Title

var — Vector autoregressive models

Syntax

var depvarlist [if] [in] [ , options ]

options

Model

noconstant suppress constant term
lags(numlist) use lags numlist in the VAR
exog(varlist) use exogenous variables varlist

Model 2

constraints(numlist) apply specified linear constraints
nolog suppress SURE iteration log
iterate(#) set maximum number of iterations for SURE; default is iterate(1600)
tolerance(#) set convergence tolerance of SURE
noisure use one-step SURE
dfk make small-sample degrees-of-freedom adjustment
small report small-sample t and F statistics
nobigf do not compute parameter vector for coefficients implicitly set to zero

Reporting

level(#) set confidence level; default is level(95)
lutstats report Lütkepohl lag-order selection statistics
nocsreport do not display constraints
display_options control column formats, row spacing, and line width
coefflegend display legend instead of statistics

You must tsset your data before using var; see [TS] tsset.
depvarlist and varlist may contain time-series operators; see [U] 11.4.4 Time-series varlists.
by, fp, rolling, statsby, and xi are allowed; see [U] 11.1.10 Prefix commands.
coefflegend does not appear in the dialog box.
See [U] 20 Estimation and postestimation commands for more capabilities of estimation commands.

Menu

Statistics > Multivariate time series > Vector autoregression (VAR)
Description

var fits a multivariate time-series regression of each dependent variable on lags of itself and on lags of all the other dependent variables. var also fits a variant of vector autoregressive (VAR) models known as the VARX model, which also includes exogenous variables. See [TS] var intro for a list of commands that are used in conjunction with var.

Options

<table>
<thead>
<tr>
<th>Model 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>noconstant; see [R] estimation options.</td>
</tr>
<tr>
<td>lags(numlist) specifies the lags to be included in the model. The default is lags(1 2). This option takes a numlist and not simply an integer for the maximum lag. For example, lags(2) would include only the second lag in the model, whereas lags(1/2) would include both the first and second lags in the model. See [U] 11.1.8 numlist and [U] 11.4.4 Time-series varlists for more discussion of numlists and lags.</td>
</tr>
<tr>
<td>exog(varlist) specifies a list of exogenous variables to be included in the VAR.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>constraints(numlist); see [R] estimation options.</td>
</tr>
<tr>
<td>nolog suppresses the log from the iterated seemingly unrelated regression algorithm. By default, the iteration log is displayed when the coefficients are estimated through iterated seemingly unrelated regression. When the constraints() option is not specified, the estimates are obtained via OLS, and nolog has no effect. For this reason, nolog can be specified only when constraints() is specified. Similarly, nolog cannot be combined with noisure.</td>
</tr>
<tr>
<td>iterate(#) specifies an integer that sets the maximum number of iterations when the estimates are obtained through iterated seemingly unrelated regression. By default, the limit is 1,600. When constraints() is not specified, the estimates are obtained using OLS, and iterate() has no effect. For this reason, iterate() can be specified only when constraints() is specified. Similarly, iterate() cannot be combined with noisure.</td>
</tr>
<tr>
<td>tolerance(#) specifies a number greater than zero and less than 1 for the convergence tolerance of the iterated seemingly unrelated regression algorithm. By default, the tolerance is 1e-6. When the constraints() option is not specified, the estimates are obtained using OLS, and tolerance() has no effect. For this reason, tolerance() can be specified only when constraints() is specified. Similarly, tolerance() cannot be combined with noisure.</td>
</tr>
<tr>
<td>noisure specifies that the estimates in the presence of constraints be obtained through one-step seemingly unrelated regression. By default, var obtains estimates in the presence of constraints through iterated seemingly unrelated regression. When constraints() is not specified, the estimates are obtained using OLS, and noisure has no effect. For this reason, noisure can be specified only when constraints() is specified.</td>
</tr>
<tr>
<td>dfk specifies that a small-sample degrees-of-freedom adjustment be used when estimating Σ, the error variance–covariance matrix. Specifically, 1/(T – m) is used instead of the large-sample divisor 1/T, where m is the average number of parameters in the functional form for y_t over the K equations.</td>
</tr>
<tr>
<td>small causes var to report small-sample t and F statistics instead of the large-sample normal and chi-squared statistics.</td>
</tr>
</tbody>
</table>
nobigf requests that var not save the estimated parameter vector that incorporates coefficients that have been implicitly constrained to be zero, such as when some lags have been omitted from a model. \texttt{e(bf)} is used for computing asymptotic standard errors in the postestimation commands \texttt{irf create} and \texttt{fcast compute}; see [\texttt{TS}] \texttt{irf create} and [\texttt{TS}] \texttt{fcast compute}. Therefore, specifying nobigf implies that the asymptotic standard errors will not be available from \texttt{irf create} and \texttt{fcast compute}. See Fitting models with some lags excluded.

