Appendix A Productivity and the price of borrowed funds: Firm-level estimates

We hypothesize that one can identify the timing of sanctions statistically by identifying the years during which the relationship between firm productivity and the interest rate on the firm's borrowing weakens uniformly across all firms, that is, irrespective of whether a firm is more productive or not. For the analysis of the relationship between firms' productivity and the interest rates on their borrowings, we gather firm-level data from the nation-wide SPARK-Interfax database.[38] The resultant sample consists of 72,880 firm–year observations over the period of 2013–2019. The firms operate in as much as 14 different sectors (two-digit classification) of the Russian economy, ranging from natural resource extraction to IT. We estimate the firms' TFPs by applying a popular methodology proposed by Wooldridge (2009). We assume a Cobb-Douglas production function with labor, capital, and materials, with constant return to scale. The estimates of firms' productivity TFP_{it} appear in Fig. A.I.(a) below.

We proxy the price of borrowed funds with the effective interest rates on bank loans as the ratio of annual interest expenses to the two-year average volume of the loans.[39] Since the interest rates are not actual we face an obstacle: we observe lower such rates for less productive firms. This is because less productive firms have lower abilities to repay bank loans, thus leading to a formally reduced amount of interest they pay than what could be initially expected. From the bank side, it implies rising non-performing loans (NPLs) on their balance sheets. We address this issue by adjusting the effective interest rates on the quality of borrowers. To do so, we run a panel FE regression of the interest rate on *net creditor payments*, controlling for firm, year, industry fixed effects.[40] We assume that the higher the net creditor payments, the lower the firms' ability to repay bank loans, the higher the interest rate. The regression reads as:

$$EIR_{it} = \alpha_i + \beta_t + \gamma NCP_{it} + Controls_{it} + \varepsilon_{it} \tag{13}$$

where i firm, t year, EIR_{it} effective interest rate on a firm's i bank loan, NCP_{it} net creditor payments computed as creditor payments net of debitor payments, $Controls_{it}$ cover the structure of assets and liabilities, growth and profitability of a firm's business.

Having estimated (13), we isolate those part of the variation in EIR_{it} originating from NCP_{it}. We thus eliminate the effect of ex-post differences in firms' credit quality from the constructed interest rates on the firms' loans. With the risk-adjusted interest rate, $\widehat{EIR}_{it}$ (see in Fig. A.I.(b)), we run the following regression:

$$\widehat{EIR}_{it} = a_i + b_t + \sum_{t=2013}^{2019} b_t TFP_{it} + \theta TFP_{it} + Controls_{it} + \epsilon_{it} \tag{14}$$

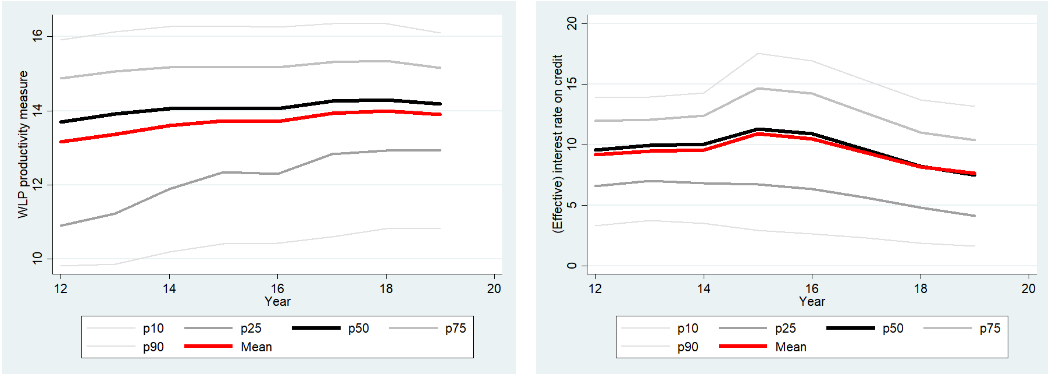
Regression results appear in Table A.I below.

First, we indeed observe a very strong positive association of NCR_{it} and effective interest rates

[38] https://spark-interfax.com/.

[39] We use nominal interest rates instead of real because adjusting interest rates for inflation would not change the results on a cross-sections of firms in a particular year.

[40] Ideally, we would use non-performing loans or interest accrued but not payed. Unfortunately, Russian firms do not disclose these data.



(a) Firm productivity TFP_{it} (b) Price of borrowed funds for firms $\widehat{EIR}_{it}$

Figure A.I: Firm productivity and the price of borrowed funds

Table A.I: Relationship between firm productivity and (effective) interest rates on credit

Dependent variable:	(Effective) interest rate		Risk-adjusted interest rate	
Explanatory variables	(1)	(2)	(3)	(4)
Firm net creditor payments, % of total assets	0.763***	1.095***		
	(0.128)	(0.145)		
Firm productivity (TFP)			–0.024***	–0.023***
			(0.003)	(0.003)
TFP × year=2014				0.0011
				(0.0009)
TFP × year=2015				–0.0006
				(0.0010)
TFP × year=2016				–0.0040***
				(0.0011)
TFP × year=2017				–0.0043***
				(0.0012)
TFP × year=2018				–0.0020
				(0.0013)
TFP × year=2019				–0.0041***
				(0.0014)
Firm FEs, Year FEs	Yes	Yes	Yes	Yes
Other firm-specific controls	No	Yes	No	Yes
N obs	79,165	78,691	43,831	43,831
N firms	32,118	31,887	17,184	17,184
R^2-within	0.128	0.133	0.059	0.060

Note: ***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Robust standard errors appear in the brackets under the estimated coefficients.

on loans (see columns (1) and (2)), meaning that the firms that are net creditors of other firms also pay more interest on bank loans than the net debtor firms. Second, firms with greater TFP enjoy *on average* lower (risk-adjusted) interest rates on bank loans (column (3)), Finally, the results in column (4) remarkably indicate that the relationship between productivity and interest rates on loans weakens during exactly the years of the firt and second sanction waves.

