# Inequality and credit growth in Russian regions

Makram El-Shagi[a], Jarko Fidrmuc*[a,b,c], and Steven Yamarik[a,d]

[a]Center for Financial Development and Stability, Henan University, China.
[b]Zeppelin University, Friedrichshafen, Germany.
[c]Faculty of Economics, Vilnius University, Lithuania.
[d]California State University Long Beach, CA, US.

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**Abstract**

We test the Rajan hypothesis using data for 75 highly heterogeneous Russian regions between the Russian crisis and the introduction of international sanctions (2000 to 2012). Applying static as well as dynamic panel data models, we show that a rise in income inequality measured by regional Gini indices is significantly correlated with the growth of personal loans. Thus, the rising inequality in Russia is likely to have implications on financial stability and occurrence of banking crises. Moreover, the correlation of inequality and corporate loans indicates that inequality affects loans growth across more channels than those implied by the Rajan hypothesis.

**Keywords:** Income inequality, bank loans, Rajan Hypothesis, Russia.
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*Corresponding author. email: jarko.fidrmuc@zu.de and jarko.fidrmuc@gmail.com. Full Address: Zeppelin University Friedrichshafen, Am Seemooser Horn 20, 88045 Friedrichshafen, Germany, Tel.: +49 7541 6009 1241, Fax: +49 7541 6009 1499.
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# 1 Introduction

In his widely-discussed book *Fault Lines*, Raghuram Rajan (2010) advanced a new cause of the U.S. Financial Crisis: income inequality. Rajan argued that in the past three decades rising income inequality created political pressure for redistribution of income. Rather than raising transfers or increasing the progressivity of taxes, U.S. politicians responded by subsidizing housing finance for the poor through affordable-housing targets, watered-down underwriting standards and new low (or even zero) down-payment mortgages. The resulting expansion of credit fueled the massive run-up in housing prices which eventually led to the banking and financial crisis of 2008-09.

The Rajan hypothesis has sparked a growing literature into the role played by inequality on credit growth.[1] In one of the first empirical papers, Bordo and Meissner (2012) examine the impact of a rise in the Top 1% income share on real credit growth across a sample of 14 OECD countries. They find *no* significant evidence linking inequality to credit growth in both the short- and long-run. Subsequent analysis has found a positive relationship between inequality and credit in the Anglo-Saxon U.S., U.K., Australia (Gu and Huang, 2014); majority voting systems U.S., U.K., Australia, Canada (Ahlquist and Ansell, 2017); U.S. states (Yamarik et al., 2016); and former Soviet republics (Latinovic and Milosevic, 2019).[2]

In this paper, we use Russian regional data for 1998 to 2013 to test the Rajan hypothesis. Our analysis provides several unique opportunities. First, Russia

[1]The second part of the Rajan hypothesis is that credit growth causes a financial crisis. There is a well-established literature that shows that growth (or cyclical deviations) of credit raises the probability and severity of a crisis for both advanced and developed countries (c.f. Kaminsky and Reinhart 1999; Schularick and Taylor 2012; El-Shagi et al. 2013). See Bazillier and Héricourt (2017) for a survey of the Rajan hypothesis along with other predictions relating inequality, credit and financial crisis.

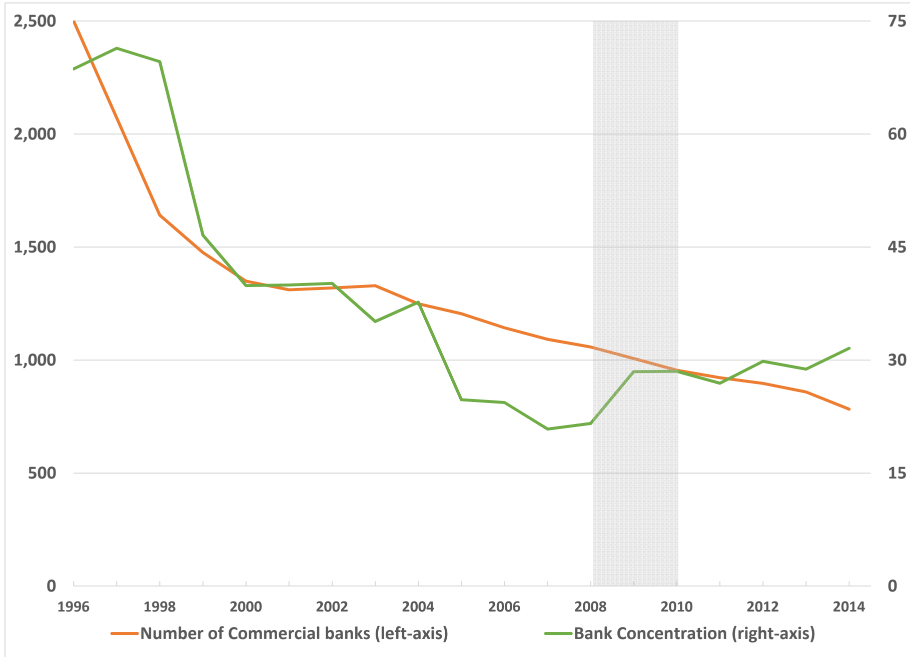
[2]In addition, researchers such as Gu and Huang (2012), Klein (2015), and Malinen (2016) find a positive long-run relationship when using error-correction methods that distinguish a long-run equilibrium and short-run dynamics.