level(#)\textbackslash{}; see [\texttt{R}] estimation options.

\texttt{lutstats} specifies that the Lütkepohl (2005) versions of the lag-order selection statistics be reported. See Methods and formulas in [\texttt{TS}] \texttt{varsoc} for a discussion of these statistics.

nocnsreport; see [\texttt{R}] estimation options.

display\_options: vsquish, cformat(\texttt{\%fmt}), pformat(\texttt{\%fmt}), sformat(\texttt{\%fmt}), and nolstretch; see [\texttt{R}] estimation options.

The following option is available with var but is not shown in the dialog box: coeflegend; see [\texttt{R}] estimation options.

Remarks and examples

Remarks are presented under the following headings:

- Introduction
- Fitting models with some lags excluded
- Fitting models with exogenous variables
- Fitting models with constraints on the coefficients

Introduction

A VAR is a model in which \( K \) variables are specified as linear functions of \( p \) of their own lags, \( p \) lags of the other \( K - 1 \) variables, and possibly exogenous variables. A VAR with \( p \) lags is usually denoted a VAR\((p)\). For more information, see [\texttt{TS}] \texttt{var intro}.

Example 1: VAR model

To illustrate the basic usage of \texttt{var}, we replicate the example in Lütkepohl (2005, 77–78). The data consists of three variables: the first difference of the natural log of investment, \texttt{dln\_inv}; the first difference of the natural log of income, \texttt{dln\_inc}; and the first difference of the natural log of consumption, \texttt{dln\_consum}. The dataset contains data through the fourth quarter of 1982, though Lütkepohl uses only the observations through the fourth quarter of 1978.

. use http://www.stata-press.com/data/r13/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
. var dln_inv dln_inc dln_consump if qtr<=tq(1978q4), lutstats dfk

Vector autoregression

<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>9.736909</td>
<td>0.1362</td>
</tr>
<tr>
<td>dln_inc</td>
<td>7</td>
<td>.011719</td>
<td>0.1142</td>
<td>8.508289</td>
<td>0.2032</td>
</tr>
<tr>
<td>dln_consump</td>
<td>7</td>
<td>.009445</td>
<td>0.2513</td>
<td>22.15096</td>
<td>0.0011</td>
</tr>
</tbody>
</table>

| dln_inv        | Coef. | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|----------------|-------|-----------|-------|-------|----------------------|
| L1.            | -.3196318 | .1254564 | -2.55 | 0.011 | -.5655218 -.0737419  |
| L2.            | -.1605508 | .1249066 | -1.29 | 0.199 | -.4053633 .0842616   |

| dln_inc        | Coef. | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|----------------|-------|-----------|-------|-------|----------------------|
| L1.            | .1459851 | .5456664 | 0.27  | 0.789 | -.9235013 1.215472   |
| L2.            | .1146009 | .5345709 | 0.21  | 0.830 | -.9331388 1.162341   |

| dln_consump    | Coef. | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|----------------|-------|-----------|-------|-------|----------------------|
| L1.            | .9612288 | .6643086 | 1.45  | 0.148 | -.3407922 2.26325    |
| L2.            | .9344001 | .6650949 | 1.40  | 0.160 | -.369162 2.237962    |

| _cons          | Coef. | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|----------------|-------|-----------|-------|-------|----------------------|
| dln_inv        | L1.   | .0439309  | .0318592 | 1.38 | 0.168 | -.018512 1.063739    |
|                | L2.   | .0500302  | .0317196 | 1.58 | 0.115 | -.0121391 .1121995  |

