bayes: var — Bayesian vector autoregressive models

Description

bayes: var fits a Bayesian vector autoregressive (VAR) model—a multivariate time-series regression of each dependent variable on lags of itself and on lags of all the other dependent variables. bayes: var also fits a variant of Bayesian VAR models known as the Bayesian VARX model, which also includes exogenous variables. The command supports four classes of priors, which are specific to VAR, including the original and the conjugate Minnesota priors. See [BAYES] bayes and [TS] var for details.

Quick start

Bayesian VAR for three time series ($K = 3$) with default two lags ($p = 2$) and using the default conjugate Minnesota prior

```
bayes: var y1 y2 y3
```

Same as above, but with three lags and exogenous variable $x_1$ ($m = 1$)

```
bayes: var y1 y2 y3, lags(1/3) exog(x1)
```

Same as above, but with random seed for reproducibility and saving simulation results in dataset `bvarsim.dta`

```
bayes, rseed(17) saving(bvarsim): var y1 y2 y3, lags(1/3) exog(x1)
```

Customize the default conjugate Minnesota prior by changing the self-variables tightness parameter from 0.1 to 1, the lag decay from 1 to 0.5, and the exogenous-variables tightness parameter from 100 to 1

```
bayes, minnconjprior(selftight(1) lagdecay(0.5) exogtight(1)): ///
    var y1 y2 y3, lags(1/3) exog(x1)
```

Report posterior summaries only for coefficients on lag 1 and lag 3 of variable $y_1$ in the first equation ($y_1$), on lag 2 of variable $y_3$ in the second equation ($y_2$), and on exogenous variable $x_1$ in the third equation ($y_3$)

```
.bayesstats summary {y1:L1.y1} {y1:L3.y1} {y2:L2.y3} {y3:x1}
```

Bayesian VAR for three time series with two lags using the original Minnesota prior with fixed AR error covariance

```
bayes, minnfixedcovprior: var y1 y2 y3
```

Same as above, but changing some of the default original Minnesota prior settings: self-variables tightness parameter from 0.1 to 0.5 and cross-variables tightness parameter from 0.5 to 0.1

```
bayes, minnfixedcovprior(selftight(0.5) crosstight(0.1)): var y1 y2 y3
```

Specify independent multivariate normal (MVN) prior for VAR coefficients and inverse-Wishart prior for error covariance

```
bayes, minniwishprior: var y1 y2 y3
```
Same as above, but specify a $3 \times 1$ zero mean vector for the MVN prior for self-variables first-lag coefficients (other coefficients are also set to 0 automatically) and a $3 \times 3$ identity scaling matrix for the inverse-Wishart prior for error covariance

\[
\text{matrix } b_0 = J(3, 1, 0)
\]
\[
\text{matrix } \Omega_0 = \text{diag}(J(3, 1, 1))
\]
\[
\text{bayes, minniwishprior(mean(b0) scale(Omega0)): var y1 y2 y3}
\]

Specify independent MVN prior for coefficients and multivariate Jeffreys prior for error covariance

\[
\text{bayes, minnjeffprior: var y1 y2 y3}
\]

Same as above, but change the default MVN prior mean vector to a $21 \times 1$ zero mean vector and covariance matrix to a $21 \times 21$ identity matrix for all $21 = 3 \times (2 \times 3 + 1)$ coefficients

\[
\text{matrix } b_0 = J(21, 1, 0)
\]
\[
\text{matrix } S_0 = \text{I}(21)
\]
\[
\text{bayes, minniwishprior(mean(b0) cov(S0)): var y1 y2 y3}
\]

Also see Quick start in [BAYES] bayes and Quick start in [TS] var.

Menu

Statistics > Multivariate time series > Bayesian models > Vector autoregression (VAR)

Syntax

\[
\text{bayes [, bayesopts]: var depvarlist [if] [in] [, options]}
\]

<table>
<thead>
<tr>
<th>options</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>noconstant</strong></td>
<td>suppress constant term</td>
</tr>
<tr>
<td><strong>lags(numlist)</strong></td>
<td>specify a list of lags for the VAR</td>
</tr>
<tr>
<td><strong>exog(varlist)</strong></td>
<td>specify exogenous variables</td>
</tr>
<tr>
<td><strong>level(#)</strong></td>
<td>set credible level; default is level(95)</td>
</tr>
</tbody>
</table>

You must tsset your data before using bayes: var; see [TS] tsset.

depvarlist and varlist may contain time-series operators; see [U] 11.4.4 Time-series varlists.
bayes: var, level() is equivalent to bayes, clevel(): var.

For a detailed description of options, see Options in [TS] var.

bayesopts Description

| **minnconjprior[(conjopts)]** | conjugate Minnesota prior for VAR coefficients and error covariance; the default |
| **minnfixedcovprior[(fixcovopts)]** | original Minnesota prior with fixed error covariance |
| **minniwishprior[(iwishopts)]** | Minnesota prior with inverse-Wishart prior for error covariance |
| **minnjeffprior[(jeffopts)]** | Minnesota prior with multivariate Jeffreys prior for error covariance show model summary without estimation |
| **dryrun**                  | show model summary without estimation             |
Simulation

nchains(#)  
   number of chains; default is to simulate one chain

mcmsize(#)  
   MCMC sample size; default is mcmsize(10000)

burnin(#)  
   burn-in period; default is burnin(2500)

thinning(#)  
   thinning interval; default is thinning(1)

rseed(#)  
   random-number seed

exclude(paramref)  
   specify model parameters to be excluded from the simulation results

Blocking

blocksummary  
   display block summary

Initialization

initial(initspec)  
   specify initial values for model parameters with a single chain

init#(initspec)  
   specify initial values for #th chain; requires nchains()

initall(initspec)  
   specify initial values for all chains; requires nchains()

nomleinit  
   suppress the use of maximum likelihood estimates as starting values

intrandom  
   specify random initial values

initsummary  
   display initial values used for simulation

*noisy  
   display output from the estimation command during initialization

Reporting

clevel(#)  
   set credible interval level; default is clevel(95)

hpd  
   display HPD credible intervals instead of the default equal-tailed credible intervals

eform([string])  
   report exponentiated coefficients and, optionally, label as string

batch(#)  
   specify length of block for batch-means calculations; default is batch(0)

saving(filename[, replace])  
   save simulation results to filename.dta

nomodelsummary  
   suppress model summary

chainsdetail  
   display detailed simulation summary for each chain

[nodots]  
   suppress dots or display dots every 100 iterations and iteration numbers every 1,000 iterations; default is nodots

dots(#[, every(#)])  
   display dots as simulation is performed

[no]show(paramref)  
   specify model parameters to be excluded from or included in the output

notable  
   suppress estimation table

noheader  
   suppress output header

title(string)  
   display string as title above the table of parameter estimates

display_options  
   control spacing, line width, and base and empty cells

Advanced

search(search_options)  
   control the search for feasible initial values

corrlag(#)  
   specify maximum autocorrelation lag; default varies

corrtol(#)  
   specify autocorrelation tolerance; default is corrtol(0.01)

*Starred options are specific to the bayes prefix; other options are common between bayes and bayesmh.

priorspec and paramref are defined in [BAYES] bayesmh.

paramref may contain factor variables; see [U] 11.4.3 Factor variables.

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

See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.
Model parameters are $K \times p$ outcome-specific regression coefficients for lagged outcome (dependent) variables plus a constant term unless `noconstant` is specified: \{\textit{depvar}_k:\textit{Ldepvar}_1 \textit{Ldepvar}_2 \ldots \textit{Ldepvar}_K \textit{cons}\}, where \textit{Ldepvar}_k denotes a list of lags for dependent variable \textit{depvar}_k such as the default \textit{L1.depvar}_k \textit{L2.depvar}_k. If `exog(varlist)` is specified, regression coefficients also include $K \times m$ outcome-specific coefficients for exogenous variables: \{\textit{depvar}_k:\textit{varlist}\}. Use the `dryrun` option to see the definitions of model parameters prior to estimation. Only one of options `minnconjprior()`, `minnfixedcovprior()`, `minniwishprior()`, or `minnjeffprior()` may be specified.

For a detailed description of `bayesopts`, see `Options` below.

<table>
<thead>
<tr>
<th>conjopts</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mean(…)</strong></td>
<td>mean vector for the MVN prior</td>
</tr>
<tr>
<td><strong>phi(matname)</strong></td>
<td>covariance product matrix $\Phi_0$ for the MVN prior; default is diagonal autoregressive-structure matrix</td>
</tr>
<tr>
<td><strong>df(#)</strong></td>
<td>degrees of freedom for the inverse-Wishart prior; default is $K + 2$</td>
</tr>
<tr>
<td><strong>scale(matname)</strong></td>
<td>scale matrix for the inverse-Wishart prior; default is proportional to AR estimate of error covariance</td>
</tr>
<tr>
<td><strong>minnopts</strong></td>
<td>Minnesota prior options</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>fixcovopts</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mean(…)</strong></td>
<td>mean vector for the MVN prior</td>
</tr>
<tr>
<td><strong>minnopts</strong></td>
<td>Minnesota prior options</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>iwishopts</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mean(…)</strong></td>
<td>mean vector for the MVN prior</td>
</tr>
<tr>
<td><strong>cov(matname)</strong></td>
<td>covariance matrix for the MVN prior; default is diagonal autoregressive-structure matrix</td>
</tr>
<tr>
<td><strong>df(#)</strong></td>
<td>degrees of freedom for the inverse-Wishart prior; default is $K + 2$</td>
</tr>
<tr>
<td><strong>scale(matname)</strong></td>
<td>scale matrix for the inverse-Wishart prior; default is proportional to AR estimate of error covariance</td>
</tr>
<tr>
<td><strong>minnopts</strong></td>
<td>Minnesota prior options</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>jeffopts</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mean(…)</strong></td>
<td>mean vector for the MVN prior</td>
</tr>
<tr>
<td><strong>cov(matname)</strong></td>
<td>covariance matrix for the MVN prior; default is diagonal autoregressive-structure matrix</td>
</tr>
<tr>
<td><strong>minnopts</strong></td>
<td>Minnesota prior options</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>meanopts</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>mean(matname)</strong></td>
<td>mean vector for the MVN prior for all $K(Kp + 1 + m)$ coefficients; default is to use 1s for $K$ self-variables first-lag coefficients and 0s otherwise</td>
</tr>
<tr>
<td><strong>mean(m_1, \ldots, m_K)</strong></td>
<td>mean values for the MVN prior for $K$ self-variables first-lag coefficients; all other means are assumed to be zero</td>
</tr>
<tr>
<td>minnopts</td>
<td>Description</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><code>selftight(#)</code></td>
<td>self-variables tightness parameter for the Minnesota prior; default is <code>selftight(0.1)</code></td>
</tr>
<tr>
<td><code>crosstight(#)</code></td>
<td>cross-variables tightness parameter for the Minnesota priors; default is <code>crosstight(0.5)</code>; not used with conjugate Minnesota prior</td>
</tr>
<tr>
<td><code>lagdecay(#)</code></td>
<td>lag decay parameter for the Minnesota prior; default is <code>lagdecay(1)</code></td>
</tr>
<tr>
<td><code>exogtight(#)</code></td>
<td>exogenous-variables tightness parameter for the Minnesota prior; default is <code>exogtight(100)</code></td>
</tr>
<tr>
<td><code>arcoav</code></td>
<td>use separate AR models to estimate error covariance</td>
</tr>
<tr>
<td><code>varcov</code></td>
<td>use VAR model to estimate error covariance</td>
</tr>
</tbody>
</table>

**Options**

- `noconstant`, `lags(numlist)`, and `exog(varlist)`; see [TS] `var`.

**Priors**

- `minnconjprior` and `minnconjprior(conjopts)` specify that a conjugate Minnesota prior be used for VAR coefficients and error covariance. `minnconjprior` is the default. The prior for VAR coefficients is MVN with mean and covariance based on the original Minnesota prior. The prior for the error covariance is an inverse-Wishart distribution. See Conjugate Minnesota prior for VAR model with unknown error covariance in Methods and formulas.

  - `conjopts` are `mean(meanspec)`, `phi(matname)`, `df(#)`, `scale(matname)`, and `minnopts`.

    - `mean(matname)` specifies the mean vector (as a Stata matrix) of the MVN prior distribution for all \( K(K_p+1+m) \) VAR coefficients. The default is to use ones for \( K \) self-variables first-lag coefficients and zeros otherwise.

    - `mean(m_1, ..., m_K | matname)` specifies \( K \) mean values or mean vector `matname` of length \( K \) of prior means for the self-variables first-lag coefficients. The rest are set to zero.

    - `phi(matname)` specifies the covariance product matrix \( \Phi_0 \) (as a Stata matrix) of the MVN prior distribution for the VAR coefficients. The default is the Minnesota factor covariance, a diagonal matrix that accounts for the autoregressive structure of the VAR model; see Methods and formulas.

    - `df(#)` specifies the degrees of freedom of the inverse-Wishart prior distribution for the error covariance. The default is \( K + 2 \), and this is the minimum allowed value.

    - `scale(matname)` specifies the scale matrix of the inverse-Wishart prior distribution for the error covariance. The default is proportional to the diagonal matrix of \( K \) AR variance estimates, one for each VAR equation; see Methods and formulas.

- `minnfixedcovprior` and `minnfixedcovprior(fixcovopts)` specify that the Minnesota prior with a fixed AR (or VAR if option `varcov` is specified) covariance be used for VAR coefficients. This is the original Minnesota prior for Bayesian VAR models. In this model formulation, the error covariance is considered fixed, thus decreasing the number of parameters needed to be simulated and speeding up computations. See Original Minnesota prior with known (fixed) error covariance in Methods and formulas.

  - `fixcovopts` are `mean(meanspec)` and `minnopts`.
\texttt{minniwishprior} and \texttt{minniwishprior(iwishopts)} specify that the MVN prior for VAR coefficients and an inverse-Wishart prior for the error covariance be used. The priors for VAR coefficients and error covariance are independent. The default MVN prior for coefficients uses the Minnesota prior mean vector and covariance matrix. See MVN-inverse Wishart prior in Methods and formulas.

\texttt{iwishopts} are \texttt{mean(meanspec), cov(matname), df(#), scale(matname), and minnopts}.

\texttt{cov(matname)} specifies the covariance matrix $\Omega_0$ (as a Stata matrix) of the MVN prior distribution for the VAR coefficients. The default is a diagonal matrix that accounts for the autoregressive structure of the VAR model; see Methods and formulas.

