Macroeconomic and Distributional Impact of Sanctions News: Evidence from Russia*

Mikhail Mamonov† Anna Pestova‡

January 15, 2026

Abstract

How much do global sanctions harm the targeted economy? We study the economic effects of sanctions on Russia using a novel high-frequency identification strategy that exploits trading in Russian sovereign bonds around U.S. sanctions announcements. We find that an exogenous sanctions news shock raises Russia's sovereign spread by 1.1–1.8 percentage points three to four days before announcements, consistent with information leakage. Textual evidence corroborates this anticipation. Sanctions significantly depress industrial production, consumption, and investment. These aggregate effects are highly uneven: losses are concentrated among the most productive firms and highest-income households, while smaller firms and poorer households are largely unaffected.

Keywords: Sanctions, International political economy, High-frequency identification, Sovereign risk, Financial markets, Macroeconomic fluctuations, Firms and households, Income distribution.

JEL: F51, F41, E32, D31, D22.

*We appreciate valuable comments and suggestions from Ruben Enikolopov, Sergei Guriev, Refet Gurkaynak, Jonathon Hazell, Marek Jarocinski, Oleg Itskhoki, Diego Känzig, Marek Kapicka, Michele Lenza (discussant), Dmitry Mukhin, Volker Nitsch (discussant), Mikkel Plagborg-Møller, Lukasz Rachel, Giovanni Ricco, Christopher Sims, and Martin Uribe. We are grateful to conference and seminar participants for comments and discussions at Barcelona School of Economics Summer Forum "*Advances in Structural Shocks Identification*" (Spain, 2025), 32nd CEPR Summer Symposium in International Macro (ESSIM, Spain, 2025), St Andrews Workshop in Macroeconomics (UK, 2025), EEA-ESEM congress (Spain, 2023), Workshop on Modelling Economic Sanctions (Australia, 2022, online), International Conference on Macroeconomic Analysis and International Finance (Greece, 2023), research seminar at the Bundesbank (Germany, 2022, online), Workshop "Price of War: The Effects of Sanctions on Russia" (Florence School of Banking and Finance, Italy, 2022, online), 2nd Ventotene Macro Workshop (Italy, 2022), CERGE-EI Brown Bag Seminar (Czech Republic, 2022), and 25th Conference "Theories and Methods in Macroeconomics" (T2M, 2022, online). This paper supersedes earlier versions of this research, which circulated under titles: "*The Price of War: Macroeconomic and Cross-Sectional Effects of Sanctions on Russia*" (CERGE-EI WP 756), "*Sorry, You're Blocked. Economic Effects of Financial Sanctions on the Russian Economy*" (CERGE-EI WP 704), and "*Should We Care? The Economic Effects of Financial Sanctions on the Russian Economy*" (BOFIT DP 13/2019). The early versions of this research were supported by BOFIT (Helsinki, 2016), the Center for Macroeconomic Analysis and Short-term Forecasting (Moscow, 2017), MGIMO-University (Moscow, 2019-2021), and SYRI research grant LX22NPO05101 (Prague, 2022).

The authors thank Princeton University (the Julis-Rabinowitz Center for Public Policy and Finance) and the University of Zurich (UZH, the Department of Finance) for hosting them while working on the current version of this paper in 2022–2023. Any errors or misstatements are our own.

†Toulouse Business School, Department of Economics and Finance. Address: 1 Place Alfonse Jourdain, 31000 Toulouse France. E-mail: m.mamonov@tbs-education.fr.

‡Toulouse Business School, Department of Economics and Finance. Address: 1 Place Alfonse Jourdain, 31000 Toulouse France. E-mail: a.pestova@tbs-education.fr.

"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 more and more, transferring the major portion of our productiveness 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, *Bethink Yourselves!* (1904)
On the Russo–Japanese War, reprinted from *The Times* (London)

1 Introduction

Since World War II, more than 100 countries have been subject to economic sanctions aimed at pressuring unfavorable political regimes by inflicting economic costs without resorting to full-scale military conflict (Levy, 1999; Etkes and Zimring, 2015; Felbermayr *et al.*, 2020; Itskhoki and Mukhin, 2025). Despite their frequent use, policymakers still face high uncertainty regarding the magnitude, timing, and distribution of the economic costs imposed by sanctions. While there is broad consensus that sanctions rarely succeed in shifting political regimes, a growing body of evidence documents their substantial economic consequences. Banks and non-financial firms targeted by sanctions are forced to sharply curtail their international financial activities (Cipriani *et al.*, 2023; Mamonov *et al.*, 2023), reduce trade flows (Crozet *et al.*, 2021; Souza *et al.*, 2024; Tyazhelnikov and Romalis, 2024), and cut employment (Ahn and Ludema, 2020).

While understanding the microeconomic effects of sanctions is important, assessing their aggregate macroeconomic impact is often central for policy evaluation. A key difficulty is that existing reduced-form estimates cannot be straightforwardly aggregated without strong structural assumptions, due to the well-known missing-intercept problem (Moll, 2022). This paper addresses this gap by leveraging recent advances in time-series identification—specifically, a high-frequency approach—to estimate the causal aggregate effects of sanctions news on the economy and to quantify their distributional consequences for households and firms in the sanctioned country.

The identification of sanctions shocks is challenging. Standard small open economy models do not explicitly incorporate sanctions shocks, reflecting in part the relatively recent academic focus on sanctions following Russia's annexation of Crimea in 2014.[1] A textbook country-

[1] A notable exception is Itskhoki and Mukhin (2025) which offers a structural framework to study the exchange

spread shock (Uribe and Schmitt-Grohe, 2017) captures exogenous changes in foreign borrowing premia but may fail to encompass the full scope of sanctions, which often involve asset freezes, trade restrictions, and technological bans in addition to financial constraints. As a result, conventional country-spread shocks may provide an incomplete representation of the full range of sanctions. In this sense, sanctions represent a compound policy shock that simultaneously alters expectations about external financing, trade access, and long-run productive capacity, rather than a pure financial shock.

Consistent with these challenges, earlier studies have struggled to obtain statistically significant macroeconomic effects of sanctions using vector autoregressive (VAR) models (Kholodilin and Netsunajev, 2019; Pestova and Mamonov, 2019). More recent work employs textual analysis of daily newspapers to construct sanctions-intensity indices that yield significant macroeconomic effects within VAR frameworks (Laudati and Pesaran, 2023; Bondarenko *et al.*, 2024). These approaches, however, rely on non-structural identification and impose potentially restrictive timing assumptions.

We take a further step by introducing a high-frequency identification of sanctions shocks. Specifically, we construct a novel instrumental variable that exploits high-frequency trading data on the sanctioned government's sovereign bonds around sanctions announcements. This approach substantially reduces identification uncertainty relative to earlier methods and delivers more precisely estimated effects. Moreover, to the best of our knowledge, this paper is the first to study the distributional impact of sanctions on both households and firms.

We focus on Russia, which provides a particularly informative laboratory for studying the effects of sanctions. First, Russia is a large economy that shares many characteristics of a small open economy and offers relatively rich macroeconomic and microeconomic data.[2] Second, from the onset of the Russia–Ukraine conflict in 2014 until the outbreak of the COVID-19 pandemic, Russia was subject to 37 sanctions announcements by the United States. This frequency provides precise event timing and substantial variation in sanctions-related news within a single country. Finally, in an era of elevated global geopolitical risk (Caldara and Iacoviello, 2022), the Russian sanctions episode offers strong external validity, as the possibility of sanctions targeting other large and systemically important economies cannot be ruled out. Our methodology and

rate response to sanctions.

[2]Following Russia's full-scale invasion of Ukraine in 2022, data quality deteriorated substantially and many series ceased to be publicly disclosed.

findings therefore speak directly to the policy design of globally coordinated sanctions.

We begin by hand-collecting detailed data on all Russia-related sanctions announcements issued by the U.S. Treasury's Office of Foreign Assets Control (OFAC) under the Russia–Ukraine, Cyberattacks, Syria, and Magnitsky programs during the 2010s. We relate these announcements to high-frequency changes in the yields to maturity (YTMs) of Russia's international sovereign bonds. This linkage captures market assessments of sanctions severity: more consequential announcements lead to sharper contractions in bond demand, reflecting deteriorating fiscal and macroeconomic fundamentals, and hence to larger increases in bond yields.

This framework allows us to test whether sanctions-induced yield movements translate into increases in Russia's aggregate country spread—the interest rate differential relative to a benchmark risk-free rate that reflects the country's cost of external borrowing. This establishes a link between our instrumental variable and an empirical small open economy model, which we use to study how sanctions propagate through the macroeconomy.

We compute daily changes in the average YTM of Russia's U.S.-dollar-denominated sovereign bonds over a window spanning five trading days before and two trading days after each sanctions announcement. Aggregating to the monthly frequency, we construct eight candidate instruments corresponding to daily yield changes from day -5 to day $+2$ relative to each announcement. Each instrument equals zero in months without sanctions announcements and reflects the relevant daily yield change in months with sanctions, summed when multiple announcements occur within the same month.

We then regress Russia's country spread on each candidate instrument, controlling for global and domestic macro-financial variables. Our first-stage results show that the country spread increases by 1.1–1.8 percentage points three and four days before sanctions announcements (significant at the 1% level), while yield changes on announcement days have little explanatory power. Corresponding first-stage F-statistics are well above conventional thresholds for the pre-announcement windows and far below them for contemporaneous changes. These findings indicate strong instrumental power for pre-announcement yield movements and low relevance on announcement days.

We corroborate this evidence with qualitative and quantitative indicators of information leakage. Anecdotal reports from major international media (e.g., BBC, CNN, *Wall Street*

Journal, Bloomberg) document leaks regarding upcoming sanctions several days before formal announcements. A systematic text-based analysis confirms a sharp rise in sanctions-related news coverage four days prior to announcements, coinciding with the yield movements that underpin our strongest instruments. Unlike monetary policy announcements, which are preceded by formal quiet periods, sanctions announcements typically lack such institutional constraints, making pre-announcement information leakage plausible.

Focusing on the most powerful instrument—the daily yield change three days prior to announcements, z_{-3}—we estimate impulse responses using a local projection instrumental variables (LP–IV) framework (Stock and Watson, 2018). In this setup, z_{-3} isolates exogenous variation in Russia's country spread in the first stage, which is then used to estimate the causal effects of sanctions on macroeconomic outcomes in the second stage. Our specification controls for global conditions, including commodity terms of trade, thereby netting out the effects of the 2014 oil price collapse and subsequent monetary tightening.

We find that a sanctions news shock equivalent to a 0.25 percentage point increase in the country spread reduces industrial production by up to 2.1%, private consumption by 1.7%, investment by 2.9%, and the trade balance by 14%. External debt declines by up to 5.2%, while the real effective exchange rate depreciates by 4.7%. Counterfactual analysis indicates that most of these effects materialized in 2015 and the first half of 2016, when macroeconomic trajectories diverged sharply from a counterfactual scenario featuring only the oil price collapse. In the subsequent period, up until the outbreak of the COVID-19 pandemic, no significant differences emerge, consistent with our finding that early sanctions announcements had substantially larger macroeconomic effects than later ones.

We validate our results through two placebo exercises. First, replacing sanctions announcement dates with randomly selected dates yields no significant first- or second-stage effects. Second, constructing placebo events based on non-sanctions-related Russian events over 2000–2019 likewise produces null results. These exercises confirm that our estimates capture sanctions-specific news shocks rather than generic calendar-time correlations.

We conduct a broad set of robustness checks. Excluding the December 2014 announcement that coincided with the "Black Monday" monetary shock leaves results largely unchanged. Replacing OFAC dates with EU sanctions announcements yields similar but less precise estimates.

OPEC oil-supply news (Känzig, 2021) never overlaps with sanctions dates and generates distinct dynamics. Excluding sanctions announcements coinciding with major geopolitical events (Caldara and Iacoviello, 2022) does not alter the results. Varying the anticipation window, pooling pre-announcement surprises, using the internal-instrument approach (Plagborg-Møller and Wolf, 2021) or SVAR-IV, and replacing bond yields with CDS spreads all confirm the baseline findings.

In the cross-sectional part of our analysis, we investigate the distributional impact of the sanctions news shock $z_{-3,t}$ on households and firms using panel local projections over four consecutive years following sanctions announcements. We exploit panel survey data on approximately 5,000 Russian households observed from 1994 to 2020 (RLMS-HSE) and a panel of roughly 500,000 Russian firms, covering both large and small enterprises and delivering 2,516,353 firm-year observations over the period 2010–2019 (SPARK-Interfax). We establish that the negative macroeconomic effects documented above are distributed unevenly across the population and across firms. According to our estimates, the most adversely affected groups are the largest and most productive firms and the richest households. By contrast, less productive firms and poorer households are barely affected by sanctions. Taken together, these results suggest that sanctions compress the income distribution in the sanctioned economy, a pattern reminiscent of the distributional effects documented for major wars (Piketty and Saez, 2006).

More specifically, our cross-sectional estimates show that the sanctions news shock leads to a decline of up to 4% in real total revenue of highly productive large firms during the first two years after the shock (statistically significant at the 1% level). In subsequent years, the effect remains negative and statistically significant. Quantitatively, this contraction accounts for approximately 16% of the observed decline in aggregate real total revenue of these firms in 2014. Turning to households, we find that individuals in the top income quintile experience a 5.5% decline in real total income in the first year following sanctions, regardless of whether they reside in regional capital cities or in other areas, including rural locations. This effect is economically meaningful and explains roughly one-third of the total income decline observed in the data. Strikingly, the corresponding estimates for individuals in the bottom income quintile are close to zero and statistically insignificant. We further find that high-income households reduce food consumption by about 1%, other nondurable consumption by 2.5%, and durable

consumption by nearly 10% in response to the sanctions news shock (all estimates are significant at the 1% level), indicating that most of the consumption adjustment of the rich occurs through durable goods purchases.

Relation to the literature. First, our paper contributes to the growing literature on high-frequency identification in empirical macroeconomics. External information has previously been used to identify aggregate shocks in a variety of contexts, including monetary policy shocks (Gertler and Karadi, 2015; Jarocinski and Karadi, 2020), oil supply news shocks (Känzig, 2021), climate policy shocks (Känzig, 2023), Brexit-related surprises (Geiger and Guntner, 2024), and fiscal announcements (Hazell and Hobler, 2025). We extend this approach to the context of international sanctions by introducing a novel high-frequency instrument that exploits institutional features and the precise timing of sanctions announcements to identify sanctions-related news shocks.

Second, our study contributes to the rapidly expanding literature on the economic effects of sanctions. Most existing studies focus on trade sanctions at the micro level, while the relatively small macroeconomic literature examines a narrow set of outcomes—most prominently the Ruble exchange rate in Dreger *et al.* (2016) and Itskhoki and Mukhin (2025), or GDP growth in Barseghyan (2019). Our work bridges these strands by jointly analyzing macroeconomic and microeconomic outcomes and by providing a comprehensive assessment across real activity, monetary conditions, financial markets, and international trade. For instance, Dreger *et al.* (2016) employ a cointegrated VAR and show that the collapse in oil prices in 2014 had a larger effect on Ruble dynamics than sanctions. Itskhoki and Mukhin (2025) develop a quantitative general equilibrium model demonstrating that the exchange rate response to sanctions following Russia's 2022 invasion of Ukraine depends critically on the type of sanctions imposed and on policy responses. Using a synthetic control approach, Barseghyan (2019) estimate that the 2014 sanctions reduced Russia's GDP by 1.5% over 2014–2017. Finally, Bondarenko *et al.* (2024) construct monthly sanctions indices based on local and global media coverage and find that Russia's GDP declines by 0.65% in response to local perceptions of sanctions. Our high-frequency identification delivers sharper identification and larger estimated macroeconomic effects than earlier studies and, in addition, provides novel evidence on the distributional consequences of sanctions across households and firms, both targeted and non-targeted.

Third, by quantifying the distributional implications of sanctions, we contribute to the growing literature on the microeconomic effects of aggregate shocks (Cloyne *et al.*, 2020; Känzig, 2023; Del Canto *et al.*, 2025; Lenza and Slacalek, 2024). A large body of evidence shows that business cycle shocks often affect households heterogeneously. Recent shocks such as the COVID-19 pandemic, the cost-push inflation surge, and climate policy tightening have been found to be regressive, disproportionately burdening lower-income households (Chetty *et al.*, 2024; Del Canto *et al.*, 2025; Känzig, 2023). By contrast, quantitative easing tends to benefit lower-income households more strongly through earnings heterogeneity (Lenza and Slacalek, 2024). Our findings suggest that sanctions differ from many other aggregate shocks in this respect: one unintended consequence of sanctions may be a compression of the income distribution in the sanctioned economy, as sanctions disproportionately reduce incomes of richer households and revenues of larger, more productive firms.

Roadmap. Section 2 describes the institutional background of sanctions, introduces our high-frequency identification strategy, and outlines the econometric framework. Section 3 presents the macroeconomic effects of the sanctions news shock. Section 4 analyzes the heterogeneous effects of sanctions on households and firms. Section 5 concludes.

2 Timing of sanctions on Russia and the high-frequency identification of the sanctions news shock

2.1 A brief history of sanctions on Russia

Sanctions on Russia were imposed by the West in three major waves. The first wave of sanctions was launched in 2014 in response to the Russo–Ukrainian conflict, including the annexation of Crimea and Russian support for separatist movements in eastern Ukraine. The main US sanctions program targeting Russia—the Ukraine-related sanctions—lists sanctions imposed between March and December 2014 (executive orders 13660, 13661, 13662, and 13685; see Welt *et al.*, 2020). Under this wave, sanctions were imposed by the US in coordination with the EU and mainly targeted the same entities (Welt *et al.*, 2020). This allows us to focus on the timing of US sanctions only.[3]

[3]Our results are robust to using EU sanctions announcements instead of OFAC (see Section 3.3).

The second wave of sanctions dates to 2017–2018 and was introduced in response to illicit cyber-enabled activities, electoral interference, and support for Syria. These sanctions were imposed mainly 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 (CAATSA), 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. 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 to loans of various maturities (more than 14 days for entities in the financial sector, more than 60 days for the energy sector, and more than 30 days 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.[4]

The third wave of sanctions unfolded in February 2022 as Russia invaded Ukraine. As noted by Berner *et al.* (2022), 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 restricted.

We now turn to developing an empirical tool that summarizes announcements of sanctions in a tractable index—an instrumental variable—and then introducing this variable into an empirical model of the Russian economy to quantify the effects of sanctions.

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

2.2 The idea of sanctions shock identification

The identification strategy of this paper is motivated as follows. Sanctions arrive in discrete "announcements" that provide a list of newly sanctioned individuals and entities. Sanctions are imposed primarily by the major powers: the US and the EU.[5] We focus on the US announcements because earlier, in 2014–2015, the US and EU introduced sanctions synchronously, and later, in 2017–2018, the US was more active in sanctioning Russia.[6] Market participants closely watch announcements of sanctions and may revisit their expectations about the Russian economy due to new information arriving with sanctions. Suppose sanctions impair the prospects of the sanctioned economy by restricting access to foreign assets and foreign debt, limiting access to new technologies, and reducing international trade; in that case, this should be reflected in sovereign bond prices and, correspondingly, in bond yields. A useful framework that links a country's economic performance, default risk, and sovereign bond pricing is described in Mendoza and Yue (2012). The idea is that sovereign default is more likely in a worse state of the economy, so if sanctions lead to a downward revision of the economy's prospects, then sanctions should increase the sovereign bond yield demanded by risk-neutral foreign investors to compensate for the higher default risk. Therefore, changes in Russia's foreign-currency sovereign bond yields around announcements of Russia-related sanctions provide useful information about foreign investors' perception of sanctions. We collect these data to construct a novel instrument for the sanctions shock.

2.3 Construction of the sanctions news shock instrumental variable

We adopt a high-frequency approach (HFI) to identify the sanctions news shock using the daily timing of sanctions announcements described above and daily data on average sovereign bond yields.

In the US, sanctions are administered by the Treasury Department's Office of Foreign Assets Control (OFAC). We hand-collect data on all announcements of sanctions under Russia-related programs published on the official OFAC website. We collect information on announcements of

[5]Several other Western countries impose sanctions too (e.g., Canada, Australia, and others) but their economic significance is lower because of lower trade and financial exposure to Russia.

[6]For example, on March 17, 2014, both EU and US introduced a first set of sanctions in response to Crimea annexation, on July 29, 2014, both responded to the downing of flight MH17 with additional sanctions and on September 12, 2014, both introduced major capital market sanctions and sanctions on oil and gas companies. See OFAC and EU Council websites. A systematic comparison is presented in Table F.I in Appendix.

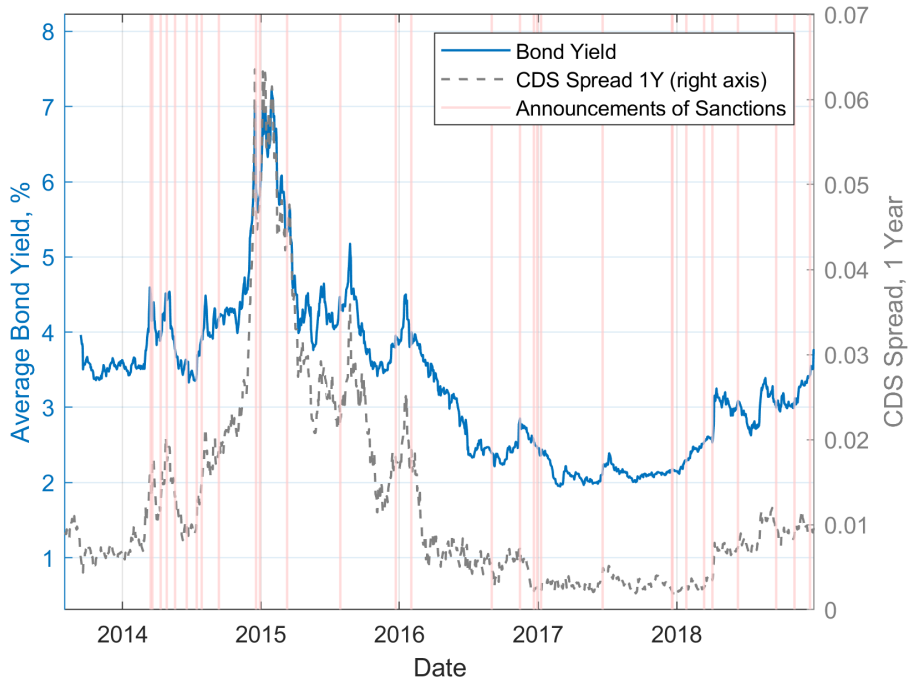
both SDN and SSI sanctions. SDN stands for Specially Designated Nationals and Blocked Persons. SDN sanctions include entities and individuals whose assets are blocked and all operations are prohibited within the US. SSI stands for Sectoral Sanctions Identifications list, which includes entities operating in specific industries, such as energy, finance, and defense, whose new debt placement of specified duration is prohibited in the US. We provide details on OFAC announcements in Appendix B.[7] All announcements are listed in Appendix Table B.I.

Figure 1 presents the daily evolution of Russia's sovereign bond yield-to-maturity (percent per annum) averaged across a comprehensive list of international US-dollar-denominated sovereign bonds reported in Refinitiv Eikon that were consistently traded over the analyzed period (8 issues), along with the dates of OFAC sanctions announcements over the same period. We provide the list of all bond issues included in the average yield in Section B.2 in the Appendix. In robustness checks, we show that replacing Russia's sovereign bond yields with Russia's CDS spread yields similar identification and almost identical impulse response functions. This is because the CDS spread and bond yields are tightly correlated (the correlation between the CDS spread and the bond yield is 0.908 over the analyzed period, Figure 1).

To be able to interpret changes in bond yields around announcements of sanctions as a valid source of exogenous information about the sanctions news shock, two conditions must be satisfied: first, changes in bond yields must be correlated with the sanctions news shock, and second, changes in bond yields around announcement days must not be correlated with other shocks affecting the economy. The argument supporting the first condition relies on the assumption that risk-neutral international investors revise the sovereign bond yield they demand once new information regarding sanctions is revealed (see the discussion in Section 2.2). The second assumption is satisfied as long as news on other important shocks affecting the economy is not systematically released on sanctions announcement days (e.g., macroeconomic forecasts, oil supply shocks, etc.). Given that sanctions are induced by military developments (e.g., downing of a civil aircraft, unconstitutional referendums) and geopolitical events (cyber-attacks, election interference), it is unlikely that sanctions are systematically announced on the same dates as economic news arrives. In the robustness check in Section 3.3, we provide evidence that yield changes on sanctions announcement days indeed capture sanctions news

[7] We focus on the pre-2022 war period as the quality of macro data deteriorated substantially since then. We also do not include the COVID-19 pandemic period to avoid ragged-end data.

Figure 1. Russia's sovereign bond yields, CDS spread, and OFAC sanctions announcements



Note: The figure plots daily data on the yield-to-maturity of Russia's international US dollar-denominated sovereign bonds averaged across eight issues that were simultaneously active during the 2010s (*blue line*), the one-year CDS spread on Russian sovereign debt (*grey dashed line*), and OFAC sanctions announcements against Russian individuals and firms between 2014 and 2019 (SSI and SDN, *light red bars*). Source: Refinitiv Eikon, Markit, OFAC.

but not other political or geopolitical events.

Similar to Känzig (2021) and Geiger and Guntner (2024), we use daily changes in bond yields instead of intra-day changes around announcements of sanctions due to data limitations, as intra-day data are not available. Differently from the previous work, we are ex ante agnostic about the precise timing of the window, i.e., whether it is a daily window around announcement days or a daily window a day before the announcement, or two days before, etc., because sanctions are known to be well-anticipated.[8] We provide evidence of media leakage several days before announcements of sanctions in B.3.

We compute daily sanctions surprise series, $Surprise_{d,k,t}$, as the changes in Russian sovereign bond yields around announcement days, varying the window day k from the announcement day minus five days, $d-5$, to the announcement day plus two days, $d+2$, while keeping the window length at one day:

[8]See, e.g., Mamonov *et al.* (2023) who document that Russian banks were anticipating and were thus well-prepared for Western sanctions.

$$Surprise_{d,k,t} = \begin{cases} YTM_{d+k,t} - YTM_{d+k-1,t} & \text{if } \mathbf{1}\{d = announcement\, day\} = 1 \\ 0 & \text{if } \mathbf{1}\{d = announcement\, day\} = 0 \end{cases} \quad (1)$$
$$k \mid k \in \mathbb{Z}, -5 \leq k \leq 2$$

where YTM denotes Russian government bond yields-to-maturity, d specifies the day of the announcement, k governs the "leakage parameter", and t denotes the month of the announcement. The parameter k varies within the set of integers from -5 to 2 with a step size of 1. k is a priori unknown; we later choose the preferred value of k based on the estimation properties of the first-stage equation using the instrumental variable constructed for each k. Intuitively, we select k such that the constructed instrumental variable yields "good" first-stage properties (F-statistics above the conventional level). Note that negative k means that meaningful YTM changes occur k days before the day of the announcement, sanctions *leakage*, if $-5 \leq k < 0$. Alternatively, for positive k, $0 \leq k \leq 2$, YTM adjusts with a k-day *delay* after the day of the announcement.

We aggregate daily $Surprise_{d,k,t}$ series to monthly $Surprise_{k,t}$ series by summing over all daily surprises within a given month t, if any, and assigning zeros if there were no announcements of sanctions in that month.

2.4 Econometric approach

We use monthly sanctions surprise series in an empirical small open economy model of the Russian economy.

LP-IV approach. Sanctions news shock as an instrumental variable. In the LP-IV approach, we use sanctions surprise series as an instrumental variable (as opposed to a direct measure of the shock in the robustness). We assume that the sanctions news shock transmits to macroeconomic variables through the cost of foreign borrowing for the economy, measured by the country spread over a risk-free benchmark.[9] Here we assume that there is no separate effect of the sanctions news shock on the economy besides the one reflected in the country interest

[9]Country interest rate fluctuations are known to play an important role in business cycles in emerging countries, Neumeyer and Perri (2005); Uribe and Yue (2006); Akinci (2013).

rate. This could be justified by the fact that the country interest rate is a "fast-moving" variable and once information on new sanctions is revealed, it adjusts to reflect the expected future state of the economy.[10]

We employ a local projection-instrumental variable (LP-IV) approach to estimate dynamic causal effects.[11] We choose LP-IV as a baseline specification for the following reasons. First, we estimate the effects of the sanctions shock on a set of macroeconomic and *microeconomic* variables. The effect on the latter is estimated with local projection to facilitate comparability between these two sets of outcomes, so we choose LP-IV instead of SVAR-IV as the baseline. Next, LP-IV is robust to potential model misspecification and does not rely on invertibility, which is possible in case we were to assume that macroeconomic variables evolve according to a VAR system. Choosing LP-IV, however, comes at the cost of increased estimation variance, Stock and Watson (2018). To reduce the variance, we add an extensive set of control variables to the LP-IV: the variables that would be included in the VAR if we were to specify a VAR model.[12] Estimating impulse responses with LP is valid as long as LP is augmented with appropriate control variables and the response horizon is limited enough, Plagborg-Møller and Wolf (2021).

Specifically, following Känzig (2023), we estimate the following set of regressions:

$$y_{i,t+h} = \alpha_{i,h} + \theta_{i,h} \cdot y_{1,t} + \delta'_{i,h}\mathbf{x}_t + v_{i,t+h}, \tag{2}$$

where $y_{i,t+h}$ is the i-th endogenous variable in month $t+h$, where $h = 1, 2...30$ is the prediction horizon, and the vector $\mathbf{x}_t$ contains up to twelve monthly lags of each endogenous and exogenous variable (described in the next subsection).[13] The variable $y_{1,t}$ is Russia's country spread. Finally, $v_{i,t+h}$ is an error term serially correlated by construction. We apply the two-step GMM estimator with Newey-West HAC standard errors to overcome this issue, as is standard in the literature.

[10] Recall the previously discussed assumption that risk-neutral international investors update their pricing of Russian foreign currency bond yields incorporating newly arrived information on sanctions.

[11] A similar approach is used in Ramey and Zubairy (2018); Jorda *et al.* (2020).

[12] VAR models for other emerging economies were employed in Uribe and Yue (2006), Akinci (2013), and Ben Zeev *et al.* (2017).

[13] In the robustness section, we also apply more parsimonious specifications of Equation (2): we use only the 1st lag, then the 1st and 2nd lags, and finally the 1st, 2nd, and 12th lags of all endogenous and exogenous variables. We always obtain results similar to the baseline (available upon request).

Under the LP-IV approach, we instrument Russia's country spread variable $y_{1,t}$ using the k-th high-frequency instrument $z_{k,t} = Surprise_{k,t}$, i.e., monthly sanctions surprise series. We deploy the $z_{k,t}$ instruments one by one: we recompute $Surprise_{k,t}$ for each leakage parameter k from -5 to 2 using Expression (1) and include the corresponding variable as an IV in the first stage underlying Equation (2).[14]

"Internal Instrument" approach. Sanctions news shock as an observable in the VAR. As a robustness check, we show that the impulse response functions are similar if we use the instrumental variable as a direct measure of the sanctions news shock and directly include it in the VAR of the Russian economy and order it first, following the "internal instrument" approach. We employ the "Internal Instrument" approach to construct the counterfactual dynamics of macroeconomic variables had sanctions not been imposed.

2.5 Model composition

The Russian economy is recognized as an open economy, which is dependent on the export of natural resources (oil, gas, etc.).[15] Therefore, studying the impact of sanctions on the Russian economy requires a specific model specification that allows us to separate domestic and external economic developments. Our empirical specification embedded in Equation (2) is based on several studies focused on small open economies including Uribe and Yue (2006), Akinci (2013), Ben Zeev *et al.* (2017) and Monacelli *et al.* (2023).