Appendix B On the advantages and limitations of the conditional forecasting exercise

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

Moreover, even though most of the companies with sanctions were state-owned, there was likely a contagion from the targeted to non-targeted (private) borrowers. Thus, the speed of debt deleveraging depends crucially on the degree of this contagion. Our approach does not distinguish between targeted and non-targeted borrowers and provides aggregated estimates.[41]

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

Regarding the obstacles that may affect precision of our Bayesian estimates of the sanction effects, we appeal to the study by (Byrne et al., 2018) and, following their explanation, note that potentially large estimation uncertainty may originate from:

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

2. *Errors in the estimated coefficients.* In our setting, we are limited by the number of available observations and the short history of comparable data, see a discussion in Section 3.1. In the face of low number of observations, our estimates are pushed towards the prior more tightly.

3. *Time variation in coefficients.* The literature on forecasting and structural analysis with VARs generally recommends the use of time-varying parameters (Primiceri, 2005; Koop, 2013). In our setting, the time variation in coefficients may stem from the shifts in monetary policy regimes occurred during the sample period. The Central Bank of Russia (CBR) switched from exchange-rate targeting to inflation targeting and from a fixed to floating exchange rate regime). We partially address this issue by applying the exchange market pressure (EMP) index in an extended version of the BVAR model to account for the switch in exchange rate regimes (see

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

robustness checks in Section 6).[42] However, since we are mostly interested in the effects of the sanctions on the real economy, the forecasting errors in the exchange rate and interest rate are not of primary interest. Moreover, using time-varying parameter models, Borzykh (2016) and Kreptsev and Seleznev (2016) show that the degree of time variability of the structural relationships is rather limited in Russia.

4. *Time-varying set of exogenous variables.* During episodes of global financial instability, the importance of the external financial conditions rises. During calm periods, these external conditions become less important for our purposes. In our conditional forecasting exercise, we condition on the same trajectories of the three exogenous conditions (CTOT, real interest rate in the U.S. economy, and Baa spread) in both scenarios, thus eliminating this concern.

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

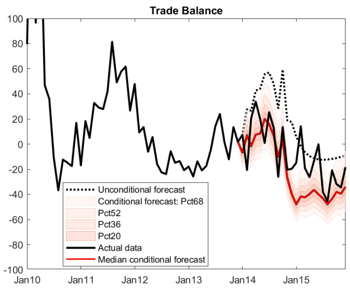
Given the limitations involved, we believe our conditional forecasting approach provides a useful insight into the problem of quantifying the economic effects of financial sanctions. It is simple and reproducible, it does not require large panels of disaggregated data, and it addresses the linkages between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

[42] The EMP is a popular measure of currency instability employed in many empirical macro studies, see, e.g., Kaminsky and Reinhart (1999). EMP is a weighted sum of the growth rates of nominal exchange rate and international reserves of the central bank. In case of fixed exchange rate regime, the reserves are used to absorb currency shocks, whereas in case of floating regime reserves are fixed and nominal exchange rate fluctuates.

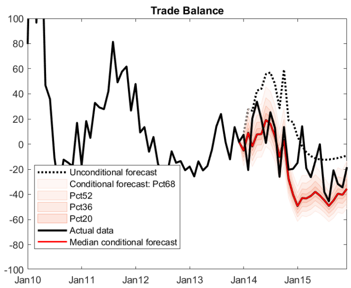
Appendix C Baseline forecasting exercise: other endogenous variables

C.1 Trade balance in Russia

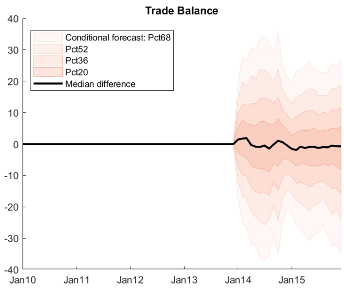
The forecasting results on the real consumption growth in Russia appear in Fig. C.I below.



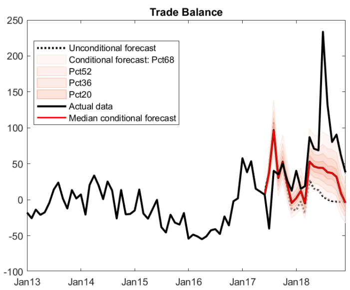
(a) 1st sanction wave: Condition 1



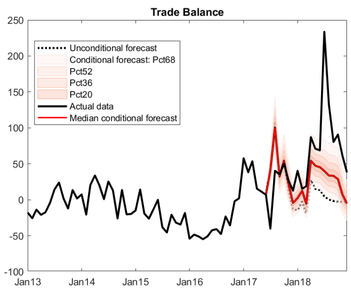
(b) 1st sanction wave: Condition 2



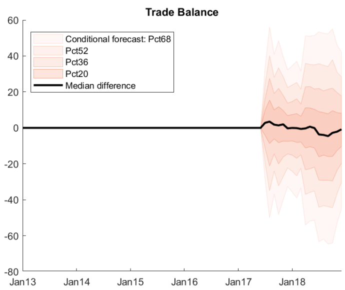
(c) 1st sanction wave: Condition 2 − Condition 1



(d) 2nd sanction wave: Condition 1



(e) 2nd sanction wave: Condition 2



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

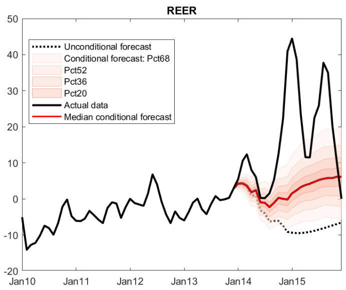
Note: The figure reports conditional forecasts of trade balance (TB_t). The growth rates are computed as the value of trade balance in current month over the value of the trade balance in corresponding month of the previous year, %.