is a post-communist transition economy which has experienced large swings in inequality. See Figure 3. However, previous tests of the Rajan hypothesis has focused on developed economies with the exception Latinovic and Milosevic (2019) and Bazillier et al. (2019). Second, the Russian data provides a large and diverse cross-section of more than 70 regions. Third, most of Russian revenue is collected at the federal level via mineral extraction (25%), corporate profit (20%), personal income taxes (20%) and value-added (19%) (Federal Tax Services of Russia, 2019). As such, the income in each region is subject to the same redistribution scheme. The one drawback however is the short length of the data, which is addressed by using panel estimators.

We find evidence to support the Rajan hypothesis in Russia. We specify an empirical model where regional credit depends upon inequality (measured as the Gini coefficient), real wage growth and other regional and national variables. We estimate the model using the change in personal, corporate and total loan share as the dependent variable. We find that increases in regional inequality has a positive impact on personal credit in Russia. Our baseline estimates imply that a 0.1 unit increase in the Gini is associated with a 0.20 to 0.24 rise in the personal credit share. The estimated effects for personal credit are quantitatively similar to those found in U.S. states by Yamarik et al. (2016) and the former Soviet republics by (Latinovic and Milosevic, 2019). We confirm the statistical and economic significance of our estimates using alternative estimators.

The rest of the paper proceeds as follows. Section 2 presents the historical background along with stylized facts and a description of the data. Section 3 provides the empirical methodology behind our panel estimators. Section 4 presents the empirical results of tests of the Rajan hypothesis. Section 5 concludes with policy implications and suggestions of future research.

