Package ‘sovereign’

January 4, 2022

Title State-Dependent Empirical Analysis

Version 1.2.1

Description A set of tools for state-dependent empirical analysis through both VAR- and local projection-based state-dependent forecasts, impulse response functions, historical decompositions, and forecast error variance decompositions.

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URL https://github.com/tylerJPike/sovereign,
https://tylerjpike.github.io/sovereign/

BugReports https://github.com/tylerJPike/sovereign/issues

Encoding UTF-8

RoxygenNote 7.1.1

Imports broom, dplyr, future, furrr, ggplot2, gridExtra, lmtest, lubridate, magrittr, mclust, purrr, randomForest, sandwich, stats, stringr, strucchange, tidyr, xts, zoo

Suggests testthat, knitr, rmarkdown, quantmod, covr

VignetteBuilder knitr

NeedsCompilation no

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R topics documented:

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Implement the deterministic volatility correction method of Lenza, Michele and Giorgio Primiceri "How to Estimate a VAR after March 2020" (2020) [NBER Working Paper]. Correction factors are estimated via maximum likelihood.

Usage

\[
covid_volatility_correction(var, theta_initial = c(5, 2, 1.5, 0.8))
\]

Arguments

<table>
<thead>
<tr>
<th>var</th>
<th>VAR object</th>
</tr>
</thead>
<tbody>
<tr>
<td>theta_initial</td>
<td>double: four element vector with scaling parameters, theta in Lenza and Primiceri (2020)</td>
</tr>
</tbody>
</table>

Value

<table>
<thead>
<tr>
<th>var</th>
<th>object</th>
</tr>
</thead>
<tbody>
<tr>
<td>var</td>
<td>object</td>
</tr>
</tbody>
</table>
**FEVD**

**See Also**

- VAR()
- var_irf()
- var_fevd()
- var_hd()

**Examples**

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2018-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var = sovereign::VAR(
  data = Data,
  horizon = 10,
  freq = 'month',
  lag.ic = 'BIC',
  lag.max = 4)

# correct VAR for COVID shock
var = sovereign::covid_volatility_correction(var)

# impulse response functions
var.irf = sovereign::var_irf(var)

# forecast error variance decomposition
var.fevd = sovereign::var_fevd(var)

# historical shock decomposition
var.hd = sovereign::var_hd(var)
```

**FEVD**

*Estimate forecast error variance decomposition*

**Description**

Estimate the forecast error variance decomposition for VARs with either short or 'IV-short' structural errors. See VAR and RVAR documentation for details regarding structural errors.
Usage

FEVD(model, horizon = 10, scale = TRUE)

Arguments

model: VAR or RVAR class object
horizon: int: number of periods
scale: boolean: scale variable contribution as percent of total error

Value

long-form data.frame

See Also

VAR()
var_fevd()
RVAR()
rvar_fevd()

Examples

# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var =
  sovereign::VAR(
    data = Data,
    horizon = 10,
    freq = 'month',
    lag.ic = 'BIC',
    lag.max = 4)

# impulse response functions
var.irf = sovereign::IRF(var)

# forecast error variance decomposition
var.fevd = sovereign::FEVD(var)

# historical shock decomposition
var.hd = sovereign::HD(var)
Description

Estimate the historical decomposition for VARs with either 'short' or 'IV-short' structural errors. See VAR and RVAR documentation for details regarding structural errors.

Usage

HD(model)

Arguments

model VAR or RVAR class object

Value

long-from data.frame

See Also

VAR()
var_hd()
RVAR()
rvar_hd()

Examples

# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date("2000-01-01"), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var =
  sovereign::VAR(
    data = Data,
    horizon = 10,
    freq = 'month',
    lag.ic = 'BIC',
    lag.max = 4)
# impulse response functions
var.irf = sovereign::IRF(var)

# forecast error variance decomposition
var.fevd = sovereign::FEVD(var)

# historical shock decomposition
var.hd = sovereign::HD(var)

---

IRF

| Estimate impulse response functions |

**Description**
See VAR, RVAR, LP, and RLP documentation for details regarding models and structural errors.

**Usage**

