Temporal Disaggregation using JDemetra+ (GUI and rjd3bench)

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INE
Instituto Nacional de Estadística

Introduction

Temporal disaggregation Methods: These methods are used to disaggregate a series from low frequency to high-frequency.

When there are high frequency related indicators, these methods provide high frequency estimations for a series whose sums,averages,last or first values are consistent with the observed low frequency series, applying a regression model where it is assumed that monthly observations (if available) of the series to be estimated satisfy a multiple regression with p related series (indicators).

Temporal disaggregation methods

Two types of temporal disaggregation methods:

1. **There is no high frequency related indicator**:
   - **Softened methods**: such as Boot, Fiebes and Lisman (1967). Identical to Denton considering as proxy a series of ones.
   - **Methods of time series**: such as: Wei and Stram (1990).
2. **There is a high frequency related indicator**: these methods are known as optimal methods and among them are Chow-Lin (1971), Fernández (1981), Litterman (1983), Santos Silva and Cardoso, and Proietti.

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High frequency model

High frequency model. It is assumed that monthly observations (if available) of the series to be estimated satisfy a multiple regression with p related series:

$$y = X\beta + u \tag{1}$$

where y is monthly observations (if available) of the series to be estimated, X is the matrix with the regression variables in columns, β is a vector of coefficients and u follows:

- **Chow-Lin**: $u_t = \phi u_{t-1} + \epsilon_t$, with $-1 < \phi < 1$ and ϵ_t white noise
- **Fernandez**: $\nabla u_t = \epsilon_t$, with ϵ_t white noise
- **Litterman**: $\nabla u_t = \phi \nabla u_{t-1} + \epsilon_t$, with $-1 < \phi < 1$ and ϵ_t white noise

Low frequency model

Low frequency model. This is the model directly estimated, obtained premultiplying the high frequency model by a matrix:

$$My = MX\beta + Mu \tag{2}$$

where

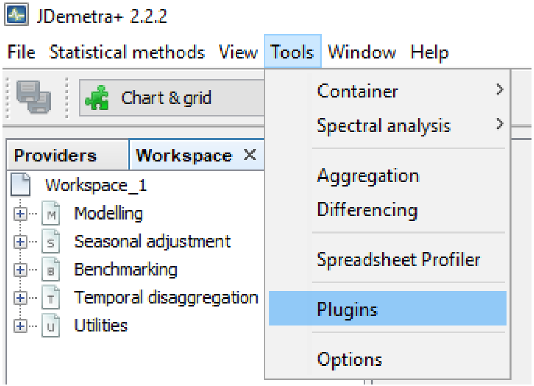
$$M = \begin{pmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & \cdots \\ \cdots & & & & & & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots \end{pmatrix}$$

$E(Mu) = ME(u) = 0$ and $Cov(Mu) = MCov(u)M^{\intercal}$

Install the plug-in I

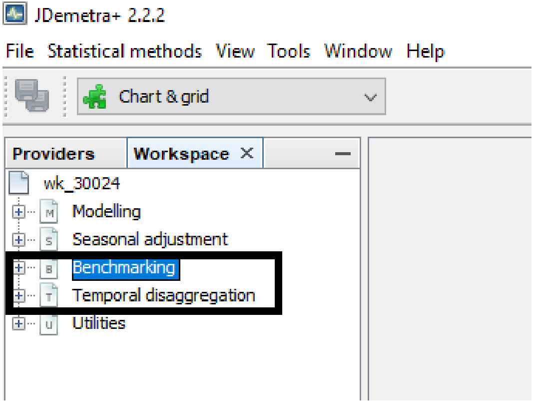
1. **Download the file nbdemetra-benchmarking-2.2.2.nbm**
   https://github.com/nbbrd/jdemetra-benchmarking/releases