Figure 1: **Number of Commercial Banks and Concentration in Russia**



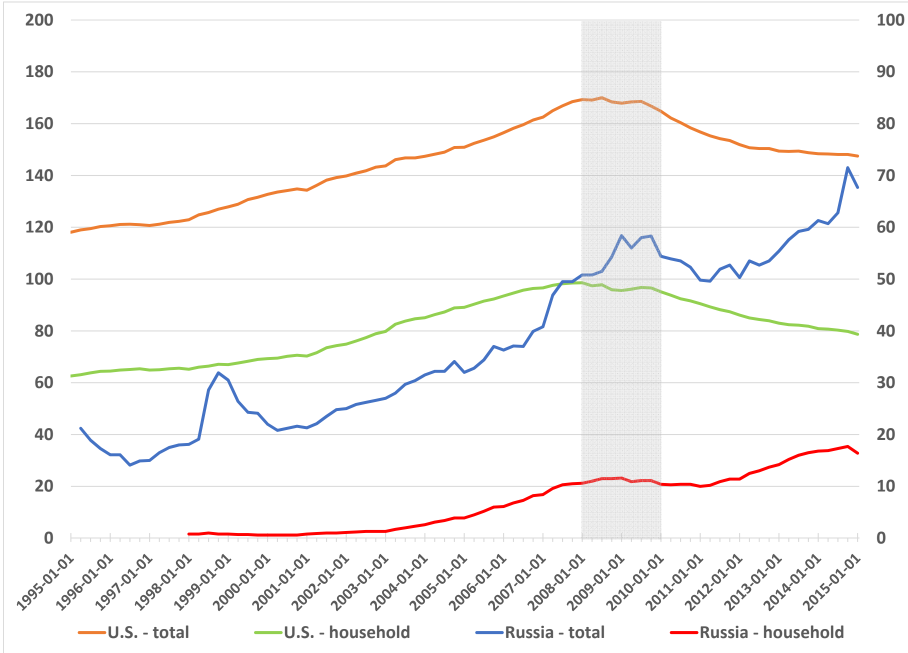

## 2 Stylized facts and data

### 2.1 Background

In 1988, the Soviet Union removed its monopoly on banking and private commercial banks began to emerge. Many of these banks exploited connections to the government and gained from access to the state budget and shares of newly privatized enterprises (Johnson, 1997). However, chronic fiscal deficits coupled with an overvalued ruble began to take its toll with the Russian government devaluing the ruble and defaulting on its domestic debt on August 17, 1998. As a result, the financial sector shrank as both the number of commercial banks and their concentration decreased markedly from 1998 to 2008. See Figure 1. From 2000 to 2008, both the number of commercial continued and their concentration. With the Financial Crisis of 2008-09, deleveraging and consolidation in the Russian bank sector led to a continued reduction in commercial banks but a higher concentration among them.

What about credit volume? Figure 2 presents total credit to private non-

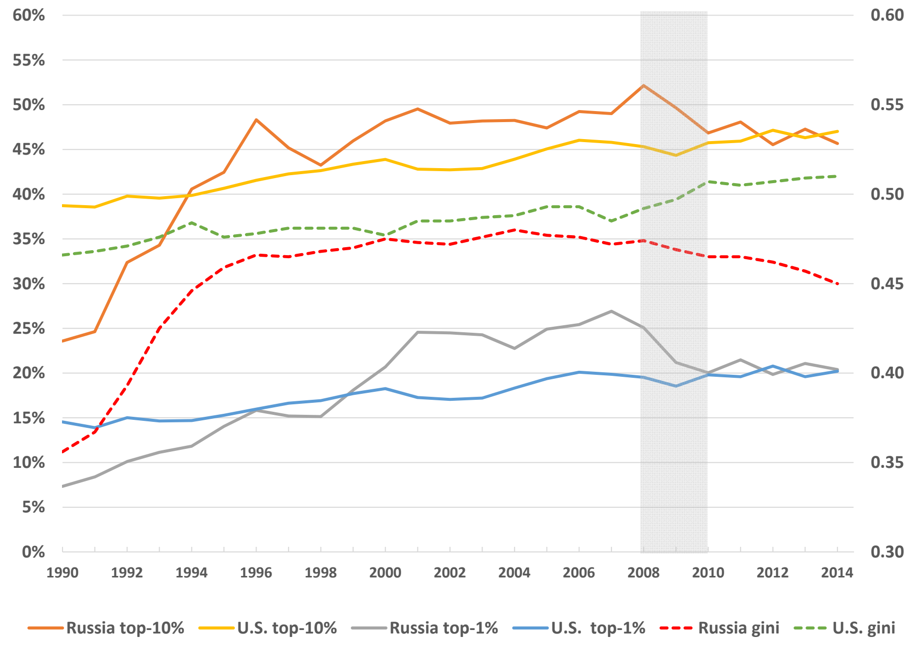
Figure 2: **Total and Household Credit in Russia and U.S. (% of GDP)**




financial sector and to households for Russia vs the U.S. The U.S. series are connected to the left axis and Russia to the right axis. Each credit series is measured as a share of GDP and is taken from Bank for International Settlements (2019). Not surprisingly, credit is much lower in Russia than in the U.S. In 1995, the share of total credit to GDP is 21 in Russia and 119 in the U.S. The difference is even greater for household credit with the Russian share never exceeding 1.0 before 2002 while the U.S. share is 60 to 70! However, Russian credit expanded much faster during the run-up to the Financial Crisis. In Russia, total credit increased nearly three-fold from 21 in 1995 to 58 in 2009 and household credit rose from 0.8 in 1998 to 11.6 in 2009. Moreover, while the U.S. economy deleveraged after the Crisis with credit shares falling to mid-2000 values, Russian credit continued to expand and reached new peaks of 71.5 for total credit and 17.7 for household credit in 2014.

