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

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**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.

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> *"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."*
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> — Leo Tolstoy, *Bethink Yourselves!* (1904)
> On the Russo–Japanese War, reprinted from *The Times* (London)

# 1 Introduction

Since World War II, economic sanctions have become a central instrument of foreign policy, intended to impose economy-wide costs on targeted regimes without resorting to full-scale military conflict (Eaton and Engers, 1992; Levy, 1999; Jayachandran and Kremer, 2006; Felbermayr *et al.*, 2020; Morgan *et al.*, 2023; Felbermayr *et al.*, 2025). This policy objective is inherently macroeconomic: sanctions seek to weaken the target economy by restricting its access to foreign finance, trade, technology, and international payment networks. We still know relatively little about when sanctions news reaches markets, how it propagates through aggregate activity and external finance, and who ultimately bears the economic cost.

Existing research provides important evidence on specific margins of sanctions transmission. Sanctions force directly targeted banks and firms to curtail their international financial activities (Cipriani *et al.*, 2023; Mamonov *et al.*, 2023), reduce trade (Crozet *et al.*, 2021; Souza *et al.*, 2024; Tyazhelnikov and Romalis, 2024), and cut employment (Ahn and Ludema, 2020). Structural work shows how sanctions transmit through exchange rates and domestic policy responses (Itskhoki and Mukhin, 2025), while recent empirical work shows that government protection of sanctioned firms can distort capital allocation and reduce aggregate productivity (Nigmatulina, 2025). These contributions identify important mechanisms, but they do not fully recover the dynamic common component of sanctions: changes in sovereign risk, exchange rates, external financing conditions, fiscal expectations, and aggregate demand that affect targeted and non-targeted agents alike.

Firm-level comparisons between sanctioned and non-sanctioned entities are well suited to identifying direct exposure and the resource-allocation effects surrounding targeted firms. Their strength is also their limitation: by differencing across firms, they remove the common macroeconomic component of sanctions, leading to the missing-intercept problem (Moll, 2022). As a result, the economic consequences of sanctions cannot be inferred solely from differences between formally targeted and non-targeted entities.

Identifying this common component is challenging because sanctions are not a single

primitive shock in standard small-open-economy models. A conventional country-spread shock (Uribe and Yue, 2006; Uribe and Schmitt-Grohe, 2017; Akinci, 2013) captures exogenous changes in foreign borrowing premia, which are an important margin of sanctions transmission. Sanctions, however, can simultaneously alter access to trade, technology, foreign investment, international payments, and external finance, while changing expected fiscal liabilities and long-run productive capacity. Treating sanctions as an ordinary country-spread shock would therefore confound sanctions news with generic emerging-market risk-premium shocks and omit important non-financial margins.

Recent studies have made important progress by constructing newspaper-based indices of sanctions intensity that generate significant macroeconomic responses (Laudati and Pesaran, 2023; Bondarenko *et al.*, 2024). These measures use news coverage to capture the evolving intensity of sanctions, including their persistence, indirect costs, and the threat of future restrictions, and are therefore well suited to studying a continuing sanctions regime. Their macroeconomic applications, however, aggregate the underlying news into quarterly or monthly indices and identify sanctions innovations through time-series restrictions and VAR ordering assumptions. They consequently do not isolate the precise trading-day window in which markets first incorporate information about a forthcoming sanctions action or fully separate that information from other contemporaneous macroeconomic and country-risk developments. This leaves two related identification challenges: determining when economically relevant sanctions news reaches markets and isolating the component of asset-price movements attributable specifically to that news.

We address both identification challenges with a complementary high-frequency strategy applied to Russian sanctions episodes in the 2010s. Specifically, we exploit daily changes in the yields on Russia's U.S.-dollar-denominated sovereign bonds around formal sanctions announcements. These bonds provide a forward-looking market price of the sovereign's exposure to the economy-wide consequences of sanctions. Restrictions on external finance, trade, technology, and payment infrastructure can reduce firms' profits, export revenues, foreign-currency earnings, and ultimately the government's tax base and debt-servicing capacity. At the same time, sanctions frequently target large banks, state-owned firms, and politically connected entities, creating incentives for the government to absorb part of their losses through capital injections, guarantees, directed credit, or other support (Ahn and Ludema, 2020; Nigmatulina, 2025). Investors should incorporate both the resulting decline in expected fiscal resources and the increase in contingent public liabilities into the yields they require on sovereign debt. Sovereign-bond repricing can therefore summarize the market's assessment of a broad sanctions package, including consequences that originate outside the public sector, without requiring sanctions to operate exclusively through sovereign borrowing costs.

Because sovereign yields also respond to other macroeconomic and geopolitical news, we focus on short windows around formal sanctions announcements. This timing re-

striction helps isolate the component of sovereign-bond repricing associated with newly arriving sanctions information from generic changes in country risk. We use the resulting high-frequency sanctions-news variation to estimate aggregate effects in an empirical small-open-economy framework and trace their incidence across firms and households.

Russia provides a particularly informative laboratory for this analysis. It is a large, internationally integrated commodity exporter with relatively rich macroeconomic and microeconomic data. From the onset of the Russia–Ukraine conflict in 2014 until the COVID-19 pandemic, the United States issued 37 discrete Russia-related sanctions announcements, generating repeated and precisely dated information events within a single target country.[1] This combination of recurring policy shocks and rich data allows us to study both aggregate dynamics and their incidence across firms and households.

We hand-collect all Russia-related announcements issued by the U.S. Treasury's Office of Foreign Assets Control (OFAC) under its Russia–Ukraine, Cyberattacks, Syria, and Magnitsky programs. Around each announcement, we construct eight candidate one-day surprises, $z_{k,t}$ for $k \in \{-5, \ldots, +2\}$, using daily changes in the average yield on Russia's U.S.-dollar-denominated sovereign bonds from five trading days before to two trading days after the formal release. We use each surprise as a candidate external instrument for Russia's country spread in an LP–IV specification (Stock and Watson, 2018). The yield change between trading days $d-4$ and $d-3$, denoted $z_{-3,t}$, delivers the strongest first-stage relevance: it predicts an increase in the country spread of approximately 1.1 percentage points and has a robust first-stage F-statistic of 24.92. We therefore use $z_{-3,t}$ as our baseline instrument. The neighboring $d-5$ to $d-4$ surprise, $z_{-4,t}$, predicts a larger but less precisely estimated increase of approximately 1.8 percentage points. By contrast, announcement-day yield movements have essentially no explanatory power. Thus, the identifying variation arises before the formal announcement rather than on the announcement day itself.

We corroborate this pre-announcement timing with several independent validation exercises. First, we conduct a systematic textual analysis of international media coverage and find a sharp increase in prospective Russia-related sanctions news three to four trading days before formal OFAC announcements, precisely when sovereign yields begin to move. Second, we show that CDS spreads exhibit a similar pre-announcement repricing pattern. Third, we find that observable global macro-financial variables—including oil prices, geopolitical risk, the VIX, U.S. equity prices, and U.S. monetary conditions—do not predict $z_{-3,t}$. Finally, we document specific cases in which major international media reported prospective sanctions before OFAC released the final measures and designations. Together, the first-stage, textual, CDS, and predictability evidence establish that economically relevant information about forthcoming sanctions is incorporated into asset

[1] Following Russia's full-scale invasion of Ukraine in 2022, the sanctions regime broadened substantially, while the availability and reliability of Russian macroeconomic data deteriorated.

prices three to four trading days before the formal announcement.[2]

Having isolated $z_{-3,t}$ as our baseline sanctions-news instrument, we use it to identify sanctions-related variation in Russia's country spread in the baseline LP–IV. We use the country spread as a forward-looking, market-based scaling variable rather than as the sole channel of transmission. It expresses the identified shock in a common and economically interpretable unit—the increase in the external borrowing premium associated with sanctions news—while allowing sanctions to affect the economy directly through trade, technology, foreign investment, payment systems, and fiscal responses.

Turning to the second stage of the baseline LP–IV, we estimate sizable macroeconomic effects of the identified sanctions-news shock, normalized to raise the country spread by 0.25 percentage points. The shock reduces industrial production by up to 2.1%, private consumption by 1.7%, and investment by 2.9%. We also find a 5.2% contraction in corporate external debt and a 4.7% medium-run depreciation of the real effective exchange rate. The estimated trade balance declines by up to 14% with a delay, although the timing and persistence of this response are more sensitive to the dynamic specification than the responses of real activity and external finance.

These impulse responses establish the dynamic effects of a normalized sanctions-news shock, but they do not reveal how much the realized sequence of shocks mattered for Russia's actual downturn. To assess their historical importance, we construct a counterfactual path that removes the identified sanctions-news shocks while leaving all other shocks unchanged. We find that sanctions news materially deepened the 2014–2016 downturn but did not cause it in its entirety: even under the counterfactual, the collapse in global oil prices would have produced a recession. The effect of sanctions news fades after 2016, consistent with markets and the targeted economy learning about and adapting to the sanctions regime.

Having established both the dynamic effects and the historical importance of sanctions news, we next show that these conclusions do not depend on using the country spread to scale the shock or on the particular LP–IV implementation. Direct local projections that enter $z_{-3,t}$ directly produce impulse responses that closely track the baseline estimates. A heteroskedasticity-identified Bayesian VAR, an internal-instrument VAR (Plagborg-Møller and Wolf, 2021), and an SVAR–IV also reproduce the central contraction in domestic activity and external finance, although the trade-balance dynamics vary more across specifications.

We then validate the baseline identification along several complementary dimensions. Sequentially excluding each OFAC announcement leaves the first-stage coefficient and the signs of the macroeconomic responses intact. Randomly selected placebo dates and

[2]This timing is institutionally plausible because sanctions announcements are not preceded by a formal quiet period comparable to that surrounding monetary-policy decisions. Information may emerge through legislative deliberations, diplomatic negotiations, consultations among allied governments, and advance media reporting before OFAC publishes the final designations.

salient domestic Russian placebo events generate neither first-stage relevance nor the joint macroeconomic response produced by sanctions news. Excluding the December 2014 "Black Monday" episode, when Russian financial markets experienced severe stress around an emergency monetary-policy tightening, strengthens rather than eliminates the estimated contraction. Finally, a detailed audit of Russia-specific geopolitical events shows that independent escalations do not systematically coincide with the particular pre-announcement window from which our identification is obtained.

Finally, we show that the results are robust to alternative constructions and measurements of the sanctions-news shock. We obtain similar responses when we use EU rather than OFAC announcements, the neighboring pre-announcement surprise $z_{-4,t}$, pooled pre-announcement yield changes, or CDS spreads in place of sovereign-bond yields. Early sanctions announcements generate stronger and more persistent effects than later announcements, consistent with declining informational content as the regime matured. Excluding several OFAC announcements that coincide with major geopolitical events also leaves the estimates essentially unchanged. Moreover, shocks constructed around other global geopolitical events (Caldara and Iacoviello, 2022) and OPEC meetings (Känzig, 2021) strongly affect Russia's country spread but generate materially different macroeconomic dynamics, indicating that the baseline shock does not merely capture generic geopolitical or commodity news.

In the cross-sectional part of our analysis, we use the baseline high-frequency sanctions-news surprise, $z_{-3,t}$, to study how sanctions-related news affects firms and households over the four years following sanctions announcements. We show that the aggregate contraction is distributed highly unevenly and extends well beyond formally targeted entities. In SPARK-Interfax data covering approximately 500,000 firms, sanctions news reduces the real revenues of large, high-productivity firms by up to 4% during the first two years. These firms also reduce wages, capital, and leverage, and their revenue losses are larger when their pre-sanctions debt capacity is low. By contrast, small high-productivity firms and low-productivity firms display little response. Turning to households, the RLMS–HSE panel shows that individuals in the top income quintile lose 5.5% of real income in the first year, irrespective of whether they reside in regional capitals or other locations. High-income households reduce food consumption by about 1%, other nondurable consumption by 2.5%, and durable consumption by almost 10%, whereas income responses at the bottom of the distribution are close to zero.

Sanctions therefore operate as system-wide economic shocks rather than narrowly targeted interventions. By disproportionately weakening large and productive firms, their spillovers may reduce aggregate productivity; by concentrating income losses among richer households, they compress the income distribution, a pattern reminiscent of the distributional consequences of major wars (Piketty and Saez, 2006). These economy-wide spillovers and distributional effects cannot be recovered from comparisons between sanc-

tioned and non-sanctioned entities alone.

Although our empirical setting is the pre-2022 Russian sanctions, the mechanisms we identify—anticipation, sovereign-risk repricing, fiscal spillovers, external-financing contraction, and adaptation—may also operate when sanctions target other internationally integrated economies. Understanding these mechanisms has become increasingly important in an environment of elevated geopolitical risk (Caldara and Iacoviello, 2022).

**Relation to the literature.** First, we contribute to the empirical macroeconomic literature that uses high-frequency external information to identify aggregate shocks, including monetary-policy shocks (Gertler and Karadi, 2015; Jarocinski and Karadi, 2020), oil-supply news (Känzig, 2021), climate-policy shocks (Känzig, 2026), Brexit surprises (Geiger and Guntner, 2024), and fiscal announcements (Hazell and Hobler, 2025). Our design is also related to studies that use asset prices around discrete events to identify sovereign and country-risk shocks (Sagawa, 2026; Hassan *et al.*, 2024; Hebert and Schreger, 2017). We extend this approach to sanctions by using sovereign-bond repricing around OFAC announcements to identify sanctions news as a distinct aggregate shock and to establish when markets incorporate information about forthcoming restrictions.

Second, we contribute to the literature on the economic effects of sanctions. Foundational and survey work studies sanctions as strategic policy instruments and documents their evolution as a major tool of foreign policy (Eaton and Engers, 1992; Levy, 1999; Felbermayr *et al.*, 2020; Morgan *et al.*, 2023; Felbermayr *et al.*, 2025), while Jayachandran and Kremer (2006) emphasize that financial sanctions have enforcement and welfare properties distinct from trade sanctions. Recent structural work analyzes sanctions through sovereign-default and exchange-rate frameworks (Bianchi and Sosa-Padilla, 2024; Itskhoki and Mukhin, 2025). Empirical macroeconomic work studies country-specific output and exchange-rate effects (Kholodilin and Netsunajev, 2019; Pestova and Mamonov, 2019; Dreger *et al.*, 2016; Barseghyan, 2019; Bondarenko *et al.*, 2024), while other empirical work examines trade and blockade-related disruptions (Etkes and Zimring, 2015; Crozet *et al.*, 2021; Souza *et al.*, 2024; Tyazhelnikov and Romalis, 2024), political support, elite exposure, average cross-country effects, and domestic credit reallocation (Gold *et al.*, 2024; Draca *et al.*, 2023; Gutmann *et al.*, 2023; Keerati, 2023). We connect these strands by identifying the common macroeconomic component of sanctions and tracing its incidence beyond directly targeted entities.

Our analysis is particularly complementary to three recent contributions. Itskhoki and Mukhin (2025) develop a structural model of the comprehensive post-2022 sanctions and show how exchange-rate adjustment depends on the restrictions imposed and on domestic policy responses. We instead study the targeted pre-2022 regime and use high-frequency asset-price variation to identify when sanctions information reaches markets and to estimate its dynamic causal effects. Nigmatulina (2025) shows that government protection of sanctioned firms reallocates capital toward targeted entities and lowers aggregate pro-

ductivity, while Keerati (2023) shows that financial sanctions redirect domestic bank credit toward sanctioned borrowers and crowd out non-sanctioned firms. These papers isolate distinct transmission mechanisms: structural exchange-rate adjustment, state-protection-driven misallocation, and domestic-credit reallocation. Our object is different but complementary. We identify the common sanctions-news innovation that simultaneously affects targeted and non-targeted agents through sovereign-risk repricing, external finance, aggregate demand, and other general-equilibrium channels. This approach allows us to quantify both the timing of sanctions news and its aggregate and distributional incidence across the firm and household populations.

Third, we contribute to the literature on the heterogeneous effects of aggregate shocks (Cloyne *et al.*, 2020; Känzig, 2026; Del Canto *et al.*, 2025; Lenza and Slacalek, 2024). The COVID-19 pandemic, cost-push inflation, and climate-policy tightening have often imposed disproportionate costs on lower-income households (Chetty *et al.*, 2024; Del Canto *et al.*, 2025; Känzig, 2026), whereas quantitative easing may benefit lower-income households through heterogeneous earnings responses (Lenza and Slacalek, 2024). In our setting, sanctions impose larger losses on high-income households and on large, productive firms. The household effects compress the income distribution, while the concentration of firm-level losses among large and productive firms points to potentially important aggregate-productivity consequences. Both patterns arise even though the formal legal incidence of sanctions is much narrower than their economy-wide effects.

**Roadmap.** The remainder of the paper proceeds as follows. Section 2 describes the sanctions regime, constructs the high-frequency sanctions-news surprises, and presents the econometric framework. Section 3 estimates the aggregate macroeconomic effects and evaluates identification and robustness. Section 4 examines the incidence across firms and households. Section 5 concludes.

# 2 Sanctions timing and high-frequency identification

## 2.1 A brief history of sanctions on Russia

Russia was subject to several waves of Western sanctions following the annexation of Crimea and the onset of the conflict in eastern Ukraine in 2014. The first wave, imposed between March and December 2014, was introduced under the Ukraine-related sanctions program and included executive orders 13660, 13661, 13662, and 13685 (Welt *et al.*, 2020). These measures targeted individuals, state-owned banks, energy companies, defense firms, and other entities viewed as connected to Russia's actions in Ukraine. During this early period, U.S. and EU sanctions were largely coordinated and often announced around the same dates, which allows us to use U.S. announcements as the baseline source of

high-frequency timing.[3]

A second wave of sanctions followed in 2017–2018 in response to cyberattacks, electoral interference, and Russia's support for the Syrian regime. These measures were introduced mainly by the United States and became more institutionalized after the passage of the Countering America's Adversaries Through Sanctions Act (CAATSA) in August 2017. CAATSA strengthened existing Ukraine-related sanctions and imposed additional restrictions on transactions with Russian financial, energy, and defense-sector entities. By 2022, before Russia's full-scale invasion of Ukraine, OFAC sectoral sanctions applied to major state-owned banks, energy companies, pipeline operators, and defense firms, restricting their access to new equity and debt financing of specified maturities.[4]

We focus on the pre-2022 sanctions episode for two reasons. First, the 2014–2019 period provides a sequence of discrete, dated announcements that can be matched to daily movements in sovereign bond markets, making it suitable for high-frequency identification. Second, the pre-2022 regime consisted primarily of targeted financial, sectoral, and individual sanctions rather than the comprehensive restrictions imposed after February 2022. The post-2022 sanctions were broader in scope, included the freezing of a large share of the Central Bank of Russia's international reserves, restrictions on SWIFT access, extensive export and import controls, and large-scale asset freezes (Berner *et al.*, 2022). They also coincided with a deterioration in the availability and reliability of Russian macroeconomic data. For these reasons, our baseline analysis ends before the COVID-19 pandemic and the full-scale invasion of Ukraine.

We next describe how we use this sequence of sanctions announcements to construct a high-frequency measure of sanctions news.

## 2.2 Sanctions news and sovereign-risk repricing

The identification strategy builds on the idea that sanctions arrive as discrete policy announcements but may change market expectations before their formal release. Each announcement provides information about newly sanctioned individuals, firms, banks, or sectors, as well as about the expected future path of the sanctions regime. Market participants therefore have incentives to reassess the outlook for the sanctioned economy when sanctions-related information becomes available.

Sanctions can affect the economy through several channels. Financial sanctions restrict access to foreign borrowing and payment infrastructure; trade and technology sanctions limit access to foreign markets, imported inputs, and capital goods; asset freezes and individual sanctions can disrupt ownership, control, and international transactions. In the Russian case, many sanctions targeted state-owned banks, energy firms, defense compa-

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

[4]The main parent entities included VTB Bank, Gazprombank, Rosselkhozbank, VEB, Rosneft, Gazpromneft, Transneft, Novatek, Rostec, Lukoil, Surgutneftegaz, and Gazprom.

nies, and politically connected entities. These restrictions may therefore affect not only the directly sanctioned firms, but also expected fiscal revenues, contingent government liabilities, external financing conditions, and aggregate demand. In Russia, these contingent liabilities were not merely hypothetical: after the 2014 sanctions, the government used the National Wealth Fund to support several major state-owned banks.[5]

Sovereign bond markets provide a natural high-frequency price in which these expectations should be reflected. A standard framework linking sovereign bond pricing, macroeconomic fundamentals, and default risk is provided by Mendoza and Yue (2012). If sanctions worsen expected future macroeconomic conditions, reduce the tax base, or increase expected fiscal support to sanctioned entities, foreign investors should require higher yields on the sanctioned government's foreign-currency debt. Sovereign yields are therefore useful not because sanctions operate only through government borrowing costs, but because they summarize investors' forward-looking assessment of the fiscal, financial, and macroeconomic consequences of sanctions news.

We exploit this logic by measuring changes in Russia's U.S.-dollar-denominated sovereign bond yields around Russia-related sanctions announcements. These high-frequency yield movements provide a market-based measure of sanctions news, which we then use to study how sanctions propagate through the Russian macroeconomy.

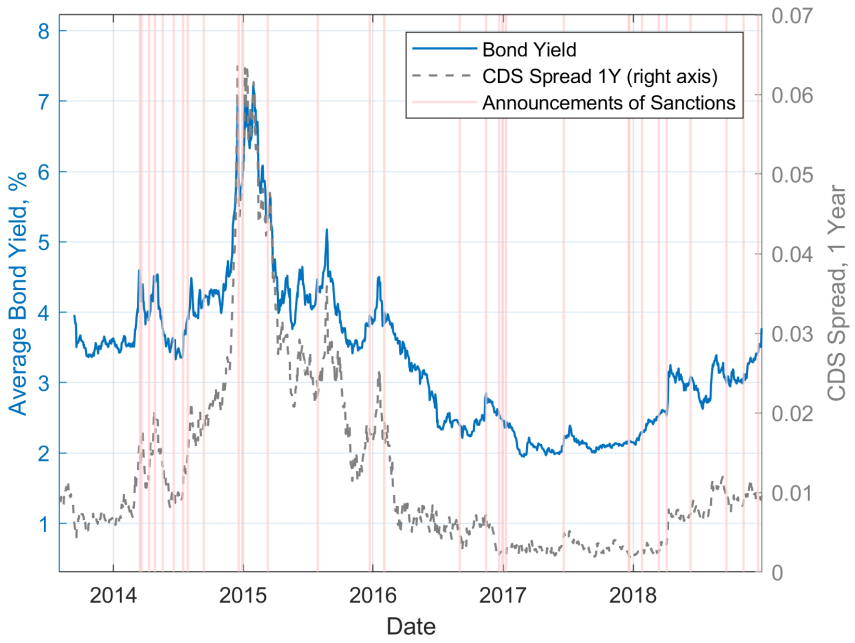
## 2.3 Constructing candidate sanctions-news surprises

We adopt a high-frequency approach to measure sanctions news using the daily timing of OFAC announcements and daily data on Russian sovereign bond yields. We hand-collect all Russia-related sanctions announcements published by the U.S. Treasury's Office of Foreign Assets Control (OFAC) before 2020. The sample includes both Specially Designated Nationals and Blocked Persons (SDN) sanctions, which block assets and generally prohibit transactions with designated individuals and entities by U.S. persons, and Sectoral Sanctions Identifications (SSI) sanctions, which restrict specified types of financing for entities operating in sectors such as finance, energy, and defense. Details on the sanctions announcements are provided in Appendix B, and the full list of announcements appears in Appendix Table B.I.

Figure 1 plots the daily evolution of Russia's sovereign yield-to-maturity, averaged across eight U.S.-dollar-denominated sovereign bonds from Refinitiv Eikon that were consistently traded during the whole sanctions period in the 2010s, together with OFAC sanctions announcements. The figure also plots the one-year CDS spread on Russian sovereign debt. The two market-based measures of sovereign risk comove closely: the correlation between the average sovereign bond yield and the CDS spread is 0.91 over the

[5]VTB, Gazprombank, and Rosselkhozbank received National Wealth Fund equity injections, while VTB also received a long-term National Wealth Fund deposit. See Moscow Times (2015).

**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 U.S.-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 entities between 2014 and 2019 (SSI and SDN, *light red bars*). Source: Refinitiv Eikon, Markit, OFAC.

sample period. In robustness checks, we show that replacing sovereign bond yields with CDS spreads delivers similar identification and nearly identical impulse responses. The full list of bond issues used to construct the average yield is reported in Appendix B.2.

Interpreting high-frequency yield movements around sanctions announcements as sanctions news requires two conditions. First, the yield movements must be relevant: they must respond to information about current or future sanctions. Second, they must be plausibly orthogonal to other news that independently affects Russian macroeconomic outcomes. The first condition follows from the sovereign-pricing logic discussed in Section 2.2: if sanctions worsen expected macroeconomic fundamentals, reduce fiscal revenues, or increase expected government support to sanctioned entities, investors should require higher yields on Russian foreign-currency sovereign debt. The second condition is more demanding because sanctions may be announced around periods of geopolitical tension or macro-financial stress. We therefore treat it as an empirical validation requirement. Section 3.3 provides evidence from event-window plots, textual leakage measures, forecastability tests, geopolitical-event audits, placebo exercises, and alternative identification strategies.

As in Känzig (2021) and Geiger and Guntner (2024), we use daily rather than intraday asset-price changes because intraday data are not available for the relevant Russian sovereign bonds. Unlike monetary policy announcements (Nakamura and Steins-

son, 2018), however, sanctions announcements are not preceded by institutional quiet periods and may be anticipated through legislative action, diplomatic negotiations, or media leaks. We therefore do not impose the formal announcement day as the relevant news window. Instead, we construct a family of candidate daily surprises around each announcement and let the first-stage evidence determine where markets systematically reprice sanctions news.[6]

Specifically, for each announcement day $d$, we compute daily sanctions surprises, $Surprise_{d,k,t}$, using changes in Russian sovereign bond yields from five trading days before to two trading days after the announcement, while keeping the window length fixed at one trading day:

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

where $YTM$ denotes the average yield-to-maturity on Russian U.S.-dollar-denominated sovereign bonds, $d$ is the announcement day, $k$ indexes the trading-day window relative to the announcement, and $t$ is the calendar month. Negative values of $k$ allow for pre-announcement information revelation, while positive values allow for delayed market adjustment after the formal announcement.

We aggregate the daily series to the monthly frequency by summing all daily surprises within each month:

$$z_{k,t} = \sum_{d \in t} Surprise_{d,k,t}, \quad (2)$$

and set $z_{k,t} = 0$ in months without OFAC announcements. This procedure yields eight candidate monthly sanctions-news surprises, one for each value of $k \in -5, \ldots, 2$. In Section 3.1, we use first-stage diagnostics to determine which candidate surprise systematically predicts movements in Russia's aggregate country spread. This approach preserves ex ante agnosticism about the precise timing of information revelation while making the baseline timing choice transparent and empirically disciplined.

## 2.4 Econometric framework

We use the monthly sanctions-news surprises $z_{t,k}$ constructed above in an empirical small open economy framework for Russia. The baseline specification treats the high-frequency sanctions surprise as an external instrument for Russia's aggregate country spread. We interpret the country spread as a forward-looking market-based summary of the fiscal,

[6] We provide direct evidence on media leakage several days before OFAC announcements in Appendix B.3.

financial, and macroeconomic risks priced by international investors, and use it to scale the macroeconomic effects of sanctions news.

This interpretation does not require sanctions to operate only through sovereign borrowing costs. Sanctions may also affect the economy through trade, technology, foreign-investment, and payment-system channels. To the extent that these channels affect expected fiscal revenues, contingent government support, or aggregate repayment capacity, they should also be reflected in foreign-currency sovereign debt prices. We nevertheless assess the importance of this scaling assumption by estimating direct local projections in which the sanctions-news surprise enters the outcome equation directly, as well as alternative specifications based on heteroskedasticity-based identification and the internal instrument VAR and SVAR-IV approaches.

**LP–IV specification.** Country interest-rate fluctuations play an important role in emerging-market business cycles (Neumeyer and Perri, 2005; Uribe and Yue, 2006; Akinci, 2013). We therefore use Russia's country spread as the endogenous variable in the baseline local-projection instrumental-variable specification.[7] Local projections facilitate comparison between the aggregate macroeconomic responses and the microeconomic responses estimated later in the paper. They also avoid imposing a fully specified VAR law of motion and do not require invertibility of the structural shocks. The cost of using LPs is higher estimation variance relative to VAR-based approaches (Stock and Watson, 2018). To reduce this variance, we augment the local projections with a parsimonious set of controls motivated by standard empirical models of small open economies (Uribe and Yue, 2006; Akinci, 2013; Ben Zeev *et al.*, 2017). As shown by Plagborg-Møller and Wolf (2021), local projections recover valid impulse responses when they are appropriately lag-augmented and the response horizon is not too long.

Following Känzig (2026), we estimate horizon-specific regressions of the form

$$y_{i,t+h} = \alpha_{i,h} + \theta_{i,h} \cdot y_{1,t} + \delta'_{i,h}\mathbf{x}^c_t + v_{i,t+h}, \tag{3}$$

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 $\mathbf{x}^c_t$ contains up to twelve monthly lags of each endogenous and exogenous variable (described in the next subsection).[8] The error term $v_{i,t+h}$ is serially correlated by construction. We therefore estimate Equation (3) using two-step GMM with Newey–West HAC standard errors.

In the first stage, we instrument $y_{1,t}$ using the candidate sanctions-news surprise $z_{k,t}$. We estimate the first stage separately for each value of the leakage parameter

[7] Similar LP–IV approaches are used in, e.g., Ramey and Zubairy (2018) and Jorda *et al.* (2020).

[8] In the robustness section, we also apply more parsimonious specifications of Equation (3): 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).

$k \in -5, \ldots, 2$, using the corresponding monthly surprise constructed from Equation (1). This procedure allows the data to reveal the trading-day window in which sanctions news is systematically priced by sovereign bond markets. Section 3.1 reports the first-stage diagnostics and selects the baseline surprise used in the main analysis.[9]

**Direct local projections.** The baseline LP–IV specification scales sanctions news by its effect on the country spread. As a complementary approach, we estimate direct local projections in which the selected sanctions-news surprise enters the outcome equation directly:

$$y_{i,t+h} = \alpha^D_{i,h} + \beta^D_{i,h} z_{k^*,t} + \gamma'_{i,h} \mathbf{x}^c_t + u_{i,t+h}. \tag{4}$$

Here $z_{k^*,t}$ denotes the baseline high-frequency sanctions-news surprise selected in Section 3.1. These direct projections do not use the country spread as an endogenous variable. They therefore provide a useful check on whether the estimated macroeconomic responses depend on the LP–IV scaling through sovereign risk.

