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Should we care?
The economic effects of financial sanctions on the Russian economy

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Abstract

We employ a Bayesian VAR model to estimate the economic effects on the Russian economy from Western financial sanctions imposed in 2014. Sanctions caused a decrease in the amount of outstanding Russian corporate external debt, but it occurred during an episode of falling oil prices. We disentangle the effects of sanctions and oil prices by computing out-of-sample projections of key Russian macroeconomic variables conditioned solely on the oil price drop and on both the oil price drop and external debt deleveraging. Declining oil prices alone do not explain the depth of economic crisis in Russia, but we get rather accurate conditional forecasts when the actual path of external debt deleveraging is added. We treat the difference between these two projections as the effect of sanctions against Russia. The effect is modest, yet significant, for most of the variables discussed. While our estimate of the impact of sanctions on GDP growth has large uncertainty, over two-thirds of the density lies in the negative area.

Keywords: financial sanctions, conditional macroeconomic forecasting, oil prices, corporate external debt, Bayesian VAR
JEL: C51, E37, E44, F34

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1 Introduction

Following the rising political tensions related to the crisis in Ukraine in the beginning of 2014, the European Union, the United States and other countries imposed financial sanctions on Russian government-owned companies and banks.[1] Initially, the sanctions only banned select Russian corporate entities from issuing new debt of certain maturities on European and US financial markets. However, contagion from the perceived risk surrounding the Russian government and businesses drastically reduced the volume of new Russian debt placements. The resulting credit drought affected state-owned companies and the private sector alike. Under the *de facto* closed primary market and following scheduled debt repayments, the stock of Russian corporate external debt shrank by 25% during 2014–2015.

The imposition of the financial sanctions on Russia in late July 2014 (see e.g. Dreger et al., 2015; Korhonen et al., 2018) caused an immediate decline in external corporate debt in Russia in 2014Q3. Russia's debt deleveraging process continued in subsequent years, and, importantly, it could not be explained by a general retreat of foreign investors from emerging markets because no similar reductions of corporate external liabilities in other large emerging economies took place in this period (Fig. 1).

Western sanctions matter for Russia. As an emerging economy with an underdeveloped domestic financial sector, the country is highly dependent on external finance. During 2014–2015, the ratio of corporate external debt to GDP averaged 30%. Restricted access to the financing resources of foreign markets inhibits investment and lowers domestic economic activity by driving up financing costs. Indeed, Russia went into an economic recession in late 2014, about six months after financial sanctions were imposed. In 2015, Russian GDP shrank 2.3% and fixed capital investment decreased by more than 10%. During 2014–2015, the ruble lost about 90% of its value.

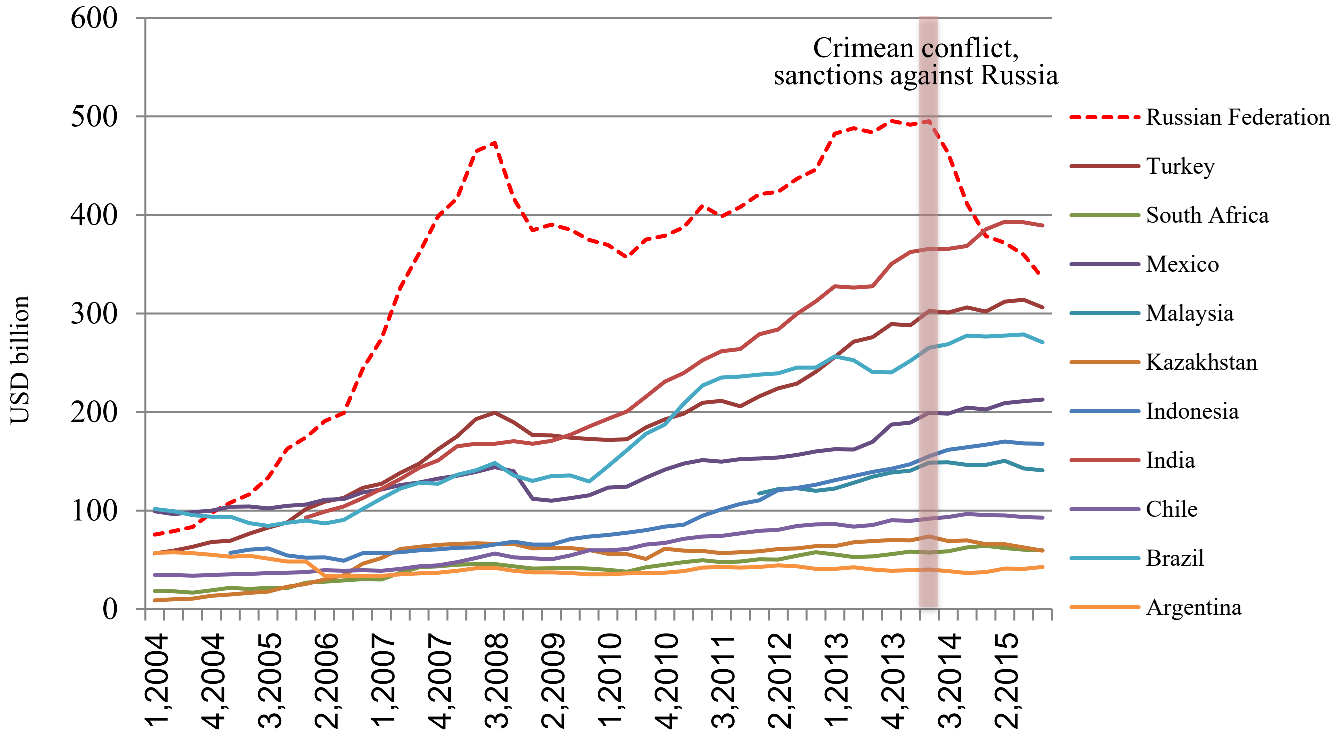
Financial sanctions were not the sole driver of Russia's economic malaise. The slowdown in growth rates started about a year before sanctions were imposed. The slowing continued throughout 2014, with annual GDP growth dropping to 0.7% (from 3.7% in 2012 and 1.8% in 2013). At the time, the slowdown was attributed mostly to structural problems of the economy such as negative demographic trends, excess regulation, and a poor business environment (OECD, 2014).

The introduction of the sanctions coincided with a dramatic oil price drop from around \$100 a barrel for Urals crude in summer 2014 to under \$40 a barrel at the start of 2016. Given that oil and gas represent about 70% of Russian goods exports, the Russian economy has traditionally

[1] Other aspects of the sanction regime not considered here include travel restrictions and asset freezes imposed on specific Russian officials and private individuals, an embargo on arms and related materials (including dual-use goods and technologies), and restrictions on technology specific to oil & gas exploration and production.

been quite sensitive to movements in commodity prices (for empirical evidence of this effect, see e.g. Korhonen and Ledyaeva, 2010; Cespedes and Velasco, 2012).

Figure 1 Corporate external debt of large emerging economies.



Source: World Bank/IMF QEDS (Quarterly External Debt Statistics).

The impacts of financial sanctions are intertwined with effects from structural stagnation and falling oil prices. Theory-based DSGE models are poorly suited to teasing out the effect of interest as they tend to be small-scale and overlook important emerging market features such as vulnerability to external shocks (see Tovar, 2009). In contrast, non-structural models such as medium- and large-scaled Bayesian vector autoregression (BVAR) models seem ideal for disentangling multiple simultaneous effects, providing the flexibility needed to account for frictions from the external sector. Thus, BVAR models provide a potential means for addressing our research question.

Our goal is to estimate the economic effects of financial sanctions on the Russian economy, controlling for the simultaneous drop in oil prices. To do that, we develop a medium-sized BVAR forecasting model for the economy and test its empirical performance by making pseudo out-of-sample scenario (conditional) forecasts for the crisis period 2014–2015.

When estimating the economic effect of financial sanctions, we are particularly interested in whether it is possible to predict the scope and the depth of the economic crisis in Russia with a

BVAR model estimated on data up to the end of 2013 if the external conditions of 2014–2015 would be known.

We focus on the 2014–2015 period for two reasons. First, it represents the most acute phase of the Russian economic crisis. GDP growth returned to positive territory in 2016. Second, a substantial deleveraging of corporate external debt occurred during the two years after financial sanctions were imposed. By 2016, the stock of the debt had stabilized.[2] Given these considerations, our estimates should be treated as the short-term effects of the financial sanctions, and, in that sense, conservative.

For effects of interest, we perform counterfactual simulations. We estimate the model parameters over the period of 2000–2013 and calculate out-of-sample forecasts for 2014–2015 conditioned on the actual paths of the external conditions. We treat the difference between a scenario solely conditioned on the oil price and a scenario conditioned on both oil price and corporate external debt as the economic effect of the financial sanctions imposed on Russia. This eliminates demand-side factors from the decline in corporate external debt driven by the slowing economy and the oil price drop, allowing us to focus on the exogenous shift in the external debt supply.[3] It also gives our setting the unique features of a quasi-natural experiment, so our conclusions should hold for similar debt-dependent emerging open economies.

This paper contributes to the literature on conditional BVAR forecasting. Previous studies have largely focused on unconditional forecasting exercises (comparing the forecasting accuracy of BVARs with other non-structural models, e.g. Banbura et al., 2010; Koop, 2013; Carriero et al., 2015; Giannone et al., 2015), so the body of work centered around conditional forecasts (e.g. Bloor and Matheson, 2011; Banbura et al., 2015) is still fairly small. We fill in this gap by documenting the usefulness of the BVAR framework for macroeconomic modeling and conditional forecasting in Russia’s emerging market context.

Our results show that the effects of financial sanctions are modest, but significant, for most variables. In particular, our median estimate for the GDP growth rates yields slowdowns of 0.43 and 0.74 percentage points in 2014 and 2015, respectively, due to the sanctions. Given that Russian GDP increased by 0.3% in 2014 and declined by 2.3% in 2015, we conclude that, the Russian economy would have fallen into recession even without sanctions. The effect on GDP is measured with large uncertainty, however, over two-thirds of the density forecast lies in the negative area. Regarding the rest of the variables considered in the model, we find financial sanctions exert a modest restraining

[2] Central Bank of Russia data show that total corporate external debt declined from $651.2 billion as of end-2013. In 2014, debt shrank by $103.5 billion in 2014 and $71.4 billion in 2015 (numbers include debt liabilities to direct investors). In 2016–2017, corporate external debt declined by $14.1 billion, or about a sixth of the average decline in 2014–2015.

[3] With respect to pre-sanctions economic conditions.

effect on consumption and investment, wages, CPI inflation, and central bank money. The negative effect is more pronounced for interest rate (but highly uncertain), imports and the ruble's exchange rate in 2015. We uncover a modest substitution effect of corporate external debt with respect to domestic bank lending. Finally, we provide a theoretical interpretation of our BVAR forecasting results through the lens of the small open-economy business-cycle model with financial frictions (Mendoza, 2010; Bianchi and Mendoza, 2018; Uribe and Schmitt-Grohe, 2017; Jermann and Quadrini, 2012), and discuss possible caveats and limitations of our forecasting approach.

The paper is structured as follows. Section 2 analyzes the literature on BVAR forecasting. Section 3 describes the model, the estimation methodology, and the data used. The empirical results are presented and discussed in Section 4. Section 5 concludes.

2 Literature review: Towards conditional forecasts with BVARs

Since the seminal paper of Sims (1980), vector autoregressive models (VAR) have gained wide popularity among economists in estimating non-structural relationships between various macroeconomic indicators (see reviews in e.g. Qin, 2011 and Chauvet and Potter, 2013).

Given the length of time series at hand, however, we must acknowledge that unrestricted VARs suffer from the curse of dimensionality: number of observations may be too small relative to the number of estimated parameters. The Bayesian approach, introduced by Doan et al. (1984), seeks to overcome this problem by imposing a prior distribution on the set of unknown parameters.[4] The key feature of Bayesian approach is that imposition of the prior distribution enables shrinkage of parameters (see an extensive survey of forecasting with Bayesian VARs in Karlsson, 2013).

Recent improvements in computational power have also given rise to fairly sophisticated BVAR models. We now see medium-size models (up to 20 endogenous variables: Carriero et al., 2015), large models (more than 20 endogenous variables: Giannone et al., 2015; Banbura et al., 2015; Berg and Hentzel, 2015), and even very large models (more than 100 endogenous variables: De Mol et al., 2008; Banbura et al., 2010).

The performance of BVAR is usually evaluated with unconditional out-of-sample forecasts (see Banbura et al., 2010; Koop, 2013; Carriero et al., 2015). Our approach draws on this work.

Banbura et al. (2010) exploit 131 macroeconomic variables and conclude that even a mid-size model of 20 key variables gains qualitatively similar results compared to the largest specification. In our study, we thus employ a medium-size BVAR with 14 variables.

[4] Dynamic factor models (DFM), first proposed by Geweke (1977) are also widely used for managing the curse of dimensionality. They provide an alternative shrinkage tool by considering the common movements (factors, or principal components) in a large number of relevant time series.

Carriero et al. (2015) assess the differences in the out-of-sample performance of BVAR models estimated under, among others, conjugate and non-conjugate priors. The authors empirically show that the non-conjugate priors deliver more accurate results for density forecasts, whereas the difference in forecasting accuracy of both types of priors is negligible for point forecasts. As we are interested in both density and point forecasts, we are motivated to employ the more time-consuming non-conjugate prior.

Recent studies conclude that the out-of-sample performance of BVAR and DFM for the same set of macroeconomic variables is similar (see comparative exercises in De Mol et al., 2008; Chauvet and Potter, 2013; Stock and Watson, 2016). Based on this insight, we follow the BVAR approach only.

While many studies address the unconditional forecast performance of BVARs, scant attention has been paid to conditional forecasts, i.e. the forecasts of endogenous variables conditioning on the actual paths of other endogenous (or exogenous) variables. The basic algorithm, implying the Gibbs sampling procedure for producing conditional forecasts under VAR, was introduced by Waggoner and Zha (1999).

