"Sorry, You're Blocked." Economic Effects of Financial Sanctions on the Russian Economy

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Abstract

How large are the macroeconomic effects of financial sanctions and how one can distinguish the sanction shocks from other aggregate shocks affecting the economy at the same time? We employ a Bayesian (S)VAR model to estimate the effects of the Western financial sanctions imposed on the Russian economy in 2014 (first wave) and 2017 (second wave). The sanctions decreased the Russia's corporate external debt and raised the country spread, but their effects were confounded by falling oil prices in 2014 (negative terms-of-trade, TOT, shock) and rising oil prices in 2017. We begin disentangling the sanction and TOT effects with a conditional forecasting approach, in which we simulate pseudo out-of-sample projections of domestic macroeconomic variables conditioned (i) solely on the oil price changes and then (ii) on both oil prices and external debt deleveraging. For each endogenous variable, we treat the difference between the two projections as the effect of sanctions. We then apply a structural approach to identify sanction shocks. Our results consistently indicate that the sanction effects were negative and non-negligible across the two sanction waves, being sizeable for the financial variables (real interest rate and corporate external debt) and moderate for the real variables (output, consumption, investment, trade balance, and the ruble real exchange rate). We argue that the estimated effects of sanctions are in line with the theoretical predictions from the literature on country spread shocks in open economies.

Keywords: Financial sanctions, Corporate external debt, Country spread shocks, Terms-of-trade shocks, Bayesian (S)VAR, Sign restrictions, Conditional forecasting, Small open economy.

1 Introduction

Following the annexation of the Crimean peninsula by Russia in early 2014, the European Union, the United States and other countries imposed *financial* sanctions on the Russian government-owned companies and banks.[1] In 2017, the Western countries launched another set of international financial restrictions on the Russian entities due to election interference, military activities in Syria, and cyber-attacks (Welt et al., 2020). In both cases, the Russian state-related corporations were blocked at international financial markets, i.e., they were prohibited to issue new debt. In this paper, we ask whether these two waves of financial sanctions had sizeable macroeconomic implications for Russia in terms of output growth, household consumption, firm investments, trade balance, and real exchange rate. Put differently, we are interested in whether the sanctions were successful in restricting the Russia's domestic economy, as the administration of the former U.S. president Obama claimed, or whether the sanctions' effects were insufficient economically, as the current administration of the Russia's president Putin assured.

One could fairly anticipate that the Western financial sanctions matter for Russia. As an emerging economy with an underdeveloped domestic financial sector, the country is highly dependent on external sources of finance. Over the period of 2014–2015, the ratio of corporate external debt to GDP averaged at 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 by 2.0% and fixed capital investment decreased by more than 10%. During 2014-–2015, the Russian domestic currency, ruble, lost about 90% of its value.

However, even after the two waves of financial (and other) sanctions, the political tension between Russia and the West is still there: the Russian government pursues the same policy as before, US and EU extend previously imposed and launch new sanctions against Russia. This may imply that the Russian government is not considering the effects of sanctions to be dramatic. Indeed, one could observe that during the last decade the Russia's government and the Central Bank of Russia were successful in macroeconomic stabilization (CPI inflation is at its historically lowest levels, around 4%; interest rate declined sharply to below 5% annually; government external debt to GDP is lower than a decade ago and than in many other countries as of beginning of the 2020s). These discrepancies make a macroeconomic analysis of the financial sanctions important and policy relevant for both parties.

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

Initially, the sanctions were targeting certain Russian entities with close ties to the Kremlin, namely, the sanctions were blocking the issuance of new debt by these entities on the European and US financial markets. However, the reputation issues soon materialized and provoked negative spillover effects: international investors turned to perceiving *all* Russian businesses, i.e., including privately held, as those under a high risk of default or as undesirable investment targets. This eventually led to a drastic reduction of 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 the scheduled debt repayments, the stock of Russian corporate external debt shrank by 25% during 2014–2015 (the "first wave" of financial sanctions), see, e.g., Dreger et al. (2016) and Korhonen et al. (2018). We argue that the fall of Russian corporate external debt in that times could not be attributed to investors' lost of interest towards emerging market economies (EMEs) as a whole: the cross-country comparisons clearly indicate that Russia was the only country among EMEs that experienced reductions of international borrowings (Fig. 1). Though somewhat stabilized in 2016, Russian corporate external debt again turned to declining in 2017–2018 (the "second wave" of financial sanctions).
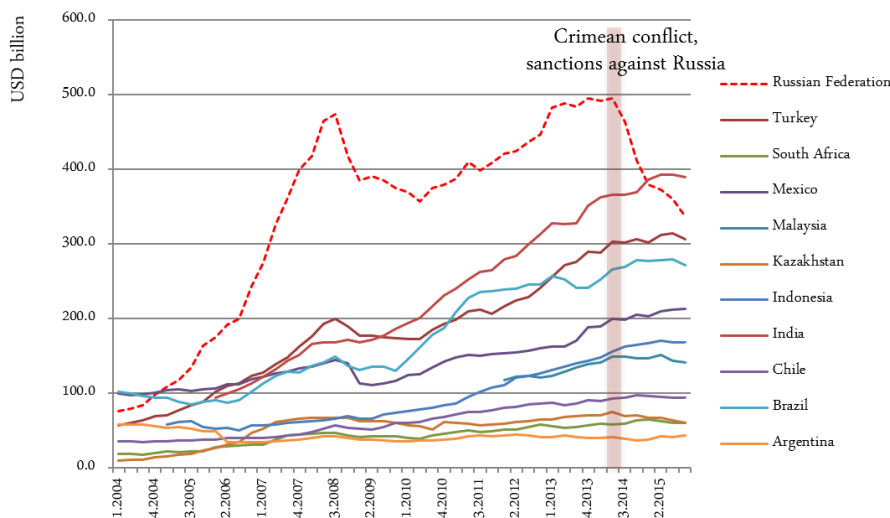
Source: World Bank/IMF QEDS (Quarterly External Debt Statistics).

Figure 1: Corporate external debt of large emerging economies

The identification of the sanction effects on the Russian economy is complicated by the fact that the first wave of financial 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 is very sensitive to movements in commodity prices (for empirical evidence on this effect, see e.g., Korhonen and Ledyaeva, 2010; Cespedes and Velasco, 2012). It is thus unlikely that the financial sanctions were the only driver of the

Russia's economic downturn occurred in 2014–2015. Moreover, the slowdown in growth rates started a year before the sanctions were imposed. The slowing continued throughout 2014, with the annual GDP growth dropping to 0.7% (from 4.0% in 2012 and 1.8% in 2013). At that time, the slowdown was attributed mostly to the structural problems of the economy such as negative demographic trends, excess regulation, and a poor business environment (OECD, 2014).

On contrary, the subsequent widening of financial sanctions in 2017–2018 (second wave), coincided with *an increase in oil prices*, thus also confounding a one's attempt to disentangle the effects of sanctions over that times. In both cases, for the first and second waves of sanctions, it is thus necessary to carefully isolate the financial sanction shocks on the Russian economy from the effects of oil price shocks, which can be more generally captured by commodity terms of trade (CTOT).

We separately study the two waves of financial sanctions, i.e., those occurred in the 2014—2015 and 2017–2018 periods, instead of pooling them all together on the full time span for the following reasons. First, the sanctions of 2014–2015 coincided with the most acute phase of the economic crisis in Russia. GDP growth returned to positive territory only in 2016. Second, deleveraging in corporate external debt was substantial only during the first wave of sanctions. By 2016, the stock of the debt had stabilized.[2] Given these two considerations, our estimates for the 2014–2015 period should be treated as those capturing the short-term effects of the financial sanctions, and, in that sense, conservative. Third, the period between 2016 and the first half of 2017 was rather calm in terms of new sanctions announcements. Thus, if we would add this specific period to our data sample, the resultant effects might be blurred. Fourth, the second wave of sanctions appeared as a consequence of elections interference and illicit cyber-enabled activities. However, the level of corporate external debt was already much smaller than on the eve of the first wave ($450 vs. $650 billion[3]). Russian firms could have already adapted to the sanctions and relied more on either internal or external non-Western sources of funding. In this sense, it is important to understand how the efficacy of the second wave compares to the one of the first wave.

Identification of the financial sanctions shocks. We follow the Bayesian VAR approach to study macroeconomic effects of the financial sanction shocks on the Russian economy. We begin our empirical analysis with a conditional forecasting exercise. Specifically, for each of the two sanction waves, we estimate the BVAR model on the pre-sanction data and then make two pseudo out-of-sample

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[2]The Central Bank of Russia data shows that total corporate external debt declined from $651.2 billion as of end-2013. In 2014, the debt shrank by $103.5 billion and by another $71.4 billion in 2015 (the 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]These figures include debt to direct investors. In the empirical part, we exclude foreign direct investments (see the data section for details).

conditional forecasts of endogenous macroeconomic variables over the length of respective sanction wave. The first forecast is conditioned on the CTOT and global financial indicators actually observed during the sanction wave. The second forecast is further conditioned on the same external indicators plus the corporate external debt of Russian companies actually observed during the same sanction wave. For each endogenous variable in the BVAR model, we then compute *the difference* between the two respective pseudo out-of-sample conditional forecasts. We argue that these differences can be treated as the effects of the financial sanction shock because they are driven exclusively by the corporate external debt dynamics while all other potential confounding factors (e.g., shocks to prices of natural resources, domestic monetary shocks, structural changes) are effectively differenced out. In this direction, we consider two versions of the Bayesian VAR model. The first (baseline) version is based on a composition of primarily real sector variables traditionally employed in the empirical literature on interest rate shocks in small open economies (Uribe and Yue, 2006; Akinci, 2013; Ben Zeev et al., 2017). The baseline BVAR model thus includes *10 variables* which encompass domestic production, final consumption, investment, trade balance, real effective exchange rate (REER), country's interest rate spread and corporate external debt; in addition, we control for exogenous global economy conditions affecting Russia by including CTOT, real interest rate in the U.S. economy, and Baa spread. The second version of the BVAR model, which we consider in the sensitivity analysis, is influenced by the non-structural macroeconomic forecasting performed in central banks (Banbura et al., 2015; Deryugina and Ponomarenko, 2015). This model includes *14 variables* and differs from the "real sector" version of the BVAR model by a broader coverage of monetary sector (broad money, loans to the real economy), domestic prices (CPI), and real wages.

An important concern arising in any conditional forecasting exercise is potentially large uncertainty around the conditional forecasts.[4] Credible bands of such forecasts account for the uncertainty on (i) the size of shocks, (ii) unknown coefficients, and (iii) the identification of shocks. The first two sources of uncertainty are inherent in BVAR models and hard to deal with aside from varying tightness of the prior (which we do in the sensitivity analysis). In contrast, the identification uncertainty stems from the fact that the differences in conditional forecasts that we compute to capture the effects of the (financial sanction) shock are equivalent to generalized impulse response functions (GIRF) to the same shock (Banbura et al., 2015). Thus, the economic effects estimated via the differences in conditional forecasts absorb the uncertainty on *all possible orderings* of the variables in recursively identified VARs.

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[4]We are grateful to anonymous referees for drawing our attention to this point and encouraging us to revise the identification strategy.

To address this concern we, therefore, suggest alternative estimations of the macroeconomic effects of the financial sanction shocks by proposing two identification schemes in structural VAR analysis. In this direction, we treat a financial sanction shock as an exogenous rise of the Russia's interest rate on foreign borrowing (also referred to as country spread shock); by "exogenous" we mean that the rise is unrelated to the country's fundamentals. The first identification strategy stems from the empirical literature on small open economies which identifies country spread shocks by recursive approach (Uribe and Yue, 2006, Born et al., 2020, Monacelli et al., 2021). The second identification strategy relies on sign restrictions approach. Specifically, we suggest separating the CTOT shock and country spread shock by imposing distinctive responses of several macroeconomic variables to the two shocks. We show that, among these identifying macroeconomic variables, *trade balance* plays a prominent role. Importantly, and looking ahead to the results section, we obtain qualitatively similar effects of the financial sanctions shocks whichever approach we use: conditional forecasting or structural VARs, though the latter is much more precise in terms of uncertainty around the estimated effects.

The contribution of this paper is threefold. First, we propose an identification procedure which separates two aggregate shocks relevant for open economies — a positive country spread shock (financial sanctions in our case) and a negative (C)TOT shock. It is a priori unclear how one can separate the two shocks. In both cases, output declines while real interest rate rises. We argue that *trade balance* reacts differently on the two shocks and thus may serve as an identifying variable. Indeed, in case of positive country spread shocks trade balance improves which is due to decreasing domestic absorption (consumption and investment), whereas in case of negative (C)TOT shocks trade balance deteriorates which follows from decreased (relative) export prices. We apply the sign restrictions approach to realize this identification procedure in the VAR framework. We also complement this analysis with a traditional recursive identification, in which we interpret the financial sanction shock as the shock to a country spread component of the real interest rate, in line with Neumeyer and Perri (2005), Uribe and Yue (2006), Chang and Fernandez (2013), and Akinci (2013).

Second, this paper contributes to the literature on conditional BVAR forecasting. Previous studies have largely focused on unconditional forecasting by performing comparisons of the forecasting accuracy of BVARs with other non-structural models (see, e.g., Banbura et al., 2010; Koop, 2013; Carriero et al., 2015; Giannone et al., 2015). Conversely, the body of work applying conditional forecasts is still relatively small. In the latter direction we emphasize the following two studies. Banbura et al. (2015) build a large-size BVAR model with a conjugate prior for the euro area to generate conditional forecasts of a wide range of macroeconomic variables under the hypothetical paths of real GDP, prices,

and interest rates. Deryugina and Ponomarenko (2015) in turn propose a medium-size BVAR model of the Russian economy with symmetric Minnesota-type prior to produce out-of-sample forecasts of key macroeconomic variables for the pre-sanction period of 2010–2014 conditioned on the actual paths of oil prices and the euro area GDP. In our paper, we use small open economy priors instead of conjugate and symmetric priors to eliminate any effect running from Russian domestic macroeconomic variables on external variables. We also differ from Banbura et al. (2015) since we do not impose conditions on domestic variables; we instead are interested in how domestic variables would evolve under specific conditions on external variables. Last but not least, we improve over Deryugina and Ponomarenko (2015) by producing more accurate conditional forecasts for the sanctions period of 2014–2015 and adding the analysis of the second wave sanctions in 2017–2018.

Third, our study contributes to the literature estimating the economic effects of the Western sanctions on Russia. Several studies have sought to quantify the effects of the sanctions, though they differ greatly in the aspect of sanctions studied and empirical approach chosen. A number of papers employs a macroeconomic approach to estimate the effects of sanctions. Dreger et al. (2016) exploit a cointegrated VAR to analyze the determinants of the ruble depreciation occurred in 2014. They find that the drop in oil prices had a greater effect on the ruble dynamics than the imposed sanctions. Kholodilin and Netsunajev (2019) investigate the bilateral effects of sanctions on the Russian and European economies using a structural VAR approach. They do not find a significant effect on either economy. Barseghyan (2019) uses the synthetic control method and estimates the effects of sanctions to be 1.5% of annual GDP over the 2014–2017 period. Another stream of research has focused on microeconomic aspects of the sanctions on Russia. For example, Belin and Hanousek (2020) show that the Russian counter-sanctions which banned Western foodstuff imports were effective while the Western sanctions imposed on the imports of extraction equipment from Russia were statistically insignificant. Ahn and Ludema (2019) find that being included into the sanction list had significantly negative effects on the balance sheets of Russian firms, e.g., on revenue, assets, and employment. None of the papers mentioned above focus on *financial sanctions* alone. In this respect, we are first to isolate the effects of restrictions on the borrowings at international financial markets. Moreover, we propose to interpret the financial sanction shock as the shock to a country interest rate which enables us to interpret the effects through the lens of small open economy business cycle literature.

Our results are consistent across the three methods employed, i.e., conditional forecasting, recursive identification and sign restrictions (SR), and imply that the sanction effects were negative and non-negligible across the two sanction waves in 2014–2015 and 2017–2018, respectively. However, the

effects differ substantially across the variables analyzed. Specifically, the effects are sizeable for those variables directly affected by the financial sanction shocks (i.e., Russia's real interest rate and corporate external debt) while they are at best modest for the real variables which are indirectly influenced by the shocks (i.e., output, consumption, investment, trade balance, and the ruble real exchange rate). In particular, our median estimates for the output annual growth rates, as measured by the 12-month moving average change in industrial production, yield slowdowns by about 2.9 percentage points in 2014 and near 1.7 percentage points in 2017, respectively, due to the financial sanctions (the SR estimates). Given that industrial production in Russia was falling by 7.6% at most during the first sanction wave in 2014–2015 and by another 2.3% over the second sanction wave in 2017–2018, we conclude that (i) the Russian economy would have fallen into recession even without sanctions in 2014–2015, but the sanctions have amplified the recession nonetheless, and (ii) the Russian economy could almost escape the output, consumption, and investment contractions in 2017–2018 if sanctions were not imposed. Theoretically, the estimated effects of financial sanctions on all variables considered in our study are in line with the small open economy business cycle literature (Neumeyer and Perri, 2005, Garcia-Cicco et al., 2010, Chang and Fernandez, 2013, and Uribe and Schmitt-Grohe, 2017).