**Heteroskedasticity-based identification.** We then implement a heteroskedasticity-based identification strategy as an alternative to the baseline LP–IV design. The idea is that the onset of the sanctions regime after the annexation of Crimea generated a higher-volatility regime for sanctions news. Identification then comes from changes in the covariance structure between the pre-sanctions and sanctions regimes, in the spirit of approaches that use changes in volatility around policy events to identify structural shocks (Altavilla *et al.*, 2019). This exercise is useful because it does not require treating the high-frequency surprise as an instrument for the country spread. We use it as an independent validation of the baseline impulse responses.

**Internal-instrument VAR and SVAR-IV.** Finally, we estimate an internal-instrument specification in which the sanctions-news surprise is included directly in a VAR for the Russian economy and ordered first Plagborg-Møller and Wolf (2021). This approach follows the logic of treating the high-frequency surprise as an observable proxy for the structural sanctions-news shock. We use this specification mainly to construct counterfactual paths for macroeconomic variables in the absence of sanctions news and to verify that the dynamic responses are not specific to the local-projection implementation. Finally, in the SVAR–IV specification, we use the same high-frequency surprise as an external instrument to identify the effects of the sanctions news shock within the VAR.

[9] As a robustness check, we also include all $Surprise_{k,t}$ series, for $k = -5, \ldots, 2$, jointly in the first-stage regression. The results are similar to the baseline.

## 2.5 Variables, controls, and sample

The empirical specification is designed for a small open economy that is highly exposed to commodity exports and global financial conditions. Russia is a natural case for such a framework: oil, gas, and related products account for a large share of exports, and fluctuations in global commodity prices and external financing conditions are central to the Russian business cycle.[10] Our control set follows empirical models of small open economies in Uribe and Yue (2006), Akinci (2013), Ben Zeev *et al.* (2017), and Monacelli *et al.* (2023).

The vector of domestic macroeconomic variables includes industrial production, private consumption, investment, the trade balance, Russia's country spread, corporate external debt, and the real effective exchange rate. Industrial production is used as the monthly proxy for domestic output. Private consumption and investment are measured in national currency at constant prices. The trade balance is expressed in U.S. dollars and deflated by the U.S. CPI. Russia's country spread is measured by JP Morgan's Emerging Markets Bond Index spread for Russia. Corporate external debt is measured as the outstanding stock of Russian corporate external debt in U.S. dollars and deflated by the U.S. CPI. The real effective exchange rate is transformed so that an increase denotes a real depreciation and a decrease denotes a real appreciation.

The vector of external controls includes commodity terms of trade, the U.S. real interest rate, and the U.S. corporate Baa spread. Commodity terms of trade capture movements in the prices of Russia's main commodity exports. This control is particularly important because oil, gas, and related products accounted for about 63

The baseline monthly sample starts in January 2000, shortly after the Russian sovereign-default crisis of the late 1990s, and ends in March 2019. We exclude the COVID-19 period because pandemic-related disruptions and ragged-end data would complicate the interpretation of the estimates. We also exclude the post-2022 period because the full-scale invasion of Ukraine led to a much broader sanctions regime and a substantial deterioration in the availability and reliability of Russian macroeconomic data. Appendix A provides data sources, definitions, and transformations.

[10] See, for example, the IMF World Economic Outlook discussion of Russia's dependence on commodity exports: http://www.imf.org/external/pubs/ft/weo/2015/02/pdf/text.pdf.

# 3 Results: macroeconomic effects of sanctions news shock

## 3.1 First stage and identifying variation

Our high-frequency design is ex ante agnostic about the precise trading-day window in which sanctions news is revealed. We therefore construct candidate monthly surprises $z_{k,t}$ for each $k \in \{-5, \ldots, 2\}$ and use first-stage diagnostics to determine where sovereign bond markets systematically price sanctions news. Specifically, for each candidate surprise, we estimate the first stage underlying Equation (3) and test whether $z_{k,t}$ predicts Russia's aggregate country spread in month $t$, conditional on the same control vector used in the baseline local projections.

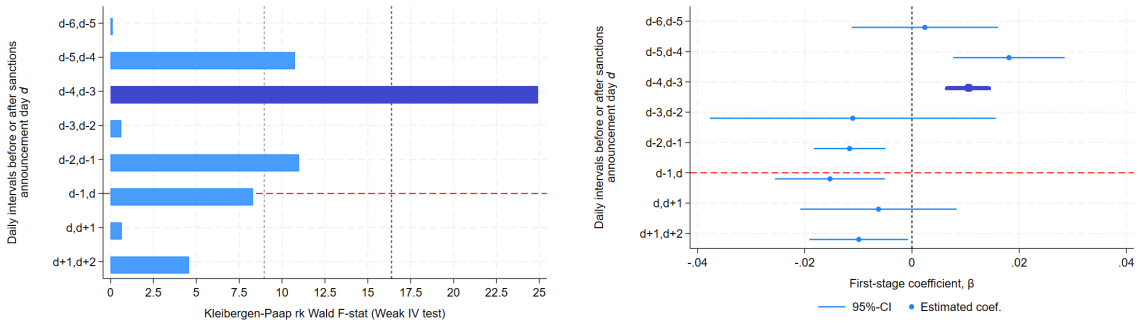
Figure 2 reports the results. Panel (a) shows the robust first-stage F-statistics, while Panel (b) shows the corresponding first-stage coefficients. The strongest first-stage relationship occurs in the pre-announcement window between trading days $d-4$ and $d-3$, corresponding to $z_{-3,t}$. This candidate surprise has the expected positive sign and a robust F-statistic of 24.92, exceeding conventional weak-instrument thresholds ($a$).[11] The next strongest instruments are $z_{-4,t}$ and $z_{-1,t}$, with robust F-statistics of 10.74 and 10.98, respectively. These values are close to conventional thresholds but remain well below the first-stage strength of $z_{-3,t}$. Neither the announcement-day surprise nor the post-announcement surprises attain comparable predictive power. These results indicate that sovereign markets price sanctions news several days before formal OFAC announcements, rather than only on the announcement day itself.

The coefficient estimates further support the interpretation of pre-announcement information revelation ($b$). Yield changes four and three trading days before OFAC announcements predict increases in Russia's country spread of about 1.8 and 1.1 percentage points, respectively. This pattern is consistent with international investors selling Russian sovereign bonds as sanctions-related information arrives. The coefficients on $z_{-1,t}$ and $z_{0,t}$ are negative, suggesting partial reversal as uncertainty about the announcement resolves. Because this adjustment pattern is concentrated before formal OFAC announcements, we interpret it as evidence of sanctions-news leakage rather than delayed announcement-day repricing.

Based on these diagnostics, we use $z_{-3,t}$ as the baseline sanctions-news surprise in the main analysis. We do not interpret this choice as imposing a specific leakage window ex ante. Rather, the first stage identifies the trading-day window in which markets systematically reprice sanctions news. In Section 3.3, we show that the results are robust to alternative timing choices, including the closest competing pre-announcement window

[11] This value also exceeds the robust weak-instrument critical value of 23.1 in Olea and Pflueger (2013) for the 5% critical value and 10% Nagar bias threshold.

**Figure 2.** First-stage estimates and instrument strength




(a) First-stage F-statistics

(b) First-stage estimates $\beta_k$

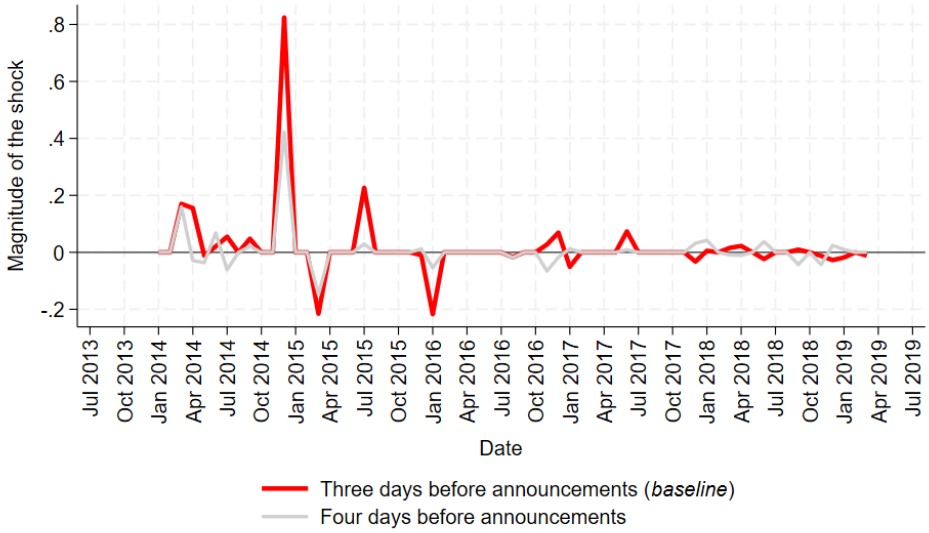
*Note*: This figure reports first-stage estimates from the LP–IV specification. Panel (*a*) presents robust F-statistics together with Stock–Yogo weak-identification critical values at 10% and 15% maximal IV size (shown as the *dark grey* and *light grey* dashed lines, respectively). Panel (*b*) reports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

and specifications that use multiple candidate surprises jointly.

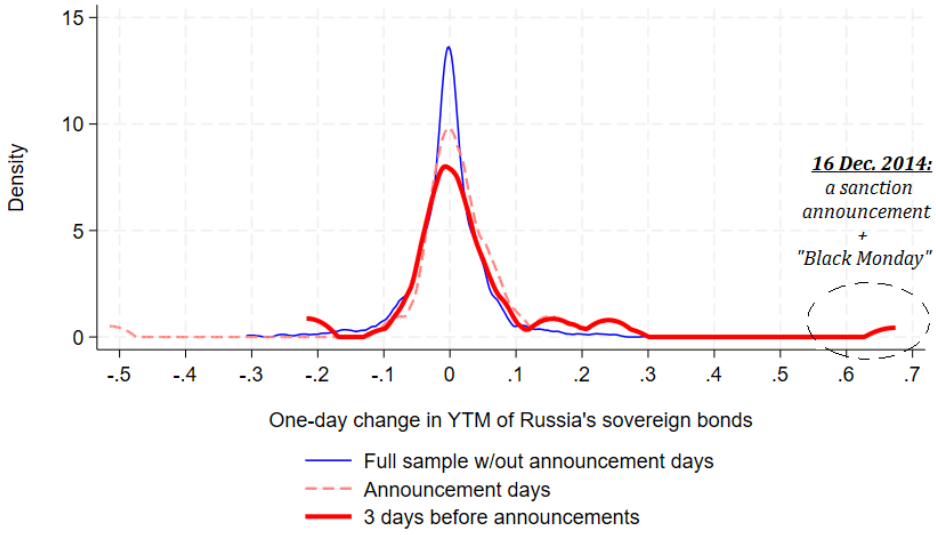
Figure 3 visualizes the resulting baseline sanctions-news shock. Panel (a) plots the monthly time series of $z_{-3,t}$, while Panel (b) compares its empirical distribution with the announcement-day surprise $z_{0,t}$ and with daily sovereign-yield changes on non-sanctions days. The largest realizations occur during the early phase of the sanctions regime in 2014–2015, when markets were learning about the scope and persistence of Western sanctions. One of these realizations corresponds to the December 2014 "Black Monday" episode, when Russian financial markets experienced severe stress around the emergency monetary-policy tightening by the Central Bank of Russia shortly before an OFAC announcement. In Section 3.3, we exclude this specific episode and obtain robust, if anything quantitatively stronger, impulse responses. The distribution of $z_{-3,t}$ also exhibits a heavier right tail than both comparison series, indicating that unusually large sovereign-yield movements occur several days before formal OFAC announcements rather than on the announcement day itself or on ordinary trading days.

**Validation**. We next validate the interpretation of $z_{-3,t}$ as sanctions news. First, we examine media coverage around the 37 OFAC announcements. Appendix Figure B.I plots the number of news items containing the words "sanctions" and "Russia" in major international media outlets, including CNN, the *Wall Street Journal*, and Bloomberg. The timing is striking. Before the fourth day prior to an OFAC announcement, sanctions-related coverage is low, typically below about 20 mentions per day. Four days before

**Figure 3.** Identifying variation in the baseline sanctions-news shock




(a) Time evolution (monthly frequency)




(b) Empirical distribution

*Note*: This figure reports the time-series behavior and empirical distribution of the baseline sanctions-news shock $z_{-3,t}$, constructed from daily changes in Russian sovereign bond yields between trading days $d-4$ and $d-3$ around OFAC sanctions announcements. The distribution is compared with the announcement-day surprise $z_{0,t}$ and with daily changes in average Russian sovereign bond yields on non-sanctions days. The marked December 2014 observation corresponds to the "Black Monday" episode, when Russian financial markets experienced severe stress around the emergency monetary-policy tightening by the Central Bank of Russia. Section 3.3 reports results excluding this episode. The figure illustrates that the right tail of sovereign-yield movements is concentrated in the pre-announcement sanctions-news window.

the announcement, the number of relevant news items jumps by more than a factor of ten. Coverage then remains elevated and reaches several thousand items on the formal

announcement day. This sharp pre-announcement jump provides independent evidence that information about forthcoming sanctions enters the public domain before OFAC acts publicly, and its timing aligns closely with the pre-announcement sovereign-yield movements that identify our baseline shock. Appendix Figure B.II reports the media sources used in the text analysis, and Appendix Figure B.III provides several examples of news reports that discussed upcoming sanctions before the official announcement.

Second, we examine event-window movements in Russian sovereign yields and CDS spreads. Appendix Figures B.IV and B.V show that, on average across the 37 OFAC announcements, both sovereign bond yields and one-year CDS spreads begin to rise before the formal announcement date, with the clearest adjustment occurring around trading day $t-3$. By contrast, the announcement day itself is associated with little additional repricing. This timing is consistent with forward-looking investors incorporating sanctions-related information into sovereign-risk premia before OFAC acts publicly. The same pattern is visible in several major episodes, including 17 March 2014, 29 July 2014, 12 September 2014, 19 December 2014, and 20 December 2016. Taken together, the event-window evidence supports the interpretation that the baseline shock captures pre-announcement sanctions news rather than delayed market reactions to the formal OFAC release.

Third, we test whether the baseline sanctions-news surprise is predictable from observable global macro-financial conditions. Because $z_{-3,t}$ is constructed from the sovereign-yield change between trading days $d-4$ and $d-3$, we shift each candidate predictor backward so that only information available before the yield window enters the forecasting set. Appendix Table B.III reports bivariate daily VAR($\ell$) models using geopolitical risk, the S&P 500, the VIX, the effective federal funds rate, and the Brent oil price (Panel A), as well as a joint multivariate VAR($\ell$) that includes all five predictors simultaneously (Panel B). None of these variables predicts the sanctions-news surprise. In the bivariate models, the $p$-values range from 0.117 to 0.990 in the full sample and from 0.130 to 0.676 in the post-2014 subsample. In the multivariate model, the joint Wald test yields $p = 0.215$ with five lags ($\ell = 5$) and $p = 0.209$ with ten lags ($\ell = 10$) in the full sample; the corresponding values in the post-2014 subsample are $p = 0.109$ and $p = 0.115$. This evidence suggests that $z_{-3,t}$ is not mechanically anticipated by standard global macro-financial indicators, including oil prices and global risk sentiment.

Finally, Appendix Figure B.VI reports the autocorrelation function of $z_{-3,t}$ at the daily frequency over the preceding 21 trading days. The autocorrelations are small and statistically indistinguishable from zero, apart from one isolated coefficient at lag $-6$ that marginally exceeds the confidence bands. We therefore find little evidence that the baseline sanctions-news surprise reflects persistent financial-market dynamics.

Taken together, the first-stage diagnostics, the media evidence, the event-window responses of yields and CDS spreads, the predictability tests, and the autocorrelation evi-

dence support interpreting $z_{-3,t}$ as a sharp sanctions-news surprise revealed several days before formal OFAC announcements.

## 3.2 Second stage: the sanctions news shock and the macroeconomy

Before turning to the formal LP–IV estimates, we first examine the raw relationship between the baseline sanctions-news shock and subsequent real activity. Figure B.VII plots the month-$t$ sanctions-news shock $z_{-3,t}$ against industrial-production growth from $t$ to $t + 12$. The relationship is clearly negative: larger sanctions-news shocks are followed by lower industrial-production growth over the subsequent year. Importantly, this relationship is not driven by the largest realization of the shock, which corresponds to the December 2014 "Black Monday" episode discussed above: excluding this observation makes the fitted slope even more negative. This raw correlation does not by itself identify causal effects, but it previews the dynamic responses estimated below.

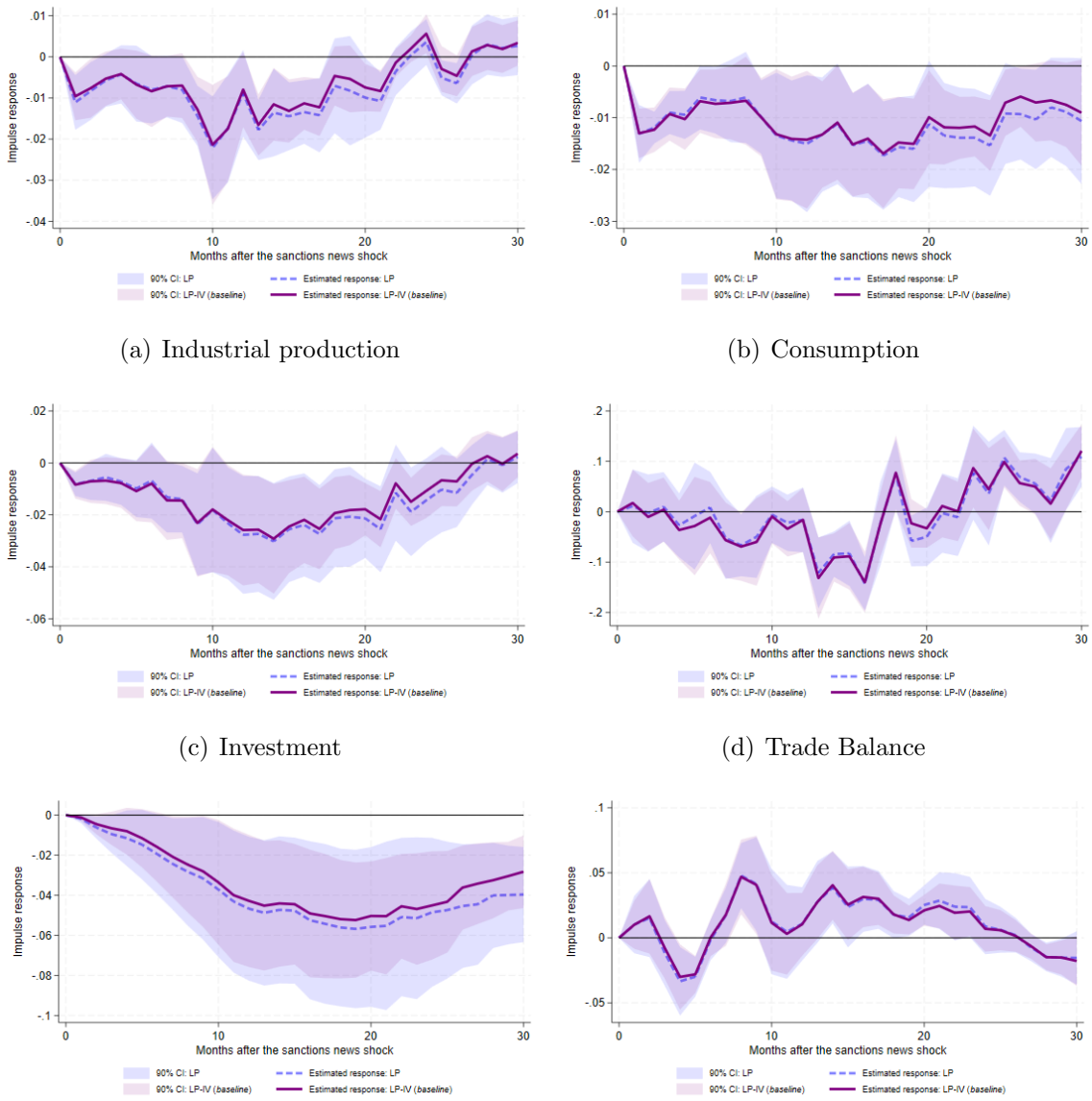
Figure 4 reports the impulse responses of Russian macroeconomic variables to the baseline sanctions-news shock $z_{-3,t}$. We normalize the shock to increase Russia's country spread by 0.25 percentage points on impact.[12] The solid lines report the baseline LP–IV estimates. The dashed lines report direct local projections using the same sanctions-news shock, providing a reduced-form benchmark for the baseline estimates.

**Economic magnitudes**. The LP–IV estimates show a sizable and persistent macroeconomic contraction. A sanctions-news shock that raises the country spread by 0.25 percentage points reduces industrial production by up to 2.1%, with the peak response after 10 months. Private consumption falls by up to 1.7%, peaking after 17 months, and investment falls by up to 2.9%, peaking after 14 months. The trade balance declines by up to 14%, with the largest response after 16 months. Corporate external debt falls by up to 5.2%, peaking after 19 months. The transformed real effective exchange rate increases by up to 4.7%, with the peak response after 8 months, indicating a medium-run real depreciation. All peak responses are statistically and economically significant.

The direct local projections deliver very similar dynamics. The shape, timing, and peak magnitudes of the direct-projection responses closely track the LP–IV responses across all outcomes. This similarity is informative: the macroeconomic contraction is already present in the reduced form of the sanctions-news shock and is not induced by the two-stage LP–IV implementation. Thus, using the country spread to scale the shock does not drive the results; it provides a market-based normalization of the same sanctions-news variation. The direct estimates have somewhat wider confidence intervals, especially

[12]This normalization is close to the second-largest realization of the baseline sanctions-news shock, 0.223, which occurred in July 2015. We do not normalize by the largest realization, 0.824, which occurred in December 2014 around the "Black Monday" episode discussed above.

**Figure 4.** The macroeconomic effect of the sanctions news shock: the baseline estimates




(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.

at longer horizons, but the main responses remain statistically significant.

**Qualitative interpretation**. The response of real activity to the sanctions-news shock is consistent with a broad macroeconomic contraction. Industrial production, private

consumption, and investment all fall quickly after the shock, and the declines accumulate during the first year. Consumption and investment respond more persistently than industrial production, consistent with the high procyclicality of consumption and investment in emerging economies (Uribe and Schmitt-Grohe, 2017).

The most direct external margin is financing. Corporate external debt declines slowly but persistently after the shock, consistent with financial sanctions restricting Russian firms' and banks' access to debt financing in Western markets. This response is consistent with micro-level evidence that Russian banks adjusted their international positions in anticipation of financial sanctions by changing foreign borrowing and foreign asset holdings (Mamonov *et al.*, 2023), and with evidence that U.S. financial sanctions halted new international borrowing by sanctioned Russian companies and reallocated domestic resources toward targeted firms (Keerati, 2023).

The trade response is slower but economically large. The trade balance does not decline significantly on impact, but falls sharply between 9 and 18 months after the shock. This delayed deterioration is consistent with sanctions affecting trade through counterparties, financing, technology restrictions, and imported-input frictions. It is also consistent with evidence from the 2014 Russia sanctions episode that trade losses reflected not only formal product restrictions, but also higher country risk in international transactions (Crozet and Hinz, 2020). The eventual attenuation of the response suggests that trade flows partly adjust over time. The delayed negative response of the trade balance distinguishes sanctions news from a standard country-spread shock, which typically improves the trade balance through import compression (Uribe and Yue, 2006).

The exchange-rate response ties these external margins together. The real effective exchange rate depreciates in the medium run. In the balance-of-payments framework of Itskhoki and Mukhin (2025), the direction of exchange-rate adjustment depends on whether a shock primarily reduces the domestic supply of foreign currency or the domestic demand for foreign currency. The evidence points to the former. The fall in external debt reduces foreign-currency inflows through the financial account, while the delayed deterioration in the trade balance reduces net foreign-currency receipts through the current account. These forces appear to dominate any offsetting decline in foreign-currency demand from lower imports; indeed, product-level evidence suggests that EU and U.S. restrictions on extraction equipment generated limited direct declines in the corresponding import flows (Belin and Hanousek, 2020). The medium-run depreciation of the ruble is therefore consistent with sanctions reducing sources of foreign currency more strongly than uses of foreign currency.

**Channels**. Overall, the impulse responses point to several mutually reinforcing channels. The *financial channel* operates through restricted access to external borrowing and a broader tightening of financing conditions. The *trade and technology channel* operates

more gradually through restrictions on dual-use goods, energy technology, and sanctioned counterparties. The *investment and expectations channel* works through lower expected profitability and greater uncertainty about future market access, which depress investment and durable consumption. Finally, the *fiscal channel* links targeted sanctions to aggregate sovereign risk because the state may absorb part of the losses of sanctioned state-owned or politically connected firms through capital injections, guarantees, directed credit, procurement contracts, or other support. This interpretation is consistent with evidence that targeted sanctions reduce the performance of sanctioned Russian firms unless they are shielded by the state (Ahn and Ludema, 2020), and with evidence that Russian government protection reallocated capital toward sanctioned firms while lowering aggregate productivity (Nigmatulina, 2025). The combined pattern—persistent external-debt contraction, delayed trade adjustment, medium-run ruble depreciation, and broad real contraction—is consistent with sanctions propagating through finance, trade, expectations, and implicit fiscal costs rather than through a single mechanism.

## 3.3 Identification, validation, and sensitivity checks

We further address the main threats to interpreting the impulse responses to $z_{-3,t}$ as the macroeconomic effects of sanctions news shock. We focus on five concerns. First, the baseline LP–IV design uses the country spread to scale sanctions news. Second, the estimates could be driven by a small number of influential OFAC announcements. Third, the design could generate similar results around placebo dates or salient non-sanctions events. Fourth, domestic monetary policy shocks, especially the December 2014 "Black Monday" episode, could contaminate the high-frequency variation. Fifth, pre-announcement yield movements could reflect Russia-related geopolitical escalation rather than sanctions news.

**Alternative identification strategies**. We first estimate a heteroskedasticity-identified Bayesian VAR that exploits the change in the covariance structure of shocks after March 2014 (Appendix C). The responses are smoother and generally smaller than the baseline LP–IV estimates, but preserve the central pattern: industrial production, consumption, investment, and external debt decline, the real exchange rate depreciates in the medium run, and the trade balance deteriorates more gradually and persistently. Because this approach does not use the high-frequency sanctions surprise as an instrument for the country spread, it provides an independent validation of the baseline contraction.

We also estimate an internal-instrument VAR that includes $z_{-3,t}$ directly and orders it first, following Plagborg-Møller and Wolf (2021), and an SVAR–IV using the same external instrument as the baseline LP–IV (Appendix D and Appendix E). The internal-instrument VAR reproduces the contraction in real activity and the medium-run depreciation, but yields a smaller external-debt response and no delayed decline in the trade

balance. The SVAR–IV produces smoother and generally larger, more persistent contractions in real activity and external debt, while preserving the depreciation; its trade-balance response begins earlier and reverses sooner than in the baseline. The greater sensitivity of the trade balance is unsurprising because it is a net outcome combining export and import responses with different signs and adjustment lags. Small differences in the timing of these margins can therefore generate sizable differences in the net response. Thus, the contraction in domestic activity and external finance is robust across identification strategies, whereas the timing and persistence of the trade-balance adjustment are less tightly identified.

**Leave-one-out OFAC jackknife**. To assess whether a few unusually large announcements drive the estimates, we sequentially exclude each of the 37 usable OFAC events, reconstruct the monthly shock, and re-estimate the baseline LP–IV system. The first-stage coefficient for the $t-3$ window remains positive in every iteration and ranges from 0.009 to 0.0135, around the baseline value of 0.0105 (Appendix Figure F.I). The second-stage signs are equally stable: the peak responses of industrial production, consumption, investment, the trade balance, and external debt remain negative in every sample, while the peak REER response remains positive (Appendix Figures F.II–F.VII). The announcements of 19 December 2014 and 30 July 2015 are quantitatively influential, but no single event overturns either instrument relevance or the qualitative macroeconomic effects.

**Placebo dates and placebo events**. We conduct two placebo exercises testing distinct dimensions of the design. First, we replace the 37 OFAC dates with 37 weekdays drawn uniformly without replacement from the sanctions period, excluding OFAC dates and their surrounding event windows. The fixed random seed makes the draw reproducible (Appendix Table G.I). The resulting instruments have coefficients close to zero across $k = -5, \ldots, 2$, robust F-statistics far below conventional thresholds, and impulse responses tightly centered around zero and economically small relative to the baseline (Appendix Figures G.I and G.II). Applying the same procedure to arbitrary dates therefore produces neither first-stage relevance nor a macroeconomic contraction.

Second, we replace OFAC announcements with 30 salient domestic Russian events between 2000 and 2019, including elections, policy reforms, statistical releases, infrastructure projects, and major social and sporting events (Appendix Table H.I). These events also generate weak first stages and fail to reproduce the joint dynamic signature of sanctions news: the responses of industrial production, consumption, and investment are small, external debt moves weakly in the opposite direction, and the real exchange rate exhibits no comparable medium-run depreciation (Appendix Figures H.I and H.II). Together, the placebo exercises show that neither arbitrary calendar dates nor salient domestic Russian news reproduce the baseline findings.

**Domestic monetary policy and the "Black Monday" episode**. We next examine

whether domestic monetary policy confounds the estimates (Appendix I). The concern is most acute in December 2014: the OFAC announcement of 19 December followed the "Black Monday" episode of 16 December, when the Central Bank of Russia raised its policy rate by 650 basis points amid surging inflation, ruble depreciation, and collapsing oil prices.[13] This announcement generates the largest realization of the baseline shock, $z_{-3,\,2014m12} = 0.824$, and may therefore combine sanctions information with extraordinary monetary-policy news.

Excluding the episode leaves the first stage strong: the coefficient rises from 0.011 to 0.014, while the robust F-statistic declines from 25 to 16.5 but remains above conventional weak-instrument thresholds. The impulse responses become approximately 1.5 to 2 times larger and remain statistically significant, although less precisely estimated (Appendix Figures I.I and I.II). The potentially contaminated observation therefore attenuates rather than generates the estimated contraction.

We also construct instruments around regular Central Bank of Russia policy announcements. Of 50 events between 2014 and 2019, we exclude five occurring on or within five days of an OFAC announcement (Appendix Table I.II). Monetary-policy instruments display weaker first-stage relevance concentrated on the announcement day and generate shorter-lived, less precise macroeconomic responses. Most notably, they produce a real appreciation rather than the medium-run depreciation following sanctions news (Appendix Figures I.III and I.IV). The sanctions-news shock therefore captures a distinct source of macroeconomic variation rather than conventional monetary transmission.