Applying the Gibbs sampling algorithm, Bloor and Matheson (2011) develop a large BVAR model with a conjugate prior for New Zealand to produce conditional forecasts for key domestic macroeconomic variables. They treat external sector as exogenous and show that foreign shocks have notable influences on the economy. As their conditions, they use the forecasts of real GDP, prices and financial series, obtained from the Reserve Bank of New Zealand. Similarly, Banbura et al. (2015) build a large-size BVAR with a conjugate prior for the euro area to generate conditional forecasts under the hypothetical paths of real GDP, prices, and interest rates. Deryugina and Ponomarenko (2015) propose a medium-size BVAR for the Russian economy with symmetric Minnesota-type prior to make out-of-sample forecasts of key macroeconomic variables for the pre-sanction period of 2010–2014 that are conditioned on oil prices and euro-area GDP. Here, we do not use conjugate and symmetric priors and do not impose conditions on domestic variables as in Bloor and Matheson (2011) and Banbura et al. (2015). Moreover, we improve over Deryugina and Ponomarenko (2015) making more accurate conditional forecasts for the sanctions period of 2014–2015.[5]

Our study focuses on the economic effects of the Western financial sanctions on Russia. To the best of our knowledge, only a handful of studies have sought to quantify the effects of these

[5] Deryugina and Ponomarenko (2015) argue that conditioning on oil prices and euro-area GDP is insufficient for accurate forecasting of Russian economic activity in 2014. Notably, they acknowledge that their 2014 prediction is on the high side, possibly due to other shocks – and *sanctions in particular*. Thus, we take on the work of Deryugina and Ponomarenko (2015) and condition on a “sanctions variable” (corporate external debt in our case). This allows us to forecast accurately the real activity indicators for both 2014 and 2015.

sanctions. Dreger et al. (2016) employ a cointegrated VAR to analyze the determinants of ruble depreciation in 2014. They find that the drop in oil prices had a greater effect on ruble dynamics than the imposed sanctions. Tuzova and Qayum (2016) reach similar empirical results with their VAR model. Kholodilin and Netsunajev (2016) investigate the bilateral effects of financial sanctions on the Russian and euro-area economies. Employing an index that measures the intensity of sanctions, they apply a structural VAR to show that the effect of the sanctions is asymmetric, i.e. GDP growth in Russia decreased by 2.3% in 2014, while the effect on euro-area GDP growth is negligible. As none of these papers apply Bayesian shrinkage, they are subject to the common critique of omitted variable bias. None focus on conditional forecasting.

Another strand of literature focuses on microeconomic aspects of sanctions. For example, Belin and Hanousek (2019) compare imports of the products under sanctions or counter-sanctions with the imports of products of the same group which did not fall under any trade restrictions. Broad product groups include foodstuffs and extraction equipment. Using a difference-in-differences approach, they show that Russian counter-sanctions which banned Western foodstuff imports were effective while the effect of Western sanctions imposed on imports of extraction equipment is small and statistically insignificant. Another paper, Ahn and Ludema (2019), studies the effects of being included into sanctions list on firms' balance sheet indicators. They find significant negative effects on firm revenue, assets, and employment. In this paper, we do not study how sanctions affected firms or industries, instead, we consider solely macroeconomic effects.

3 The data and Bayesian VAR model

In this section, we describe the data used to develop our BVAR model for the Russian economy, introducing macrofinancial linkages and addressing the small open economy restrictions.

3.1 The data

We include 14 variables divided into three groups into the benchmark BVAR specification for the Russian economy:

External sector variables (exogenous): global financial volatility (VIX index), Urals oil price, Russian exports (in constant 2007 prices).

Domestic non-financial variables**:** GDP, wages, retail sales, fixed capital investments, Russian imports (in constant 2007 prices), and CPI inflation.

***Domestic financial and monetary variables*:** corporate external debt (revaluation of the ruble part of the debt is excluded, see below), outstanding bank loans to the private sector, monetary policy interest rate (the key rate of the Central Bank of Russia, CBR), central bank money (monetary base), exchange market pressure index (EMP, weighted average of nominal ruble exchange rate and international reserves, see below).

Monthly data on all 14 variables are collected for the period from January 2000 to December 2015, giving a total of 192 observations. Three issues concern us in choosing our model variables.

First, we want to include external variables likely important for Russia's fuel-exporting economy, and specifically oil prices and oil exports. Given that the Russian economy is vulnerable to external financial shocks, we control for global financial volatility as captured by the global financial volatility index (VIX).

Second, in order to keep the model simple, tractable and relatively small, we drop all variables that measure the same concepts to arrive at standard macroeconomic variables measuring income, output, expenditures and CPI inflation. Since Russian firms tend to react to shocks through wage adjustment rather than firing and hiring of workers (see e.g. Vakulenko and Gurvich, 2016), unemployment demonstrates a limited sensitivity to the country's business cycle. Thus, we consciously do not consider standard labor-market variables such as hours worked or unemployment.[6]

Third, we include a set of financial and monetary variables (again, only one variable for each concept to keep the model relatively small). We account for both domestic and external corporate debt, and consider monetary policy instruments that have been employed by the CBR at some point within the 2000–2015 period (see below).

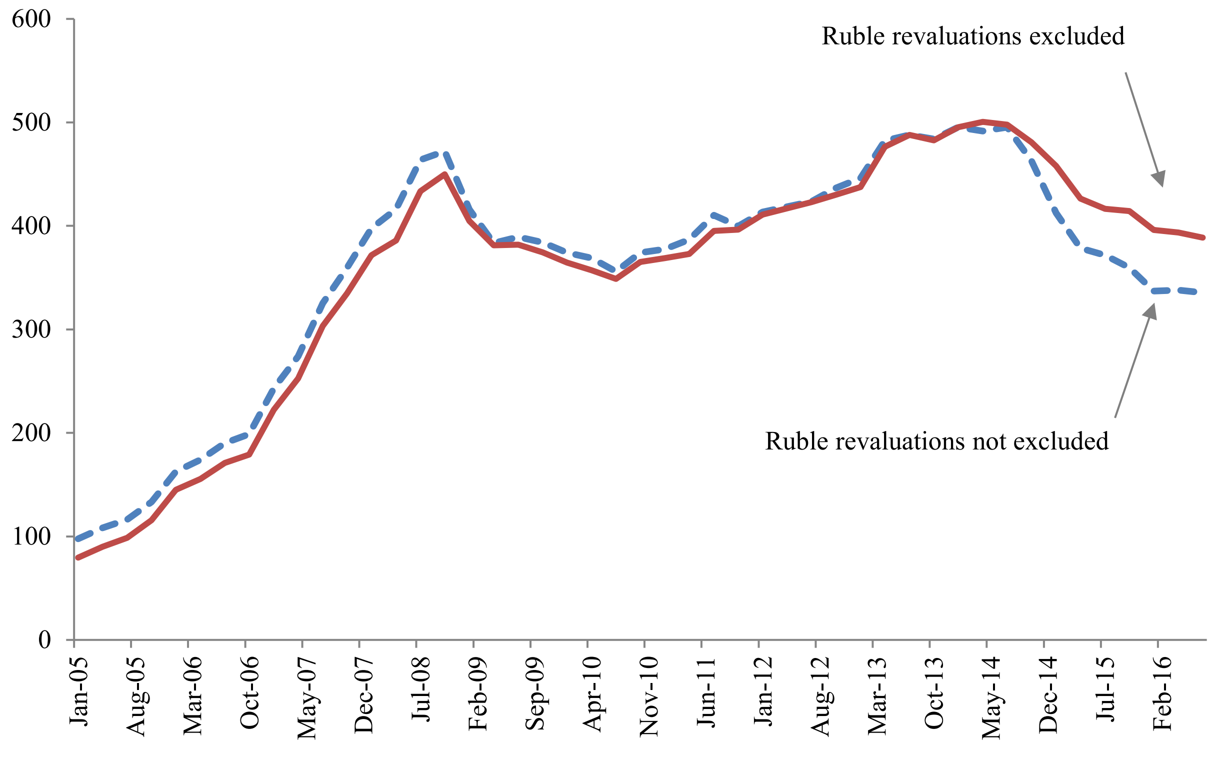
The data for our non-financial variables are retrieved from the free-access datasets of the Federal State Statistics Service of the Russian Federation (gks.ru). The financial data are obtained through the CBR's website (cbr.ru). As is standard, all variables are transformed in logs and further multiplied by 1,200 (except for the CBR key rate). We then apply the seasonal adjustment procedure X12 to export, import, GDP, wage, retail sales, investment, CPI and monetary base. The details on the sources and the data transformation are provided in Table A1 in the Appendix. The resulting time series appear in Fig. A1 (external sector variables), Fig. A2 (domestic non-financial variables), and Fig. A3 (domestic financial variables) in the Appendix.

[6] There is no reliable data on daily hours worked in Russia. Since most working places in Russia assume a fixed working day, the annual indicator of hours worked is relatively stable over time. There is also apparently no monthly indicator of hours worked in Russia. To the best of our knowledge, the Federal State Statistics Service of the Russian Federation (Rosstat) does not collect such data.

We address two other important issues for the Russian economy that could affect our BVAR estimations: *the currency composition of the corporate external debt* and *switching between monetary policy regimes*.

As roughly 20% of Russian corporate external debt is denominated in rubles, but expressed in US dollars, we eliminate the revaluation of the ruble part of the debt when considering corporate external debt in our model. We feel this is prudent because this ruble debt, when expressed in US dollars, shrinks during periods of ruble devaluation (the total amount of external debt is typically reported in the US dollars). Of course, this technical reduction does not reflect an actual decrease in corporate indebtedness – the ruble amount remains the same. To overcome this, we exclude the revaluation of the ruble part of the corporate external debt (Fig. 2). With revaluations excluded, we get a 24% decrease in the outstanding amount of the Russian corporate external debt in 2014–2015. If we would not remove the revaluation, we get a 32% decrease in the same period (Fig. 2).

Figure 2 Corporate external debt in Russia (in USD billion, estimates for the end of the period)



Note: The figure depicts our estimates of the monthly dynamics of corporate external debt (for details on the estimation procedure, see Table A1 in the Appendix).

Turning to switching monetary regimes, we see a significant change in CBR exchange rate policy in 2009, whereby the CBR shifts from strict management of the nominal exchange rate (accommodating short-run ruble fluctuations through interventions in forex markets) to a more market-based approach to managing the exchange rate. The ruble was subject to a managed-float arrangement until it was freely floated in November 2014. In other words, using nominal exchange rate for the entire period would likely bias the estimation results of our BVAR model.

To overcome this problem, we employ the Exchange Market Pressure (EMP) index to accommodates CBR exchange rate policy transitions. The EMP index, proposed by Girton and Roper (1977), is commonly used by researchers in distinguishing between successful and failed currency attacks (see also Kaminsky and Reinhart (1999), Bussiere and Fratzscher (2006), among many others). In our estimations, we use the following general representation of EMP:

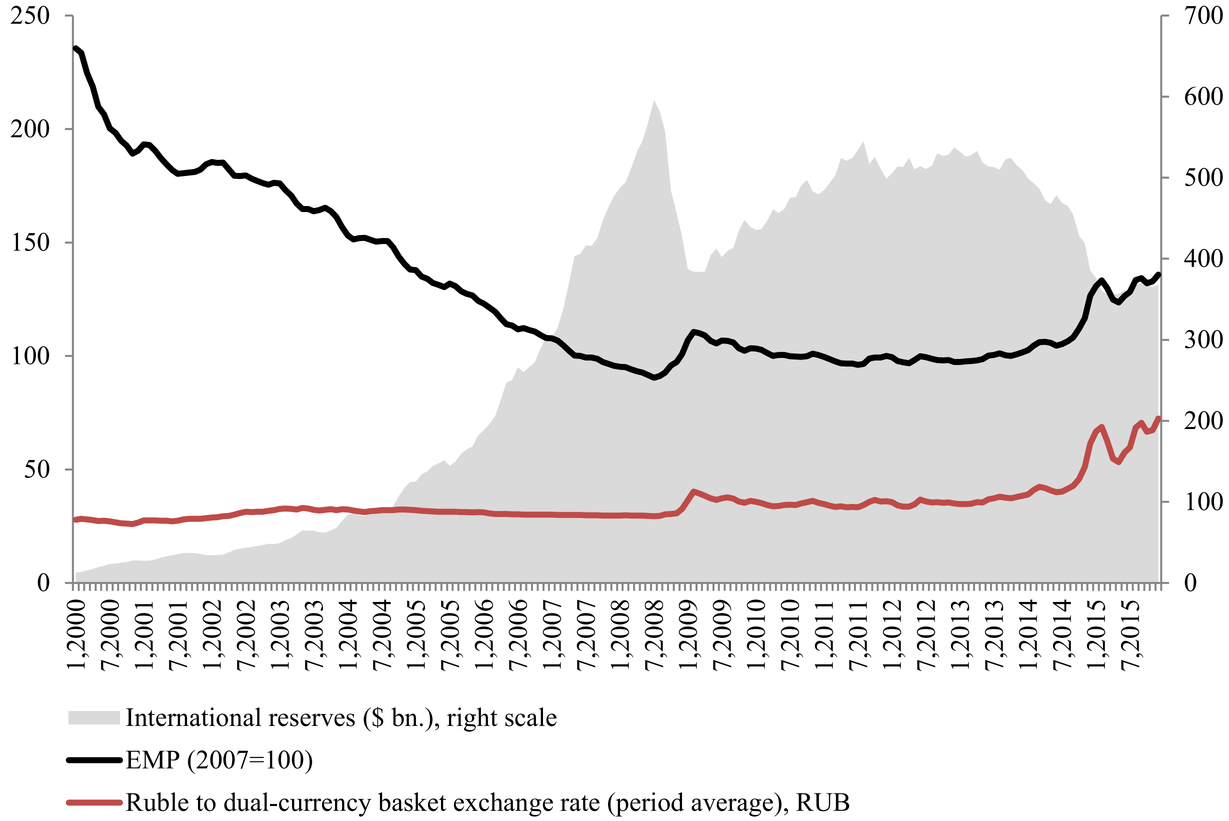
$$EMP = \frac{1}{\sigma_{ExRate}} \frac{\Delta ExRate}{ExRate} - \frac{1}{\sigma_{IntRes}} \frac{\Delta IntRes}{IntRes} \ , \tag{1}$$

where $ExRate$ is the official nominal exchange rate (ruble relative to a dual-currency basket composed of 0.55 US dollars and 0.45 euros, expressed in rubles, monthly averages). $IntRes$ is the international reserves of the CBR (USD billion). $\sigma_{ExcRate}$ and σ_{IntRes} are the whole-period standard deviations of $ExRate$ and $IntRes$, respectively.

By construction, when the ruble depreciates or the CBR sells international reserves, external pressure rises on the Russian foreign exchange market. The former corresponds to endogenous adjustment of exchange rate under a flexible exchange rate regime. The latter represents a situation in which the CBR (in a fixed exchange rate regime) withstands a currency attack by selling US dollars on its domestic market. Thus, we use this measure to capture policy regime shifts.

