Conditional forecasting and structural analysis with BVAR model for Russia

the role of oil prices, sanctions, and monetary policy

Anna Pestova, Mikhail Mamonov
Center for Macroeconomic Analysis and Short-term Forecasting and National Research University – Higher School of economics
Motivation

- Russia has been experiencing severe macroeconomic crisis since 2015. Different shocks hit the economy
  - Oil price have dropped by half (average 2015 to 2014)
  - As a result of Crimea joining Russia, EU and US has imposed financial sanctions on Russian companies. Russian corporate external debt shrunk by ¼ in 2014-2015
  - Ruble has depreciated by 90% (2014-2015), interest rates increased, income and consumption went down

- On the basis of Bayesian VAR forecasting model we estimate the impact of deteriorated external conditions as well as the effect of monetary policy tightening on the Russian economy in 2014-2015
  - We assess the empirical performance of the model by conducting counterfactual simulations
Empirical design (1)

☐ If a researcher estimated the BVAR model at the end of 2013 and knew what will happen with the external conditions in 2014-2015, could he or she predict the scope and the depth of the current crisis?

- Estimate model parameters over the period 2000-2013
- Calculate out-of-sample forecasts for 2014-2015 conditioning on the realized actual paths of external conditions

(1) Oil price and (2) Corporate external debt
Empirical design (2)

- While the oil price drop and financial sanctions were out of the government control (at least, the economic block), policymakers could still use monetary policy to deal with these shocks.

- Could the Central Bank of Russia cushion the impact of external shocks by means of less restrictive monetary policy?
  - Recall that in December 2014 CBR raised the key rate from 10.5 to 17.0%.
  - Identify monetary policy shocks and estimate their effect on the economy.
Why BVAR?

- Bayesian VAR is a recognized benchmark model for (non-structural) macroeconomic forecasting
  - Proposed by Doan, Litterman and Sims (1984)
  - Unconditional forecasting: Banbura, Giannone and Reichlin (2010), Koop (2013), Carriero, Clark and Marcellino (2013)

- In Russia, the literature on theoretically based forecasting models (DSGE) is scarce, VAR models provide viable and flexible alternative
  - It takes into account rich lag structure of macroeconomic data and feedback (second-round) effects
  - It doesn’t impose “incredible restrictions” on the coefficients of equations
  - It solves the “curse of dimensionality” (small data set problem)
  - It allows estimating the effects of different policy measures without assuming their exogeneity (e.g. policy rules)
  - It provides density forecasts that take into account both parameter uncertainty (they are not fixed values but random variables) and future shock uncertainty
Model specification

VAR(P): N endogenous variables and P lags

\[ Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \ldots + B_P Y_{t-P} + u_t \]

where \( Y_t = (Y_{1t}, Y_{2t}, \ldots, Y_{Nt})' \) is a \( T \times N \) matrix

(number of obs. × number of endogenous variables)

In a compact form:

\[ Y_t = X_t B + u_t \]

where \( X_t = (c_i, Y_{it-1}, Y_{it-2}, \ldots, Y_{it-P}) \) is a \( T \times (1 + N \times P) \) matrix

\[ E(u_t' u_s) = \Sigma, \text{ if } t = s; \ E(u_t' u_s) = 0, \text{ if } t \neq s; \ E(u_t) = 0. \]

Bayes law:

\[ p(B, \Sigma | Y_t) \propto p(Y_t | B, \Sigma) \cdot p(B, \Sigma) \]

Posterior distribution of parameters

Likelihood (data)

Prior distribution of parameters

March 2016
Variables

- 14 variables divided into 3 groups
  - **External sector variables:** global financial volatility (VIX index), Urals oil price, value of Russian export (constant 2007 prices), value of Russian import (current prices)
  - **Domestic non-financial variables:** GDP, wage, retail sales, and investment (all in constant 2007 prices); CPI inflation
  - **Domestic financial and monetary variables:** external debt of corporate sector, commercial loans of Russian banks, monetary policy interest rate (key rate), monetary base, exchange market pressure index (weighted average of nominal exchange rate and international reserves)