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.

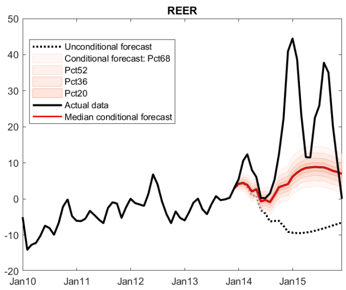
Figure C.I: Trade balance in Russia during the first and second waves of sanctions: Conditional forecasts

C.2 REER in Russia

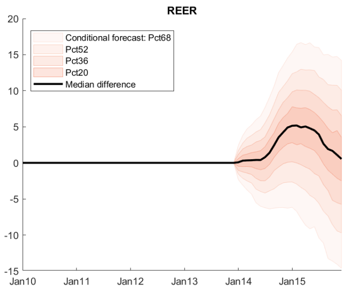
The forecasting results on the real consumption growth in Russia appear in Fig. C.II below.



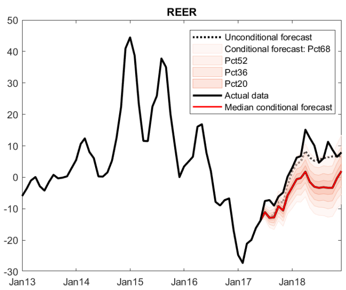
(a) 1st sanction wave: Condition 1



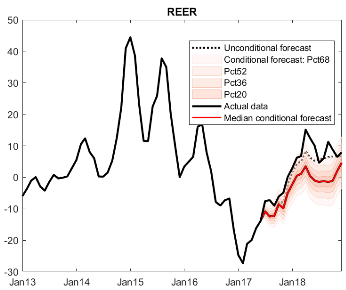
(b) 1st sanction wave: Condition 2



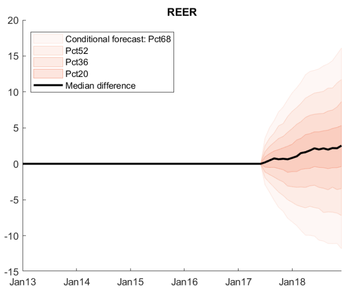
(c) 1st sanction wave: Condition 2 – Condition 1



(d) 2nd sanction wave: Condition 1



(e) 2nd sanction wave: Condition 2



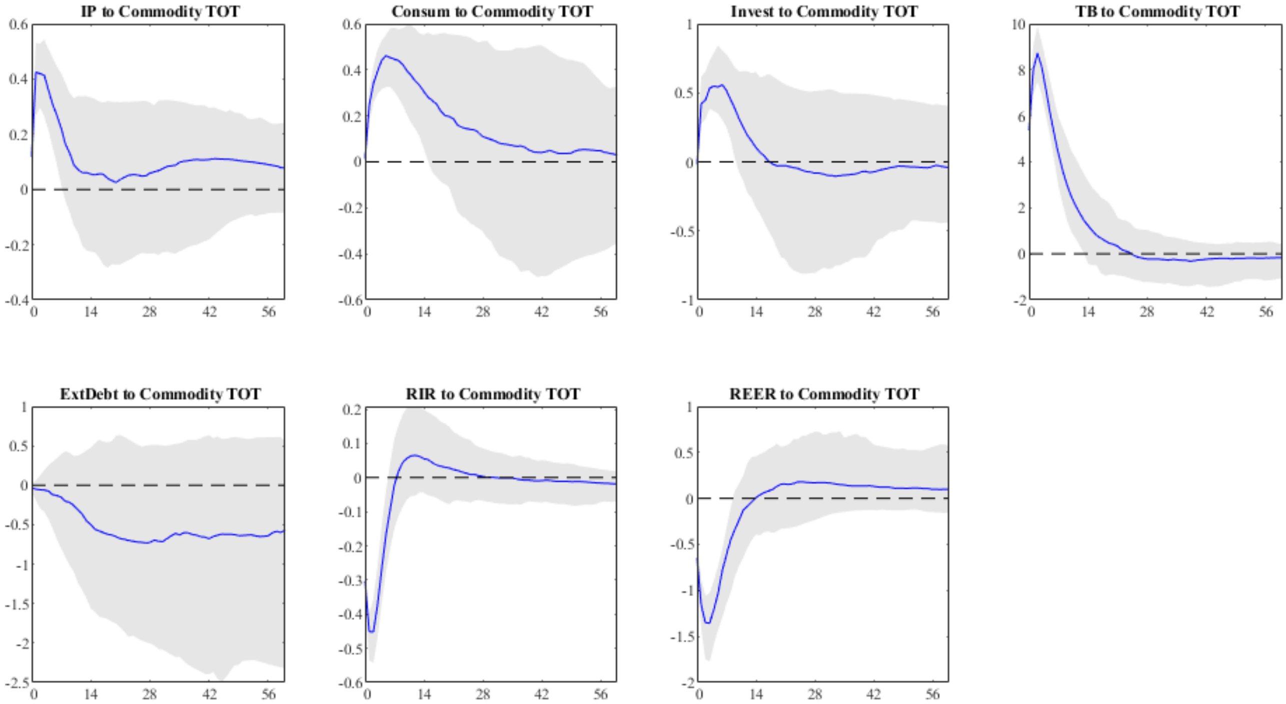
(f) 2nd sanction wave: Condition 2 – Condition 1