**Russia-related geopolitical events around OFAC dates**. A final concern is that pre-announcement yield movements capture military or geopolitical escalation rather than sanctions news. We therefore hand-collect Russia-related events occurring before the largest OFAC announcements (Appendix Table J.I). We find no systematic pattern of independent conflict escalation in the $t-3$ window used to construct the baseline shock. Although the early sanctions announcements were embedded in the broader Crimea and eastern-Ukraine crisis, the identifying yield movements do not repeatedly coincide with escalation at the same pre-announcement horizon. This exercise does not require sanctions announcements to be unrelated to the broader conflict; rather, it shows that independent geopolitical escalation does not systematically coincide with the specific $t-3$ window from which identification is obtained. This evidence reduces the concern that the instrument systematically proxies for geopolitical escalation rather than sanctions-related information.

[13]The episode received extensive international coverage; see, for example, https://www.bbc.com/news/business-30490082.

## 3.4 Additional robustness

The remaining exercises address three issues: alternative measurement of sanctions news, variation over the sanctions regime, and contamination by other shocks. First, the results are robust to alternative constructions of the sanctions-news shock. Using EU rather than OFAC announcements yields similar responses, although the strongest EU first stage, again at $k = -3$, has a robust F-statistic below 10 and produces wider confidence intervals (Appendix K). The neasrest competing pre-announcement surprise, $z_{-4,t}$, closely reproduces the baseline responses, whereas announcement-day movements, $z_{0,t}$, have little explanatory power. Pooling the pre-announcement surprises also produces similar, if anything larger, effects despite combining offsetting yield movements across the event window. Replacing sovereign-bond yields with CDS spreads leaves both the first stage and the impulse responses nearly unchanged (Appendix M).

Second, the effects vary over the life of the sanctions regime. Early announcements generate a strong first stage and sizable macroeconomic responses (Appendix N), whereas later announcements produce directionally similar but smaller and less persistent effects, together with weaker first-stage relevance (Appendix O). This pattern is consistent with sanctions being more informative when the regime was new and with subsequent learning and adaptation by markets and the sanctioned economy.

Third, the estimates do not appear to reflect broader geopolitical or commodity news. Excluding the six OFAC announcements that coincide with major geopolitical events leaves the results essentially unchanged (Appendix P). Shocks constructed around other global geopolitical events (Caldara and Iacoviello, 2022) strongly predict Russia's country spread, but their macroeconomic effects materialize sooner and are generally about half as large as the sanctions responses. OPEC-based yield movements have a first-stage coefficient approximately twice as large as the baseline coefficient, yet generate less persistent responses, particularly for external debt and the real exchange rate (Appendix Q and Appendix R). These comparisons indicate that sanctions news produces distinct macroeconomic dynamics rather than merely capturing generic geopolitical or commodity-related variation.

## 3.5 Counterfactual analysis: historical contribution of sanctions news

We quantify the historical contribution of sanctions news using the internal-instrument Bayesian VAR introduced in Section 3.3. We set the contribution of the shock identified by $z_{-3,t}$ to zero while leaving the estimated VAR dynamics and all other shocks unchanged. The model includes the same endogenous and exogenous variables as the

baseline analysis, with $z_{-3,t}$ ordered first, and is estimated using a Minnesota prior.[14] This is therefore a historical accounting exercise rather than a simulation of a permanently sanctions-free policy regime.

Figure 5(a)–(f) compares the actual twelve-month growth rates with the resulting counterfactual paths. The largest and statistically discernible gaps are concentrated in 2014–2016, while the actual and counterfactual paths converge thereafter. Importantly, the counterfactual still features the 2014–2015 recession because all non-sanctions shocks, including the collapse in global oil prices, remain in place. The exercise therefore indicates that sanctions news deepened the recession rather than caused it in its entirety.

In 2015, actual industrial-production growth averaged 5.9 percentage points below its counterfactual path. The largest gaps reach 6.4 percentage points for consumption, 8.4 percentage points for investment, and 28.6 percentage points for the trade balance; all are statistically significant. The trade balance exhibits the largest pointwise difference, although Section 3.3 shows that its precise dynamics are more specification-sensitive than the real-activity responses. For external debt, the no-sanctions path lies above the actual path, consistent with sanctions restricting access to foreign borrowing, but the credible bands overlap. During 2014–2016, the counterfactual also implies up to 15.3 percentage points less real depreciation and a country spread up to 1 percentage point lower.[15]

Overall, the decomposition attributes a material part of the initial 2014–2016 downturn to identified sanctions news shocks. The narrowing of the gaps thereafter is consistent both with the lower informational content of later announcements and with learning and adaptation by markets and the Russian economy.

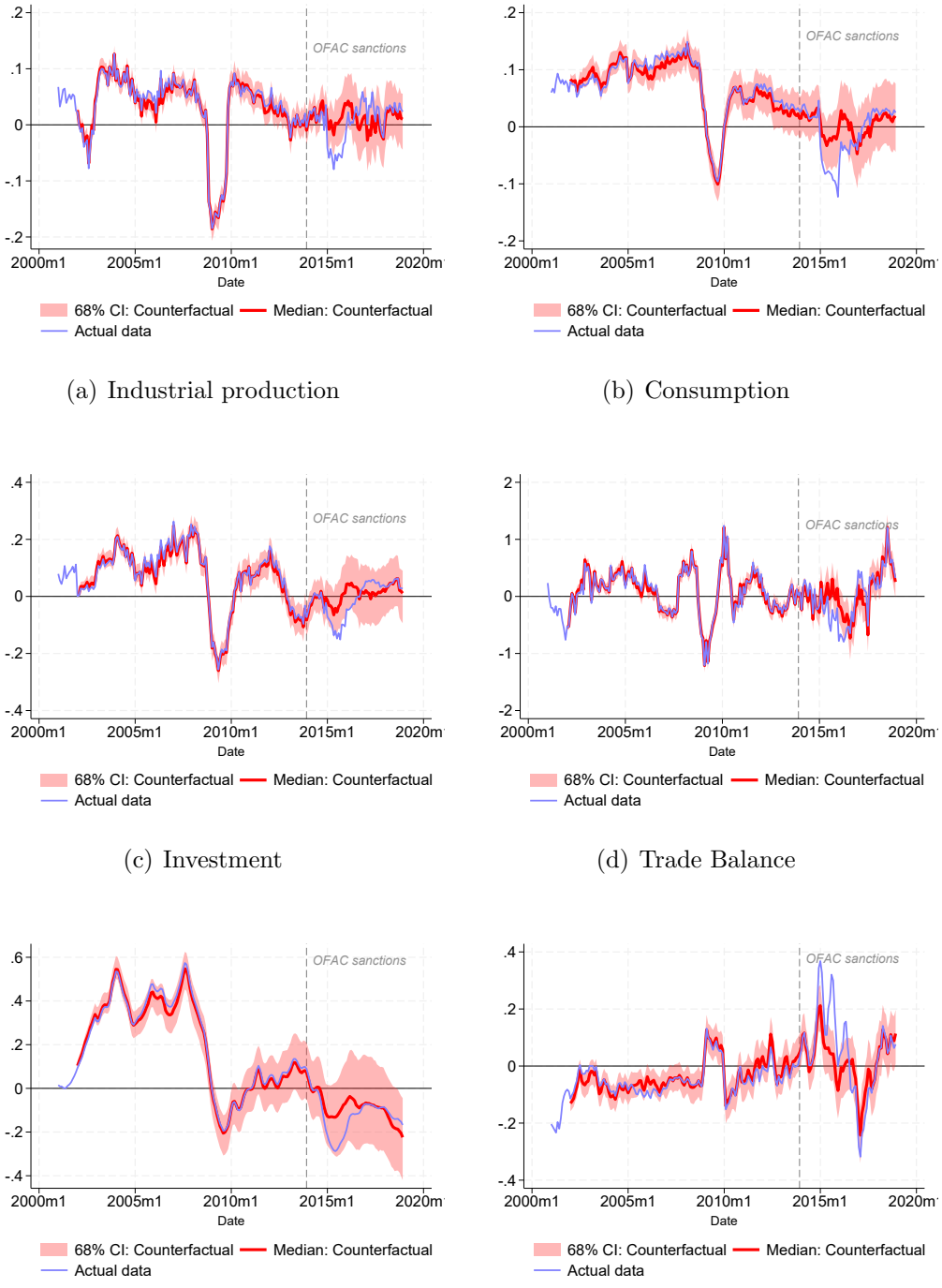
# 4 Distributional effects of sanctions news

The aggregate contraction documented above may conceal substantial heterogeneity across firms and households. We focus on two ex ante dimensions of exposure. Larger and more productive firms are likely to be more integrated into international trade and financial networks, while higher-income households are more likely to hold internationally exposed assets or work for internationally connected firms. We therefore examine how the sanctions news shock propagates across the firm and household distributions.

[14] The results are similar under a flat prior. We use the Minnesota prior because shrinkage toward persistent dynamics helps avoid explosive historical paths in the highly persistent Russian macroeconomic series.

[15] The country-spread counterfactual is not reported in Figure 5.

**Figure 5.** Counterfactual macroeconomic paths absent sanctions news shocks




(a) Industrial production

(b) Consumption

(c) Investment

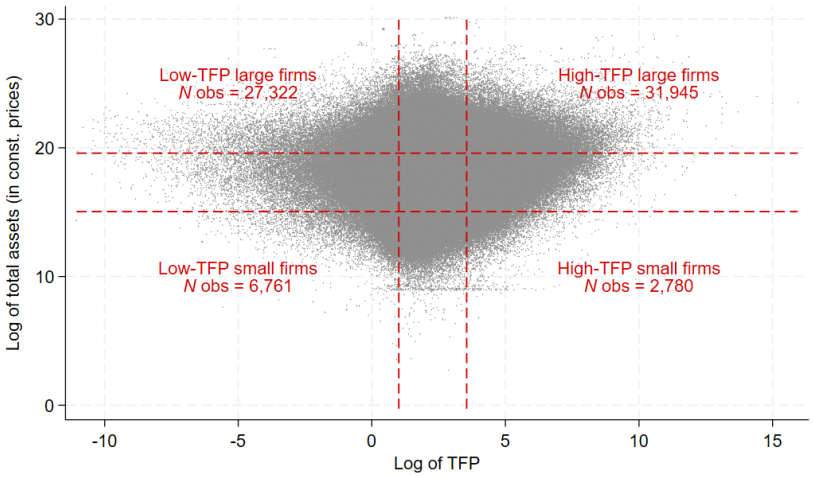
(d) Trade Balance

(e) External Debt

(f) REER

*Note*: The figure reports actual and counterfactual twelve-month growth rates obtained by setting the historical contribution of the sanctions-news shock $z_{-3,t}$ to zero in the internal-instrument Bayesian VAR. Blue lines show the actual data, red lines the posterior-median counterfactual, and shaded areas the 68% credible bands. The model is estimated using a Minnesota prior and 500 posterior draws; Appendix D reports the estimation and prior details.

**Figure 6.** Firm size and productivity, 2010–2019




*Note*: The figure plots log TFP against log total assets in the cross-section of Russian firms. The vertical and horizontal lines denote the 20th and 80th percentiles of the corresponding 2013 distributions and define the four size-productivity cells used in the analysis. Group membership is fixed at its 2013 value (the last pre-sanction year). The joint sample contains 941,677 firm-year observations for 299,998 firms. The data is sourced from SPARK-Interfax.

## 4.1 Sanctions news and the cross-section of firms

**Firm-level data and classification**. We draw firm-level data from SPARK-Interfax, which covers about 12 million Russian entities.[16] We focus on 2010–2019 and retain firms reporting total revenues, wages, fixed assets, after-tax profits, total borrowing, and total assets. The resulting sample contains approximately 500,000 firms and 2,516,353 firm-year observations.

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

$$TFP_{f,t} = \frac{Y_{f,t}}{K_{f,t}^{0.35} \cdot L_{f,t}^{0.65}} \tag{5}$$

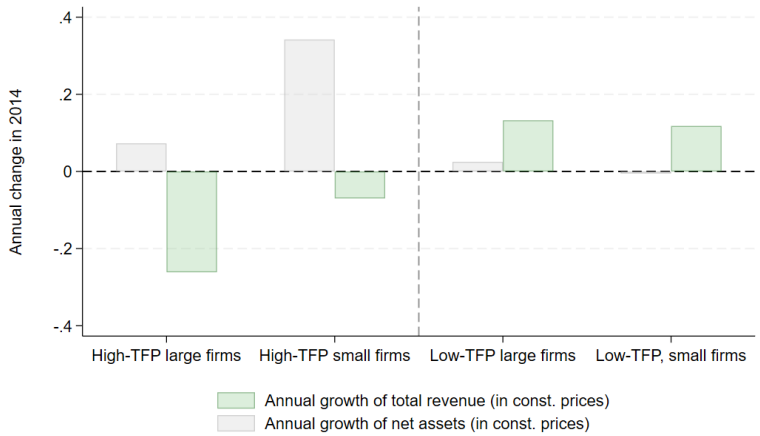
where $Y_{f,t}$ is real total revenue and $K_{f,t}$ and $L_{f,t}$ are proxied by real fixed assets and the real wage bill. We classify firms using their positions in the 2013 distributions of log TFP and log total assets, the last pre-sanctions year. High- and low-TFP firms belong to the top and bottom quintiles of the productivity distribution; large and small firms are defined analogously using total assets. We fix group membership at its 2013 value to avoid endogenous reclassification following sanctions-related adjustment or firm exit.[17]

We document large productivity differentials: High-TFP firms have productivity levels 19.1% above the sample mean, whereas low-TFP firms lie 16.3% below it (Appendix Table T.I). High-TFP firms are also larger, less capital- and labor-intensive, more prof-

[16] See spark-interfax.com.

[17] Only 47.3% of firms initially classified as high- or low-TFP remain in the same productivity group through 2019. The results are robust to using tercile and median cutoffs.

**Figure 7.** Firm growth by pre-sanctions size and productivity, 2014




*Note*: The figure reports average growth rates of real net assets and real total revenues in 2014 across the four size-productivity cells defined using the 2013 distributions (Figure 6). The data is sourced from SPARK-Interfax.

itable, more leveraged, and more dynamic than low-TFP firms. Appendix Appendix T further documents that productivity differentials in revenues, profitability, wages, and growth systematically narrow following sanctions shocks.

Figure 6 plots firms in the joint distribution of size and productivity and identifies the four extreme size-productivity cells used in the analysis. Large, high-TFP firms are economically dominant: they account for 38.6% of aggregate sample revenue in 2013, whereas the other three extreme cells together account for less than 4%.

In Figure 7, we further document a striking pattern in the raw data. In 2014, the first sanctions year, real revenues fell by approximately 25% among large, high-TFP firms and by 7% among small, high-TFP firms, while both low-TFP groups recorded revenue growth (Figure 7).[18] Because these differences may also reflect the oil-price collapse and domestic monetary tightening, we next relate firm outcomes to the identified sanctions news shock.

**Estimation strategy**. Existing studies show that firms directly targeted by sanctions experience sharper contractions in sales and employment (Ahn and Ludema, 2020; Crozet *et al.*, 2021). Our objective is broader: to estimate the incidence of sanctions news across firms, including effects operating through aggregate financing conditions, competition, and production networks. We adapt Equation (3) to panel local projections (Jorda and Taylor, 2016) and estimate the following specification separately in each size-productivity

[18]Consistent with Nigmatulina (2025), this pattern may partly reflect government support disproportionately benefiting less productive firms.

cell:

$$\ln TR_{f,t+h} = \alpha_f + \alpha_i + \alpha_s + \theta_h \cdot \overline{z}_{-3,t} + \mathbf{X}_{f,t}\mathbf{\Phi'}_h + \varepsilon_{f,t+h} \tag{6}$$

where $\ln TR_{f,t+h}$ denotes real total revenue of firm $f$ in year $t+h$, where $h = 1, \ldots, 4$ is the prediction horizon. 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.[19] With these control variables, the coefficients of interest $\theta_h$ effectively capture a part of the aggregate variation in the future magnitudes of firms' total revenues that is due to the current sanctions news shock and not to other idiosyncratic and aggregate factors. Finally, $\varepsilon_{f,t+h}$ is the regression error.

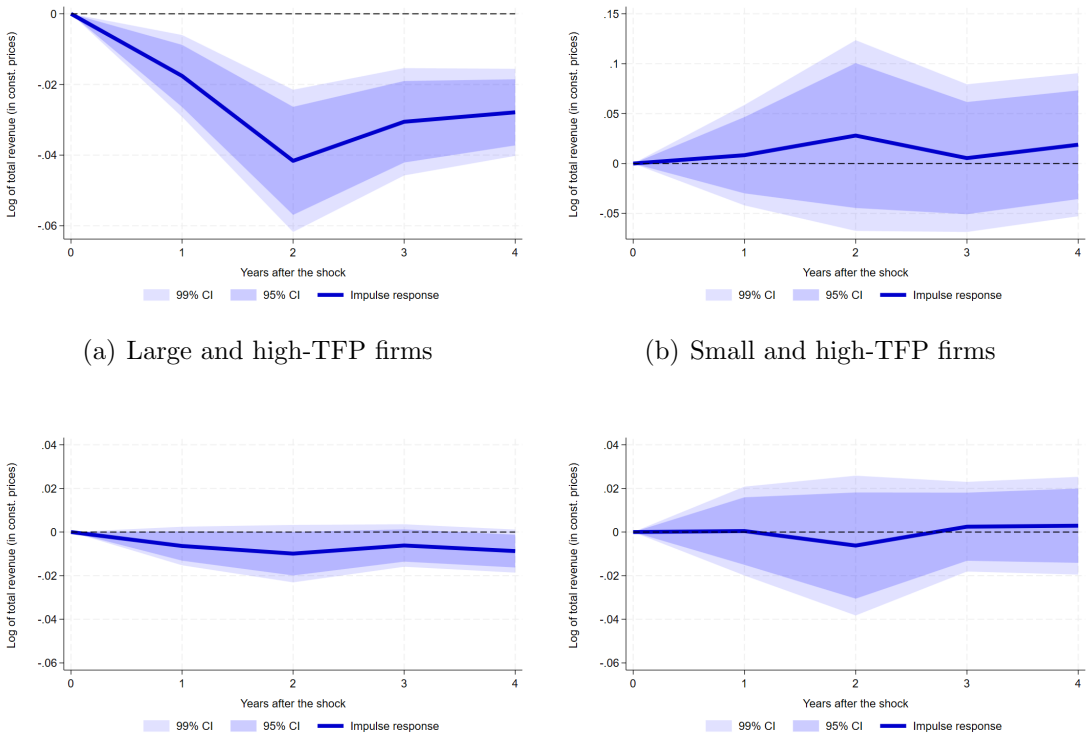
We estimate reduced-form rather than LP–IV responses. Firm outcomes are observed annually, so aggregating the monthly instrument leaves at most seven annual shock realizations over 2013–2019. This makes an annual LP–IV first stage and conventional weak-instrument diagnostics uninformative, particularly in a specification with firm fixed effects and dynamic controls. The reduced-form panel projections therefore provide a transparent way to trace the firm-level incidence of the same sanctions-news variation used in the macroeconomic analysis.

**Baseline results**. Figure 8 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 $\theta_h$ to represent responses to a 0.25 percentage point 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 computed by clustering standard errors at the industry (*okved*) $\times$ year level.

Our estimates indicate that these are exclusively large, high-TFP firms that experience pronounced and persistent revenue losses following sanctions news: real revenues fall immediately and reach a peak decline of approximately 4% during the first two years, with the estimates remaining statistically significant thereafter. These effects account

[19] 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 $\theta_h$.

**Figure 8.** Cross-sectional effects of the sanctions news shock on firm 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

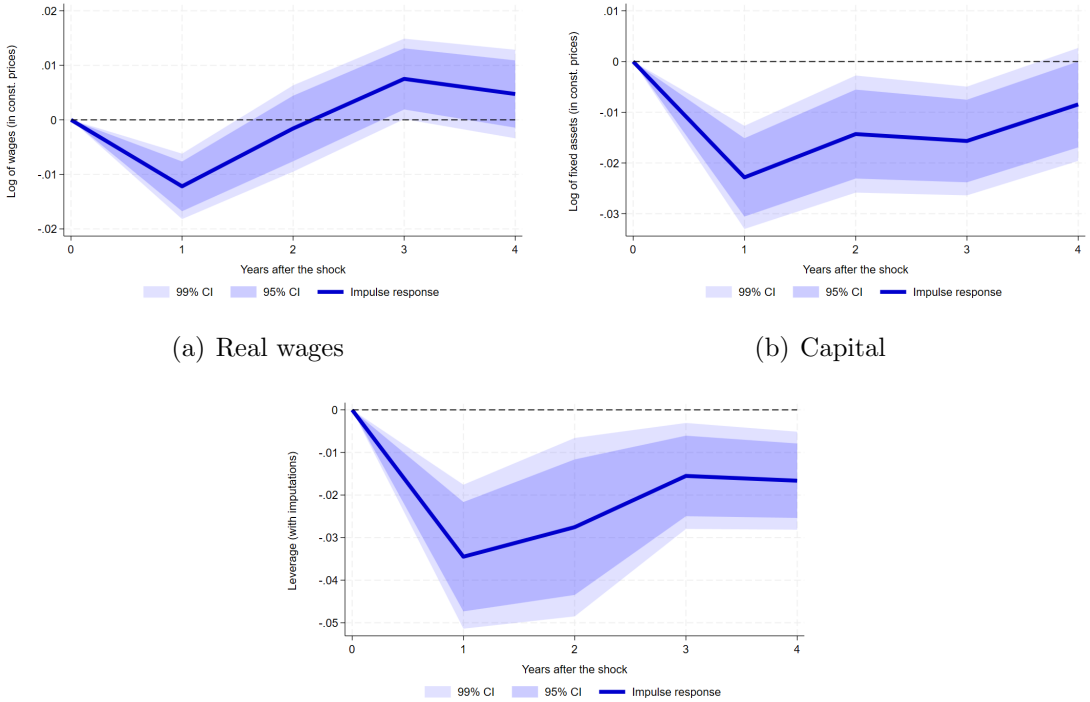
*Note*: The figure reports estimates of $\theta_h$ from Equation (6) separately for the four size-productivity cells. Responses are scaled to $\overline{z}_{-3,t} = 0.223$. Groups are defined using the 2013 distributions of TFP and total assets and held fixed thereafter. The 95% and 99% confidence intervals are computed by clustering standard errors at the industry × year level.

for approximately 16% of the observed revenue contraction among these firms in 2014–2015. By contrast, the responses of small, high-TFP firms and both low-TFP groups are economically small and statistically indistinguishable from zero.

Further estimations shows that the contraction extends beyond revenues. Among large, high-TFP firms, real wages fall by 1.2%, fixed assets by 2.3%, and leverage by 3.4 percentage points of assets in the first year after the shock, all significant at the 1% level (Figure 9). The wage response dissipates, whereas capital and leverage remain depressed, consistent with a persistent contraction in firm scale and external financing.

**Ex ante debt capacity.** We next examine whether the cross-sectional effects depend on firms' pre-sanctions capacity to obtain external debt financing. We proxy this capacity using the 2013 ratio of total borrowing to total assets, where total borrowing is the sum of short- and long-term debt. Firms in the bottom quintile of the full-sample distribution are classified as low-debt firms and those in the top quintile as high-debt firms; the classification is held fixed throughout the sample.

**Figure 9.** Adjustment margins among large, high-TFP firms




(a) Real wages

(b) Capital

(c) Leverage

*Note*: The figure reports responses of real wages, real fixed assets, and leverage among large, high-TFP firms, estimated using Equation (6). Responses are scaled to $\overline{z}_{-3,t} = 0.223$. The 95% and 99% confidence intervals are computed by clustering standard errors at the industry × year level.

The revenue estimates, reported in Appendix Figure T.I, indicate that this margin matters primarily for large, high-TFP firms. Within that group, revenues of low-debt firms fall by 2.65% on impact, whereas those of high-debt firms increase by 0.63%, producing a 3.28 percentage point difference ($p = 0.029$). By year 4, the corresponding responses are $-4.70\%$ and $-1.66\%$, leaving a 3.04 percentage point gap ($p = 0.060$). The other three size-productivity cells show no similarly consistent revenue pattern.

The remaining outcomes display a similar, although less uniformly precise, ordering. By year 4, wages are 1.30% below baseline among low-debt firms but 1.24% above baseline among high-debt firms, a 2.54 percentage point gap ($p = 0.037$). Capital falls by 2.93% among low-debt firms and is approximately unchanged among high-debt firms, although the 3.01 percentage point difference is imprecisely estimated ($p = 0.110$). Leverage declines by 0.29 and 0.16 percentage points of assets, respectively, and the difference is insignificant ($p = 0.704$). Appendix Table T.I shows only isolated differences outside the large/high-TFP cell. The results are therefore consistent with limited ex ante debt capacity amplifying the contraction among the firms most exposed to sanctions news.

**Sector composition.** Finally, we examine whether the large/high-TFP result is driven by a small number of dominant sectors. The ten largest two-digit *okved* sectors account for 81.8% of observations in this cell.[20] Sequentially excluding each sector leaves the year-1 revenue response tightly clustered between $-1.86\%$ and $-2.77\%$, with every estimate significant at the 1% level. Wholesale trade alone accounts for 44.4% of observations, yet excluding it yields an estimated response of $-2.77\%$ ($p = 0.0017$). The baseline effect therefore reflects a broad contraction among large, highly productive firms rather than exposure to any single sector (Appendix Figure T.II).

Overall, sanctions news disproportionately contracts the revenues, wages, capital, and external financing of the largest and most productive firms. The effect is amplified among firms with low pre-sanctions debt capacity and is not attributable to any single dominant sector, consistent with sanctions propagating through firms' international exposure and financing conditions.

## 4.2 Sanctions news across the household income distribution

**Household data and classification**. We examine whether sanctions disproportionately affect high-income individuals and whether this incidence varies across locations. We use the RLMS–HSE, a nationally representative longitudinal survey of approximately 5,000 Russian households conducted annually since 1994.[21] We extract information on individual income, household consumption, and socio-demographic characteristics over 2006–2019 and winsorize monetary variables at the 1st and 99th percentiles. The resulting sample contains 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).[22]

The survey distinguishes regional capital cities, other large towns, small towns, and rural areas. Average annual real income differs meaningfully across locations: it equals approximately 484 thousand rubles in regional capitals, 417 thousand in other large towns, 422 thousand in small towns, and 372 thousand in rural areas, all measured in 2014

[20] These sectors correspond to wholesale trade (46), motor vehicle trade (45), real estate (68), building construction (41), financial services (64), retail trade (47), utilities (35), specialized construction (43), food manufacturing (10), and engineering services (71).

[21] The RLMS–HSE has been widely used in the literature; see, among others, Yakovlev (2018) and Adsera *et al.* (2021).

[22] 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 10.** Income and consumption across household groups, 2014




*Note*: The figure reports average growth rates of real individual income and household consumption in the first sanctions year (2014) for individuals in the top and bottom quintiles of the 2013 income distribution, separately for regional capitals and other locations. Income-group membership is fixed at its 2013 value. The data is sourced from RLMS-HSE.

prices.[23] Thus, average income in regional capitals is about 30% higher than in rural areas, while incomes in large and small towns lie in between and are relatively similar (Appendix Table U.I). We classify individuals using their real income in 2013, the last pre-sanctions year. The top and bottom quintiles define high- and low-income individuals, whom we further separate between regional capitals and all other locations. As in the firm analysis, group membership is fixed at its pre-sanctions value to avoid endogenous reclassification after the shock.

Appendix U validates the internal consistency of the data. First, Appendix Figure U.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 U.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 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 10 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%. Because the raw differences may also reflect the oil-price collapse and monetary tightening, we next relate individual outcomes to the identified sanctions-news shock.

**Estimation strategy**. As in the firm analysis, we adapt the macroeconomic local pro-

[23]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.

jections to the annual household panel:

$$\ln Income_{i,t+h} = \alpha_i + \alpha_s + \alpha_j + \theta_h \cdot \overline{z}_{-3,t} + \mathbf{X}_{i,t}\mathbf{\Phi'}_h + \varepsilon_{i,t+h} \tag{7}$$

where $Income_{i,t+h}$ is the real income of individual $i$ and $\overline{z}_{-3,t}$ is the annualized sanctions news shock. The control vector $\mathbf{X}_{i,t}$ includes individual income, debt status, the number of children in the household, and the age of the household head, together with commodity terms of trade, industrial production, and the real effective exchange rate. Fixed effects $\alpha_i$, $\alpha_s$, and $\alpha_j$ 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.

For the same reason as in the firm analysis, we estimate reduced-form panel local projections rather than LP–IV responses. Annual aggregation leaves too few independent shock realizations for a meaningful first stage, while the reduced-form specification traces the household incidence of the same sanctions-news variation used in the macroeconomic analysis.

**Income responses**. Figure 11 reports income responses scaled to $\overline{z}_{-3,t} = 0.223$, matching the shock that raises Russia's country spread by 0.25 percentage points in the macroeconomic analysis. Panels (*a*) and (*b*) report responses of the 20% richest individuals residing in regional capital cities or other locations, respectively. Panels (*c*) and (*d*) report the corresponding estimates for the 20% poorest individuals from regional capital cities or other localities. Each panel contains 95% and 99% confidence intervals computed by clustering standard errors at the locality (PSU, primary sample unit) × year level.

Our estimates show that among high-income individuals in regional capitals, real income falls significantly during the first two years and reaches a peak decline of 5.5% in the first year (*a*). This estimate accounts for approximately one-third of the observed decline in their real income in 2014. Differently from high-TFP large firms, this negative effect attenuates gradually and dissipates after roughly three years. High-income individuals outside regional capitals experience a quantitatively similar decline, with the subsequent attenuation (*b*).

By contrast, income responses among low-income individuals are close to zero and statistically insignificant at every horizon, irrespective of location (*c*, *d*). Thus, the incidence of sanctions news is strongly related to pre-sanctions income but shows little additional heterogeneity between regional capitals and other areas.

**Consumption responses**. Because the income responses of high- and low-income individuals are similar across locations, we now pool their locations and turn to examining the composition of household consumption. Figure 12 shows that high-income households reduce food consumption by slightly more than 1%, other nondurable consumption by

**Figure 11.** Individual-income responses to the sanctions-news shock




(a) 20% richest, regional capital cities

(b) 20% richest, other localities

(c) 20% poorest, regional capital cities

(d) 20% poorest, other localities

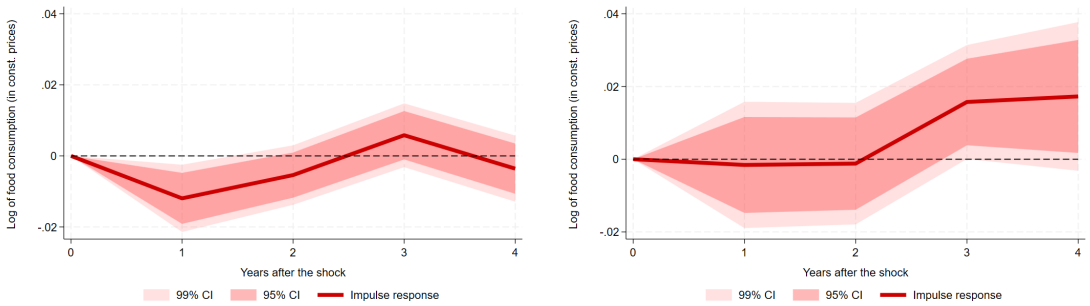
*Note*: The figure reports estimates of $\theta_h$ from Equation (7) for individuals in the top and bottom quintiles of the 2013 income distribution, separately for regional capitals and other locations. Responses are scaled to $\overline{z}_{-3,t} = 0.223$. Income-group membership is fixed at its last pre-sanctions value in 2013. The 95% and 99% confidence intervals are computed by clustering standard errors at the locality (PSU, primary sample unit) $\times$ year level.

