contain a short description of the model used and of the quality of the seasonal adjustment. Figure 4.1 and Figure 4.2 displays the results obtained for the seasonal adjustment of Belgian GDP at constant prices with the specification defined in the previous chapter.

Figure 4.1 **Main results obtained by single analysis (1)**
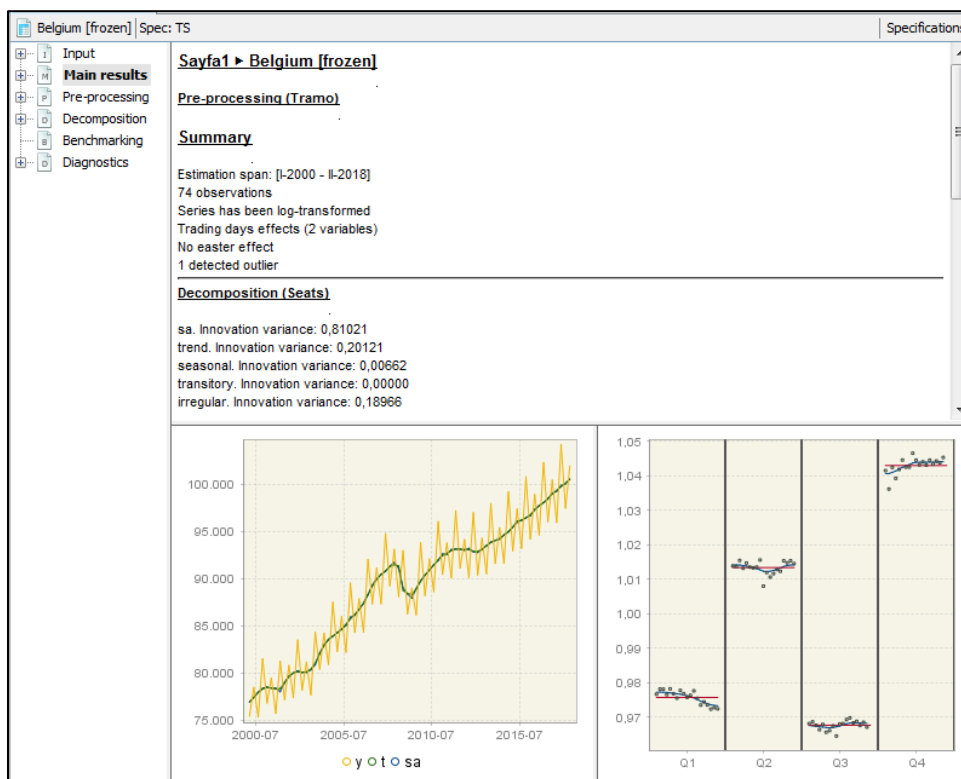
The **Main results** include the following information about the adjustment process:

- The estimation span used for identifying the seasonal pattern was from the 1st quarter of 2000 to the 2nd quarter of 2018 which contains 74 observations.
- TRAMO/SEATS applied log-transformation to the original time series so that the data would more closely meet the statistical assumptions and to help fit the model. During an additive decomposition, the model is directly fitted, but in case of the multiplicative decomposition, the original time series is log-transformed to turn it into an additive form before the model is fitted.
- There are estimated trading day effects with two variables which are already defined in the specification without any pre-testing. No significant Easter effect could be found.
- The outlier detection procedure detected one outlier in the original time series.
- The variance of the seasonal and trend-cycle component innovations was higher than that of the irregular component.
- In summary, all quality diagnostics are marked "Good", except for the spectral seasonal peaks which are marked "Uncertain". As addressed later in this chapter, this test result is considered less critical than the other diagnostic tests.

Figure 4.2 **Main results obtained by single analysis (2)**
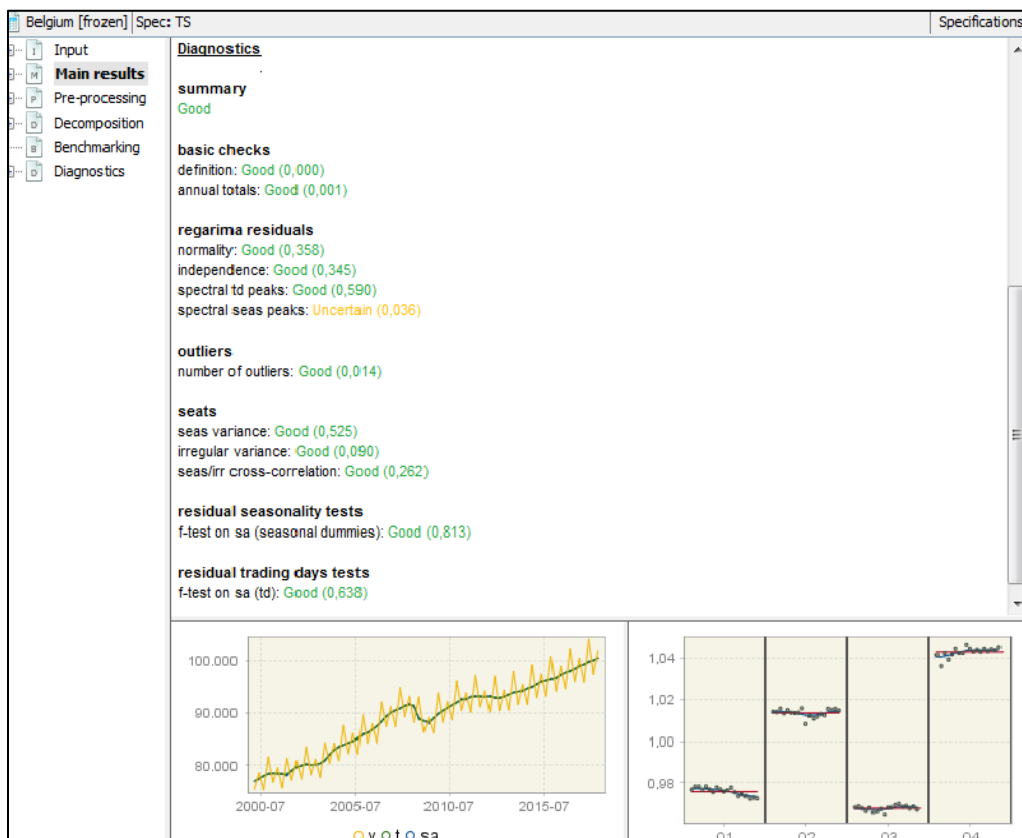
4.2.2 Visual check

The first impression of the results of the seasonal adjustment can be gained by looking at the visual tools of JDemetra+. The software displays several charts and tables under the **Main results**. The original data, trend-cycle component and seasonally adjusted series are displayed in the chart on the left, and S-I (seasonal-irregular) ratio is on the right-hand chart (Figure 4.1). Double-clicking on one of the series in the left chart opens a new window for that series only, while for the S-I chart, a double-click on a specific quarter opens a more detailed view of that single quarter (or month, if monthly data).

A detailed view of both charts can be found when opening the **Main Results** node and there **Charts/Sa, trend** for the left chart or **S-I ratio** for the right chart respectively. Under the **Charts** node there is a second useful visualization accessible by clicking on **Cal., sea., irr.** It provides the break-up of factors

into calendar (*"**Calendar effects**"*-in yellow), seasonal (*"**Seas(component)**"*-in green) and irregular (*"**Irregular**"*-in blue) components (Figure 4.3).

The user can find some initial answers to the questions about whether the original series has seasonality, trend, or calendar effects through the visual analysis of the charts. Moreover, the existence of possible outliers in the original series may be detected from the charts.

Figure 4.3 **Details of Charts node**

The **S-I ratio** chart is useful for analysing the development of the seasonal pattern, i.e. to detect seasonal breaks or moving seasonality. The blue line represents the de-trended value of the series for each quarter. A gradual increase or decrease in seasonal factors may imply a moving seasonality. But if it occurs for a specific quarter/month, it may indicate a seasonal break, e.g., a time series, which shows the peaks at a specific month/quarter over the years and then suddenly starts to persistently drop/increase in the following years, e.g. Q4 in Figure 4.4 (Azerbaijan's GDP with RSAfull). The presence of a seasonal outlier can also be formally tested.

Figure 4.4 **The S-I ratio chart**
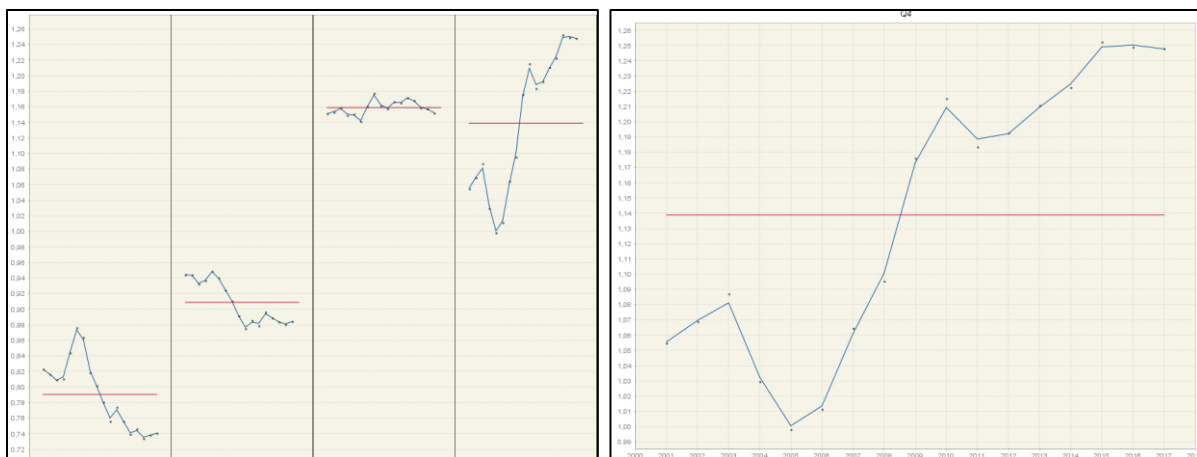
This type of problems can be solved by automatic model-based seasonal adjustment methods, but it can also be solved manually by including a parameter in the model that captures moving seasonality.

4.2.3   Models applied

JDemetra+ provides the details of seasonal adjustment in the *Pre-processing* and *Decomposition* parts of the document. The *Pre-processing* part is the same for both methods, but the *Decomposition* part differs by the method chosen. For more information on the M-statistics for X-13, see Grudkowska (2015) and for the SEATS diagnostics for TRAMO/SEATS see Maravall, López-Pavón and Pérez-Cañete (2015).

The **Pre-processing** part consists of a summary part of the ARIMA model estimation (such as the estimation span used, transformation information, the ARIMA model estimated, the estimated parameters of trading days and/or user-defined regressors, the Easter effect and outliers) and the sub-nodes: **Forecasts, Regressors, Arima, Pre-adjustment series, Residuals** and **Likelihood**. Each of these nodes provides important information to help evaluate the quality of the ARIMA model estimated for pre-processing. Especially, **Forecast** and **Residuals** present detailed tests for the validity of the ARIMA model estimated in terms of the significance of forecast and the assumptions of residuals' distribution.

Decomposition provides a summary of the scheme of the decomposition model applied and more details on variances, autocorrelations, and cross-correlations of the components obtained by SEATS. On the main page of *Decomposition,* the *innovation variance* of all theoretical model components is given. The innovation variance is the maximized variance of the model, while having the irregular component to derive the trend-cycle and seasonal components as stable as possible, meaning that no additional white noise could be removed from them. This assumption is also called "canonical decomposition". The irregular component includes random fluctuations which cannot be attributed to the other components.

Pre-processing

Pre-processing displays the properties of the pre-adjustment and contains the following information:

- Statistical properties of the ARIMA model used in seasonal adjustment
- Regressors and their coefficients
- Tables of the pre-adjusted series
- Residuals, with a complete analysis of their statistical properties, based on the diagnostics produced by TRAMO

ARIMA

Under **Pre-processing,** information on the statistical properties of the ARIMA model used in seasonal adjustment is provided. TRAMO and Reg-ARIMA identify the most suitable ARIMA model and estimate its parameters for each time series. If they are not able to find a specific ARIMA model in automatic model identification, the Airline model is used.

ARIMA models (p,d,q) are used for modelling and forecasting time series data. The ARIMA model includes three types of parameters: the autoregressive parameters (p), the order of differencing (d), and moving average parameters (q). A seasonal series usually has two sets of parameters: the regular component defined by (p,d,q) and the seasonal component (P, D, Q). Different ARIMA models could be fitted to the same series. However, it is generally recommended to choose the simplest model with the smallest number of parameters but with a satisfactory fit.

For the example of Belgium, TRAMO has selected an Airline model (0,1,1)(0,1,1), as given in Figure 4.5. The airline model is one of the most commonly used seasonal models (Box, Jenkins, Reinsel, & Ljung, 2015), first used to study time series on the number of airline passengers. The coefficients of the model are highly significant at 95% confidence level. The coefficient **Theta** indicates a stochastic (volatile) trend and **BTheta** indicates a deterministic seasonality rather than a trend.

Figure 4.5 **The estimated ARIMA model**

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

	Coefficients	T-Stat	P[|T| > t]
Theta(1)	0,2759	2,27	0,0265
BTheta(1)	-0,6960	-6,95	0,0000

In general, the automatic model identification should produce satisfactory results, and it should not be needed to manually define the model. The test results may indicate a need for refining and changes in the specifications accordingly.

Calendar effects

The parameters estimated for calendar effects are presented at the bottom part of the main page of the *Pre-processing.* The ARIMA calendar regressors and their estimated effects are provided in detail under the **Regressors** and **Pre-adjustment series** nodes. JDemetra+ provides three options for treating calendar effects:

- Trading Day – Six regressors to measure the effect of each weekday starting Sunday
- Working Day – One regressor to measure the effect of working days and weekends
- Leap-year – One regressor to measure the effect of the additional day in leap years
- Easter – One regressor to measure the effect of Easter
- None – includes only one variable for the leap year effect

Figure 4.6 represents the estimated coefficients and their relevant information for the Belgian example. In the example, the working day regressor is found statistically significant at the 99% confidence level, while the leap year effect does not even reach a statistical significance at the 90% confidence level.

Figure 4.6 **Estimation results for calendar effects**

Regression model

Working days

	Coefficients	T-Stat	P[|T| > t]
Week days	0,0004	2,90	0,0051

Leap year

	Coefficients	T-Stat	P[|T| > t]
Leap year	0,0021	1,30	0,1978

Forecasts

JDemetra+ compiles the **Forecasts** of the original time series for one year with the confidence intervals calculated according to the ARIMA model estimated in the **Pre-processing** (Figure 4.7). It also contains out-of-sample tests for forecast which indicate the statistical significance of the forecast.

Figure 4.7 **Forecasting part**
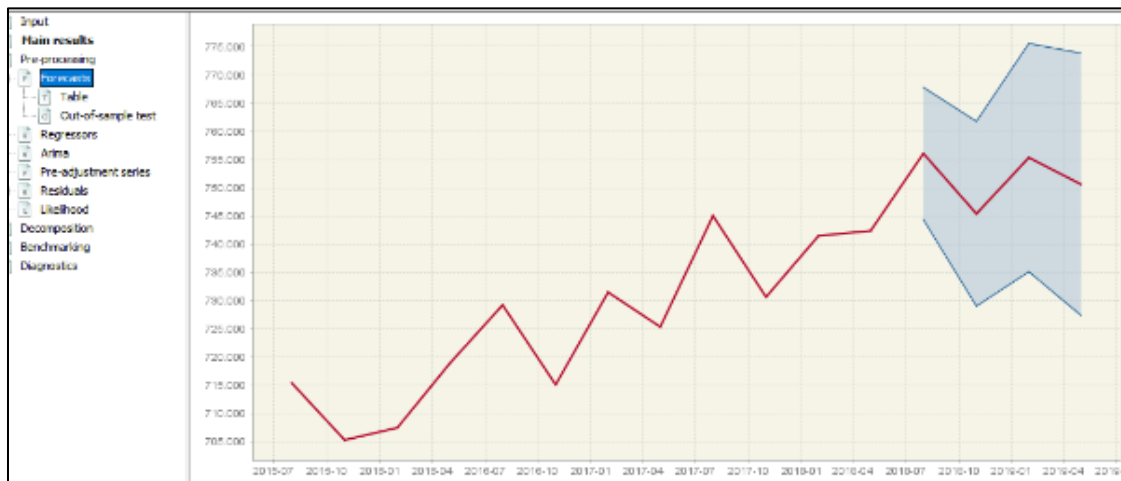
Forecasts are evaluated in terms of distribution properties. The idea behind the evaluation is that the distribution of in-sample data should be identical or similar to out-of-sample data. A statistical distribution is characterized by its mean and variance. Therefore, an out-of-sample test is performed by estimating a model for restricted in-sample (%90) and forecasting for the remaining part of the sample (out-of-sample) with fixed model parameters. Then, a comparison is performed between forecast errors (out-of-sample) and residuals (in-sample) in terms of the equality to zero for their mean and equality of

mean of the squared error. Figure 4.8 displays the results on **Forecasts/Out-of-sample test** in the case when both measures satisfy the condition.

Figure 4.8 **Tests for forecasting part**

	Mean	P-Value
In sample	-0,0002	0,7612
Out of sample	0,0007	0,7487

Mean of forecast errors can be assumed zero

	MSE
In sample	0,0000
Out of sample	0,0000

Test for equality of MSE = 0,5295
Distribution: F(6,63)
P-Value: 0,7838

Mean Squared of forecast errors can be assumed close to the Mean Squared of in sample residuals.

Outlier detection

Outliers can be defined as observed values which are outside of the assumed distribution. It is important to highlight "assumed", as an observation, which is an outlier according to one distribution, may not be an outlier according to another distribution. Therefore, an observation identified as an outlier according to one ARIMA model, may not be an outlier according to another ARIMA model.

The detected outliers and their type, positions and coefficients are provided on the main page of **Pre-processing.** TRAMO and Reg-ARIMA automatically detect and temporarily replace outliers with expected values before estimating the seasonal and calendar components. Afterwards, the estimated effects of outliers are added back into to the finalised seasonally adjusted series.

There are four types of outliers: **Additive Outlier (AO)** is a single point jump in the time series; temporary or **Transitory Change (TC)** is a point jump gradually returning to the original level; **Level Shift (LS)** is a point jump and permanent stay on the new level; and **Seasonal Outlier (SO)** is a point jump that reoccurs periodically in the following years. A more detailed description of the different types of outliers can be found in Section 2.3.2.

TRAMO and Reg-ARIMA perform tests to identify statistically significant outliers using a threshold value (called VA) for the tests. The VA defines an observation as an outlier when its unexplainable part exceeds VA. Otherwise, it is not an outlier. The default value for the VA can be modified according to the statistical requirements as explained in Outliers.

