bayesvarstable — Check the stability condition of Bayesian VAR estimates

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Description

bayesvarstable checks the eigenvalue stability condition after fitting Bayesian vector autoregression (VAR) by using bayes: var.

Quick start

Checking eigenvalue stability condition after bayes: var

bayesvarstable

Same as above, but compute 80% highest posterior density (HPD) credible intervals instead of 95% equaltailed credible intervals

bayesvarstable, hpd clevel(80)

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Syntax

bayesvarstable [, options]

options	Description
<u>est</u> imates(<i>estname</i>)	use previously stored results <i>estname</i> ; default is to use active results
<u>cl</u> evel(#)	set credible interval level; default is clevel (95)
hpd	save HPD credible intervals instead of the default equal-tailed credible intervals
<pre>mcmcsaving(filename[, replace])</pre>	save simulation results to <i>filename</i> .dta

collect is allowed; see [U] 11.1.10 Prefix commands.

Options

estimates(estname) requests that bayesvarstable use the previously obtained set of bayes: var estimates stored as estname. By default, bayesvarstable uses the active estimation results. See [R] estimates for information on manipulating estimation results.

clevel(#) specifies the credible level, as a percentage, for equal-tailed and HPD credible intervals. The default is clevel(95) or as set by [BAYES] set clevel.

hpd displays the HPD credible intervals instead of the default equal-tailed credible intervals.

mcmcsaving(*filename*[, replace]) saves simulation results in *filename*.dta. The replace option specifies to overwrite *filename*.dta if it exists. If the mcmcsaving() option is not specified, simulation results are not saved.

The saved dataset has the following structure. Variable _chain records chain identifiers. Variable _index records iteration numbers. bayesvarstable saves only states (sets of values) that are different from one iteration to another and the frequency of each state in variable _frequency. As such, _index may not necessarily contain consecutive integers. Remember to use _frequency as a frequency weight if you need to obtain any summaries of this dataset. Values for modulus of each eigenvalue are saved in a separate variable in the dataset.

Remarks and examples

Stability is an important condition for VAR model interpretation; see Remarks and examples of [TS] varstable. If the stability condition of a VAR model is not met, its impulse-response functions (IRFs) and forecast-error variance decompositions do not reach equilibrium and thus do not have clear interpretation.

Lütkepohl (2005) and Hamilton (1994) show that if the modulus of each eigenvalue of the companion matrix A is strictly less than one, the estimated VAR is stable (see Methods and formulas for the definition of the matrix A). In a Bayesian setting, we are concerned with the posterior distribution of A and its eigenvalues.

Following are two examples illustrating stable and unstable VAR models.

Example 1: Stable VAR model

We revisit example 1 from [TS] varstable. It uses lutkepohl2.dta of West Germany microeconomic quarterly data for the years between 1960 and 1978. The example studies the relationships between investment, dln_inv, income, dln_inc, and consumption, dln_consump.

```
. use https://www.stata-press.com/data/r19/lutkepohl2
. tsset
```

Using the bayes: var command, we fit a Bayesian VAR model with two lags on the dependent variables dln_inv, dln_inc, and dln_consump. Considered are observations between the second quarter of 1961 and the fourth quarter of 1978. We use the default conjugate Minnesota prior for regression coefficients and error covariance matrix.