| dln_inc        | L1.   | -.1527311 | .1385702 | -1.10 | 0.270 | -.4243237 .1188615   |
|                | L2.   | .0191634  | .1357525 | 0.14  | 0.888 | -.2469067 .2852334   |

| dln_consump    | L1.   | .2884992  | .168699  | 1.71  | 0.087 | -.0421448 .6191431   |
|                | L2.   | -.0102    | .1688987 | -0.06 | 0.952 | -.3412354 .3208353   |

| _cons          | Coef. | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|----------------|-------|-----------|-------|-------|----------------------|
| dln_consump    | L1.   | -.002423  | .0256763 | -0.09 | 0.925 | -.0527476 .0479016   |
|                | L2.   | .0338806  | .0255638 | 1.33  | 0.185 | -.0162235 .0839847   |

| dln_inc        | L1.   | .2248134  | .1116778 | 2.01  | 0.044 | .005929  .4436978    |
|                | L2.   | .3549135  | .1094069 | 3.24  | 0.001 | .1404798 .5693471    |

| dln_consump    | L1.   | -.2639695 | .1359595 | -1.94 | 0.052 | -.5304451 .0025062   |
|                | L2.   | -.0222264 | .1361204 | -0.16 | 0.870 | -.2890175 .2445646   |

| _cons          | Coef. | Std. Err. | z     | P>|z|   | [95% Conf. Interval] |
|----------------|-------|-----------|-------|-------|----------------------|
| dln_consump    | L1.   | .0129258  | .0035256 | 3.67  | 0.000 | .0060157 .0198358    |
The output has two parts: a header and the standard Stata output table for the coefficients, standard errors, and confidence intervals. The header contains summary statistics for each equation in the \textit{VAR} and statistics used in selecting the lag order of the \textit{VAR}. Although there are standard formulas for all the lag-order statistics, Lütkepohl (2005) gives different versions of the three information criteria that drop the constant term from the likelihood. To obtain the Lütkepohl (2005) versions, we specified the \texttt{lutstats} option. The formulas for the standard and Lütkepohl versions of these statistics are given in \textit{Methods and formulas} of [TS] \texttt{varsoc}.

The \texttt{dfk} option specifies that the small-sample divisor \(1/(T - \bar{m})\) be used in estimating \(\Sigma\) instead of the maximum likelihood (ML) divisor \(1/T\), where \(\bar{m}\) is the average number of parameters included in each of the \(K\) equations. All the lag-order statistics are computed using the ML estimator of \(\Sigma\). Thus, specifying \texttt{dfk} will not change the computed lag-order statistics, but it will change the estimated variance–covariance matrix. Also, when \texttt{dfk} is specified, a \texttt{dfk}-adjusted log likelihood is computed and stored in \texttt{e(ll\_dfk)}.

The \texttt{lag()} option takes a \textit{numlist} of lags. To specify a model that includes the first and second lags, type

\begin{verbatim}
. var y1 y2 y3, lags(1/2)
\end{verbatim}

not

\begin{verbatim}
. var y1 y2 y3, lags(2)
\end{verbatim}

because the latter specification would fit a model that included only the second lag.

\section*{Fitting models with some lags excluded}

To fit a model that has only a fourth lag, that is,

\[ y_t = v + A_4 y_{t-4} + u_t \]

you would specify the \texttt{lags(4)} option. Doing so is equivalent to fitting the more general model

\[ y_t = v + A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + A_4 y_{t-4} + u_t \]

with \(A_1, A_2,\) and \(A_3\) constrained to be 0. When you fit a model with some lags excluded, \texttt{var} estimates the coefficients included in the specification (\(A_4\) here) and stores these estimates in \texttt{e(b)}.

