The Real Effects of Credit Supply Shocks: Evidence from an Emerging Economy*

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Abstract

What role do credit supply shocks play in macroeconomic dynamics in an emerging economy? Is there heterogeneity in consumption and investment responses at the micro level? We exploit Russia's unique institutional setting over the last two decades enabling us to relate the credit supply shocks identified through a structural VAR model to important exogenous events such as the 2014 Western economic sanctions using narrative sign restrictions. We show that credit supply shocks have sizable macroeconomic effects in Russia with magnitudes close to those in advanced economies. An expansionary credit supply shock normalized to 0.5 p.p. reduction in lending rate leads to an increase of 2 p.p. in output growth rate, 1.5 p.p. in consumption growth rate, and 5 p.p. in investment growth rate within a quarter. We find that the heterogeneity of the household and firm responses to credit supply shocks is driven by debt-to-income and leverage ratios, with indebted poorer households and larger firms being more sensitive to fluctuations in credit conditions.

Keywords: Bank credit, Monetary policy shocks, VAR, Narrative sign restrictions, Economic sanctions, Russia.

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1 Introduction

Emerging market economies (EMEs) have long been recognized for their excessive volatility of consumption relative to output compared to advanced countries, which leaves households with fewer opportunities for consumption smoothing throughout the business cycle (Neumeyer and Perri, 2005; Uribe and Schmitt-Grohe, 2017). Another distinctive feature of EMEs is that their financial sectors have undergone substantial transformations over the past several decades: financial liberalization involving increased openness to cross-border capital flows, and the formation of institutions and a regulatory environment. The low starting point of financial sectors in EMEs entails poor initial penetration of financial services and the subsequent rapid growth of domestic banking sectors.[1] Bringing the two features together, one may naturally hypothesize that credit supply movements could have substantial effects on consumption in EMEs and, most importantly, the failure to smooth consumption may stem from (large) negative credit supply shocks during crises and (large) positive credit supply shocks when such economies are booming. In this paper, we study the effects of credit supply shocks on consumption and investment in Russia on aggregate and in the cross-sections of households and firms over the last two decades.

One may naturally ask whether Russia is a typical EME—or at least was such before the full-scale war against Ukraine in February 2022—and how generalizable are the findings on Russia for other EMEs. According to the IMF, Russia is classified as an "Emerging Market and Developing Economy"[2] with many typical features shared by EMEs, including high macroeconomic volatility and high correlation of domestic macroeconomic variables with external financial conditions (Neumeyer and Perri, 2005), underdeveloped domestic financial market and high reliance on external finance, volatile capital flows and currency exchange rate. In many respects, though, these features are taken to extremes in the Russian economy, given a very high level of government presence and pervasive corruption.[3] Like many other EMEs, Russia is dependent on commodity exports, but, in contrast to other economies, to

[1] Djankov et al. (2007) show that institutional characteristics are important determinants of credit at the country level, including in developing countries.

[2] See http://www.imf.org/external/pubs/ft/weo/2015/02/pdf/text.pdf. In addition, before the Russo-Ukrainian War in 2022, Russia was a part of the MSCI Emerging Markets Index, see https://www.msci.com/eqb/pressreleases/archive/PR_Russia_Classification.pdf, and J.P. Morgan Emerging Market Bond Index.

[3] See The Heritage Foundation Report.

a greater extent. For example, fuel exports account for around 60% of Russia's total goods exports.[4] The fraction of commodity exports in Russia is twice as large as in a "typical" EME considered in the literature (Ben Zeev et al., 2017: Argentina, Brazil, Chile, Colombia, Peru).

Further, the high reliance on commodity exports manifests in the high sensitivity of domestic business cycles to commodity price shocks: a 10% increase in oil price leads to a 1.2 to 2.2% increase in Russian GDP (Rautava, 2004; Korhonen and Ledyaeva, 2010) which contrasts to +0.36% increase in GDP in Schmitt-Grohe and Uribe (2018) in a sample of poor and emerging economies. High business cycle volatility also manifests itself in increased volatility of the ruble exchange rate. Using the sample of advanced and emerging countries, Mamonov et al. (2022) show that over the 1994-2020 period, the Russian ruble was almost twice as volatile as the Argentine peso and Brazilian real and 20% more volatile compared to the Turkish lira.[5] Russia is also affected by country spread shocks, the exogenous changes in country risk premium at the international financial market, which are known to amplify business cycle fluctuations in emerging economies (Mamonov and Pestova, 2023). To the extent that Russia is an exaggerated version of an open emerging economy with the same shocks but of higher magnitude and similar propagation mechanisms, our results on the effects of credit supply shocks may be interpreted as the upper bound of the importance of such shocks in other emerging economies.

Our research echoes the recent findings of Mian et al. (2017) and Mian and Sufi (2018), who show that credit supply shocks have been an important driver of business cycles in advanced economies over recent decades. Along with consumption, we study the effects of credit supply shocks on investment, because Bahadir and Gumus (2016) establish that credit shocks may affect investment differently from consumption depending on the composition of credit and its sectoral allocation. Mumtaz et al. (2018), in turn, reveal empirically that in the US, the contribution of credit supply shocks to investment is very small while their contribution to consumption is large.

Although we closely follow two benchmark studies on advanced economies, i.e., Gambetti and Musso (2017) and Mumtaz et al. (2018), the following features distinguish our work from

[4]Central Bank of Russia, Balance of Payments, Analytical Presentation, 2018. https://cbr.ru/eng/statistics/macro_itm/svs/#a_71637.

[5]The country with unorthodox soft monetary policy.

their research.

First, we primarily focus on the effect of credit supply shocks on the components of GDP—consumption and investment—rather than GDP itself at the macro level and complement the macro analysis with the cross-sectional analysis at the household and firm levels. While previous empirical macroeconomic studies reveal the effect of credit supply shocks on GDP and CPI inflation, empirical microeconomic studies suggest that the effect is channeled through the household consumption (Mian and Sufi, 2010) and the investment decisions of firms (Amiti and Weinstein, 2018; Gropp et al., 2019). Strikingly, less is known about the aggregate effects of credit supply shocks on consumption and investment and the heterogeneity of those effects at the micro level. The results of our macro analysis indicate that an expansionary credit supply shock, estimated from a SVAR model and re-scaled to be equivalent to an 0.5 p.p. reduction in the lending rate, leads to a 2 (2.5) p.p. increase in output growth rate, a 1.5 (4) p.p. rise in consumption growth rate, and a 5 (8) p.p. expansion of investment growth rate at 1 quarter (1 year) horizon. In addition, we estimate that the contribution of credit supply shocks to annualized consumption growth equals approximately –1 p.p. during the 2014–2015 recession in Russia (equivalent to 15% of the overall drop in consumption over this period). We conclude that credit supply shocks are important business cycle shocks with their effects in Russia comparable to the effects estimated for advanced economies.

Second, we add further empirical evidence on the Russian economy to existing studies that address specific features of EMEs (Neumeyer and Perri, 2005; Uribe and Schmitt-Grohe, 2017, among others). One such feature is that EMEs encounter relatively large shocks compared to advanced economies. In this respect, Russia serves as a valid example of a country that is subject to large shocks but manages to ride them out without defaulting or suffering from other serious financial disruptions, at the country level over the two decades.[6] Our results, in particular, suggest that such large economic shocks—as, e.g., the financial sanctions of 2014—affected credit supply in Russia similarly to global developments in the aftermath of the Global Financial Crisis of 2008—it just took longer time for these effects

[6]Last time modern Russia experienced a sovereign default crisis was in August 1998 (Panizza et al., 2009). Since then, Russia has encountered many episodes of large economic shocks, including the Global Financial Crisis in 2008, "modest" Crimea-related sanctions in 2014, COVID-19 in 2020, and harsh sanctions due to the full-scale war against Ukraine in 2022, but neither of them forced Russia to default (Ananyev and Guriev, 2018; Mamonov et al., 2023). In June 2022, Russia defaulted on its foreign dollar-denominated debt due to technical inability to pay in dollars because of the US and EU sanctions. Russia was willing to pay and could pay its debts.

to dissipate.

Third, we provide empirical evidence favoring the added value of using the narrative sign restrictions (NSR) approach of Antolin-Diaz and Rubio-Ramirez (2018) for EMEs. We sharpen the identification of credit supply and monetary shocks, initially suggested by Gambetti and Musso (2017), by including the dates of generally accepted episodes of restrictive monetary policy shocks (the "Black Monday" of 15 December 2014) and economic sanctions (various dates in 2014) into the SVAR model's set of restrictions.

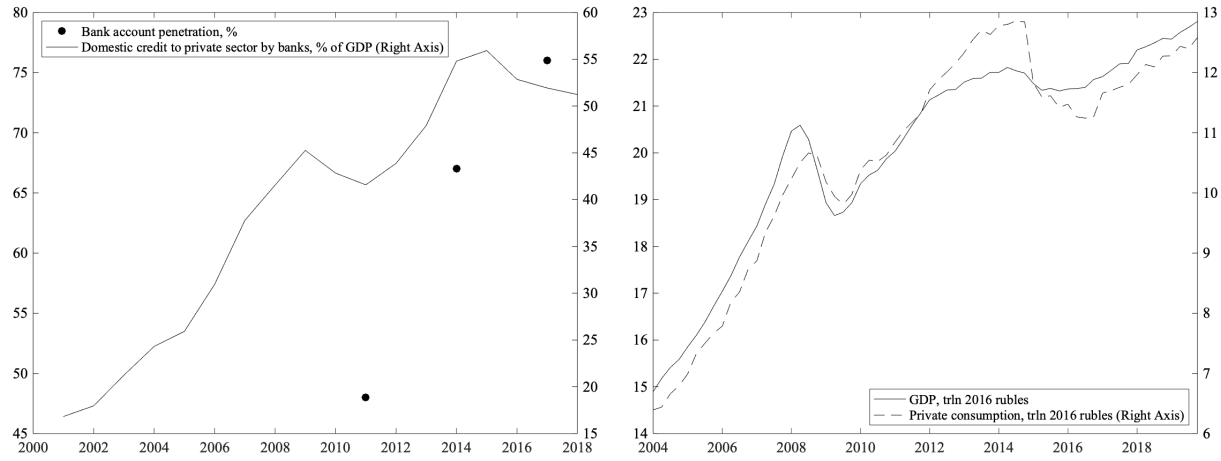
Finally, in our cross-sectional analysis, we show that the identified credit supply shocks have significant predictive power for individual consumption choices and investment decisions made by firms. We also find that the effects are stronger for more indebted households and levered firms, which complements and enlarges our corresponding macro-level results. In particular, the estimates at the household level reveal that the effects of credit supply shocks are stronger for relatively poorer households that have bank loans. In addition, our results indicate that the effects of credit supply shocks go *beyond* those stemming from monetary policy shocks, thus extending the analysis of Cloyne et al. (2020) and Kehoe et al. (2020). What concerns firms, we conclude that the effects of credit supply shocks rise with firm leverage, even when MP shocks are included in the same regression model. These results thus supplement those obtained by Cloyne et al. (2023) and Ottonello and Winberry (2020).

The remainder of this paper is structured as follows. Section 2 discusses the relevant literature and overviews the key aspects of credit markets in Russia. Section 3 describes the gathering of macro-financial data. Section 4 introduces the empirical design, including the specification of the baseline SVAR model and the choice of the SR and NSR schemes for the identification of credit supply shocks and distinguishing them from monetary policy and other aggregate shocks. Section 5 presents the baseline estimates of the SVAR model, including impulse responses and historical decomposition. Section 6 complements our macro results by tracing the impact of credit supply shocks on consumption and investment at the level of households and firms. We present our concluding thoughts in Section 7.

2 Background

2.1 Credit markets in Russia

We begin with a brief overview of credit market developments in Russia over the past two decades. Since the beginning of the 2000s, the Russian economy has been experiencing a huge growth of bank lending to both non-financial companies and households. According to the World Bank, domestic bank credit to the private sector in Russia increased from 17% of GDP in 2001 to more than 55% of GDP by 2013, although it had declined slightly since then (Figure 1). Lending was exhibiting a profound cyclical component along this growth path: the annual credit growth rates were reaching 60% by 2008 (on the eve of the Global Financial Crisis of 2007–2009), –5% at the start of 2010 (the most acute phase of the business cycle), and then recovering to 25% in 2012 (another peak of the local business cycle) before declining again to virtually zero in 2016. The latter likely reflects the joint negative effect of the oil price collapse and Western financial sanctions after the annexation of Crimea by the Government of the Russian Federation in 2014 (Ahn and Ludema, 2020; Mamonov and Pestova, 2023).



(a) Financial indicators (b) Real indicators

Figure 1: Selected Financial and Real Sector Indicators of the Russian Economy. Sources: the World Bank (a) and Rosstat (b).

While in the 2000s, the credit cycle movements could have been attributed to shifts in demand of both non-financial firms and households, in the 2010s, the situation had changed: large non-financial firms reduced their demand for domestic credit and rearranged their investment towards either their own resources or external (cheaper) funding (see, for example,

Juurikkala et al. 2011). As a result, the credit cycle movements in the last decade were mostly driven by household credit.

In this respect, tracking the effects of CS shocks on both consumption and investment is especially interesting. It is a priori unclear whether CS shocks are more important in explaining consumption or investment. On the one hand, slow credit expansions can be a limiting factor for firm investment if the investment demand is sufficiently high. On the other hand, if household credit expansions are predominantly directed towards secured housing credit then their potential to explain consumption growth can be rather limited.

2.2 Related macro-finance work on credit supply shocks

Gambetti and Musso (2017) provide several examples of the underlying events corresponding to unexpected changes in credit availability, including innovations to: (i) bank and other credit institutions' capital, (ii) their funding, (iii) their risk perception, and (iv) the degree of competition on the credit and related markets. A notable feature of CS shocks is that they are not correlated with income shocks of borrowers and are, therefore, orthogonal to credit demand. To disentangle credit supply from credit demand, it is usually assumed that CS shocks correspond to periods of increased lending and, at the same time, the decreased cost of credit, or vice versa.[7] Therefore, in this identification, movements in credit availability are unrelated to changes in the credit demand by borrowers and, therefore, represent an exogenous component of lending—the willingness to lend—driven solely by bank-side factors. In a Monte Carlo investigation, Mumtaz et al. (2018) show that the CS shock identification based on the underlying sign restriction approach correctly recovers true shocks simulated from DSGE models.

There is growing evidence that CS shocks amplify business cycle fluctuations in the output of developed economies (Eickmeier and Ng, 2015; Gambetti and Musso, 2017; Mumtaz et al., 2018).[8] Although some work for emerging economies has been done (e.g., Guevara and Rodriguez, 2020, Eickmeier and Ng, 2015, Deryugina et al., 2015), it is still not clear

[7] Credit demand shocks are identified using the assumption of a positive correlation between the amount of loans and the cost of credit.

[8] For instance, Gambetti and Musso (2017) find that GDP rises by 5–7.5% (annualized) in response to positive credit shocks where the interest rate on loans is normalized to –0.5 p.p., but this effect fades away on a four-quarter horizon.

whether CS shocks cause real fluctuations in such countries and, if they do, how it compares to the benchmark of developed countries. Specifically, Guevara and Rodriguez (2020) study the Pacific Alliance bloc (Chile, Colombia, Mexico, and Peru) where, as they argue, the banking sector (and not capital markets) is the principal source of funding for the economy. They show that a positive CS shock associated with a 0.5 p.p. decrease in the lending rate leads to a 1% contemporaneous response in GDP—the effect is five times lower compared to the one estimated in advanced economies (reported in Gambetti and Musso, 2017; the effect of similar magnitude is found in Mumtaz et al., 2018). However, they do not study the microeconomic implications of the CS shocks. Therefore, it is still relevant to study whether the effects of CS shocks are lower and, if so, by how much in emerging economies as compared to advanced countries. We answer this question using Russia's example, given the credit market developments outlined above.

There is also ample literature exploring the effects of monetary policy on consumption (see, among others, Kaplan et al., 2018 and Cloyne et al., 2020 who study the heterogeneity of consumption responses). In the past, Russia was subject to large monetary shocks. A prominent example is the "Black Monday" of 15 December 2014, when the Central Bank of Russia (CBR) raised the key rate from 10.5% to 17% to prevent the further devaluation of the ruble as a result of the drop in oil prices. We are interested in the effects of CS shocks over and above monetary surprises, and therefore, it is crucial to disentangle CS shocks from monetary disturbances. We employ a sign restriction approach and simultaneously identify both shocks: CS and monetary policy (MP). This allows us to separate the effects of the two shocks and the effects of other business cycle shocks: aggregate demand (AD) and aggregate supply (AS).

3 Macro-financial data

3.1 Choice of variables for the SVAR model

We begin by describing the variables we employ in our SVAR model. We have two important considerations. First, in specifying the list of endogenous variables, we have a clear trade-off between the tractability of the empirical model from the standpoint of existing theoretical

models (which are mostly suitable for developed countries) and accounting for the specific features of the Russian economy. Second, given the relatively short timespan typical for an emerging market economy, our empirical model should contain enough information to isolate CS shocks and separate them from other relevant business cycle shocks.

To ensure the tractability of our empirical results, we follow Gambetti and Musso (2017) and Mumtaz et al. (2018), who identify CS shocks with sign restrictions (SR) based on theoretical work by Curdia and Woodford (2010); Gertler and Karadi (2011). Both Gambetti and Musso (2017) and Mumtaz et al. (2018) study the real effects of CS shocks in several developed economies. Similar to them, we use a nine-variable specification and apply an SR scheme to identify the shocks. However, we account for crucial features of the Russian economy—the sensitivity to world oil prices, dollarization of the financial system, and high overall uncertainty—by constructing certain variables for the SVAR analysis and including the oil price in the model as an exogenous variable.

In particular, we construct a financial uncertainty measure and a financial condition index. Further, we compute and then exclude the part of total credit that is determined by the appreciation or depreciation of ruble (i.e., not by the supply of or demand for loans).[9] In constructing the uncertainty measure, we employ the basic GARCH(1,1)-model of Bollerslev (1986) using daily data from the Moscow stock exchange market. To construct the financial conditions index, we apply several country-level interest rate spreads (see Appendix A), which are likely to be countercyclical: rise in periods of low oil prices and fall when oil prices recover, thus reflecting the cycles of creditworthiness of domestic economic agents (consumers, firms, and government).

In the main part of our work, we consider a SVAR model with nine endogenous variables, as in Mumtaz et al. (2018). We include (*i*) real output growth, (*ii*) CPI inflation, (*iii*) the three-month risk-free rate implied by the government bills quotes (hereafter the risk-free rate), (*iv*) the composite lending rate (hereafter the lending rate), (*v*) the growth of total nominal bank loans to households and non-financial firms (hereafter loan volume growth),

[9] As was recently clearly demonstrated by Verner and Gyongyosi (2020) for markets with substantial shares of foreign currency loans, the revaluation of foreign currency debt may be sizable enough to affect the overall level of debt burden and trigger recessions and financial instability during the periods of large exchange rate fluctuations. Russia's credit market was dollarized to the extent that the debt revaluation effect was economically significant during the period under study (10-30% of foreign currency denominated loans in Russia compared to 69% of household lending in Hungary in 2008, see Verner and Gyongyosi (2020).

(*vi*) real investment growth, (*vii*) real consumption growth, (*viii*) the financial conditions index, and (*ix*) the financial uncertainty measure to our analysis.[10] International oil price is the only exogenous variable.

3.2 Timespan, data sources, and technical details

We now discuss the most important issues related to the data collection on the Russian economy. We describe all the details on the definition, the sources of data and its preprocessing on each of the variables in Appendix A.

We focus on domestic bank lending to domestic non-financial firms and households. Domestic banks include state-, foreign-, and privately-owned financial institutions. Foreign-owned banks were active in Russia during the period under consideration but they were subject to the same regulation as other banks and never represented a large part of the banking sector assets.[11] The two largest state-owned banks held approximately 50% of the market share and foreign banks operate only through their Russian subsidiaries, so we do not make any distinction between different banks' lending volumes. In our analysis, we also do not consider non-banks as doing so would make our definition of credit supply different from the papers we rely on in our analysis. Moreover, data on non-banks in Russia is proprietary and, we do not have access to it.

Since the history of the market economy in Russia does not extend further back than the last three decades, the first of which was dropped from the analysis as the country was undergoing a transformation crisis, we effectively have only two last decades in our SVAR estimation. We use quarterly data in our baseline estimation and monthly data in the robustness check.[12] As we switch from quarterly to monthly data, we need to find an appropriate alternative to GDP. We use the official index of basic economic activities reported by the Russian Federal State Statistics Service (Rosstat).[13] This index tracks economic activity in most of the sectors of the economy (agriculture, mining and quarrying,

[10] Variables (i), (ii), (v), (vi), and (vii) are constructed as changes of the logarithms of the respective indicators, as the literature suggests.

[11] Their share in total assets was fluctuating around 8-10% in the 2000s and 2010s, Mamonov et al. (2022).

[12] One challenge in the identification of CS shocks is to disentangle credit from monetary policy and other business cycle shocks. Monthly data may help us separate the effects of credit shocks from others especially if many shocks occurred during a particular quarter.

[13] The official Rosstat website.

manufacturing, construction, transportation, wholesale and retail trade, etc.). However, this index and detailed information on the interest rates are available only from January 2004, thus excluding all periods from the beginning of 2000 to the end of 2003 from our analysis. Overall, the rest of the relevant variables are available over the last two decades (up to 2020 which we exclude from the analysis because of the large COVID-19 shock), and thus our final timespan covers 63 quarters, from Q2 2004 to Q4 2019, or 191 months, from February 2004 to December 2019.