```r
IRF(
    model,
    horizon = 10,
    CI = c(0.1, 0.9),
    bootstrap.type = "auto",
    bootstrap.num = 100,
    bootstrap.parallel = FALSE,
    bootstrap.cores = -1
)
```

**Arguments**

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>model</code></td>
<td>VAR, RVAR, LP, or RLP class object</td>
</tr>
<tr>
<td><code>horizon</code></td>
<td>int: number of periods</td>
</tr>
<tr>
<td><code>CI</code></td>
<td>numeric vector: c(lower ci bound, upper ci bound)</td>
</tr>
<tr>
<td><code>bootstrap.type</code></td>
<td>string: bootstrapping technique to use ('auto', 'standard', or 'wild'); if auto then wild is used for IV or IV-short, else standard is used</td>
</tr>
<tr>
<td><code>bootstrap.num</code></td>
<td>int: number of bootstraps</td>
</tr>
<tr>
<td><code>bootstrap.parallel</code></td>
<td>boolean: create IRF draws in parallel</td>
</tr>
<tr>
<td><code>bootstrap.cores</code></td>
<td>int: number of cores to use in parallel processing; -1 detects and uses half the available cores</td>
</tr>
</tbody>
</table>
**Value**

data frame with columns `target`, `shock`, `horizon`, `response.lower`, `response`, `response.upper`;
regime-based models return a list with a data frame per regime.

**See Also**

`var_irf()`  
`rvar_irf()`  
`lp_irf()`  
`rlp_irf()`

**Examples**

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date("2000-01-01"), by = "month", length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var = 
  sovereign::VAR(
    data = Data,
    horizon = 10,
    freq = "month",
    lag.ic = "BIC",
    lag.max = 4

# impulse response function
var.irf = sovereign::IRF(var)

# local projection forecasts
lp = 
  sovereign::LP(
    data = Data,
    horizon = c(1:10),
    lag.ic = "AIC",
    lag.max = 4,
    type = "both",
    freq = "month")

# LP impulse response function
lp.irf = sovereign::IRF(lp)
```
Estimate local projections

Usage

LP(
    data,  
    horizons = 1,  
    freq = "month",  
    type = "const",  
    p = 1,  
    lag.ic = NULL,  
    lag.max = NULL,  
    NW = FALSE,  
    NW_lags = NULL,  
    NW_prewhite = NULL
)

Arguments

data data.frame, matrix, ts, xts, zoo: Endogenous regressors
horizons int: forecast horizons
freq string: frequency of data ("day", "week", "month", "quarter", or "year")
type string: type of deterministic terms to add ("none", "const", "trend", or "both")
p int: lags
lag.ic string: information criterion to choose the optimal number of lags ("AIC" or "BIC")
lag.max int: maximum number of lags to test in lag selection
NW boolean: Newey-West correction on variance-covariance matrix
NW_lags int: number of lags to use in Newey-West correction
NW_prewhite boolean: TRUE prewhite option for Newey-West correction (see sandwich::NeweyWest)

Value

list object with elements data, model, forecasts, residuals; if there is more than one forecast horizon estimated, then model, forecasts, residuals will each be a list where each element corresponds to a single horizon

References

See Also

LP()
lp_irf()
RLP()
rlp_irf()

Examples

# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# local projection forecasts
lp =
  sovereign::LP(
    data = Data,
    horizon = c(1:10),
    lag.ic = 'AIC',
    lag.max = 4,
    type = 'both',
    freq = 'month')

# impulse response function
irf = sovereign::lp_irf(lp)

---

lp_irf

Estimate impulse response functions

Description

Estimate impulse response functions

Usage

lp_irf(lp, CI = c(0.1, 0.9), regime = NULL)

Arguments

lp
  LP output

CI
  numeric vector: c(lower ci bound, upper ci bound)

regime
  string: indicates regime index column of data
Value

long-form data.frame with one row per target-shock-horizon identifier

See Also

LP()
lp_irf()
RLP()
rlp_irf()

Examples

# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# local projection forecasts
lp =
  sovereign::LP(
    data = Data,
    horizon = c(1:10),
    lag.ic = 'AIC',
    lag.max = 4,
    type = 'both',
    freq = 'month')

# impulse response function
irf = sovereign::lp_irf(lp)

Description

Chart residuals

Usage

plot_error(residuals, series = NULL, verticle = FALSE)
**plot_fevd**

**Arguments**
- residuals: data.frame: sovereign residuals object
- series: string: series to plot (default to all series)
- verticle: boolean: If true then stack all plots into one column

