Working Paper Series 756
(ISSN 2788-0443)

The Price of War: Macroeconomic and Cross-Sectional Effects of Sanctions on Russia

Mikhail Mamonov
Anna Pestova

CERGE-EI
Prague, June 2023

ISBN 978-80-7343-563-9 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-683-3 (Národohospodářský ústav AV ČR, v. v. i.)

The Price of War: Macroeconomic and Cross-Sectional Effects of Sanctions on Russia*

Mikhail Mamonov†‡ Anna Pestova§

May 18, 2023

Abstract

How much do sanctions harm the sanctioned economy? We examine the case of Russia, which has faced three major waves of international sanctions over the last decade (in 2014, 2017, and 2022). In a VAR model of the Russian economy, we first apply sign restrictions to isolate shocks to international credit supply to proxy for the financial sanctions shocks. We provide a microeconomic foundation for the sign restriction approach by exploiting the syndicated loan deals in Russia. We then explore the effects of the overall sanctions shocks (financial, trade, technological, etc.) by employing a high-frequency identification (HFI) approach. Our HFI is based on each OFAC/EU sanction announcement and the associated daily changes in the yield-to-maturity of Russia's US dollar-denominated sovereign bonds. Our macroeconomic estimates indicate that Russia's GDP may have lost no more than 0.8% due to the financial sanctions shock, and up to 3.2% due to the overall sanctions shock cumulatively over the 2014–2015 period. In 2017, the respective effects are 0 and 0.5%, and in 2022, they are 8 and 12%. Our cross-sectional estimates show that the real income of richer households declines by 1.5–2.0% during the first year after the sanctions shock, whereas the real income of poorer households rises by 1.2% over the same period. Finally, we find that the real total revenue of large firms with high (low) TFPs declines by 2.2 (4.0)% during the first year after the sanctions shock, whereas the effects on small firms are close to zero. Overall, our results indicate heterogeneous effects of sanctions with richer households residing in big cities and larger firms with high TFPs being affected the most. (JEL: F51, E20, E30)

Keywords: Sanctions news shock, Monetary policy, Commodity terms-of-trade, High-frequency identification (HFI), Household income, TFP

*We appreciate valuable comments and suggestions from Thorsten Beck, Ferre De Graeve, Wouter den Haan, Hans Degryse, Zuzana Fungacova, David Hendry, Michele Lenza, Marek Kapicka, Nobuhiro Kiyotaki, Gary Koop, Iikka Korhonen, Dmitry Mukhin, Steven Ongena, Giovanni Ricco, Stephanie Schmitt-Grohe, Christopher Sims, Ctirad Slavik, and Martin Uribe. We are grateful for fruitful discussions with participants of the IOS research seminar at the University of Regensburg (Germany, 2020), the Seminar on Contract Theory & Banking at the University of Zurich (2022), the 25th Conference "Theories and Methods in Macroeconomics" (T2M, London, 2022), the workshop "Price of War: The Effects of Sanctions on Russia" (Florence School of Banking and Finance, EUI, 2022), research seminar at the Bundesbank (Germany, 2022), and the 2nd Ventotene "Sailing the Macro" Workshop (Italy, 2022), CERGE-EI "Brown Bag" Seminar (2022). Mamonov and Pestova acknowledge financial support from SYRI research grant LX22NPO05101.

†CERGE-EI, a joint workplace of Charles University and the Economics Institute of the Czech Academy of Sciences, Politickych veznu 7, 111 21 Prague, Czech Republic.

‡E-mail: mikhail.mamonov@cerge-ei.cz

§E-mail: anna.pestova@cerge-ei.cz.

"It is perfectly evident that, if we continue to live as we are now living, guided in our private lives, as well as in the life of separate States, by the sole desire of welfare for ourselves and for our State, and will, as we do now, think to ensure this welfare by violence, then, inevitably increasing the means of violence of one against the other and of State against State, we shall, first, keep subjecting ourselves to bankruptcy more and more, transferring the major portion of our productivity to armaments; and, secondly, by killing in mutual wars the best physically developed men, we must become more and more degenerate and morally depraved."

— Leo Tolstoy on the Russo–Japanese war in "Bethink Yourselves!" (1904), *Times* magazine

1 Introduction

Since World War II, more than 100 countries have faced economic sanctions imposed by the West with the aim of shifting the countries' unfavorable political regimes by damaging the local economies without launching full-scale wars (Levy, 1999; Etkes and Zimring, 2015; Felbermayr *et al.*, 2020). Although there is a consensus in the literature that sanctions are seldom effective in shifting political regimes, there is strong evidence that the non-financial firms targeted by sanctions are forced to substantially reduce their international and local trade (Crozet *et al.*, 2021) and decrease employment (Ahn and Ludema, 2020). However, there are many ways to evade sanctions. As, e.g., Efing *et al.* (2019) show, German banks ceased direct lending of the sanctioned firms, but at the same time, the local demand for credit had been caught up by the German banks' subsidiaries in respective sanctioned countries. In addition, as Mamonov *et al.* (2021) and Nigmatulina (2022) find, the impact of sanctions on targeted banks and firms could be substantially softened if the sanctioned governments have accumulated sufficient buffers in terms of, e.g., the central bank's international reserves and are able to support the economy. Given potential spillovers between sanctioned and non-sanctioned economic agents, however, it is less clear what the overall economic implications of sanctions are for the sanctioned countries. In this paper, we take a broader perspective and estimate the aggregate effects of sanctions on the macroeconomy and identify the cross-sectional effects of sanctions on different parts of the population (rural vs. city, rich vs. poor) and firms (more vs. less productive, large vs. small).

For this purpose, we examine the case of Russia which provides a valid laboratory to study the effects of sanctions across time because of the three major waves of sanctions sequentially imposed on the country over the last decade. First, following the annexation of the Crimean peninsula by Russia in early 2014, the US, EU, and other Western countries introduced financial and non-financial sanctions on Russian officials, government-owned companies, and banks to restrict their abilities to borrow from abroad, invest in foreign assets, develop international trade, and attract advanced technologies.[1] Sec-

[1] In general, the sanction regime includes financial restrictions (Mamonov *et al.*, 2021), trade bans (Ahn and

ond, Western countries extended existing and launched a new set of international financial restrictions in 2017 in response to Russia's interference in the US presidential election of 2016, including cyber-attacks, and military activities that were supporting the Assad regime in Syria (Welt *et al.*, 2020). Third, after Russia's full-scale invasion of Ukraine in February 2022, Western countries introduced an unprecedented set of blocking sanctions, including freezes of half of the Russian Central Bank's international assets (USD 311 billion), private and corporate asset freezes, a ban on state-owned and politically connected privately-held banks from using the SWIFT international payment system, a full or partial ban on Russia's imports and exports, among others (Berner *et al.*, 2022). In these circumstances, we have clear timing of the sanctions imposition and a large variation in the strength of the underlying sanctions shock across time within one country.

We capture the *financial sanctions shock* by negative innovations to international credit supply (Mian *et al.*, 2017; Ben Zeev, 2019) using standard macroeconometric tools such as structural VARs. We then examine the *overall sanctions shock* by applying a high frequency identification (HFI) approach. With the use of HFI, we introduce a sanctions news shock. We extract this type of shock using daily changes in the yield-to-maturity of Russia's US dollar-denominated sovereign bonds shortly before and after the OFAC/EU announcements of each and every new portion of international restrictions on Russia's officials, state-owned or connected businesses.[2] The difference between the sign restrictions estimates and HFI estimates thus captures the effects of non-financial—trade, technological, etc.—sanctions.

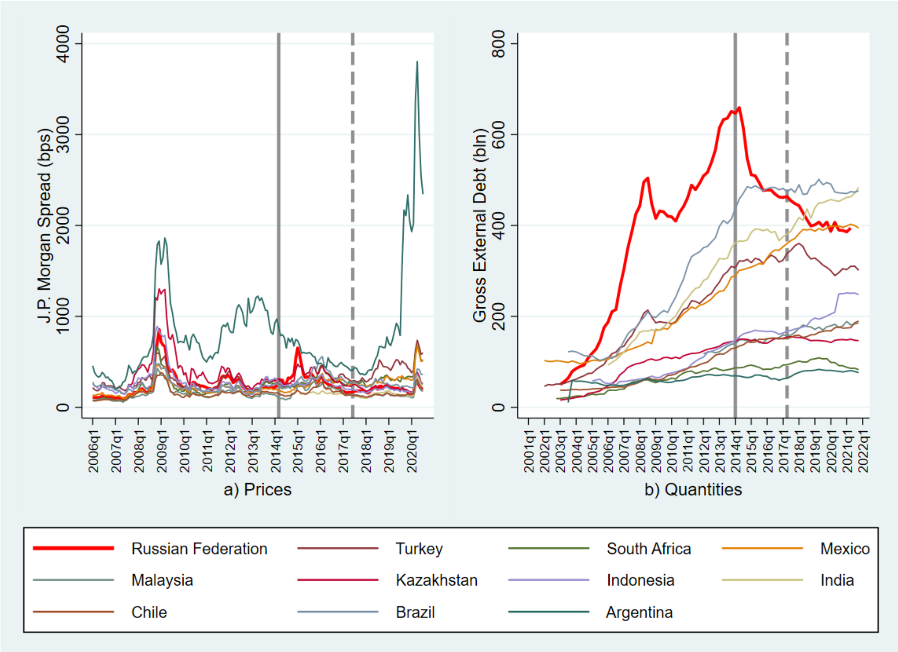
During each of the three waves of sanctions, raw data on the Russian economy reveals a rising country spread, as the price of international credit, and declining amounts of external debt, as the quantity of international credit. For example, during the first wave of sanctions in 2014 Russia's country spread, as measured by the J.P. Morgan Emerging Markets Bond Spread (EMBI+), spiked by roughly 500 bps (Fig. 1.*a*) while the amount of Russia's gross external debt slumped by about USD 103 billion (or by 20%, Fig. 1.*b*).[3] Similar but much less dramatic events occurred in 2017, i.e., during the second wave of sanctions. These events in Russia during the first two waves of sanctions are

Ludema, 2020), travel restrictions and asset freezes imposed on specific Russian officials and business people, 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.

[2]OFAC—Office of Foreign Assets Control, a division of the US Department of the Treasury responsible for administering of sanction imposition.

[3]In 2013, prior to the first wave of sanctions, the ratio of external debt to GDP amounted to 32%, meaning that the Western financial markets were crucial for Russia. 90% of the total amount of external debt was owed by the corporate sector—banks and non-financial companies. In 2014–2015, the external debt of Russia's banks fell by almost 40% and that of non-financial companies declined by 20%. Notably, 2014 and subsequent years were the first in the Russian market economy's history in which the country's corporate external debt was not rising, except for the global economic crisis of 2007–2009 when it declined by 6%.

consistent with the supply-side story.[4] Importantly, the raw data also eliminates any concerns that rising spreads and declining amounts of external debt were common trends across different emerging market economies.



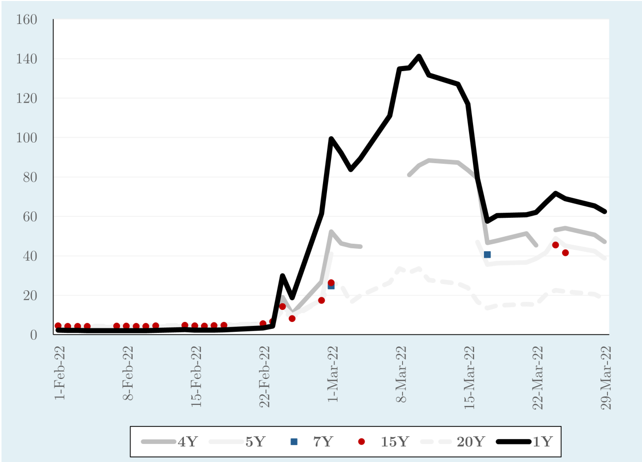
Notes: The figure plots the time evolution of the price of corporate external debt, as measured by the J.P. Morgan spread (*a*), and the amount of the debt outstanding (*b*) for Russia and other emerging market economies over the last 15-20 years. The solid vertical line marks the beginning of the first wave of sanctions against Russia (2014Q1) and the dashed vertical line reflects the start of the second wave (2017Q2).
Source: World Bank/IMF QEDS (Quarterly External Debt Statistics), J.P. Morgan.

Figure 1: *The first and second waves of sanctions*: Corporate external debt in Russia in the context of other emerging economies

As for the third wave of sanctions, data is limited because the Russian government closed access to it, but we can zoom in on the daily data on Russia's country spread during the first days of the war in Ukraine in February–March 2022. Clearly, Russia has experienced the most dramatic rise in the price of international borrowings in its history: the country's sovereign spread soared by 3,500–4,500 bps on average across the debts of different maturity (see Fig. 2).

Despite the clear timing of the sanctions, we, however, encounter certain confounders on the way to estimating the precise effects of the international restrictions on Russia. The first wave of sanctions in 2014 coincided with a *dramatic oil price drop*—from around USD 100 a barrel for Urals crude in

[4] Additional exercises with the raw data show that the first two waves of sanctions were unlikely to transmit to the Russian economy through the demand (on foreign borrowings) channel. First, the Central Bank of Russia's statistics on net foreign debt positions of different economic agents on the eve of and two years after 2014 clearly show that private foreign assets had barely changed over the years (see Appendix A for further details). Second, Russian banks' balance sheet data indicates that, as of February 2014, i.e., on the eve of the first wave of sanctions, the share of (not yet) asset-sanctioned banks' foreign asset holdings in total foreign assets of the Russian banking system was just 2%, thus limiting substantially the concerns regarding potential asset freezes by Western governments. On the contrary, the share of (not yet) debt-sanctioned banks' foreign debts in total foreign borrowings of the Russian banking system was substantial equaling 63%.



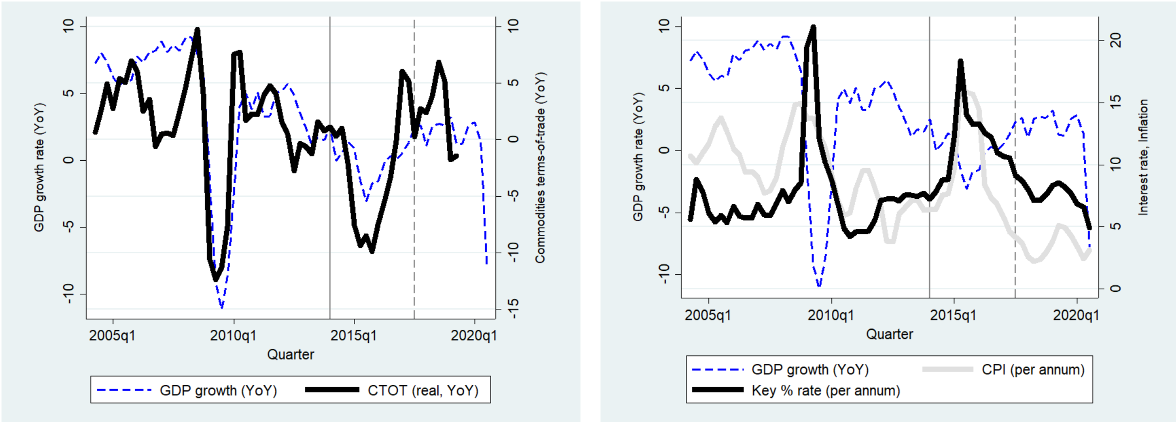
Note: The figure plots the daily data on the yields to maturity of Russia's US dollar-denominated government bonds of different maturity before and during the first weeks of the war in Ukraine in February–March 2022. *Source*: Bloomberg.

Figure 2: *The third wave of sanctions*: Soaring Russian sovereign spreads during the first weeks of the invasion of Ukraine in 2022

the summer of 2014 to under USD 50 a barrel at the start of 2015. This had largely contributed to the observed total decline in the commodities terms-of-trade (CTOT) for Russia that amounted to –10% over that period (see Fig. 3.a).[5] As a result, Russia's ruble lost 90% of its value, the price of imported goods soared and consumer price inflation in the country spiked from 6 to 11% during 2014. In these circumstances, the Bank of Russia turned from soft to tight monetary policy and *raised the regulated interest rate* from 5.5 to 17% over the same period (see Fig. 3.(b)). In contrast, the subsequent expansion of financial sanctions in 2017–2018 (the second wave) and the sanctions of 2022 (the third wave) coincided with an increase in oil prices and soft monetary policy, thus also confounding attempts to disentangle the effects of sanctions. We therefore aim to evaluate the effects of sanctions *net* of oil price fluctuations and endogenous monetary policy responses to rising prices.

We begin our empirical analysis by employing a structural VAR approach to model the Russian economy. The baseline VAR model encompasses the following sets of variables. First, following the literature on small open economies (Uribe and Yue, 2006; Akinci, 2013; Ben Zeev *et al.*, 2017) we include domestic production, final consumption, investment, trade balance, the country's interest rate spread, corporate external debt, and real effective exchange rate (REER). Second, to control for the sanctions' confounders, we include a domestic regulated real interest rate (domestic monetary policy) and a set of exogenous variables—CTOT, the US corporate bond (Baa) spread, and the real US interest rate (global monetary policy).

[5]The Russian economy is highly dependent on revenue from oil and gas exports. Oil, oil products, and gas represented 50 to 70% of Russian goods exports in various years (see, e.g., Korhonen and Ledyaeva, 2010 and Cespedes and Velasco, 2012).



(a) Commodities terms-of-trade (CTOT)

(b) Regulated interest rate in Russia

Note: The figure reports the time evolution of commodities terms-of-trade (YoY, %) and the (nominal) Key interest rate of the Central Bank of Russia (%).

Figure 3: Confounders of sanctions: commodities terms-of-trade and monetary policy responses in Russia

Using monthly data from January 2000 to December 2018, we run the VAR model and estimate the residuals. We then apply the sign restrictions approach to isolate innovations to *international credit supply* (ICS; see, e.g., Cesa-Bianchi *et al.*, 2018; Ben Zeev, 2019; di Giovanni *et al.*, 2022) from the estimated residuals. We require Russia's country spread to rise and the amount of corporate external debt to decline on impact in the baseline version (and within several months in robustness). To distinguish between supply and demand-side forces, we also isolate innovations to the demand on international credit by forcing the price and quantity variables to change in the same direction. We then plot the time evolution of our ICS shock, and we show that it contains substantial spikes in 2014, i.e., during the first wave of sanctions against Russia. These spikes are the largest after those that our ICS shock variable exhibits for the period of the 2007–9 global economic crisis. By contrast, no visible jumps are observed for the second wave of sanctions in 2017–2018.[6] These results clearly imply that we can use the variation in the estimated ICS shock to evaluate the effects of financial sanctions on the Russian economy in the 2010s.

However, before doing so, we provide microeconomic evidence favoring our sign restriction approach to back up the ICS shock. We employ data on syndicated loan deals in Russia from January 2011 to December 2017. The data contains information on the amount of loan, interest rate, currency, and maturity, as well as the structure of the underlying syndicate, thus allowing us to analyze the loan contracts between the borrowers—firms or banks, which are either sanctioned after 2014 or never-

[6]As Mamonov *et al.* (2021) find, there was a great deal of in-advance adaptation of international operations, including placing new debts, between 2014 and 2017 by not-yet-sanctioned banks in Russia. This could lower the potential strength of the second wave of sanctions, given that these sanctions were nothing new but an extension of the previous ones.

sanctioned—and their lenders, i.e., the banks that could also be either sanctioned or not. The data covers roughly 300 deals, which is not large in terms of quantity but is extremely large in terms of the volume of loans, being equivalent to nearly 30% of the Russian banking system's total loans to firms. By controlling for industry*month fixed effects, we run a difference-in-difference regression to isolate the supply effects before and after the Crimea-related sanctions.[7] We show that the syndicates with at least one sanctioned bank *reduced* the volume of loans by 72% and charged 1.4 pp *higher* interest rate on those loans after 2014 and as compared to the syndicates without sanctioned banks. The results thus clearly support the sign restriction approach we apply for our VAR analysis.

Having established the effects of financial sanctions that pertain to the ICS shock, we then consider a wider range of sanctions and employ an HFI approach. In the first stage, we run a regression of Russia's country spread on daily changes in the yield-to-maturity of Russia's US dollar-denominated sovereign bonds that occur *shortly before* sanction announcements. We show that there is an informational leakage: news on upcoming sanctions appears several (at least three) days before the official announcements. Exactly with this timing, we obtain the strongest positive coefficient at the first stage. In the second stage, we then run Jorda (2005)'s local projection (LP) approach to predict the effects of the sanctions news shock on the chosen domestic macroeconomic variables in a three-year horizon.

With the SVAR-based ICS shock estimates and the HFI-based estimates of the sanctions news shock, we then quantify the overall macroeconomic effects of each of the three waves of sanctions. Our computations at the monthly frequency show that the industrial production in Russia declines by 1.2% due to the financial sanctions shock and by 4.8% due to the overall sanctions shock cumulatively over 2014–2015. The effects of the second wave are 0 and minus 0.7% in 2017–2018, respectively. And the effects of the third wave are much more pronounced: minus 12% and 18%, correspondingly. Turning from monthly to quarterly frequency and assuming 0.67 elasticity of GDP to industrial production (linear regression estimate, significant at 1%), these numbers imply that Russia's real GDP could have lost up to –3.2% in response to the first wave of sanctions, –0.5% as a result of the second wave, and up to –12% during the third wave of sanctions (the largest decline in the Russian economy since the collapse of the USSR in 1991). Overall, these results reveal that conditional on the scope of international financial restrictions, (a) the *financial* sanctions can have substantial *real* implications for the economy, and (b) the strength of the overall sanctions shock is much larger than that of the financial sanctions shock.

We then investigate the cross-sectional implications of sanctions for the representative samples of

[7] The data is rather limited so that applying firm*month fixed effects is not feasible.

households and firms in Russia. The idea is that sanctions can hit disproportionately more: (*a*) richer households in larger cities as compared to poorer households in rural areas, and (*b*) more productive and larger firms as compared to less productive and smaller firms. We retrieve data on roughly 5,000 households across Russia from the survey database "RLMS-HSE," which has been collected by the Higher School of Economics since 1994, and the data on 7,460 firms from the SPARK-Interfax database from 2012 to 2018.

Households. Using Jorda's LP approach, we show that, in a year after sanctions (as proxied with a negative ICS shock), the real income of richer households declines by 1.5% if residing in regions' capital cities, and by 2.0% if living everywhere else (larger towns, smaller towns, or rural areas). Strikingly, poorer households enjoy rising real income during the first year after the shock: +1.2% if in regions' capital cities, and +1.1% if everywhere else. These estimates control for CTOT and domestic monetary policy and are consistent with the observation that, during crisis times, the Russian government supports first those parts of the population that are more likely to re-elect it during the next electoral cycle. The government support channel is consistent with micro evidence from Mamonov *et al.* (2021) and Nigmatulina (2022). However, as our estimates suggest, this government help is not enough: in two to three years after the shock, the real income of the poorer households starts to decline, which offsets the growth during the first year after the shock hits.

Firms. First, we apply a popular methodology to estimate firm-level TFPs put forward by Wooldridge (2009) and Levinsohn and Petrin (2012) and employed in many studies that followed (e.g., Gopinath *et al.*, 2017). Second, using Jorda's LP approach, we find that during the first year after sanctions (a negative ICS shock), the real total revenue of large firms with high TFPs declines by 2.2%. This is equivalent to 16% of these firms' overall decline in revenues, controlling for CTOT and monetary policy. For large firms with low TFPs, the effect of the sanctions peaks two years after the shock, reaching –4% (or 29% of the overall decline in revenues for these firms). This clearly shows that productivity matters in softening the effects of sanctions. Conversely, we estimate that the sanctions could have caused no larger than a 1% decline in the real total revenue of small firms with low TFPs and literally zero effect on small firms with high TFPs. This clearly suggests that smaller firms in Russia were much less affected by the sanctions than larger firms.

The contribution of this paper is fourfold. First, we introduce the sanctions news shock based on the HFI approach. In contrast to Laudati and Pesaran (2021), who build a sanctions news intensity index and employ it in a VAR model to quantify the effects of sanctions on the Iranian economy, we suggest a two-stage procedure that exploits time variation in the yield-to-maturity of Russia's bonds around the sanctions announcements by OFAC/EU (*first stage*) and then uses this variation to capture the effects of sanctions (*second stage*). The idea of the sanctions news shock is inspired by the oil news shock, as embedded in OPEC's announcements, which has been recently introduced by Kanzig (2021a).