In the Belgian example, a level shift was identified for the 4th quarter of 2008 (Figure 4.9). This implies that the Airline model for Belgian GPD cannot explain this observation. This outlier is not a surprise since it happened during the global financial crises.

Figure 4.9 **Estimation results for outliers**

Outliers

	Coefficients	T-Stat	P[|T| > t]
LS (IV-2008)	-0,0276	-5,51	0,0000

Information that can explain outliers is especially important at the end of the time series when the nature of the outlier is uncertain, as the next observations are not yet available. A later change to the type of outlier may lead to large revisions in the seasonally adjusted series.

Residuals

The residuals of the model can already indicate the quality of seasonal adjustment. The residuals should be independent and random and follow the normal distribution with a zero mean. JDemetra+ displays information on the residuals under **Pre-processing/Residuals/Statistics.**

Under **Distribution**, the main properties like autocorrelations and the distribution of the residuals are visualized (Figure 4.10, right). The main properties of the distribution, like mean, skewness, kurtosis and normality are displayed here. The residual properties are also tested by JDemetra+. The test results can be found under **Statistics** and include a *Normality* test, whether the residuals follow a normal

distribution or not, and an *independence* test (Grudkowska, JDemetra+ User Guide, 2015), whether the residuals display autocorrelation or not. The *Randomness* test measures whether the positive and negative signs of the residuals are distributed randomly or regularly. And lastly, the *linearity* test is a heteroscedasticity test for measuring whether the variance is constant over time.

Independence and *randomness* tests are of critical importance for indicating the unbiasedness of estimators while *normality* and *linearity* tests indicate the efficiency of the estimators. One may prioritize the unbiasedness and therefore the *independence* and *randomness* test results.

In the Belgian example, the tests on residuals do not suggest any statistical problems (Figure 4.10). All null hypotheses of the statistical tests are accepted at the five percent significance level. Hence, the distribution of the residuals is assumed to be random, normal and independent, meaning they do not include any information and they fulfill the theoretical requirements. The significance level is the criterion used for testing an assumption, in other words, the null hypothesis about the data. An experienced user may change the significance levels applied by JDemetra+ under **Tools/Options/Statistics**.

Figure 4.10 **Test statistics and distribution graph of the residuals**
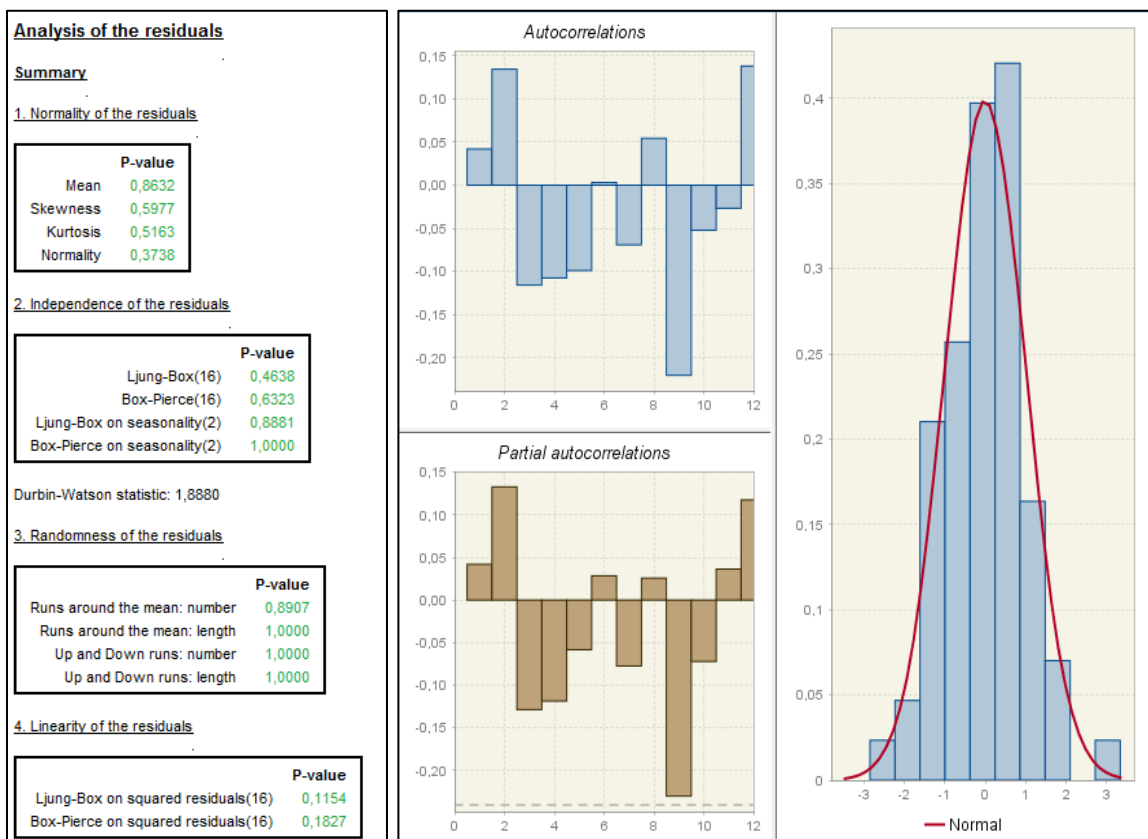
Decomposition Model

The decomposition performed by SEATS assumes that all components in a time series, i.e. trend-cycle, seasonal, and irregular, are independent of each other. This independence is also assumed for the transitory component, which is rarely identified and estimated. The decomposition is performed by maximizing the innovation variance of the irregular component. The aim is to derive a trend-cycle and a seasonal component as smooth as possible.

JDemetra+ provides the mathematical models of each component on the main page of **Decomposition** (Figure 4.11). **Decomposition** contains eight sections: **Stochastic series, Components, Wiener-Kolmogorov (WK) analysis** and **Error analysis** on the results; **Stationary Variance Decomposition** contains several intermediate results of the SEATS which can be used for informative purposes.

The **Decomposition** contains information about the ARIMA models applied by SEATS. The part presents, for SEATS, the properties of the Wiener-Kolmogorov filters which are used to extract the components from the original series. Decomposition requires that the components are uncorrelated. If X-13 is used to seasonally adjust the time series, JDemetra+ provides detailed tables (A, B, C, D and E) which contain the results of the consecutive stages of the X-11 procedures of decomposition as applied by X-13.

Figure 4.11 **General view of decomposition**
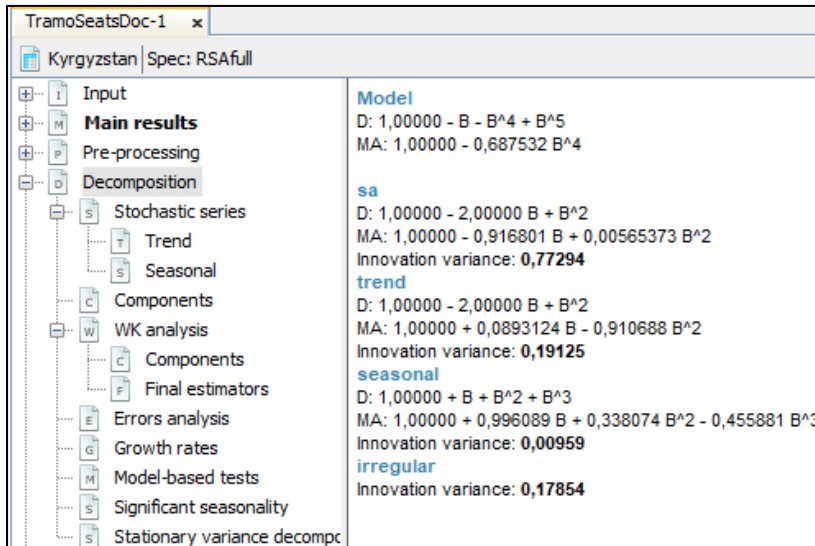
SEATS identified an ARIMA model for each component of the series of Kyrgyzstan which are the trend-cycle, seasonal and irregular component. JDemetra+ presents the mathematical formulas for each ARIMA model of a component in the main page of **Decomposition**.

There are several parts of **Decomposition** that can be used effectively by the user. These are: **Growth rates**, **Model-based test, and Significant seasonality**. In **Growth rates** (Figure 4.12), the rates of growth of the seasonally adjusted series (SA_t) or the trend component ($Trend_t$) over the period ($t, t-1$) is expressed in percentage points as:

$$((SA_t / SA_{t-1}) - 1) \times 100$$

$$((Trend_t / Trend_{t-1}) - 1) \times 100$$

The standard errors are computed using a linear approximation of the rates (Maravall, López-Pavón, & Pérez-Cañete, 2015). When period-to-period changes are large, these standard errors should be interpreted as broad approximations, that will tend to underestimate the true values.

Figure 4.12 **Growth rates for adjusted series**

Period to period growth rates

Seasonally adjusted series

Period	Growth	Std error (revisions)	Std error (total error)
II-2018	0,57%	0,14%	0,2%
I-2018	0,12%	0,14%	0,2%
IV-2017	0,61%	0,13%	0,2%
III-2017	0,19%	0,13%	0,2%
II-2017	0,7%	0,11%	0,18%
I-2017	0,35%	0,1%	0,18%
IV-2016	0,28%	0,1%	0,18%
III-2016	0,42%	0,1%	0,18%
II-2016	0,58%	0,08%	0,17%

Trend

Period	Growth	Std error (revisions)	Std error (total error)
II-2018	0,41%	0,15%	0,23%
I-2018	0,36%	0,06%	0,19%
IV-2017	0,38%	0,05%	0,18%
III-2017	0,42%	0,05%	0,18%
II-2017	0,49%	0,04%	0,18%
I-2017	0,42%	0,04%	0,18%
IV-2016	0,33%	0,04%	0,18%
III-2016	0,42%	0,04%	0,18%
II-2016	0,48%	0,03%	0,18%

Model-based tests presents the distribution of component, theoretical estimator and empirical estimate (for their stationary transformation) in terms of variance, auto-correlation, and cross-correlation. Whether (under/over adjustment) components are estimated in accordance with theoretical models can

be evaluated using the tests in this section. It is expected that estimator and estimate variances are close to each other and smaller than component variance. This is measured by the F-test with its value presented in the last column of the table in Figure 4.13.

Figure 4.13 **Variance test for components**

Variance				
.	Component	Estimator	Estimate	P-Value
Trend	0,3785	0,1650	0,1624	0,9435
Seasonally adjusted	1,5253	1,3318	0,9066	0,1312
Seasonal	0,0145	0,0012	0,0009	0,5506
Irregular	0,1911	0,0836	0,0555	0,1069

The other important part in **Model-based test** is the cross-correlation measured between the components. This gives an indication of misspecification of the components if there is an inconsistency between the component's estimator and estimate, where the consistency is measured by the F-test and it is represented with its probability value presented in the last column (Figure 4.14). The table of cross-correlations provides the user with useful information for testing whether the estimators or actual estimates of components correlate with each other or not. The results of cross-correlation are a way to test the assumption of *orthogonal* (uncorrelated) components. Figure 4.14 presents a cross-correlation table produced by SEATS for the Belgian GDP. In JDemetra+, the colour of the p-values signals the result, e.g. a green p-value indicates insignificant cross-correlation.

Figure 4.14 **Cross-correlation of components**

Cross-correlation			
.	Estimator	Estimate	P-Value
Trend/Seasonal	-0,2001	-0,0741	0,4198
Trend/Irregular	-0,0019	-0,1270	0,3852
Seasonal/Irregular	0,0837	0,2211	0,2589

Lastly, **Significant seasonality** presents the number of quarters (months) which show significant seasonal movements by the different part of the time series with 95% and 99% confidence levels. This is presented in three parts, namely *historical*, *current* and *forecasts*. The expectation is that the historical and the current period have similar seasonal periods, the forecast period also has positive seasonal periods and similar to the current.

4.2.4 Quality diagnostics

The **Diagnostics** present detailed information on the seasonal adjustment procedure. This information, often purely descriptive, is calculated in the same way for TRAMO/SEATS and for X-13 and is therefore comparable. JDemetra+ divides the diagnostics into five main parts: **seasonality tests, spectral analysis, sliding spans, revision history** and **model stability analysis.** To ensure the high quality of seasonal adjustment it is recommended to make use of the wide range of quality measures provided by JDemetra+. This *Guide* focuses on the quality diagnostics of the TRAMO/SEATS method. More details on diagnostics are provided in Grudkowska (2015).

JDemetra+ reports all test statistics as "messages" using the categorization in Table 4.1. This allows quick interpretation of the test statistics. In general, the messages *Uncertain* and **Good** can be evaluated as acceptable.

The main page of **Diagnostics** provides a summary of the test statistics and an overall summary value. This value gives a quick overall indication of the quality of the seasonal adjustment (Figure 4.15). Here, the diagnostics on **regarima residuals, out-of-sample** and **residual seasonality** are recommended as the most important results that should be checked before deciding on the seasonal adjustment model.

Table 4.1 **Messages of JDemetra+ for quality measures**

Test Statistics	Reason
Undefined	The test is probably not designed or not suitable for that process, or an unsatisfied condition to calculate the statistics.
Error	The test statistics is unacceptable and needs to be recalculated.
Severe	The test statistics is unacceptable and needs to be recalculated.
Bad	The test statistics is critical and needs to be recalculated.
Uncertain	The test statistics is acceptable, but fine-tuning could remove the uncertainty.
Good	The test statistics is acceptable, no more attempt needed.

Furthermore, under *basic checks*, very basic properties of the seasonal adjustment are tested. **Definition** tests if the decomposition respects the mathematical relations of the different components and effects (for instance, that the seasonally adjusted series should be equal to the difference between original time series and seasonal component as well as the sum of the trend-cycle component and irregular component). **Annual totals** compare the annual totals of the original series and the annual totals of the seasonally adjusted series. The difference should be low as possible.

Figure 4.15 **General view of diagnostics**
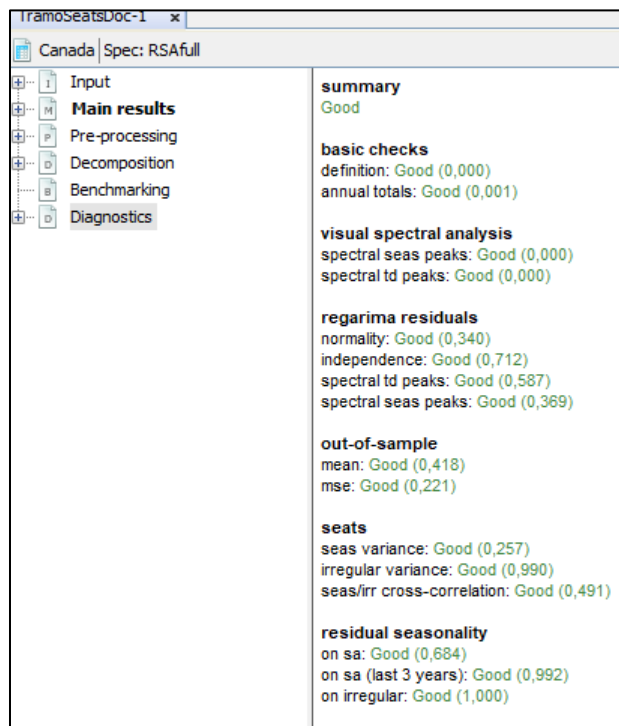
The *Spectral analysis* part of *Diagnostics* presents periodograms and Auto-regressive spectrums. The spectral graphics allows for the checking of the residuals, irregular component and seasonally adjusted series for the presence of any seasonal or trading day effects. Peaks at the seasonal frequencies (blue lines) of an adjusted series signal the inadequacy of the seasonal adjustment filters for the time interval used for spectrum estimation and therefore a different model specification or data span length should be considered. Peaks at the trading day frequencies (red lines) indicate that the regressors of the model should be revisited. If some remaining seasonality is indicated, the model specification, regressors or the time span used for modeling need to be reconsidered.

The series of Belgium show no indication of residual seasonality or residual calendar effects. In other words, there are no spectral peaks at the seasonal (blue) or trading day frequencies (red) in the Periodogram part of Figure 4.16. Peaks are only considered, when the value is higher than the threshold value of 10.

Figure 4.16 **Spectral graphics of residuals**
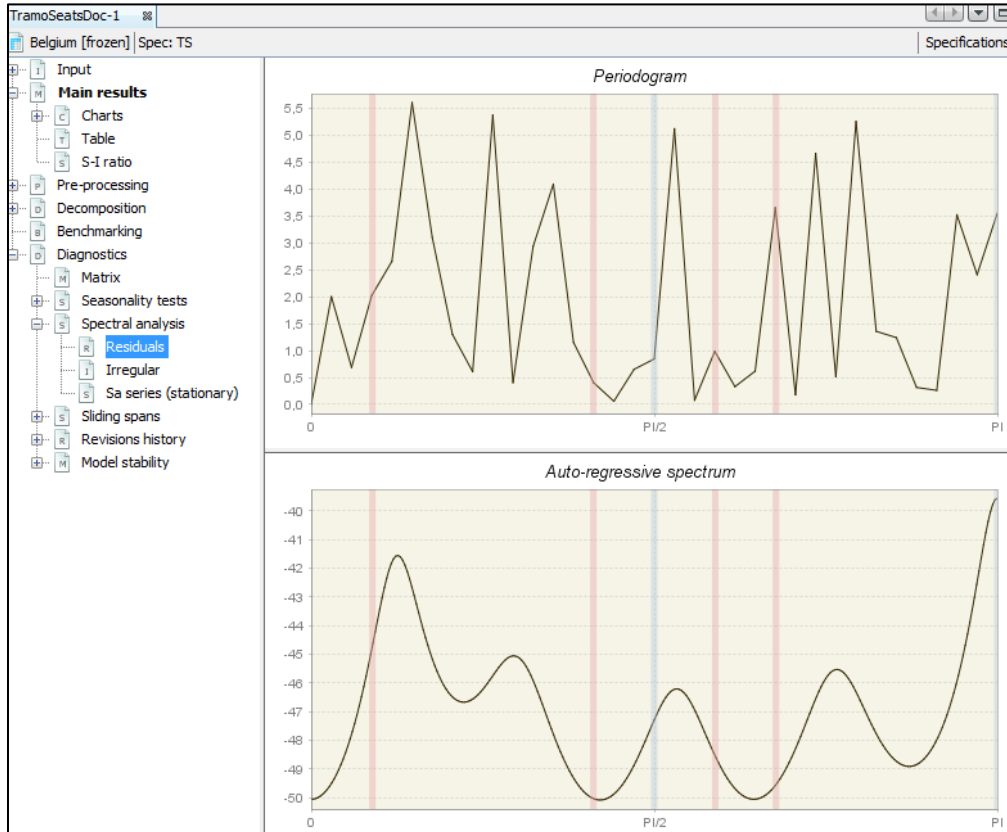
The **Seasonality tests** part of **Diagnostics** provides the results of several tests on the existence of seasonality in different time series deducted from the original series. These series include the original, linearized, residuals, etc. Explanations on the interpretation of these tests and their expected outcomes are given in Table 4.2.

