Alternative benchmark models for a large-scale BVAR: application to Russian macroeconomic data

Boris Demeshev[1] Oxana Malakhovskaya[2]

[1]Department of Applied Economics
National Research University Higher School of Economics

[2]Department of Theoretical Economics
National Research University Higher School of Economics

38th International Symposium on Forecasting, Boulder, USA,
June 18, 2018

Motivation

- Accurate macroeconomic forecasts are extremely important for policy making.
- Central banks monitor a large set of macroeconomic indicators to determine the policy.
- Therefore, a model being used for forecasting purposes must be suitable for samples with large cross-sectional dimension to avoid a potential loss of relevant information.

Motivation(2)

- Vector autoregressions have become a widely-used tool for forecasting. However, unrestricted VARs bear the risk of overparameterization even for samples of moderate size.
- Using of Bayesian estimation may alleviate the problem of overparametrization akin to unrestricted VARs.
- Recently many papers have claimed that, in terms of forecasting accuracy, medium and large BVAR outperform their small dimensional counterparts.

Our previous paper: conclusion

- In that paper, we estimate BVAR models of different size and compare their forecasting performance with RW with drift and unrestricted VAR models for 23 variables and 5 different forecast horizons.
- We show that for a majority of variables of interest BVAR produces better forecasting results than the competing models.
- However, we cannot confirm a conclusion of some studies that high-dimensional BVARs forecast better than low-dimensional models. For many variables in our sample and forecasting horizons a 6- or 7-variable BVAR can beat a 23-variable BVAR in terms of forecasting accuracy.

Objective of this paper

Research question:

- Is forecasting accuracy of medium and large BVAR significantly higher than of simple alternatives?

The objective of the paper are:

- comparison the forecasting accuracy of estimated BVAR models with simpler univariate models: autoARIMA, ETS, BVAR-LASSO.

Our underlying hypothesis is:

- BVARs outperform the competing models in terms of forecasting accuracy

BVAR problems

- long estimation time
- instability of estimation
- too many possible priors and no standard procedure for choosing one of them long estimation time makes grid search of hyperparameters infeasible

Our baseline specification is a standard BVAR with a conjugate Normal-inverted Wishart prior.

$$Y = X\Phi + E, \tag{1}$$

where $Y = [y_1, y_2, \ldots, y_T]'$,$X = [x_1, x_2, \ldots, x_T]'$,
$x_t = [y'_{t-1} \ldots y'_{t-p}\ 1]'$, $\Phi = [\Phi_1 \ldots \Phi_p\ \Phi_{ex}]'$, $E = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_T]'$
Prior distribution:

- conjugate normal – inverted Wishart prior
- sum-of-coefficients prior
- initial observation prior

The overall tightness parameter is chosen endogenously depending on the sample dimension following **banbura_al_2010**.

Model set

Univariate:

- ARIMA
- ETS

Multivariate:

- BVAR (up to 23 variables)
- VAR (up to 7 variables)
- BVAR - LASSO (up to 23 variables)

Benchmark:

- RW

Our dataset

- 23 monthly time series running from January 1996 to April 2015
- Series demonstrating seasonal fluctuations are seasonally adjusted
- Logarithms are applied to most of the series, with the exception of those already expressed in rates.

VAR in compact form:

$$Y = X\Phi + E, \tag{2}$$

VAR3/BVAR3	$Y = \{IP, CPI, R\}$
VAR4/BVAR4	$Y = \{IP, CPI, R, Z\}$
VAR6/BVAR6	$Y = \{IP, CPI, R, M2, REER, OPI\}$
VAR7/BVAR7	$Y = \{IP, CPI, R, M2, REER, OPI, W\}$
BVAR23	Y includes all 23 variables from the dataset

IP - industrial product index, CPI - consumer price index, R - nominal interbank rate, $M2$ - monetary aggregate M2, $REER$ - real effective exchange rate, OPI - Brent oil price index. Z is any variable from the dataset besides IP, CPI and R. W is any variable from the dataset besides IP, CPI, R, $M2$,$REER$, and OPI.

