Package Name: LBVAR
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Date: 2016.11.15
Add-in Type: Global
Default Proc Name: lbvar
Default Menu Text: Large Bayesian VAR
Interface: Dialog and command line
Updated (Pandemic Prior): 2022.07.18[1]

Description

We consider the following VAR(p) model:

$$Y_t = c + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + u_t$$

where u_t is an n-dimensional Gaussian white noise with covariance matrix Ψ. The VAR can be written as a system of multivariate regressions:

$$Y_{T \times n} = X_{T \times (np+1)} B_{(np+1) \times n} + U_{T \times n}$$

In order to match the Litterman prior, we add the following dummy observations:

$$Y_d = \begin{bmatrix} \dfrac{diag(\delta_1 \sigma_1, \ldots, \delta_n \sigma_n)}{\lambda} \\ 0_{n(p-1) \times n} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \dfrac{diag(\delta_1 \mu_1, \ldots, \delta_n \mu_n)}{\tau} \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ diag(\sigma_1, \ldots, \sigma_n) \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ 0_{1 \times n} \end{bmatrix} \qquad X_d = \begin{bmatrix} \dfrac{J_p \otimes diag(\sigma_1, \ldots, \sigma_n)}{\lambda} & 0_{np \times 1} \\ \cdots\cdots\cdots\cdots\cdots\cdots & \cdots\cdots \\ \dfrac{1_{1 \times p} \otimes diag(\delta_1 \mu_1, \ldots, \delta_n \mu_n)}{\tau} & 0_{n \times 1} \\ \cdots\cdots\cdots\cdots\cdots\cdots & \cdots\cdots \\ 0_{n \times np} & 0_{n \times 1} \\ \cdots\cdots\cdots\cdots\cdots\cdots & \cdots\cdots \\ 0_{1 \times np} & \varepsilon \end{bmatrix}$$

where $J_p = diag(1, 2, \ldots, p)$.

The first block of dummies imposes prior beliefs on the autoregressive coefficients, the second block constrain the sum of coefficients, third block implements the prior for the covariance matrix and the fourth block of dummies reflects the uninformative prior for the intercept.

Consider the regression model augmented with the dummies:

$$Y^*_{T_* \times n} = X_{(T_* \times (np+1)} * B_{(np+1) \times n} + U^*_{T_* \times n}$$

In order to ensure the existence of the prior expectations of Ψ it is necessary to add an improper prior $\Psi \sim |\Psi|^{-\frac{n+3}{2}}$. In that case the posterior of the VAR model has the following form:

$$vec(B)|\Psi,Y \sim N\left(vec(\tilde{B}),\Psi\otimes\left(X^{*\prime}X^*\right)^{-1}\right) \text{ and } \Psi|Y \sim iW\left(\tilde{\Sigma},T_d + 2 + T - (np+1)\right)$$

where $\tilde{B} = (X^{*\prime}X^*)^{-1}X^{*\prime}Y^*$ and $\tilde{\Sigma} = (Y^* - X^*\tilde{B})'(Y^* - X^*\tilde{B})$.

Adding dummy observations works as a regularization solution to the matrix inversion problem.
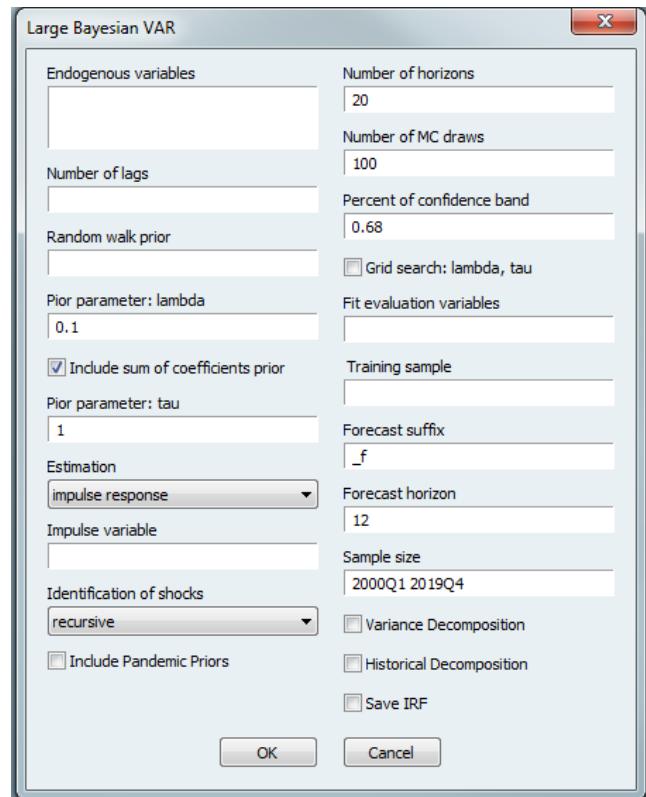
The COVID pandemic and the great lockdown caused macroeconomic variables to display complex erratic patterns that hardly follow any historical behavior. Danilo Cascaldi-Garcia (2022) propose an easy and straightforward solution to deal with these extreme episodes, as an extension of the Minnesota Prior with dummy observations by allowing for time dummies (h period):