We include the following characteristics in the set of domestic macroeconomic variables. *Industrial production* (IP) as a proxy for domestic output, *private consumption* (C), *investment* (I)—all in national currency, in constant prices. Further, *Trade balance* (TB), which we express in US dollars and deflate by US CPI. *Country spread* (Spread) is JP Morgan's Emerging Markets Sovereign Bond Spread (EMBI+) for Russia. We calculate the real amount of the *outstanding stock of Russia's corporate external debt* (D) by deflating the nominal amount in US dollars by US CPI. Finally, we include Russia's *real effective exchange rate* (REER) into the set of domestic macroeconomic variables and re-express it so that an increase denotes currency depreciation and a decrease denotes its appreciation.

[14] In the robustness, we include all $Surprise_{k,t}$ series (i.e., for $k = -5...2$) as instruments into the first stage regression (the "single equation" approach). The results do not change.

[15] See, e.g., http://www.imf.org/external/pubs/ft/weo/2015/02/pdf/text.pdf.

We include three exogenous variables: *commodity terms of trade* (CTOT), *real US interest rate* (RIR^{US}) and *US corporate bond Baa spread*, (Baa^{US}). CTOT captures movements in commodity exports that are crucial for Russia. Oil, gas, and their products accounted for 63% of total exports, and their exports to GDP ratio is as high as 27% over (2010-2016 on average). We include Baa spread as a measure of global financial risks and the real interest rate in the US as a proxy for the world risk-free interest rate.

The sample period starts in January 2000 (shortly after the sovereign default crisis of the late 1990s) and ends in December 2018. We also experimented with adding data in 2019 and found no changes relative to baseline results. We do not include the COVID-19 pandemic in our sample to avoid ragged-end issues in the data. We do not include data for the period of the war in Ukraine, as the quality of the data deteriorated substantially. All necessary details on data sources and transformations are presented in Appendix A.

3 Results: macroeconomic effects of sanctions news shock

3.1 First stage and sanctions leakage parameter

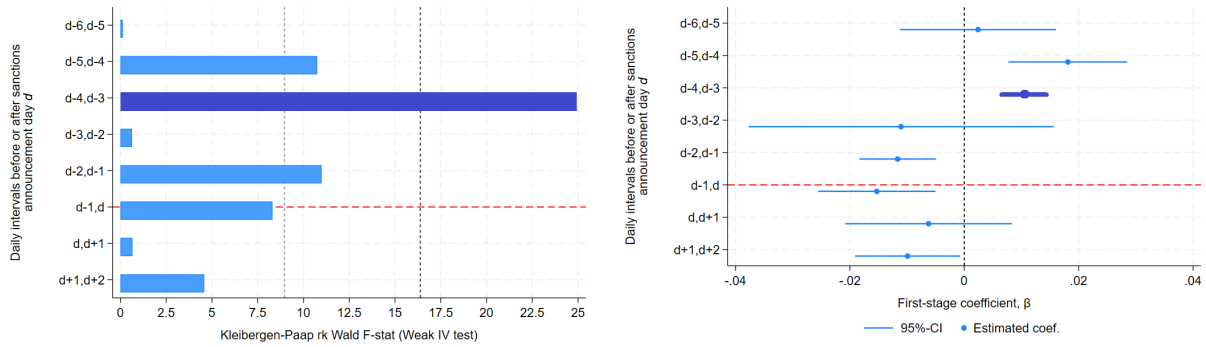
Our identification approach (i) is agnostic about k, the precise timing of the daily window around sanctions announcement days, and (ii) relies on the assumption that daily changes in sovereign yields in this window aggregated at monthly frequency are strongly correlated with Russia's country spread in the corresponding month. We empirically investigate both using the first-stage diagnostics.

Figure 2(a) below reports first-stage robust F-statistics, and Figure 2(b) shows estimates of the first-stage coefficient β that links our instruments to Russia's country spread.

According to the F-statistics pertaining to each $z_{k,t}$, the most powerful instrument is $z_{-3,t}$, i.e., daily changes in the average YTM that are observed three days before sanctions announcements (marked as $d-4, d-3$ in the figure), as its robust F-statistic is 24.92, exceeding all conventional critical values.[16] The second and third most powerful instruments are $z_{-4,t}$ and $z_{-1,t}$ whose robust F-statistics are 10.74 and 10.98, respectively. Note though that robust F-statistics associated with both $z_{-4,t}$ and $z_{-1,t}$ are below the conservative 10% critical value,

[16]Including the one in the robust test for weak instruments, 23.1 of Olea and Pflueger (2013), 5% critical value, 10% Nagar bias threshold.

Figure 2. First-stage estimates and F-test on instrument strength



(a) Robust F-statistics

(b) First-stage estimates β_k

Note: This figure reports the first-stage estimation results from the LP–IV approach. Panel (*a*) presents the robust F-statistics together with the Stock–Yogo weak identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). In panel (*b*), we report the estimated coefficient from the first-stage regression of Russia's country spread $y_{1,t}$ on the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$). The instrument $z_{k,t} = \text{Surprise}_{k,t}$ is the k-th version of the sanctions surprise, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC sanctions announcement on day d within month t. Each first-stage regression controls for all other right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West HAC standard errors, with the maximum autocorrelation lag set to 12 months.

suggesting that $z_{-3,t}$ clearly outperforms its closest competitors. Neither of the other instruments, including the one that corresponds to the sanctions announcement day, attains a similar level of predictive power and can thus be considered weak instruments. Overall, our empirical findings point to $z_{-3,t}$ being (i) the most powerful and (ii) the only strong instrument among our candidate surprises. Therefore, in the subsequent analysis, we use $z_{-3,t}$ as the baseline instrumental variable. We also use either a $z_{-4,t}$ (closest competitor) or a set of all considered $z_{k,t}$ in the robustness section. Economically, our first-stage results point to informational leakages regarding the coming sanctions in three and four days before OFAC's announcements.

To systematically validate sanctions news leakage, we run a text-based analysis of news content in major world media (e.g., CNN, WSJ, Bloomberg) around the 37 OFAC sanctions announcement days. We compute the number of news items containing the words "sanctions" and "Russia" on each day in a window before and after announcements and plot the results in Appendix Figure B.I. We observe a striking jump—more than a factor of 10—in the number of sanctions-related news on the fourth day before announcement, while all the previous days before and in between the fourth and the first day never exceed about 20 mentions. On announcement days, the number of sanctions-related news items skyrockets to about 5,000.

The major world media we use for our analysis are plotted in a diagram in Appendix Figure B.II. Combined with our first-stage regression results, we conclude that major world media indeed discuss details of upcoming sanctions a few days before announcements, and if international investors in Russia's sovereign bonds are forward-looking, they likely use these media signals to adjust their exposures before sanctions announcements. To provide specific examples of sanctions news leakage, Appendix Figure B.III also reports several pieces of anecdotal evidence that largely support our finding on information leakage prior to sanctions announcements.

It is noteworthy to discuss the magnitudes of the first-stage coefficients β_k. We obtain positive and highly significant coefficient estimates on $z_{-4,t}$ and $z_{-3,t}$ and negative and highly significant estimates on $z_{-1,t}$ and $z_{0,t}$, as can be inferred from Figure 2(b).

According to this evidence, international investors tend to sell Russia's sovereign bonds and raise Russia's country spread by 1.1 and 1.8 pp four and three days before announcements out of concern about sanctions-related risks. They then repurchase these bonds one day before the announcement and on the announcement day, lowering the spread by approximately the same amount as information uncertainty resolves and, probably, actual announcements tend to be less powerful than expected ones. Due to this complex dynamics, in the robustness section, we exploit the full set of instruments $z_{k,t}$ excluding the forward ones and obtain quantitatively similar results to the preferred single-instrument case.

We assess the properties of the baseline sanctions news shock $z_{-3,t}$ using simple diagnostic evidence from the raw data. Appendix Figure B.IV reports both the time evolution and the empirical distribution of $z_{-3,t}$. The time-series evidence shows that the largest realizations of $z_{-3,t}$ are concentrated in the early phase of the sanctions regime (2014–2015), consistent with markets reacting more strongly to the initial imposition of sanctions than to later announcements. The empirical distribution of $z_{-3,t}$ exhibits a noticeably heavier right tail than both the announcement-day shock $z_{0,t}$ and daily changes in average sovereign bond yields computed over non-sanctions days, indicating that unusually large yield movements tend to materialize several days before formal announcements rather than on the announcement day itself. Finally, Appendix Figure B.V further reports the autocorrelation function of $z_{-3,t}$ at the daily frequency over the preceding 21 days. Apart from a single isolated coefficient at lag -6 that marginally exceeds the 99% confidence bands, the autocorrelations are small and statistically

indistinguishable from zero. Given the absence of systematic serial dependence and the isolated nature of this exceedance, we interpret it as a random realization rather than evidence of predictability. Taken together, these diagnostics support interpreting $z_{-3,t}$ as a sharp, transitory news shock that captures anticipatory information about forthcoming sanctions, rather than persistent financial market dynamics or generic volatility.

3.2 Effects of the sanctions news shock on the macroeconomy

We start by documenting a clear negative correlation between the month-t sanctions news shock and future industrial production growth (Figure B.VI). The scatter plot shows that larger realizations of the baseline sanctions news shock $z_{-3,t}$ are systematically associated with lower subsequent growth in industrial production. This relationship is robust to excluding the largest realization of the shock in the sample, corresponding to the December 2014 "Black Monday" episode: the slope of the linear fit (dotted red line) remains negative and similar in magnitude to the baseline fit estimated on all observations (solid red line).

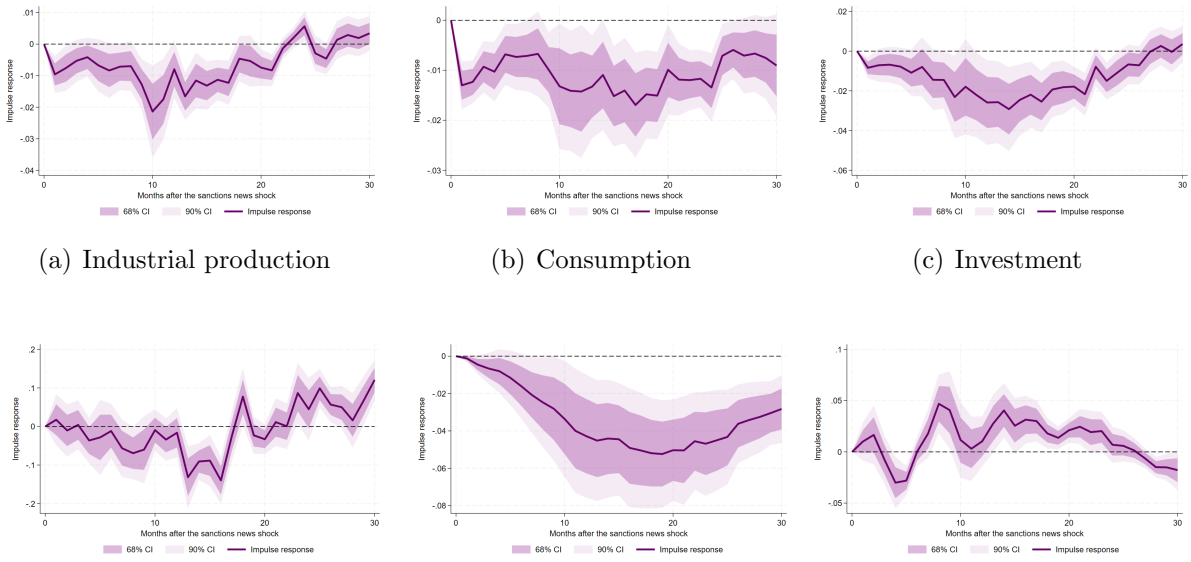
We present the baseline results on the effects of the sanctions news shock on a range of macroeconomic variables in Russia, identified using the LP-IV approach with $z_{-3,t}$ as the instrument. Figure 3(a)–(f) reports impulse responses to the sanctions news shock $z_{-3,t}$ normalized to a 0.25 percentage point increase in Russia's country spread.[17]

Qualitatively, our estimates show that the sanctions news shock leads to a significant and immediate macroeconomic contraction: industrial production, private consumption, and investment all fall in the month following the shock. Though all three responses accumulate during the first year after the shock, the estimated patterns imply deeper and more persistent declines in consumption and investment compared to industrial production. This is consistent with a higher procyclicality of consumption and investment relative to output typical in emerging economies, Uribe and Schmitt-Grohe (2017).

Trade balance does not shrink significantly on impact but then starts to plummet consid-

[17]This value is of similar magnitude as the one corresponding to the second-largest realization of the sanctions news shock $z_{-3,t}$, 0.223 corresponding to the one observed in July 2015. We do not use the largest realization (0.824), which occurred in December 2014, three days after the well-known "Black Monday" episode, when the Central Bank of Russia sharply raised its policy rate in response to the collapse in global oil prices, due to possible contamination effect. In the robustness section, we exclude "Black Monday" and show that though our estimated impulse responses become less precisely estimated, overall magnitude and direction remains unchanged.

Figure 3. The macroeconomic effect of the sanctions news shock



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure reports impulse responses to a sanctions news shock normalized to increase Russia's country spread by 0.25 pp on impact. Impulse responses are estimated based on the LP–IV approach using the sanctions news shock $z_{-3,t}$ series as an instrument. All variables are expressed in logarithms. Coefficients are estimated using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and the corresponding 68% and 90% confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to h months. A small-sample degrees-of-freedom adjustment is applied. The point estimates are depicted as solid purple lines and the 68 and 90% confidence intervals are presented as shaded areas.

erably and significantly in 9–18 months from the shock, though after 18 months the response attenuates to zero and even turns positive. Trade sanctions restrict trade, and Russia has to adjust both its exports and imports. As the initial net negative response of trade balance suggests, the negative adjustment of exports is stronger than the one of imports. The attenuation of the response to zero and eventual flip of its sign suggests an adjustment of trade flows to the sanctions shock in 18 months. The negative short-run response of the trade balance distinguishes the sanctions news shock from the textbook country spread shock, which typically features the opposite positive effect on the trade balance as has been established in previous studies, see e.g., Uribe and Yue (2006).

Corporate external debt falls slowly but very persistently as financial sanctions primarily restrict the ability of Russia's firms and banks to place new borrowings in Western financial markets.

Russian currency, the ruble, experienced several waves of depreciation against the currencies of Russia's major trade partners (though with some back and forth fluctuations during the

first 12 months after the shock). Currency depreciation is reflected in a positive medium-term response of the REER. Through the lens of the Itskhoki and Mukhin (2025) framework, our results suggest that during the 2010s, sanctions restricting supply of foreign currency at the domestic market clearly outweigh those limiting foreign currency demand. This is in line with the content of sanctions at the time and their economic effects. 2010s Western sanctions primarily restricted (i) foreign liabilities of Russian corporates, and (ii) Russian imports of dual-use and extraction equipment. While corporate external debt declined significantly (by up to 5.2%, Figure 3*e*), extraction equipment import sanctions have been shown to cause minimal-to-no decline in corresponding import flows (Belin and Hanousek, 2020). The effectiveness of foreign liabilities sanctioning coupled with the negative trade balance adjustment in response to the sanctions news shock explains lower supply of foreign currency at the domestic market and medium-run ruble exchange rate depreciation.

Regarding peak magnitudes of the responses, the sanctions news shock normalized to a 0.25 percentage-point increase in Russia's country spread on impact reduces industrial production by up to 2.1% (peak response is observed in 10 months), decreases private consumption by up to 1.7% (in 17 months), depresses investment by up to 2.9% (in 14 months), reduces trade balance by 14% (in 16 months), decreases external debt by up to 5.2% (in 19 months), and raises REER by 4.7% (in 8 months). All peak responses are statistically and economically significant.

3.3 Robustness checks

This section presents a comprehensive set of robustness exercises designed to assess the validity of the sanctions news shock and the stability of the estimated impulse responses. Each exercise addresses a distinct identification concern and is documented in detail in the Appendix.

Placebo dates. As a first robustness check, we assess whether our results could arise spuriously in the absence of sanctions-related information by replacing OFAC announcement dates with randomly selected placebo dates. Appendix C describes the construction of 37 placebo dates that mirror the timing and calendar structure of actual sanctions announcements while excluding any overlap within a ±5-day window (Appendix Table C.I). Appendix Figure C.I shows that, in the first stage, placebo instruments $\widetilde{z}_{k,t}$ yield coefficients that are close to zero and sta-

tistically insignificant across all leads and lags k ($k = -5, -4, \ldots, 2$), with robust F-statistics far below conventional weak-instrument thresholds. Correspondingly, Appendix Figure C.II shows that second-stage impulse responses based on placebo dates and $\widetilde{z}_{-3,t}$ are economically small and statistically indistinguishable from zero at all horizons. Moreover, the confidence bands around the placebo responses are sufficiently tight and, for most horizons, do not overlap with those associated with the baseline sanctions news shock $z_{-3,t}$. These placebo exercises therefore generate neither first-stage relevance nor second-stage macroeconomic effects, supporting the interpretation that our baseline results are driven by sanctions-related information rather than generic calendar-time shocks.

Placebo events. We further assess the specificity of our results by replacing OFAC sanctions announcements with randomly selected *domestic Russian events* unrelated to sanctions, including elections, major policy speeches, economic reforms, sports events, and other salient domestic developments. Appendix D describes the construction of 44 such placebo events and reports the corresponding dates (Appendix Table D.I). Appendix Figures D.I and D.II show that both first-stage coefficients and second-stage impulse responses based on placebo events are uniformly close to zero and statistically insignificant across all horizons. These results are virtually identical to those obtained using placebo dates, reinforcing the conclusion that the baseline estimates reflect sanctions-specific information rather than generic domestic news.

Domestic monetary policy. We next examine whether our results are confounded by domestic monetary policy shocks that may independently affect sovereign yields and macroeconomic outcomes (Appendix E).

Excluding the "Black Monday" episode. We assess whether the baseline results are driven by coincident domestic monetary policy news. First, we exclude the OFAC sanctions announcement of December 19, 2014, which occurred three days after the well-known "Black Monday" episode of December 16, 2014, when the Central Bank of Russia raised its policy rate by 650 basis points in response to surging inflation and a sharp ruble depreciation following the collapse in global oil prices.[18] It is worth noting that this OFAC announcement generates the largest realization of the sanctions news shock in the sample ($z_{-3,\,2014m12} = 0.824$). Given its timing, this observation likely reflects a combination of sanctions-related information and

[18]This episode followed the collapse in global oil prices and was widely covered by international media, see, e.g., https://www.bbc.com/news/business-30490082.

extraordinary domestic monetary policy news. Excluding this episode therefore provides a stringent test of whether the baseline results are driven by a single, potentially confounded observation. Figures E.I and E.II show that removing this episode has only a modest effect on the first stage. The coefficient on $z_{-3,t}$ increases slightly relative to the baseline (from 0.011 to 0.014), while the corresponding robust F-statistic declines from 25 to 16.5, remaining well above conventional weak-instrument thresholds. By contrast, the instrument $z_{-4,t}$ becomes irrelevant once this episode is excluded, reinforcing our choice of $z_{-3,t}$ as the baseline instrument. In the second stage, impulse responses are quantitatively stronger—by a factor of roughly 1.5 to 2—though estimated less precisely. Nevertheless, responses remain statistically significant at conventional levels, indicating that the baseline results do not hinge on the coincidence of sanctions announcements with extraordinary domestic monetary policy shocks.

Comparing sanctions news with monetary policy announcements. We further distinguish sanctions-related information shocks from domestic monetary policy surprises by constructing instruments around Central Bank of Russia policy announcements (Appendix Table E.II). Out of 50 monetary policy events between 2014 and 2019, five occur on or within five days of OFAC sanctions announcements and are therefore excluded. Appendix Figures E.III and E.IV compare the resulting LP–IV estimates with the baseline sanctions-based results. In the first stage, instruments based on monetary policy announcements, $\widetilde{z}_{k,t}$, yield positive coefficients for $k = -5, -4, \ldots, 1$, turning negative only at $k = 2$. Although magnitudes are comparable to those of $z_{-3,t}$, robust F-statistics are substantially lower; in particular, the robust F-statistic for $\widetilde{z}_{k,t}$ exceeds conventional thresholds only when constructed on the exact announcement day (i.e., when $k = 0$). In the second stage, monetary policy surprises generate larger short-run contractions in industrial production and consumption, but with wide confidence intervals and significance confined to the initial months. Effects on investment and the trade balance are statistically insignificant, while the real effective exchange rate appreciates significantly. These patterns differ sharply from the baseline sanctions responses, underscoring that the sanctions news shock captures a distinct channel rather than conventional monetary transmission.

EU sanctions announcements. We next identify the sanctions news shock using European Union (EU) sanctions announcements instead of U.S. OFAC announcements. Appendix F documents all 42 EU sanctions announcements against Russia between 2013 and 2019, including

both new measures and extensions of existing sanctions. Based on Appendix Table F.I, roughly one-third of EU announcements occur within a ±5-day window around OFAC announcements. Appendix Figure F.I shows that first-stage point estimates based on EU announcements $\widetilde{z}_{k,t}$ closely resemble those based on OFAC announcements, with the strongest effects again at $k = -3$, but with wider confidence intervals and the robust F-statistic well below 10. Appendix Figure F.II shows that the corresponding impulse responses are quantitatively similar—and in some cases larger—but estimated much less precisely. Overall, these results suggest that EU sanctions convey a related signal, but OFAC-based shocks deliver substantially stronger first-stage relevance and more precise second-stage estimates, justifying their use as the baseline.

Other geopolitical events. We next assess whether the baseline results are confounded by broader geopolitical developments unrelated to sanctions. First, we exclude six OFAC sanctions announcements that coincide with major non-sanctions geopolitical events identified using the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022), defined as days when $\Delta \ln GPRD_t$ exceeds the 90th percentile of its annual distribution (Appendix G).[19] Appendix Figures G.I and G.II show that excluding these dates leaves both first-stage relevance and second-stage impulse responses essentially unchanged.

Second, we directly compare sanctions news shocks with shocks constructed around major geopolitical events unrelated to Russia sanctions. Using the GPRD index, we identify 44 global geopolitical events over 2001–2019 as dates when the seven-day change in geopolitical risk exceeds the 99.5th percentile of the annual distribution (Appendix Table G.I).[20] First-stage estimates based on these events yield coefficients for $\widetilde{z}_{-3,t}$ similar in sign and magnitude to the baseline, with even stronger first-stage relevance (Appendix Figure G.III). Second-stage impulse responses closely resemble the baseline in shape but materialize more rapidly and are roughly half as large, except for investment and the trade balance, where effects are comparable (Appendix Figure G.IV). These results indicate that while global geopolitical shocks affect Russia's economy, sanctions-related news generates more persistent and economically pronounced

[19] Based on this criterion, these six OFAC sanctions announcements are as follows: (1) 29 December 2014 (Turkey–Iraq border bombing targeting PKK positions), (2) 1 February 2016 (major Syrian civil war fighting during the Aleppo offensive), (3) 14 November 2016 (heightened post–U.S. election geopolitical uncertainty), (4) 9 January 2017 (intensified U.S.–Russia cyber interference accusations), (5) 21 December 2017 (spillovers from the UN resolution on Jerusalem adopted the previous day), and (6) 5 December 2019 (U.S. Treasury warnings regarding global cyber risks).

[20] We use seven-day changes in GPRD to mitigate high-frequency noise in daily data and to better capture sustained geopolitical events dominating the news cycle.

responses.

OPEC meetings and oil supply shocks. We further compare the sanctions news shock $z_{k,t}$ with an oil supply shock $\widetilde{z}_{k,t}$ constructed around OPEC meetings (Appendix Table H.I), following Känzig (2021). None of the 77 OPEC meetings between 2000 and 2019 overlap with OFAC sanctions announcements. Appendix Figure H.I shows that the first-stage coefficient on $\widetilde{z}_{-3,t}$ is approximately twice as large as in the baseline, with a larger robust F-statistic, reflecting the strong sensitivity of Russia's sovereign risk to oil supply news. Second-stage impulse responses materialize faster and attenuate more quickly than under sanctions news, with peak effects of comparable magnitude, as depicted in Figure H.II. Differences arise for external debt and the real exchange rate, which display weaker and more transient responses. Overall, these results confirm that while oil supply shocks are powerful, they generate distinct dynamics from sanctions-related information.

Early versus later sanctions announcements. We further assess whether our baseline results are driven disproportionately by the early phase of the sanctions regime, when sanctions likely represented a novel and largely unanticipated policy instrument. We split the sample into early (2014–2015) and later (2016–2019) sanctions announcements (Appendix I and Appendix J). Estimation results show that the baseline effects are primarily driven by early announcements, which yield strong first-stage relevance and sizable second-stage responses. Later sanctions remain directionally consistent but exhibit weaker first-stage relevance and smaller, more rapidly attenuating impulse responses, consistent with adaptation and learning by the sanctioned economy.

Varying the anticipation window. Comparing the baseline anticipation lag $k = -3$ with $k = -4$ and the contemporaneous case $k = 0$ (Appendix Figures K.I and K.II, respectively), we find that impulse responses based on $z_{-4,t}$ closely match the baseline, while those based on $z_{0,t}$ are uniformly insignificant. These findings indicate that sanctions effects operate primarily through anticipatory channels rather than contemporaneous announcement effects.

Pooling pre-announcement surprises. As an additional robustness check, we assess whether our results depend on isolating a single pre-announcement window by constructing a pooled sanctions news shock that averages financial market reactions over the entire five-day period preceding the announcement. Specifically, we define an alternative instrument as $z_{-5\ldots0,t} =$

$\frac{1}{6}\sum_{k=-5}^{0} z_{k,t}$ and re-estimate the second-stage LP–IV responses (Appendix Figure K.III). While the corresponding first-stage coefficients display a sign reversal—from positive for early leads ($k = -5, -4, -3$) to negative for later ones ($k = -2, -1, 0$), consistent with partial anticipation followed by announcement-day corrections—the second-stage impulse responses obtained using the pooled instrument remain highly consistent with the baseline results. If anything, the estimated macroeconomic effects are quantitatively stronger, with similar timing and persistence across all variables. These findings indicate that our baseline results are not driven by a narrowly defined event window and instead reflect a broader accumulation of sanctions-related information in financial markets prior to formal announcements.

Alternative identification strategies. Re-estimating the model using SVAR–IV and an internal-instrument VAR (Appendix L and Appendix M), we obtain impulse responses highly consistent with the baseline. SVAR–IV delivers smoother and somewhat larger responses, while the internal-instrument approach yields slightly smaller effects. Timing and signs remain aligned across methods.

Credit default swaps (CDS).

Finally, we replace bond yield changes with CDS spread changes to account for the possibility that investors hedge sanctions risk rather than sell bonds (Appendix N). Appendix Figures N.I and N.II show that both first-stage relevance and second-stage impulse responses closely mirror the baseline, indicating that the results are robust to the pricing channel through which sanctions risk is reflected in financial markets.

3.4 Counterfactual analysis: what if there were no sanctions?

Given that we have established the significant negative effects of the sanctions news shock on the macroeconomy, we now analyze the counterfactual performance of the Russian economy in a hypothetical scenario of no sanctions in the 2010s. For this purpose, we perform a historical decomposition of the macroeconomic variables considered above using a VAR model with the sanctions news shock as an internal instrument. The model includes the same exogenous and endogenous variables as before. We include the baseline instrument $z_{-3,t}$ in the model and order it first. We estimate the model using a Bayesian approach with a standard Minnesota

prior.[21] We show that the impulse responses obtained from the VAR model are similar to our baseline responses under the LP-IV approach (Figure M.I).

Figure 4(a)–(g) reports the counterfactual dynamics of macroeconomic variables in 2014–2018 (*red lines*) against their actual evolution before and after the sanctions regime has been adopted (*blue lines*). A key finding from the Figure is that the sanctions news shock affected the economy significantly only during the first three years of sanctions, i.e., 2014–2016, when major Russian banks and firms encountered their first international restrictions, whereas the effects in the subsequent years attenuated substantially, implying the economy's adaptation to the new reality and thus a better preparedness to new sanctions announcements. Note that all counterfactuals feature a macroeconomic recession in 2014–2015, i.e., even in the absence of sanctions, which is due to the world oil price collapse captured by the commodity terms-of-trade in our regression model, although the recession would have been milder without sanctions.

More specifically, our results indicate that industrial production growth was on average 5.9 pp lower in 2015 (recession year) under sanctions compared to the "no-sanctions" scenario (the difference is significant). Private consumption could have lost even more—up to 6.4 pp of growth in 2015 (significant). Investment, in turn, could have lost 8.4 pp in 2015 (significant). The trade balance could have lost 28.6 pp in 2015 (significant).

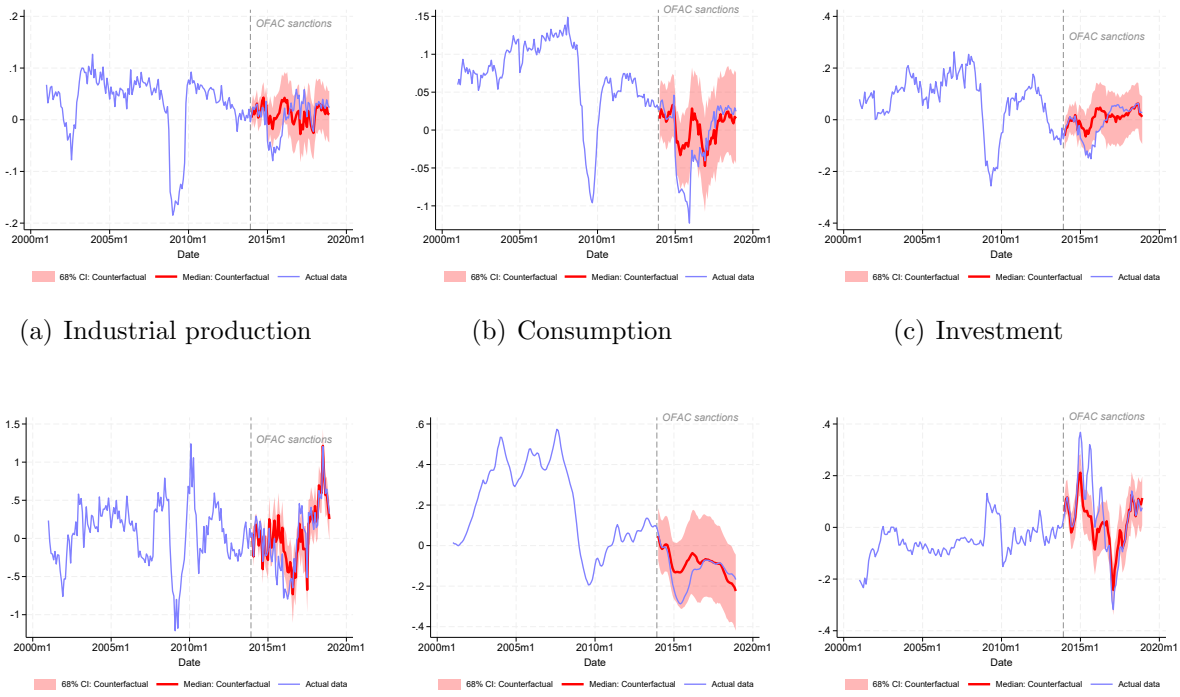
Overall, in terms of magnitudes, sanctions affected Russia's trade balance the most compared to other macroeconomic aggregates. We do not find statistically significant differences between actual and counterfactual growth of external debt, though the counterfactual lies clearly below actual. Yet the uncertainty is too large to document significant differences.

