Package ‘MSBVAR’

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Title Markov-Switching, Bayesian, Vector Autoregression Models
Maintainer Patrick Brandt <pbrandt@utdallas.edu>
Imports KernSmooth, xtable, coda, bit, mvtnorm, lattice
Description Provides methods for estimating frequentist and
Bayesian Vector Autoregression (VAR) models and Markov-switching
Bayesian VAR (MSBVAR). Functions for reduced
form and structural VAR models are also available. Includes
methods for the generating posterior inferences for these models,
forecasts, impulse responses (using likelihood-based error bands),
and forecast error decompositions. Also includes utility functions
for plotting forecasts and impulse responses, and generating draws
from Wishart and singular multivariate normal densities. Current
version includes functionality to build and evaluate models with
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A02mcmc

Converts A0 objects to coda MCMC objects

Description

Converts A0 objects from gibbs.A0.BSVAR into mcmc objects for analysis with coda

Usage

A02mcmc(x)

Arguments

x  \[ N^2 \times \text{number of free parameters in } A(0) \text{ MCMC Gibbs sample object for the B-BSVAR model } A_0 \text{ from } \text{gibbs.A0}. \text{ This matrix is a column major to row major version of } A(0) \text{ that can be used to diagnose convergence and summarize the elements of } A(0) \]

Details

Returns an object of the class mcmc, an N2 x number free parameters in A(0) matrix. This can then be fed into coda for further analysis of the posterior.

Value

Object with class mcmc

Author(s)

Patrick T. Brandt

See Also

gibbs.A0,mcmc
BCFdata Subset of Data from Brandt, Colaresi, and Freeman (2008)

Description

This data set in two matrices about the Israeli-Palestinian conflict. The first matrix is a set of endogenous variables that gives 1) monthly Goldstein scaled means that summarize the Israeli-Palestinian conflict from April 1996 - March 2005, 2) average Jewish peace index score [0 = no support to 100=full support] that measure Jewish public support of the peace process based on polls of Jewish respondents from the Tami Steinmetz Center for Peace Research. The conflict measures are dyadic or directed actions from one party towards the other. Positive values indicate an average of more cooperation and less conflict and negative values indicate an average with more conflict than cooperation. These are a subset of the Levant dataset from the Kansas / Penn State / Computational Event Data Project Levant dataset. The data are from AFP news sources and encoded into the World Event Interaction Survey (WEIS) coding system and Goldstein scalings using the Event Data Project TABARI program. Source data can be found on the site below.

Usage
data(BCFdata)

Format

Two matrices containing 108 observations. The first matrix "Y" is a multiple ts object of the endogenous series that measure the average conflict-cooperation level and the public opinion data. This matrix has three columns. Column one, "I2P", is average Goldstein scaled Israeli actions towards the Palestinians; column two, "P2I" is average Goldstein scaled Palestinian actions towards the Israelis; column three is the average Jewish peace index value for the month, "JPI".

The second matrix, "z2" is a set of nine control variables for shifts in the conflict, the Israeli prime ministerial regime, and election trends. The columns of this matrix are 1) a dummy variable for the period from the start of the second Intifada to the start of the Battle of Jenin (October 2000–April 2002, end of the second Intifada). 2) a dummy variable for the post-Battle of Jenin period (May 2002–March 2005), 3-5) dummy variables for the identities of the Israeli prime ministers in each month (one each for Netanyahu, Barak, and Sharon, with Rabin/Peres treated as the reference category). 6-9) a separate time counter that starts at the value 1 in the month after each Israeli election and increases until the time of the next constitutionally mandated election.

Source


Replication materials at http://jcr.sagepub.com/content/52/3/343
cf.forecasts

References


cf.forecasts  Compare VAR forecasts to each other or real data

Description

Computes the root mean squared error and mean absolute error for a series of forecasts or for forecasts and real data.

Usage

`cf.forecasts(m1, m2)`

Arguments

- `m1`: Matrix of VAR forecasts produced by `forecast.VAR`.
- `m2`: Matrix of VAR forecasts or a matrix of real data to compare to forecasts.

Details

Simple RMSE and MAE computation for the forecasts. The reported values are summed over the series and time points.

Value

An object with two elements:

- `rmse`: Forecast RMSE
- `mae`: Forecast MAE

Author(s)

Patrick T. Brandt

See Also

`forecast` for forecast computations
Examples

data(IrelandPalestineConflict)
Y.sample1 <- window(IrelandPalestineConflict, end=c(2002, 52))
Y.sample2 <- window(IrelandPalestineConflict, start=c(2003,1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                  lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!
forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))

# Compare forecasts to real data
cf.forecasts(forecasts[(nrow(Y.sample1)+1):nrow(forecasts),], Y.sample2)

decay.spec          Lag decay specification check

Description

Provides a quick way to visualize the lag decay specification in a BVAR model for given parameters
by computing the variance of the prior VAR coefficients across various lags.

Usage

decay.spec(qm, p, lambda)

Arguments

qm                  Periodicity parameter: either 4 or 12 for quarterly or monthly data.
p                  Number of lags
lambda                  Lag decay parameter [>0], which is lambda3 in the Sims-Zha BVAR specification in szbvar

Details

Computes the relative decay in the prior variance of the VAR prior across the lags from 1 to p.
Useful for visualizing the rate of decay or how tight the prior becomes at higher order lags.

Value

A time series of length p of the prior variances for each lag.

Author(s)

Patrick T. Brandt


dfev

References


See Also

szbvar

Examples

# Harmonic lag decay example
harmonic <- decay.spec(4, 6, 1)

# Quadratic lag decay example
quadratic <- decay.spec(4, 6, 2)

plot(cbind(harmonic, quadratic))

---

**dfev**

*Decompositions of Forecast Error Variance (DFEV) for VAR/BVAR/BSVAR models*

**Description**

Computes the m dimensional decomposition of forecast error variance (DFEV) for a VAR, BVAR, and BSVAR models. User can specify the decomposition of the contemporaneous innovations.

**Usage**

dfev(varobj, A0 = NULL, k)

**Arguments**

<table>
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<tr>
<th>Argument</th>
<th>Description</th>
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</thead>
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<tr>
<td>varobj</td>
<td>VAR/BVAR/BSVAR object created from fitting a VAR/BVAR/BSVAR model using szbvar, szbsvar, or reduced.form.var.</td>
</tr>
<tr>
<td>A0</td>
<td>Decomposition of the contemporaneous error covariance matrix. Default is to use the (lower) Cholesky decomposition of the residual error covariance matrix for VAR and BVAR models, or the inverse of $A_0$ in B-SVAR models.</td>
</tr>
<tr>
<td>k</td>
<td>Number of periods over which to compute the decomposition.</td>
</tr>
</tbody>
</table>
Details

The decomposition of the forecast error variance (DFEV) provides a measure of the relationship among forecast errors or impact of shocks to a VAR/BVAR/BSVAR system. It is computed by finding the moving average representation (MAR) of the VAR/BVAR/BSVAR model and then tracing out the path of innovations through the system. For each of the M innovations in a VAR/BVAR/BSVAR, the amount of the variance in these forecast errors or innovations is computed and returned in a table. The table can be accessed via the `print.dfev` and `summary.dfev` functions.

Value

Returns a list with

- `errors` M x M x K of the percentage of the innovations in variable i explained by the other M variables.
- `std.err` M x k dimension matrix of the forecast standard errors.
- `names` Variable names

Note

The interpretation of the DFEV depends on the decomposition of the contemporaneous residuals. In the default case of a Cholesky decomposition, this means that the ordering of the variables in the decomposition determines the effect of each innovation on the subsequent DFEVs. For high correlated series, this will mean that the DFEV is not very robust to the ordering.

Author(s)

Patrick T. Brandt

References


See Also

See also `print.dfev` and `summary.dfev` for a nicely formatted tables and an output example

Examples

data(Iceland)
varnames <- colnames(Iceland)
fitted.BVAR <- szbvar(Iceland, p=6, z=NULL,
lambda0=0.6, lambda1=0.1,
lambda2=2, lambda4=0.25, lambda5=0, mu5=0,
mu6=0, nu=3,qm=4, prior=0,
posterior.fit=FALSE)

A0 <- t(chol(fitted.BVAR$mean.S))
dat.dfev <- dfev(fitted.BVAR, A0, 24)
forc.ecdf

print(dat.dfev)
summary(dat.dfev)

---

forc.ecdf

Empirical CDF computations for posterior forecast samples

Description

Computes (pointwise over time) empirical density (error bands) and mean forecasts for a Monte
Carlo or Bayesian posterior sample of forecasts.

Usage

forc.ecdf( forecasts, probs = c(0.05, 0.95), start = c(0, 1), ... )

Arguments

forecasts  Posterior sample of VAR forecasts produced by hc.forecast.VAR() or uc.forecast.VAR()
probs     Error band width in percentiles, default is 90% error band.
start     Start value for the time series – as in the ts() for the forecast horizon
...       Other ecdf() parameters

Details

For each endogenous variable in the VAR and each point in the forecast horizon this function es-
timates the percentile based confidence interval. It then returns a time series matrix beginning at
start of the mean forecast and the limits of the confidence region for each variable in the forecast
sample.

Value

A multiple time series object is returned where the first column is the mean estimate followed by
the upper and lower bounds of the confidence region.

Author(s)

Patrick T. Brandt
**Generate forecasts for fitted VAR objects**

**Description**

Forecasting for VAR/BVAR/BSVAR/MSBVAR objects with structural (endogenous) and exogenous shocks.

**Usage**

```r
forecast(varobj, nsteps, A0=t(chol(varobj$mean.S)),
    shocks=matrix(0, nrow=nsteps, ncol=dim(varobj$ar.coefs)[1]),
    exog.fut=matrix(0, nrow=nsteps, ncol=nrow(varobj$exog.coefs)),
    N1, N2)
```

**Arguments**

- `varobj`: Fitted VAR model of the class VAR, BVAR, BSVAR, or MSBVAR produced by `reduced.form.var`, `szbvar`, `szbsvar` or `gibbs.msbvar`.
- `nsteps`: Number of periods in the forecast horizon
- `A0`: \( m \times m \) matrix of the decomposition of the contemporaneous endogenous forecast innovations for BSVAR models.
- `shocks`: Structural shocks to the VAR, BVAR, or BSVAR models. These must be scaled consistent with the structural identification in \( A_0 \).
- `exog.fut`: \( n \times m \) matrix of the future values of exogenous variable shocks. Only implemented for VAR, BVAR, and BSVAR models at present.
- `N1`: integer, number of burnin draws for the MSBVAR forecasts.
- `N2`: integer, number of final posterior draws for MSBVAR forecasts.

**Details**

**VAR / BVAR / BSVAR models:**

This function computes forecasts for the classical and Bayesian VAR models that are estimated in the MSBVAR package. Users can specify shocks to the system over the forecast horizon (both structural and exogenous shocks) for VAR, BVAR, and BSVAR models. The forecasting model is that described by Waggoner and Zha (1999) and can be used to construct unconditional forecasts based on the structural shocks and the contemporaneous decomposition of the innovation variance, \( A_0 \).

**MSBVAR:**

Generates a set of \( N_2 \) draws from the posterior forecast density. Forecasts are constructed using data augmentation, so the forecasts account for both forecast and parameter uncertainty. The function for the MSBVAR model takes as arguments `varobj`, which is the posterior parameters from a call to `gibbs.msbvar`, and `N1` and `N2` to set the burnin and number of draws from the posterior. The posterior forecasts are based on the mixture over the \( h \) regimes for the specified model.
Value

For VAR, BVAR, and BSVAR models:
A matrix time series object, \((T + nsteps) \times m\) of the original series and forecasts.
For MSBVAR models, a list of 4 elements:

- `forecasts` \(N \times nsteps \times m\) array of the posterior forecasts.
- `ss.sample` bit compressed version of the MS state space. (can be summarized with `plot.SS` or `mean.SS`.)
- `k` number of forecast steps, nsteps
- `h` integer, number of MS regimes used in the forecasts.

Note

The forecasts can be plotted using the `plot.forecast()` command to select the appropriate sample-forecast horizon.

Author(s)

Patrick T. Brandt

References


See Also

`reduced.form.var`, `szbvar` and `szbsvar` for estimation methods that create the elements needed to forecast

Examples

data(PalestineConflict)
Y.sample1 <- window(PalestineConflict, end=c(2002, 52))
Y.sample2 <- window(PalestineConflict, start=c(2003,1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                   lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!
forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))
forecasts.only <- forecasts[(nrow(Y.sample1)+1):nrow(forecasts),]

# Plot forecasts and actual data
i2p <- ts(cbind(Y.sample2[,1], forecasts.only[,1]),
          start=c(2003,1), freq=52)
p21 <- ts(cbind(Y.sample2[,2], forecasts.only[,2]),
          start=c(2003,1), freq=52)

par(mfrow=c(2,1))
plot(i2p, plot.type="single")
plot(p21, plot.type="single")

## Not run:
# MSBVAR forecasts

# Fit model
m1 <- msbvar(Y.sample1, p=1, h=2, lambda0=0.8, lambda1=0.2,
              lambda2=1, lambda4=0.2, lambda5=0, mu5=0, mu6=0,
              qm=12, prior=0)

# Gibbs sampling
mlid <- gibbs.msvar(m1, N1=1000, N2=10000, permute=FALSE, Sigma.idx=1)

# Forecast density estimation
msforc <- forecast(mlid, nsteps=nrow(Y.sample2), N1=1000, N2=10000)

# Summarize forecasts
apply(msforc$forecasts, c(2,3), mean)

## End(Not run)

gibbs.A0

Gibbs sampler for posterior of Bayesian structural vector autoregression models

Description

Samples from the structural contemporaneous parameter matrix $A_0$ of a Bayesian Structural Vector Autoregression (B-SVAR) model.

Usage

gibbs.A0(varobj, N1, N2, thin=1, normalization="DistanceMLA")

Arguments

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<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>varobj</td>
<td>A structural BVAR object created by <code>szbsvar</code></td>
</tr>
<tr>
<td>N1</td>
<td>Number of burn-in iterations for the Gibbs sampler (should probably be greater than or equal to 1000).</td>
</tr>
<tr>
<td>N2</td>
<td>Number of iterations in the posterior sample.</td>
</tr>
<tr>
<td>thin</td>
<td>Thinning parameter for the Gibbs sampler.</td>
</tr>
<tr>
<td>normalization</td>
<td>Normalization rule as defined in <code>normalize.svar</code>. Default is &quot;DistanceMLA&quot; as recommended in Waggoner and Zha (2003b).</td>
</tr>
</tbody>
</table>
Details

Samples the posterior pdf of an $A_0$ matrix for a Bayesian structural VAR using the algorithm described in Waggoner and Zha (2003a). This function is meant to be called after `szbsvar`, so one should consult that function for further information. The function draws $N_2 \times \text{thin}$ draws from the sampler and returns the $N_2$ draws that are the $\text{thin}'th$ elements of the Gibbs sampler sequence.

The computations are done using compiled C++ code as of version 0.3.0. See the package source code for details about the implementation.

Value

A list of class `gibbs.A0` with five elements:

- $A_0$.posterior: A list of three elements containing the results of the $N_2 A_0$ draws. The list contains a vector storing all of the draws, the location of the drawn elements in and the dimension of $A_0$. $A_0$.posterior$A_0$ is a vector of length equal to the number of parameters in $A_0$ times $N_2$. $A_0$.posterior$\text{struct}$ is a vector of length equal to the number of free parameters in $A_0$ that gives the index positions of the elements in $A_0$. $A_0$.posterior$m$ is $m$, an integer, the number of equations in the system.