Note: The figure reports conditional forecasts of real effective exchange rate ($REER_t$). REER is the growth rates of the inverse of real effective exchange rate. The inversion implies that higher values reflect depreciation of Ruble against the currencies of trade partners, and vice versa. The growth rates are computed as the value of REER in current month over the value of REER 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 C.II: REER in Russia during the first and second waves of sanctions: Conditional forecasts

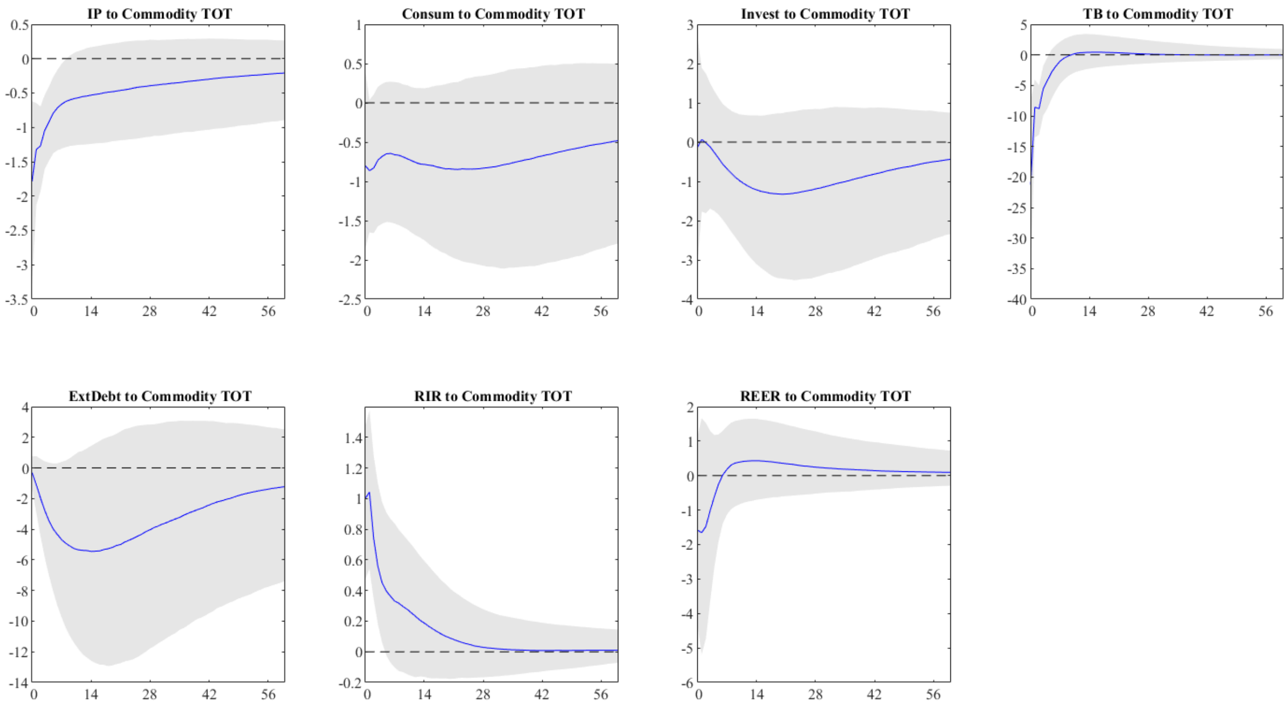
Appendix D Preliminary SVAR analysis: the effect of CTOT shock on trade balance in Russia



Note: The figure reports estimated IRFs of domestic macroeconomic variables to a positive CTOT shock identified recursively. 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 16^{th} and 84^{th} percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

Figure D.I: Impulse response functions to a *positive* CTOT shock under recursive identification

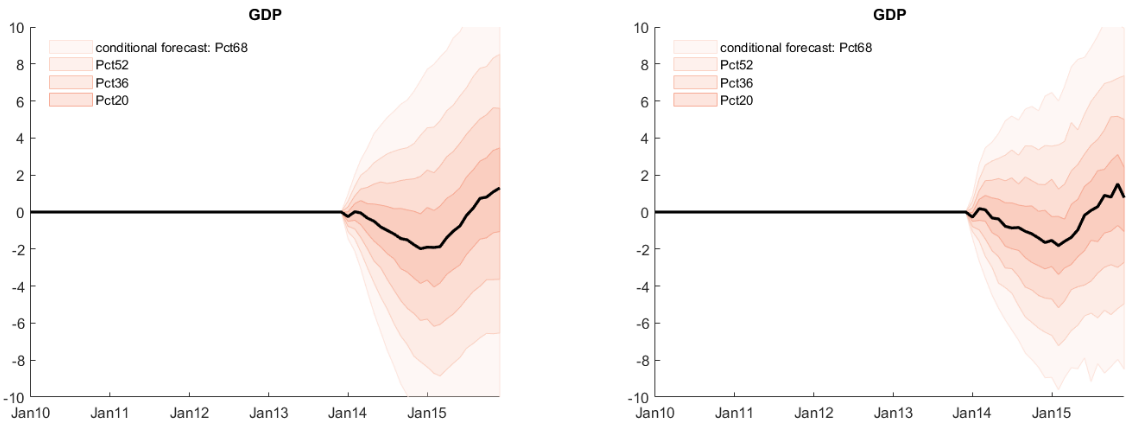
Appendix E Baseline SVAR analysis: the effects of CTOT shock on domestic macroeconomic variables