Next, as we noted above, there is an issue with proper measurement of the loan dynamics, as between 10% and 30% of all loans are denominated in foreign currency and the official ruble exchange rate is rather volatile, especially during crises. Using the ruble equivalent of total loans granted by Russian banks domestically would be misleading in the periods when the ruble was volatile. For example, if the ruble depreciates, then the ruble equivalent of foreign currency-denominated loans will rise, but this increase does not, or at least may not necessarily, reflect a change in the demand for or supply of loans. Since we are interested in the reaction of economic agents to CS shocks, we exclude the effect of ruble exchange rate movements from the loan dynamics. The details can be found in Online Appendix A.

Finally, there is an issue that interest rates for certain periods are missing, and these interest rates are used for the composite lending rate construction. For example, detailed interest rate data for all possible maturities is available only from 2011 onwards. To deal with this, we apply simple interpolation to impute missing numbers and re-construct the composite figure for the whole period. We check that the interpolation we employ works for the available data (as if it were non-existent) and carry out a robustness check by constructing the alternative composite lending rate that contains readily available data only.

3.3 Trends in the data

We present the evolution of the time series used to construct the nine endogenous variables for our SVAR analysis in the Appendix A, Figure A.I. In general, a glimpse of the data clearly reveals two complete business cycles with synchronous behavior of many real and financial quantities. Strong cyclical features of the economy are of keen interest to us since we are studying the effects of business cycle shocks that move the economy away from its long-term

path. Let us elaborate more on the key observations on the Russian macroeconomic data.

First, there is an overall positive trend in real output, consumption, and investment on the one hand, and in lending volumes on the other.

Second, most variables exhibit clear cyclical patterns, with the two most prominent recession/crisis episodes corresponding to the global financial crisis of 2007–2009 and the oil market downturn, Crimea annexation, and imposition of the first packages of sanctions in 2014–2015. The low point during the financial crisis was a 15% total drop in output (in real terms, at the monthly level). Notably, investment volatility exceeded output volatility during both episodes. Somewhat differently, consumption did not fall as dramatically as output did in 2009, whereas the opposite happened during the "combined" economic crisis of 2014–2015 (internal slowdown coupled with oil pride drop and economic sanctions). Risk-free and lending rates in the Russian economy echo this pattern.

Third, in the banking sector, lending has been growing faster than the economy throughout the entire period. Even after adjusting for exchange rate movements, bank lending has grown by approximately 1700% (cumulatively from 2004 to 2019), compared to CPI and real output total growth (300% and less than 150%, respectively).

Finally, the financial conditions index and the measure of financial uncertainty both reveal much higher spikes during the 2007–2009 crisis than in the 2014–2015 recession.

4 Empirical design

4.1 The model

To estimate CS shocks and disentangle their effects on macroeconomic aggregates from those caused by other shocks (monetary policy, etc.), we apply structural vector autoregressive models (SVAR) of the general form along the lines of Arias et al. (2018):

$$\mathbf{y}_t = \mathbf{c} + \sum_{l=1}^{p} \mathbf{A}_l \mathbf{y}_{t-l} + \mathbf{u}_t, \text{ for } 1 \leq t \leq T, \tag{1}$$

where $\mathbf{y}_t$ is a vector of (endogenous) variables (of dimension $n \times 1$) at period t, $\mathbf{A}_l$ is a matrix ($n \times n$) of parameters for $0 \leq l \leq p$, $\mathbf{c}$ is a vector of exogenous variables (in our case, constants, $n \times 1$), $\mathbf{u}_t$ is a vector of (reduced-form) residuals ($n \times 1$), p is the maximum

lag order, and T is the sample size. The vector $\mathbf{u}_t$, conditional on past information and the initial conditions $\mathbf{y}_0, ..., \mathbf{y}_{1-p}$, are assumed to be Gaussian with zero mean and covariance matrix $\mathbf{\Sigma}$.

We are interested in the structural (orthogonalized) shocks $\mathbf{e}_t$ that correspond to the following representation of Equation (1):

$$\mathbf{y}_t = \mathbf{c} + \sum_{l=1}^{p} \mathbf{A}_l \mathbf{y}_{t-l} + h(\mathbf{\Sigma})\mathbf{Q}\mathbf{e}_t, \text{ for } 1 \leq t \leq T, \tag{2}$$

where $\mathbf{Q}$ is an orthogonal matrix $(n \times n)$, and $h(\mathbf{\Sigma})$ is a $n \times n$ matrix which provides the Cholesky decomposition of the covariance matrix $\mathbf{\Sigma}$ such that $h(\mathbf{\Sigma})h(\mathbf{\Sigma})' = \mathbf{\Sigma}$, and $\mathbf{e}_t$ are Gaussian with zero mean and identity covariance matrix.

The model represented by Equation (2) does not allow us to identify $\mathbf{e}_t$ as there are potentially infinitely many $[\mathbf{c}, \mathbf{A}_1, ..., \mathbf{A}_p, \mathbf{\Sigma}]$, $\mathbf{e}_t$, and corresponding $h(\mathbf{\Sigma})$ implying the same $\mathbf{y}_t$. Thus, to identify $\mathbf{e}_t$, we employ sign restrictions (SR) together with narrative sign restrictions (NSR) on $h(\mathbf{\Sigma})\mathbf{Q}$, as discussed in Antolin-Diaz and Rubio-Ramirez (2018), to restrict the set of possible reactions of endogenous variables $\mathbf{y}_t$ in response to structural shocks $\mathbf{e}_t$. Therefore, we estimate the model specified by Equation (2) using the Bayesian methods, as described in detail in Arias et al. (2018) and Antolin-Diaz and Rubio-Ramirez (2018).

The general idea of the estimation is that we (i) draw values of $[\mathbf{c}, \mathbf{A}_1, ..., \mathbf{A}_p, \mathbf{\Sigma}]$ from the prior distribution, (ii) draw $\mathbf{Q}$ from a uniform distribution, (iii) check whether draws from (i) and (ii) give rise to $h(\mathbf{\Sigma})\mathbf{Q}$ compatible with SR (which we introduce in Section 4.2.1 below) and NSR (to be defined in Section 4.2.2), (iv) continue until a specified number of successful draws is collected. The successful draws are further stored to characterize the posterior distributions of parameters and shocks. We then build posterior estimates for impulse responses, shocks, and historical decomposition of endogenous variables using these successful draws. As a baseline, we use specification with flat priors, $p = 4$, and 5000 draws.[14]

We have at least two reasons for switching from a standard frequentist to a Bayesian approach. First, even if we use monthly instead of quarterly data, we would still be subject

[14]We stick to a rule of thumb lag length, but we also find that our results are not significantly affected by the change in this parameter. For a sensitivity analysis of priors, we apply standard Minnesota priors with the rule of thumb hyperparameters governing the prior and the same number of draws (see Online Appendix D).

to *the curse of dimensionality problem* were we to apply frequentist techniques and employ any reasonable number n of endogenous variables in our SVAR. The Bayesian methods, as opposed to the frequentist approach, manage the problem of short time series by combining priors with the data, and they are suitable for large n (Banbura et al., 2010). Second, the SR scheme with set identification is most commonly implemented within the Bayesian approach, going back to the seminal work by Uhlig (2005).

4.2 Identification strategy

The main idea of the identification strategy is to combine regular sign restrictions (SR) with some narrative sign restrictions (NSR) along the lines of Antolin-Diaz and Rubio-Ramirez (2018) to identify CS shocks in the Russian economy and, in particular, distinguish them from monetary policy and other (e.g., sanctions) shocks.

4.2.1 Sign restrictions (SR)

Following prior work, we ground our identification strategy on the idea that structural shocks should have an effect of a particular sign on one or several endogenous variables. We combine three sign restriction (SR) schemes of recent empirical studies of CS shocks by Eickmeier and Ng (2015), Gambetti and Musso (2017) and Mumtaz et al. (2018). All three approaches, as we have already mentioned in Section 3, are grounded on theoretical results from various studies that model the banking/credit sector explicitly (Gilchrist et al. 2009, Curdia and Woodford 2010, Gerali et al. 2010, Gertler and Karadi 2011). We apply a sign restrictions approach to identify CS shocks because, as Mumtaz et al. (2018) have shown in their Monte Carlo experiment, these sign restrictions can successfully match impulse responses from DSGE models.[15]

Our reference point is the SR scheme of Gambetti and Musso (2017), which identifies the four macroeconomic shocks: aggregate supply, aggregate demand, monetary policy, and credit supply (see Table 1). This scheme employs combinations of contemporaneous restrictions on the following five variables: output, CPI, loan volumes, risk-free (or policy) rate,

[15] Mumtaz et al. (2018) experiment with different CS shock identification schemes to assess whether the associated impulse responses match well with the simulated data from a DSGE model calibrated to the US data. The authors find that a pure sign restrictions scheme yields a good matching of median DSGE-based impulse responses.

and the average lending rate. A positive (expansionary) CS shock in this scheme is defined as a situation in which, (i) the lending rate falls and loan volumes rise, which thus (ii) stimulates output growth and price increase (due to the immediate increase of consumption) and (iii) forces the central bank to smooth the amplitude of the business cycle by raising the interest rate. A positive (expansionary) MP shock is defined, in turn, as an unexpected fall in the interest rate which raises output and inflation. Our study does not focus on the identification of the other two shocks, and interested readers are referred to Gambetti and Musso (2017) for detailed discussion.

We borrow the nine-variable SVAR specification from Mumtaz et al. (2018), in which the five core variables come from Gambetti and Musso (2017) and the four additional variables are introduced by the authors. To account for this extension, we restrict responses of consumption and investment to CS shocks to be of the same sign as that of GDP. We ensure that developments in the international oil market do not create omitted variable bias by adding the oil price as an exogenous variable (in the robustness section).

TABLE 1

Identification of credit supply and other business cycle shocks with sign restrictions (SR)

Shock	Output	CPI	Loan volume	Risk-free rate	Lending rate	Cons-n	Inv-t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Credit supply (CS)	+	+	+	+	−	+	+
Monetary policy (MP)	+	+		−			
Aggregate supply (AS)	+	−					
Aggregate demand (AD)	+	+		+	+		

Note: The table presents the sign restriction scheme based on Gambetti and Musso (2017). We report only the seven variables that are restricted; the remaining two variables (i.e., financial conditions and uncertainty) are unrestricted in our baseline model and are not included in the table. All sign restrictions are imposed on impact only.

4.2.2 Narrative sign restriction (NSR)

To further refine our identification, we employ the NSR approach of Antolin-Diaz and Rubio-Ramirez (2018). The idea here is to include only those draws that imply a shock of a particular sign at a given point in time in the final estimate of the posterior distribution. This increases the credibility of the identified shocks by exploiting external narrative information.

First, we start by arguing that for a small open economy such as Russia, the Global Financial Crisis of 2007–2009 likely manifested as a negative shock to the credit supply. Of course, a part of the effect of the crisis might have been stemming from the collapse of oil prices. However, as Eickmeier and Ng (2015) show for, e.g., the US economy, credit supply shocks are important and independent drivers of local credit market conditions. Thus, we require that negative CS shocks must raise lending interest rates in Q2 2008 (i.e., lead to credit conditions tightening).

Second, as we discussed above, the CBR's monetary policy in December 2014 had a well-documented and pronounced effect on the risk-free rate in the economy when the CBR raised the key rate from 10.5% to 17% in a single day (the "Black Monday" of 15 December 2014). The official press release proclaims that this policy was necessary to mitigate the rapid depreciation of the ruble exchange rate at that time and thus prevent inflation jumps.[16] Tishin (2019) employs the high-frequency identification approach and shows that this episode was quantitatively the largest MP shock during 2008–2019. With these facts at hand, and given the observation that this period also coincided with a downward phase of the domestic credit cycle, we estimate the SVAR model with a requirement that the monetary shock had a positive impact on the risk-free interest rate in Q4 2014.

Third, to account for the financial sanctions imposed against Russia in 2014, we also include in our additional estimates the NSR for the periods when different sanctions-related events occurred. In particular, we require successful draws to imply a negative CS shock in March 2014. This date corresponds to the annexation of Crimea—the key event that triggered financial sanctions against major Russian banks (see details in Mamonov et al., 2023 and Dovbnya, 2019). Following Mamonov and Pestova (2023), we treat the financial sanctions shock as a negative CS shock because it led to a roughly 30% decline in the amount of international borrowings by Russian banks and to a spike in the interest spreads. Since our baseline model is quarterly, the corresponding quarter is Q2: the former is chosen rather than Q1 to reflect certain lags in political actions following the annexation itself.[17]

[16]The official statement is available here: https://www.cbr.ru/press/PR/?file=16122014_004533dkp2014-12-16T00_39_23.htm.

[17]The US President Obama's Executive Orders (EO) 13660, 13661, and 13662 which were signed in March 2014. As shown in Welt et al. (2020), EO 13662 was authorized in July 2014 in response to the escalation of the conflict in Eastern Ukraine. This EO particularly introduced sectoral sanctions against major Russian banks that were then prohibited from having new placements of foreign debt of certain maturities at international financial markets. In the wake of the Boeing MH17 tragedy, US sectoral sanctions

Overall, by imposing an NSR in addition to the modified SR, we attempt to improve the identification precision. As we will show in the next Section, these restrictions do affect the form of impulse responses to CS shocks and the historical decomposition of macroeconomic variables by shocks and they reduce uncertainty around them. This is likely because NSRs affect the shocks not only at the periods when they are applied but also at other periods. This, in turn, is the result of the effect that NSRs have on the posteriors of all parameters of the model, such as impulse responses.

5 Macroeconomic estimates

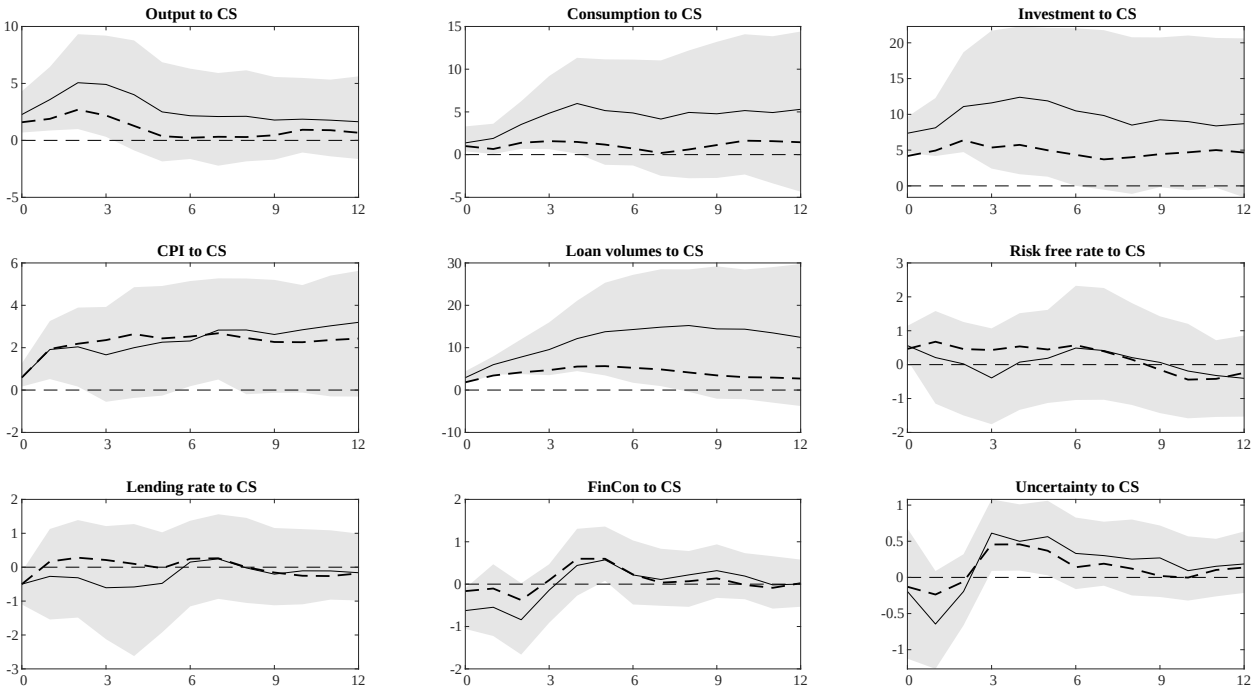
5.1 Impulse responses

5.1.1 Baseline results

We start by describing our estimation results on the impulse responses to credit supply (CS) shocks and the other three business cycle shocks, including aggregate demand (AD), aggregate supply (AS), and monetary policy (MP). Because our focus is on CS shocks, we present respective impulse responses in the main text below (see Figure 2), while the impulse responses to the other three shocks can be found in Online Appendix B. We also deliver our view on the sources of identified CS shocks in Russia over the period of 2004–2019 in Online Appendix C.

When computing impulse responses, we set the response horizon to three years (12 quarters), normalize the responses so that the on-impact effect of CS on the composite lending rate equals –0.5 p.p., and then add up the responses of output, consumption, investment, CPI, and loan volumes to obtain cumulative impulse responses. We report two responses for each of the nine endogenous variables: one estimated under the SR approach only and the other combining the SR and NSR schemes. As for the NSR scheme, we consider the 4th quarter (December) of 2014 as a period of a negative (restrictive) monetary policy shock and the 2nd quarter of 2008 and the 3rd quarter of 2014 as periods of negative (contractionary) CS shocks in the Russian economy.

were expanded in July and September 2014 (Welt et al., 2020) and the EU introduced similar restrictions. We include only Q2 2014 to reflect both the effect of immediately imposed sanctions. We let the model decide on whether Q3 2014 was a shock of similar magnitude.



Note: The figure presents the estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior (the flat prior is assumed). The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the quarters after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-quarter log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure 2: Impulse responses to the identified credit supply shock (CS): the baseline results

We obtain the following four sets of results on the estimated responses of the economy to expansionary CS shocks.

First, *compatibility with the identification schemes (SR, NSR).* as can be inferred from Figure 2), the estimated responses of all nine endogenous variables to an expansionary CS shock satisfy the imposed SR and NSR schemes (recall that we impose restrictions only on impact). The response of output is positive and significant lasting for at least three quarters. Responses of consumption and investment are also positive and significant over the four and six quarters after the shock, respectively. Loan volumes react positively so that the response is very persistent, only fading out by the end of the second year. The lending rate, in turn, reacts negatively though short-lived: the response becomes insignificant

starting from the 2nd quarter. As for the relationship between the SR and NSR schemes, we clearly observe that the NSR produces at least two times stronger responses of the quantity variables—output, consumption, investment, and loan volumes—to CS shocks than the SR counterparts.

Second, *output responses*. We find that the output growth rate rises by up to 5 p.p. in the three quarters after an expansionary CS shock (significant at 5%).[18] In addition, we estimate the on-impact elasticity of output to loan volumes to be around 1, which is strikingly in line with the corresponding estimates of Gambetti and Musso (2017) and Mumtaz et al. (2018) for developed economies.[19]

Third, *consumption and investment responses*. We find that the on-impact reaction of the consumption growth rate to an expansionary CS shock is below 2 p.p. (both SR and NSR), while the on-impact response of the investment growth rate is more than three times larger, being around 7 p.p. In the four quarters after the shock, the response of consumption growth reaches 5 p.p. and investment growth 11 p.p., which is large and at least as large (consumption) or even two times larger (investment) than the output response.

Fourth, *inflation and interest rates*. We find that the CPI inflation and the risk-free interest rate exhibit mostly positive reactions to the expansionary CS shock, with CPI rising by 2 p.p. already in one quarter after the shock and the risk-free rate rising by 0.5 p.p. on impact. However, the response of the risk-free rate dies out fast and is characterized by rather large credible bands. The latter is in line with Eickmeier and Ng (2015). We find that the reactions of the Central Bank of Russia to domestic credit cycles are not immediate and/or may go in opposite directions depending on the state of the economy.[20]

Fifth, *financial conditions*. We find that the financial conditions index and the measure

[18]For comparison, Mumtaz et al. (2018) finds that an 0.1 p.p. increase in the *credit spread* (= *the lending rate – the policy rate*) leads to a 1 p.p. lower GDP growth one year after.

[19]This may seem surprising as one would consider the banking sector (and not the capital markets) to play a major role in providing funds in Russia and, therefore, to have a larger impact on economic activity compared to the countries with more developed and diversified financial markets. However, bear in mind that the overall capacity of the Russian banking sector relative to the size of the economy is smaller compared to advanced economies: bank credit to the private non-financial sector amounted to just 50% in Russia in 2018 compared to 88% in the Euro area (Source: BIS). It is likely that these two effects compensate for each other and lead to comparable effects of the credit shock in Russia and in developed countries.

[20]For instance, although we are not directly exploring this issue, when the economy starts recovering after a recession and a positive CS shock occurs, the CBR can support the recovery by decreasing the interest rate. Conversely, if the economy is booming and a positive CS shock arises, the CBR can tighten its monetary policy. If this is so, inflation would also exhibit corresponding state-contingency in its reaction to the positive CS shock.

of financial uncertainty reveal boom-bust patterns in their responses to the expansionary CS shock, first shrinking (an improvement of conditions, a decrease of uncertainty) but then rebounding (deterioration of conditions, a rise of uncertainty). In particular, the financial conditions index tends to fall (improve) within two quarters after the shock, which is in line with rising income and suggests a decrease in the spreads (recall that the index is computed as the first principal component of several spreads, see Appendix A). The peak reaction is negative and significant at 5%, though the credible bands are rather large. The rebound in the response occurs at the beginning of the second year after the shock, peaking in the positive territory and being also significant at 5%. Credible bands are again rather wide, so we treat these estimates with caution but still believe they are indicative and are in line with the macro-finance literature.[21] Similarly, the response of the financial uncertainty index to the expansionary CS shock is negative and marginally significant in one quarter after the shock, which is also in line with rising income and other macroeconomic characteristics. As time passes, however, the response turns positive and significant during the 3rd to 6th quarters after the shock, which is in line with the rebound effect in spreads and the slowdown of income.