2.5%, and durable consumption by approximately 10% in the first year after the shock. These effects dissipate within two years. The concentration of adjustment in durables is consistent with households protecting essential consumption while postponing more discretionary purchases.

Among low-income households, food and durable consumption do not respond significantly. Other nondurable consumption falls by 2.5% in the first year, but the estimate is imprecise and reverses at longer horizons, indicating at most a limited and transitory adjustment.

Overall, sanctions news disproportionately reduces the income and consumption of high-income individuals while leaving the bottom of the income distribution largely insulated. Together with the firm-level evidence, these results indicate that the burden of sanctions is concentrated among economically stronger agents—large, productive firms and high-income households—and therefore compresses the income distribution in the targeted economy.

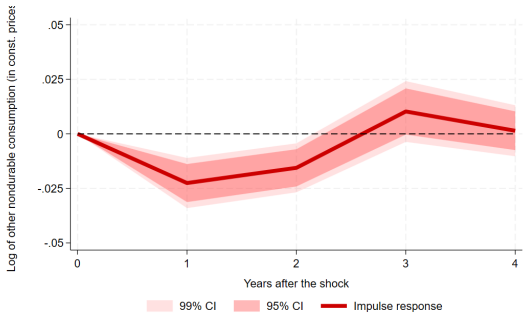
**Figure 12.** Household-consumption responses across the income distribution



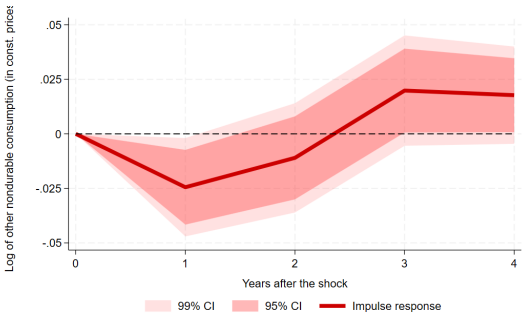

(a) 20% richest: Food consumption



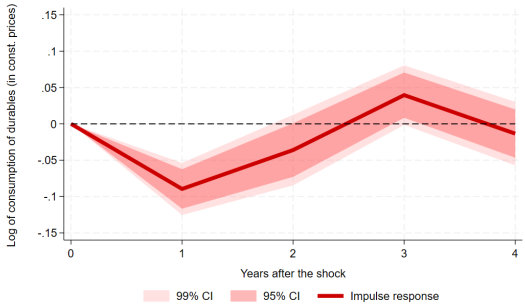

(b) 20% poorest: Food consumption



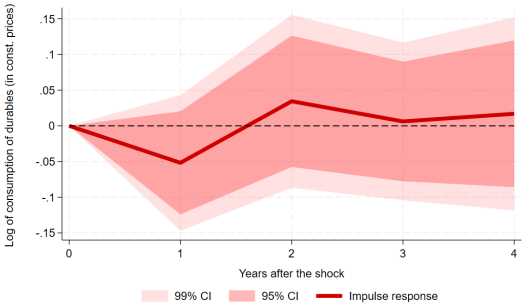

(c) 20% richest: Other nondurable consumption




(d) 20% poorest: Other nondurable consumption




(e) 20% richest: Consumption of durables




(f) 20% poorest: Consumption of durables

*Note*: The figure reports responses of real food, other nondurable, and durable consumption for individuals in the top and bottom quintiles of the 2013 income distribution. Responses are scaled to $\overline{z}_{-3,t} = 0.223$. Locations are pooled because the corresponding income responses do not differ materially across regional capitals and other areas.The 95% and 99% confidence intervals are computed by clustering standard errors at the locality (PSU, primary sample unit) × year level.

# 5 Conclusion

This paper estimates the aggregate and distributional effects of targeted sanctions using high-frequency changes in Russian sovereign-bond yields around OFAC announcements. Markets systematically reprice sanctions risk three to four days before formal announce-

ments. The identified sanctions-news shock produces persistent contractions in industrial production, consumption, investment, and external debt, together with a medium-run real depreciation. A counterfactual decomposition attributes a material part of the 2014–2016 downturn to sanctions news, while showing that the collapse in oil prices would still have generated a recession.

The costs of sanctions are highly uneven and extend well beyond directly targeted entities. Large, high-productivity firms experience persistent declines in revenues, wages, capital, and leverage, particularly when their pre-sanctions debt capacity is limited, whereas small and low-productivity firms are largely unaffected. High-income individuals suffer sizable income losses and sharply reduce durable consumption, while responses at the bottom of the income distribution are close to zero. Sanctions therefore operate as system-wide shocks rather than remaining confined to formally targeted firms. Their spillovers to non-targeted agents may reduce aggregate productivity by disproportionately weakening large and productive firms, while simultaneously compressing the income distribution. These effects cannot be recovered from comparisons between sanctioned and non-sanctioned entities alone.

The findings have two broader implications. First, sanctions affect markets when information about future restrictions becomes available, not necessarily on the formal announcement day. Empirical designs based only on announcement-day variation may therefore miss an important part of the policy shock. Second, the effects are strongest early in the sanctions regime and attenuate as markets and the targeted economy learn and adapt, implying diminishing effects of subsequent measures unless their scope changes materially. Although our empirical setting is the pre-2022 sanctions regime against Russia, the mechanisms we identify—anticipation, sovereign-risk repricing, external-financing contraction, and adaptation—are likely to be relevant for other sanctions episodes involving economically integrated target countries. Evaluating sanctions therefore requires accounting jointly for anticipation, adaptation, and distributional incidence.

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# 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.[24] 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.[25] We sum banks' and other sectors' external debt and subtract debt owed by these sectors to direct investors.[26] 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.

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

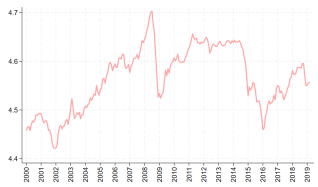
[24] Data source: Short-term economic indicators, https://rosstat.gov.ru/compendium/document/50802.

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

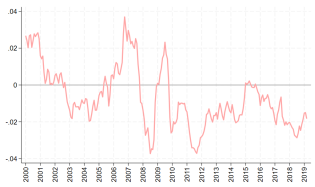
[26] A sizeable amount of Russia's corporate external debt falls into a category of debt to direct investors and direct investment enterprises. As of the end of 2013, the share of this type of corporate external debt amounted to 2% for Russian banks and 35% for Russian non-financial firms. This portion 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.

into logarithms. The resulting data is depicted in Figure A.I.

**Figure A.I.** Transformed macroeconomic data



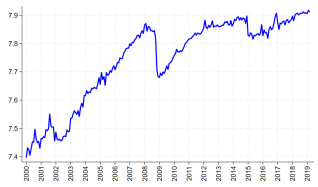
(a) Commodity terms of trade



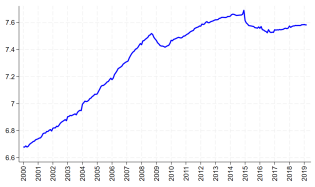
(b) Real interest rate in the US



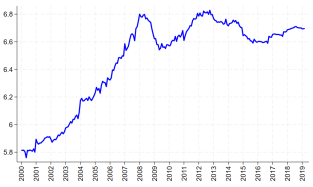
(c) US Baa spread



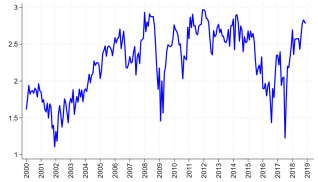
(d) Industrial production



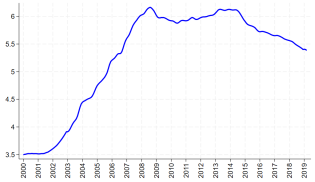
(e) Private consumption



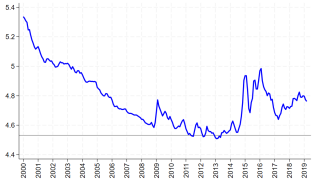
(f) Investment



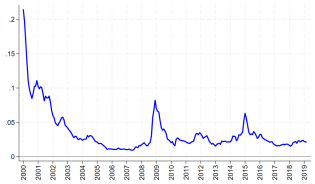
(g) Trade balance



(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

## 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.

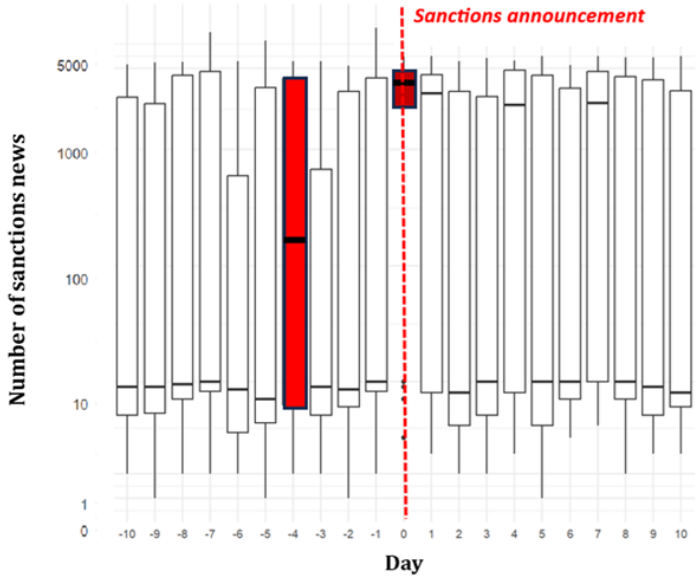
**Table B.II.** The list of Russia's US Dollar-denominated sovereign bonds

| 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.

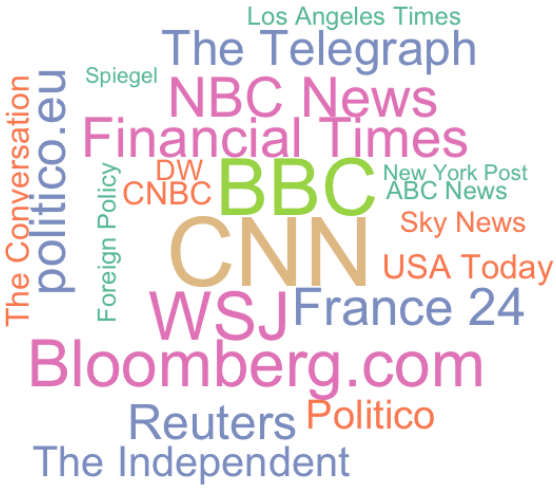
## B.3 Media Evidence of Pre-Announcement Sanctions Leakages

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



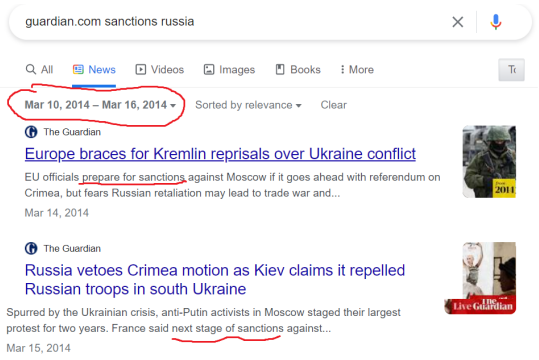

*Note*: This figure reports the number of news articles that mention both "sanctions" and "Russia" in selected international media sources (B.II) within a window centered on OFAC sanctions announcement dates. The horizontal axis spans 10 days before to 10 days after each announcement.

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

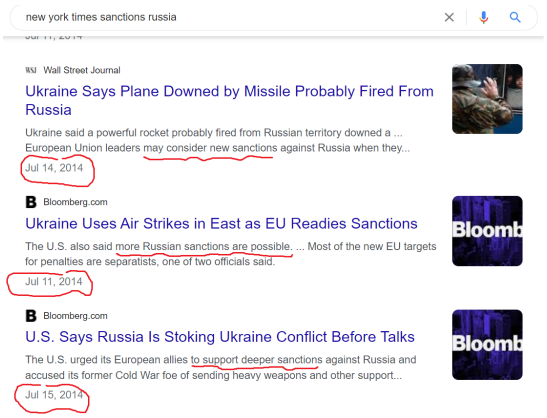



*Note*: This figure displays a word cloud of major international media outlets covering sanctions against Russia around the 37 OFAC sanctions announcements during the 2010s. The size of each outlet's name reflects the relative number of articles mentioning both "Russia" and "sanctions" during the pre-announcement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

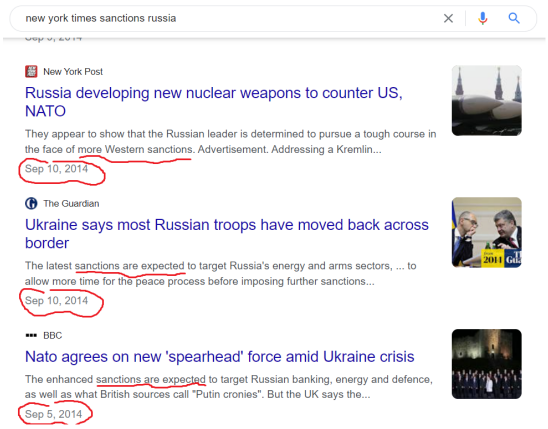
**Figure B.III.** Evidence of Sanctions Anticipation in Global Media Before OFAC Announcements




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




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

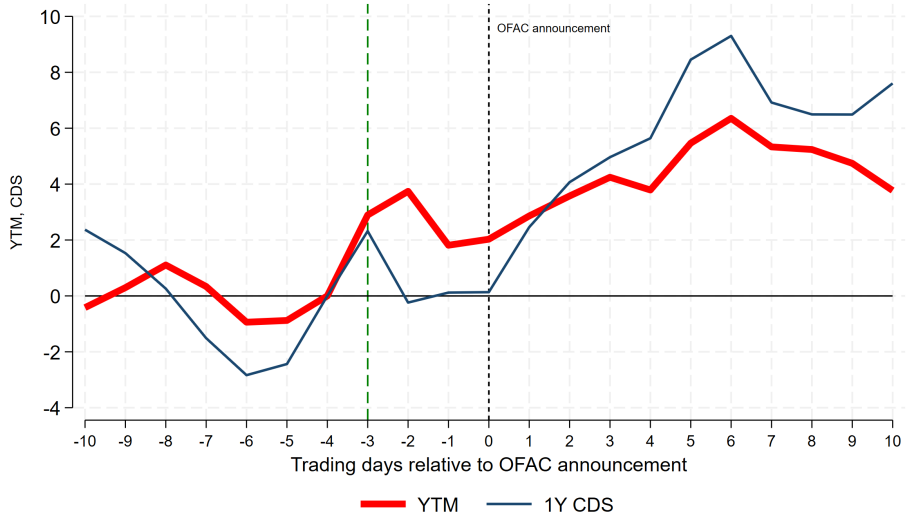



(c) During the week before OFAC announcement on Sept. 12, 2014

*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.

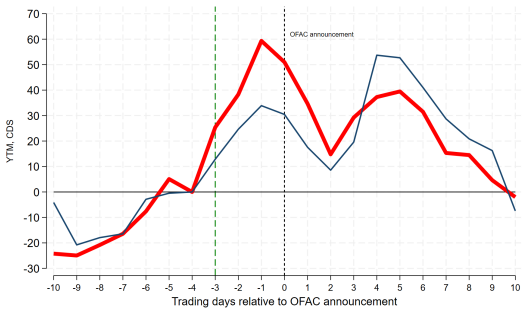
## B.4 Event-study evidence around major sanctions announcements

**Figure B.IV.** Aggregate event-study evidence around OFAC sanctions announcements

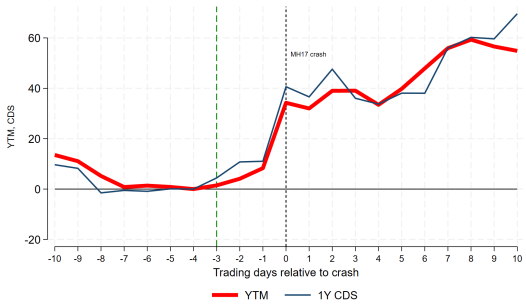



*Note*: The figure reports average cumulative changes in Russia's sovereign bond YTM and sovereign CDS around the 37 OFAC sanctions announcements in our sample, for trading days $k = -10, \ldots, 10$ relative to the announcement date $t$. Each series is normalized to zero at trading day $t-4$, so the vertical scale measures cumulative changes in basis points from $t-4$ to $t+k$. YTM denotes the average yield to maturity on Russia's US-dollar-denominated sovereign bonds, while CDS denotes Russia's one-year sovereign credit default swap spread. The red line plots YTM and the blue line plots CDS. The green vertical line marks trading day $t-3$, the black vertical line marks the OFAC announcement day $t$, and the horizontal dashed line marks zero.

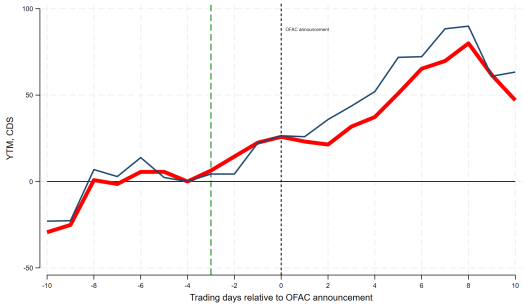
**Figure B.V.** Selected event-study evidence around OFAC sanctions announcements and the MH17 crash



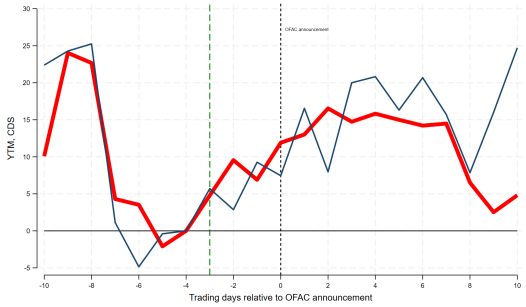

(a) 17 Mar 2014



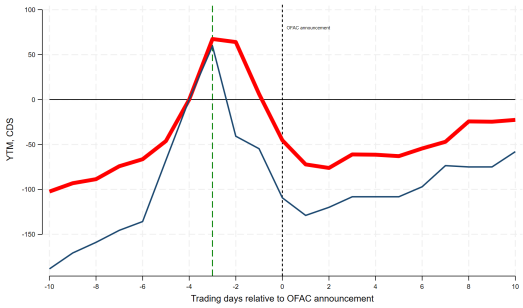

(b) MH17 crash: 17 Jul 2014



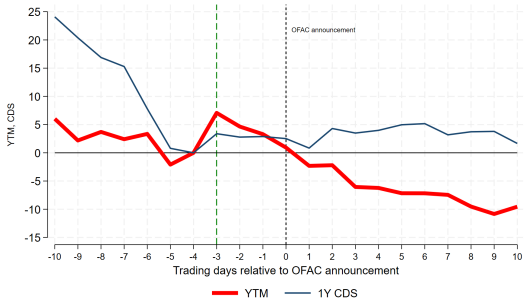

(c) 29 Jul 2014




(d) 12 Sep 2014




(e) 19 Dec 2014




(f) 20 Dec 2016

*Note*: The figure reports cumulative changes in Russia's sovereign bond YTM and sovereign CDS over trading days $k = -10, \ldots, 10$ around selected events. Each series is normalized to zero at trading day $t-4$, so the vertical scale measures cumulative changes in basis points from $t-4$ to $t+k$. YTM denotes the average yield to maturity on Russia's US-dollar-denominated sovereign bonds, while CDS denotes Russia's one-year sovereign credit default swap spread. The red line plots YTM and the blue line plots CDS. Panel $(a)$ corresponds to the OFAC sanctions announcement of 17 March 2014. Panel $(b)$ corresponds to the MH17 crash on 17 July 2014. Panels $(c)$-$(f)$ correspond to the OFAC sanctions announcements of 29 July 2014, 12 September 2014, 19 December 2014, and 20 December 2016, respectively. The green vertical line marks trading day $t-3$, the black vertical line marks event day $t$, and the horizontal dashed line marks zero. In panel $(b)$, event day $t$ is the date of the MH17 crash; in all other panels, it is the OFAC announcement day.

## B.5 Details on the baseline sanctions news shock ($z_{-3,t}$)

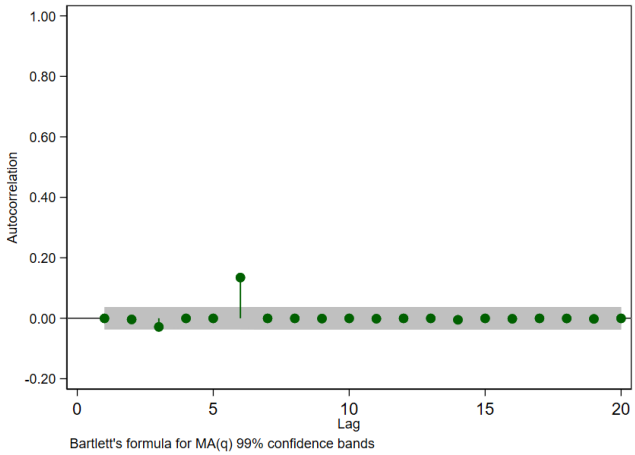
**Table B.III.** Granger-causality tests for predictability of the sanctions surprise series

| *Panel A. Bivariate VARs with five lags* | | | | |
|---|---|---|---|---|
| | Full sample | | Sanction sample | |
| Variable | 1st diff. | Level | 1st diff. | Level |
| Geopolitical risk | 0.117 | 0.410 | 0.163 | 0.489 |
| S&P 500 | 0.284 | 0.303 | 0.498 | 0.396 |
| VIX | 0.466 | 0.394 | 0.372 | 0.366 |
| Fed funds rate | 0.990 | 0.840 | 0.676 | 0.356 |
| Brent oil price | 0.279 | 0.263 | 0.156 | 0.130 |

| *Panel B. Joint multivariate VARs in levels* | | | | |
|---|---|---|---|---|
| | Full sample | | Sanction sample | |
| Test | $l = 5$ | $l = 10$ | $l = 5$ | $l = 10$ |
| All five predictors jointly | 0.215 | 0.209 | 0.109 | 0.115 |

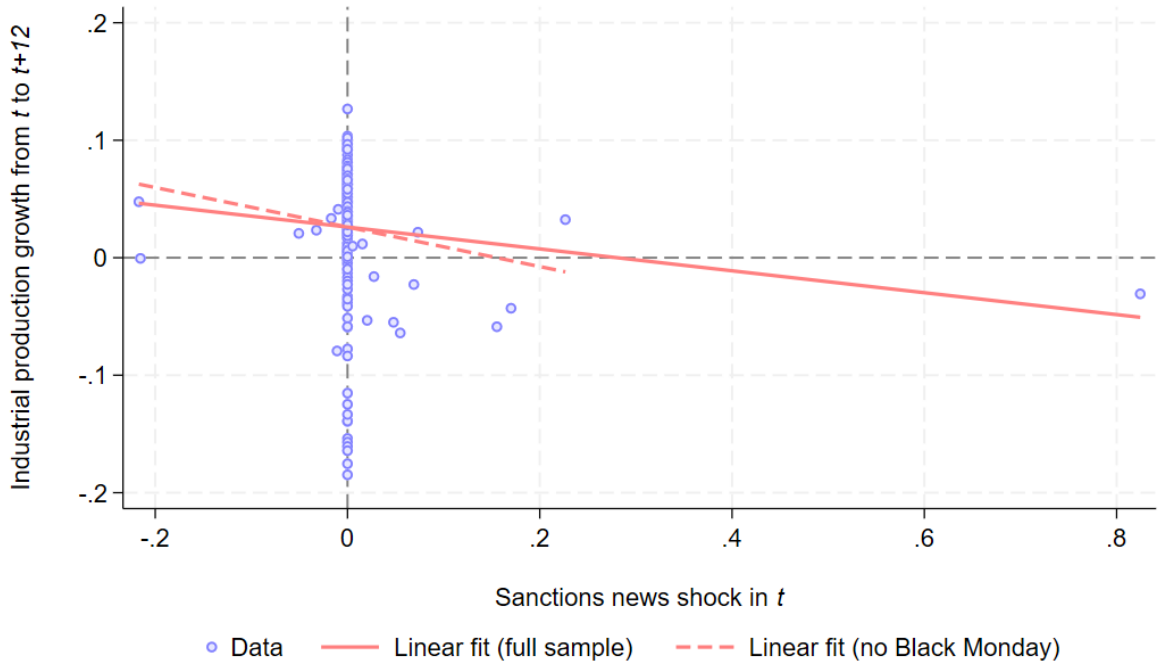
*Note:* The table reports $p$-values from Granger-causality tests of the null that lagged values of the candidate predictor(s) do not forecast the baseline sanctions surprise series, $z_{-3,t}$. Because $z_{-3,t}$ is constructed from the change in Russia's sovereign bond YTM between $t-4$ and $t-3$, all predictors are shifted back by three trading days so that the forecasting information set strictly predates the yield window entering the shock. Panel A reports bivariate daily vector autoregressions (VAR) with five daily lags. The columns labeled *1st diff.* use the first difference of the shifted predictor, while the columns labeled *Level* use the shifted predictor in levels. Panel B reports joint Wald tests from multivariate daily VARs in levels that include all five predictors simultaneously; the columns correspond to specifications with five and ten lags in *Full sample* (1 January 2000 – 31 December 2018) and in *Sanction sample* (1 January 2014 – 31 December 2018). *Geopolitical risk* is the daily geopolitical risk index from Caldara and Iacoviello (2022); *S&P 500* is the daily closing level of the S&P 500 index; *VIX* is the implied-volatility index on S&P 500 options published by the Chicago Board Options Exchange (CBOE); *Fed funds rate* is the daily effective federal funds rate; *Brent oil price* is the daily Brent spot price in US dollars per barrel.

**Figure B.VI.** 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.

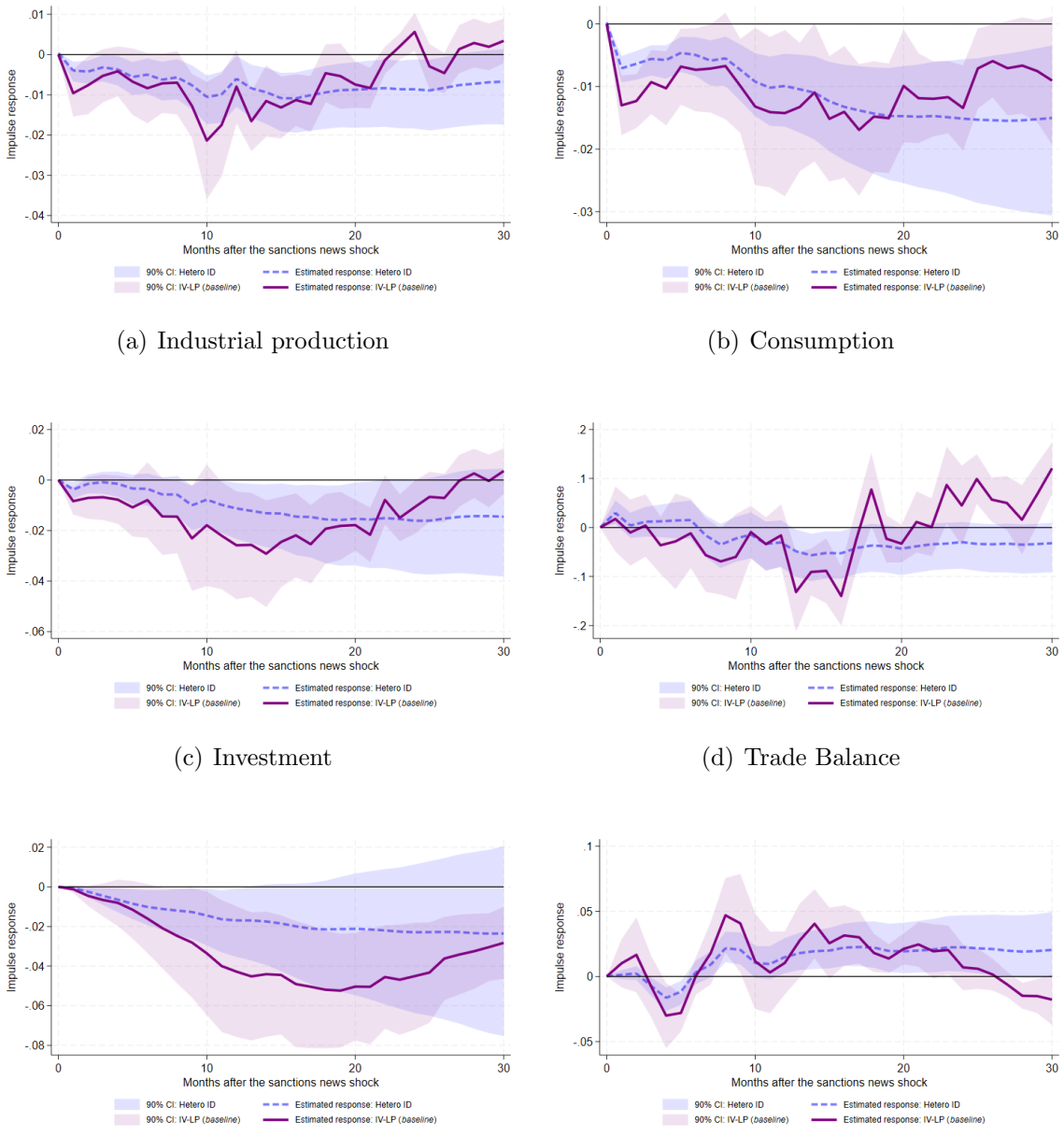
**Figure B.VII.** Future industrial production growth and the baseline sanctions news shock




*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 when the largest shock is excluded (Black Monday of December 2014).

