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RJDemetra: An R Interface To JDemetra+ Seasonal Adjustment Software

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Abstract

The abstract of the article.

Keywords: R, seasonal adjustment, calendar effects, ARIMA, time series.

1. Introduction

Since the 20th century, more and more infra-annual statistics are produced, especially by national institutes, to analyse the short-term evolution of an economy. It is for example the case of the gross domestic product (GDP), unemployment rate, household consumption of goods and industrial production indices. However, most of those time series are affected by seasonal and trading days effects. A seasonal effect is an effect that occur in the same calendar month with similar magnitude and direction from year to year. For instance, automobile production is usually lower during summer, due to holidays, and chocolate sales are usually higher in December, due to Christmas. Trading days effect is the fact that a time series can be affected by each calendar month's weekday composition. For example retail sales are usually higher on Saturday, thus they are likely to be higher in months with a surplus of weekend days.

Therefore, seasonal and trading days effects can make it difficult to analyse the infra-annual movements of a time series or to make spatial comparison. That's why time series are often seasonally and trading days adjusted and seasonal adjustment is the process of removing the effects of seasonal and trading day fluctuations.

2. Theory behind seasonal adjustment

The most popular seasonal adjustment methods are TRAMO-SEATS+[1] (Gómez and Maravall 1996; Caporello and Maravall 2004), a parametric method based on ARIMA models, and X-13-ARIMA-SEATS[2] (Findley, Monsell, Bell, Otto, and Chen 1998; Ladiray and Quenneville 2001), a non-parametric method based on moving average. Both methods are recommended by Eurostat and the European Central Bank (ECB) to seasonnaly adjust economic indicators. These methods proceed in two steps summarized in figure 1.

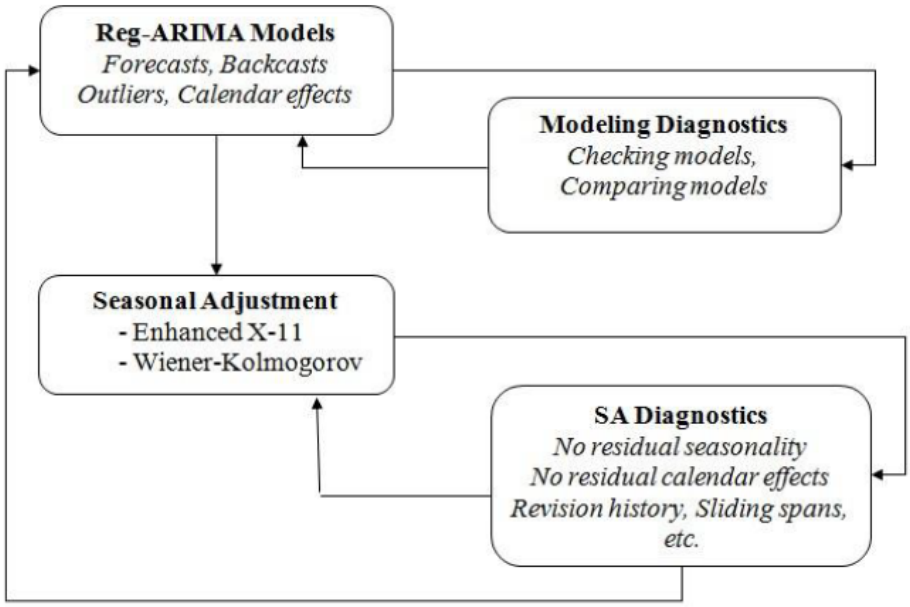


Figure 1: X-13-ARIMA-SEATS and TRAMO-SEATS+ 2-step process: pre-adjustment and decomposition.

In the **first step** of seasonal adjustment, called **pre-adjustment** or **linearisation**, consists of pre-adjusting the time series by removing from it the deterministic effects (calendar effects, outliers...) and estimating missing observations. In the **second part** of seasonal adjustment, called the **decomposition**, the pre-adjusted series is decomposed to determine the seasonal component. As a result of seasonal adjustment, the final seasonally adjusted series shall be free of seasonal and calendar-related movements.

Whereas the pre-adjustment step is very similar in X-13-ARIMA and in TRAMO-SEATS (section 2.1), this is not the case with the decomposition. In X-13-ARIMA, the X-11 algorithm decomposes the time series by means of linear filters (section 2.2). In TRAMO-SEATS+, SEATS (Signal Extraction in ARIMA Time Series) decomposes the observed series with a ARIMA-model based method (section 2.3).

2.1. Pre-adjustment with TRAMO and Reg-ARIMA models

[1]The program TRAMO-SEATS+ was developed by Gianluca Caporello and Agustin Maravall — with programming support from Domingo Perez and Roberto Lopez — at the Bank of Spain. It is based on the program TRAMO-SEATS, previously developed by Victor Gomez and Agustin Maravall.

[2]The program X-13ARIMA-SEATS is a produced, distributed, and maintained by the US-Census Bureau.

The **first step** of seasonal adjustment consists of pre-adjusting the time series by removing from it the deterministic effects and estimating missing observations. Among deterministic effects, we distinguish outliers, calendar and regression effects. In this step, also forecasts and backcasts of the pre-adjusted series are estimated which allows applying linear filters at both ends of the series in the second step of the seasonal adjustment. The pre-adjustment, linearization, of the input series is achieved with a **RegARIMA** model (model with ARIMA errors) as specified below.

$$z_t = y_t\beta + x_t$$

where

- z_t - is the original series;
- $\beta = (\beta_1, \ldots, \beta_n)$ - a vector of regression coefficients;
- $y_t = (y_{1t}, \ldots, y_{nt})$ - n regression variables (outliers, calendar effects, user-defined variables);
- x_t - a disturbance that follows the general ARIMA process:
- $\phi(B)\delta(B)x_t = \theta(B)a_t$; $\phi(B), \delta(B)$ and $\theta(B)$ are the finite polynomials in B; a_t is a white-noise variable with zero mean and a constant variance.

The polynomial $\phi(B)$ is a stationary autoregressive (AR) polynomial in B, which is a product of the stationary regular AR polynomial in B and the stationary seasonal polynomial in B^s:

$$\phi(B) = \phi_p(B)\Phi_{bp}(B^s) = (1 + \phi_1 B + \cdots + \phi_p B^p)(1 + \Phi_1 B^s + \cdots + \Phi_{bp} B^{bps})$$

where:

- p - number of regular AR terms (in the package and in JDemetra+ $p \leq 3$);
- bp - number of seasonal AR terms (in the package and in JDemetra+ $bp \leq 1$);
- s - number of observations per year (frequency of the time series).