Finally, both REER and country spread (not reported) would evolve significantly smoother during 2014–2016, and would be lower by 15.3 and 1 pp, respectively, in the no-sanctions scenario.

Our counterfactual analysis clearly shows that even relatively mild sanctions of the 2010s were efficient in restricting the sanctioned economy's economic performance in the first years of their imposition. Our analysis also highlights a reduction of sanctions effectiveness during the subsequent years as the macroeconomy adapts to the sanctions regime, and the added value of

[21] IRFs are similar if we employ a flat prior; we prefer the Minnesota prior because a slight shift of the coefficients toward those implied by unit root processes yields a non-explosive historical decomposition. This issue is probably a feature of an emerging-economy data, which is highly non-stationary given the country's rapid growth in 2000s.

Figure 4. Counterfactual analysis: macroeconomic dynamics in Russia without sanctions in the 2010s



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: The figure reports the counterfactual dynamics of macroeconomic variables absent the contribution of the sanctions news shock $z_{-3,t}$. All variables are reported in twelve-month growth rates. The VAR model was estimated using a Bayesian approach with a standard Minnesota prior (overall tightness = 3, lag decay = 0.5, scalar controlling sum-of-coefficient prior = 5, co-persistence prior = 2, prior on the covariance matrix = 2; 500 draws). Solid blue lines depict the actual time evolution of variables, solid red lines stand for their counterfactuals in a hypothetical scenario of no sanctions, and the red areas mark the 68% credible bands.

future sanctions announcements gradually diminishes.

4 Results: distributional effects of sanctions

In the macro section, we have established that even relatively moderate sanctions—such as those imposed on Russia in the 2010s—can generate sizeable aggregate contractions in household consumption and firm investment. These aggregate responses, however, may mask substantial heterogeneity across households and firms. We therefore turn to the distributional effects of sanctions.

We advance two hypotheses. First, sanctions may disproportionately affect wealthier households located in large cities, as these households are more likely to hold international assets directly targeted by sanctions and to be employed by firms engaged in international operations that are directly or indirectly constrained by sanctions. Second, sanctions may exert larger neg-

ative effects on more productive and larger firms, which tend to be more deeply integrated into global trade and financial networks, relative to smaller and less productive firms that primarily serve domestic markets.

4.1 Sanctions and the cross-section of firms

Firm-level data. We draw firm-level data from the SPARK-Interfax database, which covers approximately 12 million Russian entities over the past two decades.[22] We focus on the period 2011–2019 and retain firms that report information on total revenues, wages, fixed assets, after-tax profits, total debt, and total assets. These restrictions substantially reduce the sample to roughly 0.5 million firms and 2,516,353 firm-year observations between 2010 and 2019.

We begin by computing firm-level total factor productivity following Gopinath *et al.* (2017):

$$TFP_{f,t} = \frac{Y_{f,t}}{K_{f,t}^{0.35} \cdot L_{f,t}^{0.65}} \tag{3}$$

where $Y_{f,t}$ denotes output produced by firm f in year t, which we measure by real total revenues, while labor $L_{f,t}$ and capital $K_{f,t}$ are proxied by wages and fixed assets, respectively, all expressed in constant prices.

To classify firms by productivity, we compute the distribution of log TFP in 2013—the last pre-sanctions year—and assign firms in the top (bottom) 20% to the high-TFP (low-TFP) group.[23] We fix group membership at pre-sanctions values to avoid endogenous reclassification due to firm exit or post-sanctions adjustments.[24] Summary statistics indicate large productivity differentials: high-TFP firms exhibit TFP levels 19.1% above the sample mean, whereas low-TFP firms lie 16.3% below it (Appendix Table O.I). The productivity differences across the two groups of firms are thus substantial.

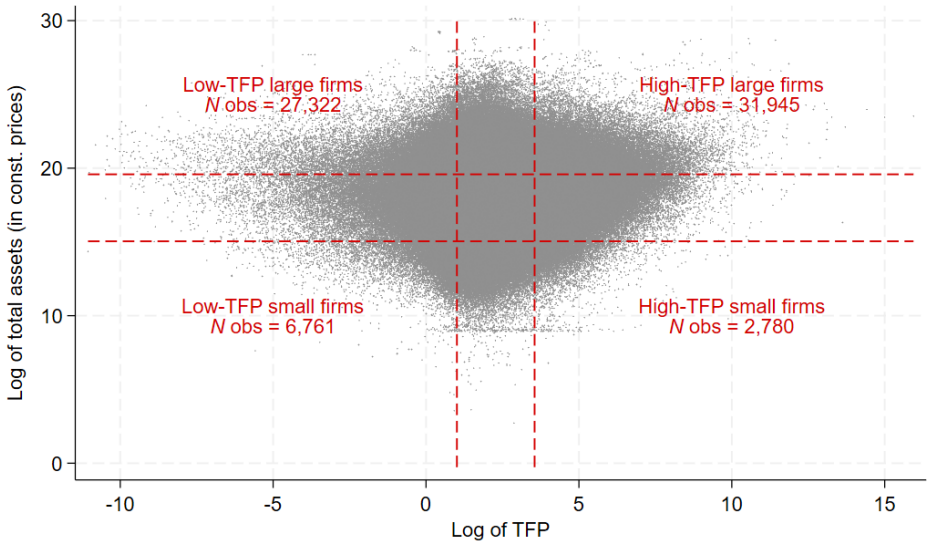
Panels 1–3 of Appendix Table O.I further show that high-TFP firms are larger in terms of sales, less capital- and labor-intensive, at least as well paid, more leveraged, more dynamic, and substantially more profitable than low-TFP firms. Appendix O provides additional validation of our TFP measure. In particular, Appendix Figure O.I shows that high-TFP firms gener-

[22] See spark-interfax.com.

[23] In robustness checks, we use alternative cutoffs of 33% and 50%.

[24] Firm mobility across productivity groups is substantial: only 47.3% of firms initially classified as high- or low-TFP remain in the same group through 2019.

Figure 5. Firm-level data: Subsamples of firms of different size and productivity, 2010–2019



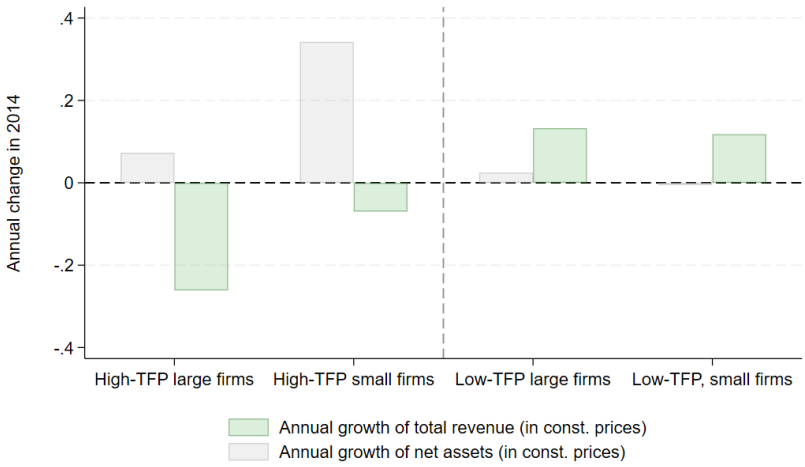
Note: The figure presents our firm-level data focusing on firms' size, as measured by the log of total assets (in constant prices), and firms' productivity, as measured by log TFP, in 2010–2019. The full sample contains 941,739 firm-year observations on TFP for 300,015 Russian firms and 2,516,353 firm-year observations on total assets for 499,572 Russian firms operating in 2,125 narrowly defined sectors of the economy (according to the national classification of economic activities, *okved*). By combining the data on TFP and size, we have 941,677 firm-year observations for 299,998 Russian firms. The two vertical lines mark the 20th and 80th percentiles of firms' distribution by the log TFP variable in 2013 (the pre-sanction year). The two horizontal lines mark the same percentiles for the log of total assets variable in 2013. Intersections of the two vertical and the two horizontal lines produce the four subsamples of firms: *high-TFP large firms* (the north-east quadrant; share in the full sample's aggregated total revenue in 2013 = 38.6%; N industries = 687), *low-TFP large firms* (the north-west quadrant; share in the full sample's aggregated total revenue in 2013 = 3.0%; N industries = 654), *low-TFP small firms* (the south-west quadrant; share in the full sample's aggregated total revenue in 2013 $<$ 0.1%; N industries = 366), *high-TFP small firms* (the south-east quadrant; share in the full sample's aggregated total revenue in 2013 $<$ 0.5%; N industries = 345). The data is sourced from SPARK-Interfax.

ate higher revenues conditional on asset growth, while Appendix Table O.II documents that productivity differentials in revenues, profitability, wages, and growth systematically narrow following sanctions shocks.

Figure 5 plots firms in the joint distribution of size (log total assets) and productivity (log TFP) using 941,677 firm-year observations over 2010–2019. Using the 20th and 80th percentiles of both variables in 2013, we define four subsamples: (1) *high-TFP large firms* (31,945 firm-year observations); (2) *high-TFP small firms* (27,322 firm-year observations); (3) *low-TFP large firms* (31,945 firm-year observations); (4) *low-TFP small firms* (6,761 firm-year observations). These groups differ sharply in economic importance: high-TFP large firms alone account for 38.6% of aggregate revenues in the pre-sanctions year, whereas the other three groups account for less than 4% of aggregate revenues.

In Figure 6, we further document a striking pattern in the raw data. In the first sanctions

Figure 6. Assets and revenues of high- and low-TFP, large and small, firms in the first year of sanctions



Note: This figure shows the average growth rates of net assets and total revenues in the four subsamples of firms described in Figure 5 during the first year of sanctions (2014). The data is sourced from SPARK-Interfax.

year (2014), high-TFP large firms experienced a collapse in real revenues of approximately 25%. By contrast, high-TFP small firms saw a decline of only 7%, while both large and small low-TFP firms recorded revenue increases.[25]

Although these raw patterns are suggestive, they may also reflect concurrent shocks—most notably the collapse in oil prices and the tightening of monetary policy in 2014. We therefore turn to formal estimation.

Estimation strategy. Existing studies document that firms directly targeted by sanctions suffer sharper contractions in sales and employment than non-targeted firms (Ahn and Ludema, 2020; Crozet *et al.*, 2021). However, sanctions likely generate broader general-equilibrium effects that extend beyond directly targeted entities, operating through financial conditions, competition, and supply chains. To capture these mechanisms, we project the sanctions news shock onto the cross-section of firms within each subsample.

We adapt time-series regression (2), which we used in the macro section above, to panel local projections (Jorda and Taylor, 2016) and estimate them separately for each of the four subsamples of firms:

$$\ln TR_{f,t+h} = \alpha_f + \alpha_i + \alpha_s + \theta_h \cdot \overline{z}_{-3,t} + \mathbf{X}_{f,t}\mathbf{\Phi}'_h + \varepsilon_{f,t+h} \tag{4}$$

[25]Consistent with Nigmatulina (2023), this pattern suggests that state support during the sanctions period may have disproportionately benefited less productive firms.

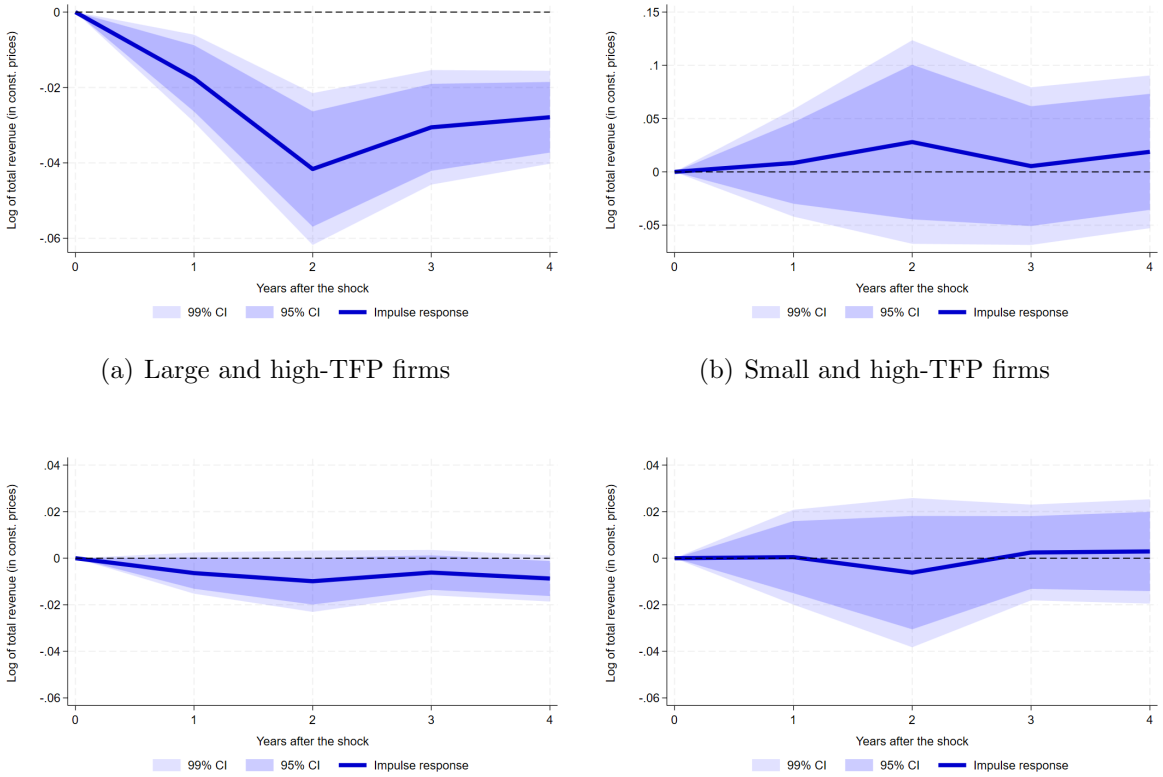
where the dependent variable $\ln TR_{f,t+h}$ is the logarithm of total revenues (in constant prices) of firm f in time $t+h$, where $h = 1...4$ is the prediction horizon (in years). The $\overline{z}_{k,t}$ variable is the annualized sanctions news shock, which we compute as the sum of the twelve monthly surprises $z_{-3,t} = Surprise_{-3,t}$. $\mathbf{X}_{f,t}$ is a set of control variables that include firm-level variables at $t = -1, 0$ (the log of total revenue itself, the annual growth of net assets, the log of wages, and the log of fixed assets) and macroeconomic variables at $t = -1, 0$ (the log of commodity terms of trade, the log of industrial production, and the log of REER). The terms $\alpha_f,\ \alpha_i,\ \alpha_s$ are firm, industry (*okved*), and operational status fixed effects, respectively.[26] With these control variables, the coefficients of interest $_h$ effectively capture a part of the aggregate variation in the future magnitudes of firms' total revenues that is due to current sanctions news shock and not due to other idiosyncratic and aggregate factors. Finally, $\varepsilon_{f,t+h}$ is the regression error.

We depart from the LP–IV framework used in the macro section and instead estimate reduced-form local projections. The reason is purely data-driven. Unlike the macroeconomic analysis, which exploits monthly variation in the sanctions news shock $z_{-3,t}$, the firm-level data are available only at the annual frequency. As a result, when aggregating $z_{-3,t}$ to the firm level, we obtain at most seven annual observations over the 2013–2019 period. This severely limits the scope for implementing an LP–IV strategy with firm-level fixed effects and dynamic controls, as first-stage estimation and weak-instrument diagnostics are not meaningful in such a short time series. Given the data constraints, the reduced-form approach represents the most transparent and statistically credible way to assess the cross-sectional effects of sanctions at the micro level.

Results. Figure 7 presents the main results at the firm level. Panels (*a*) and (*b*) report the impulse responses of real total revenues of high-TFP large- and high-TFP small firms, respectively, to the annualized sanctions news shock $\overline{z}_{-3,t}$. Panels (*c*) and (*d*) report the corresponding estimates for low-TFP large- and low-TFP small firms, respectively. As in the macro section, we rescale the estimates of θ_h to represent responses to a 0.25 percentage points rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, which implies a 0.223 magnitude of the sanctions news shock. Each panel contains 95% and 99% confidence intervals

[26] In our database, we can distinguish between the following five statuses: (*i*) currently operating (74.1% of firms), (*ii*) currently non-operating (19.7%), (*iii*) in the process of bankruptcy (2.9%), (*iv*) in the process of liquidation (2.5%), and (*v*) currently in reorganization (0.8%). Firms can switch between statuses and (*okved*) industries. We cannot include year fixed effects as they would absorb the coefficients of interest θ_h.

Figure 7. Cross-sectional effects of the sanctions news shock on firm total revenues



(a) Large and high-TFP firms

(b) Small and high-TFP firms

(c) Large and low-TFP firms

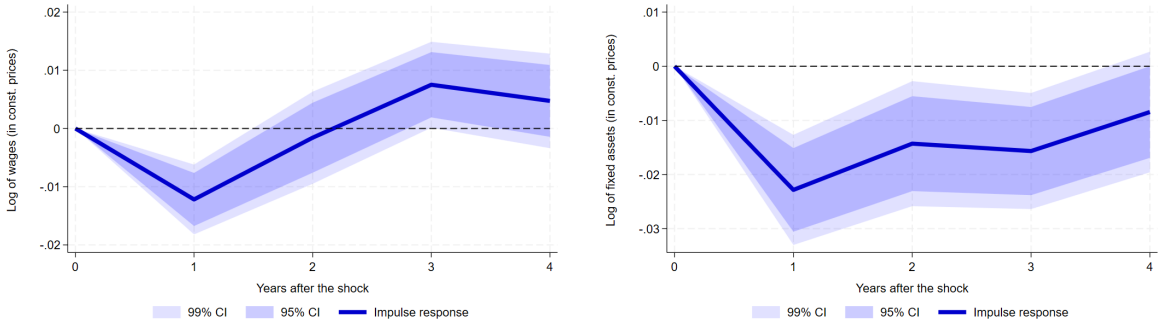
(d) Small and low-TFP firms

Note: The figure reports estimated local projections of the annualized sanctions news shock $\overline{z}_{-3,t}$ on the logarithm of firm f total revenues in year $t+h$ ($h = 1...4$), as implied by θ_h in Equation (4). Each θ_h is rescaled to represent a response to a 0.25 percentage points rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, which implies a 0.223 magnitude of the sanctions news shock. Panel (*a*) contains θ_h estimated in the subsample of large and high-TFP firms. Panel (*b*) depicts θ_h estimated in the subsample of small and high-TFP firms. Panel (*c*) shows θ_h estimated in the subsample of large and low-TFP firms. Panel (*d*) reports θ_h estimated in the subsample of small and low-TFP firms. Large (small) firm is a firm in the upper (lower) quintile of the firms' distribution by the size of total assets in 2013, i.e., the pre-sanction year. Similarly, high- (low-) TFP firm is a firm in the upper (lower) quintile of the firms' distribution by the estimated total factor productivity. The 95% and 99% confidence intervals are computed by clustering standard errors at the industry × year level.

computed by clustering standard errors at the industry (*okved*) × year level.

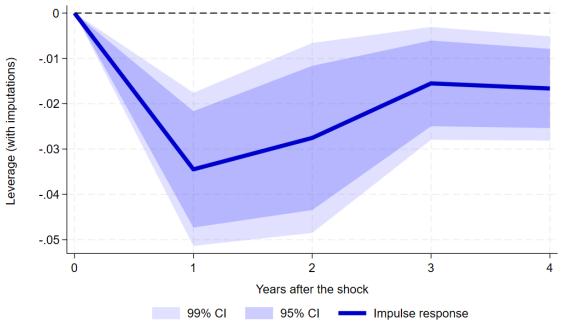
Our estimates indicate that high-TFP large firms exhibit pronounced and persistent revenue losses following the sanctions news shock: real revenues decline by about 2% in each of the first two years (significant at the 1% level), peaking at −4%, with effects remaining statistically significant thereafter. These estimates account for approximately 16% of the observed revenue contraction among these firms in 2014–2015. By contrast, high-TFP small firms display no statistically or economically meaningful response at any horizon after the sanctions news shock. Similarly, low-TFP firms—both large and small—show responses that are close to zero and statistically insignificant.

Figure 8. The cross-sectional effects of the sanctions news shock on wages, capital, and leverage of high-TFP large firms



(a) Real wages

(b) Capital



(c) Leverage

Note: The figure reports estimated local projections of the annualized sanctions news shock $\overline{z}_{-3,t}$ on the logarithm of firm f wages (a), capital (fixed assets, b), and leverage (total debt to total assets ratio, c) in year $t+h$ ($h = 1...4$), as implied by θ_h in Equation (4). Estimates are performed in the subsample of large and high-TFP firms. Each θ_h is rescaled to represent a response to a 0.25 percentage points rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, which implies a 0.223 magnitude of the sanctions news shock. A large firm is a firm in the upper quintile of the firms' distribution by the size of total assets in 2013, i.e., the pre-sanction year. Similarly, a high-TFP firm is a firm in the upper quintile of the firms' distribution by the estimated total factor productivity. The 95% and 99% confidence intervals are computed by clustering standard errors at the industry × year level.

Figure 8 explores additional margins for high-TFP large firms. In the first year after the shock, real wages decline by 1.2%, capital by 2.3%, and leverage by 3.4 percentage points of assets (all significant at the 1% level). Wage effects dissipate over time, whereas capital and leverage effects persist, mirroring the revenue response.

Overall, our cross-sectional analysis reveals that the sanctions news shock disproportionately harmed the largest and most productive firms in the Russian economy, consistent with their greater exposure to international trade and financial linkages.

4.2 Sanctions and the cross-section of households

Household data. We test the hypothesis that sanctions disproportionately affected richer

households—particularly those residing in larger cities—using household panel data from the RLMS-HSE survey. The RLMS-HSE is a nationally representative longitudinal survey of approximately 5,000 Russian households conducted annually since 1994 by the National Research University "Higher School of Economics."[27]

We extract information on individual income, household consumption, and other relevant socio-demographic characteristics for the period 2006–2019 and winsorize all monetary variables at the 1st and 99th percentiles. The resulting sample comprises 21,813 individuals and 74,356 individual-year observations.

The data allow us to identify individuals' place of residence and total real income. The breakdown of the $74,356$ observations that we have for the analysis is as follows: $31,266$ pertain to capital cities of different regions (*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 (*Rural*). The average annual income across four locations is, respectively, 483.6, 416.7, 422.4, and 371.9 thousand rubles (in constant 2014 prices).[28]

We divide all observations into the following four subsamples: (1) the 20% richest households residing in regional capital cities ($N\,obs = 31,266$), (2) the 20% poorest households residing in regional capital cities ($N\,obs = 20,836$), (3) the 20% richest households from other regional locations (large towns, small towns, or rural areas, $N\,obs = 4,460$), (4) the 20% poorest households from other regional locations ($N\,obs = 17,794$).

As in the firm-level analysis, group membership is fixed based on pre-sanctions income in 2013 to avoid endogenous reclassification driven by sanctions. Summary statistics are reported in Appendix Table P.I. Appendix Appendix P further provides validation exercises confirming the internal consistency and economic plausibility of the household data. First, Appendix Figure P.I documents a strong positive relationship between individual income and household consumption in the subsample of the 20% richest households and in the subsample of the 20% poorest households. Second, Appendix Table P.II shows that food consumption exhibits the lowest income elasticity (0.26), while tradable consumption exhibits the highest (0.53), both significant at the 1% level. The sanctions news shock is associated with a significant reduction

[27]The RLMS-HSE data have been widely used in the literature; see, among others, Yakovlev (2018) and Adsera *et al.* (2021).

[28]These numbers are equivalent to 11.6, 10.0, 10.2, and 8.9 thousand US dollars, using the average exchange rate of 41.57 rubles per U.S. dollar over 2006–2018.

Figure 9. Individual income and household consumption during the first year of sanctions



Note: This figure shows the average growth rates of real incomes and consumption in the four subsamples of households during the first year of sanctions (2014). The four subsamples are follows: (1) the 20% richest households residing in regional capital cities ($N\,obs = 31,266$), (2) the 20% poorest households residing in regional capital cities ($N\,obs = 20,836$), (3) the 20% richest households from other regional locations (large towns, small towns, or rural areas, $N\,obs = 4,460$), (4) the 20% poorest households from other regional locations ($N\,obs = 17,794$). The data is sourced from RLMS-HSE.

of the income elasticity of consumption only in the case of the 20% richest households, which provides a bridge to the subsequent regression analysis in this section.

Further, Figure 9 presents raw data evidence from the first year of sanctions. The 20% richest households experienced the sharpest decline in real income—between 29 and 33% in 2014—whereas the poorest households experienced a much smaller contraction of 5–6%. This descriptive evidence suggests that sanctions disproportionately affected higher-income households.

Estimation strategy. As in the case of firm-level analysis in the previous section, we adapt local projections used in the macro part of our analysis to explore how the annualized sanctions news shock affects individual incomes over time. The regression now reads as follows:

$$\ln Income_{i,t+h} = \alpha_i + \alpha_s + \alpha_j + \theta_h \cdot \overline{z}_{-3,t} + \mathbf{X}_{i,t}\mathbf{\Phi'}_h + \varepsilon_{i,t+h} \tag{5}$$

where $Income_{i,t+h}$ denotes real income of individual i in year $t+h$, where $h = 1...4$ is the projection horizon. The vector $\mathbf{X}_{i,t}$ includes individual-level controls (the logarithm of real income itself, the dummy variable that equals one if individual has debt, the number of children in the corresponding household, and the logarithm of household head's age) and macroeconomic controls (the logarithm of commodity terms of trade, the logarithm of industrial production,

Figure 10. The effects of the sanctions news shock on real income in the cross-sections of richest and poorest individuals



(a) 20% richest, regional capital cities

(b) 20% richest, other localities

(c) 20% poorest, regional capital cities

(d) 20% poorest, other localities

Note: The figure reports estimated local projections of the annualized sanctions news shock $\overline{z}_{-3,t}$ on the logarithm of individual i income in year $t+h$ ($h = 1...4$), as implied by θ_h in Equation (5). Each θ_h is rescaled to represent a response to a 0.25 percentage points rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, which implies a 0.223 magnitude of the sanctions news shock. Panel (a) contains θ_h estimated in the subsample of the 20% richest households residing in the regional capital cities. Panel (b) depicts θ_h estimated in the subsample of the 20% richest households residing in other locations (large towns, small towns, or rural areas). Panel (c) shows θ_h estimated in the subsample of the 20% poorest households residing in the regional capital cities. Panel (d) reports θ_h estimated in the subsample of the 20% poorest households residing in other locations. The 95% and 99% confidence intervals are computed by clustering standard errors at the locality (PSU, primary sample unit) $\times$ year level.

and the logarithm of REER, all three in constant prices). Fixed effects α_i, α_s, and α_j capture unobserved heterogeneity at the individual level, household-head gender, and household-head occupation, respectively. The term $\varepsilon_{i,t+h}$ is the regression error.

The estimation results appear in Figure 10. Panels (a) and (b) report the estimated impulse responses of real incomes of the 20% richest individuals residing in regional capital cities or other locations, respectively, to the sanctions news shock. Panels (c) and (d) report the corresponding estimates for the 20% poorest individuals from regional capital cities and other localities, respectively. We again rescale the estimates of θ_h to represent responses to a 0.25 percentage points increase in the average YTM of Russia's US-Dollar denominated sovereign

bonds, which implies a 0.223 magnitude of the sanctions news shock $\overline{z}_{-3,t}$. Each panel contains 95% and 99% confidence intervals computed by clustering standard errors at the locality (PSU, primary sample unit) $\times$ year level.

In panel (*a*) of Figure 10, we obtain negative and highly statistically significant estimates of θ_h for the 20% richest individuals residing in regional capital cities during the first two years after the sanctions news shock. Economically, the effect of $\overline{z}_{-3,t}$ peaks during the first year, reaching -5.5%, which accounts for around one-third of the total contraction of this group's real income in 2014. Differently from high-TFP large firms, this negative effect attenuates gradually and dissipates after roughly three years. In panel (*b*), we obtain quantitatively very similar estimates for the 20% richest households from other localities.

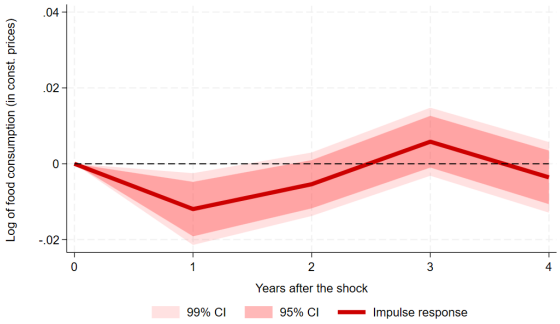
In contrast, our estimates for the subsamples of the 20% poorest households residing in regional capital cities (panel *c*) and other localities (panel *d*) appear largely insignificant and very close to zero at any prediction horizon. This indicates that the sanctions news shock barely affected the real income of the poorest households.

We next examine consumption responses across categories. Figure 11 shows that the 20% richest individuals barely reduced their consumption of food by more than 1% in response to sanctions (panel *a*), but they did contract the consumption of other (non-food) nondurables by 2.5% (panel *c*) and the consumption of durables by 10% (panel *e*) during the first year after sanctions. These effects dissipate within two years.

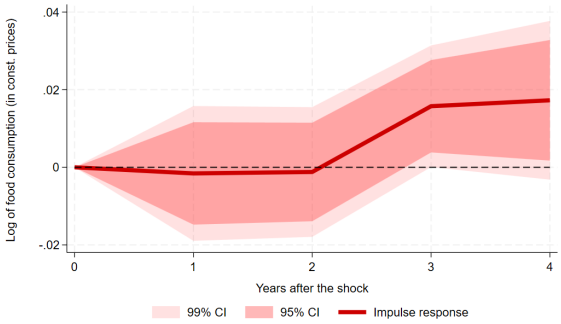
When we further turn to the 20% poorest individuals, our estimates suggest no significant effects of the sanctions news shock on their food consumption (panel *b*) and consumption of durables (*f*). We find that they reduce their consumption of other (non-food) nondurables by 2.5% in response to sanctions during the first year after the shock, but this effect is imprecisely estimated and reverses sign at longer horizons, suggesting limited and transitory adjustment.

Overall, consistent with the firm-level evidence, our analysis shows that sanctions primarily affected economically stronger agents—high-income households—while leaving the poorest households largely insulated.