\texttt{df(#)} specifies the degrees of freedom of the inverse-Wishart prior distribution for the error covariance. The default is $K + 2$, and this is the minimum allowed value.

\texttt{scale(matname)} specifies the scale matrix of the inverse-Wishart prior distribution for the error covariance. The default is proportional to the diagonal matrix of $K$ AR variance estimates, one for each VAR equation; see Methods and formulas.

\texttt{minnjeffprior} and \texttt{minnjeffprior(jeffopts)} specify that the MVN prior for VAR coefficients and the Jeffreys prior for the error covariance be used. The priors for VAR coefficients and error covariance are independent. The default MVN prior for coefficients uses the Minnesota prior mean vector and covariance matrix. See Multivariate normal-diffuse (normal-Jeffreys) prior in Methods and formulas.

\texttt{jeffopts} are \texttt{mean(meanspec), cov(matname), and minnopts}.

\texttt{cov(matname)} specifies the covariance matrix $\Omega_0$ (as a Stata matrix) of the MVN prior distribution for the VAR coefficients. The default is a diagonal matrix that accounts for the autoregressive structure of the VAR model; see Methods and formulas.

\texttt{minnopts} are \texttt{selftight(#), crosstight(#), lagdecay(#), exogtight(#), arcov, and varcov}.

\texttt{selftight(#)} specifies the self-variables tightness parameter, $\lambda_1$, for the Minnesota prior. The default is \texttt{selftight(0.1)}. The smaller this value, the more concentrated the prior distribution around the prior mean for self-variables lag coefficients. See Methods and formulas.

\texttt{crosstight(#)} specifies the cross-variables tightness parameter, $\lambda_2$, for the Minnesota prior. The default is \texttt{crosstight(0.5)}. The smaller this value, the more concentrated the prior distribution around the prior mean for cross-variables lag coefficients. \texttt{crosstight()} is not used with the conjugate Minnesota prior. See Methods and formulas.

\texttt{lagdecay(#)} specifies the lag-decay parameter, $\lambda_3$, for the Minnesota prior. This is a rate of lag-decay correction to the prior standard deviation of all endogenous-variables lag coefficients. See Methods and formulas.

\texttt{exogtight(#)} specifies the exogenous-variables tightness parameter, $\lambda_4$, for the Minnesota prior. This is a multiplicative factor to the prior standard deviation of exogenous-variables coefficients. See Methods and formulas.

\texttt{arcov}, the default, specifies that the diagonal AR matrix estimate be used as an estimate of the error covariance matrix. This AR matrix has, on the diagonal, the estimates of error variances obtained from fitting a separate AR($p$) model to each dependent variable. Only one of \texttt{arcov} or \texttt{varcov} may be specified.

\texttt{varcov} specifies that the VAR matrix estimate be used as an estimate of the error covariance matrix. The VAR matrix is an estimate of the error covariance obtained from fitting a VAR($p$) model to the dependent variables.

\texttt{arcov} and \texttt{varcov} are used with all Minnesota priors. For the original prior with a fixed error covariance, these options specify which estimate will be used for the error covariance matrix.
For other priors, these options specify which estimate will be used for the prior scale matrix of an inverse-Wishart prior for error covariance matrix.

See descriptions of other bayesopts in Options in [BAYES] bayes.

 Remarks and examples

For a general introduction to Bayesian analysis, see [BAYES] Intro. For an introduction to VAR models, see [TS] var intro. For a general introduction to Bayesian estimation using Gibbs sampling, see [BAYES] bayesmh. For remarks and examples specific to the bayes prefix, see [BAYES] bayes. For details about the estimation command, see [TS] var.

For a simple example of the bayes prefix, see Introductory example in [BAYES] bayes.

Remarks are presented under the following headings:

Advantages of Bayesian VAR models
Introductory examples
US macroeconomic examples

Examples are presented under the following headings:

Default Bayesian VAR model
Bayesian VAR model with original Minnesota prior
MVN priors with unrestricted error covariances
Testing Bayesian VAR stability
Explaining the Minnesota prior
Choosing the number of lags of a VAR model
Bayesian VAR(4) model estimation
IRFs
Forecasting
One-step-ahead Bayesian predictions

Advantages of Bayesian VAR models

Since their introduction by Doan, Litterman, and Sims (1984), Bayesian VAR models have gained popularity for several reasons. As Bayesian models in general, they benefit from a unified and coherent approach of Bayesian inference; see [BAYES] Intro. Kadiyala and Karlsson (1997), Banbura, Giannone, and Reichlin (2008), and Dieppe, Legrand, and van Roye (2016) describe advantages of Bayesian VARs. We summarize some below.

One of the major problems with traditional VAR models is overparameterization. The number of regression parameters in a VAR model is quadratic to the number of response variables and proportional to the number of lags. This leads to many parameters being estimated even for small models and thus to loss of degrees of freedom when maximum likelihood estimation is used. Overparameterized models also produce poor forecasts. The problem of overparameterization is exacerbated when VAR models are applied to small datasets, which is common in many economic applications.

In the Bayesian framework, VAR model parameters are considered random and are controlled by prior distributions. Prior selection, viewed as a limitation of Bayesian inference in the past, is now a powerful tool for flexible analysis and not purely a source of subjective inference. For example, it is easy to shrink higher-lag regression parameters through their priors and thus reduce the effective number of lags. One such example prior is the Minnesota prior (Litterman 1980). The Minnesota prior on regression coefficients and error covariance supports a wide range of models, from oversimplified to overparameterized ones. The Bayesian out-of-sample prediction errors, which can be obtained by simulation, provide a measure for choosing between oversimplified and overparameterized models (Litterman 1984). In cases of small or low-quality data, stronger priors based on existing expert knowledge can greatly enhance otherwise potentially unreliable VAR analysis.
VAR model specification requires choosing the number of lags. Within the Bayesian approach, we can use Bayes factors to compare models using different lags and choose the best one. We can use Bayes factors also for other decision-based inference such as selecting exogenous variables.

The availability of flexible priors, reliable lag-selection criteria, and efficient sampling algorithms capable of producing precise Bayesian estimates makes Bayesian VAR inference a useful alternative to the traditional VAR analysis.

Introductory examples

Example 1: Default Bayesian VAR model

Let’s revisit example 1 from [TS] var, which replicates a case from Lütkepohl (2005, 77–78). The example models the relationships between the first differences of the natural log of investment, dln\_inv, of income, dln\_inc, and of consumption, dln\_cons, registered at each quarter of the years between 1960 and 1978 in West Germany.

```
. webuse lutkepohl2
   (Quarterly SA West German macro data, Bil DM, from Lutkepohl 1993 Table E.1)
. tsset
   Time variable: qtr, 1960q1 to 1982q4
   Delta: 1 quarter
```

The original VAR in example 1 considers all observations before 1979, has two lags, and is fit using the var command.
. var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)

Vector autoregression

Sample: 1960q4 thru 1978q4    Number of obs = 73
Log likelihood = 606.307    AIC = -16.03581
FPE = 2.18e-11    HQIC = -15.77323
Det(Sigma_ml) = 1.23e-11    SBIC = -15.37691

<table>
<thead>
<tr>
<th>Equation</th>
<th>Parms</th>
<th>RMSE</th>
<th>R-sq</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>dln_inv</td>
<td>7</td>
<td>.046148</td>
<td>0.1286</td>
<td>10.76961</td>
<td>0.0958</td>
</tr>
<tr>
<td>dln_inc</td>
<td>7</td>
<td>.011719</td>
<td>0.1142</td>
<td>9.410683</td>
<td>0.1518</td>
</tr>
<tr>
<td>dln_consump</td>
<td>7</td>
<td>.009445</td>
<td>0.2513</td>
<td>24.50031</td>
<td>0.0004</td>
</tr>
</tbody>
</table>

| dln_inv    | Coefficient | Std. err. | z  |P>|z| | [95% conf. interval] |
|------------|-------------|-----------|----|-----|----------------------|
|dln_inv     |             |           |    |     |                      |
|L1.         |-.3196318    |.1192898   |-2.68|0.007|-.5534355 -.0858282  |
|L2.         |-.1605508    |.118767    |-1.35|0.176|-.39333 .0722283     |
|dln_inc     |             |           |    |     |                      |
|L1.         |.1459851     |.5188451   |0.28|0.778|-.8709326 1.162903    |
|L2.         |.1146009     |.508295    |0.23|0.822|-.881639 1.110841     |
|dln_consump |             |           |    |     |                      |
|L1.         |.9612288     |.6316557   |1.52|0.128|-2.767936 2.199251    |
|L2.         |.9344001     |.6324034   |1.48|0.140|-3.050877 2.173888    |
|_cons       |-.0167221    |.0163796   |-1.02|0.307|-.0488257 0.153814    |

| dln_inc    | Coefficient | Std. err. | z   |P>|z| | [95% conf. interval] |
|------------|-------------|-----------|----|-----|----------------------|
|dln_inv     |             |           |    |     |                      |
|L1.         |.0439309     |.0302933   |1.45|0.147|-.0154427 1.033046    |
|L2.         |.0500302     |.0301605   |1.66|0.097|-.0090833 1.091437    |
|dln_inc     |             |           |    |     |                      |
|L1.         |-.1527311    |.131759    |-1.16|0.246|-.4109741 1.055118    |
|L2.         |.0191634     |.1290799   |0.15|0.882|-2.338285 2.721552    |
|dln_consump |             |           |    |     |                      |
|L1.         |.2884992     |.1604069   |1.80|0.072|-.0258926 0.6028909    |
|L2.         |-.0102       |.1605968   |-0.06|0.949|-.3249639 0.3045639    |
|_cons       |.0157672     |.0041596   |3.79|0.000|0.0076146 0.0239198    |

| dln_consump| Coefficient | Std. err. | z   |P>|z| | [95% conf. interval] |
|------------|-------------|-----------|----|-----|----------------------|
|dln_inv     |             |           |    |     |                      |
|L1.         |-.002423     |.0244142   |-.10|0.921|.050274 0.045428     |
|L2.         |.0338806     |.0243072   |1.39|0.163|-.0137607 .0815219    |
|dln_inc     |             |           |    |     |                      |
|L1.         |.2248134     |.1061884   |2.12|0.034|0.0166879 0.4329889    |
|L2.         |.3549135     |.1040292   |3.41|0.001|1.510199 0.558807     |
|dln_consump |             |           |    |     |                      |
|L1.         |-.2639695    |.1292766   |-.20|0.041|-.517347 -0.010592    |
|L2.         |-.0222264    |.1294296   |-.17|0.864|-.2759039 .231451     |
|_cons       |.0129258     |.0033523   |3.86|0.000|0.0063554 0.0194962    |
The output table reports summaries for 21 regression coefficients. But in VAR models, it is usually more instructive to analyze how shocks on a dependent variable affect other dependent variables and the variable itself over time. In this example, we focus on technical aspects of fitting Bayesian VAR models and the immediate impact on regression coefficients and covariances. Later in example 8, we demonstrate how to use more common impulse–response functions (IRFs) to interpret results.