The polynomial $\theta(B)$ is an invertible moving average (MA) polynomial in B, which is a product of the invertible regular MA polynomial in B and the invertible seasonal MA polynomial in B^s:

$$\theta(B) = \theta_q(B)\Theta_{bq}(B^s) = (1 + \theta_1 B + \cdots + \theta_q B^q)(1 + \Theta_1 B^s + \cdots + \Theta_{bq} B^{bqs})$$

where:

- q - number of regular MA terms (in the package and in JDemetra+ $q \leq 3$);
- bq - number of seasonal MA terms (in the package and in JDemetra+ $bq \leq 1$);

The polynomial $\delta(B)$ is the non-stationary AR polynomial in B (unit roots):

$$\delta(B) = (1 - B)^d(1 - B^s)^{d_s}$$

where:

- d - regular differencing order (in the package and in JDemetra+ $d \leq 1$);
- d_s - seasonal differencing order (in the package and in JDemetra+ $d_s \leq 1$);

An automatic modelling is also implemented in both methods to: determine the decomposition of the series, detect outliers and calendar effects and to adjust residuals to an ARIMA models. A detailed description can be found in Gómez and Maravall (1998).

2.2. Decomposition with X-11

In X-11, the pre-adjusted series (y) is decomposed into the following components: trend-cycle (t), seasonal component (s) and irregular component (i). The decomposition can be:

- additive ($y = t + s + i$)
- multiplicative ($y = t * s * i$)
- log-additive ($\log(y) = \log(t) + \log(s) + \log(i)$) or
- pseudo-additive ($y = t * (s + i - 1)$)

The X-11 algorithm decomposes the time series by means of linear filters (Findley *et al.* 1998; Ladiray and Quenneville 2001).

2.3. Decomposition with SEATS

SEATS is a program for decomposing a time series into its unobserved components, following an ARIMA model based method for extracting from a time series its different signals (Gómez and Maravall 1996; Caporello and Maravall 2004). The decomposition can be additiveor multiplicative (equivalent to an additive model after taking the logarithm).

SEATS decomposes the linearised series into the following components:

- **trend-cycle component:** captures the low-frequency variation of the series and displays a spectral peak at frequency 0;
- **seasonal component:** captures the spectral peaks at seasonal frequencies;
- **irregular component:** captures erratic, white-noise behavior, and hence has a flat spectrum;
- **transitory component:** a zero-mean stationary component that picks up transitory fluctuations that should not contaminate the trend-cycle or seasonal component and are not white-noise.

The components are determined and fully derived from the structure of the ARIMA model for the observed series, which can be directly identified from the data.

The decomposition assumes orthogonal components, and each one will have in turn an ARIMA expression. In order to identify the components, we will require that (except for the irregular

one) they be clean of noise. This is called the "canonical" property, and implies that no additive white noise can be extracted from a component that is not the irregular one. The variance of the latter is, in this way, maximized, and, on the contrary, the trend-cycle and seasonal component are as stable as possible (compatible with the stochastic nature of model).

3. JDemetra+ and RJDemetra

JDemetra+ is a tool for seasonal adjustment (SA) developed by the National Bank of Belgium (NBB) in cooperation with the Deutsche Bundesbank and Eurostat in accordance with the Guidelines of the European Statistical System (ESS) (Eurostat 2015). It implements the concepts and algorithms used in the two leading SA methods: TRAMO-SEATS+ and X-12ARIMA/X-13ARIMA-SEATS. Those methods have been re-engineered using an object-oriented approach that enables easier handling, extensions and modifications.

JDemetra+ has been officially recommended, since 2 February 2015, to the members of the ESS and the European System of Central Banks as software for seasonal and calendar adjustment of official statistics.

Besides seasonal adjustment, JDemetra+ bundles other time series models that are useful in the production or analysis of economic statistics, including for instance outlier detection, nowcasting, temporal disaggregation or benchmarking. More details on the methodology used in JDemetra+ can be found in the JDemetra+ manuals and user guides (Grudkowska 2015a,b).

The package **RJDemetra** provides an R interface to the seasonal adjustment software JDemetra+. **RJDemetra** uses Java libraries of JDemetra+, thus it relies on the **rJava** (Urbanek 2018) package and Java SE 8 or later version is required. It allows to:

- perform seasonal adjustment with TRAMO-SEATS+ and X-12ARIMA/X-13ARIMA-SEATS with pre-defined (section 4) and user-defined specification (section 6);
- acces to all the output available in JDemetra+ (section 5);
- import and export JDemetra+ workspaces (section 7).

It can be installed from CRAN:

```
R> install.packages("RJDemetra")
```

The development version can be installed from GitHub with **devtools** (Wickham, Hester, and Chang 2018):

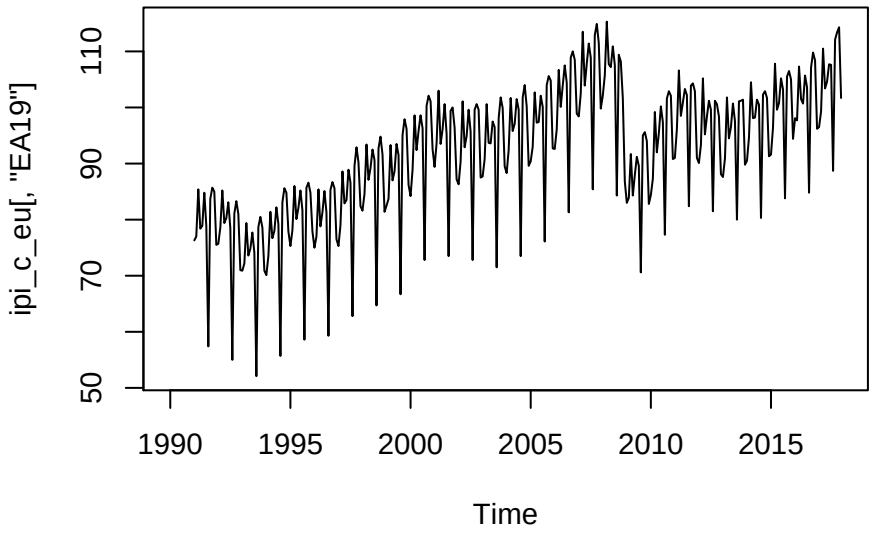
```
R> devtools::install_github("jdemetra/rjdemetra")
```