The paper is structured as follows. Section 2 highlights the timing of sanctions. Section 3 describes the model, the estimation methodologies, and the data we employ. The empirical results obtained under the conditional forecasting exercise are presented and discussed in Section 4. Section 5 then augments these results with the use of recursive identification and sign restrictions aimed at capturing the sanction effects in a structural manner. Section 6 contains robustness checks. We provide a theoretical interpretation of our results in Section 7. Section 8 concludes.

2 Timing of the financial sanctions

The first wave of financial sanctions arrived in 2014 and was related to the Russian-Ukrainian conflict, namely, to the annexation of Crimea and the support of separatist movements in the Eastern Ukraine. These sanctions were imposed by the United States and European Union in tight coordination and were targeting the same entities (Welt et al., 2020). This allows us to further focus on the timing of the U.S. sanctions only. These sanctions were are administered by the Treasury Department's Office of Foreign Assets Control (OFAC) and were divided into two groups: those blocking foreign assets of Specially Designated Nationals and Blocked Persons (SDNs) and those prohibiting lending, investment, and trading with entities on the Sectoral Sanctions Identifications (SSI) list. The latter — also called *sectoral sanctions* — is the primary object of our interest in this paper because they

effectively reduced foreign borrowing capacity of Russian companies and banks. The U.S. Ukraine-related sanctions clearly date back to March-December 2014 (executive orders 13660, 13661, 13662, and 13685; see Welt et al., 2020). As of 2020, the sectoral sanctions are still in place and apply to new equity issuance and lending of certain maturities (more than 14-day for entities in financial sector, more than 60-day lending for energy sector, and more than 30-day lending for defence sector). By 2020, OFAC included 13 Russian companies and banks and their 276 subsidiaries on the SSI list. The parent entities list includes four largest state-owned banks, one development bank, seven major oil, gas, and pipeline companies, and one state-owned defence company.[5]

The second wave of financial sanctions dates back to 2017–2018 and was introduced in response to illicit cyber-enabled activities, electoral interference, and support to Syria. These sanctions were mostly imposed by the United States, with less support from the European Union's side (Welt et al., 2020). In August 2017, the U.S. passed the Countering America's Adversaries Through Sanctions Act (CAATS) which included the Countering Russian Influence in Europe and Eurasia Act of 2017 (CRIEEA). The latter, among other measures, strengthened the Ukraine-related sanctions and established several new sanctions. In particular, CRIEEA targeted a further reduction of foreign lending to Russian financial and energy sector (Welt et al., 2020).Moreover, the new package introduced mandatory sanctions (previous package was discretionary) against foreign financial institutions involved in undesirable transactions (weapons transfer, oil projects) with Russian entities, thus more strongly reducing the access of the latter to external financial infrastructure.

To further strengthen our argument that the financial sanctions were binding in Russia during 2014–2015 and 2017–2018, we employ a firm-level regression analysis. Specifically, we investigate the time evolution of the relationship between Russian firms' total factor productivity (TFP) and the price of external financing they pay to attract international funds. Theoretical papers rationalize a negative link between country's aggregate productivity and its interest rate on borrowings by appealing to changing risk of default (e.g., sovereign default in Arellano (2008) and Mendoza and Yue (2012) and corporate risk of default in Fernandez and Gulan, 2015). We test on a panel of Russian firms whether this negative link becomes weaker during the years of the two waves of financial sanctions. We expect the weaker relationship in these cases because the observed tightening of borrowing conditions for Russia's firms was unrelated to their risk of default and productivity; the role of TFP in determining the price of international funds should therefore decline in those times. For this purpose, we collect the firm-level data from the SPARK-Interfax database covering roughly 73,000 firm-year observations over

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[5]VTB Bank, Gazprombank, Rosselkhozbank, VEB, Rosneft, Gazpromneft, Transneft, Novatek, Rostec, Lukoil, Surgutneftegaz, Gazprom, respectively.

2013–2019. Our estimation results indicate that the link between TFP and risk-adjusted interest rates is negative and highly significant and, strikingly, that exactly in 2014–2015 and 2018 this negative link is dampened (see Table A.I in Appendix Appendix A). This empirical evidence speaks in favor of negative microeconomic implications that the sanctions could have had at the firm level during the two sanction waves.

Both first and second waves of the financial sanctions have a visible impact on the dynamics of corporate external debt in Russia (Fig. 2.(a)). In particular, in 2014–2015, external debt of banks fell by almost 40% and external debt of non-financial corporations declined by 20%. The speed of debt deleveraging decreased significantly in 2016 but then again accelerated in 2017–2018 when Russian banks repaid another 20% of their external debt while corporations repaid another 8%. Notably, 2014 and subsequent years were the first episodes in the Russian market economy's history in which the country's corporate external debt was not rising.[6] In addition, initial imposition and further strengthening of the financial sanctions in 2014–2015 (first wave) and 2017–2018 (second wave), respectively, were associated with sizeable increases in the Russia's country spread, as measured by the J.P. Morgan Emerging Markets Bond Spread (EMBI+, Fig. 2.(b)).
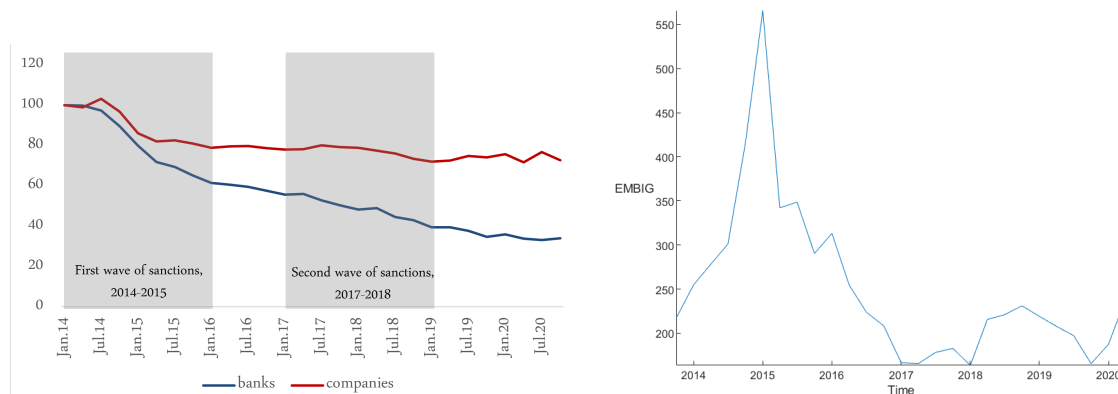
(a) Corporate external debt of Russian banks and nonfinancial companies

(b) J.P. Morgan Emerging Markets Bond Spread (EMBI+)

Sources: Bank of Russia, External Sector Statistics (a); World Bank, Global Economic Monitor (GEM) database (b).

Figure 2: Corporate external debt and country spread in Russia

As we however argue in the next section, the financial sanctions were not the only reason why corporate external debt declined and the country spread increased in Russia over the past decade. Other macroeconomic shocks affected the Russian economy during the same period: terms of trade shocks, shocks to global financial conditions, and others. Therefore, we need to separate the effects

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[6]Except for the global economic crisis of 2007–2009. However, even during that episode of global financial turmoil Russia experienced a much milder decline of its corporate external debt, by only 6%.

associated with the financial sanctions from other shocks. We describe our identification strategy in the next section.

3 Methodology and data

In this section, we outline the main steps of our empirical strategy aimed at comprehensively capturing the sanctions effects and describe the data. We start with describing our BVAR model of the Russian economy (Section 3.1). We then present the conditional forecasting exercise with the BVAR model (Section 3.2.1) and turn to the structural analysis of the sanction effects with the same BVAR model (Section 3.2.2). We complete this section with the data description (Section 3.3).

3.1 BVAR model of the Russian economy

We perform our empirical exercises on the ground of vector autoregressive models (VARs). For that purpose, we consider the following (standard) VAR process with n variables and p lags:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t \tag{1}$$

where $y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$ is a column vector containing the values of n variables at time t. Each matrix A_k comprises all unknown coefficients of each variable y_t taken with a lag j ($j = 1 \ldots p$) and thus has $n \times n$ dimension. $u_t = (u_{1t}, u_{2t}, \ldots, u_{nt})'$ is a column vector with reduced-form residuals, which are assumed to be normally distributed with zero mean and covariance matrix $E(u_t u_t') = \Sigma_u$ of $n \times n$ size, $u_t \sim N(0, \Sigma_u)$.

Following Uribe and Yue (2006), Akinci (2013), and Ben Zeev et al. (2017), we include foreign and domestic variables into our VAR model. Specifically, we consider three variables in the foreign block: commodity terms of trade (CTOT), U.S. corporate bond (Baa) spread, and real U.S. interest rate. Commodity exports matter for Russia. Oil, gas and their products account for 63% of the total export of the country whereas export to GDP ratio is as high as 27% (2010-2016 average). This taken together rationalizes the inclusion of CTOT into our VAR. Further, several studies have found that changes in world financial conditions are important for emerging economies fluctuations. Early literature focused on world interest rates, Neumeyer and Perri (2005), Uribe and Yue (2006); however, recently Akinci (2013) found that the contribution of world interest rates to business cycle fluctuations in emerging economies is negligible while this role is caught up by the global financial risk shocks. Following the studies mentioned above, we include both variables into our VAR model: Baa spread as the measure

of the global financial risk[7] and real U.S. interest rate as a proxy for risk-free interest rate.

The composition of domestic variables block builds upon empirical studies on emerging economies, Uribe and Yue (2006), Akinci (2013), Ben Zeev et al. (2017), and Monacelli et al. (2021). This literature typically includes real sector variables in VARs, empirical counterpart of those used in RBC models of Neumeyer and Perri (2005), Garcia-Cicco et al. (2010), Chang and Fernandez (2013). We follow those studies in the composition of domestic block, we include domestic output (proxied by industrial production, IP), consumption (C), investment (I), trade balance (TB): all in constant prices; and Russia's real interest rate (RIR). Distinct from the literature, we specify the model in *levels* instead of deviations from respective HP-trends because we estimate the model with the Bayesian methods which are specifically designed for models with nonstationary time series. Following recent studies of Ben Zeev et al. (2017) and Monacelli et al. (2021), we additionally include real effective exchange rate (REER) index into our model. This variable transmits terms of trade shocks to the domestic economy (domestic production and absorption, and sectoral composition; though we do not consider sectoral outputs to keep the model short). Given that we study financial sanctions shocks and we are interested in estimation of their macroeconomic effects, we also add an outstanding amount of Russia's corporate external debt (D, deflated by U.S. CPI) into the VAR model.

Ultimately, the vectors y_t and u_t can be represented as:

$$y_t = \left[CTOT_t, RIR_t^{US}, Baa_t^{US}, IP_t, C_t, I_t, TB_t, D_t, RIR_t, REER_t \right]' \tag{2}$$

$$u_t = \left[u_t^{CTOT}, u_t^{RIR^{US}}, u_t^{Baa^{US}}, u_t^{IP}, u_t^{C}, u_t^{I}, u_t^{TB}, u_t^{D}, u_t^{RIR}, u_t^{REER} \right]' \tag{3}$$

where variables 1–3 reflect external conditions (foreign block) and variables 4–10 domestic conditions for the Russian economy (domestic block). In order to ensure that domestic variables do not affect external conditions, we impose small open economy restrictions in the conditional forecasting exercise (see Section 3.2.1) and set to zero the coefficients on the variables 4–10 in equations of the variables 1–3 in the structural VAR analysis (see Section 3.2.2).

In the baseline estimates, we therefore set $n = 10$ variables and we choose $p = 2$ (month) lags.[8] In the robustness section, we consider an extension of the VAR which follows a typical specification of

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[7]Another popular measure, VIX index provided by CBOE, reflects global financial volatility and is also employed in the literature. We use this variable instead of Baa spread in the robustness section.

[8]In the sensitivity analysis, we show that the estimated signs of the sanction effects preserve if we extend the lag structure of the model by including $p = 13$ (month) lags (i.e., 12 lags to account for the monthly dimension of our data, see Section 3.3 below, and 13th lag to capture any residual seasonality in our time series (though we apply standard seasonal adjustments, where appropriate, see also Section 3.3 for details). However, computation of the $p = 2$ version of the model takes about 15 minutes with a standard laptop, whereas the $p = 13$ version takes about 25 hours. The trade-off between the size of the model and the computational costs is thus clear.

the central bank forecasting model (see Banbura et al., 2010 and Banbura et al., 2015). Central bank monetary forecasting models typically have Christiano et al. (1999) VAR model in their heart. In addition to output, prices, and interest rates, the medium-size BVAR model of Banbura et al. (2010) includes monetary aggregates, consumption, wages, and effective exchange rate among other variables. Following these lines, we add to our monetary BVAR model four variables: monetary base, domestic lending the real economy (net of revaluations of the foreign currency part of the loans), real wages and domestic CPI inflation, so that here $n = 14$; additionally, we substitute a country interest rate on foreign borrowings with domestic central bank interest rate.[9]

We estimate the model with Bayesian methods for several reasons. First, macroeconomic time series on the Russian economy are relatively short, covering at most the last two decades.[10] An appropriate response to the short time series is to apply the Bayesian techniques widely exploited in the literature on macroeconomic forecasting (Koop and Korobilis, 2010; Banbura et al., 2010; Koop, 2013; Carriero et al., 2015; Banbura et al., 2015), etc. The Bayesian methods work well in the presence of short time series, which is achieved by formulating a prior distribution of unknown parameters. Second, we perform structural VAR analysis via sign restrictions. As is argued by Kilian and Lutkepohl (2017), sign restrictions are usually implemented with the Bayesian framework.

3.2 Identification of the financial sanction shocks and their macroeconomic effects

3.2.1 Conditional forecasting exercise with the BVAR model

With the specified 10 variables BVAR model at hand, we now turn to describing the conditional forecasting exercise we develop to capture macroeconomic effects of the financial sanctions. For this exercise, we choose the so-called Independent Normal–Inverted Wishart prior for the VAR coefficients A and the innovations covariance matrix Σ_u among the universe of priors developed in the literature so far.[11] This type of prior combines advantages of the classical Minnesota prior (Doan et al., 1984) and natural conjugate priors. From the Minnesota side, our chosen prior allows us to impose restrictions on certain coefficients, which we use to set a version of small open economy restrictions (see, e.g.,

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[9]The key reason why we include domestic financial variables (corporate loans, in particular) is that tightening of external borrowing conditions is likely to increase the demand of the firms on domestic borrowings.

[10]This follows from the fact that the Russian economy is relatively young market economy, its newest history begins in 1991 with the collapse of the Soviet Union. Within the resultant 30 years, the time evolution of key macroeconomic variables in the first decade is subject to the deep transformation crisis which spanned till the end of the 1990s, thus forcing us to further reduce the time span of the time series we use.

[11]An earlier review and examination of the forecasting performance of different priors can be found in Kadiyala and Karlsson (1997). A more recent review is in Karlsson (2013).

Dungey and Fry, 2009). Specifically, we assign zero prior covariances in those parts of the coefficients' A variance-covariance matrix H that govern the covariances of the effects of domestic variables on the three external variables. This reflects our prior belief that the Russian economy does not influence the world economy. As in conjugate priors, the chosen prior treats the error covariance matrix as random so that we are able to address uncertainty about future shocks. All further technical details on the prior formulation can be found in the working paper version of this study (Pestova and Mamonov, 2019). Here we only mention the composition of matrix H to illustrate how we set the hyperparameters governing the tightness of the prior for the baseline estimates and then for robustness checks.