**Value**
grid of ggplot2 graphs

**Description**
Chart FEVDs

**Usage**
plot_fevd(fevd, responses = NULL, verticle = FALSE)

**Arguments**
- fevd: fevd object
- responses: string vector: responses to plot
- verticle: boolean: If true then stack all plots into one column

**Value**
grid of ggplot2 graphs

**plot_forecast**  

**Chart forecasts**

**Description**
Chart forecasts

**Usage**
plot_forecast(forecasts, series = NULL, verticle = FALSE)
plot_individual_error

Arguments

forecasts data.frame: sovereign forecast object
series string: series to plot (default to all series)
verticle boolean: If true then stack all plots into one column

Value

grid of ggplot2 graphs

plot_hd  

Chart HDs

Description

Chart HDs

Usage

plot_hd(hd, verticle = FALSE)

Arguments

hd hd object
verticle boolean: If true then stack all plots into one column

Value

grid of ggplot2 graphs

plot_individual_error  

Chart individual residuals

Description

Chart individual residuals

Usage

plot_individual_error(
  data,
  target,
  title = NULL,
  ylab = NULL,
  freq = NULL,
  zeroline = FALSE
)
plot_individual_fevd

Arguments

data
  data.frame: sovereign residuals object

target
  string: series to plot

title
  string: chart title

ylab
  string: y-axis label

defreq
  string: frequency (acts as sub-title)

zeroline
  boolean: if TRUE then add a horizontal line at zero

Value

ggplot2 chart

Description

Plot an individual FEVD

Usage

plot_individual_fevd(fevd, response.var, title, ylab)

Arguments

fevd
  fevd object

response.var
  string: name of variable to treat as the response

title
  string: title of the chart

ylab
  string: y-axis label

Value

ggplot2 graph
plot_individual_forecast

*Chart individual forecast*

**Description**

Chart individual forecast

**Usage**

```r
plot_individual_forecast(
  data,
  target,
  title = NULL,
  ylab = NULL,
  freq = NULL,
  zeroline = FALSE
)
```

**Arguments**

- `data`: data.frame: sovereign model forecast
- `target`: string: series to plot
- `title`: string: chart title
- `ylab`: string: y-axis label
- `freq`: string: frequency (acts as sub-title)
- `zeroline`: boolean: if TRUE then add a horizontal line at zero

**Value**

ggplot2 chart

___________________________

plot_individual_hd

*Plot an individual HD*

**Description**

Plot an individual HD

**Usage**

```r
plot_individual_hd(hd, target.var, title)
```
**plot_individual_irf**

**Arguments**

- `hd`: hd object
- `target.var`: string: name of variable to decompose into shocks
- `title`: string: title of the chart

**Value**

- ggplot2 graph

---

**plot_individual_irf**  
*Plot an individual IRF*

**Description**

Plot an individual IRF

**Usage**

```r
plot_individual_irf(irf, shock.var, response.var, title, ylab)
```

**Arguments**

- `irf`: irf object
- `shock.var`: string: name of variable to treat as the shock
- `response.var`: string: name of variable to treat as the response
- `title`: string: title of the chart
- `ylab`: string: y-axis label

**Value**

- ggplot2 graph
### plot.irf  

**Chart IRFs**

**Description**

Chart IRFs

**Usage**

plot_irf(irf, shocks = NULL, responses = NULL, verticle = FALSE)

**Arguments**

- `irf` : irf object
- `shocks` : string vector: shocks to plot
- `responses` : string vector: responses to plot
- `verticle` : boolean: If true then stack all plots into one column

**Value**

grid of ggplot2 graphs

---

### regimes  

**Identify regimes via unsupervised ML algorithms**

**Description**


**Usage**

regimes(data, method = "rf", regime.n = NULL)

**Arguments**

- `data` : data.frame, matrix, ts, xts, zoo: Endogenous regressors
- `method` : string: regime assignment technique ("rf", "kmeans", "EM", or "BP")
- `regime.n` : int: number of regimes to estimate (applies to kmeans and EM)

**Value**

data as a data.frame with a regime column assigning rows to mutually exclusive regimes
Examples