2. **Add the plugin in the GUI version 2.2.2**



Install the plug-in II

3. **Benchmarking and Temporal Disaggregation options**



Example

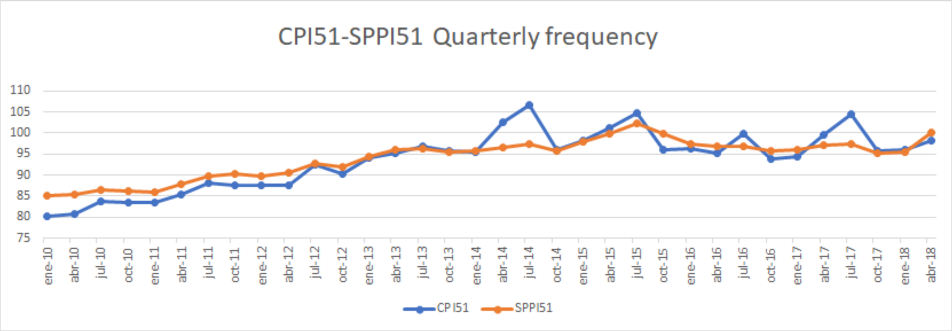
- **Input series**: The Services Producer Price Index without direct taxes with quarterly frequency: Air Transport branch.From the **first quarter of 2010** to the **first quarter of 2018**.
- **Indicator**: The CPI at constant taxes series with monthly frequency: 0733 Air Transport. From **January 2010** to **June 2018.**
- **Output series**: The Services Producer Price Index, air transport branch, with monthly frequency.

Steps to choose the method

1. Graphical Analysis
2. Cointegration Test (optional)
3. Chow-Lin
4. Fernández and Litterman
5. ADL Models: Proietti and Santos Silva and Cardoso
6. Extrapolation

1. Graphical Analysis

Series 51 Air transport: CPI vs SPPI



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2. Cointegration test

High frequency model. It is assumed that monthly observations (if available) of the series to be estimated satisfy a multiple regression with p related series:

$$y = X\beta + u \tag{3}$$

where y is monthly observations (if available) of the series to be estimated, X is the matrix with the regression variables in columns, β is a vector of coefficients and u follows:

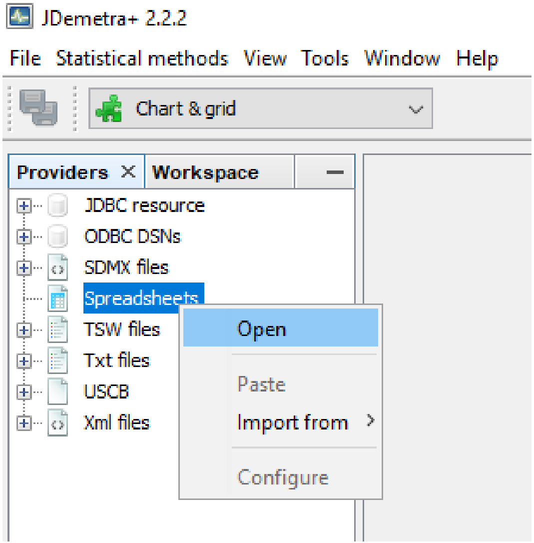
- **Chow-Lin**: $u_t = \phi u_{t-1} + \epsilon_t$, with $-1 < \phi < 1$ and ϵ_t white noise
- **Fernandez**: $\nabla u_t = \epsilon_t$, with ϵ_t white noise
- **Litterman**: $\nabla u_t = \phi \nabla u_{t-1} + \epsilon_t$, with $-1 < \phi < 1$ and ϵ_t white noise

2. Cointegration test

- If the series are **cointegrated in high frequency**, **Chow-Lin** should be applied.
- If the series are **not cointegrated** in high frequency we apply **Fernández and Litterman.**

This test can only be done in low frequency and the test conclusions **cannot be scaled from low to high frequency**.