To obtain the asymptotic standard errors for impulse–response functions and other postestimation statistics, Stata needs the complete set of parameter estimates, including those that are constrained to be zero; \texttt{var} stores them in \texttt{e(bf)}. Because you can specify models for which the full set of parameter estimates exceeds Stata’s limit on the size of matrices, the \texttt{nobigf} option specifies that \texttt{var} not compute and store \texttt{e(bf)}. This means that the asymptotic standard errors of the postestimation functions cannot be obtained, although bootstrap standard errors are still available. Building \texttt{e(bf)} can be time consuming, so if you do not need this full matrix, and speed is an issue, use \texttt{nobigf}. 

Fitting models with exogenous variables

Example 2: VAR model with exogenous variables

We use the `exog()` option to include exogenous variables in a VAR.

```
.var dln_inc dln_consump if qtr<=tq(1978q4), dfk exog(dln_inv)
```

Vector autoregression

Sample: 1960q4 - 1978q4
No. of obs = 73
Log likelihood = 478.5663
AIC = -12.78264
FPE = 9.64e-09
HQIC = -12.63259
Det(Sigma_ml) = 6.93e-09
SBIC = -12.40612

| Equation |Parms  | RMSE  | R-sq  | chi2   | P>|chi2| |
|----------|-------|-------|-------|--------|-------|-------|
| dln_inc  | 6     | .011917 | 0.0702 | 5.059587 | 0.4087|
| dln_consump | 6 | .009197 | 0.2794 | 25.97262 | 0.0001|

| dln_inc  | Coef.  | Std. Err. | z     | P>|z| | [95% Conf. Interval] |
|----------|--------|-----------|-------|-------|---------------------|
| dln_inc  | L1.    | -.1343345 | .1391074 | -0.97 | 0.334 | -.4069801 | .1383111 |
|          | L2.    | .0120331  | .1380346 | 0.09  | 0.931 | -.2585097 | .2825759 |
| dln_consump | L1. | .3235342  | .1652769 | 1.96  | 0.050 | -.0004027 | .647471 |
|           | L2.    | .0754177  | .1648624 | 0.46  | 0.647 | -.2477066 | .398542 |
| dln_inv   | _cons  | .0151546  | .0302319 | 0.50  | 0.616 | -.0440987 | .074408 |
|           | _cons  | .0145136  | .0043815 | 3.31  | 0.001 | .0059259  | .0231012 |
| dln_consump | L1. | .2425719  | .1073561 | 2.26  | 0.024 | .0321578  | .452986 |
|           | L2.    | .3487949  | .1065281 | 3.27  | 0.001 | .140036   | .5575862 |
| dln_consump | L1. | -.3119629 | .1275524 | -2.45 | 0.014 | -.5619611 | -.0619648 |
|           | L2.    | -.0128502 | .1272326 | -0.10 | 0.920 | -.2622213 | .2365209 |
| dln_inv   | _cons  | .0503616  | .0233314 | 2.16  | 0.031 | .0046329  | .0960904 |
|           | _cons  | .0131013  | .0033814 | 3.87  | 0.000 | .0064738  | .0197288 |

All the postestimation commands for analyzing VARs work when exogenous variables are included in a model, but the asymptotic standard errors for the h-step-ahead forecasts are not available.

Fitting models with constraints on the coefficients

`var` permits model specifications that include constraints on the coefficient, though `var` does not allow for constraints on $\Sigma$. See `[TS] var intro` and `[TS] var svar` for ways to constrain $\Sigma$. 
Example 3: VAR model with constraints

In the first example, we fit a full VAR(2) to a three-equation model. The coefficients in the equation for dln_inv were jointly insignificant, as were the coefficients in the equation for dln_inc; and many individual coefficients were not significantly different from zero. In this example, we constrain the coefficient on L2.dln_inc in the equation for dln_inv and the coefficient on L2.dln_consump in the equation for dln_inc to be zero.

```
  . constraint 1 [dln_inv]L2.dln_inc = 0
  . constraint 2 [dln_inc]L2.dln_consump = 0
  . var dln_inv dln_inc dln_consump if qtr<=tq(1978q4), lutstats dfk
  > constraints(1 2)
Estimating VAR coefficients
Iteration 1:  tolerance = .00737681
Iteration 2:  tolerance = 3.998e-06
Iteration 3:  tolerance = 2.730e-09

Vector autoregression
Sample: 1960q4 - 1978q4      No. of obs     =    73
Log likelihood = 606.2804     (lutstats) AIC     =  -31.69254
FPE = 1.77e-14                HQIC     =  -31.46747
Det(Sigma_ml) = 1.05e-14      SBIC     =  -31.12777

Equation        Parms       RMSE     R-sq       chi2      P>chi2
   dln_inv       6     .043895   0.1280   9.842338   0.0798
   dln_inc       6     .011143   0.1141   8.584446   0.1268
   dln_consump    7     .008981   0.2512  22.86958    0.0008

( 1) [dln_inv]L2.dln_inc = 0
( 2) [dln_inc]L2.dln_consump = 0
```
### Coefficient Table