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate regime
regime =
  sovereign::regimes(
    data = Data,
    method = 'kmeans',
    regime.n = 3)
```

**RLP**

*Estimate regime-dependent local projections*

**Description**

Estimate a regime-dependent local projection (i.e. a state-dependent LP), with an exogenous state indicator, of the specification:

\[
Y_{t+h} = X_t \beta_s + \epsilon_t
\]

where \( t \) is the time index, and \( s \) is a mutually exclusive state of the world observed at time \( t \). When the regime vector is not supplied by the user, then a two-state regime series is estimated via random forest.

**Usage**

```r
RLP(
  data,
  horizons = 1,
  freq = "month",
  type = "const",
  p = 1,
  lag.ic = NULL,
  lag.max = NULL,
  NW = FALSE,
  NW_lags = NULL,
  NW_prewhite = NULL,
  regime = NULL,
  regime.method = "rf",
  regime.n = 2
)
```
**Arguments**

- `data` : data.frame, matrix, ts, xts, zoo: Endogenous regressors
- `horizons` : int: forecast horizons
- `freq` : string: frequency of data ('day', 'week', 'month', 'quarter', or 'year')
- `type` : string: type of deterministic terms to add ('none', 'const', 'trend', or 'both')
- `p` : int: lags
- `lag.ic` : string: information criterion to choose the optimal number of lags ('AIC' or 'BIC')
- `lag.max` : int: maximum number of lags to test in lag selection
- `NW` : boolean: Newey-West correction on variance-covariance matrix
- `NW_lags` : int: number of lags to use in Newey-West correction
- `NW_prewhite` : boolean: TRUE prewhite option for Newey-West correction (see sandwich::NeweyWest)
- `regime` : string: name or regime assignment vector in the design matrix (data)
- `regime.method` : string: regime assignment technique ('rf', 'kmeans', 'EM', 'BP')
- `regime.n` : int: number of regimes to estimate (applies to kmeans and EM)

**Value**

- list of lists, one list per regime, each regime with objects with elements `data`, `model`, `forecasts`, `residuals`; if there is more than one forecast horizon estimated, then `model`, `forecasts`, `residuals` will each be a list where each element corresponds to a single horizon

**References**


**See Also**

- `LP()`
- `lp_irf()`
- `RLP()`
- `rlp_irf()`

**Examples**

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)
# add regime
Data = dplyr::mutate(Data, reg = dplyr::if_else(AA > median(AA), 1, 0))
```
# local projection forecasts
rlp = sovereign::RLP(
data = Data,
regime = 'reg',
horizon = c(1:10),
freq = 'month',
p = 1,
type = 'const',
NW = TRUE,
NW_lags = 1,
NW_prewhite = FALSE)

# impulse response function
rirf = sovereign::rlp_irf(rlp)

---

**rlp_irf**

*Estimate regime-dependent impulse response functions*

**Description**

Estimate regime-dependent impulse response functions

**Usage**

`rlp_irf(rlp, CI = c(0.1, 0.9))`

**Arguments**

- **rlp** RLP output
- **CI** numeric vector: c(lower ci bound, upper ci bound)

**Value**

list of long-form data.frame with one row per target-shock-horizon identifier

**See Also**

LP()
lp_irf()
RLP()
rlp_irf()
Examples

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)
# add regime
Data = dplyr::mutate(Data, reg = dplyr::if_else(AA > median(AA), 1, 0))

# local projection forecasts
rlp =
  sovereign::RLP(
    data = Data,
    regime = 'reg',
    horizon = c(1:10),
    freq = 'month',
    p = 1,
    type = 'const',
    NW = TRUE,
    NW_lags = 1,
    NW_prewhte = FALSE)

# impulse response function
rirf = sovereign::rlp_irf(rlp)
```

---

**RVAR**

*Estimate regime-dependent VAR, SVAR, or Proxy-SVAR*

**Description**

Estimate a regime-dependent VAR (i.e. a state-dependent VAR), with an exogenous state indicator, of the specification:

\[ Y_{t+1} = X_t \beta_s + \epsilon_t \]

where \( t \) is the time index, \( Y \) is the set of outcome vectors, \( X \) the design matrix (of \( p \) lagged values of \( Y \)), and \( s \) is a mutually exclusive state of the world observed at time \( t \). When the regime vector is not supplied by the user, then a two-state regime series is estimated via random forest.

**Usage**