3. Chow-Lin



JDemetra+ 2.2.2
File Statistical methods View Tools Window Help
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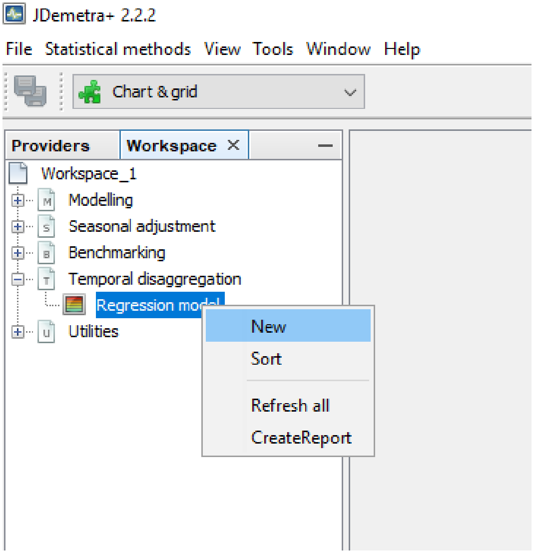
JDBC resource
ODBC DSNs
SDMX files
Spreadsheets
TSW files
Txt files
USCB
Xml files
Open
Paste
Import from
Configure

3. Chow-Lin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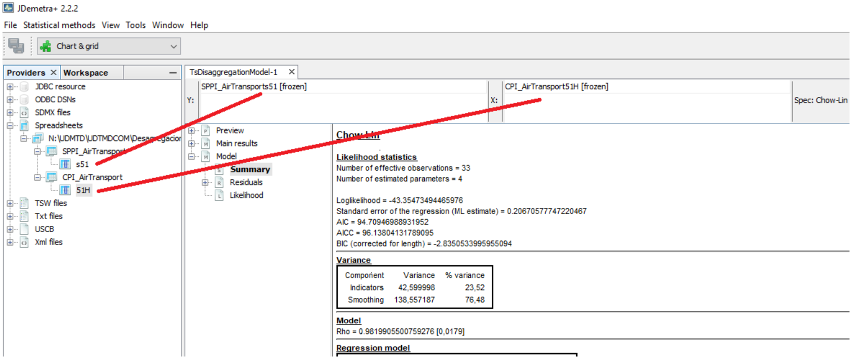
3. Chow-Lin


JDemetra+ 2.2.2
File Statistical methods View Tools Window Help
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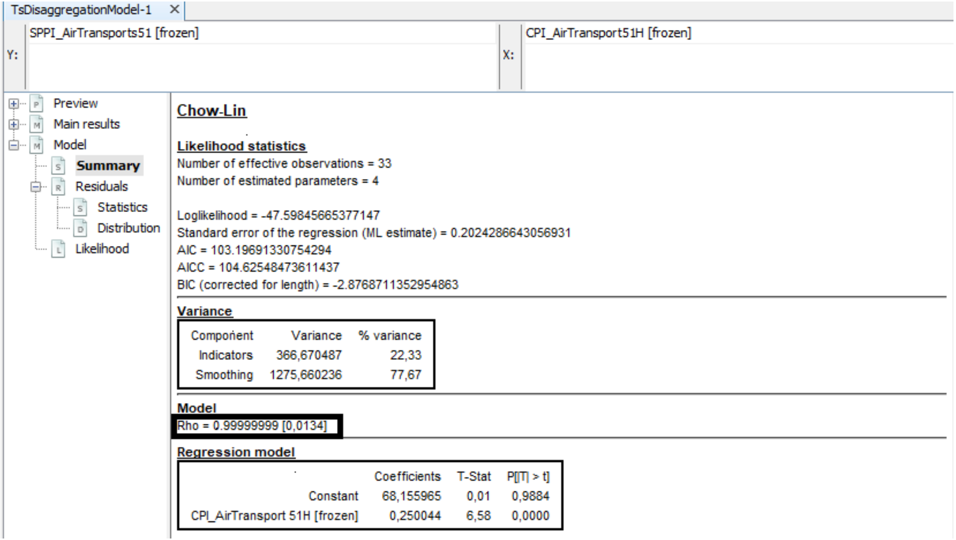
Spreadsheets
SPPI_AirTransport
s51
CPI_AirTransport
51H
TSW files
Txt files
USCB
Xml files
TsDisaggregationModel-1
Y: SPPI_AirTransports51 [frozen]
X: CPI_AirTransport51H [frozen]
Spec: Chow-Lin
Preview
Main results
Model
Summary
Residuals
Likelihood
Chow-Lin
Likelihood statistics
Number of effective observations = 33
Number of estimated parameters = 4
Loglikelihood = -43.35473494465976
Standard error of the regression (ML estimate) = 0.20670577747220467
AIC = 94.70946988931952
AICC = 96.13804131789095
BIC (corrected for length) = -2.8350533995955094
Variance
Component Variance % variance
Indicators 42,599998 23,52
Smoothing 138,557187 76,48
Model
Rho = 0.9819905500759276 [0,0179]
Regression model

