Forecasting of Russian Macroeconomic Indicators with BVAR

Oxana Malakhovskaya[1,2], **Boris Demeshev**[1]

[1] Higher School of Economics

[2] University of Paris-Saclay

omalakhovskaya@hse.ru, boris.demeshev@gmail.com

Motivation

- Recently many papers has claimed that, in terms of forecasting accuracy, medium and large BVAR outperform their small dimensional counterparts.
- Application of Bayesian econometrics on Russian data is scarce

Main Objectives

- Forecasting of macroeconomic indicators for Russian economy with BVARs of different size
- Comparing their forecasting accuracy with one of competing models (RW and unrestricted VARs)

Main Hypotheses

- BVARs outperform the competing models in terms of forecasting accuracy
- High-dimensional BVARs forecast better than low-dimensional ones

Model

The model written in a compact way:

$$Y = X\Phi + E,$$

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

- 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 et al., 2010).

Our dataset

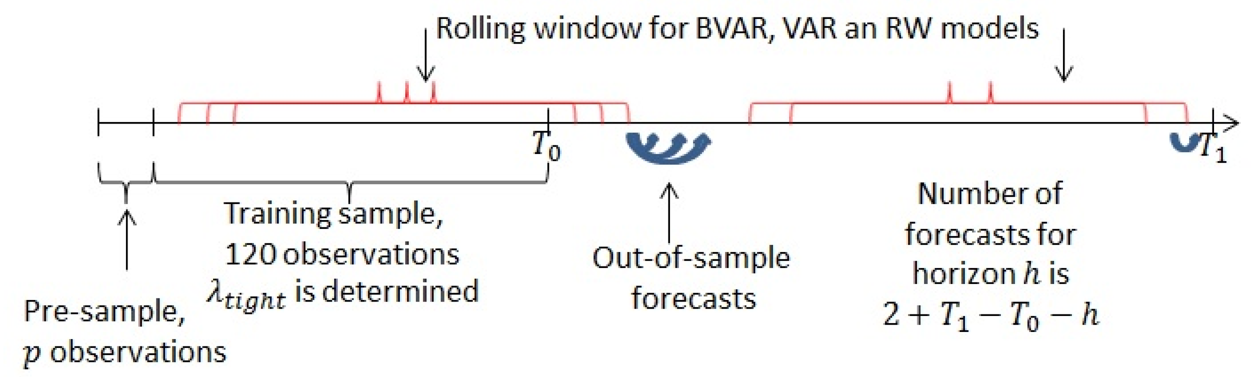
- 23 monthly time series running from January 1996 to April 2015
- Series demonstrating seasonal fluctuations are seasonally adjusted
- Logarithms are applied to most of the series, with the exception of those already expressed in rates.

Estimated models

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.

Estimation scheme



Results

In tables, relative MSFE are reported.

$$RMSFE = \frac{MSFE^{\lambda,m}_{var,h}}{MSFE^{0}_{var,h}}$$

	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*

	h=1	h=3	h=6	h=9	h=12
ind product	0.96		0.96	0.82	0.7
cpi	0.38	0.37	0.46	0.36	0.27
interb rate			0.91	0.56	0.56
agriculture	0.93	0.82	0.7	0.67	0.56
construction	0.97				
employment	0.7	0.54	0.59	0.7	0.81
export	0.57	0.62	0.71	0.8	0.86
gas price	0.7	0.42	0.22	0.31	0.51
gov balance	0.6	0.79	0.78	0.74	0.64
import	0.74	0.63	0.82	0.88	0.97
labor request	0.66	0.79	0.94	0.94	0.95
lend rate	0.95	0.89	0.79	0.71	0.66
M2	0.55	0.6	0.8	0.97	
nominal ER					
NFA of CB	0.6	0.62	0.69	0.61	0.61
oil price	0.85	0.81	0.85	0.79	0.75
ppi	0.43	0.74	0.69	0.6	0.49
real income	0.91	0.93	0.84	0.73	0.75
real invest	0.81	0.63	0.76	0.88	0.92
real ER	0.72	0.69	0.8		
retail	0.62	0.4	0.45	0.72	0.88
unemp rate	0.94	0.91	0.89	0.9	0.92
wage	0.75	0.53	0.47	0.42	0.41