- $W$.posterior: A list of three elements that describes the vectorized $W$ matrices that characterize the covariance of the restricted parameter space of each column of $A_0$. $W$.posterior$W$ is a vector of the elements of all the sampled $W$ matrices. $W$.posterior$W$.index is a cumulative index of the elements of $W$ that defines how the $W$ matrices for each iteration of the sampler are stored in the vector. $W$.posterior$m$ is $m$, an integer, the number of equations in the system.

- $\text{ident}$: $\text{ident}$ matrix from the varobj of binary elements that defined the free and restricted parameters, as specified in `szbsvar`.

- $\text{thin}$: $\text{thin}$ value that was input into the function for thinning the Gibbs sampler.

- $N_2$: $N_2$, size of the posterior sample.

Note

You must have called / loaded an `szbsvar` object to use this Gibbs sampler.

Author(s)

Patrick T. Brandt

References


See Also

szbsvar for estimation of the posterior moments of the B-SVAR model,

normalize.svar for a discussion of and references on $A_0$ normalization.

posterior.fit for computing the marginal log likelihood for the model after sampling the posterior,

and plot for a unique density plot of the $A_0$ elements.

Examples

```r
# SZ, B-SVAR model for the Levant data
data(BCFdata)
m <- ncol(Y)
ident <- diag(m)
id[1,] <- 1
ident[2,] <- 1

# estimate the model's posterior moments
set.seed(123)
model <- szbsvar(Y, p=2, z=z2, lambda0=0.8, lambda1=0.1, lambda3=1,
lambda4=0.1, lambda5=0.05, mu5=0, mu6=5,
ident, Qm=12)

# Set length of burn-in and size of posterior. These are only an
# example. Production runs should set these much higher.
N1 <- 1000
N2 <- 1000

A0.posterior.obj <- gibbs.A0(model, N1, N2, thin=1)

# Use coda to look at the posterior.
A0.free <- A02mcmc(A0.posterior.obj)

plot(A0.free)
```

gibbs.msbvar  

Gibbs sampler for a Markov-switching Bayesian reduced form vector autoregression model

Description

Draws a Bayesian posterior sample for a Markov-switching Bayesian reduced form vector autoregression model based on the setup from the msbvar function.

Usage

```r
gibbs.msbvar(x, N1 = 1000, N2 = 1000, permute = TRUE, 
               Beta.idx = NULL, Sigma.idx = NULL, Q.method="MH")
```
Arguments

- **x**: MSBVAR setup and posterior mode estimate generated using the `msbvar` function.
- **n1**: Number of burn-in iterations for the Gibbs sampler (should probably be greater than or equal to 1000).
- **n2**: Number of iterations in the posterior sample.
- **permute**: Logical (default = TRUE). Should random permutation sampling be used to explore the $h!$ posterior modes?
- **Beta.idx**: A two element vector indicating the MSBVAR coefficient matrix that is to be ordered for non-permutation sampling, i.e., the ordering of the states. The states will be put into ascending order for the parameter selected. The two elements provide for the two-dimensional array of the VAR coefficients. The first number gives the coefficient, the second the equation numbers. Coefficients are ordered by lag, then variable. So for an $m$ equation VAR where we want the AR(1) coefficient on the second variable’s equation, use $c_{2,2}$. The intercept is the last value, or $mp + 1$. So the intercept for the first equation in a 4 variable model with two lags is $c_{9,1}$.
- **Sigma.idx**: Scalar integer giving the equation variance that is to be ordered for non-permutation sampling, i.e., the ordering of the states. The states will be put into ascending order for the variance parameter selected. So if you want to identify the results based on equation three, set `Sigma.idx=3`.
- **Q.method**: Choice of the sampler step for the transition matrix, Q. default = `mh` uses a Metropolis-Hastings algorithm that assumes a stationary Markov process. The other option is `gibbs` which uses a Gibbs sampler Dirichlet draw for a non-stationary Markov-switching process. See Fruwirth-Schnatter (2006: 318, 340-341 for details).

Details

This function implements a Gibbs sampler for the posterior of a MSBVAR model setup with `msbvar`. This is a reduced form MSBVAR model. The estimation is done in a mixture of native R code and Fortran. The sampling of the BVAR coefficients, the transition matrix, and the error covariances for each regime are done in native R code. The forward-filtering-backward-sampling of the Markov-switching process (The most computationally intensive part of the estimation) is handled in compiled Fortran code. As such, this model is reasonably fast for small samples / small numbers of regimes (say less than 5000 observations and 2-4 regimes). The reason for this mixed implementation is that it is easier to setup variants of the model (E.g., Some coefficients switching, others not; different sampling methods, etc. Details will come in future versions of the package.)

The random permutation of the states is done using a multinomial step: at each draw of the Gibbs sampler, the states are permuted using a multinomial draw. This generates a posterior sample where the states are unidentified. This makes sense, since the user may have little idea of how to select among the $h!$ posterior models of the reduced form MSBVAR model (see e.g., Fruhwirth-Schnatter (2006)). Once a posterior sample has been draw with random permutation, a clustering algorithm (see `plotregimeid`) can be used to identify the states, for example, by examining the intercepts or covariances across the regimes (see the example below for details).
Only the Beta.idx or Sigma.idx value is followed. If the first is given the second will be ignored. So variance ordering for identification can only be used when Beta.idx=NULL. See plotregimeid for plotting and summary methods for the permuted sampler.

The Gibbs sampler is estimated using six steps:

**Drawing the state-space for the Markov process**  This step uses compiled code to draw the 0-1 matrix of the regimes. It uses the Baum-Hamilton-Lee-Kim (BHLK) filter and smoother to estimate the regime probabilities. Draws are based on the standard forward-filter-backward-sample algorithm.

**Drawing the Markov transition matrix**  \( Q \)  Conditional on the other parameters, this takes a draw from a Dirichlet posterior with the alpha.Nprior prior.

**Regression step update**  Conditional on the state-space and the Markov-switching process data augmentation steps, estimate a set of \( h \) regressions, one for each regime.

**Draw the error covariances, \( \Sigma_h \)**  Conditional on the other steps, compute and draw the error covariances from an inverse Wishart pdf.

**Draw the regression coefficients**  For each set of classified observations’ (based on the previous step) BVAR regression coefficients, take a draw from their multivariate normal posterior.

**Permute the states**  If permute = TRUE, then permute the states and the respective coefficients.

The state-space for the MS process is a \( T \times h \) matrix of zeros and ones. Since this matrix classifies the observations into states for the \( N \) posterior draws, it does not make sense to store it in double precisions. We use the bit package to compress this matrix into a 2-bit integer representation for more efficient storage. Functions are provided (see below) for summarizing and plotting the resulting state-space of the MS process.

**Value**

A list summarizing the reduced form MSBVAR posterior:

- **Beta.sample**  \( N2 \times h(m^2p + m) \) of the BVAR regression coefficients for each regime. The ordering is based on regime, equation, intercept (and in the future covariates). So the first \( p \) coefficients are the the first equation in the first regime, ordered by lag, not variable; the next is the intercept. This pattern repeats for the remaining coefficients across the regimes.

- **Sigma.sample**  \( N2 \times h(m(m+1)/2) \) matrix of the covariance parameters for the error covariances \( \Sigma_h \). Since these matrices are symmetric p.d., we only store the upper (or lower) portion. The elements in the matrix are the first, second, etc. columns / rows of the lower / upper version of the matrix.

- **Q.sample**  \( N2 \times h^2 \)

- **transition.sample**  An array of \( N2 \times h \times h \) transition matrices.

- **ss.sample**  List of class SS for the \( N2 \) estimates of the state-space matrices coded as bit objects for compression / efficiency.

- **pfit**  A list of the posterior fit statistics for the MSBVAR model.

- **init.model**  Initial model – a varobj from a BVAR like szbvar that sets up the data and priors. See szbvar for a description.
alpha.prior  Prior for the state-space transitions Q. This is set in the call to msbvar and inherited here.

h  integer, number of regimes fit in the model.

p  integer, lag length

m  integer, number of equations

Note

Users need to call this function twice (unless they have really good a priori identification information!) The first call will be using the random permutation sampler (so with permute = TRUE) and then some exploration of the clustering of the posterior. Then, once the posterior is identified (i.e., you have chosen one of the h! posterior modes), the function is called with permute = FALSE and values specified for Beta.idx or Sigma.idx. See the example below for usage.

Author(s)

Patrick T. Brandt

References


See Also

msbvar for initial mode finding, plot.SS for plotting regime probabilities, mean.SS for computing the mean regime probabilities, plotregimeid for identifying the regimes from a permuted sample.

Examples

```r
## Not run:
# This example can be pasted into a script or copied into R to run. It
# takes a few minutes, but illustrates how the code can be used

data(IsraelPalestineConflict)

# Find the mode of an msbvar model
# Initial guess is based on random draw, so set seed.
set.seed(123)
```
Bivariate Granger causality testing

Description

Bivariate Granger causality testing for multiple time series.

Usage

granger.test(y, p)
Arguments

$y$  
A T x m time series or matrix.

$p$  
Lag length to be used for computing the test

Details

Estimates all possible bivariate Granger causality tests for m variables. Bivariate Granger causality tests for two variables X and Y evaluate whether the past values of X are useful for predicting Y once Y’s history has been modeled. The null hypothesis is that the past p values of X do not help in predicting the value of Y.

The test is implemented by regressing Y on p past values of Y and p past values of X. An F-test is then used to determine whether the coefficients of the past values of X are jointly zero.

This produces a matrix with m*(m-1) rows that are all of the possible bivariate Granger causal relations. The results include F-statistics and p-values for each test. Tests are estimated using single equation OLS models.

Value

A matrix with 2 columns. Column 1 are the F-statistic values. Column 2 are the p-values for the F-tests. Row labels specifying the Granger causality relationship tested will be included if variables in the input time series $y$ include variable or dimnames.

Note

These are bivariate tests – not block exogeneity tests for a fitted VAR model. Note also that these tests are highly sensitive to lag length (p) and the presence of unit roots. Results in the matrix include row labels for nice printing with xtable().

Author(s)

Patrick T. Brandt

References


See Also

reduced.form.var for frequentist VAR estimation, szbvar for Bayesian VAR estimation with Sims-Zha prior, var.lag.specification for VAR lag length testing.

Examples

data(IsraelPalestineConflict)
granger.test(IsraelPalestineConflict, p=6)
HamiltonGDP

Quarterly U.S. GDP Growth, 1952Q3-1984Q4

Description

Hamilton’s (1989) quarterly data on U.S. GDP growth.

Usage

data(HamiltonGDP)

Format

ts object of quarterly GDP growth named gdp. This ts classed object has 130 observations.

Source


References


hc.forecast

Forecast density estimation of hard condition forecasts for VAR models via MCMC

Description

Implements a "hard condition" forecast density estimator for VAR/BVAR/B-SVAR models as described in Waggoner and Zha (1999). A "hard condition" forecast is one where the forecast path of one or more variables in a VAR is constrained to be an exact value. The forecast densities are estimated as the posterior sample for the VAR model using Markov Chain Monte Carlo with data augmentation to account for the uncertainty of the forecasts and the parameters. This function DOES account for parameter uncertainty in the MCMC algorithm.

Usage

hc.forecast(varobj, yconst, nsteps, burnin, gibbs, exog = NULL)
hc.forecast

Arguments

- **varobj**: VAR object produced for an unrestricted VAR or BVAR using \texttt{szbvar} or \texttt{reduced.form.var}
- **yconst**: \(n\times m\) matrix of the constrained forecasts that matches the variables in the endogenous variables of the VAR object. Unconstrained forecasts should be set to NA or zero.
- **nsteps**: Number of periods in the forecast horizon
- **burnin**: Burnin cycles for the MCMC algorithm
- **gibbs**: Number of cycles of the Gibbs sampler after the \texttt{burnin} that are returned in the output
- **exog**: \(n\times m\) matrix of the exogenous variable values for the forecast horizon. If left at the \texttt{NULL} default, they are set to zero.

Details

"Hard conditions" are restrictions of the future forecast path of a variable in a VAR. Once a variable has been constrained along the forecast path, the paths of the other variables in the VAR forecasts must be re-estimated to satisfy the forecast constraint, since the constrained variable has a forecast variance of zero (it is assumed known). Thus, an MCMC algorithm must be used to determine the posterior of the forecasts and a consistent set of VAR parameter estimates that satisfy the forecast constraints. This function accounts for the uncertainty of the VAR parameters by sampling from them in the computation of the VAR forecasts.

Value

A list with two components:

- **forecast**: \(gibbs \times nsteps \times m\) array of the samples of the VAR forecasts
- **orig.y**: \(T \times m\) time series object of the original endogenous variables

Author(s)

Patrick T. Brandt

References


See Also

\texttt{plot.forecast} for plotting, \texttt{forecast} for unconditional forecasting of forecast means, \texttt{uc.forecast} for MCMC estimation of forecast densities for unconstrained or unconditional forecasts.
Examples

```
## Not run:
## Uses the example from Brandt and Freeman 2006. Will not run unless
## you have their data from the Political
## Analysis website!
library(MSBVAR)

# Read the data and set up as a time series
data <- read.dta("levant.weekly.79-03.dta")
attach(data)

# Set up KEDS data
KEDS.data <- ts(cbind(a2i,a2p,i2a,p2a,i2p,p2i),
    start=c(1979,15),
    freq=52,
    names=c("A2I","A2P","I2A","P2A","I2P","P2I"))

# Select the sample we want to use.
KEDS <- window(KEDS.data, end=c(1988,50))

# Estimate the BVAR models

# Fit a flat prior model
KEDS.BVAR.flat <- szbvar(KEDS, p=6, z=NULL, lambda0=1,
    lambda1=1, lambda3=1, lambda4=1, lambda5=0,
    mu5=0, mu6=0, nu=0, qm=4, prior=2,
    posterior.fit=F)

# Reference prior model -- Normal-Inverse Wishart prior pdf
KEDS.BVAR.informed <- szbvar(KEDS, p=6, z=NULL, lambda0=0.6,
    lambda1=0.1, lambda3=2, lambda4=0.5,
    lambda5=0, mu5=0, mu6=0,
    nu=ncol(KEDS)+1, qm=4, prior=0,
    posterior.fit=F)

# Set up conditional forecast matrix conditions
nsteps <- 12
a2i.condition <- rep(mean(KEDS[,1]) + sqrt(var(KEDS[,1])), nsteps)
yhat<-matrix(c(a2i.condition,rep(0, nsteps*5)), ncol=6)

# Set the random number seed so we can replicate the results.
set.seed(11023)

# Conditional forecasts
conditional.forcs.ref <- hc.forecast(KEDS.BVAR.informed, yhat, nsteps,
    burnin=3000, gibbs=5000, exog=NULL)
conditional.forcs.flat <- hc.forecast(KEDS.BVAR.flat, yhat, nsteps,
```
initialize.msbvar

**Description**

Sets up the initial values for the mode optimization of an MSBVAR model with a Sims-Zha prior. This sets up the `initialize.opt` argument of the `msbvar` function. Users can inputs values outside of the defaults for the Q transition matrix and other arguments with this function. This function also serves as a model for alternative, user-defined initial values for the Gibbs sampler.