3.1. Dataset

In this package the sts_inpr_m database of Eurostat is included, which contains monthly industrial production indices in manufacturing in the European Union. It contains 37 time

series from january 1990 to december 2017 which are considered to be affected by seasonal and trading days effects. The data is a `ts` object and can be accessed using the `ipi_c_eu` object. The following snippet of code plots the industrial production index of the euro aera (EA19):

```
R> library(RJDemetra)
R> plot(ipi_c_eu[, "EA19"])
```



3.2. Print styling

By default, a color styling is used for the `print` methods of the objects created by **RJDemetra**. It can causes troubles with some outputs (for example with **rmarkdown** (Xie, Allaire, and Grolemund 2018)) and can be disabled in each `print` function with the argument `enable_print_style = FALSE` or setting the global option `enable_print_style` to `FALSE`:

```
R> options(enable_print_style = FALSE)
```

4. Estimate a pre-defined RegARIMA and SA model

As in JDemetra+, **RJDemetra** allows to perform seasonal adjustment using pre-defined model specifications. The pre-defined specifications correspond to most commonly used specifications and users are recommended to start their analysis with one of them. They are separately defined for TRAMO-SEATS and X-13ARIMA-SEATS estimation methods. It is also possible to perform only the first step of seasonal adjustment (the RegARIMA estimation). The

pre-defined model specifications are described in tables 1 and 2. They are identical for pre-adjustment (column 1) and for seasonal adjustment (column 2). With more details, setting described in tables tables 1 and 2 are:

- Transformation test: a test to choose between an additive decomposition (no transformation) and a multiplicative decomposition (logarithmic transformation).

- Pre-adjustment for leap-year (not available for TRAMO): in the case of a multiplicaive decomposition; a correction of the February values is applied to the original series (before transformation). The original values in February are multiplied by $\frac{28.25}{29}$ for leap years, by $\frac{28.25}{28}$ for non-leap years and values for other months are not modified. In the case of multiplicative models, this is equivalent to adding a leap year regressor (Bell 1992).

- Working days/trading days: a pre-test is made for a presence of a working day/trading day effect. In TRAMO an automatic choice between working days and trading days regressors is done with "RSAFull".

- Easter: a pre-test for a presence of the Easter effect. The default length of the Easter effect is 6 days (for TRAMO-SEATS specifications) and for X-13ARIMA-SEATS an automatic detection of the duration is done (1, 8 or 15 days).

- Outliers: an automatic identification of three types of outliers: AO (additive outlier), LS (level shift) and TC (transitory change), using a default critical value. The automatic identification of SO (seasonal outlier) is not enabled by default.

- ARIMA model: the choice between fixing the ARIMA model structure to (0,1,1)(0,1,1) (Airline model) or searching for the ARIMA model using an automatic model identification procedure. The Airline model is used as a default model in several TRAMO-SEATS+ and X-13ARIMA-SEATS specifications because it has been shown in many studies that this model is appropriate for many real seasonal monthly or a quarterly time series. Moreover, the Airline model approximates well many other models and provides an excellent "benchmark" model (Maravall 2009).

Four functions can be used in **RJDemetra** to perform an estimation with the pre-defined specification:

- RegARIMA
  - X-13ARIMA method: `regarima_x13()`
  - TRAMO-SEATS method: `regarima_tramoseats()`
- Seasonal adjustment
  - X-13ARIMA method: `x13()`
  - TRAMO-SEATS method: `tramoseats()`

For example:

Table 1: Pre-defined specification for TRAMO and TRAMO-SEATS

Specification								
TRAMO	TRAMO-SEATS	Transformation	Pre-adjustment for leap-year	Working days	Trading days	Easter effect	Outliers	ARIMA model
TR0	RSA0	no	no	no	no	no	no	(0,1,1)(0,1,1)
TR1	RSA1	test	no	no	no	no	test	(0,1,1)(0,1,1)
TR2	RSA2	test	no	test	no	test	test	(0,1,1)(0,1,1)
TR3	RSA3	test	no	no	no	no	test	AMI
TR4	RSA4	test	no	test	no	test	test	AMI
TR5	RSA5	test	no	no	yes	test (Standard)	test	AMI
TRfull (default)	RSAfull (default)	test	yes	test	test	test (Include Easter)	test	AMI

Table 2: Pre-defined specification for RegARIMA and X-13ARIMA-SEATS

Specification								
RegARIMA	X-13ARIMA-SEATS	Transformation	Pre-adjustment for leap-year	Working days	Trading days	Easter effect	Outliers	ARIMA model
RG0		no	no	no	no	no	no	(0,1,1)(0,1,1)
RG1	RSA1	test	no	no	no	no	test	(0,1,1)(0,1,1)
RG2c	RSA2c	test	test	test	no	test	test	(0,1,1)(0,1,1)
RG3	RSA3	test	no	no	no	no	test	AMI
RG4c	RSA4c	test	test	test	no	test	test	AMI
RG5c (default)	RSA5 (default)	test	test	no	test	test	test	AMI

```
R> myseries <- ipi_c_eu[, "EA19"]
R> regx13 <- regarima_x13(myseries, spec = "RG5c")
R> regts <- regarima_tramoseats(myseries, spec = "TRfull")
R> sax13 <- x13(myseries, spec = "RSA3", userdefined = NULL)
R> sats <- tramoseats(myseries, spec = "RSAfull", userdefined = NULL)
```

In section 6 it is presented how to modify model specifications, including the possibility to incorporate user-defined regressors.

5. Class object structure

In section 4 it was presented how to run a RegARIMA and complete seasonal adjustment estimation with pre-defined model specifications. In this section the outcome will be described in detail.