Relative MSFE(1)

	h=1	h=3	h=6	h=9	h=12
ind product	0.92		0.96	0.82	0.7
cpi	0.44	0.38	0.46	0.38	0.33
interb rate			0.66	0.52	0.58
agriculture	0.93	0.82	0.7	0.67	0.57
construction	0.97				
employment	0.67	0.42	0.43	0.6	0.72
export	0.59	0.61	0.76	0.81	0.89
gas price	0.73	0.43	0.22	0.29	0.5
gov balance	0.61	0.79	0.77	0.7	0.63
import	0.75	0.48	0.52	0.72	0.98
labor request	0.66	0.79	0.94	0.95	0.96
lend rate	0.94	0.84	0.77	0.77	0.8
M2	0.53	0.51	0.71	0.95	
nominal ER					
NFA of CB	0.6	0.56	0.75	0.65	0.6
oil price	0.88	0.81	0.88	0.81	0.77
ppi	0.43	0.75	0.69	0.59	0.49
real income	0.87	0.84	0.83	0.71	0.73
real invest	0.78	0.61	0.73	0.88	0.91
real ER	0.72	0.68	0.6		
retail	0.62	0.39	0.4	0.64	0.88
unemp rate	0.93	0.83	0.9	0.92	0.94
wage	0.74	0.51	0.46	0.42	0.41

Random walk

VAR3/4 - BVAR 3/4

VAR6/7

BVAR6/7

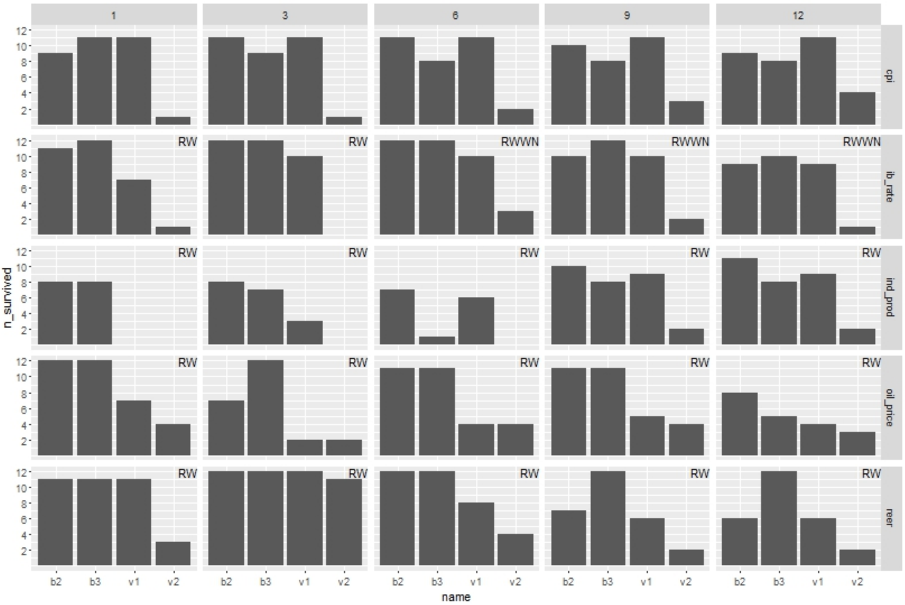
BVAR23

σ_i are std of AR(p) residuals

$\delta_i = 1$ *for nonstationary series*

$\delta_i = 0.5$ *for stationary series*

Robustness check



BVAR vs ARIMA

BVAR vs ETS

BVAR vs BVAR-LASSO

THANK YOU!

Boris Demeshev: boris.demeshev@gmail.com
Oxana Malakhovskaya: omalakhovskaya@hse.ru
Link to the repository: https://github.com/bdemeshev/bvar_om