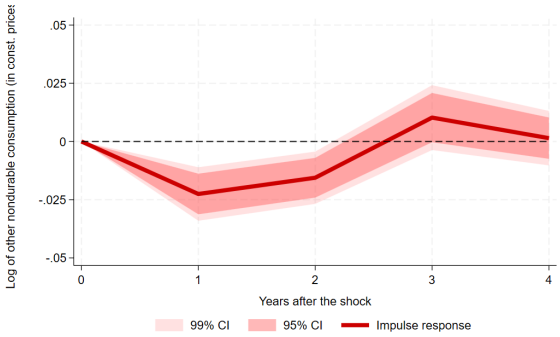
Figure 11. The effects of the sanctions news shock on consumption in the cross-sections of richest and poorest individuals



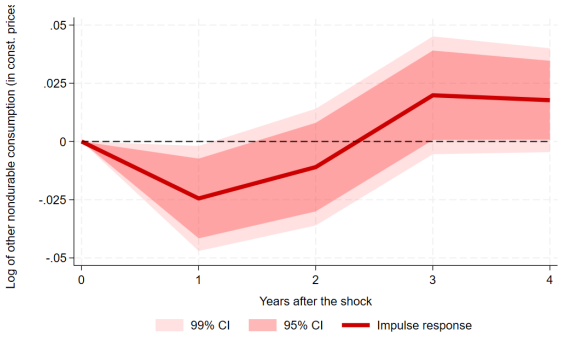
(a) 20% richest: Food consumption



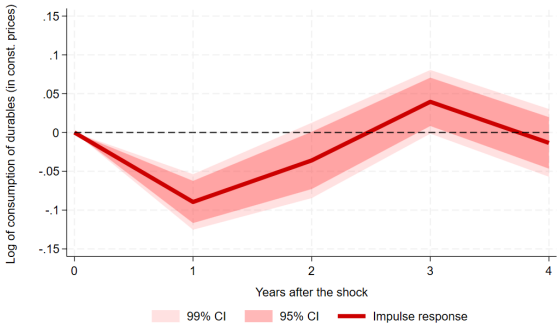
(b) 20% poorest: Food consumption



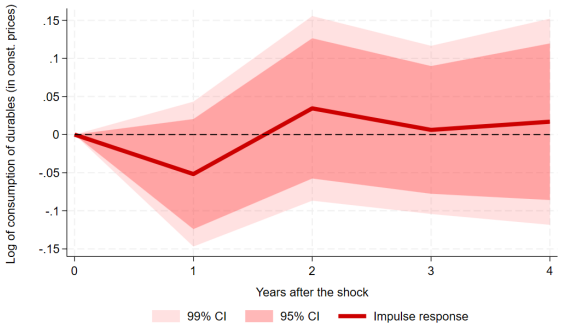
(c) 20% richest: Other nondurable consumption



(d) 20% poorest: Other nondurable consumption



(e) 20% richest: Consumption of durables



(f) 20% poorest: Consumption of durables

Note: The figure reports estimated local projections of the annualized sanctions news shock $\overline{z}_{-3,t}$ on the logarithm of individual i consumption in year $t+h$ ($h = 1...4$), as implied by θ_h in Equation (5). Each θ_h is rescaled to represent a response to a 0.25 percentage points rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, which implies a 0.223 magnitude of the sanctions news shock. Panels (*a*), (*c*), and (*e*) contain results for food consumption, other nondurable consumption, and consumption of durables, respectively, in the subsample of the 20% richest individuals. Panels (*b*), (*d*), and (*f*) contain the corresponding results for the subsample of the 20% poorest individuals. The 95% and 99% confidence intervals are computed by clustering standard errors at the locality (PSU, primary sample unit) $\times$ year level.

5 Conclusion

This paper shows that even moderate, pre-2022 global sanctions imposed on Russia had large and economically meaningful macroeconomic effects—larger than those documented in much of the existing literature. Using a novel high-frequency identification strategy based on sovereign bond yields, we find that sanctions led to sizable contractions in real activity, investment, and external borrowing. These aggregate effects are distributed unevenly across economic agents: the largest and most productive firms, as well as the richest households, bear the bulk of the economic costs. By contrast, less productive firms and poorer households are largely unaffected once we account for contemporaneous global oil-market developments and domestic monetary policy shocks.

Our results also highlight the importance of expectations and information frictions in the transmission of sanctions. Movements in sovereign bond yields around sanctions announcements reveal markets' real-time assessments of sanctions severity, and we document systematic anticipation of sanctions several days before official announcements. This pre-announcement information leakage plays a central role in identifying the sanctions news shock and in explaining why contemporaneous announcement-day movements have little explanatory power.

More broadly, our findings emphasize that sanctions influence markets through the early revelation of noisy signals about future policy actions, rather than through information disclosed on formal announcement days. An important direction for future research is to examine whether similar patterns of anticipation and information leakage arise in other policy contexts—such as oil-supply news, major geopolitical events, or large-scale policy announcements—where markets may react to informal signals well before official communication. Understanding these mechanisms is essential for designing effective and predictable economic policy in an environment of heightened geopolitical risk. Another natural direction for future research is to study how sanctioned economies adapt over time, including how firms, households, and policymakers learn about sanctions and adjust their behavior as sanctions become more persistent or predictable.

References

Adsera, A., Dalla Pozza, F., Guriev, S., Kleine-Rueschkamp, L., and Nikolova, E. (2021). Height and Well-Being During the Transition from Plan to Market, *Economic Policy* 36(105), 77–120.

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.

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.

Bondarenko, Y., Lewis, V., Rottner, M., and Schuler, Y. (2024). Geopolitical Risk Perceptions, *Journal of International Economics* 152, 104005.

Caldara, D., and Iacoviello, M. (2022). Measuring Geopolitical Risk, *American Economic Review* 112(4), 1194–1225.

Chetty R., Friedman J., Stepner M., Opportunity Insights Team (2024). The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. *Quarterly Journal of Economics* 139(2), 829–889.

Cipriani, M., Goldberg, L., and Spada, G. (2023). Financial Sanctions, Swift, and the Architecture of the International Payment System, *Journal of Economic Perspectives* 37, 31–52.

Cloyne J., Ferreira C., and Surico P. (2020). Monetary Policy When Households Have Debt: New Evidence on the Transmission Mechanism, *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

Del Canto, F., Grigsby, J., Qian, E., and Walsh, C. (2025). Are Inflationary Shocks Regressive? A Feasible Set Approach, *Quarterly Journal of Economics* 140(4), 2685–2747.

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.

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.

Geiger, M., Guntner, J. (2024). The Chronology of Brexit and UK Monetary Policy, *Journal of Monetary Economics* 142, 103516.

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, *Quarterly Journal of Economics* 132(4), 1915–1967.

Hazell, J., and S. Hobler (2025). Do Deficits Cause Inflation? A High Frequency Narrative Approach. CEPR Discussion Paper No. 19928.

Itskhoki, O., and Mukhn, D. (2025). Sanctions and the Exchange Rate. *Review of Economic Studies* rdaf085 (forthcoming).

Jarocinski, M., and Karadi, P. (2020). Deconstructing Monetary Policy Surprises—The Role of Information Shocks, *American Economic Journal: Macroeconomics* 12(2), 1–43.

Jorda, O., Schularick M., and Taylor, A. (2020). The Effects of Quasi-Random Monetary Experiments, *Journal of Monetary Economics* 112, 22-40.

Jorda, O., Taylor, A. (2016). The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy, *Economic Journal* 126 (590), 219–255.

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

Känzig, D.R. (2023). The Unequal Economic Consequences of Carbon Pricing. NBER Working Paper 31221.

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

Laudati, D., and Pesaran, M.H. (2023). Identifying the Effects of Sanctions on the Iranian Economy Using Newspaper Coverage. *Journal of Applied Econometrics* 38(3), 271–294.

Lenza, M., and Slacalek, J. (2024). How Does Monetary Policy Affect Income and Wealth Inequality? Evidence from Quantitative Easing in the Euro Area, *Journal of Applied Econometrics* 1–20.

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. (2023). Crime and Punishment? Anticipation, Diffusion, and Propagation of Global Sanctions, Swiss Finance Institute Research Paper No. 23-59.

Mendoza, E.G., and Yue, V.Z. (2012). A General Equilibrium Model of Sovereign Default and Business Cycles, *Quarterly Journal of Economics* 127(2), 889—946.

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

Moll, B. (2022). The Missing Intercept Problem When Going from Micro to Macro. mimeo

Nigmatulina, J. (2023). Sanctions and Misallocation. How Sanctioned Firms Won and Russians Lost. London School of Economics, Centre for Economic Performance Discussion Paper 1886.

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.

Olea, J. L. M., and Pflueger, C. (2013). A Robust Test for Weak Instruments, *Journal of Business & Economic Statistics* 31(3), 358–369.

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

Piketty, T., and Saez, E. (2006). The Evolution of Top Incomes: A Historical and International Perspective, *American Economic Review* 96 (2), 200–205.

Plagborg-Møller, M., and Wolf, C. (2021). Local Projections and VARs Estimate the Same Impulse Responses, *Econometrica* 89(2), 955-980.

Ramey, V., and Zubairy, S. (2018). Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data, *Journal of Political Economy* 126(2), 850-901.

Souza, G., Hu, N., Li, H., Mei, Y. (2024). (Trade) War and Peace: How to Impose International Trade Sanctions, *Journal of Monetary Economics* 146, 103572.

Stock, J., and Watson, M. (2018). Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments, *Economic Journal* 128, 917-948.

Tyazhelnikov, V., and Romalis, J. (2024). Russian Counter-Sanctions and Smuggling: Forensics with Structural Gravity Estimation, *Journal of International Economics* 152, 104014.

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

Uribe, M., and Yue, V. (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.

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 Details on macroeconomic data

A.1 Core variables

We build a monthly dataset on domestic Russian macroeconomic variables and exogenous foreign variables.

Exogenous variables. Monthly data on CTOT data is retrieved from the IMF Commodity Terms of Trade Database. We use the Commodity Net Export Price Index, in which individual commodities are weighted by the ratio of net exports to GDP (rolling weights). The index is normalized to 100 in June 2012. 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 from the Central Bank of Russia website. Industrial production, consumption, and investment are constructed based on chain indices and the nominal values and re-expressed in constant 2010 prices.[29] Trade balance is calculated as the difference between the dollar value of Russia's exports and imports and deflated by US CPI (the data comes from the IMF's International Financial Statistics database).

Data on corporate external debt in Russia is obtained from the website of the Central Bank of Russia.[30] We sum banks' and other sectors' external debt and subtract debt owed by these sectors to direct investors.[31] We linearly interpolate quarterly series to obtain monthly corporate external debt and deflate it by the US CPI.

Further, we compute country spread as the JP Morgan's EMBI country spread for Russia (J.P. Morgan Emerging Markets Sovereign Bond Spread, EMBI+), sourced from World Bank, Global Economic Monitor.

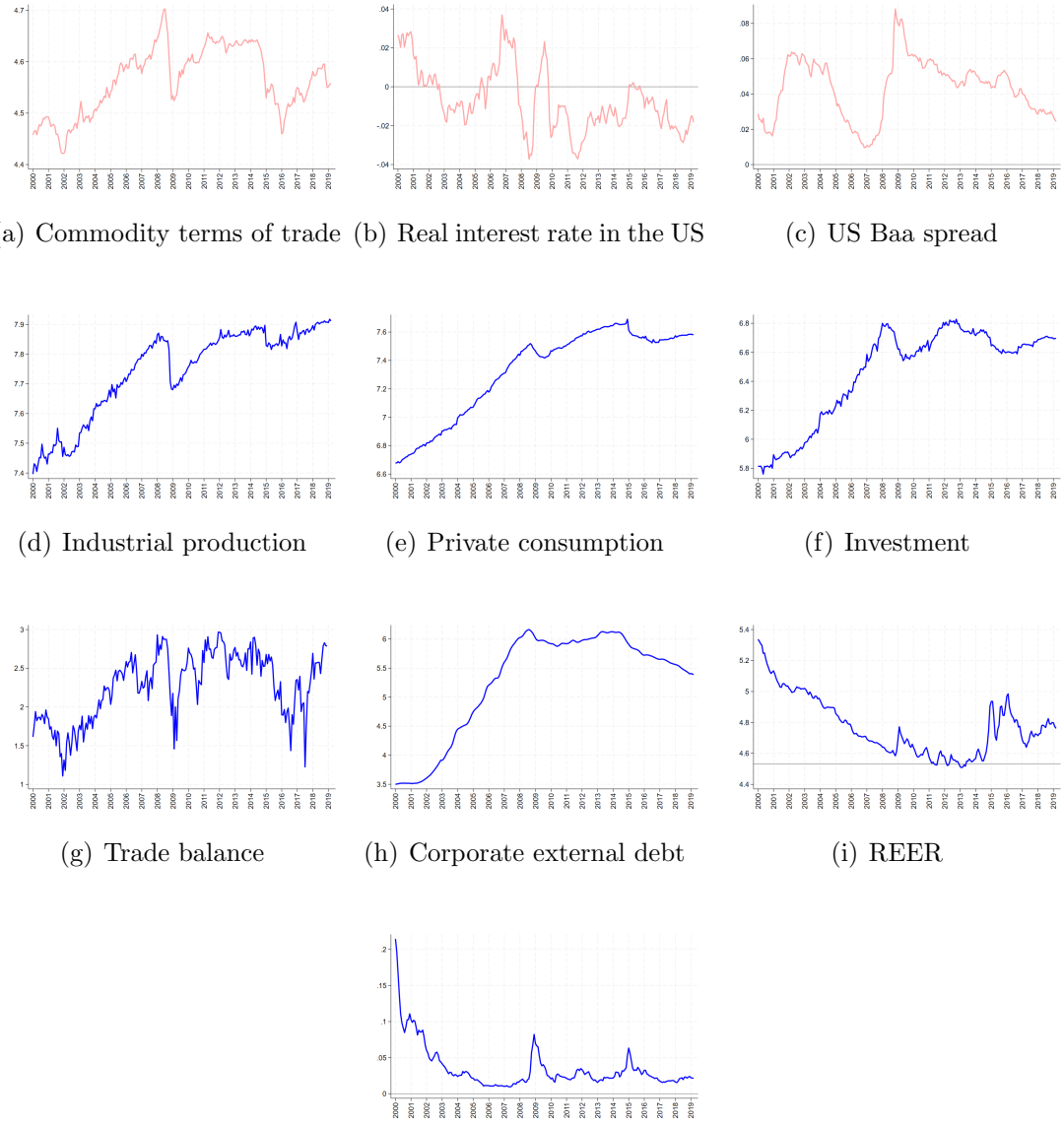
[29] Data source: Short-term economic indicators, https://rosstat.gov.ru/compendium/document/50802.

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

[31] 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 exclude debt to direct investors from the total stock of corporate external debt. Therefore, in our resulting series, only market-based part is included.

Finally, we obtain the real exchange rate (REER) from the Bank of International Settlements (BIS) website. We re-express this series as an inverse of that reported by BIS to interpret a decrease as currency appreciation and an increase as currency 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 transformed into logarithms. The resulting data is depicted in Figure A.I.

Figure A.I. Transformed macroeconomic data



(a) Commodity terms of trade (b) Real interest rate in the US (c) US Baa spread

(d) Industrial production (e) Private consumption (f) Investment

(g) Trade balance (h) Corporate external debt (i) REER

(j) Country spread

Note: The figure shows the time evolution of selected external (*light red*) and domestic (*blue*) variables employed in the LP-IV approach to estimate the macroeconomic effects of sanctions on Russia. All variables are in logarithms. The data is sourced from IMF, St. Louis FRED, the Federal State Statistics Service of the Russian Federation (Rosstat), JP Morgan, and BIS.

Appendix B Details on the high frequency identification of the sanctions news shock

B.1 OFAC sanctions announcements

In this Appendix, we provide a list of all Russia-related announcements of sanctions by the US collected from the Treasury's Office of Foreign Assets Control (OFAC) website. This list was assembled based on the search request in which we retrieved all announcements of sanctions mentioning "Russia" over the 2014-2019 period. We provide the link to the relevant request on the OFAC website, see the link to the list. We include sanctions introduced under Russia-related programs: Magnitsky Sanctions, Ukraine-/Russia-related Sanctions, Cyber-Related Sanctions, and CAATSA (The Countering America's Adversaries Through Sanctions Act). We exclude the sanctions introduced on Russian individuals and entities under programs other than Russia-related: Syria, Iran, Venezuela, and the Global Magnitsky programs. Table B.I lists all the events over the 2014-2019 period.

Table B.I. List of the US Treasury's Office of Foreign Assets Control (OFAC) sanctions announcements against Russia in 2013-2019

N	Date	Program	Content	Sanctions type		Source
				SSI	SDN	
1	12/04/2013	Magnitsky	18 Russian individuals were sanctioned under the Sergei Magnitsky Rule of Law Accountability Act for human rights abuses. They were added to OFAC's SDN list, resulting in U.S. asset freezes and transaction bans due to their roles in the mistreatment and death of Sergei Magnitsky, a Russian tax advisor responsible for revealing corruption and misconduct by the Russian government while representing client Hermitage Capital Management.		✓	Link
2	17/03/2014	Ukraine-/Russia-related	11 individuals were sanctioned under a new Executive Order expanding U.S. Ukraine-related sanctions. Targeting Russian officials and affiliates linked to destabilizing Ukraine, those sanctioned face asset freezes and transaction bans. The list includes Russian government figures, lawmakers, and former Ukrainian President Viktor Yanukovych.		✓	Link
3	20/03/2014	Ukraine-/Russia-related	19 Russian individuals and 1 entity (Bank Rossiya) were sanctioned under the expanded Ukraine-related Executive Order. The measures target high-ranking government officials, business elites, and members of President Putin's inner circle with asset freezes and transaction bans due to their role in the destabilization of Ukraine.		✓	Link
4	11/04/2014	Ukraine-/Russia-related	7 individuals and one entity, Chernomorneftegaz, were sanctioned under Ukraine-related authorities for their roles in supporting the Russian annexation of Crimea. The sanctioned persons include Crimean officials involved in local governance, electoral commissions, and security services, while the targeted entity is a Crimean-based oil and gas company.		✓	Link
5	28/04/2014	Ukraine-/Russia-related	7 Russian government officials and 17 entities were sanctioned under Ukraine-related authorities for their roles in supporting destabilizing activities in Ukraine. The designated individuals included high-ranking officials such as the Deputy Prime Minister and members of the Russian Security Council. The sanctioned entities spanned sectors such as finance, energy, transportation, and construction, including firms like SMP Bank, Stroytransgaz, and Volga Group.		✓	Link
6	20/05/2014	Magnitsky	12 individuals were sanctioned under the Sergei Magnitsky Rule of Law Accountability Act for their involvement in the detention, abuse, or cover-up of the death of Russian lawyer Sergei Magnitsky, or for gross human rights violations. The designated individuals include government officials, law enforcement officers, and others linked to the Magnitsky case.		✓	Link
7	20/06/2014	Ukraine-/Russia-related	7 individuals were sanctioned under the Ukraine-related program for actions threatening the territorial integrity and sovereignty of Ukraine. The designations include separatist leaders and officials such as Igor Girkin (a.k.a. Strelkov), Valery Bolotov, Denis Pushilin, and others involved in destabilizing eastern Ukraine or the annexation of Crimea.		✓	Link
8	16/07/2014	Ukraine-/Russia-related	OFAC expanded sanctions targeting Russia's financial services and energy sectors under Executive Order 13662 by launching the Sectoral Sanctions Identifications (SSI) List, restricting U.S. persons from transacting in new equity or debt with certain Russian firms. Sanctions were also imposed on multiple individuals—including high-ranking officials—and entities involved in undermining Ukraine's sovereignty, the arms sector, and separatist activities in Eastern Ukraine. Major firms like Rosneft, Gazprombank, Novatek, and Vnesheconombank were added to the SSI List.	✓	✓	Link
9	29/07/2014	Ukraine-/Russia-related	OFAC imposed sectoral sanctions targeting major Russian financial institutions—Bank of Moscow, Russian Agricultural Bank, and VTB Bank—prohibiting U.S. persons from transacting in new debt over 90 days or new equity with them, due to Ukraine-related actions. Additionally, the United Shipbuilding Corporation of Russia was sanctioned. These measures restrict financing and dealings linked to these entities, aiming to pressure Russia over its activities in Ukraine by limiting their access to international financial markets.	✓	✓	Link

Table B.I. List of the US Treasury's Office of Foreign Assets Control (OFAC) sanctions announcements against Russia in 2013-2019 (*continued*)

N	Date	Program	Content	Sanctions type		Source
				SSI	SDN	
10	12/09/2014	Ukraine-/Russia-related	OFAC expanded Ukraine-related sanctions targeting key Russian financial, energy, and defense sectors. Several major Russian entities—including Transneft, Lukoil, Gazprom, Rostec, Sberbank, Rosneft, Novatek, VTB Bank, and others—have been added to the Sectoral Sanctions Identifications List. These sanctions restrict U.S. persons from transacting in or financing new debt and equity of longer than 90 days maturity with these entities, aiming to limit their access to U.S. financial markets and resources amid the ongoing Ukraine conflict. General licenses allow certain winding-down transactions.	✓	✓	Link
11	19/12/2014	Ukraine-/Russia-related	The US President issued an Executive Order blocking property and prohibiting transactions with persons operating in Crimea, Ukraine. Concurrently, General License 4 authorized export of humanitarian goods. Numerous individuals and entities, including the Donbass People's Militia, Marshall Capital Partners, and the Night Wolves, were designated on OFAC's Specially Designated Nationals List pursuant to Executive Order 13660, targeting those undermining Ukraine's sovereignty and territorial integrity.		✓	Link
12	29/12/2014	Magnitsky	OFAC added individuals to the Specially Designated Nationals List under Magnitsky-related sanctions, including the Deputy Minister of Internal Affairs of Chechnya, the Chief of Staff of the Chechen Government, and other senior officials, for human rights abuses and corruption.		✓	Link
13	11/03/2015	Ukraine-/Russia-related	OFAC expanded Ukraine-related sanctions by adding separatists, Russian supporters, and former Ukrainian officials to the SDN List. Designations include former Ukrainian Prime Ministers, separatist leaders, and heads of key regional offices. Sanctioned entities include the Russian National Commercial Bank and the Eurasian Youth Union, linked to destabilizing activities in Ukraine and supporting separatist movements under Executive Order 13660.		✓	Link
14	30/07/2015	Ukraine-/Russia-related	OFAC issued a Crimea Sanctions Advisory and updated its SDN and Sectoral Sanctions Lists, targeting Russian and Ukrainian individuals—including Kalashnikov Concern executives and former officials—for evading sanctions related to Crimea. Sanctioned entities include major Crimean ports and Russian defense firms. These measures, part of broader sanctions against Russian political leaders, military officials, and organizations destabilizing Ukraine, restrict access to financial systems, travel, and markets to pressure Russia to end aggression and respect Ukraine's sovereignty.	✓	✓	Link
15	22/12/2015	Ukraine-/Russia-related	OFAC sanctioned several senior officials of Russian financial, defense, and energy-related entities for supporting Russia's activities in Ukraine and its occupation of Crimea. Designated individuals include board members and executives of major arms manufacturers and energy firms. Entities sanctioned include companies like Kalashnikov Concern, Izhevsk Mechanical Plant, and Crimean Film and Media Center. These measures aim to reinforce existing sanctions under Executive Orders 13660, 13661, 13662, and 13685 by targeting those enabling Russia's military-industrial complex and undermining Ukraine's sovereignty.	✓	✓	Link
16	01/02/2016	Magnitsky	5 Russian officials were sanctioned under the Magnitsky Act. Those designated include senior Interior Ministry officials, investigators, and a Chechen prison official. The sanctions target abuse, concealment of mistreatment, and extrajudicial killings, restricting access to U.S. financial systems and travel.		✓	Link

Table B.I. List of the US Treasury's Office of Foreign Assets Control (OFAC) sanctions announcements against Russia in 2013-2019 (*continued*)

N	Date	Program	Content	Sanctions type		Source
				SSI	SDN	
17	01/09/2016	Ukraine-/Russia-related	17 individuals and 44 entities were sanctioned for evading sanctions and supporting activities related to the conflict in Ukraine. Designations included political figures and regional administrators from Crimea and eastern Ukraine. Entities targeted were involved in construction, transport, and financial services, including companies like PJSC Mostotrest (infrastructure/construction), Sovfracht (logistics/shipping), and Glavgosexpertiza (engineering/regulatory services). Some were linked to major Russian institutions such as Gazprom and Bank Rossiya. These sanctions aimed to reinforce pressure on Russia over its annexation of Crimea and destabilizing actions in Ukraine. A general license was issued to allow limited transactions with some designated entities.	✓	✓	Link
18	14/11/2016	Ukraine-/Russia-related	6 individuals were sanctioned for their involvement in activities supporting Russia's occupation of Crimea. The designated individuals included members of the Russian State Duma representing Crimea or otherwise engaged in legitimizing the annexation of the region. These sanctions, under Executive Order 13660, aim to hold accountable those contributing to the destabilization of Ukraine and the undermining of its sovereignty.		✓	Link
19	20/12/2016	Ukraine-/Russia-related	7 individuals and 26 entities were sanctioned for supporting Russia's occupation of Crimea and destabilizing Ukraine. Entities included Crimean Ports (transport), Institut Stroyproekt (infrastructure/engineering), and LLC Ruschemtrade (chemical trade/logistics). OFAC also updated the Sectoral Sanctions Identifications List, targeting entities linked to the Russian Agricultural Bank (agriculture) and NOVATEK (energy). Additionally, General License 11 authorized limited transactions with FAU Glavgosekspertiza Rossii (engineering/regulatory services). These measures aim to disrupt sanctions evasion and economic integration of occupied territories.	✓	✓	Link
20	29/12/2016	Cyber-Related	6 individuals and 5 entities were sanctioned under amended Executive Order 13694 (now EO 13757) for malicious cyber-enabled activities. Individuals included senior Russian military intelligence officers and hackers involved in cybercrime. Entities targeted included the GRU (military intelligence), FSB (security services), and cybersecurity firms like Zorsecurity (cybersecurity/IT). These designations responded to cyberattacks and election interference, expanding U.S. authorities to sanction actors threatening democratic institutions and national security.		✓	Link
21	09/01/2017	Magnitsky	5 Russian individuals under the Magnitsky sanctions for human rights abuses. The listed individuals included senior law enforcement officials, members of parliament, and government investigators implicated in the mistreatment and death of Sergei Magnitsky and subsequent efforts to obstruct justice.		✓	Link
22	20/06/2017	Ukraine-/Russia-related	OFAC sanctioned 19 individuals and 19 entities for supporting Russia's occupation of Crimea and destabilizing eastern Ukraine. Sanctioned individuals included government officials, separatist leaders, and private military figures. Entities operated in sectors such as banking, oil transport, construction, and hospitality. Notable designations included banks active in occupied territories, infrastructure firms linked to Transneft, and the Wagner Group. These actions aimed to disrupt Russia's economic and political control over Ukrainian regions.	✓	✓	Link
23	20/12/2017	Magnitsky	OFAC issued regulations under the Magnitsky Act and designated five Russian individuals—including regional leaders, law enforcement, and legal professionals—for involvement in the Sergei Magnitsky case and other serious human rights abuses.		✓	Link

Table B.I. List of the US Treasury's Office of Foreign Assets Control (OFAC) sanctions announcements against Russia in 2013-2019 (*continued*)

N	Date	Program	Content	Sanctions type		Source
				SSI	SDN	
24	26/01/2018	Ukraine-/Russia-related	OFAC sanctioned 21 individuals and 12 entities tied to Russia's occupation of Crimea and destabilization of Ukraine. Those designated included Russian government officials, energy and defense executives, and firms across infrastructure, logistics, and oil sectors. Several entities were also added to the Sectoral Sanctions list, notably linked to Surgutneftegas.	✓	✓	Link
25	15/03/2018	Cyber-Related; CAATSA; Ukraine-/Russia-related	OFAC expanded Russia-related sanctions by issuing Cyber General License 1A, updating FAQs, and adding multiple Russian individuals and entities to the SDN List under CAATSA and cyber-related authorities. The designations target actors involved in the 2016 U.S. election interference, malicious cyberattacks, and operations linked to the FSB, GRU, and the Internet Research Agency. Thirteen individuals and the Internet Research Agency LLC were newly sanctioned, while several existing listings— including senior GRU officials and companies tied to Yevgeny Prigozhin (a Kremlin-linked oligarch)—were updated to add CAATSA or cyber-related tags. These actions strengthen pressure on Russian state-backed cyber and influence operations.		✓	Link
26	06/04/2018	Ukraine-/Russia-related	OFAC sanctioned 26 Russian individuals—including senior government officials, security chiefs, oligarchs, and business executives—and 15 entities for their involvement in malign activities linked to Russia's occupation of Crimea and aggression in eastern Ukraine. Those targeted operated across key sectors such as energy, defense, banking, and infrastructure. Notable designations included executives from Gazprombank, Rosoboronexport, and Rusal, along with entities tied to oligarchs Oleg Deripaska, Viktor Vekselberg, and Kirill Shamalov. These sanctions aimed to increase pressure on Russia's elite and state-controlled firms complicit in destabilizing Ukraine and violating international norms following the annexation of Crimea.	✓	✓	Link
27	11/06/2018	Cyber-Related; CAATSA	OFAC sanctioned 3 Russian individuals and 4 entities for cyber activities linked to the Russian Federal Security Service (FSB). The sanctioned entities—Digital Security, Divetechnoservices, Kvant Scientific Research Institute, and Embedi—were accused of enabling FSB operations, including cyber intrusions. The individuals designated were affiliated with these companies. These measures were taken under the Cyber-related Sanctions and CAATSA-Russia authorities, aiming to disrupt Russian state-backed malicious cyber capabilities and hold enablers accountable. The actions reflect broader efforts to deter threats to U.S. national security from Russia's cyber infrastructure and intelligence services.		✓	Link
28	20/09/2018	CAATSA	The U.S. sanctioned China's Equipment Development Department and its director for significant transactions with Russia's defense sector under CAATSA. While not targeting Russian entities directly, the action enforced secondary sanctions for procuring Russian military equipment, reinforcing pressure on Russia's arms industry through third-party enforcement.		✓	Link
29	08/11/2018	CAATSA; Ukraine-/Russia-related	OFAC sanctioned 3 individuals and 8 entities under Ukraine-/Russia-related and CAATSA authorities. Targets included officials and businesses supporting Russia's occupation of Crimea and control in Eastern Ukraine. Designated entities operate in infrastructure, energy, and tourism, primarily registered in Crimea under Russian jurisdiction. The Ministry of State Security in Luhansk was also sanctioned. These actions reinforce efforts to hold accountable those enabling Russia's destabilizing activities in Ukrainian territory.		✓	Link
30	19/12/2018	Cyber-Related; Ukraine-/Russia-related	OFAC notified Congress it plans to lift sanctions on En+, Rusal, and EuroSibEnergo. Simultaneously, it designated 18 Russian individuals and 4 entities under CAATSA and cyber-related sanctions. Those targeted were linked to the Main Intelligence Directorate and Russian influence operations, including election interference and disinformation campaigns. Entities included media and online outlets such as USA Really and Federal News Agency, tied to coordinated cyber and propaganda activities supporting malign state interests.		✓	Link

Table B.I. List of the US Treasury's Office of Foreign Assets Control (OFAC) sanctions announcements against Russia in 2013-2019 (*concluded*)

N	Date	Program	Content	Sanctions type		Source
				SSI	SDN	
31	27/01/2019	Ukraine-/Russia-related	OFAC lifted sanctions on En+, Rusal, and EuroSibEnergo.		✓	Link
32	15/03/2019	Ukraine-/Russia-related	OFAC sanctioned 6 Russian officials and 8 Russian entities over continued aggression in Ukraine. Those designated included senior figures from the Federal Security Service and Crimea-based institutions. Sanctioned entities spanned the shipbuilding, defense, and construction sectors, including firms like PAO Zvezda, Yaroslavsky Shipbuilding Plant, and Zelenodolsk Shipyard. These actions targeted Russia's role in undermining Ukrainian sovereignty, particularly in Crimea and eastern Ukraine, and aimed to increase pressure on Kremlin-linked operations and infrastructure.		✓	Link
33	16/05/2019	Magnitsky	OFAC designated five Russian individuals and one entity under the Magnitsky Act for involvement in the Sergei Magnitsky case and gross human rights violations. Sanctioned persons include officials linked to Russia's penal system and security services. The Terek Special Rapid Response Team, a Chechen SOBR unit, was also designated for its involvement in serious abuses. These actions target individuals and institutions complicit in repression, abuse, and impunity within Russia.		✓	Link
34	26/09/2019	Ukraine-/Russia-related	OFAC sanctioned 3 Russian individuals, 1 company, and 5 Russia-flagged vessels for facilitating jet fuel deliveries to Russian forces in Syria via Crimea. The individuals held executive positions at Sovfracht, while Maritime Assistance LLC supported the scheme. The vessels (OT-2077, PASSAT, SIG, SUDAK, YAZ) were linked to TransPetroChart Co. Ltd. These actions targeted efforts to evade sanctions and support Russia's military operations in Syria through Crimea-based logistics.		✓	Link
35	30/09/2019	Ukraine-/Russia-related	OFAC sanctioned 2 Russian individuals and 3 Seychelles-based shell companies for involvement in election interference and cyber activities linked to Yevgeniy Prigozhin and the Internet Research Agency (a Russian troll farm engaged in disinformation). 1 vessel and 3 aircraft tied to these firms were also designated. Updates to 8 existing designations added election-related authorities. These actions target Russian efforts to undermine U.S. elections through coordinated online influence and sanctions evasion.		✓	Link
36	05/12/2019	Cyber-Related	OFAC sanctioned 17 Russian cyber operators and corporate facilitators and 7 Russian entities linked to Evil Corp, a Russia-based cybercriminal group responsible for the Dridex malware (a banking Trojan that steals credentials and financial data). The designated individuals operated from Moscow and coordinated with shell companies to facilitate cybercrime activities. These sanctions aim to disrupt Evil Corp's global malware distribution infrastructure, which has compromised financial institutions and critical infrastructure worldwide, and to block the group's access to the international financial system used to launder illicit profits.		✓	Link
37	13/12/2019	Cyber-Related	OFAC delisted 3 Russia-based entities previously sanctioned for supporting cyber operations linked to Evil Corp (see the announcement from 05/12/2019). The removed entities had facilitated operations for cyber operators and corporate enablers. This update reflects administrative changes and does not signal a shift in US sanctions policy toward Russian cyber actors or their facilitators.		✓	Link

Note: This table presents the list of OFAC sanctions announcements against Russia in the 2010s and their short descriptions. *SSI* stands for "Sectoral Sanctions Identification" list and *SDN* means "Specially Designated Nationals." SSI applies to entities operating in specific industries, such as energy, finance, and defense, whose new debt placement of specified duration is prohibited in the US. SDN applies to entities and individuals whose assets are blocked and all operations are prohibited with them within the US. We include sanctions introduced under (1) Russia-related programs: Magnitsky Sanctions, (2) Ukraine-/Russia-related Sanctions, (3) Cyber-Related Sanctions, and (4) CAATSA (The Countering America's Adversaries Through Sanctions Act). We exclude several sanctions introduced on Russian individuals and entities outside Russia under programs other than Russia-related: Syria, Iran, Venezuela, and Global Magnitsky programs.