Second, our study contributes to the literature on the economic effects of sanctions. While the few existing *macroeconomic* studies focus on specific variables—Russia's ruble exchange rate in Dreger *et al.* (2016) or GDP growth rates in Barseghyan (2019)—our study is the first to provide a broader picture by covering a larger set of variables describing the real economy, domestic monetary policy, financial sector, and international trade. Dreger *et al.* (2016) exploit a cointegrated VAR and establish that the drop in oil prices in 2014 had a greater effect on the ruble dynamics than the sanctions. In turn, 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. In contrast to these studies, we use the concept of negative ICS shocks to estimate the effects of sanctions, which has a clear counterpart in the data, at both macro- and syndicated loan levels. We show that the channel of ruble depreciation is exactly the corporate debt de-leveraging due to sanctions, and we also show that GDP decreases in response to sanctions because consumption and investment fall together by more than the trade balance rises. In addition, we analyze time variation in the effects of sanctions across the three waves that occurred in 2014 after Crimea's annexation, in 2017 after the cyber-attacks in the US, and in 2022 after Russia invaded Ukraine, whereas the mentioned studies focus solely on Crimea's sanctions. Finally, Gutmann *et al.* (2021) apply an event-study approach in a cross-country setting and reveals that the sanctions lead to a 2.2% decline in consumption and a 24% decline in investment. Our estimates for consumption are larger, but are much more conservative for investment.

Third, by quantifying the cross-sectional implications of sanctions, we also contribute to the *microeconomic* studies on sanctions (Besedes *et al.*, 2017; Efing *et al.*, 2019; Belin and Hanousek, 2020; Ahn and Ludema, 2020; Felbermayr *et al.*, 2020; Crozet *et al.*, 2021; Mamonov *et al.*, 2021). While most of these studies focus on the effect of sanctions on targeted firms or banks after receiving treatment as compared to non-targeted banks and firms, we study the effects of sanctions on different parts of the population and firms. As Ahn and Ludema (2020) show, the Crimea-related sanctions forced targeted firms in Russia to reduce employment by 33% and led to a decline in total revenues by 25%. We, in turn, show that these effects are likely to be concentrated within a group of larger firms with higher levels of TFPs, whereas smaller firms with lower levels of TFPs were unlikely to be affected by the sanctions. Regarding the effects on households, Neuenkirch and Neumeier (2016) find that the sanctions lead to a rising poverty gap, which is very persistent over time. Our results for the cross-section of Russian households open a different angle regarding the effects of sanctions: we show that the real income of richer households is affected negatively by the sanctions, whereas that of poorer households grows first and then declines. An unintended consequence of the sanctions could be a reduction in economic inequality, conditional on the sanctioned government's support for the poorest.

Fourth, our results imply that credit supply shocks matter for the macroeconomy even after controlling for endogenous monetary policy responses. Schularick and Taylor (2012) and Mian *et al.* (2017) establish a negative long-run effect of credit on output in the US and other major advanced countries. However, Brunnermeier *et al.* (2021) criticize these and related works for the absence of the monetary policy reaction to rising prices in the reduced-form equations used to establish the result. In our setting with the financial sanctions as episodes of negative (international) credit supply shocks, we show that Russia's industrial production declines by 1.78% in the VAR model containing domestic regulated interest rate and by 1.95% if the model would omit the interest rate variable (as in the previous literature). The price of omitting the accommodative effect of domestic monetary policy is thus significant but not very large.

The paper is structured as follows. Section 2 describes the timing and types of sanctions. Section 3 discusses the methods: composition of the VAR model, sign restriction approach to capture the effect of sanctions, micro-level evidence for the sign restriction approach (syndicated loan deals), and the sources of data. Section 4 presents the macroeconomic estimates of the effects of sanctions and Section 5 further investigates the cross-sectional implications of sanctions. Section 6 contains our final remarks.

2 Timing of sanctions on Russia

The first wave of sanctions began in 2014 in response to the Russo-Ukrainian conflict: the annexation of Crimea, and the Russian support for separatist movements in Eastern Ukraine. These sanctions were imposed by the US in coordination with the EU and targeted the same entities (Welt *et al.*, 2020). This allows us to focus on the timing of the US sanctions only. These sanctions are administered by the Treasury Department's Office of Foreign Assets Control (OFAC) and are 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 the foreign borrowing capacity of Russian companies and banks.

The US Ukraine-related sanctions date back to March-December 2014 (executive orders 13660, 13661, 13662, and 13685; see Welt *et al.*, 2020). As of 2022, before Russia launched a full-scale war in Ukraine, the sectoral sanctions remained in place and applied to new equity issuance and the loans of various maturities (more than 14-day for entities in the financial sector, more than 60-day lending for the energy sector, and more than 30-day lending for the defense sector). By 2022, OFAC included 13 Russian companies and banks and their 276 subsidiaries on the SSI list. The parent entities list includes the four largest state-owned banks, one development bank, seven major oil, gas, and pipeline companies, and one state-owned defense company.[8]

The second wave of sanctions dates back to 2017–2018 and was introduced in response to illicit cyber-enabled activities, electoral interference, and support for Syria. These sanctions were mostly imposed by the US with less support from the European Union (Welt *et al.*, 2020). In August 2017, the US 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 Ukraine-related sanctions and established several new sanctions. In particular, CRIEEA targeted a further reduction of foreign lending to the Russian financial and energy sectors. The new package also introduced mandatory sanctions (previously discretionary) against foreign financial institutions involved in "undesirable" transactions (weapons transfers, oil projects) with Russian entities, thus more strongly reducing Russian access to external financial infrastructure.

The third wave of sanctions appeared in February 2022 as President Putin's troops invaded the territory of Ukraine. As is widely discussed by **?**, the sanctions were of unprecedented size and scope: roughly half of the total international assets of the Central Bank of Russia (CBR) were frozen, private and corporate financial and real assets in Western countries were frozen, state-owned banks that were previously under less strict sectoral sanctions now faced fully blocking sanctions, many banks—including the largest privately-held—faced sanctions and were banned from using the SWIFT international payment system, and Russia's export and import operations were substantially banned. During the first weeks after these 'tsunami' sanctions, the financial sector in Russia seemed paralyzed with massive bank runs and the depreciation of the nominal exchange rate from 75 to roughly 140 rubles per dollar. However, CBR raised the interest rate from 9.5 to 20% and imposed various forms of capital controls. Ultimately, financial stability was restored within a month after the war started. However, as of the date of writing this text, the situation in the real sector of the economy remains

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

highly uncertain due to the massive destruction of supply chains, Western corporate exodus, and concerns about Eastern countries (India, China, etc.) directly substituting Russia's lost imports.

In these circumstances, we need an empirical tool to quantify the effects of the financial and non-financial sanctions and analyze their variation in time, depending on the strength of the shock.

3 Methodology and data

3.1 A VAR model of the Russian economy

We perform our empirical exercises using vector autoregressive models (VARs). 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 a 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 in our VAR model. We consider three variables in the foreign block: commodity terms of trade (CTOT), the US corporate bond (Baa) spread, and the real US interest rate. *CTOT* captures movements in commodity exports that are crucial for Russia. Oil, gas, and their products account for 63% of total exports, and their exports to GDP ratio is as high as 27% (2010-2016 average). Further, numerous studies find that changes in world financial conditions are important for emerging economies. Early literature focused on the role played by world interest rates (Neumeyer and Perri, 2005; Uribe and Yue, 2006). However, a more recent study by Akinci (2013) finds that the contribution of world interest rates to business cycle fluctuations in emerging economies could be negligible—the major force is global financial shocks. Following these studies, our VAR model includes both the *Baa spread* as a measure of global financial risks[9] and *the real interest rate in the US economy* as a proxy for the world risk-free interest rate.

The composition of the domestic variables block builds upon the real sector variables that have

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

theoretical counterparts in the real business cycle models, e.g., Neumeyer and Perri (2005), Garcia-Cicco *et al.* (2010), Chang and Fernandez (2013). We include *industrial production* (IP) as a proxy for domestic output, *private consumption* (C), *investment* (I), *trade balance* (TB)—all in constant rubles. We also include JP Morgan's EMBI+ *country spread* for Russia to proxy for the price of international borrowings in Russia (S)[10] and the *outstanding amount of Russia's corporate external debt* to capture the quantity of international borrowings in Russia (D, in US dollars, deflated by US CPI). Both S and D are central for the identification of the sanctions shock (see Section 3.3). Following recent studies by Ben Zeev *et al.* (2017) and Monacelli *et al.* (2023), we additionally include the *real effective exchange rate* (REER), which transmits the terms of trade shocks to the domestic economy.[11] Finally, we also consider the *regulated interest rate* in Russia (RIR, in real terms) to capture endogenous monetary policy responses to the sanctions shock. Although the inclusion of this variable is not directly dictated by the literature we follow, we argue that this is clearly important for our purposes. As Brunnermeier *et al.* (2021) show, omitting the regulator's reaction to economic shocks biases substantially the estimated effects of the shock and can thus deliver a misleading conclusion.

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

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

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

where variables 1–3 reflect external conditions (foreign block) and variables 4–11 internal conditions of the Russian economy (domestic block). To ensure that domestic variables do not affect external conditions, we impose the small open economy restrictions by setting to zero the coefficients on variables 4–11 in the equations in which variables 1–3 are dependent variables.

We estimate the VAR model (1) using the Bayesian methods in a framework suggested by Antolin-Diaz and Rubio-Ramirez (2018). The usage of the Bayesian methods is justified for the following reasons. First, reliable macroeconomic time series on the Russian economy cover at most the last two decades after the transformation and sovereign default crises of the 1990s (Svejnar, 2002) and thus are relatively short—even if we consider monthly frequency. The Bayesian methods are shown to work well in the presence of short time series, by formulating a prior distribution of unknown parameters, and are widely exploited in the literature on macroeconometric forecasting (Koop and Korobilis, 2010; Banbura *et al.*, 2010; Koop, 2013; Carriero *et al.*, 2015). Second, as we discuss below, we employ sign

[10] J.P. Morgan Emerging Markets Sovereign Bond Spread, EMBI+.

[11] Domestic production and absorption, and sectoral composition (though we do not consider sectoral outputs, to keep the model short).

restrictions to isolate the sanctions shocks after estimating the VAR model. As argued by Kilian and Lutkepohl (2017), the sign restrictions perform much better and are thus usually implemented under the Bayesian framework.

Since the Bayesian methods are appropriately designed for the models with nonstationary time series, we specify the VAR model (1) in *levels* instead of deviations from respective HP-trends. In the robustness section, we nonetheless compare the results obtained with the HP-detrended time series.

However, within the Bayesian methods, we apply only the *flat* (i.e., uninformative) prior to escape subjectivity that pertains to other forms of the priors (e.g., Minnesota, inverted-Wishart, etc.). In the baseline estimates, we set $p = 2$ months.[12]

3.2 The data

We collect monthly data on each of the 11 variables entering the VAR model (1) and listed in vector y_t (2). We focus on the period from January 2000, i.e., after the sovereign default crisis of the late 1990s, to December 2018, i.e., at least a year and a half after the second wave of sanctions on Russia (see Section 2). This gives us 208 observations on each variable in total.[13]

External variables. The data on the variables reflecting external conditions for the Russian economy (i.e., the variables 1–3 in the VAR model) comes from the following sources. CTOT data is retrieved from the IMF Commodity Terms of Trade Database, where it is readily available on a monthly basis. Note that Ben Zeev *et al.* (2017) constructed the commodity terms-of-trade index for each country themselves 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 Russia's commodity bundle, in which individual commodities are weighted by the ratio of net exports to GDP.[14] Further, the real interest rate in the US economy is calculated as the US CPI-adjusted nominal 3-month Treasury Bill rate (both series come from the IMF's International Financial Statistics database). The Baa spread for the US economy is retrieved from the St. Louis FRED database.

Domestic variables. Domestic real sector variables are constructed based on the datasets of the Federal State Statistics Service of the Russian Federation (Rosstat). Financial data, in turn, is obtained through the website of the Central Bank of Russia. Industrial production, consumption, and

[12]In the sensitivity analysis, we vary the lag structure by considering different values of p.

[13]We also experimented with adding the data for each of the 12 months of 2019 and revealed no added value in terms of identification of the credit supply shocks related to the two waves of sanctions. The data from 2020 is ignored due to COVID-19 concerns.

[14]The weighting scheme transforms the series into constant prices because import prices stand in the denominator. We also consider a deflated series: we divide the commodity export price index by the US import price index of manufactured goods from industrialized countries, similarly to Ben Zeev *et al.* (2017). The results did not change.

investment are constructed based on chain indices and the nominal values and re-expressed in constant 2010 prices.[15] Trade balance is calculated as the difference between the dollar value of Russia's exports and imports and deflated by US CPI (the data is taken from the IMF's International Financial Statistics database). The data on corporate external debt in Russia is obtained from the website of the Central Bank of Russia.[16] We sum the banks' and other sectors' external debt and subtract debt owed by these sectors to direct investors.[17] We then linearly interpolate quarterly series to obtain monthly data and deflate it by the US CPI. Following Uribe and Yue (2006), we compute the real interest rate as the sum of the US real interest rate and JP Morgan's EMBI country spread for Russia (J.P. Morgan Emerging Markets Sovereign Bond Spread, EMBI+). We obtain the REER variable from the Bank of International Settlement (BIS) website. Following Ben Zeev *et al.*, 2017, we re-express this series as an inverse of that reported by BIS to interpret a decrease in this variable as REER appreciation and an increase in it as depreciation.

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 into logs. In the robustness section, we also apply an alternative approach to data transformation: we use HP-filter to compute deviations from the filtered ('long-run') values for each of the variables employed in the VAR model.

3.3 Identification of the financial sanction shock

3.3.1 Sign restriction scheme: Sanctions as an international credit supply shock

Since the financial sanctions induce an increase in the country spread and a decrease in the amount of foreign debt simultaneously, we suggest treating them as realizations of negative international credit supply shocks (Cesa-Bianchi *et al.*, 2018; Ben Zeev, 2019; di Giovanni *et al.*, 2022). It is thus natural to use a proper sign restrictions scheme that allows the separation of credit supply shocks from credit demand and other shocks (Eickmeier and Ng, 2015; Gambetti and Musso, 2017).

Formally, we first rewrite the reduced-form VAR model (1) in the companion form $Y_t = AY_{t-1} + u_t$ and then premultiply both sides by a matrix B_0 that is aimed at isolating the necessary shocks. This

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

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

[17]A sizeable amount of Russia's 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 Russian non-financial 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 a group or consortium. Thus, these creditors are likely to extend debt repayment deadlines even under sanctions. We address this issue by excluding the debt to direct investors from the total stock of corporate external debt.

yields a structural representation of the VAR model:

$$B_0 Y_t = B_1 Y_{t-1} + \varepsilon_t \tag{4}$$

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

Since an international credit supply shock is a movement of the quantity and price of foreign debt along the demand curve, whereas an international credit demand shock pushes the two along the supply curve, we thus impose the following sign restrictions to identify B_0^{-1}:

$$\begin{pmatrix} \vdots \\ u_t^{IP} \\ u_t^{C} \\ u_t^{I} \\ u_t^{TB} \\ u_t^{D} \\ u_t^{S} \\ u_t^{RIR} \\ u_t^{REER} \end{pmatrix} = \begin{pmatrix} \vdots & \vdots & \vdots & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & + & - & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & + & + & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \end{pmatrix} \begin{pmatrix} \vdots \\ \varepsilon_t^{4} \\ \varepsilon_t^{5} \\ \varepsilon_t^{6} \\ \varepsilon_t^{7} \\ \varepsilon_t^{Credit\ Demand} \\ \varepsilon_t^{Credit\ Supply} \\ \varepsilon_t^{10} \\ \varepsilon_t^{11} \end{pmatrix} \tag{5}$$

where "+" and "−" are the imposed signs that guarantee that D and S move in the same direction when a credit demand shock hits and in the opposite direction when a credit supply shock occurs. Further, "⋮" are the cells that correspond to the three exogenous variables: they may affect each other, but they are not affected by the domestic variables (the small open economy restrictions; each $\mathbf{0}$ has a 3×1 dimension, for convenience reasons). Finally, "." means a non-empty (unrestricted) element.

Using the framework of Antolin-Diaz and Rubio-Ramirez (2018), we rotate candidates for the B_0^{-1} matrix until we obtain at least 10,000 successful draws from the posterior distribution that satisfy the imposed sign restrictions. For each successful draw, we compute the time series of the international credit supply shock $\hat{\varepsilon}_t^{Credit\,Supply}$ and the impulse responses (IRFs) of the domestic macroeconomic variables to this shock h periods ahead ($h = 1, 2...60$ months). The IRFs are normalized across all variables such that the shock is equivalent to a 1 pp increase in the country spread variable. We first plot the time evolution of the resultant empirical distribution of the international credit supply shock to analyze whether we identify significant spikes around the first and second sanction waves in

2014-2015 and 2017-2018, respectively.[18] If we do identify these, we then relate them to the financial sanctions and we eventually compute the average effects of the sanctions on the i-th domestic variable as the product of the peak magnitude of respective IRF and the size of the shock in the *50th %-tile* of the shock's distribution. For the first two waves of sanctions, we do it *in-sample*:

$$\Delta^{(J)}\hat{y}_i = \max_{t \in J}\left(\hat{\varepsilon}_t^{Credit\,Supply}\right) \times \max_h \left(\frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{Credit\,Supply}}\right), \tag{6}$$

where $J = [Mar.2014 \ldots Dec.2015]$ marks the first wave and $J = [Jun.2017 \ldots Dec.2018]$ marks the second wave of sanctions. $\max_{t \in J}$ implies obtaining maximum value over the J-th wave of financial sanctions and $\max_h$ implies searching for such h at which respective IRF reaches its maximum. Therefore, $\Delta^{(J)}\hat{y}_i$ means the maximum predicted change of y_i caused by the international credit supply shock over the J-th wave of financial sanctions.

For the third wave—the 2022 war-related full-scale sanctions—we compute the *out-of-sample* predictions of the effects of sanctions. We assume that the (peak) IRFs did not change in time and the size of the shock is fully captured by the observed dramatic increase in the country spread during the first months of the war (recall Fig. 2):

$$\Delta^{(J)}\hat{y}_i = \max_{t \in J}\left(Spread_t\right)\Bigg|_{J=[Feb.2022 \ldots Apr.2022]} \times \max_h \left(\frac{\partial \hat{y}_{i,\tau+h}}{\partial \hat{\varepsilon}_\tau^{Credit\,Supply}}\right)\Bigg|_{\tau \in [Jan.2000 \ldots Dec.2018]}, \tag{7}$$

Overall, the sign restriction approach allows us to isolate international credit supply shocks while controlling for commodities terms-of-trade (first confounder) and domestic monetary policy responses to rising prices (second confounder).

3.3.2 Microeconomic justification of the aggregate credit supply shock: Evidence from syndicated loan data

We now provide evidence supporting our sign restrictions scheme at a more granular level. Specifically, we employ the data on syndicated loans in Russia that were issued between January 2011, i.e., three years before the sanctions, and December 2017, i.e., three years after. By matching banks and their corporate borrowers and employing the combinations of borrower*month fixed effects, this data enables us to separate supply from demand on loans. Of course, a typical drawback is that syndicated loans cover only a small portion of firms compared to all firms borrowing within a given country. However,

[18] Similar procedures of relating the identified shocks to specific events that are generally attributed to the episodes of particular shocks are performed in, e.g., Antolin-Diaz and Rubio-Ramirez (2018) and Brunnermeier *et al.* (2021) to ensure credibility.

these are typically very large firms that operate not only within the country but also abroad and attract loans from the syndicates of local and foreign banks. When we explore the effects of international sanctions, a decline in the supply of loans can stem from the foreign banks' decreased willingness to continue lending in the sanctioned country (Efing *et al.*, 2019).

We obtain syndicated loan data from an international financial IT-company Cbonds.[19] We reveal 294 loans granted by the syndicates of Russian and foreign banks to non-financial firms and banks operated in Russia from January 2011 to December 2017. We observe that 148 loans were issued to firms and the other 146 were issued to banks. We also witness a decline in the number of loans as the economy switches from non- to the sanctions regime: 177 loans were granted before and only 117 loans after the Crimean sanctions. We also observe in the data that the average amount of loans declines (in real US dollars) whereas the average interest rate on those loans rises when we compare 'before' and 'after' the sanctions—a pattern that is already consistent with the supply-side effects (Table 1). We see that the share of the ever-sanctioned firms and banks in the total number of borrowers in the market declines by 10 pp in the sanctions regime. We finally reveal that the total amount of the 294 syndicated loans is equivalent to roughly 30% of the total banking system's credit to firms in Russia.

Table 1: Descriptive statistics of the Russian syndicated loan market

Note: The table reports descriptive statistics for the variables employed in Equation (8). Real loans, the interest rate on loans, and the maturity of the loans match the syndicate of lending banks s, borrowing firm f (either a non-financial entity or the bank itself), and month t when the contract is signed. *Whether credit goes to ever-sanctioned firm*$_f$ is a binary variable equal to 1 if borrowing firm f ever faces sanctions after March 2014 and until the end of the sample period in 2020. Analogously, *Whether sanctioned banks in syndicate*$_{b,s}$ is a binary variable equal to 1 if bank b participating in syndicate s ever faces sanctions.

	Obs	Mean	SD	Min	Max
	(1)	(1)	(2)	(3)	(4)
Before the sanctions (Jan.2011–Feb.2014)					
Real Loan$_{s,f,t}$, USD bln 2015	177	0.762	1.450	0.006	13.152
Interest Rate$_{s,f,t}$, % annum	95	3.4	2.2	1.7	12.8
Whether credit goes to ever-sanctioned firm$_f$	177	0.2	0.4	0.0	1.0
Whether sanctioned banks in syndicate$_{b,s}$	177	0.2	0.4	0.0	1.0
Loan Maturity$_{s,f,t}$, months	177	53.9	38.4	6.0	240.0
After the sanctions (Mar.2014–Dec.2017)					
Real Loan$_{s,f,t}$, USD bln 2015	117	0.630	1.140	0.001	10.515
Interest Rate$_{s,f,t}$, % annum	34	3.6	2.4	1.2	12.8
Whether credit goes to ever-sanctioned firm$_f$	117	0.1	0.3	0.0	1.0
Whether sanctioned banks in syndicate$_{b,s}$	117	0.3	0.5	0.0	1.0
Loan Maturity$_{s,f,t}$, months	117	68.5	46.3	6.0	192.0

[19]See https://cbonds.com/.

With this data at hand, we run a difference-in-differences regression of the following type:

$$
\begin{aligned}
Y_{s,f,t} = \alpha_{i,t} &+ \beta_1 \Big(SANCTIONED_f \times POST.March2014_t \Big) \\
&+ \beta_2 \Big(SANCTIONED_f \times POST.Date_{f,t} \Big) + Controls + \varepsilon_{s,f,t}
\end{aligned} \tag{8}
$$

where $Y_{s,f,t}$ is the dependent variable—either the log of real loans issued by syndicate s to borrowing firm f in month t or the interest rate on this loan. $\alpha_{i,t}$ is a product of the firm's f industry fixed effects and year fixed effects.[20] This combination of fixed effects is intended to capture demand on loans of the firms from the same industries, in the spirit of Degryse *et al.* (2019). $SANCTIONED_f$ is a binary variable that equals 1 during each month within 2011–2017 if firm f ever faces sanctions after March 2014 until the end of the sample period in 2020 and 0 if else. $POST.March2014_t$ and $POST.Date_{f,t}$ are the binary variables that mark 'before' and 'after': i.e., before and after the first sanction announcement that occurred in March 2014 (the first variable) and before and after each and every further sanction on Russian firms that appeared after March 2014 (the second variable). These two variables are inspired by the work of Mamonov *et al.* (2021) that reveals a strong information effect of sanctions after 2014: even if not-yet-sanctioned, potentially targeted firms (banks) adapted their international operations in advance. Thus, in Equation (8) we also separate the information and direct effects of sanctions. $Controls$ include the components of the two products, maturity of loans, and whether ever-sanctioned Russian banks participate in syndicate s.

We argue that, if a negative (international) credit supply shock leads to a declining amount and a rising price of syndicated loans, then we will obtain $\beta_k < 0$ in the regression of real loans and $\beta_k > 0$ in the regression of interest rates on those loans ($k = 1, 2$). The estimation results appear in Table 2.

As the results show, this is indeed the case: we obtain a negative and significant coefficient on the $SANCTIONED_f \times POST.March2014_t$ variable when the dependent variable is the log of real loans (column 1), whereas the coefficient turns positive and significant when we switch the dependent variable to the interest rate on those loans (column 2). This means that after March 2014, the syndicates of banks started to reduce the volume of new loans and raise the interest rates on those loans for the firms that were potentially targeted by the sanctions—state-owned or controlled corporates and banks—as compared to other firms. Economically, the effects are large: the average amount of loans was reduced by 72% ($e^{-1.354} - 1$) while the interest rate was raised by 1.4 pp. Strikingly, no

[20] Since we are rather restricted in the number of observations, we are not able to include firm*month fixed effects (Khwaja and Mian, 2008). We instead have to aggregate the firms at their respective industry level and then multiply the industry dummies with the year, not month, indicator variables. In total, we have 11 industries and 7 years.