As a result of seasonal adjustment estimation (e.g. function `x13` or `tramoseats`) a S3 class object (`sa_object`) is created. It has a class `c("SA", "X13")` or `c("SA", "TRAMO_SEATS")` depending on the used estimation method. The `sa_object` consist of lists of S3 class sub-objects. For each of the class `print` and `plot` methods are defined. The complete structure of the `sa_object` is presented in table 3 for a seasonal adjustment made with `x13` and in 4 for a seasonal adjustment made with `tramoseats`. The `sa_object` contains the following five objects: **regarima**, **decomposition**, **final**, **diagnostics** and **user_defined**. Independently

which of the two estimation methods is used the regarima, final and diagnostics objects contain the same components, though with different classes (see table **??**). Whereas, the object decomposition differs for the two methods. The object user_defined is empty unless additional output was requested by the user (see sub-section 5.5). Finally, when estimating RegARIMA only the regarima object is created. All the plots methods are detailed in table 5.

Table 3: SA object structure (seasonal adjustment made with `x13`)

Object	Level	Type [RJDemetra S3 class]
sa_object	0	list [SA, X13]
regarima	**1**	**list [regarima, X13]**
specification	2	list
estimate	3	data.frame
transform	3	data.frame
regression	3	list
userdef	4	list
specification	5	data.frame
outliers	5	data.frame or NA(empty)
variables	5	list
series	6	mts, ts, matrix or NA(empty)
description	6	data.frame or NA(empty)
trading.days	4	data.frame
easter	4	data.frame
outliers	3	data.frame
arima	3	list
specification	4	data.frame
coefficients	4	data.frame or NA(empty)
forecast	3	data.frame
span	3	data.frame
arma	2	vector - numeric
arima.coefficients	2	matrix
regression.coefficients	2	matrix
loglik	2	matrix
model	2	list
spec_rslt	3	data.frame
effects	3	mts, ts, matrix
residuals	2	ts
residuals.stat	2	list
st.error	3	numeric
tests	3	data.frame [regarima_rtests]
forecast	2	mts, ts, matrix
decomposition	**1**	**list [decomposition_X11]**

specification	2	data.frame [X11_spec]
mode	2	character
mstats	2	matrix
si_ratio	2	mts, ts, matrix
s_filter	2	vector - character
t_filter	2	character
final	**1**	**list [finals]**
series	2	mts, ts, matrix
forecasts	2	mts, ts, matrix
diagnostics	**1**	**list [diagnostics]**
variance_decomposition	2	data.frame
combined_test	2	list [combined_test]
tests_for_stable_seasonality	3	data.frame
combined_seasonality_test	3	character
residuals_test	2	data.frame
user_defined	**1**	**list [user_defined]**

Table 4: SA object structure (seasonal adjustment made with `tramoseats`)

Object	Level	Type [RJDemetra S3 class]
sa_object	0	list [SA, X13]
regarima	**1**	**list [regarima, X13]**
specification	2	list
estimate	3	data.frame
transform	3	data.frame
regression	3	list
userdef	4	list
specification	5	data.frame
outliers	5	data.frame or NA(empty)
variables	5	list
series	6	mts, ts, matrix or NA(empty)
description	6	data.frame or NA(empty)
trading.days	4	data.frame
easter	4	data.frame
outliers	3	data.frame
arima	3	list
specification	4	data.frame
coefficients	4	data.frame or NA(empty)
forecast	3	data.frame
span	3	data.frame
arma	2	vector - numeric
arima.coefficients	2	matrix

regression.coefficients	2	matrix
loglik	2	matrix
model	2	list
spec_rslt	3	data.frame
effects	3	mts, ts, matrix
residuals	2	ts
residuals.stat	2	list
st.error	3	numeric
tests	3	data.frame [regarima_rtests]
forecast	2	mts, ts, matrix
decomposition	**1**	**list [decomposition_seats]**
specification	2	data.frame [seats_spec]
mode	2	character
model	2	list
model	3	matrix or empty list
sa	3	matrix or empty list
trend	3	matrix or empty list
seasonal	3	matrix or empty list
transitory	3	matrix or empty list
irregular	3	matrix or empty list
linearized	2	mts, ts, matrix
components	2	mts, ts, matrix
final	**1**	**list [finals]**
series	2	mts, ts, matrix
forecasts	2	mts, ts, matrix
diagnostics	**1**	**list [diagnostics]**
variance_decomposition	2	data.frame
combined_test	**2**	**list [combined_test]**
tests_for_stable_seasonality	3	data.frame
combined_seasonality_test	3	character
residuals_test	2	data.frame
user_defined	**1**	**list [user_defined]**

Table 5: Plots available with the **RJDemetra** package.

Object class (`x` object)	Method	Description
`regarima`	`plot(x, which = 1)`	Plot of residuals
`regarima`	`plot(x, which = 2)`	Histogram of standardized residuals and density
`regarima`	`plot(x, which = 3)`	Normal quantile-quantile (Q-Q) plot of standardized residuals
`regarima`	`plot(x, which = 4)`	Autocorrelation function (ACF) of residuals

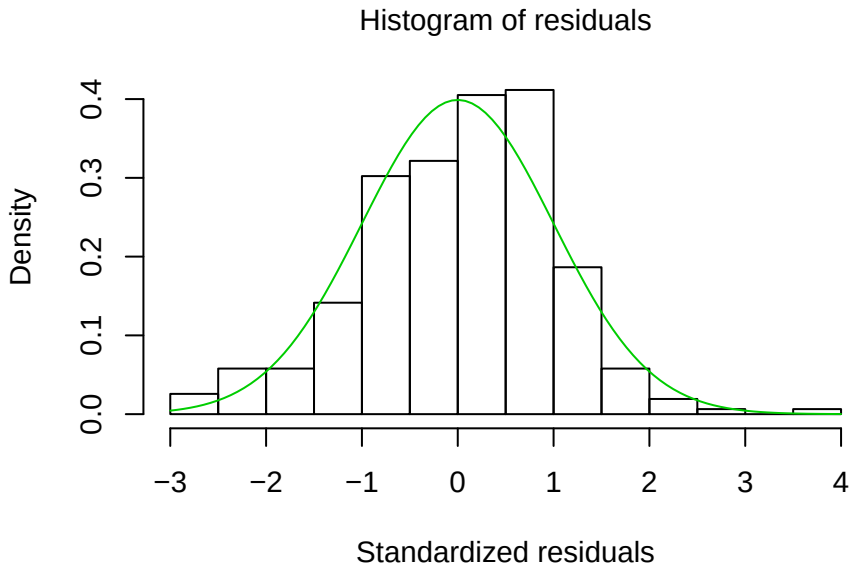
`regarima`	`plot(x, which = 5)`	Partial autocorrelation function (PACF) of residuals
`regarima`	`plot(x, which = 6)`	Raw and linearized series
`regarima`	`plot(x, which = 7)`	Plots 3 graphics: linearised series, calendar effects and outliers effects
`decomposition_X11`, `decomposition_SEATS`	`plot(x)`	S-I ratio: seasonal-irregular (S-I) component and the seasonal factors for each period of the time series (months or quarters)
`final`	`plot(x, type_chart = sa-trend)`	Plots the raw series, the seasonal adjusted series and the trend
`final` or `SA`	`plot(x, type_chart = cal-seas-irr)`	Plots the calendar effects, the seasonal component and the irregular