B.2 Russia's U.S. Dollar-denominated sovereign bonds

To calculate average bond yield changes around sanctions announcement dates, we assemble a time series of average Russian foreign currency bond yields. To do that, we requested data from the Refinitiv Eikon on September 9-12, 2022. Request parameters: all Russian foreign-currency denominated (effectively, US-denominated) government bonds that were actively traded in 2012-2022, entire history, daily frequency. Note that the macroeconomic data we use in the paper spans the period until the end of 2018. To maintain comparability of average bond yield changes across time, we preserve the composition of the bond portfolio over the period for which we have announcements of sanctions and which overlap with the macroeconomic data. Therefore, we exclude bonds matured in 2015-2018 from the calculation of the average yields and include only bonds traded during September 2013 to December 2018. We thus include eight bond issues to form a stable bond portfolio. To calculate the average bond yield, we weight them equally. In Table B.II, we present the list of available bonds and bonds selected for average yield calculation.

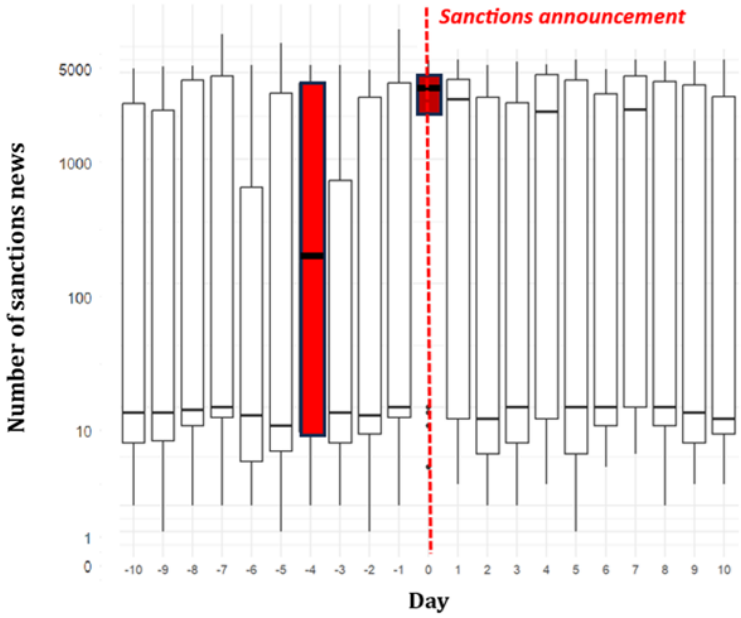
Table B.II. The list of Russia's US Dollar-denominated sovereign bonds

Eikon Identifier	Maturity date	Coverage from	Included in the average
RUGV 4.5000	04-Apr-2022	29-Mar-2012	1
RUGV 3.6250	16-Sep-2022	13-Sep-2013	1
RUGV 3.2500	04-Apr-2017	29-Mar-2012	0
RUGV 5.0000	29-Apr-2020	23-Apr-2010	1
RUGV 4.5000	04-Apr-2022	29-Mar-2012	1
RUGV 3.5000	16-Jan-2019	11-Sep-2013	1
RUGV 3.2500	04-Apr-2017	29-Mar-2012	0
RUGV 3.5000	16-Jan-2019	10-Sep-2013	1
RUGV 11.0000	24-Jul-2018	14-Feb-2001	0
RUGV 5.0000	29-Apr-2020	22-Apr-2010	1
RUGV 3.6250	29-Apr-2015	30-Apr-2010	0
RUGV 3.6250	16-Sep-2020	11-Sep-2013	1
RUGV 11.0000	24-Jul-2018	19-Aug-2005	0

Source: Refinitiv Eikon.

B.3 Media Evidence of Pre-Announcement Sanctions Leakages

Figure B.I. An Intensity of Media Coverage of Sanctions Against Russia Around OFAC Announcements



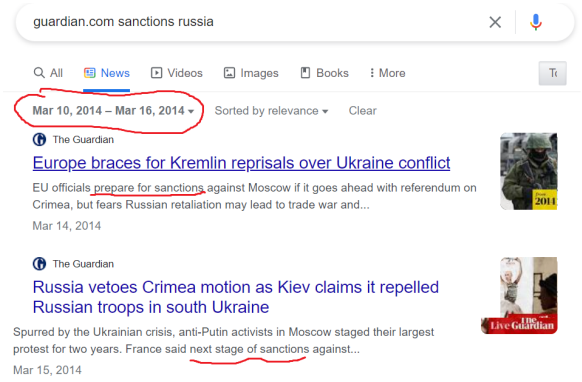
Note: This figure reports the number of news articles that mention both "sanctions" and "Russia" in selected international media sources (B.II) within a window centered on OFAC sanctions announcement dates. The horizontal axis spans 10 days before to 10 days after each announcement.

Figure B.II. Major International Media Sources Used in the Sanctions Textual Analysis

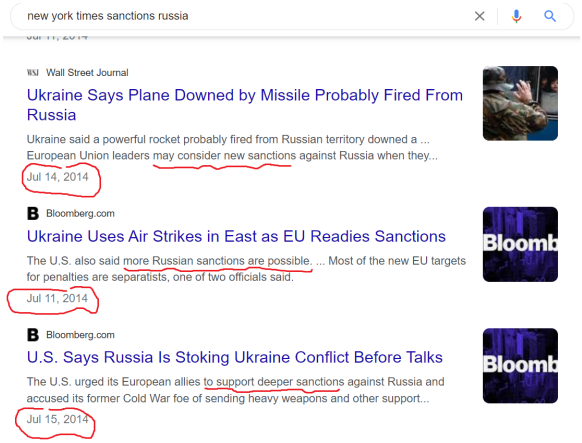


Note: This figure displays a word cloud of major international media outlets covering sanctions against Russia around the 37 OFAC sanctions announcements during the 2010s. The size of each outlet's name reflects the relative number of articles mentioning both "Russia" and "sanctions" during the pre-announcement windows, capturing the prominence of each source in the dataset.

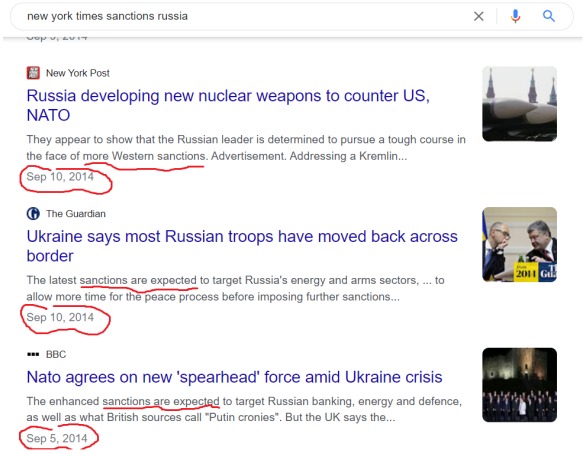
Figure B.III. Evidence of Sanctions Anticipation in Global Media Before OFAC Announcements



(a) During the week before OFAC announcement on March 17, 2014



(b) During the week before OFAC announcement on July 16, 2014

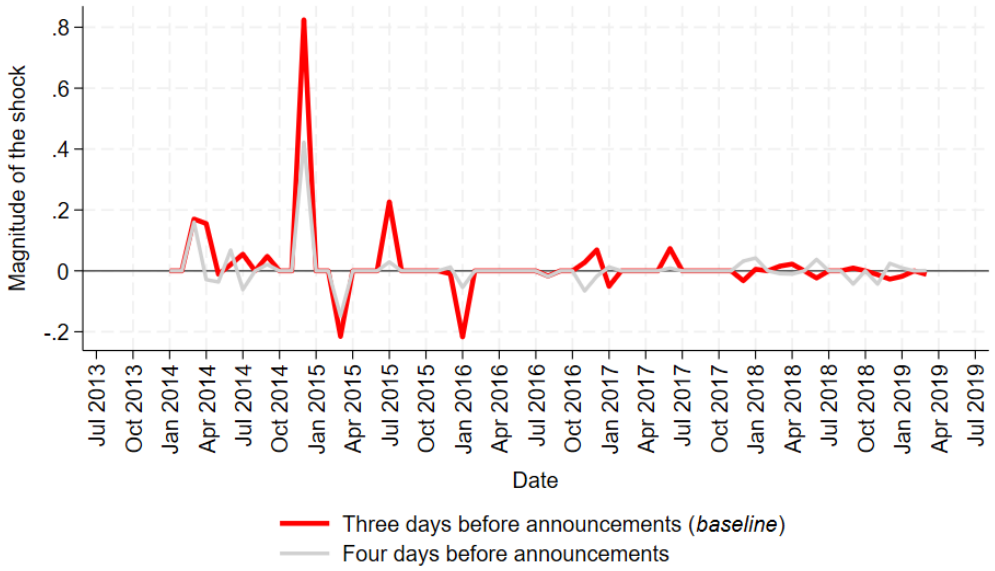


(c) During the week before OFAC announcement on Sept. 12, 2014

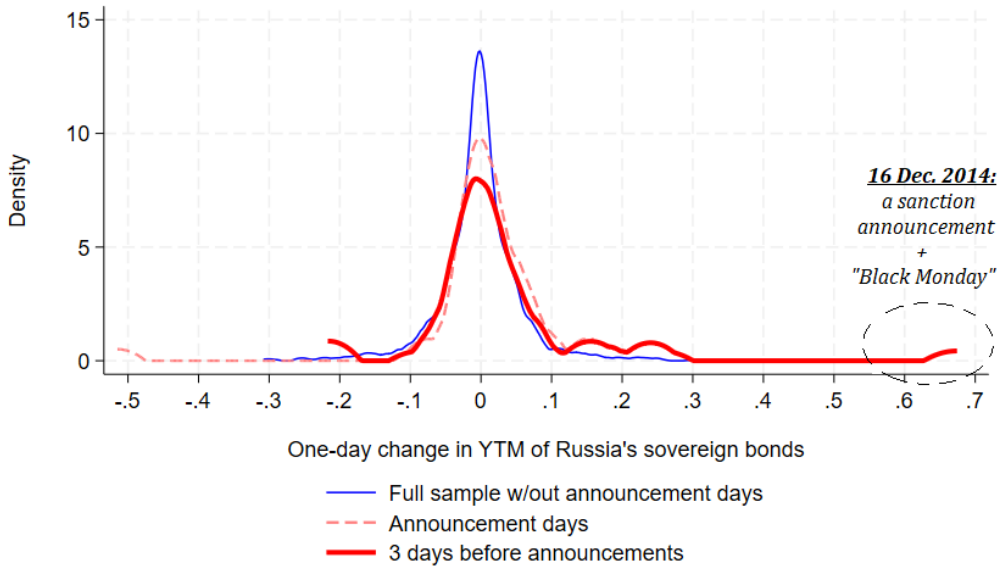
Note: This figure shows Google News search results for articles containing the terms "Russia" and "sanctions" and the name of a major media outlet, during the seven-day period preceding selected OFAC sanctions announcements. Panel (*a*) refers to the March 17, 2014 announcement; panel (*b*) to July 16, 2014; and panel (*c*) to September 12, 2014. These articles document public signals or speculation about forthcoming sanctions, suggesting potential pre-announcement information leakages.

B.4 The baseline sanctions news shock ($z_{-3,t}$)

Figure B.IV. The baseline sanctions news shock



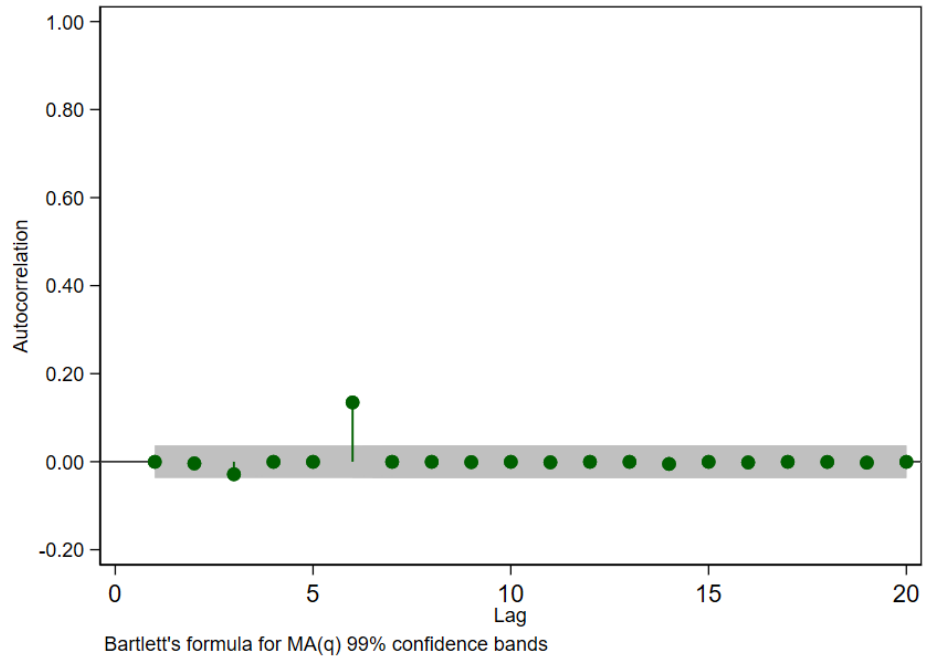
(a) Time evolution (monthly frequency)



(b) Empirical distribution

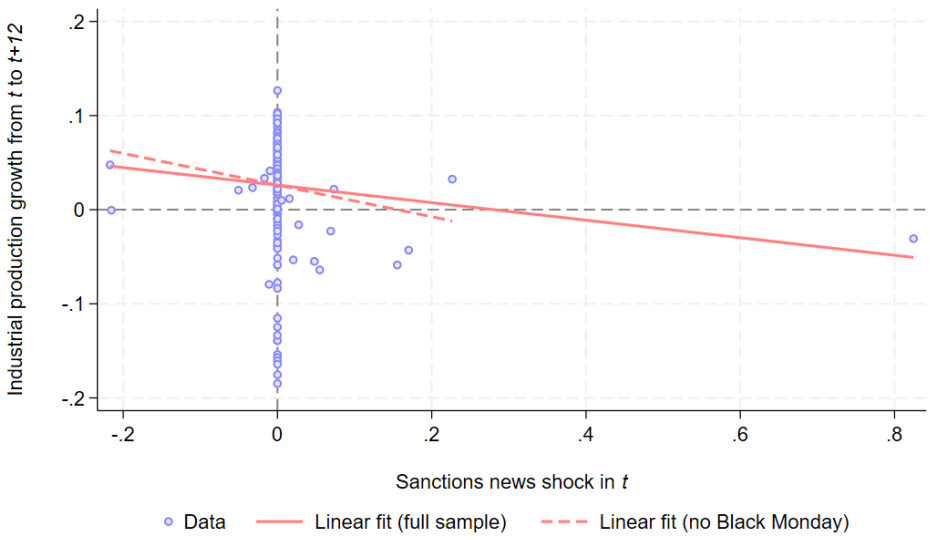
Note: This figure illustrates the time evolution and empirical distribution of the baseline sanctions news shock $z_{-3,t}$. The variable $z_{-3,t} \equiv \text{Surprise}_{-3,t}$ is constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds (see Table B.II) occurring between days $d-4$ and $d-3$ relative to each OFAC sanctions announcement on day d within month t. Subfigure (a) plots the monthly series of $z_{-3,t}$ alongside its nearest neighbor $z_{-4,t}$, which corresponds to the window $d-5$ to $d-4$. Our textual analysis (Figure B.I) documents pronounced spikes in sanctions-related media coverage during this earlier window, consistent with information leakage prior to formal announcements. Subfigure (b) compares the empirical distribution of $z_{-3,t}$ (baseline; $N = 37$, *solid red line*) with that of $z_{0,t}$ (announcement-day surprise; $N = 37$, *dashed light-red line*) and with the distribution of daily YTM changes computed over a subsample excluding the 37 OFAC sanctions announcement days (from 13 September 2013 to 31 December 2019; $N = 1{,}952$, *solid blue line*).

Figure B.V. Autocorrelation of the baseline sanctions news shock



Note: This figure reports the autocorrelation function of the baseline sanctions news shock $z_{-3,t}$ computed at the daily frequency over the preceding 21 days. Green markers denote point estimates of the autocorrelation coefficients, while the shaded grey area represents 99% confidence bands constructed using Bartlett's $MA(q)$ approximation. The absence of economically meaningful serial correlation supports the interpretation of $z_{-3,t}$ as a plausibly exogenous news shock.

Figure B.VI. Future industrial production growth and the baseline sanctions news shock



Note: This figure reports the baseline sanctions news shock $z_{-3,t}$ against future industrial production growth. Solid red line denotes linear fit estimated on all sample points while dotted red line presents linear fit if the largest shock is excluded (Black Monday of December 2014).

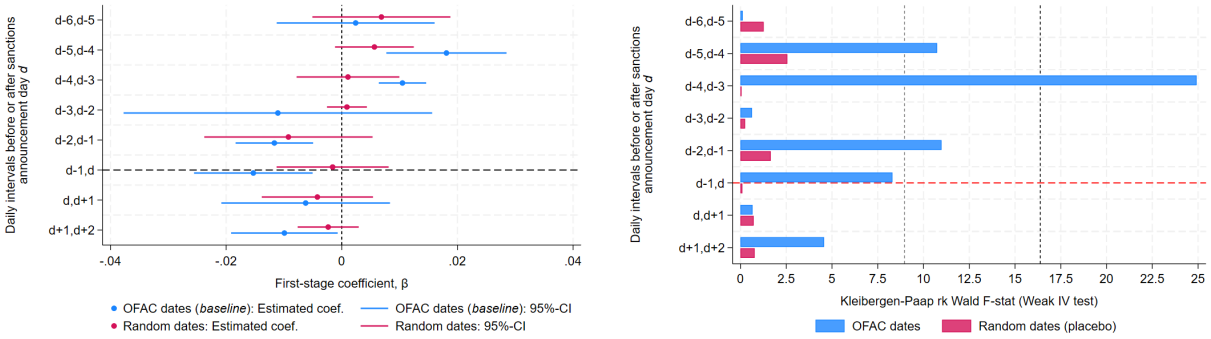
Appendix C Placebo 1: Random dates

Table C.I. The list of random dates excluding OFAC sanctions announcement dates

#	Random date	Distance to OFAC sanctions announcements	
		Previous announcement (*days before*)	Next announcement (*days after*)
1	23-Jan-2013		79
2	19-Apr-2013	-7	332
3	18-Jul-2013	-97	242
4	21-Oct-2013	-192	147
5	30-Oct-2013	-201	138
6	19-Nov-2013	-221	118
7	3-Dec-2013	-235	104
8	8-Jan-2014	-271	68
9	12-Feb-2014	-306	33
10	19-Feb-2014	-313	26
11	1-Aug-2014	-3	42
12	13-Oct-2014	-31	67
13	14-Oct-2014	-32	66
14	18-Feb-2015	-51	21
15	17-Mar-2015	-6	135
16	29-May-2015	-79	62
17	22-Jun-2015	-103	38
18	17-Oct-2016	-46	28
19	25-Dec-2016	-5	4
20	30-Jan-2017	-21	141
21	8-Mar-2017	-58	104
22	11-Jun-2017	-153	9
23	29-Jun-2017	-9	174
24	29-Sep-2017	-101	82
25	25-Dec-2017	-4	32
26	3-May-2018	-27	39
27	12-Jun-2018	-1	100
28	20-Jun-2018	-9	92
29	22-Jun-2018	-11	90
30	17-Aug-2018	-67	34
31	21-Aug-2018	-71	30
32	12-Feb-2019	-15	31
33	19-Mar-2019	-4	58
34	12-Jun-2019	-27	106
35	8-Jul-2019	-53	80
36	13-Sep-2019	-120	13
37	21-Sep-2019	-128	5

Note: This table shows random dates within the sanctions period in 2013–2019 and checks if there are any overlaps with sanctions announcement dates over the same period. We generate the random dates by constructing the full daily calendar for 1 January 2014–31 December 2019 and retaining only weekdays. From this set, we exclude all official US OFAC sanctions announcement dates and the five days immediately preceding or following each announcement. We further sample 37 placebo dates—as many as OFAC sanctions announcements—uniformly without replacement from the remaining eligible days. We set a fixed random seed to ensure identical results across replications.

Figure C.I. First-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random dates (placebo)

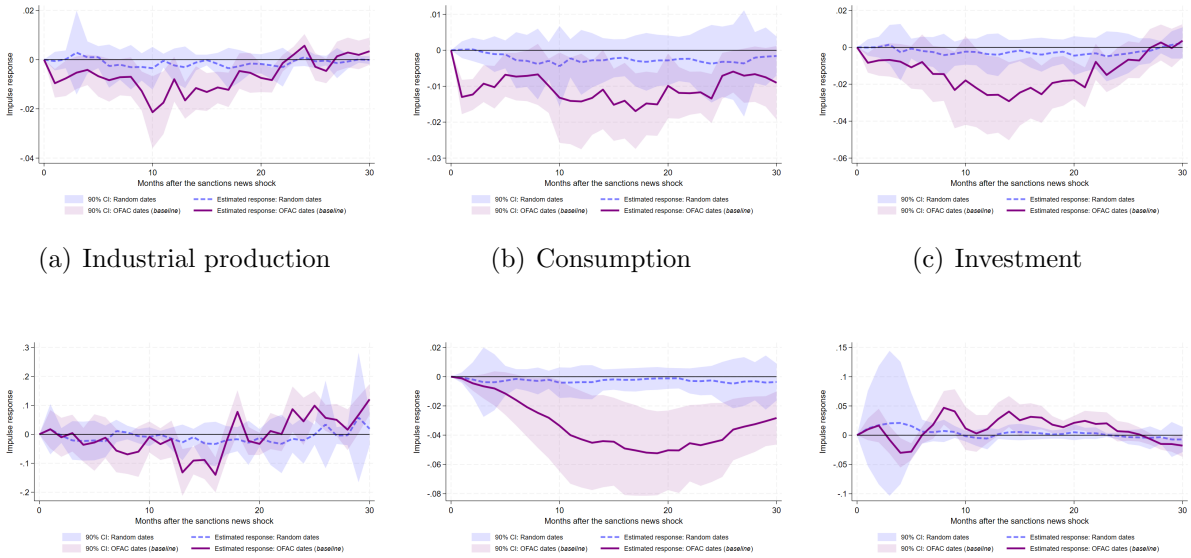


(a) First-stage estimates β_k

(b) Robust F-statistics

Note: This figure compares the baseline first-stage estimates from the LP–IV approach (*blue*), reported in Figure 2 in the main text, with placebo estimates based on 37 randomly selected dates listed in Table C.I (*red*). In panel (*a*), we plot the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$, together with the corresponding k-th placebo estimates. Panel (*b*) reports the associated robust F-statistics for both the baseline and placebo estimates, along with the Stock–Yogo weak identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). The instrument $z_{k,t} = \text{Surprise}_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC sanctions announcement on day d within month t. The corresponding k-th placebo instrument is constructed analogously, replacing OFAC announcement dates with placebo dates. Each first-stage regression controls for all other right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey-West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure C.II. Second-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random dates (placebo)



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares the baseline second-stage estimates from the LP–IV approach (*purple*), reported in Figure 3 in the main text, with placebo responses constructed using 37 randomly selected dates listed in Table C.I (*dashed blue*). The baseline responses correspond to the coefficients $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variables ($i = 1, \ldots, 6$) and h denotes the forecast horizon ($h = 1, \ldots, 30$). For each horizon h, $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread induced by the baseline sanctions news shock $z_{-3,t}$ (see Figure 2). Placebo responses are obtained by re-estimating the second-stage LP–IV model using placebo instruments constructed analogously to the baseline shock, but replacing OFAC sanctions announcement dates with the 37 randomly selected placebo dates. All variables are expressed in logarithms. The estimates are obtained using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and 90% confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to h months. A small-sample degrees-of-freedom adjustment is applied.

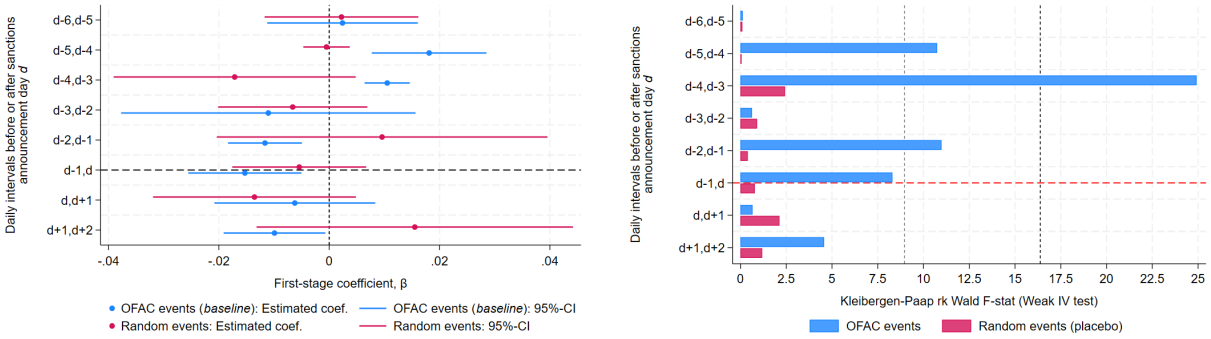
Appendix D Placebo 2: Random events

Table D.I. The list of random dates excluding OFAC sanctions announcement dates

#	Random event:				Distances to OFAC sanctions announcements:	
	Date	Category	Description	Source	Previous (*days before*)	Next (*days after*)
Panel 1: Before the sanctions period:						
1	1-Oct-2002	Social Policy	Launch of Maternity Capital policy discussions	rg.ru		
2	7-Dec-2003	Election	State Duma elections held	Wikipedia		
3	22-Jun-2005	Economic Policy	Rosstat reports 6.1% GDP growth for H1 2005	Rosstat		
4	1-Oct-2006	Social	Launch of national 'Health' project	Kremlin.ru		
5	25-Apr-2007	Statistics	Rosstat releases inflation forecast for 2007 (8%)	Rosstat		
6	2-Mar-2008	Election	Dmitry Medvedev elected President	Wikipedia		
7	1-Jul-2009	Infrastructure	Opening of St. Petersburg Ring Road	SPBGUP		
8	1-Oct-2010	Census	Russia's national population census begins	Wikipedia		
9	4-Dec-2011	Election	Parliamentary elections held	Wikipedia		
10	4-Mar-2012	Election	Vladimir Putin elected for 3rd presidential term	Wikipedia		
11	1-Aug-2012	Economic Reform	New labor law amendments introduced	Consultant.ru		
Panel 2: During the sanctions period:						
12	10-Oct-2013	Statistics	Industrial production report release (0.3% YoY)	Rosstat	-181	158
13	7-Feb-2014	Sports	Sochi Winter Olympics opening ceremony	Wikipedia	-301	38
14	21-May-2014	Energy Policy	Russia and China sign $400bn gas deal	BBC	-1	30
15	30-Nov-2015	Climate	Russia joins the Paris Climate Agreement	Interfax	-123	22
16	18-Sep-2016	Election	State Duma elections held	Wikipedia	-17	57
17	15-Dec-2016	Statistics	Life expectancy increases to 71.9 years	Rosstat	-31	5
18	26-Mar-2017	Social Movement	Anti-corruption protests held across major cities	Reuters	-76	86
19	1-Oct-2017	Tax Reform	VAT exemptions modified for several food sectors	Kommersant	-103	80
20	14-Jun-2018	Sports	FIFA World Cup opens in Moscow	Wikipedia	-3	98
21	1-Oct-2018	Social Reform	Pension reform goes into effect	TASS	-11	38
22	28-Dec-2018	Statistics	Rosstat revises GDP growth upward for 2018	Rosstat	-9	31
23	1-Jan-2019	Policy	Minimum wage increase to 11,280 rubles/month	rbc.ru	-13	27
24	18-Mar-2019	Infrastructure	Crimean Bridge railway section completed	RT	-3	59
25	1-Apr-2019	Statistics	Unemployment rate falls to lowest 4.7%	Rosstat	-17	45
26	20-Jun-2019	Social Event	Moscow hosts International Economic Forum	WEF	-35	98
27	1-Jul-2019	Ministry Report	GDP forecast downgraded to 1.3%	Vedomosti.ru	-46	87
28	1-Aug-2019	Environment	Siberian forest fire emergency declaration	BBC	-77	56
29	8-Sep-2019	Election	Moscow City Duma elections	Wikipedia	-115	18
30	9-Oct-2019	Social Event	Opening of Moscow Urban Forum	rbc.ru	-9	57

Note: This table shows the list of 30 domestic random events in Russia over the entire sample period of 2000–2019. We generate this list using ChatGPT 5.1, with the only non-random condition: that the drawn events do not not overlap with the OFAC sanctions announcements and the five days immediately preceding each announcement. The table also categorizes the obtained events, provides their short description and source, and computes the distances to preceding and subsequent sanctions announcements.