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```
. bayes, rseed(17) nomodelsummary:
> var dln_inv dln_inc dln_consump if qtr>=tq(1961q2) & qtr<=tq(1978q4)
Burn-in ...
Simulation ...
Bayesian vector autoregression
                                                 MCMC iterations =
                                                                        12,500
                                                                         2,500
Gibbs sampling
                                                 Burn-in
                                                                  =
                                                 MCMC sample size =
                                                                         10,000
Sample: 1961q2 thru 1978q4
                                                 Number of obs
                                                                 =
                                                 Acceptance rate =
                                                                         .9556
                                                 Efficiency: min =
                                                                         .9962
                                                              avg =
Log marginal-likelihood = 467.75286
                                                              max =
```

	Mean	Std. dev.	MCSE	Median	Equal- [95% cred.	tailed interval]
dln inv						
dln_inv L1. L2.	.4749526 .0062935	.1046821 .063174	.001071 .000632	.4762824 .0058376	.2706787 1181113	.6790291 .129959
dln_inc L1. L2.	.1150521 .0096558	.4145854 .2461088	.004146 .002464	.1155755 .0129206	7122031 4780951	.9358321 .490937
dln_consump L1. L2.	0693822 .0182113	.4910385 .2919327	.004828 .002919	0712677 .0169657	-1.016477 5563898	.9050535 .6010627
_cons	.0067839	.0153897	.000154	.0067986	0233363	.0367596
dln_inc dln_inv L1. L2.	.0152113 .000957	.0248328 .0149204	.000248 .000147	.0154024 .0010833	0341219 0285813	.0635173 .0306545
dln_inc L1. L2.	.600281 .011757	.0981275 .0577031	.000981 .000577	.5997577 .0123101	.4077653 1009659	.7928394 .1245041
dln_consump L1. L2.	0331359 0266197	.1151265 .0694851	.001151 .000695	0318916 0263958	2594495 1637059	.1939938 .1123704
_cons	.0084678	.0036265	.000037	.0084371	.0013034	.0155666
dln_consump dln_inv L1. L2.	0183312 .0092806	.0220482 .0135179	.00022 .000135	0182937 .0094044	062597 0171007	.0243933 .036166
dln_inc L1. L2.	0365965 .0345945	.0875614 .0520216	.000876 .000514	0368425 .0339648	2086565 0668323	.1364804 .136918
dln_consump L1. L2.	.5444814 .0555939	.1030406 .0617942	.001027 .000618	.5432019 .055126	.3416401 063175	.7489821 .1763757
_cons	.0078414	.0032597	.000033	.0078245	.001402	.0141132
Sigma_1_1 Sigma_2_1 Sigma_3_1 Sigma_2_2 Sigma_3_2 Sigma_3_3	.003945 0000314 .000138 .0002195 .0000502 .0001743	.0006693 .0001118 .0001007 .0000373 .0000238 .0000294	6.4e-06 1.1e-06 1.0e-06 3.7e-07 2.4e-07 2.9e-07	.0038783 0000291 .0001355 .0002158 .000049 .0001714	.0028446 0002548 0000512 .0001579 6.46e-06 .0001261	.0054382 .0001897 .0003478 .0003039 .0001007 .0002408

For explanation of the output of bayes: var, see Remarks and examples of [BAYES] bayes: var.

To use the bayesvarstable command, we need to save simulation results computed by bayes: var in a permanent dataset.

```
. bayes, saving(bvarex1)
note: file bvarex1.dta saved.
```

Now we are ready to check the stability condition for the above Bayesian model.

. bayesvarstal	ole					
Eigenvalue sta	Companion matrix size = 6 MCMC sample size = 10000					
Eigenvalue	Mean	Std dev	MCSE	Median	Equal-	tailed
					_00% crcu.	intervarj
1	.7295294	.0952871	.000953	.7272906	.547312	.9209245
2	.6039037	.1045099	.001045	.6094994	.3810883	.7904044
3	.428933	.1272649	.001273	.4239249	.2113325	.6645651
4	.2126552	.0780213	.00078	.1997342	.0900884	.3846134
5	.1378018	.0565196	.000565	.1349177	.0385605	.2577174
6	.0759403	.05052	.000505	.0700686	.0035577	.1847619

Pr(eigenvalues lie inside the unit circle) = 0.9966

The VAR model has a companion matrix of size 6 (3 response variables times 2 lags). The bayesvarstable command thus reports posterior summaries for the moduli of 6 eigenvalues. The maximum one has a posterior mean of 0.73, less than 1. In addition to posterior means, we also see posterior standard deviations, MCMC standard errors, medians, and credible intervals.

The bayesvarstable command estimates the probability of unit circle inclusion for all eigenvalues to be 0.9966, or essentially 1. The stability condition is thus satisfied.

We may specify the HPD credible intervals instead of the default equal-tailed ones and change the level of the intervals. This, however, would not change the estimated probability of inclusion and the overall conclusion.

. bayesvarstable, hpd clevel(80)							
Eigenvalue stability condition				Companion matrix size = 6 MCMC sample size = 10000			
Eige	nvalue					Н	PD
m	odulus	Mean	Std. dev.	MCSE	Median	[80% cred.	interval]
	1	.7295294	.0952871	.000953	.7272906	.6066106	.8490679
	2	.6039037	.1045099	.001045	.6094994	.4782224	.7449145
	3	.428933	.1272649	.001273	.4239249	.2656266	.6001815
	4	.2126552	.0780213	.00078	.1997342	.1065876	.3036596
	5	.1378018	.0565196	.000565	.1349177	.0623463	.2060198
	6	.0759403	.05052	.000505	.0700686	.0000169	.1200219

Pr(eigenvalues lie inside the unit circle) = 0.9966

As we mentioned above, a stable VAR model has IRFs that reach equilibrium in the long run. Let's verify this. We compute IRFs for 60 quarters (15 years) ahead and save them as birf estimates in birfex1.irf.