# Appendix C Heteroskedasticity-based identification

**Figure C.I.** Responses to the sanctions news shock: Baseline LP–IV *vs* heteroskedasticity-based identification




(a) Industrial production

(b) Consumption

(c) Investment

(d) Trade Balance

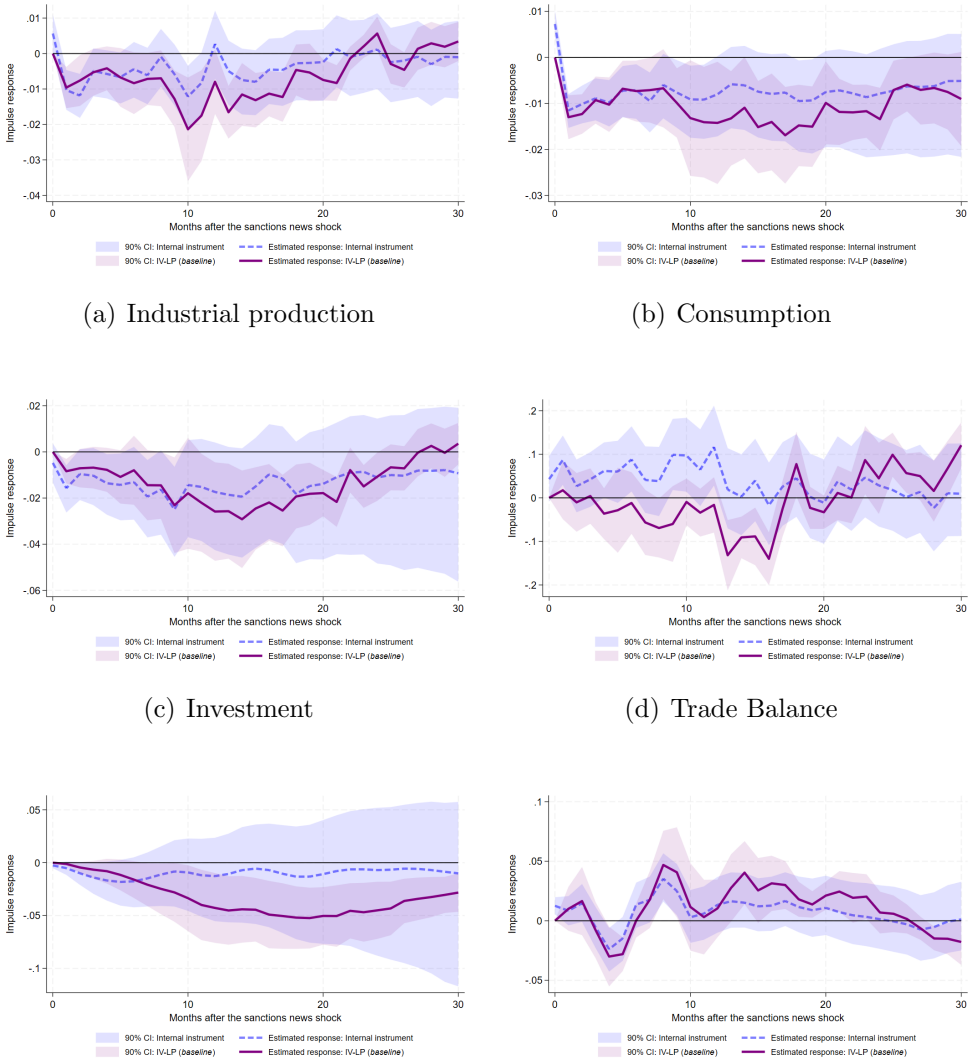
(e) External Debt

(f) REER

*Note*: This figure compares the baseline LP–IV impulse responses with impulse responses from a Bayesian VAR identified through heteroskedasticity. The identifying assumption is that the covariance matrix of shocks changes after March 2014, when the Crimea annexation and sanctions generated a high-volatility sanctions news regime. We normalize the sanctions shock to raise the country spread by 0.25 percentage points on impact.

# Appendix D VAR with internal instrument

**Figure D.I.** Responses 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

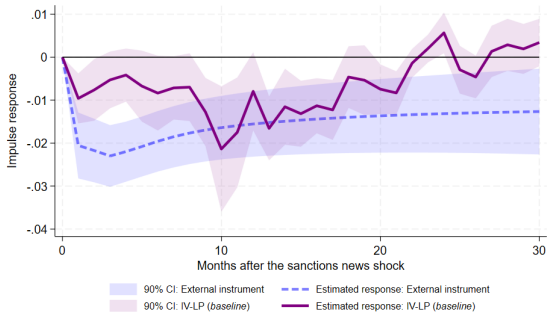
(e) External Debt

(f) REER

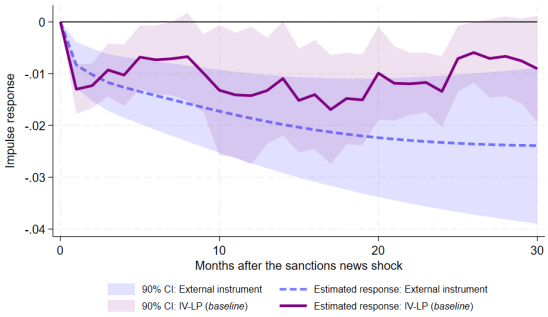
*Note*: This figure compares second-stage impulse response estimates from the baseline instrumental-variables local projections (LP–IV) approach (*purple*) with impulse responses obtained from a VAR model that includes the sanctions news shock $z_{-3,t}$ as an internal instrument (*dashed blue*). In 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 (3) 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 E SVAR-IV approach

**Figure E.I.** Responses to the sanctions news shock: Baseline LP-IV *vs* SVAR-IV approaches



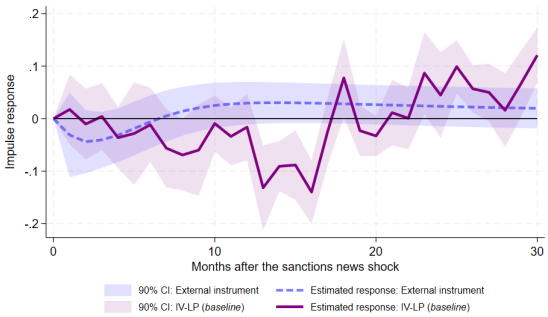

(a) Industrial production



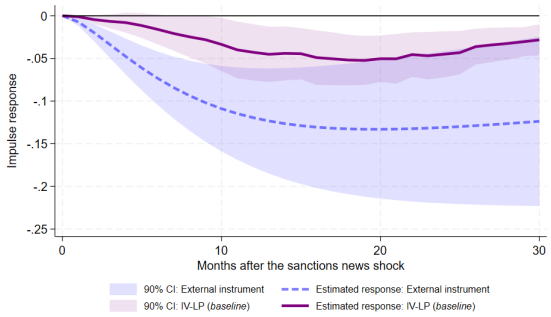

(b) Consumption



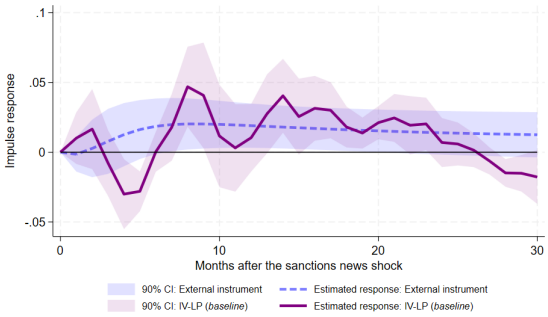

(c) Investment




(d) Trade Balance




(e) External Debt

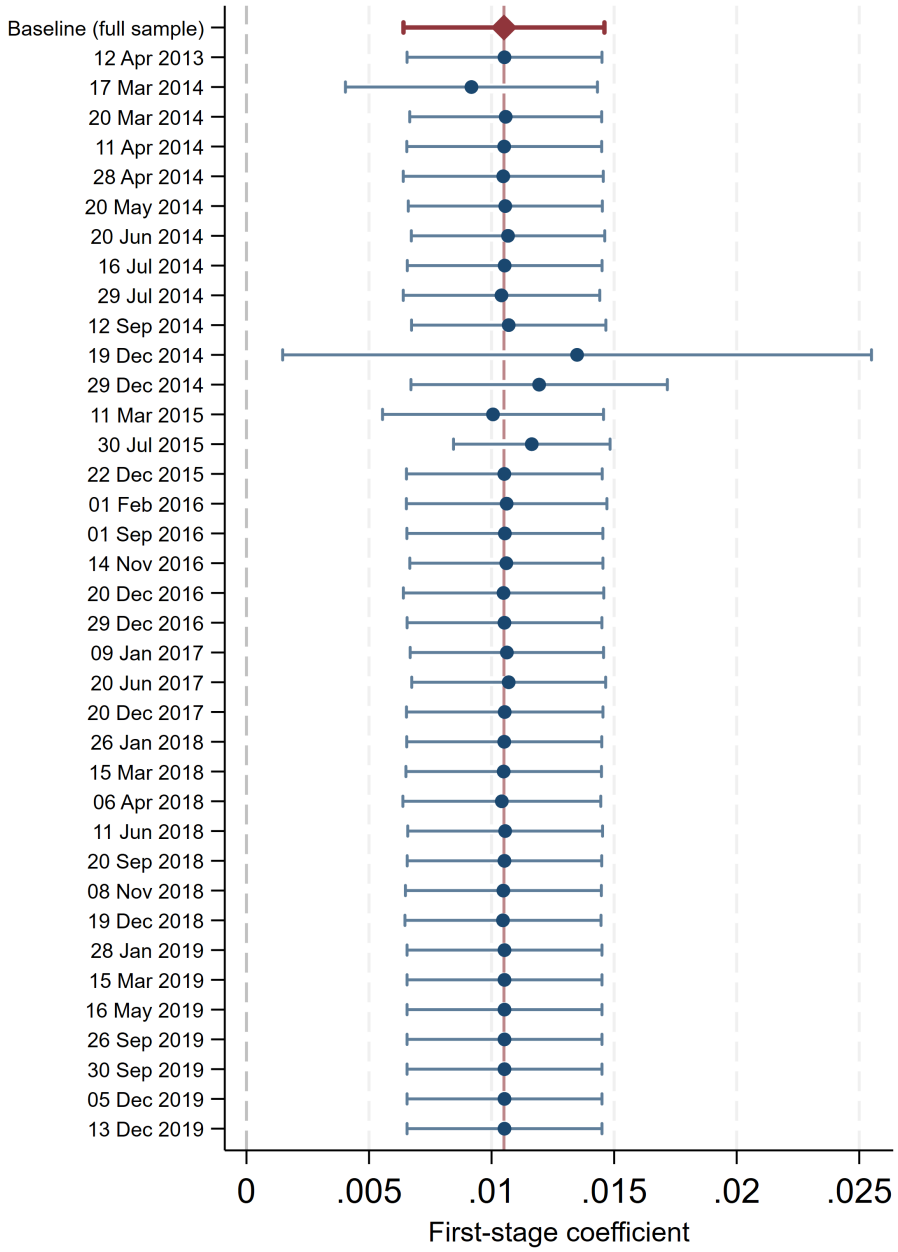



(f) REER

*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 (3) 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.

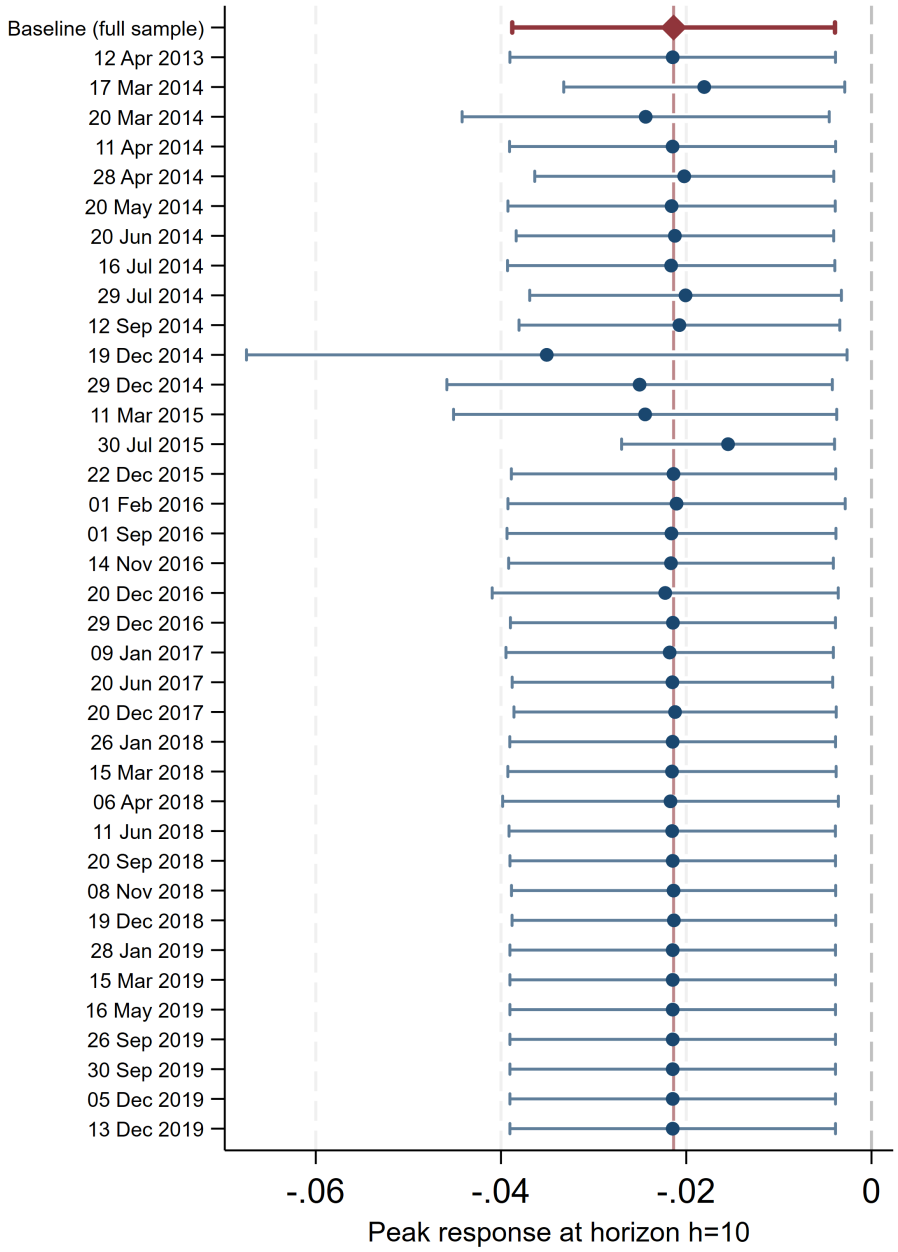
# Appendix F Leave-one-out OFAC jackknife: full results

**Figure F.I.** Leave-one-out OFAC jackknife for the baseline first stage



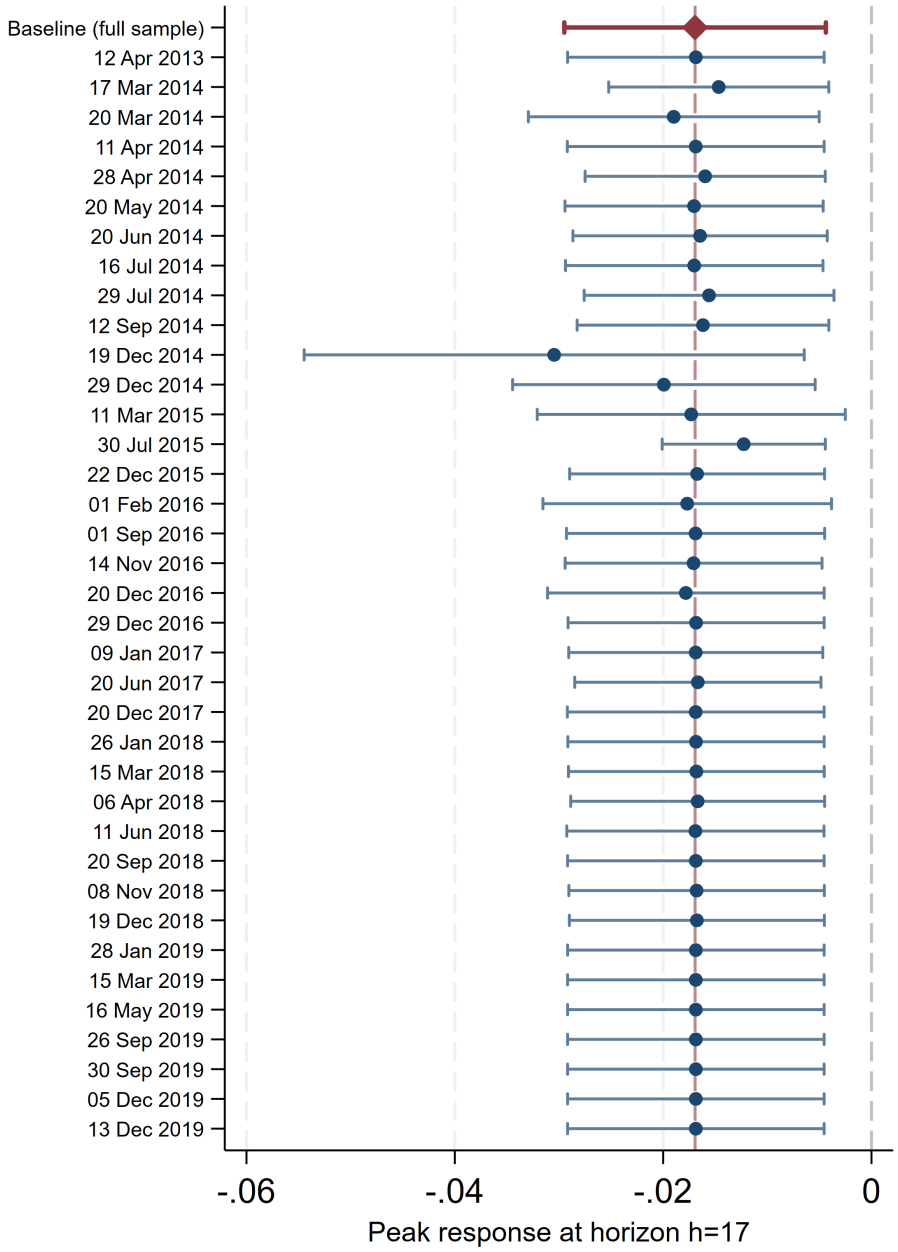

*Note*: The figure reports leave-one-out estimates of the baseline first-stage relationship between the sanctions news shock $z_{-3,t}$ and the average YTM of Russia's sovereign bonds reported in Figure 2. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals.

**Figure F.II.** Leave-one-out OFAC jackknife for the peak response of industrial production



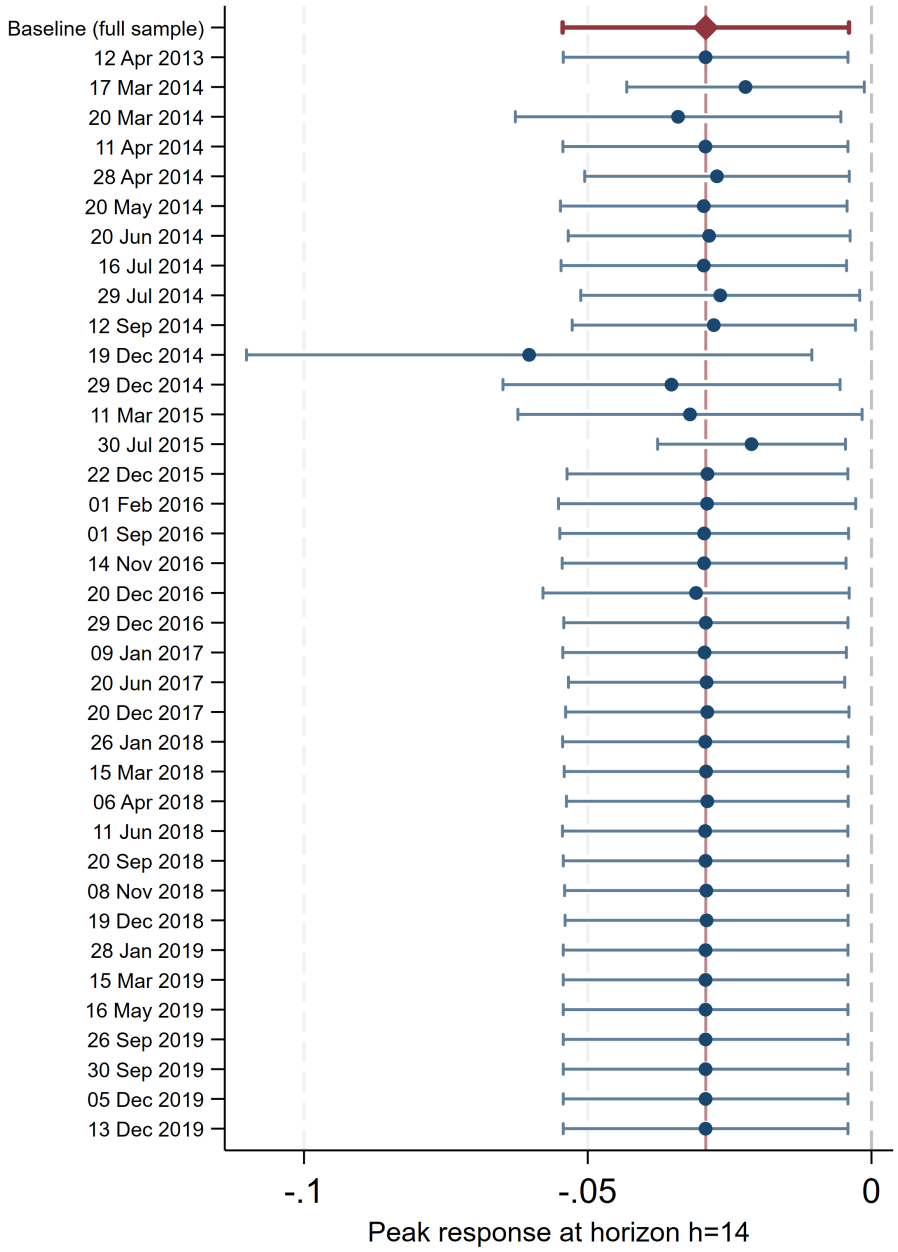

*Note*: The figure reports leave-one-out estimates of the baseline LP–IV response of log industrial production to the sanctions news shock $z_{-3,t}$ reported in Figure 4. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals. The plotted coefficient corresponds to the peak negative response in Figure 3, which occurs at horizon $h = 10$ months.

**Figure F.III.** Leave-one-out OFAC jackknife for the peak response of consumption



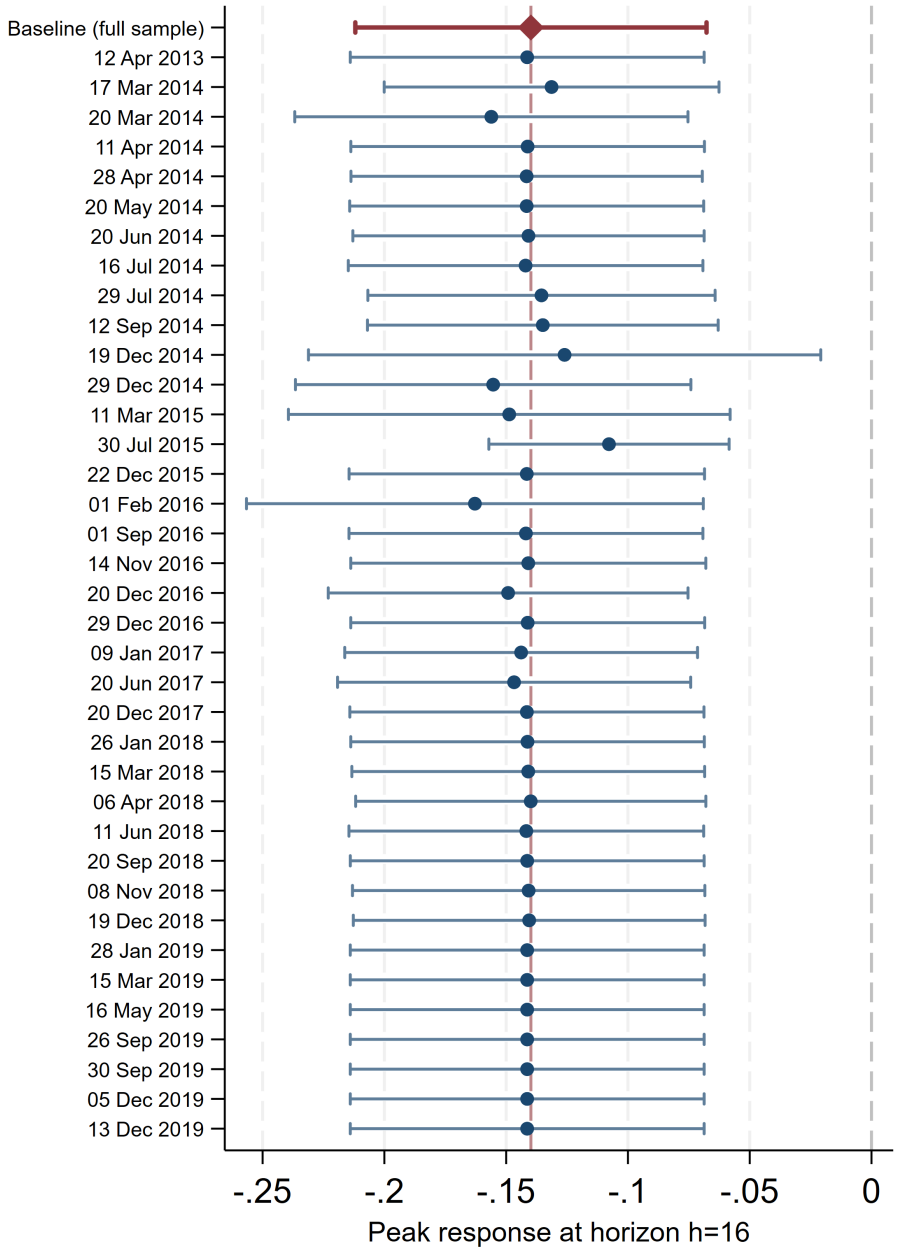

*Note*: The figure reports leave-one-out estimates of the baseline LP–IV response of log private consumption to the sanctions news shock $z_{-3,t}$ reported in Figure 4. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals. The plotted coefficient corresponds to the peak negative response in Figure 3, which occurs at horizon $h = 17$ months.

**Figure F.IV.** Leave-one-out OFAC jackknife for the peak response of investment



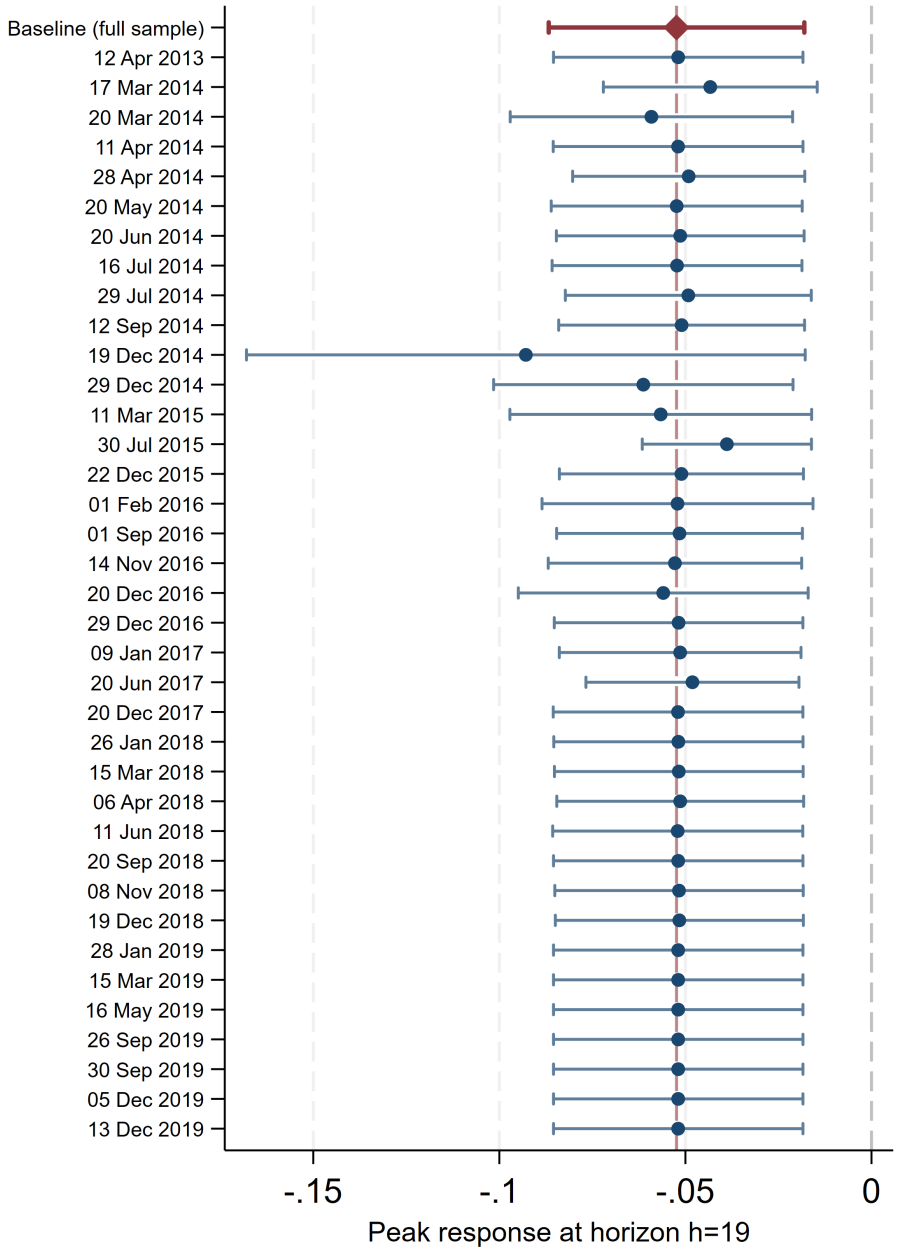

*Note*: The figure reports leave-one-out estimates of the baseline LP–IV response of log investment to the sanctions news shock $z_{-3,t}$ reported in Figure 4. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals. The plotted coefficient corresponds to the peak negative response in Figure 3, which occurs at horizon $h = 14$ months.