5.1. Regarima

The regarima object contains the provided model specification (`specification`; level 2 of the `sa_object`), the estimated coefficients for the arima processes (`arima.coefficients`) and regressors (`regression.coefficients`), including arma orders (`arma`). It includes also model quality measures (`loglik`), regarima specification after its estimation with the estimated effects (e.g. linearized input series or outliers)(`model`), the residuals of the regarima model (`residuals`), several tests' results for the residuals (`residuals.stat`) and finally the forecast of the pre-adjusted series (`forecasts`). All this information can be extracted individually by the user or a predefined output can be used by calling `print()` or `summary()` (for more detailed output) functions. Also a set of graphs is defined within the function `plot()`. For regarima by default the first six graphs are displayed, but specific ones can be chosen within the argument `which`. Table 5 summarizes all the graphs available for the `sa_object`, as well as its `plot()` options.

```
R> sax13$regarima

y = regression model + arima (1, 1, 2, 0, 1, 1)
Log-transformation: no
Coefficients:
          Estimate Std. Error
Phi(1)     -0.7603      0.096
Theta(1)   -1.1757      0.095
Theta(2)    0.4551      0.053
BTheta(1)  -0.5433      0.049

             Estimate Std. Error
AO (1-2016)     4.291      0.883
LS (1-2009)    -6.210      0.947
LS (11-2008)   -5.806      0.948
```

```
TC (3-2009)    -3.967      0.908


Residual standard error: 1.187 on 311 degrees of freedom
Log likelihood = -496.8, aic =  1012 aicc =  1012, bic(corrected for length) = 0.4898



R> summary(sax13$regarima)



y = regression model + arima (1, 1, 2, 0, 1, 1)

Model: RegARIMA - X13
Estimation span: from 1-1991 to 12-2017
Log-transformation: no
Regression model: no mean, no trading days effect, no leap year effect, no Easter effect,

Coefficients:
ARIMA:
          Estimate Std. Error  T-stat Pr(>|t|)
Phi(1)    -0.76028    0.09609  -7.912 4.49e-14 ***
Theta(1)  -1.17573    0.09515 -12.356  < 2e-16 ***
Theta(2)   0.45508    0.05285   8.612 4.44e-16 ***
BTheta(1) -0.54327    0.04932 -11.015  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Regression model:
             Estimate Std. Error T-stat Pr(>|t|)
AO (1-2016)    4.2913     0.8832  4.859 1.88e-06 ***
LS (1-2009)   -6.2105     0.9469 -6.559 2.26e-10 ***
LS (11-2008)  -5.8056     0.9479 -6.125 2.74e-09 ***
TC (3-2009)   -3.9673     0.9078 -4.370 1.69e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


Residual standard error: 1.187 on 9 degrees of freedom
Log likelihood = -496.8, aic =  1012, aicc =  1012, bic(corrected for length) = 0.4898



R> plot(sax13$regarima, which = 2)
```



5.2. Decomposition

As afore-mentioned the decomposition method differs between TRAMO-SEATS+ and X-12ARIMA/X-13ARIMA, where SEATS is based on ARIMA-model and X11-algorithm on linear filters. Therefore also the composition of this object differs when estimating with the two methods (hence the two decomposition objects in the table **??**). The only common part is the first two sub-objects with the model specification (`specification`) and information on the decomposition mode (`mode`; e.g.: additive).

Then, the `decomposition_X11` object comprises quality measures on the decomposition (`mstats`), namely the M and Q statistics. It contains also the final unmodified S-I ratios $d8$ and final seasonal factors $d10$ (`si_ratio`), as well as the information on the final seasonal filter (`s_filter`) and trend filter(`t_filter`). The code below presents the output for X11 decomposition:

```
R> sax13$decomposition

 Monitoring and Quality Assessment Statistics:
      M stats
M(1)    0.028
M(2)    0.033
M(3)    0.338
M(4)    0.376
M(5)    0.366
M(6)    0.067
M(7)    0.066
M(8)    0.157
```

```
M(9)    0.073
M(10)   0.145
M(11)   0.120
Q       0.156
Q-M2    0.171

Final filters:
Seasonal filter:  3x5
Trend filter:  13 terms Henderson moving average
```

As a reminder, in SEATS it is assumed that each component of the linearized series (received from TRAMO) is an outcome of a linear stochastic process and SEATS estimates an ARIMA model for each component (i.e. trend, seasonal, transitory and irregular). Subsequently, the `decomposition_SEATS` object contains the information on the estimated ARIMA models (`model`), the linearized components, as obtained from TRAMO (`linearized`), and the theoretical components calculated from the ARIMA models (`components`). The code below presents the output for the SEATS decomposition, with the information on the ARIMA models:

```
R> sats$decomposition

Model
AR :  1 + 0.094056 B - 0.158875 B^2 - 0.294600 B^3
D :  1 - B - B^12 + B^13
MA :  1 - 0.510600 B^12


SA
AR :  1 + 0.094056 B - 0.158875 B^2 - 0.294600 B^3
D :  1 - 2.000000 B + B^2
MA :  1 - 0.937923 B - 0.015753 B^2 - 0.007005 B^3 + 0.015440 B^4 - 0.001104 B^5
Innovation variance:  0.5777661

Trend
AR :  1 - 0.711394 B
D :  1 - 2.000000 B + B^2
MA :  1 - 0.312018 B - 0.965498 B^2 + 0.346519 B^3
Innovation variance:  0.07090723

Seasonal
D :  1 + B + B^2 + B^3 + B^4 + B^5 + B^6 + B^7 + B^8 + B^9 + B^10 + B^11
MA :  1 + 1.314878 B + 1.722951 B^2 + 2.227262 B^3 + 2.229462 B^4 + 2.119339 B^5 + 1.92645
Innovation variance:  0.08441922

Transitory
AR :  1 + 0.805449 B + 0.414116 B^2
MA :  1 - 0.452913 B - 0.547087 B^2
```

```
Innovation variance:  0.02525112

Irregular
Innovation variance:  0.07006354
```

