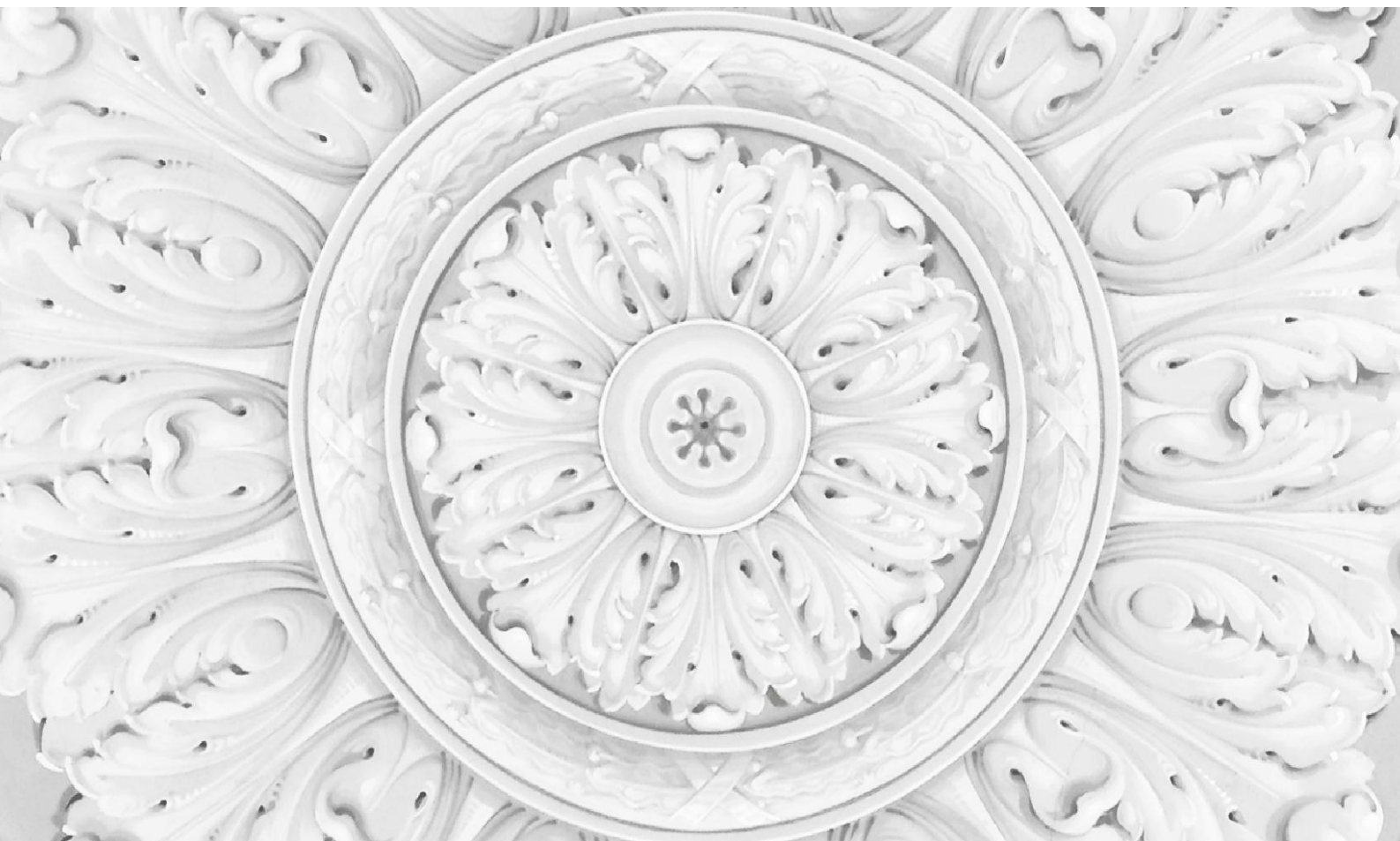# Bank of Russia

Central Bank of the Russian Federation

WORKING PAPER SERIES

Elena Deryugina
Alexey Ponomarenko

A large Bayesian vector autoregression model for Russia

Elena Deryugina
Bank of Russia. Email: DeryuginaEB@cbr.ru

Alexey Ponomarenko
Bank of Russia. Email: PonomarenkoAA@cbr.ru

Abstract

We apply an econometric approach developed specifically to address the 'curse of dimensionality' in Russian data and estimate a Bayesian vector autoregression model comprising 14 major domestic real, price and monetary macroeconomic indicators as well as external sector variables. We conduct several types of exercise to validate our model: impulse response analysis, recursive forecasting and counter factual simulation. Our results demonstrate that the employed methodology is highly appropriate for economic modelling in Russia. We also show that post-crisis real sector developments in Russia could be accurately forecast if conditioned on the oil price and EU GDP (but not if conditioned on the oil price alone).

CONTENTS

INTRODUCTION

Empirical economic modelling in Russia is a complicated task. One of the most important limitations comes from the insufficiently long time series that make estimation of a comprehensive econometric model virtually impossible. Researchers therefore have to rely on parsimonious model specifications in their work. One example is traditional macroeconometric models (e.g. Benedictow et al. (2013)) consisting of a large number of pre-specified simultaneous equations. As regards a more flexible vector autoregression (VAR) approach, a typical model for Russia would comprise an ad-hoc selection of variables (often no more than five indicators in total) that either represents a theoretical long-term macroeconomic relationship (Korhonen and Mehrotra (2010), Mehrotra and Ponomarenko (2010)), or is sufficient to identify predetermined types of economic shocks (via a structural identification scheme (Korhonen and Mehrotra (2009)) or sign restrictions on impulse response functions (Granville and Mallick (2010), Mallick and Sousa (2013))), or simply comprises the indicators that are assumed to be the most important determinants of the modelled process (Rautava (2013)).

In this environment, an econometric approach developed specifically to address the 'curse of dimensionality' may be highly relevant for Russia. In particular, the class of recently developed Bayesian VAR models (De Mol et al. (2008), Banbura et al. (2010), Giannone et al. (2012a), Banbura et al. (2014)) is known to produce adequate results even when a large number of variables are included in the model simultaneously. Arguably, a relatively large Bayesian VAR model estimated for the Russian economy using this methodology may be regarded as a novel and valuable tool for forecasting and counterfactual analysis. The aim of this paper is to implement such an approach.

The model obtained may be used for mainly non-structural, but extensive and flexible analysis, including scenario and counterfactual projections. The first type of application is of obvious value for policy-makers, since producing forecasts conditioned on certain assumptions (e.g. oil prices) is a common practice for the Russian economy. Arguably, a large Bayesian VAR model could be exceptionally suitable for this type of exercise because of its ability to produce more stable results for a larger set of variables, as compared with canonical econometric models, while still being empirically validated, which is problematic for large-scale calibrated structural models. Another application of the model is counterfactual simulations (in the spirit of Giannone et al. (2012b)) that may be helpful in detecting misalignments and irregularities in the developments of observed variables.

The paper is structured as follows. Section 2 presents the dataset and the set-up of the model. Section 3 reports the empirical results, including the impulse response analysis, recursive forecasting exercise and counterfactual simulations. Section 4 concludes.