**Figure F.V.** Leave-one-out OFAC jackknife for the peak response of the trade balance



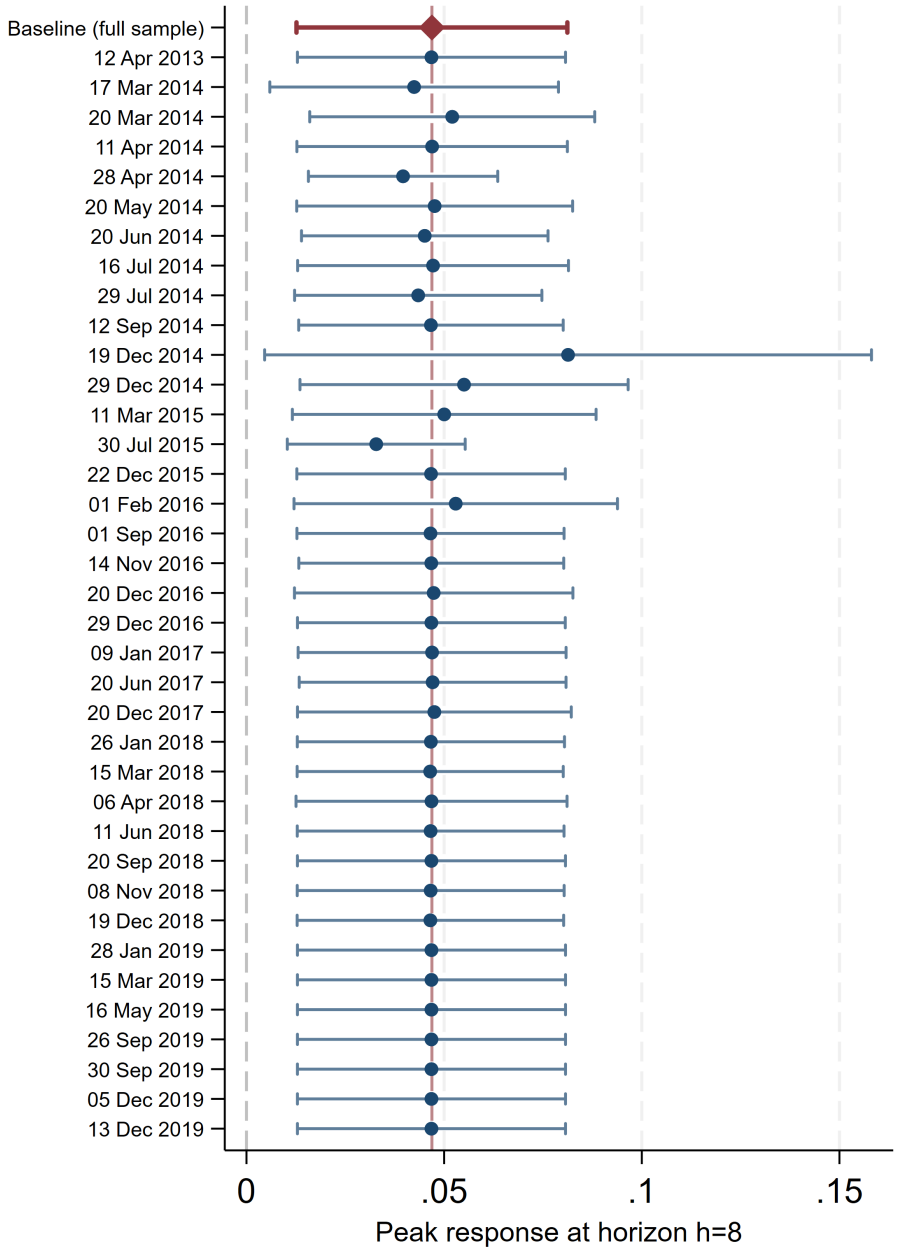

*Note*: The figure reports leave-one-out estimates of the baseline LP–IV response of the log trade balance to the sanctions news shock $z_{-3,t}$ reported in Figure 4. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals. The plotted coefficient corresponds to the peak negative response in Figure 3, which occurs at horizon $h = 16$ months.

**Figure F.VI.** Leave-one-out OFAC jackknife for the peak response of external debt




*Note*: The figure reports leave-one-out estimates of the baseline LP–IV response of log external debt to the sanctions news shock $z_{-3,t}$ reported in Figure 4. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals. The plotted coefficient corresponds to the peak negative response in Figure 3, which occurs at horizon $h = 19$ months.

**Figure F.VII.** Leave-one-out OFAC jackknife for the peak response of the real effective exchange rate




*Note*: The figure reports leave-one-out estimates of the baseline LP–IV response of log real effective exchange rate (REER) to the sanctions news shock $z_{-3,t}$ reported in Figure 4. In each iteration, one OFAC announcement is excluded from the daily sanctions-news series, the monthly shock is recomputed, and the full baseline LP–IV system is re-estimated. The red diamond in the top row reports the baseline full-sample estimate, blue circles report the leave-one-out estimates, and horizontal bars denote 95% confidence intervals. The plotted coefficient corresponds to the peak positive response in Figure 3, which occurs at horizon $h = 8$ months.

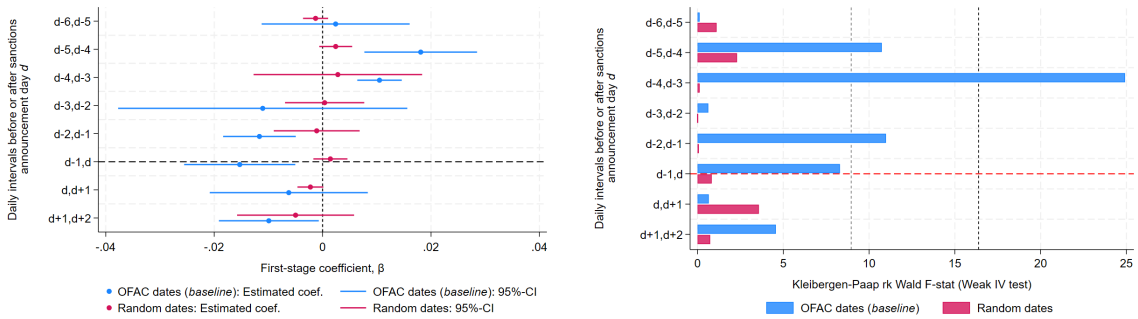
# Appendix G Placebo 1: Random dates

**Table G.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.

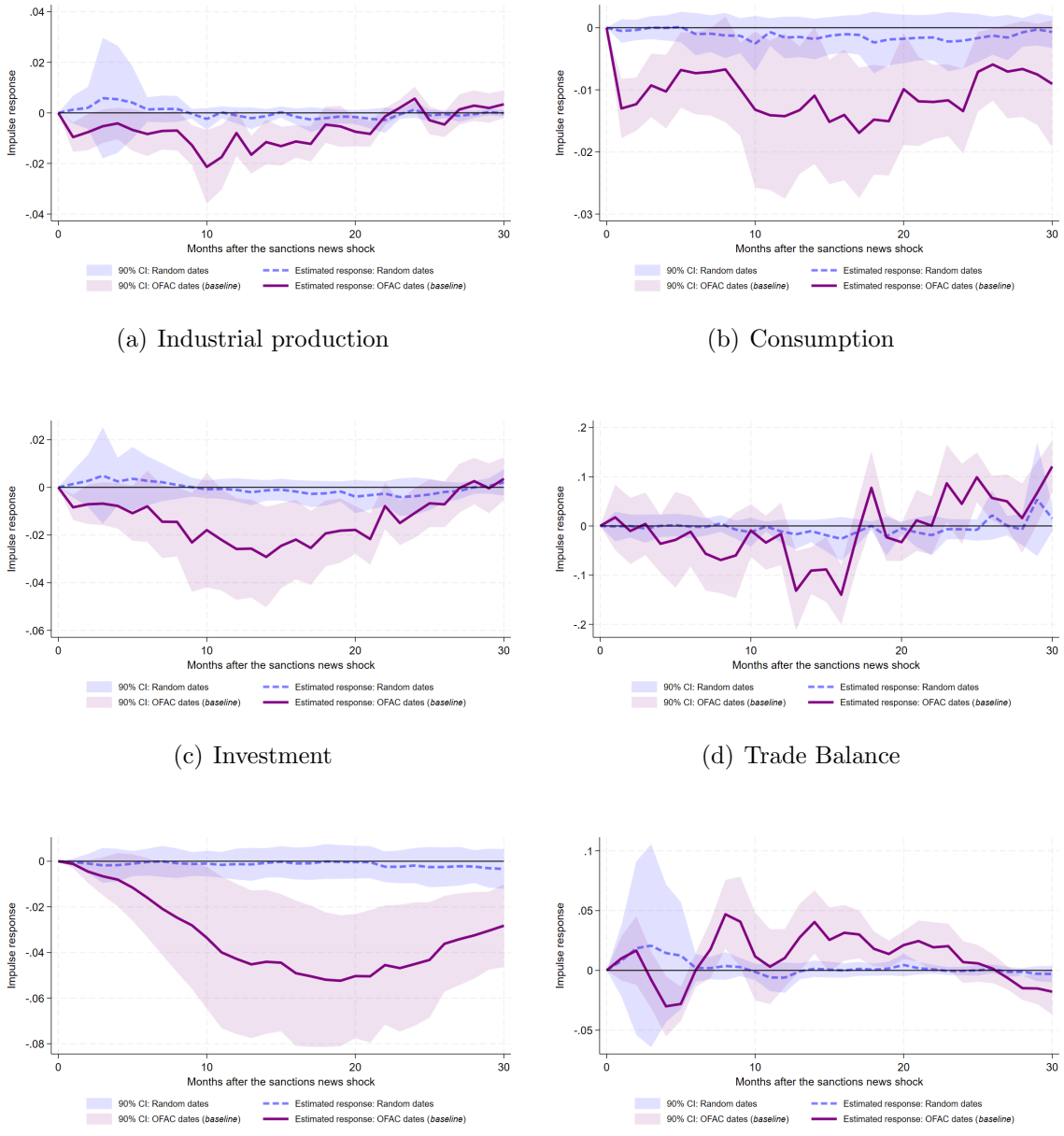
**Figure G.I.** First-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random dates (placebo)




(a) First-stage estimates $\beta_k$ (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 G.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 G.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 4 in the main text, with placebo responses constructed using 37 randomly selected dates listed in Table G.I (*dashed blue*). The baseline responses correspond to the coefficients $\theta_{i,h}$ in Equation (3), 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.

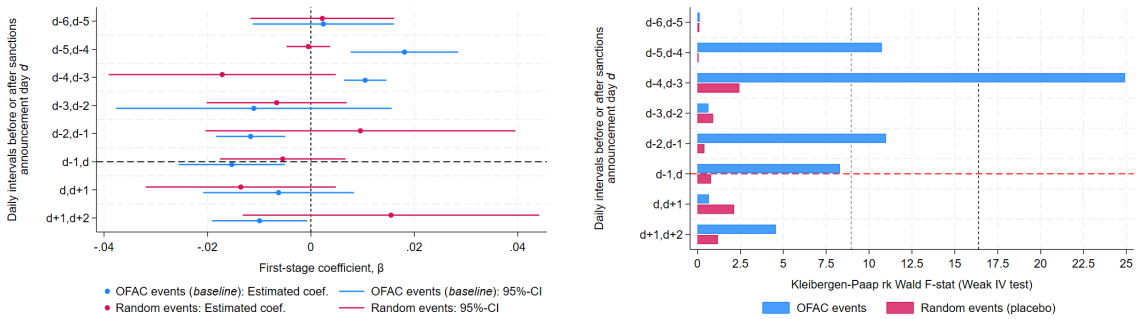
# Appendix H Placebo 2: Random events

**Table H.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.

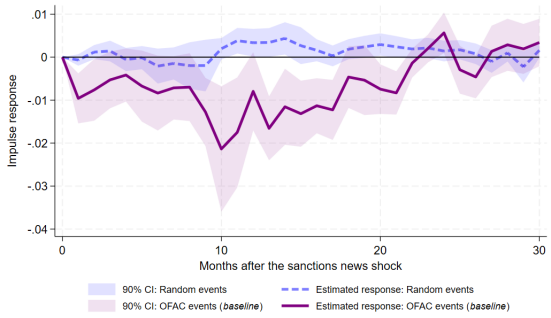
**Figure H.I.** First-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random events (placebo)



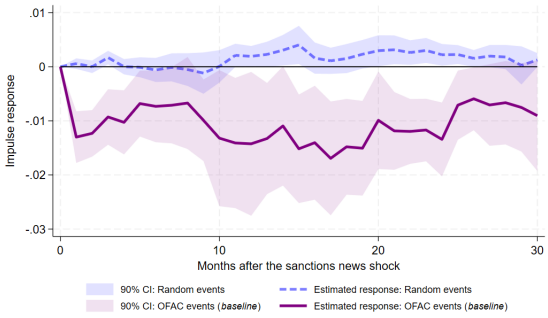

(a) First-stage estimates $\beta_k$ (b) Robust F-statistics

*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 H.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.

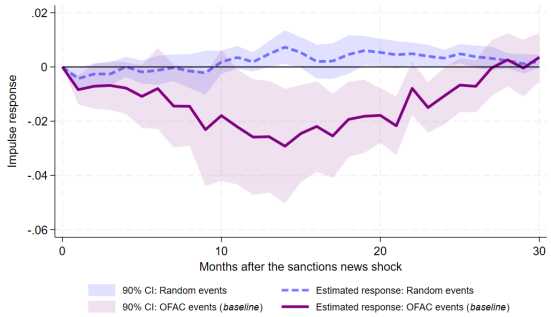
**Figure H.II.** Second-stage LP-IV estimates: sanctions news shocks (baseline) *vs* random events (placebo)



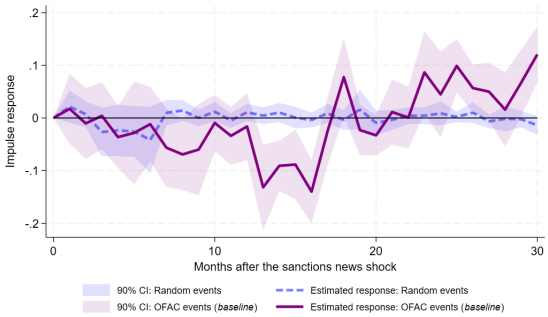

(a) Industrial production



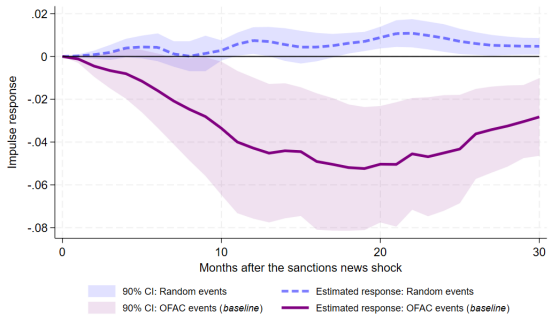

(b) Consumption



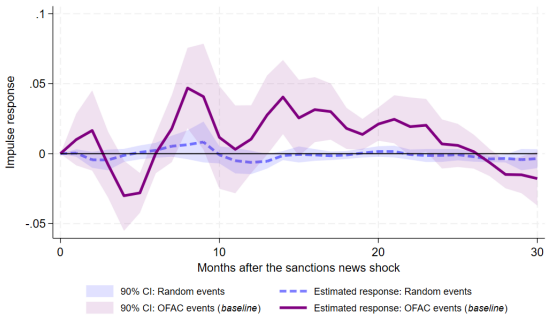

(c) Investment




(d) Trade Balance




(e) External Debt



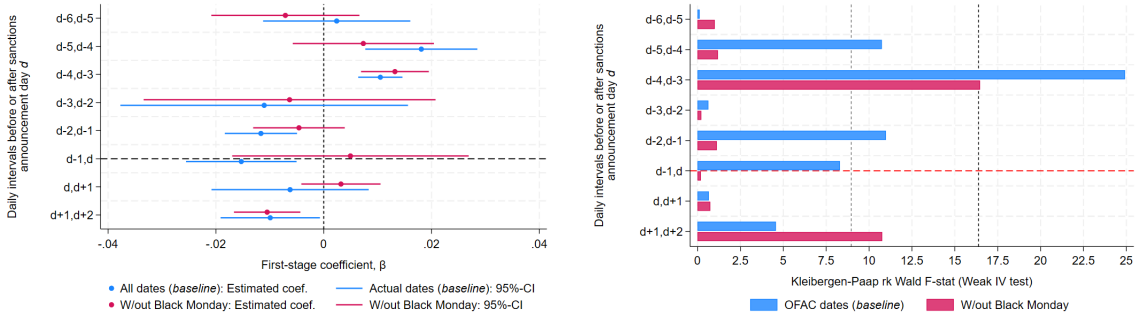

(f) REER

*Note*: This figure compares the baseline second-stage estimates from the LP-IV approach (*purple*), reported in Figure 4 in the main text, with placebo responses constructed using 30 randomly selected domestic events listed in Table H.I (*dashed blue*). The baseline responses correspond to the coefficients $\theta_{i,h}$ in Equation (3), 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 I The role of domestic monetary policy

## I.1 Excluding the coincidence with the "Black Monday" shock

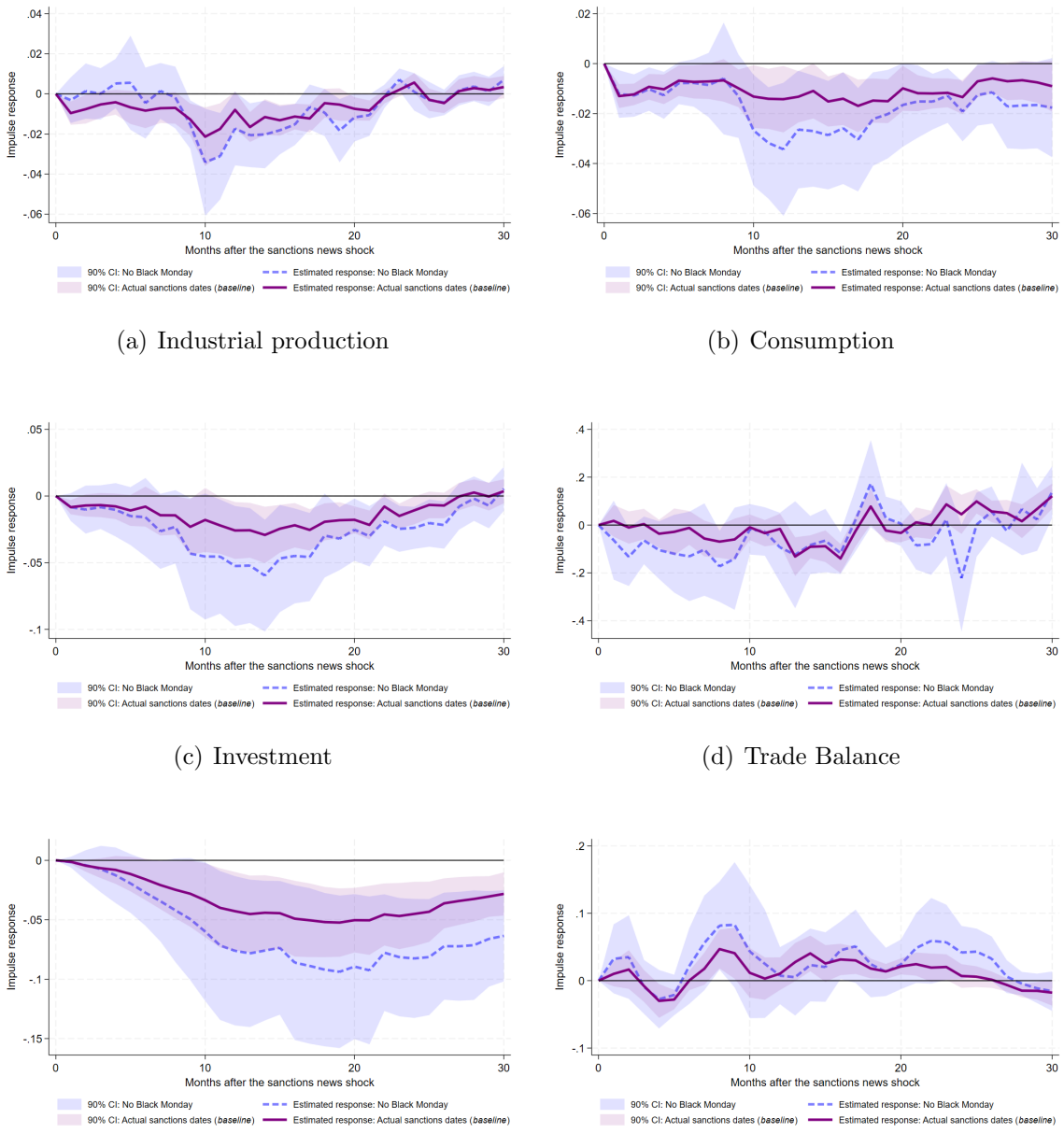
**Figure I.I.** First-stage LP–IV estimates: Sanctions news shocks with *vs* without the "Black Monday" episode




(a) First-stage estimates $\beta_k$ (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 $z_{k,t} = Surprise_{k,t}$ 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 I.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 4 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 (3), 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.

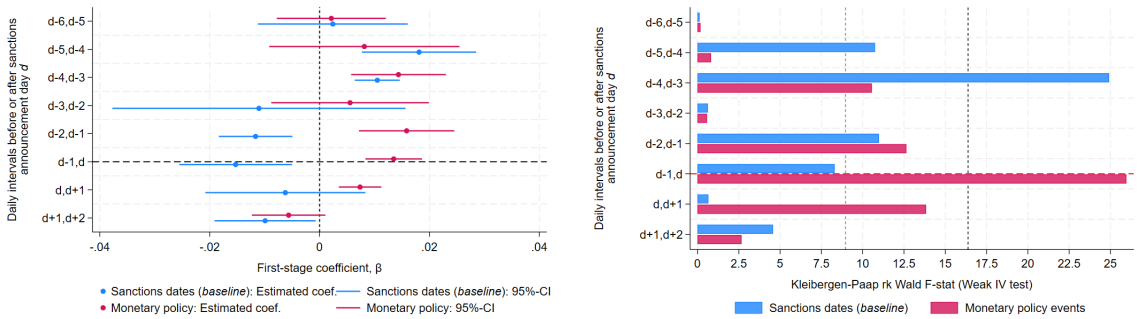
## I.2 Comparing with domestic monetary policy announcements

**Table I.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.

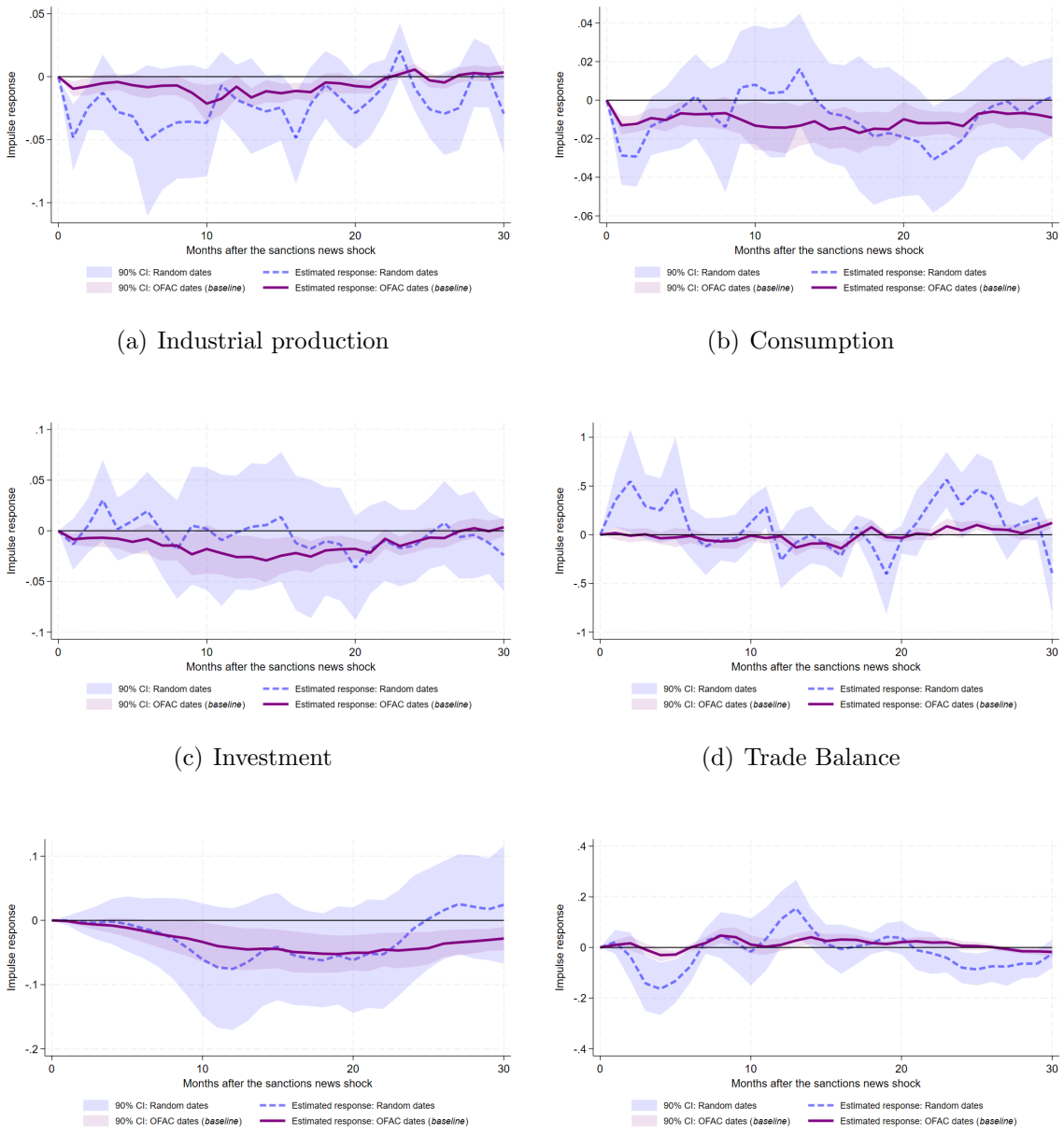
**Figure I.III.** First-stage LP–IV estimates: Sanctions news shocks *vs* domestic monetary policy announcements




(a) First-stage estimates $\beta_k$ (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 I.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 $z_{k,t} = Surprise_{k,t}$ 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 I.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 4 in the main text, with alternative second-stage estimates identified using domestic monetary policy announcements (*dashed blue*), as summarized in Table I.II. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (3), 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 J Russia-related geopolitical events around major OFAC sanctions announcements

**Table J.I.** Major Russia-related geopolitical events around selected OFAC sanctions announcements

| OFAC date | Sanctions episode | Main nearby Russia-related events | Assessment for $t-3$ |
|---|---|---|---|
| 20 Mar 2014 | Crimea-related designations and Bank Rossiya | Crimea referendum on 16 Mar; Russian recognition/annexation steps on 17–18 Mar | The pre-announcement window belongs to the same Crimea sequence; $t-3$ captures sanctions anticipation amid already public Crimea events rather than a recurring new escalation at $t-3$. |
| 28 Apr 2014 | Expanded Ukraine-related designations | Eastern-Ukraine unrest and G7 statements on additional sanctions in late Apr | No single discrete military escalation exactly at $t-3$; window mainly reflects anticipation of a sanctions package following public diplomatic warnings. |
| 16 Jul 2014 | Sectoral sanctions on financial and energy entities | Ongoing eastern-Ukraine conflict; MH17 was downed on 17 Jul, after this OFAC announcement | The major MH17 escalation occurs after the announcement; it cannot explain the $t-3$ movement for this date. |
| 29 Jul 2014 | Additional sectoral sanctions after MH17 | MH17 downing on 17 Jul; EU and US deliberations in the following days | The event window is in the aftermath of MH17, but no separate escalation occurs mechanically at $t-3$. |
| 12 Sep 2014 | Large sectoral package on finance, energy, and defense | Minsk Protocol signed on 5 Sep; ceasefire violations and troop reports continued | The days before the announcement follow the ceasefire agreement; no consistent new escalation exactly at $t-3$. |
| 19 Dec 2014 | Crimea executive order and additional measures | Ruble "Black Monday" and emergency CBR rate increase on 16 Dec | This date is potentially confounded by domestic monetary and oil-price stress rather than war escalation; it is excluded in the Black Monday robustness check. |
| 06 Apr 2018 | Oligarchs, officials, and firms under CAATSA | Skripal poisoning occurred on 4 Mar; diplomatic expulsions followed in late Mar | The sanctions were linked to broader malign-activity concerns; no Russia-Ukraine battlefield escalation exactly at $t-3$. |
| 27 Aug 2018 | Chemical and biological weapons sanctions | Skripal-related CBW determination announced earlier in Aug | The effective date implements a previously announced CBW determination; no discrete escalation exactly at $t-3$. |

*Note*: This table is intended to document whether the strongest pre-announcement window, $t-3$, systematically coincides with major Russia-related geopolitical escalations. The chronology should be finalized against the OFAC announcement list and a dated news chronology before submission.

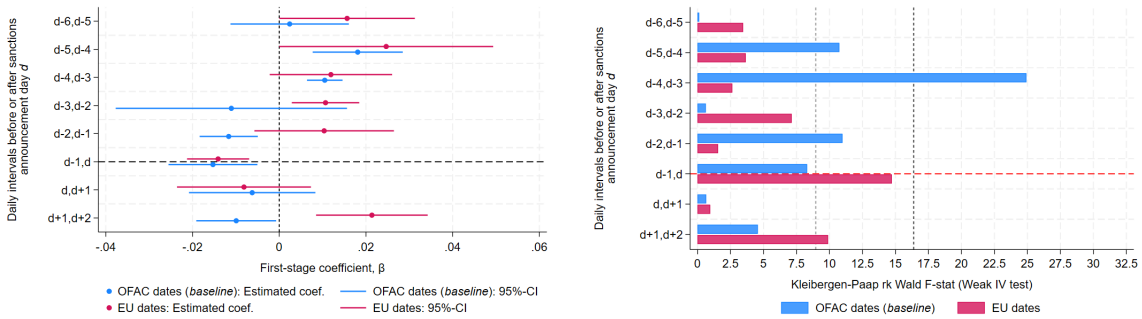
# Appendix K EU sanctions announcements

**Table K.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.

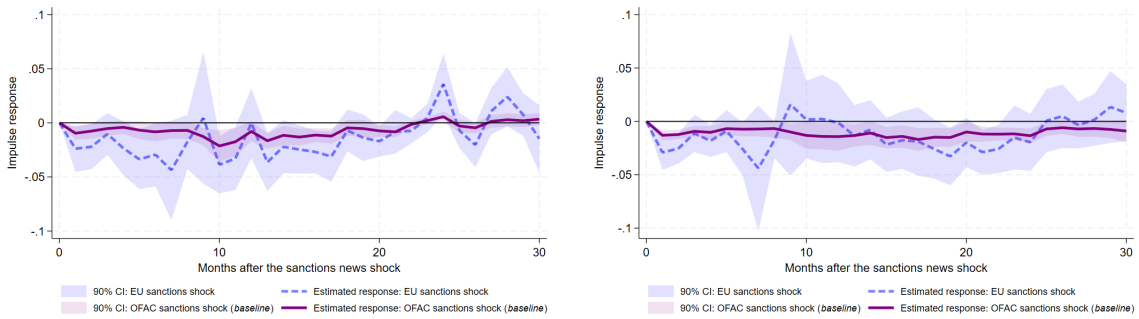
**Figure K.I.** First-stage LP–IV estimates: OFAC *vs* EU sanctions announcements




(a) First-stage estimates $\beta_k$ (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 K.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.