The $\left(n \times (1 + np)\right) \times \left(n \times (1 + np)\right)$ matrix H is assumed diagonal and can be represented as $H = \{h_{\ell\ell}\}$, where a diagonal element $h_{\ell\ell}$ for any $\ell = 1 \ldots n \times (1 + np)$ is defined as:

$$\left(\frac{\lambda_1}{\ell^{\lambda_3}}\right)^2 \text{ if } i = j; \quad \left(\frac{\sigma_i \; \lambda_1 \lambda_2}{\sigma_j \; \ell^{\lambda_3}}\right)^2 \text{ if } i \neq j; \text{ and } (\sigma_i \; \lambda_4)^2 \text{ for constants}; \quad i, j = 1 \ldots n \qquad (4)$$

In other words, for each regression $i = 1...10$ of the BVAR model the matrix H is built to shrink the coefficients A on other variables ($i \neq j$) and on deeper lags towards zero more tightly. In the baseline estimates, we use $\lambda_1 = 0.1$ (general tightness); $\lambda_2 = 0.5$ (significance of other variables); $\lambda_3 = 2$ (lag decay). In the robustness section, we relax the tightness of the prior by setting either $\lambda_1 = 0.2$, $\lambda_2 = 1$ (i.e., assuming other variables are as important as the given variable itself), $\lambda_3 = 1$ (assuming second and deeper lags are as important as the first lag).

Finally, since the priors for the BVAR coefficients A and the error covariance matrix Σ_u are independent, their joint posterior distribution has an unknown form. Thus, we launch a version of the MCMC-algorithms (Markov Switching Monte Carlo), the Gibbs sampling, to draw A and Σ_u from the posterior. In implementing the Gibbs sampling, we rely on Koop and Korobilis (2010) and Blake and Mumtaz (2012) who provide necessary technical details. In the estimations, we set 10,000 draws from the posterior, of which the first 5,000 are burned-in.[12]

Having outlined the Bayesian estimation of the VAR model, let us now describe the conditional forecasting exercise. We have two sanction waves — in 2014–2015 and 2017–2018, and we are aimed at quantifying the sanction effects on domestic macroeconomic variables $y_{4,t} \ldots y_{10,t}$ during each of the two waves. To capture the effects during the first wave, we estimate the BVAR model on the data up to December 2013, i.e., one month prior to the first sanction year. We then produce two conditional forecasts of $y_{4,t} \ldots y_{10,t}$ for $t = Jan.2014 \ldots Dec.2015$. The first forecast is conditioned on

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[12]When we decrease the number of draws to 5,000, of which 2,500 are burned-in, or when we further increase respective numbers, we obtain very similar results.

the actual time evolution of external conditions $y_{1,t}, \ldots, y_{3,t}$ over $t = Jan.2014 \ldots Dec.2015$ and thus accounts for the negative oil price shock of 2014 through the $y_{1,t} = CTOT_t$ variable. We refer to it as the *Condition 1* forecast. The second forecast is conditioned on the actual time evolution of the same three variables $y_{1,t}, \ldots, y_{3,t}$ and one more variable, $y_{8,t} = D_t$, reflecting the actual decline of corporate external debt in 2014–2015. The second forecast, therefore, encompasses both oil price shock and debt deleveraging shock. We mark it as the *Condition 2* forecast. Having computed the two forecasts, we further take the *difference* between them to isolate the debt deleveraging shock, namely, for each $y_{i,t}$, where $i = 4, \ldots, 10 \setminus 8$. The same procedure is applied to the second wave of sanctions. Thus, the economic effects of financial sanctions during both waves can be represented as:

$$First\ wave: \qquad \Delta \hat{y}_{i,t}^{(Sanction)} = \hat{y}_{i,t}^{(Oil,\,Debt)} - \hat{y}_{i,t}^{(Oil)}, \qquad t = Jan.2014 \ldots Dec.2015 \qquad (5)$$

$$Second\ wave: \qquad \Delta \hat{y}_{i,t}^{(Sanction)} = \hat{y}_{i,t}^{(Oil,\,Debt)} - \hat{y}_{i,t}^{(Oil)}, \qquad t = Jan.2017 \ldots Dec.2018 \qquad (6)$$

where $\hat{y}_{i,t}^{(Oil)}$ and $\hat{y}_{i,t}^{(Oil,\,Debt)}$ are the forecasts obtained under *Conditions 1* and *2*, respectively.

Note that since we use the Bayesian technique we obtain *density* forecasts instead of point forecasts. Specifically, we compute the forecasts for each and every post-burned-in draw, i.e., from 5,001 to 10,000. This effectively delivers empirical distributions of conditional forecasts. Then the differences in expressions (5) and (6) are computed for *the same percentile* of the two respective conditional forecasts. When computing conditional density forecasts, we employ one more Gibbs sampling algorithm, namely, the one developed by Waggoner and Zha (1999).[13] Technical details on how we implement this algorithm in our framework can be found in the working paper version (Pestova and Mamonov, 2019). Here, similarly to the first Gibbs sampler (i.e., for estimating the BVAR model), we also set 10,000 draws for the Gibbs sampling algorithm of Waggoner and Zha (1999), of which the first 5,000 are burned in.[14]

We expect rather wide credible bands for $\Delta \hat{y}_{i,t}^{(Sanction)}$ in expressions (5) and (6) because conditional forecasts are equivalent to *generalized* impulse responses of endogenous variables, Banbura et al. (2015), i.e., responses to the shock of interest under all possible orderings of these variables. These orderings, in turn, encompass many structural models. Thus, uncertainty on the ordering of variables — that is, on the identification of shocks — is added to intrinsic sources of uncertainty in the BVAR models, i.e., those related to shocks and coefficients. Those two types of uncertainty are also large for the following

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[13]Similar algorithm is applied in Bloor and Matheson (2011) to compute the conditional forecasts for the New Zealand economy. Banbura et al. (2015) exploit an alternative algorithm, based on the Kalman filtering, for conditional forecasting of the euro-area macroeconomic indicators.

[14]Similarly to the first Gibbs sampler, when we increase or decrease the number of draws, nothing changes qualitatively.

reasons. First, the period of study is relatively short, which implies that the data we use could be uninformative in determining the shape of the coefficients' posterior distribution. Second, the Russian economy witnessed several sizeable shocks during the same period.[15] Therefore, we suspect the issue of wide bands may undermine our trust in the conditional forecasting exercise. We thus address this issue by also complementing our analysis with structural VARs in the upcoming section.

3.2.2 Capturing the sanction shocks and their effects with structural BVAR model

Recursive identification. Having discussed the setup of conditional forecasting exercise, we now proceed with an alternative approach to identification of the financial sanction shock, namely, structural VAR analysis. We capture the sanction shock by an unexpected rise in the country risk premium, as opposed to the decline of outstanding corporate external debt employed in the conditional forecasting part of our analysis. Note that as we showed above, during two waves of financial sanctions both corporate external debt fell and country risk rose, i.e. there is a substitutability between these two variables. We switch to a country spread in the structural VAR analysis because, first, there is an ample literature arguing that shocks to the interest rates on international borrowings ("country spread shocks") account for a non-negligible part of the business cycle fluctuations in emerging economies, see Uribe and Yue (2006); Garcia-Cicco et al. (2010); Chang and Fernandez (2013); and second, there is an established procedure to identification of these shocks, which we follow to ensure comparability with the literature.

To isolate country spread shocks, most of the empirical literature uses standard recursive identification restrictions. In particular, the literature assumes that country spreads react contemporaneously to foreign and domestic shocks while country spread shocks affect domestic real variables with a time lag. Put differently, in recursive VAR setting employed in the literature so far the country spreads are usually ordered last (Uribe and Yue, 2006; Akinci, 2013; Born et al., 2020; Monacelli et al., 2021). Recall that we consider a larger VAR as compared to the mentioned studies, namely, we include REER into the set of domestic variables. Monacelli et al. (2021) mention that there is a potential problem if country interest rate (or spread) is ordered after real exchange rate: this would assume that REER does not react to innovations in domestic interest rate, which is dubious. Therefore, in our recursive identification, we place country interest rate *second last* and assume that REER may respond to country spread shocks contemporaneously. In the sensitivity analysis, we consider the 5-variable VAR of (Uribe and Yue, 2006) which does not contain REER and foreign block, and in which we order

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[15]For instance, global financial crisis of 2007–2009, several oil shocks, restrictive monetary shock of December 2014 in addition to the sanction shocks

country interest rate last.

Formally, we first rewrite the reduced-form VAR model in the companion form $Y_t = AY_{t-1} + u_t$ and then left premultiply both sides by a matrix B_0. This yields a structural representation of the VAR model:

$$B_0 Y_t = B_1 Y_{t-1} + \varepsilon_t$$

where ε_t is a vector of orthogonal structural shocks which are related to the original reduced-form residuals via $u_t = B_0^{-1} \varepsilon_t$.

In the recursive identification, we assume matrix B_0^{-1} to be lower triangular with unit diagonal elements. In addition, we assume that foreign block variables are exogenous with respect to domestic, i.e., they are not affected by current or past values of domestic variables and their shocks. Thus, $u_t = B_0^{-1} \varepsilon_t$ can be represented as:

$$
\begin{pmatrix} \cdots \\ u_t^{IP} \\ u_t^{C} \\ u_t^{I} \\ u_t^{TB} \\ u_t^{D} \\ u_t^{RIR} \\ u_t^{REER} \end{pmatrix}
=
\begin{pmatrix}
& & & & & & \cdots & & & \\
. & . & . & 1 & & & & & & \\
. & . & . & . & 1 & & & & & \\
. & . & . & . & . & 1 & & & & \\
. & . & . & . & . & . & 1 & & & \\
. & . & . & . & . & . & . & 1 & & \\
. & . & . & . & . & . & . & . & 1 & \\
. & . & . & . & . & . & . & . & . & 1
\end{pmatrix}
\begin{pmatrix} \cdots \\ \varepsilon_t^{IP} \\ \varepsilon_t^{C} \\ \varepsilon_t^{I} \\ \varepsilon_t^{TB} \\ \varepsilon_t^{D} \\ \varepsilon_t^{RIR} \\ \varepsilon_t^{REER} \end{pmatrix}
\tag{7}
$$

where "$\ldots$" are the cells linked to the three exogenous variables (not disclosed), "." implies a non-empty element while empty cells, by definition, contain zeros.

Having obtained an estimate of the B_0^{-1} matrix, we compute the time evolution of the estimated RIR shock, $\hat{\varepsilon}_t^{RIR}$ and, within this series, we estimate the size of the RIR shock in each of the two sanction waves in 2014–2015 and 2017–2018 (i.e., find largest positive and significant values, $\hat{\varepsilon}_I^{RIR}$ and $\hat{\varepsilon}_{II}^{RIR}$, respectively). We further multiply the size of the RIR shock by the peak reaction of each of the domestic variables to this shock. The peak reactions are obtained from respective impulse responses. The sanction effects are computed as follows:

$$\textit{First wave (I):} \quad \Delta \hat{y}_{i,I}^{(Sanction)} = \hat{\varepsilon}_I^{RIR} \times \left. \frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{RIR}} \right|_{\hat{\varepsilon}_t^{RIR} = \hat{\varepsilon}_I^{RIR}}, \quad I \in [Jan.2014\ldots Dec.2015] \tag{8}$$

$$\textit{Second wave (II):} \quad \Delta \hat{y}_{i,II}^{(Sanction)} = \hat{\varepsilon}_{II}^{RIR} \times \left. \frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{RIR}} \right|_{\hat{\varepsilon}_t^{RIR} = \hat{\varepsilon}_{II}^{RIR}}, \quad II \in [Jan.2017\ldots Dec.2018] \tag{9}$$

We expect narrower credible bands in (11) and (12) compared to the analogous estimates in the

conditional forecasting exercise (5) and (6) because now we naturally consider impulse responses (IRFs) to a shock identified with just one structural model as opposed to multiple models in the generalized IRFs considered in the previous section.

Sign restrictions approach. There are several reasons why one would want to complement recursive identification of the sanction shocks considered above with an alternative identification. First, there may be a concern that sanction shocks revealed itself not only in an unexpected increase in the country spread but, as we show above, also in a decline in external debt below domestic demand (foreign credit supply shock). Towards this end, we could capture the sanction shock as a *combination of shocks to several variables* where the shocks have certain signs. This naturally leads us to the sign restrictions approach.[16] Second, recursive identification relies on strong timing restrictions and, by construction, may underestimate the role of country spread shocks. This is because the ordering used in the literature attributes all contemporaneous correlation between domestic fundamentals and country spread to domestic shocks other than country spread shocks, therefore leaving little space for the country spread shocks to play. Thus, applying sign restrictions may yield an upper bound of the estimate of the sanction effects.

To separate sanction shock from the most important one for emerging economy — terms of trade (TOT), or productivity — we need an identification scheme under which some variables in VAR would demonstrate distinctive sign responses to these shocks. There is no ready available reference in the literature so far to rely on.

We thus suggest the following procedure. Consider negative TOT shock and a positive shock to RIR (both shocks hit the Russian economy in 2014–2015 simultaneously). Both shocks raise country interest rate, either directly (in case of RIR shock) or indirectly (in case of TOT shock, through increased risk of sovereign / corporate default, Arellano, 2008; Mendoza and Yue, 2012; Fernandez and Gulan, 2015). Both shocks decrease domestic output, Uribe and Yue (2006); Schmitt-Grohe and Uribe (2018). A potential candidate of a variable that could react differently to these two shocks is *trade balance.* A reduction of TOT is likely to decrease trade balance if perceived persistency of TOT is low (this holds for most of the countries, see Uribe and Schmitt-Grohe, 2017; Schmitt-Grohe and Uribe, 2018). In contrast, an increase of RIR leads to an improvement of trade balance through reduction of domestic absorption (consumption, investment) by more than the fall of domestic output Neumeyer and Perri, 2005).[17]

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[16]Sign restrictions approach is a popular approach in empirical macroeconomics and is used to identify, e.g., monetary shocks in Uhlig (2005), credit supply shocks in Hristov et al. (2012) and Gambetti and Musso (2017), news shocks in Crouzet and Oh (2016a), and many others.

[17]As Neumeyer and Perri (2005) show, consumption responses to the RIR shock by more than the output

Therefore, before proceeding to the proposed sign restrictions approach, we check whether a negative $CTOT$ shock worsens trade balance when using the data on the Russian economy. We do so by standard recursive identification; we order $CTOT$ first, the order of the other variables is the same as in equation (2). We indeed find that a negative $CTOT$ shock leads to a decline of trade balance in Russia during the period of study (see Fig. D.I in Appendix D).

Based on the provided arguments, we isolate the sanction shock from $CTOT$ shock by simultaneously imposing the sign restrictions summarized in equation (10). In particular, we assume that both shocks decrease domestic production and raise country interest rate. However, the $CTOT$ shock reduces trade balance whereas the sanction shock increases it.

$$
\begin{pmatrix} \cdots \\ u_t^{IP} \\ \cdots \\ u_t^{TB} \\ \cdots \\ u_t^{RIR} \\ \cdots \end{pmatrix} = \begin{pmatrix} & \cdots & \\ \cdots & \begin{array}{ccc} - & & - \\ - & \cdots & + \\ + & & + \end{array} \\ & \cdots & \end{pmatrix} \cdot \begin{pmatrix} \cdots \\ \varepsilon_t^{TOT} \\ \cdots \\ \cdots \\ \cdots \\ \varepsilon_t^{RIR} \\ \cdots \end{pmatrix} \tag{10}
$$

Finally, having estimated our 10 variables BVAR model under the sign restrictions scheme (10), we estimate the time evolution of the sanction shock, $\hat{\varepsilon}_t^{Sanction}$, and the impulse responses of domestic variables to this shock, $\frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{Sanction}}$. We then compute the third version of the economic effects of financial sanctions. The effects are obtained for the two waves of sanctions, as before, using similar expressions to those (11) and (12) that we use above under the recursive identification:

$$
\text{First wave (I):} \quad \Delta \hat{y}_{i,I}^{(Sanction)} = \hat{\varepsilon}_I^{SR} \times \left. \frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{SR}} \right|_{\hat{\varepsilon}_t^{SR} = \hat{\varepsilon}_I^{SR}}, \quad I \in [Jan.2014 \ldots Dec.2015] \tag{11}
$$

$$
\text{Second wave (II):} \quad \Delta \hat{y}_{i,II}^{(Sanction)} = \hat{\varepsilon}_{II}^{SR} \times \left. \frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{SR}} \right|_{\hat{\varepsilon}_t^{SR} = \hat{\varepsilon}_{II}^{SR}}, \quad II \in [Jan.2017 \ldots Dec.2018] \tag{12}
$$

3.3 The data

We collect the monthly data on all variables entering the BVAR model for the period from January 2000 to December 2018, which results in 208 observations. The data on the variables reflecting external conditions for the Russian economy (i.e., variables 1–3 in the BVAR model) come from various sources. CTOT data is retrieved from the IMF Commodity Terms of Trade Database, where

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does, and the RIR shock leads to a decline of investment and a rise of savings, as in standard neoclassical growth model. These taken together explain an improvement of trade balance in response to positive RIR shocks. Similar outcome arises in Chang and Fernandez (2013).

it is readily available on a monthly basis. Note that previously, the authors constructed commodity terms of trade index for each country themselves (Ben Zeev et al., 2017) based on the IMF Primary Commodity Price data set and the country-specific weights of commodities in their exports. CTOT is a net export price index of the Russia's commodity bundle in which individual commodities are weighted by the ratio of net exports to GDP[18]. Further, real interest rate in the U.S. economy is calculated as the U.S. CPI-adjusted nominal 3-month Treasury Bill rate (both series come from the IMF's International Financial Statistics database). Baa spread for the U.S. economy is retrieved from the St. Louis FRED database.