Figure D.I. First-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random events (placebo)

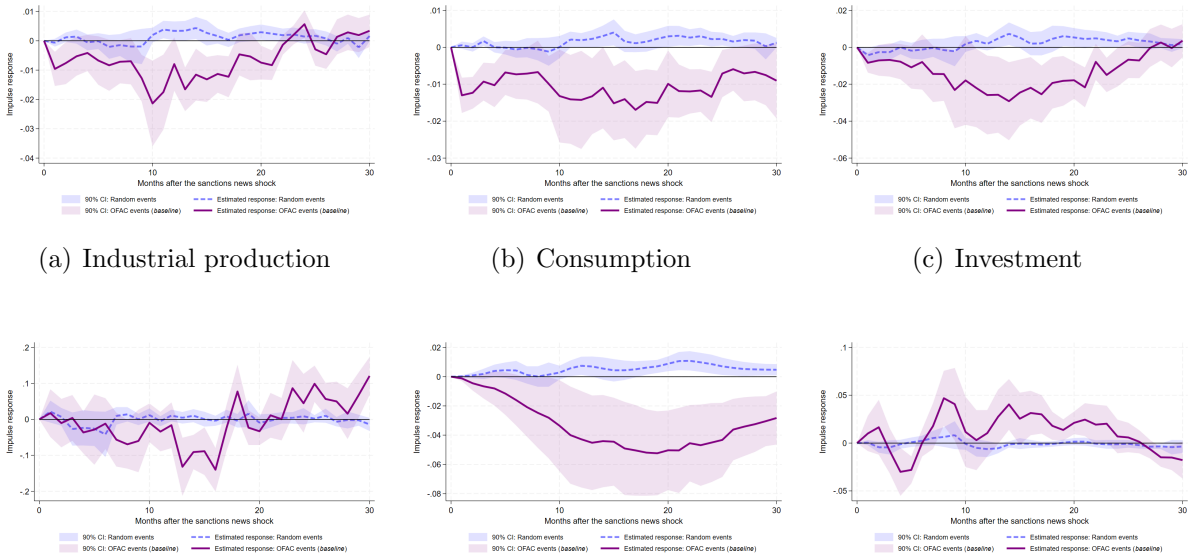


(a) First-stage estimates β_k

(b) Robust F-statistics

Note: This figure compares the baseline first-stage estimates from the LP–IV approach (*blue*), reported in Figure 2 in the main text, with placebo estimates based on 30 randomly selected domestic events listed in Table D.I (*red*). In panel (*a*), we plot the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$, together with the corresponding k-th placebo estimates. Panel (*b*) reports the associated robust F-statistics for both the baseline and placebo estimates, along with the Stock–Yogo weak identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). The instrument $z_{k,t} = \text{Surprise}_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC sanctions announcement on day d within month t. The corresponding k-th placebo instrument is constructed analogously, replacing OFAC announcement dates with placebo events. Each first-stage regression controls for all other right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey-West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure D.II. Second-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random events (placebo)



(a) Industrial production (b) Consumption (c) Investment

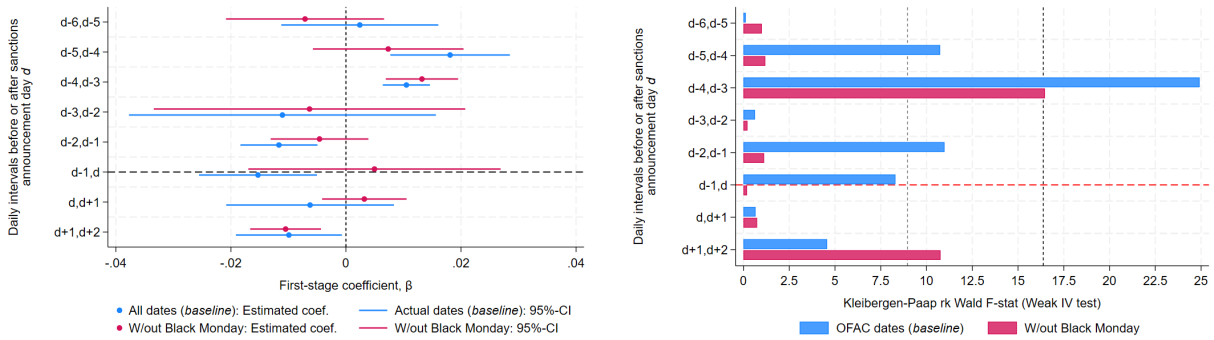
(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares the baseline second-stage estimates from the LP-IV approach (*purple*), reported in Figure 3 in the main text, with placebo responses constructed using 30 randomly selected domestic events listed in Table D.I (*dashed blue*). The baseline responses correspond to the coefficients $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variables ($i = 1, \ldots, 6$) and h denotes the forecast horizon ($h = 1, \ldots, 30$). For each horizon h, $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread induced by the baseline sanctions news shock $z_{-3,t}$ (see Figure 2). Placebo responses are obtained by re-estimating the second-stage LP–IV model using placebo instruments constructed analogously to the baseline shock, but replacing OFAC sanctions announcement dates with the 30 randomly selected placebo events. All variables are expressed in logarithms. The estimates are obtained using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and 90% confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to h months. A small-sample degrees-of-freedom adjustment is applied.

Appendix E The role of domestic monetary policy

E.1 Excluding the coincidence with the "Black Monday" shock

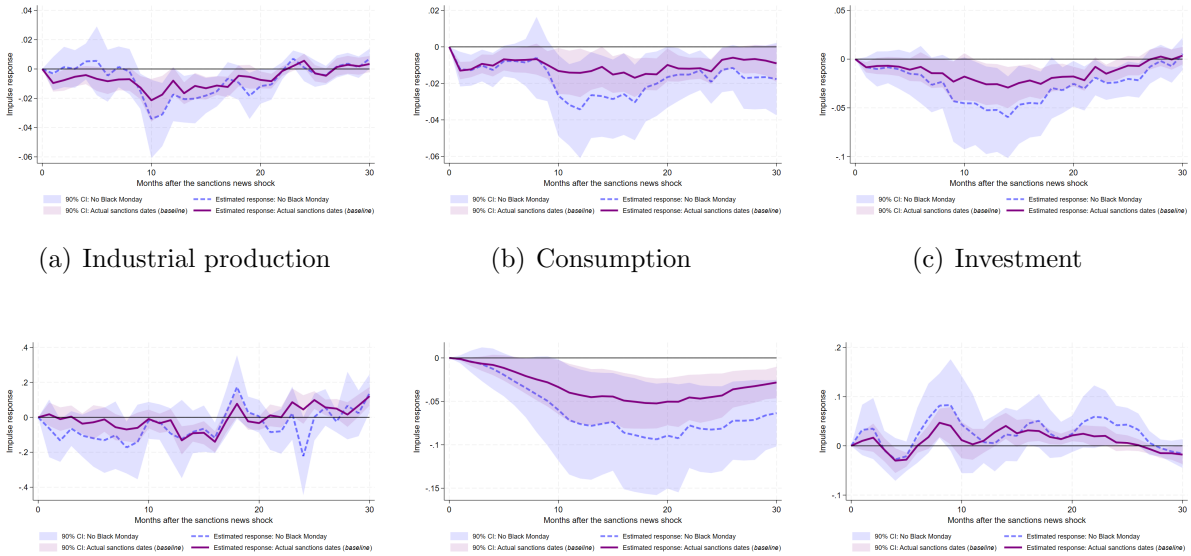
Figure E.I. First-stage LP–IV estimates: Sanctions news shocks with *vs* without the "Black Monday" episode



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares the baseline first-stage LP–IV estimates (*blue*), reported in Figure 2 in the main text, with alternative estimates obtained from a subsample that excludes one of the 37 OFAC sanctions announcements, dated 19 December 2014 (*red*). This announcement occurred three days after the well-known "Black Monday" episode of 16 December 2014, when the Central Bank of Russia raised its policy rate by 650 basis points in response to surging inflation and a sharp ruble depreciation following the collapse in global oil prices. This monetary policy shock was unrelated to sanctions and may confound inference around that episode. The purpose of this robustness exercise is to show that the baseline finding—that the effect of sanctions on Russia's country spread materializes at least three days prior to the announcement (the $k = -3$ case)—is not driven by the coincidence of monetary policy shocks and forthcoming sanctions announcements. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$, together with the corresponding estimates obtained when the 19 December 2014 announcement is excluded. Panel (*b*) reports the associated robust F-statistics for both specifications, along with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). The instrument $z_{k,t} = \mathit{Surprise}_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC sanctions announcement on day d within month t. The alternative k-th instrument is constructed analogously, but excludes the 19 December 2014 announcement. Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure E.II. Second-stage LP-IV estimates: Sanctions news shock with *vs* without the "Black Monday" episode



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares baseline second-stage impulse response estimates from the LP–IV approach, reported in Figure 3 in the main text (*purple*), with alternative estimates obtained from a subsample that excludes the OFAC sanctions announcement dated 19 December 2014 (*dashed blue*). This announcement occurred three days after the "Black Monday" episode of 16 December 2014, when the Central Bank of Russia raised its policy rate by 650 basis points in response to surging inflation and a sharp ruble depreciation following the collapse in global oil prices. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the horizon in months ($h = 1, \ldots, 30$). For each horizon h, $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread induced by the sanctions news shock $z_{-3,t}$ constructed either with or without the "Black Monday" episode (see Figure 2). All variables are expressed in logarithms. The estimates are obtained using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and 90% confidence intervals are computed using the Newey-West estimator, with the maximum autocorrelation lag set equal to h months. A small-sample degrees-of-freedom adjustment is applied.

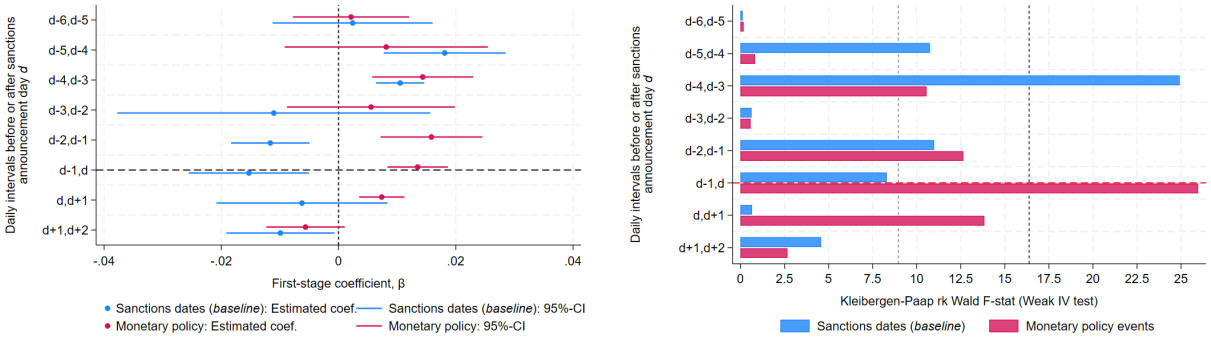
E.2 Comparing with domestic monetary policy announcements

Table E.II. Domestic monetary policy announcements, 2014–2019

#	Meeting date	The key rate:		Distances to preceding and subsequent OFAC sanctions announcements:		Excluded from the analysis
		Decision	Magnitude, %	Previous (*days before*)	Next (*days after*)	
1	2/14/2014	–	5.5	-308	31	
2	3/3/2014	↑	7	-325	14	
3	3/14/2014	–	7	-336	3	✓
4	4/25/2014	↑	7.5	-14	3	
5	6/16/2014	–	7.5	-27	4	✓
6	7/25/2014	↑	8	-9	4	
7	9/12/2014	–	8	-45	0	✓
8	10/31/2014	↑	9.5	-49	49	
9	12/11/2014	↑	10.5	-90	8	
10	12/15/2014	↑	17	-94	4	
11	1/30/2015	↓	15	-32	40	
12	3/13/2015	↓	14	-2	139	
13	4/30/2015	↓	12.5	-50	91	
14	6/15/2015	↓	11.5	-96	45	
15	7/31/2015	↓	11	-1	144	
16	9/11/2015	–	11	-43	102	
17	10/30/2015	–	11	-92	53	
18	12/11/2015	–	11	-134	11	
19	1/29/2016	–	11	-38	3	✓
20	3/18/2016	–	11	-46	167	
21	4/29/2016	–	11	-88	125	
22	6/10/2016	↓	10.5	-130	83	
23	7/29/2016	–	10.5	-179	34	
24	9/16/2016	↓	10	-15	59	
25	10/28/2016	–	10	-57	17	
26	12/16/2016	–	10	-32	4	✓
27	2/3/2017	–	10	-25	137	
28	3/24/2017	↓	9.75	-74	88	
29	4/28/2017	↓	9.25	-109	53	
30	6/16/2017	↓	9	-158	4	
31	7/28/2017	–	9	-38	145	
32	9/15/2017	↓	8.5	-87	96	
33	10/27/2017	↓	8.25	-129	54	
34	12/15/2017	↓	7.75	-178	5	
35	2/9/2018	↓	7.5	-14	34	
36	3/23/2018	↓	7.25	-8	14	
37	4/27/2018	–	7.25	-21	45	
38	6/15/2018	–	7.25	-4	97	
39	7/27/2018	–	7.25	-46	55	
40	9/14/2018	↑	7.5	-95	6	
41	10/26/2018	–	7.5	-36	13	
42	12/14/2018	↑	7.75	-36	5	
43	2/8/2019	–	7.75	-11	35	
44	3/22/2019	–	7.75	-7	55	
45	4/26/2019	–	7.75	-42	20	
46	6/14/2019	↓	7.5	-29	104	
47	7/26/2019	↓	7.25	-71	62	
48	9/6/2019	↓	7	-113	20	
49	10/25/2019	↓	6.5	-25	41	
50	12/13/2019	↓	6.25	0	0	

Note: This table reports domestic monetary policy announcements by the Central Bank of Russia (CBR) between 2014 and 2019. The column "Decision" indicates whether the policy rate was increased (↑), decreased (↓), or left unchanged (−), while "Magnitude" reports the post-meeting level of the key policy rate (in percent). The columns "Preceding" and "Subsequent" report the number of calendar days between each monetary policy announcement and the nearest preceding and subsequent OFAC sanctions announcements, respectively. The final column indicates monetary policy announcements that are excluded from the analysis (marked by ✓) because they occur within a narrow window around OFAC sanctions announcements and may therefore confound the identification of sanctions-related news shocks. The data is sourced from CBR press-releases on interest rate announcements, cbr.ru.

Figure E.III. First-stage LP–IV estimates: Sanctions news shocks *vs* domestic monetary policy announcements

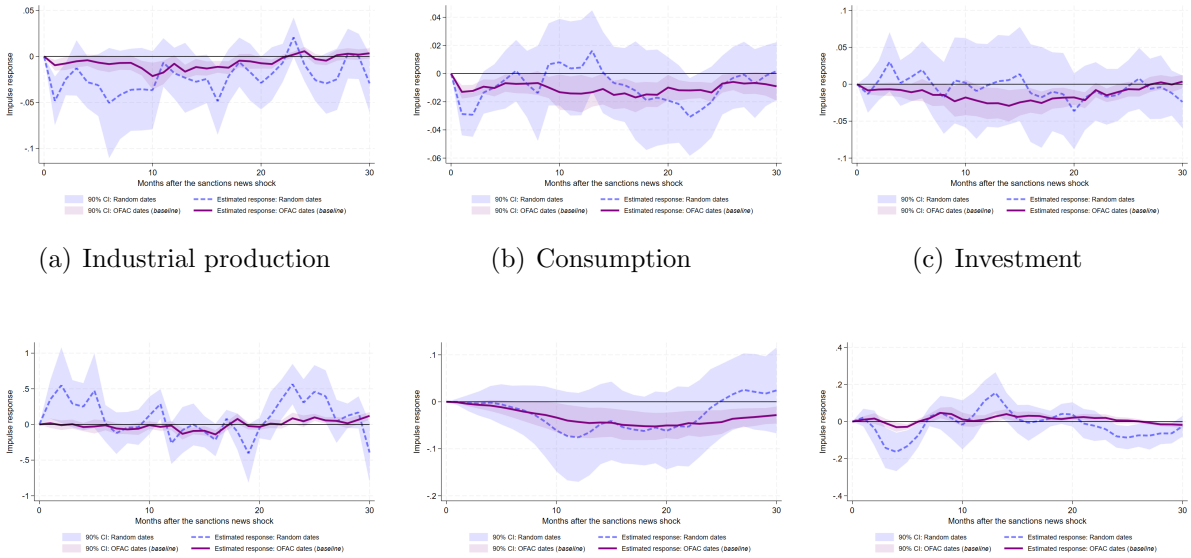


(a) First-stage estimates β_k

(b) Robust F-statistics

Note: This figure compares the baseline first-stage LP–IV estimates for the sanctions news shocks (*blue*), reported in Figure 2 in the main text, with corresponding first-stage estimates obtained using domestic monetary policy announcements as instruments (*red*), as summarized in Table E.II. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ $(k = -5, -4, \ldots, 2)$ on Russia's country spread $y_{1,t}$, where $z_{k,t}$ corresponds either to the sanctions news shock or to a shock associated with domestic monetary policy announcements. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). The instrument $z_{k,t} = \mathit{Surprise}_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC sanctions announcement on day d within month t. The k-th instrument based on domestic monetary policy announcements is constructed analogously, using the corresponding announcement dates. Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure E.IV. Second-stage LP-IV estimates: Sanctions news shock *vs.* domestic monetary policy announcements



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares baseline second-stage impulse response estimates from the LP–IV approach identified using sanctions news shocks (*purple*), reported in Figure 3 in the main text, with alternative second-stage estimates identified using domestic monetary policy announcements (*dashed blue*), as summarized in Table E.II. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$ constructed around OFAC sanctions announcements. In the alternative specification, the instrument is constructed analogously around domestic monetary policy announcement dates. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

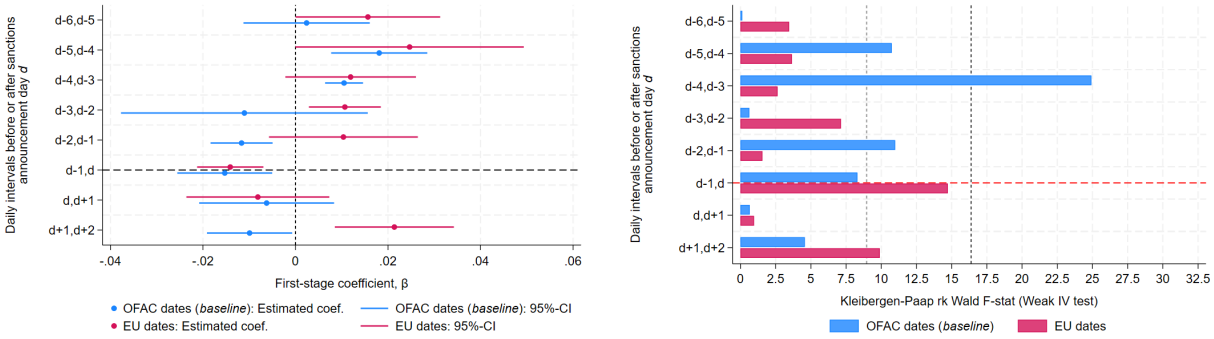
Appendix F EU sanctions announcements

Table F.I. EU sanctions announcements, 2013–2019

#	Meeting date	Sanctions:		Whether in a given window before, during, or after OFAC sanctions (in days)		
		Category	New = 1	$[-5,-1]$	0	$[1,5]$
1	3/17/2014	Individual and entities sanctions	1	0	1	0
2	3/20/2014	Individual and entities sanctions	1	0	1	0
3	4/15/2014	Individual and entities sanctions	1	0	0	1
4	5/12/2014	Individual and entities sanctions	1	0	1	0
5	6/23/2014	Trade	1	0	0	1
6	7/25/2014	Individual and entities sanctions	1	1	0	0
7	7/29/2014	Economic sanctions	1	0	1	0
8	9/12/2014	New economic sanctions	1	0	1	0
9	11/28/2014	Individual and entities sanctions extended	0	0	0	0
10	12/18/2014	Crimea investment ban	1	1	0	0
11	1/29/2015	Individual and entities sanctions extended	0	0	0	0
12	2/16/2015	Individual and entities sanctions extended	0	0	0	0
13	3/13/2015	Individual and entities sanctions extended	0	0	0	1
14	6/19/2015	Crimea-related economic sanctions extended	0	0	0	0
15	6/22/2015	Sectoral sanctions extended	0	0	0	0
16	9/14/2015	Individual and entities sanctions extended	0	0	0	0
17	12/21/2015	Sectoral sanctions extended	0	1	0	0
18	3/10/2016	Individual and entities sanctions extended	0	0	0	0
19	6/17/2016	Crimea-related economic sanctions extended	0	0	0	0
20	7/1/2016	Sectoral sanctions extended	0	0	0	0
21	11/9/2016	Individual and entities sanctions	1	1	0	0
22	12/19/2016	Sectoral sanctions extended	0	0	0	0
23	3/13/2017	Individual and entities sanctions extended	0	0	0	0
24	6/19/2017	Crimea-related economic sanctions extended	0	1	0	0
25	6/28/2017	Sectoral sanctions extended	0	0	0	0
26	8/4/2017	Individual and entities sanctions	1	0	0	0
27	9/14/2017	Individual and entities sanctions extended	0	0	0	0
28	11/21/2017	Individual and entities sanctions	1	0	0	0
29	12/21/2017	Sectoral sanctions extended	0	0	1	0
30	3/12/2018	Individual and entities sanctions extended	0	1	0	0
31	5/14/2018	Individual and entities sanctions	1	0	0	0
32	6/18/2018	Crimea-related economic sanctions extended	0	0	0	0
33	7/5/2018	Sectoral sanctions extended	0	0	0	0
34	7/31/2018	Individual and entities sanctions	1	0	0	0
35	9/13/2018	Individual and entities sanctions extended	0	0	0	0
36	12/10/2018	Individual and entities sanctions	1	0	0	0
37	12/21/2018	Sectoral sanctions extended	0	0	0	1
38	3/15/2019	Individual and entities sanctions	1	0	1	0
39	6/20/2019	Crimea-related economic sanctions extended	0	0	0	0
40	6/27/2019	Sectoral sanctions extended	0	0	0	0
41	9/12/2019	Individual and entities sanctions extended	0	0	0	0
42	12/19/2019	Sectoral sanctions extended	0	0	0	0

Note: This table reports European Union sanctions announcements against Russia between 2013 and 2019. The column "Category" describes the main type of restrictive measure adopted, while the indicator "New = 1" equals one for newly introduced sanctions and zero for extensions or renewals of existing measures. The last three columns indicate whether an EU sanctions announcement occurred within a five-day window before ($[-5,-1]$), on the same day (0), or within a five-day window after ($[1,5]$) a U.S. OFAC sanctions announcement. These indicators are used to assess the temporal proximity and potential overlap between EU and U.S. sanctions announcements when constructing alternative sanctions news shocks. The information is sourced from consilium.europa.eu.

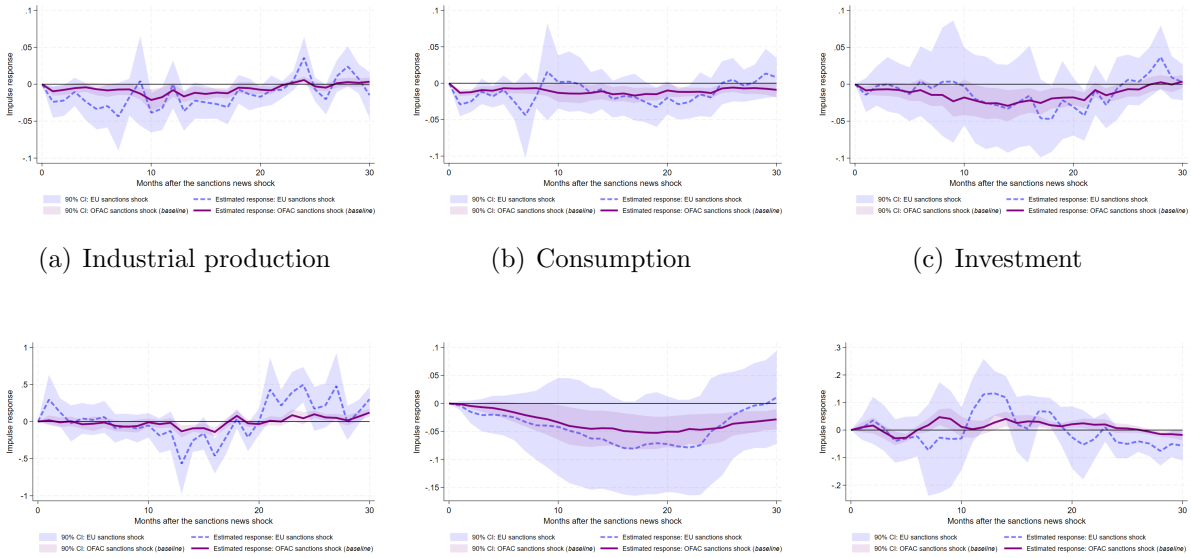
Figure F.I. First-stage LP–IV estimates: OFAC *vs* EU sanctions announcements



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares the baseline first-stage LP–IV estimates in which the sanctions news shocks is based on OFAC sanctions announcements (*blue*), reported in Figure 2 in the main text, with corresponding first-stage estimates obtained using EU sanctions announcements (*red*), as summarized in Table F.I. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$, where $z_{k,t}$ corresponds either to the OFAC-based or EU-based sanctions news shock. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). The instrument $z_{k,t} = Surprise_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC or EU sanctions announcement on day d within month t. Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure F.II. Second-stage LP–IV estimates: OFAC *vs* EU sanctions announcements



(a) Industrial production (b) Consumption (c) Investment

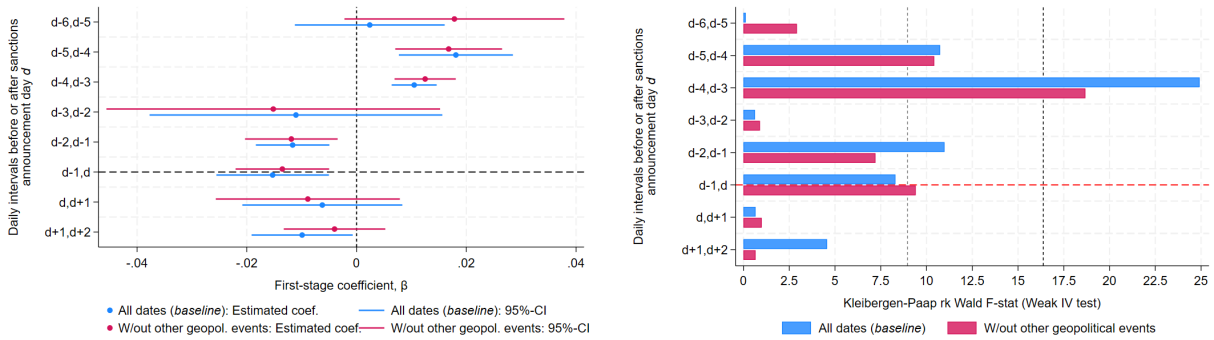
(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares baseline second-stage impulse response estimates from the LP–IV approach—where the sanctions news shock is constructed using OFAC sanctions announcements (*purple*), as reported in Figure 3 in the main text—with alternative second-stage estimates obtained by replacing OFAC with EU sanctions announcements (*dashed blue*), as summarized in Table F.I. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$ constructed around OFAC sanctions announcements. In the alternative specification, the instrument is constructed analogously around EU sanctions announcement dates. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix G Other geopolitical events

G.1 Excluding coincidences with other geopolitical events

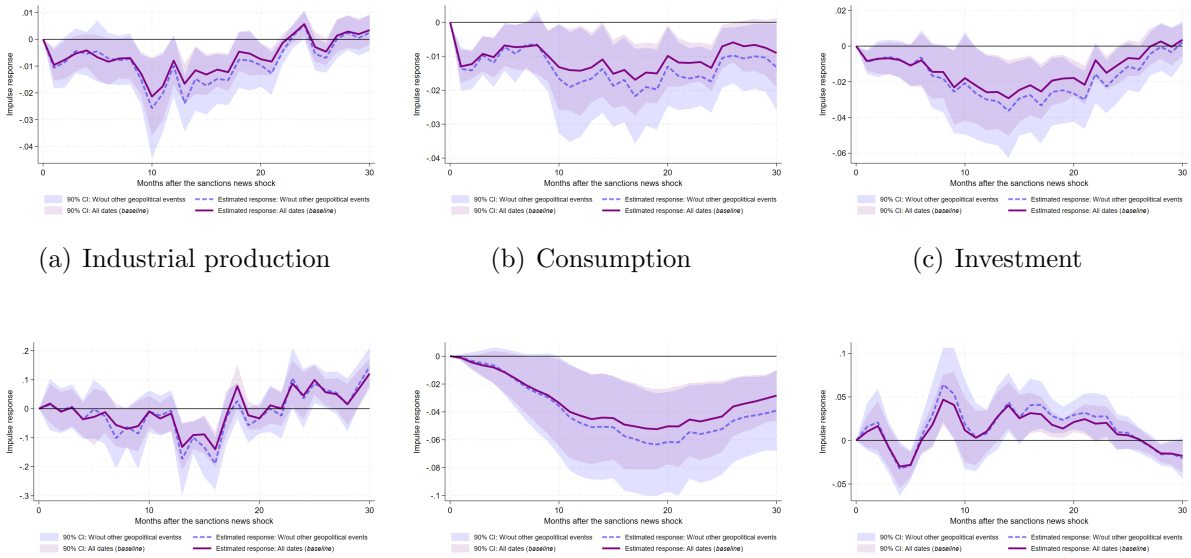
Figure G.I. First-stage LP–IV estimates: Sanctions news shocks with *vs* without coincidences with other geopolitical events



(a) First-stage estimates β_k (b) Robust F-statistics

This figure compares baseline first-stage LP–IV estimates (*blue*), reported in Figure 2 in the main text, with alternative first-stage estimates obtained after excluding OFAC sanctions announcements that coincide with major non-sanctions geopolitical events (*red*). An OFAC announcement date is excluded if it coincides with a substantial spike in the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022). We classify a spike as substantial when the one-day change in the index satisfies $\Delta \ln GPRD_d > \alpha_c$, where α_c is set to the 90th percentile of the distribution of $\Delta \ln GPRD_d$. Based on this criterion, the following OFAC sanctions announcements are excluded: 29 December 2014 (Turkey–Iraq border bombing targeting PKK positions), 1 February 2016 (major Syrian civil war fighting during the Aleppo offensive), 14 November 2016 (heightened post–U.S. election geopolitical uncertainty), 9 January 2017 (intensified U.S.–Russia cyber interference accusations), 21 December 2017 (spillovers from the UN resolution on Jerusalem adopted the previous day), and 5 December 2019 (U.S. Treasury warnings regarding global cyber risks). In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$ for both the baseline and restricted samples. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size. The instrument $z_{k,t} = Surprise_{k,t}$ is constructed by aggregating daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds over the interval from $d-k-1$ to $d-k$ around each OFAC sanctions announcement day d within month t. Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and confidence intervals are computed using Newey–West heteroskedasticity- and autocorrelation-consistent standard errors with the maximum autocorrelation lag set to 12 months.