3. Chow-Lin



TsDisaggregationModel-1

Y: SPPI_AirTransports51 [frozen]

X: CPI_AirTransport51H [frozen]

- Preview
- Main results
- Model
  - Summary
  - Residuals
    - Statistics
    - Distribution
  - Likelihood

Chow-Lin

Likelihood statistics

Number of effective observations = 33
Number of estimated parameters = 4

Loglikelihood = -47.59845665377147
Standard error of the regression (ML estimate) = 0.2024286643056931
AIC = 103.19691330754294
AICC = 104.62548473611437
BIC (corrected for length) = -2.8768711352954863

Variance

Component	Variance	% variance
Indicators	366,670487	22,33
Smoothing	1275,660236	77,67

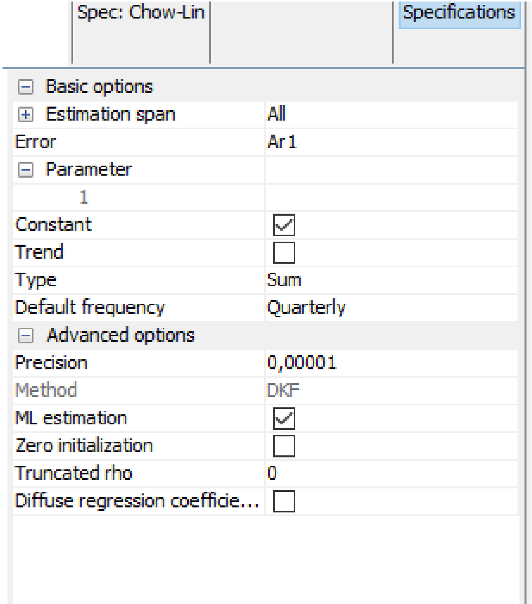
Model

Rho = 0.99999999 [0,0134]

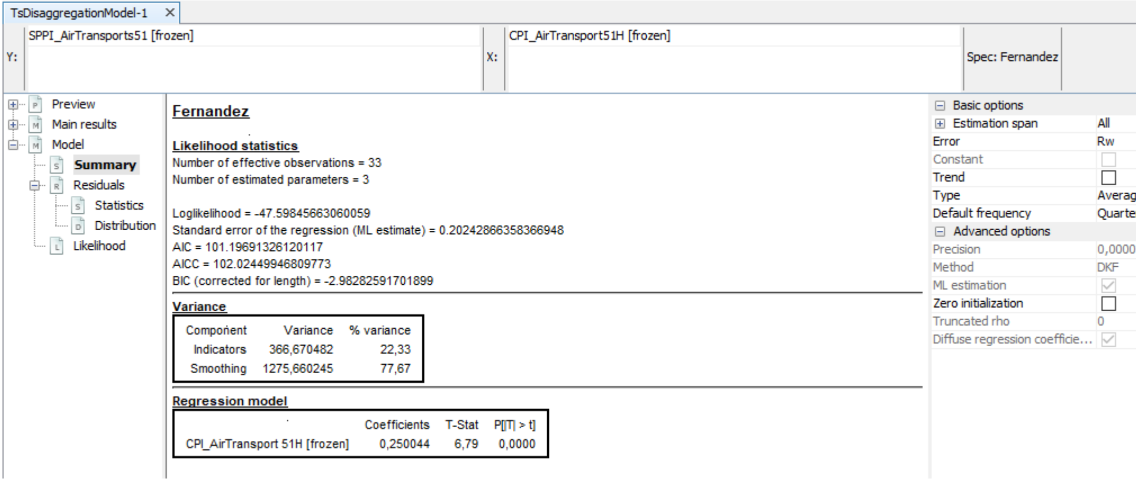
Regression model

	Coefficients	T-Stat	P[|T| > t]
Constant	68,155965	0,01	0,9884
CPI_AirTransport 51H [frozen]	0,250044	6,58	0,0000