The different testing methods used for testing the seasonality in the series in question are: Autocorrelation at seasonal lags, Friedman, Kruskal-Wallis, Spectral peaks, Periodogram, Seasonal dummies, and Seasonal dummies (AMI).

Figure 4.17 gives the general picture of the seasonality test results. In the example, the results are fully in line with the expectations explained in Table 4.2. There is no residual seasonality in the entire duration of the series, but there may be residual seasonality for the last three years of the series. This can be ignored though since overall the results reflect good conditions for identifying the seasonal pattern.

A more thorough explanation of the tests can be found in Grudkowska (2015). If the test results are contradictory for any of the series, it is recommended to give more weight to the parametric tests rather than the non-parametric ones. The parametric tests are the 1st, the 6th, and the 7th tests.

Table 4.2 **Seasonality tests for seasonal adjustment**

No	Type of test	Expected result	Explanation
1	Original (transformed) series	YES	There are several types of test. It is desired that most of the test approves the existence of seasonality in the original time series to be seasonally adjusted.
2	Linearized series	YES	This is the original time series corrected for outliers and calendar effects if any. The explanation is the same as the original time series.
3	Full residuals	NO	This is the part of the original time series unexplained by the ARIMA model estimated. The presence of seasonality in the residuals is to be avoided.
4	Combined test	Identifiable seasonality present	This test consists of three separate tests which measure the stability, the presence and the evolution of seasonality. Seasonal adjustment should only be considered if identifiable seasonality is present.
5	SA series	NO	This is the seasonally adjusted (SA) series which is adjusted from seasonality and calendar effect if any. It is desired that most of the test does not approve the existence of seasonality in SA series according to *idempotency* criteria.
6	Irregular	NO	This is the unexplained part of the original time series by SEATS decomposition part. The presence of seasonality in the Irregular part is not desirable.
7	Residuals (last periods)	NO	Same as the 3rd row in the table, but the tests are applied to the last 3 years of the series in question.
8	SA series (last periods)	NO	Same as the 5th row in the table, but the tests are applied to the last 3 years of the series in question.
9	Irregular (last periods)	NO	Same as the 6th row in the table, but the tests are applied to the last 3 years of the series in question.
10	Residual seasonality	NO	It is the test for the residual seasonality with the same purpose as the 3rd test, but with a different statistical approach. It measures the residual seasonality in both full and restricted part of the residuals.

Figure 4.17 **Results for seasonality tests**
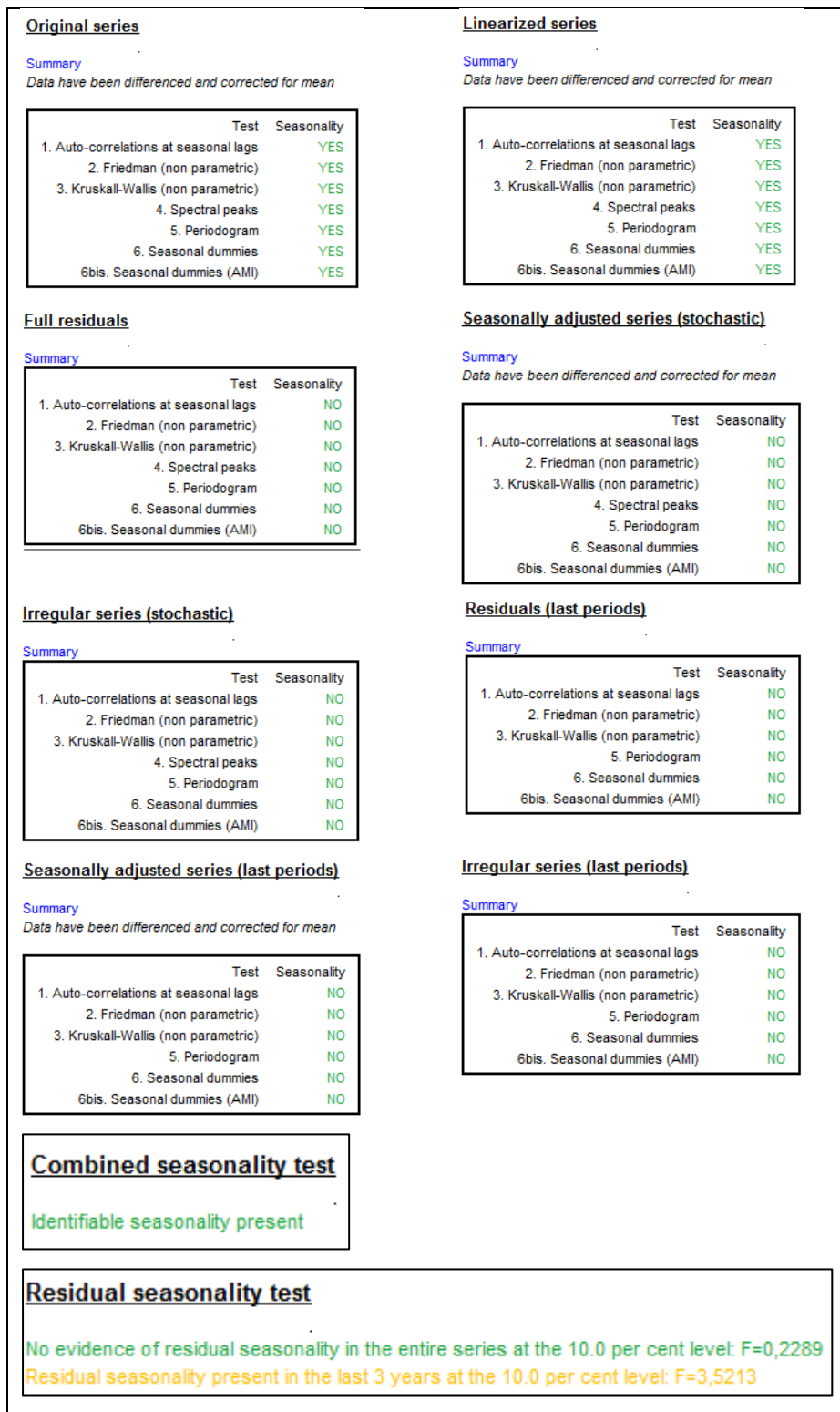
The **Sliding spans** analysis part of **Diagnostics** is originally used in X-13. It is particularly useful for a series with changes in seasonality or many outliers. From the analysed time series, the program extracts time spans with the length of eight years. In this example, it extracts four time spans which are separated from each other by one year. The sliding spans are computed for the seasonal component, the trading day effect, if any, and the seasonally adjusted series. When an additive decomposition is used the sliding-spans analysis is based on absolute differences, otherwise it is based on the ratio of factors. The threshold

to detect abnormal values is set to three percent. Any larger value is unstable. Abnormal values can be analysed in detail on the relevant parts of the components. In Figure 4.18, the seasonal factors appear to be identifiable while the seasonal component has a moving structure according to the sliding spans analysis of the GDP of Belgium.

Figure 4.18 **Sliding spans analysis**

Sliding spans summary

Time spans
Span 1: from I-2007 to II-2015
Span 2: from I-2008 to II-2016
Span 3: from I-2009 to II-2017
Span 4: from I-2010 to II-2018

Tests for seasonality

	Span 1	Span 2	Span 3	Span 4
Stable seas.	14847,3	6002,3	2449,8	4911,3
Kruskal-Wallis	30,9	30,9	30,9	30,9
Moving seas.	7,0	3,5	1,7	5,7
Identifiable seas.	YES	YES	YES	YES

Means of seasonal factors

	Span 1	Span 2	Span 3	Span 4
Q1	0,9758	0,9753	0,9756	0,9748
Q2	1,0118	1,0125	1,0120	1,0131
Q3	0,9685	0,9685	0,9687	0,9685
Q4	1,0441	1,0446	1,0439	1,0436

The fourth part of **_Diagnostics_** presents the **_revision history_** of the series. It analyses what kind of revisions the adding of new observations at the end of the series causes. It presents charts both for the seasonally adjusted, trend-cycle series and their growth rates. JDemetra+ displays the revision history for both methods, TRAMO/SEATS, and X-13.

In Figure 4.19, each blue circle on the chart depicts the initial adjustment when this point is the last observation. The red line presents the results at the current state. The analysis starts by estimating the model for the complete time span. From there on, the time span is shortened progressively and the decomposition re-estimated. For each period, a series of successive estimations is obtained. By default, only the parameters of the model are re-estimated. However, the program allows a complete re-estimation and a re-identification of the outliers if the option is changed.

By clicking on a dot in the graph, for example the observation of November 2006, a pop-up window appears. It shows the successive estimations of a specific date for the different time spans, for instance, the 2nd quarter of 2015 and its estimates for successive periods are given in Figure 4.19.

For the example of Belgian GDP, the pop-up window confirms that revisions are not significant after three years. This part also contains a revision history table, called _Relative differences_, that presents the differences between the first estimates and the last estimates for the last four years. If the decomposition is additive, JDemetra+ displays absolute revisions; otherwise it uses relative differences. To enable quicker analysis, JDemetra+ displays the largest differences in red. Any red observations are, in absolute terms, larger than two times the root mean squared error of the absolute or relative revisions. The series of Belgium includes only one observation in 2015 which exceeds the given critical limit.

The results are stable if adding or removing observations doesn't cause a lot of change in the results. The stability is generally a good indicator of the quality of adjustment. However, for some time series, even the best possible seasonal adjustment may be unstable. In such a case, balancing between quality and the extent of revisions will be a challenge. One may try to change the model specification if an unstable seasonal component is detected. In 5, revision policies are discussed in more detail.

Figure 4.19 **Revision history for seasonal adjustment**
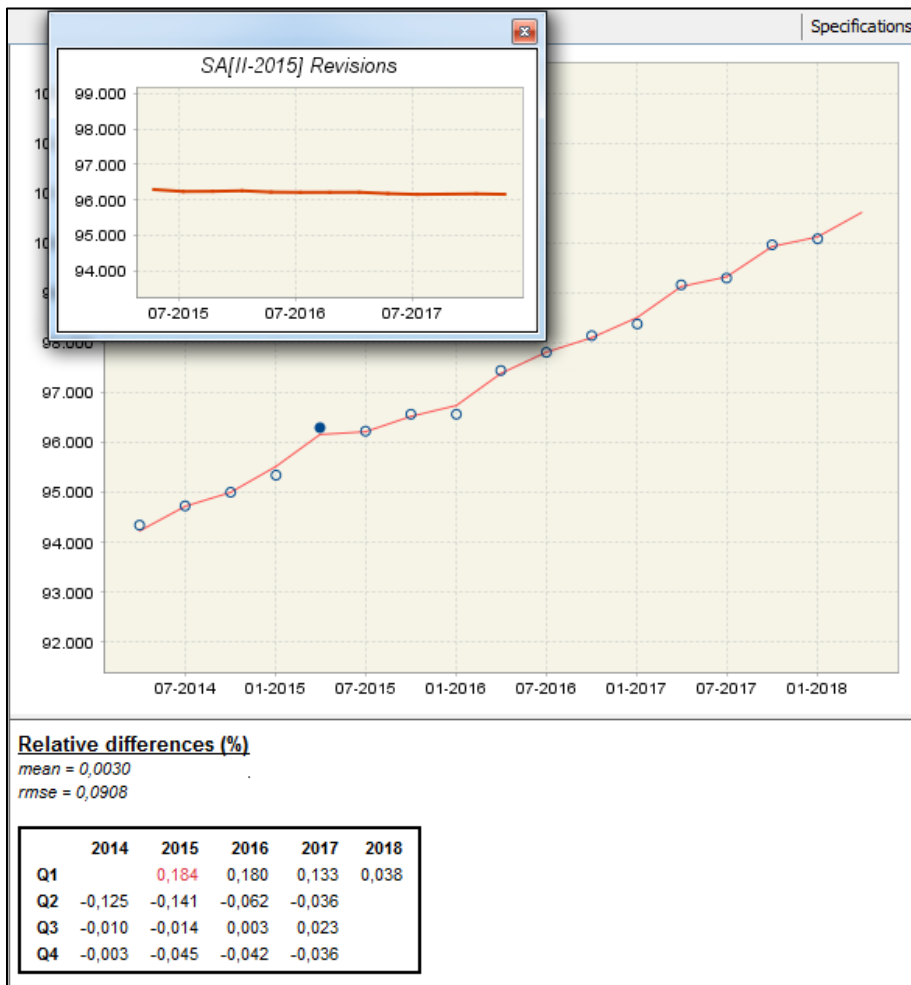
The last part of ***Diagnostics*** provides ***Model stability*** analysis which checks the stability of ARIMA parameters and coefficients of the regressors for different periods. It shows the results in a visual form. The model stability analysis computes the results on a moving window of eight years which slides by one year at a time. The displayed points correspond to the successive estimations of parameter values.

Figure 4.20 **Model stability analysis**
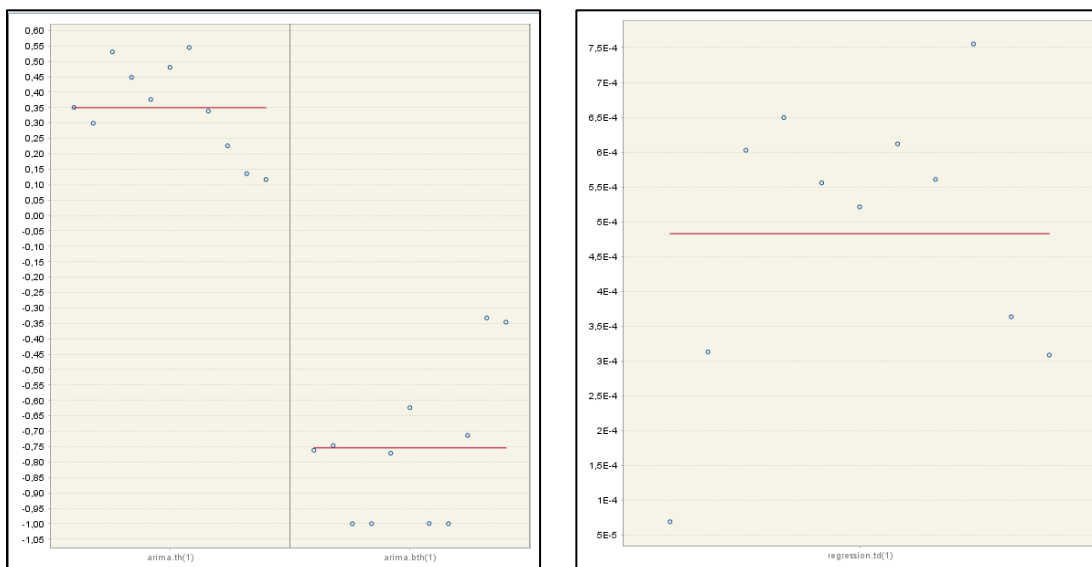
The model stability analysis for Belgium includes the time spans for 2000-2008, 2001-2009, 2002-2010 and so on (Figure 4.20). In the Airline model (left graph), the regular moving average parameter represents the structure of the trend-cycle component, whereas the seasonal moving average parameter reflects the seasonal component. The graph displays stable movements of regular and seasonal moving average parameters, but it shows an unstable movement in recent years for both parameters. The trading day parameter (right graph) also shows the volatile pattern for recent years. This all means that the findings for the recent year may be subject to revision. The results should be evaluated attentively.

4.2.5 Benchmarking

Benchmarking contains limited information to evaluate the quality of the process. There are four parts to the benchmarking results (Figure 4.21). The first graph displays the seasonally adjusted series before and after benchmarking. The next graph presents the numerical difference in seasonally adjusted series between before and after benchmarking. This difference should be as low as possible. In the event of outliers in the original time series, this difference may be higher, but it is not necessarily an indication for low quality. The information of both graphs is combined in the table next to them, including the values for: the seasonally adjusted series before benchmarking (original), the seasonally adjusted series after benchmarking (result), and the differences. The last part of the results contains some descriptive statistics on the difference, such as maximum, minimum, average and standard deviation. In the example of Belgian GDP, the difference is relatively close to zero. This means, the stochastic structure of the seasonally adjusted series is not damaged after the benchmarking process.

Figure 4.21 **Benchmarking results for seasonal adjustment**

	original	result	Differences
I-2000	76.958,784	76.964,15	0
II-2000	77.460,592	77.464,429	0
III-2000	78.071,495	78.072,202	0
IV-2000	78.464,203	78.460,13	-0
I-2001	78.567,316	78.556,831	-0
II-2001	78.435,735	78.422,802	-0
III-2001	78.387,381	78.375,911	-0
IV-2001	78.107,425	78.101,348	-0
I-2002	79.054,46	79.057,664	0
II-2002	79.747,871	79.756,873	0
III-2002	79.989,131	80.000,237	0
IV-2002	80.326,21	80.335,712	0
I-2003	80.099,941	80.104,028	0
II-2003	80.115,499	80.116,866	0
III-2003	80.423,833	80.425,153	0
IV-2003	80.964,191	80.968,176	0
I-2004	82.166,814	82.176,318	0
II-2004	83.029,868	83.043,296	0
III-2004	83.658,004	83.673,661	0
IV-2004	83.978,692	83.994,799	0
I-2005	84.315,589	84.330,393	0
II-2005	84.694,365	84.708,15	0

Relative differences

Max :2.00703248674822725E-4
Min :-1.89167740631934876E-4
Average :6.429417927060364E-5
Stdev :9.244980858659855E-5

4.2.6   Refining results

In general, several diagnostic tests may fail after the first seasonal adjustment run. One of the main features of JDemetra+ is that it allows an exploration of the seasonal adjustment process. For each round of seasonal adjustment, the user may change any option in the specifications and will see immediately the effect on the change. It is very useful to test the options and their effects to further understand the data and the possibilities offered by the software. Figure 4.22 illustrates how to read the current specification used and to modify it by using the **Specification** menu of the document. Pressing **Apply** is enough to immediately see the effects of the changes on the results.