Figure G.II. Second-stage LP–IV estimates: Sanctions news shocks with *vs* without coincidences with other geopolitical events



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares baseline second-stage impulse response estimates from the LP–IV approach (*purple*), reported in Figure 3 in the main text, with alternative estimates obtained after excluding OFAC sanctions announcements that coincide with major non-sanctions geopolitical events (*dashed blue*). An OFAC announcement date is excluded if it coincides with a substantial spike in the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022). We classify a spike as substantial when the one-day change in the index satisfies $\Delta \ln GPRD_t > \alpha_c$, where α_c is set to the 90th percentile of the annual distribution of $\Delta \ln GPRD_t$. Based on this criterion, the following OFAC sanctions announcements are excluded: 29 December 2014 (Turkey–Iraq border bombing targeting PKK positions), 1 February 2016 (major Syrian civil war fighting during the Aleppo offensive), 14 November 2016 (heightened post–U.S. election geopolitical uncertainty), 9 January 2017 (intensified U.S.–Russia cyber interference accusations), 21 December 2017 (spillovers from the UN resolution on Jerusalem adopted the previous day), and 5 December 2019 (U.S. Treasury warnings regarding global cyber risks). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread induced by the sanctions news shock $z_{-3,t}$. In the baseline specification, $z_{-3,t}$ is constructed using the full set of OFAC sanctions announcements. In the restricted specification, the instrument is constructed analogously but excludes sanctions announcements that overlap with major geopolitical events as identified by the GPRD criterion. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

G.2 Comparing with other geopolitical events

Table G.I. Major geopolitical events before and during the sanctions against Russia

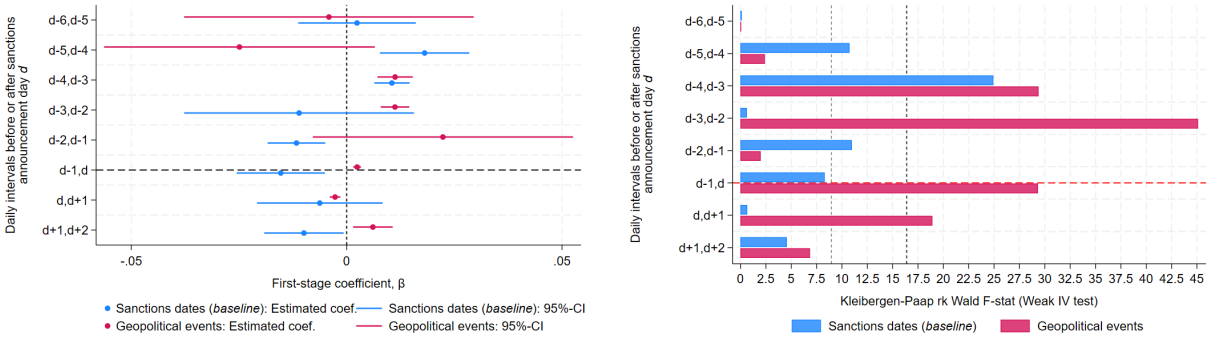
#	Events with $\Delta \ln GPR \geq \alpha_c$ in year t			Distances to OFAC sanctions announcements:	
	Date	Category	Description	Previous (*days before*)	Next (*days after*)
Panel 1: Before the sanctions against Russia					
1	29-Nov-2001	Afghanistan War	Northern Alliance advances against Taliban		
2	30-Nov-2001	Afghanistan War	Kabul stabilization operations intensify		
3	01-Dec-2001	Afghanistan War	US targets al-Qaeda Tora Bora		
4	02-Dec-2001	Afghanistan War	Heavy bombing around mountain hideouts		
5	03-Dec-2001	Afghanistan War	al-Qaeda resistance continues in caves		
6	04-Dec-2001	Afghanistan War	US escalates operations near Tora Bora		
7	05-Dec-2001	Terrorism	Strasbourg bombing plot uncovered		
8	25-Dec-2001	India–Pakistan Crisis	India–Pakistan mobilize after Parliament attack		
9	04-Apr-2002	Israel–Palestine Conflict	Israel advances into Jenin camp		
10	26-Aug-2002	Iraq War Buildup	US officials push Iraq intervention case		
11	21-Nov-2003	Major Terror Attack	Istanbul bombings hit bank, consulate		
12	22-Nov-2003	Major Terror Attack	Istanbul attack investigations widen internationally		
13	16-Mar-2004	Major Terror Attack	Madrid bombing network traced across Europe		
14	30-May-2004	Terrorism	Saudi militants attack oil facilities		
15	08-Jul-2005	London Bombings	London bombing aftermath investigations continue		
16	14-Jul-2005	London Bombings	UK expands counter-terrorism raids nationwide		
17	13-Nov-2006	Israel–Palestine Conflict	Israel–Gaza clashes escalate sharply		
18	14-Nov-2006	Iran Nuclear Standoff	UN debates sanctions on Iran		
19	01-Dec-2007	Pakistan Unrest	Venezuela referendum on presidential power		
20	28-Dec-2007	Pakistan Unrest	Pakistan destabilized after Bhutto assassination		
21	13-Aug-2008	Russia–Georgia Conflict	Fighting continues despite ceasefire agreement		
22	29-Oct-2008	Global Security Strike	US targets militants inside Syria		
23	26-Apr-2009	Pakistan Militancy	Pakistan launches Swat Valley offensive		
24	29-Dec-2009	Terrorism	Global probes follow failed airliner bombing		

Table G.I. Major geopolitical events before and after sanctions against Russia (*continued*)

#	Events with $\Delta \ln GPR \geq \alpha_c$ in year t			Distances to OFAC sanctions announcements:	
	Date	Category	Description	Previous (*days before*)	Next (*days after*)
25	19-May-2010	Korean Peninsula	North Korea blamed for Cheonan sinking		
26	02-Nov-2010	US Geopolitics	US elections shift foreign-policy stance		
27	23-Aug-2011	Libya Conflict	Rebels seize Tripoli amid heavy fighting		
28	24-Aug-2011	Libya Conflict	Gaddafi loyalists resist rebel control		
29	24-Feb-2012	Syrian Civil War	Heavy bombardment devastates Homs districts		
30	10-Jun-2012	Syrian Civil War	Major clashes erupt across Syrian cities		
Panel 2: During the sanctions against Russia					
31	18-Aug-2013	Egypt Crisis	Cairo protest camps violently dispersed	-128	211
32	08-Dec-2013	Ukraine Crisis	Kyiv protests intensify after crackdown	-240	99
33	19-Jan-2014	Ukraine Crisis	Violent clashes escalate in Kyiv	-282	57
34	01-Mar-2014	Crimea Annexation	Russian troops enter Crimea positions	-323	16
35	11-Jan-2015	Paris Attacks Aftermath	Global rally after Charlie Hebdo killings	-13	59
36	18-Nov-2015	Paris Attacks Aftermath	Paris raid targets attack perpetrators	-111	34
37	19-Jun-2016	Syrian Civil War	Raqqa frontline battles intensify	-139	74
38	14-Oct-2016	Syria / Russia–US	Syria airstrikes raise US–Russia tension	-43	31
39	11-Mar-2017	ISIS Conflict	Intense urban battles inside Mosul	-61	101
40	31-Jul-2017	North Korea	North Korea tests advanced missile	-41	142
41	12-Apr-2018	Syria Chemical Response	US-UK-France prepare Syria strike	-6	60
42	11-Sep-2018	Syrian Civil War	Russia–Syria forces attack Idlib	-92	9
43	10-Jan-2019	Venezuela Crisis	Venezuela enters severe political breakdown	-22	18
44	03-Nov-2019	ISIS Conflict	ISIS leader killed, leadership collapse	-34	32

Note: This table reports major global geopolitical events identified using the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022). The table is split into two parts for expositional convenience. Event dates are selected when the seven-day change in the index satisfies $\Delta_7 \ln GPRD_t > \alpha_c$, where α_c is set to the 99.5^{th} percentile of the daily distribution of $\Delta_7 \ln GPRD_t$ over the period 2001–2019. This stringent threshold isolates the two to three most salient geopolitical events per year, yielding a total of 44 events—comparable in magnitude to the 37 OFAC sanctions announcements used in the baseline analysis. Panel 1 lists events occurring prior to the introduction of sanctions against Russia, while Panel 2 reports events occurring during the sanctions period. The last two columns report the number of calendar days between each geopolitical event and the nearest preceding and subsequent OFAC sanctions announcement, where applicable.

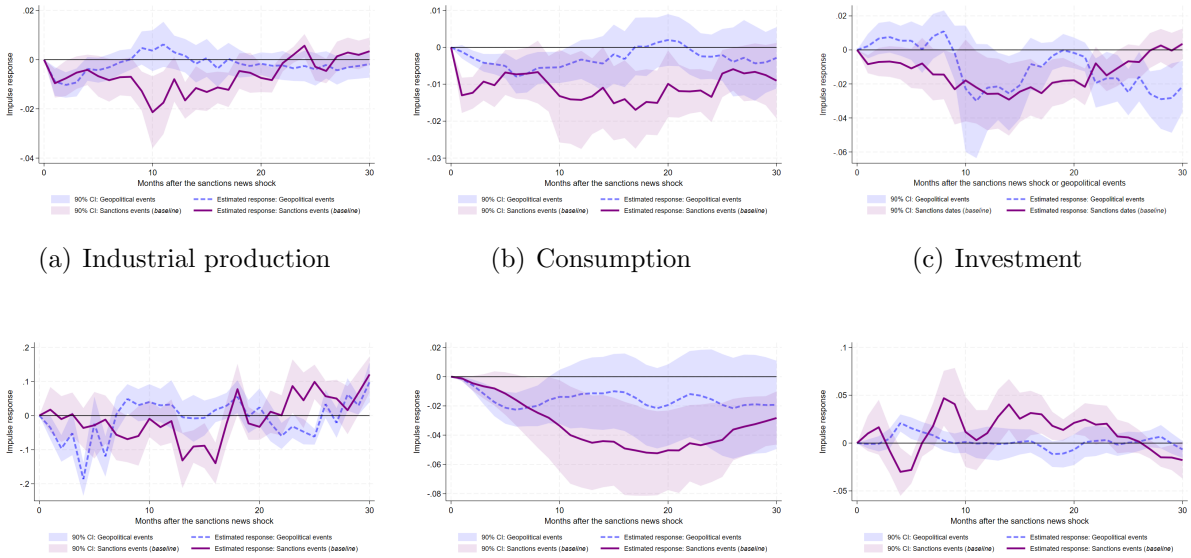
Figure G.III. First-stage LP–IV estimates: Sanctions news shocks *vs* major geopolitical events



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares baseline first-stage LP–IV estimates based on sanctions news shocks constructed around OFAC sanctions announcements (*blue*), reported in Figure 2 in the main text, with corresponding first-stage estimates obtained using major geopolitical events identified from the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022) (*red*). Major geopolitical events are identified using the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022). An event date is selected when the seven-day change in the index satisfies $\Delta_7 \ln GPRD_t > \alpha_c$, where α_c is set to the 99.5^{th} percentile of the annual distribution of $\Delta_7 \ln GPRD_t$ over the period 2001–2019. This stringent threshold isolates the two to three most salient geopolitical events per year, yielding a total of 44 events (see Table G.I), a number comparable to the 37 OFAC sanctions announcements used in the baseline analysis. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$, where the instrument is constructed either around OFAC sanctions announcements or around major geopolitical events. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the dark and light grey dashed lines, respectively). For each event type, the instrument $z_{k,t} = Surprise_{k,t}$ is constructed by aggregating daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around the event date d within month t. Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure G.IV. Second-stage LP–IV estimates: Sanctions news shocks *vs* major geopolitical events



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates identified using sanctions news shocks constructed around OFAC sanctions announcements (*purple*), reported in Figure 3 in the main text, with alternative impulse responses identified using major geopolitical events drawn from the geopolitical risk index (GPRD) of Caldara and Iacoviello (2022) (*dashed blue*). These events are identified when the seven-day change in the geopolitical risk index satisfies $\Delta_7 \ln GPRD_t > \alpha_c$, where α_c is set to the 99.5^{th} percentile of the annual distribution of $\Delta_7 \ln GPRD_t$ over 2001–2019. This procedure isolates the most severe geopolitical events over 2001–2019 (see Table G.I) while yielding an event count comparable to the number of OFAC sanctions announcements. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$ constructed around OFAC sanctions announcements. In the alternative specification, the country spread is instrumented using an analogous shock constructed around major geopolitical events. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix H OPEC meetings and the oil supply shock

Table H.I. OPEC meetings, 2000–2019

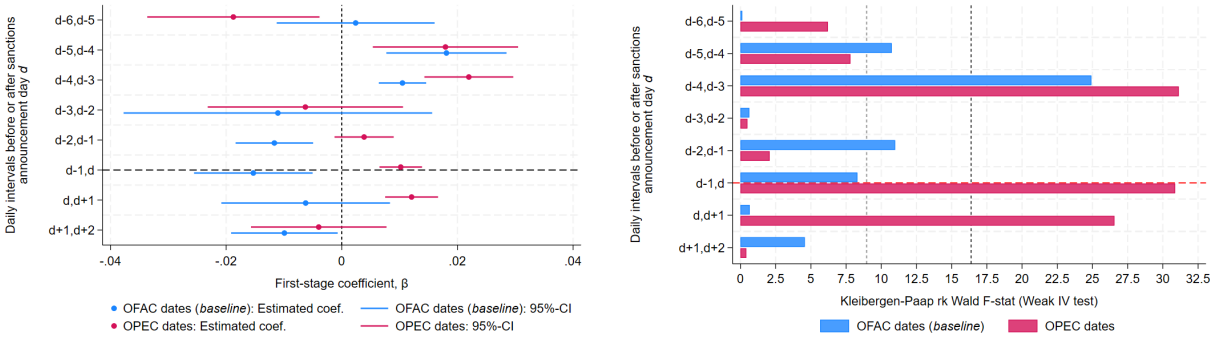
#	Meeting date	Description	Extraordinary = 1
1	3/29/2000	109th OPEC meeting	0
2	6/21/2000	110th OPEC meeting	1
3	9/11/2000	111th OPEC meeting	0
4	11/13/2000	112th OPEC meeting	1
5	1/17/2001	113th OPEC meeting	1
6	3/17/2001	114th OPEC meeting	0
7	6/5/2001	115th OPEC meeting	1
8	7/3/2001,	116th OPEC meeting	1
	7/25/2001		1
9	9/27/2001	117th OPEC meeting	0
10	11/14/2001	118th OPEC meeting	1
11	12/28/2001	Consultative OPEC meeting	0
12	3/15/2002	119th OPEC meeting	0
13	6/26/2002	120th OPEC meeting	1
14	9/19/2002	121st OPEC meeting	0
15	12/12/2002	122nd OPEC meeting	1
16	1/12/2004	123rd OPEC meeting	1
17	3/11/2003	124th OPEC meeting	0
18	4/24/2003	Consultative OPEC meeting	0
19	6/11/2003	125th OPEC meeting	1
20	7/31/2003	126th OPEC meeting	1
21	9/24/2003	127th OPEC meeting	0
22	12/4/2003	128th OPEC meeting	1
23	2/10/2004	129th OPEC meeting	1
24	3/31/2004	130th OPEC meeting	0
25	6/3/2004	131st OPEC meeting	1
26	9/15/2004	132nd OPEC meeting	0
27	12/10/2004	133rd OPEC meeting	1
28	1/30/2005	134th OPEC meeting	1
29	3/16/2005	135th OPEC meeting	0
30	6/15/2005	136th OPEC meeting	0
31	9/20/2005	137th OPEC meeting	0
32	12/12/2005	138th OPEC meeting	1
33	1/31/2006	139th OPEC meeting	1
34	3/8/2006	140th OPEC meeting	0
35	6/1/2006	141st OPEC meeting	1
36	9/11/2006	142nd OPEC meeting	0
37	10/20/2006	Consultative OPEC meeting	0
38	12/14/2006	143rd OPEC meeting	1
39	3/15/2007	144th OPEC meeting	0
40	9/11/2007	145th OPEC meeting	0
41	12/5/2007	146th OPEC meeting	1
42	2/1/2008	147th OPEC meeting	1
43	3/5/2008	148th OPEC meeting	0
44	9/10/2008	149th OPEC meeting	0
45	10/24/2008	150th OPEC meeting	1
46	12/17/2008	151st OPEC meeting	1
47	3/15/2009	152nd OPEC meeting	0
48	5/28/2009	153rd OPEC meeting	1
49	9/10/2009	154th OPEC meeting	0
50	12/22/2009	155th OPEC meeting	1

Table H.II. OPEC meetings, 2000–2019 (*continued*)

#	Meeting date	Description	Extraordinary = 1
51	3/17/2010	156th OPEC meeting	0
52	10/14/2010	157th OPEC meeting	0
53	12/11/2010	158th OPEC meeting	1
54	6/8/2011	159th OPEC meeting	0
55	12/14/2011	160th OPEC meeting	0
56	6/14/2012	161st OPEC meeting	0
57	12/12/2012	162nd OPEC meeting	0
58	5/31/2013	163rd OPEC meeting	0
59	12/4/2013	164th OPEC meeting	0
60	6/11/2014	165th OPEC meeting	0
61	11/27/2014	166th OPEC meeting	0
62	6/5/2015	167th OPEC meeting	0
63	12/4/2015	168th OPEC meeting	0
64	6/2/2016	169th OPEC meeting	0
65	9/28/2016	170th OPEC meeting	1
66	11/30/2016	171st OPEC meeting	0
67	12/10/2016	OPEC and non-OPEC ministerial meeting (JMMC)	0
68	5/25/2017	172nd OPEC meeting	0
69	11/30/2017	173rd OPEC meeting	0
70	4/20/2018	OPEC and non-OPEC ministerial meeting (JMMC)	0
71	6/22/2018	174th OPEC meeting	0
72	6/23/2018	OPEC and non-OPEC ministerial meeting (JMMC)	0
73	9/23/2018	OPEC and non-OPEC ministerial meeting (JMMC)	0
74	11/11/2018	OPEC and non-OPEC ministerial meeting (JMMC)	0
75	12/3/2018	Qatar gives notice of its withdrawal from OPEC	0
76	12/6/2018	175th OPEC meeting	0
77	3/18/2019	OPEC and non-OPEC ministerial meeting (JMMC)	0

Note: This table reports official meetings of the Organization of the Petroleum Exporting Countries (OPEC) over the period 2000–2019. The table is split into two parts for expositional convenience. Each entry corresponds to an OPEC Conference or consultative meeting at which production targets or policy guidance were discussed. The indicator *Extraordinary = 1* denotes meetings explicitly classified by OPEC as extraordinary or emergency sessions, as opposed to regularly scheduled meetings. $JMMC$ stands for Joint Ministerial Monitoring Committee. Dates and meeting classifications follow the chronology compiled in Känzig (2021) and are updated using more recent events from official OPEC press releases disclosed on opec.org.

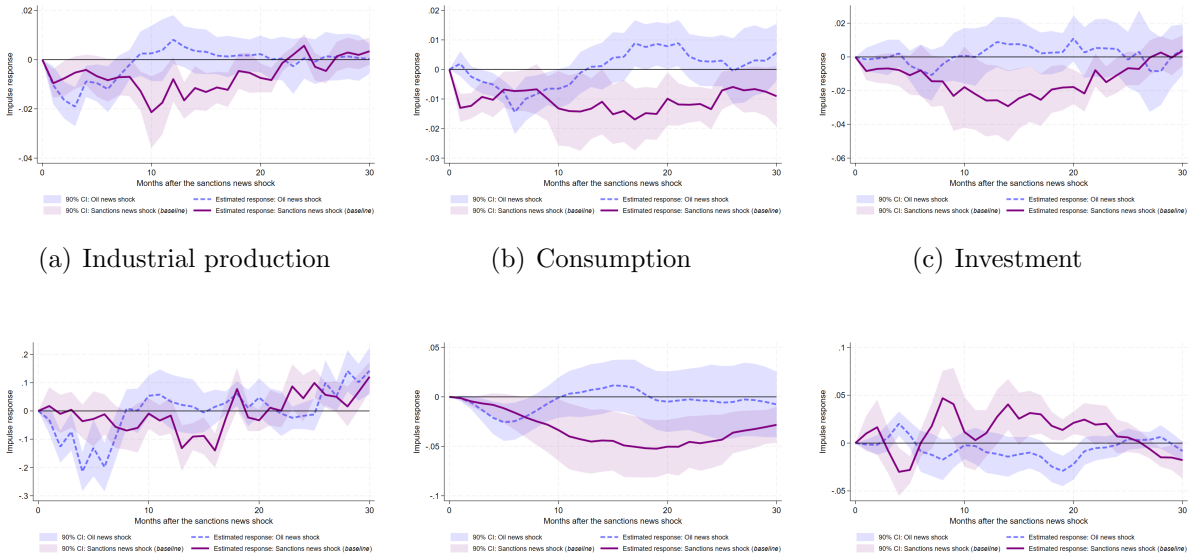
Figure H.I. First-stage LP–IV estimates: Sanctions news shocks *vs* OPEC meeting events



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares baseline first-stage LP–IV estimates based on sanctions news shocks constructed around OFAC sanctions announcements (*blue*), reported in Figure 2 in the main text, with corresponding first-stage estimates obtained using OPEC meeting events in 2000–2019 (*red*). Typically, there are two regular OPEC meetings per year, and there may be up to several extraordinary meetings (Känzig, 2021; see also Table G.I). In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$, where the instrument is constructed either around OFAC sanctions announcements or around OPEC meeting events of any type. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the dark and light grey dashed lines, respectively). For each event type, the instrument $z_{k,t} = \mathit{Surprise}_{k,t}$ is constructed by aggregating daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around the event date d within month t. Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West HAC standard errors with the maximum autocorrelation lag set to 12 months.

Figure H.II. Second-stage LP–IV estimates: Sanctions news shocks *vs* OPEC meeting events



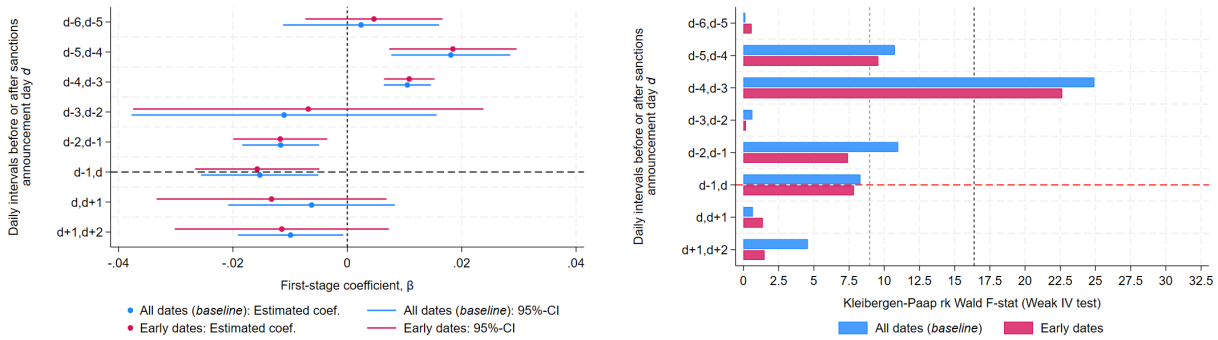
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates identified using sanctions news shocks constructed around OFAC sanctions announcements (*purple*), reported in Figure 3 in the main text, with alternative impulse responses identified using OPEC meeting events (*dashed blue*). Typically, there are two regular OPEC meetings per year, and there may be up to several extraordinary meetings (Känzig, 2021, see also Table G.I). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$ constructed around OFAC sanctions announcements. In the alternative specification, the country spread is instrumented using an analogous shock constructed around OPEC meeting events. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix I Early *vs* all OFAC sanctions announcements

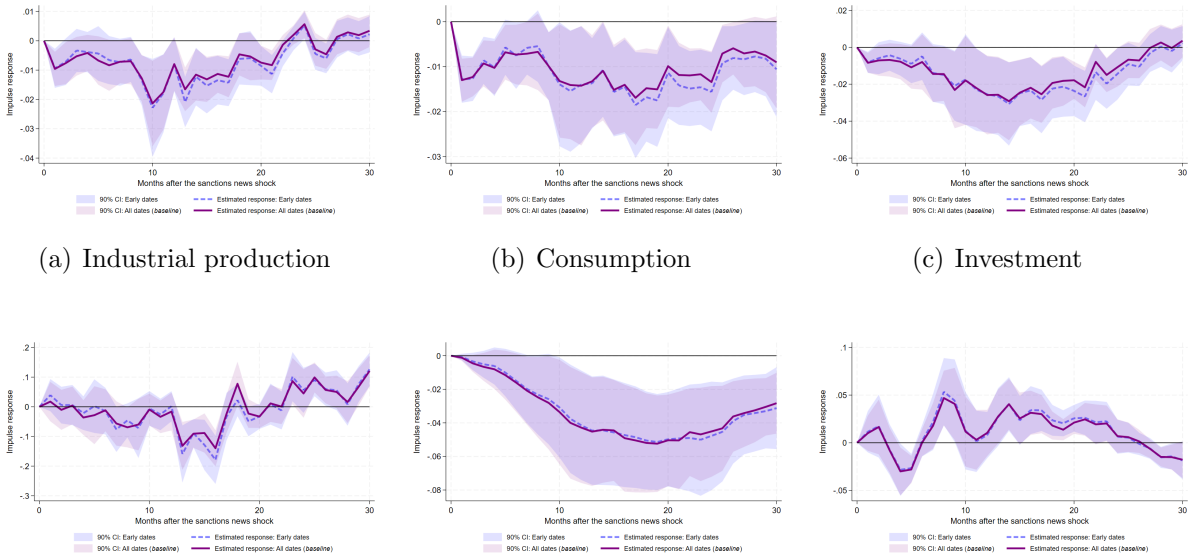
Figure I.I. First-stage LP–IV estimates: Full sample *vs* early sanctions



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares baseline first-stage LP–IV estimates constructed using the full set of 37 OFAC sanctions announcements over 2014–2019 (*blue*) with alternative estimates based solely on early sanctions announcements occurring in 2014–2015 (*red*). The purpose of this comparison is to assess whether the strength and timing of the sanctions news shock differ between the early phase of the sanctions regime and the full sample. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$. The instrument $z_{k,t} = \text{Surprise}_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d - k - 1$ and $d - k$ around each OFAC sanctions announcement on day d within month t—either in the full sample or in the early-sanctions subsample. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, with the maximum autocorrelation lag set to 12 months.

Figure I.II. Second-stage LP–IV estimates: Full sample *vs* early sanctions



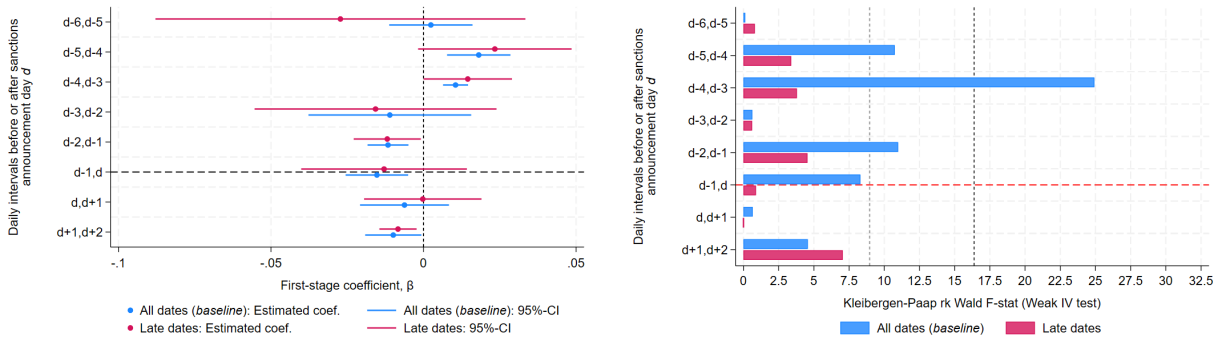
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates identified using the full set of OFAC sanctions announcements over 2014–2019 (*purple*) with corresponding impulse responses identified using only early sanctions announcements from 2014–2015 (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In both specifications, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$, constructed around OFAC sanctions announcements occurring either in the full sample or restricted to the early-sanctions subsample. The instrument aggregates daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-4$ and $d-3$ around each announcement date d within month t. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix J Late *vs* all OFAC sanctions announcements

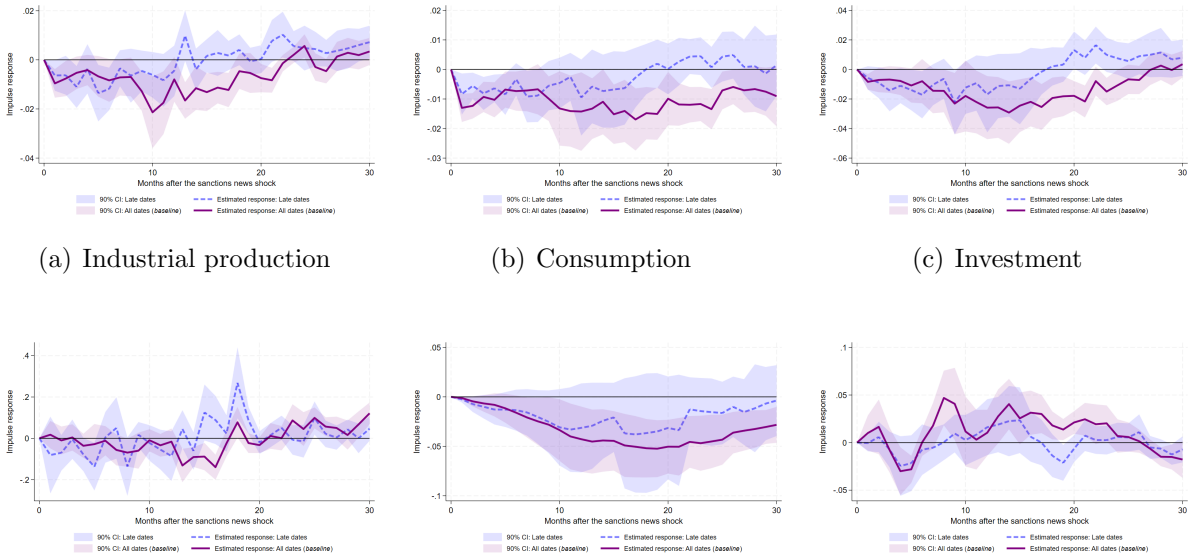
Figure J.I. First-stage LP–IV estimates: Full sample *vs* later sanctions



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares baseline first-stage LP–IV estimates constructed using the full set of 37 OFAC sanctions announcements over 2014–2019 (*blue*) with alternative estimates based solely on later sanctions announcements occurring in 2016–2019 (*red*). The purpose of this comparison is to assess whether the strength and timing of the sanctions news shock differ between the later phase of the sanctions regime and the full sample. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$. The instrument $z_{k,t} = \text{Surprise}_{k,t}$ denotes the k-th variant of the sanctions news shock, constructed by aggregating all daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d - k - 1$ and $d - k$ around each OFAC sanctions announcement on day d within month t—either in the full sample or in the later-sanctions subsample. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, with the maximum autocorrelation lag set to 12 months.