- All variables are taken in logs (with the exception of interest rate). Seasonal adjustment procedure was applied to export, import, GDP, wage, retail sales, investment, CPI, and monetary base; X12 in EViews)

- **Monthly data** starting from January 2000 up to September 2015 (189 obs.). Maximum time lag \( k = 13 \) month (to capture residual seasonality, if any)

- Number of estimated coefficients = \( N \times (NP + 1) = 2562 \)
Model specification

- Exchange market pressure (EMP) index
  - Takes into account exchange rate policy shift from fixed (managed floating) to flexible exchange rate regime
  - If either ruble depreciates or the CBR sells international reserves → external pressure on exchange market increases

\[
EMP = \frac{1}{\sigma_\varepsilon} \frac{\Delta \varepsilon}{\varepsilon} - \frac{1}{\sigma_{IntRes}} \frac{\Delta IntRes}{IntRes}
\]

- Graph showing EMP (2007=100) and international reserves ($ bn.), right scale
Prior specification

- Modern Gibbs-sampler version of *Minnesota prior*
  - *Independent* normal inverted Wishart prior distribution of VAR coefficients $B$ and innovations covariance matrix $\Sigma$
  - External variables are not dependent on domestic ones (small open economy prior) so that we need to shrink coefficients in different equations differently. This is achieved at the expense of getting non-conjugate prior
  - Consequently, the analytical representation of the posterior for $B$ is no longer available. Thus, we need to employ MCMC-methods (time consuming Gibbs sampling algorithm)

- VAR coefficients $B$ in equation for $Y_{it}$:
  - of $Y_{it-1}$: b equals 1 (if $Y_{it}$ is non-stationary or OLS estimate from respective AR(1) representation of $Y_{it}$);
  - of $Y_{it-p}$ for all $p = 2 \ldots P$: equal to 0;
  - of $Y_{jt-p}$ for all $j \neq i$ and $p = 1 \ldots P$: equal to 0;

- Covariance matrix of $B$ is built to shrink the coefficients of other variables and of deeper lags towards zero more tightly: rule of thumb: $\lambda_1 = 0.1$ (general tightness); $\lambda_2 = 0.5$ (significance of other variables); $\lambda_3 = 1$ (own lags decay)
## Optimization of prior hyperparameters

- **Rule of thumb:** \( \lambda_1 = 0.1 \) (general tightness); \( \lambda_2 = 0.5 \) (tightness on other variables); \( \lambda_3 = 1 \) (tightness on own lags decay)