```r
RVAR(
  data,  
  horizon = 10,  
  freq = "month",
```
type = "const",
  p = 1,
  lag.ic = NULL,
  lag.max = NULL,
  regime = NULL,
  regime.method = "rf",
  regime.n = 2,
  structure = "short",
  instrument = NULL,
  instrumented = NULL
)

Arguments

data data.frame, matrix, ts, xts, zoo: Endogenous regressors
horizon int: forecast horizons
freq string: frequency of data ('day', 'week', 'month', 'quarter', or 'year')
type string: type of deterministic terms to add ('none', 'const', 'trend', or 'both')
p int: lags
lag.ic string: information criterion to choose the optimal number of lags ('AIC' or 'BIC')
lag.max int: maximum number of lags to test in lag selection
regime string: name or regime assignment vector in the design matrix (data)
regime.method string: regime assignment technique ('rf', 'kmeans', 'EM', or 'BP')
regime.n int: number of regimes to estimate (applies to kmeans and EM)
structure string: type of structural identification strategy to use in model analysis (NA, 'short', 'IV', or 'IV-short')
instrument string: name of instrumental variable contained in the data matrix
instrumented string: name of variable to be instrumented in IV and IV-short procedure; default is the first non-date variable in data

Details

The regime-dependent VAR is a generalization of the popular threshold VAR - which trades off estimating a threshold value for an endogenous variable for accepting an exogenous regime that can be based on information from inside or outside of the system, with or without parametric assumptions, and with or without timing restrictions. Moreover, the RVAR may be extended to include structural shocks, including the use of instrumental variables.

State dependence. The RVAR augments the traditional VAR by allowing state-dependence in the coefficient matrix. The RVAR differs from the more common threshold VAR (TVAR), due to the fact that states are exogenously determined. As a result, the states (i.e. regimes) do not need to be based on information inside the model, moreover, regimes can be determined by any process the user determines best fits their needs. For example, regimes based on NBER dated recessions and expansions are based on a judgmental process considering hundreds of series, potentially none of
which are in the VAR being modeled. Alternatively, a user may use unsupervised machine learning to assign regimes - this is the process the `sovereign::regimes` function facilitates.

**Structural shocks.** See Sims (1980) for details regarding the baseline vector-autoregression (VAR) model. The VAR may be augmented to become a structural VAR (SVAR) with one of three different structural identification strategies:

1. short-term impact restrictions via Cholesky decomposition, see Christiano et al (1999) for details (`structure = 'short'`)
2. external instrument identification, i.e. a Proxy-SVAR strategy, see Mertens and Ravn (2013) for details (`structure = 'IV'`)
3. or a combination of short-term and IV identification via Lunsford (2015) (`structure = 'IV-short'`)

Note that including structure does not change the estimation of model coefficients or forecasts, but does change impulse response functions, forecast error variance decomposition, and historical decompositions. Historical decompositions will not be available for models using the 'IV' structure. Additionally note that only one instrument may be used in this estimation routine.

**Value**

List of lists, where each regime is a list with items:

1. data: data.frame with endogenous variables and 'date' column.
2. model: list with data.frame of model coefficients (in psuedo-companion form), data.frame of coefficient standard errors, integer of lags p, integer of horizons, string of frequency, string of deterministic term type, numeric of log-likelihood, regime indicator
3. forecasts: list of data.frames per horizon; data.frame with column for date (day the forecast was made), forecast.date (the date being forecasted), target (variable forecasted), and forecast
4. residuals: list of data.frames per horizon; data.frame of residuals
5. structure: string denoting which structural identification strategy will be used in analysis (or NA)
6. instrument: data.frame with 'date' column and 'instrument' column (or NULL)
7. instrumented: string denoting which column will be instrumted in 'IV' and 'IV-short' strategies (or NULL)

**References**

2. Lunsford, Kurt "Identifying Structural VARs with a Proxy Variable and a Test for a Weak Proxy" 2015.
See Also

VAR()
RVAR()
IRF()
FEVD()
HD()

Examples

```r
# simple time series
AA <- c(1:100) + rnorm(100)
BB <- c(1:100) + rnorm(100)
CC <- AA + BB + rnorm(100)
date <- seq.Date(from = as.Date("2000-01-01"), by = "month", length.out = 100)
Data <- data.frame(date = date, AA, BB, CC)
Data <- dplyr::mutate(Data, reg = dplyr::if_else(AA > median(AA), 1, 0))