Figure J.II. Second-stage LP–IV estimates: Full sample *vs* later sanctions



(a) Industrial production (b) Consumption (c) Investment

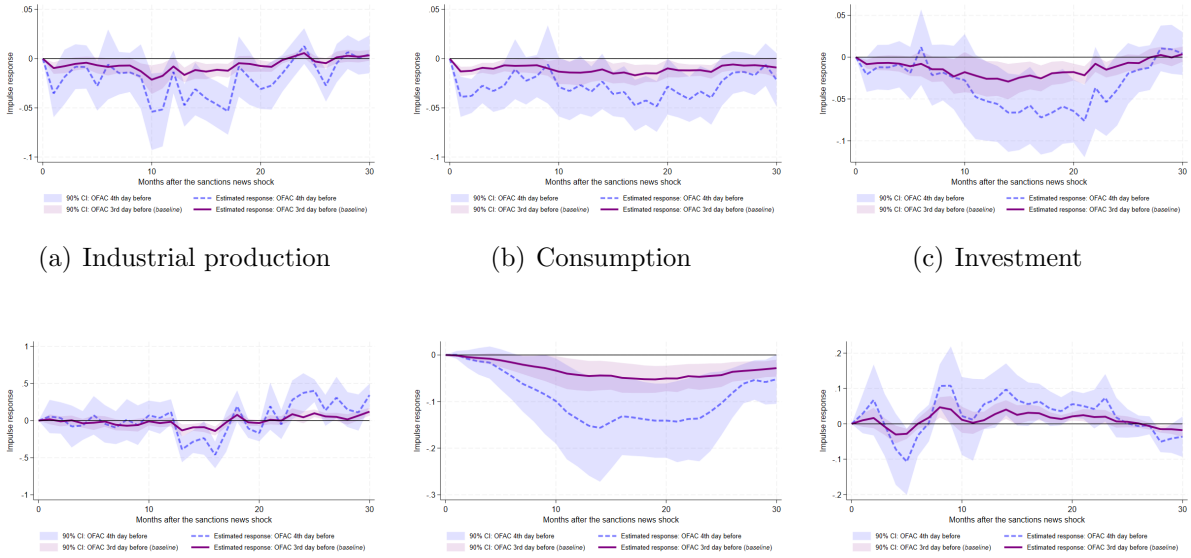
(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates identified using the full set of OFAC sanctions announcements over 2014–2019 (*purple*) with corresponding impulse responses identified using only later sanctions announcements from 2016–2019 (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In both specifications, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$, constructed around OFAC sanctions announcements occurring either in the full sample or restricted to the later-sanctions subsample. The instrument aggregates daily changes in the average yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-4$ and $d-3$ around each announcement date d within month t. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix K Varying the leakage parameter k

K.1 Longer anticipation horizon

Figure K.I. Second-stage LP–IV estimates: Baseline ($z_{-3,t}$) *vs* a longer anticipation horizon ($z_{-4,t}$)



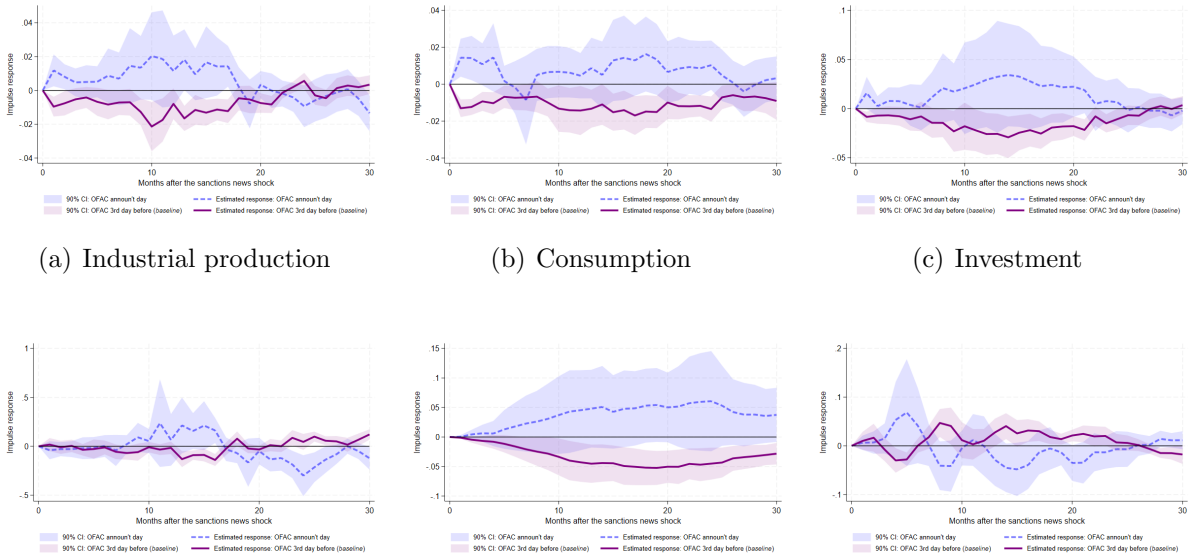
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates obtained using the baseline sanctions news shock constructed from the third day prior to OFAC sanctions announcements, $z_{-3,t}$ (*purple*), with alternative impulse responses identified using a deeper anticipation lag, $z_{-4,t}$ (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$, which aggregates daily changes in the average yield-to-maturity of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-4$ and $d-3$ around each OFAC sanctions announcement on day d within month t. In the alternative specification, the instrument $z_{-4,t}$ is constructed analogously using daily changes occurring between days $d-5$ and $d-4$, capturing a deeper anticipatory response to forthcoming sanctions announcements. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

K.2 Announcement day sanctions surprise

Figure K.II. Second-stage LP–IV estimates: Baseline ($z_{-3,t}$) *vs* announcement day shock ($z_{0,t}$)



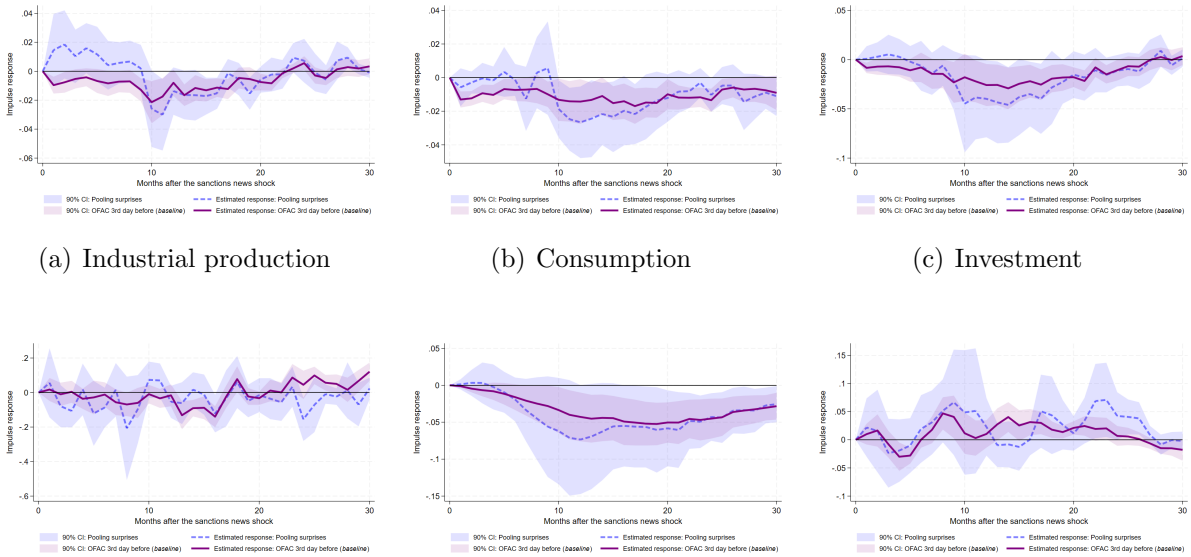
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates obtained using the baseline sanctions news shock constructed from the third day prior to OFAC sanctions announcements, $z_{-3,t}$ (*purple*), with alternative impulse responses identified using a contemporaneous sanctions news shock, $z_{0,t}$ (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$, which aggregates daily changes in the average yield-to-maturity of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-4$ and $d-3$ around each OFAC sanctions announcement on day d within month t. In the alternative specification, the instrument $z_{0,t}$ aggregates daily changes in sovereign bond yields occurring between days $d-1$ and d, capturing financial market reactions contemporaneous with sanctions announcements. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

K.3 Pooling all pre-announcement surprises

Figure K.III. Second-stage LP–IV estimates: Baseline ($z_{-3,t}$) *vs* pooling all surprises ($z_{-5\ldots0,t}$)



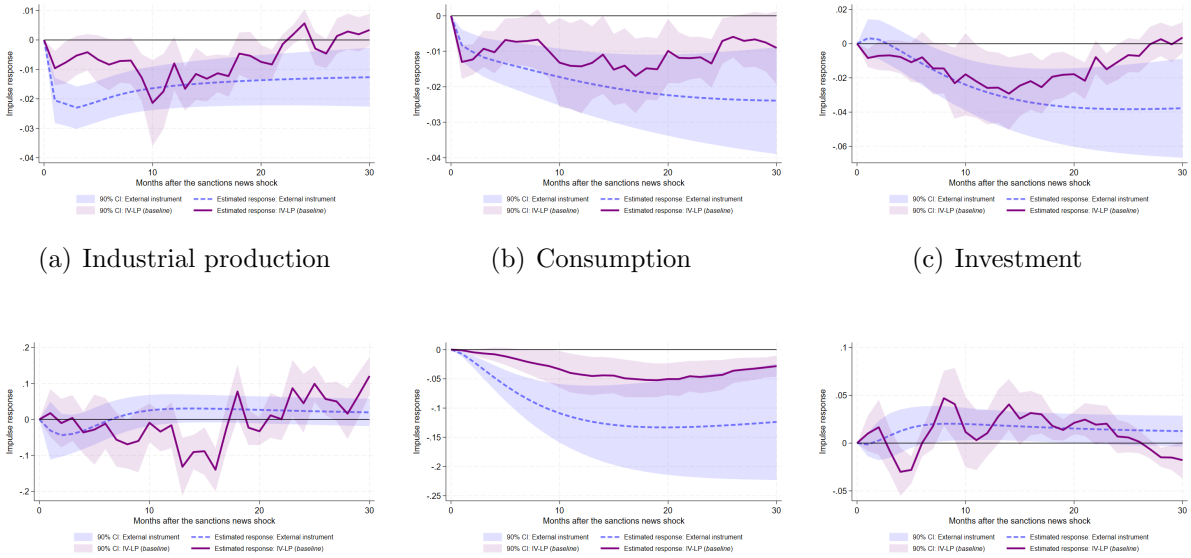
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates obtained using the baseline sanctions news shock constructed from the third day prior to OFAC sanctions announcements, $z_{-3,t}$ (*purple*), with alternative impulse responses identified using the average of all sanctions news shocks $z_{k,t}$ for $k = -5, -4, ..., 0$ (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$, which aggregates daily changes in the average yield-to-maturity of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-4$ and $d-3$ around each OFAC sanctions announcement on day d within month t. In the alternative specification, the instrument $z_{-5\ldots0,t}$ aggregates daily changes in sovereign bond yields occurring between days $d-5$ and d, capturing the average financial market reactions during the last five pre-sanctions days. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix L SVAR-IV approach

Figure L.I. Second-stage results: Baseline LP-IV *vs* SVAR-IV approaches



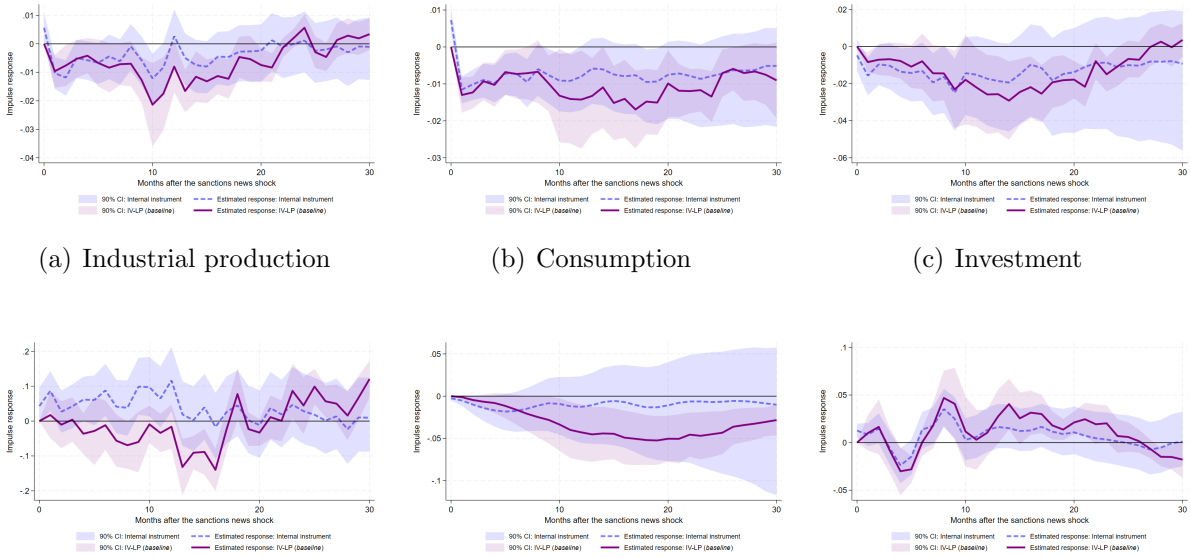
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage impulse response estimates obtained from the baseline instrumental-variables local projections (IV–LP) approach (*purple*) with corresponding impulse responses estimated using an instrumental-variables structural VAR (SVAR–IV) framework (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2) for the IV–LP model and the analogous structural responses implied by the SVAR–IV specification, where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). In both approaches, identification relies on the same sanctions news shock $z_{-3,t}$ constructed from financial market reactions to OFAC sanctions announcements, ensuring comparability across methods. For each horizon h, the reported response measures the effect of an exogenous increase in Russia's country spread induced by the sanctions news shock. All variables are expressed in logarithms. The IV–LP estimates are obtained using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h, and a small-sample degrees-of-freedom adjustment is applied. The SVAR–IV impulse responses are computed from the estimated structural VAR using the same instrument and sample period, with confidence intervals constructed using the corresponding robust variance–covariance matrix.

Appendix M VAR with internal instrument

Figure M.I. IRFs to the sanctions news shock: Baseline LP-IV *vs* a VAR with the internal instrument



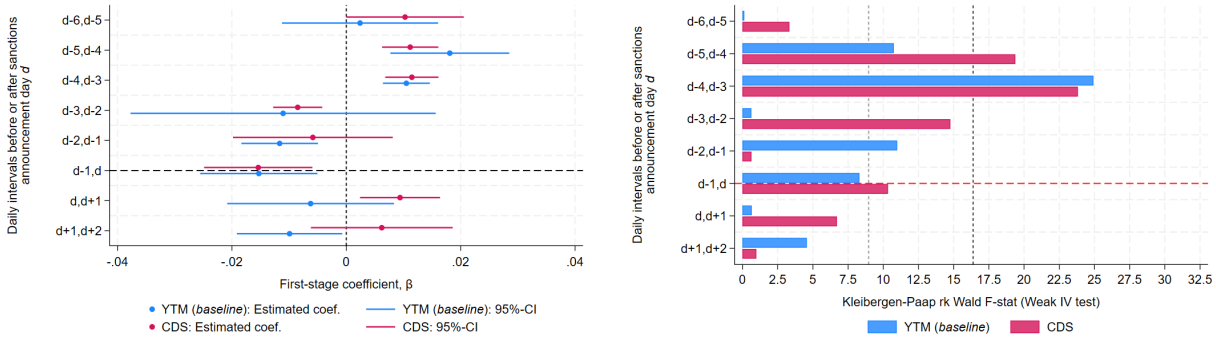
(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage impulse response estimates from the baseline instrumental-variables local projections (LP–IV) approach (*purple*) with impulse responses obtained from a VAR model that includes the sanctions news shock $z_{-3,t}$ as an internal instrument (*dashed blue*). In the VAR specification, $z_{-3,t}$ enters the system explicitly as an endogenous variable and is ordered first among all variables, and identification relies on a recursive (Cholesky) ordering. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2) for the LP–IV model and the analogous responses implied by the VAR for the Cholesky-identified shock. The index i denotes the endogenous variable ($i = 1, \ldots, 6$), and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the reported response measures the effect of an exogenous increase in Russia's country spread induced by the sanctions news shock. In both approaches, the sanctions news shock $z_{-3,t}$ is constructed from financial market reactions to OFAC sanctions announcements, ensuring a common economic interpretation across specifications. All variables are expressed in logarithms. LP–IV estimates are obtained using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h and a small-sample degrees-of-freedom adjustment applied. VAR impulse responses are computed using Bayesian estimation with standard Minnesota prior (overall tightness = 3, lag decay = 0.5, scalar controlling sum-of-coefficient prior = 5, co-persistence prior = 2, prior on the covariance matrix = 2; 500 draws) and same sample period. Lag length is set to 12 with credible sets constructed using draws from posterior distributions.

Appendix N Credit Default Swaps (CDS)

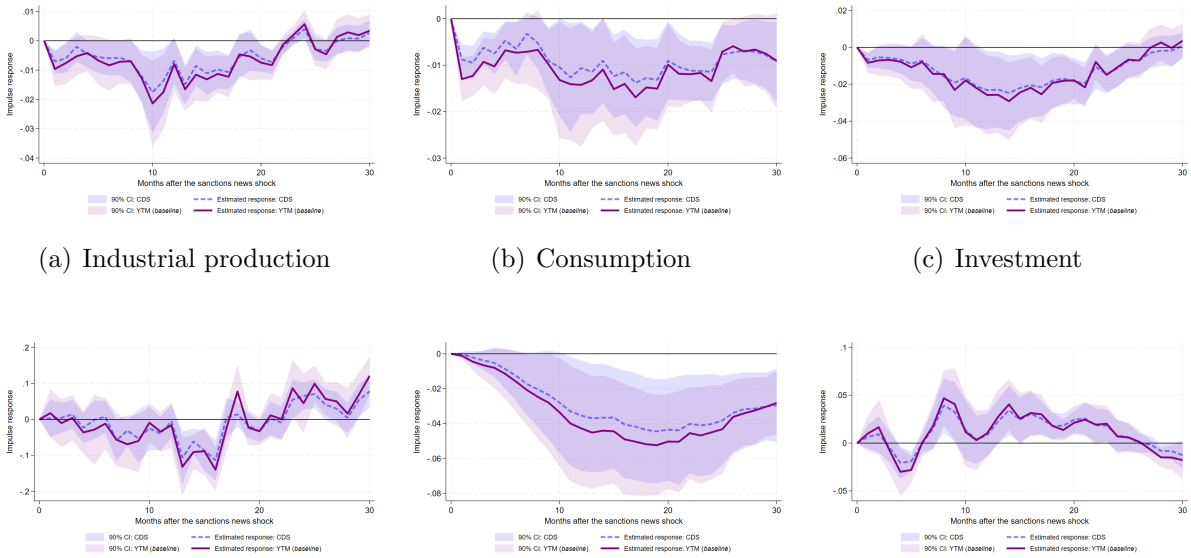
Figure N.I. First-stage LP–IV estimates: Sovereign bond YTMs *vs* CDS-based identification



(a) First-stage estimates β_k (b) Robust F-statistics

Note: This figure compares baseline first-stage LP–IV estimates in which the sanctions news shock is identified using changes in the yield-to-maturity (YTM) of Russia's U.S. dollar–denominated sovereign bonds (*blue*) with alternative first-stage estimates in which the shock is identified using changes in Russia's sovereign credit default swap (CDS) spreads (*red*). The purpose of this comparison is to assess the robustness of the sanctions news shock to the choice of financial instrument used to measure sovereign risk. In panel (*a*), we report the estimated effect of the k-th instrument $z_{k,t}$ ($k = -5, -4, \ldots, 2$) on Russia's country spread $y_{1,t}$. In the baseline specification, the instrument $z_{k,t} = \text{Surprise}_{k,t}$ aggregates all daily changes in the average YTM of Russia's U.S. dollar–denominated sovereign bonds occurring between days $d-k-1$ and $d-k$ around each OFAC sanctions announcement on day d within month t. In the alternative specification, the instrument is constructed analogously using daily changes in Russia's CDS spreads around the same announcement dates. Panel (*b*) reports the associated robust F-statistics for both specifications, together with the Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). Each first-stage regression controls for the full set of right-hand-side variables included in the second stage. Estimates are obtained using the two-step GMM estimator, and 95% confidence intervals are computed using Newey–West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, with the maximum autocorrelation lag set to 12 months.

Figure N.II. Second-stage LP–IV estimates: Sovereign bond YTMs *vs* CDS-based identification



(a) Industrial production (b) Consumption (c) Investment

(d) Trade Balance (e) External Debt (f) REER

Note: This figure compares second-stage LP–IV impulse response estimates identified using the sanctions news shock constructed from Russia's sovereign bond yields (*purple*) with alternative impulse responses identified using a sanctions news shock constructed from Russia's CDS spreads (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (2), where i indexes the endogenous variable ($i = 1, \ldots, 6$) and h denotes the response horizon in months ($h = 1, \ldots, 30$). For each horizon h, the coefficient $\theta_{i,h}$ measures the response of the i-th endogenous variable to an exogenous change in Russia's country spread. In the baseline specification, this spread innovation is instrumented using the sanctions news shock $z_{-3,t}$ constructed from daily changes in the yield-to-maturity of Russia's U.S. dollar–denominated sovereign bonds around OFAC sanctions announcements. In the alternative specification, the instrument is constructed analogously using daily changes in Russia's CDS spreads around the same announcement dates. All variables are expressed in logarithms. Estimation is conducted using the two-step GMM estimator with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. HAC standard errors and confidence intervals are computed using the Newey–West estimator, with the maximum autocorrelation lag set equal to the response horizon h. A small-sample degrees-of-freedom adjustment is applied.

Appendix O Details on the cross-section of firms

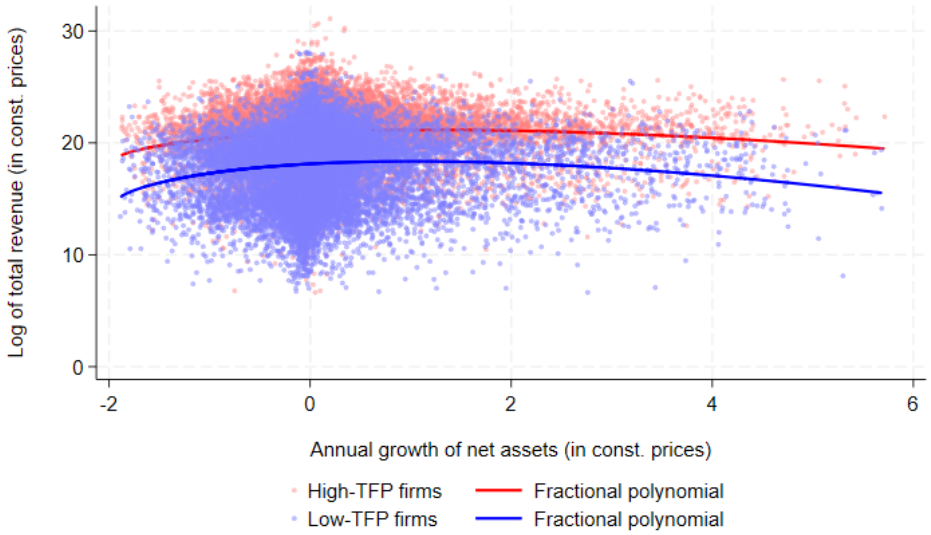
O.1 Firm-level data description

Table O.I. Summary statistics for the sample of firms

	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)
The full sample of firms					
$\ln TR_{f,t}$	2,235,286	17.1	2.5	0.0	31.1
$\ln W_{f,t}$	1,428,912	14.8	2.5	0.8	26.9
$\ln K_{f,t}$	1,629,154	15.5	2.9	–0.3	30.0
$\ln TFP_{f,t}$	1,201,238	10.4	1.8	–3.2	24.9
$ROA_{f,t}$	2,130,049	0.040	0.2	–0.6	0.6
$Leverage_{f,t}$	2,230,933	0.5	1.8	–3.0	18.7
$Net\ asset\ growth_{f,t}$	1,761,401	0.19	0.81	–1.90	5.81
The subsample of the 20% most productive firms (in terms of TFP)					
$\ln TR_{f,t}$	127,050	19.5	2.2	6.6	31.1
$\ln W_{f,t}$	85,580	15.9	2.1	5.2	25.0
$\ln K_{f,t}$	116,268	14.7	2.8	4.0	27.9
$\ln TFP_{f,t}$	75,078	12.4	1.7	0.1	22.4
$ROA_{f,t}$	123,427	0.040	0.1	–0.6	0.6
$Leverage_{f,t}$	118,557	1.1	2.6	–3.0	18.7
$Net\ asset\ growth_{f,t}$	104,069	0.19	0.73	–1.90	5.71
The subsample of the 20% least productive firms (in terms of TFP)					
$\ln TR_{f,t}$	141,282	17.0	2.3	3.2	28.1
$\ln W_{f,t}$	102,879	16.1	2.1	3.0	26.9
$\ln K_{f,t}$	142,293	17.5	2.5	3.6	29.5
$\ln TFP_{f,t}$	100,788	8.7	1.3	–3.2	19.4
$ROA_{f,t}$	134,878	–0.009	0.1	–0.6	0.6
$Leverage_{f,t}$	132,838	0.4	1.7	–3.0	18.7
$Net\ asset\ growth_{f,t}$	118,651	0.03	0.58	–1.90	5.81

Note: The table reports summary statistics on a range of firms' characteristics including total revenue $TR_{f,t}$, Wage bills $W_{f,t}$, Capital (fixed assets) $K_{f,t}$, Total Factor Productivity $TFP_{f,t}$, net profits over net assets $ROA_{f,t}$, leverage $Leverage_{f,t}$, and the growth rate of net assets $Net\ asset\ growth_{f,t}$, all in constant 2014 prices. The data is sourced from SPARK-Interfax.

Figure O.I. Asset growth and total revenues in subsamples of high- and low-TFP firms



Note: Subfigure (*a*) describes subsamples of high-TFP firms (*red dots*) and low-TFP firms (*blue dots*) by focusing on the relationship between firms' dynamism, as measured by the annual growth rate of net assets (hereinafter, in constant prices), and the log of the firms' total revenue across 2011–2019. The data is sourced from SPARK-Interfax.

Table O.II. Firm performance and the sanctions news shock

	Dependent variable:					
	$\ln TR_{f,t}$	$\Delta \ln TR_{f,t}$	$Leverage_{f,t}$	$ROA_{f,t}$	$\ln W_{f,t}$	$\ln K_{f,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln TFP_{f,t}$	0.703***	0.508***	–0.008***	0.022***	0.141***	–0.282***
	(0.002)	(0.003)	(0.003)	(0.000)	(0.003)	(0.003)
$\ln TFP_{f,t} \times$ Sanction news shock	–0.006***	–0.013***	0.035***	–0.002***	–0.028***	0.010***
	(0.001)	(0.002)	(0.003)	(0.000)	(0.001)	(0.002)
Firm, Status, and Industry FEs	✓	✓	✓	✓	✓	✓
N obs	1,155,015	972,259	1,037,895	1,073,587	646,042	1,155,015
N firmns	253,608	231,373	232,827	240,678	167,398	253,608
R^2 (adj.)	0.926	0.292	0.524	0.398	0.913	0.892

Note: The table reports estimates of regression $Y_{f,t} = \alpha_f + \alpha_i + \alpha_s + \beta_1 \ln TFP_{f,t} + \beta_2 \cdot \ln TFP_{f,t} \times \overline{z}_{-3,t} + \varepsilon_{f,t}$, where $Y_{f,t}$ is firm's f total revenue (1), the annual growth of total revenue (2), leverage (3), return on assets (4), wages (5), or fixed assets (6) in year t (all in constant prices), $TFP_{f,t}$ is firm's f total factor productivity, as computed using Expression (3), $\overline{z}_{-3,t}$ is the sanctions news shock, as computed using Expression (1) with $k = -3$ (daily changes in the average yield-to-maturity of Russia's US Dollar-denominated sovereign bonds occurred three days before sanction announcements), α_f, α_i, α_s are firm, industry (*okved*), and operational status fixed effects, and $\varepsilon_{f,t}$ is the regression error. The data is sourced from SPARK-Interfax and Rosstat.

***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Appendix P Details on the cross-section of households

Table P.I. Summary statistics for the sample of households

	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)
The full sample of households					
$\ln Y_{h,t}$	80,246	6,3	0,6	4,8	7,8
$\ln C_{h,t}$	83,682	5,8	0,7	4,3	7,8
$\ln C^D_{h,t}$	41,731	3,5	1,5	0,2	7,0
$\ln C^N_{h,t}$	83,693	5,7	0,6	4,2	7,5
The subsample of the 20% richest households					
$\ln Y_{h,t}$	13,128	6,6	0,6	4,8	7,7
$\ln C_{h,t}$	15,387	6,0	0,7	4,3	7,4
$\ln C^D_{h,t}$	9,377	3,6	1,5	0,2	6,8
$\ln C^N_{h,t}$	15,321	5,9	0,7	4,2	7,2
The subsample of the 20% poorest households					
$\ln Y_{h,t}$	9,400	5,7	0,4	4,8	7,6
$\ln C_{h,t}$	9,109	5,3	0,5	4,3	7,4
$\ln C^D_{h,t}$	2,771	3,3	1,4	0,2	6,6
$\ln C^N_{h,t}$	9,147	5,3	0,5	4,2	7,1

Note: The table reports 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, over 2006–2018. The data is sourced from RLMS-HSE.

Figure P.I. Individual income and household consumption in the full sample of households



Note: The figure reports scatter-plots of real income (X axis) and real consumption (Y axis) of the 20% reachest and the 20% poorest households in Russia over 2006–2019. The data is sourced from RLMS-HSE.

Table P.II. Income, consumption, and sanctions in the cross-section of households

	Dependent variable: $\ln C^{(\jmath)}_{h,t}$				
$\jmath =$	Total	Tradab	Nontrad	Food	Non-food
	(1)	(2)	(3)	(4)	(5)
$\ln Income_{h,t}$	0.367***	0.529***	0.325***	0.262***	0.336***
	(0.010)	(0.041)	(0.009)	(0.011)	(0.014)
$\ln Income_{h,t} \times$ Sanction news shock	-0.022	0.157*	-0.011	-0.010	-0.055**
	(0.019)	(0.091)	(0.017)	(0.020)	(0.026)
$\ln Income_{h,t} \times$ Sanction news shock $\times$ 20% richest	-0.068**	-0.203	-0.079***	-0.032	0.004
	(0.033)	(0.167)	(0.031)	(0.036)	(0.046)
$\ln Income_{h,t} \times$ Sanction news shock $\times$ 20% poorest	0.064	-0.276	0.040	-0.012	0.182**
	(0.056)	(0.224)	(0.051)	(0.056)	(0.084)
Household, Head's sex, and Head's job type FEs	✓	✓	✓	✓	✓
N obs	38,346	20,901	38,536	38,893	41,220
N households	8,900	5,786	8,897	8,938	9,283
R^2 (adj.)	0.629	0.269	0.657	0.599	0.567

Note: The table reports estimates of the following regression: $\ln C^{(\jmath)}_{h,t} = \alpha_h + \alpha_s + \alpha_j + \beta_1 \ln Income_{h,t} + \beta_2 \cdot \ln Income_{h,t} \times \overline{z}_{-3,t} + \beta_3 \cdot \ln Income_{h,t} \times \overline{z}_{-3,t} \times Highest\,20\%_{h,t} + \beta_4 \cdot \ln Income_{h,t} \times \overline{z}_{-3,t} \times Lowest\,20\%_{h,t} + \varepsilon_{h,t}$, where $C^{(\jmath)}_{h,t}$ is household h total consumption (1), consumption of tradables (2), total consumption of nontradables (3), consumption of food (4), and consumption of non-food as a part of nontradables (5), $\overline{z}_{-3,t}$ is the sanctions news shock, as computed using Expression (1) with $k = -3$ (daily changes in the average yield-to-maturity of Russia's US Dollar-denominated sovereign bonds occurred three days before sanction announcements), α_h, α_s, α_j are household, sex of household's head, and job type of household's head fixed effects, and $\varepsilon_{h,t}$ is the regression error. The data is sourced from RLMS-HSE and Rosstat.

***, **, * denote an estimate is significant at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the household level and appear in the brackets under the estimated coefficients.