5.3. Final

The final object has a simple structure as it includes the input series, final seasonally adjusted series and the final components (i.e. t - trend-cycle, s - seasonal component and i - irregular component) (`series`), as well as their forecasts (`forecasts`).

```
R> sats$final
```

```
Last observed values
             y       sa        t             s           i
Jan 2017  96.5 102.9317 102.6366  -6.431739755  0.29515069
Feb 2017  99.3 102.3815 102.7523  -3.081452963 -0.37082579
Mar 2017 110.5 103.2230 103.0587   7.276971010  0.16431902
Apr 2017 103.4 103.3950 103.4579   0.004977088 -0.06292068
May 2017 104.6 104.1023 103.8400   0.497657700  0.26230153
Jun 2017 107.7 103.8403 104.2863   3.859652578 -0.44596785
Jul 2017 107.6 105.1862 104.9032   2.413785110  0.28301107
Aug 2017  88.7 105.5484 105.5999 -16.848375561 -0.05151353
Sep 2017 112.1 106.2889 106.3305   5.811052841 -0.04159101
Oct 2017 113.4 106.9003 107.1101   6.499696169 -0.20982123
Nov 2017 114.3 108.3110 107.7487   5.988950554  0.56232415
Dec 2017 101.7 107.7534 108.1104  -6.053350690 -0.35709913

Forecasts:
               y_f     sa_f      t_f         s_f           i_f
Jan 2018 102.49061 108.4010 108.4016  -5.9103802 -0.0005820963
Feb 2018 105.85284 108.8666 108.7446  -3.0137577  0.1219532717
Mar 2018 116.21918 108.9840 109.0820   7.2351710 -0.0979861094
Apr 2018 108.90762 109.4437 109.4153  -0.5360850  0.0284199810
May 2018 110.11320 109.7634 109.7457   0.3498301  0.0176868066
Jun 2018 114.47710 110.0480 110.0740   4.4290998 -0.0260150048
Jul 2018 112.47723 110.4145 110.4009   2.0627149  0.0136293681
Aug 2018  93.98244 110.7265 110.7267 -16.7440681 -0.0002045225
Sep 2018 116.57469 111.0463 111.0518   5.5283721 -0.0054794124
Oct 2018 118.30580 111.3809 111.3764   6.9249450  0.0044980848
Nov 2018 117.56621 111.6992 111.7005   5.8670241 -0.0013538638
Dec 2018 105.59658 112.0237 112.0245  -6.4271099 -0.0007722619
```

5.4. Diagnostics

This part of the `sa_object` includes several diagnostics on the presence of seasonality in the input series and on the quality of the seasonal adjustment.

The test for the seasonality presence (`combined_test`) are performed both on the entire series and in the last 3 years.

Whereas, the quality checking is grouped into two sets. The first looks at the contribution of each estimated component to the variance of the original series (`variance_decomposition`). The second verifies, with different tests, that there is no seasonal pattern left in the seasonally adjusted series and in the irregular component (`residuals_test`).

All the checks (except `combined_seasonality_test`), together with a detailed description, are displayed when printing the diagnostics object.

```
R> sats$diagnostics
```

```
Relative contribution of the components to the stationary
portion of the variance in the original series,
after the removal of the long term trend
Trend computed by Hodrick-Prescott filter (cycle length = 8.0 years)
          Component
Cycle        15.148
Seasonal     83.993
Irregular     0.174
TD & Hol.     0.076
Others        0.049
Total        99.441

Combined test in the entire series
Non parametric tests for stable seasonality
                                                          P.value
  Kruskall-Wallis test                                      0.000
  Test for the presence of seasonality assuming stability   0.000
  Evolutive seasonality test                                0.027

Identifiable seasonality present

Residual seasonality tests
                                    P.value
qs test on sa                         1.000
qs test on i                          1.000
f-test on sa (seasonal dummies)       1.000
f-test on i (seasonal dummies)        1.000
Residual seasonality (entire series)  1.000
Residual seasonality (last 3 years)   0.999
f-test on sa (td)                     0.994
f-test on i (td)                      0.922
```

5.5. user defined

As presented in the table **??** and in the previous sections the `sa_object` has a defined structure with a defined content. Nevertheless the user can extract additional output from the seasonal adjustment estimation that will be stored under `user_defined` object in a form of a list. In order extract the additional output the extra variables need to be defined as characters under the argument `userdefined` of the functions `x13()` or `tramoseats()`.

For example, to extract the additional tables $c10$ and $d16$ the following need to be specified in the function argument:

```
R> sa_usrdef <- x13(myseries, spec = "RSA3",
R+                  userdefined = c("decomposition.c10", "decomposition.d16"))
R> sa_usrdef$user_defined

Names of additional variables (2):
decomposition.c10, decomposition.d16
```

The list of all available variables can be extracted with the following functions:

- `user_defined_variables("X13-ARIMA")`
- `user_defined_variables("TRAMO-SEATS")`

6. Model specification: creation and modification

The user can also create its own specification, modifying a pre-defined specification (described in tables 1 and 2) or a previously defined specification. For that, they are two functions for each method (RegARIMA model or seasonal adjustment with X-13ARIMA or TRAMO-SEATS):

1. One to create a specification from a pre-defined JDemetra+ model specification. The corresponding functions are: `regarima_spec_x13()` and `regarima_spec_tramoseats()` for the RegARIMA model, and `x13_spec()` and `tramoseats_spec()` for the entire seasonal adjustment model (including the pre-adjustment with a RegARIMA model).
2. One to create a specification from a previous specification or a model. The corresponding functions are: `regarima_spec_x13()` and `regarima_tramoseats()` for the RegARIMA model, and `x13_spec()` and `tramoseats_spec()` for the entire seasonal adjustment model (including the pre-adjustment with a RegARIMA model).

Once the specification is created, the regARIMA model can be performed by `regarima()`, the seasonal adjustment with X-13ARIMA by `x13()` and with TRAMO-SEATS by `tramoseats()`.