# estimate regime-dependent VAR
rvar =
  sovereign::RVAR(
    data = Data,
    horizon = 10,
    freq = "month",
    regime.method = "rf",
    regime.n = 2,
    lag.ic = "BIC",
    lag.max = 4)

# impulse response functions
rvar.irf = sovereign::rvar_irf(rvar)

# forecast error variance decomposition
rvar.fevd = sovereign::rvar_fevd(rvar)

# historical shock decomposition
rvar.hd = sovereign::rvar_hd(rvar)
```

**rvar_fevd**  Estimate regime-dependent forecast error variance decomposition

**Description**

Estimate forecast error variance decomposition for RVARs with either short or 'IV-short' structural errors.
Usage

```r
rvar_fevd(rvar, horizon = 10, scale = TRUE)
```

Arguments

- `rvar` (RVAR output)
- `horizon` (int: number of periods)
- `scale` (boolean: scale variable contribution as percent of total error)

Value

- list, each regime returns its own long-form data.frame

See Also

`VAR()`
`var_irf()`
`var_fevd()`
`var_hd()`
`RVAR()`
`rvar_irf()`
`rvar_fevd()`
`rvar_hd()`

Examples

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date("2000-01-01"), by = "month", length.out = 100)
Data = data.frame(date = date, AA, BB, CC)
Data = dplyr::mutate(Data, reg = dplyr::if_else(AA > median(AA), 1, 0))

# estimate VAR
rvar =
  sovereign::RVAR(
    data = Data,
    horizon = 10,
    freq = "month",
    regime.method = "rf",
    regime.n = 2,
    lag.ic = "BIC",
    lag.max = 4)

# impulse response functions
```
\[ rvar_{\text{hd}} = \text{sovereign}::\text{rvar}_{\text{hd}}(rvar) \]

\# forecast error variance decomposition
\[ rvar_{\text{fevd}} = \text{sovereign}::\text{rvar}_{\text{fevd}}(rvar) \]

\# historical shock decomposition
\[ rvar_{\text{hd}} = \text{sovereign}::\text{rvar}_{\text{hd}}(rvar) \]

\section*{rvar_{\text{hd}}}

\textit{Estimate regime-dependent historical decomposition}

\section*{Description}

Estimate historical decomposition for RVARs with either short or 'IV-short' structural errors.

\section*{Usage}

\[ \text{rvar}_{\text{hd}}(rvar) \]

\section*{Arguments}

\begin{itemize}
  \item \texttt{rvar} \hspace{1em} RVAR output
\end{itemize}

\section*{Value}

long form data.frames

\section*{See Also}

\begin{itemize}
  \item \texttt{VAR()}
  \item \texttt{var_{\text{irf}}()}
  \item \texttt{var_{\text{fevd}}()}
  \item \texttt{var_{\text{hd}}()}
  \item \texttt{RVAR()}
  \item \texttt{rvar_{\text{irf}}()}
  \item \texttt{rvar_{\text{fevd}}()}
  \item \texttt{rvar_{\text{hd}}()}
\end{itemize}
**rvar_irf**

Estimate regime-dependent impulse response functions

**Description**

Estimate regime-dependent impulse response functions

**Usage**

```r
rvar_irf( 
  rvar, 
  horizon = 10, 
  CI = c(0.1, 0.9), 
  bootstrap.type = "auto", 
  bootstrap.num = 100, 
)```

**Examples**

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)
Data = dplyr::mutate(Data, reg = dplyr::if_else(AA > median(AA), 1, 0))

# estimate VAR
rvar =
  sovereign::RVAR( 
    data = Data, 
    horizon = 10, 
    freq = 'month', 
    regime.method = 'rf', 
    regime.n = 2, 
    lag.ic = 'BIC', 
    lag.max = 4)

# impulse response functions
rvar.irf = sovereign::rvar_irf(rvar)

# forecast error variance decomposition
rvar.fevd = sovereign::rvar_fevd(rvar)

# historical shock decomposition
rvar.hd = sovereign::rvar_hd(rvar)
```
### Arguments