**Usage**

`initialize.msbvar(y, p, z = NULL, lambda0, lambda4, lambda5, mu5, mu6, nu, qm, prior, h, Q = NULL)`

```r
initialize.msbvar

# Unconditional forecasts
unconditional.forcs.ref <- uc.forecast(KEDS.BVAR.informed, nsteps,
  burnin=3000, gibbs=5000)

unconditional.forcs.flat <- uc.forecast(KEDS.BVAR.flat, nsteps,
  burnin=3000, gibbs=5000)

# Set-up and plot the unconditional and conditional forecasts. This # code pulls for the forecasts for I2P and P2I and puts them into the # appropriate array for the figures we want to generate.
uc.flat <- NULL
hc.flat <- NULL
uc.ref <- NULL
hc.ref <- NULL

uc.flat$forecast <- unconditional.forcs.flat$forecast[,5:6]
hc.flat$forecast <- conditional.forcs.flat$forecast[,5:6]
uc.ref$forecast <- unconditional.forcs.ref$forecast[,5:6]
hc.ref$forecast <- conditional.forcs.ref$forecast[,5:6]

par(mfrow=c(2,2), omi=c(0.25,0.5,0.25,0.25))
plot(uc.flat, hc.flat, probs=c(0.16, 0.84), varnames=c("I2P", "P2I"),
  compare.level=KEDS[nrow(KEDS),5:6], lwd=2)
plot(hc.ref, hc.flat, probs=c(0.16, 0.84), varnames=c("I2P", "P2I"),
  compare.level=KEDS[nrow(KEDS),5:6], lwd=2)
```

## End(Not run)
Arguments

\( y \) \( T \times m \) multiple time series object created with \( \text{ts()} \).

\( p \) Lag length, an integer

\( z \) NOT IMPLEMENTED AT PRESENT: THIS SHOULD BE A \( T \times k \) matrix of exogenous variables. Can be \( z = \text{NULL} \) if there are none (the default).

\( \lambda_0 \) \([0, 1]\), Overall tightness of the prior (discounting of prior scale).

\( \lambda_1 \) \([0, 1]\), Standard deviation or tightness of the prior around the AR(1) parameters.

\( \lambda_3 \) Lag decay \((>0, \text{with 1=harmonic})\)

\( \lambda_4 \) Standard deviation or tightness around the intercept \(>0\)

\( \lambda_5 \) Standard deviation or tightness around the exogeneous variable coefficients \(>0\)

\( \mu_5 \) Sum of coefficients prior weight \(\geq 0\). Larger values imply difference stationarity.

\( \mu_6 \) Dummy initial observations or drift prior \(\geq 0\). Larger values allow for common trends.

\( \nu \) Prior degrees of freedom, \( m + 1 \)

\( q_m \) Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"

\( \text{prior} \) One of three values: \(0\) = Normal-Wishart prior, \(1\) = Normal-flat prior, \(2\) = flat-flat prior (i.e., akin to MLE)

\( h \) Number of regimes / states, an integer

\( Q \) \( h \) dimensional transition matrix for the MS process. \( h \times h \) Markov transition matrix whose rows sum to 1 with the main weights on the diagonal elements. Default is \(\text{NULL} \) and the initial value is defined by \( q_{\text{tune}} \).

Details

This function sets the initial or starting values for the the optimization algorithm for the mode of the MSBVAR models in \textit{msbvar}. This is an attempt to (1) allow for a robust, smart guess for starting the block-optimization algorithm and (2) allow for user inputs to \textit{initialize.opt}.

The function does three things:

1. Estimates an initial \textit{szbvar} model as a baseline, non-regime switching model.

2. Estimates a set of \( h \) VAR regressions based on a \textit{kmeans} clustering of the time series with \( h \) clusters or centers. The VAR models fit to each of the \( h \) subsets of data are used to initialize the \textit{msbvar} function.

3. Sets an initial value for \( Q \) in the block optimization algorithm for the mode of the MLE / posterior for the MSBVAR model. If \( Q = \text{NULL} \), for an \( h \times h \) transition matrix \( Q \), this initial value is set based on the results from the \textit{kmeans} clustering of the data. If the user inputs a value of \( Q \), this is used and error checked to make sure it has the correct format (i.e., rows sum to 1, etc.)
irf

Value

A list with three elements (these are the inputs for the initialize.opt argument in msbvar)

*init.model* An object of the class SZBVAR, see szbvar for details

*thetahat.start* The starting values for the regression parameters for the block optimization algorithm in msbvar. This is an \( m \times (mp + 1 + m) \times h \) array of the initial coefficients. For the \( i \)th element of the array, the \( m \) rows refer to the equations, the first column elements are the intercepts, the next \( 2 : (mp + 1) \) columns are the AR(p) coefficients, and the final \( m \times m \) elements are the error covariance for the regime, for that array element.

*Qhat.start* Initial value of \( Q \)

Note

This function can be used to model other ways to set the initial conditions. The subsequent calls to the msbvar function only require an object that satisfies having the elements returned from this function — computed by this function or the user in some way.

Author(s)

Patrick T. Brandt

See Also

msbvar

Examples

```R
##
```

irf

*Impulse Response Function (IRF) Computation for a VAR*

Description

Computes the impulse response function (IRF) or moving average representation (MAR) for an \( m \)-dimensional set of VAR/BVAR/B-SVAR coefficients.

Usage

`irf(varobj, nsteps, A0= NULL)`
Arguments

- **varobj**: VAR, BVAR, or BSVAR objects for a fitted VAR, BVAR, or BSVAR model from `szbvar`, `szbsvar` or `reduced.form.var`.

- **nsteps**: Number of steps, or the horizon over which to compute the IRFs (typically 1.5 to 2 times the lag length used in estimation).

- **A0**: Decomposition contemporaneous error covariance of a VAR/BVAR/BSVAR, default is a Cholesky decomposition of the error covariance matrix for VAR and BVAR models, $A0 = \text{chol}(\text{varobj}$mean$\text{.S}$), and the inverse of $A0$ for B-SVAR models, $A0 = \text{solve}(\text{varobj}$A0$\text{.mode}$).

Details

This function should rarely be called by the user. It is a working function to compute the IRFs for a VAR model. Users will typically want to use one of the simulation functions that also compute error bands for the IRF, such as `mc.irf` which calls this function and simulates its multivariate posterior distribution.

Value

A list of the AR coefficients used in computing the IRF and the impulse response matrices:

- $B_{m \times m \times \text{nstep}}$: Autoregressive coefficient matrices in lag order. Note that all AR coefficient matrices for $\text{nstep} > p$ are zero.

- $\text{mhat}_{m \times m \times \text{nstep}}$: Impulse response matrices. $\text{mhat}[\text{, , i}]$ are the impulses for the $i$'th period for the $m$ variables.

Note

The IRF depends on the ordering of the variables and the structure of the decomposition in $A0$.

Author(s)

Patrick T. Brandt

References


See Also

See also `dfev` for the related decompositions of the forecast error variance, `mc.irf` for Bayesian and frequentist computations of IRFs and their variances (which is what you probably really want).
**Examples**

```r
data(IsraelPalestineConflict)
rf.var <- reduced.form.var(IsraelPalestineConflict, p=6)
plot(irf(rf.var, nsteps = 12))
```

---

**IsraelPalestineConflict**

*Weekly Goldstein Scaled Israeli-Palestinian Conflict Data, 1979-2003*

**Description**

This data set gives Goldstein scaled totals that summarize the Israeli-Palestinian conflict from April 1979 - December 2003. These are dyadic or directed actions from one party towards the other. Data are weekly starting April 15, 1979. Positive values indicate cooperation, negative values indicate aggression. These are a subset of the Levant dataset from the Kansas / Penn State Event Data System Levant dataset. The data are from Reuters and AFP news sources and encoded into the World Event Interaction Survey (WEIS) coding system and Goldstein scalings using the Penn State Event Data System TABARI program. Source data can be found on the KEDS site below.

**Usage**

```r
data(IsraelPalestineConflict)
```

**Format**

A matrix containing 1278 observations. Column one, "i2p", is the Israeli actions towards the Palestinians and column two, "p2i" is the Palestinian actions towards the Israelis.

**Source**


**References**


Computational Event Data Project [http://eventdata.parusanalytics.com](http://eventdata.parusanalytics.com)
ldwishart

Log density for a Wishart variate

Description
Computes log density for a Wishart random variable.

Usage
ldwishart(W, v, S)

Arguments
- W: Wishart variate for which the log density is to be computed
- v: degrees of freedom for the Wishart variate
- S: scale factor for the Wishart variate (typically the inverse covariance if you are working with a multivariate random normal setup)

Details
Computes the log density for a Wishart variate with mean $S$ and degrees of freedom $v$. Special care has been taken to avoid underflow in the computation.

Value
A scalar, the value of the log density for the variate $W$ with mean $S$ and degrees of freedom $v$.

Note
This is modified from the log density function in MCMCpack. It better handles underflows.

Author(s)
Patrick T. Brandt

See Also
rwishart

Examples
```r
x <- matrix(rnorm(100), 50, 2)
XX <- crossprod(x)
ldwishart(solve(XX), 50, diag(2))
```
list.print

Prints a list object for the VAR and BVAR models in MSBVAR

Description
Provides a smartly formatted print method for the list objects created by MSBVAR objects. This will provide a table of estimates for the VAR and BVAR methods in this package.

Usage
list.print(x)

Arguments
x Fitted model object from szbvar or szbsvar

Details
This is a way to view the coefficients from a B(S)-VAR model fit with this package.

Value
None. Results are send to STDOUT.

Author(s)
Patrick T. Brandt and Justin Appleby.

See Also
szbvar, szbsvar

mae
Mean absolute error of VAR forecasts

Description
Computes the mean absolute error of VAR forecasts

Usage
mae(m1, m2)

Arguments
m1 \(nsteps \times m\) matrix of VAR forecasts
m2 \(nsteps \times m\) matrix of VAR forecasts or true values
mc.irf

Monte Carlo Integration / Simulation of Impulse Response Functions

Description

Simulates a posterior of impulse response functions (IRF) by Monte Carlo integration. This can handle Bayesian and frequentist VARs and Bayesian (structural) VARs estimated with the szbvar, szbsvar or reduced.form.var functions. The decomposition of the contemporaneous innovations is handled by a Cholesky decomposition of the error covariance matrix in reduced form (B)VAR object, or for the contemporaneous structure in S-VAR models. Simulations of IRFs from the Bayesian model utilize the posterior estimates for that model.

Usage

mc.irf(varobj, nsteps, draws=1000, A0.posterior=NULL, sign.list=rep(1, ncol(varobj$Y)))
Arguments

- **varobj**: VAR objects for a fitted VAR model from either `reduced.form.var`, `szbvar` or `szbsvar`.
- **nsteps**: Number of periods over which to compute the impulse responses.
- **draws**: Number of draws for the simulation of the posterior distribution of the IRFs (if not a `szbsvar` object. For the MSBVAR model, this is the value of $N^2$ from the MCMC sampling (default). You probably should use more than the default given here.
- **A0.posterior**: Posterior sample objects generated by `gibbs.A0()` for B-SVAR models, based on the structural identification in `varobj$ident`.
- **sign.list**: A list of signs (length = number of variables) for normalization given as either 1 or -1.

Details

**VAR/BVAR**: Draws a set of posterior samples from the VAR coefficients and computes impulse responses for each sample. These samples can then be summarized to compute MCMC-based estimates of the responses using the error band methods described in Sims and Zha (1999).

**B-SVAR**: Generates a set of $N^2$ draws from the impulse responses for the Bayesian SVAR model in `varobj`. The function takes as its arguments the posterior moments of the B-SVAR model in `varobj`, the draws of the contemporaneous structural coefficients $A_0$ from `gibbs.A0`, and a list of signs for normalization. This function then computes a posterior sample of the impulse responses based on the Schur product of the sign list and the draws of $A_0$ and draws from the normal posterior pdf for the other coefficients in the model.

The computations are done using compiled C++ code as of version 0.3.0. See the package source code for details about the implementation.

**MSBVAR**: Computes a set of regime specific impulse responses. There will be $h$ of the $m \times$ responses, per the discussion above (shocks in columns, equations / responses in rows. The default is for these to be presented serially. Finally, a regime averaged set of responses, based on the ergodic probability of being in each regime is presented as the "long run" responses. At present this is experimental and open to changes.

Value

**VAR/BVAR**: An `mc.irf.VAR` or `mc.irf.BVAR` class object object that is the array of impulse response samples for the Monte Carlo samples.

- **impulse**: `draws \times nsteps \times m^2` array of the impulse responses.

**B-SVAR**: `mc.irf.BSVAR` object which is an $(N^2, nsteps, m^2)$ array of the impulse responses for the associated B-SVAR model in `varobj` and the posterior $A_0$.

**MS-BVAR**: `mc.irf.MSBVAR` object which is a list of two arrays. The first array are $(N^2, nsteps, m^2, h)$ array of the short-run, regime specific impulse shock-response combinations. The second array are
the regime averaged, long run responses based on the ergodic regime probabilities. This second list item is an array of dimensions \((N^2, nsteps, m^2)\).

**Note**

Users need to think carefully about the number of steps and the size of the posterior sample in \(A_0\), since enough memory needs to be available to store and process the posterior of the impulse responses. The number of bytes consumed by the impulse responses will be approximately \(m^2 \times nsteps \times N^2 \times 16\) where \(N^2\) is the number of draws of \(A_0\) from the gibbs.A0. Be sure you have enough memory available to store the object you create!

**Author(s)**

Patrick T. Brandt

**References**


**See Also**

See also as `plot.mc.irf` for plotting methods and error band construction for the posterior of these impulse response functions, `szbsvar` for estimation of the posterior moments of the B-SVAR model, `gibbs.A0` for drawing posterior samples of \(A_0\) for the B-SVAR model before the IRF computations, and `msbvar` and `gibbs.msbvar` for the specification and computation of the posterior for the MSBVAR models.

**Examples**

```r
# Example 1
data(IsraelPalestineConflict)
varnames <- colnames(IsraelPalestineConflict)

fit.BVAR <- szbvar(Y=IsraelPalestineConflict, p=6, z=NULL,
lambda0=0.6, lambda1=0.1,
lambda3=2, lambda4=0.25, lambda5=0, mu5=0,
mu6=0, nu=3, qm=4,
prior=0, posterior.fit=FALSE)

# Draw from the posterior pdf of the impulse responses.
posterior.impulses <- mc.irf(fit.BVAR, nsteps=10, draws=5000)

# Plot the responses
```
mcmc.szbsvar

Gibbs sampler for coefficients of a B-SVAR model

Description

Draws a posterior sample of the reduced form coefficients for a Bayesian SVAR model

Usage

mcmc.szbsvar(varobj, A0.posterior)

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>varobj</td>
<td>A B-SVAR object created by szbsvar</td>
</tr>
<tr>
<td>A0.posterior</td>
<td>A posterior sample object generated by gibbs.A0</td>
</tr>
</tbody>
</table>

Details

This function draws the parameters from the Bayesian SVAR model described by Waggoner and Zha (2003). The details can be found in szbsvar. The draws are done for the SVAR model and then translated into the reduced form parameters.

Value

A list of the class "mcmc.bsvar.posterior" with the following components:

- A0.posterior: $m \times m \times N^2$ array of the posterior matrices $A_0$.
- B.sample: $N^2 \times ncoeff$ matrix of the reduced form coefficients for the SVAR.
Summary measures and plots for MS-B(S)VAR state-spaces

Description

Provides a summary and plotting methods for the SS class objects produced from sampling the posterior of an MSBVAR model. These functions provide the mean regime probabilities and a plotting method for them.