| Variable | Coef.  | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|----------|--------|-----------|-------|------|----------------------|
| dln_inv  |        |           |       |      |                      |
| L1.      | -.320713 | .1247512  | -2.57 | 0.010 | -.5652208 -.0762051  |
| L2.      | -.1607084 | .124261   | -1.29 | 0.196 | -.4042555 .0828386   |
| dln_inc  |        |           |       |      |                      |
| L1.      | .1195448 | .5295669  | 0.23  | 0.821 | -.9183873 1.157477   |
| L2.      | -2.55e-17 | 1.18e-16  | -0.22 | 0.829 | -2.57e-16 2.06e-16   |
| dln_consump |      |           |       |      |                      |
| L1.      | 1.009281 | .623501   | 1.62  | 0.106 | -.2127586 2.231321   |
| L2.      | 1.008079 | .5713486  | 1.76  | 0.078 | -.1117438 2.127902   |
| _cons    | -.0162102 | .016893  | -0.96 | 0.337 | -.0493199 .0168995   |

None of the free parameter estimates changed by much. Whereas the coefficients in the equation dln_inv are now significant at the 10% level, the coefficients in the equation for dln_inc remain jointly insignificant.
Stored results

`var` stores the following in `e()`:

Scalars

- `e(N)` number of observations
- `e(N_gaps)` number of gaps in sample
- `e(k)` number of parameters
- `e(k_eq)` number of equations in `e(b)`
- `e(k_dv)` number of dependent variables
- `e(df_eq)` average number of parameters in an equation
- `e(df_m)` model degrees of freedom
- `e(df_r)` residual degrees of freedom (small only)
- `e(ll)` log likelihood
- `e(ll_dfk)` dfk adjusted log likelihood (dfk only)
- `e(obs_#)` number of observations on equation #
- `e(k_#)` number of parameters in equation #
- `e(df_m#)` model degrees of freedom for equation #
- `e(df_r#)` residual degrees of freedom for equation # (small only)
- `e(r2_#)` R-squared for equation #
- `e(ll_#)` log likelihood for equation #
- `e(chi2_#)` $\chi^2$ for equation #
- `e(F_#)` F statistic for equation # (small only)
- `e(rmse_#)` root mean squared error for equation #
- `e(aic)` Akaike information criterion
- `e(hqic)` Hannan–Quinn information criterion
- `e(sbic)` Schwarz–Bayesian information criterion
- `e(fpe)` final prediction error
- `e(mlag)` highest lag in VAR
- `e(tmin)` first time period in sample
- `e(tmax)` maximum time
- `e(detsig)` determinant of `e(Sigma)`
- `e(detsig_ml)` determinant of $\hat{\Sigma}_{ml}$
- `e(rank)` rank of `e(V)`
When there are no constraints placed on the coefficients, the \texttt{VAR}(p) is a seemingly unrelated regression model with the same explanatory variables in each equation. As discussed in Lütkepohl (2005) and Greene (2008, 696), performing linear regression on each equation produces the maximum likelihood estimates of the coefficients. The estimated coefficients can then be used to calculate the residuals, which in turn are used to estimate the cross-equation error variance–covariance matrix $\Sigma$.