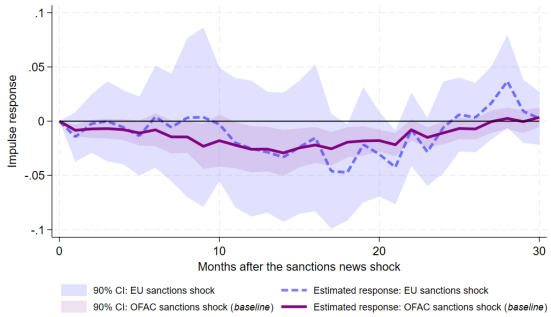
**Figure K.II.** Second-stage LP–IV estimates: OFAC *vs* EU sanctions announcements



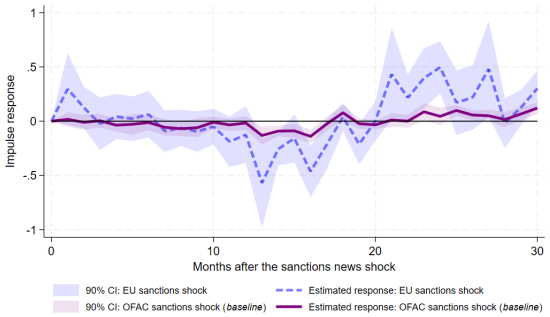

(a) Industrial production



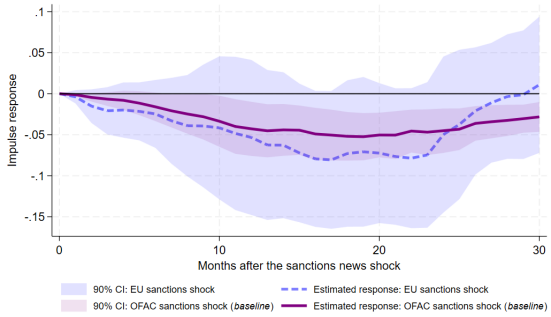

(b) Consumption



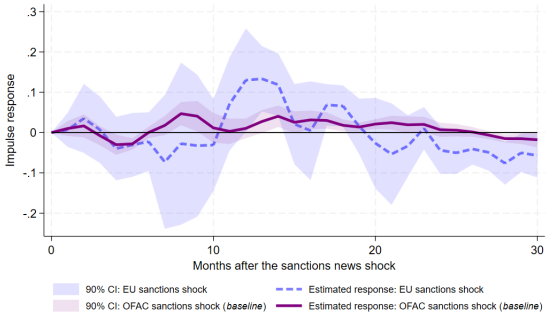

(c) Investment




(d) Trade Balance




(e) External Debt



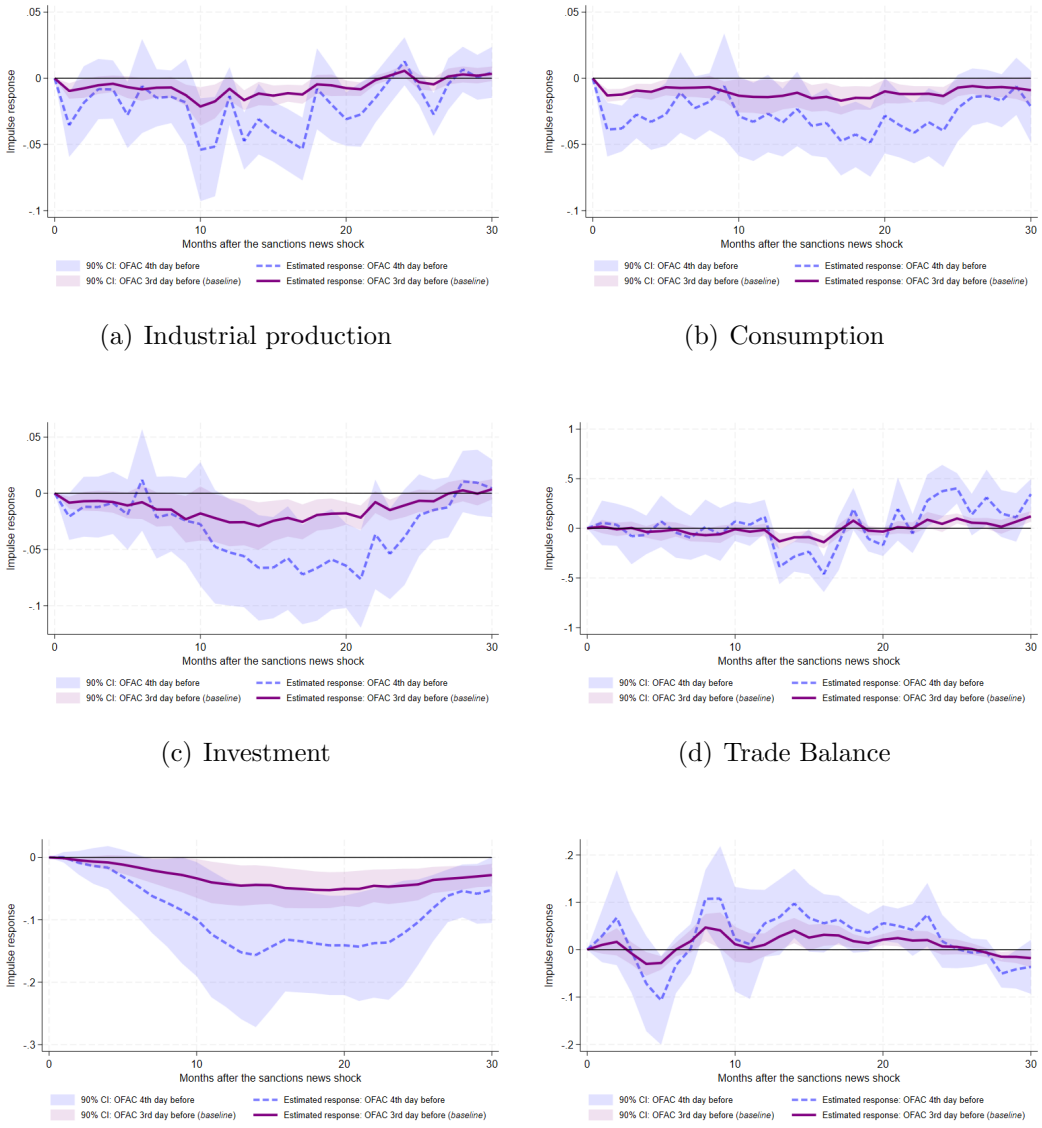

(f) REER

*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 4 in the main text—with alternative second-stage estimates obtained by replacing OFAC with EU sanctions announcements (*dashed blue*), as summarized in Table K.I. Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (3), 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 L Varying the leakage parameter $k$

## L.1 Longer anticipation horizon

**Figure L.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

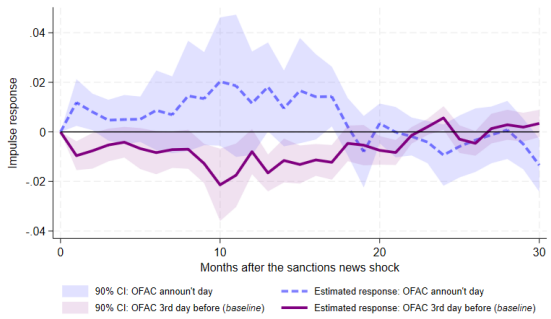
(e) External Debt

(f) REER

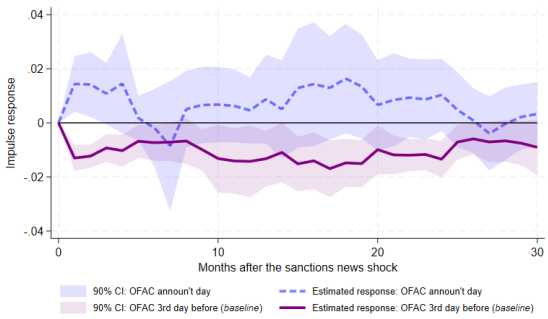
*Note*: This figure compares second-stage LP–IV impulse response estimates obtained using the baseline sanctions news shock constructed from the third day prior to OFAC sanctions announcements, $z_{-3,t}$ (*purple*), with alternative impulse responses identified using a deeper anticipation lag, $z_{-4,t}$ (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (3), 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.

## L.2 Announcement day sanctions surprise

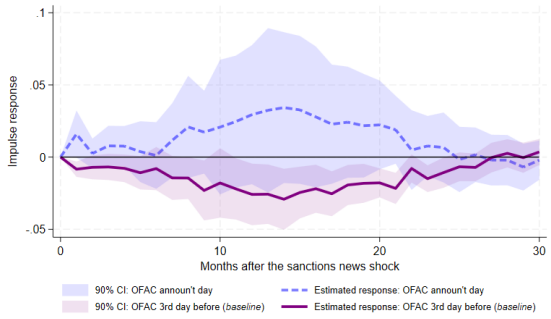
**Figure L.II.** Second-stage LP–IV estimates: Baseline ($z_{-3,t}$) *vs* announcement day shock ($z_{0,t}$)



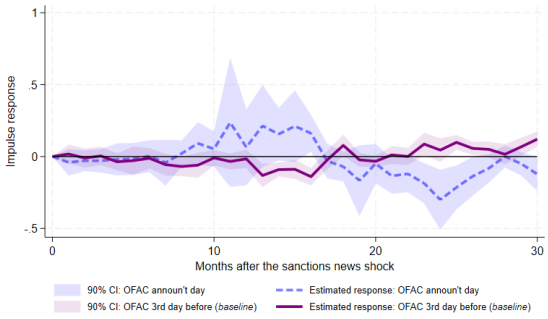

(a) Industrial production



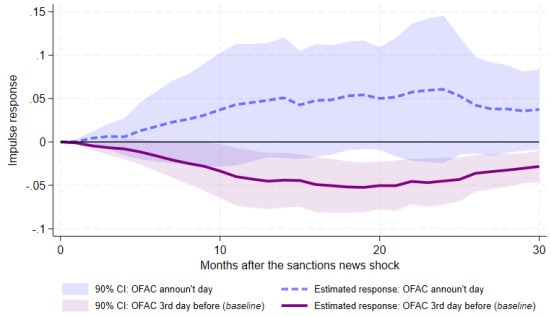

(b) Consumption



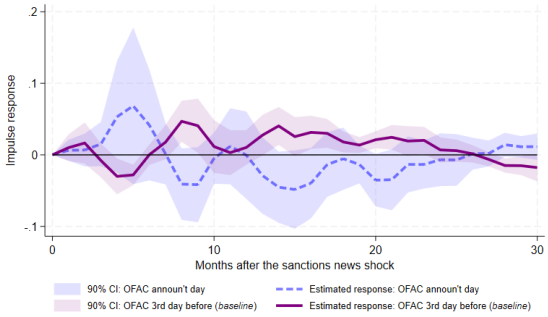

(c) Investment




(d) Trade Balance




(e) External Debt

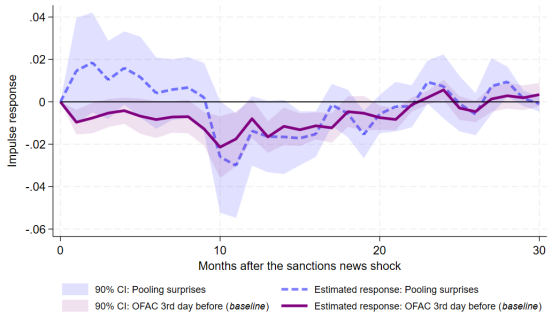



(f) REER

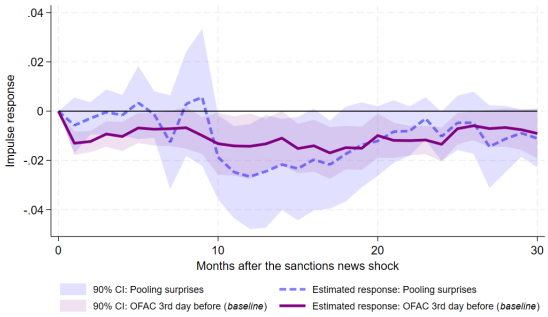
*Note*: This figure compares second-stage LP–IV impulse response estimates obtained using the baseline sanctions news shock constructed from the third day prior to OFAC sanctions announcements, $z_{-3,t}$ (*purple*), with alternative impulse responses identified using a contemporaneous sanctions news shock, $z_{0,t}$ (*dashed blue*). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (3), 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.

## L.3 Pooling all pre-announcement surprises

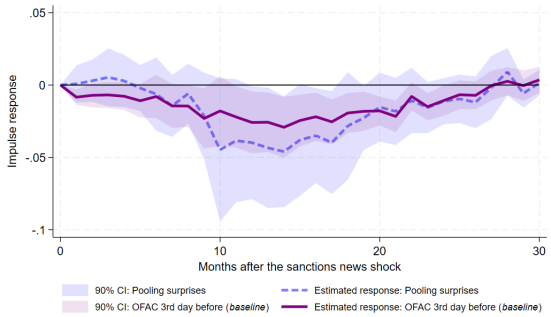
**Figure L.III.** Second-stage LP–IV estimates: Baseline ($z_{-3,t}$) *vs* pooling all surprises ($z_{-5...0,t}$)



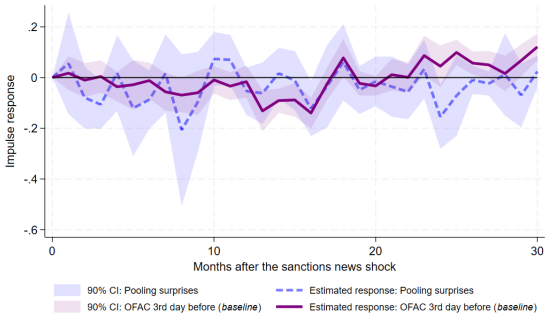

(a) Industrial production



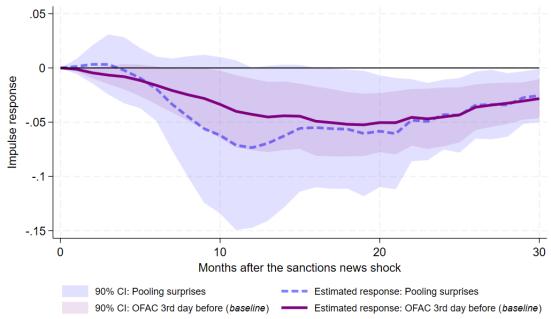

(b) Consumption



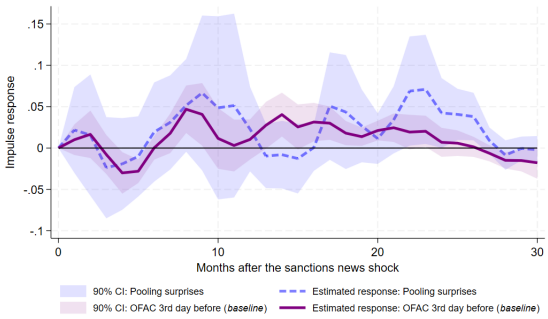

(c) Investment




(d) Trade Balance




(e) External Debt

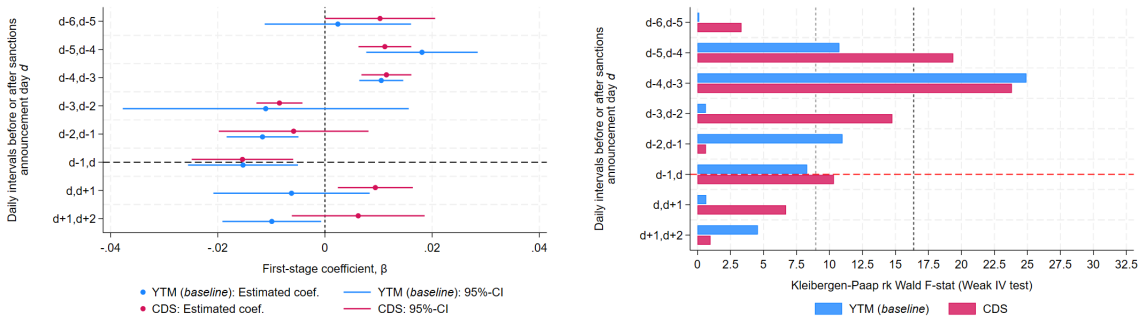



(f) REER

*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 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 (3), 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 $z_{-5...0,t}$ 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 M Credit Default Swaps (CDS)

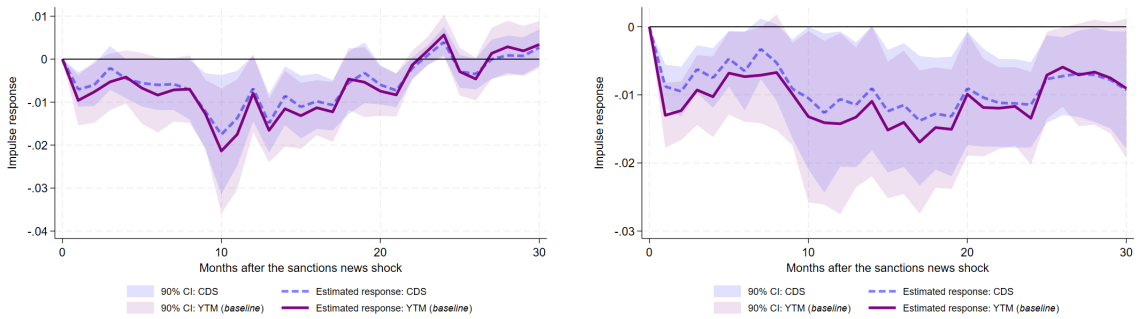
**Figure M.I.** First-stage LP–IV estimates: Sovereign bond YTMs *vs* CDS-based identification




(a) First-stage estimates $\beta_k$ (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.

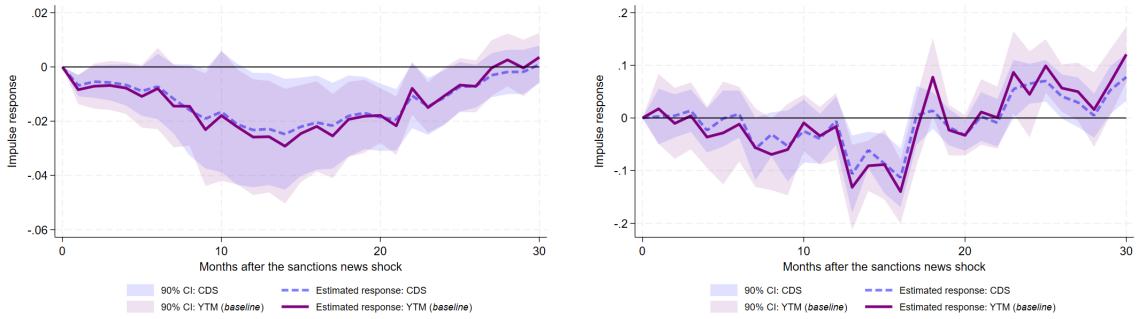
**Figure M.II.** Second-stage LP–IV estimates: Sovereign bond YTMs *vs* CDS-based identification




(a) Industrial production



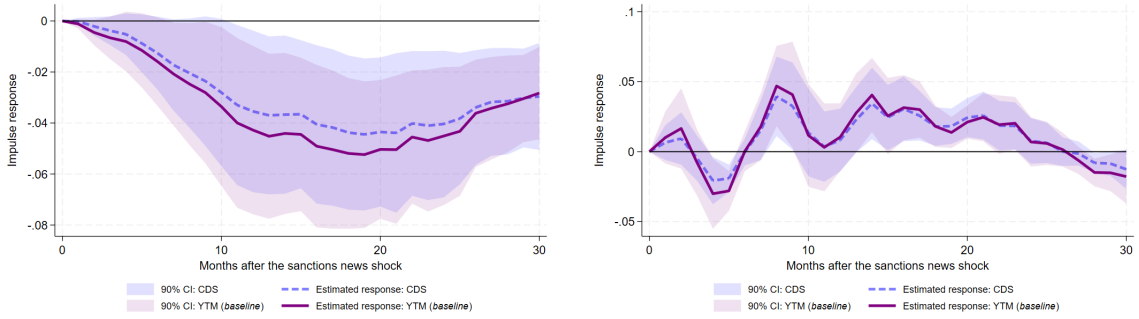

(b) Consumption




(c) Investment




(d) Trade Balance




(e) External Debt

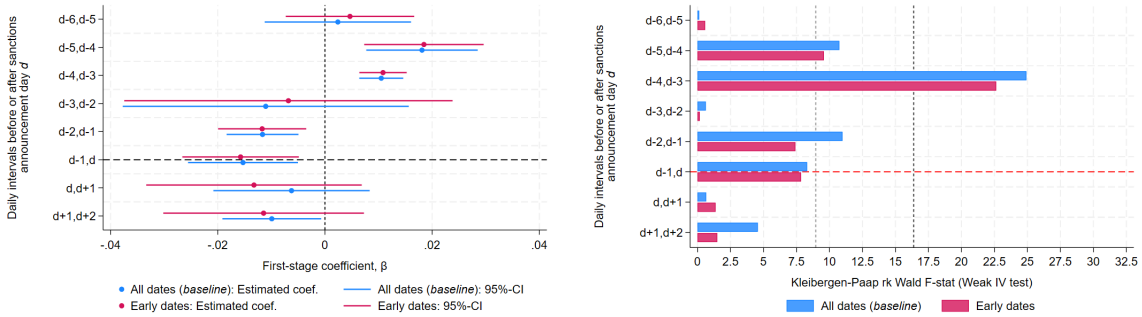



(f) REER

*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 (3), 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 N Early *vs* all OFAC sanctions announcements

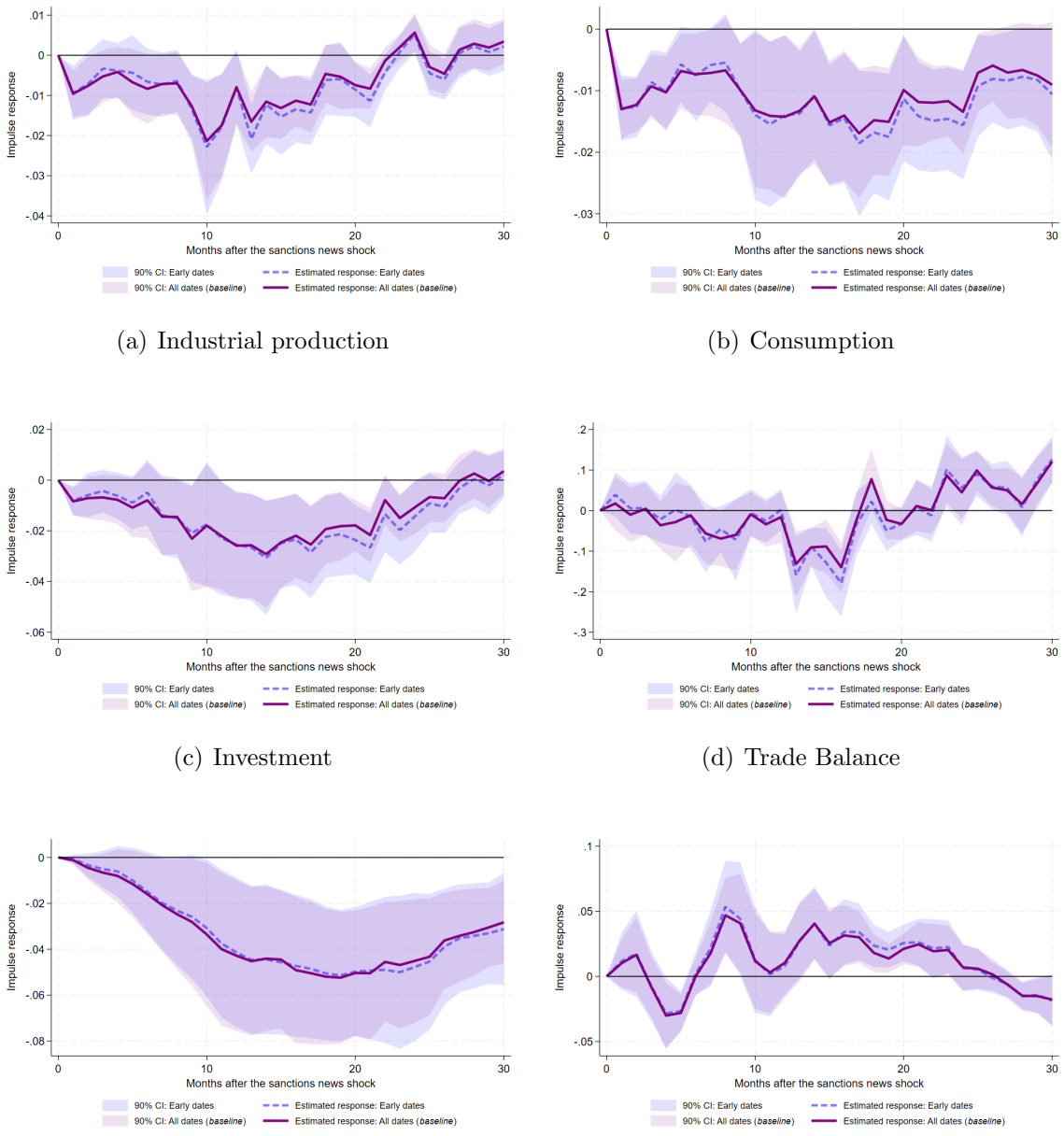
**Figure N.I.** First-stage LP–IV estimates: Full sample *vs* early sanctions




(a) First-stage estimates $\beta_k$ (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 N.II.** Second-stage LP–IV estimates: Full sample *vs* early sanctions




(a) Industrial production

(b) Consumption

(c) Investment

(d) Trade Balance

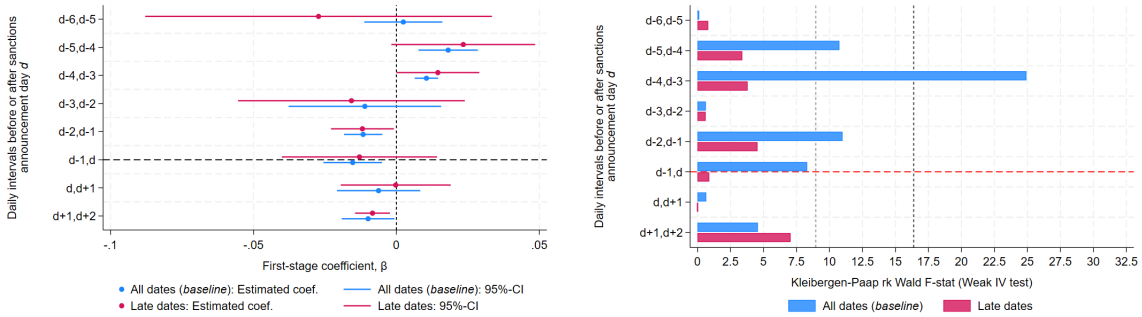
(e) External Debt

(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 (3), 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 O Late *vs* all OFAC sanctions announcements

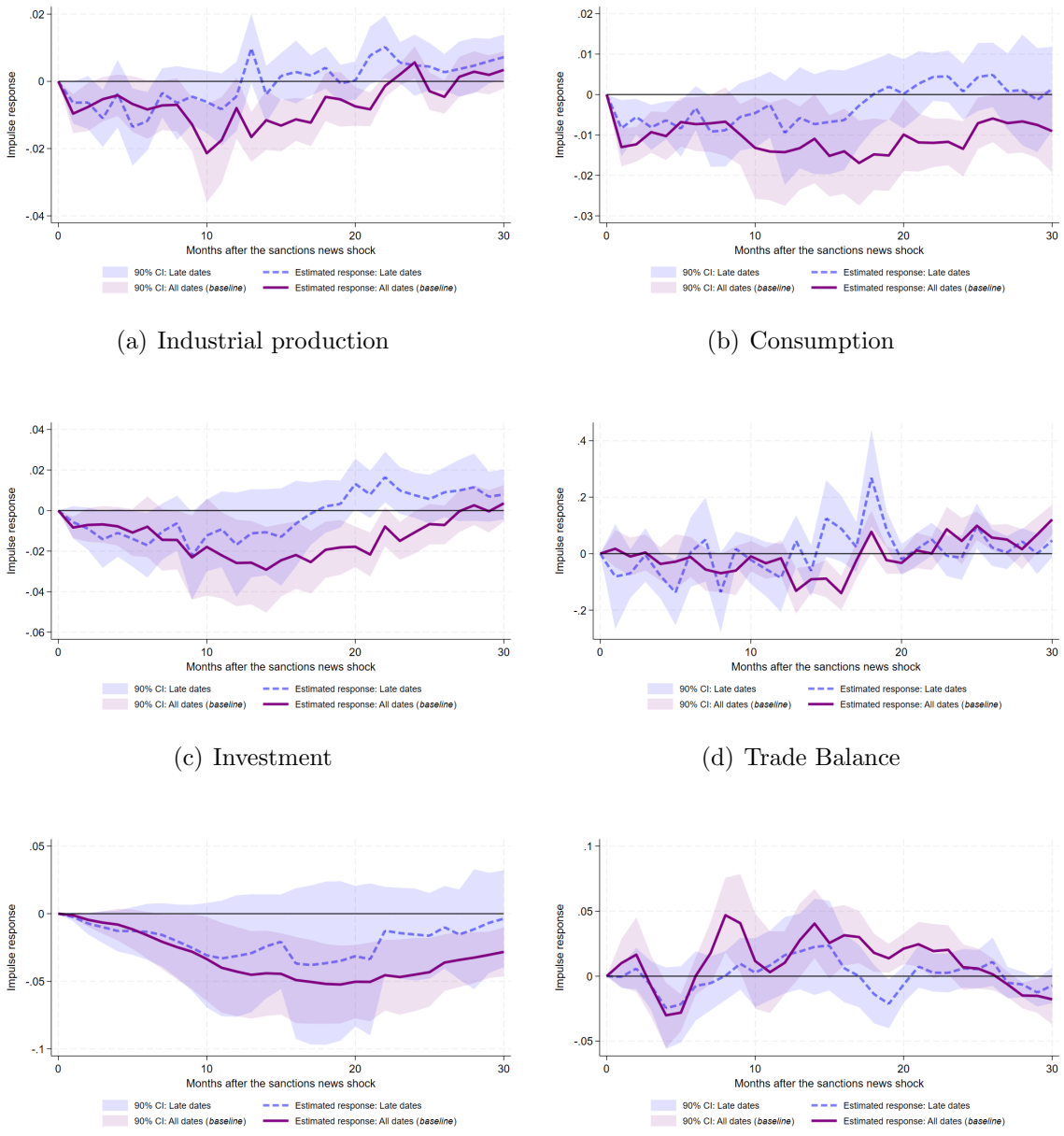
**Figure O.I.** First-stage LP–IV estimates: Full sample *vs* later sanctions




(a) First-stage estimates $\beta_k$ (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 O.II.** Second-stage LP–IV estimates: Full sample *vs* later sanctions




(a) Industrial production

(b) Consumption

(c) Investment

(d) Trade Balance

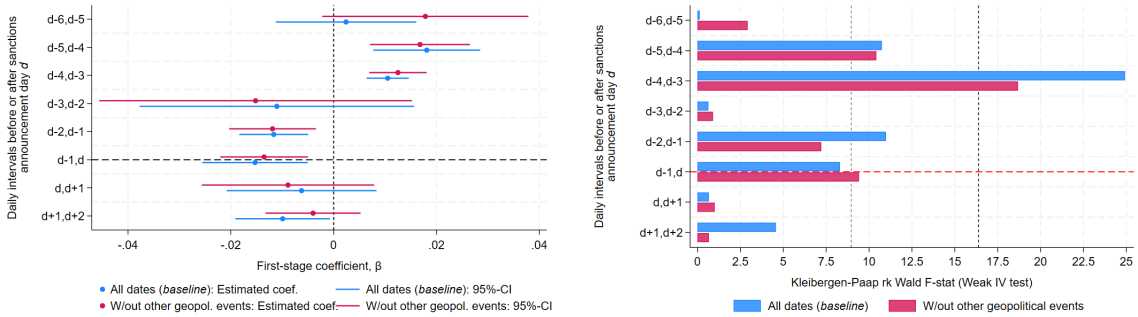
(e) External Debt

(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 (3), 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 P Excluding coincidences with other geopolitical events

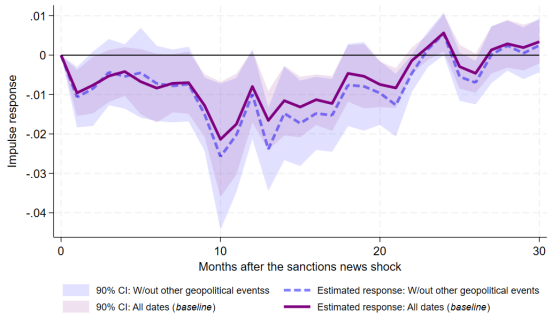
**Figure P.I.** First-stage LP–IV estimates: Sanctions news shocks with *vs* without coincidences with other geopolitical events



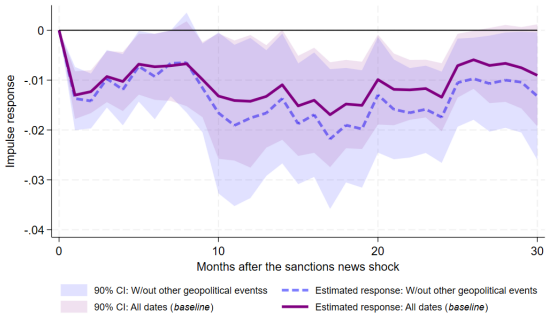

(a) First-stage estimates $\beta_k$ (b) Robust F-statistics

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 $\alpha_c$ is set to the $90^{\text{th}}$ 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.