Usage

```r
## S3 method for class 'SS'
mean(x, ...)
## S3 method for class 'SS'
sum(x, ...)
## S3 method for class 'SS'
plot(x, ylab="State Probabilities", ...)
```

Arguments

- `x` SS class object produced by sampling the posterior of a Markov-switching BVAR model in MSBVAR. These are produced by `gibbs.msbvar`.
- `ylab` y-axis label for the regime plot.
- `...` Other argument or graphics parameters for `plot`. 
mountains

Details

The first two provide the sum and mean of the number of time periods in each state of Markov-process. The last produces a time series plot of the regime or state probabilities. These are computed from the Markov Chain Monte Carlo sample computed from `gibbs.msbvar`.

Value

Mean and sum are $T \times h$ matrices for the first two summary functions. The plot function generates a plot in the current device. These are the posterior probability measures of the Markov process regimes across $T$ periods.

Author(s)

Patrick T. Brandt

See Also

gibbs.msbvar, msbvar

mountains

Mountain plots for summarizing forecast densities

Description

"Mountain plots" summarize the bivariate density of 2 variables for two competing forecasts of those variables.

Usage

`mountains(fcasts1, fcasts2, varnames, pts, ...)`

Arguments

- `fcasts1`: `gibbs` × 2 set of forecasts from model 1
- `fcasts2`: `gibbs` × 2 set of forecasts from model 2
- `varnames`: `c("name1","name2")` object of the variable names
- `pts`: `c(pt1,pt2)` which are reference points to be plotted.
- `...`: Other graphics parameters.
Details
A "mountain plot" provide a $2 \times 2$ graph of plots that summarize the bivariate forecasts for two competing forecasts. This function presents four perspectives on the bivariate density or 'hills' for a set of forecasts. Starting from the bottom right plot and working counter-clockwise, the first plot is the bivariate density of the two competing forecasts. The next plot is a contour map that provide the topography of the densities. The third and fourth plots are projections of densities in each variable. The first forecast in the function is presented in black, the second in red. The densities are estimated from the Gibbs Monte Carlo sample of forecasts using the bkde2D bivariate kernel density estimator with an optimal plug-in bandwidth selected using dpill.

Value
None. Produces the mountain plot described above in the current graphics device.

Note
This function requires the bivariate kernel smoother in the package bkde2D

Author(s)
Patrick T. Brandt

References

See Also
bkde2D for details of the density estimators

Examples
```r
## Not run:
data(IsraelPalestineConflict)

# Fit a BVAR model
fit.BVAR <- szbvar(IsraelPalestineConflict, p=6, z=NULL, lambda0=0.6, lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0, mu5=0, mu6=0, nu=3, qm=4, prior=0, posterior.fit=FALSE)

# Fit a flat prior / MLE model
fit.FREQ <- szbvar(IsraelPalestineConflict, p=6, z=NULL, lambda0=0.6, lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0, mu5=0, mu6=0, nu=3, qm=4, prior=2, posterior.fit=FALSE)

# Generate unconditional forecasts for both models
forecast.BVAR <- uc.forecast.var(fit.BVAR, nsteps=2,
```
msbvar

Markov-switching Bayesian reduced form vector autoregression model setup and posterior mode estimation

Description
Sets up and estimates the posterior mode of a reduced form Markov-switching Bayesian vector autoregression model with a Sims-Zha prior. This is the setup and input function for the Gibbs sampler for this model.

Usage

```r
msbvar(Y, z=NULL, p, h, lambda0, lambda1, lambda3,
      lambda4, lambda5, mu5, mu6, qm,
      alpha.prior=100*diag(h) + matrix(2, h, h),
      prior=0, max.iter=40, initialize.opt=NULL)
```

Arguments

- **Y**: A $T \times m$ multiple time series object created with `ts()`.
- **z**: NOT IMPLEMENTED AT PRESENT: THIS SHOULD BE A $T \times k$ matrix of exogenous variables. Can be `z = NULL` if there are none (the default).
- **p**: Lag length, an integer
- **h**: Number of regimes / states, an integer
- **lambda0**: Value in $[0, 1]$, Overall tightness of the prior (discounting of prior scale).
- **lambda1**: Value in $[0, 1]$, Standard deviation or tightness of the prior around the AR(1) parameters.
- **lambda3**: Lag decay ($> 0$, with $1=$harmonic)
- **lambda4**: Standard deviation or tightness around the intercept $> 0$
- **lambda5**: Standard deviation or tightness around the exogeneous variable coefficients $> 0$
- **mu5**: Sum of coefficients prior weight $\geq 0$. Larger values imply difference stationarity.
mu6  Dummy initial observations or drift prior $\geq 0$. Larger values allow for common trends.

qm  Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"

alpha.prior  Prior for the Dirichlet process for the MS process. Default is $100 \ast \text{diag}(h) + \text{matrix}(2, h, h)$, but the model will be sensitive to this.

prior  One of three values: 0 = Normal-Wishart prior, 1 = Normal-flat prior, 2 = flat-flat prior (i.e., akin to MLE). The conjugate prior is the first one, which is the default.

max.iter  Maximum number of iterations for the block EM algorithm used to fit an initial guess of the model posterior. Default value is 40 iterations. Larger problems will need more iterations.

initialize.opt  Initial values for the block optimization algorithm. If default=NULL initialize.msbvar is called to provide values. User can specify values as long as they conform to the structure produced by initialize.msbvar.

Details

This function estimates the posterior mode of a reduced form Bayesian Markov-switching VAR model. The MSVAR model is estimated using block EM algorithm where the blocks are 1) the BVAR regression coefficients for each regime (separating optimands for intercepts, AR coefficients, and error covariances) and 2) the transition matrix. Starting values are randomly drawn, so a random number seed should be set prior to calling the function in order to make the results replicable.

The steps of the blockwise optimization follow the suggestions of Sims, Waggoner, and Zha (2008). The joint optimization problem is partitioned into the following separate blocks. For each block, a separate call to optim is made, holding all of the other blocks constant:

1. Maximize over the intercepts
2. Maximize over the AR(p) coefficients
3. Maximize over the error covariances $\Sigma$
4. Maximize over the transition matrix $Q$

These four blocks are iterated a total of max.iter times. Internal to each block, the state-space filtering algorithm for the regime classifications is computing using compiled Fortran code for speed. Despite the use of compiled code, this algorithm can take several minutes to compute.

The user should try multiple starting values and number of iterations to ensure convergence. The algorithm will improve with each step of the optimization, although sometimes this can be very incremental improvement.

The results for posterior sampling via gibbs.msbvar will be sensitive to the choice of alpha.prior. This is the prior for the independent Dirichlet process for the MS process. Note that the prior is roughly proportionate to the number of time periods spent in each regime, since the estimated MS probabilities map to the duration of the regime via $1/(1 - p)$ where $p$ is the probability of staying in the regime.
This function should NOT be used for inference, since it only finds the posterior mode of the model. This function is intended to generate starting values for the Gibbs sampling of the model. See `gibbs.msbvar` for further details of the Gibbs sampling.

**Value**

A list describing the posterior mode of the MSBVAR model and the inputs necessary for the subsequent Gibbs sampler.

- `init.model`: An object of the class BVAR that describes the setup of the model. See `szbvar` for details.
- `hreg`: A list containing the regime-specific moment matrices, VAR coefficients, and error covariances.
- `Q`: The $h \times h$ Markov transition matrix.
- `fp`: The $T \times h$ matrix of the filtered regime probabilities. First column is the first regime, etc.
- `m`: Integer, the number of endogenous variables in the system.
- `p`: Integer, the lag length of the VAR.
- `h`: Integer, the number of regimes in the MS process.
- `alpha.prior`: The $h \times h$ matrix for the prior for the Dirichlet density for the MS process.

**Note**

Users should consult the reference papers and the (coming) package vignette to see how this function is used to setup an MSBVAR model. An example is currently in `gibbs.msbvar`.

**Author(s)**

Patrick T. Brandt

**References**

See Also

gibbs.msvar for the MCMC sampler after using this function, szbvar for a non-switching, Bayesian VAR and more details.

Examples

```r
## Not run:
# Simple replication of Hamilton (1989) as in
# Kim and Nelson (1999: 79, 220)

data(HamiltonGDP)
set.seed(214)
m2 <- msvar(HamiltonGDP, p=1, h=2,
  lambda0=0.8, lambda1=0.15, lambda3=1, lambda4=0.25,
  lambda5=1, mu5=0, mu6=0, q=12,
  alpha.prior=c(100, 30)*diag(2) +
  matrix(12, 2, 2), prior=0, max.iter=30,
  initialize.opt=NULL)

# Now plot the filtered probabilities of a recession
# Compare to Kim and Nelson (1999: 79, 220)

fp.rec <- ts(m2$fp[1], start=tsp(HamiltonGDP)[1],
  freq=tsp(HamiltonGDP)[3])
plot(fp.rec)

## End(Not run)
```

---

**msvar**  
*Markov-switching vector autoregression (MSVAR) estimator*

**Description**

Estimates a Markov-switching vector autoregression (MSVAR) model with \( h \) regimes (states) by maximum likelihood. The Hamilton filtering algorithm is used to estimate the regimes. The numerical optimization to compute the MLE is based on the block-wise algorithm of Sims, Waggoner and Zha (2008).

**Usage**

```r
msvar(Y, p, h, niterblkopt = 10)
```
Arguments

Y \quad T \times m \text{ multiple time series object created with ts().}

p \quad \text{Lag length, an integer}

h \quad \text{Number of regimes / states, an integer}

niterblkopt \quad \text{Number of iterations to allow for the block-wise optimization.}

Details

This function computes ML estimates for an MSVAR(p,h) model where \( p \) is the number of lags and \( h \) is the number of regimes. The model is estimated using the block-wise algorithm of Sims, Waggoner, and Zha (2008). This ML optimization algorithm splits the parameter space of the MSVAR model into separate block components: (1) the transition matrix \( Q \), (2) the intercepts, (3) the autoregressive coefficients, (4) the error covariances. The algorithm does 4 separate optimizations for each \( niterblkopt \) calls. Each component of the model is optimized separately over the \( niterblkopt \) values using separate calls to \texttt{optim}. Within each \texttt{optim} call, Fortran code is used to do the work of the filtering algorithm for the regimes in the model.

Value

A list of class \texttt{MSVAR} and the appropriate inputs objects to feed the results into subsequent functions like \texttt{gibbs.msbvar} (though you should use \texttt{msbvar} and specify a prior!).

\begin{itemize}
  \item \texttt{init.model} \quad \text{Description of ‘comp1’}
  \item \texttt{hreg} \quad \text{Description of ‘comp2’}
  \item \texttt{Q} \quad h \times h \text{ Markov transition matrix}
  \item \texttt{fp} \quad T \times h \text{ Transition probability matrix}
  \item \texttt{m} \quad \text{Integer, number of equations}
  \item \texttt{p} \quad \text{Integer, number of lags}
  \item \texttt{h} \quad \text{Integer, number of regimes}
  \item \texttt{llfval} \quad \text{Vector of length niterblkopt}
  \item \texttt{DirectBFGSLastSuccess} \quad \text{\texttt{optim} convergence code returned in the last optimization used in the last block-wise optimization}
\end{itemize}

Note

Consult the \texttt{msbvar} function for more details on the model. This function is only included as a baseline or helper to the overall estimation goal of fitting MSVAR models.

Author(s)

Patrick T. Brandt and Ryan Davis
normalize.svar

References


See Also

msbvar for the Bayesian estimator, szbvar for the Bayesian, non-regime-switching version, gibbs.msbvar for posterior sampling.

Examples

```r
## Not run:
# Simple replication of Hamilton (1989) as in
# Kim and Nelson (1999: 79, 220)

data(HamiltonGDP)
set.seed(1)

m2 <- msvar(HamiltonGDP, p=1, h=2, niterblkopt=20)

# Now plot the filtered probabilities of a recession
# Compare to Kim and Nelson (1999: 79, 220)

fp.rec <- ts(m2$fp[,1], start=tsp(gdp)[1], freq=tsp(gdp)[3])
plot(fp.rec)

## End(Not run)
```

normalize.svar

**Likelihood normalization of SVAR models**

Description

Computes various sign normalizations of Bayesian structural VAR (B-SVAR) models.

Usage

```r
normalize.svar(A0unnormalized, A0mode, 
    method = c("DistanceMLA", "DistanceMLAhat", 
        "Euclidean", "PositiveDiagA", 
        "PositiveDiagAinv", "Unnormalized"), 
    switch.count = 0)
```
Arguments

A0unnormalized $m \times m$ unnormalized matrix value of $A_0$ in an B-SVAR

A0mode $m \times m$ matrix of the $A_0$ to normalize around

method string that selects the normalization method

switch.count counter that counts the number of sign switches. Can be non-zero if you want to track the sign switches iteratively.

Details

The likelihood of VAR models are invariant to sign changes of the structural equation coefficients across equations. Thus a VAR with $m$ equations has a likelihood with $2^m$ identical peaks, each a different set of signs (but with the same posterior peak). Normalization is used to choose among these peaks. The most common choice is to select the peak where the diagonal elements of $A_0$ are all positive, but will not be possible in all cases since no such normalization may exist. Thus, one should select a single peak and map all of the draws back to that peak.

The available normalization methods are 1) "DistanceMLA" : normalize around the ML peak of $A0mode$, 2) "DistanceMLAhat" : normalize around the ML peak of inv($A0mode$) 3) "Euclidean" : normalize by minimizing the distance between the two matrices. 4) "PositiveDiagA" : normalize by making the diagonal positive 5) "PositiveDiagAinv" : normalize by making the diagonal of inv($A0$) positive. 6) "Unnormalized" : no normalization is performed and the function returns $A0$ unnormalized.

Value

A list with two elements

A0normalized $m \times m$ matrix, the normalized value of $A_0$ according to the selected normalization rule.

switch.count Number of signs changed in the normalization

Note

This function is called in gibbs.A0.BSVAR, the Gibbs sampling of szbsvar models. In those functions, the $A_0$ produced by szbsvar is unnormalized. The Gibbs sampled draws are then normalized using the "DistanceMLA" method, which is consistent with the positive system shocks typically seen in the literature, if such a normalization exists. Note that Waggoner and Zha prefer the "DistanceMLA" method.

Author(s)

Patrick T. Brandt

References


null.space

Find the null space of a matrix

Description

Computes the null space of A for an arbitrary linear system of the form Ax = b.

Usage

null.space(x)

Arguments

x \hspace{1cm} m \times n \hspace{0.5cm} A \hspace{0.5cm} \text{matrix of a linear system } Ax = b

Details

Computes the null space via singular value decomposition (SVD) of A by finding the columns of the SVD of A that correspond to the non-singular column vectors that span A.

Value

Returns an \( m \times q \) matrix that is the null space, where \( q \) is the rank of \( A \).

Author(s)

Patrick T. Brandt

See Also

svd
Description

Plots mean VAR forecasts and pointwise error bands

Usage

```r
## S3 method for class 'forc.ecdf'
plot(x, probs = c(0.05, 0.95),
     xlab = "", ylab = "", ylim = NA, ...)
```

Arguments

- `x`: N x nstep matrix of forecasts
- `probs`: width of error band probabilities, default is 90% quantiles or `c(0.05, 0.95)`
- `xlab`: x-axis labels
- `ylab`: y-axis labels
- `ylim`: Bounds for y-axis in standard format `c(lower, upper)`
- `...`: other plot parameters

Details

Plots the mean forecast and the pointwise empirical confidence region for a posterior sample of VAR forecasts.