Domestic real sector variables are constructed based on the datasets of the Federal State Statistics Service of the Russian Federation (Rosstat) and the financial data is obtained through the Bank of Russia's website, respectively. Industrial production, consumption, and investment are constructed based on chain indices and 2010 nominal values and reexpressed in constant 2010 prices.[19] Trade balance is calculated as the difference between dollar value of Russia's exports and imports and deflated by U.S. CPI (the data is taken from IMF's International Financial Statistics database). The data on corporate external debt in Russia is obtained from the Bank of Russia's website.[20] We sum banks' and other sectors' external debt and subtract debt owed by these sectors to direct investors[21]. We then linearly interpolate quarterly series to get monthly data and deflate by U.S. CPI. Following Uribe and Yue (2006), the country's real interest rate is computed as the sum of the U.S. real interest rate and the JP Morgan's EMBI country spread for Russia (J.P. Morgan Emerging Markets Sovereign Bond Spread, EMBI+). We obtain REER variable from the Bank of International Settlement (BIS) website. We reexpress this series as an inverse of the one reported by BIS to interpret a decrease in this variable as REER appreciation and an increase – as depreciation (following Ben Zeev et al., 2017).

We apply the seasonal adjustment procedure X13 to industrial production IP_t, consumption C_t, investment I_t, and trade balance TB_t. All variables are further transformed to logs. More details on the sources and the data transformation are provided in Table A1 in Appendix.

---

[18]The applied weighting scheme already transforms the series into the constant prices because import prices stand in the denominator. We also considered a deflated series: we divided commodity export price index by the U.S. import price index of manufactured goods from industrialised countries, similarly to Ben Zeev et al. (2017). The results did not change.

[19]Data source: Short-term economic indicators, https://rosstat.gov.ru/compendium/document/50802.

[20]External Sector Statistics, http://cbr.ru/eng/statistics/macro_itm/svs.

[21]A sizeable amount of Russian corporate external debt falls into a category of debt to direct investors and direct investment enterprises. As of the end of 2013, the share of this 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 under sanctions. We address this issue by excluding the debt to direct investors from the total stock of corporate external debt.

4 Estimation results: Capturing the effects of financial sanctions through differences in conditional forecasts

4.1 Exogenous conditions: commodity terms of trade and the global financial conditions

Let us begin with describing the time evolution of the three exogenous variables in our BVAR model during the first (2014–2015) and second (2017–2018) waves of sanctions. These variables are TOT_t, RIR_t^{US}, and Baa_t^{US}. It is crucially important for understanding our results because we use these three variables to construct *Conditions 1* and *2* forecasts, along with corporate external debt. Their dynamics is plotted on Fig. 3.(a)–(c) below, where we also add two vertical lines depicting the first month of each of the two sanction waves (March 2014 and August 2017, as discussed in Section 2).

(a) CTOT annual growth rates   (b) Interest rate in the US economy   (c) Baa spread
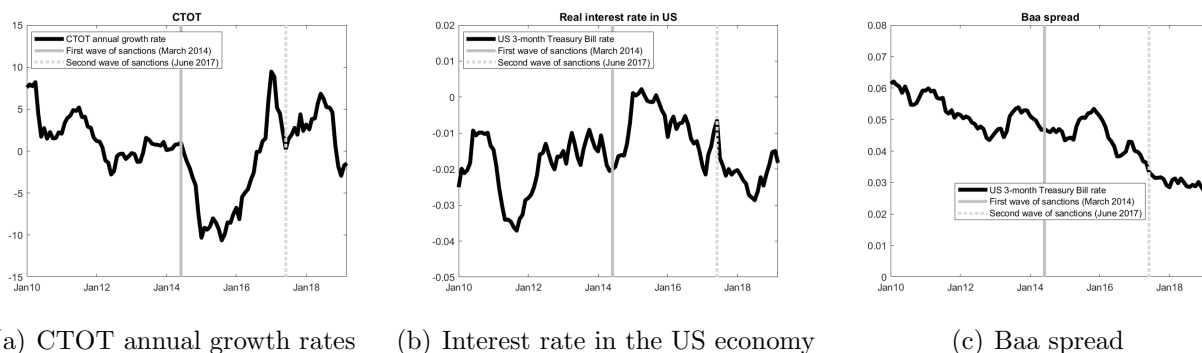
Note: The figure reports time evolution of TOT_t, RIR_t^{US}, and Baa_t^{US}, i.e., the first three variables in our BVAR model, see (2). The growth rates are computed as the value of CTOT in current month over the value of CTOT in corresponding month of the previous year, %.

Figure 3: Exogenous conditions for the Russian economy during the
first and second waves of the sanctions

Interestingly, the presented time evolution suggests that exogenous conditions for the Russian economy were substantially different across the two waves of sanctions. First, CTOT felt sharply in the beginning of the first wave (by 10% annually) whereas it was improving during the first months of the second wave (by 7%). This clearly illustrates that the Russian economy, being heavily dependent on the export of natural resources (gas, oil, etc.), would exhibit declining trends in output and other macroeconomic variables in 2014 and their expansionary dynamics in 2017, thus confounding the effects of financial sanctions, which are expected to be negative during *both* waves. It is thus important to difference out the effects of CTOT. Second, the same applies to the global financial conditions, as measured by the real interest rate in the U.S. economy, RIR^{US}. The world witnessed a sizeable rise of RIR^{US} which coincided with the first months of the first sanction wave. It created additional

incentives for international investors to withdraw funds from Russia (and other EMEs), thus posing a negative pressure on Russia's domestic fundamentals. On contrary, the first months of the second wave coincided with a reduction of RIR^{US}. Third, the Baa spread in the U.S. economy was either stable or even declining, thus reflecting low global financial risks during the periods of both sanction waves. Overall, we conclude that exogenous conditions for the Russian economy were very different during the two waves of financial sanctions, and ignoring them when estimating the effects of the sanctions would likely contaminate the results.

4.2 Financial conditions on international borrowings

4.2.1 Corporate external debt deleveraging as a result of sanctions

Let us now focus on the outstanding amount of corporate external debt D_t, the main variable of interest. Under *Condition 1*, we produce the forecasted path of D_t conditioned on the three exogenous variables discussed above, i.e., TOT_t, RIR_t^{US}, and Baa_t^{US}, and we compare thus obtained forecasted time evolution of D_t with its actual dynamics over the two waves of sanctions. Since the actual dynamics fully internalizes the financial sanctions, the difference between the actual and conditionally forecasted values represents the effect of sanctions on D_t and is thus expected to be negative during both waves. We also provide unconditional forecasts for the sake of comparison. Recall that D_t enters the conditioning set for the *Condition 2* forecast, which we describe in the next sections. The forecasting results appear in Fig. 4.(a)–(b) below.

Several outcomes emerge from figure 4. First, the line representing the median forecasted path of D_t lies above the actual data on D_t during both waves of sanctions. This implies that, in the absence of debt restrictions, the Russian economy would enjoy greater international borrowings during both periods. The conditional forecasts reveal that D_t would, however, still exhibit a downward trend during the first wave of sanctions (Fig. 4.a). This is due to a decreased demand for international borrowings against the background of CTOT deterioration driven by the drop of oil prices in 2014.[22] During the second wave in 2017–2018, the observed improvement of CTOT could facilitate a rise of D_t if there were no sanctions (Fig. 4.b).

Second, economically the negative difference between the actual and forecasted paths of D_t is substantial during both sanction waves. Specifically, the largest difference over the first wave is estimated at –20 percentage points (in terms of annual growth rates), which was reached in the first

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[22]Decreased oil prices force international investors to re-evaluate the risks associated with lending to the Russian companies and may decrease the demand of the Russian companies on foreign borrowings.
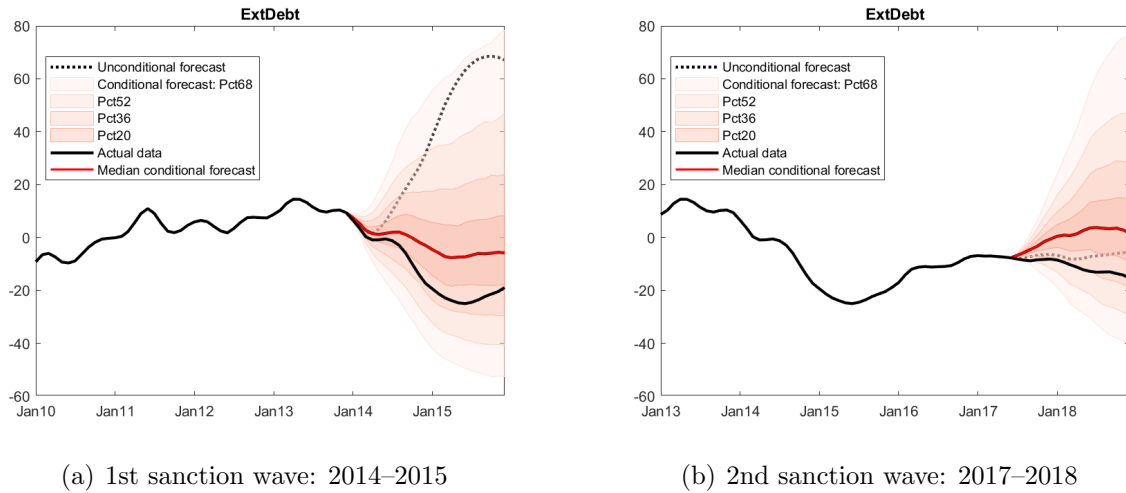
(a) 1st sanction wave: 2014–2015	(b) 2nd sanction wave: 2017–2018

Note: Hereinafter, the conditioning set also contains the actual path of CTOT, US interest rate, and Baa spread. For density forecasts, we report four percentile ranges. For instance, $Pct20$ means 20% of respective distribution around the median forecast. Conventional thresholds (16th and 84th) are reflected by $Pct68$. The figure results from two Gibbs samplers, as discussed in the text, with 10,000 draws in each (the first 5,000 draws are burned in). The growth rates are computed as the value of debt in current month over the value of the debt in corresponding month of the previous year, %.

Figure 4: Annual growth rates of external corporate debt in Russia
during the first and second waves of sanctions: Conditional forecasts

half of 2015 when D_t decreased by as much as 25%. Note that just two years before, the annual growth rate of D_t was at a local peak equaling +17%. If one would not consider conditional forecast of D_t, she could misleadingly attribute the whole difference between the peak of 2013 and the trough of 2015, i.e., 42 percentage points = 17% – (–25%), to the sanctions. The effect would thus be at least two times over-estimated. During the second wave, the difference was also sizeable reaching again about –20 percentage points at minimum (mid-2018, a year after the sanctions were introduced).

Third, we highlight the wide credible bands of the conditional forecast, meaning that we face a very high uncertainty regarding the future path of corporate external debt when we condition on only external variables TOT_t, RIR_t^{US}, and Baa_t^{US}. We anticipated this outcome (see methodological discussion in Section 3.2.1 above).

Fourth, we also stress that unconditional forecast of D_t is unlikely to capture the sanction effects, which necessitates the use of conditional forecasts. For instance, during the first wave of sanctions the unconditional forecast implies an abnormally rapid growth of D_t. During the second wave, the unconditional forecast is closer to the actual data than the conditionally forecasted path, thus indicating that the intrinsic state of the Russian economy *after* the recession of 2014–2015 and the first wave of sanctions was much worse than one could predict based on exogenous conditions.

Overall, the estimated difference between the actual and forecasted values of corporate external debt is indeed negative during both waves of sanctions, as we expected. This implies the sanctions posed additional pressure on foreign debt of the Russian companies (debt deleveraging) *beyond* that

caused by the global exogenous forces.

4.2.2 Real interest rate in the Russian economy: rising risk premium

Having outlined the time evolution of the three exogenous (global) conditions and corporate external debt of the Russian companies during the two waves of sanctions, we now proceed to describing the main results of our conditional forecasting exercise. Hereinafter, we present the conditional forecasts of each of the seven domestic endogenous variables in our BVAR model $(y_{4,t}, \ldots, y_{10,t})$ in separate figures. Each figure contains conditional density forecasts, unconditional forecasts, and actual data divided into six subfigures: (a),(b),(c) pertain to the first wave of sanctions, (d),(e),(f) to the second. Subfigures (a),(b) and (d),(e) provide the forecasts under *Conditions 1* and *2*, respectively, while subfigures (c) and (f) illustrate the difference between the two corresponding forecasts.

We start with the results on the real interest rate in the Russian economy, RIR, see Fig. 5 below.
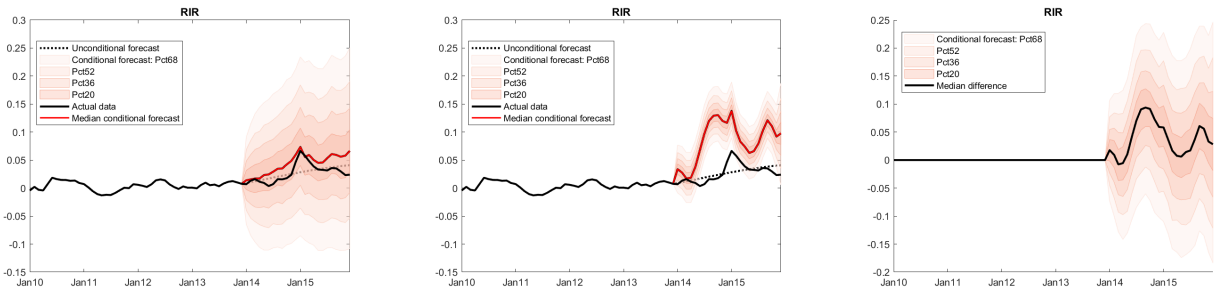
(a) 1st sanction wave: Condition 1   (b) 1st sanction wave: Condition 2   (c) 1st sanction wave: Condition 2 − Condition 1
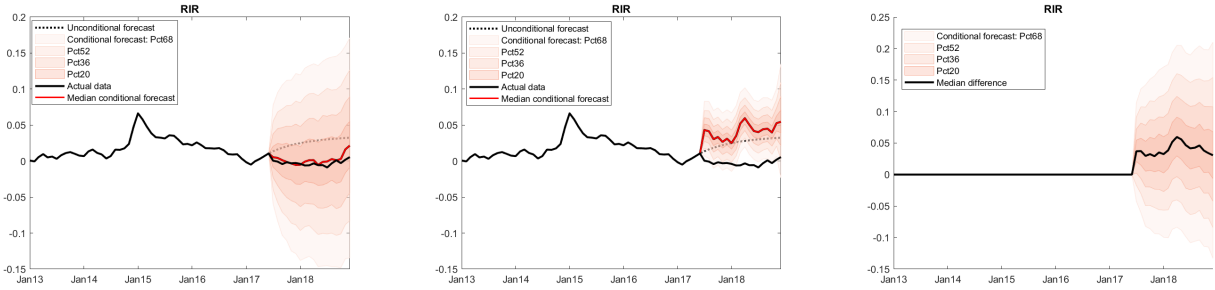
(d) 2nd sanction wave: Condition 1   (e) 2nd sanction wave: Condition 2   (f) 2nd sanction wave: Condition 2 − Condition 1

Note: The figure reports conditional forecasts of the real interest rate (RIR_t).
Condition 1 includes of the actual dynamics of CTOT (commodities terms-of-trade), real interest rate in the US economy and Baa spread over the forecasting horizon of 2014–2015 (1st sanction wave) and 2017–2018 (2nd sanction wave), see Fig. 3. Condition 2 includes Condition 1 and adds the actual paths of external corporate debt over respective sanction wave, see Fig. 4. The economic effects of sanctions are estimated via expressions (5) for the first wave and (6) for the second wave.