5.1.2 Sensitivity analysis

To assess the robustness of our baseline macro results, we introduce several modifications to the estimation. First, we switch from the quarterly to the monthly data of all endogenous variables. Second, we re-estimate the model using the System of National Accounts (SNA) data. Third, we augment the baseline model with an exogenous variable reflecting oil prices. Fourth, we explore the comparative importance of monetary policy and sanction shocks when setting the NSR scheme. Fifth, we substitute some of the variables for their alternative measures. Sixth, we investigate the role of the increased volatility of the ruble exchange rate during the sample period on our baseline results. In particular, we analyze how the depreciation of the ruble during the sanction and oil price collapse period in 2014 affected the baseline impulse responses by artificially increasing the FX component of the total loans in the Russian banking system. Seventh, we modify the lag structure of the SVAR model

[21] Lopez-Salido et al. (2017) establish that credit spreads predict a boom-bust pattern in GDP growth rates. Our results further indicate that expansionary CS shocks may predict reversals in credit spreads.

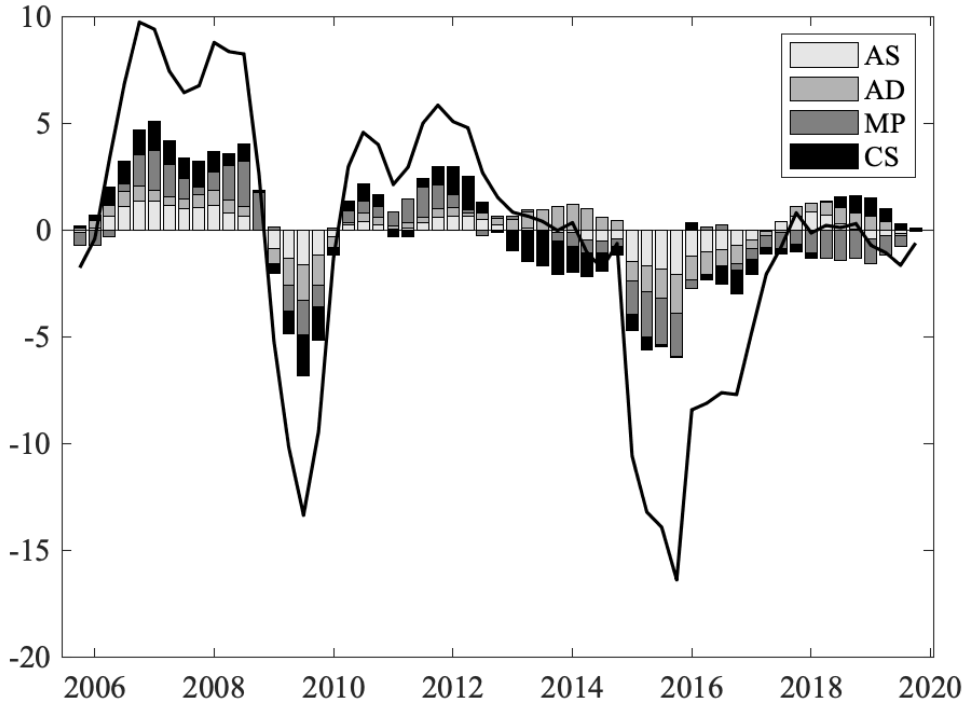
by adding one more quarter lag of each endogenous variable to address the issue of residual seasonality in the time series. Finally, we replace the nine-variable SVAR model of Mumtaz et al. (2018), which we use as a baseline, with a more parsimonious model of Gambetti and Musso (2017), which contains only output, prices, regulated interest rate, lending rate, and amount of outstanding loans. Online Appendix D contains the full description of each of these exercises. Overall, our baseline results do not change much and survive qualitatively.

5.2 Historical decomposition: credit supply vs. other shocks

Having estimated the effects of CS shocks in the Russian economy, we proceed to the analysis of the historical contribution of these shocks to consumption and investment, in comparison with the other three shocks identified in our SVAR model. Figure 3 below presents the results of this exercise for consumption growth. The figure reports the estimates based on the combination of SR and NSR schemes. In the figure, we (i) transform the quarterly growth rates of consumption expenditures into the four-quarter growth rates and (ii) subtract deterministic components to center the consumption dynamics around zero.

The results of historical decomposition indicate that CS shocks are economically important for consumption in the Russian economy, explaining a significant share of the total variation in retail sales over the last two decades. The four identified shocks jointly explain around 40% of the consumption forecast error variance (FEV) at a one-year horizon, with CS shocks absorbing 8 p.p. of the total contribution. We reveal that the joint historical contribution of the four shocks is substantial during the boom periods of 2006–2008 and 2010–2013 and during the bust episodes of 2008–2009 and 2014–2016. Overall, the CS shocks play as important role in consumption as each of the other three (standard) business cycle shocks, which is consistent with the literature on the economic effects of CS shocks and financial disintermediation (see, e.g., Gambetti and Musso, 2017; Jensen and Johannesen, 2017; Gertler et al., 2019). Another notable finding here is that the identified MP shocks affect consumption no less than the other three shocks.

A similar picture arises when we turn to the historical decomposition of investment growth depicted in Figure 4. The identified shocks jointly explain around 40% of the investment forecast error variance (FEV) at a one-year horizon, and CS shocks account for 30% of FEV



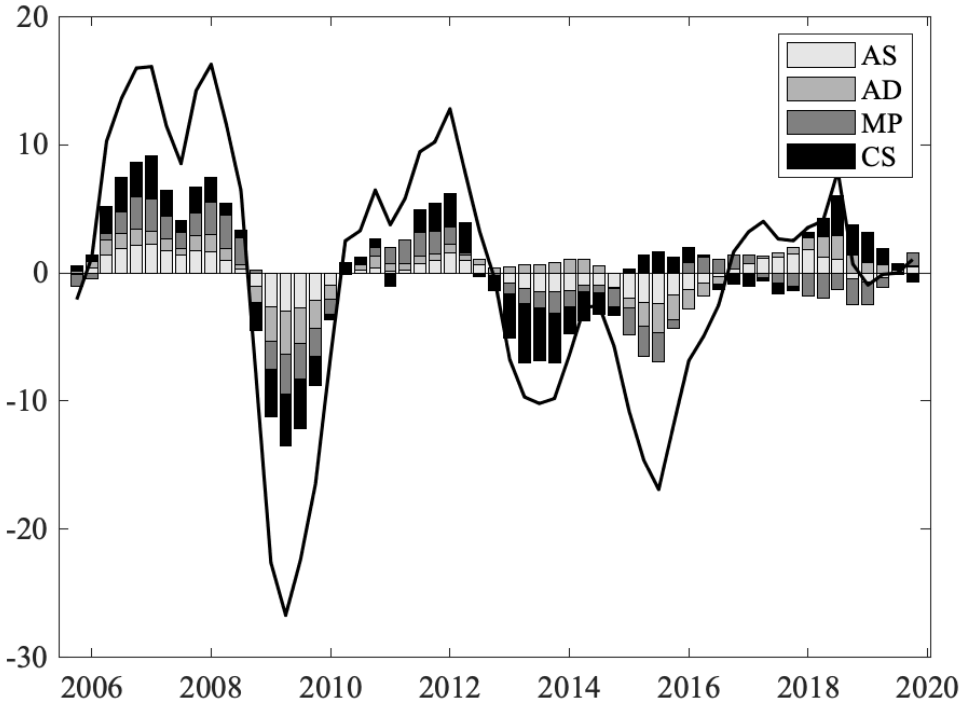
Note: The figure displays the four-quarter growth rate of consumption (retail sales) and its estimated historical decomposition (HD) to the four identified shocks in the nine-variable SVAR with SR and NSR schemes imposed. The growth rate does not include deterministic components (constant term and initial conditions) to make figures and the contributions of the shocks centered around zero. The NSR scheme treats 2014 Q4 as a period of negative (restrictive) monetary policy, and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The X-axis shows the corresponding dates.

Figure 3: Historical contribution of credit supply (CS) and other shocks to consumption

on impact. As suggested by the impulse responses presented above, the effect is long-lasting; for example, we can observe that the CS contribution to the investment growth is negative throughout 2014 and only slightly positive in 2015–2016, i.e., two years after the imposition of sanctions and the oil price collapse.

Overall, we estimate that the contribution of CS shocks to the forecast error variance of consumption is 8% at the one-year horizon and that of investment is 13% at the same horizon. Firms are thus more sensitive to CS shocks than households. These estimates differ from Mumtaz et al. (2018) who reveal for a set of developed countries the opposite pattern: the contribution of CS shocks to consumption is 23% and to investment is only 5% at the same one-year horizon.

Another interesting result that we obtain is that the cumulative contribution of CS shocks to output growth rates during the (local) crisis of 2014-–2015 is comparable in magnitude



Note: The figure displays the four-quarter growth rate of investment and its estimated historical decomposition (HD) with respect to four identified shocks in the nine-variable SVAR with SR and NSR schemes imposed. The growth rate does not include deterministic components (constant term and initial conditions) to make the figure and contribution of shocks more tractable. The NSR scheme treats 2014 Q4 as a period of negative (restrictive) monetary policy, and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The X-axis shows the corresponding dates.

Figure 4: Historical contribution of credit supply (CS) and other shocks to investment

to that in the (global) crisis of 2008—2009. This contribution equals approximately 1 p.p. in terms of the aggregate output growth rate. For comparison, Gambetti and Musso (2017) deliver similar magnitudes of the estimated contribution of CS shocks to the GDP decline during the Great Recession.

6 Cross-sectional estimates

Following the rich tradition of using micro-level analysis to complement macro-level results (see a review by Nakamura and Steinsson, 2018), we gather survey data on Russian households and balance sheet data on Russian firms to further examine (i) how aggregate shocks obtained in the SVAR analysis propagate at the micro level and (ii) explore the heterogeneity of consumption and investment responses to CS shocks.

6.1 Credit supply shocks and household-level consumption

In this section, we investigate how the aggregate consumption response to CS shocks varies across households with different credit-related characteristics.

6.1.1 Survey data on the panel of Russian households: RLMS-HSE

We use the Russia Longitudinal Monitoring Survey – Higher School of Economics (RLMS-HSE).[22] This is a long-span country-representative panel survey that provides information on household income, expenditures, debt, and multiple demographic characteristics. RLMS-HSE is the most comprehensive open source on household- and individual-level survey data that is available from 1994 onwards and intensively used for research on Russian households (see, e.g., Decancq and Lugo, 2012; Adsera et al., 2021; Lorenz and Yakovlev, 2021). However, the survey data on household borrowings from banks is unavailable before 2006, and we therefore have to focus on a shorter period of 2006–2019.

We construct consumption as a sum of annualized household expenditures on goods that are considered the elements of retail trade by the Federal State Statistics Service (Rosstat).[23] To be consistent with macro-level data in previous sections, we compute the following measure of consumption growth: $\frac{Consumption_t}{Consumption_{t-1}} - 1$. As a measure of CS shock, we use the baseline SVAR estimate that is grounded on both the SR and NSR restrictions described in Section 5 above. We annualize the estimated quarterly data on CS shocks to align it with the annualized frequency of the household data. In the final sample, we have up to 51,286 household-year observations over 2006–2019 and we reveal that the annual income of the average household is less than 10 ths US dollars (in the 2019 prices), of which roughly 50% cover consumption expenditures and 7% cover debt servicing. We also observe that poorer households are less likely to have debts and exhibit lower growth rates of consumption than richer households. We provide the full description of household data processing

[22]Source: "Russia Longitudinal Monitoring Survey (RLMS-HSE)" conducted by Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS. (RLMS-HSE web sites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms).

[23]The following categories are included in RLMS-HSE: consumption expenditures reported monthly (food, medical goods, cleaning goods, self-care goods, cosmetics, fuels) and consumption expenditures reported quarterly (mobile phones, computer and other cultural goods, refrigerator, washing machines, furniture, carpets, construction materials, clothing and shoes, books, bicycles, motorbikes, cars). We convert both into annual levels by multiplying monthly expenditures by 12 and quarterly expenditures by 4.

and summary statistics in Section E.1 of Online Appendix E.

6.1.2 Regression design

Our cross-sectional analysis pursues two goals: evaluate the effect of CS shocks on household consumption and explore the heterogeneity of consumption responses to these shocks. We run this analysis in two steps. In the first step, we estimate the following equation:

$$\Delta C_{it} = \alpha \Delta C_{it-1} + \beta_1 CS_{t-k} + \gamma_1 MP_{t-k} + \Omega Demography_{it} + p^n(t) + a_i + u_{it} \tag{3}$$

where ΔC_{it} stands for consumption growth of household i in year t, CS_{t-k} and MP_{t-k} are expansionary credit supply and monetary policy shocks (median shocks from the Bayesian estimations) in year $t-k$ ($k=0$ or $k=1$).[24] The shocks are identified from our quarterly SVAR model and further annualized by summing up four quarterly values within each year t. $Demography_{it}$ includes demographic controls: the number of household members, number of children, household head's age, gender, marital status, and education level, $p^n(t)$ is a time polynomial ($n=1$ in the baseline), a_i are household fixed effects (FEs), and u_{it} is the regression error.

A clear limitation to our approach is that we cannot control for time FEs when estimating Equation (3). This is because our focus variable, the CS shock, is measured at the year level and is the same for all households. Time FEs would perfectly absorb the CS shock variable. In other words, in the cross-section of households, our CS shock variable may capture not only credit supply movements but also other aggregate forces. This issue is, however, partly addressed by including MP shocks—that is, another aggregate force—in the regression specification (in the baseline estimates). Moreover, we also check whether the results survive if we include the other two business cycle shocks, AD and AS, in the model (in the robustness checks).

The specification we employ is based on the work of Cloyne et al. (2020), where the authors use a similar strategy to estimate the heterogeneity of the effect of monetary shocks

[24] We tested for both cases, $k=0$ or $k=1$, and found that the results are significant and consistent with those at the macro level described above only if $k=1$, whereas with $k=0$ the effects are insignificant. This implies households may react to the shock with some lag. The latter could be a result of data collection and construction: recall that respondents of RLMS-HSE data answer survey questions in October or November, and they report their past consumption over a month or a quarter while CS shocks cover the full year, i.e., including December. It is therefore natural to expect that shocks affect consumption with a one-period lag.

on consumers. We expand Cloyne et al. (2020)'s analysis as we consider both CS and MP shocks to show that both of them have their independent effects on consumer behavior.[25] In addition, to be consistent with our macro-level investigations, we consider consumption growth as our dependent variable. We use time trend as a control even though we consider consumption growth as a dependent variable because our time span is comparatively short and consumption growth has a trend over the considered period. The period under study includes two crises (2008 and 2014) and only a few non-crisis years so we expect to see a negative trend in consumption growth rates.

In the second step of our micro-analysis, we explore whether having bank debts at the household level is able to capture the heterogeneity of consumption responses to CS shocks. We modify Equation (3) as follows:

$$\begin{aligned}\Delta C_{it} =& \alpha \Delta C_{it-1} + \beta_1 CS_{t-k} + \gamma_1 MP_{t-k} + \Omega Demography_{it} \\ &+ \delta_1 \Big(CS_{t-k} \times HaveDebt_{it-1} \Big) + \delta_2 HaveDebt_{it-1} + p^n(t) + a_i + u_{it}, \end{aligned} \tag{4}$$

where *Have Debt* is a dummy variable that equals 1 if a household has bank credit (self-reported presence of any type of credit from a financial institution: consumer loan, mortgage credit, etc.) and 0 otherwise. Other notation is the same as before.

We conjecture that the presence of debt leads to a larger response of consumption to CS shocks, i.e., $\delta_1 > 0$. First, indebted households are presumably more sensitive to negative CS shocks (credit tightening): given their lower ability to roll over debt on favorable conditions, they may cut spending by more than households without credit. Second, indebted households may also be more sensitive to positive CS shocks (credit easing): given existing relationships with their banks, the banks may offer new credit products or extensions of credit lines to them than to new customers, thus relaxing the indebted households' budget constraints.

6.1.3 Estimation results

In Table 2 below we present the estimation results of regressions (3) and (4) with the one-year lag of all explanatory variables ($k = 1$). In column (1), we consider only the CS

[25] Our baseline regression model is as parsimonious as possible. In the sensitivity analysis, we further expand it by controlling for the other two business cycle shocks estimated from our SVAR model, namely, AD and AS.

shock variable, controlling for households' demographic characteristics and time trends (not reported to save space). In column (2), we add the MP shock variable. In column (3), we include the interaction of the CS shock variable with the indicator variable of whether a household has bank credit. In column (4), we further check whether the effect of the interaction term is preserved if the MP shock variable is added. In columns (5) and (6), we finally test whether the results are different in the sub-samples of poorer vs. richer households, as measured by total real income.

TABLE 2

CS shocks and consumption: regression results at the household level

	Full sample				Subsamples	
	CS	+MP	+Interaction	All	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)
CS shock$_{t-1}$	0.943***	1.564***	0.544*	1.182***	1.069*	1.346***
	(0.257)	(0.334)	(0.295)	(0.360)	(0.627)	(0.481)
Have debt$_{t-1}$ × CS shock$_{t-1}$			1.042**	1.087**	2.680***	–0.0285
			(0.487)	(0.488)	(0.878)	(0.636)
MP shock$_{t-1}$		–1.795***		–1.891***	–2.289**	–1.525*
		(0.634)		(0.634)	(1.099)	(0.866)
N obs	19,180	19,180	19,142	19,142	7,721	11,421
N households	6,925	6,925	6,917	6,917	3,650	4,847

Note: The table presents estimates of Equation (3), in which the dependent variable is consumption growth at the household level. CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. *Have debt* = 1 if a household has a bank loan (self-reported) and 0 otherwise. The reference group is "no debt." All regressions contain the full set of controls, including the lagged dependent variable, demographic characteristics (the household head's age, gender, education, marital status, and the number of household members and children), linear time trend, and household FEs. The data covers the period from 2006 to 2019. *Top-50%* means the upper 50% of the distribution of households by real income, i.e., richer households. *Bottom-50%* means the opposite, i.e., poorer households.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses.

In column (1), we obtain a positive and highly significant estimate of the coefficient on the CS shock variable in our most parsimonious regression specification. In column (2), we again obtain the same result, despite we now control for MP shocks. This means that expansionary CS shocks tend to increase household consumption, and this effect goes *beyond* the effects of the monetary policy. A 0.5 p.p. decrease in lending rate raises consumption growth by 1.6 p.p. in one year. Notably, we find that the opposite effect pertains to MP

shocks in Russia: consumption accelerates in response to monetary tightenings, not easings, as in developed countries.[26]

The important result is that CS shocks have additional explanatory power when we control for MP shock. Comparing columns (1) and (2), we can observe that the magnitude of the coefficient on CS shock rises by more than one-third when we add MP shocks as a control. It indicates that without controlling for MP shocks, the effect of CS shocks is likely underestimated: it may partly capture the negative impact of MP shocks on consumption growth. In other words, both shocks seem to be important drivers of consumption growth at the household level.

Further, column (3) reports the average and heterogeneous effects of CS shocks on consumption growth. We obtain a positive and significant coefficient not only on the CS shock itself, as in the previous column, but also on the interaction of the *CS shock* and *Have debt* variables. The estimates imply that in a year after a positive CS shock hits (the lending rate falls by 0.5 p.p.), the growth rate of consumption accelerates by 2.3 p.p. for households with bank credit. For households without bank credit, the growth rate of consumption also rises but by only 1.2 p.p. This result implies that the effects of CS shocks are unlikely to be equal across all consumers and tend to vary with the level of indebtedness. In column (4), we further show that these effects become even more powerful when we control for MP shocks, in line with our results above.

We finally investigate the heterogeneity by considering the two subsamples of households: "poorer" and "richer" families defined relative to the median total income. We first note that the size of the subsample of poorer households is lower by one-third than that of richer households. This difference comes from the fact that poorer households tend to underreport the presence of debt, i.e., they report having debt less frequently compared to richer households. According to our results presented in columns (5) and (6), we obtain a positive and highly significant estimate of the interaction term between the *CS shock* and *Have debt* variables for the subsample of poorer households and close to zero and insignificant estimate for richer households. Overall, we conclude that the consumption response to CS shock is

[26]For instance, Cloyne et al. (2020) find that in the UK and the US, both advanced economies, monetary easings facilitate consumption. A possible explanation for why we obtain the opposite result for Russia can be that our empirical model detects an association between monetary tightenings during exchange rate depreciations (as was the case, for example, in 2008 and 2014) and spikes in consumption growth due to rush shopping of import goods (see Charnavoki, 2019).

heterogeneous between the two groups of households, and this heterogeneity is at least partly driven by the presence of debt. Poorer households display a less sizable response to credit shock on average, but once they are indebted (and, probably, liquidity constrained), they are significantly more sensitive to changes in credit conditions than richer households.[27]

Historical decomposition. Having presented the baseline estimation results at the household level, we now analyze the contribution of CS shocks to consumption growth over time. Recall that we already obtained this contribution at the macro level in Figure 3 of Section 5.2 above, so it is particularly interesting to see how this compares to the same contribution estimated now at the micro level. Figure F.I in Online Appendix F reports the micro-based contribution of CS shocks to consumption growth. First, it shows that there is a visible negative trend in the household-level consumption growth over the sample period of 2006–2019. Second, it establishes that CS shocks are important drivers of household consumption, especially for indebted households which we find to be roughly two times more sensitive to CS shocks than households without bank loans. Therefore, the macro- and micro-based estimates of the contribution of CS shocks to consumption appear to be well aligned with each other. We discuss the micro-based results in more detail in Online Appendix F.

Sensitivity analysis. We then perform a battery of robustness checks and present them in Online Appexndix G.1. First, we address the *income distribution and regression specification* concerns. Columns (1) and (2) of Table G.I report the estimates of an extended version of Equation (3), which includes not only CS and MP shocks but the other two estimated business cycle shocks, AD and AS, and their interactions with the *Have debt* variable. The results indicate that the effect of the CS shock remains qualitatively unchanged. This is in line with our expectations, because, by construction, the four shocks are independent. Quantitatively, the estimated effect becomes larger than in the baseline.