After calculating the growth rates of EMP index according to Eq. (1), we build the base EMP index, setting the value of EMP at the mid-2007 equal to 100. The results are shown in Fig. 3. Note the increased positive pressure on the ruble during the period of high oil prices and capital inflows (up to mid-2008 just ahead of the 2008–2009 financial crisis). During this time, the CBR prevented ruble appreciation by diverting oil earnings to its international reserves. As a result, the nominal exchange rate was stable, but the "shadow currency" appreciated (i.e. if the ruble was already floating freely). In the crisis periods 2008–2009 and 2014–2015, we see both the international reserves decline and the ruble exchange rate depreciation. In 2014, after the shift to a floating exchange rate in November, we see a sharper decrease in the ruble's exchange rate than in the 2008–2009 financial crisis.

Figure 3 The Exchange Market Pressure (EMP) index and its components in Russia



Sources: CBR data, author's calculations.

3.2 The BVAR model

We consider the following standard VAR process with N endogenous variables and P lags:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + _{\dots} + B_P Y_{t-P} + \varepsilon_t \ , \qquad (2)$$

where $Y_t = (Y_{1t}, Y_{2t}, \dots, Y_{Nt})'$ is a column vector containing the values of N endogenous variables at time t. $\varepsilon_t = (\varepsilon_{1t},\ \varepsilon_{2t}, \dots, \varepsilon_{Nt})'$ is a column vector with respective regression errors, which are assumed to be normally distributed with zero mean and covariance matrix $E(\varepsilon_t \varepsilon_t') = \Sigma$ of $N \times N$ size, $\varepsilon_t \sim N(0, \Sigma)$. Each matrix B_k comprises all unknown coefficients of all endogenous variables Y_t taken with lag k ($k = 1 \dots P$) and has $N \times N$ dimension. Therefore, each of N equations has $K = 1 + N * P$ unknown coefficients to be estimated.

According to Bayes law, the posterior distribution of unknown parameters $p(B, \Sigma | Y_t)$ is proportional to the product of the likelihood (data) $p(Y_t | B, \Sigma)$ and the prior distribution of parameters $p(B, \Sigma)$:

$$p(B, \Sigma | Y_t) \propto p(Y_t | B, \Sigma) \cdot p(B, \Sigma) . \tag{3}$$

We employ the non-conjugate prior, i.e. the Independent Normal-Inverted Wishart prior for the VAR coefficients B and the innovations covariance matrix Σ:

$$p(b, \Sigma) = p(b) \cdot p(\Sigma) . \tag{4}$$

We specify our prior for $b = vec(B)$ as $p(b) \sim N(b_0, H)$ and for Σ as $p(\Sigma) \sim IW(S_0, v)$, where b_0 is the $[N * (1 + N * P)] \times 1$ vector of prior means, H is the coefficients' covariance matrix of $[N * (1 + N * P)] \times [N * (1 + N * P)]$ size, S_0 is the scaling matrix and v is a parameter governing the degrees of freedom (see Blake and Mumtaz, 2012).

Prior means b_0 of the VAR coefficients B in each equation are set to:

(i) 1 (or, alternatively, an OLS-estimate from respective AR(1) representation of Y_{it}) at the first own lag, i.e. at Y_{it-1};

(ii) 0 at the deeper own lags, i.e. at Y_{it-p} for all $p = 2 \ldots P$; and finally,

(iii) 0 at all lags of the other variables, i.e. at Y_{jt-p} for all $j \neq i$ and $p = 1 \ldots P$.

The diagonal matrix $H = \{h_{kk}\}$ is the covariance matrix of the VAR coefficients B, where a diagonal element h_{kk} for any $k = N * (1 + N * P)$ is defined as:

$$\left(\frac{\lambda_1}{k^{\lambda_3}}\right)^2 \text{ if } i = j; \quad \left(\frac{\sigma_i \, \lambda_1 \lambda_2}{\sigma_j \, k^{\lambda_3}}\right)^2 \text{ if } i \neq j; \qquad \text{and } \left(\sigma_i \, \lambda_4\right)^2 \text{ for the constant terms; } i, j = 1 \ldots N . \tag{5}$$

The covariance matrix H is built to shrink the coefficients B of other variables and deeper lags towards zero more tightly. As is standard in the BVAR literature, we use as our rule-of-thumb values λ_1= 0.1 (general tightness), λ_2= 0.5 (significance of other variables), and $\lambda_3 = 1$ (own lags decay).

Once we set the independent priors for the BVAR coefficients B and the error covariance matrix Σ, we arrive at their joint posterior distribution of unknown form. Thus, we need to launch a Markov Switching Monte Carlo (MCMC) algorithm (Gibbs sampling in this case) to draw B and Σ from the posterior. We exploit the fact that the posterior distribution of $b = vec(B)$ conditional on Σ is Normal, and that the posterior distribution of Σ conditional on b is an inverted Wishart distribution. Both posteriors have known parameters (Koop and Korobilis, 2010; Blake and Mumtaz, 2012). The implementation of the Gibbs sampling using these facts is described by Blake and

Mumtaz (2012). In our basic specifications, we set 2,000 draws for the Gibbs sampling procedure, of which the first 1,000 are burned in.[7]

The described prior combines the advantages of the classical Minnesota prior (Doan et al., 1984) and natural conjugate priors. The prior allows for imposing small open economy restrictions on the coefficients (see e.g. Buckle et al., 2007; Dungey and Fry, 2009) and treats the error covariance matrix as random, allowing us to address the uncertainty about future shocks. In our version of small open economy restrictions, we place the external variables VIX, oil prices, and Russian exports on the first three positions in the BVAR, assigning zero prior covariances for the coefficients h_{kk} $(k = 1,2,3)$ to reflect our prior belief that the Russian economy does not influence the economies of other countries. For these three external variables, we suppose (i) that VIX can affect oil prices and Russian exports, (ii) that oil prices do not affect the VIX, but may influence Russian exports, and (iii) that Russian exports do not affect the VIX or oil prices. Additionally, we assume that Russian domestic variables cannot influence Russian exports as the latter are determined by the external demand for oil, gas and their products.

3.3 Choosing hyperparameters through unconditional out-of-sample forecasting

Before proceeding to the conditional forecast exercises, we optimize the values of the prior hyperparameters $\lambda_1, \lambda_2, \lambda_3$ on a grid that includes our rule-of-thumb values (0.1, 0.5, 1). We then estimate respective BVAR models on the various subsamples. We start from the period January 2000 to December 2011, then compute the unconditional out-of-sample forecasts for the rest of the time period in the sample (January 2012 to December 2015). For each forecast, we calculate the root mean squared forecast errors (RMSFEs). Specifically, we use the estimated BVAR parameters to produce the out-of-sample unconditional forecasts for 3, 6, and 12 months ahead. For each variable, we store its RMSFEs at each forecasting horizon. Further, we add one month into the sample (e.g. the sample ends with January 2012 instead of December 2011, and so on), obtain new coefficients and repeat the forecasting exercise. We do so until we reach the end of the sample (e.g. December 2015). Finally, for each forecasting horizon, we take the average of the calculated RMSFEs to obtain a single measure of forecasting accuracy. For each variable Y_i $(i = 1 \dots 14)$, the RMSFEs are calculated in absolute terms and then divided by their respective time-series average.

The estimation results are presented in Table 1. Panel 1 contains the RMSFEs for a 3-month forecasting horizon, Panel 2 for a 6-month horizon, and Panel 3 for a 12-month horizon. The

[7] Increasing the number of draws to 5,000 (10,000), of which 2,000 (5,000) are burned-in, yields similar results.

comparisons show that the lowest values of RMSFEs for most variables are achieved under the following combination of hyperparameters: $\lambda_1 = 0.1,\ \lambda_2 = 0.5,\ \lambda_3 = 2$. This holds for all forecasting horizons considered. In the next step, conditional forecasting, we employ this specific combination of hyperparameters.

Table 1 Unconditional out-of-sample performance of the BVAR model

Hyper			RMSFE																
λ_1	λ_2	λ_3	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	Y_9	Y_{10}	Y_{11}	Y_{12}	Y_{13}	Y_{14}
Panel 1: Forecasting horizon = 3 months																
0.1	0.5	1	5.95	2.2	1.15	0.049	0.16	0.09	0.30	1.86	0.12	0.56	0.17	9.13	0.24	1.39
0.1	0.1	2	5.88	1.9	1.32	0.057	0.18	0.10	0.30	1.90	0.13	0.43	0.15	8.86	0.21	1.36
0.1	0.1	1	5.86	2.0	1.22	0.058	0.17	0.10	0.30	1.86	0.13	0.45	0.15	8.25	0.23	1.37
0.1	0.5	2	6.05	1.6	1.19	0.053	0.15	0.10	0.28	1.51	0.14	0.43	0.12	6.83	0.21	0.98
0.05	0.1	1	5.86	1.9	1.24	0.055	0.18	0.11	0.32	1.88	0.13	0.44	0.14	6.97	0.21	1.36
0.05	0.5	2	5.91	2.0	1.17	0.054	0.18	0.09	0.31	1.80	0.13	0.45	0.16	8.19	0.22	1.37
0.05	0.1	2	5.98	2.0	1.37	0.057	0.19	0.11	0.32	1.86	0.13	0.45	0.14	8.00	0.19	1.34
0.05	0.5	1	5.86	2.0	1.16	0.051	0.18	0.09	0.31	1.84	0.13	0.48	0.16	6.69	0.23	1.39
Panel 2: Forecasting horizon = 6 months																
0.1	0.5	1	6.71	3.0	1.30	0.064	0.22	0.15	0.36	2.90	0.24	0.99	0.25	13.57	0.36	2.20
0.1	0.1	2	6.99	2.6	1.60	0.080	0.23	0.17	0.36	2.85	0.26	0.79	0.21	13.94	0.31	2.14
0.1	0.1	1	6.93	2.7	1.42	0.083	0.23	0.18	0.36	2.82	0.26	0.83	0.20	12.44	0.34	2.13
0.1	0.5	2	6.68	2.3	1.25	0.058	0.17	0.18	0.33	2.23	0.22	0.85	0.20	9.76	0.30	1.60
0.05	0.1	1	6.90	2.7	1.50	0.077	0.23	0.17	0.37	2.81	0.25	0.79	0.19	11.45	0.29	2.15
0.05	0.5	2	6.76	2.8	1.35	0.071	0.22	0.15	0.34	2.72	0.26	0.82	0.25	11.67	0.30	2.13
0.05	0.1	2	7.00	2.7	1.72	0.080	0.24	0.18	0.38	2.79	0.25	0.77	0.17	12.15	0.25	2.10
0.05	0.5	1	6.85	2.8	1.32	0.065	0.23	0.15	0.34	2.76	0.25	0.87	0.24	11.71	0.32	2.15
Panel 3: Forecasting horizon = 12 months																
0.1	0.5	1	7.98	4.6	1.43	0.139	0.34	0.33	0.51	5.18	0.47	1.79	0.37	20.51	0.58	3.50
0.1	0.1	2	8.61	4.0	2.03	0.158	0.36	0.32	0.53	4.86	0.50	1.45	0.30	21.52	0.51	3.36
0.1	0.1	1	8.41	4.2	1.70	0.166	0.36	0.33	0.53	5.06	0.51	1.51	0.28	17.90	0.58	3.36
0.1	0.5	2	8.01	4.6	1.35	0.131	0.31	0.50	0.46	4.33	0.49	1.92	0.35	16.29	0.49	2.89
0.05	0.1	1	8.50	4.2	1.90	0.158	0.36	0.34	0.56	4.94	0.48	1.45	0.23	18.13	0.49	3.34
0.05	0.5	2	8.29	4.3	1.60	0.132	0.34	0.30	0.43	4.71	0.49	1.46	0.39	17.90	0.49	3.31
0.05	0.1	2	8.62	4.2	2.26	0.162	0.37	0.34	0.58	4.87	0.47	1.44	0.22	17.63	0.42	3.22
0.05	0.5	1	8.38	4.3	1.53	0.131	0.34	0.30	0.45	4.81	0.48	1.52	0.37	18.74	0.51	3.35

Note: The table contains the root mean squared forecast errors (RMSFE, as a % of average). Estimation period: January 2000 – December 2011. Out-of-sample forecasting period: January 2012 – September 2015. Minimal obtained values of the RMSFE are marked in red (by columns).

Prior hyperparameters: λ_1 stands for the general tightness of prior, λ_2 for tightness on other variables, and λ_3 for tightness on own lags decay.

External sector: Y_1 is the VIX, Y_2 the Urals oil price, and Y_3 Russian exports in constant 2007 prices.

Domestic non-financial variables: Y_4 represents GDP, Y_5 wages, Y_6 retail sales, Y_7 investment, Y_8 Russian imports (Y_4 to Y_8 in constant 2007 prices), and Y_9 CPI inflation.

Domestic financial and monetary variables: Y_{10} is corporate external debt, Y_{11} outstanding bank loans to the private sector, Y_{12} the monetary policy interest rate (CBR key rate), Y_{13} for the monetary base, and Y_{14} the exchange market pressure index (weighted average of nominal exchange rate and international reserves, EMP).

Our preferred combination of hyperparameters largely corresponds to the rule-of-thumb values used in the literature (see e.g. Carriero et al., 2015), with the difference that we choose a higher value for the own lags decay parameter (stricter λ_3). Given the relatively small number of observations in our sample, we are likely subject to larger uncertainty when considering deeper lags in the BVAR model. We also consider a more detailed grid for the values of hyperparameters, allowing for the hyperparameters values corresponding to a looser prior. We compare the results of our conditional forecasts produced under the chosen set of hyperparameters with those generated with less strict alternatives in the additional exercise in Section 4.7 below.

3.4 Conditional forecasting with the BVAR model

We test the empirical performance of estimated BVAR model by computing pseudo out-of-sample scenario forecasts, built on the basis of known (realized) external conditions for the period of 2014–2015, when the Russian economy is hit simultaneously by two external shocks (Western financial sanctions and falling oil prices). Details on this empirical application are discussed below in Section 4. Here, we briefly outline the algorithm of conditional forecasting with BVAR.

Conditional forecasts can be treated as restrictions on the future paths of certain endogenous variables. These restrictions, in turn, may be considered as constraints for the future shocks of the variables that force their future paths to deviate from their respective unconditional forecasts. This is the basic idea for obtaining point conditional forecasts as described by Doan et al. (1984), who also derived the optimal least-square solution for constrained shocks.[8] Technically, this idea implies drawing all shocks ε that satisfy the constraint $R\varepsilon = r$, where R is a matrix composed of impulse responses of all conditioned (restricted) variables to all shocks ε, and r is a vector that contains the deviations of the scenario paths of conditioned variables from their respective unconditional forecasts.

[8] Also see Robertson and Tallman (1999) for a simple empirical illustration.

