Title

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varbasic — Fit a simple VAR and graph IRFs or FEVDs

Description

`varbasic` fits a basic vector autoregressive (VAR) model and graphs the impulse–response functions (IRFs), the orthogonalized impulse–response functions (OIRFs), or the forecast-error variance decompositions (FEVDs).

Quick start

Fit vector autoregressive model for dependent variables `y1`, `y2`, and `y3` and their first and second lags, and graph orthogonalized impulse responses using `tsset` data

```
varbasic y1 y2 y3
```

As above, but include second and third lags instead of first and second lags

```
var y1 y2 y3, lags(2 3)
```

As above, but produce forecast-error variance decompositions instead of impulse responses

```
var y1 y2 y3, lags(2 3) fevd
```

As above, but set the forecast horizon for the forecast-error variance decompositions to be 12 periods

```
var y1 y2 y3, lags(2 3) fevd step(12)
```

Menu

Statistics > Multivariate time series > Basic VAR

Syntax

`varbasic` *depvarlist* [*if*] [*in*] [, *options*]

options	Description
Main	
`lags(`*numlist*`)`	use lags *numlist* in the model; default is `lags(1 2)`
`irf`	produce matrix graph of IRFs
`fevd`	produce matrix graph of FEVDs
`nograph`	do not produce a graph
`step(#)`	set forecast horizon # for estimating the OIRFs, IRFs, and FEVDs; default is `step(8)`

You must `tsset` your data before using `varbasic`; see **[TS] tsset**.

depvarlist may contain time-series operators; see **[U] 11.4.4 Time-series varlists**.

`rolling`, `statsby`, and `xi` are allowed; see **[U] 11.1.10 Prefix commands**.

See **[U] 20 Estimation and postestimation commands** for more capabilities of estimation commands.

Options

Main

`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 instance, `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.

`irf` causes `varbasic` to produce a matrix graph of the IRFs instead of a matrix graph of the OIRFs, which is produced by default.

`fevd` causes `varbasic` to produce a matrix graph of the FEVDs instead of a matrix graph of the OIRFs, which is produced by default.

`nograph` specifies that no graph be produced. The IRFs, OIRFs, and FEVDs are still estimated and saved in the IRF file `_varbasic.irf`.

`step(`*#*`)` specifies the forecast horizon for estimating the IRFs, OIRFs, and FEVDs. The default is eight periods.

Remarks and examples

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`varbasic` simplifies fitting simple VARs and graphing the IRFs, the OIRFs, or the FEVDs. See [TS] **var** and [TS] **var svar** for fitting more advanced VAR models and structural vector autoregressive (SVAR) models. All the postestimation commands discussed in [TS] **var postestimation** work after `varbasic`.

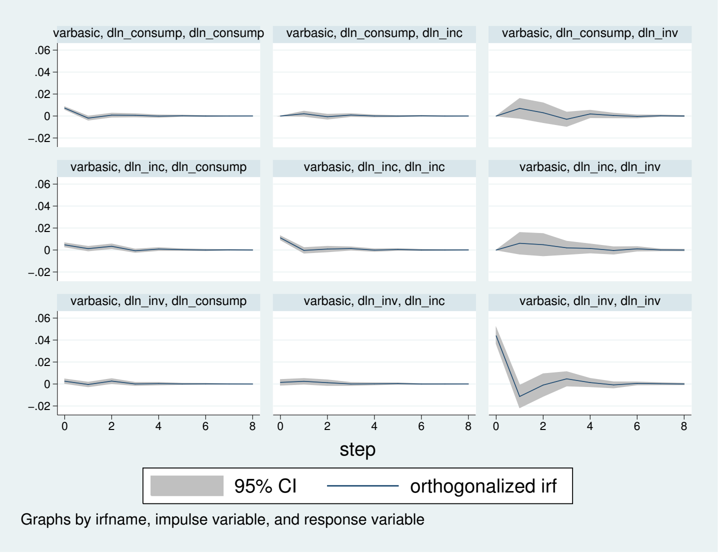
This entry does not discuss the methods for fitting a VAR or the methods surrounding the IRFs, OIRFs, and FEVDs. See [TS] **var** and [TS] **irf create** for more on these methods. This entry illustrates how to use `varbasic` to easily obtain results. It also illustrates how `varbasic` serves as an entry point to further analysis.

▷ Example 1

We fit a three-variable VAR with two lags to the German macro data used by Lütkepohl (2005). The three variables are the first difference of natural log of investment, `dln_inv`; the first difference of the natural log of income, `dln_inc`; and the first difference of the natural log of consumption, `dln_consump`. In addition to fitting the VAR, we want to see the OIRFs. Below we use `varbasic` to fit a VAR(2) model on the data from the second quarter of 1961 through the fourth quarter of 1978. By default, `varbasic` produces graphs of the OIRFs.