Columns (3) and (4) of Table G.I mimic the baseline results for the subsamples of poorer and richer households presented in columns (5) and (6) of Table 2 above. The difference is that now we consider the bottom 30% and the top 30% of the distribution of households by real income, thus sharpening the definition of poorer and richer. As one can infer, we still obtain the same result: poorer households are more sensitive to CS shocks, and more so if

[27]Note that this result is in line with the finding of Cloyne et al. (2020) who reveal that only liquidity-constrained households react to monetary shocks.

they have bank loans, than richer households.[28]

Columns (5) and (6) of Table G.I extend Equation (3) by including the interaction of the *MP shock* and *Have debt* variables. The concern is the unequal treatment of CS and MP shocks in the baseline estimates presented in columns (5) and (6) of Table 2 above: in the absence of the interaction with MP shocks, the coefficient on the interaction term of the *CS shock* and *Have debt* variables may partly get the omitted effect on its side. However, our new estimates show that this is not the case: the baseline results are preserved when we add this omitted effect.

Second, we address the issue of *generated regressors* by using the bootstrap method to compute standard errors of the estimated coefficients. Table G.II uses 1,000 draws (with replications) and presents the results. As one can observe, bootstrapping increases the magnitudes of estimated standard errors but for the full sample of households, it never changes the results on CS and MP shocks qualitatively. For the subsample of poorer households, the average effect of CS shock, which was marginally significant in the baseline, renders insignificant but its interaction with the *Have debt* variable preserves significance. For the subsample of richer households, the average effect of CS shock becomes less precise but still significant at the 5% level. In addition, Figure G.I employs the Bayesian approach to estimating the credible bands of the effect of CS shocks on consumption growth at the household level and compares it with the conventional, i.e., frequentist, approach. As one can infer from this comparison, the underlying estimate is still significant.

Third, we address the *endogeneity concerns* arising due to the use of the lagged dependent variable as a control in the baseline estimates. Table G.III re-estimates Equation (3) using the (Arellano and Bond, 1991)'s approach (the one-step differences GMM estimator). Although the results are not directly comparable because of the sizeable reduction in the number of observations, we still obtain a positive and statistically significant estimate of the effect of CS shocks on consumption growth rates, controlling for MP shocks, as we have in the baseline. However, the p-value of the Hansen test (0.078) is somewhat below the 0.10 threshold, thus signaling a lack of validity of the overidentifying restrictions on the set of instruments. We therefore treat the results we obtain using the Arellano and Bond (1991)'s estimator with

[28]For consumption of the poorer households, however, both CS and MP shocks lose their significance. This is possibly due to the sharp decrease in the sample size as many poorer households do not report their debt status.

caution.

Fourth, we switch from the *Have debt* binary variable to the debt-to-income ratio, which is a continuous measure of a household's indebtedness. Table G.IV mimics the baseline estimates. For the full sample, we obtain still positive but now insignificant estimates on the interaction between the Debt to income and *CS shock* variables, whereas we still achieve a positive and significant estimate of the same coefficient for the subsample of poorer households. This means that poorer households are more responsive to CS shocks at the intensive margin, i.e., the sensitivity rises with the load of bank loans on their income. For the subsample of richer households, the corresponding effect is again insignificant, as we have it in the baseline results.

Fifth, our next exercise is to split the total consumption on the consumption of *durables* and *non-durables* at the household level to understand which part of private expenditures drives the baseline result.[29] Table G.V and Table G.VI deliver the comparative estimates for the consumption of non-durables and durables, respectively. We obtain clear evidence that our baseline result is driven by the consumption of non-durables: the estimates of the average effect of CS shocks are always positive and significant and the estimate of the cross-term with having debts is also positive and significant for the subsample of poorer households, as in the baseline. Conversely, all estimates are insignificant for the case of durable consumption. These results suggest that bank credit is more likely to be used to smooth non-durable consumption, i.e., the consumption of necessities and basic services rather than investment-type goods.

Sixth, we perform a panel version of Jorda (2005)'s local projections to complement the estimates of Equation (3) and compare responses of consumption to CS shocks at the household level with our baseline macro responses from Section 5.1. Figure G.II presents the results: in response to an expansionary CS shock (scaled to be equivalent to a –0.5 p.p. decrease in the lending rate) consumption rises by 1.6 p.p. in one year, another 1.6 p.p. in

[29] *Durable consumption* includes quarterly expenditures on shoes and clothing, cultural goods, mobile phones, furniture, home appliances, cars, motorbikes, garages, construction materials, houses, land, country houses, books, and sport. To make them annual, we multiply them by 4. *Non-durable consumption*, in turn, includes monthly expenditures on food, fuel, wood, gas, drugs, detergents, personal care goods, cosmetics, pets, educational activities for adults, various services (transport, personal care, postal, children's, cultural, medical care, dental care, TV and repair services for shoes and clothing, cultural goods, home and cars), funerals, mobile and internet connection, payments for rent and utilities, recreational activities, rent of county-house or land, parking and garage, regular payments for county-house and garage. To make them annual, we multiply them by 12.

two years, and another 1 p.p. in three years (the first two estimates are significant and the third one is not). However, in the four years after the CS shock, the effect on consumption is negative and significant, reaching –3 p.p. This flip of the sign of the consumption response is consistent with the boom-bust mechanism of credit expansions (Mian and Sufi, 2018). The overall effect is positive and significant, as in the baseline macro estimates. However, the difference is that the peak response at the macro level is achieved in the four years after a CS shock and its magnitude reaches 6 p.p.—this is much larger than at the household level. This is likely because macro estimates (SVAR) reflect general equilibrium effects, whereas micro estimates (panel consumption regression model) capture partial equilibrium effects, which do not account for investment, monetary policy, and other important fundamentals.

Finally, we switch from growth rates to *the log of real consumption*, as in Cloyne et al. (2020), to analyze whether CS shocks shift not only changes in consumption but also its overall levels.[30] Table G.VII and reports the estimates of Equation (3) assuming $n = 2$ in time polynomial. The results clearly show that CS shocks have a highly significant positive effect on the levels of consumption, even after controlling for MP shocks. Figure G.III delivers the estimated contribution of CS shocks to the log of consumption through time. Even though the log of consumption in levels (on the right axis) has different overall dynamics compared to CS shock contributions (the left axis), the direction of consumption movements is well positively correlated with CS shock contributions: the increase (decline) phases of consumption coincide with positive (negative) contributions of CS shocks. This explains why we consider changes in consumption in our baseline estimates. In addition, the picture shows that the log of consumption is somewhat hump-shaped, which allows us to assume a quadratic trend and confirms our choice of $n = 2$ in time polynomial.

Overall, we conclude that the estimation results obtained from our micro analysis at the household level are consistent with the macro results from the previous section. *On average*, the estimated effect of CS shocks on household consumption at the household level is quantitatively smaller than its analog at the macro level. In response to a 0.5 p.p. decrease in the lending rate households raise consumption by 1.6 p.p., while the aggregate consumption growth rate rises by 3 p.p. The difference between the two effects may stem from the general

[30] We also perform the micro analysis with the *log-differences* of consumption at the household level instead of conventional growth rates used in the main text. The estimation results are qualitatively the same and quantitatively are even somewhat larger than in the baseline (available upon request).

equilibrium effect which is ignored in the micro estimates. Further, the micro results reveal that the effects of CS shocks are *heterogeneous* depending on the household debt status. The effects are stronger for households with bank debts and, among them, are even stronger for relatively poor households (whose total income is below the median). Importantly, our results indicate that the effect of CS shocks on consumption goes *beyond* the one caused by MP shocks, thus extending the analysis of Cloyne et al. (2020) and Kehoe et al. (2020).

6.2 Credit supply shocks and firm investment

Our macro-level analysis above has established a sizeable effect of CS shocks on aggregate investment. We now turn to analyzing the heterogeneity of these effects at the firm level. For this purpose, we retrieve the firm-level data from the nationwide SPARK-Interfax database.[31]

When collecting the data from SPARK-Interfax, we require that firms report their bank borrowings and the number of employees for at least one year during the last decade. This dramatically reduces the number of firms in our sample—from a total of 12 mln to less than 0.4 mln entities. The resultant sample consists of roughly 1,309,038 firm-year observations throughout 2011–2019. Over this period, we observe that the average growth rate of net assets was rather small, less than 1% per year, and the firms were characterized by on average very small levels of leverage. We provide all the details on firm data processing and summary statistics in Section E.2 of Online Appendix E.

6.2.1 Regression design

With the firm-level data at hand, we estimate the effects of CS shocks on firm investment, as proxied by the net asset growth rate.[32] Our specification is based on Ottonello and Winberry (2020) and Cloyne et al. (2023), in which the authors study the response of firm investments to monetary policy (MP) shocks. We thus also control for MP shocks in our regressions. In the benchmark papers, the authors consider interactions of the MP shock with firm size and leverage, because these variables measure the strength of financial constraints. We follow

[31] https://spark-interfax.com/. This database has been recently used in Korovkin and Makarin (2023) to study the effects of Crimea's annexation on trade intensities between Russia and Ukraine.

[32] The micro data on investment is not available directly in the SPARK-Interfax dataset, so we use simple accounting statistics such as the growth rate of net assets as a proxy for realized investments (Hsiao and Li, 2012).

this line and specify the firm-level regression model in the following way:

$$\begin{aligned}\Delta I_{it} =& \phi CS_{t-k} + \theta MP_{t-k} \\ &+ \beta_1(CS_{t-k} \times lnEmployment_{i,t-1}) + \beta_2\, lnEmployment_{i,t-1} \\ &+ \delta_1(CS_{t-k} \times Leverage_{i,t-1}) + \delta_2 Leverage_{i,t-1} \\ &+ \gamma_1(CS_{t-k} \times lnTotalAssets_{i,t-1}) + \gamma_2\, lnTotalAssets_{i,t-1} \\ &+ a_i + p^n(t) + u_{it}, \end{aligned} \tag{5}$$

where ΔI is the net asset growth rate of firm i in year t relative to the previous year as a proxy for investment growth rate, CS_{t-k} and MP_{t-k} are the credit supply and monetary policy shocks identified with our SVAR model and taken with k lag ($k = 0$ or $k = 1$).[33] *lnEmployment* is the logarithm of the number of workers in firm i in year $t-1$, *Leverage* is the total debt over net value of assets, and *lnTotalAssets* is the logarithm of the total assets. $p^n(t)$ is a time polynomial ($n = 1$ in the baseline),[34] a_i is a firm fixed effect, and u_{it} is an error term.

6.2.2 Estimation results

The estimates of Equation (5) appear in Table 3. We begin with the results obtained in the full sample of firms, see column (1) (controls are not reported to preserve space). Finally, in columns (2) and (3) we check whether the results are different for the subsamples of small vs. large firms, as measured by firm total assets (in constant prices).

First, we obtain an insignificant estimate of the coefficient on the CS shock variable itself in columns (1)–(3), whereas the estimated coefficient on the MP shock variable is always negative, as was the case with household consumption above, and highly significant. However, as can also be inferred from column (1), we obtain a positive and highly significant

[33] We tested both cases and found that the estimated effects of CS and MP shocks are significant and consistent with macro results above only with $k = 0$ whereas with $k = 1$ the effects disappear. In what follows we thus report the $k = 0$ case. This differs from the results on households discussed above, where we had $k = 1$. This difference may imply that firms react faster to the shocks than households do. This may also be related to the fact that firms report financial statements over the whole year while households report consumption over a month or a quarter at the end of the year. In other words, the annual reporting of the firm-level data is better aligned with the annual macroeconomic data than the household survey data, which lags behind and covers only the end of the year.

[34] The same limitation arises as in the case with the analysis of households above: we cannot control for time FEs, because our CS shock variable would be perfectly absorbed and dropped from the estimations. Thus, we cannot fully rule out the possibility that our CS shock variable may capture also other aggregate shocks in the cross-section of firms.

TABLE 3

CS shocks and investment: regression results at the firm level

	Full sample	Subsamples	
		Bottom 50%	Top 50%
	(1)	(2)	(3)
CS shock$_t$	–0.027	0.034	–0.100
	(0.025)	(0.046)	(0.063)
ln Employment$_{t-1}$ × CS shock$_t$	0.005***	0.003	0.002
	(0.001)	(0.003)	(0.001)
Leverage$_{t-1}$ × CS shock$_t$	0.351***	0.212	0.371***
	(0.084)	(0.173)	(0.101)
ln Total Assets$_{t-1}$ × CS shock$_t$	–0.001	–0.002	0.005
	(0.001)	(0.003)	(0.003)
MP shock$_t$	–0.060***	–0.056***	–0.054***
	(0.003)	(0.004)	(0.003)
N obs	1,309,038	596,097	712,941
N firms	389,988	222,869	209,549

Note: The table presents estimates of Equation (5), in which the dependent variable is the growth rate of net assets at the firm level. CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. All regressions contain firm FEs, the full set of firm controls (the log of the number of workers, leverage as a sum of short- and long-term debts over total assets, the log of total assets), their interactions with the CS shock variable, and the linear time trend. The data cover the period from 2011 to 2019. *Top-50%* means the upper 50% of the distribution of firms by total assets, i.e., larger firms. *Bottom-50%* means the opposite, i.e., smaller firms. *Leverage* is divided by 100 for the sake of representation of the estimated coefficient on its interaction with the CS shock variable.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses.

estimate of the coefficient on the interaction of the *CS shock* and *firm leverage* variables, despite we control for the monetary policy. The estimates imply that in response to a 0.5 p.p. expansionary CS shock, a firm with a 1 p.p. higher leverage ratio increases its net asset growth rates by an additional 0.35 p.p. When we further split the sample into smaller and larger firms, we again obtain positive estimates on the interaction term with leverage for both types of firms, see columns (2) and (3). However, the interaction is only significant for larger firms and insignificant for smaller entities. This implies that the larger firms may be much more sensitive to CS shocks than their smaller rivals.

In column (1), we also obtain a positive and highly significant estimate of the coefficient on the interaction of the CS shock and firm employment variables. In columns (2) and (3),

the corresponding effects turn, however, insignificant. Though with caution, we conclude that on average more labor-dependent firms are more sensitive to CS shocks.[35] We finally find that the size of firm assets does not capture the heterogeneity of the CS shock effects on firm investment neither in the full sample nor in the two subsamples of larger and smaller firms.

Historical Decomposition. We present the contribution of CS shocks to net asset growth rates in Figure F.II (see Online Appendix F). As one can infer, this contribution is substantial across years, especially before and during the first crisis year of 2014, when CS shocks were among the main restrictive forces that pushed net asset growth rates down. The negative contributions of CS shocks across the years are even larger in magnitude than the corresponding magnitudes of net asset growth rates themselves. This may suggest that the tightening of prudential regulation and financial sanctions—the underlying sources of CS shocks (Online Appendix C)—may have severely restricted firm growth in Russia.[36] First, this result implies that our micro-level estimates are consistent with those obtained in the macro part of the paper. Second, it also suggests that the contribution of CS shocks to firm investment largely *exceeds* the contribution of CS shocks to household consumption (see Figure F.I).

Robustness checks. First, we address specification concerns by adding interactions of MP shocks with the same heterogeneity characteristics as we have for CS shocks when estimating regression (5) for the subsamples of smaller (*Bottom-50%*) and larger (*Top-50%*) firms. Table G.VIII in Online Appendix G.2 delivers the results. As we show in columns (1) and (2), the presence of new controls does not change our baseline results: firm leverage is still as potent in capturing the heterogeneity of CS shock effects on firm investment as in the baseline estimates. However, in this extended specification, we substantially refine the baseline estimates regarding the role of firm employment. Specifically, we obtain a positive and now significant estimate of the joint effect of CS shocks and firm employment in the subsample of smaller firms. Put differently, relatively small firms may be more sensitive to CS shocks if they are more labor-dependent. The corresponding result becomes even stronger in

[35] This result is intuitively clear if firms finance (a part of) their wage bills by bank credit.

[36] This result echoes the findings of Ahn and Ludema (2020), which established substantial negative effects of the 2014 sanctions on non-strategic firms in Russia (the vast majority of firms are non-strategic).

columns (3) and (4), where we consider the *Bottom-30%* and the *Top-30%* of firms: in both cases, the joint effect of CS shocks and firm employment is significant and quantitatively larger. This means that very small and very large firms are both more sensitive to CS shocks compared to mid-sized firms.

Second, we carry out a panel version of the local projection exercise (Jorda, 2005) to complement the macro analysis of investment responses to CS shocks. As we report in Figure G.IV, the largest effect is reached simultaneously, as in the baseline estimates at the firm level, whereas starting from a year after an expansionary CS shock, the effects on investment shrink in size by a factor of 6 compared to the simultaneous effect and flip their sign around the zero level. Recall that at the macro level, the effect of CS shocks on investment is very large reaching +11 p.p. in four years after the shock. This implies that the general equilibrium effect of CS shocks on investments largely exceeds their partial equilibrium counterpart—even more than in the case of household consumption (see the discussion of robustness checks in Section 6.1.3).

Overall, we conclude that CS shocks affect firm investments, as proxied by the net asset growth rate, at the firm level even in the presence of MP shocks. The results thus extend the findings of Cloyne et al. (2023) and Ottonello and Winberry (2020) because they imply that CS shocks have an added value in explaining firm investment compared to MP shocks. We also find that the effect of CS shocks transmits through firm leverage in the case of relatively large firms and through employment in the case of relatively small firms.

7 Conclusion

In this paper, we provide empirical evidence of the role that credit supply (CS) shocks play in the business cycles of emerging market economies using Russia's example. By employing macroeconomic data available for the economy, we make use of the narrative sign restrictions SVARs proposed in Antolin-Diaz and Rubio-Ramirez (2018) to identify the core macroeconomic shocks. We show that CS shocks play an important role, and amplify volatility of the business cycle. We also show that country-specific events are as important as global events when it comes to the real effects of CS shocks.

We complement our macro analysis with micro-level data estimation on Russian households and firms in 2006-2019 and provide evidence that CS shocks have significant effects on individual consumption and investment decisions (the latter are proxied by net asset growth). In addition, we study the heterogeneity of the effects of CS shocks and show that poor households with debt and highly leveraged firms are the most responsive to CS shocks.

We admit that our micro-level analysis has several limitations that come from data availability, and we thus treat our results as the first step to investigating the heterogeneity of agents' responses to CS shocks. However, we show that our results are qualitatively similar in the micro and macro parts of our paper. This makes us believe that the combination of the two brings a valuable conclusion that CS shocks matter for both consumption and investment and that the effects of CS shocks go *beyond* monetary policy (MP) shocks, thus extending the analysis of Cloyne et al. (2020) and Kehoe et al. (2020) for household consumption and Cloyne et al. (2023) and Ottonello and Winberry (2020) for firm investments.

As for the policy applications, our framework makes it possible to predict the effects of abrupt changes in credit supply. A promising avenue for future research could be a nowcasting of CS shocks, their disaggregation to the bank level, and tracing their impact on consumer choice and the real decisions made by firms.

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Appendix A Data transformation

Below we provide details on the variables employed in our SVAR analysis of credit supply (CS) shocks. We list the variables, describe the data transformations used in preprocessing and provide the data sources. In the baseline analysis, we convert all the data to quarterly frequency.

1. *Real output growth.* We use an index of basic economic activities as a proxy for real GDP dynamics. This index includes a weighted average of real activity in agriculture, mining and quarrying, manufacturing, electricity and gas, water, construction, transportation and storage, and wholesale and retail trade. It is available on a monthly basis. We seasonally adjust it using the basic X13 procedure in the IRIS toolbox and convert it to quarterly levels. The resulting series tracks quarterly real GDP closely. Source: Federal State Statistics Service (Rosstat, https://eng.gks.ru/).

2. *Growth in the total volume of loans to households and nonfinancial corporations.* We compute this variable using aggregate data on the nominal bank debt of households and non-financial corporations corrected for exchange rate reevaluations (see also Online Appendix A). Source: Central Bank of Russia (CBR, https://www.cbr.ru/eng/).

3. *Consumer price index growth.* We seasonally adjust monthly data using the X13 procedure in the IRIS toolbox. Source: Rosstat.

4. *Risk free rate.* As the CBR's regulated key rate is not available for the whole period, we use the three-month rate from a yield curve of the Russian government bonds. Source: CBR.

5. *Composite lending rate.* Neither CBR nor other statistical agencies in Russia report a single interest rate that could reflect the average price of loans for households and non-financial companies. We construct such a rate using the data on the interest rates on new ruble loans weighted by the corresponding amount of outstanding debt at different maturities—from overnight to more than three years. The data is partly fragmented in 2004-–2010, and we thus interpolate average interest rates from the available numbers at different maturities of ruble-denominated loans. Due to gaps in the original sources,

we also have to extrapolate the data for 2019 Q2 using the last available observations. Source: CBR.

6. *Real investment growth.* We use monthly data on investment in fixed capital available from 2004 to 2015 and its estimates calculated by interpolating quarterly data on investment in fixed capital starting from 2016. Seasonally adjusted using the basic X13 procedure in the IRIS toolbox and then aggregated to quarterly levels. Source: Rosstat, short-term economic indicators.