<table>
<thead>
<tr>
<th>( \lambda_1 )</th>
<th>( \lambda_2 )</th>
<th>( \lambda_3 )</th>
<th>Y1</th>
<th>Y2</th>
<th>Y3</th>
<th>Y4</th>
<th>Y5</th>
<th>Y6</th>
<th>Y7</th>
<th>Y8</th>
<th>Y9</th>
<th>Y10</th>
<th>Y11</th>
<th>Y12</th>
<th>Y13</th>
<th>Y14</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>1</td>
<td>5.95</td>
<td>2.2</td>
<td>1.15</td>
<td>0.049</td>
<td>0.16</td>
<td>0.09</td>
<td>0.30</td>
<td>1.86</td>
<td>0.12</td>
<td>0.56</td>
<td>0.17</td>
<td>9.13</td>
<td>0.24</td>
<td>1.39</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>2</td>
<td>5.88</td>
<td>1.9</td>
<td>1.32</td>
<td>0.057</td>
<td>0.18</td>
<td>0.10</td>
<td>0.30</td>
<td>1.90</td>
<td>0.13</td>
<td>0.43</td>
<td>0.15</td>
<td>8.86</td>
<td>0.21</td>
<td>1.36</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
<td>5.86</td>
<td>2.0</td>
<td>1.22</td>
<td>0.058</td>
<td>0.17</td>
<td>0.10</td>
<td>0.30</td>
<td>1.86</td>
<td>0.13</td>
<td>0.45</td>
<td>0.15</td>
<td>8.25</td>
<td>0.23</td>
<td>1.37</td>
</tr>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>2</td>
<td>6.05</td>
<td>1.6</td>
<td>1.19</td>
<td>0.053</td>
<td>0.15</td>
<td>0.10</td>
<td>0.28</td>
<td>1.51</td>
<td>0.14</td>
<td>0.43</td>
<td>0.12</td>
<td>6.83</td>
<td>0.21</td>
<td>0.98</td>
</tr>
<tr>
<td>0.05</td>
<td>0.1</td>
<td>1</td>
<td>5.86</td>
<td>1.9</td>
<td>1.24</td>
<td>0.055</td>
<td>0.18</td>
<td>0.11</td>
<td>0.32</td>
<td>1.88</td>
<td>0.13</td>
<td>0.44</td>
<td>0.14</td>
<td>6.97</td>
<td>0.21</td>
<td>1.36</td>
</tr>
<tr>
<td>0.05</td>
<td>0.5</td>
<td>2</td>
<td>5.91</td>
<td>2.0</td>
<td>1.17</td>
<td>0.054</td>
<td>0.18</td>
<td>0.09</td>
<td>0.31</td>
<td>1.80</td>
<td>0.13</td>
<td>0.45</td>
<td>0.16</td>
<td>8.19</td>
<td>0.22</td>
<td>1.37</td>
</tr>
<tr>
<td>0.05</td>
<td>0.1</td>
<td>2</td>
<td>5.98</td>
<td>2.0</td>
<td>1.37</td>
<td>0.057</td>
<td>0.19</td>
<td>0.11</td>
<td>0.32</td>
<td>1.86</td>
<td>0.13</td>
<td>0.45</td>
<td>0.14</td>
<td>8.00</td>
<td>0.19</td>
<td>1.34</td>
</tr>
<tr>
<td>0.05</td>
<td>0.5</td>
<td>1</td>
<td>5.86</td>
<td>2.0</td>
<td>1.16</td>
<td>0.051</td>
<td>0.18</td>
<td>0.09</td>
<td>0.31</td>
<td>1.84</td>
<td>0.13</td>
<td>0.48</td>
<td>0.16</td>
<td>6.69</td>
<td>0.23</td>
<td>1.39</td>
</tr>
</tbody>
</table>

*Notes:* minimal obtained values of RMSFE are marked with red color (by columns)
Optimization of prior hyperparameters

- **Rule of thumb:** $\lambda_1 = 0.1$ (general tightness); $\lambda_2 = 0.5$ (tightness on other variables); $\lambda_3 = 1$ (tightness on own lags decay)