When producing out-of-sample scenario forecasts, the results need to be compared against the actual paths of respective variables, so we need certain bounds. A natural way of getting such bounds is density forecasting. Waggoner and Zha (1999) propose a Gibbs sampling algorithm for density forecasting under given conditions via VAR and prove that the estimation results for conditional forecasts do not depend on how the shocks are identified.

The initial challenge here is adapting the forecasting algorithm of Waggoner and Zha (1999) to our BVAR model. Adaptation implies two separate Gibbs sampling algorithms instead of just one, i.e. one for the BVAR model and another for the conditional forecast. Blake and Mumtaz (2012) document seven estimation steps:

(i) Estimation of BVAR model, under chosen priors, on actual data using the first Gibbs sampling and then the orthogonalization of shocks, under the chosen scheme, most often, Cholesky (A).
(ii) Computation of unconditional forecast via BVAR ($y_1 = xB$).
(iii) Calculation of the deviations of scenario conditions from the unconditional forecasts of respective variables (r).
(iv) Estimation of the impulse response functions for the conditioned variables on all shocks (R).
(v) Estimation of the paths of constrained shocks for the conditioned variables (ε).
(vi) Computation of point conditional forecasts ($y_2 = xB + \mathrm{A}\varepsilon$).
(vii) Launching the second Gibbs sampling with the loop containing the following typical iteration: Iteration j ($j = 1 ... Q$): estimation of BVAR on extended data, comprised of actual y and point forecasts $y_{2,\, iter\, j-1}$, and then repetition of the steps 1–6 and getting the new point forecast $y_{2,\, iter\, j}$.

Eventually, the empirical density forecast is achieved with these Q point forecasts.

A similar algorithm is employed in Bloor and Matheson (2011) to compute the conditional forecasts for the New Zealand economy. Banbura et al. (2015) apply an alternative algorithm, based on the Kalman filtering, for conditional forecasting of euro-area macroeconomic indicators.

In our estimations, we set 2,000 draws for the Gibbs sampling algorithm of Waggoner and Zha (1999), of which the first 1,000 are discarded (burned in).[9]

[9] When we increase the number of draws to 5,000 (10,000), of which 2,000 (5,000), are burned-in, we get qualitatively similar conclusions.

4 Empirical results: Conditional forecasts with the BVAR model

In this section, we describe the out-of-sample conditional forecasts that we produce with our preferred BVAR specification. Recall that we are producing the hypothetical situation of an econometrician in 2013, who knows the model parameters as of end-2013 and the actual paths of external conditions in 2014–2015. This prescient econometrician then attempts to uncover two possible trajectories of the macroeconomic development in Russia in 2014–2015: one where a single negative shock occurs (a drop in oil prices), and a second where two negative shocks realize (an oil price drop and imposition of financial sanctions). In both cases, global financial volatility is known to the econometrician and thus set at the levels produced by our unconditional forecast. Essentially, the difference between the two trajectories represents our estimate of the economic effect of the Western sanctions on Russia.

We present the forecasting results in the following order. We start with GDP growth rates as the main indicator reflecting the state of the economy. Second, we provide the results for the growth rates of retail sales and investment, which give a clue of the behavior of the GDP components, i.e. consumption and investment. We do not present the results for Russian exports, because the supply of exports fully adjusts to demand from international markets. We also assume that Russia cannot influence prices or quantities of exported goods (at least in the short run). Third, we present the forecasting results for the growth rates of real wages. Fourth, we examine the results for CPI inflation and the ruble's exchange rate as captured by EMP. Fifth, we consider the forecasts for Russian imports. Finally, we discuss the forecasting results for the financial variables of our BVAR model: the main interest rate (CBR key rate), and the growth rates of the stock of domestic commercial loans and monetary base. We thus cover ten of the 14 variables in our model, recalling that three variables (corporate external debt, oil prices, and VIX) are used as conditions and that one variable (exports) is omitted deliberately.

For each of the 10 variables presented, we provide two graphs corresponding to the forecasted paths under Condition 1 (known oil prices) and Condition 2 (known oil prices and corporate external debt). We stress that it is unclear *ex ante* which variables will be better forecasted than others in terms of RMSFE. Moreover, we do not expect to achieve good forecasts in all ten cases. Indeed, good forecast performance is not assured in the case of the Russian economy as we cannot account fully for certain rigidities (e.g. labor market). Instead, our focus is (i) on the size of the difference between forecasts under Conditions 1 and 2, and (ii) on whether a forecast under Condition 2 is closer to actual values than a forecast under Condition 1.

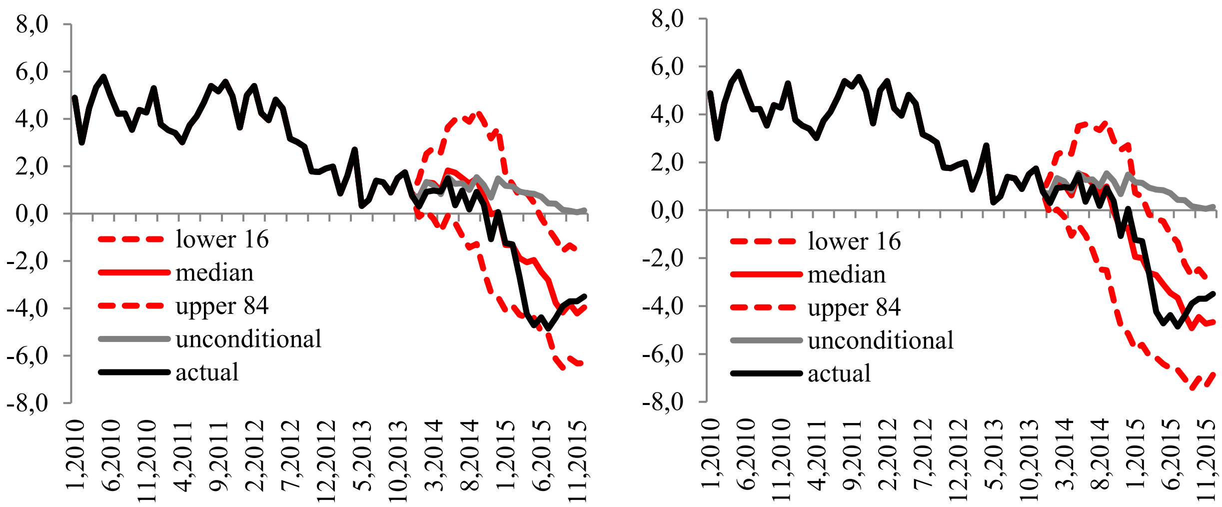
4.1 GDP growth rates

The forecasting results for the GDP growth rates appear on Fig. 4 below. The results suggest that, under Condition 2, which conditions on both the actual drop in the Urals oil price and the restricted access to the external market of corporate debt caused by financial sanctions (Fig. 4B), we can better reproduce the GDP growth decline in Russia in 2014–2015 than under Condition 1 (Fig. 4A). In graphical terms, the solid red line representing the median conditional forecast, is closer to the actual-path black line in Fig. 4B than in Fig. 4A. Moreover, the actual path lies inside the credible set of our BVAR conditional forecast.

Further calculations show financial sanctions are responsible for slowing GDP growth rates by 0.43 percentage points in 2014 and 0.74 percentage points in 2015. Thus, the cumulative effect for 2014–2015 can be estimated as 1.17 percentage points (median estimate).

The economic effect of the Western sanction on the GDP growth rates in Russia is substantial, given that the actual growth rates in 2014 and 2015 were 0.7% and –2.3%, respectively. In other words, we say the impact of the effect more than negligible but less than devastating. The forecasted and actual numbers imply that an economic crisis would have happened independent of financial sanctions.

Figure 4 Conditional forecasts for ***GDP growth*** rates in Russia under the two scenario conditions (month over the corresponding month in the previous year, %).



A) Condition 1: Urals oil price drop

B) Condition 2: Urals oil price drop and introduction of financial sanctions

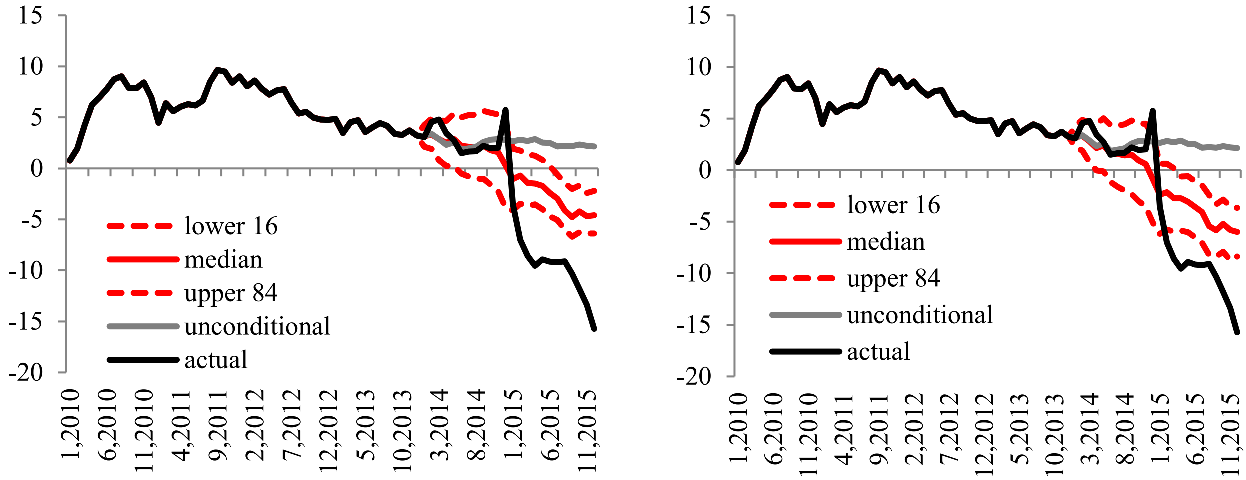
Note: Both conditions also contain the actual path of the VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

Importantly, if we calculate the difference between the GDP forecasts under the two scenarios, we see that the median line lies in the negative area in each month. However, we obtain high uncertainty about the exact quantitative effect of the sanctions, which is reflected by rather wide credible sets (see Fig. A4 in the Appendix). On average, 61% of the probability mass in 2014 and 70% in 2015 are located in the negative area. Therefore, we conclude with high probability that the effect of the sanctions on the Russian GDP growth rates is negative.

4.2 Retail sales and investment

The forecasting results for retail sales (Fig. 5) suggest that the forecasted path under Condition 2 is closer to the actual path than under Condition 1. The effect of financial sanctions on retail sales is negative, but the actual decline of retail sales during the economic crisis in Russia in 2014–2015 is so deep that we are unable to capture it with our BVAR conditional forecasts. Thus, the actual path lies below the lower bound of the credible set in both cases. We stress that both conditional forecasts lie in the area of negative values, as does the actual path, while the unconditional forecast remains positive. The latter provides an additional support for the importance of accounting for external shocks when forecasting for an open economy like Russia.

Figure 5 Conditional forecasts for ***retail sales*** growth rates under the two scenario conditions (month over the corresponding month of the previous year, %)



A) Condition 1: Urals oil price drop

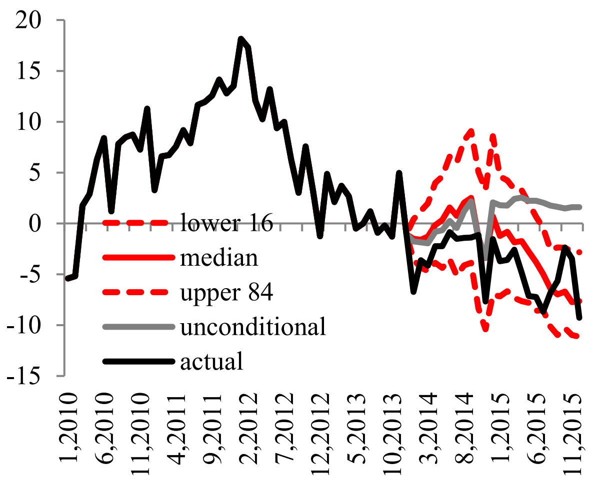
B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of the VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

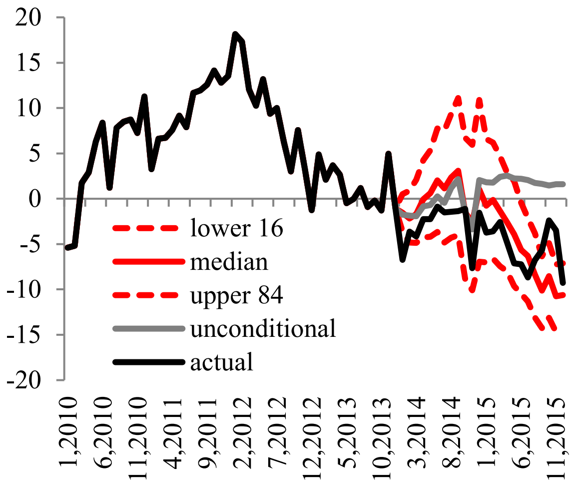
Further analysis indicates that financial sanctions are responsible for a decline in the retail sales growth rate of 0.54 percentage points in 2014 and 1.24 percentage points in 2015. The cumulative effect for the two years is 1.77 percentage points, which is a third greater than the effect on GDP growth rates. Given the actual path of retail sales growth, which imply 5.7% growth in 2014 and a contraction of 15% in 2015, the estimated effect of the financial sanctions is modest at best.

For the other GDP component, investment growth rates (Fig. 6), we obtain better conditional forecasts *per se* than for retail sales. Both forecasted paths are closer to the actual path, and the actual path lies within the credible set. Unlike the two previous cases, the slowdown from financial sanctions becomes evident only in the second year after sanctions are introduced. Financial sanctions causes a slowing in the investment growth rates of 1.37 percentage points in 2015. In 2014, the difference between growth rates under Condition 2 and Condition 1 is slightly positive, 0.18 percentage points. The cumulative effect amounts to 1.19 percentage points decline for the two years, which is quite similar to the effect obtained for GDP growth rates. Clearly, financial sanctions have caused a decline in investment in Russia. They pushed Russian firms with external debt to deleverage, tightening their financing constraints. However, as our conditional forecasts imply, the effect of the sanctions on investment is also modest.