Table 2: Difference-in-differences estimation results: Supply-side effects of sanctions at the syndicated loan level

Note: The table reports the estimates of Equation (8) with the dependent variable being either the log of the real amount of loan issued by syndicate s to borrowing firm f in month t (column 1) or the interest rate on this loan (column 2). $SANCTIONED_f$ is a binary variable that equals 1 during each month within 2011–2017 if firm f ever faces sanctions after March 2014 until the end of the sample period in 2020 and 0 if else. $POST.March2014_t$ and $POST.Date_{f,t}$ are the binary variables that mark 'before' and 'after': i.e., before and after the first sanction announcement that occurred in March 2014 (the first variable) and before and after each and every further sanction on Russian firms that appeared after March 2014 (the second variable). $Loan.Maturity_{s,f,t}$ is loan maturity, in months. *Whether sanctioned Russian banks in syndicate* is a binary variable equal to 1 if syndicate s contains Russian bank(s) under sanctions. *Industry* is a set of 11 binary variables equal to 1 if firm f belongs to the respective industry and 0 if else.

Dependent variable, $Y_{s,f,t}$:	$\ln(\text{Real.Loan})_{s,f,t}$	$\text{Interest.Rate}_{s,f,t}$
	(1)	(2)
$\text{SANCTIONED}_f \times \text{POST.March2014}_t$	–1.354***	+1.380***
	(0.548)	(0.397)
$\text{SANCTIONED}_f \times \text{POST.Date}_{f,t}$	0.516	–5.331
	(0.976)	(4.135)
SANCTIONED_f	1.612***	–0.095
	(0.277)	(0.397)
POST.March2014_t	0.830	2.959
	(0.569)	(3.720)
$\ln(\text{Loan.Maturity}_{s,f,t})$	0.078	–0.337
	(0.136)	(0.503)
Whether sanctioned Russian banks in syndicate	0.579***	2.711***
	(0.213)	(0.765)
Industry × Year FE	Yes	Yes
N obs	294	129
R^2	0.569	0.745

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the loan level and appear in the brackets under the estimated coefficients.

such effects are obtained for any other sanction announcements once we control for the one associated with March 2014.

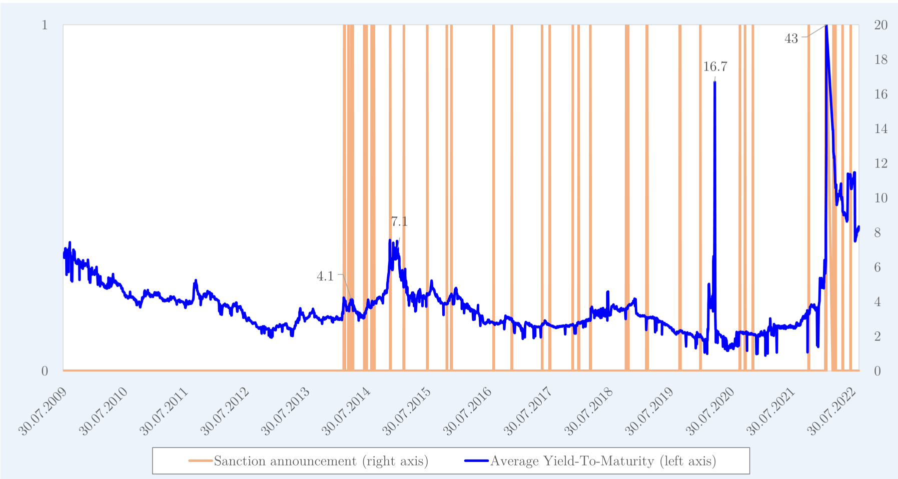
We therefore obtain microeconomic evidence that the sanctions led to a decrease in borrowings and an increase in the price of borrowed funds for the firms targeted by the sanctions. This evidence backs up our sign restrictions scheme introduced above (Section 3.3) and favors our usage of the concept of credit supply shocks at the aggregate level in the rest of this paper.

3.4 Identification of the overall sanction shock

We now employ the high-frequency identification (HFI) approach to uncover the effects of all sanctions, not only financial sanctions. HFI has been widely used to capture monetary policy shocks using the

Fed's announcements on the interest rate (Gertler and Karadi, 2015) and then, more recently, oil news shock using OPEC's announcements on oil extraction quotas (Kanzig, 2021a), climate policy shocks using the EU's announcements on future CO_2 emission quotas (Kanzig, 2021b), and policy shocks using the UK's Brexit announcements (Geiger and Guntner, 2022).

We adopt HFI to identify the *sanctions news shocks* using daily dates on the OFAC/EU announcements of sanctions against Russia's politicians, state-connected businessmen, and corporations (both firms and banks) that fell on either the SDN or SSI lists. The idea is that we observe substantial spikes in the yield-to-maturity of Russia's US dollar-denominated sovereign bonds around sanction announcements because investors are likely to re-evaluate risks and start selling bonds once the bad news arrives. This is indeed what we can observe in Fig. 4, which presents the daily evolution of the yield-to-maturity averaged across 15 different (partly overlapping) issues of Russia's Ministry of Finance US dollar-denominated bonds on the background of more than 30 OFAC sanction announcement dates that occurred between 20 March 2014 and 21 July 2022.[21]



Note: The figure reports the average daily yield-to-maturity across 15 issues of Russia's US dollar-denominated sovereign bonds over 2001 to 2022 (*blue line*) and 31 OFAC daily announcements of sanctions against Russia's individuals and firms between 2014 and 2021 (SSI and SDN).

Figure 4: Average yield-to-maturity of Russia's US dollar-denominated sovereign bonds and the OFAC sanction announcements

Therefore, we can attribute (some of the) daily changes in the yield-to-maturity (YTM) to the announcements of sanctions, or anticipation of these announcements, and apply these sanction-driven changes as an instrument to isolate exogenous variation in the reduced-form residuals u of the country spread S regression at the first stage:

$$u_t^{(S)} = \alpha_k + \beta_k \cdot \Delta\overline{YTM}_{k,t} + \xi_{k,t}, \tag{9}$$

[21]Recall, however, that the macroeconomic data available for our VAR analysis is limited by the year 2019.

where $u_t^{(S)}$ is obtained from the VAR model (1), $\Delta\overline{YTM}_{k,t}$ is a cumulative within-month t sum of one-day changes in the average yield-to-maturity $\overline{YTM}$ of Russia's US dollar-denominated sovereign bonds around sanction announcement days, which is defined as:

$$\Delta\overline{YTM}_{k,t} = \sum_{\tau(t)=1}^{R_t} \Delta_1\overline{YTM}_{\tau(t)+k}, \tag{10}$$

where $\tau(t)$ is a day of sanction announcement within a month t and R_t is the total number of sanction announcements that occur within that month. $\Delta_1\overline{YTM}_{\tau(t)+k}$ is a one-day change in the average daily YTM that occurs $\tau(t)+k$ days before (if $k<0$) or after (if $k>0$) the sanction announcement. The k parameter governs potential *leakage* of the information on upcoming sanctions that may appear shortly before the announcements (e.g., $-5 \leq k < 0$ days) or traces potential delays in the reaction of financial markets to the news on already announced sanctions (e.g., $0 \leq k \leq 5$). International media sources provide direct evidence on such leakages.[22] In turn, delays may take place because global investment funds may not be able (or not allowed) to sell all the bonds within one day, which is aimed at restricting the negative systemic effects on the financial markets that such sales could entail.

If our instrument works well in the first stage, we then proceed to the second stage of the HFI approach. Specifically, we apply Jorda (2005) local projection (LP) approach to build impulse responses of domestic macroeconomic variables to the sanctions shock, as measured with the fitted values $\widehat{u}_t^{(S)} = \widehat{\beta}_k \cdot \Delta_1\overline{YTM}_{k,t}$ from the first stage. As discussed, e.g., in Mian *et al.*, 2017, Jorda's LP is more flexible in terms of control variables than VARs and is thus more robust to functional misspecification. We use the following regression form:

$$y_{i,t+h} = \omega_{i,h} + \gamma_{i,h} \cdot \widehat{u}_t^{(S)} + \delta'_{i,h}\mathbf{X}_t + \mu_{i,t+h} \tag{11}$$

where $y_{i,t}$ is ith ($i = 1,2...8$) domestic macroeconomic variable considered in the VAR model (1) above, t is month from January 2000 to December 2018 and $h = 1,2...36$ is prediction step ahead of the sanction shock. $\mathbf{X}_t$ contains control variables: all monthly lags of $\widehat{u}_t^{(S)}$ from $1st$ until $12th$, thus

[22] We run a series of Google searches of the following form: "[*Name of the media*] Russia sanctions" in a five-day time interval $[\tau-5,\tau)$ across such medias as *The Guardian*, *Wall Street Journal*, *New-York Post*, *BBC*, *Bloomberg*, etc. In all cases, we find that the sanction announcements were highly expected one to five days in advance. Essentially, this is not surprising because an adverse action—another episode of Putin's aggression—and the response of the West to it—economic sanctions—are clearly separated in time. After the action and before the sanction announcement, the sanction's preparation stage takes place during which leakage may occur. See Appendix B for examples of media reports on expected sanctions on the eve of the most important announcements in 2014: on March 17th (politicians responsible for the annexation of Crimea and the *Rossiya Bank*, the so-called "Putin's wallet"), July 16th (most of the largest state-owned banks, excluding the top-1, Sberbank), and September 12th, Sberbank).

covering the whole previous year, and the current values and 12th month lagged values of each of the eleven variables in y_t.[23] Born *et al.* (2020) apply a similar procedure of unfolding the effects of spread shocks on macroeconomic variables.

4 Results: Macroeconomic effects of sanctions

In this section, we present the macroeconomic estimates of the sanctions shock and its impact on the system of domestic macroeconomic variables. We begin with the effects of *financial sanctions* that we capture using the sign restrictions (SR) approach and the concept of international credit supply slump. We then turn to the effects of *all sanctions*, which include not only financial sanctions, but also restrictions on trade, politicians, and technology. For this purpose, we employ the high-frequency identification approach (HFI). We then summarize the effects we obtain under SR and HFI attributing the difference between them to the other (non-financial) sanctions.

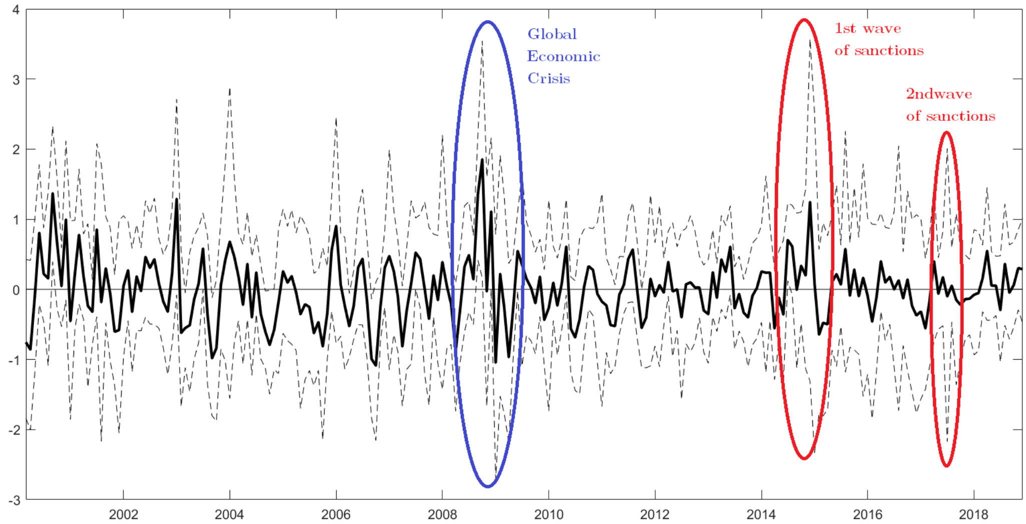
4.1 Sign restrictions: The effects of financial sanctions

We start with the preliminary results that we obtain from a version of the VAR model (1) with the domestic interest rate being dropped from the list of endogenous variables. Domestic monetary policy is typically ignored in the VAR models of EMEs because the literature assumes that local financial regulators simply follow world interest rate cycles determined by global central banks, see, e.g., Uribe and Yue (2006). Recall that we have the real interest rate in the US economy among the external variables in our models. In the next section, we add the domestic interest rate to close the model and reveal whether there is an added value in terms of the estimated effects of sanctions.

Using the sign restriction scheme (5), we first isolate a *negative* international credit supply (ICS) shock from the residuals of the VAR model (1) and we then analyze the time evolution of the isolated shock (Fig. 5). By construction, positive values of the ICS shock correspond to unexpected declines in the supply of external borrowings, and negative values—to unexpected rises. We plot the median extraction from the posterior distribution of the estimated ICS shock and the conventional bands formed by the 16th and 84th %-tiles of the same distribution. We infer that the resultant time series contain substantial spikes around the first wave of the financial sanctions in 2014. The peak of these

[23] Recall that all variables in y_t are taken in levels so that it is enough to consider their $0th$ and $12th$ lags to cover the previous year. Our results remain the same if we include each lag from $1st$ until $12th$ of each of the eleven variables in y_t. We do not consider it a baseline because it is much less parsimonious than what is implied by Equation (11), given the relatively short time span that we have. We also stress that the results remain the same if we drop the $1st$ to $12th$ lags of $\widehat{u}_t^{(S)}$ from $\mathbf{X}_t$.

spikes is the largest one in the 2010s and is comparable to the maximum value of the estimated ICS shock—the one that corresponds to the global financial crisis of 2008–2009. Conversely, we observe no jumps around the second wave of the financial sanctions in 2017–2018. These results are in line with our expectations and the findings of Mamonov *et al.* (2021), which show that sanctioned banks in Russia adapted their international operations after 2014 but in advance of actually facing the restrictions.

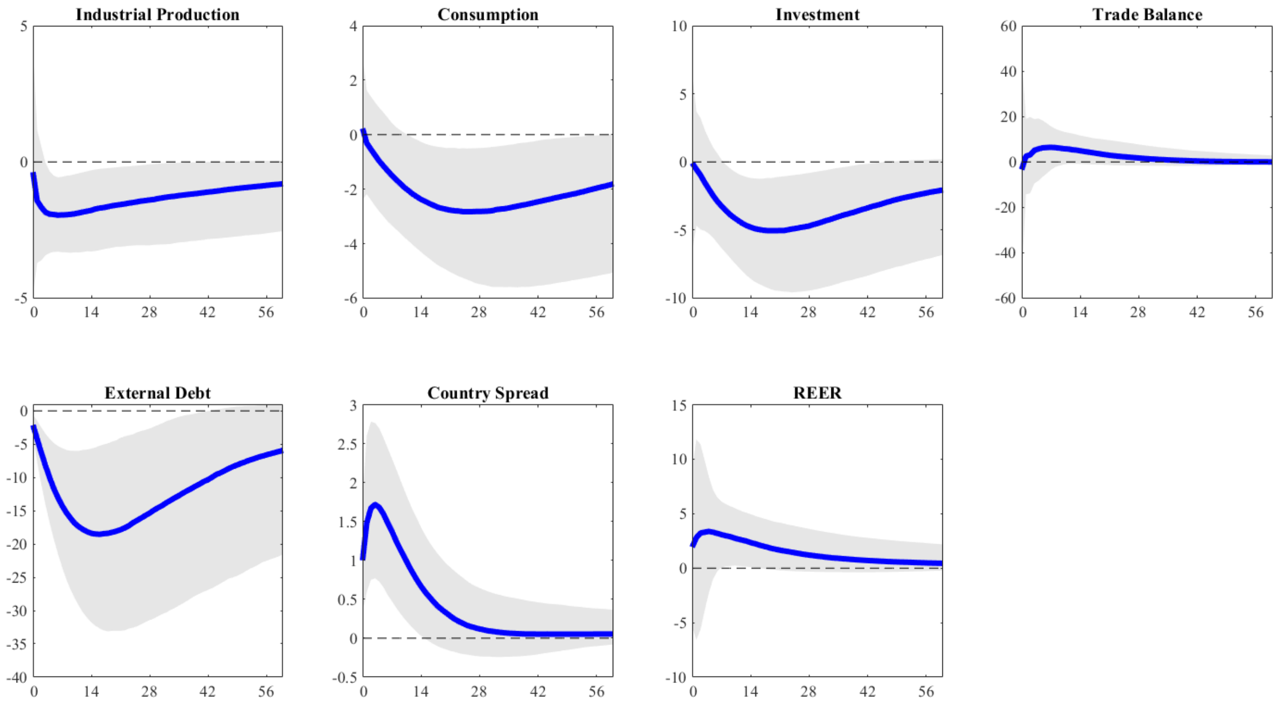


Note: The figure reports the time evolution of the sanctions shock estimated with the BVAR model containing 10 variables. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and we discard the first 5,000 draws. Conventional credible bands comprised of the 16^{th} and 84^{th} percentiles of the post-burned-in estimated IRFs are reported. Substantial spikes in the time series of the estimated shock are identified for the first but not for the second wave of sanctions at the end of 2014 and 2017, respectively. One more is identified for the period of the 2008–2009 global economic crisis and is reported for comparative reasons.

Figure 5: Time evolution of a negative shock to the international credit supply identified under the sign restrictions scheme

With a plausible estimate of the ISC shock, we now turn to analyze the responses of the domestic endogenous variables. The estimation results appear in Fig. 6 below. We report the estimated impulse responses over five years of the domestic variables to a *negative* ISC shock defined above. For the sake of representation, the shock is re-scaled to a +1 pp increase in the country spread on impact, and the responses are re-scaled accordingly.

First, we find that after the initial impulse, the country spread's response peaks at +1.7 pp half a year after the ICS shock and then it attenuates towards zero in the following three years. We also find that corporate external debt, i.e., our second restricted variable, declines by 18 pp one year after the shock. Second, we obtain significantly negative and persistent reactions of the real economy to the ICS shock: industrial production declines by 1.95 pp within half a year after the shock, private consumption falls by 3 pp two years after the shock, and investments slump by 5 pp in the second



Note: The figure reports the estimated IRFs of domestic macroeconomic variables to the sanction shock identified using the sign restrictions scheme as an international credit supply shock. The IRFs are re-scaled so that the shock is equivalent to a +1 pp rise of $Country.Spread_t$. The BVAR model contains 10 variables: external characteristics—commodity terms-of-trade ($CTOT_t$), the Baa corporate bond spread ($Baa.Spread_t$), the real interest rate in the US economy ($US.Real.Interest.Rate_t$); domestic indicators—industrial production (IP_t), private consumption ($Consum_t$), investments ($Invest_t$), trade balance (TB_t), corporate external debt ($ExtDebt_t$), Russia's country spread ($Country.Spread_t$), the real effective exchange rate ($REER_t$). Monetary policy reaction to the sanctions shock is ignored in this version of the model. The $Country.Spread_t$ 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 6: Impulse response functions to the international credit supply shock identified under the sign restriction scheme

year after the shock.[24] Third, the results show that the international trade balance, in contrast, reacts positively to the ICS shock, which may imply that imports decline by more than exports; however, the estimated reaction is barely significant. Finally, our estimates indicate that REER also rises in response to the ISC shock, peaking at +4 pp in a quarter after the shock. REER depreciates because Russia's economic agents are forced to repay their external debts, which means a greater demand for foreign currencies in Russia and their outflows abroad. Trade balance rises because agents need to earn enough income in foreign currencies to be able to repay their external debts.

4.1.1 Accounting for endogenous monetary policy responses

As argued by Brunnermeier *et al.* (2021), we can be sure that we capture the real effects of credit supply shocks only if we properly account for the monetary policy changes in response to such shocks.

[24]The more strong reaction of private consumption as compared to industrial production is consistent with the lack of consumption smoothing over the business cycle typically observed in EMEs Neumeyer and Perri (2005); Uribe and Schmitt-Grohe (2017).

In our setting, the idea is that negative shocks to international credit supply can provoke rises of credit supply by domestic financial institutions, holding the demand on loans at the same level (substitution channel), which in turn can create upward pressure on domestic prices. Clearly, domestic financial regulators may step in and raise the interest rate to curb inflation. A well-known side effect of this policy is the depression of economic activity. Therefore, we eventually could have a double negative effect on the macroeconomy—one stemming from the international credit supply shock and the other from the monetary contraction. It is a-priori unclear which of the two negative effects dominates and how they relate to each other. To address these concerns, we add the domestic regulated interest rate (in real terms) to the list of endogenous variables employed in the VAR model (1) and re-run the same exercises as in the previous section.

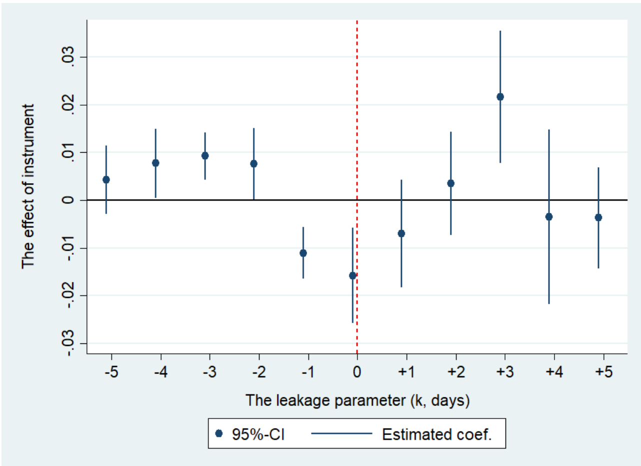
As can be inferred from Fig. C.I, the time evolution of the re-estimated ICS shock remains very close to the baseline (see Appendix C). The re-estimated impulse responses show that the Central Bank of Russia indeed tends to raise the key domestic interest rate in response to negative ICS shocks (Fig. C.II). The peak increase reaches +1.4 pp half a year after the ICS shock. However, this has only a minor quantitative impact on our previous results: we find that the estimated responses of the other domestic variables remain almost the same as before. For instance, industrial production declines by 1.78 pp at most, which is only 0.17 lower in magnitude than the respective estimate in the previous section, where the domestic regulated interest rate was ignored.

Overall, accounting for endogenous monetary policy reactions to negative ICS shocks leads to only a small reduction of the estimated responses of domestic macroeconomic variables to these shocks. As an alternative and more conventional approach, we also employ *recursive scheme* (Cholesky ordering) and analyze the effects of financial sanctions by isolating innovations to country spread (S) instead of international credit supply (ICS). The results are largely in line with what we obtain with the ICS shock and are reported in Appendix D.

4.2 High-frequency identification (HFI) approach: The effects of all sanction packages

We report the first-stage estimation results in Fig. 7, as implied by Equation (9). Strikingly, we obtain positive and highly significant β_k estimate when the leakage parameter is set at three days *before* the sanction announcement ($k = -3$). Moreover, this is the only case when the associated first-stage F-statistic exceeds the threshold of 10 (13.5), meaning that the underlying instrument is not weak. For deeper values of the leakage parameter k we either obtain an insignificant estimate ($k = -5$) or still significant but the corresponding F-statistic falls largely below 10 ($k = -4$). For smaller lags, we either obtain an insignificant positive estimate ($k = -2$) or even a negative and highly significant one ($k = 0, 1$). The negative estimates may indicate a reversal from the (over)selling of bonds at deeper k's to buying those at smaller k's. Apparently, this implies that the financial markets expect harsher sanctions than they ultimately are.

With regard to the *after the announcement* days, we find that YTMs start rising during the first three days, and the associated effect that pertains to the third day ($k = 3$) becomes positive and highly significant. This effect is the highest across all days before and after the announcement, exceeding its counterpart that we find significant at $k = -3$ by a factor of 2. Interestingly, if one is willing to consider the average effect across all $k \in [-3, 3]$ to balance the different forces that take place before and after sanction announcements, then the resultant sum (0.0082) is surprisingly similar to the single effect at $k = -3$ (0.0092). Effectively, this means that the overall inference at the second stage would be the same. We thus stick to the β_{-3} case.

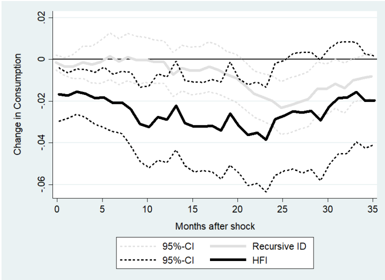


Note: The figure reports the estimation results from the first stage, as implied by Equation (9). A sanction announcement takes place on day 0 (*red line*). The estimated coefficients (*blue dots*) show the effect of sanction announcements on Russia's country spread at *monthly* frequency that runs through the changes in the average yield-to-maturity of Russia's US dollar-denominated sovereign bonds that occur k *days* prior to the sanction announcements ($-5 \leq k < 0$, *leakage*) or after it ($0 \leq k \leq 5$, *delay*).

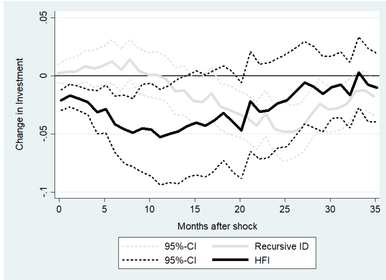
Figure 7: High frequency identification of the effects of sanctions: 1st stage estimation results

As for the second-stage results, we present the estimated impulse responses to the HFI-based sanction shock in Fig. 8(a)–(h), as implied by the local projection Equation (11). Each subfigure plots the time evolution of the estimated impulse responses $\gamma_{i,h}$ of a given variable $y_{i,t}$ to the HFI shock $\widehat{u}_t^{(S)}$ against the background of the recursively identified SVAR-based shock $\varepsilon_t^{(S)}$. The 95% confidence intervals are computed with bootstrap (500 draws, with replications) to account for the estimated nature of the shocks. The responses are re-scaled to a +1 pp rise in Russia's country spread variable.