Figure 4.22 **Modification of specification**
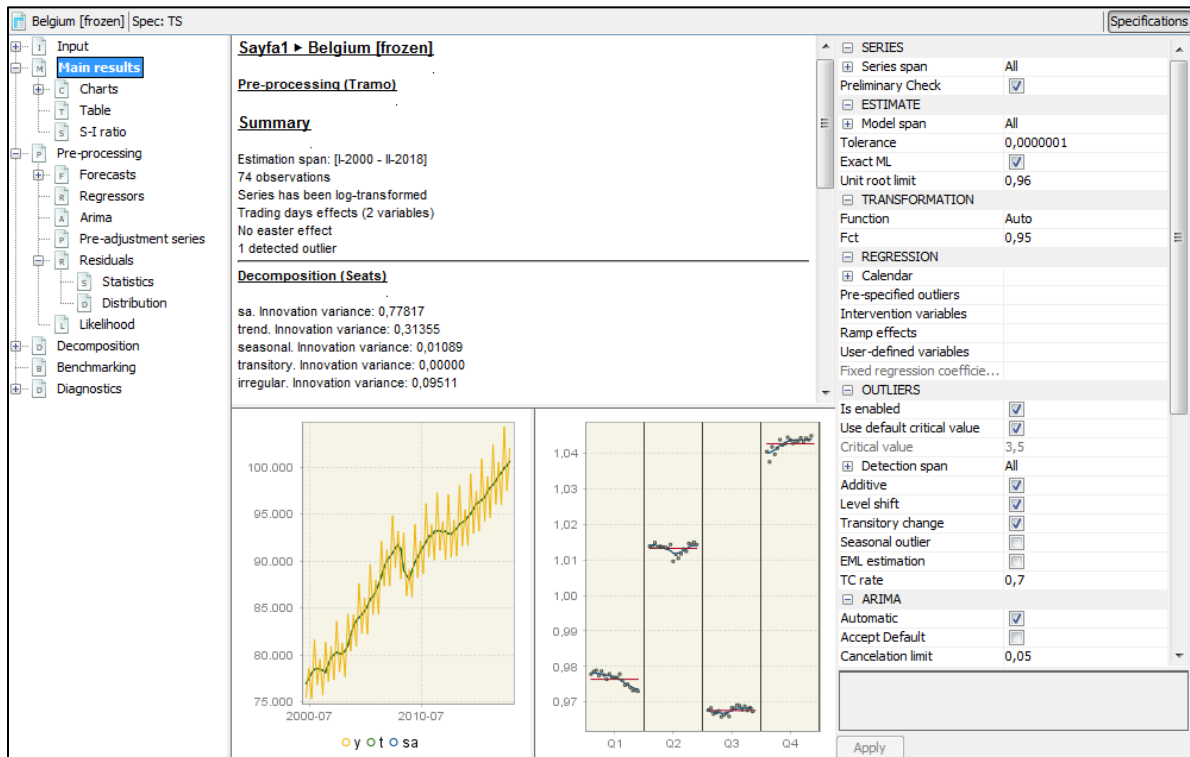
4.3   Multi-processing

4.3.1   Processing page

An overview of the main results presents the main conclusions of the multi-processing for each series (Figure 4.23). This overview includes:

- **Series** names
- used **Method** (*TS* indicates of user-defined specifications)
- **Estimation** type (such as Current, Parameters, Last outlier, Outliers, Arima (+ Outliers) and Concurrent)
- **Status** of the series within the multiprocessing (e.g. *Unprocessed, No data* and *Valid*)
- **Priority** (value 10 indicates a priority for log/level selection)
- overall **Quality** of the seasonal adjustment
- possible **Warnings**, e.g. for a short time series, non-decomposable models (SEATS) or no identified seasonality

A single click on the name of the series opens the results panel for each series as in Single-processing.

Figure 4.23 **Processing page of multi-processing**

4.3.2 Summary

The **Summary** gives general information on the model used for the set of series (Figure 4.24). In the example, 47 time-series of a total of 52 time-series are analysed as five time-series have **No Data**. 41 of the analysed time series are modeled as logarithmic transformation of the original time series. For nearly half of all 47 time-series, TRAMO/SEATS identified an Airline-like model. The total number of outliers detected is 59 and outlier per series is approximately 1.

Figure 4.24 **Summary results for the set of series**

The most detected type of outlier is the level shift among the series as it is expected due to the global financial crisis. The relatively few detections of the default trading day effect (12.27%) may points out the need for user-defined calendar regressors for countries' GDP series. An Easter effect is detected for nine time series.

4.3.3 Matrix

Matrix contains summary information for each series on the following: the main statistical properties of the ARIMA model used in pre-adjustment phase (**Main)**, the calendar specification results (**Calendar**), the outlier structure of each series (**Outliers)**, the ARIMA parameter values (**Arima**) and the significance

tests (**Tests**). In the **Tests** part, a table with the p-values of tests on residuals and other information can be found, including annual discrepancies between raw and adjusted data as well as spectral visual peaks (Figure 4.25).

Figure 4.25 **View of the matrix in a multiprocessing**

	N	Seasonal	Log	Mean	P	D	Q	BP	BD	BQ	BIC	SE(res)	Q-val
vertical format_oldAlbania	38	1	0	0	0	1	1	0	1	0	16,998488...	4393,8775...	10,225412
vertical format_oldArmenia	60	1	1	1	1	0	0	0	1	0	-5,667292...	0,052846965	21,090869
vertical format_oldAustria	74	1	1	0	0	1	0	0	1	1	-9,357795...	0,008273514	9,249238

	Leap Year	T-Stat	TD(1)	T-Stat	TD(2)	T-Stat	TD(3)	T-Stat	TD(4)	T-Stat	TD(5)	T-Stat
vertical format_oldAlbania												
vertical format_oldArmenia												
vertical format_oldAustria			0,000906	2,228								

	OUT(1)	OUT(2)	OUT(3)	OUT(4)	OUT(5)
vertical format_oldAlbania	AO (II-201...	AO (III-20...			
vertical format_oldArmenia	LS (IV-200...	AO (I-2004...			
vertical format_oldAustria	TC (I-2010...	LS (I-2009)...	LS (IV-200...		

	phi(1)	t-stat	phi(2)	t-stat	phi(3)	t-stat	th(1)	t-stat	th(2)	t-stat	th(3)	t-stat	bphi(1)
vertical format_oldAlbania							-0,522594	-3,357					
vertical format_oldArmenia	-0,499406	-4,157											
vertical format_oldAustria													

	Skewness	Kurtosis	Ljung-Box	LB. on Seas	LB on sq.	Bias	TD peak	Seas peak	Visual TD p...	Visual Seas...
vertical format_oldAlbania	0,0084	0,0169	0,8053	0,9983	0,9965	0,003	0,449	0,199	Good	Good
vertical format_oldArmenia	0,2733	0,0607	0,134	0,6431	0,2219	0,027	0,097	0,247	Good	Good
vertical format_oldAustria	0,8809	0,5698	0,8641	0,7049	0,2285	0,001	0,356	0,443	Good	Good

The **Matrix** parts can be copied (Ctrl+c) into the clipboard and pasted (Ctrl+v) to another program. It can also be exported to a CSV file as explained in "Exporting results and metadata".

4.3.4   Quality review

Based on the first results obtained from the multi-processing (Figure 4.23), it can be assumed that TRAMO/SEATS can perform adequate seasonal adjustment of quarterly GDP for all countries except obviously for those countries without any observations. There are several warnings (**!** and/or **!!**) in the **Warnings** column which are related to the decomposition part or existence of seasonality in the series. If there is a warning about the existence in seasonality, it may mean that the series has no seasonality or changing seasonality by means of periodical composition. But there may be no need for action to fix these warnings since TRAMO/SEATS generally detects any changes in the pattern of seasonality.

When the diagnostic statistics are analysed in detail, some *uncertain* statements in the normality test for some countries can be found. This is not crucial for seasonal adjustment.

The details displayed in the view of Figure 4.23 are automatically refreshed when changing the selected series in the multi-processing window. The multi-processing results can be sorted by clicking on a column header. Sorting may be helpful when the processing contains many series.

4.3.5   Refining results

For the multi-processing it is possible to change the specification of a single series as explained in the Single processing section. The specifications of multiple series can be changed by selecting the series in the **Processing window**, right click and **Specification/Select**. A pop-up window opens (Figure 4.26).

As explained in Section 3.5, one specification can be used for many series as well as one series can be seasonally adjusted using several specifications. This can be beneficial for finding the best specifications for the series. It can be especially useful to create and test different specifications when there are different options in the inclusion of user regressors for the calendar. JDemetra+ cannot test the statistical significances of different user regressors in one specification.

Figure 4.26 **Modifying specification in multi-processing**
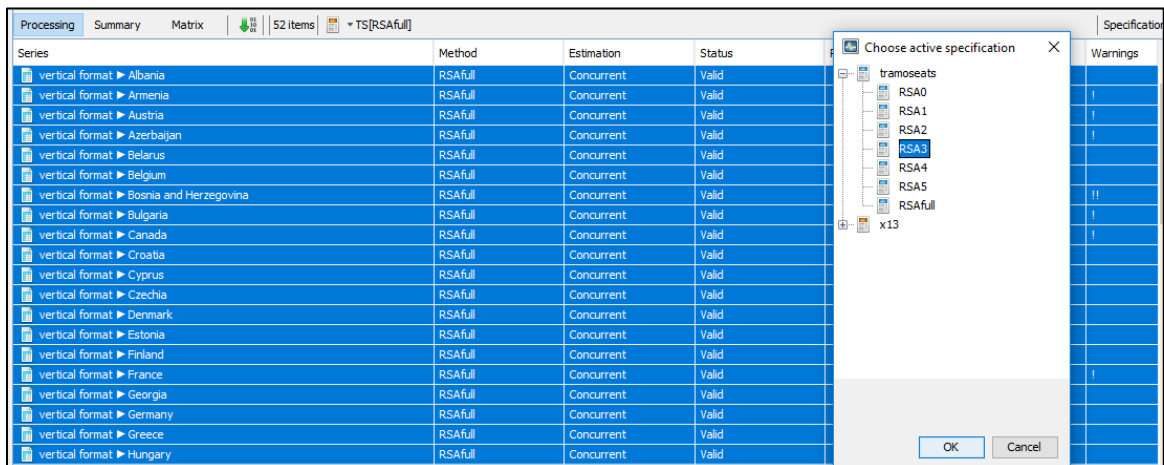
If it appears that the quality of the processes for several time series is insufficient (unlike Figure 4.23), one can try to change the specification of the problematic time series to obtain better results (Figure 4.27). It should be noted that clicking on **Apply** only applies the changed specifications to the series in question. **Restore** restores the changes applied and **Save** saves the changes applied. **Restore** does not work after a change in specification is saved.

Figure 4.27 **Refining a series in multi-processing**
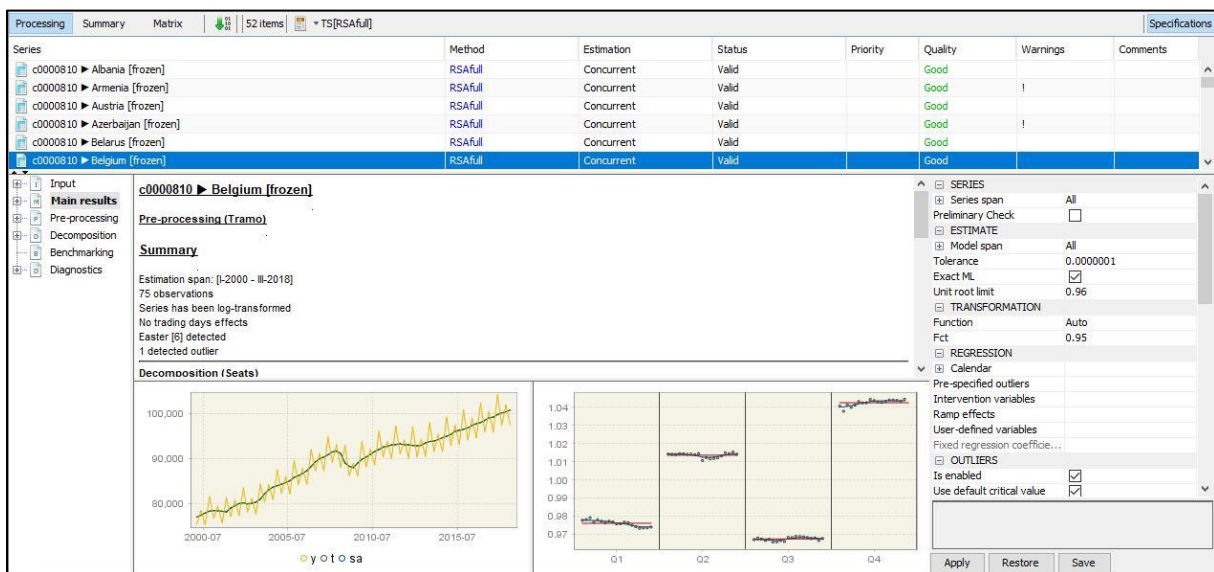
Only after re-running the multi-processing by clicking on the green button, are the **Summary** and **Matrix** parts updated according to the changes made.

4.4 Refreshing and exporting results

4.4.1 Refreshing results

For official statistics, seasonal adjustment is not a once off operation. Usually, seasonal adjustment is run on a monthly or quarterly basis as soon as new data becomes available. Although the models themselves are not re-estimated every month/quarter, the seasonal adjustment process should be re-run every period new data becomes available with resulting revisions to the seasonally adjusted series.

In JDemetra+, revisions to the existing seasonal adjustment process and adjustments to new data are easy. To be able to successfully refresh a multi-processing with new data, the following conditions must be fulfilled:

- The data source must be imported to JDemetra+ using **Providers**.
- The **Workspace** including the multi-processing for seasonal adjustment should be saved in a folder whose path or name should not be changed (Figure 4.28).
- Name, location and data structure of the source file need to remain unchanged from the start.
- The source file should be updated with new time series data and user-defined regressors.

Figure 4.28 **Saving workspace for future processing**
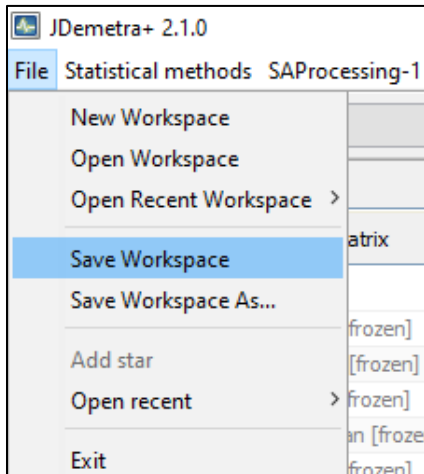
Single-processing

The refreshment process can be performed for single processing or multi-processing. The first step is always to reload the previously saved **Workspace** (Figure 4.29).

Figure 4.29 **Reload Workspace**
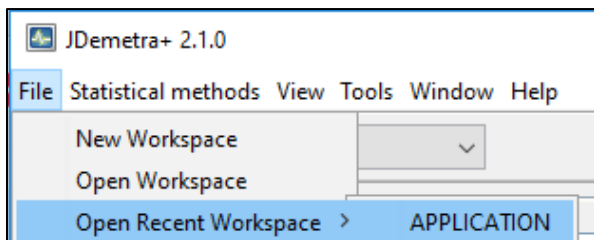
Figure 4.30 **Recall and refresh the single processing**
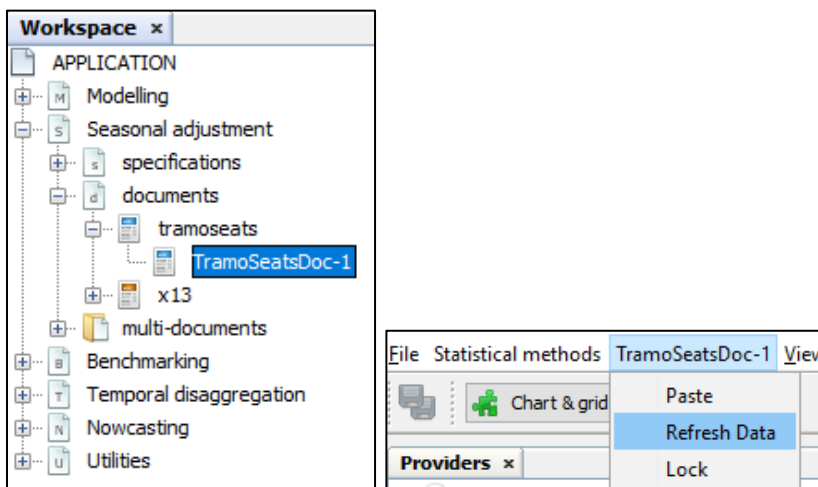
For a single process, the document for the seasonal adjustment (here *TramoSeatsDoc-1)* that can be found under **Workspace/documents** is opened by a double-click on it (Figure 4.30, left). It contains the *frozen* results of the previous seasonal adjustment.

The document can now be refreshed using the updated data (provided the source file is updated) using the item for the document (here *TramoSeatsDoc-1)* in the menu bar. In this menu, a click on **Refresh Data** refreshes the seasonal adjustment process (Figure 4.30, right) and the document now displays the updated results. Alternatively, **Refresh data** can be reached by right-clicking on the document in the **workspace**. The refreshment strategy is fixed to the specification used at the beginning.

The data source file is checked immediately, and the updated data is integrated with the seasonal adjustment process (Figure 4.31). The results for the series show that the estimation time span is extended to the 2nd quarter 2018 and has now 74 observations. The time series has still logarithmic transformation, with Easter effect and 2 detected outliers, and with Trading-days detected (which has not identified for 73 observations).