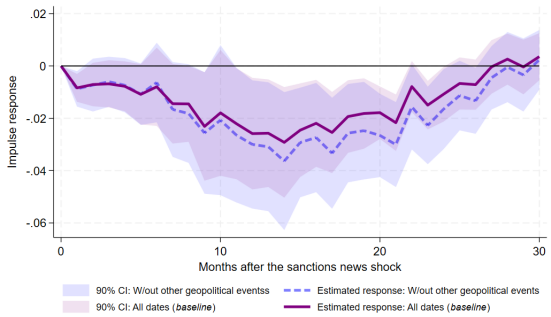
**Figure P.II.** Second-stage LP–IV estimates: Sanctions news shocks
with *vs* without coincidences with other geopolitical events



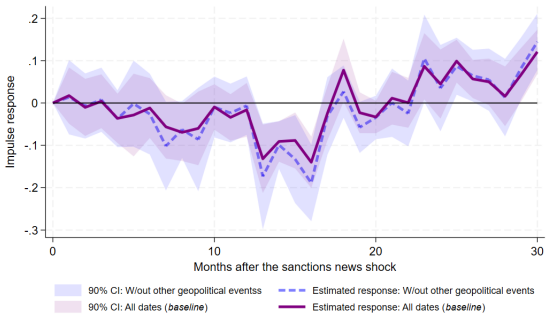

(a) Industrial production



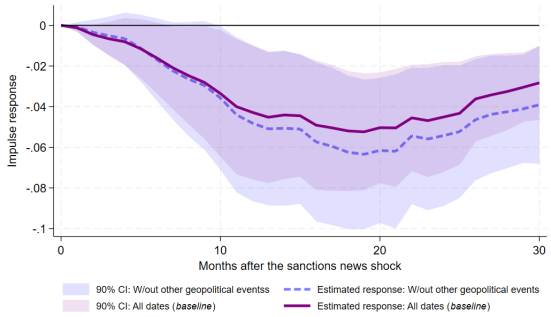

(b) Consumption



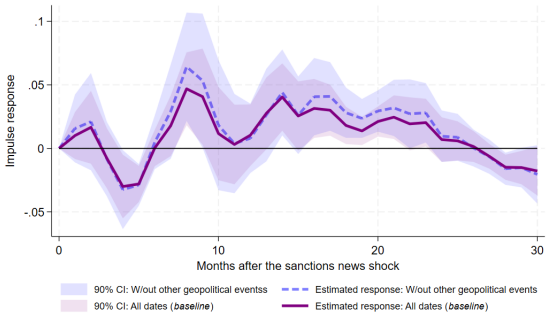

(c) Investment




(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 4 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 $\alpha_c$ is set to the $90^{\text{th}}$ 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 (3), 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.

# Appendix Q Comparing with other geopolitical events

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

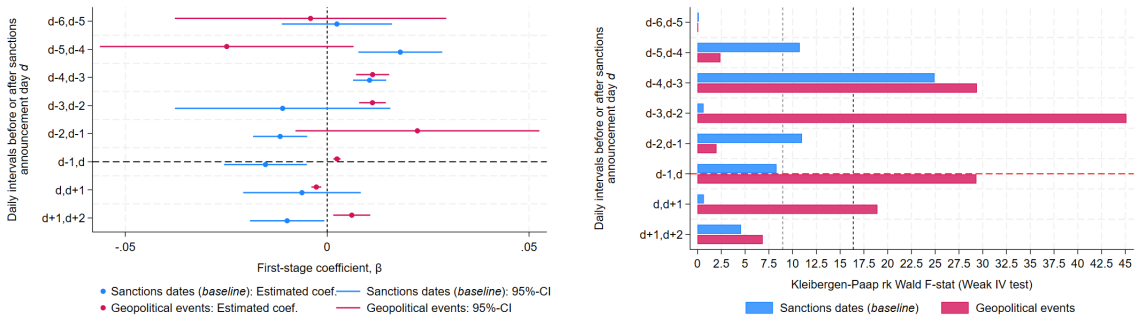
| # | Events with $\Delta \ln GPR \geq \alpha_c$ in year $t$ | | | Distances to OFAC sanctions announcements: | |
|---|---|---|---|---|---|
| | Date | Category | Description | Previous (*days before*) | Next (*days after*) |
| **Panel 1: Before the sanctions against Russia** | | | | | |
| 1 | 29-Nov-2001 | 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 Q.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 $\alpha_c$ is set to the $99.5^{\text{th}}$ 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.

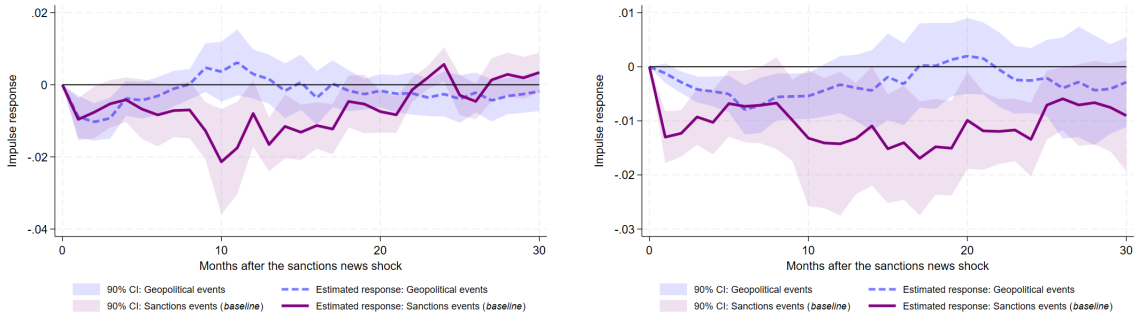
**Figure Q.I.** First-stage LP–IV estimates: Sanctions news shocks *vs* major geopolitical events




(a) First-stage estimates $\beta_k$ (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 $\alpha_c$ is set to the $99.5^{\text{th}}$ 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 Q.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.

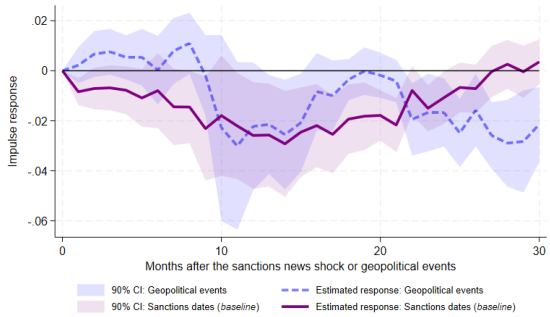
**Figure Q.II.** Second-stage LP–IV estimates: Sanctions news shocks *vs* major geopolitical events



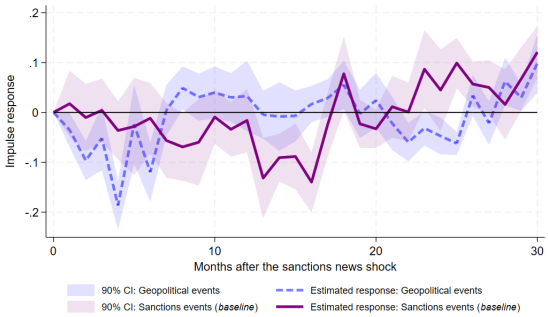

(a) Industrial production



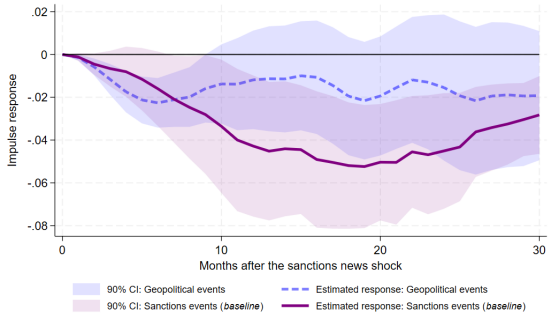

(b) Consumption



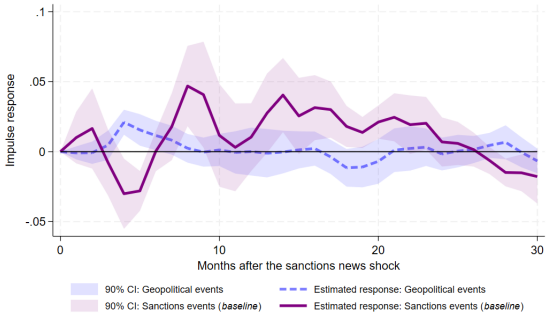

(c) Investment




(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 4 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 $\alpha_c$ is set to the $99.5^{\text{th}}$ 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 Q.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 (3), 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 R OPEC meetings and the oil supply shock

**Table R.I.** OPEC meetings, 2000–2019

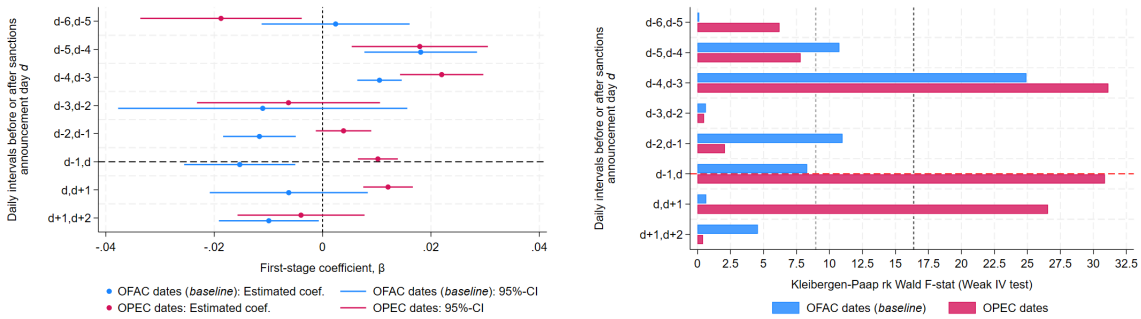
| # | Meeting date | Description | Extraordinary = 1 |
|---|---|---|---|
| 1 | 3/29/2000 | 109th OPEC meeting | 0 |
| 2 | 6/21/2000 | 110th OPEC meeting | 1 |
| 3 | 9/11/2000 | 111th OPEC meeting | 0 |
| 4 | 11/13/2000 | 112th OPEC meeting | 1 |
| 5 | 1/17/2001 | 113th OPEC meeting | 1 |
| 6 | 3/17/2001 | 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 R.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.

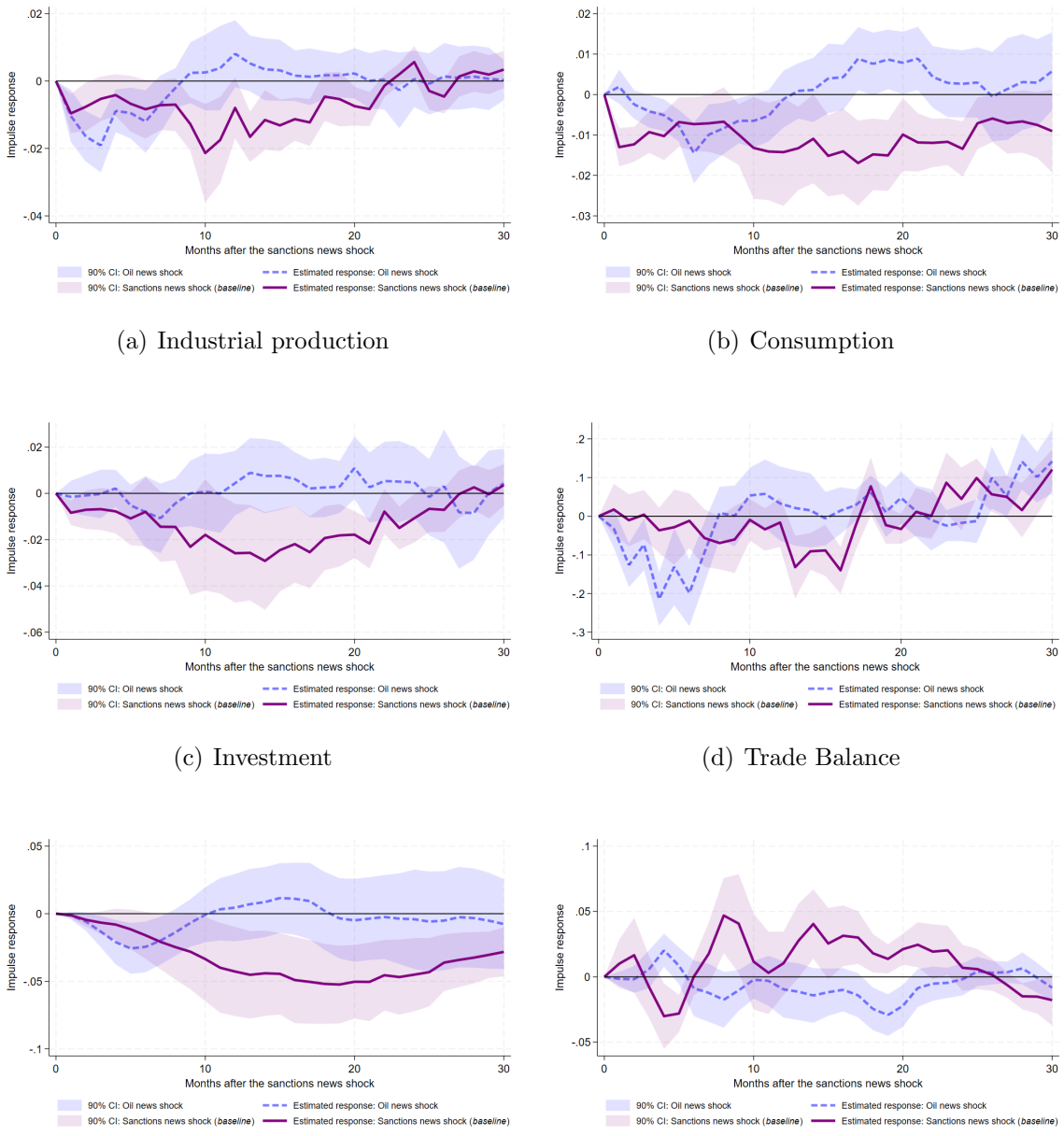
**Figure R.I.** First-stage LP–IV estimates: Sanctions news shocks *vs* OPEC meeting events




(a) First-stage estimates $\beta_k$ (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 Q.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 R.II.** Second-stage LP–IV estimates: Sanctions news shocks *vs* OPEC meeting events




(a) Industrial production

(b) Consumption

(c) Investment

(d) Trade Balance

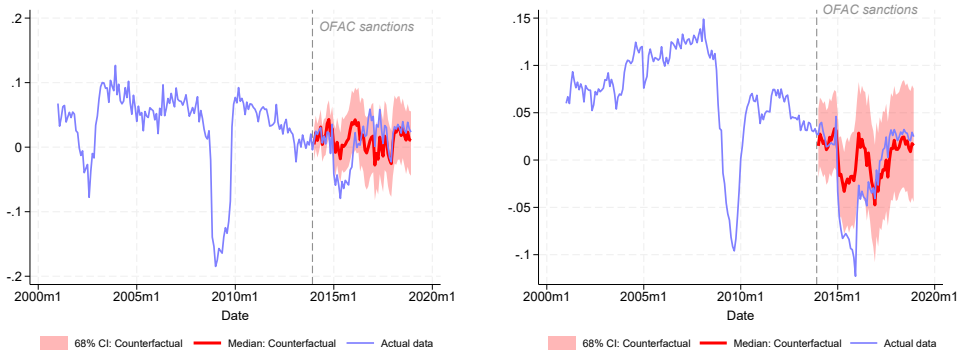
(e) External Debt

(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 4 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 Q.I). Each panel reports impulse responses corresponding to $\theta_{i,h}$ in Equation (3), 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 S Alternative historical decomposition

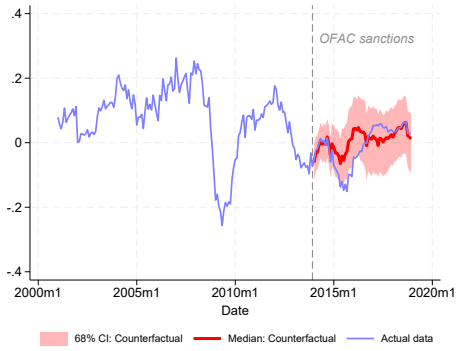
**Figure S.I.** Counterfactual analysis: macroeconomic dynamics in Russia without sanctions in the 2010s



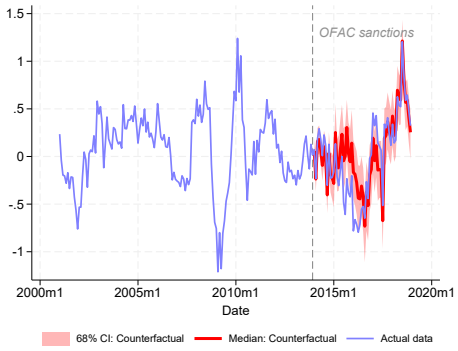

(a) Industrial production



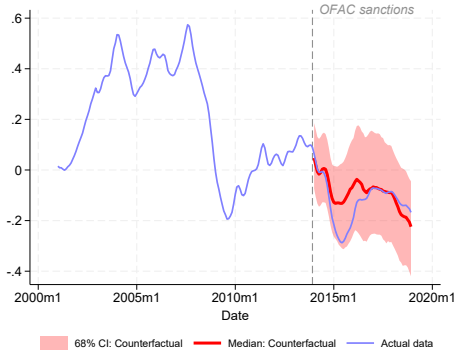

(b) Consumption



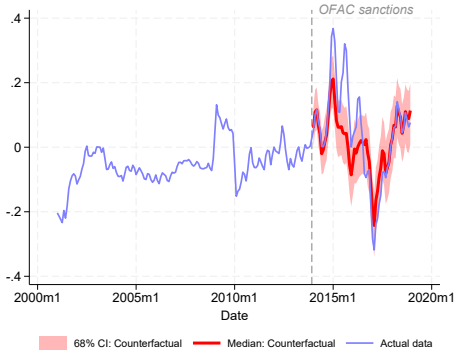

(c) Investment




(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.

# Appendix T Details on the cross-section of firms

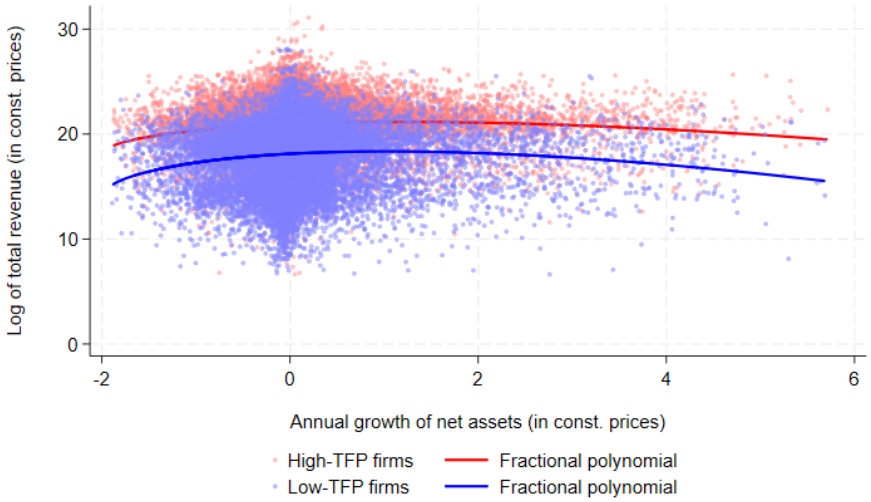
## T.1 Firm-level data description

**Table T.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 T.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 T.II.** Firm performance and the sanctions news shock

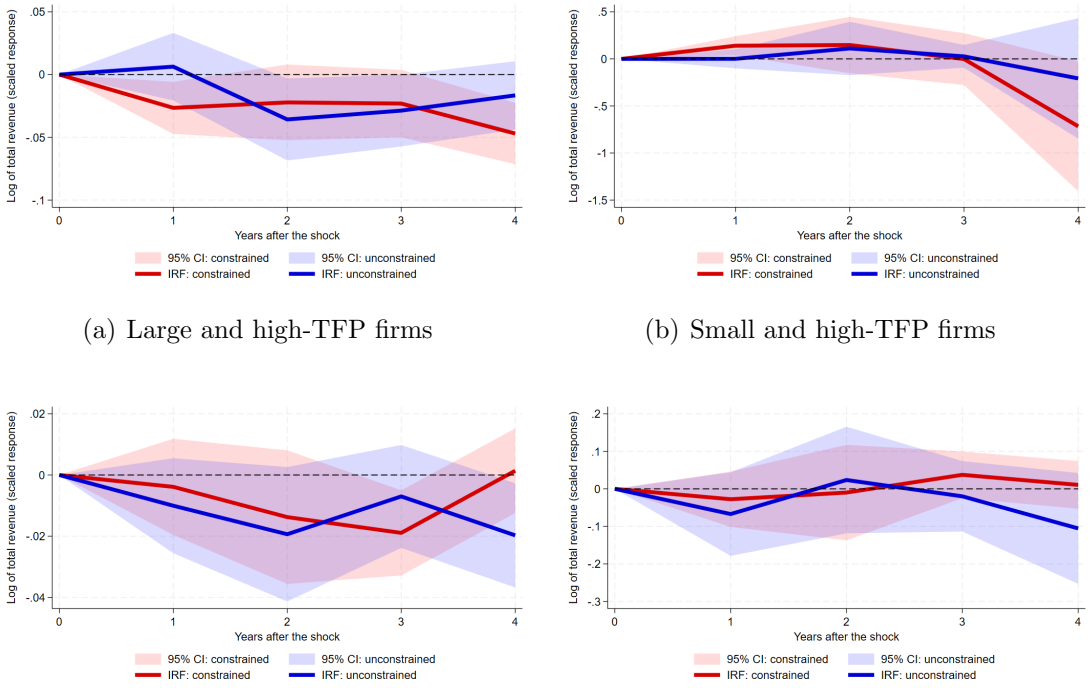
| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | $\ln TR_{f,t}$ | $\Delta \ln TR_{f,t}$ | $Leverage_{f,t}$ | $ROA_{f,t}$ | $\ln W_{f,t}$ | $\ln K_{f,t}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\ln TFP_{f,t}$ | 0.703*** | 0.508*** | –0.008*** | 0.022*** | 0.141*** | –0.282*** |
| | (0.002) | (0.003) | (0.003) | (0.000) | (0.003) | (0.003) |
| $\ln TFP_{f,t}$ × 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 (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), $\alpha_f$, $\alpha_i$, $\alpha_s$ 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.

## T.2 Details on the financial constraints exercise

**Figure T.I.** Financial constraints and the 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 $t+h$ ($h = 1, \ldots, 4$), using Equation (6) augmented with an interaction between the sanctions news shock and an indicator for financially constrained firms. Panel ($a$) contains estimates for large and high-TFP firms. Panel ($b$) depicts estimates for small and high-TFP firms. Panel ($c$) shows estimates for large and low-TFP firms. Panel ($d$) reports estimates for small and low-TFP firms. The red line reports the response of financially constrained firms, while the blue line reports the response of financially unconstrained firms. Financially constrained firms are firms in the bottom quintile of the full-sample 2013 distribution of bank debt to total assets, where bank debt is the sum of long-term and short-term borrowing; financially unconstrained firms are firms in the top quintile of the same distribution. A 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, a high- (low-) TFP firm is a firm in the upper (lower) quintile of the firms' distribution by the estimated total factor productivity. Each response is rescaled to represent a 0.25 percentage point rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, which implies a 0.223 magnitude of the sanctions news shock. The shaded areas denote 95% confidence intervals computed by clustering standard errors at the industry × year level.

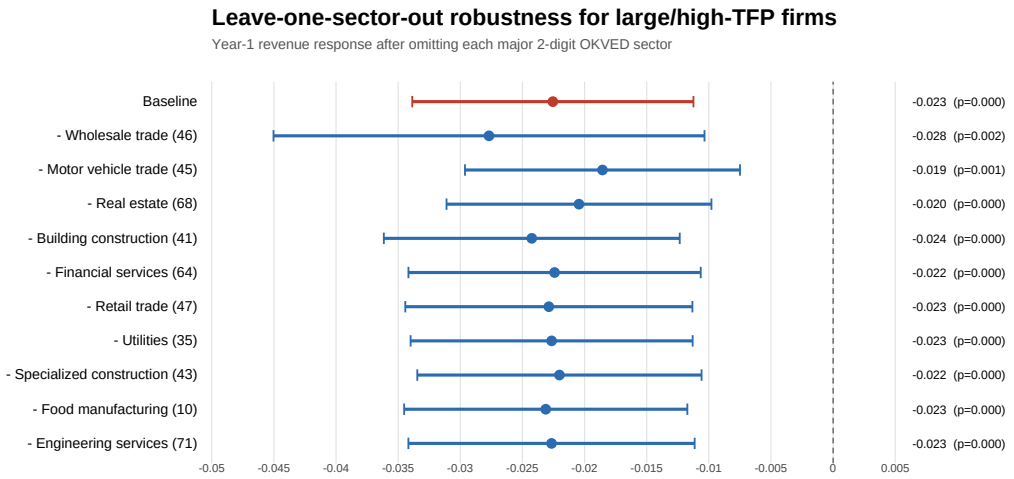
**Table T.I.** Selected-horizon financial-constraint heterogeneity in wages, capital, and leverage

| | Large/high-TFP | Small/high-TFP | Large/low-TFP | Small/low-TFP |
|---|---|---|---|---|
| *Panel A: Wages (year 4; percent)* | | | | |
| Constrained | -1.302 | -1.771 | -0.200 | 4.039* |
| | (0.894) | (3.510) | (0.532) | (2.290) |
| Unconstrained | 1.236 | -2.224 | -1.049* | 0.923 |
| | (1.060) | (3.367) | (0.573) | (4.776) |
| *p-value: diff=0* | *0.037* | *0.907* | *0.187* | *0.438* |
| *Panel B: Capital (year 4; percent)* | | | | |
| Constrained | -2.933** | 12.488* | -1.052* | -1.031 |
| | (1.390) | (7.553) | (0.557) | (3.424) |
| Unconstrained | 0.074 | 10.824* | -2.254*** | 2.488 |
| | (1.813) | (5.607) | (0.589) | (5.037) |
| *p-value: diff=0* | *0.110* | *0.766* | *0.067* | *0.438* |
| *Panel C: Leverage (year 1; debt-to-assets ratio)* | | | | |
| Constrained | -0.288 | 0.006 | 0.002 | 0.048 |
| | (0.204) | (0.260) | (0.006) | (0.044) |
| Unconstrained | -0.156 | -0.349* | -0.025* | 0.054 |
| | (0.255) | (0.199) | (0.014) | (0.051) |
| *p-value: diff=0* | *0.704* | *0.158* | *0.042* | *0.873* |
| Constrained firms | 667 | 151 | 497 | 57 |
| Unconstrained firms | 432 | 48 | 833 | 150 |

*Note:* For compactness, the table reports the most informative horizon for each outcome: year 4 for wages and capital, and year 1 for leverage. Rows *Constrained* and *Unconstrained* report the scaled local-projection responses for firms in the bottom and top quintiles, respectively, of the full-sample 2013 distribution of bank debt to total assets. Standard errors are reported in parentheses. The $p$-value row reports the test of equality between the constrained and unconstrained coefficients within each firm group. Entries in Panels A and B are in percent; entries in Panel C are in levels of the debt-to-assets ratio. Superscripts ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Standard errors are clustered at the industry × year level.

## T.3 Details on the sector composition exercise

**Figure T.II.** Leave-one-sector-out robustness for the effect of the sanctions news shock on revenues of large and high-TFP firms




*Note:* The figure reports the estimated year-1 local-projection response of log firm revenues to the annualized sanctions news shock for the large and high-TFP group from Figure 8. The baseline specification is re-estimated after omitting each of the ten largest 2-digit OKVED sectors one at a time. These ten sectors account for 81.8 percent of the large/high-TFP panel observations. The point estimates are rescaled to represent a 0.25 percentage point rise in the average YTM of Russia's US-Dollar denominated sovereign bonds, corresponding to a 0.223 magnitude of the sanctions news shock. Horizontal bars denote 95% confidence intervals computed using standard errors clustered at the industry × year level.

# Appendix U Details on the cross-section of households

**Table U.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 U.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 U.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), $\alpha_h$, $\alpha_s$, $\alpha_j$ 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.