varbasic — Fit a simple VAR and graph IRFs or FEVDs

Description	Quick start	Menu	Syntax
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References	Also see		

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
```

Same as above, but include second and third lags instead of first and second lags

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

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

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

Same 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**.
`collect`, `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

varbasic simplifies fitting simple VAR models 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.

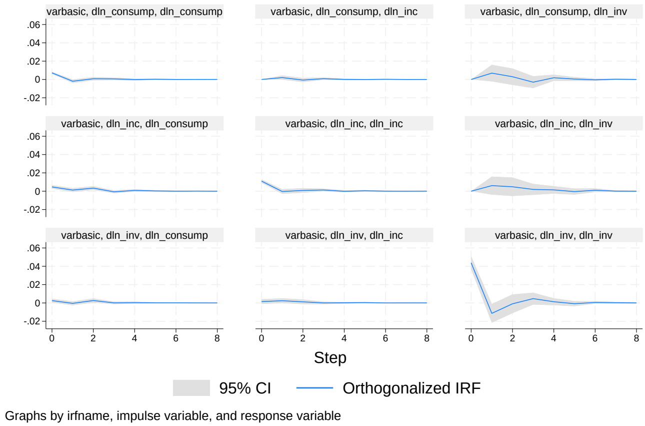
This entry does not discuss the methods for fitting a VAR model or the methods surrounding the IRFs, OIRFs, and FEVDs. See [TS] **var** and [TS] **irf create** for more on these methods. This entry illustrates how to use varbasic to easily obtain results. It also illustrates how varbasic serves as an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

▷ Example 1

We fit a three-variable VAR model 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 model, 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.

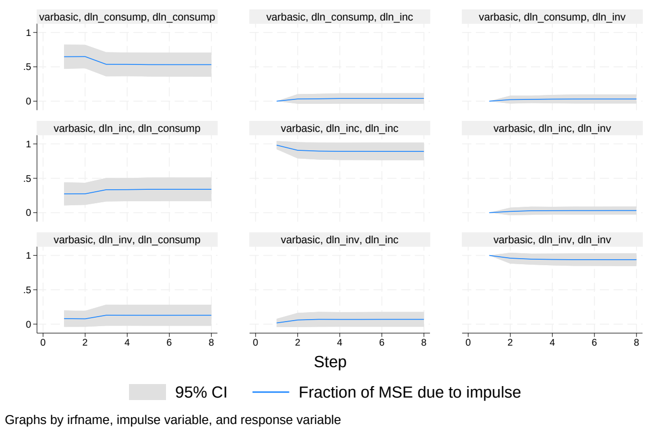
```
. use https://www.stata-press.com/data/r19/lutkepohl2
(Quarterly SA West German macro data, Bil DM, from Lutkepohl 1993 Table E.1)
```

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

Sample: 1960q4 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

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
----------------------------------------------------------------

------------------------------------------------------------------------------
             | Coefficient  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 model 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 intro** — Introduction to vector autoregressive models

[TS] **var ivsvar** — Instrumental-variables structural vector autoregressive models

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

[U] 20 Estimation and postestimation commands