Value

None.

Author(s)

Patrick T. Brandt

See Also

`plot.forecast`

Examples

```r
## Not run:
data(IsrealPalestineConflict)

# Fit a BVAR model
fit.BVAR <- szbvar(IsrealPalestineConflict, p=6, z=NULL, lambda0=0.6,
                   lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
```
plot.forecast

Plot function for forecasts

Description
Generates simple plots of forecasts obtained from forecast.VAR / forecast.BVAR / forecast.B-SVAR

Usage

## S3 method for class 'forecast'
plot(x, ...)

Arguments

- **x**: Plots generated from forecast generated through fitted VAR, BVAR, or B-SVAR model from forecast.
- **...**: Other graphics parameters

Details
Generates a plot in the current graphics device for the m time series in the respective (B)VAR model.

Value

None. Generates a plot in the current graphics device.

Author(s)

Patrick T. Brandt
plot.gibbs.A0

See Also

summary

Examples

## Not run:
plot(x)

## End(Not run)

plot.gibbs.A0  
Plot a parameter density summary for B-SVAR A(0) objects

Description

Generates an $m \times m$ matrix of density plots for each free parameter in an szbsvar $A_0$ object produced by gibbs.A0, with associated highest posterior density (HPD) regions.

Usage

## S3 method for class 'gibbs.A0'
plot(x, hpd = 0.68, varnames=attr(x, "eqnames"), ...)

Arguments

x  
An $A_0$ posterior object created by szbsvar.

hpd  
Probability width of the highest posterior density region, default is 0.68 or approximately one standard deviation around the mode of the parameter

varnames  
List of variable names for labeling the equations and variables. Default are the names of the variables for the input data to szbsvar as fed through gibbs.A0. For an SVAR, users often want to relabel these as economic sectors or groups of actors for the time series and this is the place this can be done.

...  
optional graphics arguments

Details

This function plots an $m \times m$ matrix of densities for the posterior of the $A_0$ free parameters for a B-SVAR model. The plot is arranged such that the unrestricted parameters for each contemporaneous effect of each variable on an equation are in the row for that equation. So the first row shows densities for the contemporaneous effects of the column variables (as in an impulse response plot like plot.irf or plot.mc.irf). Elements of $A_0$ that were restricted to zero are left empty in the matrix of densities. The pattern of the densities will match the *transpose* of the ident matrix passed to szbsvar.

Highest posterior density regions are plotted using Hyndman’s (1996) density quantile algorithm. These HPDs are defined by a set of vertical bars over the HPD interval. The vertical line in each plot measures the value of the density at the boundaries of the HPD region. The HDR is superimposed at the bottom of each density.
Value

None. Main purpose is to plot density summaries and HPDs for each of the free parameters in an \( A_0 \) matrix.

Note

The plot will tend to be large, so be sure to adjust the size of your plotting device accordingly so things are visible.

Author(s)

Patrick T. Brandt

References


HPD code is borrowed from Hyndman’s hdrcde package, version 2.07.

See Also

plot.mcmc, summary.mcmc, and A02mcmc.

Examples

```
# SZ, B-SVAR model for the Levant data
data(BCFdata)
m <- ncol(Y)
ident <- diag(m)
ident[1,] <- 1
ident[2,] <- 1

# estimate the model's posterior moments
set.seed(123)
model <- szbsvar(Y, p=2, z=z2, lambda0=0.8, lambda1=0.1, lambda3=1, lambda4=0.1, lambda5=0.05, mu5=0, mu6=5, ident, qm=12)

# Set length of burn-in and size of posterior. These are only an example. Production runs should set these much higher.
N1 <- 1000
N2 <- 10000

A0.posterior.obj <- gibbs.A0(model, N1, N2, thin=1)

# Plot the matrix of the densities
dev.new()
plot.gibbs.A0(A0.posterior.obj, hpd=0.68, varnames=colnames(Y))
```
plot.irf  Plots impulse responses

Description

Plots the m x m matrix of impulse responses produced by irf.

Usage

## S3 method for class 'irf'
plot(x, varnames = attr(x, "eqnames"), ...)

Arguments

x
  Impulse response object produced by irf

varnames
  Names of equations and shocks in the format c("name1","name2",...). Default is to use the names of the input variables from the estimation method.

...
  other plot arguments

Details

Generates a plot in the current plotting device of the impulse responses in irf. See below for functions that allow one to add error bands and confidence regions to the impulse responses. Impulses or shocks are in the columns and the rows are the responses.

Value

None. Draws a graph in the current device.

Note

This function should NOT be used for Monte Carlo samples of IRFs. Use plot.mc.irf for this purpose.

Author(s)

Patrick T. Brandt

References


See Also

irf to produce impulse responses from a VAR object, mc.irf, and plot.mc.irf for methods that allow frequentist and Bayesian error bands in the impulse responses
Examples

data(israelPalestineConflict)
rff.var <- reduced.form.var(israelPalestineConflict, p=6)
plot(irff(rff.var, nsteps = 12))

plot.mc.irf

Plotting posteriors of Monte Carlo simulated impulse responses

Description

Provides a plotting method for the mc.irf Monte Carlo sample of impulse responses. Responses can be plotted with classical or Bayesian error bands, as suggested by Sims and Zha (1999).

Usage

## S3 method for class 'mc.irf'
plot(x, method=c("Percentile", "Normal Approximation", "Sims-Zha1", "Sims-Zha2", "Sims-Zha3"), component=1, 
     probs=c(0.16, 0.84), varnames = attr(x, "eqnames"), 
     regimelabels=NULL, ask=TRUE, ...)

Arguments

x
Output of the mc.irf function

method
Method to be used for the error band construction. Default method is to use the eigendecomposition method proposed by Sims and Zha. Defined methods are "Percentile" (error bands are based on percentiles specified in probs), "Normal Approximation" (Gaussian approximation for interval of width probs), "Sims-Zha1" (Gaussian approximation with linear eigendecomposition), "Sims-Zha2" (Percentiles with eigendecomposition for each impulse response function), "Sims-Zha3" (Percentiles with eigendecomposition of the full stacked impulse responses)

component
If using one of the eigendecomposition methods, the eigenvector component to be used for the error band construction. Default is the first or largest eigenvector component.

probs
is the width of the error bands. Default is c(0.16, 0.84) which is a 68% band that is approximately one standard deviation, as suggested by Sims and Zha.

varnames
List of variable names of length m for labeling the impulse responses. Default are the input variable names from the relevant estimation method.

regimelabels
For MSBVAR models from mc.irf, a character vector of length h for the regime-specific IRFs. Default of NULL leads to automatic generation of "Regime 1", "Regime 2", etc.

ask
Default = TRUE, ask before showing the next regime’s IRFs for MSBVAR models?

... Other graphics parameters.
Details

This function plots the output of a Monte Carlo simulation of (MS)(B)(BS)VAR impulse response functions produced by mc.irf. The function allows the user to choose among a variety of frequentist (normal approximation and percentile) and Bayesian (eigendecomposition) methods for constructing error bands around a set of impulse responses. Impulses or shocks are in the columns and the rows are the responses.

Value

The primary reason for this function is to plot impulse responses and their error bands. Secondarily, it returns an invisible list of the impulses responses, their error bands, and summary measures of the fractions of the variance in the eigenvector methods that explain the total variation of each response.

responses Responses and their error bands
eigenvector.fractions Fraction of the variation in each response that is explained by the chosen eigenvectors. NULL for non-eigenvector methods.

Author(s)

Patrick T. Brandt

References


See Also

See Also mc.irf for the computation of Monte Carlo samples of impulse responses, szbsvar for estimation of the posterior moments of the B-SVAR model, gibbs.0 for Gibbs sampling the posterior of the $A_0$ for the model, and

Examples

```r
## Not run:
data(IsrealPalestineConflict)
fit.BVAR <- szbvar(IsrealPalestineConflict, p=6, z=NULL, lambda0=0.6,
                   lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
                   mu5=0, mu6=0, nu=3, qm=4, prior=0,
                   posterior.fit=FALSE)

posterior.impulses <- mc.irf(fit.BVAR, nsteps=12, draws=1000)
plot(posterior.impulses, method = c("Percentile"))

## End(Not run)
```
plot.ms.irf  

Color plot of MSBVAR impulse response functions

Description

Provides an overplotted, color-coded version of the MSBVAR IRFs plot. This is an experimental function using color rather than the separate plots produced in plot.mc.irf.

Usage

```r
## S3 method for class 'ms.irf'
plot(x, method = "Sims-Zha2", component = 1,
     probs = c(0.16, 0.84), varnames = attr(x, "eqnames"), ...)
```

Arguments

- `x`: Output of the `mc.irf` function for an MSBVAR model via `gibbs.msbvar`
- `method`: Method to be used for the error band construction. Default method is to use the eigendecomposition method proposed by Sims and Zha. Defined methods are "Percentile" (error bands are based on percentiles specified in `probs`), "Normal Approximation" (Gaussian approximation for interval of width `probs`), "Sims-Zha1" (Gaussian approximation with linear eigendecomposition), "Sims-Zha2" (Percentiles with eigendecomposition for each impulse response function), "Sims-Zha3" (Percentiles with eigendecomposition of the full stacked impulse responses)
- `component`: If using one of the eigendecomposition methods, the eigenvector component to be used for the error band construction. Default is the first or largest eigenvector component.
- `probs`: is the width of the error bands. Default is `c(0.16, 0.84)` which is a 68% band that is approximately one standard deviation, as suggested by Sims and Zha.
- `varnames`: List of variable names of length `m` for labeling the impulse responses. Default are the input variable names from the relevant estimation method.
- `...`: Other graphics parameters.

Details

This function plots the output of a Monte Carlo simulation of MSBVAR impulse response functions produced by `mc.irf`. The function allows the user to choose among a variety of frequentist (normal approximation and percentile) and Bayesian (eigendecomposition) methods for constructing error bands around a set of impulse responses. Impulses or shocks are in the columns and the rows are the responses. Here the plot colors the responses for each regime, per the R default color palette for colors 1:h.
Value

The primary reason for this function is to plot impulse responses and their error bands. Secondarily, it returns an invisible list of the impulses responses, their error bands, and summary measures of the fractions of the variance in the eigenvector methods that explain the total variation of each response.

responses Responses and their error bands
eigenvector.fractions Fraction of the variation in each response that is explained by the chosen eigenvectors. NULL for non-eigenvector methods.

Author(s)

Patrick T. Brandt

References


See Also

plot.mc.irf

Examples

```r
## Not run:
data(IsraelPalestineConflict)
m1 <- msbvar(IsraelPalestineConflict, p=1, h=2, lambda0=0.6, 
        lambda1=0.1, lambda3=1, lambda4=0.5, lambda5=0, 
        mu5=0, mu6=0, qm=12, alpha.prior=matrix(10, 2, 2), 
        prior=0, max.iter=20)
m2p <- gibbs.msivar(m1, N1=1000, N2=10000, permute=FALSE, Sigma.idx=1)

irf2 <- mc.irf(m2p, nsteps=12)
plot.ms.irf(irf2)

## End(Not run)
```
plotregimeid

Clustering and plotting function for msbvar permuted sample output

**Description**
Identifies and plots regime-specific coefficients from the random permutation sampler for regime identification.

**Usage**
```r
plotregimeid(x,
    type = c("all", "intercepts", "AR1", "Sigma", "Q"),
    ask = TRUE, ...)
```

**Arguments**
- **x**: Gibbs sampler output of class MSBVAR from the posterior of an MSBVAR model, a call to the `gibbs.msbvar` function.
- **type**: Items to be clustered and plots to be produced to identify the posterior regimes / modes of the Gibbs sampler based on the randomly permuted draws. The type can be "intercepts" where the clustering of the posterior draws and the plots are based on the intercepts in each equation (so a change in equilibrium model), "AR1" where the clustering of the posterior draws are based on the coefficients in the VAR(1) matrices across the regimes, "Sigma" or the variances of the equations across the regimes, or "Q" based on the elements of the transition matrix, Q. The option "all" generates the plots and clustering for all of the above options and is the default.
- **ask**: logical, default=TRUE. Ask about which plots to show, ala the syntax in coda. If TRUE then all relevant responses are displayed on the current graphical device with user input. Otherwise, all plots run by in the current device as generated.
- **...**: Optional graphical and lattice parameters to be fed to the plots. There is no assurance that these will work. E-mail if you have inputs on this that do not work, but that you think should.

**Details**
The posterior of a Markov-switching (MS) model estimated by an unrestricted Gibbs sampler has \( h! \) identical posterior modes. The modes are identical in the sense that they are merely relabelings of the regime labels. Since the analyst may not apriori know what defines or separates the regimes in the parameter space, this function allows one to explore the randomly permuted labelings that are generated by the `gibbs.msbvar` function.

This function takes the permuted output of `gibbs.msbvar` and shows colored pairs, scatter, density plots, and traceplots for the posterior parameters. The coloring follow standard R color pallates. The determination of how the regimes are identified is based on a `kmeans` clustering of either the the parameters "intercepts", "AR1", "Sigma" (variances), or "Q" transition probabilities. This is the method suggested by Fruhwirth-Schanatter (2001, 2006). The utility here is that this function
plotsregimeid handles subsetting the data, setting up the clustering and plotting and labeling the results for the user.

Regime identification and labeling is necessary so that one can sample from a single mode of the posterior to get sensible regime classification plots from say plot.SS or regime probabilities from say mean.SS.

Value
None. A series of plots are produced in the current graphics device.

Note
This is the first version of this function. Future versions may use a slightly different syntax and only use one input argument.

