Forecasting Russian Macroeconomic Indicators with BVAR

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36th International Symposium on Forecasting, Santander, Spain, June 21, 2016

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 this problem. The Bayesian shrinkage is done by imposing restrictions on parameters in the form of prior distributions.
- Recently many papers have 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

Objective of the paper

The objectives of the paper are:

- forecasting of macroeconomic indicators for Russian economy with BVARs of different sizes
- comparing their forecasting accuracy with forecasting accuracy of competing models (RW and unrestricted VARs)

Our underlying hypotheses are:

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

BVAR in data-rich environment

- While BVAR in low-dimensional space were widely used for macroeconomic analysis, their use for data-rich environment was limited until 2010. The reason was a general agreement that the Bayesian shrinkage is insufficient to solve the overparameterization problem in high cross-sectional dimension samples.
- De Mol, Giannone, and Reichlin (2008) show that the Bayesian methods can be successfully applied in data-rich environment if the degree of shrinkage is set relative to the cross-sectional dimension of the sample.
- Bańbura, Giannone, and Reichlin (2010) confirm and develop this claim for BVAR applied to a large set of US time-series.

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

VAR in reduced form:

$$y_t = \Phi_{ex} + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma), \quad (1)$$

where y_{it} is a $m \times 1$ vector of variables.

The model can also be written in a more compact way:

$$Y = X\Phi + E, \quad (2)$$

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

The conjugate normal – inverted Wishart prior is defined as:

$$\begin{cases} \Sigma \sim \mathcal{IW}(\underline{S}, \underline{\nu}) \\ \Phi|\Sigma \sim \mathcal{N}(\underline{\Phi}, \Sigma \otimes \underline{\Omega}) \end{cases}, \tag{3}$$

In addition to otherwise standard normal - inverse Wishart distribution we use two modifications of the prior that appeared to increase the forecasting performance in some other papers:

- sum-of-coefficients prior
- initial observation prior

The overall tightness parameter is chosen endogenously depending on the sample dimension following Bańbura, Giannone, and Reichlin (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

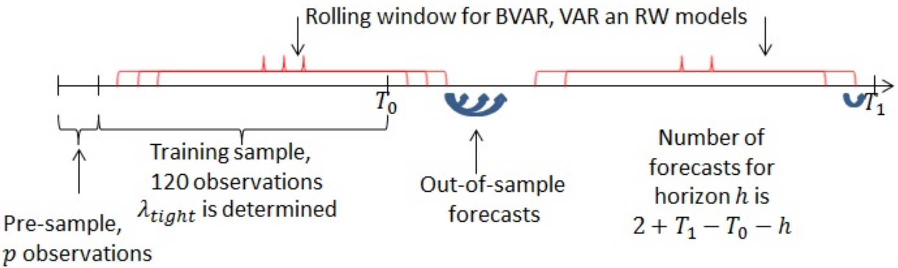
VAR in compact form:

$$Y = X\Phi + E, \tag{4}$$

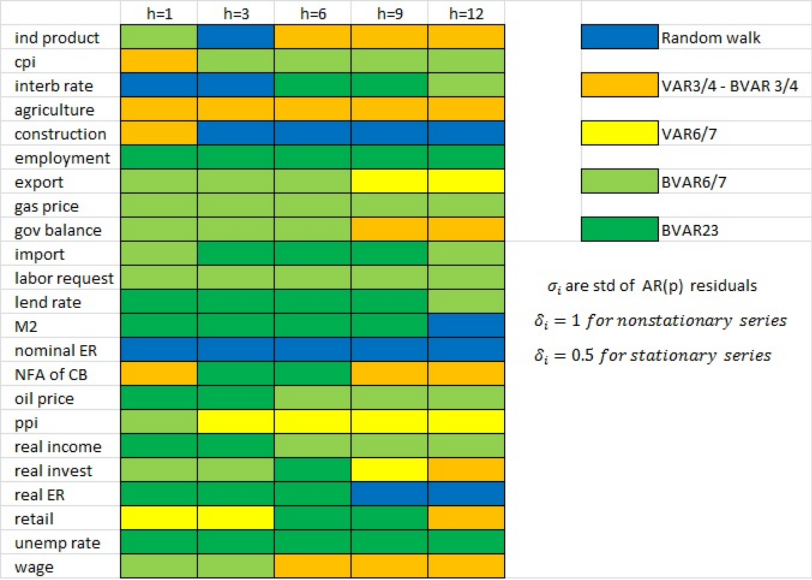
VAR3/BVAR3	$Y = \{IP, CPI, R\}$
VAR4/BVAR4	$Y = \{IP, CPI, R, Z\}$
VAR6/BVAR6	$Y = \{IP, CPI, R, M2, REER, OPI\}$
VAR7/BVAR7	$Y = \{IP, CPI, R, M2, REER, OPI, W\}$
BVAR23	Y includes all 23 variables from the dataset