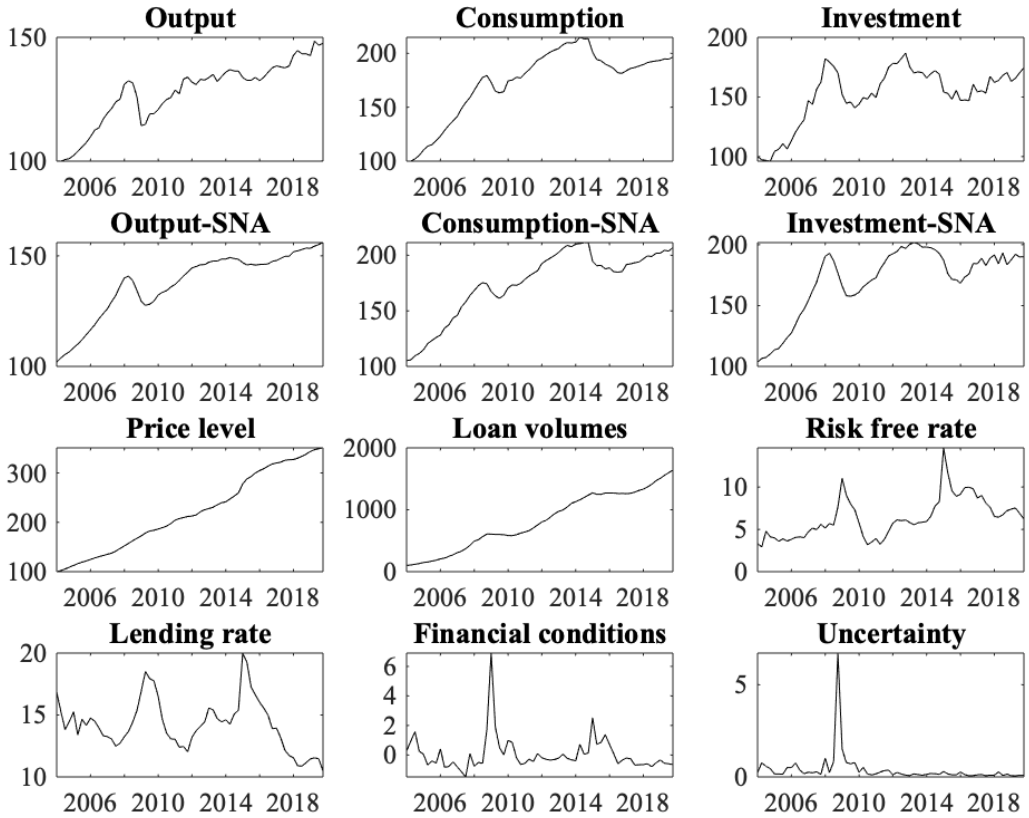
7. *Real consumption growth.* We use monthly data on the retail sales available from 2004 to 2019 to proxy for consumption. The retail sales closely follow the dynamics of private consumption at the quarterly frequency. The monthly data on the retail sales is seasonally adjusted using the basic X-13 procedure in the IRIS toolbox and then converted to the quarterly data. Source: Rosstat, short-term economic indicators.

8. *Financial conditions index.* We extract one common factor from three spreads: (1) the corporate bond yield three-month risk-free rate; (2) the JP Morgan Emerging Markets Bond Index (EMBI) spread for Russia, and (3) the interbank rate to the three-month risk-free rate described above. This simple benchmark is in the spirit of financial stress indicators, such as the Federal Reserve Bank of Kansas City.[37] Sources: Cbonds. (http://cbonds.com/), The World Bank database[38] (https://data.worldbank.org/), CBR.

9. *Uncertainty index.* We estimate a simple GARCH(1,1) model on daily returns of the Russian main stock index, MOEX, and use conditional variance estimates as in Bollerslev (1986) as a proxy for the level of macroeconomic uncertainty. Source: MOEX (https://www.moex.com/en/).

10. *Oil price.* We use the data on the Brent oil prices measured in the US dollars. We transform the nominal to real prices using the US CPI index growth. Sources: Energy Information Administration (EIA) (https://www.eia.gov/), FRED (https://fred.stlouisfed.org/).

[37] `https://www.kansascityfed.org/research/indicatorsdata/kcfsi`
[38] Incomplete data for EMBI for 2019 - extrapolated using last observations.



Note: The figures report the time evolution of the main endogenous variables that we use for our SVAR analysis, in levels, at the quarterly frequency. Base indices are normalized to 100 as of January 2004. Interest rates and spreads are in percent per annum or percentage points. *Output* stands for the index of basic economic activities. *Consumption* stands for the index of retail sales. *Investment* is the investment index. *Output-SNA* stands for the gross domestic output index measured according to the System of National Accounts (SNA). *Consumption-SNA* stands for the index of consumption measured according to the SNA. *Investment-SNA* is the investment index measured according to the SNA. *Price level* is the consumer price index. *Loan volumes* is the outstanding amount of bank loans. *Risk-free rate* is the short-term government bond yields, which proxies policy rate. *Lending rate* is the weighted average of bank lending rates. *Financial conditions* is an index of financial spreads. *Uncertainty* is an index of macroeconomic uncertainty implied by stock market volatility (unit-free).

Figure A.I: Quarterly data on real and financial variables on the Russian economy

Online Appendix A Exchange rate movements and the revaluation of bank loans

Below we outline the procedure that we apply to re-evaluate the foreign-denominated debt of the Russian economy. We convert this debt to rubles using the changes in the USD/RUB exchange rate. R and C denote outstanding loans denominated in rubles and foreign currencies, respectively, at period t, in rubles:

$$R_t + C_t.$$

The ruble equivalent of the outstanding amount of foreign currency loans changes in time due to the actual changes in volumes (measured in original foreign currency) and the actual changes in the USD/RUB exchange rate:[39]

$$C_{t+1} = C_t(1 + g_{t+1} + \Delta FX_{t+1})$$

Assumption: the ruble equivalent of the foreign currency loans changes one to one with USD/RUB exchange rate ΔUSD:

$$C_{t+1} = C_t(1 + g_{t+1} + \Delta USD_{t+1})$$

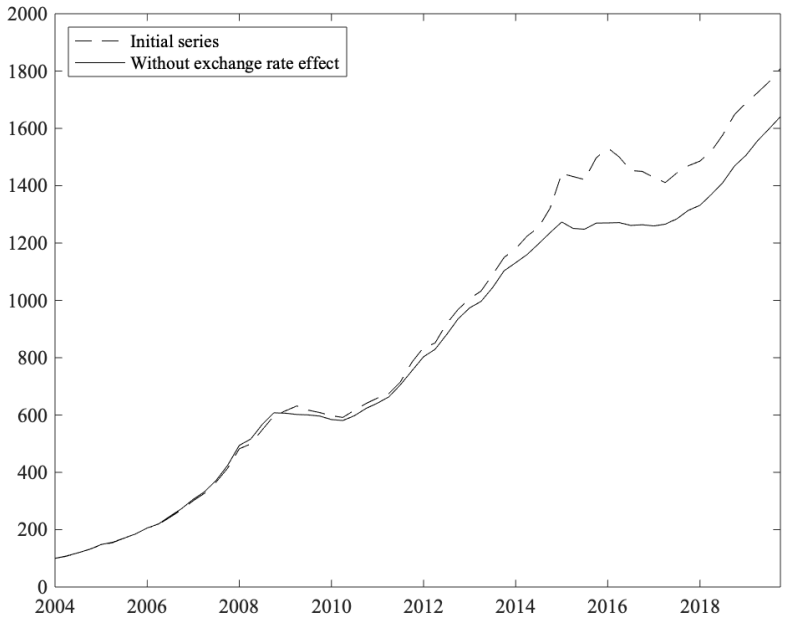
$$1 + g_{t+1} = C_{t+1}/C_t - \Delta USD_{t+1}.$$

Finally, the total amount of loans corrected for FX re-valuation is:

$$R_{t+1} + C_{t+1} = R_{t+1} + (1 + g_{t+1})C_t.$$

Thus, the resulting variable corresponds to the dynamics of ruble and foreign currency debt, with the latter converted to rubles at the January 2010 exchange rate.

[39] According to the annual reports of the Central Bank of Russia for various years in the 2010s and the beginning of the 2020s, the average share of the banking system's total assets denominated in foreign currency ranges between 20 and 25%, of which roughly 60 percentage points belong to the USD (see, e.g., https://cbr.ru/Collection/Collection/File/43816/analytical_review_bs-2022.pdf).

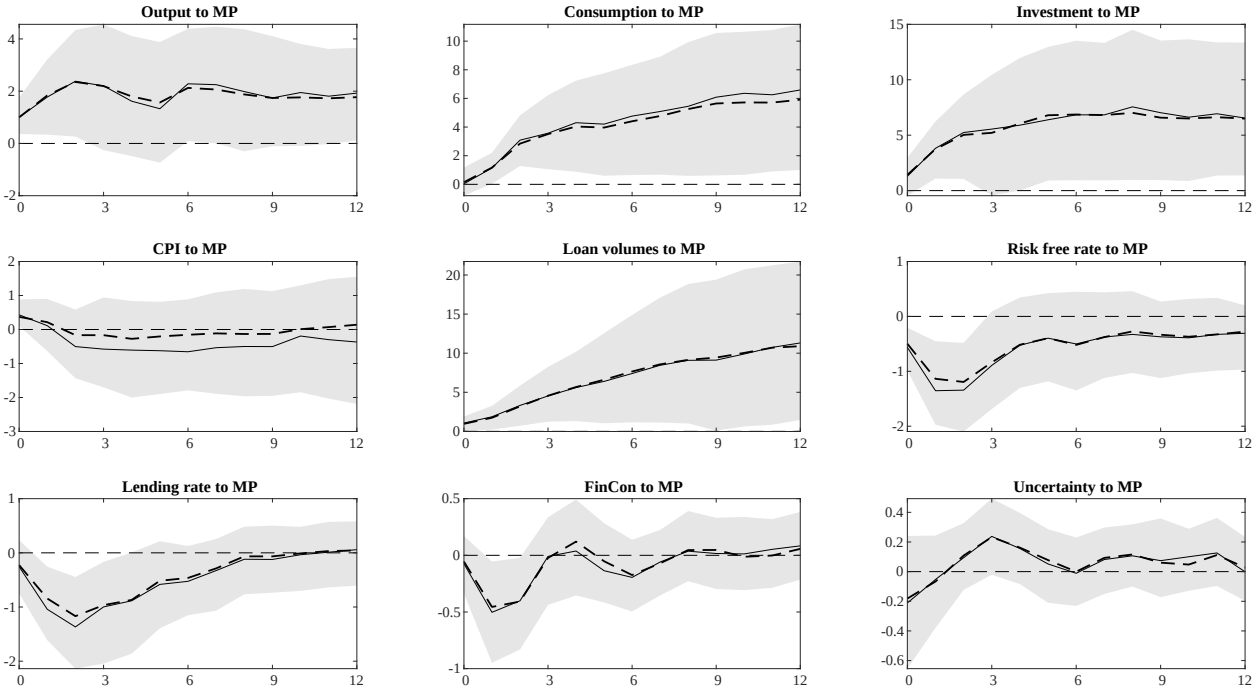


Note: The figure displays the official outstanding amount of total loans in the Russian banking system (the dashed line) and its analog adjusted for the FX re-valuation caused by the movements in the USD/RUB exchange rate (the solid line). The latter could be described as the series with foreign exchange loans evaluated at January 2010 exchange rates. Both are rescaled to the level of January 2004 equal to 100.

Figure A.I: Total loans of the Russian banking system before and after adjusting for the FX re-valuation (*January 2004 = 100*)

Online Appendix B Baseline results: impulse responses to other (business cycle) shocks

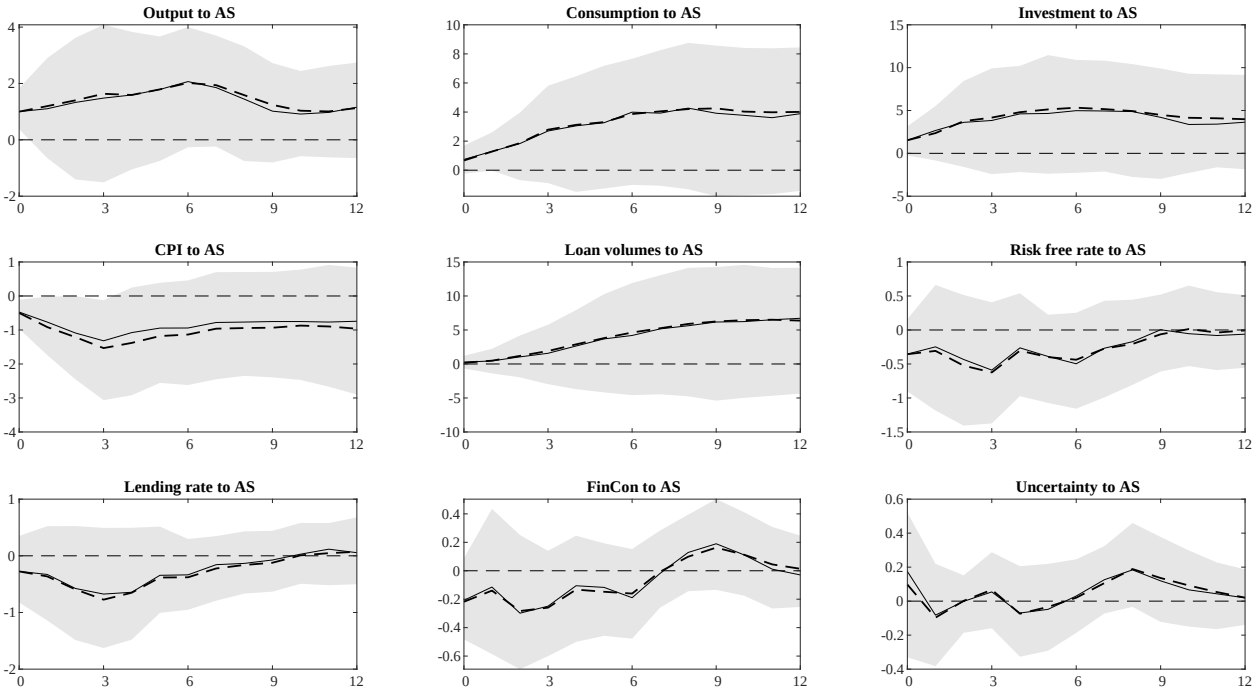
B.1 Expansionary monetary policy (MP) shock



Note: The figures present the estimated impulse responses to identified expansionary monetary policy (MP) shocks in the nine-variable SVAR model. The solid line denotes the responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the responses under the SR scheme only (see the main text for details). The NSR scheme considers 2014 Q4 as a period of restrictive monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as periods of contractionary credit supply (CS) shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior (the flat prior is assumed). The light grey area marks the credible bands for the combination of SR and NSR schemes. We omit the credible bands for the SR case as they are almost identical to the light grey area and never change the results qualitatively. The X-axis shows the quarters after an expansionary MP shock. All estimated responses are normalized so that the output rises by 1 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-quarter log-differences from the period –1 to t, i.e., $log(y_t) - log(y_{-1})$.

Figure B.I: Impulse responses to the identified expansionary monetary policy (MP) shock: other (non-credit) baseline results

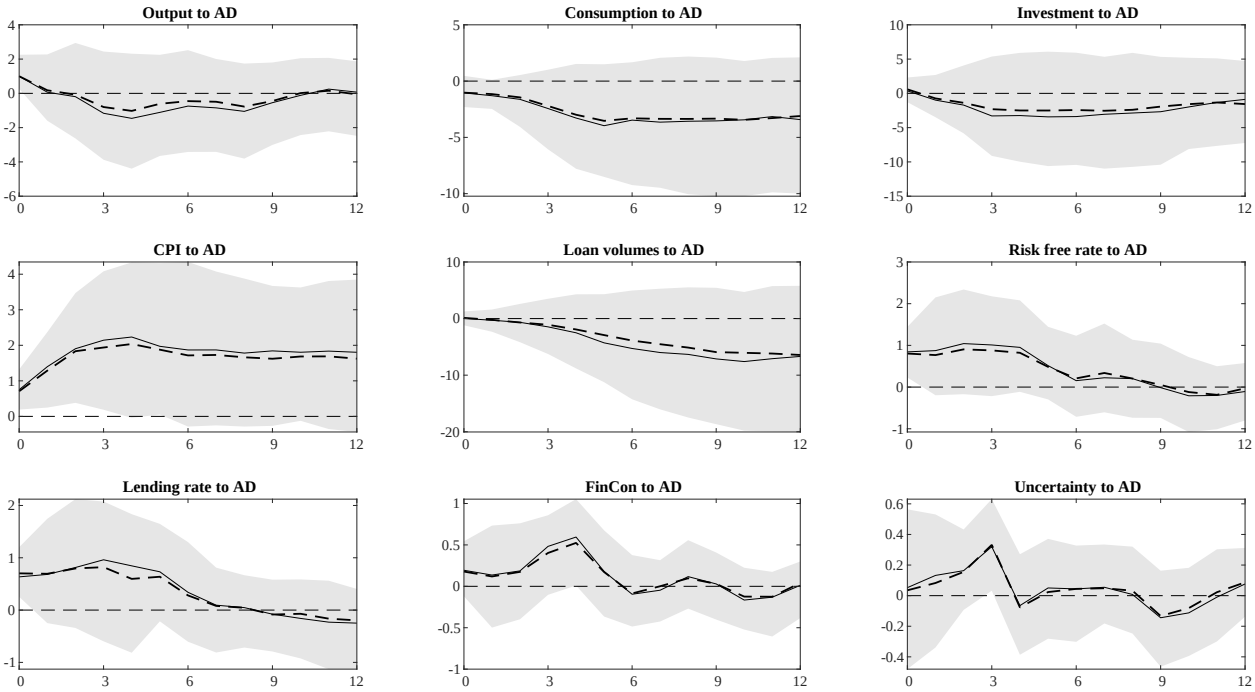
B.2 Expansionary aggregate supply (AS) shock



Note: The figures present the estimated impulse responses to identified expansionary aggregate supply (AS) shocks in the nine-variable SVAR model. The solid line denotes the responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the responses under the SR scheme only (see the main text for details). The NSR scheme considers 2014 Q4 as a period of restrictive monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as periods of contractionary credit supply (CS) shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior (the flat prior is assumed). The light grey area marks the credible bands for the combination of SR and NSR schemes. We omit the credible bands for the SR case as they are almost identical to the light grey area and never change the results qualitatively. The X-axis shows the quarters after an expansionary AS shock. All estimated responses are normalized so that the output rises by 1 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the the cumulative growth rates, i.e., the sum of one-quarter log-differences from the period –1 to t, i.e., $log(y_t) - log(y_{-1})$.

Figure B.II: Impulse responses to the identified aggregate supply (AS) shock: other (non-credit) baseline results

B.3 Expansionary aggregate demand (AD) shock



Note: The figures present the estimated impulse responses to identified expansionary aggregate demand (AD) shocks in the nine-variable SVAR model. The solid line denotes the responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the responses under the SR scheme only (see the main text for details). The NSR scheme considers 2014 Q4 as a period of restrictive monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as periods of contractionary credit supply (CS) shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior (the flat prior is assumed). The light grey area marks the credible bands for the combination of SR and NSR schemes. We omit the credible bands for the SR case as they are almost identical to the light grey area and never change the results qualitatively. The X-axis shows the quarters after an expansionary AD shock. All estimated responses are normalized so that the output rises by 1 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-quarter log-differences from the period –1 to t, i.e., $log(y_t) - log(y_{-1})$.

Figure B.III: Impulse responses to the identified aggregate demand (AD) shock: other (non-credit) baseline results

Online Appendix C Discussion of the potential sources of credit supply shocks in the 2010s

In this section, we discuss the potential sources of CS shocks and attempt to relate them to the economic trends observed in the Russian economy in the second half of the 2010s. In the main text, we demonstrate that the period of 2015–2016 witnessed prolonged episodes of negative CS shocks that decreased household consumption and limited investment opportunities for non-financial firms. We will now discuss these trends in more detail.

As we see it, there are at least three events that could give rise to negative CS shocks and at least one development that could partially mitigate them.

First, *tightened prudential regulation* (Goncharenko et al., 2022). Since the middle of 2013, there has been a dramatic decrease in the number of commercial banks operating in Russia. According to the Central Bank of Russia (CBR), 956 credit organizations were active in the Russian Federation as of July 1, 2013. By January 1, 2020, this number had shrunk to 442. This downward trend has been caused by the CBR's policy of revoking the licenses of fraudulent banks, which was enacted with the appointment of its new governor, Elvira Nabiullina, on June 24, 2013. The tightened regulation policy was aimed at stopping the illegal practices and fraudulent schemes used by banks at the time.[40] Importantly, the majority of licenses (62% of the total number for 2013–2019) were revoked in the period 2013–2015. Likely, the removal of banks from the market and the corresponding decrease in the level of competition between financial institutions had a knock-on effect in terms of the increased cost of credit for borrowers, that is, rising interest rates on loans due to negative CS shocks in 2013–2016.[41]

Second, *Western financial sanctions* (Mamonov et al., 2023). The negative effect of revoking banking licenses on the supply of credit was further amplified by the financial sanctions that were first imposed in March 2014 in response to Crimea's annexation by the Kremlin. Over the following five years, as many as 44 of Russia's largest banks with recognized political connections had been almost completely excluded from important international fi-

[40] The policy affected both small and relatively large banks, including those in the top-30 list of financial institutions in terms of asset size. A summary is available via this link.

[41] However, we do not interpret anti-fraud measures as having exclusively negative effects on the economy. Even in our parsimonious macroeconomic framework, positive CS shocks can have negative effects, which are reflected in worsening financial conditions and rising uncertainty in longer horizons, as Figure 2 shows.

nancial markets in the United States and the European Union.[42] The financial sanctions effectively blocked most banks from being able to borrow on international financial markets, which led to an exogenous rise in the cost of external funds for banks (see, for example, Dovbnya, 2019). The unavailability of foreign funding was partially cushioned by government support.It is rather natural that negative CS shocks would occur in such a "double shock" environment (tightened regulation and sanctions), because banks had to behave more cautiously to survive than the market would otherwise expect.

Third, an *increased requirement on loan loss reserves under the IFRS-9*. Starting in 2018, all banks that provided financial statements under IFRS standards had to switch from an incurred (backward-looking) loss model to an expected (forward-looking) loss model in calculating loan loss provisions. Under the new model of provisioning, banks were obliged to create loan loss provisions that accounted for the risk of a borrower defaulting *before* the respective asset matures. Moreover, it implied a stricter reflection of arrears. According to Fitch's estimates, this caused Russian banks to lose as much as 1 trillion rubles in capital by early 2019, which is equivalent to 1% of the country's GDP.[43] Clearly, this regulation also had a negative (short-run) effect on the supply of bank credit in Russia.