1. DATA AND MODEL SPECIFICATION

1.1 The data

The dataset includes 14 quarterly variables that come from four categories[1]: real, monetary, price and external (Table 1). The real variables include GDP, gross capital formation and households' final consumption. The price variables category contains the respective GDP and fixed capital formation deflators and the CPI. We have also added asset (housing and stock) prices to our dataset. The monetary category is represented by broad money, broad monetary base and rouble loans to non-financial corporations (NFCs) and households. The external sector is represented by the rouble oil price[2] and EU GDP.

All real and price (except stock price) variables are provided by Rosstat. All monetary variables are provided by the Bank of Russia. Stock prices are represented by the rouble RTS index. EU GDP series are taken from the OECD website and oil prices from Bloomberg.

All series are in logs of levels and seasonally adjusted. The time sample ranges from 2000Q1 to 2013Q2 and is determined by data availability.

Table 1. Dataset

Category	*Indicator*
Real	GDP
	Households' final consumption
	Fixed capital formation
Price	CPI
	GDP deflator
	Fixed capital formation deflator
	House prices
	Stock prices
Monetary	Broad money
	Broad monetary base

---

[1] We have deliberately excluded monetary policy variables (i.e. exchange rate and interest rate) from the final specification of the model. The results obtained in the presence of these variables (e.g. the impulse response functions) were ambiguous and provided little information about monetary policy effects. One possible explanation is that the monetary policy regime in Russia had undergone substantial transformation from a heavily managed to a more flexible exchange rate. Accordingly, the exchange rate and interest rate determination factors varied substantially over our time sample (see Lainela and Ponomarenko (2012) for a review). Presumably, the macroeconomic effects of changes in the interest rate were also inconstant. In such an environment it may be appropriate to employ additional modelling techniques to capture the time-varying effect or a nontrivial shock identification strategy. This task lies beyond the objectives of this paper.

[2] Expressing oil prices in roubles would partially help to capture the exchange rate effect, although may admittedly not be fully theoretically grounded. Expressing oil prices in USD would not change our results.

	Loans to non-financial corporations
	Loans to households
External	Oil price
	EU GDP

1.2 The model

Let X_t be the vector including the n variables defined in Table 1. We estimate a VAR model with p (=5) lags:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} \ldots + A_p X_{t-p} + \varepsilon_t \tag{1}$$

We address the possible over-fitting issue by shrinking the model's coefficients towards a prior model that is parsimonious but naïve (see De Mol et al. (2008), Banbura et al. (2010)). In practice, we use the 'Minnesota' (random walk), the 'sum-of-coefficients' and 'dummy-initial observation' priors originally proposed by Litterman (1980), Doan et al. (1984) and Sims (1993). For details on the implementation, see Banbura et al. (2010). As suggested in Giannone et al. (2012a), we select the degree of informativeness of the prior distributions by maximizing the marginal likelihood.

More specifically, the model (1) can be rewritten as following:

$$y_t = x_t \beta + \varepsilon_t ,$$

where $y_t = X_t$, $x_t = I_n \otimes [1 \; X'_{t-1} \ldots X'_{t-p}]$, $\beta \equiv vec([A_0, A_1, \ldots, A_p]')$, $\varepsilon_t \sim N(0, \Sigma)$.

The baseline prior is a version of the so-called "Minnesota" prior:

$$E\big[(A_s)_{ij} \mid \Sigma\big] = \begin{cases} 1, & if \quad i = j, \quad s = 1 \\ 0, & otherwise \end{cases}$$

$$\operatorname{cov}\big[(A_s)_{ij}, (A_r)_{hm} \mid \Sigma\big] = \begin{cases} \lambda^2 \dfrac{1}{s^2} \dfrac{\Sigma_{ih}}{\psi_j /(d-n-1)}, & if \quad m = j, \quad r = s \\ 0, & otherwise \end{cases}$$

where λ controls overall tightness of the prior, ψ_j equals the residual variance of an AR(1) of j-th variable, Σ_{ih} / ψ_j account for the relative scale of the variables, $d = n + 2$ - degrees of freedom of the IW distribution. The prior for the intercept is diffuse.

The "sum-of-coefficients" prior is implemented via the following dummy observations:

$$y^+ = diag\left(\frac{\bar{y}_0}{\mu}\right)$$

$$x^+ = \begin{bmatrix} 0, & y^+, & \ldots, & y^+ \end{bmatrix},$$

where $\bar{y}_0$ is an $n \times 1$ vector containing the average of the first p observations for each variable, μ controls the tightness of the prior.

The "dummy-initial observation" prior organized as following:

$$y^{++} = \frac{\bar{y}'_0}{\delta}$$

$$x^{++} = \begin{bmatrix} \frac{1}{\delta}, & y^{++}, & \ldots, & y^{++} \end{bmatrix},$$

where δ controls the tightness of the prior.

We follow Giannone et al. (2012a) using hierarchical modeling approach to make inference about the informativeness of the prior distribution. For hyperparameters λ, μ, δ we employ hyperpriors in form of Gamma distribution with mode equal to 0.2, 1, 1 and standard deviations equal to 0.4, 1, 1 respectively and for $\psi_j /(d - n - 1)$ - Inverse-Gamma distribution with scale and shape equal to $(0.02)^2$.

We adopt Empirical Bayesian method, in which a prior distribution is estimated from the data. The standard Metropolis algorithm is used to simulate the posterior of the coefficients of the BVAR, including the hyperparameters. This procedure automatically selects the "appropriate" amount of shrinkage, namely tighter priors when the model involves many unknown coefficients relative to the available data, and looser priors in the opposite case.

For the implementation of conditional forecasting we rewrite our model in the following state space representation (see Banbura et al. (2014) for the details).

Measurement equation
$$X_t = \begin{pmatrix} I_n & 0_{n \times np} \end{pmatrix} \begin{pmatrix} X_t \\ \vdots \\ X_{t-p+1} \\ A_0 \end{pmatrix} + v_t,$$

Transition equation

$$\begin{pmatrix} X_t \\ \vdots \\ X_{t-p+1} \\ A_0 \end{pmatrix} = \begin{pmatrix} A_1 & A_2 & \ldots & A_p & I_n \\ I_n & 0_n & \ldots & 0_n & 0_n \\ \vdots & \ddots & \ldots & \vdots & \vdots \\ 0_n & \ldots & I_n & 0_n & 0_n \\ 0_n & \ldots & 0_n & 0_n & I_n \end{pmatrix} \begin{pmatrix} X_{t-1} \\ \vdots \\ X_{t-p} \\ A_0 \end{pmatrix} + w_t,$$

where

$$E[v_t] = 0 \ , \ \ E[v_t v_{t-s}^{'}] = 0, \forall s$$

$$E[w_t] = 0, \ \ E[w_t w_{t-s}^{'}] = 0, \forall s \neq 0 \ , \ \ E[w_t w_t^{'}] = \begin{pmatrix} \Sigma & \ldots & 0_n \\ \vdots & \ddots & \vdots \\ 0_n & \ldots & 0_n \end{pmatrix}$$

$$E[v_t w_s^{'}] = 0, \forall t, s$$

In order to obtain conditional forecasts, we adopt the solution proposed for forecasting with ragged edge data sets using a Kalman filter methodology, In fact, the variables for which we do not assume the knowledge of a future path can be considered as time series with missing data. This procedure allows us to deal with high dimensional data and long forecast horizons.