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



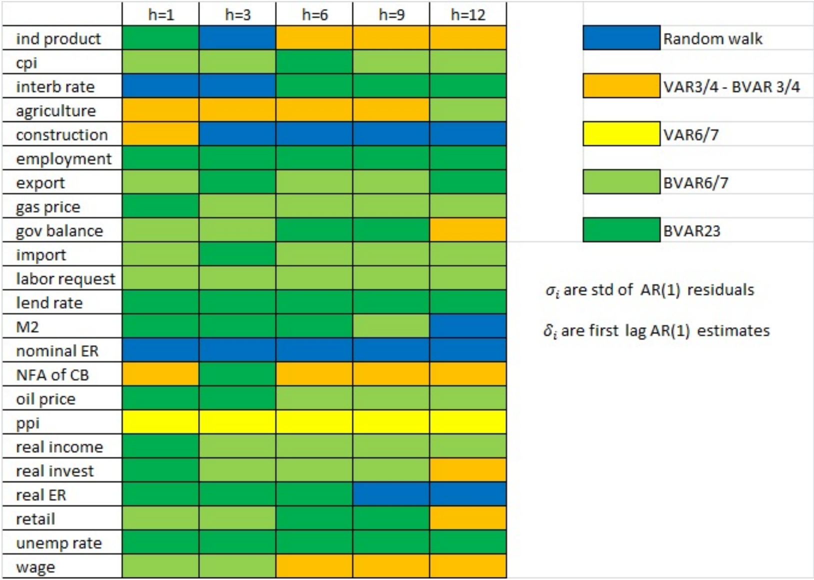
Results(1)



σ_i are std of AR(p) residuals

$\delta_i = 1$ *for nonstationary series*

$\delta_i = 0.5$ *for stationary series*



σ_i are std of AR(1) residuals

δ_i are first lag AR(1) estimates

Forecast accuracy

We measure out-of-sample forecast accuracy in terms of mean squared forecast error...

$$MSFE_{var,h}^{\lambda,m} = \frac{1}{T_1 - T_0 - h + 1} \sum_{\tau=T_0}^{T_1-h} (y_{var,\tau+h|\tau}^{\lambda,m} - y_{var,\tau+h|\tau})^2 \quad (5)$$

... and report relative MSFE, i.e. the ratio of MSFE of the model in question by the MSFE of a benchmark (RW with drift in our case):

$$RMSFE = \frac{MSFE_{var,h}^{\lambda,m}}{MSFE_{var,h}^{0}} \quad (6)$$

where *var* is any variable in the dataset

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

(blue)	Random walk
(orange)	VAR3/4 - BVAR 3/4
(yellow)	VAR6/7
(light green)	BVAR6/7
(dark green)	BVAR23

σ_i are std of AR(p) residuals

$\delta_i = 1$ *for nonstationary series*

$\delta_i = 0.5$ *for stationary series*

Relative MSFE(2)

	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

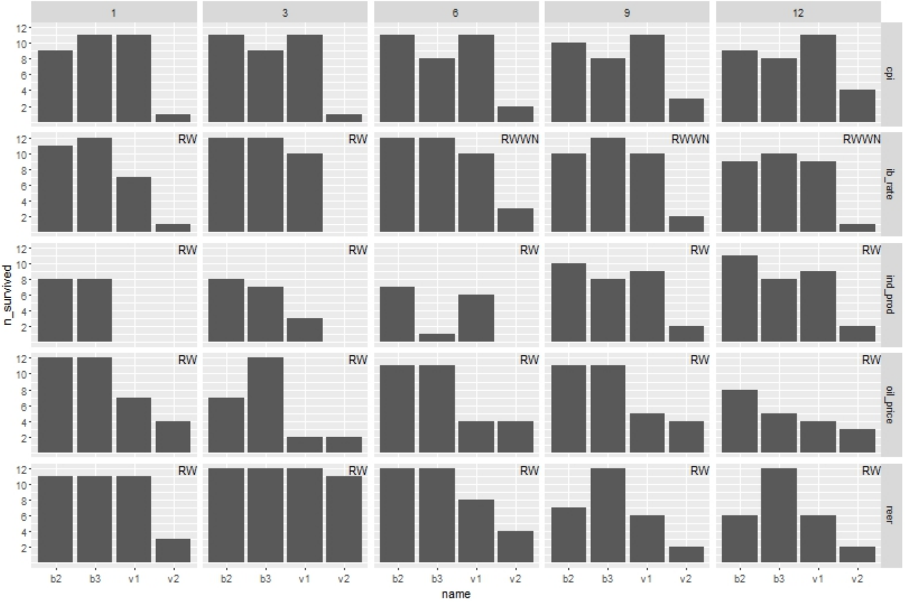
BVAR6/7

BVAR23

σ_i are std of AR(1) residuals

δ_i are first lag AR(1) estimates

Robustness check



- For many variables and forecasting horizons in interest, BVAR outperforms random walk and unrestricted VAR.
- Though medium BVAR is the best option for some cases, it is often beaten by a BVAR model with relatively low number of variables (6 or 7).
- For some variables and some forecasting horizons VARs (either restricted or not) cannot beat RW, for example, nominal exchange rate (long-lasting consensus in economics)
- Nonetheless, the oil price index can be forecast by BVAR much better than by RW.

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.

THANK YOU FOR YOUR ATTENTION!

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Link to the repository: https://github.com/bdemeshev/bvar_om