3. Chow-Lin


Spec: Chow-Lin
Specifications
Basic options
Estimation span
All
Error
Ar1
Parameter
1
Constant
Trend
Type
Sum
Default frequency
Quarterly
Advanced options
Precision
0,00001
Method
DKF
ML estimation
Zero initialization
Truncated rho
0
Diffuse regression coefficie...

4. Fernandez


TsDisaggregationModel-1
Y:
SPPI_AirTransports51 [frozen]
X:
CPI_AirTransport51H [frozen]
Spec: Fernandez
Preview
Main results
Model
Summary
Residuals
Statistics
Distribution
Likelihood
Fernandez
Likelihood statistics
Number of effective observations = 33
Number of estimated parameters = 3
Loglikelihood = -47.59845663060059
Standard error of the regression (ML estimate) = 0.20242866358366948
AIC = 101.19691326120117
AICC = 102.02449946809773
BIC (corrected for length) = -2.98282591701899
Variance
Component Variance % variance
Indicators 366,670482 22,33
Smoothing 1275,660245 77,67
Regression model
Coefficients T-Stat P[|T| > t]
CPI_AirTransport 51H [frozen] 0,250044 6,79 0,0000
Basic options
Estimation span All
Error Rw
Constant
Trend
Type Averag
Default frequency Quarte
Advanced options
Precision 0,0000
Method DKF
ML estimation
Zero initialization
Truncated rho 0
Diffuse regression coefficie...

4. Litterman

Preview
Main results
Model
Summary
Residuals
Likelihood

Litterman

Likelihood statistics

Number of effective observations = 33
Number of estimated parameters = 4

Loglikelihood = -42.97055716264021
Standard error of the regression (ML estimate) = 0.15681419618642797
AIC = 93.94111432528042
AICC = 95.36968575385185
BIC (corrected for length) = -3.387522952751936

Variance

Component	Variance	% variance
Indicators	350,623615	21,19
Smoothing	1304,120243	78,81

Model

Rho = 0.29166666374999994 [0,3218]

Regression model

	Coefficients	T-Stat	P[|T| > t]
Hoja1 51H [frozen]	0,244512	7,01	0,0000

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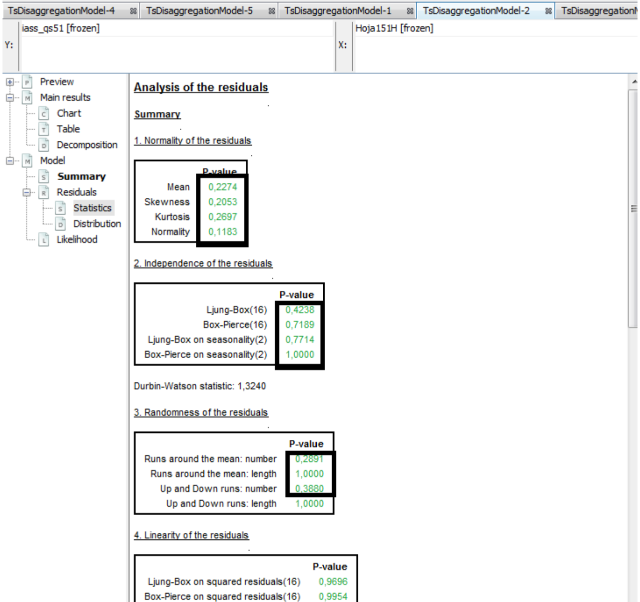
4. Analysis of the residuals