2. Empirical results

2.1 Impulse response analysis

Before presenting our main results we make sure that the linkages between the variables established by the model are plausible and statistically significant (which may not be the case if the model is over fitted or, contrarily, reduced to the random walk process by the tight priors). With this purpose we conduct impulse response analysis. The model is not intended for structural analysis, so, instead of assuming some type of identification scheme, we compute generalized impulse response functions (Pesaran and Shin (1998)). Although these results do not have clear economic interpretation they may be used to extract information on the cross correlation and lag-lead relationship of the series of interest implied by the model. We present the impulse responses to shocks of four variables: oil price, EU GDP, broad money and GDP (Figures 1-4)[3].

The obtained impulse responses are generally consistent with expectations. Expansionary shocks to the aforementioned variables increase real activity, nominal monetary indicators and prices. The reaction of the real sector variables is particularly distinct and statistically significant in all cases. So is the reaction of monetary variables, although in case of an oil price shock the re-

---

[3] The impulse responses to the shocks of other variables in the model were also examined and were in line with expectations

sponses are only marginally significant. The results for price variables are less uniform. GDP and fixed capital formation deflators as well as house prices increase unambiguously in response to all shocks (except an oil price shock, when the response of house prices is not significant). CPI reacts rapidly only to shocks to the oil price and broad money, while in case of shocks to EU and Russian GDP the response only becomes marginally significant after 6 quarters. Somewhat surprisingly, the responses of stock prices are significant only in the short-run.

Figure 1. Impulse responses to an oil price shock (the median and the 16th and 84th quantiles of the distribution)
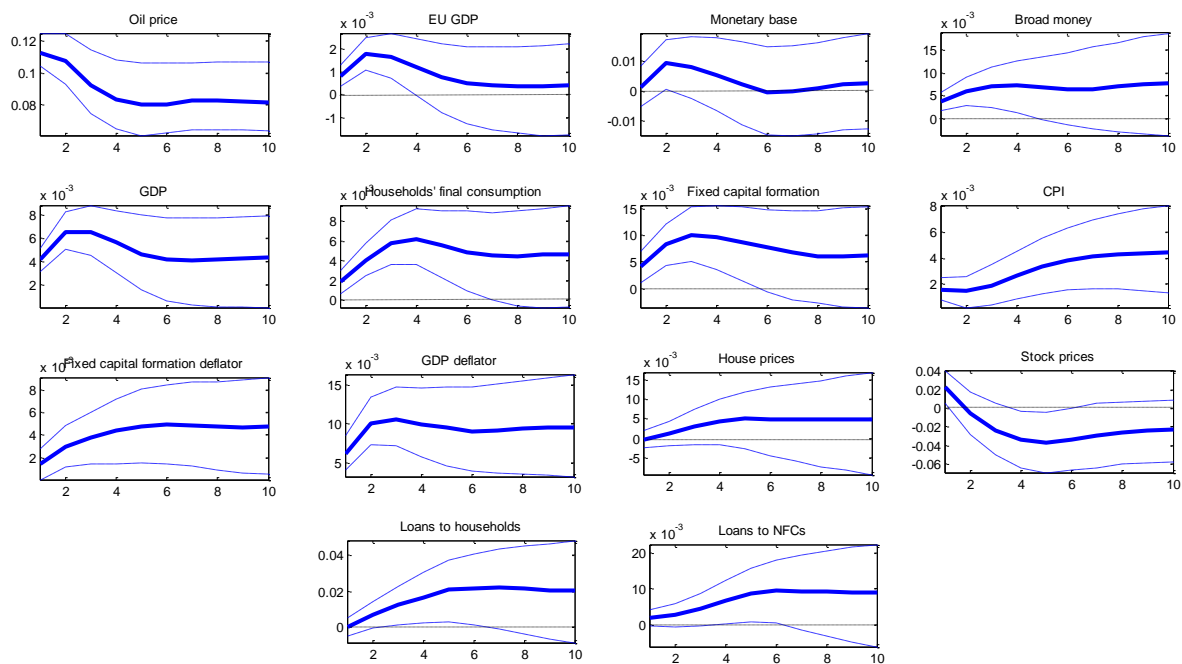
Figure 2.   Impulse responses to an EU GDP shock (the median and the 16th and 84th quantiles of the distribution)

Figure 3.   Impulse responses to a broad money shock (the median and the 16th and 84th quantiles of the distribution)