For example, to create its own RegARIMA model for the TRAMO-SEATS method by adding an additive outlier in October 2009:

```
R> regarima_ts_spec <- regarima_spec_tramoseats(spec = "TRfull",
R+              usrdef.outliersEnabled = TRUE,
R+              usrdef.outliersType = "AO",
```

```
R+              usrdef.outliersDate = "2009-10-01")
R> regarima_ts_model <- regarima(series = ipi_c_eu[, "EA19"],
R+                               spec = regarima_ts_spec)
R> regarima_ts_model

y = regression model + arima (3, 1, 0, 0, 1, 1)
Log-transformation: no
Coefficients:
          Estimate Std. Error
Phi(1)     0.09633      0.055
Phi(2)    -0.16551      0.055
Phi(3)    -0.29422      0.056
BTheta(1) -0.50637      0.051

             Estimate Std. Error
Monday       -0.23323      0.094
Tuesday      -0.01617      0.094
Wednesday     0.29430      0.095
Thursday     -0.35287      0.095
Friday        0.13248      0.094
Saturday      0.30763      0.095
AO (10-2009) -0.80480      0.787
AO (1-2016)   3.25565      0.807


Residual standard error: 1.226 on 311 degrees of freedom
Log likelihood = -506.6, aic =  1039 aicc =  1040, bic(corrected for length) = 0.6292
```

And to modify the specification of the x-13ARIMA model of the object `sa_usrdef`, defined in section 5.5, changing the seasonal filter and performing a working day adjustment:

```
R> sa_x13_spec <- x13_spec(spec = sa_usrdef,
R+                         tradingdays.option = "WorkingDays",
R+                         x11.seasonalma = "S3X3")
R> sa_x13_model <- x13(series = ipi_c_eu[, "EA19"],
R+                     spec = sa_x13_spec)
```

Almost all the specification variables available in JDemetra+ can be used in **RJDemetra**. For more details see the help of the corresponding function or the documentation of JDemetra+.

To prevent from wrong user-defined specification, they are also automatic checks in **RJDemetra**, like in JDemetra+. For example, to pre-specify an outlier or a user-defined variable you have to enable them (setting the parameter `usrdef.outliersEnabled` or `usrdef.varEnabled` to `TRUE`); or to fix the coefficient of an outlier or a user-defined regressor you have to specify the transformation function (`transform.function`, it cannot be automatic). Those checks are done each time a new specification is create. Therefore, some specifications cannot be set in two stages. For example, fixing the coefficient of an outlier has to be done at the same

time when the outliers are defined. The following code doesn't fix the coefficient of the outlier previously in January 2001:

```
R> regarima_wrong_spec <- regarima_spec_tramoseats(spec = regarima_ts_model,
R+              transform.function = "Log",
R+              usrdef.outliersCoef =  -0.8)
```

To fix it you have to re-defined the outlier:

```
R> regarima_good_spec <- regarima_spec_tramoseats(spec = regarima_ts_model,
R+              transform.function = "Log",
R+              usrdef.outliersType = "AO",
R+              usrdef.outliersDate = "2009-10-01",
R+              usrdef.outliersCoef =  -0.8)
```

The documentation for the functions modifying specifications provide information on the interdependencies between different arguments. The package offers also functions to display different part of the model specification. These are presented under the entry `specification` of the package documentation. For instance, from the example above, we can check which user defined variables were enabled and with which parameters.

In the first case (wrongly specified), an outlier was pre-defined but its coefficient was not fixed:

```
R> s_usrdef(regarima_wrong_spec)

 outlier outlier.coef variables variables.coef
    TRUE        FALSE     FALSE          FALSE

R> s_preOut(regarima_wrong_spec)

  type       date coeff
1   AO 2009-10-01    NA
```

In the second case, the coefficient was correctly fixed:

```
R> s_usrdef(regarima_good_spec)

 outlier outlier.coef variables variables.coef
    TRUE         TRUE     FALSE          FALSE

R> s_preOut(regarima_good_spec)

  type       date coeff
1   AO 2009-10-01  -0.8
```

7. Manipulate JDemetra+ workspaces

RJDemetra allows to interact with JDemetra+ workspace that can be openned by the software. A workspace includes:

- The XML file that enables the user to import the workspace to JDemetra+ and to display it content;
- A folder containing several sub-folfders that correspond to the different types of items created by the user.

Each workspace can contain several multi-processings and each multi-processing stores the results of the seasonal adjustment procedure performed with the TRAMO-SEATS or X-13ARIMA-SEATS methods.

Export models to workspace allows to store easily the seasonal adjustment models, to change the specifications with the JDemetra+ graphical interface and to give models users unfamiliar with R.

7.1. Export a workspace

Four functions have to be used to export models:

- `new_workspace()` to create a workspace;
- `new_multiprocessing()` to create a multi-processing in a workspace;
- `add_sa_item()` to add a seasonal adjustment model to a multi-processing;
- `save_workspace()` to export the workspace.

The following command export the seasonal adjustment models compute by TRAMO-SEATS+ and X-13ARIMA-SEATS:

```
R> myseries <- ipi_c_eu[, "EA19"]
R> sa_x13 <- x13(myseries)
R> sa_ts <- tramoseats(myseries)
```

To create a workspace and a multi-processing names “MP-1”:

```
R> wk <- new_workspace()
R> new_multiprocessing(wk, name = "MP-1")
```

The two models will be added in the multiprocessing “MP1”: the name of the seasonal adjustment model computed with X-13ARIMA-SEATS will be “SA with X13” and the one with TRAMO-SEATS+ will be “SA with TramoSeats”:

```
R> add_sa_item(wk, multiprocessing = "MP-1",
R+             sa_obj = sa_x13, name =  "SA with X13")
R> add_sa_item(wk, multiprocessing =  "MP-1",
R+             sa_obj = sa_ts, name = "SA with TramoSeats")
```

The workspace exported is named "workspace.xml":

```
R> dir <- tempdir()
R> save_workspace(wk, file =  file.path(dir, "workspace.xml"))
```

7.2. Import a workspace

Height functions can be used to import a workspace:

- `load_workspace()` to load a workspace;
- `compute()` to compute the multi-processings: by default a workspace only contains definitions, computation is needed to get the seasonal adjustment model;
- `get_model()` to get the seasonal adjusted models;
- `get_ts()` to get the input raw time series, `get_object()` and `get_all_objects` to navigate inside the workspace (extract a multi-processing or a seasonal adjustment model), `get_name()` to get the names of the multiprocessings or the seasonal adjustment models and `count()` to count the number of multiprocessing or seasonal adjustment models.