$$X_{pd} = \begin{bmatrix} \frac{0_{np\times h}}{\cdots\cdots} \\ \frac{0_{n\times h}}{\cdots\cdots} \\ \frac{0_{n\times h}}{\cdots\cdots} \\ 1_{1\times h}\times\varphi \end{bmatrix}$$

In other words, we should concatenate X_d and X_{pd} matrices ($[X_d\ X_{pd}]$).

Dialog

Upon running the add-in from the menus, a dialog will appear:

Large Bayesian VAR

Endogenous variables

Number of lags

Random walk prior

Pior parameter: lambda
0.1

☑ Include sum of coefficients prior

Pior parameter: tau
1

Estimation
impulse response ▾

Impulse variable

Identification of shocks
recursive ▾

☐ Include Pandemic Priors

Number of horizons
20

Number of MC draws
100

Percent of confidence band
0.68

☐ Grid search: lambda, tau

Fit evaluation variables

Training sample

Forecast suffix
_f

Forecast horizon
12

Sample size
2000Q1 2019Q4

☐ Variance Decomposition

☐ Historical Decomposition

☐ Save IRF

OK   Cancel

The first box lets you specify the endogenous variables for Large BVAR. On the next box enter a number of the lag. On the third box enter a vector of the random walk prior: 1 for non-stationary, 0 for stationary variables. On the fourth box put the impulse variable. If you ticked the grid search, you have to select the fit evaluation variables and the training sample. Other boxes are optional.

Command line:

lbvar(options) lag rw_prior impulse_variable @ endogenous_variables

for Banbura example:

vector irw=@ones(7)
lbvar(grid=1, fit="emp cpi ffr", tsample="1960m2 1970m1", sample="1961m1 2002m12") 13 irw ffr @ emp cpi commpr ffr m2 totres nonborr

Pandemic prior example:

lbvar(sum=1, lambda=0.2, tau=2, sample="1975m1 2022m3", pand=1, dummy="dum1 dum2 dum3 dum4 dum5", covper=5, eps=0.001) 12 irw_s ebp @ ebp sp500l fedfunds pcel pcepil payemsl indprol unrate

Pandemic prior forecasting example:

lbvar(estimate=2, fhorizon=12, sum=1, lambda=0.2, tau=2, sample="1975m1 2022m3", pand=1, dummy="dum1 dum2 dum3 dum4 dum5", covper=5, eps=0.001) 12 irw_s ebp @ ebp sp500l fedfunds pcel pcepil payemsl indprol unrate

Option

lambda	Prior parameter lambda (lambda=0.1)
sum	Includes sum of coefficients prior
tau	Prior parameter tau (tau=1)
estimate	estimation: 1 – impulse response function 2 – forecasting
horizon	Number of horizons for IRF
mcdraw	Number of Monte Carlo Draws
cband	percent of confidence band
grid	Grid search
fit	Fit evaluation variables
tsample	Training sample size (tsample="1960m1 1970m1")
suffix	Forecast suffix
fhorizon	Forecast horizons
sample	Sample size
vd	Variance decomposition (vd=0)
hd	Historical decomposition (hd=0)
save	Save IRF to matrix
ident	Identification of shocks (1 = Cholesky, 2=Generalized)

Option for Pandemic Priors

pand	Includes Pandemic Prior
covper	Number of Covid periods
dummy	Dummy variables
phi	φ for dummy observations
eps	ϵ prior parameter for intercept

References:

Banbura, M., Giannone, D., and Reichlin, L., 2010. Large Bayesian Vector Autoregressions, *Journal of Applied Econometrics* 25, 71-92

Cascaldi-Garcia D., 2022. Pandemic Priors, *Working paper*, Federal Reserve Board