Figure 5: Real interest rate in Russia during the first and second waves
of sanctions: Conditional forecasts

Within the first sanction wave, the effect of sanctions on RIR, as measured by the difference

between the *Conditions 1* and *2* forecasts, reached up to +10 percentage points by the end of 2014 (see Fig. 5.c). The effect is large, however, is not surprising given the Russia's pre-history. The same rise of RIR occurred in Russia during the global financial crisis in 2009. It is instructive to see the composition of the estimated effect. As can be inferred from Fig. 5.(a), the BVAR model over-predicts RIR under *Condition 1* during the first wave: the median forecasted line lies above the actual line. One could anticipate the opposite because the actual line should internalize the sanction effect.[23] Fortunately, as can further be inferred from 5.(b), the BVAR model even more over-predicts RIR so that the difference between the two forecasted paths depicted in Fig. 5.(c) is positive, as we have already described and as is in line with one's expectations. We also observe wide credible bands of the conditional forecasts of RIR under *Condition 1.* It is notable how strong the reduction of uncertainty of the forecasts under *Condition 2* is: this implies the potency of corporate external debt in reducing the forecast uncertainty exceeds those of the three exogenous (global) conditions during the period under study.

As for the second wave of sanctions, we obtain very similar results: most importantly, the difference between the two forecasts of RIR is positive, equals +5 percentage points (reached in mid-2018), and again we obtain wide credible bands (see Fig 5.f).

Overall, according to our estimates, the sanctions led to a substantial rise of RIR during both waves, thus reflecting an increased risk premium in the price of borrowings for the Russian companies (note that we control for U.S. interest rate in all conditional forecasts, which means that any rise of domestic rates comes from elevated country risk premium). Combining these outcomes with those obtained in the previous section (i.e., that the sanctions led to a decrease of external corporate debt over the two waves), we conclude that financial sanctions are a supply-side shock in their essence. Therefore, in the absence of sanctions, Russian firms would borrow internationally more compared with their actual borrowings and at lower price. This allows us to hypothesize that the real effects of financial sanctions should be negative.[24] We test it in the upcoming section.
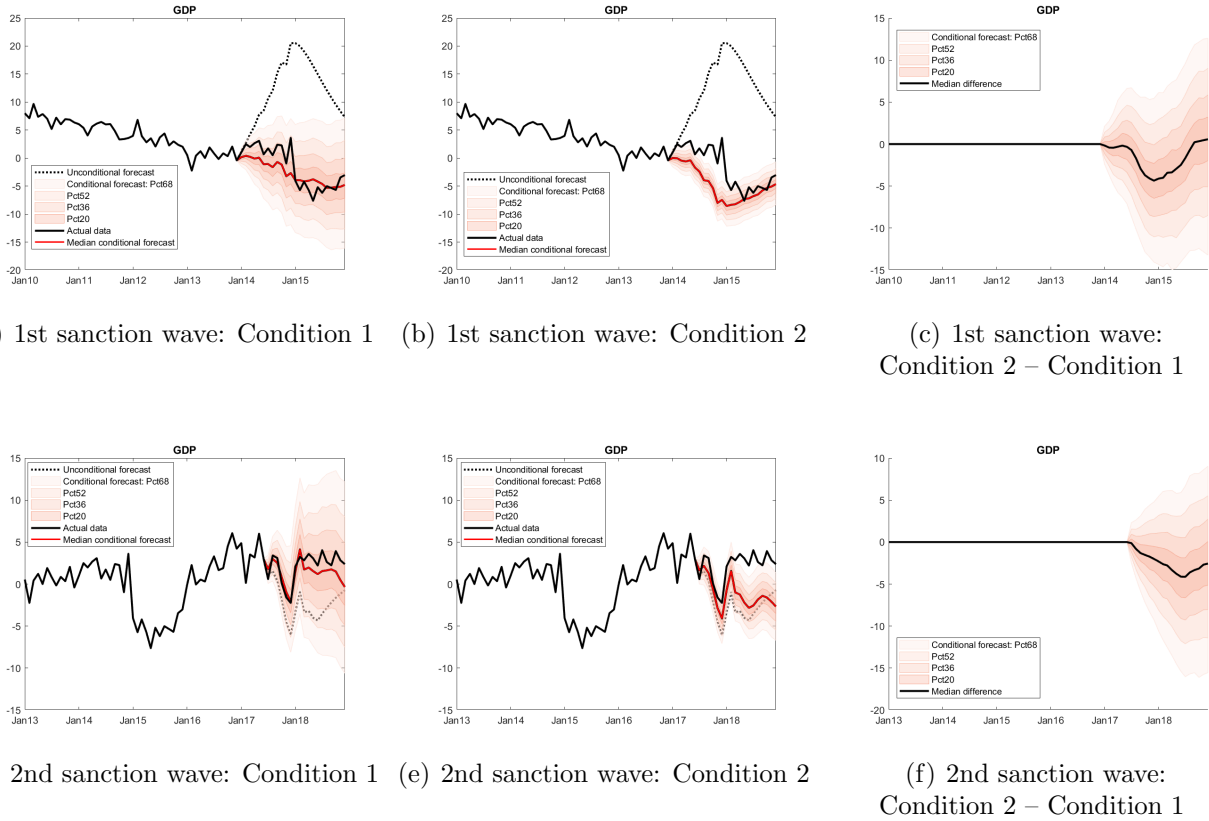
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[23]This is the reason why we do not include RIR in the conditioning set for *Condition 2*, as one could be willing to do to be ex-ante sure that she is capturing the supply-side effects. As is clear from comparing Fig. 5.(a) and Fig. 5.(b), this would misleadingly lead us to the conclusion that sanctions had a downward effect on RIR. This would further produce confusing result that household consumption is rising as a result of sanctions (as would be predicted by the households' Euler equation).

[24]By showing that the supply-side factors were at place, we eliminate a concern that the observed reduction of corporate external debt was driven by (solely) demand-side factors. If the reduction would be driven by demand factors, we would observe a *positive* correlation between real interest rate and the outstanding amount of debt (movement along the supply curve of debt due to shifts in demand). Instead, we find the correlation to be negative, therefore indicating supply shocks in place which move price and quantity along the demand curve.

4.3 Domestic macroeconomic variables

4.3.1 Output growth rates in Russia

Having described the effects of sanctions on financial conditions, let us now turn to the real effects of sanctions on the Russian economy. We start with industrial production IP_t, as a proxy for output. For the sake of convenience, we present the conditional forecasting results in annual growth rates, not in levels. The forecasting results on the output growth appear in Fig. 6 below.

(a) 1st sanction wave: Condition 1   (b) 1st sanction wave: Condition 2   (c) 1st sanction wave: Condition 2 − Condition 1

(d) 2nd sanction wave: Condition 1   (e) 2nd sanction wave: Condition 2   (f) 2nd sanction wave: Condition 2 − Condition 1

Note: The figure reports conditional forecasts of output growth, as measured by industrial production (IP_t). GDP is not available at a monthly frequency, and we thus proxy it with the monthly index of industrial production. The growth rates are computed as the value of the index in current month over the value of the index in corresponding month of the previous year, %. .

Condition 1 includes of the actual dynamics of CTOT (commodities terms-of-trade), real interest rate in the US economy and Baa spread over the forecasting horizon of 2014–2015 (1st sanction wave) and 2017–2018 (2nd sanction wave), see Fig. 3. Condition 2 includes Condition 1 and adds the actual paths of external corporate debt over respective sanction wave, see Fig. 4. The economic effects of sanctions are estimated via expressions (5) for the first wave and (6) for the second wave.

Figure 6: Industrial production in Russia during the first and second waves of sanctions: Conditional forecasts

Our forecasting results reveal sizable negative effects of the financial sanctions on industrial production in the Russian economy during both waves of sanctions. As Fig. 6.(c) shows, the first wave's peak negative effect reaches –5 percentage points by the end of 2014 (in terms of annual growth rates of IP_t). Interestingly, we find the same –5 percentage points to be the second wave's peak negative reaction of IP_t on sanctions, and this peak was reached by mid-2018, see Fig. 6.(f). Economically, the effects are indeed large, given that the mean and standard deviation of the annual growth rate

of IP_t equal 2.8% and 5.5 percentage points, respectively. Qualitatively, this implies sanctions had a role *beyond* negative oil price shock in 2014. However, we treat our results with caution because we again obtain rather wide credible bands of our forecasts.

The problem of wide credible bands again is more acute for the forecasts under *Condition 1*, see Fig. 6.(a) and Fig. 6.(d) for the first and second waves, respectively. We have already seen the same outcome above, when we described the forecasting results on RIR_t. When we then add corporate external debt into the conditioning set, the bands narrow dramatically, as is visible from Fig. 6.(b) and Fig. 6.(e) for the first and second waves, respectively. However, the forecasts of IP_t under *Condition 2* also reveal a drawback: the median conditional forecasts underpredict the actual path of industrial production, and this is true over both sanction waves. In this sense, the median conditional forecasts under *Condition 1* are closer to the actual dynamics of IP_t.

We also note that unconditional forecasts of IP_t are unreliable during the first wave of sanctions, implying unrealistically high growth of output in the Russian economy. Recall that unconditional forecast could be interpreted as if the economy would follow the intrinsic inertia solely and face no sanctions or other shocks. This outcome could be driven by corporate external debt — recall we had a similarly unrealistically high unconditional forecasts of D_t, see Fig. 4.(a) in Section 4.2.1. Conversely, the unconditional forecast of IP_t during the second wave of sanctions remains within the observed historical domain of industrial production.

Overall, we conclude that the effect of financial sanctions on the industrial production of the Russian economy could be rather large during both waves, though the estimates are uncertain in both cases. Structural analysis in the following sections is thus vital to refine the estimates and make final conclusion.

4.3.2 Consumption dynamics

Let us now analyze the effects of sanctions on the components of domestic demand. The conditional forecasting results on consumption appear in Fig. 7 below. We again present the results in annual growth rates, for convenience reasons.

Not surprisingly, our results indicate that Russian households were forced to decrease aggregate consumption C_t in response to sanctions during both waves. Though not reported, the reduction applies to both consumption of tradables and nontradables.[25] Economically, the effects are comparable with those obtained for output in the previous section, but somewhat lower (by 1 percentage points),

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[25]The results available from the authors upon request. In some BVAR specifications, we considered tradable and nontradable consumption separately.
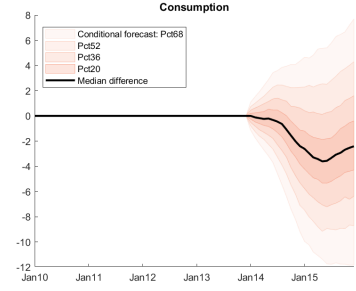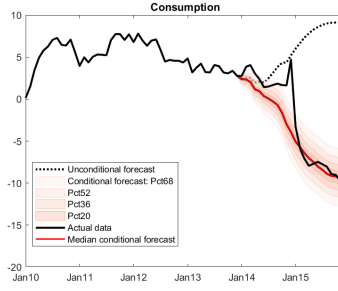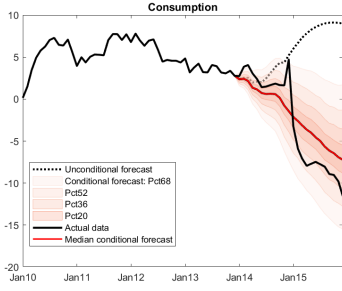
(a) 1st sanction wave: Condition 1   (b) 1st sanction wave: Condition 2   (c) 1st sanction wave: Condition 2 – Condition 1
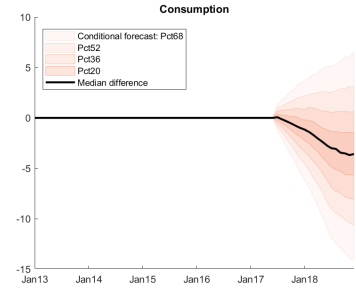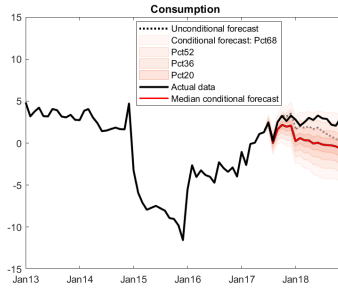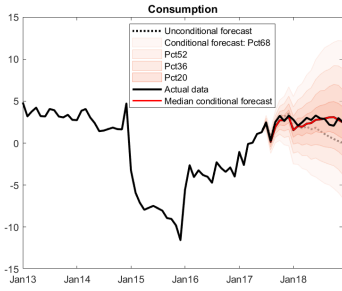
(d) 2nd sanction wave: Condition 1   (e) 2nd sanction wave: Condition 2   (f) 2nd sanction wave: Condition 2 – Condition 1

Note: The figure reports conditional forecasts of final consumption (C_t). The growth rates are computed as the value of real consumption in current month over the value of the real consumption in corresponding month of the previous year, %.

Condition 1 includes of the actual dynamics of CTOT (commodities terms-of-trade), real interest rate in the US economy and Baa spread over the forecasting horizon of 2014–2015 (1st sanction wave) and 2017–2018 (2nd sanction wave), see Fig. 3. Condition 2 includes Condition 1 and adds the actual paths of external corporate debt over respective sanction wave, see Fig. 4. The economic effects of sanctions are estimated via expressions (5) for the first wave and (6) for the second wave.

Figure 7: Consumption in Russia during the first and second waves of sanctions: Conditional forecasts

and again are characterized by wide credible bands. Interestingly, we obtain a more persistent and deeper decline of consumption during the second wave as compared to the first wave, which speaks to a lack adaptation to external shocks.[26]

Specifically, we estimate the peak negative reaction of C_t during the first wave as –4 percentage points (median forecast), being reached by the first quarter of 2015, i.e., one year after the sanctions were imposed, see Fig. 7.(c). Uncertainty around the median forecast is large: 84% credible bands range from –12 to 4 percentage points. We address this issue in Section 5 below by employing a structural model. The uncertainty again rests in the *Condition 1* forecast, whereas under *Condition 2* it shrinks substantially. Notably, when being conditioned on only external variables, the forecast of C_t over-predicts the decline of consumption in 2014 but seriously under-predicts it in 2015, see Fig.

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[26]One could expect that, after the first wave, the second wave could have a milder effect on consumption because households might accumulate additional savings to dampen negative effects of possible sanctions in the future. Our conditional forecasting exercise does not find evidence to support this view. However, we treat the results with a caution due to wide credible bands.

7.(a). The spike in C_t in the end of 2014 has a behavioral nature, not being accounted for in the model: in a month after the dramatic ruble depreciation occurred in that times (recall negative oil price shock) households directed their savings to buy imported goods while the latter were affordable. The sharp decline of C_t which followed in 2015 is very well captured only when we add the actual time evolution of corporate external debt into the conditioning set, see Fig. 7.(b). Overall, the actual consumption decline during the first wave equals –15 percentage points, and our results here indicate that one third of this decline could be attributed to the effect of sanctions.

Somewhat differently, during the second wave of sanctions in 2017–2018 there was no such abrupt reductions of C_t: consumption was recovering after the crisis years of 2014–2015 rather fast, but then turned to a slowdown in mid-2017. The median forecast under *Condition 1* already captures this slowdown very well, even without conditioning on the sanctions, see Fig. 7.(d). This is surprising at first sight since the external conditions were rather favorable to Russia during that times, as we show in Section 4.1 above. However, note that the unconditional forecast also points to the slowdown of consumption. This may be interpreted as a depletion of internal forces that drove recovery of consumption, in the absence of new growth-enhancing forces. Our forecasting results suggest that accounting for the sanction-driven reduction of external corporate debt under *Condition 2* produces a greater decline of C_t, see Fig. 7.(e). However, given wide credible bands around forecasts and sizable under-prediction of consumption growth during the second wave of sanctions, we conclude that conditional forecasting with BVAR had hard time to account for actual dynamics of consumption in 2017-2018.

4.3.3 Investment dynamics in Russia

Let us now consider the effects of sanction on the next component of output, namely, investment. The conditional forecasting results on investment growth appear in Fig. 8 below.