Figure 4.31 **The updated results**
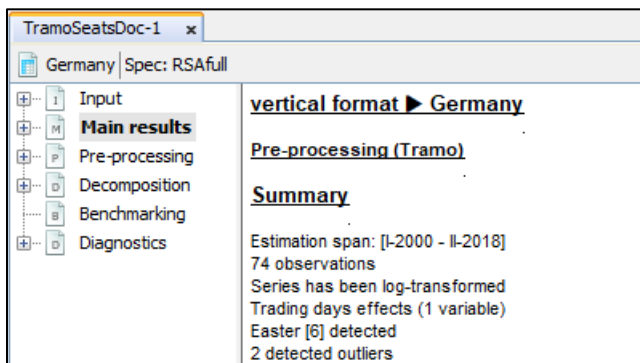
Multi-processing

Figure 4.32 **Steps for refreshing the multi-processing**

Step-1 Opening the Workspace	Step-2 Selecting the multi-processing

Step-3 Select the refreshment strategy	Step-4 Confirm
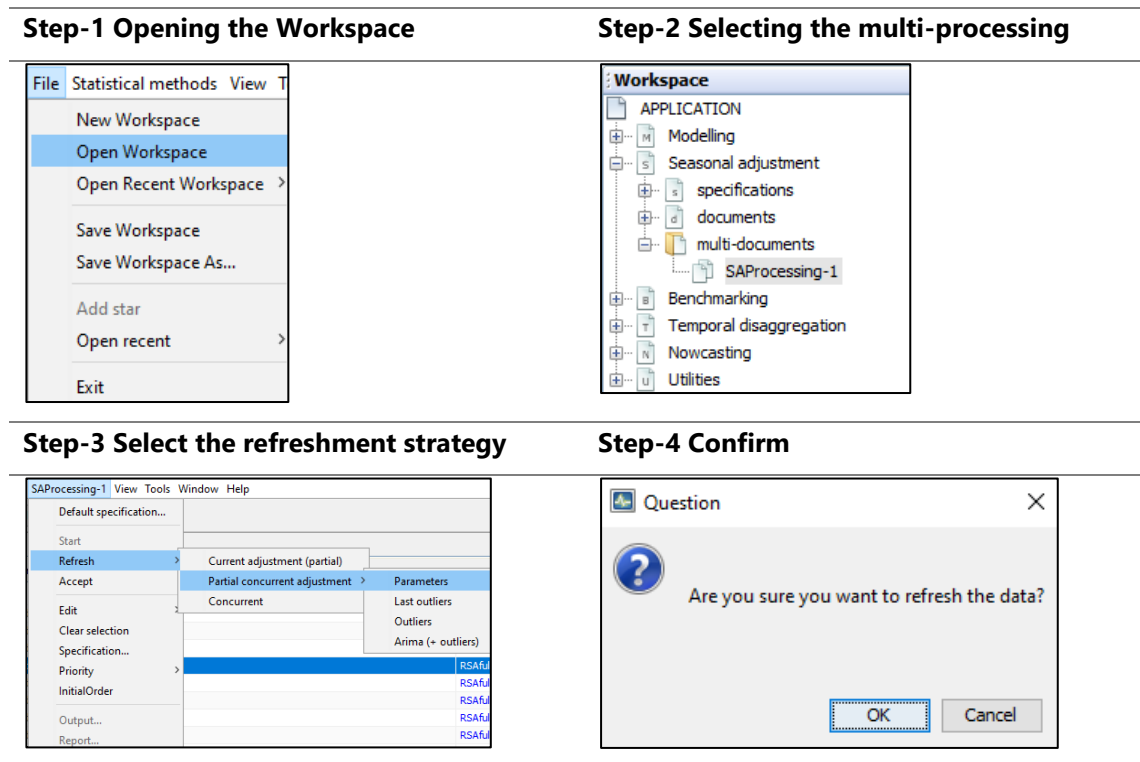
After saving the **Workspace** and provided the conditions above are fulfilled (Figure 4.28), one can get the refreshed seasonal adjustment results of the existing multi-processing by following the steps given below (Figure 4.32):

- The previously saved Workspace is opened in JDemetra+. One can also use **Open Recent Workspace** and select the workspace in question (Step-1).
- The multi-processing document in question (here *SAProcessing-1)* is opened under **workspace/multi-documents** using a double-click (Step-2).
- The item for the multi-processing document (here *SAProcessing-1)* appears in the menu bar. In this menu, under **Refresh**, the refreshment strategy can be chosen (Step-3).
- JDemetra+ asks the user whether the data should be refreshed or not. By clicking **OK**, the multi-processing is updated and the updated results for seasonal adjustment are produced (Step-4).

The main three types of refreshment strategies in JDemetra+ are:

- **Current adjustment (partial):** Adjustment with fixed specifications, user-defined regressors can be updated. Current adjustment means that the model, filters, outliers, and calendar variables are re-identified, and the respective parameters and factors re-estimated at review periods that have been set in advance. The method forecasts the seasonal model and its parameters and uses this information until the next review period which usually takes place once a year. Thus, current adjustment implies that the seasonal and calendar factors applied with new raw data in-between the review periods are fixed.

- **Partial concurrent adjustment:** Partial concurrent adjustment is usually used in case the model, filters, outliers, and calendar variables are re-identified once a year by the user. And, this refreshment strategy re-estimates the respective parameters and factors every time new or revised observations become available. It is possible to modify the partial concurrent adjustment with the following options:

  - **Parameters**: Re-estimation of the coefficients of the fixed the ARIMA model, outliers and calendar effects.
  - **Last outlier:** Same as the previous in addition to re-identification of the last outliers.
  - **Outliers:** Same as the previous in addition to re-identification of all outliers.
  - **Arima (+outliers):** Same as the previous with re-identification of the ARIMA model.

- **Concurrent adjustment:** Adjustment with the RSAs (all things are re-identified). Concurrent adjustment means that the seasonal adjustment method re-identifies the model, filters, outliers and regression parameters with the respective parameters and factors every time new or revised data become available.

In general, concurrent adjustment leads to more revisions, but at the same time, to more accurate results. Therefore, a compromise between concurrent and current adjustment is the most common seasonal adjustment strategy. The decision should consider the properties of the series in question. Stability is an important feature of the seasonally adjusted data. If TRAMO/SEATS or X-13 suggests a different model in the annual update, the diagnostics need to be examined to find out whether the model is notably better than the previous one. It is also important to assess their effect on historical data and to check the significance of the regressors to identify any need for changes. In 5, the issue of defining a seasonal adjustment strategy will be addressed.

4.4.2   Exporting results and metadata

The results and metadata of the seasonal adjustment should be exported for further processing and dissemination of data. JDemetra+ provides several alternative ways for exporting data and supports several kinds of outputs, e.g. .xls, .csv, .txt, etc.

For a single analysis, the information can be manually copied of the summary statistics, e.g. the main page of **Main results, Pre-processing, Decomposition,** and **Diagnostics.** The statistical information provided here can make a good basis for the metadata, adding a few words of conclusion regarding the quality of the seasonally adjusted series. The time series data can be manually copied from **Main results/Table.**

Figure 4.33 **Exporting results for multi-processing**
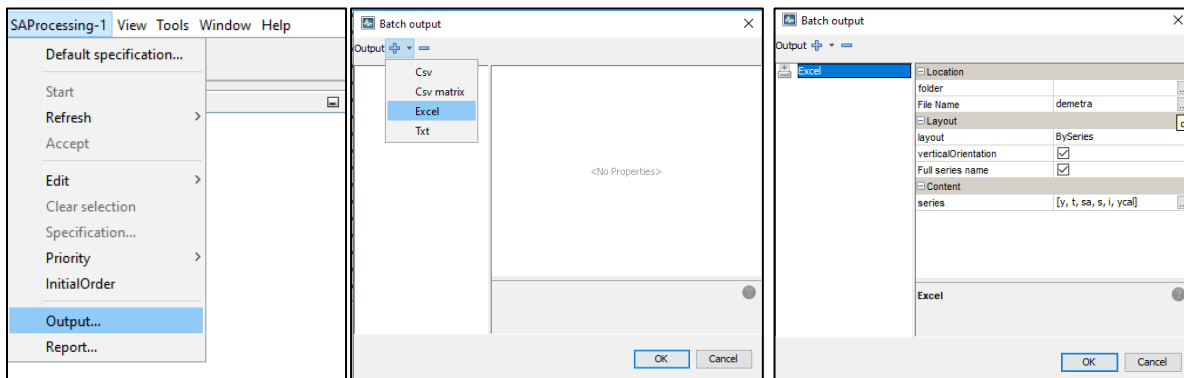
In multi-processing, seasonal adjustment data can be exported using the document menu item (here *SAProcessing-1*), clicking on **Output** and selecting the option required (Figure 4.33). The diagnostics and other results can be exported using the *csv matrix* option. The **Batch output** window (Figure 4.33, right) allows to set the location, name, layout, and content of the output file. A more thorough explanation of the properties can be found in Grudkowska (2015). Under **Content**, it is advised to at least include the three series *y, yc,* and *benchmarking.result*. Here, *y* is the original time series, *yc* the calendar adjusted series, and *benchmarking.result* the seasonally adjusted and benchmarked series.

Figure 4.34 **Reports on seasonal adjustment**
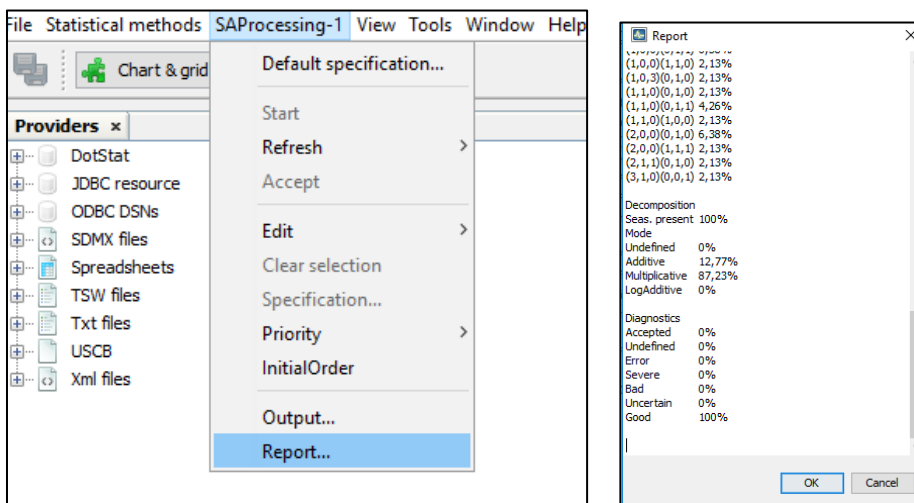
Furthermore, a report can be generated by using the document item in the main menu (here *SAProcessing-1)* and then **Report**. This provides some useful diagnostics that can be used for the statistical metadata of the seasonal adjustment (Figure 4.34).

5 User communication

5.1 Introduction

Only used statistics are useful statistics - this principle applies to seasonally adjusted data as well. The seasonal adjustment process does not end with the confirmation of the quality of results. This chapter looks at the final phase of seasonal adjustment dealing with how to support users of statistics in using seasonally adjusted data. It includes an examination of how to:

- Draft internal and external documentation
- Define a seasonal adjustment policy
- Revise seasonally adjusted data
- Prepare data releases
- Provide users with the necessary support

Seasonal adjustment of economic time series aims to support the users of statistics in interpreting economic development. It removes the repeating patterns of data which may hide the underlying development or trend-cycle. However, seasonal adjustment is a complex estimation technique that transforms the original time series resulting in a theoretical understanding of reality.

Sufficient internal and external documentation on seasonal adjustment is particularly important because of the complexity of the method. General explanations are necessary, so the users can better understand the technique and it helps them to interpret the data correctly. Without proper documentation, seasonally adjusted data could confuse the users. Internally, proper archiving of seasonally adjusted data and clear working instructions help produce robust results of seasonal adjustment and increase the clarity of the process among staff.

A clear and institutional seasonal adjustment policy improves the quality and consistency of the national statistics. The policy includes decisions on a common software and the method to be applied. It takes a stance on the timing and methods of revising the seasonal models, treatment of outliers and contents of documentation. Therefore, an individual statistician does not have to make all these difficult decisions alone.

Revisions are an important element to seasonally adjusted time series and the underlying original series. Therefore, seasonal adjustment policy should reflect the choices of a common revision policy for producing the regular statistics. The revision policy provides users with the necessary information to cope with revisions. A well-established revision policy defines a predetermined schedule for revisions and is reasonably stable from year to year. The revisions to seasonally adjusted data should be in line with the producer's overall revision policy.

In this chapter, the need to re-design statistical releases considering the features of seasonally adjusted data is discussed. The release practices are for each office to design, according to its own policy, resources, and user demand. This chapter merely offers several ideas for consideration in developing release practices for seasonally adjusted data.

The users of statistics need adequate support in using seasonally adjusted data. Anyone may read from the newspaper that "the seasonally adjusted industrial production grew in May by 0.5 percent from April". It tells the reader that production has increased and when it happened, but the reader may not be familiar with the concept of seasonal adjustment. The job of statisticians does not end in index calculation since the users will need support in understanding and interpreting statistics.

5.2 Documentation

The process of seasonal adjustment should produce several types of documentation: metadata for user, documents needed for production and revision, and the resulting data itself.

To make use of statistics, the users need to know how statistics have been compiled and for what purposes the data can be used. The users have different uses for the seasonally adjusted data, and thus they have varying needs related to the levels of metadata. Good documentation not only benefits the users of statistics, but it is also a prerequisite for sound statistical production within the organization.

Eurostat (2015) pays attention to storing the outputs of seasonal adjustment. At least raw and seasonally adjusted data should be stored within a secure and usable database environment.

Additionally, the database could include the related time series such as calendar adjusted data, trend-cycle and seasonal components. The database would ideally enable comparison of the seasonally adjusted series for each separate time span. For this purpose, it would need to contain separately all the published seasonally adjusted series, the so-called data vintages.

This way the database would be highly useful in revision analysis both for disseminating average revisions and for analysing the appropriateness of the selected seasonal adjustment model and specifications. With archived time series, the quality of seasonal adjustment can be improved in the longer term. It makes it possible to analyse the behaviour of the seasonally adjusted series, for example, during a turning point in the economy.

The purpose of internal documentation is to make it possible to maintain the high quality of seasonal adjustment. Internal documentation comprises the following:

- Step-by-step working instructions for performing the seasonal adjustment.
- Internal quality reports describing the quality and special features of the seasonally adjusted and the raw data.
- Regularly updated lists of national holidays, if JDemetra+ does not include them in the predefined calendars.
- Lists for monitoring and enumerating the reasons for outliers.

Internal documentation should allow any colleague acquainted with seasonal adjustment to repeat the process. Sufficient documentation helps preserve the skills needed in seasonal adjustment in the organization and is useful for briefing and training others.

JDemetra+ presents a considerable amount of quality diagnostics depending on the chosen seasonal adjustment method. By using the XML files generated by JDemetra+, one can also share the metadata. For the key series, the information of the summary statistics of the *Results* panel, i.e. the first page of Main results, Pre-processing, Decomposition, and Diagnostics can be copied (as explained in Exporting results and metadata). It will be useful to be able to go back to old quality diagnostics and compare the quality of new results to the previous diagnostics, especially after re-estimating the seasonal model and parameters. More time should be invested in preparing and reading the documentation of the results of key time series.

It is recommended that a more comprehensive quality analysis should be undertaken every year. This is because new data points becoming available during the year may change the tendency of the time series and this may affect the model used in the seasonal adjustment. For regular use, an internal quality report should be simple so that the statistician can easily update it, but it should contain the most relevant details. It should be understandable to colleagues not acquainted with seasonal adjustment, and it could favour charts and tables due to their easy readability. User documentation is usually more concise than the internal quality reports, but it could make use of the same contents. User documentation is often more fixed, and therefore, quick to update as part of the monthly or quarterly production process.

There are several international guidelines stressing the need to foster transparency of statistical production. UN (2014) emphasize the importance of transparency in statistical production: "To facilitate a correct interpretation of the data, the statistical agencies are to present information according to scientific standards on the sources, methods, and procedures of the statistics."

In the excess of information available in the society, the content of metadata for the users of statistics needs to be well designed. It should include only relevant information. Metadata should enable the users

of statistics to understand the idea of seasonal adjustment, use the data, and if needed, replicate the results of seasonal adjustment. Eurostat (2015) suggests a metadata template in SDMX format. In addition, OECD (2007) provides further details on data and metadata presentation.

Franchet (1993) provides a definition for metadata. Metadata provide information on data and about processes of producing and using data. Metadata describe statistical data and - to some extent - processes and tools involved in the production and usage of statistical data. Eurostat (2015) include recommendations on metadata related to seasonal adjustment. The Guidelines include a metadata template that offers ideas for defining the contents of metadata that fits national needs.

First, users need an explanation of seasonal adjustment aimed at the general public, including instructions on how to interpret and use the results. Many statistical offices maintain explanations about their methods and practices on a dedicated part of their website, labeled, for example, "Understanding statistics". The Australian Bureau of Statistics (ABS) offers on their website information on the basics of time series methodologies, including easily understandable explanations to the concept of time series, seasonal effects, components of time series and identifying seasonality. They use the SEASABS software in their seasonal adjustment. It is based on X-11 and X-12-ARIMA. They explain the need for seasonal adjustment in the following way (ABS, 2017):

"Seasonal adjustment is the process of estimating and then removing from a time series influences that are systematic and calendar related. Observed data need to be seasonally adjusted, as seasonal effects can conceal both the true underlying movement in the series as well as certain non-seasonal characteristics which may be of interest to analysts."

In addition to the general explanation of seasonal adjustment, the user documentation should offer details on how seasonal adjustment is performed and include preferably the following information:

- The seasonal adjustment method (e.g. TRAMO/SEATS or X-13) and software (e.g. JDemetra+) used.
- General decision rules applied in the process of seasonal adjustment.
- Description of the quality of the raw data.
- Means for outlier detection and correction and information about the events causing outliers in the key time series.
- The choices in calendar adjustment and treatment of national and moving holidays.
- Set of quality indicators for assessing the quality of data.
- The timing and reasons for revisions to the seasonally adjusted data.
- Contact information to the experts.

The general decision rules refer, for example, to the application of direct or indirect seasonal adjustment for aggregation of time series. The following section on seasonal adjustment policy will discuss these choices. The main quality indicators used for approving the results of seasonal adjustment are also part of these general decision rules.

The description of the quality of the raw data can simply be included in the usual metadata of statistics. For seasonal adjustment, it would be then sufficient to note that the length and the qualities of the series are appropriate for seasonal adjustment. The metadata should also inform the user about any breaks in the series. If generalized based on Bierbaumer-Polly & Bilek-Steindl (2017), the metadata of the statistical indicator would already explain the definitions being measured, limitations of use, index compilation methods, weighting system, treatment of changes and departures from international standards.

Understanding the story behind outliers helps in the interpretation of seasonally adjusted data. Outliers stay visible in the adjusted data. They contain information about events in the economy. The criteria for identifying outliers and the methods for treating these abrupt changes need an explanation. The producers of seasonally adjusted data could also remind the users of statistics about the events that caused the outliers of the key time series, i.e. strikes. A difficulty is the treatment of outliers at the end of the series, where the duration and type of the outlier are not yet known.

As recommended by OECD (2007), statistical offices should provide at least a minimum amount of information that would enable assessment of the reliability of each seasonally adjusted series. The statistical offices should maintain enough metadata to enable users to seasonally adjust, in a consistent way, other series that may not have been seasonally adjusted.

The United States Bureau of Economic Analysis (BEA) provides a site including frequently asked questions related to seasonal adjustment.[11] The BEA applies X-12-ARIMA in their seasonal adjustment, and they have defined a minimum set of quality diagnostics which they publish together with statistical releases. Among other quality indicators, they publish the overall quality assessment statistics and some indicators which analyze the stability of estimates and the presence of moving seasonality in the key time series. Their explanation about the reasons for revising seasonally adjusted figures are the following:

"There are two reasons that we revise seasonal factors: We revise factors when we revise the unadjusted data to achieve a better fit to the revised data." and "…when future data become available, we use them to obtain improved seasonal factor estimates for the most recent years of the series. These revised factors lead to revised seasonal adjustments of higher quality."