Figure 3 shows income inequality measures for the U.S. and Russia. The share of national income earned by the top-10% and top-1% correspond to the left axis and the Gini coefficient to the right axis. The data are taken from

Figure 3: **Income Inequality in Russia and U.S.**




WID.world (2019) and Solt (2019), respectively. In 1990, Russia had lower levels of inequality. However, Russia experienced sharp increases in income inequality as each individual measure surpassed the U.S. by 2000. The Russian income share of the top-1% (10%) increased from 7% (23%) in 1990 to 25% (52%) in 2008. In contrast, the U.S. income share of the top-1% (10%) in the U.S. increased from 15% (38%) to 20% (45%) during the same time period. After 2008, inequality dropped in Russia but continued to rise in the U.S.

## 2.2 Data

We utilize a socio-economic data set on Russian regions, collected by Markus et al. (2016) and expanded by Fidrmuc et al. (2015) and Fidrmuc and Gundacker (2017). The sample is a balanced panel of 75 federal districts (regions) from 2000 to 2012.[3] The sample starts in 2000 with the end of Russian crisis and the collection of regional credit data. The end of the sample is given by

[3]During the sample period, there were 83 federal subjects in total: 21 republics, 9 krais (territories), 46 oblasts (regions), 2 federal cities, 1 autonomous oblast and 4 autonomous okrugs (districts). We dropped the conflict-ridden Republics of Chechenia, Dagestan, Ingushetia and North Ossetia-Alania and the 4 autonomous okrugs due to incomplete loan data.

the introduction of sanctions against Russia after the annexation of Crimea in 2014 as well as methodological changes in Russian statistics, which make longer comparisons difficult. Although short in duration, our sample is quite diverse as it includes large urban centers (Moscow and St. Petersburg) as well as large geographic regions in Siberia and the Far East.

The original data comes from several sources. Regional macroeconomic data comes from the Russian Federal State Statistics Service or Rosstat. The financial sector data at regional level comes from the Central Bank of the Russia (CBR). In some cases, we access this data from the CEIC Russia Premium Database.[4]

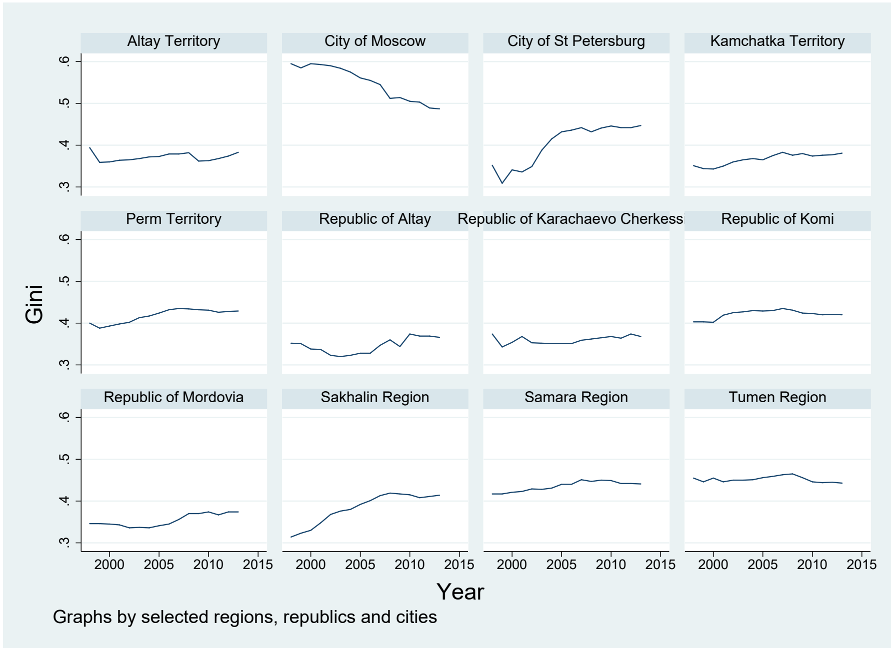
**Inequality data** Russia is an especially interesting case for understanding regional structural differences and inequality. The rise of the inequality is one of the more interesting outcomes of the economic reforms in Russia. Although reliable data is rarely available for the period before the economic reforms, it is generally agreed that inequality was low in the Soviet Union before 1990, approximately at the same level as in Scandinavia (Fidrmuc and Gundacker, 2017). By 1994, the national Gini coefficient for Russia was estimated at 0.45, which is comparable to most Latin American countries. During the subsequent two decades, the national Gini coefficients has ranged between 0.45 to 0.48 (Figure 3).