In line with the results from the previous sections, we find that the financial sanctions had negative effects on investment I_t during both waves of sanctions. The estimated magnitudes of the effects are again comparable to those obtained before: the peak negative reaction equals –6 percentage points within the first wave, see Fig. 8.(c), and –5 percentage points over the second wave, see Fig. 8.(e). Credible bands are also wide, and again are due to uncertainty in the *Condition 1* forecast. The *Condition 2* forecasts reveal no such uncertainty, analogously to what was obtained in the previous sections.
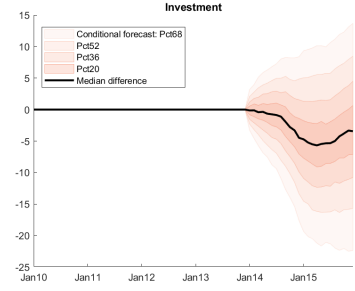
Similarly to the results on consumption, we obtain that during the first wave of sanctions the
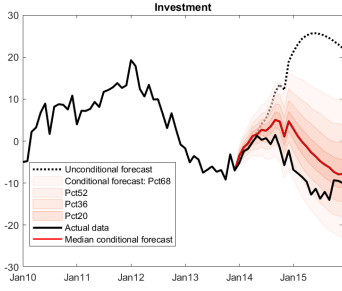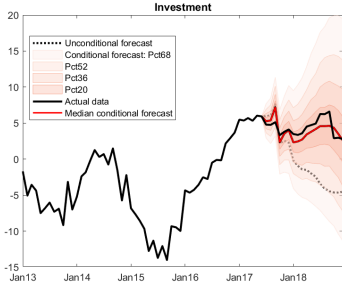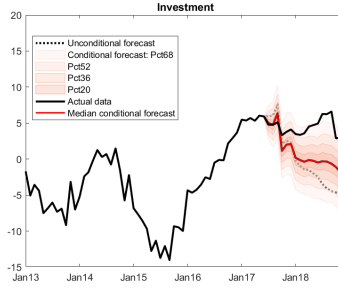
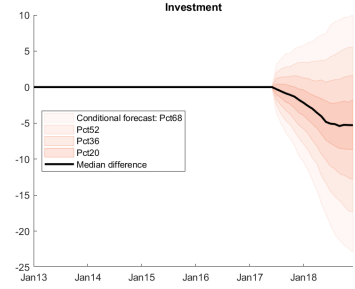(a) 1st sanction wave: Condition 1 (b) 1st sanction wave: Condition 2 (c) 1st sanction wave:
Condition 2 – Condition 1
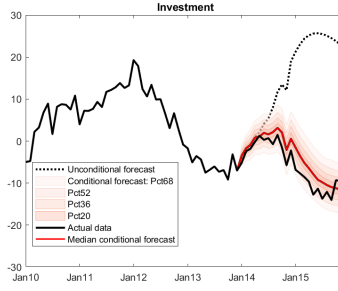
(d) 2nd sanction wave: Condition 1 (e) 2nd sanction wave: Condition 2 (f) 2nd sanction wave:
Condition 2 – Condition 1

Note: The figure reports conditional forecasts of investment (I_t). The growth rates are computed as the value of real investment in current month over the value of the real investment in corresponding month of the previous year, %.

Condition 1 includes of the actual dynamics of CTOT (commodities terms-of-trade), real interest rate in the US economy and Baa spread over the forecasting horizon of 2014–2015 (1st sanction wave) and 2017–2018 (2nd sanction wave), see Fig. 3. Condition 2 includes Condition 1 and adds the actual paths of external corporate debt over respective sanction wave, see Fig. 4. The economic effects of sanctions are estimated via expressions (5) for the first wave and (6) for the second wave.

Figure 8: Investment dynamics in Russia during the first and second
waves of sanctions: Conditional forecasts

forecasts under-predict the actual data under *Condition 1* and fit the actual data very well under *Condition 2*, compare Fig. 8.(a) and Fig. 8.(b). This suggests that the investment activities of Russian firms were dependent on international borrowings, and that those activities were substantially reduced due to the first wave of imposed sanctions. During the second wave, we again observe that *Condition 1* predicts the actual data very well, while *Condition 2* under-predicts the actual data, appeal to Fig. 8.(d) and Fig. 8.(e). The latter prevents us from interpreting the difference between conditional forecasts under second wave of sanctions as the effect of those sanctions, similar conclusion to what was obtained for consumption in the previous section.

4.3.4 The rest of endogenous variables

Finally, we briefly outline the conditional forecasting results on trade balance TB_t and real effective exchange rate $REER_t$. Since these are not the focus variable, we move the graphical illustrations of the forecasts into the Appendix C.

Regarding TB_t, our conditional forecasts imply nearly zero effect of the financial sanctions during both waves, see Fig. C.I.(c) and Fig. C.I.(e). This is surprisingly, because one could expect positive effects due to declining consumption of importables and reduced international borrowings. Given we again face wide credible bands, we treat this result with caution.

The forecasting results on $REER_t$ are much more consistent with one's expectations. We find that $REER_t$ depreciates in response to sanctions, and that this holds over both waves of sanctions, see C.II.(c) and Fig. C.II.(e). The two respective effects equal +5 and +3 percentage points (in terms of annual growth rates). Indeed, demand-driven reduction of the consumption of nontradables deteriorates the prices of nontradables, given the same supply. As is known from the theory on open economy macroeconomics, this situation leads to a rise of $REER_t$ (Uribe and Schmitt-Grohe, 2017). The Russian economy became cheaper compared to the rest of the world during both waves of sanctions, i.e., the sanction effects go *beyond* those of CTOT negative (in 2014) or positive dynamics (in 2017).

# 5 Alternative estimates of the sanction effects: Structural VAR approach

The conditional forecasting results in the previous section indicate that both waves of financial sanctions had negative effects on domestic macroeconomic variables *beyond* those caused by oil price shocks: (i) real interest rates increased; (ii) output, final consumption and investment declined, and (iii) real effective exchange rate depreciated. However, all the forecasts possess wide credible bands, thus posing high uncertainty on the interpretation of the results. In this section, we thus address this issue by means of a structural analysis based on the same 10 variables BVAR specification, namely, we apply recursive identification (Christiano et al., 1999) and sign restriction (Uhlig, 2005) approaches to capture the sanction shocks and their effects during both waves, thus complementing the analysis conducted so far. In both cases we employ the approach to estimating IRFs in VAR models developed by Antolin-Diaz and Rubio-Ramirez (2018).

5.1 Recursive identification: the focus on real interest rate shocks

The order of the 10 variables employed in the BVAR model remains as in expression (2). We estimate the model on the full sample accommodating $Jan.2000, \ldots, Dec.2019$ and further recover IRFs of domestic macroeconomic variables (4–10) to a +1 percentage point RIR shock (9th variable in the

ordering). The estimation results appear in Fig. 9 below.
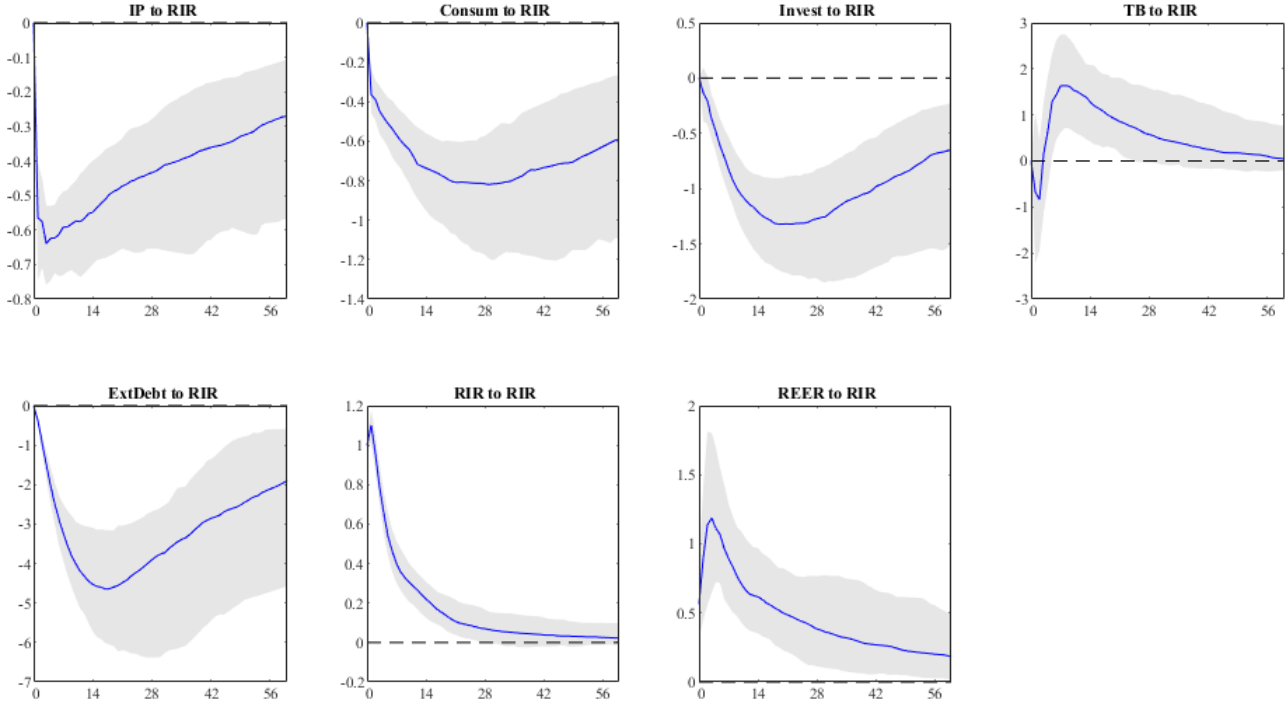
Note: The figure reports estimated IRFs of domestic macroeconomic variables to a +1 percentage point shock in RIR. The BVAR model contains 10 variables, and the RIR variable is ordered second last. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and we discard the first 5,000 draws. Conventional credible bands comprised of the 16th and 84th percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

Figure 9: Impulse response functions to the RIR shock identified under
the recursive scheme

The main outcome from the estimated IRFs is that, quantitatively, the effects of the recursively identified RIR on domestic macroeconomic variables are all credible and exhibit predictable signs. Qualitatively, the effects are very similar to those obtained with our conditional forecasting exercise before. Specifically, we have that in response to an unexpected rise of interest rate the corporate external debt declines; output, consumption, and investment fall; REER depreciates. However, some important differences are also revealed. First, in absolute terms, the response of consumption to the RIR shock exceeds the response of output, which is more consistent with the stylized facts on EMEs (problems with consumption smoothing, see Neumeyer and Perri, 2005; Uribe and Schmitt-Grohe, 2017) compared to what we had before. Second, we now obtain a positive reaction of trade balance to the RIR shock, which was muted in the conditional forecasting exercise above.

Let us now check whether the estimated time evolution of the RIR shock contains any *positive* and credible values during the first and second waves of sanctions. In Fig. 10 below we plot the median time evolution of the shock and its 84% credible bands conventionally used in the Bayesian literature.

The estimated time evolution of the RIR shock is remarkable. First, we observe a sharp spike in
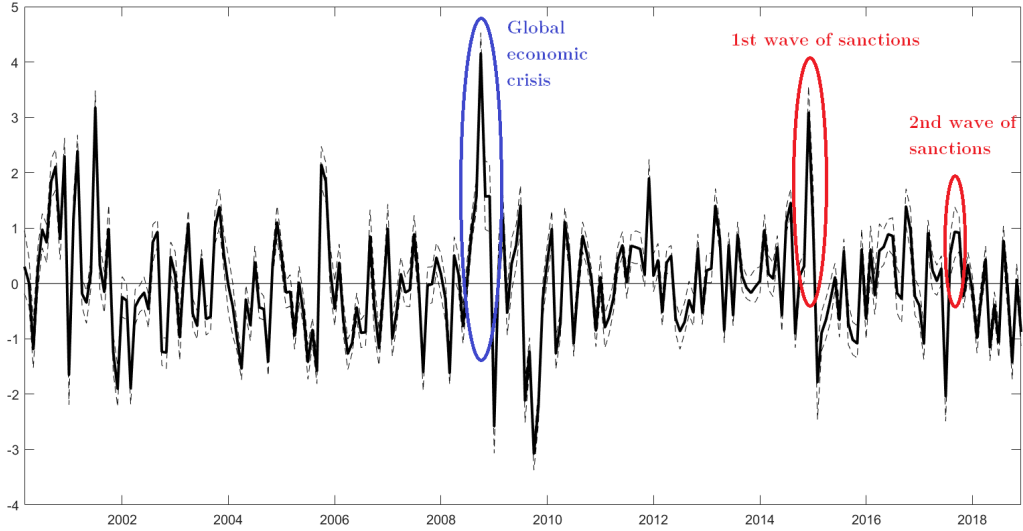
Note: The figure reports the time evolution of the RIR shock estimated with the BVAR model containing 10 variables. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and we discard the first 5,000 draws. Conventional credible bands comprised of the 16th and 84th percentiles of the post-burned-in estimated IRFs are reported. Significant positive RIR shocks are identified for the first and second waves of sanctions in the end of 2014 and 2017, respectively. The positive RIR shock occurred during the global economic crisis is shown for comparative reasons.

Figure 10: Time evolution of the RIR shock identified under the
recursive scheme

the end of 2014 which can clearly be attributed to the first wave of financial sanctions. The size of

the shock equals +3.56 percentage points which is, according to our estimates, the second most strong

shock over the last two decades after the shock associated with the global economic crisis of 2007–

2009 (+4.7 percentage points, in the beginning of 2009). Second, when we turn to the second wave

of sanctions, we are recognize a credible positive shock in the second half of 2017 but the size of the

shock is at least three times lower than during the first wave. This implies that the second wave was

much less harmful in terms of macroeconomic effects compared to the first one in 2014. Interestingly,

this conclusion is much more consistent with the nature and timing of sanctions discussed above

(see Section 2) than the estimation results of the conditional forecasting exercise which delivered

quantitatively *similar* effects over the both waves. This speaks in favor of the recursive identification

of the effects of financial sanctions.[27] We also note that RIR shocks of the size comparable to that of

the second wave of sanctions occur very often, according to the presented estimates.

Since the estimated IRFs to the RIR shock have predictable signs and are credible and the esti-

mated time evolution of the shock have meaningful spikes attributable to each of the two sanction

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[27]However, we are not strict in this judgement and argue that the effects of the second wave could still be comparable to those materialized during the first wave *if* the information component of the sanction announcement in 2017 produced more negative effects than the actually realized sanctions themselves. Such disaggregation is an interesting avenue for future research.

waves, we can apply formulas (11) and (12) to re-estimate the peak effects of sanctions. We simulate the confidence bands for the product of peak IRF reaction and the size of RIR shock by computing the products of each post-burned-in percentiles of respective IRF distribution with each post-burned-in percentiles of the RIR shock distribution. The estimation results are as follows (all numbers are in terms of annual growth rates of respective variables).

First, regarding corporate external debt D_t, the variable we use to identify the sanction effects in the conditional forecasting exercise, we obtain a similar quantitative effect for the first wave of sanctions, $-4.8 \times 3.56 = -17.1$ percentage points[28] (-20 in the conditional forecasts). However, the effect during the second wave is now very much different, $-4.8 \times 0.92 = -4.4$, than before (-20 in the conditional forecasts). However, wide credible bands inherent to the conditional forecasts include both these effects. Here, we benefit from a sharper identification under recursive scheme than in the case of conditional forecasts.

Second, under the recursive identification, the estimated peak effect of the RIR shock on output, as measured by industrial production IP_t, equals $-0.64 \times 3.56 = -2.3$ percentage points for the first wave of sanctions and just $-0.64 \times 0.92 = -0.6$ percentage points for the second wave.[29] These estimates are more precise and imply less strong effects of sanctions than those obtained in the conditional forecasting exercise (recall that, in case of IP_t, the median difference between *Conditions 1* and *2* equaled -5 percentage points for both waves, see Fig. 6). Note, however, again that the wide credible bands of the conditional forecasts encompass the estimates we obtain with the recursive identification here.

Third, qualitatively, the same conclusion applies to final consumption C_t and investment I_t. Quantitatively, the estimated peak effects of the RIR shock on C_t equal $-0.81 \times 3.56 = -2.9$ percentage points for the first wave of sanctions and $-0.81 \times 0.92 = -0.7$ percentage points for the second wave (-5 and -4 in the conditional forecasts, respectively). These effects are equivalent to 0.5 and 0.12 standard deviations of C_t (6.2 percentage points), respectively, thus indicating that the effects are non-trivial. For I_t the effects of the RIR shock are $-1.35 \times 3.56 = -4.8$ for the first and $-1.35 \times 0.92 = -1.2$ for the second wave of sanctions (conditional forecasts were -5 and -6, respectively). These effects are, in turn, also large, being equivalent to 0.46 and 0.11 standard deviations of I_t during the full sample period (11 percentage points) .

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[28]Hereinafter, if not explicitly indicated, the provided estimates are significant in the sense that zero is not included in their credible bands. We do so to preserve space. Full results are available from the authors upon request.