Figure 4.   Impulse responses to a GDP shock (the median and the 16th and 84th quantiles of the distribution)
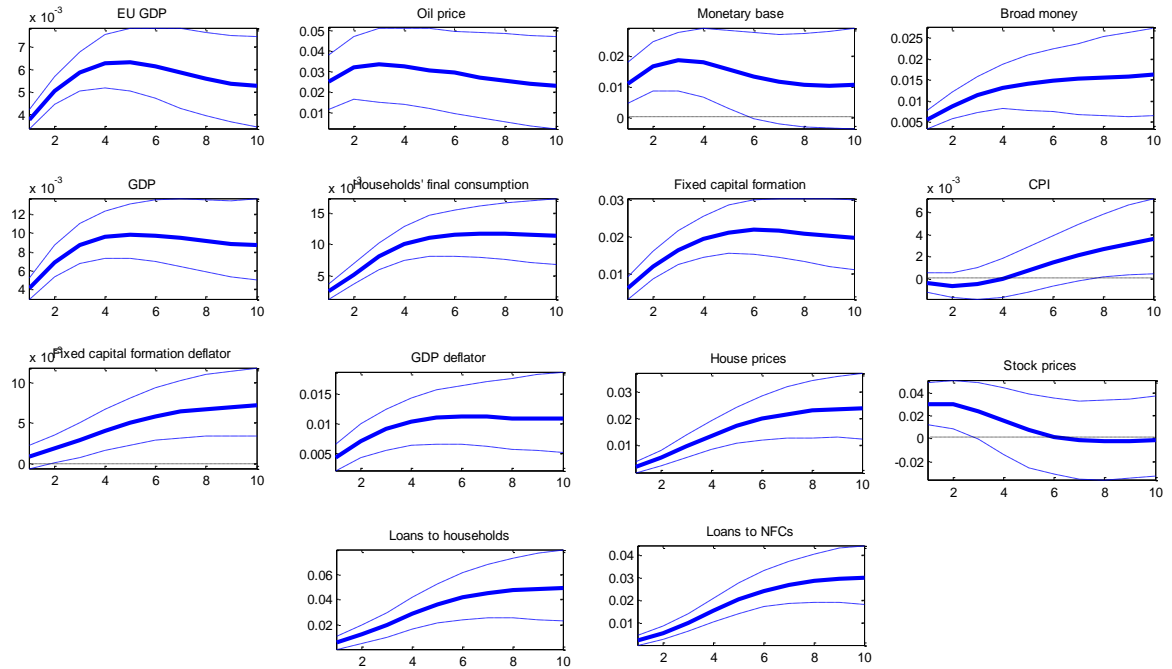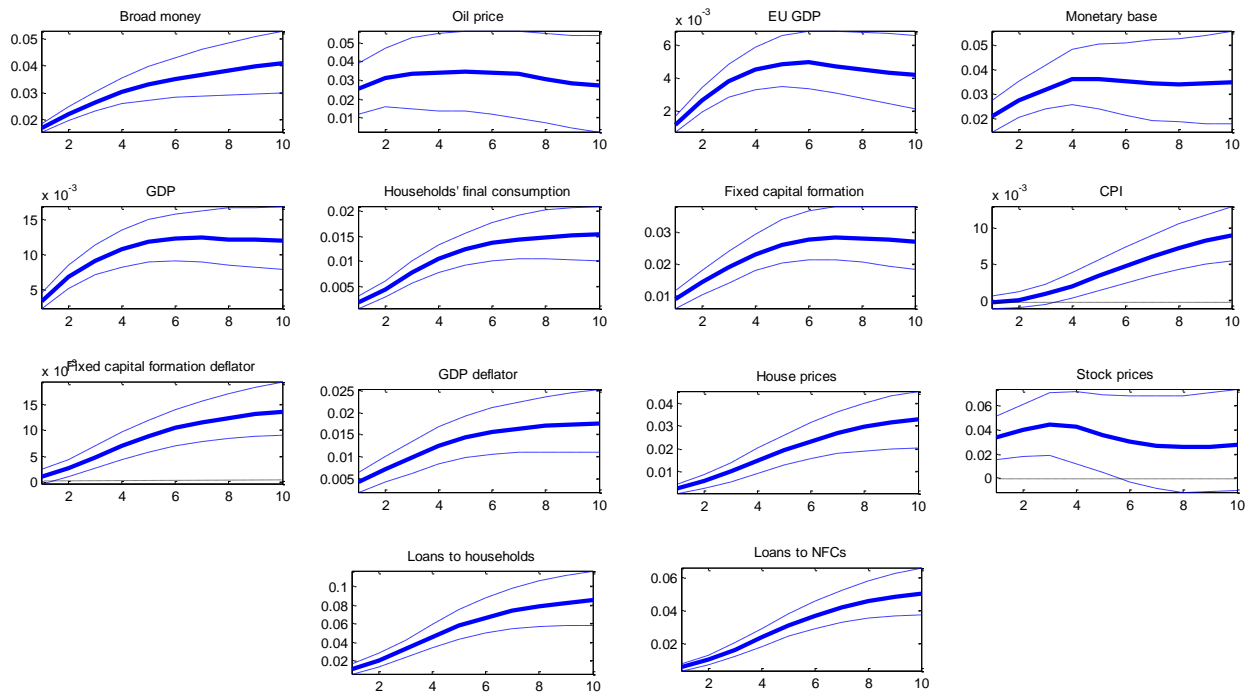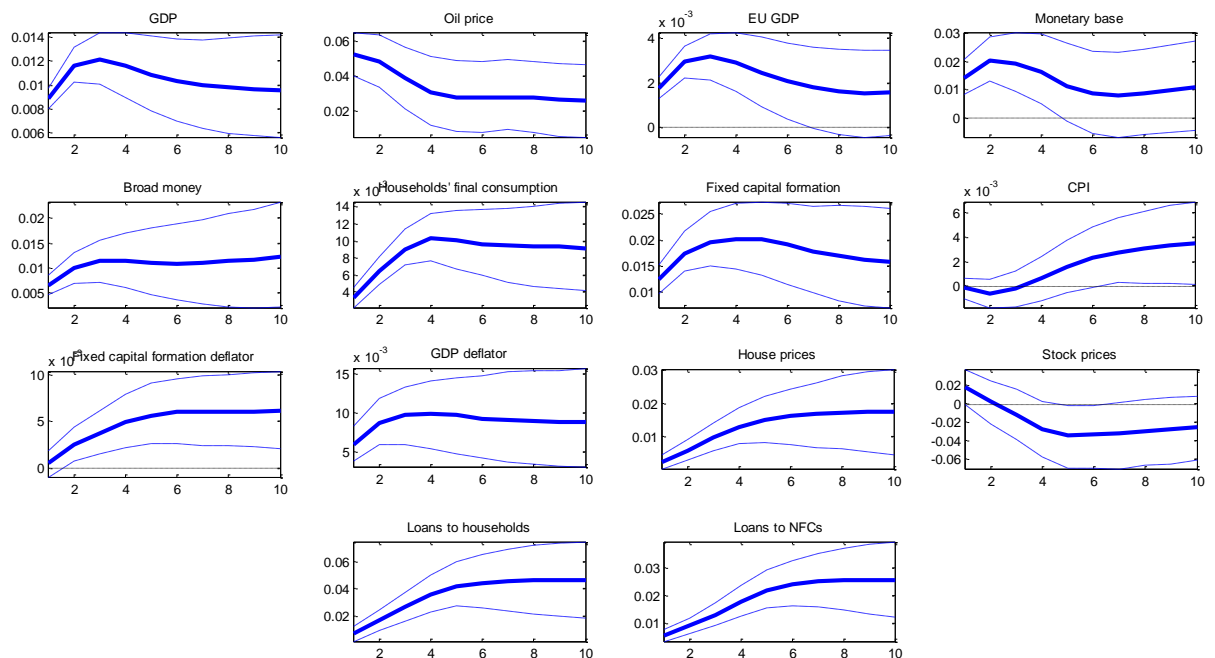
2.2 Forecast evaluation

We further validate our model by running a recursive out-of-sample forecasting evaluation exercise. Since the size of our model is relatively large, we want to make sure that we are not over-fitting the data. In that case, forecasting performance would be poor.

We start by estimating the model from 2000Q1 to 2009Q2[4], produce a forecast and then iterate the procedure by recursively updating our estimation sample by one quarter until the end of the sample, 2013Q2. We calculate the forecast in the form of growth rate averaged over h quarters. We consider three horizons: h=2, h=4 and h=6. Results are reported in terms of ratio of the Mean Squared Forecast Errors (MSFE) of our model versus the MSFE of the benchmark competitor models. Numbers smaller than one imply that our model improves over the benchmark.

The set of competitor models consists of:

•   Random walk (RW). The forecast for a given variable is its average growth rate over the previous observations.

•   BVAR with 'Minnesota' prior (M BVAR). We re-estimate our model using a dogmatic BVAR with a dogmatic 'Minnesota' prior. This approach may be regarded as another representation of the random walk model.

•   Autoregressive model (AR(5)). A univariate autoregressive model with 5 lags for each variable.

•   Canonical VAR (VAR). We estimate a collection of small canonical VARs each comprising 5 lags of EU GDP, oil price, broad money, CPI, and GDP plus the variable to be forecast.