Figure 4 shows the Gini coefficient for selected regions.[5] Income inequality varies significantly across the regions. The highest levels of inequality are reported for the Cities of Moscow and St. Petersburg and the regions abundant in energy and raw materials like Komi, Perm, Samara and Tumem. These regions also contain a large number of oligarchic firms, whose presence are positively cor-

[4]The data was made available by BOFIT. We appreciate its generous hospitality and research support.

[5]At the regional level, only Gini coefficients are reported. However, Figure 3 shows a high correlation between the Gini coefficient and the top 1- and top 10-percent income group for Russia as a whole.

Figure 4: **Regional Income Inequality (Gini) for Selected Regions**

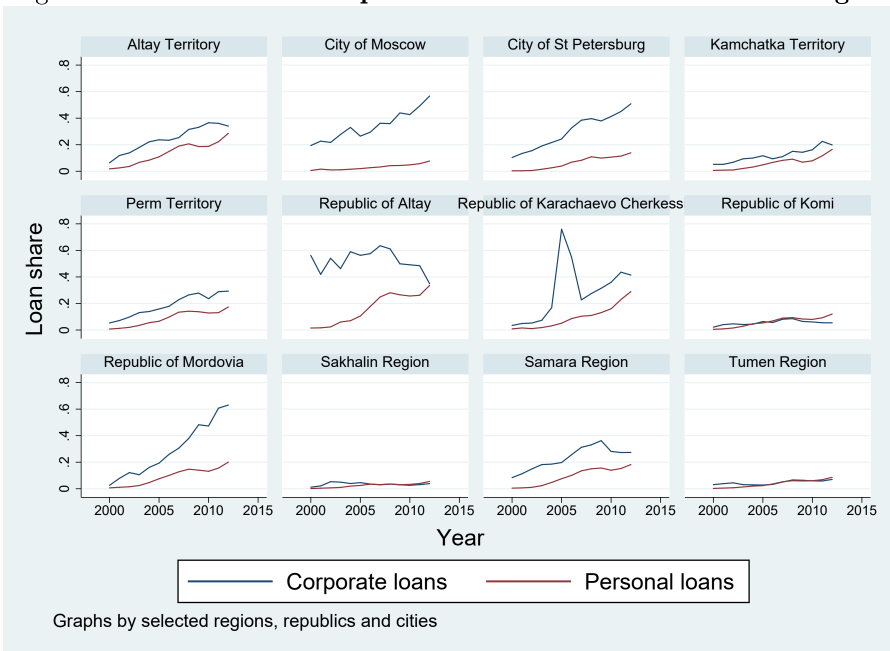



related with inequality (Fidrmuc and Gundacker, 2017). On the opposite side, regions in Siberia like Altay and in North-Kaukasus like Karachaevo Cherkessia have lower levels of inequality.

**Credit data** We measure credit as personal, corporate or total loans divided by gross regional product (GRP). We focus on personal loans given the predictions of the Rajan hypothesis. However, we also consider corporate and total loans because private and corporate borrowing cannot be so easily separated for large private investors in Russia. These private investors and oligarchs were especially important during the early phase of economic reforms at the beginning of the 1990s, as privatization deals often followed the so called 'loans-for-shares' approach in which insider-investors received underpriced state assets in return for loans, while the loans were collateralized by shares of privatized companies (Guriev and Rachinsky, 2005; Desai, 2005).

Figure 5 shows the personal and corporate loan share of GRP for selected regions. In general, each regional credit share follows the national trend of an

Figure 5: **Personal and Corporate Loan Shares for Selected Regions**




upward trajectory from 2000 to 2008, followed by a leveling off or even decline during the Financial Crisis. There are however important differences across regions. The Southern agricultural Republics of Altay, Karachaevo Cherkessia and Mordovia have the highest credit shares, while the Far Eastern regions of Kamchatka and Sakhalin and Volga regions of Perm have low credit shares.

**Other data** We also use additional regional and national economic indicators as controls. For regional controls, we include the log of real wages, unemployment rate, urban share, higher education share and the ratio of foreign direct investment (FDI) to gross regional product (GRP). For national controls, we use the CPI inflation rate, lending rate and GDP growth rate.