```
. bayesirf create birf, step(60) set(birfex1)
(file birfex1.irf created)
(file birfex1.irf now active)
(file birfex1.irf updated)
```

See *Remarks and examples* for details about [BAYES] **bayesirf create**. We check the long-term behavior of the cumulative orthogonalized IRFs using the bayesirf graph command.



. bayesirf graph coirf

Graphs by irfname, impulse variable, and response variable

In particular, we look at the cumulative shock effects of impulse variables on themselves (the graphs on the diagonal). It is clear that all shocks reach long-term equilibrium after about 2 years (all graphs converge to horizontal asymptotes). These are the types of graphs we expect to see from a stable VAR model.

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Example 2: Unstable VAR model

In this example, we show how the specification of a strong prior may violate the stability condition of a VAR model.

We consider the same VAR model as in the previous example, but now we reduce the number of lags from 2 to 1 and strengthen the default Minnesota prior. In particular, we change the selftight() suboption of minnconjprior() from its default value of 0.1 to 0.001. This option determines the prior variance of regression coefficients; see *self-variables tightness parameter*. A value of 0.001 will shrink the regression coefficients to their prior mean values, which are 1 for self-variables first-lag coefficients and

0 otherwise. The shrinkage is thus toward a *random-walk* behavior, which is known to be unstable. Given the modest sample size of 90 observations, we expect the prior to dominate the information available in the data.

```
. bayes, minnconjprior(selftight(0.001)) rseed(17) saving(bvarex2) nomodelsummary:
> var dln_inv dln_inc dln_consump, lags(1)
Burn-in ...
Simulation ...
Bayesian vector autoregression
                                                   MCMC iterations =
                                                                          12,500
Gibbs sampling
                                                                           2,500
                                                   Burn-in
                                                                    =
                                                   MCMC sample size =
                                                                           10,000
Sample: 1960q3 thru 1982q4
                                                   Number of obs
                                                                    =
                                                                               90
                                                   Acceptance rate =
                                                                               1
                                                   Efficiency:
                                                                            .9779
                                                                min =
                                                                            .9988
                                                                avg =
Log marginal-likelihood =
                             590.1324
                                                                max =
                                                                                1
                                                                Equal-tailed
                    Mean
                            Std. dev.
                                          MCSE
                                                    Median
                                                            [95% cred. interval]
dln_inv
     dln inv
         L1.
                 .9999075
                            .0015466
                                       .000015
                                                  .9999005
                                                             .9968787
                                                                         1.002993
     dln inc
                                                            -.0113532
         L1.
               -.0001024
                            .0057483
                                       .000056
                                                -.0000905
                                                                         .0112184
 dln consump
         L1.
                 .0000347
                            .0062553
                                       .000063
                                                  .0000484 -.0122773
                                                                         .0124097
       _cons
               -.0000218
                            .0050112
                                        .00005
                                                -4.42e-06
                                                             -.009838
                                                                         .0097902
dln inc
     dln_inv
         L1.
                5.87e-06
                            .0003621
                                       3.6e-06
                                                 6.24e-06
                                                           -.0006947
                                                                          .000714
     dln_inc
         L1.
                .9999134
                            .0013413
                                       .000013
                                                  .9999053
                                                             .9973009
                                                                         1.002532
 dln_consump
               -.0000275
         L1.
                            .0014526
                                       .000015
                                                -.0000321
                                                            -.0028922
                                                                         .0028222
       _cons
               -.0001133
                            .0011346
                                       .000011
                                                -.0001213
                                                             -.002378
                                                                         .0021637
dln_consump
     dln inv
               -7.21e-06
         L1.
                            .0003546
                                       3.5e-06 -8.11e-06 -.0007066
                                                                         .0006912
     dln inc
         L1.
               -.0000405
                             .001341
                                       .000014 -.0000284 -.0027065
                                                                          .002576
 dln_consump
                .9998961
                            .0014424
                                       .000014
                                                  .9999152
                                                                         1.002728
         L1.
                                                             .9970457
       _cons
                -.000031
                            .0011446
                                       .000011 -.0000338 -.0022769
                                                                         .0022331
```

Sigma_1_1	.004672	.0006967	7.0e-06	.0046044	.0034928	.00625
Sigma_2_1	0000808	.0001147	1.1e-06	0000799	0003115	.0001442
Sigma_3_1	.0002439	.0001158	1.2e-06	.00024	.0000266	.0004826
Sigma_2_2	.0002519	.0000382	3.8e-07	.0002482	.0001879	.000336
Sigma_3_2	.000067	.0000275	2.8e-07	.0000655	.0000169	.0001243
Sigma_3_3	.0002483	.0000366	3.7e-07	.0002447	.0001869	.0003288

file bvarex2.dta saved.

The posterior mean estimates of regression coefficients are very close to their prior mean values. We use bayesvarstable to check the stability condition.

. bayesvarstal	ble					
Eigenvalue stability condition				Companion matrix size = 3 MCMC sample size = 10000		
Eigenvalue modulus	Mean	Std. dev.	MCSE	Median	Equal- [95% cred.	tailed interval]
1 2 3	1.001409 .9998958 .9984138	.0012333 .0011205 .0012513	.000012 .000011 .000013	1.001324 .9998891 .998492	.999263 .997711 .9957189	1.004065 1.002059 1.000603

Pr(eigenvalues lie inside the unit circle) = 0.1194

The reported probability that all three eigenvalues lie in the unit circle is only about 12% and is clearly insufficient to claim the stability of the estimates.

We can also look at IRFs for visual confirmation of the instability of the model. We compute IRFs for 60 quarters ahead and save them as birf estimates in birfex2.irf.