Note: The figure reports estimated IRFs of domestic macroeconomic variables to a negative CTOT shock identified with sign restrictions: IP_t falls, RIR_t rises, TB_t declines. 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 16^{th} and 84^{th} percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

Figure E.I: Impulse response functions to a *negative* CTOT shock under sign restrictions

Appendix F BVAR model with monetary sector: the estimates of the sanctions' effects

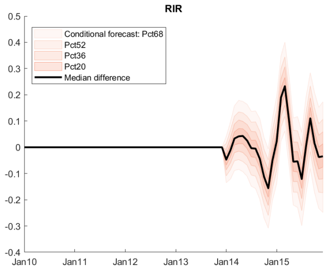


(a) Baseline prior: $\lambda_1 = 0.1$

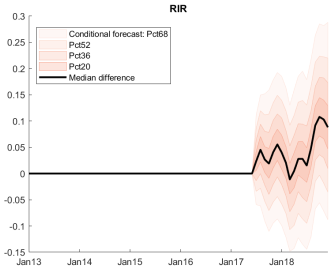
(b) Loose prior: $\lambda_1 = 0.2$

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

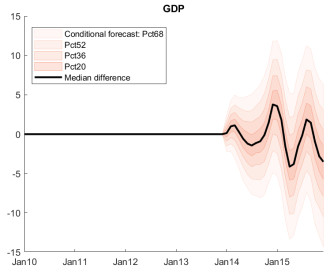
Appendix G Sensitivity: deeper time lags, $L = 13$ months



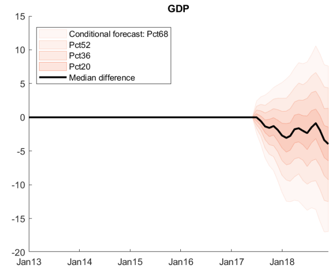
(a) 1st wave of sanctions



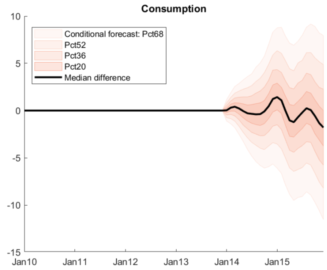
(b) 2nd wave of sanctions



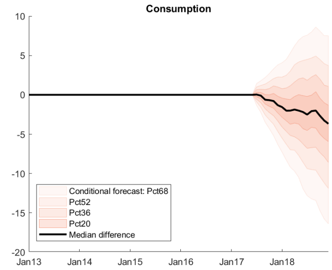
(c) 1st wave of sanctions



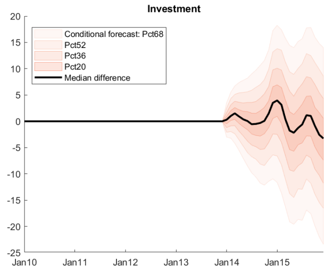
(d) 2nd wave of sanctions



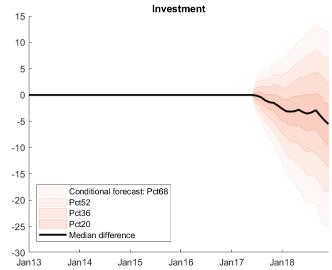
(e) 1st wave of sanctions



(f) 2nd wave of sanctions



(g) 1st wave of sanctions

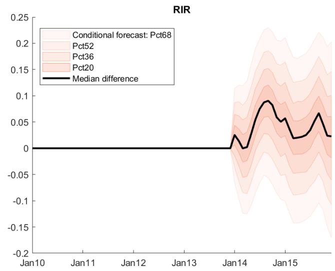


(h) 2nd wave of sanctions

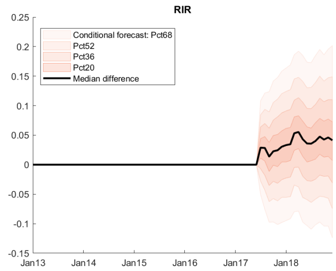
Note: The table reports the estimated effects of the financial sanctions computed with the BVAR model in which we set the deepest lag $L = 13$ months instead of $L = 2$. The values of hyperparameters remains the same: $\lambda_1 = 1$, $\lambda_2 = 0.5$, and $\lambda_3 = 2$.

Figure G.I: Sensitivity of the estimated sanctions' effects to the hyperparameters governing the prior in the BVAR model