**Summary statistics** Table 1 provides the summary statistics of our regional data. The personal loan share ranges between 0.003-0.442 (0.3-44.2%), while the corporate loan share ranges between 0.017-3.310 (1.7-331.0%).[6] In terms of

[6]In the Republic of Kalmykia, the corporate (and total) loan share is 1.7 to 3.3 or 170 to 330% percent for 2001, 02 and 03, which is likely a recording error. No other region has a corporate loan rate above 1. We kept Kalmykia in our sample for completeness.

Table 1: Descriptive Statistics

| Description | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|
| *personal loans as a share of GRP* | 0.096 | 0.069 | 0.003 | 0.442 |
| *corporate loans as a share of GRP* | 0.195 | 0.183 | 0.017 | 3.310 |
| *total loans as a share of GRP* | 0.291 | 0.211 | 0.026 | 3.318 |
| *Gini coefficient* | 0.379 | 0.036 | 0.302 | 0.593 |
| $\Delta$ *personal loans share* | 0.016 | 0.020 | -0.046 | 0.126 |
| $\Delta$ *corporate loans share* | 0.017 | 0.121 | -0.936 | 3.016 |
| $\Delta$ *total loans share* | 0.033 | 0.122 | -0.913 | 3.021 |
| $\Delta$ *Gini coefficient* | 0.004 | 0.008 | -0.033 | 0.039 |
| *real wage growth* | 0.022 | 0.132 | -0.260 | 0.544 |
| *national inflation*, $\log(1+pi)$ | 0.109 | 0.037 | 0.049 | 0.195 |
| *national lending rate* | 0.119 | 0.025 | 0.091 | 0.165 |
| *national GDP growth*, $\log(1+g)$ | 0.046 | 0.041 | -0.081 | 0.082 |
| *unemployment rate* | 0.081 | 0.034 | 0.008 | 0.249 |
| *urban share of population* | 0.686 | 0.144 | 0.203 | 1.000 |
| *higher education share in pop.* | 0.236 | 0.053 | 0.126 | 0.499 |
| *FDI to GRP ratio* | 0.006 | 0.023 | 0.000 | 0.357 |

*Note:* There are 75 regions for 2000-2012 for a total of 900 observations.

variation, the loan shares have a coefficient of variation of 70-94%, while the Gini coefficient has one of less than 10%. In first-differences $\Delta$, the coefficient of variation rises above 100% for personal loans, 200% for Gini and 700% for corporate loans.[7]

# 3 Methodology

## 3.1 Benchmark specification

We start by testing the stationarity of the loan share data and the Gini coefficient using the panel unit root tests of Im et al. (2003) and the Fisher-type test of Maddala and Wu (1999). For each loan share, there is strong evidence of non-stationarity as we fail to reject the null of a unit root under both tests. The evidence for non-stationarity of inequality is more mixed. The Im et al. (2003) test fails to reject, but the Fisher-type test rejects the null of a unit root for small lag orders. To be safe, we treat both the loan share and Gini as

[7] If we remove Kalmykia, the coefficient of variation for corporate loans falls to 240%.

non-stationary and include them as first-differences.[8] Our basic model therefore takes the following form:

$$\Delta \ln credit_{i,t} = \beta \Delta Gini_{i,t} + BZ_{i,t} + \Gamma R_t + \alpha_i + \varepsilon_{i,t}, \tag{1}$$

where $\Delta \ln credit$ is the change in the loan share; $\Delta Gini$ is the change in the Gini coefficient; $Z$ is a vector of region-specific controls; $R$ is a vector of national controls; $\beta$, $B$, and $\Gamma$ are coefficients and coefficient vectors to be estimated; $\alpha$ is the region-specific effect; and $\varepsilon$ is the idiosyncratic component of the error term. To avoid overparameterization, our estimation includes a vector of national controls $R$ rather than fixed time effects to account for joint movements driven by the Russian business cycle.

Our preferred specification does not explicitly control for potential endogeneity. Since financial markets move much faster than the (fairly sluggish) inequality, it seems more plausible to interpret a correlation of credit (growth) and inequality as causality going from inequality to credit rather than the other way round.