The *adoption of the Basel-III regulation* in Russia helped partly "soften" the negative CS shocks of the second half of the 2010s. To align domestic prudential regulation with best international practices after the Global Financial Crisis of 2007–2009, the CBR declared a gradual transition towards the Basel-III starting in 2014. The CBR updated the rules of equity capital accounting and refined capital adequacy and liquidity requirements. In particular, the CBR lowered the capital adequacy ratio (H1.0) from 10% to 8%, thus effectively providing banks a buffer of 2 p.p., which may have supported the CS in the economy. However, following BIS recommendations, the CBR also defined a list of systemically important financial institutions (SIFIs) that included the 11 largest banks in Russia back in the time and established a 1 to 2.5 p.p. "price" of being an SIFI (an additional capital cushion in terms of H1.0). This could have partially constrained the banks' lending operations but the net effect was still positive.

[42] On 20 March 2014, the US government began the sanction policy against Russia by including the Bank Rossiya, which is not directly state-owned but has close ties to the Kremlin, on the so-called Specially Designated Nationals and Blocked Persons List (the SDN List) prohibiting any type of foreign operations (new borrowings and foreign asset holdings) with the US economic agents. See more details via this link.

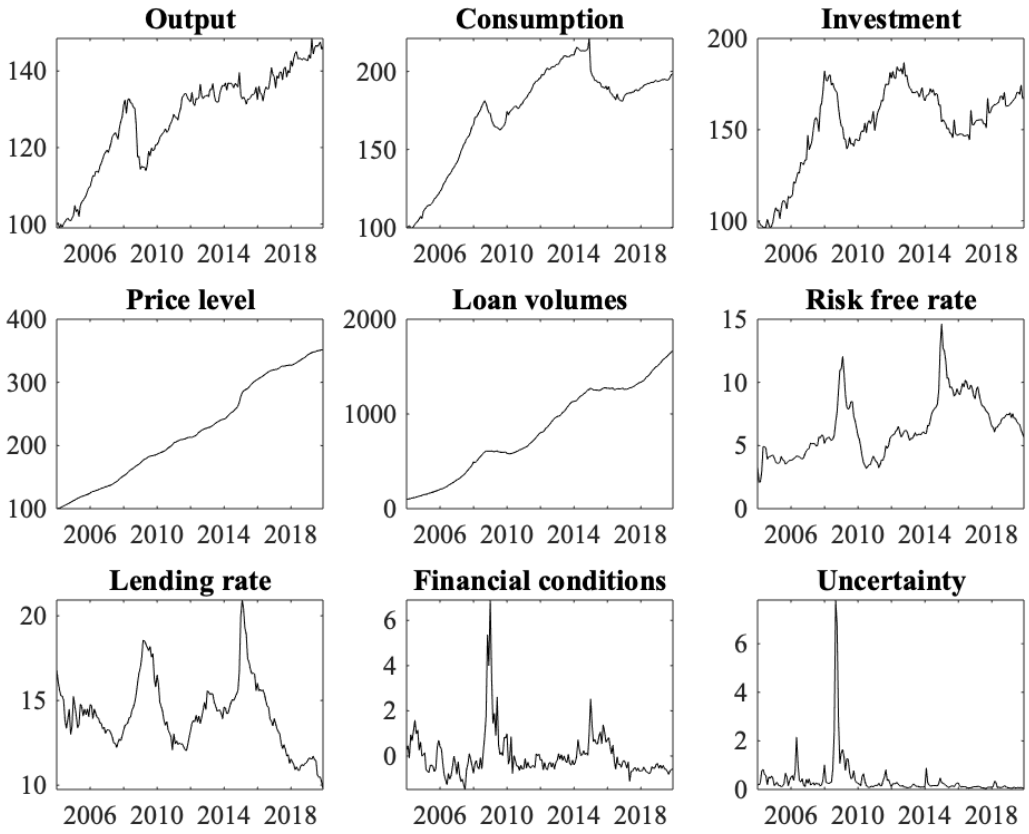
[43] The details are available via this link.

To sum up, all the factors combined could have had significant implications for the real economy, but it was not clear whether the real effects of the credit supply disruptions would be more serious than those of the Global Financial Crisis. Our estimates show that the former could have been much stronger. More precisely, our macroeconomic identification scheme does not allow us to argue that the abovementioned developments played a major role in shaping the credit supply, nor does it allow us to distinguish between the effects of the underlying policies. However, we do argue that these policies provide a solid ground for our analysis of CS shocks.

Online Appendix D Robustness checks for the macro analysis

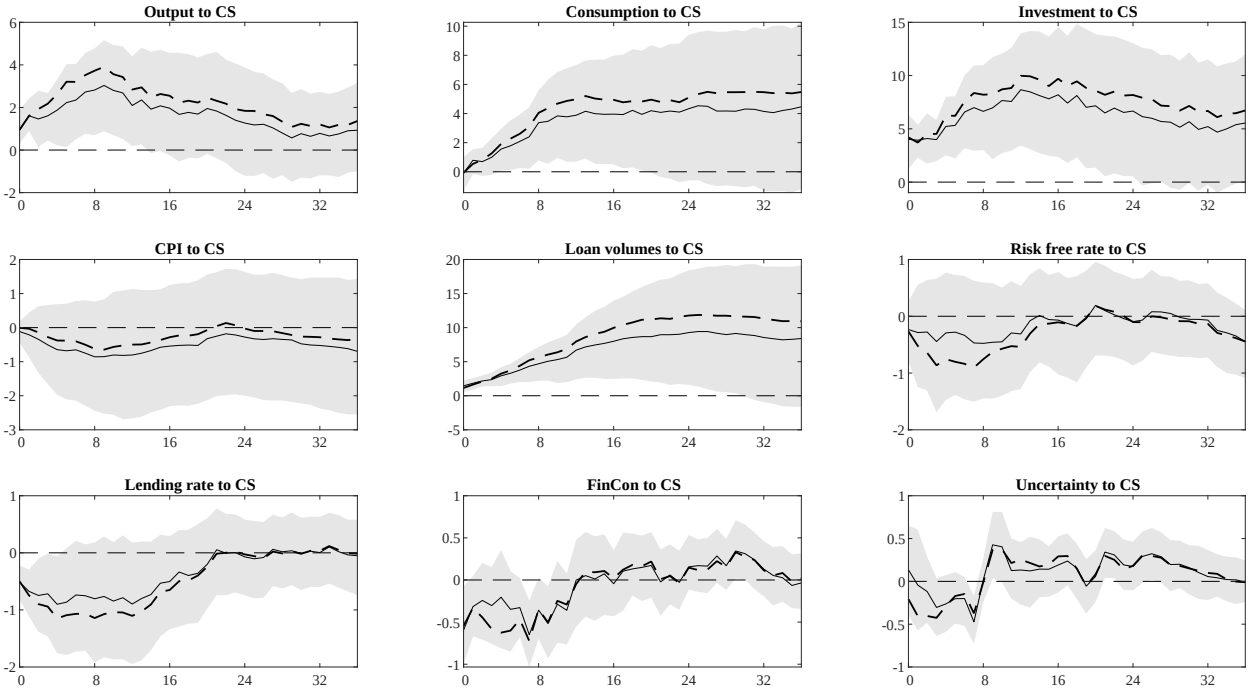
D.1 Monthly data

We re-run our baseline nine-variables SVAR model using the monthly data instead of their quarterly aggregates. We present the monthly data in Figure D.I and the SVAR-based responses to CS shocks in Figure D.II. As follows from the comparison with the baseline results, qualitatively both impulse responses are similar, though in the case of monthly data, responses to the identified shocks are more volatile.



Note: The figures report the time evolution of the main endogenous variables that we use for our SVAR analysis, in levels, at the monthly frequency. The figures are thus the monthly analogs to their quarterly counterparts presented in Figure A.I above so that all the previous notations and details apply here.

Figure D.I: Monthly data on real and financial variables on the Russian economy

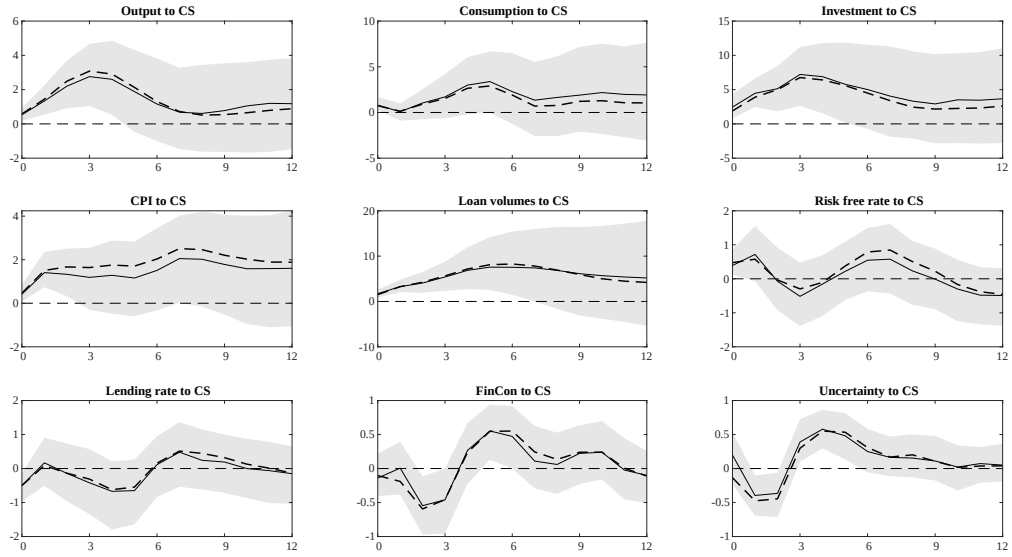


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model using the monthly instead of the quarterly data. The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 36 months. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.II: Impulse responses to the identified credit supply shock (CS) using the monthly data

D.2 The quarterly data from the System of National Accounts (SNA)

We re-estimate the baseline model using the official quarterly System of National Accounts data on consumption, investment, and real activity. The reason why our baseline model instead features alternative measures of output, consumption, and investment presented in Appendix A is that these measures are available at the monthly frequency and are well-aligned with the SNA measures in all other aspects. As Figure D.III implies, we confirm that qualitatively, all the main results are preserved if we use SNA data. The reason is that SNA-based data on consumption, investment, and real activity are well aligned with quarterly estimates we made from monthly data on the index of basic economic activity, retail consumption, and investment, see Figure A.I. With the quarterly SNA data, the responses of real variables to CS shocks turn lower in magnitude compared to the baseline quarterly data but are still significant (Figure D.III). In addition, the share of CS shocks in FEVD renders lower for investment compared to the baseline results.

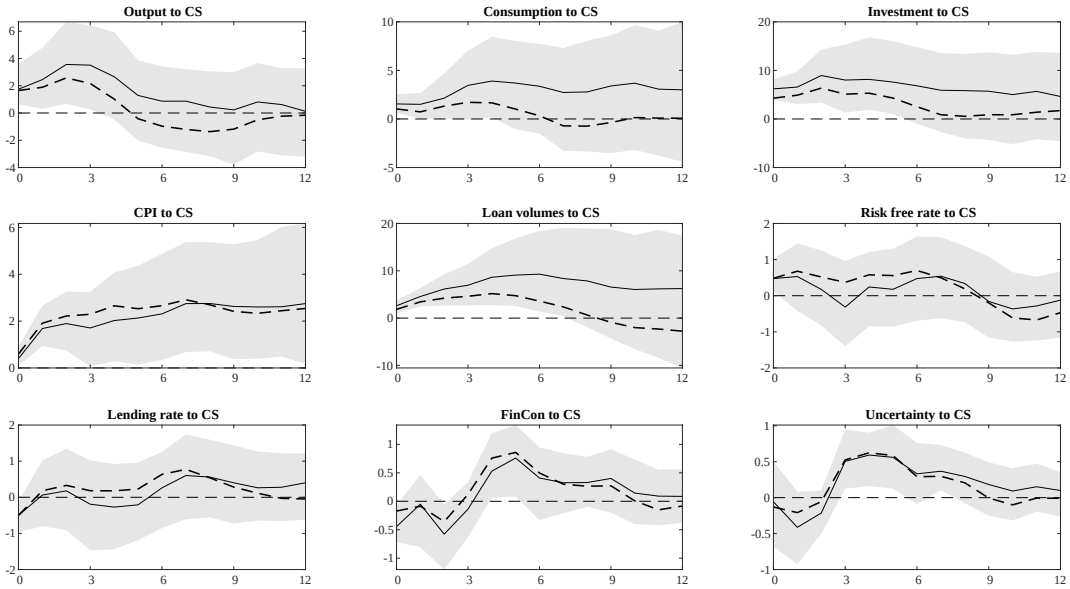


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model using the official quarterly SNA data. The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.III: Impulse responses to the identified credit supply shock (CS) using the official quarterly SNA data

D.3 Oil prices

Our baseline specification of the SVAR model, which we borrow from Mumtaz et al. (2018), is missing exogenous variables. A commodity exporter like Russia depends heavily on the global oil market conditions, and therefore it might be reasonable to include oil prices in the model to estimate the effect of an expansionary CS shock that is net of any exogenous movements in oil prices. We re-estimate the baseline model with real oil prices (deflated by the US CPI inflation) as an exogenous variable. As can be inferred from Figure D.IV, we obtain results that are very similar to what we obtain in our baseline specification. The main quantitative difference is that the peak responses decreased compared to the baseline but are still significant. For example, the output peak response decreases from +5 p.p. to +4 p.p. in three quarters after an expansionary CS shock while still remaining significant. Overall, controlling for oil prices absorbs a part of the CS shock effect though it remains sizable and significant.

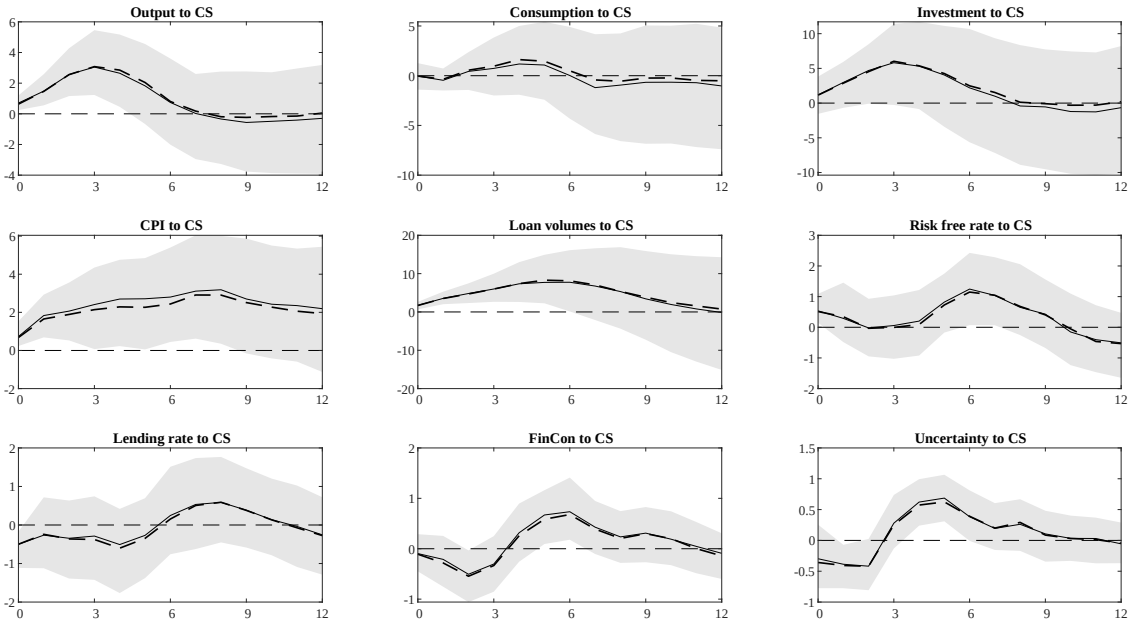


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the ten-variable SVAR model where the 10th variable reflects oil prices and is set as exogenous. The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.IV: Impulse responses to the identified credit supply shock (CS) controlling for oil prices

D.4 Monetary policy and sanctions

In the main text, we argue that financial sanctions are one of the driving forces behind negative credit supply shocks of 2014–2019 (see also Online Appendix C). To verify that this assumption helps us improve the identification of CS shocks, we re-estimate the baseline model with narrative sign restriction only on monetary policy, as discussed in Antolin-Diaz and Rubio-Ramirez (2018), and ignore the timing of sanctions (Mamonov et al., 2023). We require the successful draws to contain negative monetary policy shock in Q4 2014. As argued in Section 4.1, this date corresponds to the largest monetary policy shock for the whole period. Figure D.V depicts impulse responses to the identified CS shocks for this version of the model. The results are consistent with our baseline estimates, yet the identification yields lower importance of CS shocks for consumption and investment. We interpret this as supporting evidence to the baseline model that uses narrative information on sanctions as an additional input.

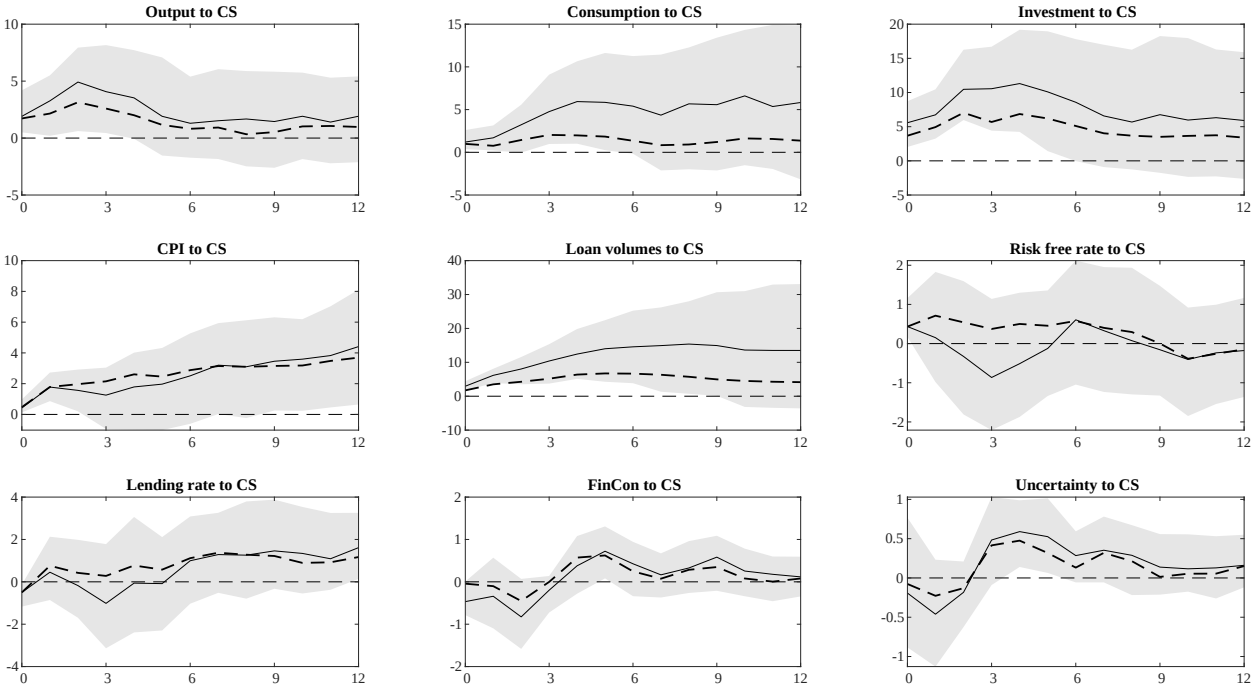


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model with the NSR scheme with only MP shock in December 2014 and without restrictions on the timing of CS shock. The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.V: Impulse responses to the identified credit supply shock (CS) ignoring the timing of sanctions as an input to NSR

D.5 Alternative interest rates

To check whether the average bank lending rate we construct for this paper does not introduce some systemic bias into the estimation, we re-estimate the baseline model using a simple average of the only two lending rates that were available from the source for the entire sample period from 2004 to 2019 (the Central Bank of Russia): the interest rate for 6- to 12-month consumer loans and the interest rate for 6- to 12-month ruble loans to non-financial organizations. Figure D.VI reports the results. As one can see, they remain qualitatively, and even quantitatively, very close to the baseline.