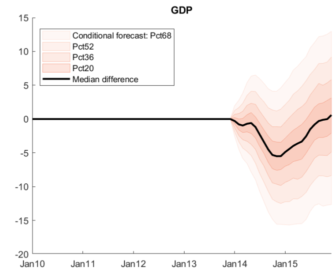
Appendix H Sensitivity: looser priors



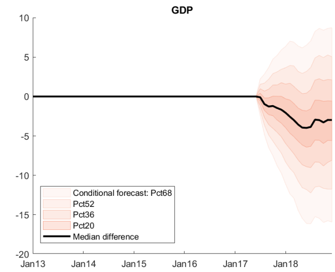
(a) 1st wave of sanctions



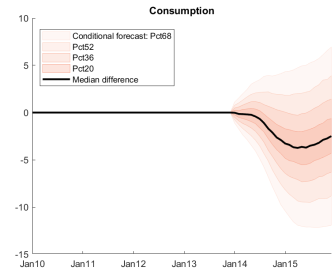
(b) 2nd wave of sanctions



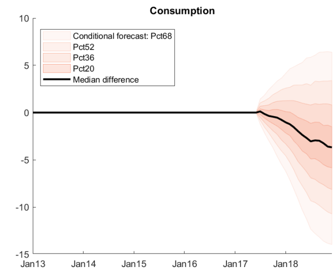
(c) 1st wave of sanctions



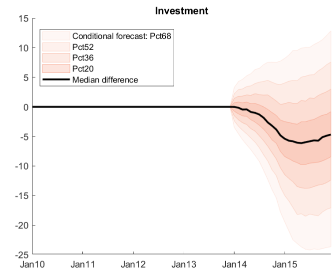
(d) 2nd wave of sanctions



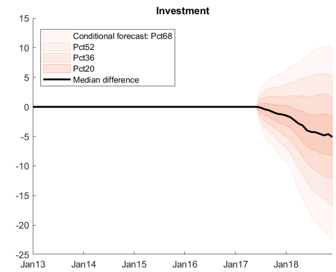
(e) 1st wave of sanctions



(f) 2nd wave of sanctions



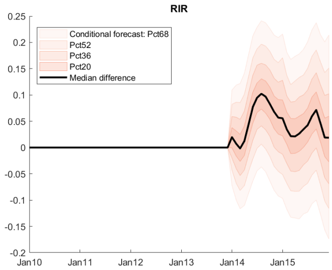
(g) 1st wave of sanctions



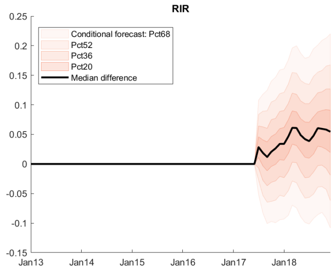
(h) 2nd wave of sanctions

Note: The table reports the estimated effects of the financial sanctions computed with a looser general tightness prior in the BVAR model: $\lambda_1 = 0.2$. In the baseline estimations $\lambda_1 = 0.1$. $L = 2$ months (lag order of endogenous regressors).

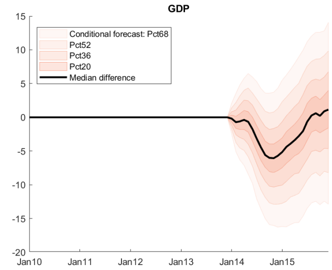
Figure H.I: Sensitivity of the estimated sanction effects to the hyperparameters governing the prior in the BVAR model: loosing general tightness of the prior (λ_1)



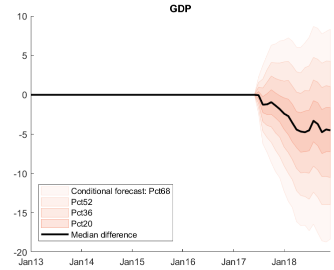
(a) 1st wave of sanctions



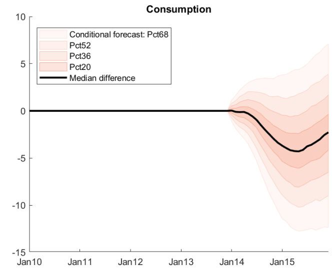
(b) 2nd wave of sanctions



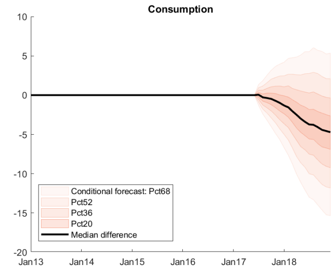
(c) 1st wave of sanctions



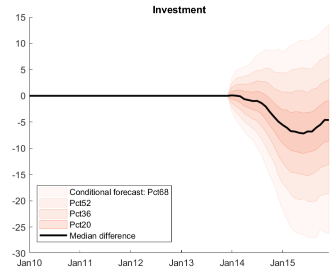
(d) 2nd wave of sanctions



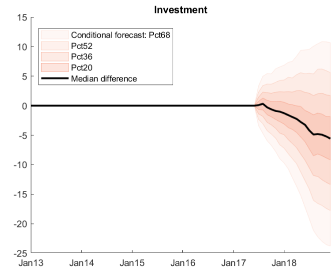
(e) 1st wave of sanctions



(f) 2nd wave of sanctions



(g) 1st wave of sanctions

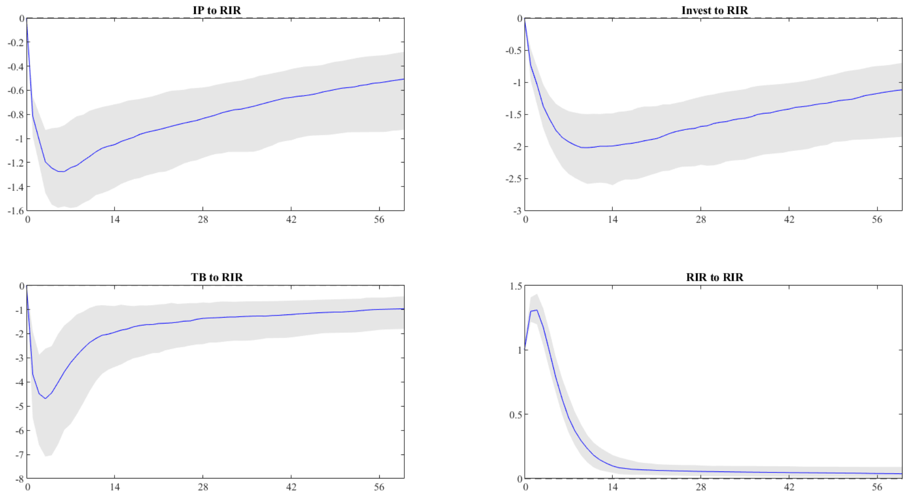


(h) 2nd wave of sanctions

Note: The table reports the estimated effects of the financial sanctions computed with a looser general tightness prior in the BVAR model $\lambda_1 = 0.2$, tightness of other variables $\lambda_2 = 1$, tightness of deeper lags $\lambda_3 = 1.5$. In the baseline estimations $\lambda_1 = 0.1$, $\lambda_2 = 0.5$, $\lambda_3 = 2$. $L = 2$ months (lag order of endogenous regressors).