Let us start by fitting the same VAR model using the `bayes: var` command with the default model prior—conjugate Minnesota prior for regression coefficients and error covariance. In addition to the `bayes` prefix, we specify the `rseed()` option for reproducibility and run three MCMC chains to compute a Gelman–Rubin convergence diagnostic; see Convergence diagnostics using multiple chains.

```
. bayes, rseed(17) nchains(3):
> var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)
Chain 1
Burn-in ...
Simulation ...
Chain 2
Burn-in ...
Simulation ...
Chain 3
Burn-in ...
Simulation ...

Model summary

Likelihood:
\[ dln_inv \sim dln_inc \sim dln_consump \sim \text{mvnormal}(3, xb_{dln_inv}, xb_{dln_inc}, xb_{dln_consump}, \{\Sigma, m\}) \]

Priors:
\[
\{dln_inv:L(1 2), dln_inv\} (1) \\
\{dln_inv:L(1 2), dln_inc\} (1) \\
\{dln_inv:L(1 2), dln_consump\} (1) \\
\{dln_inc:_cons\} (1) \\
\{dln_inc:L(1 2), dln_inv\} (2) \\
\{dln_inc:L(1 2), dln_inc\} (2) \\
\{dln_inc:L(1 2), dln_consump\} (2) \\
\{dln_consump:_cons\} (2) \\
\{dln_consump:L(1 2), dln_inv\} (3) \\
\{dln_consump:L(1 2), dln_inc\} (3) \\
\{dln_consump:L(1 2), dln_consump\} (3) \\
\{dln_consump:_cons\} \sim \text{varconjugate}(3, 2, 1, b0, \{\Sigma, m\}, _\Phi0) (3) \\
{\Sigma, m} \sim \text{iwishart}(3, 5, _\Sigma0) (1)
\]
(1) Parameters are elements of the linear form \( xb_{dln_inv} \).
(2) Parameters are elements of the linear form \( xb_{dln_inc} \).
(3) Parameters are elements of the linear form \( xb_{dln_consump} \).

Bayesian vector autoregression

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Number of chains</th>
<th>Per MCMC chain:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Iterations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Burn-in</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sample size</td>
</tr>
</tbody>
</table>

Sample: 1960q4 thru 1978q4

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Number of obs</th>
<th>Avg acceptance rate</th>
<th>Avg efficiency: min</th>
<th>Max Gelman–Rubin Rc</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>73</td>
<td>1</td>
<td>.9755</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>.994</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Avg log marginal-likelihood = 483.43596

Max Gelman–Rubin Rc = 1
<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev.</th>
<th>MCSE</th>
<th>Median [95% cred. interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>dln_inv</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln_inv</td>
<td>.4808475</td>
<td>.103581</td>
<td>.000598</td>
<td>.480019 .2786408 .6837882</td>
</tr>
<tr>
<td>L1.</td>
<td>.0068788</td>
<td>.0627703</td>
<td>.000362</td>
<td>.0069781 -.1167651 .1290908</td>
</tr>
<tr>
<td>L2.</td>
<td>.1026098</td>
<td>.4103202</td>
<td>.002369</td>
<td>.1044135 -.7070827 .8989748</td>
</tr>
<tr>
<td>dln_inc</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.0320344</td>
<td>.2434573</td>
<td>.001406</td>
<td>.032674 -.4520181 .5169279</td>
</tr>
<tr>
<td>L2.</td>
<td>.0068788</td>
<td>.0627703</td>
<td>.000362</td>
<td>.0069781 -.1167651 .1290908</td>
</tr>
<tr>
<td>dln_consump</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>-.0181305</td>
<td>.4774359</td>
<td>.002766</td>
<td>-.0166627 -.9574952 .9252084</td>
</tr>
<tr>
<td>L2.</td>
<td>.0297566</td>
<td>.2885481</td>
<td>.001687</td>
<td>.0288948 -.5385765 .5989857</td>
</tr>
<tr>
<td>_cons</td>
<td>.0063813</td>
<td>.0152462</td>
<td>.000088</td>
<td>.0063497 -.0235027 .0364822</td>
</tr>
<tr>
<td><strong>dln_inc</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln_inv</td>
<td>.0148781</td>
<td>.245811</td>
<td>.000142</td>
<td>.0149684 -.033299 .0630655</td>
</tr>
<tr>
<td>L1.</td>
<td>.001391</td>
<td>.0147206</td>
<td>.000086</td>
<td>.0013496 -.0272677 .0306663</td>
</tr>
<tr>
<td>L2.</td>
<td>.5782111</td>
<td>.096633</td>
<td>.000564</td>
<td>.5787724 .3873585 .7675225</td>
</tr>
<tr>
<td>dln_consump</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.0130696</td>
<td>.0576478</td>
<td>.000333</td>
<td>.0131284 -.0985297 .126328</td>
</tr>
<tr>
<td>L2.</td>
<td>-.0315052</td>
<td>.143589</td>
<td>.000664</td>
<td>-.0311991 -.2557682 .1961411</td>
</tr>
<tr>
<td>_cons</td>
<td>.0087345</td>
<td>.036292</td>
<td>.00021</td>
<td>.0087388 .0016601 .0158279</td>
</tr>
<tr>
<td><strong>dln_consump</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln_inv</td>
<td>-.0183338</td>
<td>.021607</td>
<td>.000125</td>
<td>-.0182276 -.0610608 .0238827</td>
</tr>
<tr>
<td>L1.</td>
<td>.0086858</td>
<td>.0131225</td>
<td>.000076</td>
<td>.0087476 -.0172135 .0344555</td>
</tr>
<tr>
<td>L2.</td>
<td>.0283731</td>
<td>.0857885</td>
<td>.000498</td>
<td>.0287275 -.1961209 .1409767</td>
</tr>
<tr>
<td>dln_inc</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.0344015</td>
<td>.0508225</td>
<td>.000297</td>
<td>.0344959 -.0658067 .1335025</td>
</tr>
<tr>
<td>L2.</td>
<td>.5452017</td>
<td>.1011028</td>
<td>.000584</td>
<td>.5452941 .3461853 .7423402</td>
</tr>
<tr>
<td>_cons</td>
<td>.0078026</td>
<td>.003240</td>
<td>.00019</td>
<td>.0077938 .0015249 .014078</td>
</tr>
<tr>
<td>Sigma_1_1</td>
<td>.0039149</td>
<td>.0006512</td>
<td>3.8e-06</td>
<td>.0038459 .002843 .0054003</td>
</tr>
<tr>
<td>Sigma_2_1</td>
<td>-.0000195</td>
<td>.0001079</td>
<td>6.2e-07</td>
<td>-.0000193 -.0002359 .0001924</td>
</tr>
<tr>
<td>Sigma_3_1</td>
<td>.0001329</td>
<td>.000097</td>
<td>5.6e-07</td>
<td>.0001291 -.0000493 .0003346</td>
</tr>
<tr>
<td>Sigma_2_2</td>
<td>.000219</td>
<td>.0000365</td>
<td>2.1e-07</td>
<td>.0002148 .0001587 .0003014</td>
</tr>
<tr>
<td>Sigma_3_2</td>
<td>.0000463</td>
<td>.0000232</td>
<td>1.3e-07</td>
<td>.0000451 4.14e-06 .000096</td>
</tr>
<tr>
<td>Sigma_3_3</td>
<td>.0001703</td>
<td>.0000282</td>
<td>1.6e-07</td>
<td>.0001673 .0001239 .0002344</td>
</tr>
</tbody>
</table>

Note: Default initial values are used for multiple chains.

The simulation is performed using Gibbs sampling, which provides high sampling efficiency, 0.99 on average. The maximum Gelman–Rubin $R_c$ statistic is a perfect 1, which suggests no convergence issues. Because of this and to speed up computation, we will use only one chain in subsequent examples.
The model summary provides description of the model. We have an MVN likelihood for the error terms. Regression coefficients are assigned a conjugate Minnesota prior, which is labeled as \texttt{varconjugate(3,2,1,_b0,\{Sigma,m\},_Phi0)} in the output. The arguments are the number of dependent variables (3), number of lags (2), number of exogenous variables (0) plus a constant term per equation (1), default prior mean vector (_b0), error covariance matrix parameter (\{Sigma,m\}), and Minnesota factor covariance (_Phi0), which is a function of tightness parameters that control the concentration of the prior around its mean. The conjugate Minnesota prior for the coefficients is MVN with mean vector \(\beta_0\) and covariance \(\Sigma \otimes \Phi_0\), where \(\beta_0\) and \(\Phi_0\) are defined in \textit{Methods and formulas}. We discuss the Minnesota prior in detail in example 5. If you are not familiar with this prior, you may want to look at this example.

Error covariance \{Sigma,m\} is assigned an inverse-Wishart prior with default degrees of freedom \(df = K + 2 = 5\) and scale matrix \_Scale0\((df – K – 1)_\Sigma0 = \Sigma0\), where \_Sigma0 is the diagonal AR covariance matrix, a diagonal matrix formed by error-variance estimates from fitting a separate AR model to each dependent variable; see \textit{VAR model specification} in \textit{Methods and formulas}.

The table of results contains three groups of regression parameters, one for each dependent variable, just like the output from the \texttt{var} command. \texttt{bayes: var} additionally displays the estimates of the error covariance \{Sigma,m\}. The output table reports standard Bayesian posterior summaries (\texttt{[BAYES] bayesstats summary}).

The prior mean vector \_b0 is 1 for the coefficients corresponding to the first own lags of dependent variables, which we also refer to as self-variables first-lag coefficients, and 0 otherwise. In the output table, these are labeled as \{dln\_inv:L1.dln\_inv\}, \{dln\_inc:L1.dln\_inc\}, and \{dln\_consump:L1.dln\_consump\}. As such, the prior is centered around each variable being a univariate random walk. The estimated posterior means for the coefficients reflect the strong prior assumptions in the model. For example, the estimated posterior mean of \{dln\_inv:L1.dln\_inv\} is 0.48 with a 95% CrI of [0.28, 0.68] compared with the estimates from the \texttt{var} command of \(-0.32\) with a 95% CI of \(-0.55, -0.086\), which are quite different. Similarly, the posterior mean estimate for \{dln\_inc:L1.dln\_inc\} is 0.58 versus \(-0.15\) and for \{dln\_consump:L1.dln\_consump\} is 0.55 versus \(-0.26\). Continuing with the \texttt{dln\_consump} equation, we see that the posterior mean estimates of cross-variable lag coefficients are small. The estimated posterior mean of the first lag of income, \{dln\_consump:L1.dln\_inc\}, is \(-0.03\), and its 95% CrI includes 0. From the \texttt{var} results, \{dln\_consump:L1.dln\_inc\} is \(-0.22\) and is statistically significantly different from 0 (with \(p\)\text{-value}= 0.034).

All three self-variables first-lag coefficients have positive posterior estimates: means, medians, and 95% CrIs. Posterior estimates of remaining coefficients are close to 0. The results suggest a strong AR impact for each dependent variable and weak cross-correlations between the variables. The \{Sigma,m\} estimates show that there is some residual correlation in the error terms unexplained by the regression coefficients. The prior thus dominates the information about regression coefficients available in the data. This can be partially explained by the relatively small sample size of only 73 observations given the number of estimated parameters.

The results from the VAR models rely on the stability assumption. Thus, it is important to test this assumption, as we demonstrate in \textit{example 4}. When the assumption is satisfied, as it is for these data, you may consider specifying priors for regression coefficients that are centered around zero; for instance, using these priors for our dataset produces results that are similar to those from \texttt{var} (example 2).
Example 2: Bayesian VAR model with original Minnesota prior

In early work on Bayesian VAR (Doan, Litterman, and Sims 1984 and Litterman 1986), researchers simplified the model prior by assuming a known, fixed-error covariance matrix. The covariance $\Sigma$ in the MVN likelihood is replaced by an estimate $\hat{\Sigma}$. A typical choice for $\hat{\Sigma}$ is a diagonal matrix of variance estimates obtained by fitting a separate AR model to each dependent variable. The prior covariance for regression coefficients is then obtained from $\hat{\Sigma}$ as described in Original Minnesota prior with known (fixed) error covariance in Methods and formulas. This prior specification is known as the original Minnesota prior. Also see example 5.

To fit a model with the original Minnesota prior, we specify the `minnfixedcovprior` option with `bayes: var`.

```plaintext
. bayes, minnfixedcovprior rseed(17):
> var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)
Burn-in ...
Simulation ...
Model summary

Likelihood:
dln_inv
dln_inc
dln_consump ~ mvnormal(3,xb_dln_inv,xb_dln_inc,xb_dln_consump,_Sigma0)

Priors:
{dln_inv:L(1 2).dln_inv} (1)
{dln_inv:L(1 2).dln_inc} (1)
{dln_inv:L(1 2).dln_consump} (1)
{dln_inv:.cons} (1)
{dln_inc:L(1 2).dln_inv} (2)
{dln_inc:L(1 2).dln_inc} (2)
{dln_inc:L(1 2).dln_consump} (2)
{dln_inc:.cons} (2)
{dln_consump:L(1 2).dln_inv} (3)
{dln_consump:L(1 2).dln_inc} (3)
{dln_consump:L(1 2).dln_consump} (3)
{dln_consump:.cons} ~ minnesota(3,2,1,.b0,.Sigma0,.1,.5,1,100) (3)