- **rvar**: RVAR output
- **horizon**: int: number of periods
- **CI**: numeric vector: c(lower ci bound, upper ci bound)
- **bootstrap.type**: string: bootstrapping technique to use ('auto', 'standard', or 'wild'); if auto then wild is used for IV or IV-short, else standard is used
- **bootstrap.num**: int: number of bootstraps
- **bootstrap.parallel**: boolean: create IRF draws in parallel
- **bootstrap.cores**: int: number of cores to use in parallel processing; -1 detects and uses half the available cores

### Value

list of regimes, each with data.frame of columns target, shock, horizon, response.lower, response, response.upper

### See Also

- `VAR()`
- `var_irf()`
- `var_fevd()`
- `RVAR()`
- `rvar_irf()`
- `rvar_fevd()`

### Examples

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)
Data = dplyr::mutate(Data, reg = dplyr::if_else(AA > median(AA), 1, 0))

# estimate VAR
rvar = sovereign::RVAR(
  bootstrap.parallel = FALSE,
  bootstrap.cores = -1
)```
data = Data,
horizon = 10,
freq = 'month',
regime.method = 'rf',
regime.n = 2,
lag.ic = 'BIC',
lag.max = 4)

# impulse response functions
rvar.irf = sovereign::rvar_irf(rvar)

# forecast error variance decomposition
rvar.fevd = sovereign::rvar_fevd(rvar)

# historical shock decomposition
rvar.hd = sovereign::rvar_hd(rvar)

---

VAR Estimate VAR, SVAR, or Proxy-SVAR

**Description**

Estimate VAR, SVAR, or Proxy-SVAR

**Usage**

```r
VAR(
  data, 
  horizon = 10,
  freq = "month",
  type = "const",
  p = 1,
  lag.ic = NULL,
  lag.max = NULL,
  structure = "short",
  instrument = NULL,
  instrumented = NULL
)
```

**Arguments**

- **data**: data.frame, matrix, ts, xts, zoo: Endogenous regressors
- **horizon**: int: forecast horizons
- **freq**: string: frequency of data (‘day’, ‘week’, ‘month’, ‘quarter’, or ‘year’)
- **type**: string: type of deterministic terms to add (‘none’, ‘const’, ‘trend’, or ‘both’)

\[ p \quad \text{int: lags} \]
\[ \text{lag.ic} \quad \text{string: information criterion to choose the optimal number of lags ('AIC' or 'BIC')} \]
\[ \text{lag.max} \quad \text{int: maximum number of lags to test in lag selection} \]
\[ \text{structure} \quad \text{string: type of structural identification strategy to use in model analysis (NA, 'short', 'IV', or 'IV-short')} \]
\[ \text{instrument} \quad \text{string: name of instrumental variable contained in the data matrix} \]
\[ \text{instrumented} \quad \text{string: name of variable to be instrumented in IV and IV-short procedure; default is the first non-date variable in data} \]

**Details**

See Sims (1980) for details regarding the baseline vector-autoregression (VAR) model. The VAR may be augmented to become a structural VAR (SVAR) with one of three different structural identification strategies:

1. short-term impact restrictions via Cholesky decomposition, see Christiano et al (1999) for details (\text{structure} = 'short')
2. external instrument identification, i.e. a Proxy-SVAR strategy, see Mertens and Ravn (2013) for details (\text{structure} = 'IV')
3. or a combination of short-term and IV identification via Lunsford (2015) (\text{structure} = 'IV-short')

Note that including structure does not change the estimation of model coefficients or forecasts, but does change impulse response functions, forecast error variance decomposition, and historical decompositions. Historical decompositions will not be available for models using the 'IV' structure. Additionally note that only one instrument may be used in this estimation routine.

**Value**

1. data: data.frame with endogenous variables and 'date' column.
2. model: list with data.frame of model coefficients (in pseudo-companion form), data.frame of coefficient standard errors, integer of lags p, integer of horizons, string of frequency, string of deterministic term type, numeric of log-likelihood
3. forecasts: list of data.frames per horizon; data.frame with column for date (day the forecast was made), forecast.date (the date being forecasted), target (variable forecasted), and forecast
4. residuals: list of data.frames per horizon; data.frame of residuals
5. structure: string denoting which structural identification strategy will be used in analysis (or NA)
6. instrument: data.frame with 'date' column and 'instrument' column (or NULL)
7. instrumented: string denoting which column will be instrumented in 'IV' and 'IV-short' strategies (or NA)
References