[29]Recall that a one standard deviation of the annual growth rates of IP_t over the full sample period equals 5.5 percentage points.

Fourth, qualitatively different outcome pertains to trade balance TB_t. Under recursive identification, the peak effect of the RIR shock is $1.7 \times 3.56 = 6.1$ percentage points for the first wave of sanctions and $1.7 \times 0.92 = 1.6$ percentage points for the second wave (0 and 0 in the conditional forecasts, respectively). However, when compared to the standard deviation of TB_t over the full sample period (0.46), the effects are only 0.13 and 0.03, thus still indicating a moderate economic consequences of the RIR shocks on trade balance dynamics in Russia.

Fifth, the effects of the RIR shock on $REER_t$ are rather close to those achieved in the conditional forecasting exercise: $1.2 \times 3.56 = 4.3$ percentage points (+5 in the conditional forecasts) for the first wave and $1.2 \times 0.92 = 1.1$ percentage points (+3). The effects equal 0.4 and 0.1 standard deviations of $REER_t$ (10.7 percentage points).

Overall, most of the effects of sanctions obtained with the conditional forecasting exercise are confirmed under recursive identification, at least qualitatively, and in some cases (D_t, I_t, and $REER_t$) the effects are quantitatively close. At the same time, a sharper identification of the sanction shock with the recursive scheme resolves the issue of wide credible bands inherent to the conditional forecasts, and, in that sense, the results now are more reliable. We also note that our results achieved even under the recursive identification imply the sanctions had moderate, but non-negligible, effects after controlling for oil price drops (in contrast to the findings of Ahn and Ludema, 2019).

## 5.2 Sign restrictions: the role of trade balance

In this section, we provide the final refinement of the sanction effects by suggesting a sign restriction approach which is able to distinguish the effects of sanctions from those of CTOT. As we discuss in the methodology section, our sign restriction approach relies on the distinctive roles that TB_t plays during the sanction and CTOT shocks. During sanctions, TB_t should rise whereas it should fall when the economy faces negative CTOT shocks. In the previous sections, we have already shown the sanctions effects on TB_t are likely to be positive.

Our approach thus depends crucially on whether negative CTOT shocks lead to negative reaction of TB_t. We therefore first test whether this indeed holds in our data. To do so, we run a separate recursive identification of the CTOT shock. As the estimated IRFs indicate (see Fig. D.I in Appendix D), TB_t indeed falls during the periods of negative $CTOT$ shocks. We thus are able to proceed to the sign restriction approach, as described in expression (10).

In what follows, we identify two shocks — the sanction shock and CTOT shock. We require the

sign restrictions to hold at least three months.[30]

IRFs to the sanction shock estimated under the sign restriction approach appear in Fig. 11 below.[31] As can be inferred from the figure, qualitatively, the estimated reactions of domestic macroeconomic variables to the sanction shock are similar to those obtained under the recursive identification of the RIR shock above: the signs of respective reactions are the same, and all the reactions are estimated precisely. The only difference is that the effects under the sign restrictions are much larger quantitatively than those under the recursive scheme. This is in line with our expectations and is likely due to a more specific focus on sanctions and their clear separation from the CTOT shock (see discussion in Section 3.2.2).
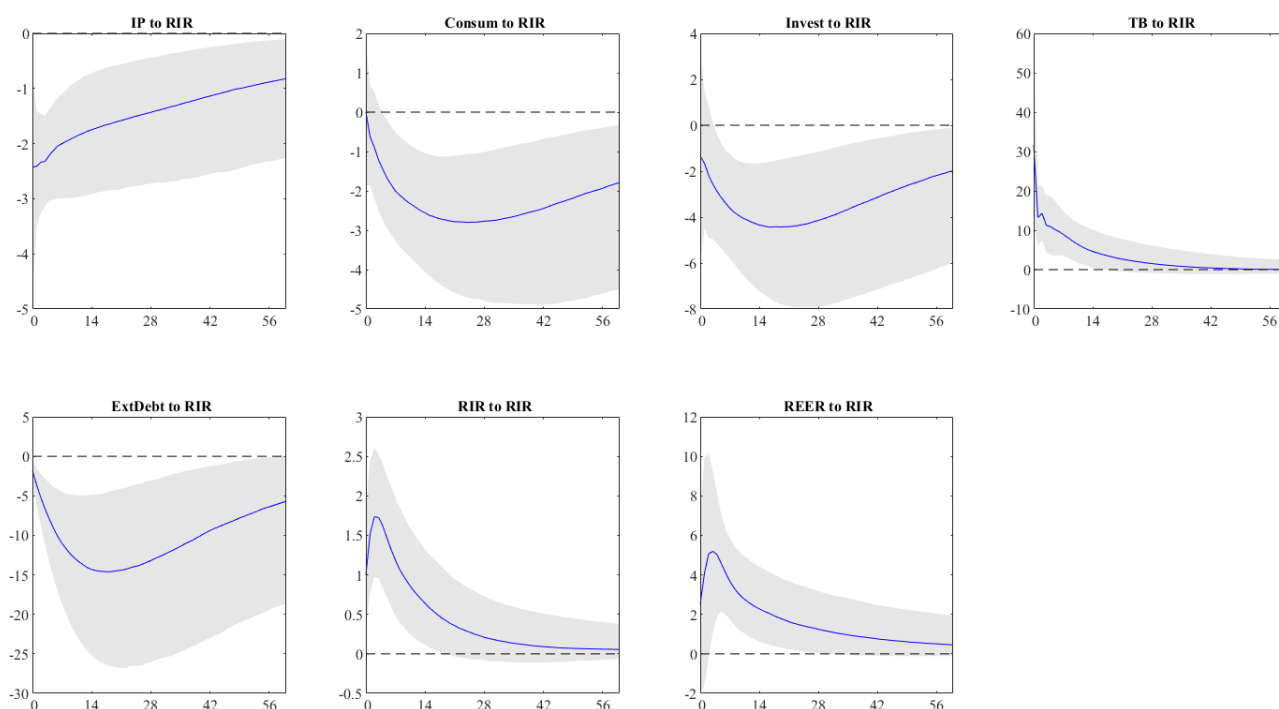
Note: The figure reports estimated IRFs of domestic macroeconomic variables to a sanction shock identified with sign restrictions: IP_t falls, RIR_t rises, TB_t increases during the first three months after the shock. The shock is normalized to +1 percentage points of RIR_t on impact. The BVAR model contains 10 variables. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and we discard the first 5,000 draws. Conventional credible bands comprised of the 16th and 84th percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

Figure 11: Impulse response functions to the sanction shock identified
under sign restrictions

Further, the time evolution of the sanction shock identified through the sign restriction approach

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[30]In the robustness section, we show that switching to on-impact, one- or two months restrictions leads to very similar results quantitatively.

[31]IRFs to the CTOT shock identified under the same sign restriction scheme can be found in Fig. E.I (see Appendix E). Since it is not our primary focus, we just mention that the reactions of output and trade balance are negative, as implied by the scheme, and deliver less strong effects of CTOT shocks compared to sanction shocks (note that both sets of IRFs are normalized so that the on-impact reaction of interest rate equals +1 percentage point). What is important for us is that the data confirm *opposing* reaction of trade balance on sanction and CTOT shocks.

is depicted in Fig. 12 below. We again are able to recognize both waves of sanctions, as before, in the end of 2014 and in the end of 2017, and make a conclusion that the first-wave sanction shock is comparable to the global economic crisis in terms of a joint event of RIR_t unexpected rises and IP_t and TB_t unexpected declines. We note, though, that for the second wave the positive shock identified in 2017Q4 includes zero in its credible bands. Therefore, applying it in further analysis would produce the sanction effects subject to a high uncertainty regarding the potency of the second set of international restrictions, as was the case with the conditional forecasts. However, we can also, without loss of generality, consider the positive shock occurred in 2018Q2 as the one associated with the second wave of sanctions: it is fairly inside the 2017–2018 horizon and the deepest decline of industrial production took place exactly in 2018Q2. Economically, both candidates for the sanction shock have almost identical size.
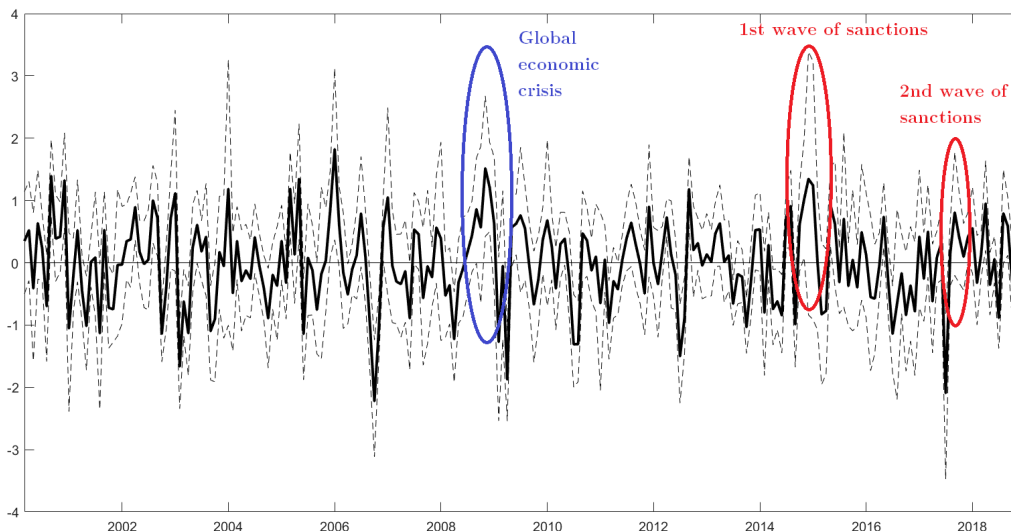
Note: The figure reports the time evolution of the sanction shock estimated with the BVAR model containing 10 variables. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and we discard the first 5,000 draws. Conventional credible bands comprised of the 16th and 84th percentiles of the post-burned-in estimated IRFs are reported. Significant positive sanction shocks are identified for the first and second waves of sanctions in the end of 2014 and 2017, respectively. The positive RIR_t shock occurred during the global economic crisis is shown for comparative reasons.

Figure 12: Time evolution of the sanction shock identified under sign restrictions

Finally, we compute the sanctions effects, as implied by expressions (5) and (6). Confidence bands of the effects are again simulated as we did it in case of recursive identification.[32] For comparison reasons, we gather the estimated effects under sign restriction, recursive identification, and conditional forecasts for both sanction waves in one place, see Table 1 below.

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[32]Again, as in the recursive identification case, if not explicitly stated, the estimated effect is significant (i.e., zero is not in the confidence band).

Table 1: Summary of macroeconomic effects of the financial sanctions

Sanction wave:	First (2014–2015)			Second (2017–2018)		
Estimation method:	SR	RID	CF	SR	RID	CF
Domestic macroeconomic variables:	(1)	(2)	(3)	(4)	(5)	(6)
Industrial production (IP_t)	–2.9	–2.3	–5.0	–1.7	–0.6	–5.0
Final consumption (C_t)	–3.5	–2.9	–5.0	–2.1	–0.7	–4.0
Investment (I_t)	–5.0	–4.8	–5.0	–3.0	–1.2	–6.0
Trade balance (TB_t)	36.0	6.1	0.0	21.6	1.6	0.0
Corporate external debt (D_t)	–18.0	–17.1	–20.0	–10.8	–4.4	–20.0
Real effective exchange rate ($REER_t$)	6.0	4.3	5.0	3.6	1.1	3.0

Note: "SR" is sign restrictions, "RID" is recursive identification, and "CF" is conditional forecasts. The presented estimates reflect *median* percentage points change (in terms of annual growth rates of a given domestic macroeconomic variable) in response to respectively identified sanction shock.

The comparative results of the estimated sanction effects are as follows. First, with respect to the quantity variables IP_t, C_t, I_t, and D_t the median effects of sanctions estimated under the sign restrictions are bounded between those obtained with recursive identification (lower bound) and the conditional forecasting exercise (upper bound), which is true during both waves of sanctions. For instance, the median effect on IP_t peaked at –2.9 percentage points over the first wave of sanctions. Recall that the actual decline of IP_t during 2014–2015 equaled –7.6% reached in 2015Q2. We thus conclude that about one third of the observed decline is due to international restrictions during that times. Interestingly, for the second wave we have the estimated median sanction effect peaked at –1.7 percentage points and the actual decline approached just –2.3% by the end of 2017; that is, the observed output contraction can almost fully be attributed to the second set of international restrictions. This makes sense because, as opposed to 2014, there was no negative CTOT shocks over that times (as we show in Section 4.1 above). For comparisons, the recursive identification delivered a much lower effect, –0.6 percentage points, and the conditional forecasts produced a much larger effect, –5 percentage points. It seems that the former under-estimates the sanction effects, whereas the latter over-estimates them. The reason is that, in 2017–2018, there were no meaningful negative shocks other than the sanctions.[33]

Second, as for the other quantity variable, TB_t, the results are different: the largest effects are obtained under the sign restrictions, the lowest (actually, zero) — with the conditional forecasts. The effects under sign restrictions are also much larger than those delivered by the recursive identification, by factors of 6 for the first wave and 15 for the second. This does not mean, however, that the sign restriction results are unreliable. The effects are +36 and +22 percentage points (in terms of annual

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[33]Indeed, monetary policy were permanently easing, following a declining CPI inflation; CTOT exhibited improved trading conditions for Russia; etc.

growth rates), which are lower than the TB_t standard deviation by respectively 10 and 24 percentage points.[34]

Third, as concerns the price variable, $REER_t$, the sign restrictions also delivers the largest effects of sanctions across the three methods considered. However, quantitatively, the differences are rather mild. During the first wave, $REER_t$ could depreciate by up to 6 percentage points and, during the second wave, by another 3.6 percentage points at most, which are equivalent to 0.6 and 0.3 standard deviations of $REER_t$ over the full sample period.

Overall, we conclude that our structural exercises, and especially the sign restriction approach, lead to substantial improvement of the results obtained under the conditional forecasting exercise. We thus treat the sign restriction results as final.

6 Sensitivity analysis

We perform several robustness checks. First, we specify a larger BVAR model with monetary sector and re-estimate all the effects for both the first and second sanctions waves. Results remain the same. See, for example, Appendix F in which we show that the difference between the *Conditions 1* and *2* forecasts of output growth is still near 2 percentage points.

Second, we raise the number of lags in the BVAR model from 2 to 13 months to address a concern that we could lost valuable information contained in deeper lags of endogenous variables. The results are qualitatively the same but now exhibit spurious non-monotonicity (fluctuations) around the trend (see Appendix G). This non-monotonicity could signal on an over-fitting of the model. We thus treat these results with a caution and suggest that feeding less time lags into the model may be more desirable since it is more in line with the theoretical predictions on the RIR shocks and their effects on macroeconomic variables (Neumeyer and Perri, 2005; Uribe and Yue, 2006; Uribe and Schmitt-Grohe, 2017) (that is, that the effects are unlikely to be non-monotone).

Third, we vary the tightness of hyperparameters governing the priors when perform Bayesian estimations of our (S)VAR models. We loose the general tightness of the prior (λ_1), see Fig. H.I in Appendix H, and then we loose all three hyperparameters, see Fig. H.II. The results are remarkably stable.

Fourth, we run a recursive identification of the RIR shock using a 5-variable VAR, as suggested by Uribe and Yue (2006). The results appear in Appendix I and indicate that output falls by more

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[34]Also note that the largest spike in the actual growth rates witnessed during the first wave equaled 36% (in the beginning of 2014) and during the second 230% (in mid-2018).

than in our 10-variable baseline specification, investment also falls by more, but trade balance declines whereas in the baseline trade balance rises. The estimated time evolution of thus identified RIR shock still allows us to recognize a positive, and much stronger than in the baseline, shock in 2014 (first wave) while no such significant shocks in 2017–2018 (second wave). Quantitatively, the first wave effects on output and investment are substantially over-estimated, though qualitatively the same. We thus prefer our 10 variable specification.

Fifth, we switch from a 3-months to on-impact sign restrictions and, using the 10 variables BVAR model, re-estimate the IRFs of domestic macroeconomic indicators to the sanction shock over the first and second waves. As we show in Fig. J.I (see Appendix J), with this less strict identification of the shock we still arrive mostly at the same results as before. The obtained effects are a little less strong quantitatively than those in the baseline version, though are still significant and of the same signs. The two exceptions are the effects on trade balance and REER which are still positive but now insignificant. Further, we compute the time evolution of the identified shock, as before. We still observe positive spikes during both sanction waves, however, the spikes contain zeros in their credible bands, thus leaving us uncertain regarding the shock Fig. J.II. For these two reasons we prefer to extend the period during which we require the sign restrictions to hold.