Figure 6 Conditional forecasts for ***investment*** growth rates under the two scenario conditions (month over corresponding month of the previous year, %)



A) Condition 1: Urals oil price drop



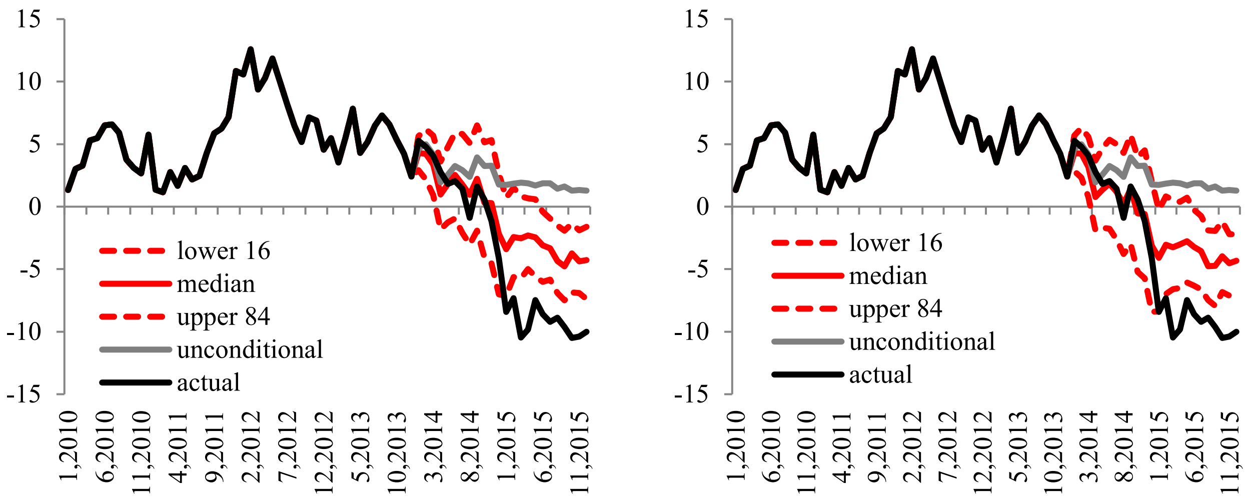
B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

4.3 Real wages

For growth rates of real wages (Fig. 7), the forecasting results are qualitatively quite similar to those obtained for retail sales. Both conditional forecasts of the BVAR lie in the negative area, but fail to predict the depth of the actual decline of real wages. The unconditional forecast of the BVAR lies in the positive area, and thus unable to predict actual dynamics. The overall effect of financial sanctions is again modest at best, accounting for 0.53 percentage points decline in the growth rates of real wages in 2014 and a 0.35 percentage points decline in 2015. The cumulative effect is 0.88 percentage points for the two years.

Figure 7 Conditional forecasts of ***real wage*** growth rates under the two scenario conditions (month over corresponding month of the previous year, %)



A) Condition 1: Urals oil price drop

B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

4.4 CPI inflation and exchange market pressure (EMP) on the ruble

For CPI inflation (Fig. 8), the forecasting results clearly show we are unable to capture under Condition 1 or Condition 2 the actual surge in the price level that took place during the 2014–2015 economic crisis. While the model shows an acceleration of CPI inflation in both scenarios, the median, and even upper bound, of the forecasted paths lie below the actual values. One possible explanation is that we have underestimated ruble exchange rate depreciation observed in 2014 in our model. This would likely be due to a missing component for negative speculative expectations as expectations would increase ruble exchange rate volatility.[10] Such volatility might then affect Russian domestic prices, given a large average share of imports at domestic markets for goods and services (35% in 2014). In addition, we might have underestimated the duration, and thus strength, of the exchange rate pass-through effect. This is because our choice for the optimal shrinkage of the deeper lags in the BVAR model is rather strict (the optimal λ_3 equals 2).[11] Finally, the inability of the model to capture the CPI inflation surge might be explained by Russian counter-sanctions. In August 2014, Russia banned imports of certain agricultural goods from countries that target Russia with sanctions. The subsequent rise of the foodstuff prices on the Russian domestic market could contribute to CPI inflation in the aftermath of counter-sanctions. Due to the challenges of making an aggregate indicator that captures intensity of the food embargo, we forego dealing with counter-sanctions in this study.

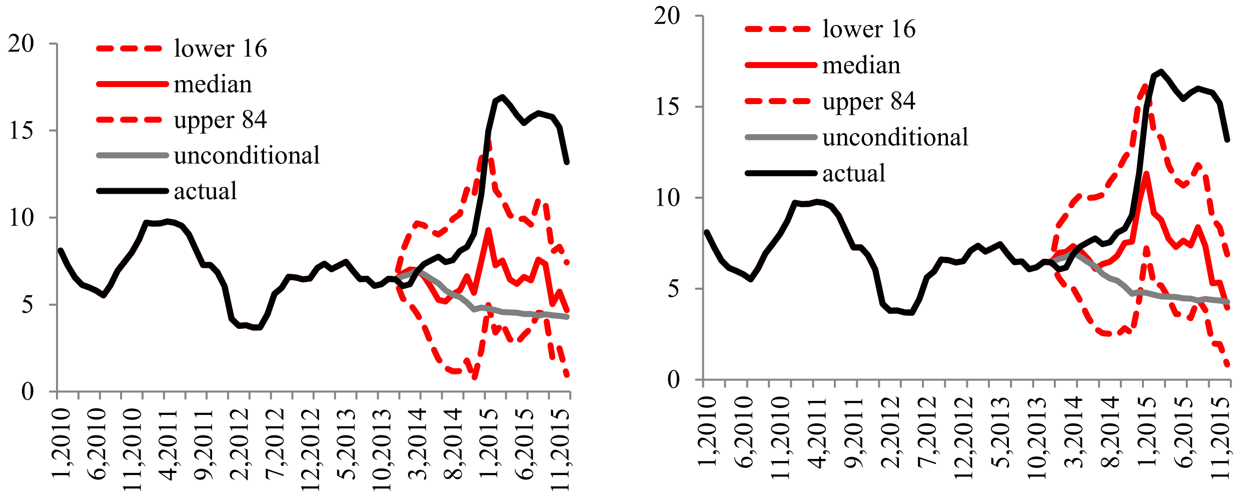
Further calculations demonstrate that financial sanctions imposed by Western countries caused a significant, but modest, acceleration of CPI inflation in Russia. Specifically, the difference between the forecasted paths under Condition 2 and Condition 1 is 0.89 percentage points in 2014 and 0.80 percentage points in 2015, with a cumulative effect of 1.69 percentage points for the two years (year average). This corresponds to 13% of overall CPI inflation at the end of 2015.

Our BVAR forecasting results already suggest that underestimation of CPI inflation may partially explain our overestimation of the retail sales paths in Fig. 5 and real wages in Fig. 7. As mentioned earlier, these indicators are measured in constant prices.

[10] This could be addressed with a stochastic volatility component. We do not consider the heteroscedastic case here, because estimating the parameters of the model can become computationally burdensome when applied to the medium-sized model with non-conjugate prior, Moreover, addressing stochastic volatility would unlikely change the forecast median.

[11] We might also miss the changed sensitivity of domestic prices to external shocks due to the shift in the exchange rate regime in 2009 (see above). Under a floating exchange rate regime, the response of prices to deterioration of external conditions is more pronounced than in the case of a fixed exchange rate regime, where the CBR has ceased to fight ruble depreciation by selling the its international reserves. Thus, the inflationary effect appears to be stronger under the new regime.

Figure 8 Conditional forecasts for ***CPI inflation*** under the two scenario conditions (month over the corresponding month of the previous year, %)



A) Condition 1: Urals oil price drop

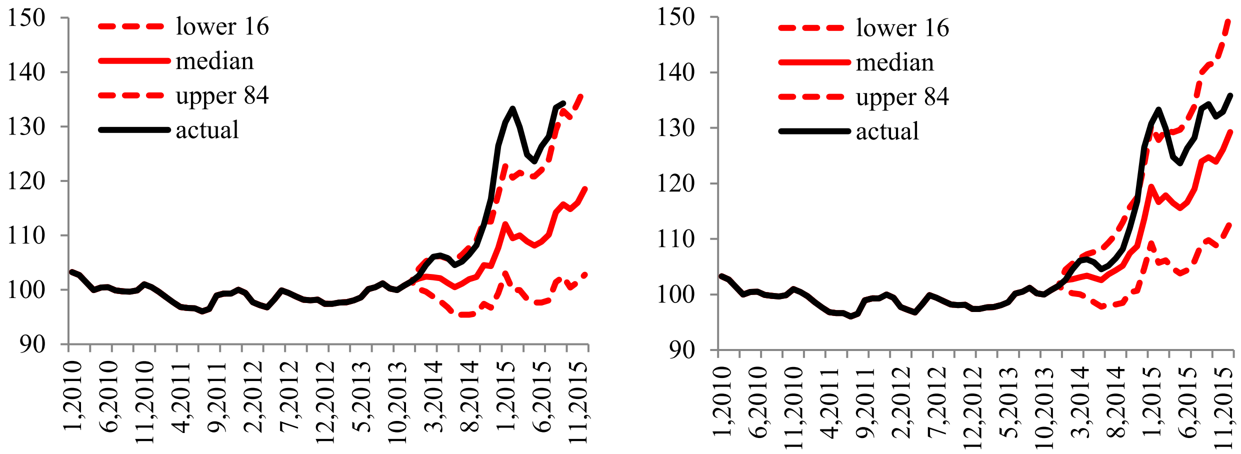
B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

For exchange market pressure on the ruble (Fig. 9), the forecasting results suggest that the forecasted path under Condition 2 clearly outperforms the forecast under Condition 1. The actual path of EMP is bounded by the credible set in the former case, and even the upper bound lies below the actual line in the latter case. In other words, conditioning on both shocks (oil prices drop and the sanctions) allows us to better reproduce the actual dynamic of EMP than conditioning on just one shock (oil prices drop). The implied difference between the two conditional forecasts indicate that financial sanctions contributed to further ruble depreciation, despite the fact that Russia had moved from a *de facto* fixed exchange rate regime to the floating arrangement in 2009.[12] Specifically, this difference equals 6 percentage points of EMP in 2014 and 11 points in 2015, i.e. 17 points for the two years. Given that the actual change of the EMP index equaled 25 points in 2014 and 9 points in 2015, we can conclude that in 2014, the effect of the sanctions was, while this effect became predominant, even quantitatively overshooting the actual dynamics of EMP in 2015.

[12] Before 2009, external shocks were largely absorbed by the CBR's foreign exchange interventions.

Figure 9 Conditional forecasts for ***exchange market pressure*** index (EMP, base index, 2007 = 100) under the two scenario conditions



A) Condition 1: Urals oil price drop

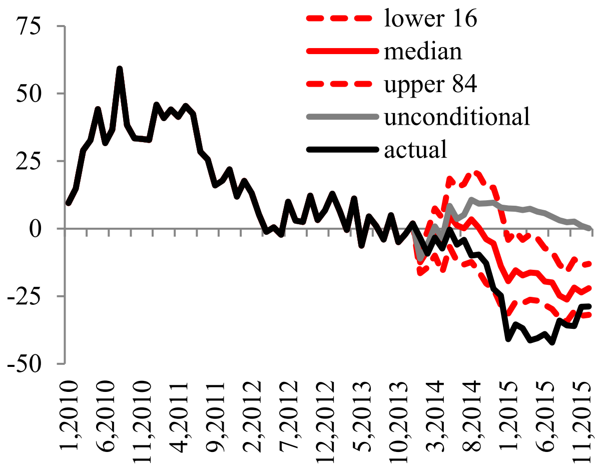
B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

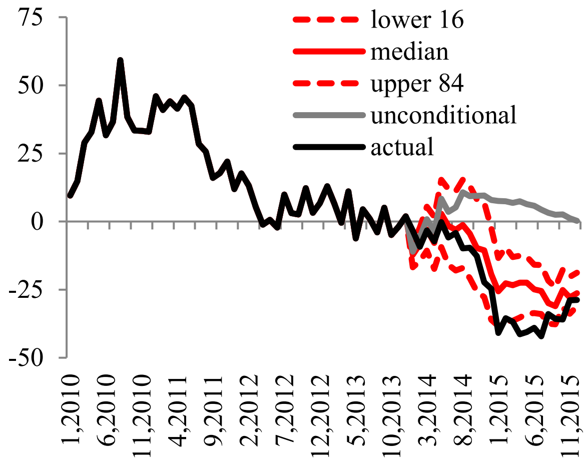
4.5 Imports

For the import growth rates (Fig. 10), the forecasting results suggest the BVAR model is able to capture the decline in the demand for import, caused by the recession in Russia. Moreover, with the corporate external debt in the conditioning set (i.e., under condition 2), we reproduce the actual dynamic of the Russian import better than without (i.e., under condition 1). In addition, the actual path lies within the credible set most of the time. Further calculations emphasize the effect of the sanctions – a 3.0 slowdown in imports in 2014 and 5.4 percentage points in 2015. The cumulative effect reaches thus 8.4 percentage points for the two years, which constitutes 36% of the observed decline in the Russian import. Unlike our previous variables, we obtain a substantial effect from financial sanctions. Note that approximately 50% of the Russian imports came from the EU countries, meaning that sanctions may have also negatively affected Russia’s EU trading partners.

Figure 10 Conditional forecasts for ***import*** growth rates under the two scenario conditions (month over corresponding month of the previous year, %)



A) Condition 1: Urals oil price drop



B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

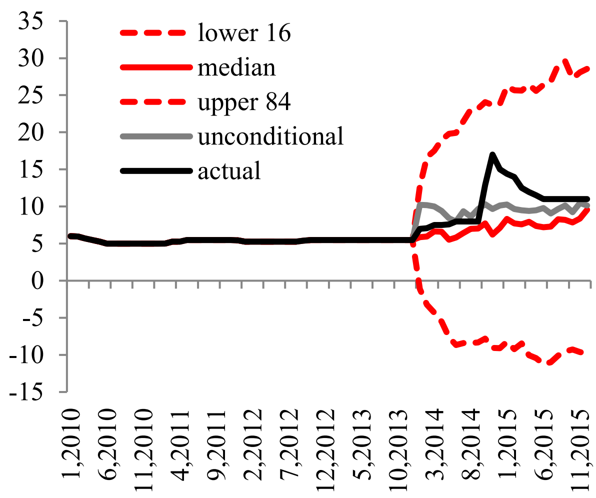
4.6 Financial variables: Interest rates, commercial loans, and monetary base

Turning to the CBR's key rate (Fig. 11), we note the large uncertainty on the forecasting horizon. It is substantially larger than for the other variables under Conditions 1 and Condition 2. In the first half of the forecasting window, i.e. before the CBR's decision to raise the rate from 10.5% to 17% in December the forecasted path under Condition 1 fits the actual dynamics of the key rate much better than under Condition 2. Conversely, on the second half of the forecasting window, the situation reverts: the forecasted path under Condition 2 captures the actual dynamic of the key rate, while the forecast under Condition 1 fails to fit the surge of the key rate. Our BVAR model indicates that the CBR, instead of implementing policy through a single, abrupt rate hike, could have begun raising the key rate at the start of 2014 and gradually raised the key rate during the year.