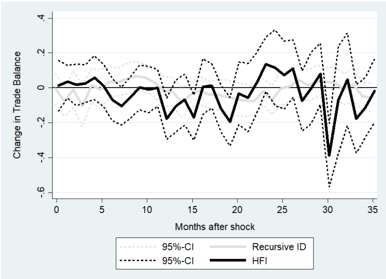
(a) Industrial production



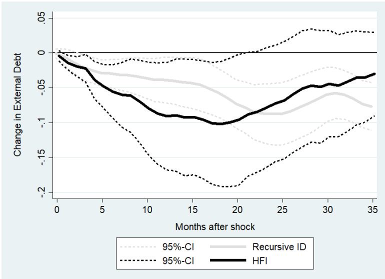
(b) Consumption



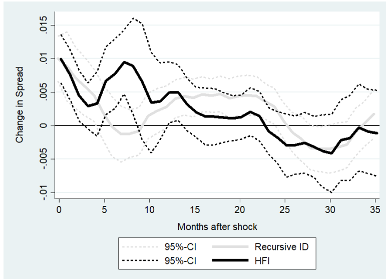
(c) Investment



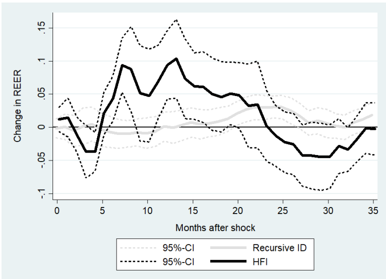
(d) Trade Balance



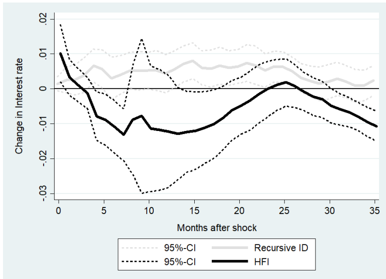
(e) External Debt



(f) Spread



(g) REER



(h) Interest rate

Note: The figure reports impulse responses to a positive country spread shock identified with the high-frequency approach (*HFI*) and recursive identification scheme (*Recursive ID*). The responses are obtained under Jorda's LP approach, as implied by $\beta_{j,h}$ in Equation (11). The 95% confidence intervals are computed with bootstrap (500 draws, with replications).

Figure 8: Impulse responses to the country spread shock identified under the high-frequency approach

We find that industrial production declines faster and two times more intensively in response to the HFI shock than to the country spread shock (a). The peak reaction to the HFI shock reaches –4 pp by the end of the first year after the shock hits (significant at 1%), whereas the maximal response to the country spread shock is only –2 pp that is reached by the end of the second year after the shock. A similar pattern holds for private consumption (b) and investment (c) whose declines reach 3.2 and 5 pp within a year after the shock. For the trade balance, we do not obtain significant results (d) under either the HFI or recursive identification. For external debt (e) we find that the peak reaction is comparable to what we get with the recursive identification (around –10 pp), but again this happens much faster—within the first year (HFI), not the second year (recursive). For the REER (g), we also obtain that Russia's ruble depreciates following the HFI-based sanction shock, as we get under the recursive scheme; however, the peak depreciation is larger, +10 pp, and this happens faster, within a year after the shock. Finally, we estimate that domestic monetary policy accommodates the sanction shock on impact—by raising the key interest rate by 1 pp—but then turns to easing, by 1.2 pp within half a year after the shock (HFI). Overall, under the HFI approach, we find that the reaction of macroeconomic variables to the sanction shock is much deeper and it materializes faster than under the SVAR-based approach.

4.3 Summary of macroeconomic estimates

We have so far isolated the trajectories of the shocks to country spread (S) and international credit supply (ICS) using the VAR model (1) and the sanctions news shock using the HFI approach (9)–(11). With these trajectories at hand, we then estimated the peak responses of domestic macroeconomic variables to these shocks and established the spikes in the shocks' trajectories around 2014–2015 (the first wave of sanctions), 2017–2018 (the second wave), and 2022 (the third wave). By exploiting the *peak responses* and the *sizes of the shocks*, we now compute the resultant macroeconomic effects of the financial sanctions using Expressions (6) for the first two waves of sanctions (in-sample) and (7) for the third wave (out-of-sample). We report the computation results in Table 3. The table compares the effects obtained under the sign restrictions (*Sign*) in an 11-variable VAR model and under the Jorda (2005) Local Projection (*LP*) and the HFI approach. For comparison, we also report the effects obtained under the recursive identification (*Recurs*). We treat the HFI approach as the one capturing the overall effects of sanctions, whereas *Sign* captures only the effects of financial sanctions.

Corporate external debt. We start the description of our results with the effect of sanctions on the targeted variable—(corporate) external debt (D_t) of the Russian economy. Our estimations indicate that this characteristic is the most responsive variable across all of Russia's macroeconomic variables. With the HFI approach, we estimate that the corporate external debt declines by 11% in response to the first wave of sanctions, as cumulative during 2014–2015.[25] This accounts for roughly half of the overall decline of corporate external debt during that period. Given that the strength of the second wave of sanctions is much lower, we get that its effect on the corporate external debt is just –1.7%.[26] During the third wave of sanctions, the shock is so large that our model predicts a 40% decline of

[25] The effect is computed as the product of the first stage coefficient (0.93), the cumulative sanctions news shock over the period (1.20), and the peak response estimated at the second stage (−10).

[26] The effect is computed similarly to the previous one, with the size of the sanctions news shock being replaced from 1.20 by 0.18.

Table 3: Macroeconomic effects of sanctions on Russia: Estimation summary

Note: The table contains the (median) estimates of the macroeconomic effects across three waves of financial sanctions, as implied by Expressions (6) and (7). The estimates are obtained with the use of either a structural VAR model or Jorda (2005) local projection (LP) and the HFI approach. Under the VAR model, the identification methods are: recursive ordering (*Recurs*) or sign restrictions (*Sign*). *Recurs* identifies a positive shock to Russia's country spread and *Sign* isolates a negative shock to the international credit supply. *HFI* identifies a sanctions news shock that pushes investors to sell Russia's sovereign bonds. D_t is Corporate external debt, IP_t is Industrial production, C_t is Final consumption, I_t is Investment, TB_t is Trade balance, $REER_t$ is Real effective exchange rate.

1^{st} and 2^{nd} wave estimates: *in-sample* predictions (Jan.2000–Dec.2018). 3^{rd} wave estimates: *out-of-sample* predictions (2022) based on (*i*) the realized shock to Russia's country spread during the first weeks of Russia's war over Ukraine and (*ii*) the impulse responses estimated for the period of Jan.2000–Dec.2018.

Sanction wave:	First (2014–2015)			Second (2017–2018)		Third (2022)		
Approach:	SVAR		HFI + Jorda LP	SVAR	HFI + Jorda LP	SVAR		HFI + Jorda LP
ID scheme:	Recurs	Sign		*both*		Recurs	Sign	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_t	–20.0	–11.9	–11.2	0	–1.7	$\sim$ –100	$\sim$ –100	–38.5
$REER_t$	+7.0	+2.0	+11.2	0	1.7	+61.3	+17.9	+38.5
TB_t	+4.0	+5.1	0	0	0	+35.0	+44.6	0
IP_t	–3.8	–1.2	–4.8	0	–0.7	–34.1	–11.7	–17.6
GDP_t	–2.5	–0.8	–3.2	0	–0.5	–22.9	–7.9	–11.8
C_t	–4.5	–1.5	–4.5	0	–0.7	–23.9	–8.2	–12.3
I_t	–5.4	–3.4	–5.6	0	–0.9	–51.2	–17.6	–26.5

corporate external debt in 2022 in response to the 'tsunami' sanctions. Notably, the estimates that we obtain under the *Recurs* and *Sign* approaches predict a complete shutdown of international borrowings for Russia's economic agents. This clearly speaks in favor of the HFI approach whose results are more realistic, given that Russian firms may still (though partly at best) substitute Western financial funds with those attracted from Asian financial markets.

International trade and exchange rate. Clearly, sanctions force Russia's economic agents to accelerate payments on their external debts. To be able to repay, the agents have to earn relatively more income from international trade—or the government has to support them directly—and then service the external debts. This must cause the outflows of foreign currencies from Russia and, eventually, lead to a depreciation of the ruble.

As our computations under the HFI approach show, the real effective exchange rate ($REER_t$) of the ruble depreciated by 11% in response to the first wave of sanctions in 2014–2015, by another 2% due to the second wave, and by roughly 40% in response to the sanctions news shock in February–March 2022. These estimates mirror those for the corporate external debt that we have just described above. As for the trade balance (TB_t), our HFI estimates produce a zero reaction to the sanctions news across all three waves, meaning that the associated declines in exports could be as large as the declines in imports. If so, then in order to repay external debts, the agents have to appeal for government support. As has been recently shown by Nigmatulina (2022), the government support channel was indeed strong over the above periods. We note, however, that the two other approaches we use, *Recurs* and *Sign*, deliver different results that are consistent with the agents' abilities to repay the debts using growing income from international trade. That is, under these two approaches, Russia's trade balance increased in response to the first and third waves of sanctions. We assume both channels were at work.

Industrial production and GDP growth. Given the depreciation of the ruble and the decline in international borrowings by Russian firms in response to the sanctions, we can anticipate real negative effects on the Russian economy.[27] Indeed, with our HFI approach, we estimate that industrial production in Russia could have lost nearly 5% in response to the first wave of sanctions cumulatively in 2014–2015.[28] This accounts for 63% of the overall decline in industrial production during that period (–7.6%). The effect of the second wave is much (six times) smaller and equals just 0.7% of lost industrial production in 2017–2018. This explains 32% of the overall decline in industrial production over the respective period (–2.3%). Conversely, when it comes to the third wave, the estimated effect turns dramatically high: minus 17.6% of losses in terms of industrial production dynamics in 2022, which is roughly four times larger than during the first wave and twenty-five times larger than in the second wave.[29] We stress that, by the construction of our local projection equation (11), these estimated effects go beyond the effects of CTOT movements and monetary policy responses to changing prices that occurred during the three waves of sanctions.[30]

Given that monthly data on GDP does not exist, we uncover the effects of the three waves of sanctions on Russia's final output by using a simple linear mapping from industrial production to GDP estimated at the quarterly frequency (0.67, significant at 1%, see Appendix L). With this mapping,

[27] The firms heavily relied on international borrowings as a source of funds: corporate external debt was equivalent to 30% of GDP in Russia on the eve of the first wave of sanctions.

[28] The effect is computed as the product of the first stage coefficient (0.93), the cumulative sanctions news shock over the period (1.20), and the peak response estimated at the second stage (−4.3).

[29] The estimate is built up similarly to the two previous ones, with the sanctions news shock being replaced by 4.14. The computation is $100\% \cdot \left(\left(1+\frac{1}{100}\cdot 0.0093\cdot 4.14\cdot(-4.3)\right)\cdot\Big((1-0.007)(1-0.006)\Big)-1\right) = -17.6\%$. Here, we have also accounted for the monthly growth rates of industrial production that we observe for the pre-war January and February 2022 (−0.7% and −0.6%, respectively) before the data was closed by the Russian government as the war raged.

[30] As an example of relative contribution during the first wave of sanctions, we find that the oil price slump and monetary contraction explain jointly 4.4 pp of the decline of industrial production. This means that together with the sanctions news effects (4.8 pp), the three shocks accommodate a 9.2 pp decline in industrial production over those times. Recall that the actual decline equals 7.6%. This implies that a conservative estimate of the strength of the government support channel (when the Russian government was supporting sanctioned firms, see Nigmatulina, 2022) can be equivalent to at least 1.6 pp.

we find that real GDP in Russia could have lost 3.2% during the first wave of sanctions in 2014–2015, 0.5% in 2017–2018, and that in could lose nearly 12% in 2022. Importantly, one should not confuse these estimates with the overall forecast of GDP dynamics in the respective years. Instead, these estimates capture the potential of initial sanctions shock: a pure sanction effect originating from the size of the sanctions news shock to Russia's US dollar-denominated sovereign bonds that had occurred on the eve of the sanction announcements. These estimates thus do not take into account responses to sanctions by the Russian government, the Central Bank of Russia, and the international partners across the world that help Russia to evade the universe of global restrictions.[31]

In almost all cases, our estimates exceed those in the literature (between 0% in Kholodilin and Netsunajev (2019) and –1.5% in Barseghyan, 2019), analyst reports (–0.2% by the IMF, 2019), and our own estimates obtained with the use of the VAR models under *Recurs* or *Sign*. For instance, under the *Sign* approach, we estimate that the effect of the ICS shock on GDP is 2.4 pp less strong during the first wave of sanctions and 3.9 pp less strong during the third wave.[32] We argue that these discrepancies in the estimated effects arise exactly because we use an innovative measure of the sanctions shock stemming from the news on upcoming sanctions which we accommodate with the HFI approach (*external instrument*) rather than using the ICS concept originating from the residuals of (VAR) regressions based on macroeconomic time series themselves.

Consumption and investment. With the HFI approach, we find that the sanctions news shock could have led to a decline in private consumption of 4.5% and investment of 5.6% during the first wave of sanctions, as cumulative over 2014–2015. This implies much stronger negative reactions than that of GDP which we described above—by 1.3 and 2.4 pp on magnitude, respectively. We then obtain the negative effects on consumption and investment turn substantially milder (five to six times) during the second wave in 2017–2018, being bounded by –1% and still exceeding the effect on GDP. Our computations then indicate that the sanctions news shock at the beginning of the third wave in February–March 2022 is able to trigger a slump in consumption of 12% and investment of more than 25%, which are comparable only to the effect of the USSR collapse in the early 1990s.[33]

[31]For the overall forecasts of Russia's GDP, one could be directed to the IMF predictions produced, e.g., in August 2022, according to which Russia's GDP could lose around 6% in 2022. At the moment of this text writing in mid-2023, the final figure for 2022 is just –2%. Therefore, one can compare our estimate of the sanction potential, –12%, and this final figure, –2%, and think of the difference, i.e., 10 pp, as of the effect of sanction evasion in 2022.

[32]Note that the size of the ICS shock is not observed in 2022 because we do not have the data on the amount of external debt decline. To overcome this issue, we assume that the ratio between the peak magnitudes of the country spread and ICS shocks remains constant in time—in 2014 when both are observed, and in 2022 when only the country spread is observed. This allows us to uncover the assumed size of the ICS shock in 2022 and compute the effect on industrial production and other macroeconomic variables.

[33]These out-of-sample computations exploit a linear mapping between private consumption and industrial production (0.69, see Appendix L) and between investment and industrial production (1.5, see Appendix L),

Again, as was the case with GDP, our estimates obtained with the *Sign* approach indicate a less strong reaction of both consumption and investment than those obtained with HFI. Clearly, this highlights the key difference between the two approaches: while *Sign* captures only the reduced *supply* of international funds, HFI encompasses both the reduced supply of these funds and the depressed *aggregate demand* in the economy due to negative feedback loops. Put differently, sanctions first shrink the supply of international finance—this then raises the likelihood that firms' and households' borrowing constraints become binding—this, in turn, forces consumption and investment to shrink, and thus the agents demand less in the economy than before the sanctions hit. We argue that the expectations of this chain of events by financial markets are included in the prices of Russia's sovereign bonds and thus are fully captured by our HFI approach, whereas *Sign*, by construction, ignores the demand side of the story.

Our results are partially consistent with the cross-country event-study estimates of Gutmann *et al.* (2021), who find that consumption falls by 2.2% during the first year after sanctions while investment decreases by 24% in two years after the sanctions. Our results point to more equal reactions of consumption and investment to the international financial sanctions.

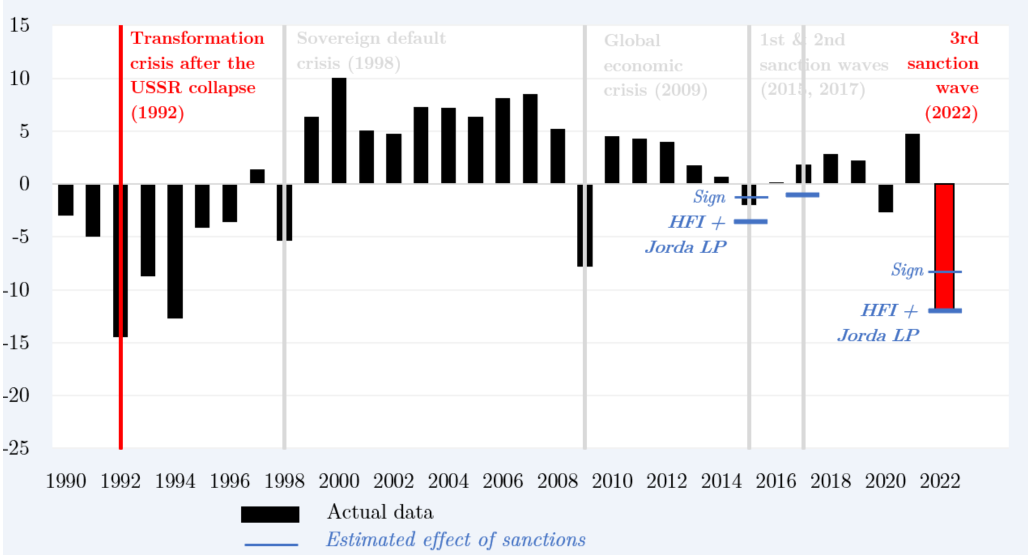
Overall, we document that financial sanctions have multiple effects: they not only change the flows of international borrowing funds but also have significant real effects on the domestic (sanctioned) economy. These effects clearly depend on the size of the sanction shock and on whether and how much other shocks affect the economy at the same time. But even in 2014–2015, when the Russian economy encountered a deep negative oil price shock and similarly deep restrictive monetary response, we show that the sanctions were still responsible for at least 50% of the total decline in industrial production and GDP. In 2022, by contrast, external conditions were more than favorable but the sanction shock was unprecedentedly high causing the largest decline in the economy since the collapse of the USSR (Fig. 9). Of course, the latter estimate should be perceived as a pure effect of the sanctions *prior to* the Russian government's response to the shock, including the imposition of capital controls by the Central Bank of Russia in early March 2022.

4.4 Other robustness checks

The rest of the sensitivity analysis is devoted to understanding how much our estimated impulse responses depend on the modelling assumptions and data transformation.

First, instead of imposing the sign restrictions (5) on impact, we assume a wider time period during

respectively.



Note: The figure reports the time evolution of real GDP growth rates over the last 30 years in Russia and marks the episodes of economic crises. *Sign*, *Jorda LP* and *Recurs* are the methods we apply to obtain the estimates of the effects of sanctions: sign restrictions (5), Jorda's local projection (11), and recursive identification (12).

Figure 9: Sanctions and the history of business cycles from the collapse of the USSR until the war in Ukraine, 1990–2022

which the restrictions must hold. We consider 1, 2, and 3 months when estimating the VAR models using the approach of Antolin-Diaz and Rubio-Ramirez (2018). In all cases, we obtain virtually the same time series of the estimated ICS and country spread shocks and the patterns of impulse responses. The quantitative differences with respect to the baseline results are negligible (available upon request).

Second, the empirical macroeconomic literature that relies on frequentist (i.e., non-Bayesian) estimation methods typically exploits detrended time series to ensure stationarity and comparability with theoretical literature (Akinci, 2013). Though we apply the Bayesian methods that are robust to non-stationarity in the data, we also perform a portion of VAR estimates with HP-detrended time series. The results obtained under the recursive identification scheme appear in Appendix H and those under the sign restriction in Appendix I. Qualitatively, we obtain the same results as in the baseline: real variables—industrial production, private consumption, investment—contract, trade balance improves, REER appreciates, and external debt and the domestic regulated interest rate rise. Only one exception is the response of investment in the recursive case, which turns positive but remains insignificant during the whole prediction horizon. Quantitatively, the recursive case delivers significant responses, whereas the sign restrictions produce mostly insignificant responses when the data is HP-detrended. Under the recursive case, interestingly, the estimated responses are 2 to 3 times lower in magnitude as compared with the baseline (Fig. H.I), and the size of the shock in 2014 is also lower by 1 pp than in the baseline estimates (Fig. I.II).

Third, we run a more parsimonious model—a 5-variable VAR from Uribe and Yue (2006)—and perform the recursive identification of the country spread shock. We report the results in Appendix J, which indicate that output falls by slightly more (–1.1 pp) than in our 11-variable VAR specification. Investment, by contrast, falls slightly less (–1.1 pp) than in the baseline. In this regard, the results are very much robust. However, with regard to the trade balance, we encounter a wedge in the results: in the 5-variable VAR, we find that the trade balance reacts negatively, not positively, to a positive country-spread shock. This contradicts the theory that we use (Uribe and Yue, 2006; Chang and Fernandez, 2013; Uribe and Schmitt-Grohe, 2017). Clearly, for an export-oriented economy like Russia, being strongly dependent on the export prices of fuel goods, omitting commodity terms-of-trade as well as REER may pose a serious challenge for recovering the full space of shocks. Nonetheless, even in this case the estimated time evolution of the identified shock to country spread still allows us to recognize a substantial spike in 2014 (the first wave of sanctions) and no significant shocks in 2017 (the second wave of sanctions).

Fourth, we use Jorda's LP approach to re-estimate the impulse responses obtained with our VAR model (1). The estimation results are reported in Fig. K.I.(a)–(h) (see Appendix K). Each subfigure plots the time evolution of the estimated impulse responses of a given variable $y_{i,t}$ to the shock $\hat{\varepsilon}_t^{(j)}$ that is computed either with the recursive or sign restriction schemes. We find that in most cases (except for industrial production), the results are quantitatively larger under the VAR than Jorda's LP methods but remain qualitatively the same. Therefore, we conclude that our baseline results are supported by Jorda's LP approach and are thus robust to misspecification.

5 Results: Cross-sectional effects of sanctions

Having established significant macroeconomic implications of the financial sanctions for the Russian economy in 2014–2015 and 2022, we now ask how the aggregated sanctions shock affects the cross-sections of households and firms. We are specifically interested in the heterogeneity of the effects of sanctions. We may expect that the current sanctions have larger negative effects on the economic agents that are less likely to support the political regime in Russia: richer households in large cities, as they may have international assets and are more competitive in international labor markets, and more productive firms, as they are more likely to be well-integrated into the world economy. Conversely, the sanctions are less likely to hit the regime's proponents: poorer households in rural areas and local firms with lower levels of productivity.

5.1 Sanctions and the cross-section of firms

We collect firm-level data from the SPARK-Interfax database over the period from 2012 to 2018.[34] We require firms to simultaneously have non-missing non-negative values on total assets, total revenue, value added, number of employees and wages, capital and intermediate inputs (materials), and bank and non-bank borrowed funds. We also require the firms to operate for at least three consecutive years. The final sample consists of 7,460 large and small firms resulting in 40,381 firm–year observations over the period of 2012–2018.[35] The firms operate in as many as 16 different sectors of the Russian economy (two-digit classification) ranging from natural resources extraction to IT.

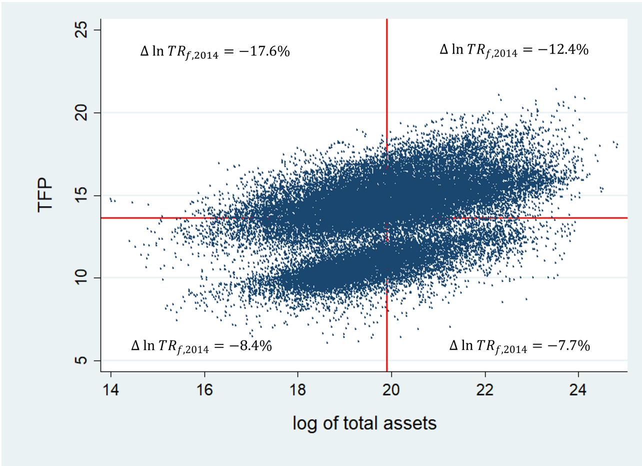
With this data at hand, we estimate the firms' TFPs by applying a popular methodology proposed by Wooldridge (2009) and Levinsohn and Petrin (2012). We assume a Cobb-Douglas production function with the real value added as the dependent variable and labor, capital, and materials as the explanatory variables. We also impose constant returns to scale. The summary statistics on the variables employed in the estimation and the estimates of firm productivity $TFP_{f,t}$ appear in Table M.I (see Appendix M). The estimates show that the magnitude of productivity averaged across all firms and years equals 13.6, being bounded between 6.1 and 21.4 and thus indicating a large variation in firms' $TFP_{f,t}$ (note that the mean magnitude of the real value added is 18.5). Plotting the time evolution of the firms' distribution by $TFP_{f,t}$ and size, as proxied with the log of the firms' total assets (in constant prices) $\ln TA_{f,t}$, we observe a slightly positive trend in the firms' productivities, despite the sanctions shock in 2014, and a visible negative trend in the firms' size, especially during 2014 (see Fig. M.I.(a) and (b) in Appendix M). In both cases, the observed variation across firms remains large and stable over time.