Finally, non-Bayesian empirical macroeconomic literature usually exploits time series in deviations from trends to insure stationarity and a clear interpretation based on cyclicalities in the data. Though we apply the Bayesian methods that are designed to account for non-stationarities in the data, we also perform another layer of estimations in which we employ our 10 variables in their deviations from HP-trends. The IRFs estimation results under the recursive identification scheme appear in Fig. K.I and the underlying time evolution of the RIR_t shock is reported in Fig. K.II (see Appendix K). As can be inferred from the figures, the all the results except those on trade balance remain unaffected. The IRF representing the trade balance reaction to the RIR_t shock is negative, not positive, as the theory to which we appeal in the main text predicts. Our baseline results are free of this drawback.

7 Theoretical interpretation of the effects of financial sanctions

There are several theoretical models which can rationalize the effects of a financial sanction shock. Recall that in our structural quantitative analysis above, we interpret this shock as an exogenous rise of a country's interest rate, in particular, an increase in the country risk premium over the world

interest rate. To study such shocks, the literature suggests to use a small open economy business cycle model with financial shocks and frictions. Prominent examples of such models are delivered by Neumeyer and Perri (2005), Garcia-Cicco et al. (2010), and Chang and Fernandez (2013).[35] In these models, domestic agents have access to international financial market where they trade (one-period) discount bonds. Firms are subject to a working capital constraint: they have to pay in advance a fraction of wage bill for which they borrow internationally. The interest rate on international loans is a sum of exogenously given world interest rate and a country spread. The spread is assumed to be a function of domestic fundamentals (productivity, or aggregate debt, which is the "induced" country risk in the terminology of Neumeyer and Perri, 2005) and, at the same time, it is subject to exogenous shocks ("independent" country risk).

The literature provides us a clue on the macroeconomic effects of country spread shocks. According to theoretical impulse response functions, an exogenous rise of a country spread decreases consumption and investment by more than output,[36] raises domestic savings and, correspondingly, leads to an improvement of trade balance.[37] Intuitively, and as predicted by households' Euler equation, an increase in a country's interest rate induces households to decrease their consumption and rise their desired savings. Moreover, an existence of working capital constraint amplifies the negative consumption response through decreased labor demand and employment. A reduction in employment, via production function, rationalizes negative response of output.

The literature on small open economy business cycles is however silent on the effects of country spread shocks on domestic real exchange rate (REER). We thus take this effect from a simple endowment economy model with tradable and nontradable goods (TNT model of Uribe and Schmitt-Grohe, 2017). This model offers an analytical representation of the equilibrium response of REER to a tem-

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[35] An alternative theoretical interpretation of financial sanction shocks could be reached in similar RBC modes which introduce a collateral constraint as a source of financial frictions. Under financial sanctions, this constraint may be exogenously tightened which leads to negative macroeconomic implications, see, e.g., Mendoza (2010) and Bianchi and Mendoza (2018). However, there is no corresponding empirical VAR literature that would identify shocks to external debt. In contrast, existing empirical literature considers country spread shocks. That is why we rely on the empirical and theoretical literature with country spread shocks to study the effects of financial sanctions.

[36] This explains excess volatility of consumption relative to output, which is observed in emerging market economies, Uribe and Schmitt-Grohe (2017).

[37] See Fig. 7 in Neumeyer and Perri (2005) and Fig. 3 in Chang and Fernandez (2013). Note that both figures present impulse responses to an international interest rate shock. However, given that country spread and international rate enter the equation for domestic interest rate loglinearly, the effects of a country spread shock would be the same as that of a shock to international interest rate. Note also that Neumeyer and Perri (2005) calibrate the parameters of their model to the Argentinian data and Chang and Fernandez (2013) perform the Bayesian estimation of the parameters of their model using the Mexican data. This means that the same conclusion regarding the effects of interest rate shocks is achieved in two different models estimated or calibrated on the data on two different countries. We therefore expect that the Russian case is not an exception and the same conclusion applies here, given that Russia is also an emerging market economy.

porary country interest rate shock. According to Uribe and Schmitt-Grohe, 2017, REER depreciates in response to an exogenous rise in the interest rate. An interpretation would be that an increase in the interest rate reduces consumption demand, including the demand for nontradables, and thus decreases the price of nontradables. The price of nontradables, in turn, is negatively related to REER.

Given the provided analysis, we conclude that, in our empirical exercises, we obtain the same signs and order of magnitudes for the responses of the Russian macroeconomic variables to financial sanction shocks as the theoretical literature predicts.

8 Conclusion

In this paper, we build a medium-sized Bayesian (S)VAR model to estimate the economic effects of Western financial sanctions imposed on the Russian economy in 2014 (first wave) and 2017 (second wave). 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 by the beginning of 2021, supported and extended by the administration of the U.S. president and political establishment in euro area. With these findings and trends in hand, we see an evolving path for research on medium- and long-term effects of financial sanctions.

References

Ahn, D., and Ludema, R. (2019). The Sword and the Shield: The Economics of Targeted Sanctions. CESifo Working Paper 7620.

Akinci, O. (2013). Global Financial Conditions, Country Spreads and Macroeconomic Fluctuations in Emerging Countries. *Journal of International Economics*, 91(2), 358–371.

Antolin-Diaz J., and Rubio-Ramirez J. (2018). Narrative Sign Restrictions. *American Economic Review*, 108(10), 2802—2829.

Arellano, C. (2008). Default Risk and Income Fluctuations in Emerging Economies. *American Economic Review*, 98(3), 690—712. https://doi.org/10.1257/aer.98.3.690

Banbura, M., Giannone, D., and Lenza, M. (2015). Conditional Forecasts and Scenario Analysis with Vector Autoregressions for Large Cross–Sections. *International Journal of Forecasting*, 31, 739–756. https://doi.org/10.1016/j.ijforecast.2014.08.013

Banbura, M., Giannone, D. and Reichlin, L. (2010). Large Bayesian Vector Autoregressions. *Journal of Applied Econometrics*, 25, 71–92. https://doi.org/10.1002/jae.1137

Barseghyan, G. (2019). Sanctions and Counter-Sanctions: What Did They Do? BOFIT Discussion Papers No. 24/2019.

Belin, M., and Hanousek J. (2020). Which Sanctions Matter? Analysis of the EU/Russian Sanctions of 2014. *Journal of Comparative Economics*, 49(1), 244–257.

Ben Zeev, N., E. Pappa, and A. Vicondoa (2017). Emerging Economies Business Cycles: The Role of Commodity Terms of Trade News. *Journal of International Economics*, 108, 368—376.

Bianchi, J., and Mendoza, E.G. (2018). Optimal, Time-Consistent Macroprudential Policy. *Journal of Political Economy*, 126, 588–634. https://doi.org/10.1086/696280

Blake, A., and Mumtaz, H. (2012). Applied Bayesian Econometrics for Central Bankers. Technical Handbook, No. 4. Bank of England. Centre for Central Banking Studies.

Bloor, C., and Matheson, T. (2011). Real–Time Conditional Forecasts with Bayesian VARs: An Application to New Zealand. *The North American Journal of Economics and Finance*, 22, 26–42. https://doi.org/10.1016/j.najef.2009.10.003

Born, B., Muller, G., Pfeifer, J., and Wellmann, S. (2020). Different No More: Country Spreads in Advanced and Emerging Economies. Unpublished manuscript.

Borzykh, O. (2016). The Bank Credit Channel: Estimation Of the TVP-FAVAR Model. *Applied Econometrics*, 43, 96–117. (in Russian)

Byrne, J., Korobilis, D. and Ribeiro, P. (2018). On the Sources of Uncertainty in Exchange Rate Predictability. *International Economic Review*, 59, 329–357. https://doi.org/10.1111/iere.12271

Carriero, A., Clark, T. E., and Marcellino, M. (2015). Bayesian VARs: Specification Choices and Forecast Accuracy. *Journal of Applied Econometrics*, 30, 46–73. https://doi.org/10.1002/jae.2315

Cespedes, L. S., and Velasco, A. (2012). Macroeconomic Performance During Commodity Price Booms and Busts. *IMF Economic Review*, 60, 570–599. https://doi.org/10.1057/imfer.2012.22

Chang, R., and Fernandez, A. (2013). On the Sources of Aggregate Fluctuations in Emerging Economies. *International Economic Review*, 54(4), 1265—1293. https://doi.org/10.1111/iere.12036

Christiano, L.J., Eichenbaum, M., and Evans, C. L. (1999). Monetary Policy Shocks: What Have We Learned and to What End? In *Handbook of Macroeconomics*, 1, 65–148. Elsevier. https://doi.org/10.1016/S1574-0048(99)01005-8

Deryugina, E., and Ponomarenko, A. (2015). Accounting for Post–Crisis Macroeconomic Developments in Russia: A Large Bayesian Vector Autoregression Model Approach. *Emerging Markets Finance and Trade*, 51, 1261–1275. https://doi.org/10.1080/1540496X.2015.1069125

Doan, T., Litterman, R., and Sims, C.A. (1984). Forecasting and Conditional Projection Using Realistic Prior Distributions. *Econometric Reviews*, 3, 1–100. https://doi.org/10.1080/07474938408800053

Dreger, C., Kholodilin, K. A., Ulbricht, D., and Fidrmuc, J. (2016). Between the Hammer and the Anvil: The Impact of Economic Sanctions and Oil Prices on Russia's Ruble. *Journal of Comparative Economics*, 44, 295–308. https://doi.org/10.1016/j.jce.2015.12.010

Dungey, M., and Fry, R. (2009). The Identification of Fiscal and Monetary Policy in a Structural VAR. *Economic Modelling*, 26, 1147–1160. https://doi.org/10.1016/j.econmod.2009.05.001

Garcia-Cicco, J., Pancrazi, R., and Uribe, M. (2010). Real Business Cycles in Emerging Countries? *American Economic Review*, 100(5), 2510—2531. https://doi.org/10.1257/aer.100.5.2510

Giannone, D., Lenza, M., and Primiceri, G.E. (2015). Prior Selection for Vector Autoregressions. *The Review of Economics and Statistics*, 97, 436–451. https://doi.org/10.1162/REST_a_00483

Fernandez, A., and Gulan, A. (2015). Interest Rates, Leverage, and Business Cycles in Emerging Economies: The Role of Financial Frictions. *American Economic Journal: Macroeconomics*, 7(3), 153-–188. https://doi.org/10.1257/mac.20120141

Kadiyala, K.R., and Karlsson, S. (1997). Numerical Methods for Estimation and Inference in Bayesian VAR-Models. *Journal of Applied Econometrics*, 12(2), 99–132.

Kaminsky, G., and Reinhart, C. (1999). The Twin Crises: Causes of Banking and Balance–of–Payments Crises. *American Economic Review*, 89, 473–500. https://doi.org/10.1257/aer.89.3.473

Karlsson, S. (2013). Forecasting with Bayesian Vector Autoregression. In: Elliott G., Timmermann A. (eds.). *Handbook of Economic Forecasting*, Vol. 2B. Amsterdam (The Netherlands): Elsevier, pp. 791–897. https://doi.org/10.1016/B978-0-444-62731-5.00015-4

Kilian, L., and Lutkepohl, H. (2017). Structural Vector Autoregressive Analysis. Cambridge University Press.

Kholodilin, K.A., and Netsunajev, A. (2019). Crimea and Punishment: The Impact of Sanctions on Russian Economy and Economies of the Euro Area. *Baltic Journal of Economics*, 19, 39–51. https://doi.org/10.1080/1406099X.2018.1547566

Koop, G. (2013). Forecasting with Medium and Large Bayesian VARs. *Journal of Applied Econometrics*, 28, 177–203. https://doi.org/10.1002/jae.1270

Koop, G., and Korobilis, D. (2010). Bayesian Multivariate Time Series Methods for Empirical Macroeconomics. *Foundations and Trends in Econometrics*, 3, 267–358.

Korhonen, I., and Ledyaeva, S. (2010). Trade Linkages and Macroeconomic Effects of the Price of Oil. *Energy Economics*, 32, 848–856.

Korhonen, I., Simola H. and Solanko L. (2018). Sanctions, counter-Sanctions and Russia — Effects on Economy, Trade and Finance. BOFIT Policy Brief No. 4. https://doi.org/10.1016/j.eneco.2009.11.005

Korhonen, I. (2019). Sanctions and Counter-Sanctions — What are Their Economic Effects in Russia and Elsewhere? *Journal of the New Economic Association*, 43(3), 184-–190.

Kreptsev, D. and Seleznev, S. (2016). The Impact of the Interest Rates of the Money Market on Credit Interest Rates. The Bank of Russia Working Papers Series, 9.

Liu, E., Mian, A., and Sufi, A. (2020). Low Interest Rates, Market Power, and Productivity Growth. Unpublished manuscript.

Mendoza, E.G. (2010). Sudden Stops, Financial Crises, and Leverage. *American Economic Review*, 100, 1941–1966. DOI: 10.1257/aer.100.5.1941

Mendoza, E.G., and Yue, V.Z. (2012). A General Equilibrium Model of Sovereign Default and Business Cycles. *The Quarterly Journal of Economics*, 127(2), 889—946. https://doi.org/10.1093/qje/qjs009

Monacelli, T., Sala, L., and Siena, D. (2021). Real Interest Rates and Productivity in Small Open Economies. Unpublished manuscript.

Neumeyer, P.A., Perri, F. (2005). Business Cycles in Emerging Economies: The Role of Interest Rates. *Journal of Monetary Economics*, 52(2), 345—380. https://doi.org/10.1016/j.jmoneco.2004.04.011

OECD (2014). OECD Economic Surveys: Russian Federation. January 2014, Overview.

Pestova, A., and Mamonov, M. (2019). Should We Care? The Economic Effects of Financial Sanctions on the Russian Economy. BOFIT Discussion Paper No. 13/2019, The Bank of Finland, Helsinki.

Primiceri, G. (2005). Time Varying Structural Vector Autoregressions and Monetary Policy. *Review of Economic Studies*, 72, 821–852. doi.org/10.1111/j.1467-937X.2005.00353.x

Schmitt-Grohe, S., and Uribe, M. (2018). How Important are Terms-of-Trade Shocks? *International Economic Review*, 59(1), 85—111. https://doi.org/10.1111/iere.12263

Uhlig, H. (2005). What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure. *Journal of Monetary Economics*, 52(2), 381–419.

Uribe, M., and Schmitt-Grohe, S. (2017). Open Economy Macroeconomics. Princeton University Press.

Uribe, M., and Yue, V.Z. (2006). Country Spreads and Emerging Countries: Who Drives Whom?" *Journal of International Economics*, 69, 6–36.

Waggoner, D. F., and Zha, T. (1999). Conditional Forecasts in Dynamic Multivariate Models. *The Review of Economics and Statistics*, 81, 639–651.

Welt, C., Archick, K., Nelson, R., and Rennack, D. (2020). U.S. Sanctions on Russia. Congressional Research Service Report No. R45415. https://fas.org/sgp/crs/row/R45415.pdf.

Wooldridge, J. M. (2009). On Estimating Firm-Level Production Functions Using Proxy Variables to Control for Unobservables. *Economics letters*, 104(3), 112–114.

Abstrakt

Jak velké jsou makroekonomické dopady externích finančních šoků pro rozvojovou ekonomiku? Zkoumáme dobře identifikovaný šok vnějšího oddlužení Ruska spojeného s růstem úrokových sazeb půjček na zahraničních trzích, který byl způsoben finančními sankcemi uvalenými v roce 2014. Oddělujeme efekt sankcí od efektu směnných relací s použitím přístupu podmíněných předpovědí. Také využíváme rekursivní a znaménkově omezený strukturální VAR model k identifikaci sankčních šoků. Naše výsledky konzistentně naznačují, že sankce měly nezanedbatelné negativní efekty a byly značné pro finanční veličiny (reálná úroková míra a korporátní vnější zadlužení) a mírnější pro reálné veličiny (ekonomický výstup, spotřeba, investice, obchodní rovnováha a reálný směnný kurz rublu). Odhadnuté dopady sankcí jsou v souladu s teoretickými předpověďmi literatury věnované šokům v rozvojových ekonomikách.

Klíčová slova: finanční sankce, korporátní vnější dluh, šok zahraničních úrokových měr, šok směnných relací, Bayesovský (S)VAR, znaménková omezení, podmíněné předpovědi, malá otevřená ekonomika

The appendix to this working paper is available at https://www.cerge-ei.cz/working-papers/.