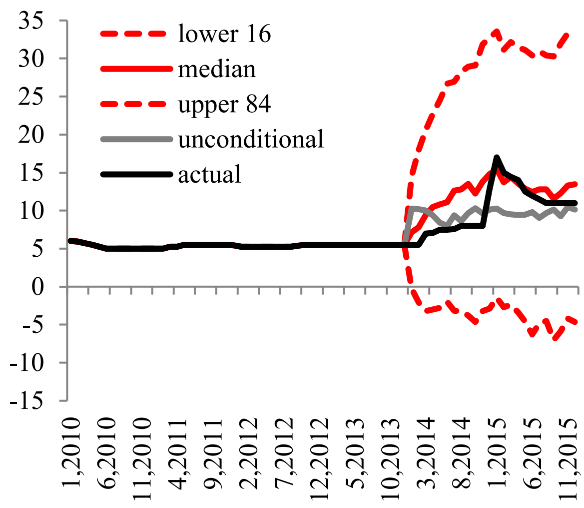
In interpreting these findings, we recall that interest rate in our model reacts to both exchange rate and the CBR's international reserves (accommodated by EMP). During 2014, the CBR sold reserves to counteract depreciation pressures on the ruble. It also postponed its decision on raising the key rate. In other words, the CBR still felt in 2014 that it could conduct interest rate policy by ignoring the effects from sanctions and focusing solely on the oil price drop. The tightening of restrictions on external debt and capital outflows were eventually impossible to brush aside, and during 2015, dealing with these effects came to rival the oil price drop in the CBR interest rate policy. Finally, we observe huge uncertainty around the interest rate path due to a change in the monetary policy regime (the CBR switched to full inflation-targeting in late 2014, starting to manage interest rates only), which took place *after* the in-sample period, leaving no chance for the model to capture this switching effect.

Further calculations show that financial sanctions may have been responsible for upward pressure on the key rate of 4.9 percentage points in 2014 and 5.3 percentage points in 2015. The effect is huge, given that the key rate was 5.5% at the end of 2013. Naturally, we treat these results with caution due to the large uncertainty in the forecasted paths discussed above.

Figure 11 Conditional forecasts for the ***CBR key rate*** under the two scenario conditions (monthly average, %)



A) Condition 1: Urals oil price drop



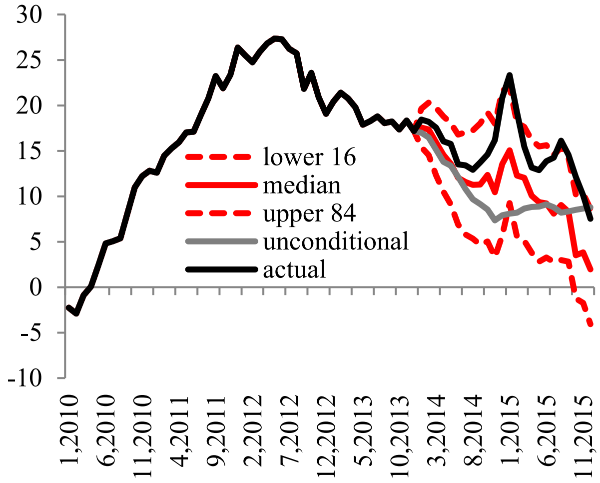
B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

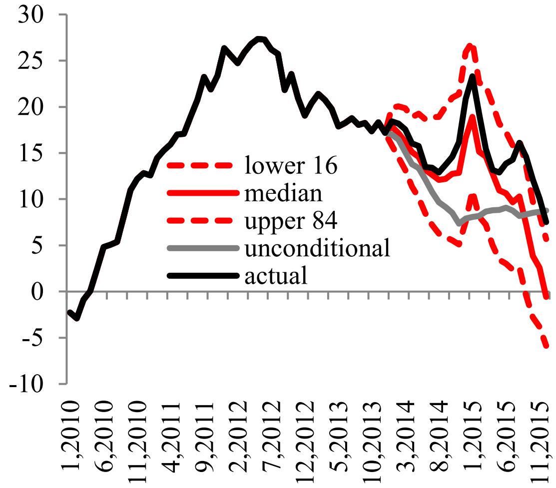
For the loans issued by the domestic banking system to domestic non-financial firms and households (Fig. 12), several outcomes emerge from the forecasting results. First, the slowdown of the bank loans had started in early 2014, six months before sanctions were introduced. This is captured by both conditional forecasts, as well as by the unconditional forecast, which may reflect internal drivers in Russia's macroeconomic recession.

Second, the rebound in the dynamics of loans, which started in mid-2014 and lasted through 2015, is likely to reflect the substitution effect of sanctions and ruble depreciation (the on-paper increase and decrease back the ruble-equivalent of the part of the loans denominated in foreign currency). This substitution effect means domestic non-financial borrowers replace external debt with loans from Russian banks. As in the previous cases, taking the difference between the two conditionally forecasted paths should eliminate the second effect, thus revealing the effect of the sanctions. This calculation shows that the effect of the sanctions is not that large, amounted to +1.0 and +1.1 percentage points in 2014 and 2015, respectively. The cumulative effect for the two years is an increase of 2.1 percentage points (annualized loan growth equaled 18% at the end of 2013), meaning that a part of the corporate external debt reduction was replaced with loans from domestic financial institutions.

Figure 12 Conditional forecasts for growth rates of ***bank loans*** to non-financial firms and households under the two scenario conditions (month over corresponding month of the previous year, %).



A) Condition 1: Urals oil price drop

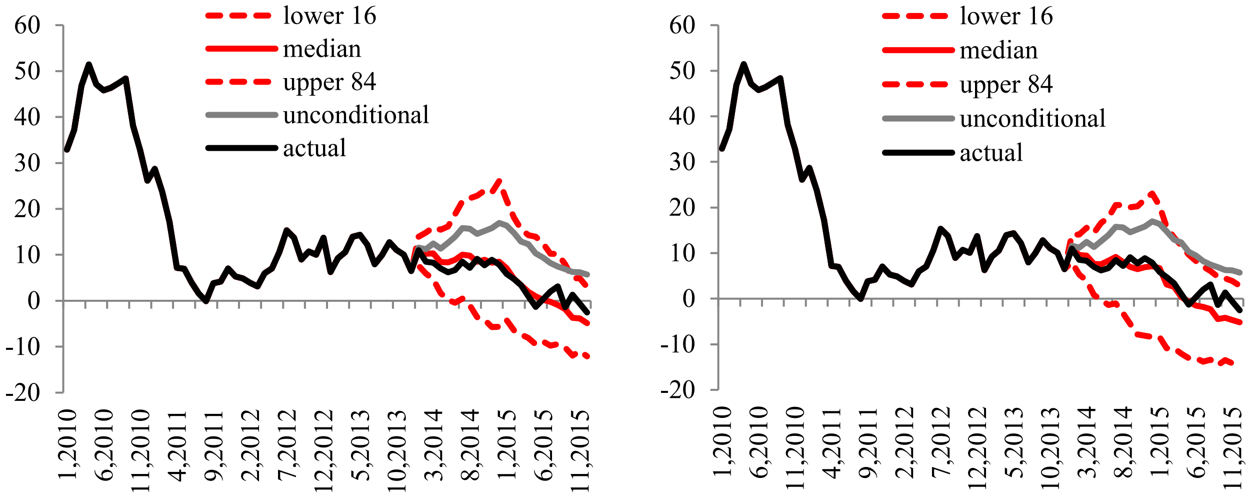


B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

For the monetary base (Fig. 13), the forecasting results demonstrate an excellent fit under both Conditions 1 and 2. Although it predicts on average a faster expansion of the monetary base, even the unconditional forecast lies within the credible sets of each of the two conditional forecasts. This good fit may partially be explained by the inclusion of EMP into the model. EMP contains a component for the CBR's international reserves, which are connected to the monetary base via the CBR's balance sheet. Further calculations show that the sanctions could lead to an average annual slowdown of the monetary base dynamics by 1.1 percentage points in 2014 and 1.3 percentage points in 2015. These effects are quite modest, given that average growth rate in recent years was approximately 10%.

Figure 13 Conditional forecasts for ***monetary base*** growth rates under the two scenario conditions (month over corresponding month of the previous year, %)



A) Condition 1: Urals oil price drop

B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

4.7 Varying hyperparameter tightness: A comparison of conditional forecasts

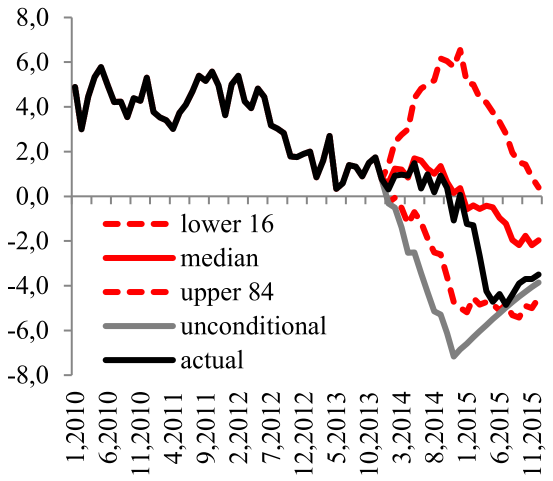
In this section, we discuss the sensitivity of the conditional forecasting results after relaxing the hyperparameters governing our priors. In Section 3.3, we chose $\lambda_1 = 0.1,\ \lambda_2 = 0.5,\ \lambda_3 = 2$, as they are the rule-of-thumb in the literature. We now vary general tightness of the prior by considering $\lambda_1 = 0.15$ and $\lambda_1 = 0.2$, and then repeating the unconditional out-of-sample exercise from Section 3.3.[13]

The results suggest that $\lambda_1 = 0.2,\ \lambda_2 = 0.1,\ \lambda_3 = 2$ (looser overall tightness with increased tightness for some variables) delivers slightly better unconditional out-of-sample forecasts in terms of RMSFE than our baseline choice.[14] Using this new set of hyperparameters, we repeat our conditional forecasting exercises for all variables considered in Sections 4.1–4.6. Overall, the results are qualitatively similar to the baseline case. Unsurprisingly, the credible sets of the new forecasts become wider for most variables, reflecting increased uncertainty. We demonstrate this result below by comparing the conditional forecasts of the GDP growth rates obtained under strict and loose hyperparameters (Fig. 14).

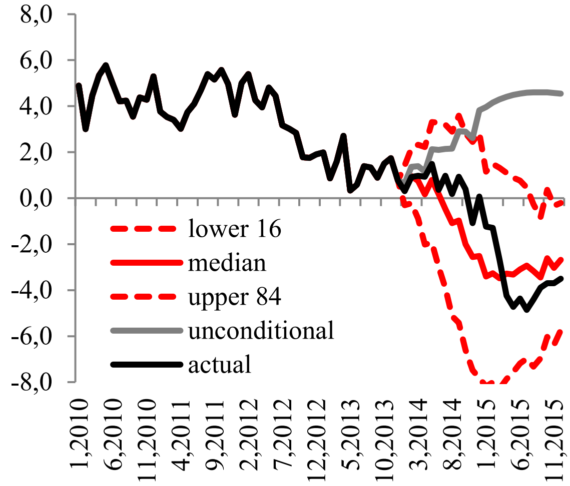
[13] The full results are available from the authors upon request.
[14] Other combinations of hyperparameters fared worse in unconditional out-of-sample forecasting performance.

Figure 14 Varying prior tightness: Conditional forecasts for ***GDP*** growth rates (month over the corresponding month in the previous year, %).

Panel 1: Loose prior

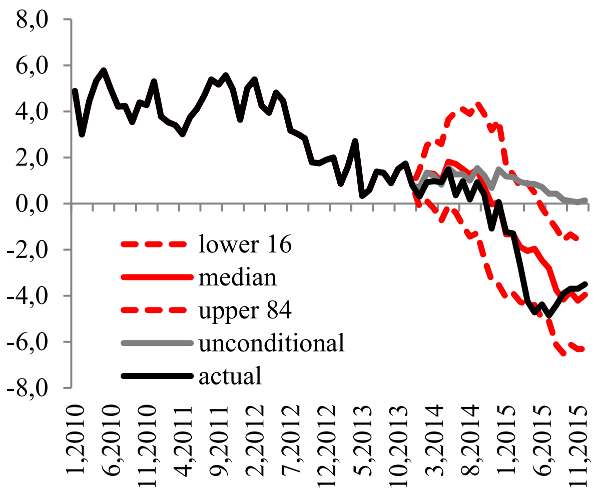


A) Condition 1: Urals oil price drop

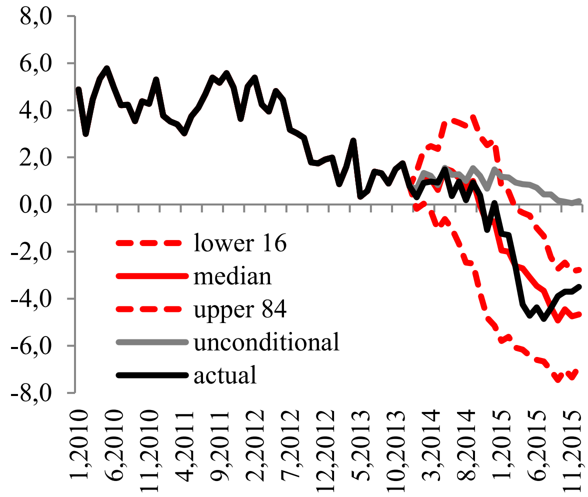


B) Condition 2: Urals oil price drop and introduction of financial sanctions

Panel 2: Tight prior (baseline case)



A) Condition 1: Urals oil price drop



B) Condition 2: Urals oil price drop and introduction of financial sanctions

Note: Both conditions also contain the actual path of VIX. The solid red line depicts the median conditional forecast; the dotted red lines represent the credible set of the median conditional forecast (16th and 84th percentiles). The gray line is the unconditional forecast, and the black line is the actual path.

As can be inferred from Fig. 14, the credible set widens in the case of the loose prior (Panel 1) relative to the tight prior (Panel 2) under both Conditions 1 and 2. Importantly, using the loose prior leads to less accurate forecasted paths, which, together with the wider confidence sets, increase uncertainty regarding the effect of interest. Even accounting for these revealed limitations, the results indicate that the effect of the financial sanctions is negative and *even stronger* than in our baseline case. With the loose prior, we find that financial sanctions could have been responsible for 1.5 percentage points in 2014 and 1.9 percentage points decline in 2015. In the baseline case, the corresponding numbers are only 0.4 and 0.7 percentage points decline. Given the larger uncertainty under the loose prior, we prefer the more conservative estimates obtained under the tight prior, which is also close to the values typically used in the literature.