(1) Parameters are elements of the linear form xb_dln_inv.
(2) Parameters are elements of the linear form xb_dln_inc.
(3) Parameters are elements of the linear form xb_dln_consump.
```
Compared with the default conjugate Minnesota prior from example 1, the error covariance matrix $\{\Sigma, m\}$ in the likelihood is replaced with a fixed matrix $\Sigma_0$, a diagonal AR covariance estimate. The regression coefficients are assigned the \texttt{minnesota(3,2,1,$b_0$,$\Sigma_0$,.1,.5,1,100)} prior. Most of the prior arguments are as we described in example 1, except the covariance matrix...
is now formed by \_\texttt{Sigma0} and tightness parameters \((0.1, 0.5, 1, 100)\); see \textit{Original Minnesota prior with known (fixed) error covariance}. Specifically, the default for the self-variables tightness parameter \(\lambda_1\) is 0.1 (option \texttt{selftight()}), the default for the cross-variables tightness parameter \(\lambda_2\) is 0.5 (option \texttt{crosstight()}), the default for the lag-decay parameter \(\lambda_3\) is 1 (option \texttt{lagdecay()}), and the default for the exogenous-variables tightness parameter is 100 (option \texttt{exogtight()}).

Like the default conjugate Minnesota prior, the original Minnesota prior places the same strong prior assumptions on regression coefficients: the prior mean vector \_\texttt{b0} contains 1 for self-variables first-lag coefficients and 0s for all other coefficients. The strength of the shrinkage toward the prior mean \_\texttt{b0} is controlled mainly by the tightness parameter \(\lambda_1\), which can be reset using the Minnesota prior option \texttt{selftight()}. Coefficients of exogenous variables, including the constant terms, are shrunk toward 0 but are given wide prior variance controlled by the tightness parameter \(\lambda_4\) and specified in the \texttt{exogtight()} option.

As expected, the results assuming the original Minnesota prior are closer to those assuming the default conjugate Minnesota prior than to those from the \texttt{var} command. In the absence of strong information about model parameters in the data, the Minnesota prior may introduce a stronger time dependence in the results. For example, the prior mean value for \{\texttt{dln\_inv:L1.dln\_inv}\} is 1 and the posterior mean estimate is 0.48, whereas the estimate from the \texttt{var} command is −0.32. It is completely acceptable to have a negative first-lag correlation in the change of investments at quarterly level. The Minnesota prior, however, expects an increase in investments to be followed by another increase in investment in the next time period. The question of whether this is a reasonable prior expectation is an empirical question. It is thus important to understand the behavior of the default Minnesota prior and use it carefully.

To relax the time-dependence assumption of the Minnesota prior, we can change the prior mean \_\texttt{b0} to be a zero vector and decrease the tightness of the prior by increasing the \(\lambda_1\) parameter from the default of 0.1 to 1. The prior for the self-variables first-lag coefficients thus changes from \(N(1, 0.01)\) to \(N(0, 1)\) and those for the cross-variables first-lag coefficients from \(N(0, 0.0025)\) to \(N(0, 0.25)\).

We change the defaults by specifying the respective suboptions within the \texttt{minnfixedcovprior()} option. There are several ways to specify the prior mean values. We can provide a full \(1 \times 21\) vector of mean values. Or, if we want to change the default values only for self-variables first-lag coefficients, we can specify a vector of lower dimension, \(1 \times 3\) in our example. The remaining coefficients will be automatically set to zeros. Alternatively, for self-variables first-lag coefficients, we can list the values directly in the \texttt{mean()} suboption, that is, \texttt{mean(0,0,0)}. We use the second approach below and specify a zero mean vector for self-variables first-lag coefficients.
. matrix b0 = J(1,3,0)
. bayes, minnfixedcovprior(mean(b0) selftight(1)) rseed(17): > var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)
Burn-in ... Simulation ...
Model summary

Likelihood:
dln_inv
dln_inc
dln_consump ~ mvnormal(3, xb_dln_inv, xb_dln_inc, xb_dln_consump, _Sigma0)

Priors:
{dln_inv:L(1 2).dln_inv} (1)
{dln_inv:L(1 2).dln_inc} (1)
{dln_inv:L(1 2).dln_consump} (1)
{dln_inv:_cons} (1)
{dln_inc:L(1 2).dln_inv} (2)
{dln_inc:L(1 2).dln_inc} (2)
{dln_inc:L(1 2).dln_consump} (2)
{dln_inc:_cons} (2)
{dln_consump:L(1 2).dln_inv} (3)
{dln_consump:L(1 2).dln_inc} (3)
{dln_consump:L(1 2).dln_consump} (3)
{dln_consump:_cons} ~ minnesota(3,2,1,b0,_Sigma0,1,.5,1,100) (3)

(1) Parameters are elements of the linear form xb_dln_inv.
(2) Parameters are elements of the linear form xb_dln_inc.
(3) Parameters are elements of the linear form xb_dln_consump.

Bayesian vector autoregression
Gibbs sampling
Sample: 1960q4 thru 1978q4
Log marginal-likelihood = 539.71278

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev.</th>
<th>MCSE</th>
<th>Median</th>
<th>95% cred. interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>dln_inv</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln_inv</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>-.2987647</td>
<td>.1218328</td>
<td>.001218</td>
<td>-.300605</td>
<td>-.5383571 -.0590116</td>
</tr>
<tr>
<td>L2.</td>
<td>-.1415209</td>
<td>.1192125</td>
<td>.001192</td>
<td>-.1439763</td>
<td>-.3729553 .0926795</td>
</tr>
<tr>
<td>dln_inc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.2014271</td>
<td>.5068694</td>
<td>.005069</td>
<td>.2036</td>
<td>-.7741228 1.196341</td>
</tr>
<tr>
<td>L2.</td>
<td>.1683548</td>
<td>.4567907</td>
<td>.004512</td>
<td>.1662872</td>
<td>-.7269593 1.058442</td>
</tr>
<tr>
<td>dln_consump</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.8313647</td>
<td>.6128113</td>
<td>.006128</td>
<td>.8291778</td>
<td>-.3631793 2.037414</td>
</tr>
<tr>
<td>L2.</td>
<td>.6988162</td>
<td>.554944</td>
<td>.005549</td>
<td>.6984739</td>
<td>-.3870548 1.810489</td>
</tr>
<tr>
<td>_cons</td>
<td>-.0124058</td>
<td>.016376</td>
<td>.000161</td>
<td>-.0123152</td>
<td>-.0449067 .0197023</td>
</tr>
</tbody>
</table>
Now the posterior mean estimates of regression coefficients are similar to the estimates from the original var command. For example, the posterior mean estimate of \( \{dln\_inv:L1.dln\_inv\} \) is about \(-0.30\) compared with var’s estimate of \(-0.32\).

The original Minnesota prior always assumes no correlation between cross-equation error terms. The following two priors relax this assumption.

\[ \text{Example 3: MVN priors with unrestricted error covariances} \]

What if we want to relax the assumption about the error covariance imposed by the original Minnesota prior? We can use a MVN-inverse-Wishart prior (option minniwishprior) or MVN-Jeffreys prior (option minnjeffprior). These priors use the same default MVN prior for the regression coefficients as the original Minnesota prior, but they assume an unrestricted error covariance and use the respective inverse-Wishart or Jeffreys prior for it.

Let’s start with an MVN-inverse-Wishart prior. Continuing with example 2, we change the default prior means for the regression coefficients to be zeros by specifying zero values for the three self-variables first-lag coefficients in the mean() option. This specification automatically assigns zero prior means for all other coefficients. We also use the self-variables tightness parameter of 1 instead of the default 0.1 to loosen the prior variance tightness.
. bayes, minniwishprior(mean(0,0,0) selftight(1)) rseed(17):  
> var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)  
Burn-in ...  
Simulation ...  
Model summary  

Likelihood:  
dln_inv  
dln_inc  
dln_consump ~ mvnormal(3,xb_dln_inv,xb_dln_inc,xb_dln_consump,{Sigma,m})  

Priors:  
{dln_inv:L(1 2).dln_inv} (1)  
{dln_inv:L(1 2).dln_inc} (1)  
{dln_inv:L(1 2).dln_consump} (1)  
{dln_inv:.cons} (1)  
{dln_inc:L(1 2).dln_inv} (2)  
{dln_inc:L(1 2).dln_inc} (2)  
{dln_inc:L(1 2).dln_consump} (2)  
{dln_inc:.cons} (2)  
{dln_consump:L(1 2).dln_inv} (3)  
{dln_consump:L(1 2).dln_inc} (3)  
{dln_consump:L(1 2).dln_consump} (3)  
{dln_consump:.cons} ~ varmvnormal(3,2,1,(0,0,0),_Omega0) (3)  
{Sigma,m} ~ iwishart(3,5,_Sigma0)  

(1) Parameters are elements of the linear form xb_dln_inv.  
(2) Parameters are elements of the linear form xb_dln_inc.  
(3) Parameters are elements of the linear form xb_dln_consump.  

Bayesian vector autoregression  
MCMC iterations = 12,500  
Gibbs sampling  
Burn-in = 2,500  
MCMC sample size = 10,000  
Sample: 1960q4 thru 1978q4  
Number of obs = 73  
Acceptance rate = 1  
Efficiency: min = .8113  
avg = .9438  
max = 1  

Log marginal-likelihood = 527.12015  

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev.</th>
<th>MCSE</th>
<th>Median</th>
<th>[95% cred. interval]</th>
<th>Equal-tailed</th>
</tr>
</thead>
<tbody>
<tr>
<td>dln_inv</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln_inv</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1</td>
<td>-.2510453</td>
<td>.1176975</td>
<td>.001153</td>
<td>-.2528143</td>
<td>-.4765424</td>
<td>-.0235274</td>
</tr>
<tr>
<td>L2</td>
<td>-.1063315</td>
<td>.116444</td>
<td>.001164</td>
<td>-.1059882</td>
<td>-.3344738</td>
<td>.1229004</td>
</tr>
<tr>
<td>dln_inc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1</td>
<td>.2446635</td>
<td>.3498178</td>
<td>.003498</td>
<td>.2500731</td>
<td>-.4573745</td>
<td>.9259674</td>
</tr>
<tr>
<td>L2</td>
<td>.095764</td>
<td>.219266</td>
<td>.002193</td>
<td>.0971031</td>
<td>-.3381891</td>
<td>.5251107</td>
</tr>
<tr>
<td>dln_consump</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1</td>
<td>.3645458</td>
<td>.3744485</td>
<td>.003811</td>
<td>.3680423</td>
<td>-.3646316</td>
<td>1.108422</td>
</tr>
<tr>
<td>L2</td>
<td>.1400995</td>
<td>.2298</td>
<td>.002392</td>
<td>.1395888</td>
<td>-.310524</td>
<td>.5901507</td>
</tr>
<tr>
<td>_cons</td>
<td>.0074369</td>
<td>.0119759</td>
<td>.000123</td>
<td>.0073878</td>
<td>-.0153556</td>
<td>.0307578</td>
</tr>
</tbody>
</table>
In the model summary, the regression coefficients are assigned the `varmvnormal()` prior, in which the prior covariance matrix \(_\Omega_0\) is a function of tightness parameters, the same as with the original Minnesota prior.

The inverse-Wishart prior for the error covariance matrix is controlled by the degrees of freedom and the scaling matrix. The default degrees of freedom \(df = K + 2 = 3 + 2 = 5\), and the default scale is \(_{\text{Scale0}} = (df - K - 1){_{\text{Sigma0}} = _{\text{Sigma0}}}\). The low degrees of freedom of the inverse-Wishart prior constrain the \(_{\{\text{Sigma,m}\}}\) matrix parameter to be close to the scaling matrix \(_{\text{Sigma0}}\).

The results are somewhat similar to those using the original Minnesota prior, but the error covariance matrix is now being estimated. Some of the covariance estimates are bounded away from zero based on their estimated CrIs, which suggests that the assumption of no correlation between the error terms imposed by the original Minnesota prior may not be appropriate for these data. Note that these results are closer to the results obtained from the `var` command.

<table>
<thead>
<tr>
<th>dln_inc</th>
<th>dln_inv</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1.</td>
<td>.046923</td>
</tr>
<tr>
<td>L2.</td>
<td>.0505845</td>
</tr>
</tbody>
</table>

| dln_inc | L1. | -.1526888 | .1310382 | .00131 | -.1527139 | -.4111528 | .5662822 |
| L2.     | -.0118679 | .1209026 | .001225 | -.0130416 | -.2506488 | .2254785 |

| dln_consump | L1. | .2586053 | .1552061 | .001552 | .259664 | -.0444987 | .5662822 |
| L2.     | -.013651 | .1354632 | .001407 | -.0124392 | -.27863 | .2532518 |

| _cons   | .0170262 | .041118 | .000043 | .0170605 | .0090405 | .0250246 |

| dln_consump | dln_inv |
| L1.     | .000902 | .0253473 | .000253 | .0008 | -.0484133 | .0512205 |
| L2.     | .0365412 | .025467 | .000261 | .0366538 | -.0138045 | .0861043 |

| dln_imp | L1. | .2124569 | .1058319 | .001058 | .2127713 | .019291 | .421758 |
| L2.     | .2993713 | .0940064 | .000973 | .2987598 | .1160611 | .4852742 |

| dln_consump | L1. | -.2757223 | .1279485 | .001279 | -.2756011 | -.5238806 | -.0256011 |
| L2.     | -.0293205 | .1199357 | .001199 | -.029558 | -.269714 | .2049208 |

| _cons   | .0146112 | .003401 | .00035 | .0145617 | .0080611 | .0213525 |

| Sigma_1_1 | .0021287 | .0003691 | 3.9e-06 | .0020854 | .0015264 | .0029714 |
| Sigma_2_1 | .0000718 | .0000664 | 7.3e-07 | .0000693 | -.0000518 | .0002108 |
| Sigma_3_1 | .0001215 | .0000558 | 6.1e-07 | .0001178 | .000212 | .0002401 |
| Sigma_2_2 | .0001363 | .0000239 | 2.6e-07 | .0001338 | .000971 | .001908 |
| Sigma_3_2 | .0000601 | .0000153 | 1.7e-07 | .0000858 | .000341 | .000943 |
| Sigma_3_3 | .0000892 | .0000155 | 1.7e-07 | .0000875 | .000638 | .001243 |
Instead of assuming an inverse-Wishart prior for the error covariance, we can use the multivariate Jeffreys prior.

\[
\text{bayes, minnjeffprior(mean(0,0,0) selftight(1)) rseed(17):}
\]
\[
> \text{var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)}
\]
\[
\text{Burn-in ...}
\]
\[
\text{Simulation ...}
\]
\[
\text{Model summary}
\]

Likelihood:
\[
dln_inv
dln_inc
dln_consump \sim \text{mvnormal}(3, xb_{dln_inv}, xb_{dln_inc}, xb_{dln_consump}, \{\Sigma, m\})
\]

Priors:
\[
\{\text{dln_inv:}L(1\ 2).\text{dln_inv}\} \sim \text{L(1)}
\]
\[
\{\text{dln_inv:}L(1\ 2).\text{dln_inc}\} \sim \text{L(1)}
\]
\[
\{\text{dln_inv:}L(1\ 2).\text{dln_consump}\} \sim \text{L(1)}
\]
\[
\{\text{dln_inv:}._\text{cons}\} \sim \text{L(1)}
\]
\[
\{\text{dln_inc:}L(1\ 2).\text{dln_inv}\} \sim \text{L(2)}
\]
\[
\{\text{dln_inc:}L(1\ 2).\text{dln_inc}\} \sim \text{L(2)}
\]
\[
\{\text{dln_inc:}L(1\ 2).\text{dln_consump}\} \sim \text{L(2)}
\]
\[
\{\text{dln_consump:}L(1\ 2).\text{dln_inv}\} \sim \text{L(3)}
\]
\[
\{\text{dln_consump:}L(1\ 2).\text{dln_inc}\} \sim \text{L(3)}
\]
\[
\{\text{dln_consump:}L(1\ 2).\text{dln_consump}\} \sim \text{L(3)}
\]
\[
\{\text{dln_consump:}._\text{cons}\} \sim \text{varmvnormal}(3,2,1,(0,0,0),_\Omega_0) \sim \text{jeffreys(3)}
\]

(1) Parameters are elements of the linear form \(xb_{dln_inv}\).
(2) Parameters are elements of the linear form \(xb_{dln_inc}\).
(3) Parameters are elements of the linear form \(xb_{dln_consump}\).

Bayesian vector autoregression
MCMC iterations = 12,500
Burn-in = 2,500
MCMC sample size = 10,000
Sample: 1960q4 thru 1978q4
Number of obs = 73
Acceptance rate = 1
Efficiency: min = .8186
avg = .9489
max = 1

Log marginal-likelihood = 535.28175

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. dev.</th>
<th>MCSE</th>
<th>Median</th>
<th>[95% cred. interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>dln_inv</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dln_inv</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>-.2455836</td>
<td>.1221811</td>
<td>.001236</td>
<td>-.2462348</td>
<td>-.4869383</td>
</tr>
<tr>
<td>L2.</td>
<td>-.1025647</td>
<td>.1181023</td>
<td>.001181</td>
<td>-.102274</td>
<td>-.3362211</td>
</tr>
<tr>
<td>dln_inc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.2298239</td>
<td>.3566309</td>
<td>.003566</td>
<td>.2342159</td>
<td>-.4802715</td>
</tr>
<tr>
<td>L2.</td>
<td>.0920532</td>
<td>.2204407</td>
<td>.002259</td>
<td>.0922503</td>
<td>-.332021</td>
</tr>
<tr>
<td>dln_consump</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.3544481</td>
<td>.3829504</td>
<td>.00383</td>
<td>.3546005</td>
<td>-.4036804</td>
</tr>
<tr>
<td>L2.</td>
<td>.1308923</td>
<td>.230888</td>
<td>.002307</td>
<td>.130488</td>
<td>-.3293822</td>
</tr>
<tr>
<td>_cons</td>
<td>.00804</td>
<td>.012356</td>
<td>.000125</td>
<td>.0080513</td>
<td>-.0161679</td>
</tr>
</tbody>
</table>
The results are similar to the MVN-inverse-Wishart prior results. The change in the prior for the error covariance did not change its estimates much, which again confirms that the data contribution to the posterior model is weak.

Example 4: Testing Bayesian VAR stability

A VAR model has meaningful interpretation in terms of IRFs and forecast-error variance decompositions only if the time-series process it represents is stable. The default Minnesota prior is based on the assumption that each dependent variable follows a univariate random walk, which is an unstable process. In the absence of strong information about model parameters in the data, the posterior is shrunk more toward the prior, so it is possible that Bayesian posterior estimates may not satisfy the stability assumption even when the frequentist estimates from the VAR model do. Thus, a stability check for a Bayesian VAR is particularly important.

In a frequentist setting, VAR stability can be checked by inspecting the eigenvalues of the companion matrix using the \texttt{TS varstable} command. In a Bayesian setting, the companion matrix and its eigenvalues are random, so we must inspect their posterior distributions. The Bayesian command for testing stationarity, \texttt{bayesvarstable}, reports posterior summaries for the eigenvalue moduli. Stability is declared when all eigenvalues are within the unit circle with high probability.
Let us refit the Bayesian VAR model from example 1 using the default prior options. In addition, we save simulation results in bvarsex1.dta, which is required by bayesvarstable. Because we already discussed the estimation results, we rerun the command quietly.