Author(s)
Patrick T. Brandt

References


See Also
msbvar, plot.SS, mean.SS, gibbs.msbvar

Examples
```r
## Not run:
# This example can be pasted into a script or copied into R to run. It
takes a few minutes, but illustrates how the code can be used
data(IsraelPalestineConflict)

# Find the mode of an msbvar model
# Initial guess is based on random draw, so set seed.
set.seed(123)

xm <- msbvar(IsraelPalestineConflict, p=1, h=2,
 lambda0=0.8, lambda1=0.15,
 lambda3=2, lambda4=1, lambda5=0, mu5=0,
 mu6=0, qm=12,
 alpha.prior=matrix(c(100,40,30,50), 2, 2))

# Plot out the initial mode
plot(ts(xm$fp))```
posterior.fit

Estimates the marginal likelihood or log posterior probability for BVAR, BSVAR, and MSBVAR models

Description

Computes the marginal log likelihood other posterior fit measures for BVAR, BSVAR, and MSBVAR models fit with szbvar, szbsvar and, msbvar (and their posterior samplers).

Usage

posterior.fit(varobj, A0.posterior.obj=NULL, maxiterbs=500)

Arguments

varobj Varies for BVAR, BSVAR, or MSBVAR models. For a BVAR model, varobj = output from a call to szbvar. For a BSVAR model, varobj = output from a call to szbsvar. For MSBVAR models, varobj = output from a call to gibbs.msvar.

A0.posterior.obj MCMC Gibbs object for the B-SVAR model A0 from gibbs.A0

maxiterbs Number of iterations for the bridge sampler for computing the marginal likelihood for MSBVAR models
Details

Estimates the marginal log likelihood, also known as a log marginal data density for the various models. For the BVAR models, this can be computed in closed form. For the BSVAR models the MCMC data augmentation method of Chib (1995) is employed. For the MSBSVAR models, the importance sampler, reciprocal importance sampler, and bridge sampler methods of Fruwirth-Schnatter (2006) are used. Consult these references for details (or look at the source code).

The computations are done using compiled C++ and Fortran code as of version 0.3.0. See the package source code for details about the implementation.

Value

BVAR:
A list of the class "posterior.fit.BVAR" that includes the following elements:

- **data.marg.11f**: Log marginal density, the probability of the data after integrating out the parameters in the model.
- **data.marg.post**: Predictive marginal posterior density
- **coefficient.post**: Contribution to the posterior fit from the pdf of the coefficients.

BSVAR:
A list of the class "posterior.fit.BSVAR" that includes the following elements:

- **log.prior**: Log prior probability
- **log.11f**: $T \times 1$ list of the log probabilities for each observation conditional on the parameters.
- **log.posterior.Aplus**: Log marginal probability of $A_1, \ldots, A_p$ conditional on the data and $A_0$
- **log.marginal.data.density**: Log data density or marginal log likelihood, the probability of the data after integrating out the parameters in the model.
- **log.marginal.A0k**: $m \times 1$ list of the log probabilities of each column (corresponding to the equations) of $A_0$ conditional on the other columns.

MSBSVAR:
A list of the class "posterior.fit.MSBSVAR" that includes the following elements:

Note

The log Bayes factor for two model can be computed using the log.marginal.data.density:

$$\log BF = \log{\text{marginal.data.density.1}} - \log{\text{marginal.data.density.2}}$$

Note that at present, the scale factors for the BVAR and B-SVAR models are different (one used the concentrated likelihood, the other does NOT). Thus, one cannot compare fit measures across the two functions. To compare a recursive B-SVAR to a non-recursive B-SVAR model, one should estimate the recursive model with `szbsvar` using the appropriate `ident` matrix and then call `posterior.fit` on the two B-SVAR models!
Author(s)

Patrick T. Brandt and W. Ryan Davis

References


See Also

`szbvar`, `szbsvar`, `gibbs.A0`, `gibbs.msbvar`, and `print.posterior.fit` for a print method.

Examples

```r
## Not run:
varobj <- szbsvar(Y, p, z = NULL, lambda0, lambda1, lambda3, lambda4,
                   lambda5, mu5, mu6, ident, qm = 4)
A0.posterior <- gibbs.A0(varobj, N1, N2)
fit <- posterior.fit(varobj, A0.posterior)
print(fit)

## End(Not run)
```

Description

Prints decomposition of forecast error variance tables

Usage

```r
## S3 method for class 'dfev'
print(x, latex = F, file = NULL, ...)

## S3 method for class 'dfev'
summary(object, latex = F, file = NULL, ...)
```
Arguments

- **x**: DFEV object created by `dfev`
- **object**: DFEV object created by `dfev`
- **latex**: Logical. T = format results in LaTeX tables, default is F, text output
- **file**: File for the results. If NULL, prints to standard output device.
- **...**: Other print and summary arguments

Details

Prints DFEV results in a table using `xtable` functions.

Value

None.

Author(s)

Patrick T. Brandt

See Also

See `dfev` for an example.

description

Prints objects of the classes "posterior.fit.VAR", "posterior.fit.BVAR", and "posterior.fit.BSVAR".

Usage

```r
## S3 method for class 'posterior.fit'
print(x, ...)
```

Arguments

- **x**: object produced by `posterior.fit`
- **...**: other print options

Details

Called for its side effect — printing the output of `posterior.fit`
rdirichlet

Random draws from and density for Dirichlet distribution

Description
Generate draws from a random Dirichlet distribution or compute its density.

Usage
rdirichlet(n, alpha)
ddirichlet(x, alpha)

Arguments
n Number of draws
alpha Scale matrix, \( h \times h \)
x value to compute density

Details
Draws \( n \) values for an \( h \times h \) Dirichlet random variable or computes the density.

Value
\( x \) An \( n \times h \) matrix of the draws
Note

Based on code from Kevin Quinn in the MCMCpack package and the gregmisc package.

References

MCMCpack and gregmisc

Examples

```r
dirichlet(2, matrix(rep(1, 4), 2, 2))
```

---

**reduced.form.var**

*Estimation of a reduced form VAR model*

**Description**

Estimates a reduced form VAR using equation-by-equation seemingly unrelated regression (SUR).

**Usage**

```r
reduced.form.var(Y, p, z=NULL)
```

**Arguments**

- **Y**: $T \times m$ multiple time series object created with `ts()`.
- **p**: Lag length
- **z**: $T \times k$ exogenous variables in a matrix of $T$ rows. Can be `NULL` if there are none.

**Details**

This is a frequentist VAR estimator. This is a workhorse function — you will want to use other functions such as `irf.mc.irf` or `dfev` to report and interpret the results of this object.

**Value**

List of class "VAR" with elements,

- **intercept**: Row vector of the $m$ intercepts.
- **ar.coefs**: $m \times m \times p$ array of the AR coefficients. The first $m \times m$ array is for lag 1, the $p$'th array for lag $p$.
- **Bhat**: $(mp + k + 1) \times m$ matrix of the coefficients, where the columns correspond to the variables in the VAR. Intercepts follow the AR coefficients, etc.
- **exog.coefs**: $k \times m$ matrix of exogenous coefficients, or `NA` if $z=NULL$
- **vcv**: $m \times m$ matrix of the maximum likelihood estimate of the residual covariance
- **mean.S**: $m \times m$ matrix of the posterior residual covariance.
regimeSummary

- `hstar` - $mp \times mp$ right hand side variables crossproduct.
- `X` - Right hand side variables for the estimation of BVAR
- `Y` - Left hand side variables for the estimation of BVAR
- `y` - Input data (Y)

**Author(s)**

Patrick T. Brandt

**References**


**See Also**

See also `szbvar` for BVAR models with the Sims-Zha prior and `szbsvar` for Bayesian SVAR models with the Sims-Zha prior.

**Examples**

```r
data(IsraelPalestineConflict)
rf.var <- reduced.form.var(IsraelPalestineConflict, p=6)
plot(irf(rf.var, nsteps=12))
```

---

**Description**

Provides summary and quantile computations for regime probabilities and regime durations based on MSBVAR MCMC output.

**Usage**

```r
regimeSummary(x, quantiles = c(0.025, 0.25, 0.5, 0.75, 0.975))
```

**Arguments**

- `x` - output from `gibbs.msvbvar`, the MCMC sampler for the MSBVAR models
- `quantiles` - quantiles one wants to compute, as is done in the coda package. Defaults are as given above.
Details

This function is mainly a wrapper for calls to the coda package to summarize the MCMC output for the transition matrix of an MSBVAR model estimated from `gibbs.msbvar`. It adds labels to the output so one knows which regime is which in the output. In the summary of the transition matrix $Q'$'s elements $q_{ij}$ for the transition from regime $i$ to regime $j$.

The ergodic regime probabilities are computed for draw $k$ of the MSBVAR MCMC sampler as described in Kim and Nelson (1999):

```r
teta <- solve(rbind(cbind(diag(h-1) - t(Q)[1:(h-1),1:(h-1)], t(Q)[1:(h-1),h]), rep(1,h)))
```

This gives $N2$ draws of the ergodic probabilities of being in regime $k$. These are summarized again using coda functions.

Finally, the ergodic regime probabilities can be used to estimate expected long run regime durations. For $\eta_k$ the expected duration is $1/(1 - \eta_k)$. This again is summarized over the $N2$ draws using coda functions.

Value

Invisible list with 3 elements:

- `Q.summary`: Summary and quantiles of the sample draws of the transition matrix
- `lrQ`: Summary and quantiles of the long run or ergodic regime probabilities
- `durations`: Summary and quantiles of the estimated regime durations

Author(s)

Patrick T. Brandt

References


See Also

`gibbs.msbvar`, `plotregimeid`, `msbvar`

Examples

```r
## Not run:
regimeSummary(x)

## End(Not run)```
restmtx

Utility function for generating the restriction matrix for hard condition forecasting

Description

Generates the restriction matrix for a set of hard condition forecasts. See hc.forecast for details.

Usage

restmtx(nsteps, m)

Arguments

nsteps Number of periods in the forecast horizon
m Number of endogenous variables in the VAR.

Details

Builds the appropriately dimensioned and filled restriction matrix of zeros and ones for hard condition forecasting.

Value

A matrix of dimensions (nsteps x m*nsteps) that can be used to represent the restrictions in hard condition forecasting using hc.forecast

Author(s)

Patrick T. Brandt

References


See Also

hc.forecast
rmse

Root mean squared error of a Monte Carlo / MCMC sample of forecasts

Description
Computes the root mean squared error (RMSE) of a Monte Carlo sample of forecasts.

Usage
rmse(m1, m2)

Arguments
m1  Forecast sample for model 1
m2  Forecast sample for model 2

Details
User needs to subset the forecasts if necessary.

Value
Forecast RMSE.

Author(s)
Patrick T. Brandt

See Also
mae, forecast

Examples

```r
data(IsraelPalestineConflict)
Y.sample1 <- window(IsraelPalestineConflict, end=c(2002, 52))
Y.sample2 <- window(IsraelPalestineConflict, start=c(2003, 1))

# Fit a BVAR model
fit.bvar <- szbvar(Y.sample1, p=6, lambda0=0.6, lambda1=0.1, lambda3=2,
                   lambda4=0.25, lambda5=0, mu5=0, mu6=0, prior=0)

# Forecast -- this gives back the sample PLUS the forecasts!
forecasts <- forecast(fit.bvar, nsteps=nrow(Y.sample2))

# Compare forecasts to real data
rmse(forecasts[(nrow(Y.sample1)+1):nrow(forecasts),], Y.sample2)
```
Multivariate Normal Random Number Generator

Description

Generates multivariate normal random variates for given mean and covariance vectors. Can also handle generation of multivariate normal deviates with singular covariance distributions via singular value decomposition (SVD).

Usage

```r
rmultnorm(n, mu, vmat, tol = 1e-10)
```

Arguments

- `n`: Number of variates to draw.
- `mu`: `m` column matrix of multivariate means.
- `vmat`: `m × m` covariance matrix.
- `tol`: Tolerance level used for SVD of the covariance. Default is 1e-10.

Details

Generates `n` draws from a multivariate normal distribution with mean matrix `mu` and covariance matrix `vmat`.

Value

Matrix of the random draw that is conformable with the input `mu`.

Note

Based on code by Jeff Gill. This function is called in the hard condition forecasting in `hc.forecast` for simulating the structural innovations.

Author(s)

Patrick T. Brandt

See Also

`rnorm`

Examples

```r
rmultnorm(1, matrix(c(1,2),2,1), vmat=matrix(c(1,1,0,1),2,2))
```
**rwishart**

*Random deviates from a Wishart distribution*

**Description**

Draws random deviates from a Wishart pdf.

**Usage**

```
rwishart(N, df, Sigma)
```

**Arguments**

- **N**: Number of random deviates to draw.
- **df**: Degrees of freedom for Wishart distribution
- **Sigma**: Mean of the Wishart from which to draw the deviates

**Details**

Draws N matrices of draws from a Wishart with mean Sigma. This is used to draw error covariances for the VAR and BVAR models which are distributed inverse Wisharts deviates.

**Value**

Returns an N dimensional array of dim(Sigma) square matrices for the Wishart random deviates. If N=1, it returns a single matrix.

**Author(s)**

Patrick T. Brandt

**See Also**

See also as `rmultnorm` for multivariate normal deviates, `rgamma` for the univariate analog to drawing Wishart deviates, and `ldwishart` for computing the log density for a Wishart variate.

**Examples**

```
x <- matrix(rnorm(100), 50, 2)
XX <- crossprod(x)
tmp <- rwishart(1, 50, XX)
```
Simulate (univariate) Markov-switching autoregressive (MSAR) data

**Description**

Simulate (univariate) Markov-switching autoregressive (MSAR) data

**Usage**

```r
simulateMSAR(bigt, Q, theta, st1, y1)
```

**Arguments**

- `bigt` Integer, number of observations to generate.
- `Q` \( h \times h \) dimensional transition matrix for the MS process. \( h \times h \) Markov transition matrix whose rows sum to 1 with the main weights on the diagonal elements.
- `theta` Matrix of the MSAR coefficients with \( h \) rows and \( m \times p + 2 \) columns. The first column is the constants, the next \( m \times p + 1 \) columns are the autoregressive coefficients (by lag – so the first \( m \times 1 \) are the AR(1) coefficients, etc.) and the last \( m \times 1 \) elements are the error variances (remember, this is univariate!)
- `st1` Starting regime, an integer less than or equal to \( h \)
- `y1` Starting value for simulated data in regime \( st1 \)

**Details**

This function simulates a univariate MSAR model. The user needs to input the transition matrix \( Q \) and the autoregression coefficients via \( \theta \). The assumption in this model is that the error process is Gaussian.

**Value**

A list with two elements:

- `Y` The simulated univariate MSAR time series
- `st` A vector of integers identifying the regime of each observation in \( Y \)

**Author(s)**

Patrick T. Brandt and Ryan Davis

**References**

simulateMSVAR

See Also

simulateMSVAR for the multivariate version

Examples

## Example of call here

#### simulateMSVAR

*Simulate a Markov-switching VAR (MSVAR) process*

**Description**

Simulate Markov-switching vector autoregression data

**Usage**

```r
simulateMSVAR(big_t, m, p, var.beta0, var.betas, e.vcv, Q, seed = 214)
```

**Arguments**

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>big_t</code></td>
<td>Integer, number of observations to generate.</td>
</tr>
<tr>
<td><code>m</code></td>
<td>Integer, number of equations in the VAR process</td>
</tr>
<tr>
<td><code>p</code></td>
<td>Integer, lag length of the VAR(p) process.</td>
</tr>
<tr>
<td><code>var.beta0</code></td>
<td>Array of dimension $m \times 1 \times h$ of the VAR intercepts for each regime (h)</td>
</tr>
<tr>
<td><code>var.betas</code></td>
<td>Array of dimension $m \times m \times h$ of the autoregressive coefficients. In each element of the array, rows correspond to equations, columns to lags. The first $m \times m$ columns are the AR(1) coefficients, etc.</td>
</tr>
<tr>
<td><code>e.vcv</code></td>
<td>Array of dimension $m \times m \times h$ of the error covariances. The $m \times m$ matrices are the error covariances for each regime.</td>
</tr>
<tr>
<td><code>Q</code></td>
<td>$h$ dimensional transition matrix for the MS process. $h \times h$ Markov transition matrix whose rows sum to 1 with the main weights on the diagonal elements.</td>
</tr>
<tr>
<td><code>seed</code></td>
<td>Integer. Random number seed.</td>
</tr>
</tbody>
</table>

**Details**

This function simulates a multivariate Markov-switching model, MSVAR with $m$ equations, $p$ lags and $h$ regimes. The assumption is that the error process is Gaussian.