4.8 Theoretical interpretation: Sanctions as a tightening of collateral constraints

In this section, we provide a theoretical interpretation of our results based on the literature on the small open economy business cycles with financial shocks and frictions (Mendoza, 2010; Bianchi and Mendoza, 2018; Uribe and Schmitt-Grohe, 2017; Jermann and Quadrini, 2012). In this literature, the debt of a representative agent is assumed to be limited by a fraction (κ) of either the market value of physical capital (stock collateral constraints) or income (flow collateral constraint):

$$d_{t+1} \leq \kappa q_t k_{t+1} \qquad (stock) \tag{6}$$

$$d_{t+1} \leq \kappa (y_t^T + p_t y_t^N) \qquad (flow) \tag{7}$$

where d_{t+1} is foreign debt issued at t and maturing at $t+1$, k_{t+1} is the stock of capital in the economy, q_t is the price of physical capital, $y_t^T + p_t y_t^N$ is income expressed in real terms (sum of tradable and non-tradable goods, with p_t representing the relative price of non-tradables).

In Bianchi and Mendoza (2018), κ is interpreted as the tightness of collateral constraints, which can shift exogenously, due e.g. to unexpected changes in creditor beliefs. This makes a bridge to our setting: we can treat the financial sanctions as an exogenous tightening of collateral constraints, which thereby governs the maximum amount of the corporate external debt of Russian firms.

Following Bianchi and Mendoza (2018), we perform a thought experiment in which we shrink κ. Before financial sanctions were introduced, Russian firms were increasing their borrowing on international financial markets. Their collateral constraints were not binding. With the implementation of sanctions in 2014 and 2015, Russian firms were forced to deleverage rapidly. This could indicate that their collateral constraints had become binding.[15] Given the relative stabilization

[15] See Footnote 2 for details.

in the amount of outstanding corporate external debt occurred in 2016–2017, we assume that collateral constraints once again ceased to be binding. Thus, financial frictions are largely limited to the first two years following the introduction of the sanctions.

If we consider the model with a flow collateral constraint as in Uribe and Schmitt-Grohe (2017) and Schmitt-Grohe and Uribe (2017), then, in equilibrium (given market clearing condition for non-tradable goods), the budget constraint of a representative household reads as:

$$c_t^T + i_t + d_t = A_t F(k_t) + \frac{d_{t+1}}{1+r} \tag{8}$$

where c_t^T is the consumption of tradable goods, and i_t is investment in physical capital, augmenting the stock of capital through the standard law of motion. A_t is a technological parameter, $F(k_t)$ is the production function of tradable goods, and r is the interest rate on foreign borrowing.

Under this budget constraint, we infer that, in the absence of income shocks, the consumption of tradable goods c_t^T and domestic investment i_t should decline in response to the debt deleveraging associated with shrinking κ. This conclusion directly corresponds to our BVAR forecasting results for retail sales and investment (see Section 4.2).

As a result of debt deleveraging, there is a decline in domestic demand for all types of goods that leads to a decrease in the relative prices of non-tradable goods as the supply of non-tradables is assumed to be fixed. By definition, this decline implies a depreciation of real exchange rate. This partly corresponds to our BVAR forecasting result on the EMP's rising (see Section 4.4), which we treat as depreciation of the *nominal* exchange rate under Russia's flexible exchange rate regime.

The decline in the prices of non-tradable goods and the depreciation of exchange rate can lead to a decrease in income expressed in the amount of tradable goods ($y_t^T + p_t y_t^N$). This further amplifies the initial financial shock by tightening the collateral constraint (7), thus inducing even larger debt deleveraging.

As a result of debt deleveraging and a subsequent consumption spending cut, according to the theoretical model of Uribe and Schmitt-Grohe (2017), the trade balance should improve. This partly corresponds to our BVAR forecasting result showing declining imports (see Section 4.5).

If we consider a model with a stock collateral constraint instead of one with a flow collateral constraint, and additionally introduce a working capital constraint as in Mendoza (2010), we can observe that the binding collateral constraint distorts the optimality conditions for factor demands, making working capital financing more expensive and raising labor costs. The latter, in turn, decreases the demand on corresponding production factors, which could explain the fall in production. This corresponds with our BVAR forecasting results for GDP growth rates (see Section 4.1).

Uribe and Yue (2006) describe the negative correlation between output and a country's interest rate in the case of emerging economies. We interpret our finding of an increase in the CBR's key rate (see Section 4.6) as evidence of the central bank's efforts to equalize domestic and foreign returns.

Given the decrease in output and consumption and investment expenditures, we can expect a decline in money demand and contracting demand for domestic loans, which are both observed in our BVAR results (see Section 4.6). The substitution effect, which pushes the demand for domestic loans up, fails to overcome the negative demand effect from the overall decrease of spending in the economy.

4.9 Discussion of the forecasting results

For proper interpretation of our conditional forecasting results, we now discuss the limitations of our approach and sources of uncertainty in our forecasts.

To get some perspective on the limitations of corporate external debt as a variable in measuring the intensity of sanctions, we compute the difference between two macroeconomic scenarios. In the first, we fix the stock of corporate external debt at its actual values in 2014–2015. In the second, we let corporate external debt react endogenously to falling oil prices and the structural slowdown of the Russian economy. We assume that the *excessive* decline in corporate external debt, as captured by the difference between the two scenarios, is driven by the imposition of financial sanctions.

There are potential limitations to this approach. Financial sanctions prohibited placements of new debt on foreign markets, meaning that sanctions got applied to the flow of debt while we were using the stock of debt. As the actual dynamics of the stock depended on the payment schedule, the larger the share of the short-term liabilities, the faster the observed debt deleveraging. In our exercise, we take the payment schedule as given and fixed, i.e. we abstract from possible renegotiations in response to the sanctions and assume no forward-looking borrowers who managed to place sizeable amounts of long-term debt in the month preceding the sanctions. Thus, we focus on the actual amount of borrowed funds available to the Russian corporate sector (stock of debt), the decline of which had macroeconomic consequences in our view.

Moreover, even though most of the companies with sanctions were state-owned, there was *contagion* from the targeted to non-targeted (private) borrowers. Thus, the speed of debt deleveraging depends crucially on the degree of this contagion.

Sanctions against selected state-owned non-financial firms such as Rosneft and Gazpromneft, or specific banks such as Sberbank and VTB, seem to have colored all Russian debt. International investors self-imposed sanctions against all Russian firms (state-owned and private, non-financial firms and banks) – even those with high ratings. These self-imposed sanctions were driven by political uncertainty and non-discriminatory. Thus, the estimated effects in our setting are a combination of targeted sanctions and contagion effects. While it is difficult to distinguish where sanctions stop and contagion effects begin, it is clear that the contagion effects stem from the targeted sanctions.

The flow and the stock of corporate external debt were subject to *idiosyncratic shocks* such as sizeable new debt placements resulting from the unanticipated success of some companies.

A sizeable amount of corporate external debt falls within a category of debt to *direct investors* and direct investment enterprises. At the end of 2013, the share of these type of corporate external debt amounted to 2% for Russian banks and 35% for non-financial Russian firms. This portion of debt is characterized by non-market behavior as the creditors are tightly connected to the borrowers through a common ownership structure such as group or consortium. Thus, these creditors are likely to extend debt repayment times even with sanctions.[16] In our estimations, we address this issue by excluding the debt to direct investors from the total stock of corporate external debt.

Looking to factors that might prevent precise estimation of the role of sanctions, we recap by first noting the large estimation uncertainty that may originate from (Byrne et al., 2018):

I Random or unpredictable fluctuations observed in the data. In our setting, we work with the emerging economy data that is characterized by larger measurement errors and numerous data revisions. Large shifts in investor sentiment are common for emerging economies, and these could lead to substantial adjustments in financial market variables. This may explain the ruble exchange rate overshoots during the financial and currency crises.

II Errors in the estimated coefficients. In our setting, we are limited by the number of available observations and the short history of comparable data. The history of Russia's movement towards a market economy starts in early 1990s. The growing pains of the 1990s culminated in a transformative crisis that involved a malfunctioning payment system and several financial distress for most Russians. Therefore, we exclude

[16] The debt to foreign direct investors contracted by only 10% in 2014. If we exclude this type of debt, the contraction was 32% for the same period.

this period from our sample and impose tight prior on the model's coefficients (basically, the model itself favors the tight prior based on the out-of-sample unconditional forecasting, see Section 3.3). In the face of low number of observations, this produces a stronger bias of our estimates towards the prior.

III Time variation in coefficients. The literature on forecasting and structural analysis with VARs generally recommends the use of time-varying parameters (Primiceri, 2005; Koop and Korobilis, 2013). In our setting, the time variation in coefficients may stem from the shifts in monetary policy regimes, occurred during the sample period (the CBR switched from exchange-rate targeting to inflation targeting and from a fixed to floating exchange rate). We partially address this issue by applying the EMP variable to accommodate for the switch in exchange rate regimes. However, since we are mostly interested in the effects of the sanctions on the real economy, the forecasting errors in the exchange rate and interest rate are not of primary interest. Moreover, using time-varying parameter models, Borzykh (2016) and Kreptsev and Seleznev (2016) show that the degree of time variability of the structural relationships is rather limited in Russia.

IV Time-varying set of exogenous variables. During episodes of global financial instability, the importance of the external financial conditions (measured as VIX) rises. During calm periods, these external conditions become less important for our purposes. In our conditional forecasting exercise, we condition on the same trajectories of VIX in both scenarios, thus eliminating this concern.

Finally, we assume that the dynamics of the ruble's exchange rate are governed mostly by changes in trade and financial flows, and not the other way around. This assumption allows us to disentangle the effects of falling oil prices (which corresponds to changes in currency flows due to trade) and sanctions (which directly affect Russia's financial account) from the exchange rate shock.

Given the limitations involved, we believe our conditional forecasting approach provides a useful insight into the problem of quantifying the economic effects of financial sanctions. It is simple and reproducible, it does not require large panels of disaggregated data, and it addresses the linkages between the real economy, financial sector, and monetary policy.

5 Conclusions

In this paper, we build a medium-sized Bayesian VAR forecasting model to estimate the economic effects of Western financial sanctions imposed on the Russian economy in 2014. We start with 14 macroeconomic variables divided into three groups: external, domestic non-financial and domestic financial variables. Since sanctions reduced the ability of Russian firms to place new debt on the international financial markets, we include corporate external debt variable in our model. We apply a non-conjugate prior (Independent Normal-Inverted Wishart prior) to estimate our BVAR model as it allows us to impose small open economy restrictions on the coefficients of the model so that Russian domestic variables do not affect external variables.

An empirical challenge of quantifying the economic effects of the Western sanctions on Russia is that they were imposed during a period of falling oil prices, i.e. a period when the Russian economy was experiencing two external shocks simultaneously. To disentangle the effects of these shocks, we perform two counterfactual experiments with the BVAR model. Specifically, we compute two out-of-sample conditional forecasts of the key Russian macroeconomic variables for 2014–2015. The first forecast is conditioned solely on the drop in oil prices, while the second forecast is based on the known trajectories of oil prices and the decrease in the stock of the Russian corporate external debt. We treat the difference between the second and the first conditional forecasts as the economic effects of financial sanctions that originate from the decrease in the stock of corporate external debt in Russia. Taking this difference, we eliminate the effect of the demand-side factors that may have affected our forecasts. For computing the conditional forecasts, we employ the algorithm proposed by Waggoner and Zha (1999), which produces density forecasts using Gibbs sampling.

The conditional forecasting results suggest that the decline in oil prices alone cannot explain the depth of the Russia's recent macroeconomic recession. Part of the recession seems to have been driven by limited access of Russian companies to international financial markets due to sanctions. However, our results indicate that the effects of sanctions are modest at best (but still significant) for most of the variables considered in our model. The cumulative depression of GDP growth rates amount to 1.2 percentage points for the 2014–2015 period. At the same time, we are uncertain about the exact effect of sanctions on GDP. According to our inference, 61% of the probability mass in 2014 and 70% in 2015 fall into the negative area, so we can conclude with some confidence that sanctions reduced Russia's GDP growth rate.

Overall, our analysis suggests that the lack of access of Russian firms to new debt issuance amplified Russia's economic and financial crisis. Sanctions were still in place at the end of 2018, and further sanctions have been imposed on the Russian economy since 2016. With these findings in hand, we see an evolving path for research on medium- and long-term effects of sanctions.