2. Lunsford, Kurt "Identifying Structural VARs with a Proxy Variable and a Test for a Weak Proxy" 2015.


See Also

VAR()
var_irf()
var_fevd()
var_hd()

Examples

# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date("2000-01-01"), by = "month", length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var = sovereign::VAR(
    data = Data,
    horizon = 10,
    freq = 'month',
    lag.ic = 'BIC',
    lag.max = 4)

# impulse response functions
var.irf = sovereign::var_irf(var)

# forecast error variance decomposition
var.fevd = sovereign::var_fevd(var)

# historical shock decomposition
var.hd = sovereign::var_hd(var)
Estimate forecast error variance decomposition

Description

Estimate forecast error variance decomposition for VARs with either short or 'IV-short' structural errors.

Usage

```r
var_fevd(var, horizon = 10, scale = TRUE)
```

Arguments

- `var`: VAR output
- `horizon`: int: number of periods
- `scale`: boolean: scale variable contribution as percent of total error

Value

long-form data.frame

See Also

- `VAR()`
- `var_irf()`
- `var_fevd()`
- `var_hd()`
- `RVAR()`
- `rvar_irf()`
- `rvar_fevd()`
- `rvar_hd()`

Examples

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var =
```
sovereign::VAR(
  data = Data,
  horizon = 10,
  freq = 'month',
  lag.ic = 'BIC',
  lag.max = 4)

# impulse response functions
var.irf = sovereign::var_irf(var)

# forecast error variance decomposition
var.fevd = sovereign::var_fevd(var)

# historical shock decomposition
var.hd = sovereign::var_hd(var)

---

var_hd | Estimate historical decomposition

**Description**

Estimate historical decomposition for VARs with either short or 'IV-short' structural errors.

**Usage**

```
var_hd(var)
```

**Arguments**

- `var` : VAR output

**Value**

long-from data.frame

**See Also**

- VAR()
- var_irf()
- var_fevd()
- var_hd()
- RVAR()
- rvar_irf()
- rvar_fevd()
- rvar_hd()
Examples

# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date('2000-01-01'), by = 'month', length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var =
  sovereign::VAR(  
  data = Data,
  horizon = 10,
  freq = 'month',
  lag.ic = 'BIC',
  lag.max = 4)

# impulse response functions
var.irf = sovereign::var_irf(var)

# forecast error variance decomposition
var.fevd = sovereign::var_fevd(var)

# historical shock decomposition
var.hd = sovereign::var_hd(var)

---

### var_irf

#### Estimate impulse response functions

**Description**

Estimate impulse response functions

**Usage**

```
var_irf(
  var,
  horizon = 10,
  CI = c(0.1, 0.9),
  bootstrap.type = "auto",
  bootstrap.num = 100,
  bootstrap.parallel = FALSE,
  bootstrap.cores = -1
)
```
Arguments

- **var**: VAR output
- **horizon**: int: number of periods
- **CI**: numeric vector: c(lower ci bound, upper ci bound)
- **bootstrap.type**: string: bootstrapping technique to use (‘auto’, ‘standard’, or ‘wild’); if auto then wild is used for IV or IV-short, else standard is used
- **bootstrap.num**: int: number of bootstraps
- **bootstrap.parallel**: boolean: create IRF draws in parallel
- **bootstrap.cores**: int: number of cores to use in parallel processing: -1 detects and uses half the available cores

Value
data.frame with columns target, shock, horizon, response.lower, response, response.upper

See Also

- VAR()
- var_irf()
- var_fevd()
- var_hd()
- RVAR()
- rvar_irf()
- rvar_fevd()
- rvar_hd()

Examples

```r
# simple time series
AA = c(1:100) + rnorm(100)
BB = c(1:100) + rnorm(100)
CC = AA + BB + rnorm(100)
date = seq.Date(from = as.Date("2000-01-01"), by = "month", length.out = 100)
Data = data.frame(date = date, AA, BB, CC)

# estimate VAR
var = sovereign::VAR(
    data = Data,
    horizon = 10,
    freq = "month",
    lag.ic = "BIC",
```
lag.max = 4)

# impulse response functions
var.irf = sovereign::var_irf(var)

# forecast error variance decomposition
var.fevd = sovereign::var_fevd(var)

# historical shock decomposition
var.hd = sovereign::var_hd(var)
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