In addition to the revisions due to changes in the unadjusted original data and the Reg-ARIMA model, revisions are also caused by the two-sided filter and the use of forecasts in seasonal adjustment. In TRAMO/SEATS and X-13, the main seasonal adjustment filters are two-sided meaning that the estimator of the seasonal component depends on the observations prior to and after a certain period. Thus, the estimator for recent periods requires observations not yet available. First, the preliminary estimators are obtained by ARIMA forecasts and, later, as new observations become available the estimators will be revised until the filter is completed, and the historical estimator is obtained.

To anticipate revisions, JDemetra+ includes a revision history test of Findley et al (1990) to indicate which series may have excessive revisions. SEATS also provides the standard deviation of the revision in the seasonal and trend-cycle component. When it is excessively high the series may not be worth adjusting.

Usually, statistical offices inform the users in advance about the timetable for revising the seasonal models and parameters. Some do this reanalysis once, some twice a year and some offices more frequently. The average historical revisions of the key economic indicators would provide the user of statistics with a useful tool for anticipating the magnitude of future revisions. For example, the average revisions of the month-on-month changes during the last 24 months give an indication of the expected future revisions. Transparency about the past revisions assists the user in making conclusions based on the data. If no such information is available, the revision can be an unpleasant surprise.

Ensure easy access to the relevant metadata for the users of statistics. Any release of statistics should include metadata and direct the reader to the more detailed information. It is a widespread practice to publish a link to the metadata in the statistical release. The link may lead to a quality report for the statistical indicator in question and to an archive of the historical quality descriptions.

5.2.1 Seasonal adjustment and revision policy

Seasonal adjustment policy

Many statistical offices need to produce a massive amount of seasonally adjusted data. Often, the production units perform the seasonal adjustment of the indicators themselves. In other cases, the responsibility of applying seasonal adjustment is vested in the methodology unit. Due to the hectic schedule of statistical production, some degree of decentralization is necessary in the division of work. This calls for the definition of a clear and practical policy for seasonal adjustment.

Defining seasonal adjustment policies to reflect international guidelines would help achieve, gradually, more comparability of data between countries. The policy should also reflect the needs of national users of statistics and the resources available in the organization for implementing the policy.

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[11] https://www.bea.gov/newsreleases/national/gdp/2010/pdf/gdp1q10_adv.pdf

Even with the available modern software, seasonal adjustment is time-consuming. The key statistical aggregates will be the main focus of attention of the national and international users. Consequently, the statistician needs to spend more time on the seasonal adjustment of these aggregate time series. For the wider use of seasonal adjustment, the organization needs adequate computer resources, for the dissemination of data and storage of the data vintages.

Before starting a large-scale seasonal adjustment, the producer should consider the advantages and disadvantages of seasonal adjustment. Comprehensive testing of seasonal adjustment methods and choices should precede the formulation of the policy. Defining policies to be implemented throughout an entire organization requires consideration and experience.

The policy could be developed in stages, first to cover the basic choices, such as the seasonal adjustment software and method, the timing of revisions and guidelines for releasing the adjusted data and its metadata. As experience accumulates, the policy could expand to more detailed instructions for statisticians with problematic time series, breaks in time series and to applying seasonal adjustment at times of economic uncertainty. Similarly, the scope of releasing seasonally adjusted data could be gradually increased.

A seasonal adjustment policy should reflect the knowledge gained in practice and vested in statisticians within the organization, and it should respond to the expectations set by the international guidelines and the users of statistics. The policy should cover at least the following issues:

- A common seasonal adjustment method to be applied.
- Software solutions for seasonal adjustment, dissemination, and storage of data.
- Methods and timing of re-analysis, i.e. a revision policy for seasonal adjustment.
- Means of aggregation from lower levels of industrial activity classification to higher levels, or from regional indicators to the country level and in time.
- Treatment of outliers.
- Requirements for the internal documentation and the metadata for users.
- Guidelines for releasing seasonally adjusted data as part of the regular release programme.

Not all statistical offices have decided to select one seasonal adjustment method. Sometimes, for example, the national accounts, industrial, trade, and labour statistics could all apply their own practice. However, for clarity and better consistency, it could be a good idea to choose one method to be applied in the entire organization bearing in mind the usefulness of regular comparison of the results of alternative methods.

Using commonly applied software and methods increases international comparability of the produced statistics. To this end, JDemetra+ is a useful solution as Eurostat maintains and develops it constantly around the two methods: TRAMO/SEATS and X-13. Releasing seasonally adjusted data may require changes in the dissemination software. The users appreciate access to time series data in a format that enables the data to be reprocessed without excess manual handling. Seasonal adjustment multiplies the number of data cells produced for each statistical indicator which makes dissemination databases a sensible choice for releasing the longer time series. Solid database structures are also needed for storing the results of seasonal adjustment, especially for revision analysis.

Revising the seasonally adjusted data

An essential question in formulating a seasonal adjustment policy is to define the revision practices. As seasonal adjustment is based on estimation, it is subject to revisions. As explained by the BEA, seasonally adjusted data is revised, first, due to corrections of raw data and new observations. Second, the refreshed and accumulated data lead to better estimates of the seasonal pattern and to revisions in the Reg-ARIMA model, filters and forecasts. Revisions are welcomed, as they derive from improved raw data and the forecasts used in seasonal adjustment become replaced with new observations based on the raw data. This also influences identifying the seasonal pattern which causes revisions in the historical data as well.

The next charts illustrate the influence of new observations and the refreshment strategy on the seasonally adjusted data (Figure 5.1). The GDP of Italy has been seasonally adjusted using partial concurrent adjustment, which is one of the recommended refreshment methods. In other words, the model, filters, outliers, and calendar variables are re-identified once a year and the respective parameters and factors re-estimated when new or revised data become available. The seasonal model itself has not been revised during these presented releases. The revisions are moderate, but the most recent quarters are notably high (Istat, 2019).

Figure 5.1 **Revision of seasonal adjusted series**
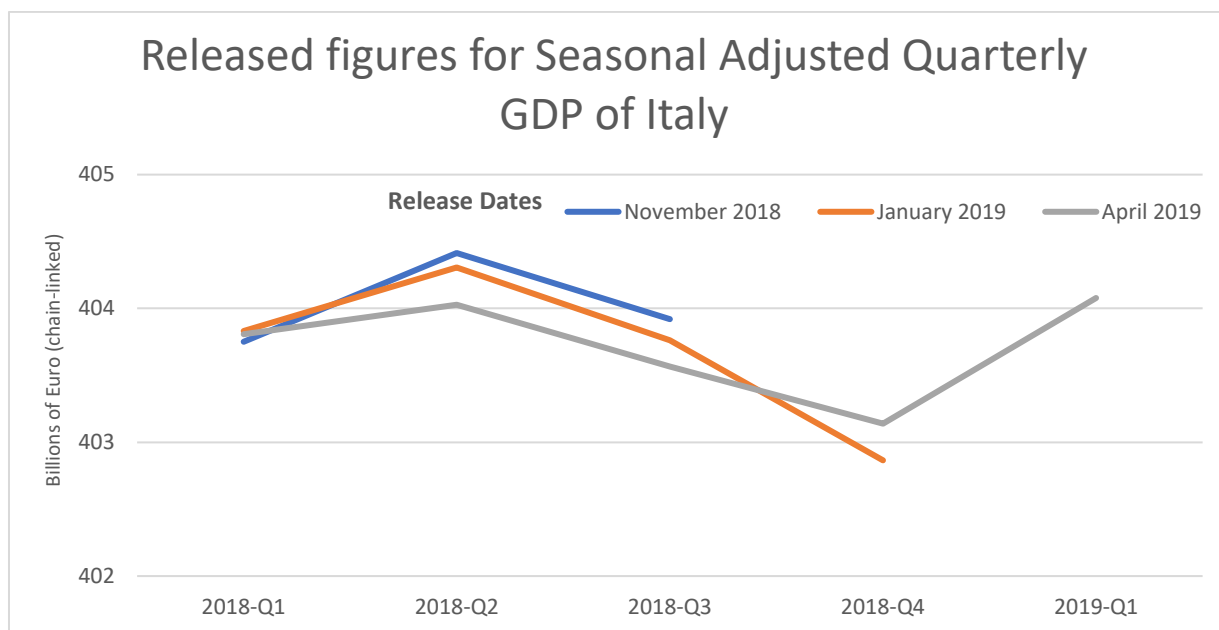
Eurostat & ECB (2002) defined general guidelines on revision practices for sub-annual statistics. Countries should establish and maintain a revision policy for producing regular statistics and have it publicly available. The revision policy would provide the users with the necessary information to cope with revisions. According to Eurostat & ECB (2002), a well-established revision policy:

- Defines a predetermined schedule for revisions.
- Is reasonably stable from year to year.
- Is transparent.
- Gives notice of larger revisions due to conceptual or methodology changes.
- Offers adequate documentation of revisions.

The recommendation of Eurostat & ECB (2002), to carry revisions back several years to give consistent time series is important for the quality of seasonal adjustment. Eventually, users will be reassured if they see that revisions take place within the framework of a policy and according to a predetermined schedule.

The revision practice as part of the seasonal adjustment policy is worth careful consideration. To identify the specific needs of users, consult the main users about the planned revision policy. The policy defines the process for updating the estimates of the published seasonally adjusted data. It consequently defines the frequency of revisions to seasonally adjusted data. However, the intensity of revisions depends on the choices made during seasonal adjustment, e.g. the quality of the forecasts used to extend the series and from the revision to the original data.

The revision policy for seasonal adjustment should address at least the following points:

- Select methods for refreshing the seasonally adjusted data.
- Set the timing for refreshing the adjusted data.
- Define the time period over which the raw and the seasonally adjusted data will be revised.

- Convey the relative size of revisions of the seasonally adjusted data and the main causes of revisions.
- Set the timing of publication of revisions to the seasonally adjusted data and publication of the revisions to the raw data.

In theory, the quality of forecasts used in seasonal adjustment increases with the frequency of updates of the underlying model. There is thus a trade-off between the cost of performing frequent revisions and the quality of data published. However, to complete the equation, the very frequent updates of the seasonal model could also lead to weaker stability of results and revisions in opposing directions.

As discussed in the previous chapter, the current adjustment strategy minimizes the frequency of revision, and the concurrent adjustment strategy generates the most accurate seasonally adjusted data but will lead to more revisions. The seasonal adjustment policy should select between the alternative refreshment strategies. The balanced alternatives between these two extremes may provide a better quality of adjustment.

Partial concurrent adjustment is a widely used strategy. In its basic form, it keeps the model, filters, outliers, and calendar variables fixed until the annual or biannual re-identification. It re-identifies the respective parameters and factors every time new or revised data become available.

As already seen, JDemetra+ offers all together four choices of different partial concurrent adjustment strategies to choose from. Eurostat (2015) suggests following one of these balanced approaches between the extremes of current and concurrent adjustment. The choice of the refreshment strategy also depends on the properties of the series.

The optimal frequency of updating the seasonal models is once a year, at least, according to Eurostat (2015). However, if any problem is detected between the updates, it should be promptly corrected. There are more degrees of freedom for the frequency of updating the parameters of seasonal models. As a general rule, when the series are shorter than seven years, the specification of the parameters used for pre-treatment and seasonal adjustment could be checked more often, for example, twice a year in order to deal with the higher degree of instability of such series. As already seen, series shorter than three years should not be seasonally adjusted. Back-recalculated time series are particularly useful to stabilize the seasonal adjustment. User documentation should alert for the greater instability of seasonally adjusted data for relatively short time series (Buono & Kocak, 2010).

In the annual re-analysis, revisions need to be examined and balanced between accuracy and stability. Stability is also important for the quality of seasonally adjusted data. If TRAMO/SEATS or X-13 selects a different model in the annual update, the diagnostics need to be examined to find out whether it is notably better than the previous one. Also, the effect on historical data needs to be assessed and the significance of the regressors checked to identify any need for changes in the new specifications.

The refreshment policy needs to consider the period over which the results are revised. Revisions resulting from the revised seasonal models may be but do not necessarily have to be published in their entirety. Carrying out a full revision from the beginning of the series promotes a methodically uniform treatment of all values and the easy replication of the seasonally adjusted results. However, some statisticians have questioned whether a newly added figure contains relevant information for significant revisions in the historical seasonal pattern. To balance with the information gain and the revisions, some offices have chosen to limit the period of revision of the seasonally adjusted data to a period that is about four years longer than the revision period for the original data. For the earlier periods, some offices have chosen to keep their seasonal factors unchanged. The information provided by diagnostics – such as the sliding spans and the revision history – may support making the choice of the appropriate revision horizon.

In case of any limits to the revision horizon, this needs to be communicated clearly to the users of statistics. In situations where the raw data are revised from the beginning of the series – for example, due to changes in definitions or sampling scheme – the entire seasonally adjusted series should be revised. The consistency between the raw and the seasonally adjusted series should be preserved.

The revision practice, as part of the seasonal adjustment policy, will be based on the analysis of the size of the expected revisions and the effect of the different choices made during seasonal adjustment. It provides information on revisions and their causes to inform the users of statistics. Furthermore, as recommended by Eurostat & ECB (2002), the general revision policy introduces a foreseeable framework for revisions.

In general, statistical offices publish revisions to the seasonally adjusted series at the same time as they add a new month or a quarter to the statistical indicator. Often, changes of the seasonal adjustment method are linked to other changes, such as changes of base year, classification or methods. Advance information about the forthcoming methodological changes should precede the actual revisions. If mistakes were made an additional release to correct the information may be needed. Otherwise, revisions of seasonally adjusted data are usually linked with the regular release schedule of statistics.

The approach to time aggregation should be included in the seasonal adjustment policy. Seasonality is not neutral over the year. It is possible to force the sum, or average, of seasonally adjusted data over each year to equal the sum, or average, of the raw data. It may be difficult for some users to understand why the annual change differs between the seasonally adjusted and the original data. However, from a theoretical point of view, there is no justification for forcing the annual changes to be equal.

Up to now, only mixed evidence has been provided on the superiority of either direct or indirect aggregation of seasonally adjusted data (Eurostat, 2015). The direct approach means that the aggregate time series and the sub-component series are each seasonally adjusted independently. The indirect approach derives the higher levels by aggregating the seasonally adjusted series of the component time series by using a weighting scheme.

The direct approach is preferred for its transparency and accuracy, especially when the component series show similar seasonal patterns. The indirect approach may be preferred when the components of the series show seasonal patterns differing in a significant way. Regardless of the simplicity of the direct approach, the indirect approach could be useful in addressing strong user requirements for consistency between lower and higher-level aggregates. If indirect seasonal adjustment is chosen, the presence of residual seasonality needs to be monitored carefully.

5.2.2 Release practices

Without seasonal adjustment, changes can be calculated between a month (quarter) and the same month (quarter) in the previous year, i.e. comparing January to January, February to February etc. However, this comparison is not free from calendar effects, as the number and assortment of different days in a month vary between the years. Thus, making comparisons with calendar adjusted series is more robust than the original time series and in the case of year-on-year comparisons, this is the preferred series one should compare.

One of the benefits of seasonally adjusted data is that it allows to compare two consecutive months or quarters. This may provide a faster indication of changes in the economy, as the changes do not have to be calculated from 12 months back. This works only if the underlying series is not too volatile. Additionally, users may be interested to know the change from the same month one year earlier. The calendar adjusted is a good source for calculating this measure. Cumulative growth rates may be useful as additional information. The choice of growth rates for statistical releases requires careful judgement by the producer of statistics.

Period-to-period growth rates are the rates of change over the previous period, month or quarter. Such rates are expressed as $(M_t/M_{t-1})-1$ or $(Q_t/Q_{t-1})-1$. M_t denotes the value of a monthly time series in month t and Q_t the value of a quarterly time series in quarter t.

Year-on-year growth rates are the rates of change expressed over the same period, month or quarter, of the previous year. They may be referred to as year-over-year growth rates, year-to-year growth rate, the rate of change from the previous year, or 12-month rate of change. Such rates are expressed as $(M_t/M_{t-12})-1$ or $(Q_t/Q_{t-4})-1$.

Year-to-date growth rates are data expressed in cumulative terms from the beginning of the year; sometimes referred to as cumulative data. For example, they may compare the sum of values from January 2019 to April 2019, to the same period of 2018.

Table 5.1 **Interpretation of different kinds of growth rates**

Type	Original time series	Original time series	Calendar adjusted series	Calendar adjusted series	Seasonal and calendar adjusted series	Seasonal and calendar adjusted series
Jdemetra+ name	y	y	ycal	ycal	result	result
Growth rates	q-to-q	y-o-y	q-to-q	y-o-y	q-to-q	y-o-y
Note	Not informative	slowest	Not informative	slow	fast	fast
Q1-2017	-6,1%	2,0%	-6,2%	1,7%	0,5%	1,7%
Q2-2017	4,5%	1,5%	4,8%	1,8%	0,6%	1,8%
Q3-2017	-4,4%	1,4%	-4,5%	1,4%	0,1%	1,4%
Q4-2017	8,6%	1,9%	8,6%	1,9%	0,7%	1,9%
Q1-2018	-6,4%	1,5%	-6,4%	1,7%	0,3%	1,7%
Q2-2018	4,5%	1,5%	4,4%	1,3%	0,2%	1,3%

The above-mentioned growth rates may be calculated for any components of time series, e.g. for the original time series, calendar adjusted series, seasonal and calendar adjusted series or trend-cycle.[12]

Table 5.1 is compiled using different growth rates based on quarterly GDP of Belgium. The growth rates of the original time series are not informative since year-on-year (y-o-y) growth rates include the variation of calendar effects. That is why the calendar adjusted y-o-y growth rates give a true signal (an increase) at the 1st quarter of 2018, while the original time series implies a decrease for the same period. The seasonal and calendar adjusted series give a true signal for both y-o-y growth rates and q-o-q growth rates, but they are generally used for q-o-q growth rates.

The period-to-period growth rates of the original series are influenced by seasonality, as they compare different months of the year which are influenced by seasonality.

As highlighted in Eurostat (2015), in all cases, the information contained within the statistical release should adhere to the principles of ensuring transparency and assisting users in making informed decisions. One should ensure adequate resources and enough time for analysing the results of seasonal adjustment before publishing the data for the first time. Introducing seasonal adjustment requires re-structuring the content of the website to facilitate easy access to time series data. It requires time to re-design the statistical news releases so that they would support the users.