For instance, to import the workspace created in section 7.1 and to get the first multiprocessing and the first seasonal adjustment model:

```
R> wk <- load_workspace(file =  file.path(dir, "workspace.xml"))
R> mp1 <- get_object(wk, 1)
R> sa_item1 <- get_object(mp1, 1)
```

To get the number of seasonal adjustment models in the multiprocessing:

```
R> count(mp1)

[1] 2
```

And the name of the first seasonal adjustment model in JDemetra+:

```
R> get_name(sa_item1)

[1] "SA with X13"
```

Raw time series and seasonal adjustment model can now be imported:

```
R> raw_ts <- get_ts(sa_item1)
R> compute(wk)
R> sa_model1 <- get_model(sa_item1, workspace = wk)
```

`get_ts()` and `get_model()` can also be used directly to the workspace or a multiprocessing to import all the raw time series or all the seasonal adjustment model:

- for a multiprocessing the result is a list which each element contains the information of a seasonal adjustment model;
- for a workspace the result is a list of length the number of multi-processing and which each element contains a list with the information of each seasonal adjustment model.

For example to get all raw time series of the workspace and all seasonal adjustmen models of the first multi-processing:

```
R> all_raw_ts <- get_ts(wk)
R> sa_models_of_mp1 <- get_model(mp1, workspace = wk)
```

The imports of seasonal adjustment models from a workspace works well when it has been created throw **RJDemetra**. They may be some troubles when importing a workspace created with JDemetra+, in particular:

- Seasonal adjustment models with ramp effect or intervention variables will be partially imported: the result of the imported model will be correct but changing the specification (throw `x13_spec()` or `tramoseats_spec()`) will erase them.
- Seasonal adjustment models with no pre-processing (X-11 specification) are not supported: `NULL` object will be returned.

8. Advanced usage and examples

By default, `x13()`, `tramoseats()`, `regarima_x13()` and `regarima_tramoseats()` export a lot of diagnostics and indicators. However, it can be really time-consuming, specially when we deal with a lot of times series and if we only need a few indicators. To customize the output and only get what is needed, they are four associated functions extract the Java model associated to the seasonal adjustment: `jx13()`, `jtramoseats()`, `jregarima_x13()` and `jregarima_tramoseats()`. Three other functions can be used to manipulate this objects:

- `get_dictionary()` to get the list of indicators that can be extracted;
- `get_indicators()` to get some indicators;

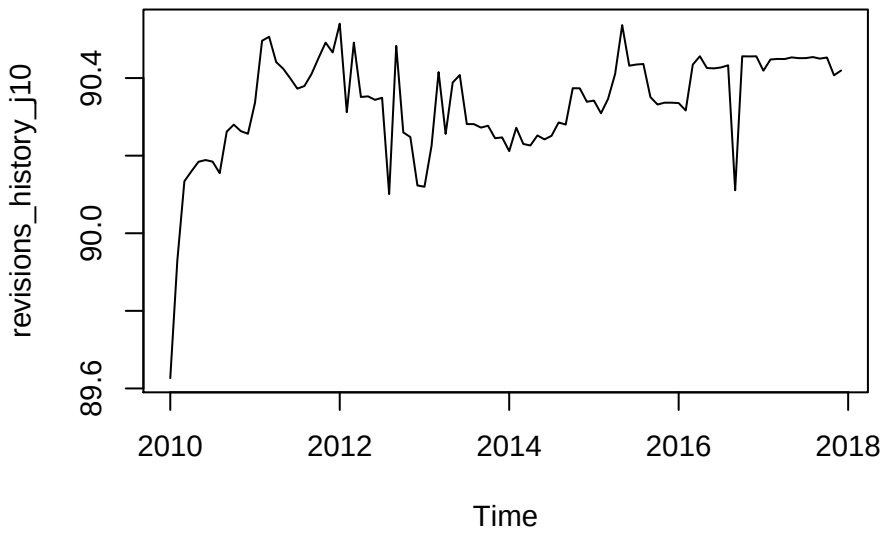
- `jSA2R()` to get the corresponding formatted seasonal adjustment or Reg-ARIMA model.

For example to only get the seasonally adjusted time series:

```
R> sa_jx13 <- jx13(myseries)
R> head(get_dictionary(sa_jx13))

[1] "y"    "y_f"  "t"    "t_f"  "sa"   "sa_f"

R> sa_series <- get_indicators(sa_jx13, "sa")
R> plot(sa_series[["sa"]])
```

To compute the revisions of the seasonal adjusted series of January 2010 with an automatic modeling:

```
R> dates <- window(time(myseries), start = 2010)
R> revisions_history_j10 <- sapply(dates,function(last_date){
R+   sa_jx13 <- jx13(window(myseries, end = last_date))
R+   window(get_indicators(sa_jx13, "sa")[["sa"]],
R+          start = 2010,
R+          end = 2010)
R+ })
R> revisions_history_j10 <- ts(revisions_history_j10,
R+                             start = 2010, frequency = 12)
R> plot(revisions_history_j10)
```



When performing seasonal adjustment on a large database, the most common error comes from the preliminary check used to check the quality of the input series and exclude highly problematic ones (with too much indendical observations and/or missing values). However, no error is returned when using the `jx13()` function but `get_indicators()` will only return `NULL` objects:

```
R> identical_ts <- ts(0,start = 2010, end = 2015, frequency = 12)
R> get_indicators(jx13(identical_ts), "sa", "sa_f")

$sa
NULL

$sa_f
NULL
```

To disable this preliminary check, you just have to create a new specification with the parameter `preliminary.check = FALSE`:

```
R> myspec <- x13_spec(preliminary.check = FALSE)
R> my_indicators <- get_indicators(jx13(identical_ts, myspec)
R+                                 , "sa", "sa_f")
```

It can then be done to for example to perform a large scale seasonal adjustment. Here, with our database on industrial production indices:

```
R> ipi_sa_series <- lapply(colnames(ipi_c_eu),function(series){
R+   sa_jx13 <- jx13(ipi_c_eu[,series], myspec)
R+   get_indicators(sa_jx13, "sa")[["sa"]]
R+ })
R> ipi_sa_series <- do.call(ts.union,ipi_sa_series)
R> colnames(ipi_sa_series) <- colnames(ipi_c_eu)
```

9. Conclusion

10. Acknowledgments

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