Random walk

VAR3/4 - BVAR 3/4

VAR6/7

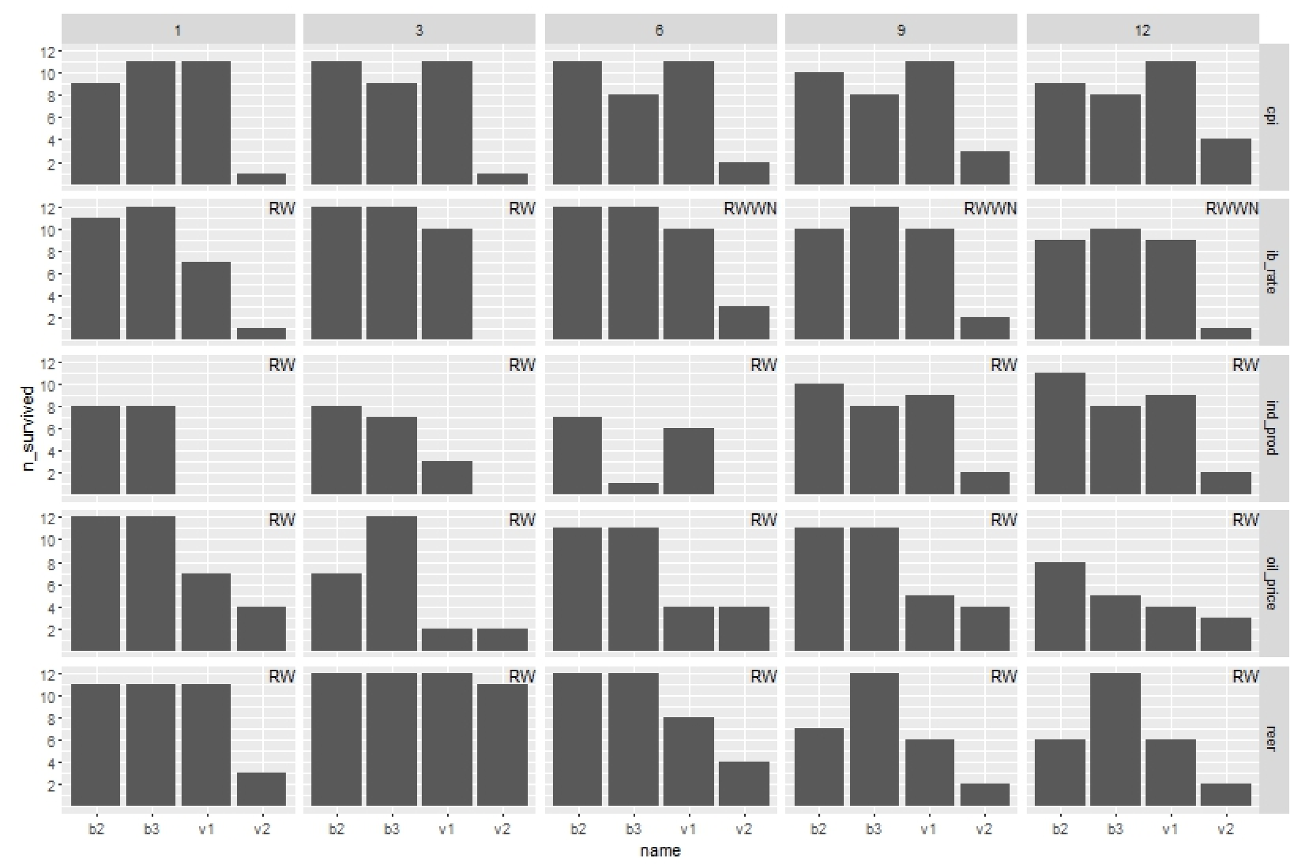
BVAR6/7

BVAR23

σ_i are std of AR(1) residuals

δ_i are first lag AR(1) estimates

Robustness check



Conclusion

- In the 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.