```
. quietly bayes, rseed(17) saving(bvarsex1):
> var dln_inv dln_inc dln_consump if qtr<=tq(1978q4)
```

Now we call bayesvarstable to check the stability condition.

```
. bayesvarstable
```

<table>
<thead>
<tr>
<th>Eigenvalue modulus</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>MCSE</th>
<th>Median [95% cred. interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7204885</td>
<td>0.0946585</td>
<td>0.000947</td>
<td>0.7185141 [.5401149 .911899]</td>
</tr>
<tr>
<td>2</td>
<td>0.5959965</td>
<td>0.1036993</td>
<td>0.001037</td>
<td>0.6005058 [.3817847 .7834288]</td>
</tr>
<tr>
<td>3</td>
<td>0.4271097</td>
<td>0.1243872</td>
<td>0.001244</td>
<td>0.4243446 [.2125586 .6563634]</td>
</tr>
<tr>
<td>4</td>
<td>0.2109317</td>
<td>0.0790968</td>
<td>0.000791</td>
<td>0.1972916 [.0886465 .3853979]</td>
</tr>
<tr>
<td>5</td>
<td>0.1357284</td>
<td>0.0561101</td>
<td>0.000561</td>
<td>0.1322702 [.0390514 .254025]</td>
</tr>
<tr>
<td>6</td>
<td>0.075227</td>
<td>0.0499245</td>
<td>0.000499</td>
<td>0.0688643 [.0033007 .1854592]</td>
</tr>
</tbody>
</table>

Pr(eigenvalues lie inside the unit circle) = 0.9975

The companion matrix is of dimension 6 (3 dependent variables times 2 lags), so the output table reports posterior summaries for the moduli of 6 eigenvalues. The eigenvalues are displayed in decreasing order of their moduli. The largest eigenvalue modulus has a posterior mean of 0.72 and is within the unit circle. The command also reports the posterior probability that all eigenvalues lie in the unit circle, 0.9975. The high value of this probability provides confidence that the stability condition is satisfied.

### US macroeconomic examples

In the next set of examples, we will use usmacro.dta, quarterly macroeconomic data extracted from the Federal Reserve Economic Database that spans from 1954 to 2010.

```
. use https://www.stata-press.com/data/r17/usmacro
(Federal Reserve Economic Data - St. Louis Fed)
. describe
Contains data from https://www.stata-press.com/data/r17/usmacro.dta
Observations: 226
Variables: 4
  4 Dec 2020 12:39
```

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Storage type</th>
<th>Display format</th>
<th>Value label</th>
</tr>
</thead>
<tbody>
<tr>
<td>fedfunds</td>
<td>double</td>
<td>%10.0g</td>
<td>Federal funds rate</td>
</tr>
<tr>
<td>date</td>
<td>int</td>
<td>%tq</td>
<td>Date (quarters)</td>
</tr>
<tr>
<td>inflation</td>
<td>float</td>
<td>%9.0g</td>
<td>Annual rate of inflation</td>
</tr>
<tr>
<td>ogap</td>
<td>float</td>
<td>%9.0g</td>
<td>GDP gap</td>
</tr>
</tbody>
</table>

Sorted by: date

```
. tsset
Time variable: date, 1954q3 to 2010q4
Delta: 1 quarter
```
Observed are three dependent variables: fedfunds, for federal funds rate, inflation, for annual rate of inflation, and ogap, for the GDP output gap, or the difference between actual and potential GDP. The date variable registers the quarterly periods.

Example 5: Explaining the Minnesota prior

Consider the following simple VAR(2) model for usmacro.dta with dependent variables ogap and inflation:

\[
\text{ogap} = a_{11} L \cdot \text{ogap} + a_{12} L^2 \cdot \text{ogap} + a_{21} L \cdot \text{inflation} + a_{22} L^2 \cdot \text{inflation} + a_0 + u_1
\]
\[
\text{inflation} = b_{11} L \cdot \text{ogap} + b_{12} L^2 \cdot \text{ogap} + b_{21} L \cdot \text{inflation} + b_{22} L^2 \cdot \text{inflation} + b_0 + u_2
\]

In the specification of the original Minnesota prior, \((u_1, u_2)\) is assumed to follow a bivariate normal distribution with 0 means and fixed error covariance \(\Sigma_0 = \text{diag}(\hat{\sigma}_1^2, \hat{\sigma}_2^2)\), which we define later.

Consider the vector \(\beta\) of 8 endogenous regression coefficients \(a_{ij}\)'s and \(b_{ij}\)'s and 2 exogenous constant terms \(a_0\) and \(b_0\). Specifically, we refer to \(a_{11}, a_{12}, b_{21}, \text{ and } b_{22}\) as endogenous-self-variables lag coefficients (or simply self-variables coefficients); to \(a_{21}, a_{22}, b_{11}, \text{ and } b_{12}\) as endogenous-cross-variables lag coefficients (or simply cross-variables coefficients); and to \(a_0\) and \(b_0\) as “exogenous-variables” coefficients. We used quotes for \(a_0\) and \(b_0\) because, technically, these are constant terms that do not correspond to any exogenous variables. But in what follows, we will treat them as such. In the presence of exogenous variables, we would refer to their coefficients as exogenous-variables coefficients. We also refer to \(a_{11}\) and \(b_{21}\) as self-variables first-lag coefficients, also know as first own lag coefficients.

The original Minnesota prior for \(\beta\) is MVN with \(10 \times 1\) mean vector \(\beta_0\) and \(10 \times 10\) covariance \(\Omega_0\), where \(\beta_0\) and \(\Omega_0\) are defined in Original Minnesota prior with known (fixed) error covariance. \(\beta_0\) contains 1 for all self-variables first-lag coefficients and 0 for all the other coefficients. \(\Omega_0\) is a diagonal matrix in which diagonals are functions of error variance estimates from individual AR models and tightness parameters. Because the covariance matrix \(\Omega_0\) is diagonal, all regression coefficients are assumed uncorrelated a priori.

In our example, the error variance estimates are the ordinary least-squares (OLS) residual variance estimates \(\hat{\sigma}_1^2\) and \(\hat{\sigma}_2^2\) obtained from fitting separately the following two AR models,

\[
\text{ogap} = c_{11} L \cdot \text{ogap} + c_{12} L^2 \cdot \text{ogap} + c_3 + e_1
\]
\[
\text{inflation} = d_{11} L \cdot \text{inflation} + d_{12} L^2 \cdot \text{inflation} + d_3 + e_2
\]

where \(e_i \sim N(0, \sigma_i^2)\) for \(i = 1, 2\).

The Minnesota prior has four control (tightness) parameters: \(\lambda_1, \lambda_2, \lambda_3, \text{ and } \lambda_4\), with default values of 0.1, 0.5, 1, and 100. These parameters can be reset using the selftight(), crosstight(), lagdecay(), and exogtight() Minnesota prior options, respectively.

Below, we show the default prior distributions for all coefficients. Let \(l\) denote the current lag.

Priors for endogenous-self-variables first-lag and second-lag coefficients are

\[
a_{11}, b_{21} \sim N(1, 0.01)
\]
\[
a_{12}, b_{22} \sim N(0, 0.0025)
\]

where \(\lambda_1^2/\lambda_2^2 = \lambda_3^2 = 0.01\) for \(l = 1\) and \(\lambda_1^2/\lambda_2^2 = 0.0025\) for \(l = 2\).
Priors for endogenous-cross-variables first-lag and second-lag coefficients are

\[ a_{21} \sim N(0, 0.0025 \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2}) \]
\[ b_{11} \sim N(0, 0.0025 \frac{\hat{\sigma}_2^2}{\hat{\sigma}_1^2}) \]
\[ a_{22} \sim N(0, 0.000625 \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2}) \]
\[ b_{12} \sim N(0, 0.000625 \frac{\hat{\sigma}_2^2}{\hat{\sigma}_1^2}) \]

where \((\lambda_1^2 \lambda_2^2)/l^2 \lambda_3^3 = \lambda_1^2 \lambda_2^2 = 0.0025\) for \(l = 1\) and \((\lambda_1^2 \lambda_2^2)/l^2 \lambda_3^3 = 0.000625\) for \(l = 2\).

Priors for exogenous constant terms are

\[ a_0 \sim N(0, 100\hat{\sigma}_1^2) \]
\[ b_0 \sim N(0, 100\hat{\sigma}_2^2) \]

where \(\lambda_1^2 \lambda_4^2 = 100\).

The default prior variances for the coefficients of all endogenous variables are rather small. The Minnesota prior essentially assumes that we have two independent time series each representing a univariate random walk:

\[ \text{ogap} = L_1 \cdot \text{ogap} + \epsilon_1 \]
\[ \text{inflation} = L_1 \cdot \text{inflation} + \epsilon_2 \]

The prior variances shrink as the lag \(l\) increases as long as \(\lambda_3\) is positive. Also, cross-variables variances shrink by a factor of \(\lambda_3^2\) from self-variables variances. All variances are proportional to \(\lambda_1^2\). If we increase \(\lambda_1\) from 0.1, the default, to 1, all variances will increase by a factor of 100.

In the specification of the conjugate Minnesota prior, \((u_1, u_2)\) is assumed to follow a bivariate normal with 0 means and an unknown error covariance \(\Sigma\).

The prior for \(\beta\) is conditional on \(\Sigma\). The prior mean stays the same, but the prior covariance matrix \(\Omega_0\) is replaced by \(\Sigma \otimes \Phi_0\), where \(\Phi_0\) has a structure similar to \(\Omega_0\) but of dimension 5 instead of 10,

\[ \Phi_0 = \text{diag} \left( \frac{1}{\hat{\sigma}_1^2} 0.01, \frac{1}{\hat{\sigma}_2^2} 0.01, \frac{1}{\hat{\sigma}_1^2} 0.0025, \frac{1}{\hat{\sigma}_2^2} 0.0025, 100 \right) \]

where \(\lambda_1^2/l^2 \lambda_3^3 = \lambda_1^2 = 0.01\) for \(l = 1\), \(\lambda_1^2/l^2 \lambda_3^3 = 0.0025\) for \(l = 2\), and \(\lambda_1^2 \lambda_4^2 = 100\).

In this case, the prior assumption on \(\beta\) implies that the multivariate process consists of two dependent random walks.

Error covariance \(\Sigma\) is assigned an inverse-Wishart prior with default degrees of freedom \(K + 2 = 4\), and the default scale matrix \(S_0\) is a diagonal matrix formed by the AR variance estimates. The effect of this prior can be interpreted as a lack of contemporaneous correlation among the error terms.
Example 6: Choosing the number of lags of a VAR model

Consider usmacro.dta. Let’s look at time series of the three dependent variables.

```
. use https://www.stata-press.com/data/r17/usmacro
   (Federal Reserve Economic Data - St. Louis Fed)
. tsline inflation ogap fedfunds
```

Time-series plots suggest a relationship between the three dependent variables that we would like to explore using a Bayesian VAR model.

Our goal is to model the dynamics of the three time series using VAR. We will use the `bayes: var` command to fit a Bayesian VAR model with the default conjugate Minnesota prior for the regression coefficients and error covariance. We will use all observations before the 1st quarter of 2004 to fit the model and leave out the later observations to test the forecasting ability of the model.

An important consideration in specifying the model is choosing the maximum number of lags. An expert in the field may have an optimal choice based on theoretical or empirical knowledge, but for us, it is not immediately clear whether we should use 2, 4, or more lags. In a classical setting, one can use the `varsoc` command to choose the maximum lag. It is not uncommon for `varsoc` to suggest too large of a lag length. For example, if we run `varsoc` on our data using up to 12 lags,
Bayes: var — Bayesian vector autoregressive models

Lag-order selection criteria
Sample: 1958q3 thru 2010q4 Number of obs = 210

<table>
<thead>
<tr>
<th>Lag</th>
<th>LL</th>
<th>LR</th>
<th>df</th>
<th>p</th>
<th>FPE</th>
<th>AIC</th>
<th>HQIC</th>
<th>SBIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1488.6</td>
<td>296.509</td>
<td>14.2057</td>
<td>14.225</td>
<td>14.2535</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-723.715</td>
<td>1529.8</td>
<td>9</td>
<td>0.000</td>
<td>7.00681</td>
<td>7.08413</td>
<td>7.19807</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-689.089</td>
<td>69.252</td>
<td>9</td>
<td>0.000</td>
<td>6.76275</td>
<td>6.89806</td>
<td>7.09746*</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-673.171</td>
<td>31.836</td>
<td>9</td>
<td>0.000</td>
<td>6.69686</td>
<td>6.89017</td>
<td>7.17502</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-661.806</td>
<td>22.729</td>
<td>9</td>
<td>0.000</td>
<td>6.67434</td>
<td>6.92564</td>
<td>7.29595</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-639.015</td>
<td>45.583</td>
<td>9</td>
<td>0.000</td>
<td>6.543</td>
<td>6.85228</td>
<td>7.30805</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-619.85</td>
<td>38.329</td>
<td>9</td>
<td>0.000</td>
<td>6.4619</td>
<td>6.81346*</td>
<td>7.35469</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>-615.967</td>
<td>7.7663</td>
<td>9</td>
<td>0.558</td>
<td>6.49492</td>
<td>6.92019</td>
<td>7.54687</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>-610.886</td>
<td>10.161</td>
<td>9</td>
<td>0.338</td>
<td>6.53225</td>
<td>7.0155</td>
<td>7.72765</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>-587.182</td>
<td>47.409</td>
<td>9</td>
<td>0.000</td>
<td>6.39221</td>
<td>6.93345</td>
<td>7.73105</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>-581.902</td>
<td>10.559</td>
<td>9</td>
<td>0.307</td>
<td>6.42764</td>
<td>7.02688</td>
<td>7.90993</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>-567.442</td>
<td>28.921*</td>
<td>9</td>
<td>0.001</td>
<td>6.37564*</td>
<td>7.03286</td>
<td>8.00137</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>-565.064</td>
<td>4.7562</td>
<td>9</td>
<td>0.855</td>
<td>6.4387</td>
<td>7.15392</td>
<td>8.20789</td>
<td></td>
</tr>
</tbody>
</table>

* optimal lag
Endogenous: inflation ogap fedfunds
Exogenous: _cons

the AIC criterion suggests a maximum lag of 11. A VAR model with 11 lags for our data will have 102 coefficients, which is likely too many given the sample size of 190. The resulting imprecision in the estimates would lead to wide forecast intervals.

From a Bayesian viewpoint, an optimal way to solve this problem is to use Bayesian model comparison. First, we choose a reasonable set of possible lags, 1, . . . , \( p_{\text{max}} \). Then, for each lag \( p \), we fit a Bayesian VAR(\( p \)) model. Finally, we compare the fitted models using their log-marginal likelihoods. Except the number of lags, all other model specifications, including the choice of priors, stay the same.

In this example, we consider six possible VAR models with lags ranging from 1 to 6. We specify two options with bayes: var: rseed(17), for reproducibility, and saving() to save the simulation results. The latter is required by estimates store to store Bayesian model estimation results. We run the models quietly to suppress lengthy estimation output.