```
. bayesirf create birf, step(60) set(birfex2)
(file birfex2.irf created)
(file birfex2.irf now active)
(file birfex2.irf updated)
```

Then we plot the cumulative orthogonalized IRFs using bayesirf graph.

. bayesirf graph coirf



Graphs by irfname, impulse variable, and response variable

It is clear that the shocks of impulses on themselves (the graphs on the diagonal) do not reach equilibrium and continue to increase beyond the 60-quarter period. This is a typical behavior of an unstable VAR model.

This particular instability problem arises because the used prior strongly favors an unstable, randomwalk model, and there is not enough information in the data to outweigh this prior. For instance, if we specified zero prior means for all coefficients, we would not run into this problem. What constitutes a strong prior depends on the sample size and the amount of information contained in the data about model parameters. The conclusion in this example may not hold for other VAR models and datasets. We thus recommend checking the stability condition after fitting any VAR model before proceeding with postestimation analysis.

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Stored results

bayesvarstable stores the following in r():

```
      Scalars
      r(prob_incl)
      probability of unit circle inclusion of all eigenvalues

      r(mcmcsize)
      MCMC sample size

      r(compsize)
      companion matrix size

      Matrices
      r(summary)

      matrix with posterior summary statistics for eigenvalues
```

Methods and formulas

Consider a companion matrix A defined in *Methods and formulas* of [TS] **varstable**. In a Bayesian setting, A is a random matrix with a posterior distribution that depends on the prior distribution of regression coefficients and error covariance matrix. The Bayesian computations use the MCMC sample created by the bayes : var command that contains draws from the posterior distribution of the regression coefficients/matrices and error covariance.

For each draw, the eigenvalue moduli of the companion matrix \mathbf{A}^* that corresponds to that draw are computed and saved in an MCMC sample. Finally, the resulting MCMC samples of eigenvalue moduli are summarized, and standard Bayesian statistics such as posterior mean, medians, and credible intervals are reported.

The posterior probability of the unit circle inclusion is estimated as the proportion of MCMC observations for which all eigenvalues of A^* 's are strictly within the unit circle.

References

Hamilton, J. D. 1994. Time Series Analysis. Princeton, NJ: Princeton University Press. https://doi.org/10.2307/j. ctv14jx6sm.

Lütkepohl, H. 2005. New Introduction to Multiple Time Series Analysis. New York: Springer.

Also see

[BAYES] bayes: var postestimation — Postestimation tools for bayes: var

[BAYES] **bayes: var** — Bayesian vector autoregressive models

[TS] varstable — Check eigenvalue stability condition

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