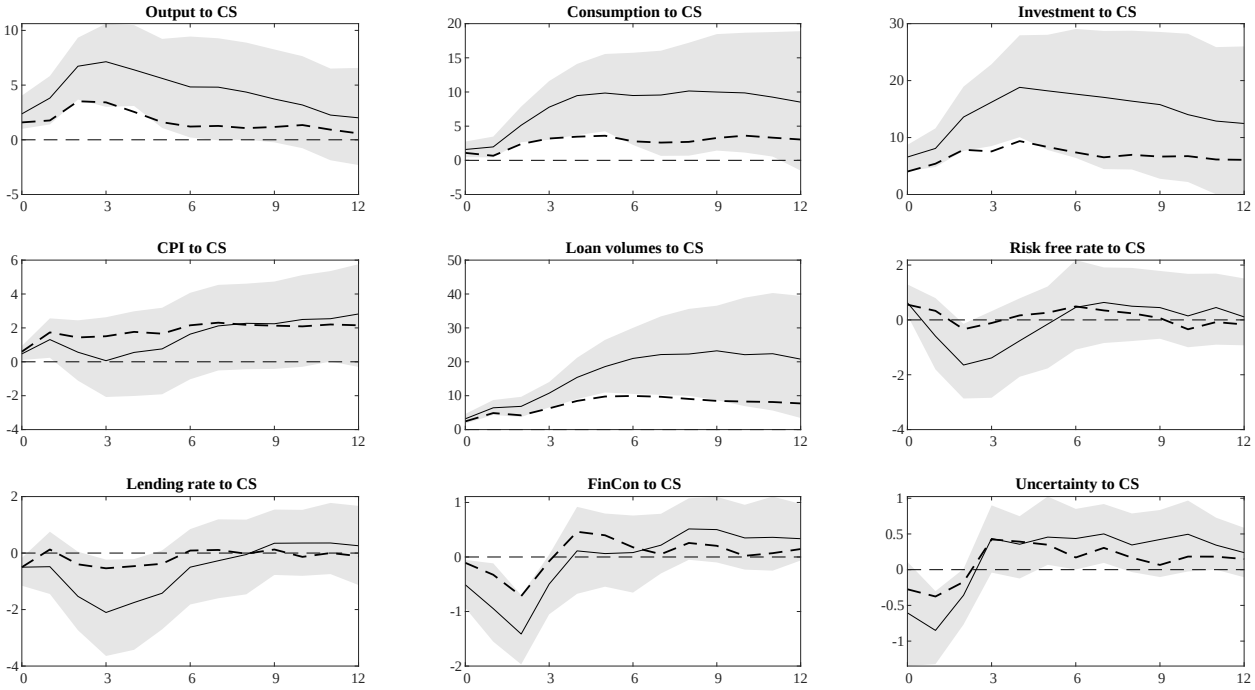


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model with the lending interest rate being re-defined as a weighted average of only the 6- to 12-month consumer loans and 6- to 12-month business loans (differently from other frequencies, the data on loans at these frequencies is available for the whole time sample of 2014–2019). The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.VI: Impulse responses to the identified credit supply shock (CS) using an alternative definition of interest rates

D.6 FX re-valuation

As we discuss in Subsection 3.2, the share of loans denominated in foreign currency (FX-loans) in the total amount of loans vary from 10% to 30% while the ruble lost more than 100% of its value during our sample period (2004–2019). Therefore, the observed changes in the total amount of loans are due not only to the movements in the supply of and demand for loans but the depreciation of the ruble. In the main text, we adjust the growth rates of loans so that they are not affected by the ruble exchange rate (see details in Online Appendix A). Without this adjustment, the SVAR impulse responses to the CS shock are larger and more often statistically different from zero, see Figure D.VII. For example, the peak reaction of output to an expansionary CS shock increases from +5 to +7 p.p. in the three quarters after the shock if we do not adjust for the FX re-valuation.

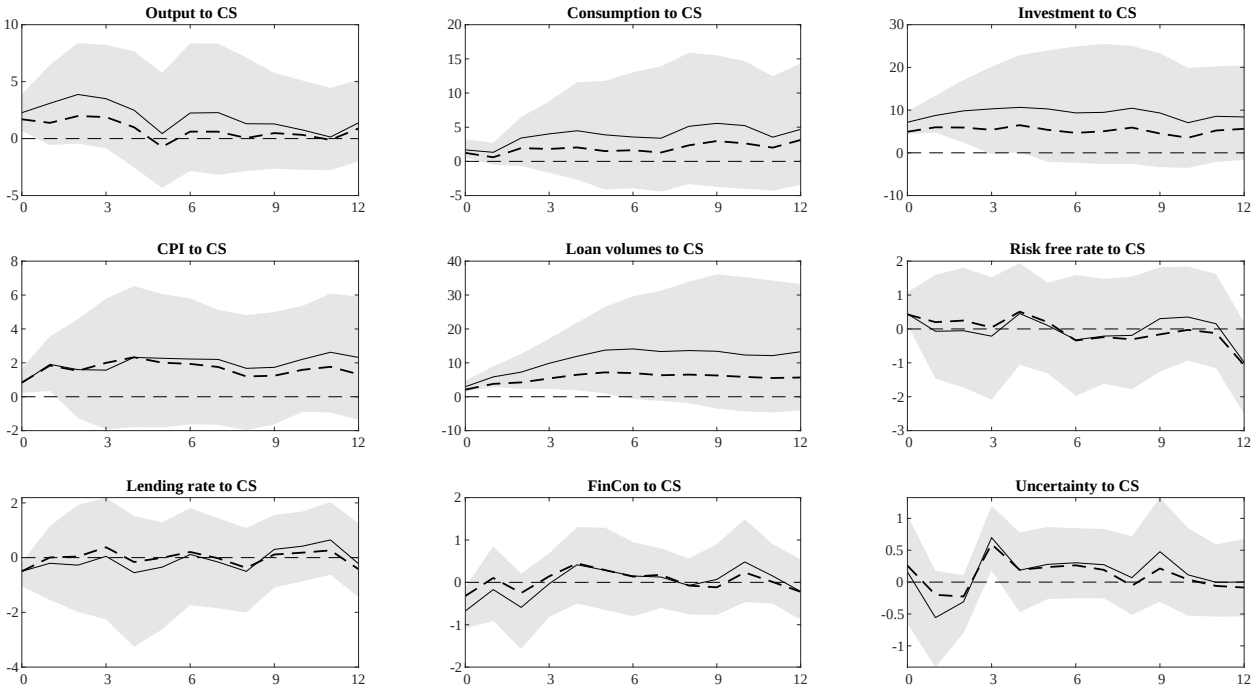


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model with the amount of loans being unadjusted for the movements in the nominal ruble exchange rate. The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.VII: Impulse responses to the identified credit supply shock (CS) without FX re-valuation

D.7 Residual seasonality

In the main text, we use four-quarter lags of all endogenous variables in our SVAR model. However, a model with five-quarter lags may be more resilient to residual seasonality in the data, if any. Figure D.VIII shows that this manipulation with model lags makes the credible bands wider but delivers no qualitative changes to the baseline results.

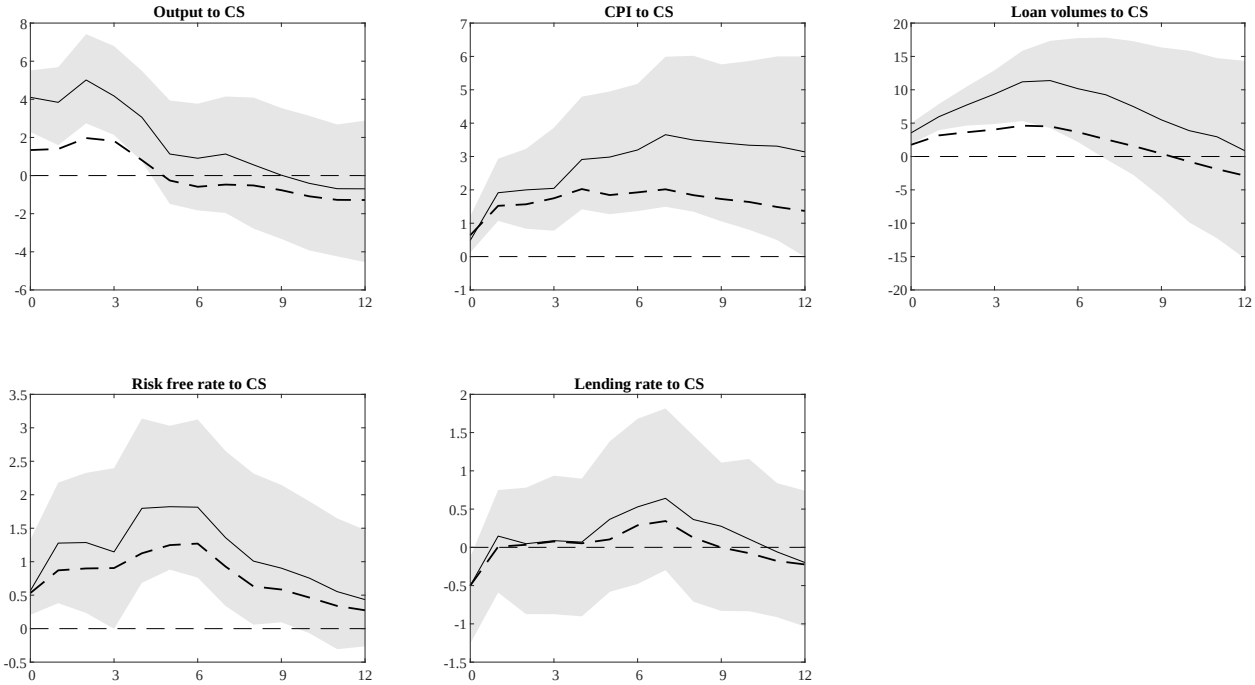


Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the nine-variable SVAR model with the five quarter lags of all endofenous variables. The baseline analog is Figure 2 in the main text, which contains four quarter lags. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.VIII: Impulse responses to the identified credit supply shock (CS) with the fifth-quarter lag

D.8 The five-variable SVAR of Gambetti and Musso (2017)

We use a version of the model provided in Gambetti and Musso (2017) to confirm that the identified shocks are generally consistent across the five variables and nine variables versions of the model. This version of the model only includes output growth, inflation, outstanding amount of loans to the real economy, the risk-free rate, and the lending rate. As Figure D.IX, we obtain results that are qualitatively similar to our baseline specification.



Note: The figure presents the re-estimated impulse responses to the identified credit supply (CS) shock in the five-variable SVAR model of Gambetti and Musso (2017). The baseline analog is Figure 2 in the main text. The solid line denotes the median responses obtained with a combination of the sign restriction (SR) and narrative sign restriction (NSR) schemes, while the dash-dotted line reflects the median responses under the SR scheme only (see Table 1 for the details). The NSR scheme considers the three months of 2014 Q4 as a period of negative monetary policy (contractionary MP shock), and 2008 Q2 and 2014 Q2 as the periods of contractionary CS shocks in the Russian economy. The credible bands are defined as the range bounded by the 16th and 84th percentiles of distribution constructed from the successful draws from the posterior. The light grey area stands for the NSR case. We omit credible bands for the SR case as they are almost identical in width to the NSR scheme and never change the results qualitatively. The X-axis shows the months after an identified CS shock. The response horizon is set at 12 quarters. Impulse responses are normalized so that the lending rate reacts by –0.5 p.p. on impact. Finally, the impulse responses for output, consumption, investment, CPI, and loan volumes are cumulative, that is, they represent the effects of shocks on the cumulative growth rates, i.e., the sum of one-month log-differences from the period –1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure D.IX: Impulse responses to the identified credit supply shock (CS) in the five-variable SVAR model

Online Appendix E Data processing and summary statistics for the micro analysis

E.1 Household data

As we discuss in the main text, we use the RLMS-HSE survey data on Russian households. The survey is conducted once a year, generally in October and November, and respondents answer questions about expenditures and income during either the last month or the last three months. We annualize the respondents' numeric answers by multiplying them by respectively 12 or 4. We then convert the data on nominal values to the 2019 rubles using CPI, which is publicly disclosed through the website of the Federal State Statistic Service (Rosstat). To remove outliers, we further winsorize all variables at the 5th and 95th percentiles, except for consumption growth, for which it is enough to winsorize at the 1st and 95th percentiles. Table E.I presents summary statistics for the main variables reflecting credit and demographic characteristics at the household level that we use in our regression analysis in Section 6.1. In addition, Table E.II provides more details on the household head's marital status and education, which both may be important in determining the level of the household's indebtedness.

TABLE E.I

Summary statistics for the selected household characteristics

	Mean	Sd	Min	Max	Observations
Number of household members	2.73	1.44	1	14	51,286
Number of children	0.56	0.85	0	9	51,286
Head's age (years)	42.68	10.82	20	60	39,348
Head's gender (0—male, 1—female)	0.22	0.41	0	1	39,348
Annual income (2019 ths rubles)	570	321	85	1,767	46,364
Annual consumption (2019 ths rubles)	230	140	27	847	51,286
Consumption growth	6.27	46.15	–77.93	158.71	51,286
Have debt (1—yes, 0—no)	0.26	0.44	0	1	51,204
Credit supply (CS) shock (*a SVAR estimate*)	–0.23	1.54	–2.02	2.68	51,286

Note: The table presents summary statistics for the main variables that we use in our regression analysis of the heterogeneity of CS shock effects across households with different credit-related characteristics (Section 6.1). The survey data comes from the RLMS-HSE open source and covers the period from 2006 to 2019.

In our sample, most household heads are males, the average age of the head is about 43 years. Most of the household heads are married and have a secondary school education. On average, the sample consists of 27 members per ten households, among which 6 members

TABLE E.II

Additional socio-economic characteristics at the household level

Head's marital status	%	Head's education	%
Never married	10.6	0-6 grade	0.1
Married	59.0	Unfinished secondary school	2.6
Not registered, living together	13.2	Unfinished secondary school + training	7.6
Divorced	12.3	Secondary school	37.0
Widowed	4.1	Vocational secondary school	24.9
Registered, not living together	0.7	Higher education	27.8
Observations	29,533	Observations	29,539

Note: The survey data comes from the RLMS-HSE open source and covers the period from 2006 to 2019.

are children. The annual income of the average household is around 570 thousand rubles (in 2019 prices), which is below 10 thousand US dollars, with almost half of it covering consumption expenditures. Debt accounts for 7% of the average household's income.

Table E.III further shows how the household summary statistics change across the different percentiles of the household distribution by income. We observe that poorer households are less indebted and have lower consumption growth than richer families.

TABLE E.III

Breakdown of the summary statistics across the distribution of household income

Subsamples by income	<30%	<50%	>50%	>70%
Number of household members	1.81	2.24	3.27	3.33
Number of children	0.27	0.41	0.74	0.75
Head's age (years)	44.57	43.21	42.26	42.41
Head's gender (0—male, 1—female)	0.38	0.30	0.15	0.14
Annual income (2019 ths rubles)	242	350	878	982
Annual consumption (2019 ths rubles)	134	172	293	304
Consumption growth	4.08	4.97	7.72	7.72
Have debt	0.14	0.20	0.33	0.34
Observations	6,772	17,536	19,257	13,574

Note: The survey data comes from the RLMS-HSE open source and covers the period from 2006 to 2019.

E.2 Firm data

We download the firm-year data net assets, number of employees, short- and long-term debts, and total assets from the SPARK-Interfax database. We then compute firm leverage as the sum of the short- and long-term borrowings divided by net assets. Data for all monetary variables is in current prices, and we adjust it to 2019 rubles using the CPI provided by Rosstat. To exclude outliers, we winsorize all variables at the 1st and 99th percentiles. Table E.IV reports the summary statistics.

TABLE E.IV

Summary statistics for the main variables (firm level)

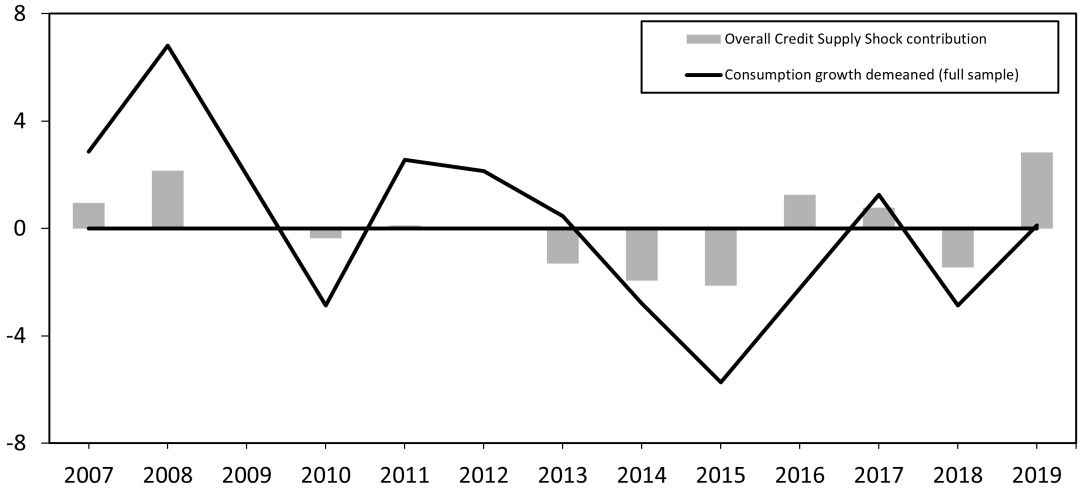
	Mean	SD	Min	Max
Net assets growth	0.4	3.5	–27	76
Number of workers	86	441	1	303,000
Leverage	–0.26	6.17	–129	217
Total assets (mln rubles, 2019 prices)	249	657	0.01	17,144

Note: The table presents summary statistics for the main variables that we use in our regression analysis of the heterogeneity of CS shock effects across firms of different sizes, employment, and leverage (Section 6.2). The firm-level data comes from the SPARK-Interfax database and covers the period from 2011 to 2019. Leverage is calculated as the total amount of borrowings divided by net assets. Borrowings are always non-negative, whereas net assets can be either negative or positive. Therefore, by construction, leverage can take negative values. $N = 1,309,038$.

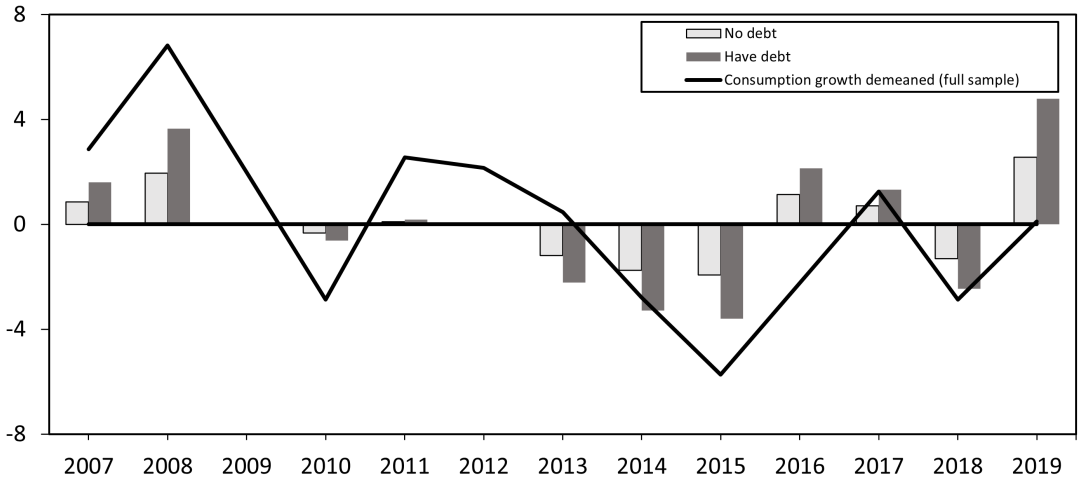
In our sample, we observe substantial variation across firms in terms of size, leverage, number of employees, bank debt, and net asset growth rates. Notably, the average magnitude of net asset growth rate is below 1% over the last decade, meaning that the crisis related to economic and financial sanctions and the oil price collapse that both occurred in 2014–2015 had substantially restricted the growth potential of Russian firms. Among other margins, we also note that our sample, even after winsorization, contains firms with more than 300,000 workers (this excludes the largest companies such as Gazprom or the Russian Railway Company with the total number of employees reaching up to 600,000 people). Finally, the average level of firm indebtedness is very small, with the leverage ratio being just –0.26%.

Online Appendix F Contribution of credit supply shocks to consumption and investment

F.1 Consumption



(a) Overall contribution

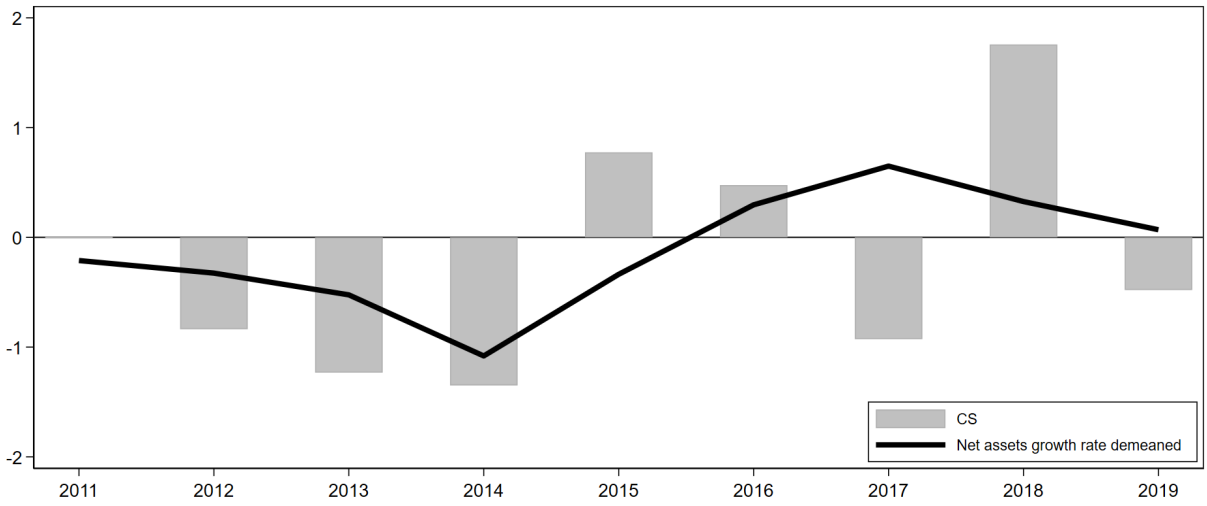


(b) Contribution by the debt status (with vs. without debts)

Note: The figure displays the growth rate of household consumption and the estimated contribution of CS shocks to the consumption of households with and without debts. We compute the contribution of CS shocks at the household level by multiplying the estimated coefficient from the regression of consumption on CS shocks in the micro part of our analysis (Section 6.1) and the magnitude of the estimated CS shock in each year obtained from the macro part of our analysis (Section 5). For the sake of the graphical representation, we aggregate the household-level growth rates of consumption using household income as weights. We then demean the growth rate of consumption to achieve the comparability of results with the macro part of our analysis. Due to changes in the pool of surveyed households in 2009, we cannot estimate the contribution of CS shocks to consumption in this particular year.