```
. quietly bayes, rseed(17) saving(bvarsim,replace):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/1)
. estimates store bvar1
. quietly bayes, rseed(17) saving(bvarsim,replace):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/2)
. estimates store bvar2
. quietly bayes, rseed(17) saving(bvarsim,replace):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/3)
. estimates store bvar3
. quietly bayes, rseed(17) saving(bvarsim,replace):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/4)
. estimates store bvar4
. quietly bayes, rseed(17) saving(bvarsim,replace):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/5)
. estimates store bvar5
. quietly bayes, rseed(17) saving(bvarsim,replace):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/6)
. estimates store bvar6
```
We compare the models using the `bayestest model` command. All six models are assumed equally probable a priori, as can be seen from the second column of the output table. The third column shows posterior model probabilities; the model with the highest probability is the best.

| Model   | log(ML)      | P(M)  | P(M|y) |
|---------|--------------|-------|-------|
| bvar1   | -690.7037    | 0.1667| 0.0000|
| bvar2   | -680.1811    | 0.1667| 0.0000|
| bvar3   | -674.5212    | 0.1667| 0.0065|
| bvar4   | -670.3258    | 0.1667| 0.4313|
| bvar5   | -670.7045    | 0.1667| 0.2953|
| bvar6   | -670.8059    | 0.1667| 0.2669|

Note: Marginal likelihood (ML) is computed using Laplace–Metropolis approximation.

The model with four lags has the highest posterior probability, 0.43, and thus four is our choice for the number of lags. Incidentally or not, four lags corresponds to a period of one year.

» Example 7: Bayesian VAR(4) model estimation

Continuing with example 6, we proceed with Bayesian estimation of the chosen VAR(4) model. We rerun the model but this time showing the MCMC summary and output tables. The model summary is suppressed for brevity, but as we mentioned in example 6, we use the default conjugate Minnesota prior.
. bayes, nomodelsummary rseed(17):
> var inflation ogap fedfunds if date < tq(2004q1), lags(1/4)
Burn-in ...
Simulation ...

Bayesian vector autoregression

<table>
<thead>
<tr>
<th></th>
<th>MCMC iterations</th>
<th>Burn-in</th>
<th>MCMC sample size</th>
<th>Sample: 1956q3 thru 2003q4</th>
<th>Number of obs</th>
<th>Acceptance rate</th>
<th>Efficiency:</th>
<th>Log marginal-likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>min</td>
<td>-670.32584</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>avg</td>
<td></td>
</tr>
</tbody>
</table>

MCMC sample size = 10,000
Sample: 1956q3 thru 2003q4
Number of obs = 190
Acceptance rate = 1
Efficiency: min = .9322
avg = .993
max = 1

<table>
<thead>
<tr>
<th></th>
<th>Equal-tailed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>inflation</td>
<td></td>
</tr>
<tr>
<td>inflation</td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>1.107465</td>
</tr>
<tr>
<td>L2.</td>
<td>-.064825</td>
</tr>
<tr>
<td>L3.</td>
<td>-.0358872</td>
</tr>
<tr>
<td>L4.</td>
<td>-.0397985</td>
</tr>
<tr>
<td>ogap</td>
<td></td>
</tr>
<tr>
<td>ogap</td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.0646785</td>
</tr>
<tr>
<td>L2.</td>
<td>.0071294</td>
</tr>
<tr>
<td>L3.</td>
<td>-.002015</td>
</tr>
<tr>
<td>L4.</td>
<td>-.0088532</td>
</tr>
<tr>
<td>fedfunds</td>
<td></td>
</tr>
<tr>
<td>fedfunds</td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>.0770026</td>
</tr>
<tr>
<td>L2.</td>
<td>-.0351476</td>
</tr>
<tr>
<td>L3.</td>
<td>-.0151671</td>
</tr>
<tr>
<td>L4.</td>
<td>-.0190271</td>
</tr>
<tr>
<td>_cons</td>
<td>.1225433</td>
</tr>
<tr>
<td>ogap</td>
<td></td>
</tr>
<tr>
<td>inflation</td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>-.068909</td>
</tr>
<tr>
<td>L2.</td>
<td>.0073091</td>
</tr>
<tr>
<td>L3.</td>
<td>.0098226</td>
</tr>
<tr>
<td>L4.</td>
<td>.0146217</td>
</tr>
<tr>
<td>ogap</td>
<td></td>
</tr>
<tr>
<td>inflation</td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>1.030706</td>
</tr>
<tr>
<td>L2.</td>
<td>-.0533506</td>
</tr>
<tr>
<td>L3.</td>
<td>-.0463432</td>
</tr>
<tr>
<td>L4.</td>
<td>-.0243524</td>
</tr>
<tr>
<td>fedfunds</td>
<td></td>
</tr>
<tr>
<td>fedfunds</td>
<td></td>
</tr>
<tr>
<td>L1.</td>
<td>-.0080148</td>
</tr>
<tr>
<td>L2.</td>
<td>-.0513393</td>
</tr>
<tr>
<td>L3.</td>
<td>.0096443</td>
</tr>
<tr>
<td>L4.</td>
<td>.0028706</td>
</tr>
<tr>
<td>_cons</td>
<td>.3851112</td>
</tr>
</tbody>
</table>
The Gibbs sampling used to simulate the posterior distribution has high efficiency of 99% on average and the perfect acceptance rate of 1. There is no indication of convergence problems.

There are 39 regression coefficients in the model, which would be difficult to interpret directly. The posterior estimates for the error covariance matrix \( \{\text{Sigma},m\} \) suggest a positive correlation between \textit{fedfunds} and \textit{inflation} and \textit{fedfunds} and \textit{ogap}; see the estimates for \( \{\text{Sigma}_{31}\} \) and \( \{\text{Sigma}_{32}\} \).

Because we did not use the \texttt{saving()} option with \texttt{bayes: var}, the simulation results are saved in a temporary dataset. If you plan to use one of the postestimation commands such as \texttt{bayesirf} or \texttt{bayesfcast}, you need to save the simulation results to a permanent dataset. We can do this by using the \texttt{saving()} option on replay.

```
.bayes, saving(bvarex2)
note: file bvarex2.dta saved.
```
Before continuing with postestimation analysis, let’s check the stability condition of the model using the `bayesvarstable` command.

```
.bayesvarstable

Eigenvalue stability condition
Companion matrix size = 12
MCMC sample size = 10000

<table>
<thead>
<tr>
<th>Eigenvalue</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>MCSE</th>
<th>Median</th>
<th>[95% cred. interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.9473</td>
<td>.0199</td>
<td>.0001</td>
<td>.9481</td>
<td>.9057    .9838</td>
</tr>
<tr>
<td>2</td>
<td>.9417</td>
<td>.0257</td>
<td>.0002</td>
<td>.9453</td>
<td>.8776    .9811</td>
</tr>
<tr>
<td>3</td>
<td>.8184</td>
<td>.0716</td>
<td>.0007</td>
<td>.8274</td>
<td>.7637    .9323</td>
</tr>
<tr>
<td>4</td>
<td>.5930</td>
<td>.0931</td>
<td>.0009</td>
<td>.5836</td>
<td>.4256    .7733</td>
</tr>
<tr>
<td>5</td>
<td>.4859</td>
<td>.0897</td>
<td>.0008</td>
<td>.4867</td>
<td>.3306    .6555</td>
</tr>
<tr>
<td>6</td>
<td>.3659</td>
<td>.0417</td>
<td>.0004</td>
<td>.3635</td>
<td>.2915    .4592</td>
</tr>
<tr>
<td>7</td>
<td>.3499</td>
<td>.0368</td>
<td>.0003</td>
<td>.3497</td>
<td>.2767    .4214</td>
</tr>
<tr>
<td>8</td>
<td>.3156</td>
<td>.0389</td>
<td>.0004</td>
<td>.3173</td>
<td>.2348    .3856</td>
</tr>
<tr>
<td>9</td>
<td>.3014</td>
<td>.0397</td>
<td>.0004</td>
<td>.3039</td>
<td>.2177    .3736</td>
</tr>
<tr>
<td>10</td>
<td>.2670</td>
<td>.0472</td>
<td>.0005</td>
<td>.2718</td>
<td>.1583    .3475</td>
</tr>
<tr>
<td>11</td>
<td>.2361</td>
<td>.0556</td>
<td>.0006</td>
<td>.2414</td>
<td>.1136    .3298</td>
</tr>
<tr>
<td>12</td>
<td>.1887</td>
<td>.0806</td>
<td>.0008</td>
<td>.2036</td>
<td>.0152    .3103</td>
</tr>
</tbody>
</table>

Pr(eigenvalues lie inside the unit circle) = 0.9977
```

The command reports that the companion matrix of our model is of size 12 (three response variables times four lags) and thus reports posterior summaries for the moduli of 12 eigenvalues. The posterior probability that all eigenvalues lie in the unit circle is estimated to be essentially 1, so the stability condition is satisfied.

The main postestimation tools for interpreting VAR models are IRFs and forecasting, which we illustrate in the following examples.

### Example 8: IRFs

IRFs are commonly used to summarize a VAR model. IRFs measure the effect of a shock in one variable, also called an impulse variable, on a given response variable. The effect of the shock on the response variable is traced out over a predefined number of future steps. We compute a number of IRF statistics associated with our model using the `bayesirf` command, whose syntax is similar to the frequentist `irf` command. For computational details, see Methods and formulas of [BAYES] bayesirf create.

The `bayesirf create` command computes IRF results and stores them in a dataset with a special structure and with the `.irf` extension. One `.irf` dataset may contain several sets of IRF results.

Continuing with example 7, let’s compute the effect of shocks for up to 15 years (60 quarter periods) into the future. We name the set of results `birf1` and save them in `birfex2.irf`.

```
.bayesirf create birf1, step(60) set(birfex2)
```

It is easier to visualize the effect of a shock in one response variable on all other response variables and itself by using the `bayesirf graph` command. The command draws the posterior mean estimates of IRF coefficients along with 95% CrIs. Let’s inspect the effect of shock on `fedfunds`. Shocks of interests are specified using the `impulse()` option.
IRFs are obtained by setting the error vector in the likelihood model to (0,0,1) (1 for fedfunds and 0 otherwise) at step 0 and propagating this unit vector in time according to the VAR equations. For example, the response of inflation (second graph) starts from 0 at step 0, slightly increases during the first year, then slowly decreases during the next 4 years, and finally converges to a small positive value at the end of our 15-year period. According to the third graph, after a monetary shock from the Federal Reserve, the output gap decreases during the first two years, then slowly increases for the following eight years, and finally stabilizes at a small positive value. Notably, the shock effect on all response variables reach equilibrium after about 12 years.

We can examine IRF coefficients in more detail by listing them in a table using `bayesirf table`. For example, let’s inspect how the output gap is responding to a shock in federal funds in the first two years. This particular choice is made using the `response()`, `impulse()`, and `step()` options.

```
. bayesirf table irf, response(ogap) impulse(fedfunds) step(7)
```

<table>
<thead>
<tr>
<th>Step</th>
<th>irf</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.008015</td>
<td>0.089753</td>
<td>0.072662</td>
</tr>
<tr>
<td>1</td>
<td>-0.072428</td>
<td>-0.205354</td>
<td>0.059264</td>
</tr>
<tr>
<td>2</td>
<td>-0.128667</td>
<td>-0.296316</td>
<td>0.039592</td>
</tr>
<tr>
<td>3</td>
<td>-0.174391</td>
<td>-0.361456</td>
<td>0.009988</td>
</tr>
<tr>
<td>4</td>
<td>-0.208873</td>
<td>-0.409928</td>
<td>-0.009742</td>
</tr>
<tr>
<td>5</td>
<td>-0.232076</td>
<td>-0.444489</td>
<td>-0.021792</td>
</tr>
<tr>
<td>6</td>
<td>-0.245563</td>
<td>-0.466458</td>
<td>-0.028681</td>
</tr>
</tbody>
</table>
```

Posterior means reported.
95% equal-tailed credible lower and upper bounds reported.
(1) irfname = birf1, impulse = fedfunds, and response = ogap.
The `bayesirf` table command reports posterior mean estimates (first column), lower 95% credible limits (second column), and upper 95% credible limits (third column). We see that a 1% increase in `fedfunds` leads to about a 0.01 units decrease in `ogap` after 1 quarter and to 0.25 units decrease in `ogap` after 8 quarters (2 years). That is, in the short term, an increase in federal spending increases the gap between real and potential GDP.

The regular IRF functions do not account for the fact that the shocks in different impulse variables are generally not independent. For example, in our case, shocks in federal funds and inflation are likely dependent. A better representation of the dynamics between variables is provided by the so-called orthogonalized IRFs (OIRFs), referred to as `oirf` in `bayesirf` commands. The latter depends on the preset causal ordering of the impulse variables, as specified using the `order()` option. The default order is the order in which the variables are listed in the `bayes: var` command specification.

For example, let's examine the following causal order: `inflation → fedfunds → ogap`. In other words, let's assume that `fedfunds` has no immediate effect on `inflation` and that `ogap` has no immediate effect on `inflation` and `fedfunds`.

```
.bayesirf create birf2, step(60) set(birfex2) order(inflation fedfunds ogap)
(file birfex2.irf now active)
(file birfex2.irf updated)
```

The new IRF statistics are saved as `birf2` in `birfex2.irf`.