Table 2. MSFE in forecasts of individual variables (as ratio to the MSFE of the competitor models, forecast horizon h=2)

Variable	*Competitor model*			
	RW	*M BVAR*	*AR(5)*	*VAR*
GDP	0.20	0.59	0.29	0.01
Households final consumption	0.28	1.24	0.27	0.14
Fixed capital formation	0.42	1.16	0.74	0.08
CPI	0.66	1.42	0.92	0.09
GDP deflator	0.48	0.96	0.63	0.03
Fixed capital formation deflator	0.83	1.69	1.15	0.01
House prices	0.42	0.24	1.08	0.00
Stock prices	0.24	0.56	0.72	0.00
Broad money	0.54	2.11	0.64	0.06

---

[4] We report the results for the time sample that excludes the period of sharp real contraction in 2009Q1-Q2. Given that the time sample used for the recursive forecasting exercise is rather short and the fluctuations of variables are particularly large during this period, we believe that reporting results for the tranquil period may be more representative. Nevertheless, the inclusion of the recession episode into the time sample would worsen the forecasting performance of our model relative to other models (in particular at longer horizons).

Monetary base	0.52	0.82	0.46	0.02
Loans to NFCs	0.36	0.16	0.65	0.04
Loans to households	0.81	0.30	1.25	0.01
Oil price	0.37	0.38	0.45	0.01
EU GDP	0.23	0.25	0.19	0.02

Table 3. MSFE in forecasts of individual variables (as ratio to the MSFE of the competitor models, forecast horizon h=4)

Variable	*Competitor model*			
	RW	*M BVAR*	*AR(5)*	*VAR*
GDP	0.08	0.47	0.38	0.01
Households final consumption	0.21	1.41	0.11	0.02
Fixed capital formation	0.19	0.88	0.64	0.08
CPI	0.64	2.08	1.06	0.15
GDP deflator	0.26	1.03	0.73	0.02
Fixed capital formation deflator	1.07	2.72	1.43	0.00
House prices	0.38	0.47	1.26	0.00
Stock prices	0.19	0.83	0.77	0.01
Broad money	0.27	2.16	0.47	0.02
Monetary base	0.21	0.80	0.49	0.00
Loans to NFCs	0.14	0.19	0.68	0.03
Loans to households	0.38	0.50	1.51	0.01
Oil price	0.26	0.38	0.56	0.02
EU GDP	0.11	0.27	0.13	0.01

Table 4. MSFE in forecasts of individual variables (as ratio to the MSFE of the competitor models, forecast horizon h=6)

Variable	*Competitor model*			
	RW	*M BVAR*	*AR(5)*	*VAR*
GDP	0.07	0.37	0.40	0.01
Households final consumption	0.12	0.64	0.04	0.01
Fixed capital formation	0.13	0.79	0.66	0.02
CPI	0.98	5.60	1.51	0.08
GDP deflator	0.30	1.09	1.59	0.01
Fixed capital formation deflator	1.93	2.87	1.24	0.00
House prices	0.29	0.62	1.28	0.00
Stock prices	0.07	0.45	0.57	0.00
Broad money	0.34	4.22	0.61	0.04
Monetary base	0.24	0.98	0.58	0.00
Loans to NFCs	0.09	0.24	0.69	0.00
Loans to households	0.23	0.56	1.37	0.01
Oil price	0.20	0.26	0.43	0.01
EU GDP	0.08	0.24	0.15	0.02

Our results are presented in Tables 2-4. The shaded rows represent the cases when our model was clearly outperformed by at least one of the competitor models (MSFE ratio > 1.2). We find that the forecasts of our model were most accurate for the real variables (in particular for long horizons). The results are quite opposite in the case of price variables, where our model is not able to outperform the best competitor model (which in most cases is the 'Minnesota' BVAR[5]). These results are consistent with other findings indicating that the random walk forecasts are often the most accurate for this category of variables (D'Agostino et al. (2006), Stock and Watson (2006), Fischer et al. (2009)). The results for monetary variables are mixed. For example, while in the case of loans to NFCs the forecasting performance our model was exceptionally good, the forecasts of loans to households were less accurate than those obtained from the autoregressive model. This result may indicate that developments of loans to households were less attached to fundamentals and therefore forecasting this variable in the richer information environment was not helpful.

2.3 Counterfactual simulation

The exercises conducted in the previous sections are helpful in examining the validity and adequacy of our model, but arguably the model's main purpose is not structural analysis or unconditional forecasting. Rather, this model's capabilities may be most useful in constructing medium-term scenario projections. In this section, we examine the applicability of the model in this respect by testing its stability via counterfactual exercises. On the other hand, the results of this exercise may be used to assess whether the Russian economy behaved in accordance with historical regularities after the crisis or whether some of the developments were untypical.

For the counterfactual exercise we estimate the model on the pre-crisis time sample 2000Q4–2008Q2 and make the simulation for the remaining period of 2008Q3–2013Q2. We begin by conditioning our projections only on the oil price, which is widely regarded as an important driver of economic growth in Russia. The results for the real sector are shown in Figure 5. The projected growth rates are invariable and the confidence band is relatively wide. The information on the oil price helps predict neither the sharp contraction in 2009 nor the slowdown of GDP and fixed capital formation growth in 2012–2013. The relatively high growth of household consumption after the crisis is, however, in line with the model's projection.

---

[5] Interestingly, the performance of the canonical VAR model in this exercise is exceptionally poor, indicating the importance of imposing priors on the model's parameterization.

Figure 5. Projections of real sector variables' y-o-y growth conditional on **oil price** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band
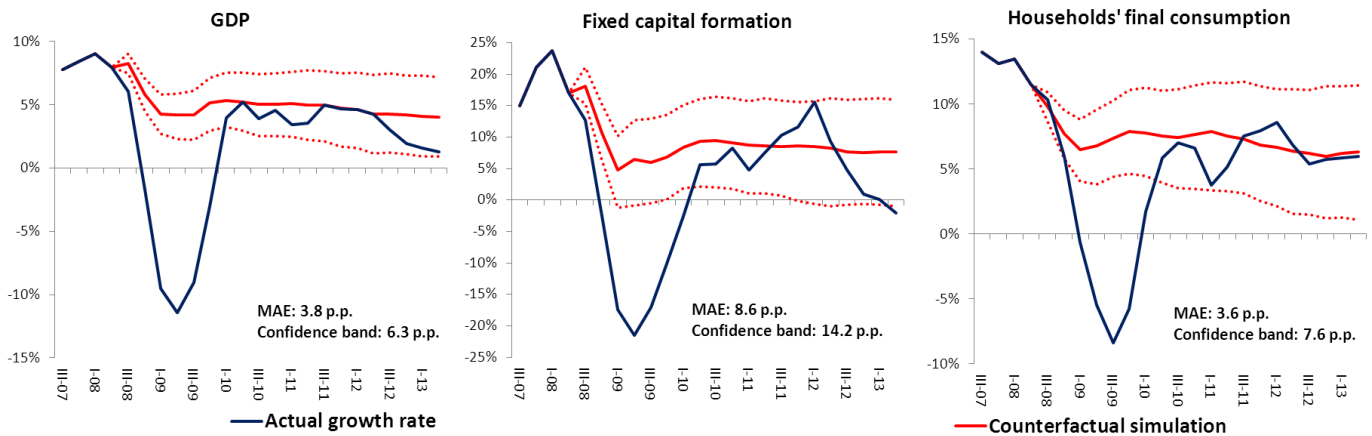
Our next step is making the same simulation conditional on both the actual oil price and actual EU GDP. The results are strikingly different (Figure 6). The information on developments with these two external variables was sufficient to explain most of the variation in domestic real sector variables' growth rate. The confidence bands are also substantially smaller. The contraction in 2009 is fully explained in the cases of fixed capital formation and household consumption. The slowdown in 2012–2013 is also projected for GDP and fixed capital formation (accordingly the growth rates of consumption are regarded as unexpectedly high in this case). These results provide a clear evidence of the vulnerability of the Russian economy to external shocks6 that is in line with other studies (see e.g. IMF (2014)). Another key finding, however, is that the oil price alone should not necessarily be regarded as a conclusive summary indicator of these shocks.