4. Disaggregated series (Fernández)

TsDisaggregationModel-1

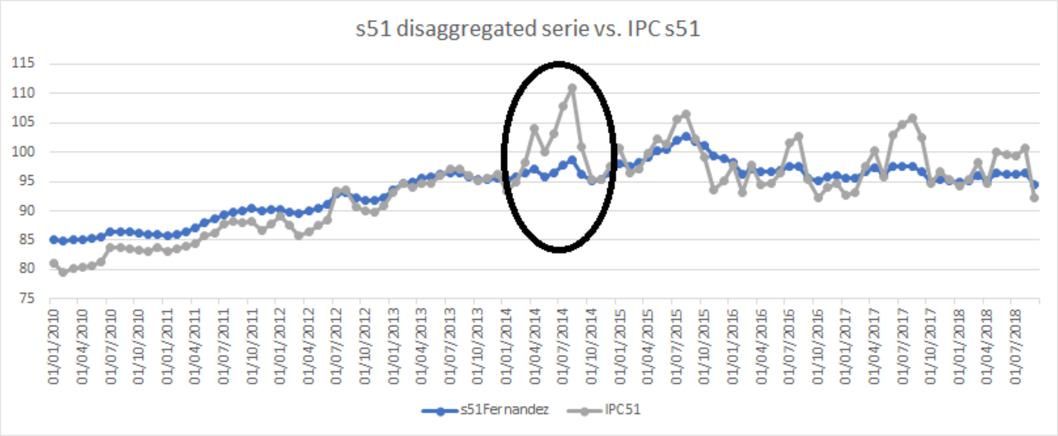
Y: SPPI_AirTransports51 [frozen]

X: CPI_AirTransport51H [frozen]

- Preview
- Main results
  - Chart
  - Table
  - Decomposition
- Model
  - **Summary**
  - Residuals
    - Statistics
    - Distribution
  - Likelihood

	disaggregation	disggregationError
1-2010	85,188	0,425
2-2010	84,84	0,292
3-2010	85,055	0,397
4-2010	85,131	0,373
5-2010	85,305	0,285
6-2010	85,636	0,371
7-2010	86,433	0,371
8-2010	86,488	0,285
9-2010	86,459	0,37
10-2010	86,29	0,37
11-2010	86,101	0,285
12-2010	86,094	0,37
1-2011	85,734	0,37
2-2011	85,936	0,285
3-2011	86,423	0,37
4-2011	87,166	0,37
5-2011	88,071	0,285
6-2011	88,612	0,37
7-2011	89,338	0,37

4. Results: Air transport (Fernández)



rjd3bench

- https://github.com/rjdemetra/rjd3bench/releases
- temporaldisagggregation function:

```
function (series, constant = T, trend = F, indicators = NULL,
    model = c("Ar1", "Rw", "RwAr1"), freq = 4, conversion = c("Sum",
        "Average", "Last", "First", "UserDefined"), conversion.obsposition = 1,
    rho = 0, rho.fixed = F, rho.truncated = 0, zeroinitialization = F,
    diffuse.algorithm = c("SqrtDiffuse", "Diffuse", "Augmented"),
    diffuse.regressors = F)
```

5. ADL Models

In **Santos Silva and Cardoso** the model is:

$$y_t = \phi y_{t-1} + x_t\beta + \epsilon_t \tag{4}$$

In **Proietti** the model is:

$$y_t = \phi y_{t-1} + m + gt + x_t\beta + x_{t-1}\gamma + \epsilon_t \tag{5}$$

where ϵ_t is a white noise process with variance σ^2

5. ADL Models

- Likelihood ratio test:
  - Proietti and Santos Silva Cardoso
  - Proietti and Chow-Lin
- Analysis of the residuals

6. Extrapolation

Using 8 quarters of extrapolated data.

- Chow-Lin:
$$RMSE = 0{,}60 \tag{6}$$

- Fernandez:
$$RMSE = 0{,}59 \tag{7}$$

- Fernandez:
$$RMSE = 0{,}70 \tag{8}$$