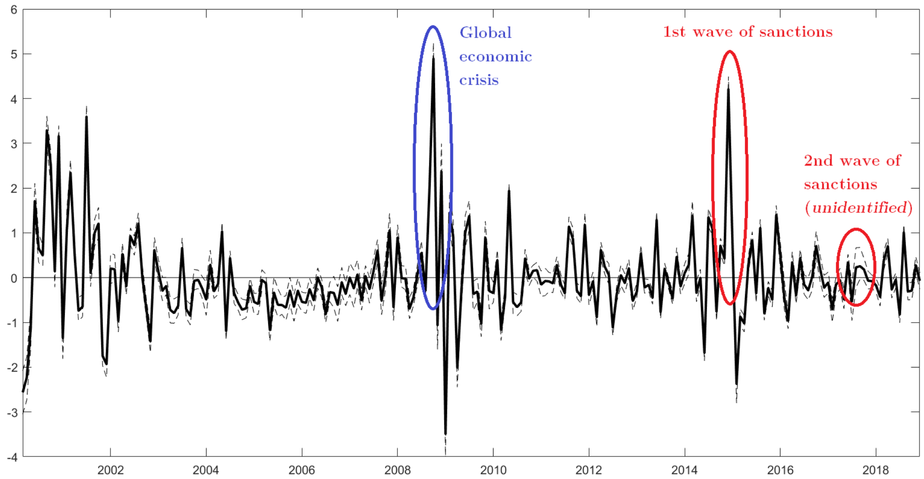
Figure H.II: Sensitivity of the estimated sanction effects to the hyperparameters governing the prior in the BVAR model: loosing all tightness parameters $(\lambda_1, \lambda_2, \lambda_3)$

Appendix I SVAR analysis of sanctions effect: recursive identification in a 5 variables model of Uribe and Yue (2006)



Note: The figure reports estimated IRFs of domestic macroeconomic variables to a +1 percentage point shock in RIR. The BVAR model contains 5 variables, and the RIR variable is ordered 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 16^{th} and 84^{th} percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

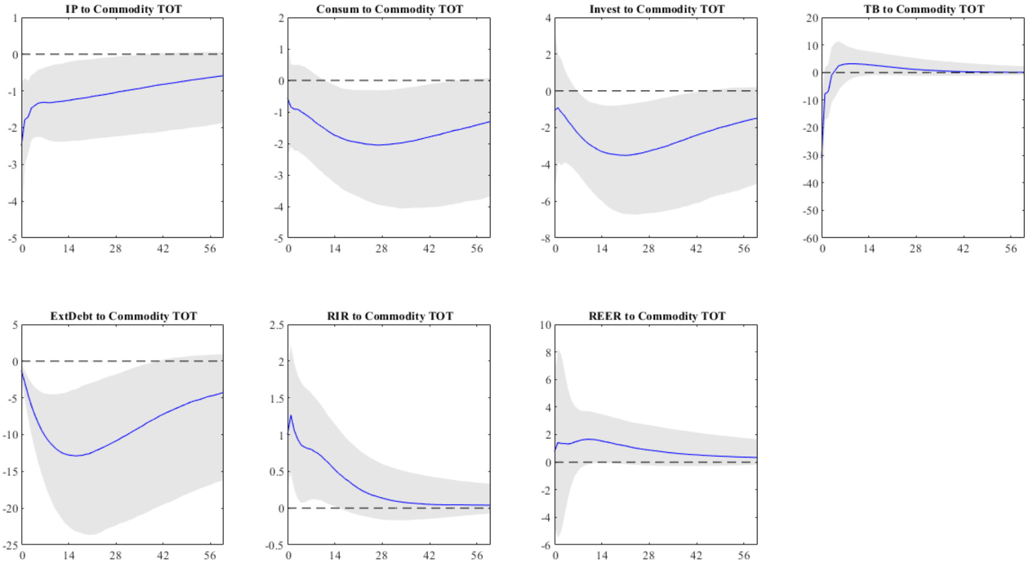
Figure I.I: Impulse response functions to the RIR shock identified under the recursive scheme



Note: The figure reports the time evolution of the RIR shock estimated with the 5 variables BVAR model. Significant positive RIR shocks are identified for the first and second waves of sanctions in the end of 2014 and 2017–2018, respectively. The positive RIR shock occurred during the global economic crisis is shown for comparative reasons.