<table>
<thead>
<tr>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>$\lambda_3$</th>
<th>Y1</th>
<th>Y2</th>
<th>Y3</th>
<th>Y4</th>
<th>Y5</th>
<th>Y6</th>
<th>Y7</th>
<th>Y8</th>
<th>Y9</th>
<th>Y10</th>
<th>Y11</th>
<th>Y12</th>
<th>Y13</th>
<th>Y14</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>1</td>
<td>6.71</td>
<td>3.0</td>
<td>1.30</td>
<td>0.064</td>
<td>0.22</td>
<td>0.15</td>
<td>0.36</td>
<td>2.90</td>
<td>0.24</td>
<td>0.99</td>
<td>0.25</td>
<td>13.57</td>
<td>0.36</td>
<td>2.20</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>2</td>
<td>6.99</td>
<td>2.6</td>
<td>1.60</td>
<td>0.080</td>
<td>0.23</td>
<td>0.17</td>
<td>0.36</td>
<td>2.85</td>
<td>0.26</td>
<td>0.79</td>
<td>0.21</td>
<td>13.94</td>
<td>0.31</td>
<td>2.14</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
<td>6.93</td>
<td>2.7</td>
<td>1.42</td>
<td>0.083</td>
<td>0.23</td>
<td>0.18</td>
<td>0.36</td>
<td>2.82</td>
<td>0.26</td>
<td>0.83</td>
<td>0.20</td>
<td>12.44</td>
<td>0.34</td>
<td>2.13</td>
</tr>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>2</td>
<td>6.68</td>
<td>2.3</td>
<td>1.25</td>
<td>0.058</td>
<td>0.17</td>
<td>0.18</td>
<td>0.33</td>
<td>2.23</td>
<td>0.22</td>
<td>0.85</td>
<td>0.20</td>
<td>9.76</td>
<td>0.30</td>
<td>1.60</td>
</tr>
<tr>
<td>0.05</td>
<td>0.1</td>
<td>1</td>
<td>6.90</td>
<td>2.7</td>
<td>1.50</td>
<td>0.077</td>
<td>0.23</td>
<td>0.17</td>
<td>0.37</td>
<td>2.81</td>
<td>0.25</td>
<td>0.79</td>
<td>0.19</td>
<td>11.45</td>
<td>0.29</td>
<td>2.15</td>
</tr>
<tr>
<td>0.05</td>
<td>0.5</td>
<td>2</td>
<td>6.76</td>
<td>2.8</td>
<td>1.35</td>
<td>0.071</td>
<td>0.22</td>
<td>0.15</td>
<td>0.34</td>
<td>2.72</td>
<td>0.26</td>
<td>0.82</td>
<td>0.25</td>
<td>11.67</td>
<td>0.30</td>
<td>2.13</td>
</tr>
<tr>
<td>0.05</td>
<td>0.1</td>
<td>2</td>
<td>7.00</td>
<td>2.7</td>
<td>1.72</td>
<td>0.080</td>
<td>0.24</td>
<td>0.18</td>
<td>0.38</td>
<td>2.79</td>
<td>0.25</td>
<td>0.77</td>
<td>0.17</td>
<td>12.15</td>
<td>0.25</td>
<td>2.10</td>
</tr>
<tr>
<td>0.05</td>
<td>0.5</td>
<td>1</td>
<td>6.85</td>
<td>2.8</td>
<td>1.32</td>
<td>0.065</td>
<td>0.23</td>
<td>0.15</td>
<td>0.34</td>
<td>2.76</td>
<td>0.25</td>
<td>0.87</td>
<td>0.24</td>
<td>11.71</td>
<td>0.32</td>
<td>2.15</td>
</tr>
</tbody>
</table>

*Notes:* minimal obtained values of RMSFE are marked with red color (by columns)
# Optimization of prior hyperparameters

- **Rule of thumb:** \( \lambda_1 = 0.1 \) (general tightness); \( \lambda_2 = 0.5 \) (tightness on other variables); \( \lambda_3 = 1 \) (tightness on own lags decay)