We can now summarize `oirf` statistics of `ogap` response to impulse in the third equation, referred to as `fedfunds`, corresponding to the new order we have specified.

```
.bayesirf table oirf, irf(birf2) response(ogap) impulse(fedfunds) step(7)
```

<table>
<thead>
<tr>
<th>Step</th>
<th>oirf</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>.257325</td>
<td>.148406</td>
<td>.370283</td>
</tr>
<tr>
<td>1</td>
<td>.258308</td>
<td>.128963</td>
<td>.395361</td>
</tr>
<tr>
<td>2</td>
<td>.195725</td>
<td>.041816</td>
<td>.35614</td>
</tr>
<tr>
<td>3</td>
<td>.123306</td>
<td>-.047116</td>
<td>.30244</td>
</tr>
<tr>
<td>4</td>
<td>.050238</td>
<td>-.130222</td>
<td>.241047</td>
</tr>
<tr>
<td>5</td>
<td>-.014137</td>
<td>-.201699</td>
<td>.186256</td>
</tr>
<tr>
<td>6</td>
<td>-.067159</td>
<td>-.261451</td>
<td>.13775</td>
</tr>
<tr>
<td>7</td>
<td>-.109004</td>
<td>-.309117</td>
<td>.103761</td>
</tr>
</tbody>
</table>

Posterior means reported.
95% equal-tailed credible lower and upper bounds reported.

(1) `irfname = birf2`, `impulse = fedfunds`, and `response = ogap`.

We observe notable differences between `oirf` and `irf` estimates reported above. A shock in the `fedfunds` equation now starts at 0.26 at step 0 and initially has little effect on closing the positive output gap, but after 4 steps (about a year), `ogap` becomes negative. As in the case with `irf` values, we see that a shock in federal funds has a negative effect on the output gap in a short term. OIRFs have the benefit of accounting for the correlation between `inflation` and `fedfunds`.

The interpretation of OIRFs very much depends on the causal order of response variables. Choosing an order can be difficult when there is no obvious choice based on expert knowledge. Next, for easier comparison, we show how to use `bayesirf graph` to plot the OIRFs from both `birf1` and `birf2`, which differ only in the response variable ordering.
The first row shows OIRFs for the original order, \textit{inflation} → \textit{ogap} → \textit{fedfunds}, and the second row shows results for the new order, \textit{inflation} → \textit{fedfunds} → \textit{ogap}. As we remarked above, there are differences between the OIRF results corresponding to different orderings.
Another way to follow the dynamics in \texttt{ogap} is to inspect the cumulative OIRF, \texttt{coirf}. Cumulative IRF statistics accumulate the shock effects over time. The following graph compares the cumulative OIRFs of \texttt{birf1} and \texttt{birf2} to a shock in \texttt{fedfunds}.

\begin{verbatim}
.bayesirf graph coirf, impulse(fedfunds)
\end{verbatim}

All two shock effects reach equilibrium after about 10 years. In the long term, a monetary shock reduces inflation and decreases the output gap.

Another set of IRFs that are useful for interpreting VAR models is the forecast error variance decompositions, or FEVDs. FEVDs measure the contribution, in terms of variability, of impulse variables to the forecast error in response variables. FEVDs, similar to OIRFs, depend on the causal ordering of the response variables.
For illustration, let's inspect the FEVDs of the response variable \textit{fedfunds} for the \texttt{birf2} results corresponding to the \textit{inflation} $\rightarrow$ \textit{fedfunds} $\rightarrow$ \textit{ogap} order. First, we show FEVD graphs.

\texttt{. bayesirf graph fevd, irf(birf2) response(fedfunds)}

\begin{figure}
\centering
\includegraphics[width=\textwidth]{fevd_graphs.png}
\caption{FEVD graphs for \textit{fedfunds} in response to \textit{inflation} and \textit{ogap}.}
\end{figure}

In the long term, half the forecast error of \textit{fedfunds} is contributed by \textit{fedfunds} itself, whereas \textit{inflation} and \textit{ogap} contribute by a quarter each.
A table of FEVD estimates gives us more details.

\[ . \texttt{bayesirf table fevd, irf(birf2) response(fedfunds) step(7)} \]

Results from birf2

<table>
<thead>
<tr>
<th>Step</th>
<th>fevd</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0.095083</td>
<td>0.027875</td>
<td>0.180163</td>
</tr>
<tr>
<td>2</td>
<td>0.102093</td>
<td>0.029869</td>
<td>0.192633</td>
</tr>
<tr>
<td>3</td>
<td>0.114495</td>
<td>0.034531</td>
<td>0.216095</td>
</tr>
<tr>
<td>4</td>
<td>0.128495</td>
<td>0.038329</td>
<td>0.242878</td>
</tr>
<tr>
<td>5</td>
<td>0.142093</td>
<td>0.041094</td>
<td>0.268065</td>
</tr>
<tr>
<td>6</td>
<td>0.155334</td>
<td>0.043475</td>
<td>0.293326</td>
</tr>
<tr>
<td>7</td>
<td>0.16808</td>
<td>0.045986</td>
<td>0.318506</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step</th>
<th>fevd</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0.904917</td>
<td>0.819837</td>
<td>0.972125</td>
</tr>
<tr>
<td>2</td>
<td>0.885277</td>
<td>0.794215</td>
<td>0.957829</td>
</tr>
<tr>
<td>3</td>
<td>0.852453</td>
<td>0.751346</td>
<td>0.936377</td>
</tr>
<tr>
<td>4</td>
<td>0.818721</td>
<td>0.702946</td>
<td>0.917391</td>
</tr>
<tr>
<td>5</td>
<td>0.789353</td>
<td>0.659076</td>
<td>0.902321</td>
</tr>
<tr>
<td>6</td>
<td>0.763024</td>
<td>0.619474</td>
<td>0.890185</td>
</tr>
<tr>
<td>7</td>
<td>0.739026</td>
<td>0.582641</td>
<td>0.879954</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Step</th>
<th>fevd</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0.01263</td>
<td>0.002624</td>
<td>0.027988</td>
</tr>
<tr>
<td>2</td>
<td>0.033052</td>
<td>0.00823</td>
<td>0.069683</td>
</tr>
<tr>
<td>3</td>
<td>0.052784</td>
<td>0.013287</td>
<td>0.111021</td>
</tr>
<tr>
<td>4</td>
<td>0.068554</td>
<td>0.016546</td>
<td>0.144177</td>
</tr>
<tr>
<td>5</td>
<td>0.081642</td>
<td>0.018741</td>
<td>0.174098</td>
</tr>
<tr>
<td>6</td>
<td>0.092895</td>
<td>0.020159</td>
<td>0.199897</td>
</tr>
</tbody>
</table>

Posterior means reported.
95% equal-tailed credible lower and upper bounds reported.

(1) irfname = birf2, impulse = inflation, and response = fedfunds.
(2) irfname = birf2, impulse = fedfunds, and response = fedfunds.
(3) irfname = birf2, impulse = ogap, and response = fedfunds.

The command output contains three tables, one for each impulse. At step 1, which corresponds to one-step-ahead predictions, FEVD posterior mean estimates are about 0.095 for inflation, 0.905 for fedfunds, and 0 for ogap due to the imposed order. The sum of FEVDs across impulses is 1. Most of the forecast error in fedfunds is because of the variability in fedfunds itself. At step 8, however, FEVD estimates become 0.18 for inflation, 0.72 for fedfunds, and 0.10 for ogap. The predominant effect of its own variability in FEVD estimates is an indirect effect of the Minnesota prior that shrinks self-variables first-lag coefficients to 1 and all others to 0.
Example 9: Forecasting

Bayesian dynamic forecasting is a special case of Bayesian predictions that uses posterior predictive distributions conditional on time to predict a response variable at multiple steps into the future; see Methods and formulas of [BAYES] bayesfcast compute.

bayesfcast compute is the Bayesian counterpart of the [TS] fcast compute command, which is used for Bayesian forecasting after the bayes: var command.

Let’s compute dynamic forecasts starting with the first quarter of 2004 until the end of the observed time frame, or 28 quarter periods ahead.

```
. bayesfcast compute b_, step(28) dynamic(tq(2004q1))
```

By default, bayesfcast compute computes and saves in the current dataset the posterior mean estimates of the predicted response variables along with the 95% credible intervals. The new variables are prefixed with b_.

It would be interesting to compare the Bayesian forecast results with the frequentist ones obtained by fcast compute after fitting the var command on the same model.

```
. quietly var inflation ogap fedfunds if date < tq(2004q1), lags(1/4)
. fcast compute f_, step(28) dynamic(tq(2004q1))
```

We can use the bayesfcast graph command to plot the observed and forecasted values along with their 95% CIs for the frequentist and 95% CrIs for the Bayesian results. Frequentist results are on the left, and Bayesian results are on the right.

```
. bayesfcast graph f_inflation b_inflation f_ogap b_ogap f_fedfunds b_fedfunds, 
  > observed byopts(rows(3) title("Frequentist (left) vs. Bayesian (right)"))
```

In the forecast period before 2008, the Bayesian forecasts seem to fit the observed response variables slightly better. The 95% CrIs include the observed values most of the time, except for ogap at the
second half of 2008 during the great recession. We should not expect a VAR model to forecast extreme events such as recessions.

Example 10: One-step-ahead Bayesian predictions

One-step-ahead Bayesian predictions are a special case of Bayesian forecasts, where current observed responses are used to make predictions for the next time period. In contrast to dynamic predictions, one-step-ahead predictions can be computed using the general postestimation command for Bayesian predictions, `bayespredict`.

For illustration, let’s compute predicted posterior means for the three responses starting with the first quarter of 2004 and save the results as new variables `pr1_inflation`, `pr1_ogap`, and `pr1_fedfunds`.

```stata
. bayespredict pr1_inflation pr1_ogap pr1_fedfunds if date>=tq(2004q1), mean
Computing predictions ...
```

Because these are one-step-ahead predictions, we expect them to be fairly close to the observed responses, much more so than dynamic forecasts with multiple prediction steps ahead. To verify that, let’s look at the prediction errors computed as the difference between the observed and predicted responses and plot them as time series.

```stata
. generate err1_inflation = inflation - pr1_inflation
(198 missing values generated)
. generate err1_ogap = ogap - pr1_ogap
(198 missing values generated)
. generate err1_fedfunds = fedfunds - pr1_fedfunds
(198 missing values generated)
. tsline err1_inflation err1_ogap err1_fedfunds if date>=tq(2004q1), yline(0)
```

Recall that the measurement units in this example are percentage growth rates for inflation and federal funds and percentage deviation from trend for the output gap. We see that one-step-ahead predictions perform well right before the beginning of the great recession in 2008, within a margin of 1 unit; that is, prediction errors are within 1 percentage point of realized values. After that, all three errors become negative for a period of time, which means they commit overprediction,
but then stabilize again at the end of 2009. The predictions for inflation are particularly off, overpredicting before the second quarter of 2009 and underpredicting after that until the end of 2009. A logical conclusion is that our model, fit on the data before the great recession, cannot capture the macroeconomic disruption of 2008 and 2009.

Finally, for those of you interested in comparing Bayesian and classical one-step-ahead predictions, we show the computation for the latter.

. quietly var inflation ogap fedfunds if date < tq(2004q1), lags(1/4)
. predict pr2_inflation, equation(inflation)
(option xb assumed; fitted values)
(8 missing values generated)
. predict pr2_ogap, equation(ogap)
(option xb assumed; fitted values)
(8 missing values generated)
. predict pr2_fedfunds, equation(fedfunds)
(option xb assumed; fitted values)
(8 missing values generated)
. generate err2_inflation = inflation - pr2_inflation
(8 missing values generated)
. generate err2_ogap = ogap - pr2_ogap
(8 missing values generated)
. generate err2_fedfunds = fedfunds - pr2_fedfunds
(8 missing values generated)
. tsline err2_inflation err2_ogap err2_fedfunds if date>=tq(2004q1), yline(0)

Bayesian and classical one-step-ahead predictions are similar, both failing to follow the dynamics of 2008–2009. However, Bayesian predictions for federal funds appear to be more precise.
Stored results

See Stored results in [BAYES] bayes. In addition, bayes: var stores the following in e():

Scalars
- e(tmin) first time period in sample
- e(tmax) maximum time
- e(nlag) highest lag in VAR
- e(selftight) self-variables tightness parameter in Minnesota priors
- e(crosstight) cross-variables tightness parameter in Minnesota priors (not with conjugate Minnesota prior)
- e(lagdecay) lag-decay parameter in Minnesota priors
- e(exogtight) exogenous-variables tightness parameter in Minnesota priors
- e(dfcov) degrees of freedom of inverse-Wishart prior

Macros
- e(cmdname) var
- e(prefix) bayes
- e(command) var command specification
- e(varprior) prior model for VAR coefficients and error covariance
- e(endog) names of endogenous variables
- e(exog) names of exogenous variables, and their lags, if specified
- e(exogvars) names of exogenous variables, if specified
- e(lags) lags in model
- e(exlags) lags of exogenous variables in model, if specified
- e(timevar) time variable specified in tsset
- e(tsfmt) format for the current time variable

Matrices
- e(exlagsm) matrix mapping lags to exogenous variables (with exog())
- e(phi) covariance product matrix $\Phi_0$ for conjugate Minnesota prior
- e(arcov) AR covariance matrix (with arcov)
- e(varcov) VAR covariance matrix (with varcov)
- e(mvnmean) mean vector of MVN prior
- e(mvncov) covariance matrix of MVN prior (with mvniwishprior() or mvnjeffprior())
- e(scalecov) scale matrix of inverse-Wishart prior

Methods and formulas

Methods and formulas are presented under the following headings:

- VAR model specification
  - Original Minnesota prior with known (fixed) error covariance
  - Conjugate Minnesota prior for VAR model with unknown error covariance
  - MVN-inverse Wishart prior
  - MVN-diffuse (normal-Jeffreys) prior

VAR model specification

Let $y_t$ be a $K \times 1$ vector of endogenous (dependent) variables at time $t$ for $t = 1, \ldots, T$ and $x_t$ be a $m \times 1$ vector of exogenous regressors including the constant terms.

A $p$-order VAR model, $\text{VAR}(p)$, can be defined according to Lütkepohl (2005) as

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + C x_t + u_t, \quad u_t \sim N(0, \Sigma)$$

where $p$ is the number of lags;

$A_l = (a_{ij}^l)$ are $K \times K$ matrices of unknown endogenous-variables lag coefficients ($l = 1, \ldots, p$);

$C = (c_{is})$ is a $K \times m$ matrix of exogenous-variables coefficients; and

$u_t$ is a $K \times 1$ vector of error terms with a $K \times K$ covariance matrix $\Sigma$. 
A VAR($p$) model can be written in a more compact form as

$$Y = XB + U$$

where

$$Y = \begin{pmatrix} y_1' \\ \vdots \\ y_T' \end{pmatrix}, \quad X = \begin{pmatrix} y_0' & y_{-1}' & \cdots & y_{-p}' & x_1' \\ \vdots \\ y_{T-1}' & y_{T-2}' & \cdots & y_{T-p}' & x_T' \end{pmatrix}, \quad B = \begin{pmatrix} A_1' \\ \vdots \\ A_p' \\ C' \end{pmatrix}, \quad U = \begin{pmatrix} u_1' \\ \vdots \\ u_T' \end{pmatrix}$$

$Y$ is a $T \times k$ matrix, $X$ is a $T \times (Kp + m)$ matrix, $B$ is a $(Kp + m) \times K$ matrix of all coefficients, and $U$ is a $T \times K$ matrix.