Given the estimated firms' $TFP_{f,t}$ and sizes $\ln TA_{f,t}$, we divide our sample into four parts: (*i*) large firms with high TFP ($N\,obs = 14,126$), (*ii*) large firms with low TFP ($N\,obs = 5,198$), (*iii*) small firms with high TFP ($N\,obs = 9,684$), and (*iv*) small firms with low TFP ($N\,obs = 11,373$). We use the mean value of $\ln TA_{f,t}$ to separate 'large' and 'small' firms. 'High' and 'low' productivities are defined accordingly using the mean value of $TFP_{f,t}$. Fig. 10 visualizes the resultant four cells of firm–year observations and reports the growth rate of firms' total revenue (in constant prices) during

[34]See https://spark-interfax.com/.

[35]Initial sample consists of roughly 300,000 firms. The substantial decline in the number of firms is caused by many missing values on employee and wage data in the firms' balance sheets and the requirement to work for at least three years in a row. We cannot remove the condition imposed on employees and wages because this data is essential for estimating TFP. If we remove the condition on at least three years of operations, then the number of firms rises to 32,790, i.e., by a factor of four, and the number of firm–year observations increases to 81,004. The results on the cross-sectional effects of sanctions do not change in this case (see below). We prefer to keep this condition to relax the 'survivorship bias' problem.

the first year of the financial sanctions in each of the four cells. In line with the anecdotal evidence discussed above, we indeed observe that holding the firms' size constant, more productive firms faced larger declines in real revenues than less productive firms. Regarding large firms, more productive firms experienced a 12.4% decline in real revenues in 2014 while less productive firms encountered only a 7.7% drop during the same year. Concerning small firms, more productive firms reported a 17.6% slump in real revenues in 2014 while less productive firms experienced only an 8.4% reduction over the same period. These figures also imply that larger firms were able to better support their revenues than smaller firms, and more so for more productive firms.[36]



Note: The figure reports the scatter-plot of 40,381 firm–year observations (7,460 firms over the 2012–2018 period) on the log of total assets (in constant prices, X axis) and firms' TFPs, as estimated using the Wooldridge (2009) and Levinsohn and Petrin (2012) approach (Y axis). The horizontal and vertical red lines mark the mean levels of the firms' TFPs and total assets, respectively. For each of the four resultant cells, the figure also reports the growth rate of real total revenue $\Delta \ln TR_{f,t}$ that the firms reported in their balance sheets by the end of 2014, i.e., the first year of the Crimea-related sanctions.

Figure 10: Firm size, TFP, and decline in firms' real income during the first year of sanctions

Clearly, the raw data shows that all firms in Russia experienced a deterioration of their real revenues in the first year of the Crimea-related sanctions. However, given the negative CTOT shock and restrictive monetary policy stance in 2014, we ask what part of the deterioration could be attributed to the sanctions. From the previous literature, we only know that the firms directly targeted by the sanctions encountered a more pronounced decline in employment and sales compared to non-targeted firms (Ahn and Ludema, 2020; Crozet *et al.*, 2021). We take a broader perspective and apply the Jorda (2005) LP approach to reveal the effects of sanctions in the four cells of firms outlined above.

For the purpose of estimation, we employ the same regression (11) as before but adapted to the

[36] An interesting side outcome from Fig. 10 is a clustering of the scatter-plot: there are two clusters of firms—more productive and less productive, given the same firm size. Probably, this could be related to the exporting statuses of the firms. Our data, however, does not allow us to elaborate more on this topic. We leave it for future research.

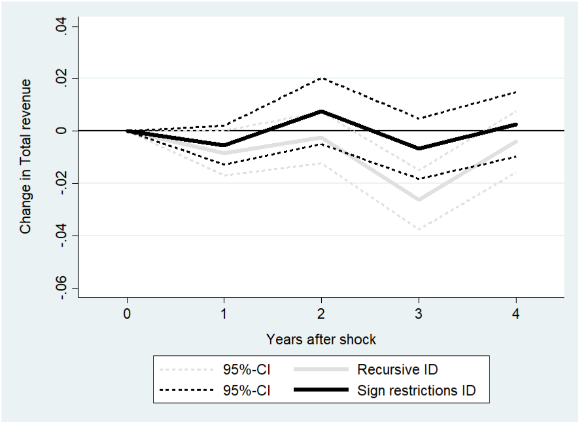
firm level. The dependent variable $y_{f,t+h}$ is the log of total revenue (in constant prices). The key explanatory variable remains the same—either the *ICS* or *country spread* shocks isolated from our VAR models. The monthly estimates of the shocks are aggregated to the annual level by means of summation within each year. We also adjust the control variables $\mathbf{X}_{f,t}$ so that they contain the current values of the total revenue, number of employees, investment, and, importantly, the interest expenses on the firms' loans from domestic banks and the CTOT variable. The two last variables are intended to capture the restrictive monetary policy of the Central Bank of Russia in 2014 and the tumble in world oil prices during the same period.

The estimation results appear in Fig. 11. The figure contains the same four cells of firms and in the same order as in Fig. 10 above. First, the estimates suggest that during the first year of the financial sanctions (*ICS*) shock, the real total revenue of the *large firms with high TFP* and *large firms with low TFP* both decline by 2.0–2.2 pp. These are equivalent to 16% and 29% of the total decline in real revenues of these firms, respectively.[37] This means the sanctions had economically significant effects on the performance of large firms in Russia beyond the effects of the oil price collapse and monetary contraction back in 2014. Interestingly, for the large firms with high TFPs, the effect of the sanctions turns to declining from the 2nd year, though still significant, whereas the same effect for the large firms with low TFPs continues to expand, reaching almost −4%. This implies that productivity matters for the absorption of the effect of the sanctions. Starting from the 3rd year, the effect on both types of firms attenuates to zero. We also note that the results remain the same, and even stronger quantitatively, if we consider *country spread* instead of ICS shock.

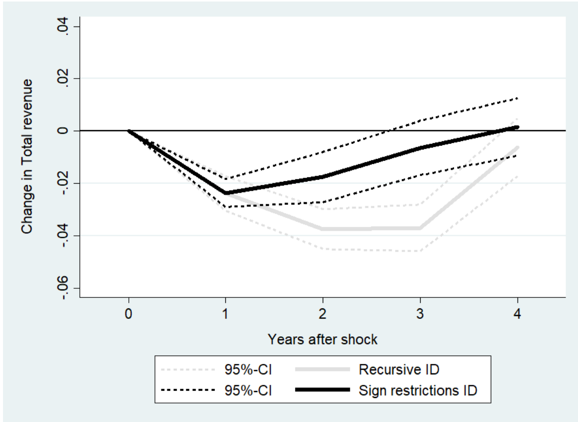
Second, the estimates indicate that, during the first year after the ICS shock, the real revenue of the *small firms with high TFP* decreases by 0.5 pp. This decrease, however, is insignificant. During the 2nd to 4th years after the ICS shock, the estimated response remains close to zero and insignificant. (Only in the case of the country spread shock does the response turn significant during the 3rd year, but we treat it with caution). Qualitatively, almost the same results pertain to the group of *small firms with low TFP*: during the first year after the ICS shock their real revenue declines by 1 pp (or 12% of the overall decline in 2014),[38] but this effect is much lower than for the large firms and it turns virtually zero from the 2nd year onwards. Strikingly, the small firms experienced much larger total declines in their real revenue than did the large firms (recall Fig. 10) but, as our estimates suggest, these declines are barely explained by the sanctions.

[37] The shares are computed as $-\frac{2.0}{12.4} = -0.16$ and $-\frac{2.2}{7.7} = -0.29$.

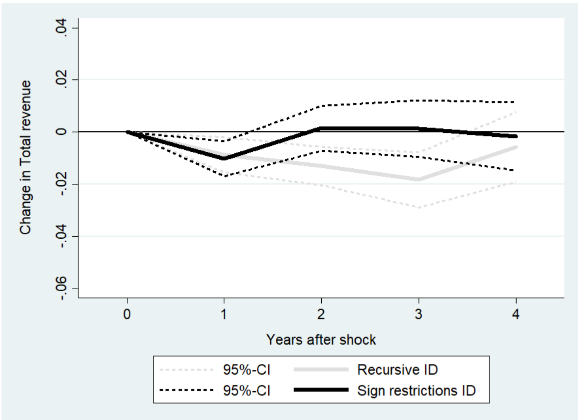
[38] The share is computed as $-\frac{1.0}{8.4} = -0.12$.



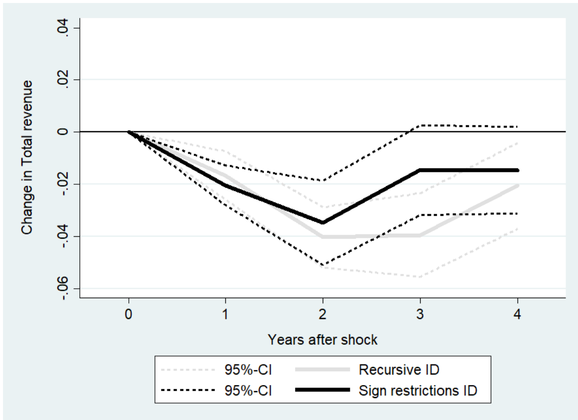
(a) Small firms with high TFP



(b) Large firms with high TFP



(c) Small firms with low TFP



(d) Large firms with low TFP

Note: The figure reports the impulse responses of the firms' total revenues (in constant prices) to the imposition of sanctions, as measured with the ICS (*Sign restrictions ID*) and country spread (*Recursive ID*) shocks. The responses are obtained using Jorda (2005) local projection approach. The sample contains 40,381 firm–year observations for 7,460 firms over the period of 2012–2018. The condition that the firms must operate for at least three consecutive years is imposed. The monthly estimates of the ICS and country spread shocks, as measures of the financial sanctions, are aggregated to the annual level by summation of the monthly magnitudes within a given year.

Figure 11: The effects of the sanctions shock on the real total revenue in a cross-section of firms

Finally, we argue that the results remain the same if we drop our condition that the firms in the sample must operate for at least three years. Indeed, as can be inferred from Fig. M.II, the sanctions shock negatively affects large firms, and less so if TFP is higher, and the shock has virtually no effect on smaller firms, regardless of their TFP (see Appendix M).

5.2 Sanctions and the cross-section of households

To test the hypothesis that richer households in larger cities were more adversely affected by the sanctions than poorer households in rural areas we need appropriate survey data. This data comes from the RLMS-HSE database, a rich survey of 5,000 Russian households that the National Research University "Higher School of Economics" has been conducting across Russia since 1994.[39] We extract the data on income and consumption for the period from 2006 to 2018 and winsorize the data below 1 and above 99%-tiles, which resulted in 21,813 individuals from different households and 74,356 observations in total.

The data allows us to trace the place of living and total income of each individual, among other things. The breakdown of the 74,356 observations that we have for the analysis is as follows: 31,266 pertain to a region's capital city (*Region's capital*), 20,836 belong to large towns other than the capital (*Large town*), 4,460 are in smaller towns (*Small town*), and 17,794 are attributed to rural areas within a region (*Rural*). Mean annual income across the four locations is, respectively, 483.6, 416.7, 422.4, and 371.9 thousand rubles (in constant 2014 prices).[40]

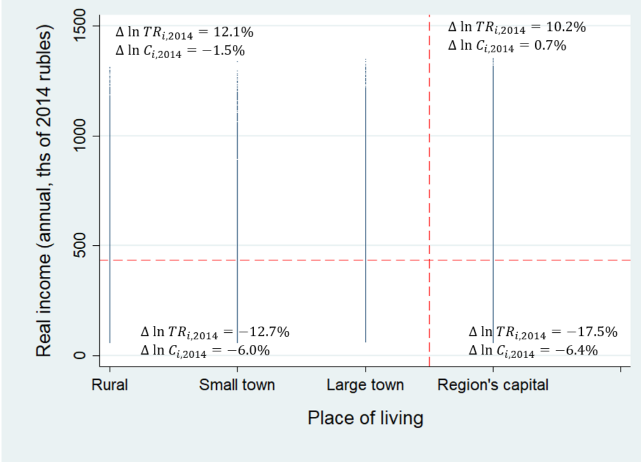
With these preliminaries at hand, we divide all observations into four cells: (*i*) richer individuals residing in regions' capital city ($N\,obs = 31,266$), (*ii*) poorer individuals residing in regions' capital city ($N\,obs = 20,836$), (*iii*) richer individuals residing in regions' other locations ($N\,obs = 4,460$), and (*iv*) poorer individuals residing in regions' other locations ($N\,obs = 17,794$). Within these four cells, the raw data shows that richer households experienced growing, not declining, income during the first year of sanctions in 2014, whereas poorer households suffered from a substantial decline in income (Fig. 12). Indeed, the annual growth rate of real income equaled 10.2% and 12.1% for richer households residing in regions' capital cities and other places, respectively. Conversely, the same figures for the poorer households were –17.5% and –12.7%, respectively. These numbers imply that the overall variation in real income rose dramatically during the first wave of the sanctions.[41] However, as was the case with firms in the previous section, the question arises as to whether we can fully attribute this increased variation in households' income to the effects of sanctions, given the other important adverse shocks hitting the households during the same period (oil price slump and monetary tightening).

Interestingly, the rise in real income of the richer households in 2014 was apparently not enough to sustain their consumption—the annual growth rates of real total consumption were either positive but low or even negative. For the poorer households, the growth rates of real total consumption were

[39] The data is representative and has been already used in many different areas of economics research, see, e.g., Yakovlev (2018).

[40] These numbers are equivalent to 11.6, 10.0, 10.2, and 8.9 thousand US dollars, assuming the exchange rate of 41.57 rubles per US dollar, as an average over 2006–2018.

[41] Though it is out of the scope of this paper and our data does not allow us to explore this issue, we can cautiously assume that richer households possess substantially higher savings denominated in foreign currencies than poorer households back in 2014. The ruble lost 90% of its value against the US dollar during that year.



Note: The figure reports the scatter-plot of 74,356 individual–year observations (21,813 individuals over 2006–2018) on the place of living (X axis) and annual real income (Y axis). The horizontal dashed red line marks the mean levels of the individuals' income. The vertical dashed red line separates observations on the individuals residing in a region's capital city from the others living in either rural areas, small or large towns different from the capital. For each of the four resultant cells, the figure also reports the growth rate of real income and total consumption by the end of 2014, i.e., the first year of the Crimea-related sanctions.

Figure 12: Individual income, consumption, and the place of living in a cross-section of households

even much more negative, implying a substantial decline in their standards of living during the first year of sanctions (Fig. 12).[42] It is also important to understand how the financial sanctions impacted total consumption and its components, consumption of durables and non-durables. We report the descriptive statistics on these variables in Table N.I (see Appendix N).

To answer the question as to how the financial sanctions affect different parts of the population, we again explot the *ICS* and *country spread* shocks and apply the Jorda (2005) LP approach, as we did for firms in the previous section. The estimation results appear in Fig. 13. The figure contains the same four cells of households and in the same order as in Fig. 12 above.

Richer households. The estimates suggest that the real income of richer households does not respond to the sanctions (*ICS*) shock during the first year after the shock occurs. However, during the second year after the shock, the real income declines by 1.5 pp if the households live in regions' capital cities, and by 2.0 pp if they live everywhere else (all estimates are significant at 5%). Interestingly, in regions' capital cities, the effect on real income persists in time, remaining negative and significant even during the 3rd and 4th years after the shock. For the other places of living, by contrast, the effect on real income weakens starting from the 3rd year. If we switch to the country spread shock, we get an even more pronounced contraction of income during already the 1st year after the shock. A

[42] Again, though our data does not contain this information, we can assume that all households had to substantially increase the interest payments on their loans, given that the key interest rate had been raised by the Central Bank of Russia from 5.5 to 17% during 2014. This dramatic rise in the price of money had negatively affected the households' consumption at that time, as the literature on consumption and monetary policy predicts (Cloyne *et al.*, 2020).

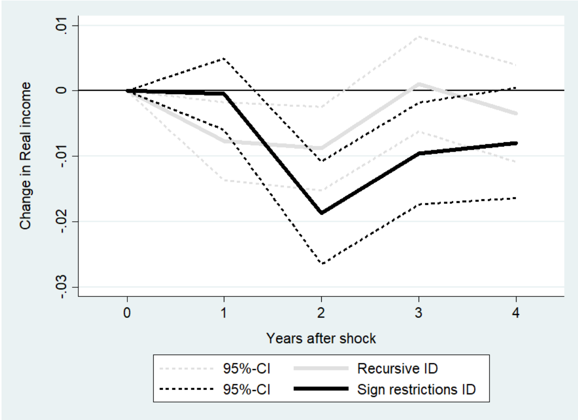
further disaggregation analysis reveals that the effects on total consumption of the richer households are driven by the reduction in the consumption of non-durables, while the consumption of durables was barely affected by the sanctions (Fig. N.I, see Appendix N).

Poorer households. Strikingly, the estimates further indicate that the real income of poorer households responds positively, not negatively, to the ICS shock during the first year. The positive reactions are 1.2 pp for the poorer households residing in regions' capital cities and 1.1 pp for the poorer households everywhere else (all estimates are significant at 5%). However, during the second year after the ICS shock, the reactions flip the sign negative, reaching –1.5 and –2.1 pp, respectively (all estimates are significant at 5%). The 3rd and 4th years' reactions vanish and are insignificant. As is the case with richer households, our further disaggregation analysis shows that the positive effect of sanctions during the first year is triggered by rising consumption of non-durables (Fig. N.I, see Appendix N).

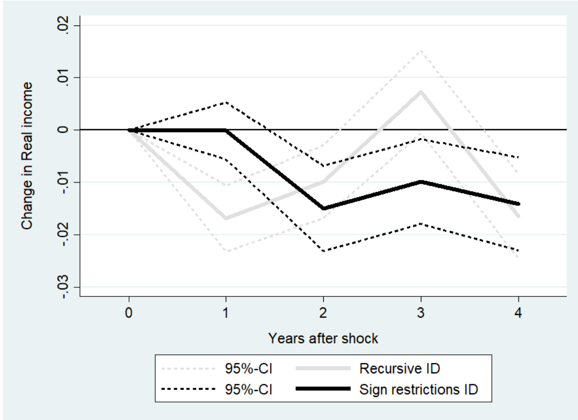
By pooling the results for richer and poorer households together, we argue that the financial sanctions could have the unintended effect of reducing income inequality. This is because the sanctions could have (partly) closed the doors for the international businesses of richer households while forcing the Russian government to support poorer households through the redistribution of income and taxes. The government support channel is established by the micro evidence from Mamonov *et al.* (2021) and Nigmatulina (2022).

Indeed, recall from our description of the raw data above that richer households enjoyed growing real income in 2014, whereas poorer households suffered from a slump in their income. As Ananyev and Guriev (2018) show, a decline in income causes the destruction of trust in the government in Russia. Moreover, as the findings of Simonov and Rao (2022) suggest, an average consumer of (state-owned) media news in Russia—at least back in the 2010s—has a distaste for pro-governmental ideology. This, when coupled with the declining income of poorer households, may have produced a large negative unintended effect on the Russian government, which is clearly not what the Kremlin's policy aims to achieve.

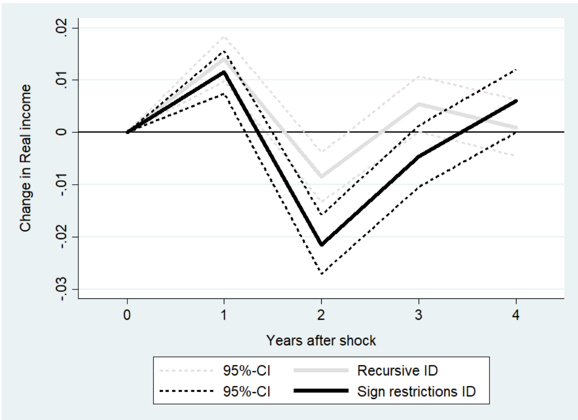
Our findings contrast with those of Neuenkirch and Neumeier (2016), who reveal that US sanctions typically led to a rising poverty gap in the sanctioned countries in the past, i.e., prior to the Crimea-related restrictions. The authors did not account for the potential support for the poorer population by the sanctioned government. The unintended effect of reducing income inequality that we find is, however, unlikely to persist over time, since our estimates show that the positive effect on the poorer households lasted for only one year.



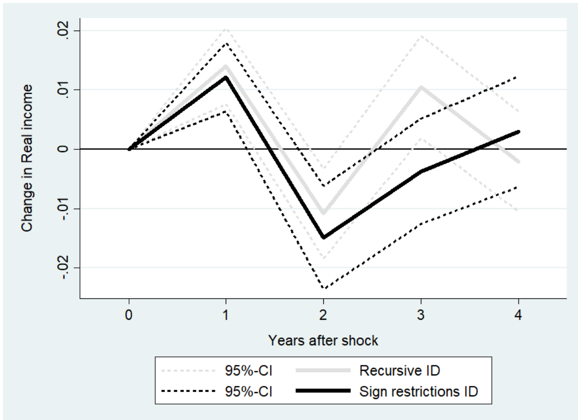
(a) High income, region's other places of living



(b) High income, region's capital city



(c) Low income, region's other places of living



(d) Low income, region's capital city

Note: The figure reports the impulse responses of the individuals' income (in constant prices) to the imposition of sanctions, as measured with the ICS (*Sign restrictions ID*) and country spread (*Recursive ID*) shocks. The responses are obtained using Jorda (2005) LP approach. The sample contains 74,356 individual–year observations for 21,813 individuals over the period of 2006–2018. The monthly estimates of the ICS and country spread shocks, as measures of the financial sanctions, are aggregated to the annual level by summation of the monthly magnitudes within a given year.

Figure 13: The effects of the sanction shock on the real income in a cross-section of households

6 Conclusion

Our analysis shows that the effects of financial sanctions on the Russian economy in the 2010s were at best modest. In 2014-2015 (*the first wave of sanctions*), the economy would have fallen into recession—even without sanctions—due to the oil prices shock and endogenous monetary policy response. In 2017–2018 (*the second wave of sanctions*), the macro effects of sanctions were near zero.

However, in the 2020s, with Russia's invasion of the Eastern and Southern territories of Ukraine, the situation is dramatically different (*the third wave of sanctions*). The war and the sanctions, even absent of a potential oil and gas embargo, are likely to produce one of the deepest economic crises in Russia over the last three decades, most comparable to the transformation crisis (1992) that followed the Soviet Union's collapse and possessing some features of the sovereign default crisis (1998). The Russian economy will nonetheless continue to rely on the existing export model, which is difficult to change. The population will struggle with the 'new poor' who will be appealing to the mechanisms of household adaptation to deep crises widely employed in the 1990s (switching from the informal sector of the economy and turning to home production of food due to high inflation). As a negative unintended spillover effect, this will not only impact the Russian population but also households in many developing countries across the globe (Artuc *et al.*, 2022).

The key question, which is difficult to answer and quantify, is whether the international coordination of sanctions against Russia will be strong enough to combat Russia's attempts to restore broken supply chains through the use of 'gray' export-import arrangements with China and other Eastern countries that have not formally joined the Western sanctions.

References

Ahn, D., and Ludema, R. (2020). The Sword and the Shield: The Economics of Targeted Sanctions, *European Economic Review*, 130(C), 103587.

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

Ananyev, M., and Guriev, S. (2018). Effect of Income on Trust: Evidence from the 2009 Economic Crisis in Russia, *Economic Journal*, 126(619), 1082–1118.

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

Artuc, E., Falcone, G., Porto, G., and Rijkers, B. (2022). War-Induced Food Price Inflation Imperils the Poor, VoxEU.org, 1 April.

Banbura, M., Giannone, D. and Reichlin, L. (2010). Large Bayesian Vector Autoregressions. *Journal of Applied Econometrics*, 25, 71–92.

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

Berner, R., Cecchetti, S., and Schoenholtz, K. (2022). Russian Sanctions: Some Questions and Answers, VoxEU.org, 21 March.

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.

Ben Zeev, N., (2019). Global Credit Supply Shocks and Exchange Rate Regimes, *Journal of International Economics*, 116, 1—32.

Besedes, T., Goldbach, S., and Nitsch, V. (2017). You're banned! The effect of sanctions on German cross-border financial flows. *Economic Policy*, 32(90), 263–318.

Born, B., Muller, G., Pfeifer, J., and Wellmann, S. (2020). Different No More: Country Spreads in Advanced and Emerging Economies. CEPR Discussion Paper 14392.

Brunnermeier, M., Palia, D., Sastry, K.A., and Sims, C.A. (2021). Feedbacks: Financial Markets and Economic Activity, *American Economic Review*, 111(6), 1845–1879.