<table>
<thead>
<tr>
<th>( \lambda_1 )</th>
<th>( \lambda_2 )</th>
<th>( \lambda_3 )</th>
<th>Y1</th>
<th>Y2</th>
<th>Y3</th>
<th>Y4</th>
<th>Y5</th>
<th>Y6</th>
<th>Y7</th>
<th>Y8</th>
<th>Y9</th>
<th>Y10</th>
<th>Y11</th>
<th>Y12</th>
<th>Y13</th>
<th>Y14</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>1</td>
<td>7.98</td>
<td>4.6</td>
<td>1.43</td>
<td>0.139</td>
<td>0.34</td>
<td>0.33</td>
<td>0.51</td>
<td>5.18</td>
<td>0.47</td>
<td>1.79</td>
<td>0.37</td>
<td>20.51</td>
<td>0.58</td>
<td>3.50</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>2</td>
<td>8.61</td>
<td>4.0</td>
<td>2.03</td>
<td>0.158</td>
<td>0.36</td>
<td>0.32</td>
<td>0.53</td>
<td>4.86</td>
<td>0.50</td>
<td>1.45</td>
<td>0.30</td>
<td>21.52</td>
<td>0.51</td>
<td>3.36</td>
</tr>
<tr>
<td>0.1</td>
<td>0.1</td>
<td>1</td>
<td>8.41</td>
<td>4.2</td>
<td>1.70</td>
<td>0.166</td>
<td>0.36</td>
<td>0.33</td>
<td>0.53</td>
<td>5.06</td>
<td>0.51</td>
<td>1.51</td>
<td>0.28</td>
<td>17.90</td>
<td>0.58</td>
<td>3.36</td>
</tr>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>2</td>
<td>8.01</td>
<td>4.6</td>
<td>1.35</td>
<td>0.131</td>
<td>0.31</td>
<td>0.50</td>
<td>0.46</td>
<td>4.33</td>
<td>0.49</td>
<td>1.92</td>
<td>0.35</td>
<td>16.29</td>
<td>0.49</td>
<td>2.89</td>
</tr>
<tr>
<td>0.05</td>
<td>0.1</td>
<td>1</td>
<td>8.50</td>
<td>4.2</td>
<td>1.90</td>
<td>0.158</td>
<td>0.36</td>
<td>0.34</td>
<td>0.56</td>
<td>4.94</td>
<td>0.48</td>
<td>1.45</td>
<td>0.23</td>
<td>18.13</td>
<td>0.49</td>
<td>3.34</td>
</tr>
<tr>
<td>0.05</td>
<td>0.5</td>
<td>2</td>
<td>8.29</td>
<td>4.3</td>
<td>1.60</td>
<td>0.132</td>
<td>0.34</td>
<td>0.30</td>
<td>0.43</td>
<td>4.71</td>
<td>0.49</td>
<td>1.46</td>
<td>0.39</td>
<td>17.90</td>
<td>0.49</td>
<td>3.31</td>
</tr>
<tr>
<td>0.05</td>
<td>0.1</td>
<td>2</td>
<td>8.62</td>
<td>4.2</td>
<td>2.26</td>
<td>0.162</td>
<td>0.37</td>
<td>0.34</td>
<td>0.58</td>
<td>4.87</td>
<td>0.47</td>
<td>1.44</td>
<td>0.22</td>
<td>17.63</td>
<td>0.42</td>
<td>3.22</td>
</tr>
<tr>
<td>0.05</td>
<td>0.5</td>
<td>1</td>
<td>8.38</td>
<td>4.3</td>
<td>1.53</td>
<td>0.131</td>
<td>0.34</td>
<td>0.30</td>
<td>0.45</td>
<td>4.81</td>
<td>0.48</td>
<td>1.52</td>
<td>0.37</td>
<td>18.74</td>
<td>0.51</td>
<td>3.35</td>
</tr>
</tbody>
</table>

*Notes: minimal obtained values of RMSFE are marked with red color (by columns)*

The lowest values of RMSFE are achieved under the following configuration of hyper parameters: \( \lambda_1 = 0.1 \), \( \lambda_2 = 0.5 \) and \( \lambda_3 = 2 \). It holds for all forecasting horizon considered (3, 6 and 12 months)
Conditional forecasting: preliminaries

- We test the empirical performance of estimated BVAR model by making pseudo out-of-sample scenario forecasts built on the basis of known (realized) external conditions for
  - The crisis period of 2014-2015 (presented below)
  - «Calm period» of 2012-2013 (in Appendix)

- Conditional forecast = restrictions on future paths of some variables = restrictions on future shocks (these shocks force variables to deviate from its respective unconditional forecast)

- Methodology: we apply the Gibbs sampling algorithm of Waggoner and Zha (1999) to compute density forecasts with BVAR
Conditional forecasts: results for 2014-2015 (1)

GDP growth rates, %,

(1) Conditioned on global volatility VIX and Urals price

(2) Conditioned on VIX, Urals price and external debt stock

Restricted access to external debt market, together with the oil price drop, is able to explain current GDP decline. Due to sanctions Russian GDP growth rates was 0.7 p.p. lower on average in 2014-2015.
Conditional forecasts: results for 2014-2015 (2)

CPI Inflation, %,

(1) Conditioned on global volatility VIX and Urals price

(2) Conditioned on VIX, Urals price and external debt stock

External factors are not capable to predict the scope of inflation acceleration in 2014-2015. Possible reason – underestimation of exchange rate depreciation due to unaccounted negative and speculative expectations. Additionally, exchange rate pass-through is underestimated (recall $\lambda_3=2$)
Conditional forecasts: results for 2014-2015 (3)

EMP index, 2007=100

(1) Conditioned on global volatility VIX and Urals price

(2) Conditioned on VIX, Urals price and external debt stock

The specification with EMP delivers more precise forecasts of exchange rate than the model with nominal exchange rate (previously studied, not shown here). Exchange rate shock is fully endogenous, doesn’t “fall from the sky”, instead of this it is cause by double shock from the balance of payment (current account and financial account)
Conditional forecasts: results for 2014-2015 (4)