The OLS estimates of $B$ and $\Sigma$ are

$$\hat{B} = (X'X)^{-1}X'Y$$

$$\hat{\Sigma}_{OLS} = \hat{U}'\hat{U}/(T - Kp - m - 1), \quad \hat{U} = Y - X\hat{B}$$

Vectorizing the above matrix equation, we obtain

$$y = X^*\beta + u$$

where $y = \text{vec}(Y)$ is $KT \times 1$ vector, $X^* = I_K \otimes X$ is a $KT \times K(Kp + m)$ matrix ($\otimes$ is the Kronecker product and $I_K$ is a $K \times K$ identity matrix), $\beta = \text{vec}(B)$ is a $K(Kp + m) \times 1$ vector of all coefficients, and $u = \text{vec}(U)$ is a $KT \times 1$ error vector with a $KT \times KT$ covariance matrix $\Sigma^* = \Sigma \otimes I_T$.

An essential component of every Bayesian VAR model is specifying a suitable prior for the vector of coefficients $\beta$. In what follows, we will describe several commonly used priors, all based on a so-called Minnesota prior. But before we continue, let’s define components that are used by all of these priors.

Consider a univariate AR($p$) model for each outcome $k = 1, \ldots, K$,

$$y_{k,t} = a_1 y_{k,t-1} + \cdots + a_p y_{k,t-p} + a_0 + e_{k,t}$$

where $e_{k,t} \sim N(0, \sigma_k^2)$. All priors considered below use the OLS estimate, $\hat{\sigma}_k^2$, of $\sigma_k^2$. Some of the priors also use a diagonal covariance estimate formed by $K$ error-variance estimates from separate AR($p$) models: $\hat{\Sigma}_{\text{diag}} = \text{diag}(\hat{\sigma}_1^2, \ldots, \hat{\sigma}_K^2)$.

**Original Minnesota prior with known (fixed) error covariance**

The original Bayesian VAR model with a Minnesota prior (Litterman 1980, 1986) assumes that the covariance matrix of the error vectors $u_t$ is known, $\Sigma = \Sigma_0$; that is,

$$u \sim N(0, \Sigma_0 \otimes I_T)$$
The original formulation (suboption arcov in minnopts) used a diagonal matrix with the estimated error variances from $K$ separate AR models (2) on the diagonal as a covariance estimate, $\Sigma_0 = \hat{\Sigma}_{\text{diag}} = \text{diag}(\hat{\sigma}_1^2, \ldots, \hat{\sigma}_K^2)$. Litterman thus proposed to estimate the VAR model equation by equation, rather than as a system of equations, to reduce the computational burden, which at the time was a serious problem. Another formulation (suboption varcov in minnopts) used the OLS estimate of the covariance matrix from the VAR model, $\Sigma_0 = \hat{\Sigma}_{\text{OLS}}$, defined in (1).

This prior is implemented by the minnfixedcovprior option of bayes: var, but it is not the default prior. The default prior is the conjugate Minnesota prior (option minnconjprior) described in the next section, which uses a less restrictive prior covariance. But we describe the original Minnesota prior first because the conjugate Minnesota prior is its extension.

The Minnesota prior for coefficient vector $\beta$ is an MVN prior,

$$\beta \sim N(\beta_0, \Omega_0)$$

where a $KT \times 1$ vector $\beta_0$ and a $KT \times KT$ matrix $\Omega_0$ are defined in a way that accounts for the special time-series structure of the VAR($p$) model, which we describe next.

The regression vector $\beta$ is formed by the endogenous-variables lag coefficients $a_{l_{ij}}$ ($l = 1, \ldots, p$ and $i, j = 1, \ldots, K$) and exogenous-variables coefficients $c_{is}$ ($i = 1, \ldots, K$ and $s = 1, \ldots, m$). The Minnesota priors assumes that expected values for all coefficients are zero, except for the self-variables first-lag coefficients; that is,

$$E(a_{l_{ij}}) = \delta_{ii} \delta_{ij}$$

where $\delta_{ij} = 1$ if $i = j$ and 0 otherwise, so the prior mean vector $\beta_0$ is a $K(Kp + m) \times 1$ vector of 0s and 1s, with 1s corresponding to the self-variables first-lag coefficients.

The original Minnesota prior assumes that there is no correlation between the coefficients of $\beta$. The Minnesota covariance $\Omega_0$ is thus a diagonal matrix, its diagonal formed by the prior variances $\sigma_{a_{l_{ij}}}^2$ for the endogenous-variables lag coefficients and $\sigma_{c_{is}}^2$ for the exogenous-variables coefficients. The prior variances are based on the OLS estimates of error variances, $\hat{\sigma}_k^2$’s, and are defined below.

For endogenous-self-variables lag coefficients, the prior variances are

$$\sigma_{a_{l_{ii}}}^2 = \left(\frac{\lambda_1}{l\lambda_3}\right)^{2}$$

For endogenous-cross-variables lag coefficients ($i \neq j$), the prior variances are

$$\sigma_{a_{l_{ij}}}^2 = \left(\frac{\hat{\sigma}_i^2}{\hat{\sigma}_j^2}\right) \left(\frac{\lambda_1 \lambda_2}{l\lambda_3}\right)^{2}$$

For exogenous-variables coefficients, the prior variances are

$$\sigma_{c_{is}}^2 = \hat{\sigma}_i^2 (\lambda_1 \lambda_4)^{2}$$

In the above formulas, $\lambda_1$ controls the tightness of the prior variance for self-variables lag coefficients and can be specified in the selftight() suboption of the Minnesota prior options, minnopts; $\lambda_2$ controls the cross-variables lag coefficients spread and can be specified in the crosstight() suboption; $\lambda_3$ controls the lag attenuation and can be specified in the lagdecay() suboption (the higher the lag, the tighter the prior variances); and $\lambda_4$ controls the prior variance of the exogenous-variables coefficients and can be specified in the exogtight() option. Default values for these control parameters are $\lambda_1 = 0.1$, $\lambda_2 = 0.5$, $\lambda_3 = 1$, and $\lambda_4 = 100$. 

Litterman thus proposed to estimate the VAR model equation by equation, rather than as a system of equations, to reduce the computational burden, which at the time was a serious problem. Another formulation (suboption varcov in minnopts) used the OLS estimate of the covariance matrix from the VAR model, $\Sigma_0 = \hat{\Sigma}_{\text{OLS}}$, defined in (1).
The prior mean $\beta_0$ and diagonal covariance matrix $\Omega_0$ described above define the original Minnesota prior, which is available by specifying the minnfixedcovprior option with \texttt{bayes: var}. You can customize this prior by specifying the minnfixedcovprior(\texttt{fixcovopts}) option.

In the model-summary output of \texttt{bayes: var}, we refer to the defaults $\Sigma_0$ and $\beta_0$ as \_\texttt{Sigma0} and \_\texttt{b0}, respectively. $\Omega_0$ is viewed as a function of \_\texttt{Sigma0} and prior control parameters $\lambda$'s.

### Conjugate Minnesota prior for VAR model with unknown error covariance

Another framework of Bayesian VAR models assumes that error vectors $u_t$ have an unknown covariance matrix $\Sigma$. In this case, $u \sim N(0, \Sigma \otimes I_T)$.

Karlsson (2013) proposed a prior for $\beta$ with the prior covariance having a similar form to the covariance matrix $\Sigma$. Specifically, the author defined the prior covariance as a product of $\Sigma$ and another covariance matrix, $\Phi_0$, which we refer to as a Minnesota factor covariance,

$$\beta \sim N(\beta_0, \Sigma \otimes \Phi_0)$$

The prior mean vector $\beta_0$ is the same as in the original Minnesota prior, and $\Phi_0$ is a fixed $(Kp + m) \times (Kp + m)$ covariance matrix as defined below.

$$\Phi_0 = \text{diag}\left(\left\{\sigma^2_{a_l} \right\}^{K_p}_{j=1,l=1}, \left\{\sigma^2_{c_s} \right\}^{m}_{s=1}\right)$$

is set to be a diagonal matrix similar to the Minnesota covariance $\Omega_0$ but of a lower dimension $(Kp + m) \times (Kp + m)$ compared with $KT \times KT$. The elements of $\Phi_0$ are defined below for $l = 1, \ldots, p$, $j = 1, \ldots, K$, and $s = 1, \ldots, m$.

For endogenous-variables lag coefficients,

$$\sigma^2_{a_l} = \left(\frac{1}{\hat{\sigma}^2_j}\right)\left(\frac{\lambda_1}{\lambda_3}\right)^2$$

And for exogenous-variables coefficients,

$$\sigma^2_{c_s} = (\lambda_1 \lambda_4)^2$$

In the above formulas, $\lambda_1$, $\lambda_3$, and $\lambda_4$ have the same interpretation as in the original Minnesota prior. In this formulation, $\lambda_2$ is not used because there is no distinction between the self- and cross-variables.

The covariance parameter $\Sigma$ has an inverse-Wishart prior with a scale matrix $S_0$ and degrees of freedom $K + 2$ (default):

$$\Sigma \sim \text{InvWishart}(\alpha_0, S_0)$$

You can specify $\alpha_0$ in the \texttt{df()} suboption and $S_0$ in the \texttt{scale()} suboption of the minnconjprior() option. The default values are $\alpha_0 = K + 2$, the minimum possible value such that the mean exists, and $S_0 = (\alpha_0 - K - 1)\Sigma_0$, where $\Sigma_0$ is as it is defined for the original Minnesota prior. With these default values, the prior mean of $\Sigma$ is $\Sigma_0$.

The conjugate Minnesota prior is the default prior for \texttt{bayes: var}, and it corresponds to the minnconjprior option, which is implied by default. You can customize this prior by specifying the minnconjprior(\texttt{conjopts}) option.

In the model-summary output of \texttt{bayes: var}, we refer to the defaults $\Phi_0$ as \_\texttt{Phi0}, $\beta_0$ as \_\texttt{b0}, and $S_0$ as \_\texttt{Scale0}. With degrees of freedom $K + 2$ (default), $S_0$ is displayed as \_\texttt{Sigma0}. 
MVN-inverse Wishart prior

You can also specify an MVN-inverse Wishart prior for the \( \text{VAR} \) coefficients and error covariance. This prior also assumes an unknown error covariance \( \Sigma, \mathbf{u} \sim N(0, \Sigma \otimes I_T) \).

The regression vector \( \mathbf{\beta} \) has an MVN prior

\[
\mathbf{\beta} \sim N(\tilde{\mathbf{\beta}}, \tilde{\Omega})
\]

with a fixed mean vector \( \tilde{\mathbf{\beta}} \) and a covariance matrix \( \tilde{\Omega} \), which can be specified independently.

The covariance parameter \( \Sigma \) has an inverse-Wishart prior with a scale matrix \( S_0 \) and degrees of freedom \( \alpha_0 \),

\[
\Sigma \sim \text{InvWishart}(\alpha_0, S_0)
\]

You can specify this prior by using the \texttt{minniwishprior(iwishopts)} option. You can specify \( \tilde{\mathbf{\beta}} \) using the \texttt{mean()} suboption and \( \tilde{\Omega} \) using the \texttt{cov()} suboption. Default values for \( \tilde{\mathbf{\beta}} \) and \( \tilde{\Omega} \) are the prior mean and covariance, \( \beta_0 \) and \( \Omega_0 \), of the original Minnesota prior.

You can specify \( \alpha_0 \) using the \texttt{df()} suboption and \( S_0 \) using the \texttt{scale()} suboption. The default values are \( \alpha_0 = K + 2 \), the minimum possible value such that the mean exists, and \( S_0 = (\alpha_0 - K - 1)\Sigma_0 \).

In the model-summary output of \texttt{bayes: var}, we refer to the defaults \( \beta_0 \) as \_b0, \( \Omega_0 \) as \_Omega0, and \( S_0 \) as \_Scale0. With degrees of freedom \( K + 2 \) (default), \( S_0 \) is displayed as \_Sigma0.

MVN-diffuse (normal-Jeffreys) prior

Instead of an inverse-Wishart prior for the covariance matrix, as in the previous section, one may consider a diffused (multivariate Jeffreys) prior. As before, \( \mathbf{u} \sim N(0, \Sigma \otimes I_T) \).

The prior for \( \mathbf{\beta} \) is still the MVN prior, as defined in \textit{MVN-inverse Wishart prior},

\[
\mathbf{\beta} \sim N(\tilde{\mathbf{\beta}}, \tilde{\Omega})
\]

with a mean vector \( \tilde{\mathbf{\beta}} \) and a covariance matrix \( \tilde{\Omega} \). But the covariance matrix \( \Sigma \) has a multivariate Jeffreys prior,

\[
\pi(\Sigma) \propto \left| \Sigma \right|^{(K+1)/2}
\]

You can specify the \texttt{minnjeffprior(jeffopts)} option for this prior. You can specify \( \tilde{\mathbf{\beta}} \) using the \texttt{mean()} suboption and \( \tilde{\Omega} \) using the \texttt{cov()} suboption. As with MVN-inverse Wishart prior, the default values for \( \tilde{\mathbf{\beta}} \) and \( \tilde{\Omega} \) are the prior mean and covariance, \( \beta_0 \) and \( \Omega_0 \), of the original Minnesota prior.

In the model-summary output of \texttt{bayes: var}, we refer to the defaults \( \beta_0 \) and \( \Omega_0 \) as \_b0 and \_Omega0, respectively.

Also see \textit{Methods and formulas} in \texttt{[BAYES] bayesmh}. 

References


Also see

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

[BAYES] bayes — Bayesian regression models using the bayes prefix

[TS] var — Vector autoregressive models

[BAYES] Bayesian postestimation — Postestimation tools for bayesmh and the bayes prefix

[BAYES] Bayesian estimation — Bayesian estimation commands

[BAYES] Bayesian commands — Introduction to commands for Bayesian analysis

[BAYES] Intro — Introduction to Bayesian analysis

[BAYES] Glossary