---

[6] Admittedly, the exact channels of the transmission of these shocks to the Russian economy may not be fully identified based on this model. We can only state that these shocks are closely correlated with economic activity in the EU. Further research is obviously needed in order to identify these channels and examine how robust this link is (see e.g. Bank of Russia (2014) for an example of adding balance-of-payment variables into the model).

Figure 6. Projections of real sector variables' y-o-y growth conditional on oil price and **EU GDP** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band
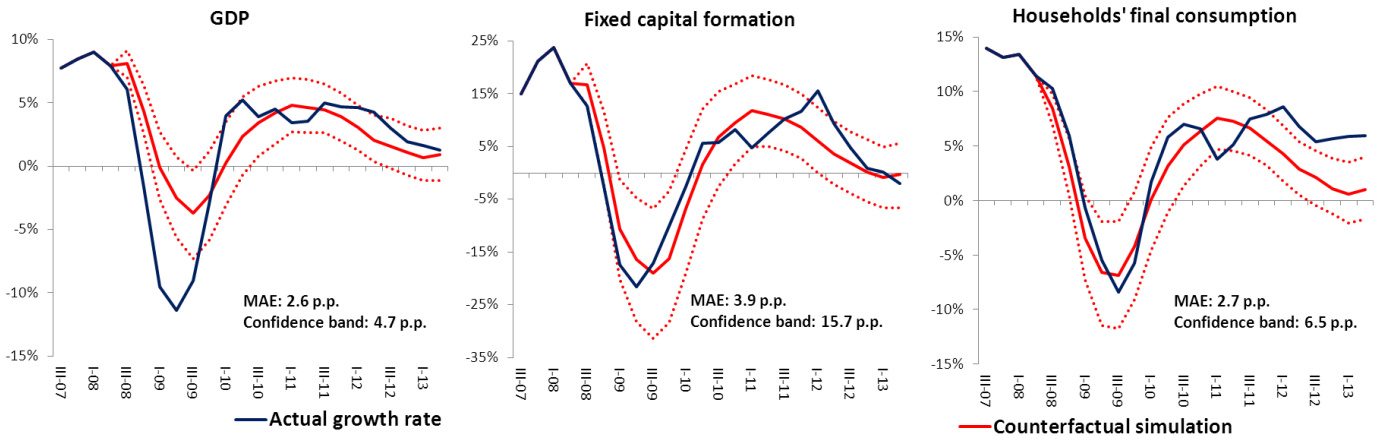
The projections for price variables obtained via the same simulation are, however, much less accurate (Figure 7). The prices growth rates are systematically underestimated starting from 2010. Interestingly, the projected growth of broad money is also continually lower than actual (Figure 8). This result in itself is not surprising, because, rather than being closely linked to macroeconomic fundamentals, money supply in Russia is subject to large exogenous shocks (see Ponomarenko et al. (2012) for discussion). For example, the substantial fiscal stimulus in 2009–2010 was partially financed from Russian sovereign funds and had a mechanical expansionary effect on the money stock. Therefore, it may be appropriate to examine the results of the counterfactual simulation based on actual monetary developments.

Figure 7. Projections of price variables' y-o-y growth conditional on oil price and **EU GDP** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band

Figure 8. Projections of broad money's y-o-y growth conditional on oil price and **EU GDP** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band
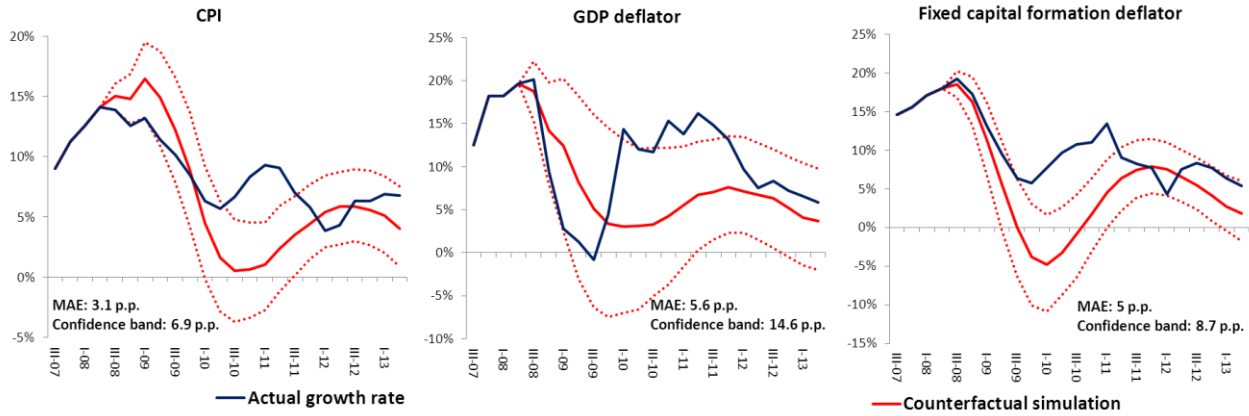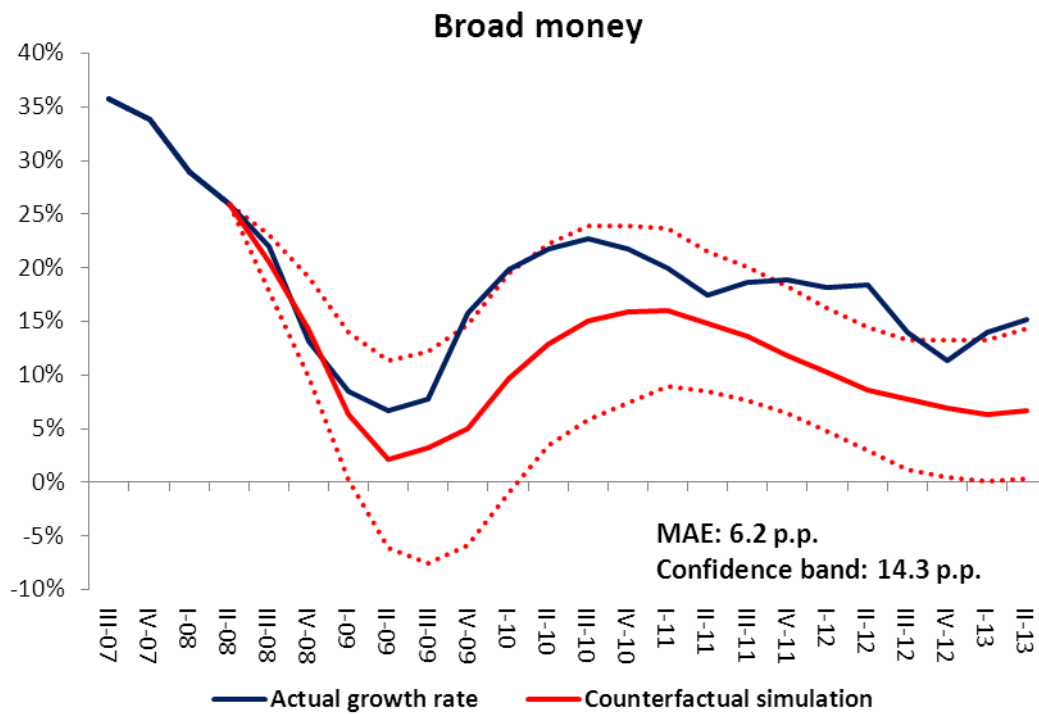