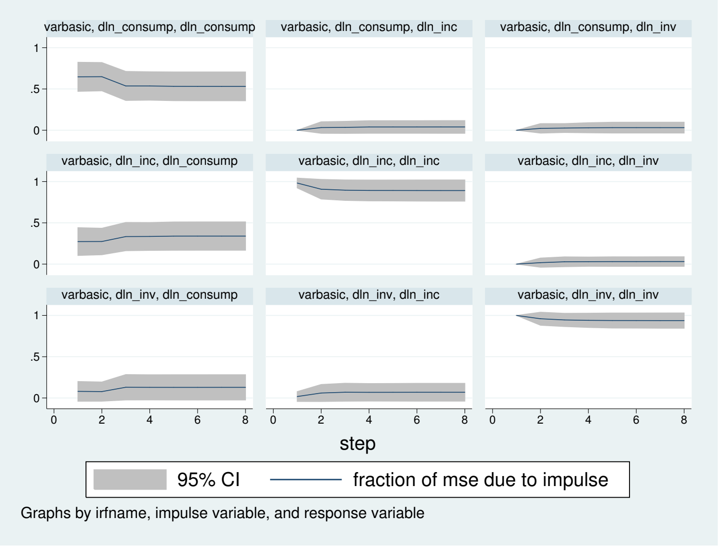
```
. use http://www.stata-press.com/data/r15/lutkepohl2
(Quarterly SA West German macro data, Bil DM, from Lutkepohl 1993 Table E.1)
```

```
. varbasic dln_inv dln_inc dln_consump if qtr<=tq(1978q4)

Vector autoregression

Sample:  1960q4 - 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

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dln_inv               7     .046148   0.1286   10.76961   0.0958
dln_inc               7     .011719   0.1142   9.410683   0.1518
dln_consump           7     .009445   0.2513   24.50031   0.0004
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dln_inv      |
     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    -.2767936    2.199251
         L2. |   .9344001   .6324034     1.48   0.140    -.3050877    2.173888
             |
       _cons |  -.0167221   .0163796    -1.02   0.307    -.0488257    .0153814
-------------+----------------------------------------------------------------
dln_inc      |
     dln_inv |
         L1. |   .0439309   .0302933     1.45   0.147    -.0154427    .1033046
         L2. |   .0500302   .0301605     1.66   0.097    -.0090833    .1091437
             |
     dln_inc |
         L1. |  -.1527311    .131759    -1.16   0.246    -.4109741    .1055118
         L2. |   .0191634   .1290799     0.15   0.882    -.2338285    .2721552
             |
 dln_consump |
         L1. |   .2884992   .1604069     1.80   0.072    -.0258926    .6028909
         L2. |     -.0102   .1605968    -0.06   0.949    -.3249639    .3045639
             |
       _cons |   .0157672   .0041596     3.79   0.000     .0076146    .0239198
-------------+----------------------------------------------------------------
dln_consump  |
     dln_inv |
         L1. |   -.002423   .0244142    -0.10   0.921     -.050274     .045428
         L2. |   .0338806   .0243072     1.39   0.163    -.0137607    .0815219
             |
     dln_inc |
         L1. |   .2248134   .1061884     2.12   0.034     .0166879    .4329389
         L2. |   .3549135   .1040292     3.41   0.001     .1510199     .558807
             |
 dln_consump |
         L1. |  -.2639695   .1292766    -2.04   0.041     -.517347    -.010592
         L2. |  -.0222264   .1294296    -0.17   0.864    -.2759039     .231451
             |
       _cons |   .0129258   .0033523     3.86   0.000     .0063554    .0194962
------------------------------------------------------------------------------
```



Because we are also interested in looking at the FEVDs, we can use `irf graph` to obtain the graphs. Although the details are available in [TS] **irf** and [TS] **irf graph**, the command below produces what we want after the call to `varbasic`.

```
. irf graph fevd, lstep(1)
```



❑ Technical note

Stata stores the estimated IRFs, OIRFs, and FEVDs in a IRF file called `_varbasic.irf` in the current working directory. `varbasic` replaces any `_varbasic.irf` that already exists. Finally, `varbasic` makes `_varbasic.irf` the active IRF file. This means that the graph and table commands `irf graph`, `irf cgraph`, `irf ograph`, `irf table`, and `irf ctable` will all display results that correspond to the VAR fit by `varbasic`.

❑

Stored results

See *Stored results* in [TS] **var**.

Methods and formulas

`varbasic` uses `var` and `irf graph` to obtain its results. See [TS] **var** and [TS] **irf graph** for a discussion of how those commands obtain their results.

References

Lütkepohl, H. 1993. *Introduction to Multiple Time Series Analysis*. 2nd ed. New York: Springer.

——. 2005. *New Introduction to Multiple Time Series Analysis*. New York: Springer.

Also see

[TS] **varbasic postestimation** — Postestimation tools for varbasic

[TS] **tsset** — Declare data to be time-series data

[TS] **var** — Vector autoregressive models

[TS] **var svar** — Structural vector autoregressive models

[U] **20 Estimation and postestimation commands**

[TS] **var intro** — Introduction to vector autoregressive models