**Value**

A list with two elements:

- `Y` The simulated MSVAR time series in a `ts` object of dimension $big_t \times m$.  
- `st` A vector of integers identifying the regime of each observation in `Y`. 
Author(s)

Patrick T. Brandt and Ryan Davis

References


See Also

simulateMSAR for the univariate version; msbvar

Examples

```r
## Not run:
# Example: simulate an MS(h)-VAR(p) model with two equations.
# Have h = 2, m=2, and p=1, simplest case

# VAR simulation parameters
bigt <- 500  # number of observations
m <- 2      # number of endogenous variables
p <- 1      # lag length
h <- 2      # number of regimes

# setup transition matrix with two states
Q <- matrix(c(.98, .02,
      .05, .95), nrow=h, byrow=TRUE)

# theta stores parameter values
# 1st column is intercept
# 2:m*p are the AR coefficients
# (mp+2)'th columns are variance

# regime 1
var.beta0.st1 <- c(1,2)  # intercepts
var.betas.st1  <- matrix(c(.7, .1,
                        .1, .7), m, byrow=TRUE)
# regime 2
var.beta0.st2 <- c(0,0)  # intercepts
var.betas.st2  <- matrix(c(.2, .1,
                        .2, .1), m, byrow=TRUE)

# Build the array
var.beta0 <- array(NA, c(m,1,h))
var.betas  <- array(NA, c(m,p*m,h))
var.beta0[,,1] <- var.beta0.st1
var.beta0[,,2] <- var.beta0.st2
var.betas[,,1] <- var.betas.st1
var.betas[,,2] <- var.betas.st2

# Variance-Covariance Matrix for
## SS.ffbs

State-space forward-filter and backwards-sampler for a Markov-switching VAR model

### Description

This function estimates the $h$ state probabilities for all of the observations for a Gaussian likelihood.

### Usage

```r
SS.ffbs(e, bigt, m, p, h, sig2, Q)
```

### Arguments

- `e`: $bigt \times m \times h$ array of the residuals for an MSBVAR process
- `bigt`: integer, number of observations in the model
m integer, number of equations or variables in the MSBVAR model
p integer, number of lags in the model
h integer, number of regimes in the MSBVAR model
sig2 $m \times m \times h$ array of the covariances for each regime (can be the same for each of the $h$ regimes)
Q $h \times h$ first order Markov transition matrix; each row must sum to 1

Details
The estimation of an MSBVAR model requires an efficient classifier of the states for the observed filtered probabilities. This function provides a way to accomplish this and is one of the workhorses in the estimation in the msbvar and gibbs.msbvar function.

This function uses compiled Fortran code to draw the 0-1 matrix of the regimes. It uses the Baum-Hamilton-Lee-Kim (BHLK) filter and smoother to estimate the regime probabilities. Draws are based on the standard forward-filter-backward-sample algorithm.

Value
A $T \times h$ matrix of the sampled regimes. Each row corresponds to an identity matrix element giving the regime classification for the observation.

Note
This function assumes that the innovation in the MSBVAR model are multivariate normal. The resulting filter and sample follows that in the references listed above. This function is provided so users can build their own customized MSBVAR models. Users can write functions to generate the (B)VAR residuals for their own customized MSBVAR models than then provide the residuals and their covariances and transition matrix $Q$. This function can then be used to estimate / sample the regime probabilities. So if you need an MSBVAR model where only certain parameters change — rather than all of them as in the existing msbvar and gibbs.msbvar functions — you can build your own estimator using this function. This function takes care of the hard part of building an MSBVAR model.

Author(s)
Patrick T. Brandt

References
See Also

msbvar, gibbs.msbvar

Examples

# Simple example to show how data are input to the filter-sampler.
# Assumes a simple bivariate regression model with switching means and
# variances.

TT <- 100
h <- 2
m <- 2
set.seed(123)
x1 <- rnorm(TT)
x2 <- rnorm(TT)
y1 <- 5 + 2*x1 + rnorm(TT)
y2 <- 1 + x2 + 5*rnorm(TT)

Y <- rbind(cbind(y1[1:(0.5*TT)], y2[1:(0.5*TT)]),
           cbind(y2[((0.5*TT)+1):TT], y1[((0.5*TT)+1):TT]))
X <- rbind(cbind(x1[1:(0.5*TT)], x2[1:(0.5*TT)]),
           cbind(x2[((0.5*TT)+1):TT], x1[((0.5*TT)+1):TT]))

u1 <- Y - tcrossprod(cbind(rep(1, TT), X), matrix(c(5,2,0,1,1,0), 2, 3))
u2 <- Y - tcrossprod(cbind(rep(1, TT), X), matrix(c(1,1,0,5,2,0), 2, 3))

u <- array(0, c(TT, m, h))
u[,1] <- u1
u[,2] <- u2

Sik <- array(0, c(m, m, h))
Sik[,,1] <- diag(c(1,25))
Sik[,,2] <- diag(c(25,1))

Q <- matrix(c(0.9,0.2,0.1,0.8), h, h)

# estimate the states 100 times
ss <- replicate(100, SS.ffbs(u, TT, m, p=1, h, Sik, Q, simplify=FALSE))

# Get the state estimates from the 100 simulations
ss.est <- matrix(unlist(ss), nrow=(h*TT + h^2))

ss.prob <- matrix(rowMeans(ss.est[1:(h*TT),]), ncol=h)
ss.transition <- matrix(rowMeans(ss.est[((h*TT)+1):((h*TT) + h^2),]),
                        h, h)
Description

Prints a summary of the coefficient matrices for various VAR / BVAR / B-SVAR model objects to standard output.

Usage

```r
summary(object, ...)
```

Arguments

- `object` Fitted VAR, BVAR, or B-SVAR model from either `reduced.form.var`, `szbvar`, or `szbsvar`
- `...` other arguments

Details

Prints (posterior) coefficient matrices for each lag and error covariance summaries as appropriate.

Value

None.

Author(s)

Patrick T. Brandt

See Also

`summary`

Examples

```r
## Not run:
summary(x)
```

## End(Not run)
**Summary functions for forecasts obtained through VAR / BVAR / B-SVAR model objects**

**Description**
Prints a summary of the mean and quantile values for the forecasts generated through VAR / BVAR / B-SVAR model objects to standard output.

**Usage**
```r
## S3 method for class 'forecast'
summary(object, probs = c(0.16, 0.84), ...)
```

**Arguments**
- `object`: Forecast object generated through fitting a VAR, BVAR, or B-SVAR model from either `forecast::forecast`, `forecast::BVAR`, or `forecast::BSVAR`.
- `probs`: Vector list of probability range for quantiles. Default: `c(0.16, 0.84)` or a 68% region (approximately one standard deviation on each side of the mean).
- `...`: Optional arguments (ignored, but included for S3 consistency).

**Details**
Prints a summary of the mean and quantile values for the forecasts.

**Value**
Returns the mean forecast and the specified posterior probability interval for the forecasts.

**Author(s)**
Patrick T. Brandt

**See Also**
`summary`

**Examples**
```r
## Not run:
summary(x)
## End(Not run)```
SZ.prior.evaluation  Sims-Zha Bayesian VAR Prior Specification Search

Description

Estimates posterior and in-sample fit measures for a reduced form vector autoregression model with different specifications of the Sims-Zha hyperparameters values.

Usage

SZ.prior.evaluation(Y, p, lambda0, lambda1, lambda3, lambda4, lambda5, mu5, mu6, z = NULL, nu = ncol(Y) + 1, qm, prior = 0, nsteps, y.future)

Arguments

Y  T x m matrix of endogenous variables for the VAR
p  Lag length
lambda0  List of values, e.g, c(0.7, 0.8, 0.9) in [0,1], Overall tightness of the prior (discounting of prior scale).
lambda1  List of values, e.g, c(0.05, 0.1, 0.2) in [0,1], Standard deviation or tightness of the prior around the AR(1) parameters.
lambda3  List of values, e.g, c(0, 1, 2) for Lag decay (>0, with 1=harmonic)
lambda4  List of values, e.g, c(0.15, 0.2, 0.5) for Standard deviation or tightness around the intercept [>0]
lambda5  Single value for the standard deviation or tightness around the exogeneous variable coefficients [>0]
mu5  Single value for sum of coefficients prior weight [>=0]
mu6  Single value for dummy Initial observations or cointegration prior [>=0]
z  Exogenous variables
nu  Prior degrees of freedom = m+1
qm  Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"
prior  One of three values: 0 = Normal-Wishart prior, 1 = Normal-flat prior, 2 = flat-flat prior (i.e., akin to MLE)
nsteps  Number of periods in the forecast horizon
y.future  Future values of the series, nsteps x m for computing the root mean squared error and mean absolute error for the fit
Details

This function fits a series of BVAR models for the combinations of \( \lambda_0 \), \( \lambda_1 \), \( \lambda_3 \), and \( \lambda_4 \) provided. For each possible value of these parameters specified, a Sims-Zha prior BVAR model is fit, posterior fit measures are computed, and forecasts are generated over \( n_{steps} \). These \( n_{steps} \) forecasts are then compared to a new set of data in \( y_{\text{future}} \) and root mean squared error and mean absolute error measures are computed.

Value

A matrix of the results with columns corresponding to the values of "\( \lambda_0 \)", "\( \lambda_1 \)", "\( \lambda_3 \)", "\( \lambda_4 \)", "\( \mu_5 \)", "\( \mu_6 \)", "RMSE", "MAE", "MargLLF", "MargPosterior".

Note

The matrix of the results can be usefully plotted using the lattice package. See the example below.

Author(s)

Patrick T. Brandt

References


See Also

szbvar

Examples

```r
Y <- EuStockMarkets
results <- SZ.prior.evaluation(window(Y, start=c(1998, 1), end=c(1998,149)),
                               p=3,
                               lambda0=c(1,0.9),
                               lambda1=c(0.1,0.2),
                               lambda3=c(0,1),
                               lambda4=c(0.1,0.25),
                               lambda5=0,
                               mu5=4,
                               mu6=4, z=NULL,
                               nu=ncol(Y)+1, qm=4,
                               prior=0,
                               nstep=20,
                               y_future=window(Y, start=c(1998,150)))

# Now plot the RMSE and marginal posterior of the data for each of the
# 6 period forecasts as a function of the prior parameters. This can
```
szbsvar  Structural Sims-Zha Bayesian VAR model estimation

Description

Estimates the posterior mode for a Bayesian Structural Vector Autoregression (B-SVAR) model using the prior specified by Sims and Zha (1998)

Usage

szbsvar(y, p, z = NULL, lambda0, lambda1, lambda3, lambda4, lambda5, mu5, mu6, ident, qm = 4)

Arguments

y  $T \times m$ multiple time series object created with ts() with no NAs.

p  integer lag length for the model

z  $T \times k$ matrix of exogenous variables (not including an intercept)

lambda0  $[0, 1]$, Overall tightness of the prior (discounting of prior scale).

lambda1  $[0, 1]$, Standard deviation or tightness of the prior around the AR(1) parameters.

lambda3  Lag decay (> 0, with 1=harmonic)

lambda4  Standard deviation or tightness around the intercept > 0

lambda5  Standard deviation or tightness around the exogenous variable coefficients > 0

mu5  Sum of coefficients prior weight $\geq 0$. Larger values imply difference stationarity.

mu6  Dummy Initial observations or drift prior $\geq 0$. Larger values allow for common trends.

ident  $m \times m$ matrix of binary indicators for the identification of the free and restricted contemporaneous parameters in $A_0$.

qm  Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"
Details

This function estimates the posterior mode for the Bayesian structural VAR (B-SVAR) model described by Sims and Zha (1998) and Waggoner and Zha (2003). This B-SVAR model is based on a specification of the dynamic simultaneous equation representation of the model. The prior is constructed for the structural parameters.

The basic SVAR model has the form of Waggoner and Zha (2003):

\[ y_t' A_0 = \sum_{\ell=1}^{p} Y_{t-\ell} A_{\ell} + z_t' D + \epsilon_t', \quad t = 1, \ldots, T, \]

where \( A_\ell \) are \( m \times m \) parameter matrices for the contemporaneous and lagged effects of the endogenous variables, \( D \) is an \( h \times m \) parameter matrix for the exogenous variables (including an intercept), \( y_t \) is the \( m \times 1 \) matrix of the endogenous variables, \( z_t \) is a \( h \times 1 \) vector of exogenous variables (including an intercept) and \( \epsilon_t \) is the \( m \times 1 \) matrix of structural shocks. NOTE that in this representation of the model, the columns of the \( A_\ell \) matrices refer to the equations!

The structural shocks are normal with mean and variance equal to the following:

\[ E[\epsilon_t|y_1, \ldots, y_{t-1}, z_1, \ldots z_{t-1}] = 0 \]
\[ E[\epsilon_t\epsilon_t'|y_1, \ldots, y_{t-1}, z_1, \ldots z_{t-1}] = I \]

The reduced form representation of the SVAR model can be found by post-multiplying through by \( A_0^{-1} \):

\[ y_t' A_0 A_0^{-1} = \sum_{\ell=1}^{p} Y_{t-\ell} A_{\ell} A_0^{-1} + z_t' D A_0^{-1} + \epsilon_t' A_0^{-1} \]

\[ y_t' = \sum_{\ell=1}^{p} Y_{t-\ell} B_\ell + z_t' \Gamma + \epsilon_t' A_0^{-1}. \]

The reduced form error covariance matrix is found from the crossproduct of the reduced form innovations:

\[ \Sigma = E[(\epsilon_t' A_0^{-1})(\epsilon'_t A_0^{-1})'] = [A_0 A_0']^{-1}. \]

Restrictions on the contemporaneous parameters in \( A_0 \) are expressed by the specification of the iden matrix that defines the shocks that "hit" each equation in the contemporaneous specification. If \( \text{iden} \) is defined as in the following table,

<table>
<thead>
<tr>
<th>Equations</th>
<th>Eqn 1</th>
<th>Eqn 2</th>
<th>Eqn 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var. 1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Var. 2</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Var. 3</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
then the corresponding \( A_0 \) is restricted to

<table>
<thead>
<tr>
<th>Variables</th>
<th>Eqn 1</th>
<th>Eqn 2</th>
<th>Eqn 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var. 1</td>
<td>( a_{11} )</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Var. 2</td>
<td>( a_{12} )</td>
<td>( a_{22} )</td>
<td>0</td>
</tr>
<tr>
<td>Var. 3</td>
<td>0</td>
<td>( a_{23} )</td>
<td>( a_{33} )</td>
</tr>
</tbody>
</table>

which is interpreted as shocks in variables 1 and 2 hit equation 1 (the first column); shocks in variables 2 and 3 hit the second equation (column 2); and, shocks in variable 3 hit the third equation (column 3).

As in Sims and Zha (1998) and Waggoner and Zha (2003), the prior for the model is formed for each of the equations. To illustrate the prior, the model is written in the more compact notation

\[
y_t' A_0 = x_t' F + \epsilon_t'
\]

where

\[
x_t' = [y_{t-1} \cdots y_{t-p}, z_t']
\]

\[
F' = [A_1' \cdots A_p' D']
\]

are the matrices of the right hand side variables and the right hand side coefficients for the SVAR model.

The general form of this prior is then

\[
a_i \sim N(0, \bar{S}_i) \quad \text{and} \quad f_i|a_i \sim N(\bar{P}_i a_i, \bar{H}_i)
\]

where \( \bar{S}_i \) is an \( m \times m \) prior covariance of the contemporaneous parameters, and \( \bar{H}_i \) is the \( k \times k \) prior covariance of the parameters in \( f_i|a_i \). The prior means of \( a_i \) are zero in the structural model, while the "random walk" component is in \( \bar{P}_i a_i \).