Figure F.I: Contribution of credit supply (CS) shocks to consumption at the household level

F.2 Investment



Note: The figure displays the growth rate of firm net assets and the estimated contribution of CS shocks to it across the years. We compute the contribution of CS shocks at the firm level by multiplying the estimated coefficient from the regression of net asset growth rates on CS shocks in the micro part of our analysis (Section 6.2) and the magnitude of the estimated CS shock in each year obtained from the macro part of our analysis (Section 5). For the sake of the graphical representation, we aggregate the firm-level growth rates of net assets using the firm's total assets as weights. We then demean the growth rate of net assets to achieve the comparability of results with the macro part of our analysis.

Figure F.II: Contribution of credit supply (CS) shocks to net asset growth rates at the firm level

Online Appendix G Robustness checks for the cross-sectional analysis

G.1 Households

G.1.1 Income distribution and specification concerns

TABLE G.I

Credit supply (CS) shocks and consumption: additional results at the household level

	Full sample		Subsamples			
	Four shocks	+ Cross-terms	Bottom 30%	Top 30%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)
CS shock$_{t-1}$	2.751***	2.414***	2.084	1.358**	1.227*	1.423***
	(0.409)	(0.451)	(1.413)	(0.572)	(0.653)	(0.503)
Have debt$_{t-1}$ × CS shock$_{t-1}$		0.878	4.168**	0.636	2.192**	–0.242
		(0.670)	(2.013)	(0.752)	(1.110)	(0.725)
MP shock$_{t-1}$	–2.786***	–2.970***	–3.057	–1.764*	–2.853**	–1.856*
	(0.825)	(0.970)	(2.287)	(1.037)	(1.264)	(1.064)
Have debt$_{t-1}$ × MP shock$_{t-1}$		0.310			1.738	0.875
		(1.548)			(2.244)	(1.609)
AS shock$_{t-1}$	0.650	0.863				
	(0.629)	(0.792)				
Have debt$_{t-1}$ × AS shock$_{t-1}$		–0.663				
		(1.361)				
AD shock$_{t-1}$	–2.142***	–2.027***				
	(0.376)	(0.459)				
Have debt$_{t-1}$ × AD shock$_{t-1}$		-0.185				
		(0.776)				
N obs	19,180	19,142	2,356	8,673	7,721	11,421
N households	6,925	6,917	1,445	4,009	3,650	4,847

Note: The table presents estimates of Equation (3), in which the dependent variable is consumption growth at the household level. The table enlarges the results presented in Table 2 of the main text. CS, MP, AD, and AS shocks are estimates of credit supply, monetary policy, aggregate demand, and aggregate supply shocks obtained from the baseline SVAR model (Section 5). The shock estimates are re-scaled so that negative values represent contractions or tightenings and positive values stand for expansions or easings, respectively. *Have debt* = 1 if a household has a bank loan (self-reported) and 0 otherwise. The reference group is "no debt." All regressions contain the full set of controls, including the lagged dependent variable, demographic characteristics (the household head's age, gender, education, marital status, and the number of household members and children), linear time trend, and household FEs. The data covers the period from 2006 to 2019. *Top-30%* (*50%*) means the upper 30% (*50%*) of the distribution of households by real income. *Bottom-30%* (*50%*) means the lower 30% (*50%*) in the distribution of households.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors are in parentheses.

G.1.2 Addressing the problem of generated regressors

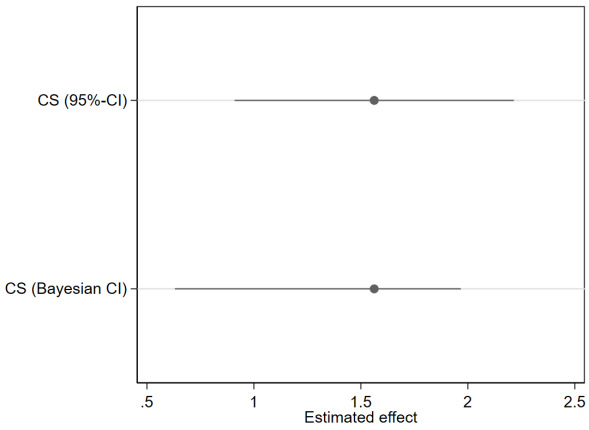
TABLE G.II

CS shock and household-level consumption: regression results with bootstrap standard errors

	Full sample				Subsamples	
		+MP	+Interaction	+All	Bottom-50%	Top-50%
	(1)	(2)	(3)	(4)	(5)	(6)
CS shock$_{t-1}$	0.943***	1.564***	0.544*	1.182***	1.069	1.346**
	(0.243)	(0.343)	(0.303)	(0.358)	(0.687)	(0.609)
Have debt$_{t-1}$ × CS shock$_{t-1}$			1.042**	1.087**	2.680***	-0.029
			(0.503)	(0.502)	(1.038)	(0.816)
MP shock$_{t-1}$		–1.795***		–1.891***	–2.289*	–1.525
		(0.619)		(0.656)	(1.209)	(1.020)
N obs	19,180	19,180	19,142	19,142	7,721	11,421
N household	6,925	6,925	6,917	6,917	3,650	4,847

Note: The table presents estimates of Equation (3), in which the dependent variable is consumption growth at the household level. The table mimics the results presented in Table 2 of the main text but it now exploits bootstrap to compute standard errors (1,000 draws with replications). CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. *Have debt* = 1 if a household has a bank loan (self-reported) and 0 otherwise. The reference group is "no debt." All regressions contain the full set of controls, including the lagged dependent variable, demographic characteristics (the household head's age, gender, education, marital status, and the number of household members and children), linear time trend, and household FEs. The data covers the period from 2006 to 2019. *Top-50%* means the upper 50% of the distribution of households by real income, i.e., richer households. *Bottom-50%* means the opposite, i.e., poorer households.

*** p<0.01, ** p<0.05, * p<0.1, bootstrapped standard errors are in parentheses.



Note: The figure displays the estimated coefficient in the regression of household consumption on the CS shock reported in column (2) of Table 2 with two types of confidence intervals. The first is the standard 95% confidence interval around the coefficient estimate in the regression of household consumption on the median CS shock as reported in column (2) of Table 2. The second interval shows the range of the coefficient's estimates obtained from the same regression specification, with the lower bound estimated using the 16th percentile of the CS shock distribution and the upper bound using the 84th percentile of the same distribution.

Figure G.I: Coefficients in the regression of the household consumption on the median CS shock: the frequentist vs the Bayesian significance

G.1.3 Addressing endogeneity concerns

TABLE G.III

Credit supply (CS) shocks and consumption: the Arellano-Bond estimator

Consumption growth$_{t-1}$	–0.239***
	(0.010)
CS shock$_{t-1}$	0.791**
	(0.383)
MP shock$_{t-1}$	–0.355
	(0.766)
N obs	11,147
N households	3,780
AR(1)	0.000
AR(2)	0.017
Hansen test	0.078

Note: The table presents the results we obtain by applying the Arellano and Bond (1991)'s estimator to Equation (3), in which the dependent variable is consumption growth at the household level. The table mimics the results presented in Table 2 of the main text. CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. The estimated regression contains the full set of controls, including demographic characteristics (the household head's age, gender, education, marital status, and the number of household members and children), linear time trend, and household FEs. The data covers the period from 2006 to 2019.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors are in parentheses.

G.1.4 Continuous version of the "Have debt" variable

TABLE G.IV

CS shock, consumption, and debt to income: regression results at the household level

	Full sample				Subsamples	
	CS	+MP	+Interaction	All	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)
CS shock$_{t-1}$	0.943***	1.564***	0.689**	1.386***	1.378**	1.297**
	(0.257)	(0.334)	(0.297)	(0.379)	(0.652)	(0.511)
Debt to income$_{t-1}$ × CS shock$_{t-1}$			2.509	2.755	6.261**	0.115
			(1.817)	(1.822)	(2.624)	(2.829)
MP shock$_{t-1}$		–1.795***		–2.057***	–2.323**	–1.542
		(0.634)		(0.708)	(1.181)	(0.999)
N obs	19,180	19,180	16,024	16,024	6,905	9,119
N households	6,925	6,925	6,197	6,197	3,349	4,214

Note: The table presents estimates of Equation (3), in which the dependent variable is consumption growth at the household level. The table mimics the results presented in Table 2 of the main text but it now exploits a continuous version of the *Have debt* variable, namely, the debt-to-income ratio (*Debt to income*). CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. All regressions contain the full set of controls, including the lagged dependent variable, demographic characteristics (the household head's age, gender, education, marital status, and the number of household members and children), linear time trend, and household FEs. The data covers the period from 2006 to 2019. *Top-50%* means the upper 50% of the distribution of households by real income, i.e., richer households. *Bottom-50%* means the opposite, i.e., poorer households.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors are in parentheses.

G.1.5 The breakdown of consumption on durables and non-durables

TABLE G.V

CS shocks and non-durable consumption: regression results at the household level

	Full sample				Subsamples	
	CS	+MP	+Interaction	All	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)
CS shock$_{t-1}$	0.845***	1.182***	0.605**	0.952***	0.396	1.315***
	(0.207)	(0.263)	(0.248)	(0.291)	(0.501)	(0.394)
Have debt$_{t-1}$ × CS shock$_{t-1}$			0.590	0.617	1.702**	0.0399
			(0.387)	(0.388)	(0.683)	(0.525)
MP shock$_{t-1}$		–0.970*		–1.027**	–0.934	–0.852
		(0.517)		(0.518)	(0.869)	(0.726)
N obs	20,704	20,704	20,665	20,665	7,275	12,390
N households	7,205	7,205	7,194	7,194	3,866	5,021

TABLE G.VI

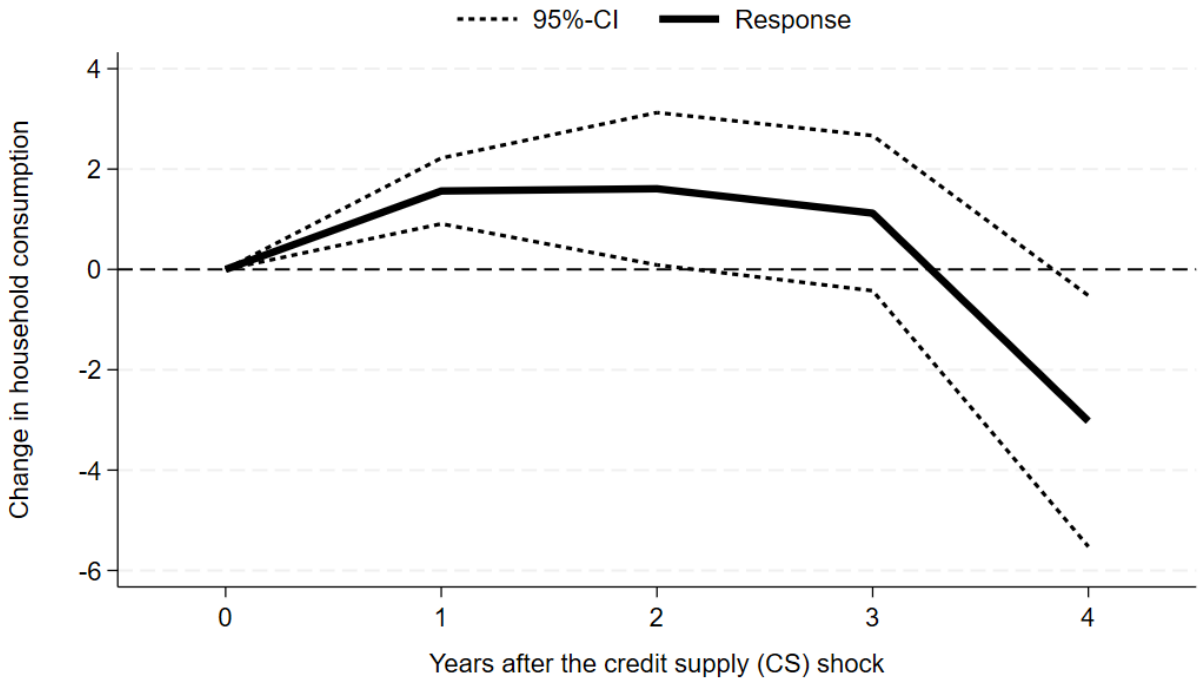
CS shocks and durable consumption: regression results at the household level

	Full sample				Subsamples	
	CS	+MP	+Interaction	All	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)
CS shock$_{t-1}$	1.175	1.202	1.139	1.320	–3.476	1.604
	(2.177)	(2.934)	(2.775)	(3.355)	(5.795)	(4.477)
Have debt$_{t-1}$ × CS shock$_{t-1}$			–0.455	–0.457	7.943	0.217
			(4.107)	(4.107)	(7.928)	(5.347)
MP shock$_{t-1}$		–0.0795		–0.516	5.747	–5.451
		(5.684)		(5.698)	(10.11)	(7.808)
N obs	6,280	6,280	6,267	6,267	2,083	4,184
N households	3,007	3,007	3,004	3,004	1,261	2,191

Note: Tables G.V and present estimates of Equation (3), in which the dependent variable is consumption growth at the household level. The tables mimic the results presented in Table 2 of the main text but now they use consumption of non-durables and durables, respectively.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses.

G.1.6 Jorda (2005)'s local projections



Note: The figure displays local projections of the CS shock on household consumption (Jorda, 2005). The regression specification follows Equation (3), with MP shocks as controls (as in column (2) of Table 2 in the main text) and the dependent variable modified to ΔC_{t+k} $(k = 1, 2, 3)$.

Figure G.II: Local projections of CS shocks on household consumption

G.1.7 Modification of the dependent variable: consumption in levels

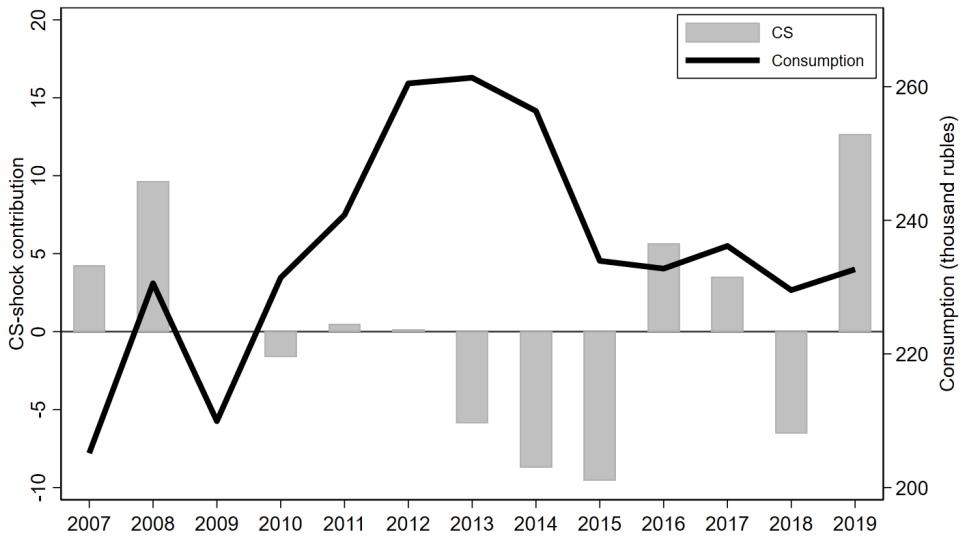
TABLE G.VII

CS shocks and the log of consumption: regression results at the household level

CS shock$_{t-1}$	4.734***
	(0.651)
MP shock$_{t-1}$	–11.665***
	(1.083)
N obs	31,638
N households	9,862

Note: The table presents estimates of Equation (3), in which the dependent variable is the log of consumption instead of consumption growth at the household level. CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. The regression contains the full set of controls, including the lagged dependent variable, demographic characteristics (the household head's age, gender, education, marital status, and the number of household members and children), linear time trend, and household FEs. The data covers the period from 2006 to 2019.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors are in parentheses.



Note: The figure displays the retail consumption (right axis) and its estimated historical decomposition with respect to CS shock (left axis). For 2009 due to the change of the pool of households, it is not possible to estimate the contribution.

Figure G.III: Historical Decomposition of Credit Supply (CS) to Retail Consumption

G.2 Firms

G.2.1 Asset distribution and specification concerns

TABLE G.VIII

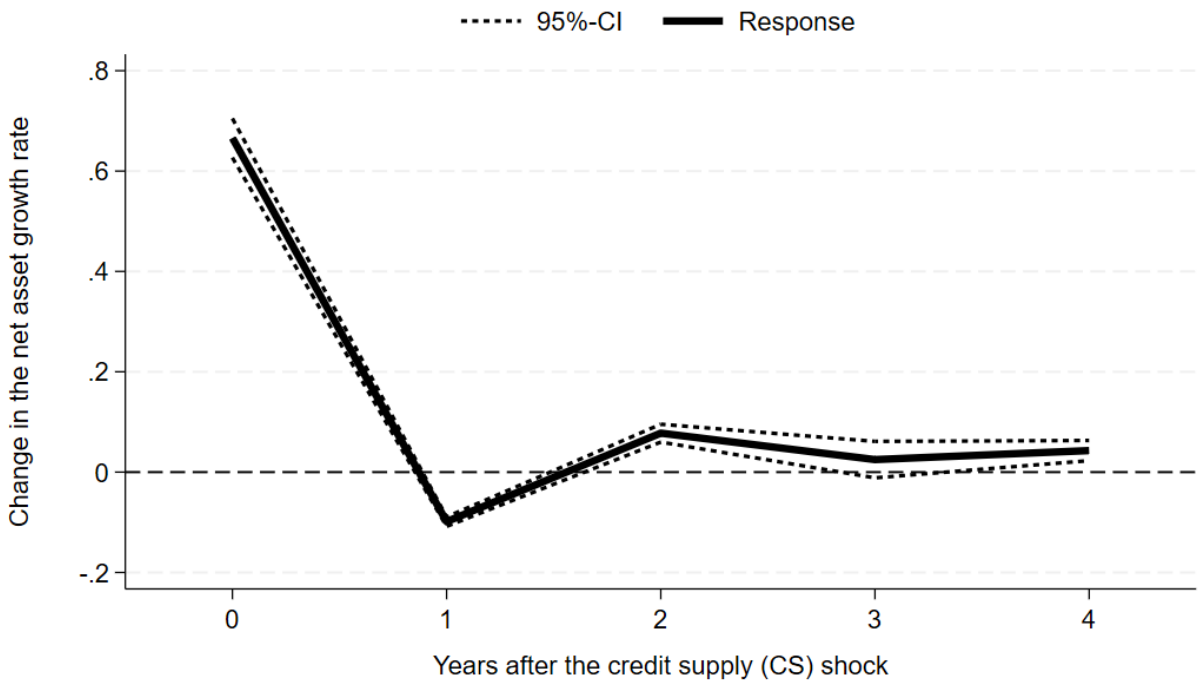
Credit supply (CS) shocks and investment: additional results at the firm level

	Subsamples			
	Bottom-50%	Top-50%	Bottom-30%	Top-30%
	(1)	(2)	(3)	(4)
CS shock$_t$	0.060	–0.135**	0.167**	0.020
	(0.048)	(0.063)	(0.069)	(0.108)
ln Employment$_{t-1}$ × CS shock$_t$	0.007**	0.002	0.012***	0.004***
	(0.003)	(0.001)	(0.005)	(0.002)
Leverage$_{t-1}$ × CS shock$_t$	0.196	0.376***	–0.010	0.354***
	(0.177)	(0.100)	(0.253)	(0.120)
ln Total Assets$_{t-1}$ × CS shock$_t$	–0.003	0.007**	–0.008**	–0.001
	(0.002)	(0.009)	(0.004)	(0.005)
MP shock$_t$	0.155**	–0.783***	0.345***	–0.981***
	(0.065)	(0.078)	(0.097)	(0.128)
ln Employment$_{t-1}$ × MP shock$_t$	0.022***	0.012***	0.027***	0.015***
	(0.004)	(0.002)	(0.007)	(0.002)
Leverage$_{t-1}$ × MP shock$_t$	–0.383	–0.261**	–0.630*	–0.250*
	(0.234)	(0.130)	(0.343)	(0.150)
ln Total Assets$_{t-1}$ × MP shock$_t$	–0.006*	0.041***	–0.017***	0.049***
	(0.004)	(0.004)	(0.006)	(0.006)
N obs	596,097	712,941	332,424	426,668
N firms	222,869	209,549	138,357	128,641

Note: The table presents additional estimates of Equation (5), in which the dependent variable is the growth rate of net assets at the firm level. Compared to the baseline estimates reported in Table 3 of the main text, we now add interactions of MP shocks with firm employment, leverage, and total assets to treat both shocks equally, and we also split the sample of firms into subsamples depending on firm size. CS and MP shocks are estimates of credit supply and monetary policy shocks obtained from the baseline SVAR model (Section 5). Both estimates are re-scaled so that negative values represent credit contractions or monetary tightenings and positive values stand for credit expansions or monetary easings, respectively. All regressions contain firm FEs, the full set of firm controls (the log of the number of workers, leverage as a sum of short- and long-term debts over total assets, the log of total assets), their interactions with the CS shock variable, and the linear time trend. The data cover the period from 2011 to 2019. *Top-50%* means the upper 50% of the distribution of firms by total assets, i.e., larger firms. *Bottom-50%* means the opposite, i.e., smaller firms. *Leverage* is divided by 100 for the sake of representation of the estimated coefficient on its interaction with the CS shock variable.

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors in parentheses.

G.2.2 Jorda (2005)'s local projections



Note: The figure displays local projections of the CS shock on firm investment (Jorda, 2005). The regression specification follows Equation (5) (as in column (1) of Table 3 in the main text) and the dependent variable modified to ΔI_{t+k} $(k = 0, 1...4)$.

Figure G.IV: Local projections of CS shocks on firm investment