Accordingly, we condition our next simulation on actual broad money developments as well as the oil price and EU GDP. This helps to improve the average accuracy of the price varia-

ble projections (Figure 9). For example, even though the short-run fluctuations[7] in the CPI are still not reflected in the estimated growth rates, the cumulative error (i.e. difference in price levels) between the actual and projected CPI amounted to just 2% (as compared with 8% error in the case when the projection was not conditioned on actual broad money growth).

Figure 9. Projections of price variables' y-o-y growth conditional on oil price, EU GDP and **broad money** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band
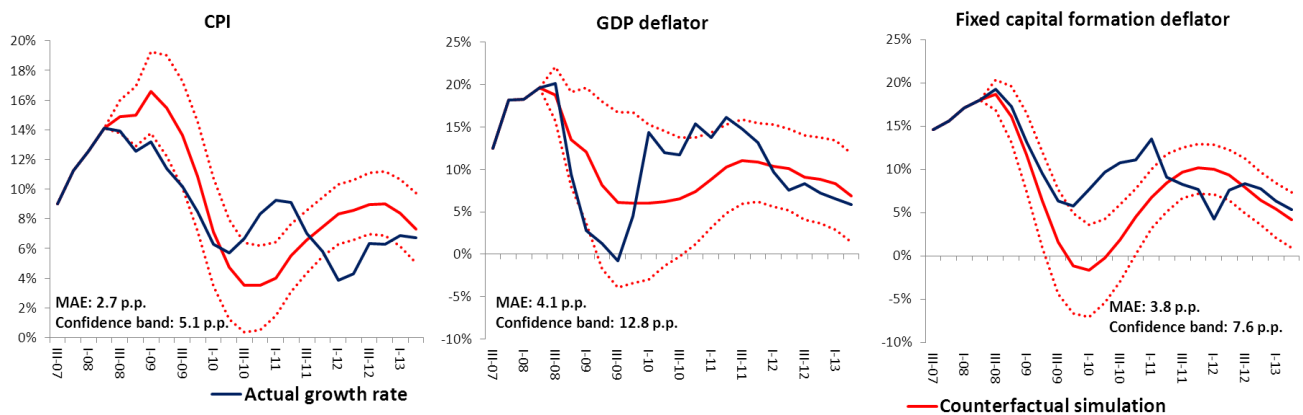
The accuracy of projections of other variables is also in general satisfactory. The median projections for asset prices' growth (Figure 10) are in line with actual data although the confidence band in the case of the stock prices projection is very large. Similarly to the unconditional forecasting exercise, the results for monetary variables are mixed (Figure 11). The projection of loans to NFCs proved to be extremely precise. On the contrary, the projection of loans to households explained very little of the variability in actual growth rates, while being associated with a very high degree of uncertainty, thus providing another indication of the difficulties in identifying the link between this variable and macroeconomic fundamentals.

---

[7] Essentially, these fluctuations did not seem to be determined by any fundamentals. The increases in the inflation rate in late 2010 was at least partly due to food price shocks, caused by drought, while the sharp decrease in early 2012 was associated with the suspension of administered price indexation. See e.g. the Bank of Russia Quarterly Inflation Review (2011 Q1 and 2012 Q1) for a more detailed review of these episodes.

Figure 10. Projections of asset price variables' y-o-y growth conditional on oil price, EU GDP and **broad money** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band

House prices — MAE: 6.3 p.p. Confidence band: 16.5 p.p.

Stock prices — MAE: 31.6 p.p. Confidence band: 134.3 p.p.

Actual growth rate — **Counterfactual simulation**

Figure 11. Projections of asset price variables' y-o-y growth conditional on oil price, EU GDP and **broad money** (the median and the 16th and 84th quantiles of the distribution), mean absolute error and average confidence band
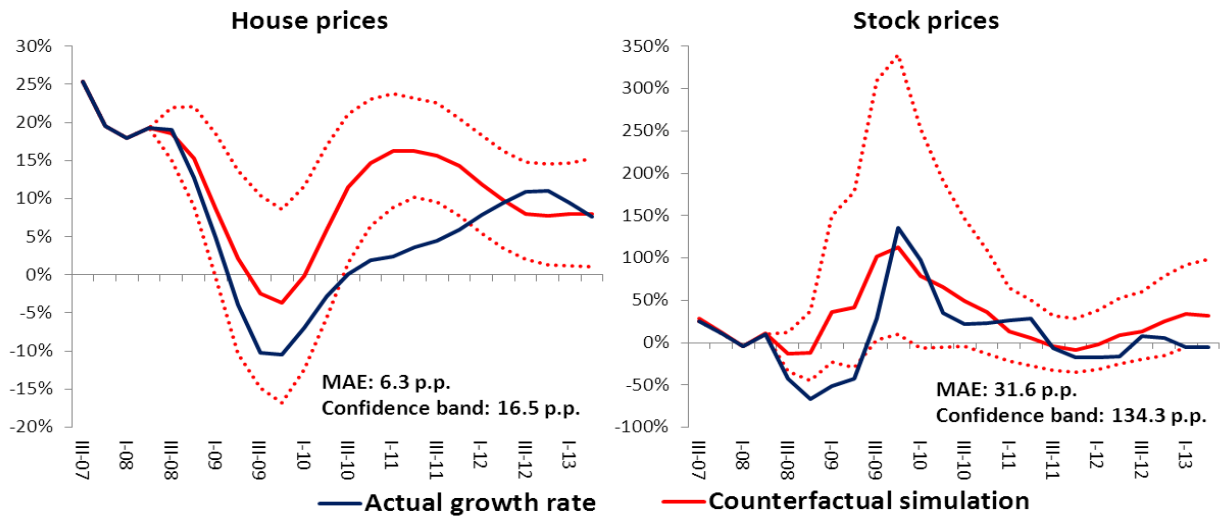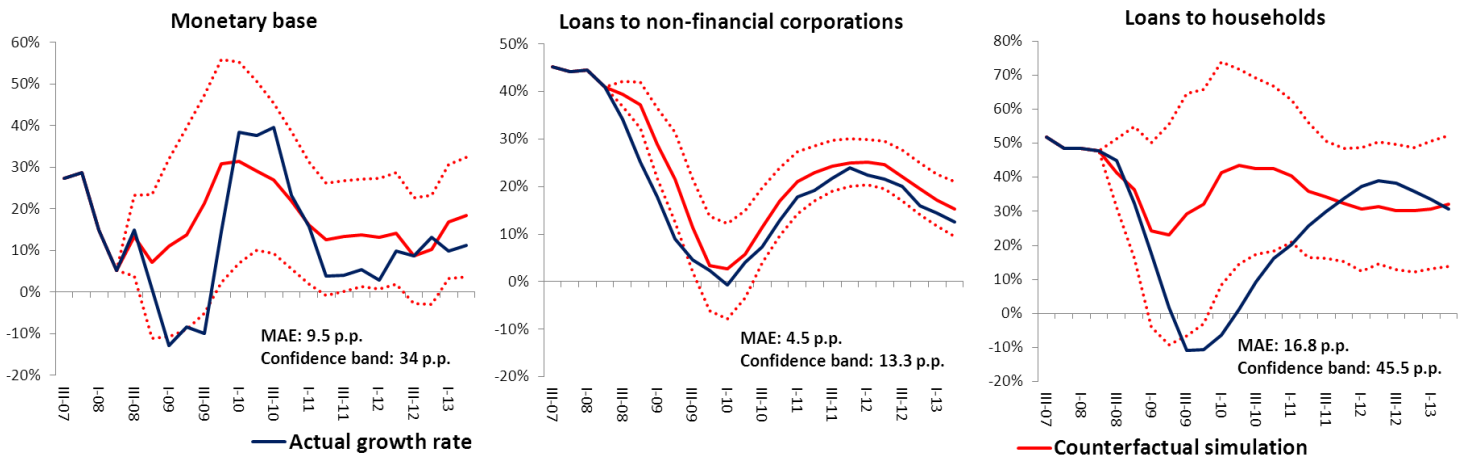