The prior covariance matrix of the errors, \( \bar{S}_i \), is initially estimated using a VAR(p) model via OLS, with an intercept and no demeaning of the data.

The Bayesian prior is constructed for the unrestricted VAR model and then mapped into the restricted prior parameter space, as discussed in Waggoner and Zha (2003a).

**Value**

A list of the class "BSVAR" that summarizes the posterior mode of the B-SVAR model

- \( XX \) : \( X'X + H_0 \) crossproduct moment matrix for the predetermined variables in the model plus the prior
- \( XY \) : \( X'Y \) for the model, including the dummy observations for mu5 and mu6
- \( YY \) : \( m \times m \) Crossproduct for the Y's in the model
- \( y \) : \( T \times m \) input data in dat plus the m dummy observations for dat
- \( \text{structural.innovations} \) : \( T \times m \) structural innovations for the SVAR model
- \( \text{ui} \) : \( m \times q_i \) Null space matrices that map the columns of \( A_0 \) to the free parameters of the columns
szbsvar

$H_{\text{pinv.tilde}}$ Prior covariance for the predetermined and exogenous regression in the B-SVAR

$H_{\text{Oinv.tilde}}$ $m$ dimensional list of the prior covariances for the free parameters of the i’th equation in the model’s $A_0$ matrix

$P_{\text{tilde}}$ list of $(m^2p + 1 + h) \times q_i$ matrices of the prior for the parameters for the predetermined variables in the model

$H_{\text{pinv.posterior}}$ $(m^2p + 1 + h) \times m$ matrix of the posterior of the structural parameters for the predetermined variables

$P_{\text{posterior}}$ list of $(m^2p + 1 + h) \times m$ matrices of the posterior of the parameters for the predetermined variables in the model

$H_{\text{Oinv.posterior}}$ $m$ dimensional list of the posterior covariances for the free parameters of the i’th equation in the model’s $A_0$ matrix

$A_{\text{0.mode}}$ posterior mode of the $A_0$ matrix

$F_{\text{posterior}}$ $(m^2p + 1 + h) \times m$ matrix of the posterior of the structural parameters for the predetermined variables

$B_{\text{posterior}}$ $(m^2p + 1 + h) \times m$ matrix of the posterior of the reduced form parameters for the predetermined variables

$\text{ar.coefs}$ $(m^2p)\times m$ matrix of the posterior of the reduced form autoregressive parameters

$\text{intercept}$ $m$ dimensional vector of the reduced form intercepts

$\text{exog.coefs}$ $h \times m$ matrix of the reduced form exogenous variable coefficients

$\text{prior}$ List of the prior parameter: c($\lambda_0, \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \mu_5, \mu_6$).

$\text{df}$ Degrees of freedom for the model: $T +$ number of dummy observations - lag length.

$n0$ $m$ dimensional list of the number of free parameters for the $A_0$ matrix for equation $i$.

$\text{ident}$ $m \times m$ identification matrix $\text{ident}$.

**Warning**

If you do not understand the model described here, you probably want the models described in `szbvar` or `reduced.form.var`

**Author(s)**

Patrick T. Brandt

**References**


See Also

`szbvar` for reduced form Bayesian VAR models, `reduced.form.var` for non-Bayesian reduced form VAR models, `gibbs.A0` for drawing from the posterior of this model using a Gibbs sampler, `posterior.fit` for assessing the posterior fit of the model, and `mc.irf` for computing impulse responses for this model.

Examples

```r
# SZ, B-SVAR model for the Levant data
data(BCFdata)
m <- ncol(Y)
ident <- diag(m)
ident[1,] <- 1
ident[2,] <- 1

# estimate the model's posterior moments
model <- szbvar(Y, p=2, z=z2, lambda0=0.8, lambda1=0.1,
                 lambda2=1, lambda3=0.1, lambda4=0.05,
                 mu5=0, mu6=5, ident, qm=12)
```

---

**szbvar**  
Reduced form Sims-Zha Bayesian VAR model estimation

**Description**

Estimation of the Bayesian VAR model for just identified VARs described in Sims and Zha (1998)

**Usage**

```r
szbvar(Y, p, z = NULL, lambda0, lambda1, lambda2, lambda3, lambda4, lambda5,
        mu5, mu6, nu = ncol(Y)+1, qm = 4, prior = 0,
        posterior.fit = FALSE)
```

**Arguments**

- `Y`  
  \(T \times m\) multiple time series object created with `ts()`.
- `p`  
  Lag length
- `z`  
  \(T \times k\) matrix of exogenous variables. Can be `z = NULL` if there are none.
- `lambda0`  
  \([0, 1]\), Overall tightness of the prior (discounting of prior scale).
szbvar

\[ [0, 1], \text{Standard deviation or tightness of the prior around the AR(1) parameters.} \]
\[ \text{Lag decay (> 0, with 1=harmonic)} \]
\[ \text{Standard deviation or tightness around the intercept > 0} \]
\[ \text{Standard deviation or tightness around the exogeneous variable coefficients > 0} \]
\[ \text{Sum of coefficients prior weight} \geq 0. \text{Larger values imply difference stationarity.} \]
\[ \text{Dummy initial observations or drift prior} \geq 0. \text{Larger values allow for common trends.} \]
\[ \text{Prior degrees of freedom,} \ m + 1 \]
\[ \text{Frequency of the data for lag decay equivalence. Default is 4, and a value of 12 will match the lag decay of monthly to quarterly data. Other values have the same effect as "4"} \]
\[ \text{One of three values:} \ 0 = \text{Normal-Wishart prior,} \ 1 = \text{Normal-flat prior,} \ 2 = \text{flat-flat prior (i.e., akin to MLE)} \]
\[ \text{logical,} \ F = \text{do not estimate log-posterior fit measures,} \ T = \text{estimate log-posterior fit measures.} \]

Details

This function estimates the Bayesian VAR (BVAR) model described by Sims and Zha (1998). This BVAR model is based a specification of the dynamic simultaneous equation representation of the model. The prior is constructed for the structural parameters. The basic SVAR model used here is documented in szbsvar.

The prior covariance matrix of the errors, \( \bar{S}_i \), is initially estimated using a VAR(p) model via OLS, with an intercept and no demeaning of the data.

Value

Returns a list of multiple elements. This is a workhorse function to get the estimates, so nothing is displayed to the screen. The elements of the list are intended as inputs for the various post-estimation functions (e.g., impulse response analyses, forecasting, decompositions of forecast error variance, etc.)

Returns a list of the class "BVAR" with the following elements:

- **intercept** \( m \times 1 \) row vector of the \( m \) intercepts
- **ar.coefs** \( m \times m \times p \) array of the AR coefficients. The first \( m \times m \) array is for lag 1, the \( p' \)th array for lag \( p \).
- **exog.coefs** \( k \times m \) matrix of the coefficients for any exogenous variables
- **Bhat** \( (mp + k + 1) \times m \) matrix of the coefficients, where the columns correspond to the variables in the VAR
- **vcv** \( m \times m \) matrix of the maximum likelihood estimate of the residual covariance
- **vcv.Bh** Posterior estimate of the parameter covariance that is conformable with Bhat.
- **mean.S** \( m \times m \) matrix of the posterior residual covariance.
- **St** \( m \times m \) matrix of the degrees of freedom times the posterior residual covariance.
hstar \( (mp + k + 1) \times (mp + k + 1) \) prior precision plus right hand side variables crossproduct.

hstarinv \( (mp + k + 1) \times (mp + k + 1) \) prior covariance crossproduct solve(hstar)

H0 \( (mp + k + 1) \times (mp + k + 1) \) prior precision for the parameters

S0 \( m \times m \) prior error covariance

residuals \( (T - p) \times m \) matrix of the residuals

X \( T \times (mp+1+k) \) matrix of right hand side variables for the estimation of BVAR

Y \( T \times m \) matrix of the left hand side variables for the estimation of BVAR

y \( T \times m \) input data in dat

z \( T \times k \) exogenous variables matrix

p Lag length

num.exog Number of exogenous variables

qm Value of parameter to match quarterly to monthly lag decay (4 or 12)

prior.type Numeric code for prior type: 0 = Normal-Wishart, 1 = Normal-Flat, 2 = Flat-Flat (approximate MLE)

prior List of the prior parameter: c(lambda0,lambda1,lambda3,lambda4,lambda5, mu5, mu6, nu)

marg.llf Value of the in-sample marginal log-likelihood for the data, if posterior.fit=T

marg.post Value of the in-sample marginal log posterior of the data, if posterior.fit=T

coef.post Value of the marginal log posterior estimate of the coefficients, if posterior.fit=T

Note

This is a work horse function. You will probably want to use other functions to summarize and report the BVAR results.

Author(s)

Patrick T. Brandt, based on code from Robertson and Tallman and Sims and Zha.

References


See Also

reduced.form.var szbsvar
Examples

```r
### Not run:
data(ISraelPalestineConflict)
varnames <- colnames(ISraelPalestineConflict)

fit.BVAR <- szbvar(ISraelPalestineConflict, p=6, z=NULL,
lambda0=0.6, lambda1=0.1,
lambda2=2, lambda4=0.25, lambda5=0, mu5=0,
u06=0, nu=3, qm=4,
prior=0, posterior.fit=FALSE)

# Draw from the posterior pdf of the impulse responses.
posterior.impulses <- mc.irf(fit.BVAR, nsteps=10, draws=5000)

# Plot the responses
plot(posterior.impulses, method=c("Sims-Zha2"), component=1,
    probs=c(0.16,0.84), varnames=varnames)

### End(Not run)
```

---

**uc.forecast**

*Forecast density estimation unconditional forecasts for VAR/BVAR/BSVAR models via MCMC*

**Description**

Implements unconditional forecast density estimator for VAR/BVAR/BSVAR models described in Waggoner and Zha (1999). The unconditional forecasts place no restriction on the paths of the forecasts (cf. `hc.forecast`). The forecast densities are estimated as the posterior sample for the VAR/BVAR/BSVAR model using Markov Chain Monte Carlo with data augmentation to account for the uncertainty of the forecasts and the parameters. This function DOES account for parameter uncertainty in the MCMC algorithm.

**Usage**

```r
uc.forecast(varobj, nsteps, burnin, gibbs, exog = NULL)
```

**Arguments**

- **varobj**: VAR or BVAR object produced for a VAR or BVAR using `szbvar` or `reduced_form.var`
- **nsteps**: Number of periods in the forecast horizon
- **burnin**: Burnin cycles for the MCMC algorithm
- **gibbs**: Number of cycles of the Gibbs sampler after the `burnin` that are returned in the output
- **exog**: `num.exog x nsteps` matrix of the exogenous variable values for the forecast horizon. If left at the `NULL` default, they are set to zero.
Details

Produces a posterior sample of unconstrained VAR/BVAR/BSVAR forecasts via MCMC. This function accounts for the uncertainty of the VAR/BVAR/BSVAR parameters by sampling from them in the computation of the VAR/BVAR/BSVAR forecasts and then regenerating the forecasts. Data augmentation is used to account for the impact of the forecast uncertainty on the parameters.

Value

A list with three components:

- `yforc` Forecast sample
- `orig.y` Original endogenous variables time series
- `hyperp` values of the hyperparameters used in the BVAR estimation / MCMC

Author(s)

Patrick T. Brandt

References


See Also

- `hc.forecast`

Examples

```r
## Not run:
## Uses the example from Brandt and Freeman 2006. Will not run unless
## you have their data from the Politcal
## Analysis website!
library(MSBVAR)  # Brandt's package for Bayesian VAR models

# Read the data and set up as a time series
data <- read.dta("levant.weekly.79-03.dta")
attach(data)

# Set up KEDS data
KEDS.data <- ts(cbind(a2i,a2p,i2a,p2a,i2p,p2i),
               start=c(1979,15),
               freq=52,
               names=c("A2I","A2P","I2A","P2A","I2P","P2I"))

# Select the sample we want to use.
KEDS <- window(KEDS.data, end=c(1988,50))
```
### Estimate the BVAR models

# Fit a flat prior model
KEDS.BVAR.flat <- szbvar(KEDS, p=6, z=NULL, lambda=1,
lambda1=1, lambda3=1, lambda4=1, lambda5=0,
mu5=0, mu6=0, nu=0, qm=4, prior=2,
prior.fit=F)

# Reference prior model -- Normal-IW prior pdf
KEDS.BVAR.informed <- szbvar(KEDS, p=6, z=NULL, lambda=0.6,
lambda1=0.1, lambda3=2, lambda4=0.5, lambda5=0,
mu5=0, mu6=0, nu=ncol(KEDS)+1, qm=4, prior=0,
prior.fit=F)

# Set up conditional forecast matrix conditions
nsteps <- 12
a2i.condition <- rep(mean(KEDS[,1]) + sqrt(var(KEDS[,1])), nsteps)
yhat<-matrix(c(a2i.condition,rep(0, nsteps*5)), ncol=6)

# Set the random number seed so we can replicate the results.
set.seed(11023)

# Conditional forecasts
conditional.forcs.ref <- hc.forecast(KEDS.BVAR.informed, yhat, nsteps,
burnin=3000, gibbs=5000, exog=NULL)
conditional.forcs.flat <- hc.forecast(KEDS.BVAR.flat, yhat, nsteps,
burnin=3000, gibbs=5000, exog=NULL)

# Unconditional forecasts
unconditional.forcs.ref <- uc.forecast(KEDS.BVAR.informed, nsteps,
burnin=3000, gibbs=5000)
unconditional.forcs.flat <- uc.forecast(KEDS.BVAR.flat, nsteps,
burnin=3000, gibbs=5000)

# Set-up and plot the unconditional and conditional forecasts. This
# code pulls for the forecasts for I2P and P2I and puts them into the
# appropriate array for the figures we want to generate.
uc.flat <- NULL
hc.flat <- NULL
uc.ref <- NULL
hc.ref <- NULL

uc.flat$forecast <- unconditional.forcs.flat$forecast[,5:6]
hc.flat$forecast <- conditional.forcs.flat$forecast[,5:6]
uc.ref$forecast <- unconditional.forcs.ref$forecast[,5:6]
hc.ref$forecast <- conditional.forcs.ref$forecast[,5:6]
### var.lag.specification

#### Automated VAR lag specification testing

**Description**

Estimates a series of test statistics and measures for VAR lag length selection.

**Usage**

```r
var.lag.specification(y, lagmax = 20)
```

**Arguments**

- `y`: `T x m` multiple time series
- `lagmax`: Maximum lag order to be evaluated. Function will return lag length tests for all lag orders less than `lagmax`.

**Details**

Estimates a series of frequentist VAR models for 1 to `lagmax` and returns a sequence of $\chi^2$ tests, AIC, BIC and Hannan-Quinn criterion values for each lag length.

**Value**

Results are printed to standard output (screen or file). In addition, a list of two matrices is returned:

- `ldets`: Lag length, log-determinants, $\chi^2$ tests, and p-values for each lag length, compared to the null of the next shorter lag length
- `results`: Lag length, AIC, BIC, and HQ criteria for each lag length. Selection criteria should be minimized.

**Note**

Sizes of p-values are uncorrected for multiple testing. Use cautiously.

**Author(s)**

Patrick T. Brandt
References


See Also

See Also `reduced.form.var` for frequentist VAR estimation, `szbvar` for Bayesian VAR estimation, and `szbsvar` for Bayesian Structural VAR estimation.

Examples

```r
data(IsraelPalestineConflict)
var.lag.specification(IsraelPalestineConflict, lagmax=12)
```
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