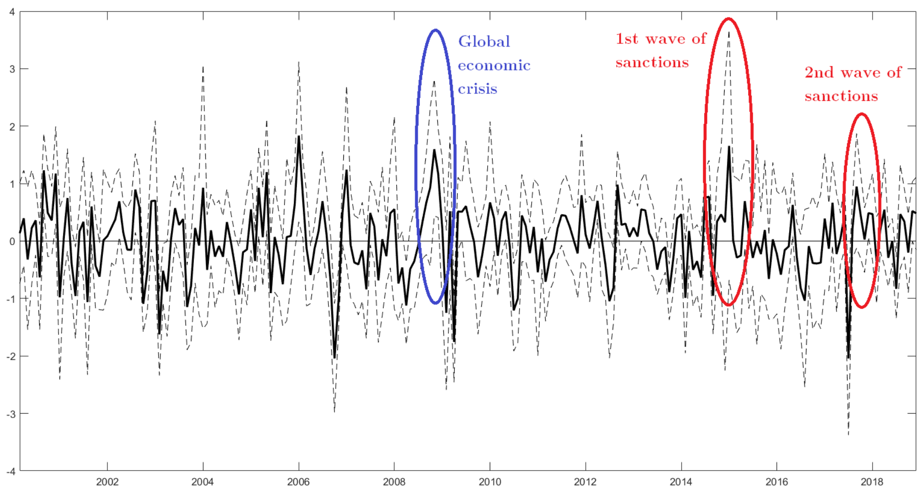
Figure I.II: Time evolution of the RIR shock identified under the recursive scheme

Appendix J SVAR analysis of sanctions effect: *on-impact* sign restrictions



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 on impact. 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 16^{th} and 84^{th} percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

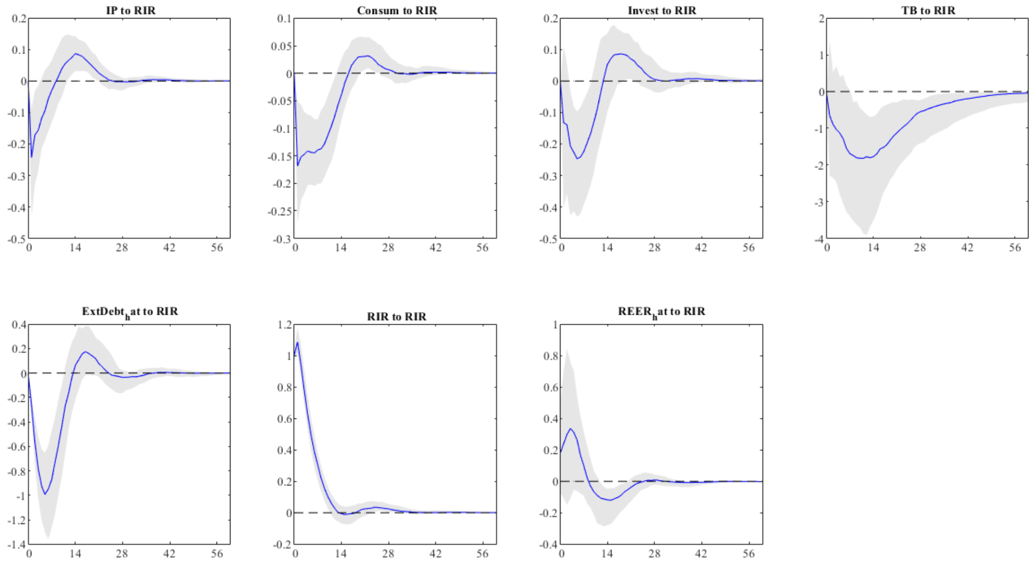
Figure J.I: Impulse response functions to the sanction shock identified under sign restrictions



Note: The figure reports the time evolution of the RIR shock estimated with the 10 variables BVAR model. Significant positive RIR shocks are identified for the first and second waves of sanctions in the end of 2014 and 2017–2018, respectively. The positive RIR shock occurred during the global economic crisis is shown for comparative reasons.

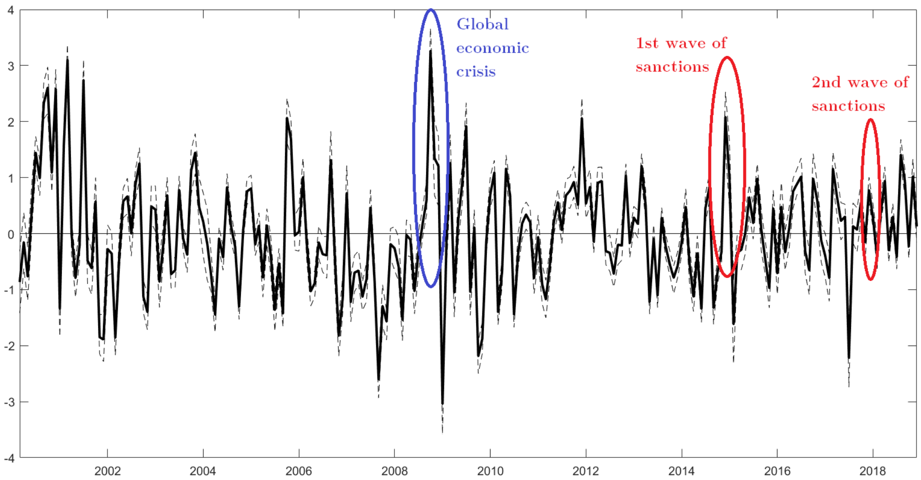
Figure J.II: Time evolution of the RIR shock identified under sign restrictions

Appendix K SVAR analysis of sanctions effect: recursive identification, HP-filtered time series



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 16^{th} and 84^{th} percentiles of the post-burned-in estimated IRFs are reported (grey shaded area).

Figure K.I: Impulse response functions to the sanction shock identified under the recursive scheme



Note: The figure reports the time evolution of the RIR shock estimated with the 10 variables BVAR model. Significant positive RIR shocks are identified for the first and second waves of sanctions in the end of 2014 and 2017–2018, respectively. The positive RIR shock occurred during the global economic crisis is shown for comparative reasons.

Figure K.II: Time evolution of the RIR shock identified under the recursive scheme