The challenge with statistical releases is to offer the relevant information in a concise form while keeping the message simple and understandable. At the same time, the release should contain enough information so that the users can draw meaningful conclusions. To help statistical offices with this challenge, OECD (2007) comprises a set of practical recommendations on releasing seasonally adjusted data. The recommendations have been drafted in international cooperation based on the experience of several experienced short-term statisticians. The following text draws on those recommendations.

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[12] For further detail see OECD (2007)

When seasonality is present and identifiable, seasonal adjustment would improve the readability of statistics. In these cases, the statistical office should release the data in the seasonally adjusted form. The producer can choose the level of detail for providing seasonally adjusted data by considering the user demands and the available resources. They can increase the amount of available seasonally adjusted data over time.

If seasonality influences the indicator ideally the statistical release should focus on the seasonally adjusted data. Users should also have access to the original series, either in the publication or by reference to it. The original series contains all characteristics of the data. The seasonally adjusted data contain the news of the series by combining the trend-cycle and the irregular component. As press releases aim to provide news, seasonally adjusted data are the appropriate kind of data to be presented. Where there is a user demand, the producer may also disseminate components of seasonal adjustment, e.g. the calendar day adjusted and/or the trend-cycle series.

Statistical releases for data with seasonal influences should at least provide period-to-period growth rates for the latest period. If the statistical tradition includes publishing levels of the measured variable, and if space permits, the change or the value in levels may also be published in the release. Cumulative growth rates may be useful as additional information, but not as the main focus.

The year-on-year growth rate is not always the same for the original and the seasonally adjusted data unless the seasonal pattern is stable. As previously discussed, seasonality may evolve over time as reflected in the seasonally adjusted series.

Several statistical offices release both the change from the previous period based on the seasonally adjusted data and the change from the same period of the previous year based on the calendar adjusted or original data. This approach is recommended by the International Recommendations for the Index of Industrial Production (UN, International Recommendations for the Index of Industrial Production 2010, 2013). The following extract illustrates how DESTATIS (2019) releases their Gross Domestic Product (Figure 5.2).

Figure 5.2 **Press release of DESTATIS on quarterly GDP**

Press release 454 / 2018-11-23

Detailed gross domestic product results for the 3rd quarter of 2018

Gross domestic product, 3rd quarter of 2018
-0.2% on the previous quarter (price, seasonally and calendar adjusted)
+1.1% on the same quarter a year earlier (price adjusted)
+1.1% on the same quarter a year earlier (price and calendar adjusted)

WIESBADEN – German economic growth has stalled. As the Federal Statistical Office (Destatis) already reported in its first release of 14 November 2018, the gross domestic product (GDP) in the third quarter of 2018 was by 0.2% lower - upon price, seasonal and calendar adjustment - than in the second quarter of 2018. This was the first quarter-on-quarter decrease since the first quarter of 2015. In the first half of 2018, the GDP had increased, by 0.5% in the second quarter and by 0.4% in the first quarter.

The release of DESTATIS interprets the calendar adjusted series for the comparisons with the same quarter of previous year and the seasonal and calendar adjusted series for the comparisons with the previous quarter.

The seasonally adjusted data are the best way of presenting period-to-previous-period changes, even if the irregular component which belongs to the seasonally adjusted data, is relatively large (OECD, 2007). For highly volatile seasonally adjusted series, the period-to-period changes may change direction frequently. It is, therefore, useful to analyse the behaviour of these changes to see the kind of message they would deliver to the reader. The statistical releases focus on the key economic indicators which are usually higher-level aggregates and less volatile than individual economic activities.

Another example is the press release of international passenger survey of the United Kingdom's Office for National Statistics (ONS, 2019). In this release, seasonally adjusted data is used for monthly comparison of the number of visitors and their expenditures (Figure 5.3).

Figure 5.3 **Press release of ONS for tourism**

Table 2: Main visit and spending estimates for UK residents' visits abroad in September 2018

	Visits (thousands)	% change from year earlier	Expenditure (£ million)	% change from year earlier
Non seasonally adjusted				
Sep 2018	7,708	-3	5,217	+1
Jul to Sep 2018	24,180	+1	16,410	+3
Year to date 2018	57,370	-1	36,630	+1
Latest 12 months	72,110	-1	45,230	+0
Seasonally adjusted				
Apr	6,070	+0	3,550	-6
May	6,070	+3	3,890	+17
Jun	6,040	-4	3,860	-6
Jul	6,090	+4	3,880	+7
Aug	6,170	+3	3,830	+2
Sep	6,040	-5	3,730	-0

The rate of change compared with the same period of the previous year, i.e. the year-on-year changes should be calculated based on the calendar day adjusted series, or if unavailable, based on the original series. The calendar day adjusted series, i.e. the working day or trading day adjusted data, make the same months of different years more comparable by correcting the variation caused by the number of working days etc. Any special events in the previous year affect the year-on-year changes. Where necessary, the reader should be reminded of these effects when presenting year-on-year changes. The example related to moving holidays in Section 2.4.5 illustrates clearly the utmost importance of noting these special events. The statistical release of (Statistics Finland, 2019) from November 2018 provides the reader with alternative growth rates and mentions the difference in working days compared with November 2017 (Figure 5.4).

Statistical releases can only contain a limited amount of information. Nonetheless, the main contributors to change are interesting to the users of statistics. Sometimes, the aggregate growth rate may remain the same regardless of many changes in the development of the sub-populations. Statistical offices often have the sole access to large data sets and could inform the user of the variety of important changes in the subpopulations.

UN (2013) recommends presenting the development of those product groups or industries that are primarily responsible for the monthly movement in the aggregate index.

Figure 5.4 **Press release of Statistics Finland on industrial output**

> Published: 10 January 2019
>
> ## Industrial output grew in November both year-on–year and from the previous month
>
> Seasonally adjusted industrial output (TOL BCD) grew by 0.4 per cent in November from the month before. According to Statistics Finland, industrial output adjusted for working days was 1.6 per cent higher in November 2018 than in November 2017. Adjusted for working days, industrial output went up by 3.9 per cent in January to November from one year back.

The most useful form for seasonally adjusted data is a time series format. Users of statistics need an access, preferably electronically, to the complete time series. The website should offer the original and the seasonally adjusted data in their full length. In addition, the users may prefer access to the trend-cycle and the calendar day adjusted time series. Index numbers, in a time series form, enable comparison of different sectors of the economy or different regions or countries more easily than levels or individual change percentages. It is not enough to provide the users of statistics only with the latest growth rate without any time series.

Users need to be informed about the so-called end-point problem of the trend-cycle series. Significant revisions may occur in the end of the trend-cycle series mainly due to the accumulation of new observations. Turning points can often only be identified reliably after several months. Therefore, the trend-cycle series of the most recent observations should be presented to users with caution (if at all), as they are uncertain and can suffer of phase-shift problems.

The ESS Guidelines on Seasonal Adjustment (Eurostat, 2015) do not recommend showing the most recent values of the trend-cycle estimates because of the end-point problem. In addition, the producers should publish information on average revisions of at least the seasonally adjusted series.

Several international guidelines give advice for redesigning the process and content of statistical releases. For example, UN (2013) provides a set of general recommendations for releasing industrial production indices. Among other things, it states that data should be released as soon as possible but notes the trade-off between timeliness and quality. The releases should follow an advance release calendar and consistent release practices. The statistical offices should make data available to all users at the same time and foster the confidentiality of individual survey respondents. Providing users with the contact details of relevant statisticians who can answer various questions would be a good practice.

5.2.3 Social media

In recent years, it has become more and more common to publish official statistics also via social media platforms. The motivation for using social media is that it reaches a wide audience in a very efficient way. Publishing statistics on social media has some very specific advantages and disadvantages compared to conventional press releases.

- Advantages are the ability to deliver (visual) content to a wider audience, instantaneously.
- Disadvantages lie in a more limited space, connected to shorter messages and resulting in often more superficial contents.

Even though there are several studies in the literature on the publication of statistics on social media (the most important one is from Everson, Gundlach and Miller (2013)), none of them show specific interest on using seasonally adjusted data.

Some examples are given in Figure 5.5. DESTATIS presents the situation of the German industrial production index by showing monthly levels of seasonally adjusted production for the overall industry and the construction sector together (top left). The Central Statistics Office Ireland presents the situation

of the labour market by displaying monthly level changes (in absolute numbers) of the seasonally adjusted data (top right). Eurostat presents the governmental deficit situation in the Euro area as time series in relative terms to GDP (bottom left). The data is seasonally adjusted. The Bureau of Labor Statistics of the United States presents some wage statistics as seasonally adjusted weekly median earnings in USD (bottom right). The presented time series spans 10 years of time.

Figure 5.5 **Examples of publishing official statistics**
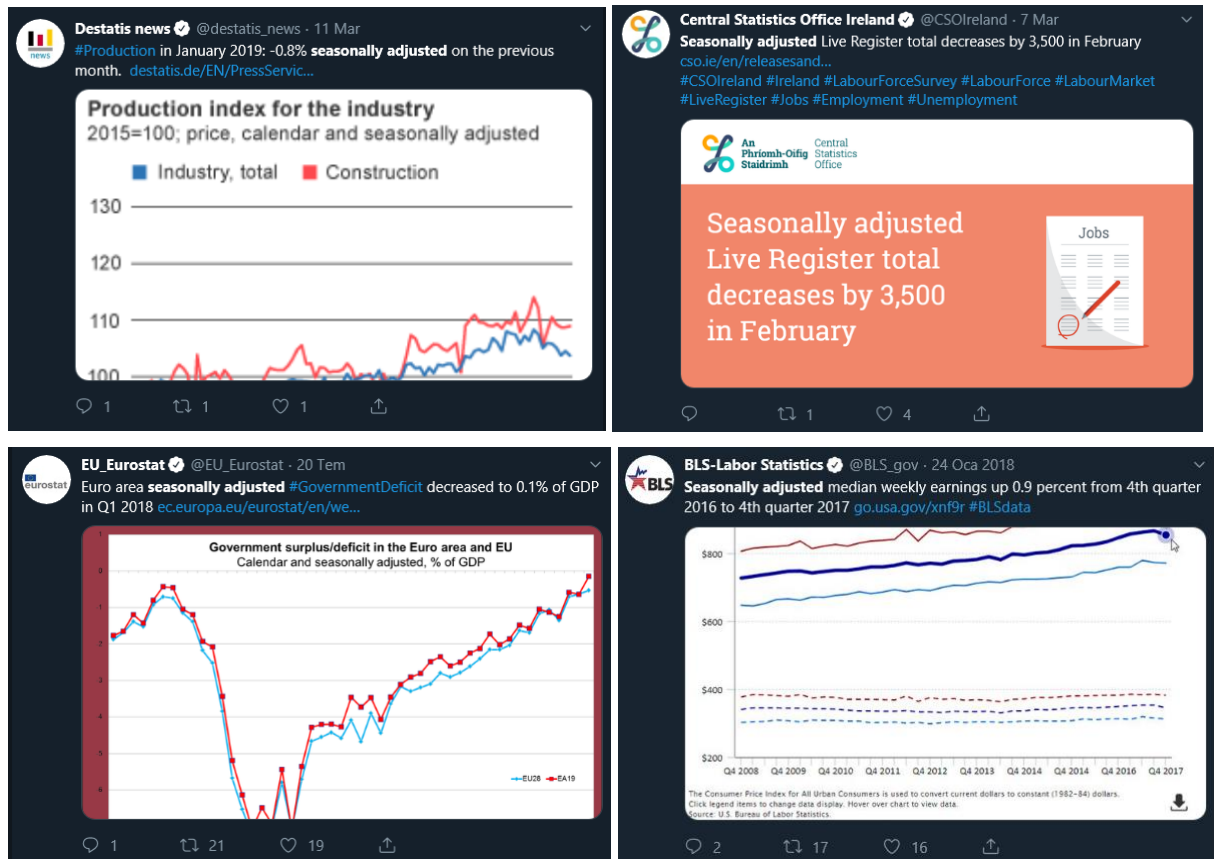
5.3   User support

Statistical offices are facing a growing demand for timely statistical information on economic development. At the same time, the increasing level of information can overload the users of statistics, whilst the rapid development of new communication tools changes the way information is exchanged. Releasing statistical information doesn't occur in isolation. There are distinct differences between the users of statistics, in their technical abilities and understanding of statistics. This brings about challenges for supporting the users in making correct conclusions.

A regular user of statistics benefits from the availability of seasonally adjusted data. As discussed earlier, it makes it possible to compare development in different industries and countries and offer faster indication of changes in the economy. Some users may re-process the results further in their own work. For example, economists and analysts base their forecasting models on seasonally adjusted data. Sometimes, they may perform their own seasonal adjustment with their own specifications. Therefore, the data should be in an easily accessible format, and additional data, such as different components of the original data, could be made available on request.

As mentioned in the previous text, user support is based on the transparency of metadata, availability of general explanations on the statistical methods applied and on the good design of statistical releases and websites. An effective news release is one that (UNECE, 2009):

- Tells a story about the data.
- Has relevance for the public.

- Catches the reader's attention quickly with a headline or image.
- Is easily understood, interesting and, if possible, entertaining.
- Encourages others, including the media, to use statistics appropriately to add impact to what they are communicating.

The internet provides increasing possibilities for disseminating statistical data, but at the same time, it consists of an excess of data with different qualities. The internet is an efficient data dissemination tool, but it requires efforts from the data producers to keep track of the unknown users of statistics to understand their needs and problems in using statistical data. The first section of this chapter discussed documentation issues related to seasonal adjustment. It mentioned some examples of statistical offices having created a website for helping the users in "understanding statistics". These sites often comprise a set of frequently asked questions that provide useful user support.

Society has developed a snack culture in information consumption (UNECE, 2009). This has already influenced the statistical releases used in delivering news in statistics. The releases are concise and start from the most important message they wish to convey. Therefore, the releases usually start with the most recent information and the main conclusions, based on the seasonally adjusted data.

Prior to releasing seasonally adjusted data, the staff needs to be ready to explain the procedures and guide the users in the correct use and interpretation of data. One should allocate enough resources and time into examining seasonal adjustment and training staff for providing the users with the guidance needed for better interpretation of statistics.

The release would ideally provide the contact information for the users of statistics to obtain further information about concepts, definitions, and statistical methodologies. The contact could be a generic contact point that directs the requests to the experts. An expert responsible for the released data could be available to reply to users' questions on the latest statistical releases to share their expertise. The responsibility of statistical offices doesn't end in the release, on the contrary, according to the *Fundamental principles of National Official Statistics* (UN, 2014) statistical agencies are entitled to comment on erroneous interpretation and misuse of statistics.

The producer of statistics benefits from consulting the users of statistics. Many statistical offices carry out stakeholder analyses, conduct user surveys and organize seminars and conferences to discuss statistics with the main users. This kind of interaction helps the producer stay relevant by learning from user needs, and the user to understand the work and methods applied by the producer. Customer training services on analyzing economic development by using statistics could include tips for understanding and using the seasonally adjusted data.

The purpose of seasonal adjustment is to meet users' needs for relevant and comparable short-term statistics that provides information about cyclical movements and turning points. The job of the statistician is to provide the best possible data with sufficient documentation and explanation to support users in correct use and interpretation of the statistics.

Annex: Establishing best practices

This annex suggests concrete recommendations for statistical offices for establishing best practices in seasonal adjustment of short-term statistics.

Establishing best practices

- Review short-term time series that may need to be seasonally adjusted, based on user needs and applying international recommendations.
- Draft a policy for seasonal adjustment based on international recommendations, such as e.g. the *ESS guidelines on seasonal adjustment* (Eurostat, 2015).
- Ideally, the policy for seasonal adjustment should cover all steps of the production of seasonal adjusted series, including principles and methods applied, quality assurance, revision policy and dissemination.
- Choose one seasonal adjustment approach – TRAMO/SEATS or X-13-ARIMA-SEATS – to be used for the seasonal adjustment of all series.
- Choose one software solution for the entire office. JDemetra+ is recommended as open source software. JDemetra+ is recommended by Eurostat.

Building capacity

- Develop training material and workshops based on the selected seasonal adjustment approach and its practical implementation.
- Depending on resources, develop dedicated seasonal adjustment expertise within the office.
- Establish an internal seasonal adjustment user group to share ideas and experiences.

Exploit international resources

- Exploit the extensive resources available from the international seasonal adjustment community. These include the following:
- ESS Guidelines on seasonal adjustment (Eurostat, 2015)
- Handbook on seasonal adjustment (Eurostat, 2018b)
- JDemetra+ Software webpage[13] including JDemetra+ User Guide (Grudkowska, JDemetra+ User Guide, 2015) and reference manual (Grudkowska, 2016)
- X-13-ARIMA-SEATS Reference Manual (U. S. Census Bureau, 2017)
- US Census Bureau seasonal adjustment website[14]
- Guide to Seasonal Adjustment with X-12-ARIMA (Draft) (ONS, 2007).

Practical tips for seasonal adjustment

- Only seasonally adjust time series with identifiable seasonality.
- Use RegARIMA models to estimate and remove outliers and calendar effects before seasonal adjustment.
- As a first step model and seasonally adjust all series using automatic software functions.
- To save on resources only quality assure high profile series. Use statistical and graphical diagnostics to analysis and provide solutions for problematic series. Manually refine the seasonal adjustment models of problematic series to improve quality.
- Hold models constant for one year and then review these models on an annual basis. Be conservative in making changes to the models.

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[13] https://jdemetradocumentation.github.io/JDemetra-documentation/

[14] https://www.census.gov/srd/www/x13as/

- Re-estimate parameter and factors every time new data becomes available. In this way the seasonally adjusted data is revised every month/quarter but the size of the revisions is usually small.
- Seek seasonal adjustment expertise to model seasonal breaks/outliers.
- Seek seasonal adjustment expertise to assess the appropriateness of publishing the trend of the time series.

Glossary

The glossary provides explanations of key terms and concepts in relation to seasonal adjustment. The explanations are mainly drawn from existing international recommendations. In some cases, the explanation has been modified to suit the context of this *Guide*. Terms that are used in the explanation and that can be found in this glossary are written in **bold**.