Per Lütkepohl (2005), we write the \texttt{VAR}(p) with exogenous variables as

$$y_t = AY_{t-1} + B_0 x_t + u_t$$  \hspace{1cm} (5)

where

$y_t$ is the $K \times 1$ vector of endogenous variables,
$A$ is a $K \times Kp$ matrix of coefficients,
$B_0$ is a $K \times M$ matrix of coefficients,
\( \mathbf{x}_t \) is the \( M \times 1 \) vector of exogenous variables, 
\( \mathbf{u}_t \) is the \( K \times 1 \) vector of white noise innovations, and

\[ \mathbf{Y}_t \text{ is the } Kp \times 1 \text{ matrix given by } \mathbf{Y}_t = \begin{pmatrix} \mathbf{y}_t \\ \vdots \\ \mathbf{y}_{t-p+1} \end{pmatrix} \]

Although (5) is easier to read, the formulas are much easier to manipulate if it is instead written as

\[ \mathbf{Y} = \mathbf{BZ} + \mathbf{U} \]

where

\[ \mathbf{Y} = (\mathbf{y}_1, \ldots, \mathbf{y}_T) \quad \mathbf{Y} \text{ is } K \times T \]
\[ \mathbf{B} = (\mathbf{A}, \mathbf{B}_0) \quad \mathbf{B} \text{ is } K \times (Kp + M) \]
\[ \mathbf{Z} = \begin{pmatrix} \mathbf{Y}_0, \ldots, \mathbf{Y}_{T-1} \\ \mathbf{x}_1, \ldots, \mathbf{x}_T \end{pmatrix} \quad \mathbf{Z} \text{ is } (Kp + M) \times T \]
\[ \mathbf{U} = (\mathbf{u}_1, \ldots, \mathbf{u}_T) \quad \mathbf{U} \text{ is } K \times T \]

Intercept terms in the model are included in \( \mathbf{x}_t \). If there are no exogenous variables and no intercept terms in the model, \( \mathbf{x}_t \) is empty.

The coefficients are estimated by iterated seemingly unrelated regression. Because the estimation is actually performed by \texttt{reg3}, the methods are documented in [R] \texttt{reg3}. See [P] \texttt{makecns} for more on estimation with constraints.

Let \( \hat{\mathbf{U}} \) be the matrix of residuals that are obtained via \( \mathbf{Y} - \hat{\mathbf{B}} \mathbf{Z} \), where \( \hat{\mathbf{B}} \) is the matrix of estimated coefficients. Then the estimator of \( \Sigma \) is

\[ \hat{\Sigma} = \frac{1}{\tilde{T}} \hat{\mathbf{U}}'\hat{\mathbf{U}} \]

By default, the maximum likelihood divisor of \( \tilde{T} = T \) is used. When \texttt{dfk} is specified, a small-sample degrees-of-freedom adjustment is used; then, \( \tilde{T} = T - m \) where \( m \) is the average number of parameters per equation in the functional form for \( y_t \) over the \( K \) equations.

\texttt{small} specifies that Wald tests after \texttt{var} be assumed to have \( F \) or \( t \) distributions instead of chi-squared or standard normal distributions. The standard errors from each equation are computed using the degrees of freedom for the equation.

The “gamma” matrix stored in \texttt{e(G)} referred to in \textit{Stored results} is the \( (Kp + 1) \times (Kp + 1) \) matrix given by

\[ \frac{1}{\tilde{T}} \sum_{t=1}^{T} (1, \mathbf{Y}_t')(1, \mathbf{Y}_t')' \]

The formulas for the lag-order selection criteria and the log likelihood are discussed in [TS] \texttt{varsoc}. 
Acknowledgment

We thank Christopher F. Baum of the Department of Economics at Boston College and author of the Stata Press books *An Introduction to Modern Econometrics Using Stata* and *An Introduction to Stata Programming* for his helpful comments.

References


Also see

- `var postestimation` — Postestimation tools for var
- `tsset` — Declare data to be time-series data
- `dfactor` — Dynamic-factor models
- `forecast` — Econometric model forecasting
- `mgarch` — Multivariate GARCH models
- `sspace` — State-space models
- `var svar` — Structural vector autoregressive models
- `varbasic` — Fit a simple VAR and graph IRFs or FEVDs
- `vec` — Vector error-correction models
- `[U] 20 Estimation and postestimation commands`
- `var intro` — Introduction to vector autoregressive models