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Appendix

Table A1 Data description

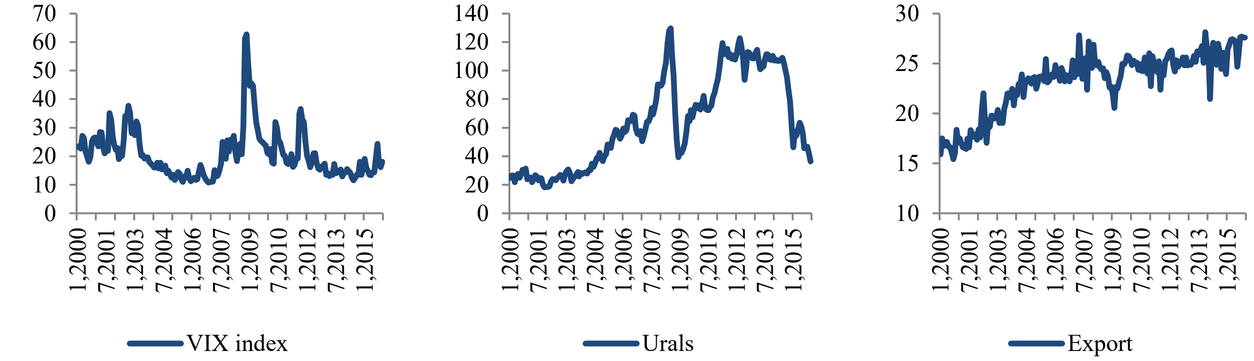
#	Variable name	Transfor-mation	Description	Source
Panel 1: External sector variables (exogenous)				
1	Global finan-cial volatility (VIX index)	$1200 \cdot \ln(Y_1)$	The implied volatility of S&P 500 (provided by the Chicago Board Options Exchange, CBOE).	cboe.com
2	Urals oil price	$1200 \cdot \ln(Y_2)$	Monthly average of the daily data on the clos-ing price of Urals oil (USD per barrel).	topoilnews.com
3	Russian exports (in 2007 prices)	$1200 \cdot \ln(Y_3)$	Seasonally adjusted[1] Russian exports (in 2007 prices, USD billion). We estimate the Russian exports in constant prices by taking the monthly goods composition of exports in phys-ical terms and multiplying it by the average 2007 prices of these goods (Source: Russian customs). We then sum these products to ob-tain Russian exports in 2007 prices.	customs.ru[2]
Panel 2: Domestic non-financial variables				
4	GDP	$1200 \cdot \ln(Y_4)$	Seasonally adjusted gross domestic product (in 2007 prices, RUB billion). We estimate monthly GDP in the following way. First, we take the yearly nominal GDP data for 2007 (source: gks.ru) and interpolate it in months using the data on the index of the output by basic economic activities: agriculture, mining, manufacturing, electricity production and dis-tribution, gas and water, construction, transport, retail and wholesale trade (source: gks.ru). Second, we take the Ministry of Eco-nomic Development (MinEc) data on the monthly GDP growth rates (month over corre-sponding month of the previous year). Taking our data on GDP in average 2007 prices for 2007 and the MinEc data on the monthly GDP growth rates, we construct the series of monthly GDP in 2007 prices for the other years of the dataset.	gks.ru[3] economy.gov.ru/minec[4]
5	Wages	$1200 \cdot \ln(Y_5)$	Seasonally adjusted average monthly wages per employee in 2007 ruble prices. We transform average monthly nominal wages per employee to real 2007 prices using the data on the monthly wages growth rate (month over corre-sponding month of the previous year).	gks.ru

6	Retail sales	$1200 \cdot \ln(Y_6)$	Seasonally adjusted retail trade turnover, (in 2007 prices, RUB billion). Nominal monthly retail trade turnover is transformed to real 2007 prices using the data on the monthly retail trade turnover growth rate (month over corresponding month of the previous year).	gks.ru
7	Investment	$1200 \cdot \ln(Y_7)$	Seasonally adjusted fixed capital investments (in 2007 prices, RUB billion). Nominal monthly fixed capital investments are transformed to real 2007 prices using the data on the monthly fixed capital investments growth rate (month over corresponding month of the previous year).	gks.ru
8	Russian imports	$1200 \cdot \ln(Y_8)$	Seasonally adjusted monthly data on goods imports.	gks.ru
9	CPI inflation	$1200 \cdot \ln(Y_9)$	Seasonally adjusted monthly data on the consumer price index.	gks.ru
Panel 3: Domestic financial and monetary variables				
10	Corporate external debt	$1200 \cdot \ln(Y_{10})$	Monthly transformation of quarterly data on the external debt of non-financial corporations and banks (including debt securities, but excluding debt liabilities to direct investors and direct investment enterprises; in USD billion). First, the monthly transformation is carried out using the monthly and quarterly data on the foreign liabilities of the Russian banking sector. The correlation between the first differences of both quarterly series is 69% over 1999Q1–2015Q4. The OLS-estimated coefficient in the bivariate regression of the first differences of corporate external debt on the first differences of foreign liabilities is 0.6 (significant at the 1% level). This coefficient is used to obtain an estimate of the monthly dynamics of corporate external debt. We rebalance our monthly estimates within each quarter to ensure that they correspond to the actual value in the respective quarter. Second, having the rebalanced estimates at hand, we eliminate the monthly revaluations from the US dollar equivalent for ruble-denominated corporate external debt. These revaluations originate from shifts in the ruble exchange rate. To obtain a revaluation at time t, we calculate the two US dollar equivalents of the ruble-denominated part of corporate external debt. The first is the product of ruble debt at month t and the ruble-dollar exchange rate at month t. The second is the product of ruble	cbr.ru[5]

			debt at month t and the ruble-dollar exchange rate at month $t-1$. The revaluation at time t is then calculated as the difference between the two equivalents. Third, we take these monthly revaluations and compute the monthly dynamics of the stock of corporate external debt, taking the value of the debt at January 1, 2014 as the base.	
11	Outstanding bank loans to the private sector	$1200 \cdot \ln(Y_{11})$	Monthly data on the stock of the banking system loans to Russian non-financial firms and households (in RUB billion).	cbr.ru
12	Monetary policy interest rate (key rate)	Y_{12}	Monthly averages of the daily data on monetary policy interest rate (CBR refinancing rate before 2013, CBR key rate in 2013–2015)	cbr.ru
13	Monetary base	$1200 \cdot \ln(Y_{13})$	Seasonally adjusted monthly data on the monetary base (national definition). The monetary base is the sum of cash (M0), banking system requirements to the CBR (correspondent accounts, deposits and bonds acquired), and the mandatory reserves of the banking system held by the CBR.	cbr.ru
14	Exchange Market Pressure (EMP) index	$1200 \cdot \ln(Y_{14})$	Monthly data on the cumulative EMP index with the value of the index in June 2007 taken as 100. The EMP is computed as the difference between the monthly growth rates of the nominal ruble exchange rate and international reserves, where both components are adjusted to their respective unconditional standard deviations. The nominal exchange rate is the ruble rate with respect to a dual-currency basket (monthly average). The basket is composed of 0.55 US dollars and 0.45 euros.	cbr.ru

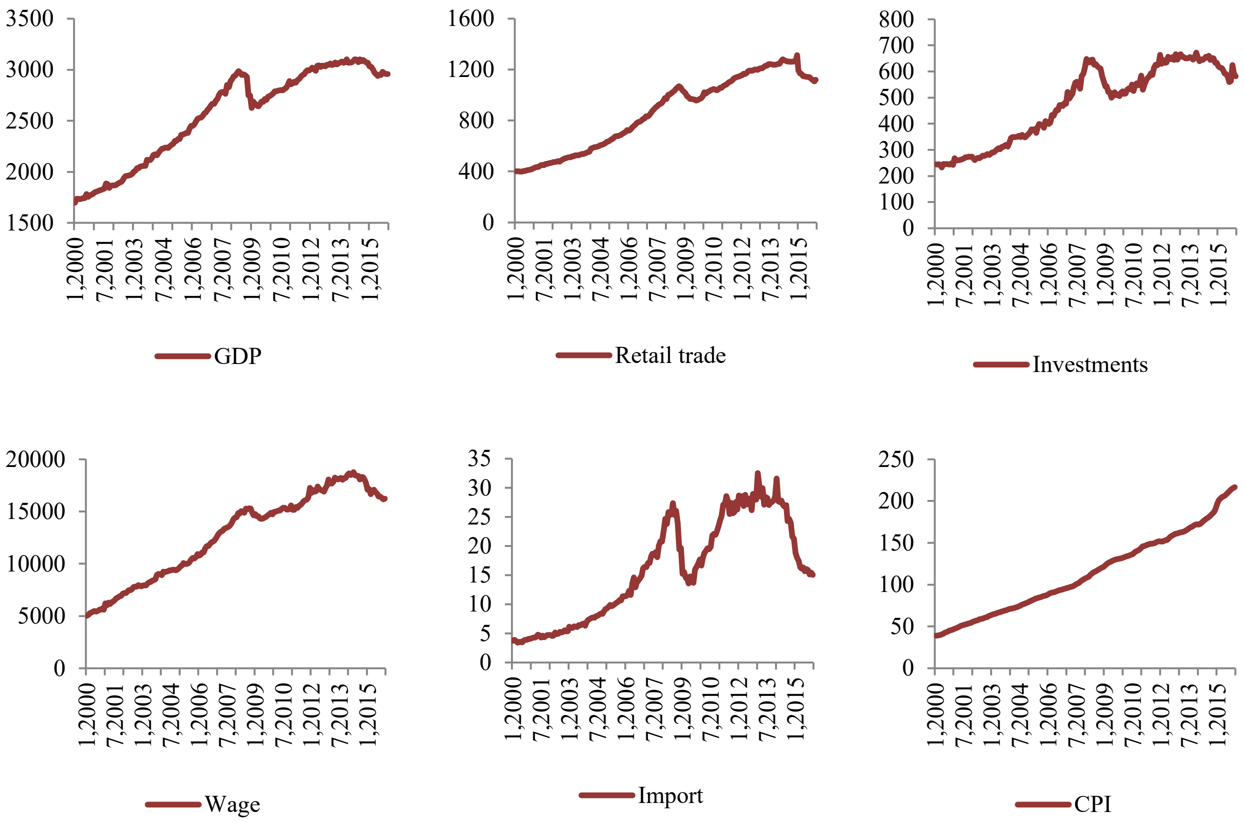
Notes:
[1] Seasonal adjustments are performed with X12 routine in EViews.
[2] customs.ru is the official website of the Federal Customs Service of the Russian Federation.
[3] gks.ru is the official website of the Federal State Statistics Service of the Russian Federation.
[4] economy.gov.ru/minec is the official website of the Ministry of Economic Development of the Russian Federation.
[5] cbr.ru is the official website of the Central Bank of Russia.

Figure A1 External indicators for the Russian economy used in the BVAR model (before taking logs).



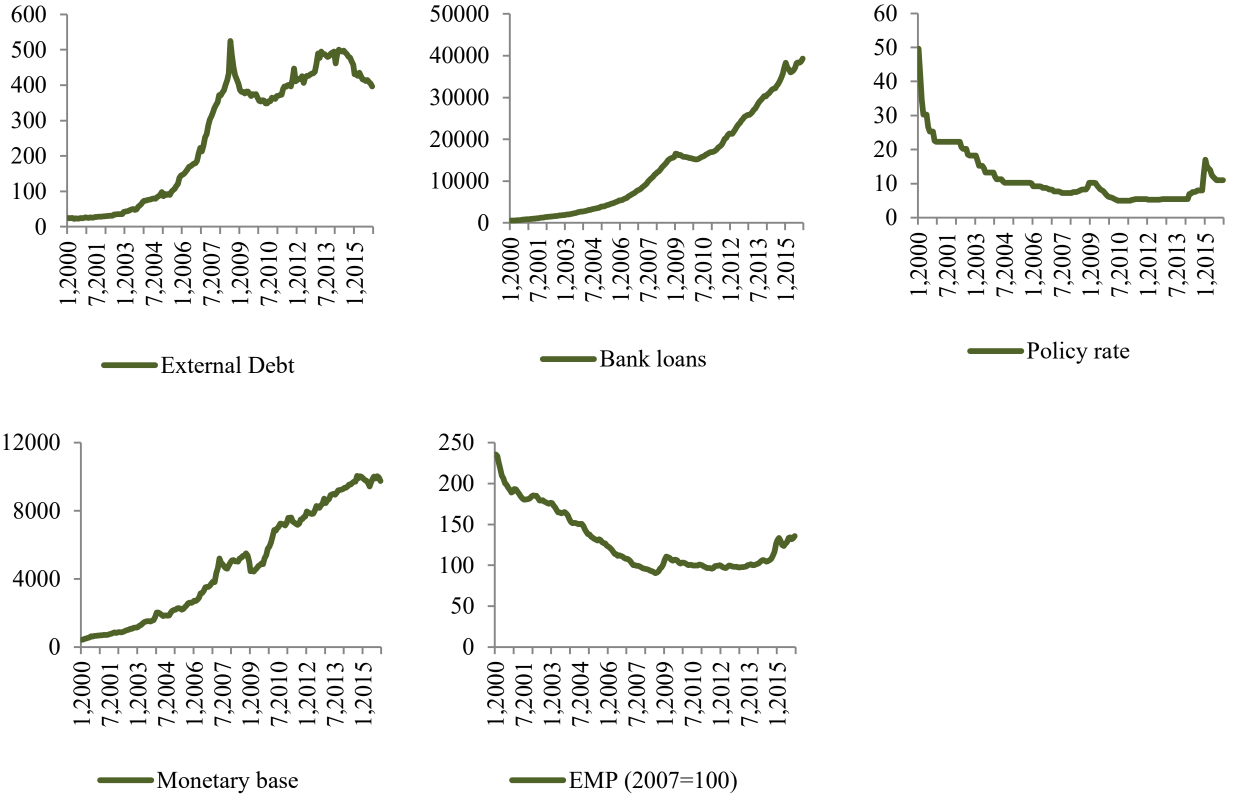
Note: Urals oil price and exports in USD billion. VIX is the global financial volatility index.

Figure A2 Domestic non-financial indicators on the Russian economy used in the BVAR model (before taking logs).



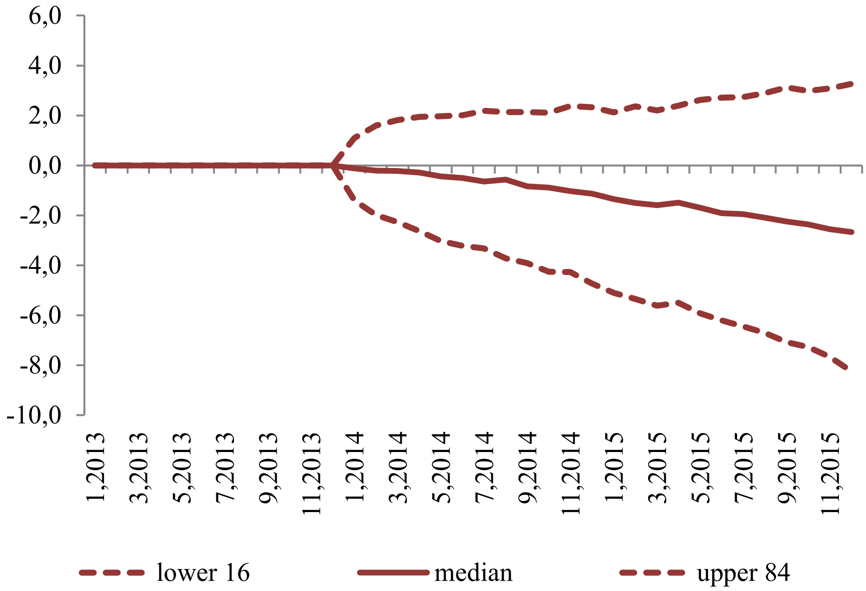
Note: GDP, retail trade turnover, fixed capital investment and average monthly wages in RUB billion. CPI is a cumulative index (2007 = 100).

Figure A3 Domestic financial indicators on the Russian economy used in our BVAR model (before taking logs).



Note: Bank loans and monetary base are in RUB billion; external debt in USD billion. Policy rate is given in percentages. EMP is the cumulative index of market pressure on the ruble.

Figure A4 The difference between the two conditional forecasts for GDP growth rates (month over corresponding month of the previous year, %).



Note: The solid red line stands for the median conditional forecast (forecasted GDP growth rates in the scenario with oil price drop, only minus the same in the scenario with oil price drop and reduction of corporate external debt). The dotted red lines depict the credible set of this forecast (16th and 84th percentiles).

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