Name	Explanation
Additive decomposition	Additive **decomposition** means that a **time series** is split into its independent additive components: **trend-cycle** + **seasonal** + **irregular**(/**transitory**). Their sum returns the original time series. For additive time series, the magnitude of seasonal or irregular variations does not change as the level of the trend-cycle changes. Usually in **seasonal adjustment**, any series with zero or negative values are treated as an additive series.
Additive outlier	An additive **outlier** affects only the value of one observation. Random effects of strikes or bad weather might cause this kind of outliers. A pre-announced price increase could cause an additive outlier by increasing the sales dramatically before the price change.
Advance release calendar	A statement on the schedule of release of data in terms of periodicity and timeliness. It provides prior notice of the precise release dates on which specified statistical information are released to the public (OECD, 2007).
Autocorrelation	Autocorrelation is the correlation within a **time series**, or a signal, with its own past and future values. In other words, it refers to the linear dependence between the values for different periods of a random variable. It is also called "lagged correlation" or "serial correlation".
Auto-regressive spectrum	An auto-regressive spectrum reformulates the content of the **stationary time series'** autocovariances in terms of amplitudes at frequencies of half a cycle per month or less in a spectral plot (Grudkowska, JDemetra+ User Guide, 2015). In JDemetra+, seasonal frequencies are marked as grey vertical lines in the auto-regressive spectrum, while the purple lines correspond to trading day frequencies. Peaks at the seasonal or trading day frequencies indicate the presence of **seasonality** or **trading day effects**.
Benchmarking	Benchmarking refers to the case where there are two sources of data for the same target variable, in the case of **seasonal adjustment** with different frequencies, and is concerned with correcting inconsistencies between the different estimates, e.g. quarterly and annual estimates of value-added from different sources (OECD, 2002). Benchmarking distributes (or interpolates) low-frequency series to construct **time series** of benchmarked estimates and extrapolates high-frequency estimates for a period for which benchmarks are not yet available (Eurostat, 2015).
Calendar adjustment	Calendar adjustment refers to the correction for calendar variations. Such calendar adjustments include working day adjustments or the incidence of **moving holidays** (such as Easter and Chinese New Year). The terms "calendar adjustment" and "working day adjustment" (also known as "**trading day adjustment**") are often used interchangeably. However, the main difference between the two terms is that working day adjustment is merely one type of calendar adjustment (OECD, 2007).
Calendar effects	Calendar effects capture the impact of working/trading days (number and composition), fixed and **moving holidays**, leap years and other calendar phenomena (e.g., bridging days) on the **time series** under review. The calendar effect resumes periodical effects on a time series which are, directly or indirectly, linked to specific calendar situations. While the Christmas effect on economic activity is always caught by the month of December/fourth quarter (therefore it is to a large extent assigned to the **seasonal component**), the effect of Easter, as well as other moving holidays, may concern varying months or quarters (Catholic Easter can affect March or April, i.e. the first or the second quarter) (Eurostat, 2008).

Glossary

Canonical decomposition	Canonical **decomposition** maximizes the variance of the **irregular component**. This maximizes the smoothness of the seasonal and **trend-cycle component** so that no additive white noise can be removed from them. Each component of a series should follow an ARIMA model, except for the irregular component assumed to be white noise.
Chain-linking	Joining together two indices that overlap in one period by rescaling one of them to make its value equal to that of the other in the same period, thus combining them into a single **time series**. More complex methods may be used to link together indices that overlap by more than one period (ILO, IMF, OECD, Eurostat, & World Bank, 2004). Unlike the fixed weight approach, the chain approach does not re-calculate the entire historical series whenever the weights are updated but rather chains or splices together the two-index series to produce a coherent time series (UN, 2013).
Concurrent adjustment	Concurrent adjustment is one of the alternative **refreshment strategies** in **seasonal adjustment**. This means that the model, filters, **outliers**, and regression parameters are re-identified with the respective parameters and factors every time new or revised data become available (Eurostat, 2015). This adjustment strategy can lead to instability of the seasonal pattern, although it produces accurate results relying on the available data for each period. Often balanced alternatives between this approach and **current adjustment** are used.
Cross-correlation	Cross-correlation is a measure for the degree to which two series are correlated. In **seasonal adjustment**, the theoretical components of a **time series** are assumed to be uncorrelated. Each component is expected to follow an ARIMA model, except for the **irregular component** which consists of white noise. The estimators of the components are correlated, but the correlation is usually small. The quality **diagnostics** include tests on the cross-correlation of the estimators and actual estimates of components.
Current adjustment	Current adjustment is one of the alternative **refreshment strategies** in **seasonal adjustment**. This means that the model, filters, **outliers**, and regression parameters are re-identified, and the respective parameters and factors re-estimated at review periods that have been set in advance. This approach makes use of the forecasted seasonal and calendar factors until the next review period (Eurostat, 2015). The reviews usually take place once or twice a year. Due to the use of forecasts, this strategy can lead to imprecise estimation of the latest adjusted figures.
Decomposition	Decomposition refers to the act of splitting a **time series** into its constituent parts by using statistical methods (OECD, 2007). Typically, **seasonal adjustment** identifies the **trend-cycle component**, the **seasonal component** and the **irregular component** from the **original series**. Sometimes a **transitory component** may also be identified by SEATS. Once the components have been estimated, the irregular and transitory components can be combined to the irregular/transitory component. The components form the original series either by addition, i.e. in case of **additive decomposition**, or by multiplication, i.e. in case of **multiplicative decomposition**.
Diagnostics	Diagnostics are used to assess the quality of the seasonally adjusted data. Among others, the absence of **residual seasonal** and/or **calendar effects** as well as the stability of the seasonally adjusted pattern must be carefully assessed. The validation of seasonally adjusted data can be performed by means of several graphical, descriptive, non-parametric and parametric criteria included in the output of the **seasonal adjustment** program (Eurostat, 2015).
Differencing	The process of subtracting successive terms in a series of equi-spaced observations. Used in numerical analysis and as a simple method for removing trends in **time series** (Upton & Cook, 2014). Regular and seasonal differencing are often used to transform the series, removing trend and seasonal effects, to achieve a clearer view of the underlying behaviour of the series. See **Stationary**.
Flow variable	Statistical series presented as flow series/data are accumulated during the reference period, for example, passenger car registrations, where the figure for the reference period is the sum of daily registrations (OECD, 2007).

Friedman test	The Friedman test is a non-parametric statistical test developed by the U.S. economist Milton Friedman. It is used to determine if stable **seasonality** is present in a series. Stable seasonality means the intra-year variation in the **seasonal component** is repeated constantly over the years. If it evolves from year to year, it is called moving seasonality. If the p-value of the test is lower than 0.1% the **null hypothesis** of no stable seasonality is rejected; Otherwise, the series is considered non-seasonal (Grudkowska, 2015).
Irregular component	The irregular component of a **time series** is the residual time series after the **trend-cycle** and the **seasonal component** (including **calendar effects**) have been removed. It corresponds to the high frequency fluctuations of the series. It results from short term fluctuations in a series which are not systematic and in some instances not predictable, e.g. uncharacteristic weather patterns, and it is assumed to include only white noise (OECD, 2007) When it contains short-term fluctuations that are neither white noise, nor can they be assigned to the trend-cycle or seasonal component, SEATS captures these **stationary** fluctuations as a **transitory component**.
Kurtosis	Kurtosis is a measure of how peaked or flat a distribution is relative to the normal distribution. The higher the value the more peaked the data are.
Kruskal-Wallis test	A Kruskal-Wallis test is a non-parametric test on stable **seasonality** that compares samples of two or more groups to see whether the samples originate from the same distribution. The **null hypothesis** states that all months or quarters have the same mean (Grudkowska, 2015).
Level shift	A level shift refers to a permanent change of the time series into higher or lower values. Level shifts may happen due to e.g. changes in behaviour, legislation, definitions or classifications. For example, if salaries increase for some profession, the level of that **time series** becomes higher permanently, but the seasonal pattern does not change.
Metadata	Metadata provide information on data and about processes of producing and using data (UNECE, 1995).
Moving average	A moving average is a method for smoothing **time series** by averaging (with or without weights) a fixed number of consecutive terms. The averaging "moves" over time, in that each data point of the series is sequentially included in the averaging, while the oldest data point in the span of the average is removed. In general, the longer the span of the average, the smoother the resulting series is likely to be. A moving average replaces each value of a time series by a (weighted) average of p preceding values, the given value, and f following values of a series. (OECD, 2007). Moving averages are sometimes referred to as **sliding spans**.
Moving holidays	Moving holidays are holidays which occur each year, but where the exact timing shifts. Examples of moving holidays include Easter, Chinese New Year and Ramadan (OECD, 2007).
Multiplicative decomposition	Multiplicative **decomposition** means that the original **time series** is the product of its components: **trend-cycle** x **seasonal** x **irregular**(/**transitory**). The multiplicative decomposition implies that as the trend of the series increases, the amplitude of the seasonal component also increases. Most economic time series exhibit a multiplicative relation between the components.
Multi-Processing	It is a JDemetra+ process to seasonally adjust two or more **time series**.
Normality test	Normality test is a standard statistical test of the assumption that the model residuals are normally distributed. This assumption is needed for estimation of the model, for the adequacy of several of the **diagnostics** and for valid inference. Rejection of the hypothesis indicates that non-linear effects are present. Those affecting asymmetry (**skewness**) are more damaging than those affecting the thickness of the tails (**kurtosis**).
Null hypothesis	In general, this term relates to a particular hypothesis under test, as distinct from the alternative hypotheses which are under consideration. It is therefore the hypothesis which determines the probability of the type I error. In some contexts, however, the term is restricted to a hypothesis under test of "no difference" (Marriott, 1992). The null hypothesis typically corresponds to a general or default position, for example, that the components of a **time series** are uncorrelated.

Glossary

Original series	In the context of this publication, original series refers to the raw data that have not been transformed and may be expressed as values or indices. Both random and systematic fluctuations influence the original series. It may contain seasonal effects and effects related to the calendar.
Outlier	An observation that is very different to other observations in a set of data (Upton & Cook, 2014). They can manifest themselves in several ways, the most important being **additive** or impulse outliers, **transitory changes**, and **level shifts** (Eurostat, 2015).
Partial concurrent adjustment	Partial concurrent adjustment is one of the alternative **refreshment strategies** in **seasonal adjustment**. It is one of the balanced alternatives between the **current** and **concurrent** approaches. Partial concurrent adjustment means that the model, filters, outliers and calendar variable are re-identified, usually once a year, but that the parameters and factors are updated every time new or revised observations become available (Eurostat, 2015).
Periodogram	A periodogram is a spectral plot to alert the user about the presence of remaining seasonal and **trading day effects**. A spectral plot involves a change from the time domain (x-axis) to the frequency domain. The periodicity of a phenomenon at the frequency f is $2\pi/f$ (Grudkowska, 2015). In JDemetra+, the seasonal frequencies are marked as grey vertical lines in the periodogram, while the purple lines correspond to trading day frequencies. Peaks at the seasonal or trading day frequencies indicate the presence of **seasonality** or trading day effects.
Period-to-period changes	Period-to-period changes are rates of change expressed with respect to the previous period, for example, from April to May. They may be referred to as month-on-previous-month growth rates, month-over-month growth rates, 1-month rate of change, or rate of change on the previous month. Such rates are expressed as (M_t/M_{t-1}) -1 or (Q_t/Q_{t-1}) -1. M_t denotes the value of a monthly **time series** in month t and Q_t the value of a quarterly time series in quarter t (OECD, 2007).
Refreshment strategy	Refreshment strategy refers to the choice of method for updating the seasonally adjusted series when new or revised observations accumulate. The choice of refreshment strategy affects the frequency of **revisions** and the accuracy of seasonally adjusted data. The most common alternatives are: **current adjustment** (fixed), controlled current adjustment, **partial concurrent adjustment**, and **concurrent adjustment**, where everything is revised during each update just as in the first **seasonal adjustment** of any **time series**.
Regressor	When a variable y is expressed as a function of variables $x1$, $x2$, ..., plus a stochastic term the x's are known as "independent variables" (Marriott, 1992). Other terms are explanatory variables or regressors. The regressors explain another variable, here the original **time series**. Regressors can be modelled to capture the effect of **moving holidays**, working and trading days. TRAMO/SEATS and X-13 remove the effect of the regressors to estimate the seasonal pattern, but some of these effects are returned to the seasonally adjusted series, **outliers**, for example. A regressor should only be applied if the series is influenced by the effect in question and the statistical tests approve its use.
Residual seasonality	Residual **seasonality** test is one of the seasonality tests included in JDemetra+ that tests if there is any seasonality left in the residuals after the **seasonal adjustment** process. The presence of residual seasonality is a concrete risk which could negatively affect the interpretation of seasonally adjusted data, since it indicates that the model does not capture all seasonality in the data (Eurostat, 2015).
Revisions	Data revisions are defined broadly as any change in the value of a statistic released to the public by an official national statistical agency (OECD, 2007). It is a regular procedure in case of unadjusted (raw) data and seasonally adjusted data. Raw data may be revised due to improved information set (in terms of coverage and/or reliability). Revisions of seasonally adjusted data can also take place because of a better estimate of the seasonal pattern due to new information provided by new components. A revision shows the degree of closeness of an initial estimate to a subsequent or final estimate (Eurostat, 2014b). In **seasonal adjustment**, a revision is necessary once the estimators based on forecasts are revised with new observations.

Glossary

RSA	This is an abbreviation for "routine for **seasonal adjustment**". A large number of commands and parameters need to be set to perform seasonal adjustment in JDemetra+. There are several standard combinations of commands and parameters, which are already set up in the RSA and can thus be selected by choosing the corresponding RSA.
Seasonal adjustment	Statistical technique used to remove the effects of seasonal and calendar influences operating on a data series. Seasonal adjustment removes the effects of events that follow a more or less regular pattern each year. These adjustments make it easier to observe the cyclical and other non-seasonal movements in a data series (SDMX, 2019).
Seasonal component	The seasonal component is that part of the variation in a **time series** representing intra-year fluctuations that are more or less stable year after year with respect to timing, direction and magnitude (OECD, 2007). The seasonal component depicts systematic, calendar-related movements in a time series. These regular movements do not give a clear indication of the underlying long-term development, which is why they are removed by **seasonal adjustment**.
Seasonality	A pattern in a **time series** that repeats in a regular way—for example, daily average temperatures rise each summer (Upton & Cook, 2014). Seasonality may stem from external rhythms, such as the 24-hour rotation of days and social habits, such as holiday periods and consumption habits depending on the season. It may also include the impact of business habits, such as quarterly provisional tax payments or periodic invoicing and administrative procedures, such as the timing of tax returns.
Signal extraction	In **time series**, signal extraction refers to the estimation of the signal, i.e. the value of measurement that would be observed if the measurement was not contaminated by random errors in the data (Upton & Cook, 2014). In SEATS, signal extraction implies minimum mean square error estimation of the signal (seasonal and other components) contained in the model identified for the observed series. Sometimes it is called smoothing of the data.
Single Processing	It is a JDemetra+ definition which describes a process to seasonally adjust single **time series**.
Skewness	Skewness is a measure of how asymmetrical a distribution is. A symmetrical distribution has a skewness of zero.
Sliding spans analysis	It is a type of analysis which measures the consistency of estimated components over time by applying the method of **moving averages**.
Specification	It represents the set of commands and parameters used for the **seasonal adjustment**. Each **RSA** provides a specification. In JDemetra+, the user can create own specifications for seasonal adjustment.
Spectral analysis	Part of **time series** analysis that analyses its spectrum (frequency domain). The spectrum is often visualized in a **periodogram**.
Stationarity	**A time series** is stationary when its mean, variance and **autocorrelation** are constant over time. Stationarity is a fundamental condition to avoid spurious models. A non-stationary series may be made stationary by applying adequate **differencing**.
Stock variable	Statistical data presented as stock series/data are measured at the end of the reference period, for example, money supply data which can refer to an observation on the last working day of the reference period (OECD, 2007).
Time series	A time series is a collection of observations for a variable over time. It is measured at regular time intervals, e.g. monthly or quarterly. For **seasonal adjustment**, a time series must be measured at time intervals shorter than one year, because seasonal fluctuations are intra-annual, and tend to repeat one year after the other. In addition, the series must be compiled for discrete periods of time, e.g. for every month or quarter.
Trading day effect	Recurring day-of-week effects and leap year effects in monthly (or quarterly) economic **time series** are called trading day effects (Findley & Soukup, 2000). The effects of trading days are estimated by counting the proportion of them in the month (or quarter) (Eurostat, 2015). The trading day effect includes variations in the measured activity depending on the day of the week. For example, sales may be higher on Fridays than on Tuesdays.

Trading/working day adjustment	Trading/working day adjustment aims at obtaining a seasonally adjusted series whose values are independent of the length and the composition in days (number of Mondays, Tuesdays, etc./number of working days and weekend days) of the month (or quarter) (Eurostat, 2015). Most often, trading and working day adjustment are used as synonyms, but in some cases, working day adjustment focuses on the difference between working days and non-working days, whereas trading day adjustment refers to the effect of different days of the week.
Transitory change	A transitory change is a type of **outlier** in a **time series**, namely a point jump followed by a smooth return to the original path. It remains visible in the seasonally adjusted series. Transitory changes may occur, for example, due to deviations from average monthly weather conditions. If in winter weather becomes suddenly colder, it may lead to a peak in energy consumption. When weather gradually returns to its regular level, the consumption should settle back to normal.
Transitory component	An additional component of the decomposed **time series** that may be identified by SEATS. It picks up highly transitory variation that is not white noise and should not be assigned to the seasonal or **trend-cycle component**. Its model is a low-order **stationary** ARMA model, with spectral peaks at non-seasonal and non-trend frequencies. Not all series need this additional component.
Trend-cycle component	The trend-cycle component includes both very long-term and medium-term developments. Out of these two, the trend component depicts the long-term evolution of the series that can be observed over several decades, i.e. the structural variations. It reflects the underlying level of the series and is typically the result of influences such as population growth, technological development, and general economic development. The cycle component, on the other hand, is the relatively smooth movement around the long-term trend. It is a rhythmic cycle caused by economic variation from expansion to recession.
Year-on-year growth rates	Year-on-year growth rates are rates of change expressed over the same period, month or quarter, of the previous year. They may be referred to as year-over-year growth rates, year-to-year growth rate, the rate of change from the previous year, or 12-month rate of change. Such rates are expressed as (M_t/M_{t-12})-1 or (Q_t/Q_{t-4})-1 (OECD, 2007).
Year-to-date growth rates	Year-to-date data, sometimes referred to as cumulative data, are expressed in cumulative terms from the beginning of the year and compared with the same period of the previous year (OECD, 2007). For example, they may compare the sum of values from January 2011 to April 2011, to the same period of 2010.

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Practical Guide to Seasonal Adjustment with JDemetra+

From source series to user communication

This Guide introduces seasonal adjustment and gives practical guidance to national statistical offices in producing seasonal adjusted monthly or quarterly time series covering all steps in the production process, from the evaluation of the original data series to the dissemination and communication of the seasonally adjusted series. The Guide can be used in introducing new staff to seasonal adjustment, in training courses or as a complement to other material on seasonal adjustments. The Guide is based on the use of JDemetra+ which is an open source software for seasonal adjustment.

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