Monetary base — MAE: 9.5 p.p. Confidence band: 34 p.p.

Loans to non-financial corporations — MAE: 4.5 p.p. Confidence band: 13.3 p.p.

Loans to households — MAE: 16.8 p.p. Confidence band: 45.5 p.p.

Actual growth rate — **Counterfactual simulation**

CONCLUSIONS

The main objective of this paper is to build a relatively large VAR model for Russia while relying on insufficiently long time series for its estimation. To this effect we apply the recent econometric approach developed specifically to address the 'curse of dimensionality'. Using this methodology, we estimate a Bayesian VAR model comprising 14 major domestic real, price and monetary macroeconomic indicators as well as external sector variables. We conduct several types of exercise to validate our model. These are impulse response analysis, recursive forecasting and counterfactual simulation.

Our results demonstrate that the employed methodology is highly appropriate for economic modelling in Russia. The impulse response functions indicate that theoretically plausible linkages between variables in our model may be identified. The results of recursive forecasting show that the model performs satisfactorily and does not suffer from the problem of over-fitting. The forecasting performance is particularly good for real sector variables at a longer horizon. The counterfactual projections indicate that post-crisis real sector developments in Russia were generally in line with the observed external variables (although the growth rate of households' final consumption was unexpectedly high). Interestingly, the oil price alone did not contain sufficient information for producing an accurate forecast, while conditioning the projections on both the oil price and EU GDP growth improves the accuracy significantly. The model is not fully able to capture short-run fluctuations in the inflation rate, but makes a good prediction of price levels if conditioned on actual broad money growth. Our results also indicate that loans to NFCs in Russia seem to be closely linked to fundamentals, while for loans to households such a link is somewhat vague.

Admittedly, the presented version of the model is an illustrative example of its applicability rather than the ultimate specification. The composition of the dataset may obviously be further altered depending on the task addressed. Most notably, the link between domestic and foreign sectors may be explored in more detail by adding foreign trade, capital flows and uncertainty variables into the model. Given that (unlike canonical VARs) the number of variables that can be simultaneously included in the model is not severely limited, these possibilities seem particularly promising. Another challenge that clearly remains is the introduction of monetary policy variables into the model.

REFERENCES

1. Banbura, M., Giannone, D., Lenza, M. (2014) Conditional forecasts and scenario analysis with vector autoregressions for large cross-sections. ECARES working paper 2014–15.

2. Banbura, M., Giannone, D., Reichlin, L. (2010) 'Large Bayesian VARs'. Journal of Applied Econometrics, vol. 25(1), 71–92.

3. Bank of Russia (2014) External conditions affecting the Russian economy. Monetary Policy Report No. 3(7), 8–9.

4. Benedictow, A., Fjærtoft, D., Løfsnæs, O. (2013) 'Oil dependency of the Russian economy: An econometric analysis'. Economic Modelling 32, 400–428.

5. De Mol, C., Giannone, D., Reichlin, L. (2008) 'Forecasting using a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components?' Journal of Econometrics, 146(2), 318–328.

6. Doan, T., Litterman, R., Sims, C.A. (1984) 'Forecasting and Conditional Projection Using Realistic Prior Distributions'. Econometric Reviews, 3, 1–100.

7. Granville, B., Mallick, S. (2010) 'Monetary Policy in Russia: Identifying exchange rate shocks'. Economic Modelling 27, 432–444.

8. Giannone, D., Lenza, M., Primiceri, G.E. (2012a) Prior Selection for Vector Autoregressions. ECB Working Paper Series 1494.

9. Giannone, D., Lenza, M., Reichlin, R. (2012b) Money, Credit, Monetary Policy and the Business Cycle in the Euro Area, ECARES working paper 2012-008.

10. IMF (2014) 'On the receiving end? External conditions and the emerging markets growth before, during and after the global financial crisis'. Chapter 4 in World Economic Outlook (April)

11. Korhonen, I., Mehrotra, A. (2009) Real exchange rate, output and oil: Case of four large energy producers. BOFIT Discussion Papers 6.

12. Korhonen, I., Mehrotra, A. (2010) 'Money demand in post-crisis Russia: de-dollarisation and re-monetisation'. Emerging Markets Finance and Trade, 46 (2), 5–19.

13. Lainela, S., Ponomarenko, A. (2012) Russian Financial Markets and Monetary Policy Instruments. BOFIT Online no. 3.

14. Litterman, R. (1980) A Bayesian Procedure for Forecasting with Vector Autoregression. Working paper, Massachusetts Institute of Technology, Department of Economics.

15. Mallick, S.K., Sousa, R.M. (2013) 'Commodity Prices, Inflationary Pressures, and Monetary Policy: Evidence from BRICS Economies'. Open Economies Review, Volume 24, Issue 4, 677–694.

16. Mehrotra, A., Ponomarenko, A. (2010) Wealth effects and Russian money demand. BOFIT Discussion Paper Series 13.

17. Pesaran, H., Shin, Y. (1998) 'Generalized impulse response analysis in linear multivariate models'. Economic Letters, 58(1), 17–29.

18. Ponomarenko, A., Vasilieva, E. Schobert, F. (2012) Feedback to the ECB's monetary analysis: The Bank of Russia's experience with some key tools. ECB Working Paper Series 1471.

19. Rautava, J. (2013) Oil prices, Excess Uncertainty and Trend Growth: a Forecasting Model for Russia's Economy. Focus on European Economic Integration Q4/13.

20. Sims, C.A. (1993) 'A Nine-Variable Probabilistic Macroeconomic Forecasting Model, in Business Cycles, Indicators and Forecasting'. NBER Chapters, 179–212. National Bureau of Economic Research, Inc.