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

Cesa-Bianchi, A., Ferrero, A., and Rebucci, A. (2018). International Credit Supply Shocks, *Journal of International Economics*, 112, 219–237.

Cespedes, L. S., and Velasco, A. (2012). Macroeconomic Performance During Commodity Price Booms and Busts. *IMF Economic Review*, 60, 570–599.

Chang, R., and Fernandez, A. (2013). On the Sources of Aggregate Fluctuations in Emerging Economies. *International Economic Review*, 54(4), 1265—1293.

Cloyne J., Ferreira C., and Surico P. (2020). Monetary Policy when Households have Debt: New Evidence on the Transmission Mechanism, *The Review of Economic Studies*, 87 (1): 102–129.

Crozet, M., Hinz, J., Stamman, A., and Wanner, J. (2021). Worth the pain? Firms' exporting behaviour to countries under sanctions, *European Economic Review*, 134, 103683

Degryse, H., De Jonghe, O., Jakovljevic, S., Mulier, K., Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications, *Journal of Financial Intermediation*, 40 (C): 100813.

di Giovanni, G., Kalemli-Ozcan, S., Ulu, M.F., and Baskaya, US (2022). International Spillovers and Local Credit Cycles, *Review of Economic Studies*, 89(2), 733–773.

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.

Efing, M., Goldbach, S., and Volker, N. (2019). "Freeze! Financial Sanctions and Bank Responses." CESifo Working Paper 7424.

Eickmeier, S., and Ng, T. (2015). How Do US Credit Supply Shocks Propagate Internationally? A GVAR Approach, *European Economic Review*, 74, 128-145.

Etkes, H., and Zimring, A. (2015). When Trade Stops: Lessons from the Gaza Blockade 2007-2010, *Journal of International Economics*, 95(1), 16–27.

Felbermayr, G., Kirilakha, A., Syropoulos, C., Yalcin, E., and Yotov, Y. (2020). The Global Sanctions Database, *European Economic Review*, 129(C), 103561.

Gambetti L., and Musso A. (2017). Loan Supply Shocks and Business Cycle, *Journal of Applied Econometrics*, 32, 764–782.

Garcia-Cicco, J., Pancrazi, R., and Uribe, M. (2010). Real Business Cycles in Emerging Countries? *American Economic Review*, 100(5), 2510—2531.

Geiger, M., Guntner, J. (2022). The Chronology of Brexit and UK Monetary Policy. Economics working papers 2022-06, Department of Economics, Johannes Kepler University Linz, Austria.

Gertler, M., and Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity, *American Economic Journal: Macroeconomics*, 7(1), 44–76.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., and Villegas-Sanchez, C. (2017). Capital Allocation and Productivity in South Europe, *The Quarterly Journal of Economics*, 132(4), 1915–1967.

Gutmann, J., Neuenkirch, M., and Neumeier, F. (2021). The Economic Effects of International Sanctions: An Event Study. CESifo Working Paper No. 9007

International Monetary Fund (2019). Russian Federation – Article IV Staff Report, Washington D.C.

Jorda, O. (2005). “Estimation and Inference of Impulse Responses by Local Projections,” *American Economic Review*, 95(1), 161-182.

Kanzig, D.R. (2021a). The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements, *American Economic Review*, 111(4), 1092–1125.

Kanzig, D.R. (2021b) The Unequal Economic Consequences of Carbon Pricing. SSRN Working Paper 3786030

Khwaja, A.I., and Mian, A. (2008). Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market, *American Economic Review*, 98, 1413–1442.

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.

Koop, G. (2013). Forecasting with Medium and Large Bayesian VARs. *Journal of Applied Econometrics*, 28, 177–203.

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.

Laudati, D., and Pesaran, M.H. (2021). Identifying the Effects of Sanctions on the Iranian Economy Using Newspaper Coverage. CESifo Working Papers 9217.

Levinsohn, J., and Petrin, A. (2012). Measuring Aggregate Productivity Growth Using Plant-Level Data, *The RAND Journal of Economics*, 43(4), 705–725.

Levy, P. (1999). Sanctions on South Africa: What Did They Do? *American Economic Review*, 89(2), 415–420.

Mamonov, M., Pestova, A., and Ongena, S. (2021). “Crime and Punishment?” How Russian Banks Anticipated and Dealt with Global Financial Sanctions, CEPR Discussion paper 16075.

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.

Mian, A., Sufi, A., and Verner, E. (2017). “Household Debt and Business Cycle Worldwide,” *Quarterly Journal of Economics*, 132, 1755–1817.

Monacelli, T., Sala, L., and Siena, D. (2023). Real Interest Rates and Productivity in Small Open Economies. *Journal of International Economics*, 142, 103746.

Nigmatulina, J. (2022). US Sanctions against Russia Helped the Very Companies They Intended to Target. But Russia Still Lost. Mimeo.

Neuenkirch, M., and Neumeier, F. (2016). The Impact of US Sanctions on Poverty, *Journal of Development Economics*, 121, 110–119.

Neumeyer, P.A., and Perri, F. (2005). Business Cycles in Emerging Economies: The Role of Interest Rates. *Journal of Monetary Economics*, 52(2), 345—380.

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

Schularick, M., and Taylor, A. (2012). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles and Financial Crises 1870—2008, *American Economic Review*, 102, 1029-–1061.

Simonov, A., and Rao, J. (2022). Demand for Online News under Government Control: Evidence from Russia, *Journal of Political Economy*, 130(2), 259–309.

Svejnar, Jan (2002). Transition Economies: Performance and Challenges, *Journal of Economic Perspectives*, 16(1), 3–28.

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

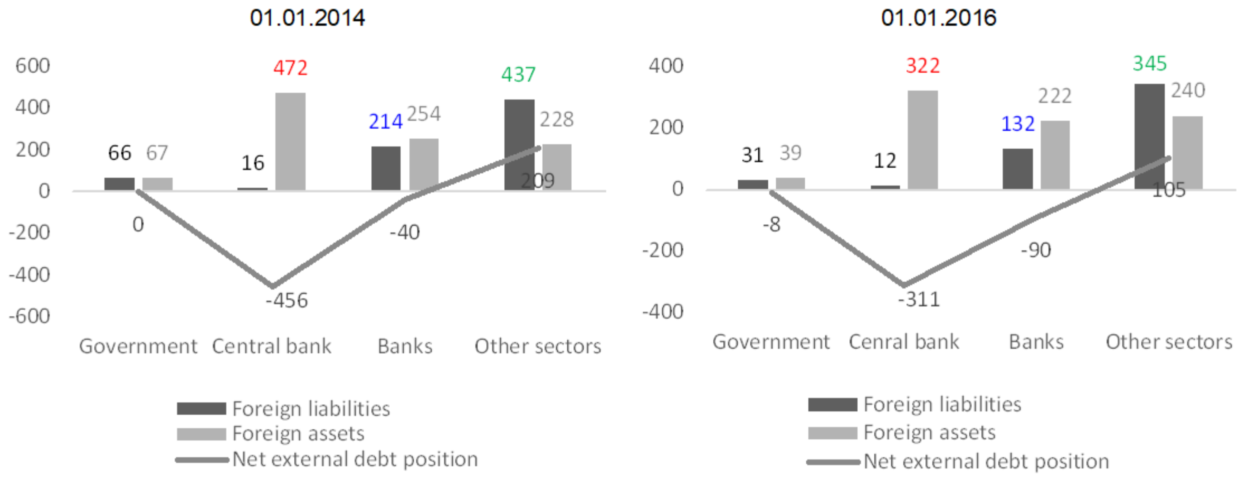
Uribe, M., and Yue, V.Z. (2006). Country Spreads and Emerging Countries: Who Drives Whom? *Journal of International Economics*, 69, 6–36.

Welt, C., Archick, K., Nelson, R., and Rennack, D. (2020). US Sanctions on Russia. Congressional Research Service Report No. R45415.

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

Yakovlev, E. (2018). Demand for Alcohol Consumption in Russia and its Implication for Mortality, *American Economic Journal: Applied Economics*, 10(1), 106–149.

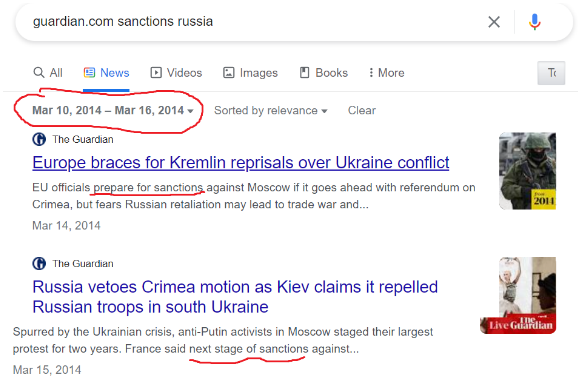
Appendix A Net foreign debt positions



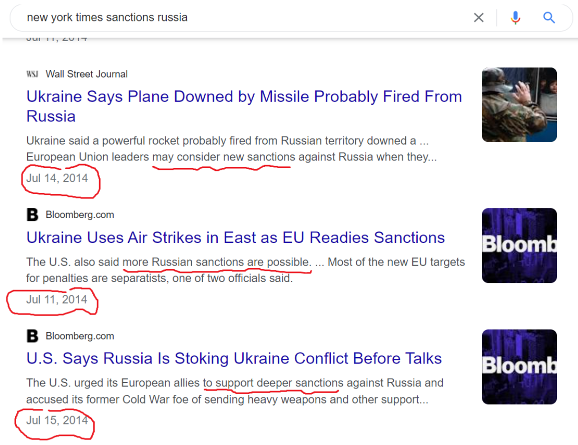
Source: The Central Bank of Russia

Figure A.I: Net foreign debt position of different sectors of the Russian economy before and after the 2014 sanctions

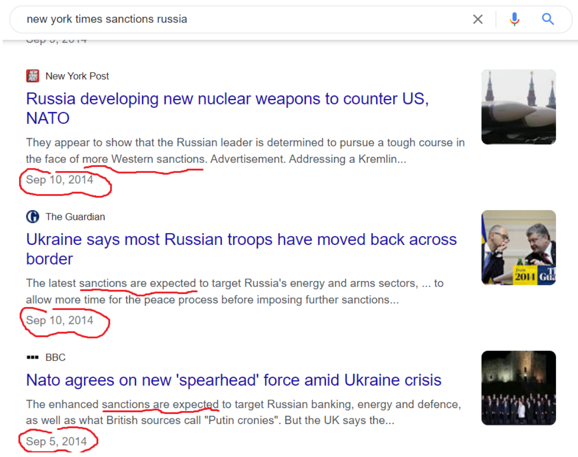
Appendix B News on upcoming sanctions



(a) Before 20 March 2014



(b) Before 16 July 2014

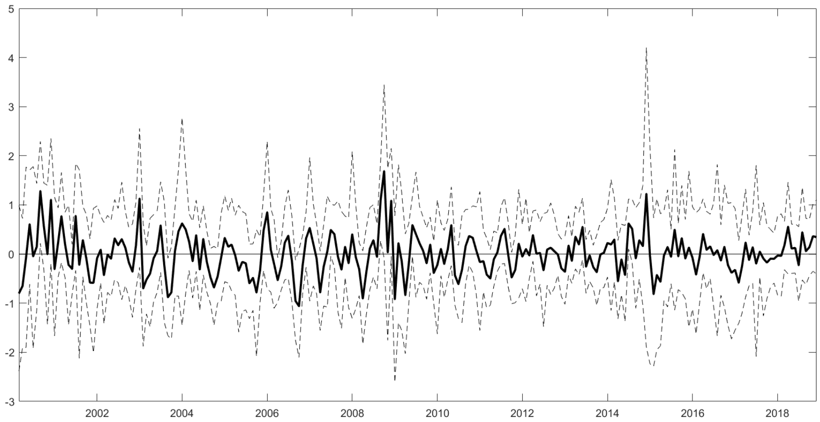


(c) Before 12 September 2014

Note: The figure reports news search results of the following form "[*Name of the media* Russia sanctions] in a five-day time interval before the sanction announcements by OFAC on 20 March 2014 (*a*, 16 July 2014 (*b*), and 12 September 2014 (*c*).

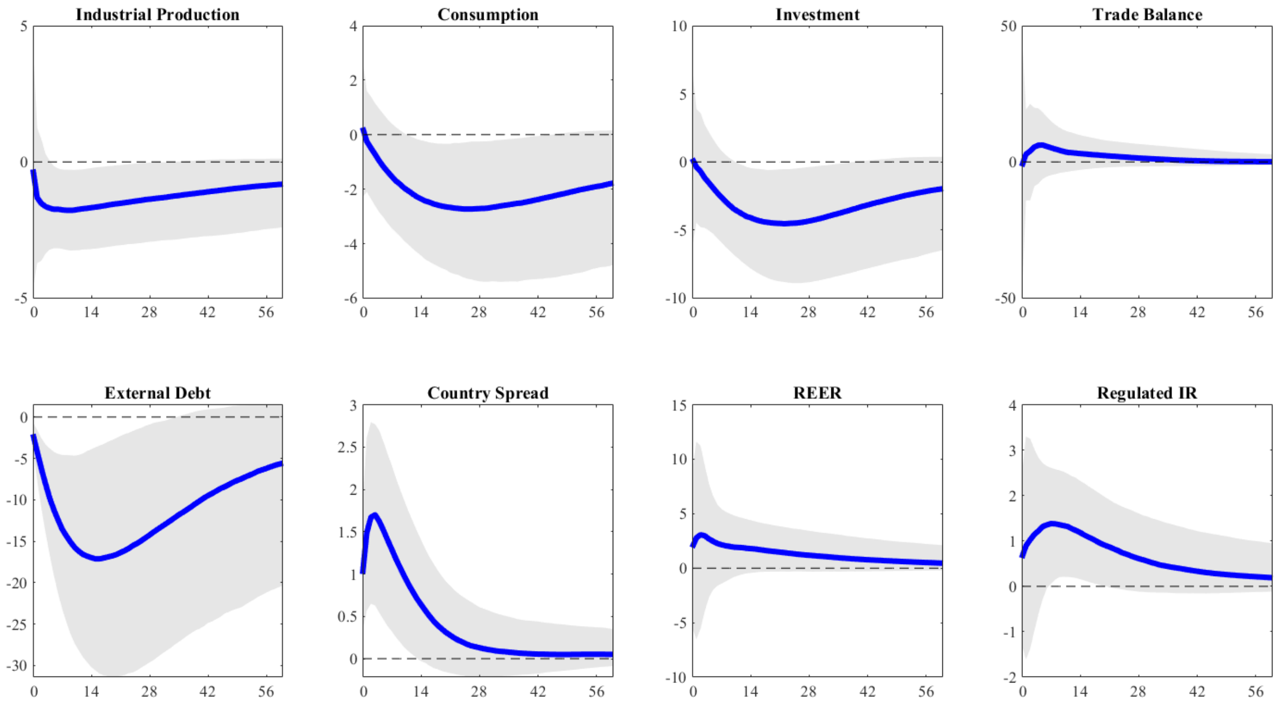
Figure B.I: Anticipation of sanctions (informational leakage) on the eve of sanction announcements

Appendix C International credit supply shock in a VAR model with monetary policy



Note: The figure reports the time evolution of the estimated negative shock to the international credit supply (ICS) shock isolated with the use of 11-variable VAR model. Positive values of the shock variable reflect unexpected declines of ICS, and vice versa.

Figure C.I: Time evolution of the international credit supply shock identified under the sign restrictions



Note: The figure reports the estimated IRFs of domestic macroeconomic variables to the sanction shock identified using the sign restrictions scheme as an international credit supply shock. The IRFs are re-scaled so that the shock is equivalent to a +1 pp rise of $Country.Spread_t$. The BVAR model contains 11 variables: external characteristics—commodity terms-of-trade ($CTOT_t$), the Baa corporate bond spread ($Baa.Spread_t$), the real interest rate in the US economy ($US.Real.Interest.Rate_t$); domestic indicators—industrial production (IP_t), private consumption ($Consum_t$), investments ($Invest_t$), trade balance (TB_t), corporate external debt ($ExtDebt_t$), Russia's country spread ($Country.Spread_t$), real effective exchange rate ($REER_t$), and the regulated interest rate (real, $Regulated.IR_t$). The last variable captures the monetary policy reaction to the sanctions shock. The $Country.Spread_t$ variable is ordered third 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 C.II: Impulse response functions to the international credit supply shock identified under the sign restriction scheme that accounts for endogenous monetary policy reactions

Appendix D Back-up for the sign restrictions: Recursive identification

We now discuss an alternative approach: instead of capturing a negative ICS shock using the sign restriction approach (5), we isolate a positive shock to country spread—an unexpected rise in the country risk premium—by applying a more conventional recursive identification. First, the sign restriction approach applied in the main text lacks identification of other important shocks (CTOT, monetary policy, etc.), which could also affect the economy during the sanctions shock (as it was in 2014). Second, there is ample literature arguing that country spread shocks account for a non-negligible part of business cycle fluctuations in EMEs (Uribe and Yue, 2006; Garcia-Cicco *et al.*, 2010; Chang and Fernandez, 2013). Moreover, there is an established procedure for the identification of these shocks, which we follow to ensure comparability with the literature and support our baseline results from the previous section.[43]

To isolate a country spread shock using the recursive identification, the literature typically assumes that the *country spread* variable reacts to the shocks to other variables immediately, whereas a *shock* to the country spread affects other (domestic) variables only with a time lag. Put differently, the country spread variable is usually ordered last (Uribe and Yue, 2006; Akinci, 2013; Born *et al.*, 2020; Monacelli *et al.*, 2023).

Recall, however, that we study a larger VAR model than in prior studies: we include REER in the set of domestic variables as one of the channels through which the sanctions transmit to the economy. Monacelli *et al.* (2023) mention that there is a potential problem if the country interest rate (or spread) is ordered *after* REER: this would imply that REER does *not* react to innovations in domestic interest rate, which is clearly dubious. Therefore, in our recursive identification, we place REER *last*, the domestic regulated interest rate *second last*, and the country spread *third last*.[44] The matrix B_0^{-1} is thus assumed to have the following structure, being lower triangular with unit elements on the main diagonal:

$$
\begin{pmatrix} \vdots \\ u_t^{IP} \\ u_t^{C} \\ u_t^{I} \\ u_t^{TB} \\ u_t^{D} \\ u_t^{S} \\ u_t^{RIR} \\ u_t^{REER} \end{pmatrix}
=
\begin{pmatrix}
\ddots & & & & & & & & \\
\dots & 1 & & & & & & & \\
\dots & . & 1 & & & & & & \\
\dots & . & . & 1 & & & & & \\
\dots & . & . & . & 1 & & & & \\
\dots & . & . & . & . & 1 & & & \\
\dots & . & . & . & . & . & 1 & & \\
\dots & . & . & . & . & . & . & 1 & \\
\dots & . & . & . & . & . & . & . & 1
\end{pmatrix}
\begin{pmatrix} \vdots \\ \varepsilon_t^{IP} \\ \varepsilon_t^{C} \\ \varepsilon_t^{I} \\ \varepsilon_t^{TB} \\ \varepsilon_t^{D} \\ \varepsilon_t^{S} \\ \varepsilon_t^{RIR} \\ \varepsilon_t^{REER} \end{pmatrix}
\qquad (12)
$$

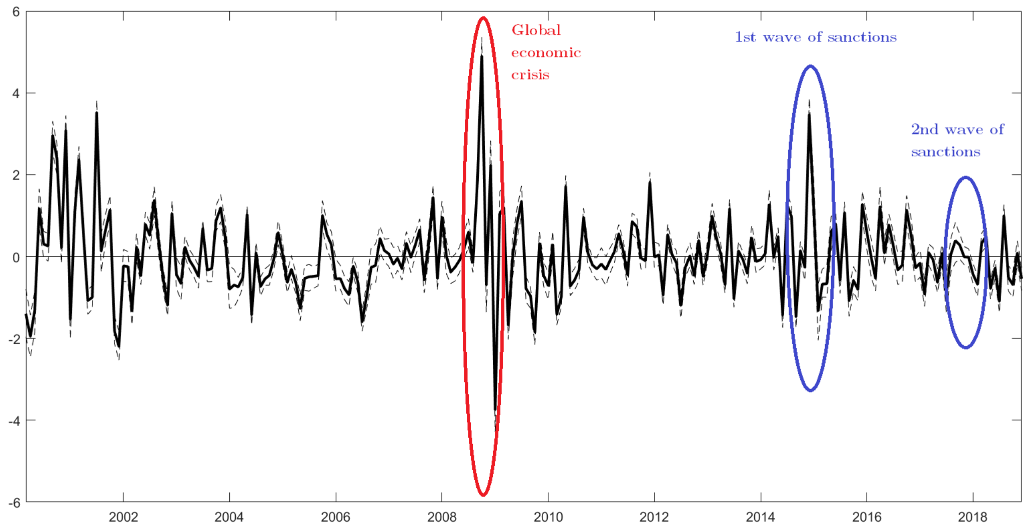
where "$\vdots$" and "…" correspond to the three exogenous variables, "." implies a non-empty element, and the empty cells, by the construction of the lower triangular, contain zeros.

[43]In addition, credible bands for the estimated impulse responses are likely to be more narrow under the recursive scheme (RS) as compared to the sign restrictions (SR). This is because RS uses just one structural model to identify shocks and impulse responses to them; conversely, SR effectively uses multiple models to produce generalized impulse responses.

[44]In the sensitivity analysis, we also consider the 5-variable VAR from Uribe and Yue (2006) which does not contain REER or a foreign block, and in which we order country interest rate last.

In contrast to the sign restrictions approach (5), we now have a shock to the country spread ε_t^S instead of a shock to ICS $\varepsilon_t^{Credit\,Supply}$. We also now obtain shocks to CTOT ε_t^{CTOT} and the domestic regulated interest rate ε_t^{RIR}. The latter allows us to be sure that we do not confuse the sanctions shock of 2014 with a slump in the world oil price and the dramatic rise in the domestic regulated interest rate that both occurred during the same time. However, the drawback of (12) is that it does not distinguish demand- and supply-driven forces in the dynamics of external debt.

We now turn to the estimation results we obtain under the recursive identification (12). As can be inferred from Fig. D.I, the time evolution of the estimated country spread shock ε_t^S is remarkable. First, we observe a sharp spike in the end of 2014, which can clearly be attributed to the first wave of the financial sanctions. The size of the shock equals +4 pp, which, according to our estimates, is the second strongest shock over the last two decades after the shock associated with the global economic crisis of 2007–2009 (+5 pp, at the beginning of 2009). Further, when we turn to the second wave of sanctions, we recognize a credible positive shock in the second half of 2017, but its size is at least three times lower than during the first wave. This again implies that the second wave could have much less harmful macroeconomic effects. We also note that ε_t^S shocks of a size comparable to that of the second wave of sanctions occur very often, according to our estimates. Overall, we obtain qualitatively the same result for the dynamics of the country spread shock as that under the sign restriction approach presented in the main text (see Fig. 5).



Note: The figure reports the time evolution of the sanctions shock estimated with the BVAR model containing 11 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. Substantial spikes in the time series of the estimated shock are identified for the first but not for the second wave of sanctions at the end of 2014 and 2017, respectively. One more is identified for the period of 2008–2009 global economic crisis and is reported for comparative reasons.

Figure D.I: Time evolution of a positive shock to the country spread identified under the recursive identification approach

The estimated impulse responses to the identified country spread shock appear in Fig. D.II.[45] As before, all impulses were re-scaled to a +1 pp shock to the country spread. First, we obtain a negative

[45]Estimated responses from a recursive identification approach that ignores monetary policy imply the same results and are reported in Appendix E.