Investment growth rates, %

(1) Conditioned on global volatility VIX and Urals price

(2) Conditioned on VIX, Urals price and external debt stock

Investment dynamics is well described. Possible explanation - macroeconomic downturn is captured and in the second case deficit of sources of investment financing is taken into account (reduction of external debt).
Conditional forecasts: results for 2014-2015 (5)

Import growth rates, %

(1) Conditioned on global volatility VIX and Urals price

(2) Conditioned on VIX, Urals price and external debt stock
Discussion of the results

- Knowing the paths of external variables does not guarantee that the forecast values will be close to the actual ones
  - During the crisis forecasting error could be large
  - But, in the "calm period" BVAR model shows a good approximation of the actual trajectories
  - In both cases the model captures the direction of external shocks influence on the economy

- We show that the accuracy of conditional forecasts is higher than unconditional ones (knowing the external conditions helps to forecast)

- The fall in oil prices alone does not fully explain the depth of the current recession in the Russian economy which is partly driven by the limited access of Russian companies to international financial markets as a result of sanctions (-1.5 p.p. cumulative decline in GDP growth rates in 2014-2015 is attributed to sanctions).
The role of monetary policy – structural analysis (IRFs)

- We were not able to estimate the effects of monetary policy shocks on the basis of forecasting model estimated for the period of 2000-2015
  - The dynamics of monetary policy interest rate is poorly explained on the whole data sample as there were policy shifts (monetary base targeting → exchange rate targeting → interest rate control)
  - As a result, the shocks originated from the deviation of the key rate from its unconditional path does not add up useful information about the evolution of other variables

- Restricting the sample on 2009-2015 resulted in explosive behavior of some variables → differencing is needed
  - We estimated the small model in y-o-y differences (preliminary results)
    - 7 variables: oil price, GDP growth, inflation, bank loans, monetary base, nominal exchange rate, policy interest rate; 13 lags
The role of monetary policy – structural analysis (IRFs)

Recursive identification (IR ordered last)
Init. shock = +0.4

GDP growth

Sign restrictions (IR “+”, MB “-”)
Init. shock = +0.2

CPI Inflation

Sign restrictions (IR “+”, MB “-”, CPI “-”)
Init. shock = +0.1

Nominal exchange rate

Monetary policy tightening has strong recessionary effect. At the same time it neither helped to stabilize the exchange market nor constrained inflation. Instead of this, it only exacerbated recession, mostly in line with Mallick and Sousa (2012). 5 p.p. increase in policy rate yields [-0.5; -2.0] effect on GDP growth in the following year.
Directions of future work

- **Model fine-tuning**
  - Time-varying parameter VAR (TVP-VAR) to account for monetary policy shifts
  - Soft differencing prior combined with small open economy restrictions (?)

- **Optimization of the prior**
  - Is non-conjugate prior useful for forecasting?
  - What lag length is optimal?

- **Monetary policy shocks identified through policy rule, through combination of zero and sign restrictions** *(Arias et al., 2015)*
  - Does prior affect the result?
Appendix
Conditional forecasting: Additional experiment

- For crisis periods, forecasting errors may be large, but crisis is a big challenge for any model.
- So what about normal periods?
- Experiment 2:
  - Compute out-of-sample forecast for the “calm” period of 2012-2013 under the known paths of the following variables:
    1. Global financial volatility (VIX index) and
    2. Urals oil Price
- Counterfactual simulations of other 14-2=12 variables using these two known paths within 2012-2013 period
Conditional forecasts for 2012-2013: results (1)

Conditional forecast of GDP growth rates, %:

-4.0 -2.0 0.0 2.0 4.0 6.0 8.0 10.0 12.0
lower 16 median upper 84
unconditional actual

Conditional forecast of CPI inflation, %:

-6.0 -4.0 -2.0 0.0 2.0 4.0 6.0 8.0 10.0 12.0
lower 16 median upper 84
unconditional actual
Conditional forecasts for 2012-2013: results (2)

Conditional forecast of nominal exchange rate (bi-currency basket), ruble

Conditional forecast of investment, %:

lower 16  median  upper 84
unconditional  actual