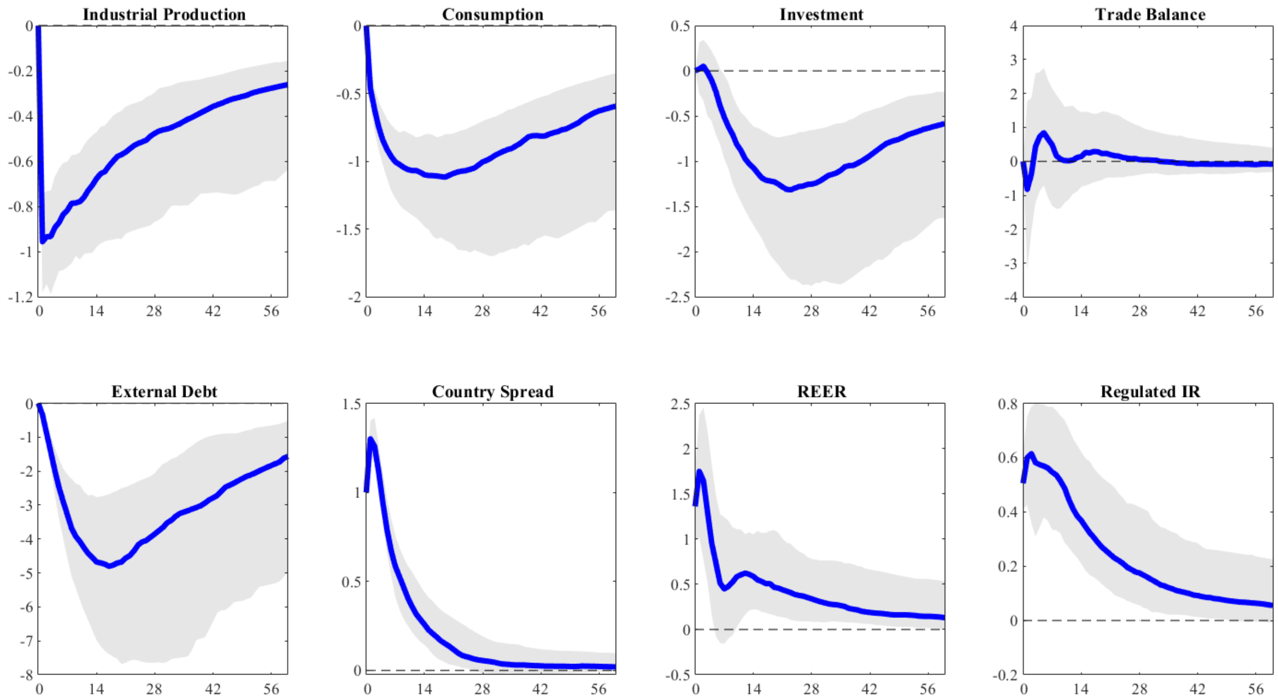
and significant reaction of the volume of external debt, with the peak response being equal –5 pp. On one hand, it implies that supply-driven forces dominate over demand for external debt. On the other hand, this peak reaction is at least three times lower in magnitude than the analogous estimate under the sign restriction scheme. This indirectly implies that demand also plays a large role in determining the inflows of external debt to Russia.

Second, the real economy also reacts negatively to the country spread shock: industrial production declines by almost 1 pp, private consumption by slightly more than 1 pp, and investment by 1.4 pp. Strikingly, these estimates are two to three times lower in magnitude as compared to their analogs obtained under the sign restrictions in the previous section. However, the credible bands indeed become much more narrow than before. What is also remarkable is that the estimated responses are now much less persistent than before. Overall, the results obtained with the recursive identification are qualitatively the same as those achieved with the sign restrictions, thus supporting our baseline findings.

Third, trade balance tends to respond positively to the positive country spread shock, however, the response is again insignificant, as it was before. REER also reacts positively and significantly, with a response peaking at +1.8 pp. This is again lower than in the baseline, by a factor of two. As before, the depreciation of the ruble in response to the positive country spread shock is justified by the necessity to repay external debts (i.e., the magnitude of the external debt's decline), which, in turn, becomes possible via (marginal) improvement of the trade balance.

Finally, the domestic regulated interest rate also reacts positively to the country's spread shock, thus accommodating the increased price of foreign borrowings. The estimated peak reaction equals +0.6 pp, which is less than one and is lower than in the baseline by a factor of three.

Therefore, the results obtained under the recursive identification fully support our baseline results, although the estimated impulse responses differ quantitatively. Recall, however, that the estimated size of the ICS shock in 2014, i.e., during the first wave of the financial sanctions, is lower by a factor of three as compared to the size of the country's spread shock during the same time. This means that the resulting estimates of the effects of sanctions are expected to be comparable across the two SVAR-based identification schemes (see Section 4.3 in the main text).



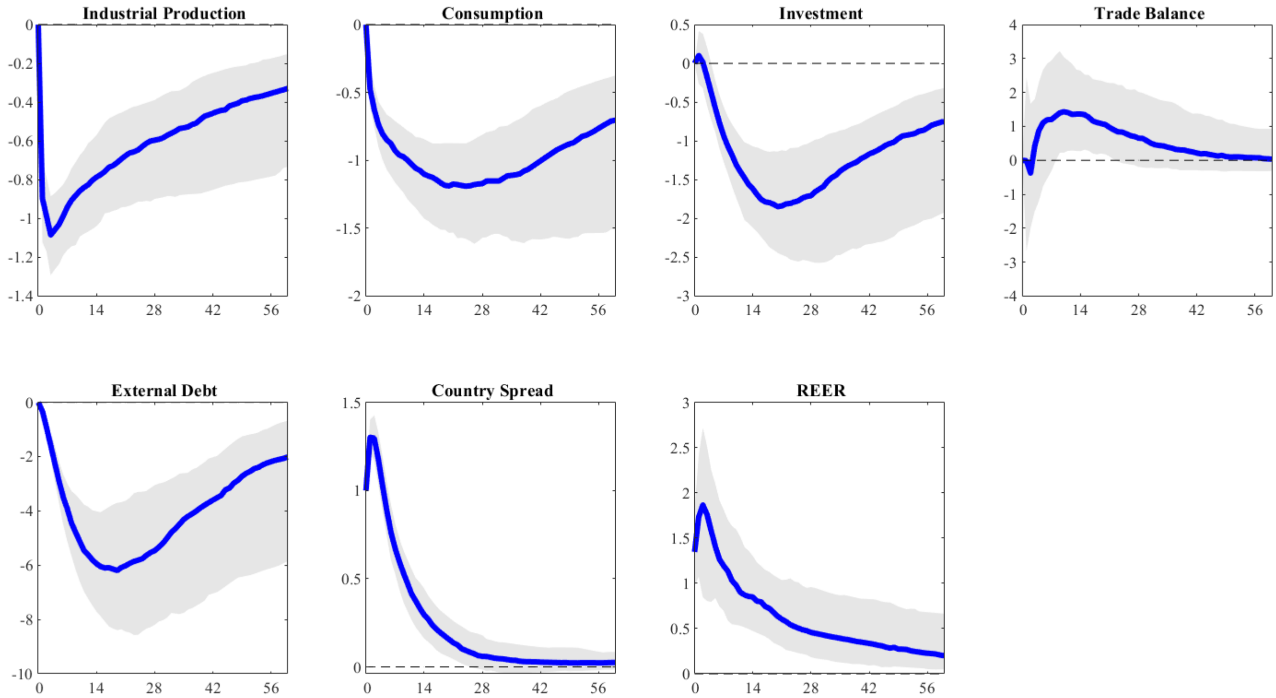
Note: The figure reports the estimated IRFs of domestic macroeconomic variables to the sanction shock identified using the recursive scheme as a shock to country spread. The IRFs are re-scaled so that the shock is equivalent to a +1 pp rise of $Country.Spread_t$. The BVAR model contains 11 variables: external characteristics—commodity terms-of-trade ($CTOT_t$), the Baa corporate bond spread ($Baa.Spread_t$), the real interest rate in the US economy ($US.Real.Interest.Rate_t$); domestic indicators—industrial production (IP_t), private consumption ($Consum_t$), investments ($Invest_t$), trade balance (TB_t), corporate external debt ($ExtDebt_t$), Russia's country spread ($Country.Spread_t$), the real effective exchange rate ($REER_t$), and the regulated interest rate (real, $Regulated.IR_t$). The last variable captures the monetary policy reaction to the sanctions shock. The $Country.Spread_t$ variable is ordered third 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 D.II: Impulse response functions to the country spread shock identified under the recursive approach that accounts for endogenous monetary policy reactions

Another issue we elaborate on in this section is how important for the economy are the shocks to the country spread in comparison with the shocks to CTOT and domestic monetary policy (MP), as identified through the recursive approach. Impulse responses of the domestic macroeconomic variables to the (positive) CTOT and (restrictive) MP shocks are reported in Appendix F and Appendix G, respectively. Recall that the country spread shock was set at +1 pp when we were computing the effects of this shock above. If we now re-scale both responses to the CTOT and MP shocks so that they are equivalent to +1 pp rises of the country spread, then we obtain the following result. Industrial production reacts negatively and significantly to both (negative) CTOT and (restrictive) MP shocks, with the peaks reaching –2 pp $(+0.4 \times (-5))$ and –2.4 pp (-0.47×5), respectively.[46] This result means that oil price drops, as captured by negative CTOT shocks, and rises in domestic interest rate, as captured by restrictive MP shocks, both force the Russian economy to decline deeper than the shocks to the country spread. This argument exhibits its importance in Section 4.3 of the main text where we compute the final effects of the financial sanctions.

[46] Here, -5 and 5 are the re-scaling factors that force the country spread to reach a +1 pp rise in response to CTOT and MP shocks.

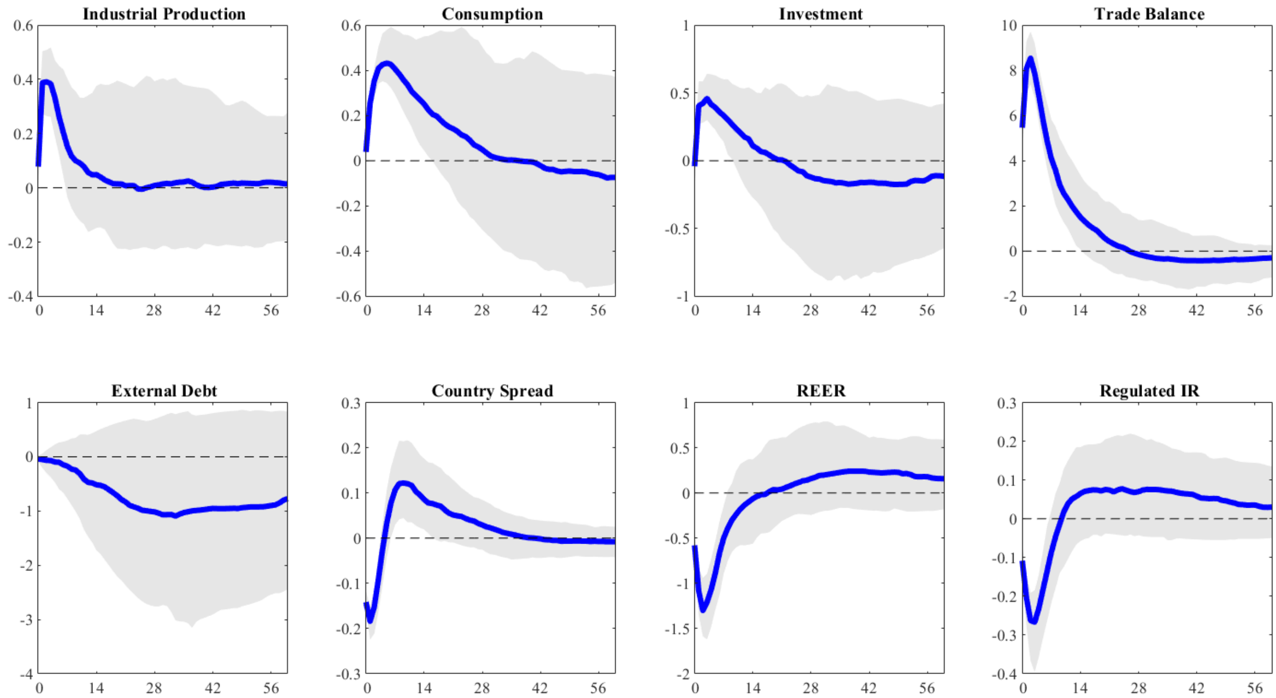
Appendix E Recursive identification of the country spread shock ignoring monetary policy



Note: The figure reports the estimated IRFs of domestic macroeconomic variables to the sanction shock identified using the recursive approach as a shock to country spread. The IRFs are re-scaled so that the shock is equivalent to a +1 pp rise in $Country.Spread_t$. The BVAR model contains 10 variables: external characteristics—commodity terms-of-trade ($CTOT_t$), the Baa corporate bond spread ($Baa.Spread_t$), the real interest rate in the US economy ($US.Real.Interest.Rate_t$); domestic indicators—industrial production (IP_t), private consumption ($Consum_t$), investments ($Invest_t$), trade balance (TB_t), corporate external debt ($ExtDebt_t$), Russia's country spread ($Country.Spread_t$), real effective exchange rate ($REER_t$). Monetary policy response to the sanctions shock is ignored in this version. The $Country.Spread_t$ variable is ordered third 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 E.I: Impulse responses to the country spread shock identified under the recursive approach

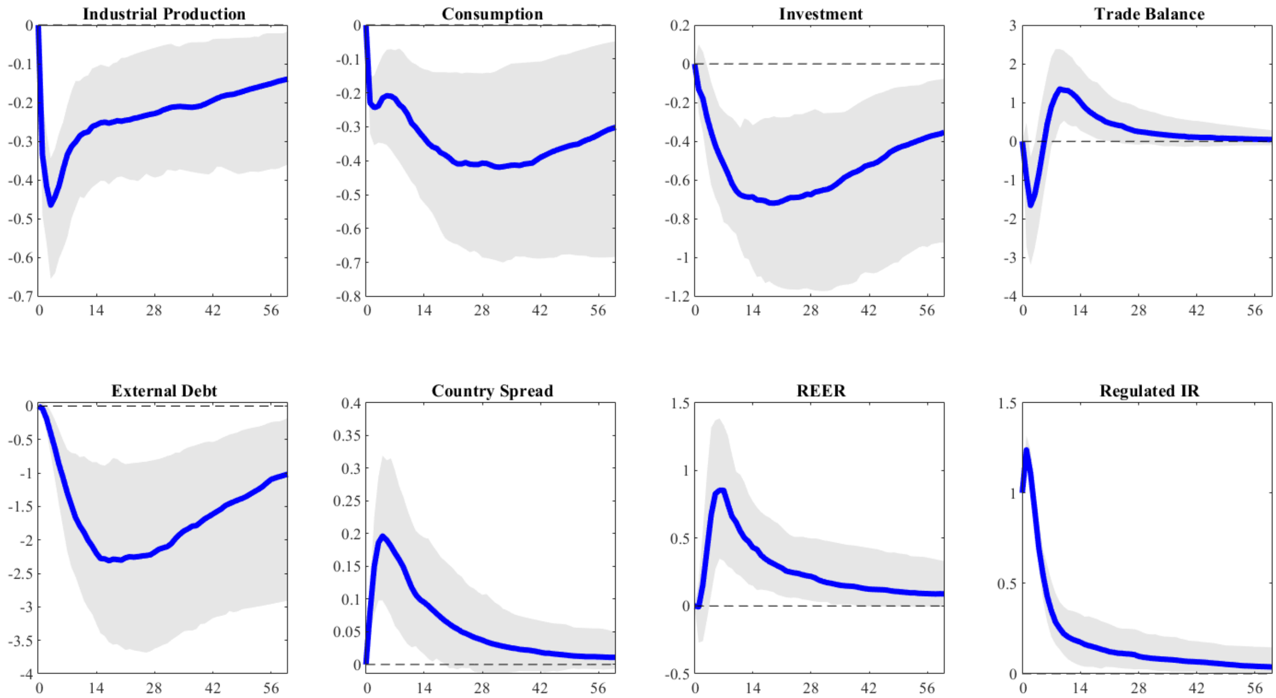
Appendix F The effects of a CTOT shock on domestic macroeconomic variables



Note: The figure reports estimated IRFs of domestic macroeconomic variables to a positive CTOT shock identified recursively. The BVAR model contains 11 variables. Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and 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 F.I: Impulse responses to a *positive* CTOT shock identified under the recursive approach

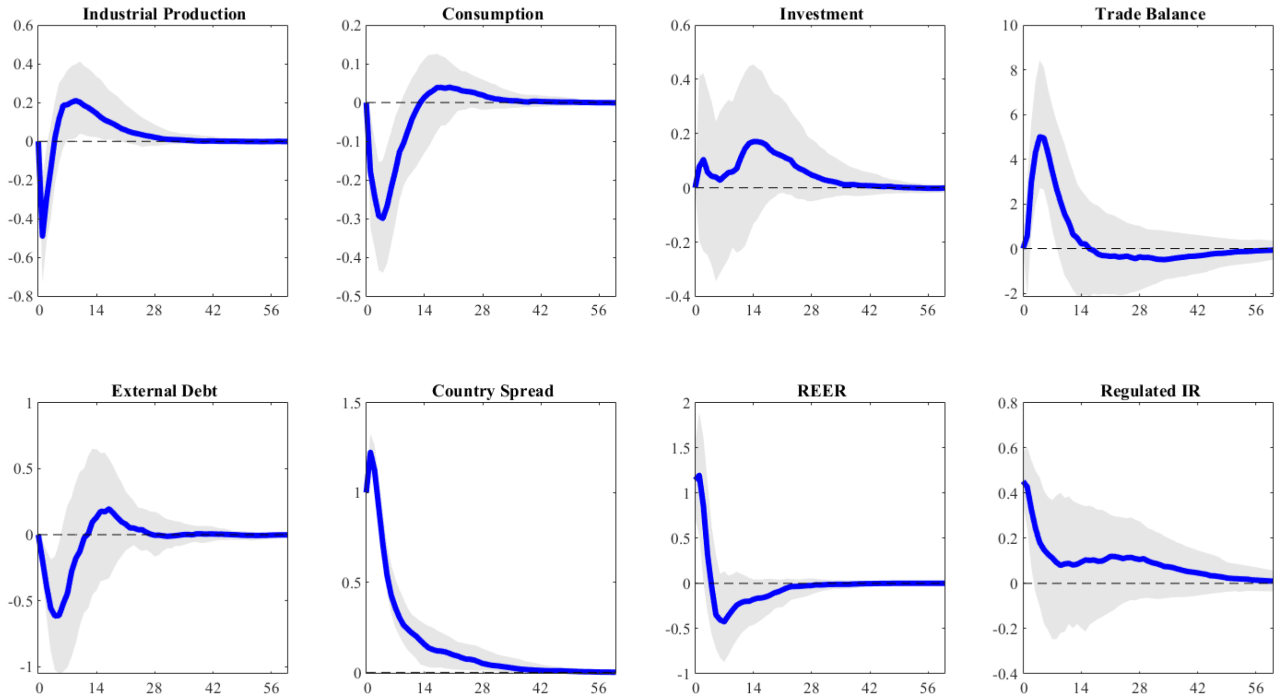
Appendix G The effects of a monetary policy shock on domestic macroeconomic variables



Note: The figure reports estimated IRFs of domestic macroeconomic variables to a restrictive monetary policy shock identified recursively. The shock is normalized to a +1 pp rise in the regulated interest rate on impact. The BVAR model contains 11 variables. Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and 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).

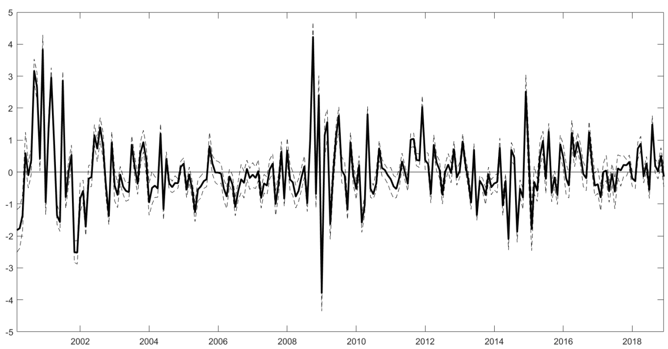
Figure G.I: Impulse responses to a *restrictive* monetary policy shock identified under the recursive approach

Appendix H Recursive identification with the HP-filtered time series



Note: The figure reports estimated impulse responses of domestic macroeconomic variables to a +1 pp shock in the country spread variable. The VAR model contains 11 variables, and the country spread variable is ordered third last, i.e., before the REER and domestic regulated interest rate variables. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and discard the first 5,000 draws. Conventional credible bands comprised of the 16^{th} and 84^{th} percentiles of the post-burned-in estimated responses are reported (grey shaded area).

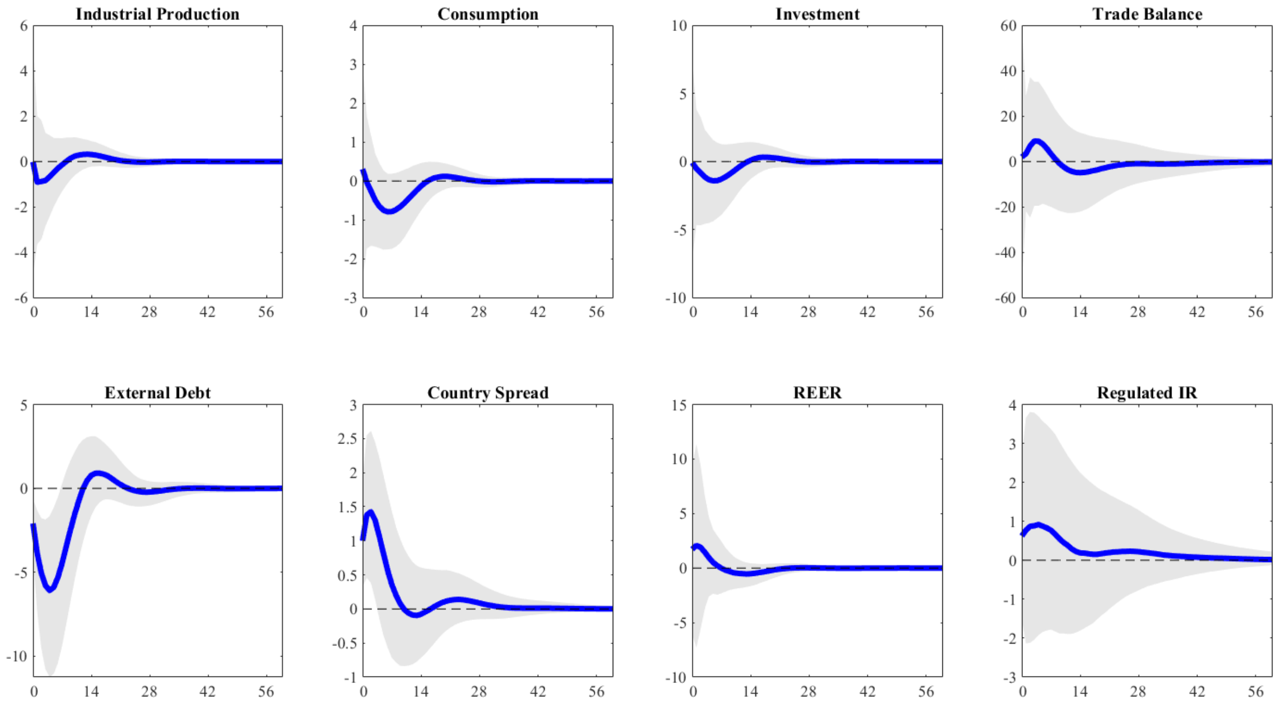
Figure H.I: Impulse responses to the country spread shock identified under the recursive scheme



Note: The figure reports the time evolution of the positive shock to the country spread estimated with the 11-variable VAR model. Positive values of the shock variable reflect unexpected rises of Russia's country spread, and vice versa.

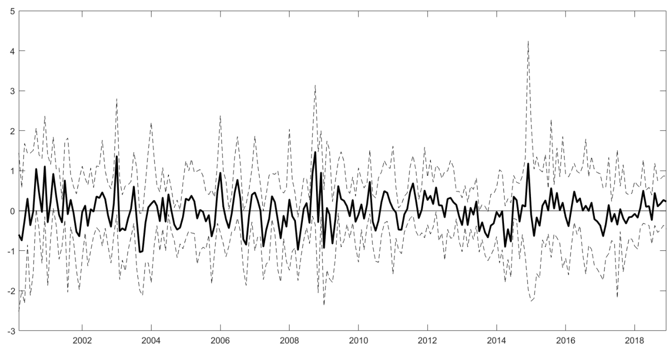
Figure H.II: Time evolution of the country spread shock identified under the recursive scheme

Appendix I Sign restrictions with the HP-filtered time series



Note: The figure reports estimated impulse responses of domestic macroeconomic variables to a negative international credit supply (ICS) shock. The shock is re-scaled so that it is equivalent to a +1 pp rise in the country spread variable. The VAR model contains 11 variables. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and discard the first 5,000 draws. Conventional credible bands comprised of the 16^{th} and 84^{th} percentiles of the post-burned-in estimated responses are reported (grey shaded area).

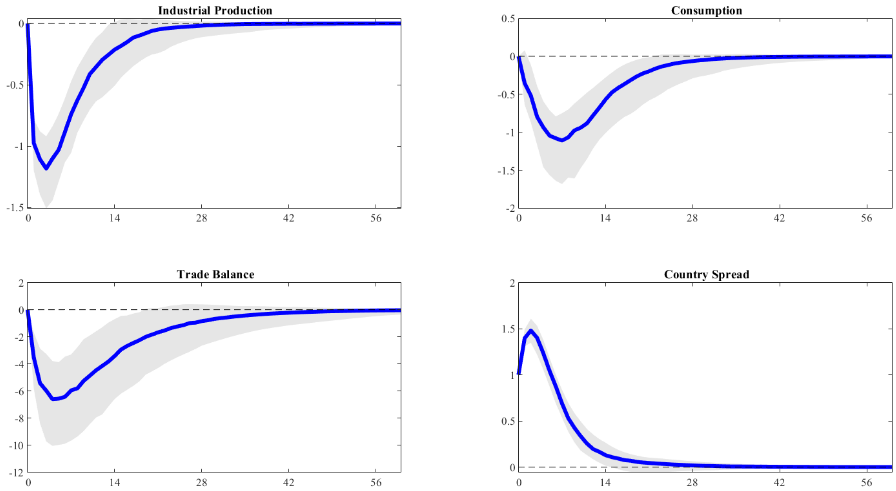
Figure I.I: Impulse responses to the international credit supply shock identified under the sign restrictions approach



Note: The figure reports the time evolution of the estimated negative shock to the international credit supply (ICS) shock isolated with the use of 11-variable VAR model. Positive values of the shock variable reflect unexpected declines in ICS, and vice versa.

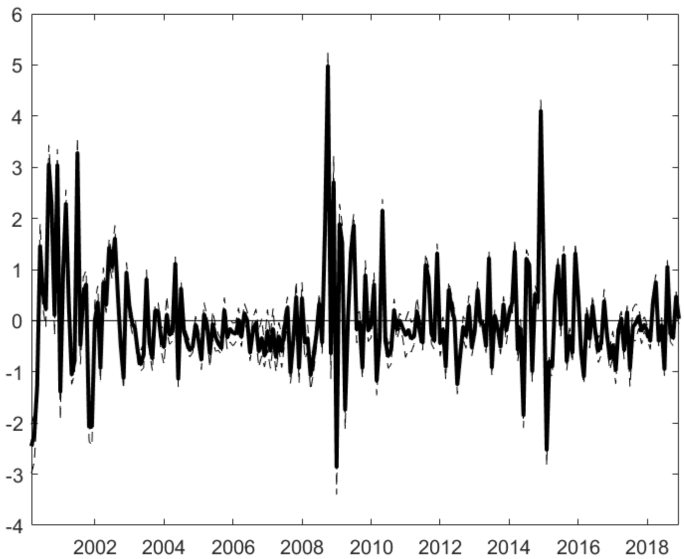
Figure I.II: Time evolution of the international credit supply shock identified under the sign restrictions approach

Appendix J Recursive identification in the 5-variable VAR model from Uribe and Yue (2006)



Note: The figure reports estimated impulse responses of domestic macroeconomic variables to a +1 pp shock in the country spread variable. The VAR model contains the five variables, as in Uribe and Yue (2006). The country spread variable is ordered last. The Bayesian estimates are obtained with the flat (uninformative) prior. We set 10,000 draws from the posterior distribution and 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 responses to the country spread shock identified under the recursive approach in a 5-variable VAR model



Note: The figure reports the time evolution of the positive shock to the country spread estimated with the 5-variable VAR model. Positive values of the shock variable reflect unexpected rises in Russia's country spread, and vice versa.

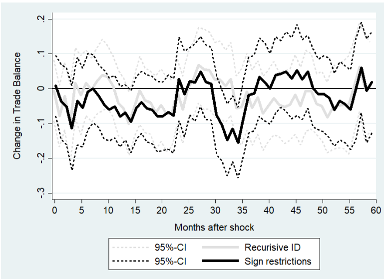
Figure J.II: Time evolution of the country spread shock identified under the recursive approach in a 5-variable VAR model

Appendix K Jorda's local projection

(a) Industrial production

(b) Consumption

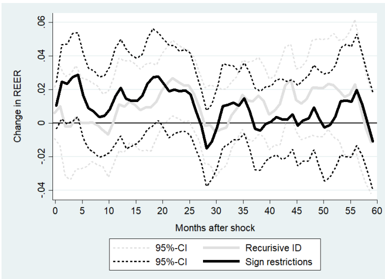
(c) Investment



(d) Trade Balance

(e) External Debt

(f) Spread



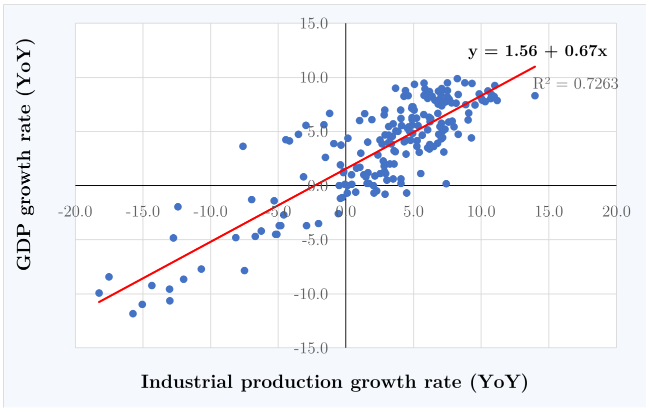
(g) REER

(h) Interest rate

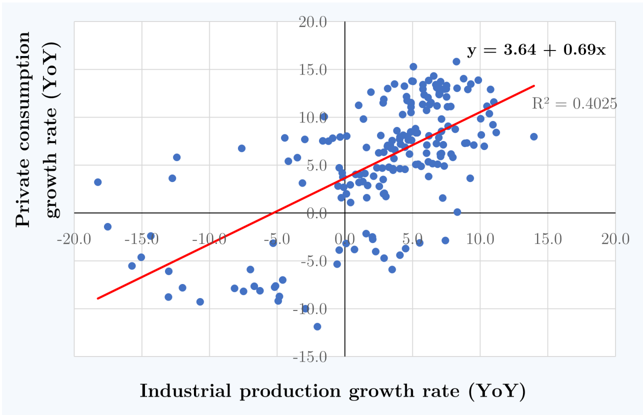
Note: The figure reports impulse responses to a positive country spread shock (*Recursive ID*) and a negative ICS shock (*Sign restrictions*). The responses are obtained under Jorda (2005) local approach, as implied by $\beta_{j,h}$ in the following equation: $y_{i,t+h} = \alpha_{i,j,h} + \beta_{j,h} \cdot \hat{\varepsilon}_t^{(j)} + \gamma'_{i,j,h}\mathbf{X}_t + \mu_{i,j,t+h}$, where $y_{i,t}$ is ith domestic macroeconomic variable considered above ($i = 1, 2...8$), t is month from January 2000 to December 2018 and $h = 1, 2...60$ is prediction step ahead of the shock $\hat{\varepsilon}_t^{(j)}$, where $j = 1$ stands for the recursive identification (*country spread shock*) and $j = 2$ the sign restrictions scheme (*ICS shock*). $\mathbf{X}_t$ contains control variables: all monthly lags of $\hat{\varepsilon}_t^{(j)}$ from $1st$ till $12th$, thus covering the whole previous year, and the current values and 12th month lags of each of the eleven variables in y_t.. The 95% confidence intervals are computed with bootstrap (500 draws, with replications).

Figure K.I: Impulse responses to the international credit supply shock and country spread shock estimated with Jorda's local projection

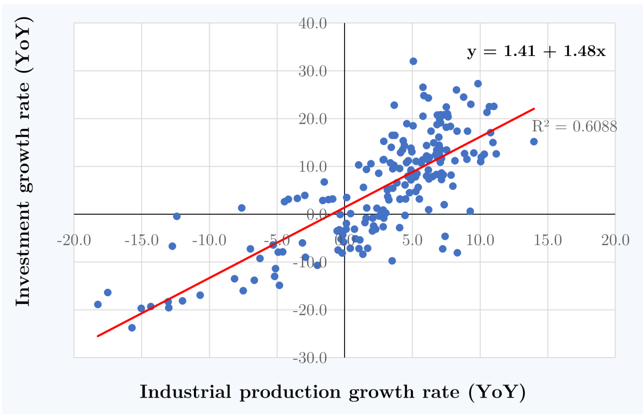
Appendix L Industrial production and GDP components



(a) GDP



(b) Private consumption



(c) Investment

Note: The figure reports empirical relationships between industrial production and various macroeconomic characteristics of the Russian economy. The data covers the period from January 2000 to December 2018.

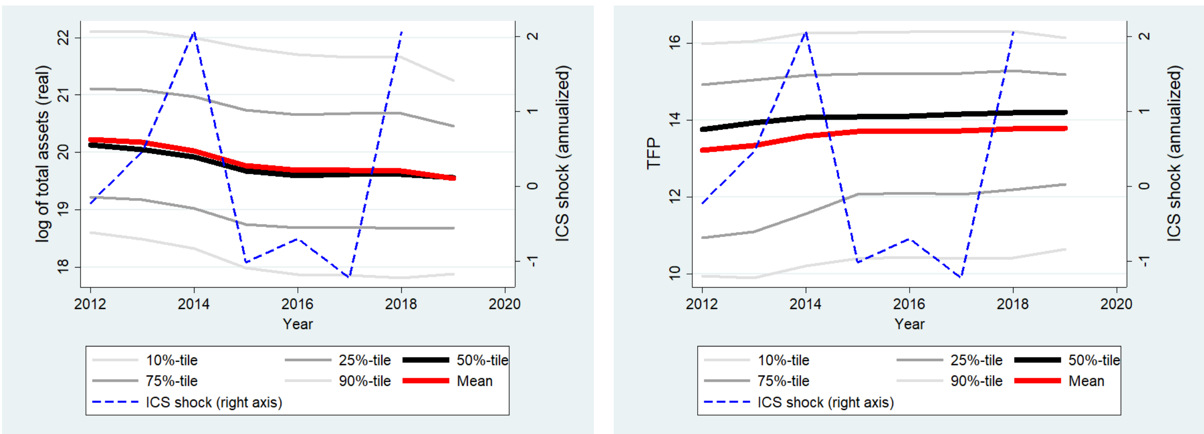
Figure L.I: Relationship between industrial production and GDP components

Appendix M Details on the cross-section of firms

Table M.I: Summary statistics for production function estimates

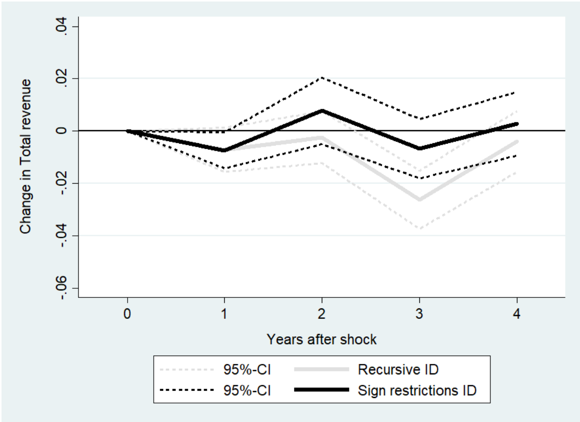
Note: The table reports the estimates of firms' total factor productivity, $TFP_{f,t}$, and the summary statistics for the variables employed in its estimation. We apply the methodology of Wooldridge (2009) and Levinsohn and Petrin (2012) to estimate a production function with the real value added $Y_{f,t}$ as a dependent variable and the number of employees $L_{f,t}$, capital (as proxied with fixed assets) $K_{f,t}$, and intermediate inputs (materials, as proxied with payments to suppliers) $M_{f,t}$. The estimation period is 2012–2019.

	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)
$TFP_{f,t}$	40,381	13.6	2.2	6.1	21.4
$\ln Y_{f,t}$	40,381	18.5	1.5	12.2	23.2
$\ln L_{f,t}$	40,381	5.1	1.6	0.0	8.8
$\ln K_{f,t}$	40,381	18.3	2.0	8.9	23.8
$\ln M_{f,t}$	40,381	19.3	1.8	11.0	24.4

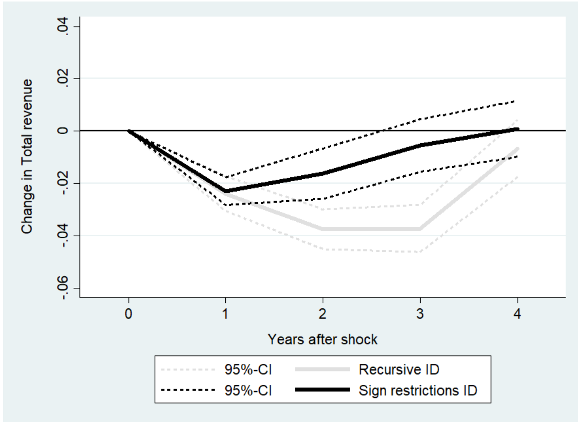


(a) Firm size $lnTA_{f,t}$ (b) Firm productivity $TFP_{f,t}$

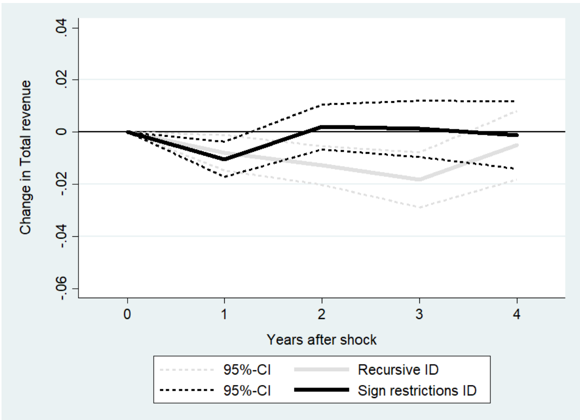
Figure M.I: Firm size and productivity



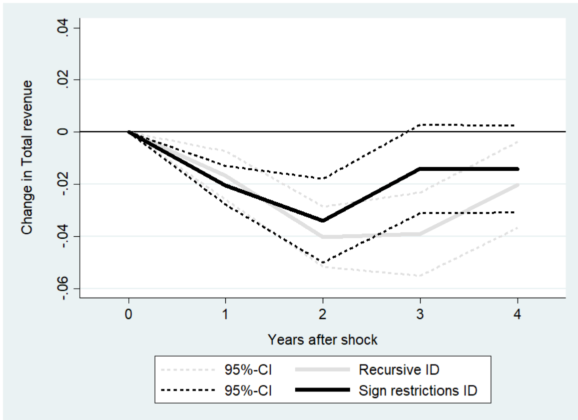
(a) Small firms with high TFP



(b) Large firms with high TFP



(c) Small firms with low TFP



(d) Large firms with low TFP

Note: The figure reports the impulse responses of the firms' total revenue (in constant prices) to the imposition of sanctions, as measured with the ICS (*Sign restrictions ID*) and country spread (*Recursive ID*) shocks. The responses are obtained using Jorda (2005) LP approach. The sample contains 81,004 firm–year observations for 32,790 firms over 2012–2018. The condition that the firms must operate for at least three consecutive years is not imposed. The monthly estimates of the ICS and country spread shocks, as measures of the financial sanctions, are aggregated to the annual level by summation of the monthly magnitudes within a given year.

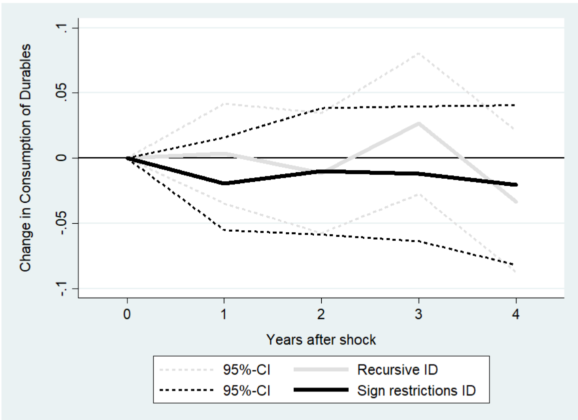
Figure M.II: The effects of the sanctions shock on the real total revenue in a cross-section of firms

Appendix N Details on the cross-section of households

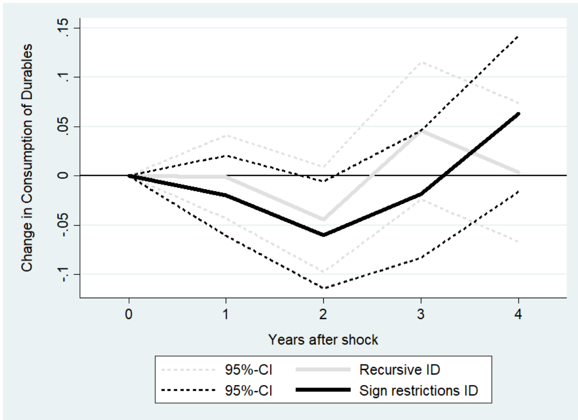
Table N.I: Summary statistics for the sample of households

Note: The table reports the summary statistics on individuals' total income $Y_{i,t}$, total consumption $C_{i,t}$, consumption of durables $C^D_{i,t}$, and consumption of non-durables $C^N_{i,t}$, all in constant 2014 prices. The sample contains 21,813 individuals over the period of 2006–2018.

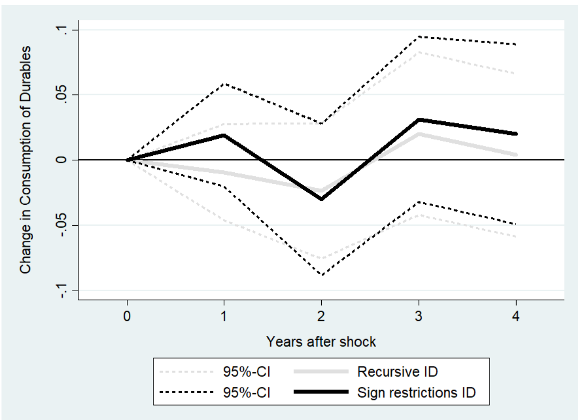
	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)
ln$Y_{h,t}$	74,356	5.9	0.6	4.1	7.2
ln$C_{h,t}$	74,356	5.5	0.6	3.6	7.0
ln$C^D_{h,t}$	74,356	3.1	1.7	–3.4	8.9
ln$C^N_{h,t}$	74,356	5.3	0.7	–1.0	10.2



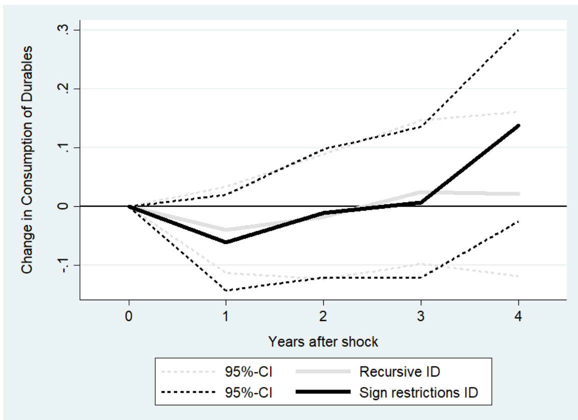
(a) High income, region's other places of living



(b) High income, region's capital city

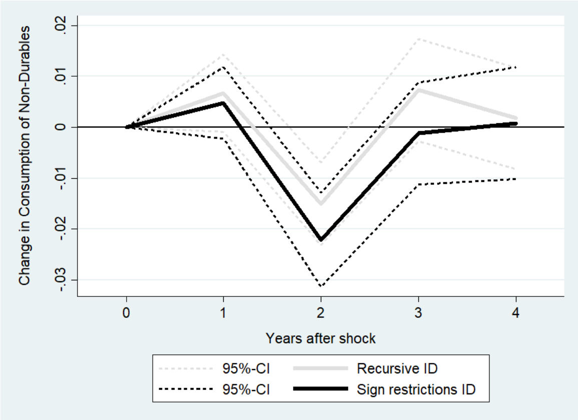


(c) Low income, region's other places of living

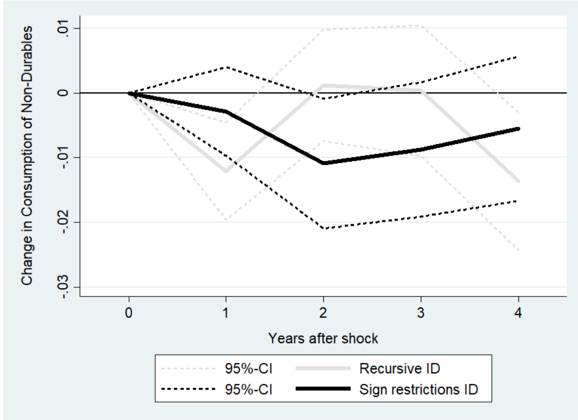


(d) Low income, region's capital city

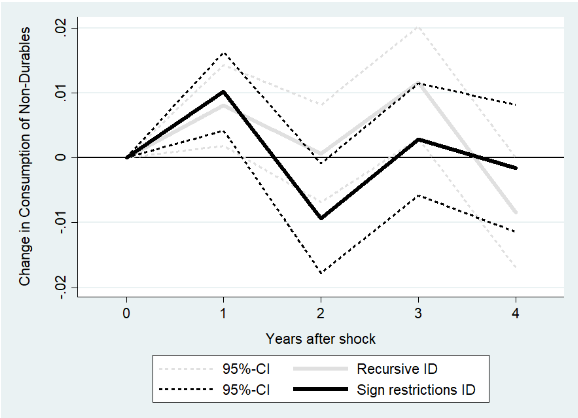
Figure N.I: The effects of the sanctions shock on consumption of durables in a cross-section of households (*beginning*)



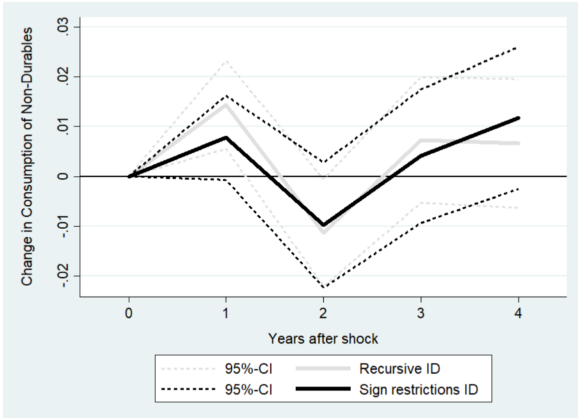
(e) High income, region's other places of living



(f) High income, region's capital city



(g) Low income, region's other places of living



(h) Low income, region's capital city

Note: The figure reports the impulse responses of the individuals' income (in constant prices) to the imposition of sanctions, as measured with the ICS (*Sign restrictions ID*) and country spread (*Recursive ID*) shocks. The responses are obtained using Jorda (2005) LP approach. The sample contains 74,356 individual–year observations for 21,813 individuals over 2006–2018. The monthly estimates of the ICS and country spread shocks, as measures of the financial sanctions, are aggregated to the annual level by summation of the monthly magnitudes within a given year.

Figure N.I: The effects of the sanctions shock on consumption of durables in a cross-section of households (*ending*)

Abstrakt

Jak moc sankce poškozují sankcionovanou ekonomiku? Zkoumáme případ Ruska, které čelilo třem vlnám mezinárodních sankcí za poslední desetiletí (v roce 2014, 2017 a 2022). Ve VAR modelu ruské ekonomiky nejprve zavádíme znaménková omezení, abychom izolovali šoky do mezinárodní nabídky úvěrů jako aproximace šoků z finančních sankcí. Poskytujeme mikroekonomický základ pro přístup znaménkového omezení využíváním syndikovaných úvěrových obchodů v Rusku. Poté zkoumáme účinky celkových sankčních šoků (finančních, obchodních, technologických atd..) použitím vysokofrekvenční identifikace (HFI). Naše HFI je založena na každém oznámení sankcí OFAC/EU a souvisejících denních změnách výnosu do splatnosti ruských státních dluhopisů denominovaných v amerických dolarech. Naše makroekonomické odhady naznačují, že ruský HDP pravděpodobně neztratil více než 0,8 % v důsledku finančního sankčního šoku a až 3,2 % v důsledku celkového sankčního šoku kumulativně za období 2014–2015. V roce 2017 jsou příslušné efekty 0 a 0,5 % a v roce 2022 je to 8 a 12 %. Naše průřezové odhady ukazují, že reálný příjem bohatších domácností se během prvního roku po sankčním šoku snižuje o 1,5–2,0 %, zatímco reálný příjem chudších domácností roste o 1,2 % za stejné období. Nakonec zjišťujeme, že skutečné celkové příjmy velkých firem s vysokým (nízkým) TFP během prvního roku po sankčním šoku klesají o 2,2 (4,0) %, zatímco dopady na malé firmy se blíží nule. Celkově naše výsledky naznačují významnější heterogenní dopady sankcí na bohatší domácnosti s bydlištěm ve velkých městech a na větší firmy s vysokým TFP.

Working Paper Series
ISSN 2788-0443

Individual researchers, as well as the on-line version of the CERGE-EI Working Papers (including their dissemination) were supported from institutional support RVO 67985998 from Economics Institute of the CAS, v. v. i.

Specific research support and/or other grants the researchers/publications benefited from are acknowledged at the beginning of the Paper.

Published by
Charles University, Center for Economic Research and Graduate Education (CERGE)
and
Economics Institute of the CAS, v. v. i. (EI)
CERGE-EI, Politických vězňů 7, 111 21 Prague 1, tel.: +420 224 005 153, Czech Republic.
Phone: + 420 224 005 153
Email: office@cerge-ei.cz
Web: https://www.cerge-ei.cz/

Editor: Byeongju Jeong

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

ISBN 978-80-7343-563-9 (Univerzita Karlova, Centrum pro ekonomický výzkum a doktorské studium)
ISBN 978-80-7344-683-3 (Národohospodářský ústav AV ČR, v. v. i.)