We estimate equation 1 using fixed effects (FE) and a random coefficients model where both $\alpha_i$ and $\beta$ are allowed to vary across regions. The Arellano (1993) test rejects the null of random effects in favor of fixed effects for each specification.[9] The likelihood of the random coefficients model (with variation in intercept and the slope coefficients) slightly outperforms a standard random effects model (with variation in only the intercept). Additionally, when we compare the fixed effects model to a model with individually-estimated slope coefficients, the latter barely outperforms the former. As a result, there is little

[8] The 12-year time dimension of our sample is too short for a meaningful cointegration analysis.

[9] The test proposed by Arellano (1993) is technically a test for overidentifying restrictions – in this case the structure imposed on the covariance matrix by a random effects estimator. It is better suited to deal with (cluster) robust estimates of the covariance matrix than the seminal Hausman (1978) test that is typically used to compare random and fixed effects models.

random variation in the slope coefficients, making the fixed effects specification our preferred model.

### 3.2 Dynamic specification

To account for the inherent dynamics of credit growth, we also estimate a dynamic version of our model by adding a once and twice-lagged credit growth variable:

$$\Delta \ln credit_{i,t} = \phi_1 \Delta \ln credit_{i,t-1} + \phi_2 \Delta \ln credit_{i,t-2} + \beta Gini_{i,t} + BZ_{i,t} + \Gamma R_t + \alpha_i + \varepsilon_{i,t}. \tag{2}$$

where the $\phi$'s are the autoregressive (AR) coefficients.

In the past decades, the estimation of dynamic panels with country-specific effects has been dominated by the GMM approach introduced by Arellano and Bond (1991) and – possibly even more – the system GMM approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998), which is especially suitable to persistent data and has often been employed when stationarity of the endogenous variable is questionable. However, those models were originally developed for (very) small $T$. Shortly after their publication, Judson and Owen (1999) showed that the efficiency loss caused by instrumentation overcompensates the bias correction when $T$ hits 30. Even for much smaller time dimensions, the models are prone to overinstrumentation (see e.g. Okui, 2009). More importantly, Moral-Benito (2013) in a recent paper demonstrates that fixed effects models are superior to both GMM and system GMM regarding the estimation of the impact of most coefficients in a dynamic model, except the AR coefficients themselves, if the variable of interest is non-stationary (as credit)[10] or has a very low persistence (as credit growth). Since we are interested $\beta$ rather than

[10]The key problem is that system GMM is made for persistent *but stationary* data, and not data following a unit root process.

the $\phi$'s, this applies to the problem at hand. Therefore, as before, the simple FE estimator is our preferred specification.

## 4 Results

Table 2 presents the baseline results using the fixed effects estimator. The first three columns include the log of real wage and the national economic indicators as controls and the last three use real wage, national indicators along with region-specific controls. The coefficients for the national control variables have their correct sign and are generally significant but only the region-specific real wage and unemployment are significant.

The results for columns 1 and 4 indicate a positive relationship between inequality and personal loan growth of 0.20 to 0.25. In particular, an increase in the Gini coefficient of 0.01 (which is about a one standard deviation in first-differences) corresponds to an increase in the loan share of 0.25 percentage points (roughly 1/8 of the standard deviation of personal loan share in first-differenes). This result is not only statistically significant (at the 1%) level but also an economically meaningful impact.

For corporate and total loans, the point estimates for Gini are considerably larger but insignificant. Yet, this insignificance is in line with the original Rajan hypothesis where increased inequality spurs calls for redistribution that is met with more consumer credit instead. In other words, increased inequality should lead to more personal credit, in particular private "sub prime" credit.

Table 3 show the results of the random coefficients model where $\beta$ is allowed to vary across regions. The results are very similar to FE. Real wage growth and the national lending and GDP growth rate have a positive impact on credit, while national inflation has a negative effect. More importantly, the coefficient for Gini is positive and significant for personal loan growth and insignificant

Table 2: Fixed Effects Results

| credit share | (1) personal | (2) corp. | (3) total | (4) personal | (5) corp. | (6) total |
|---|---|---|---|---|---|---|
| $\Delta Gini$ | 0.241*** | 1.061 | 1.302 | 0.205*** | 0.969 | 1.175 |
| | (0.057) | (0.988) | (0.990) | (0.060) | (0.941) | (0.944) |
| *real wage growth* | 0.047*** | 0.144 | 0.191 | 0.046*** | 0.135 | 0.181 |
| | (0.003) | (0.148) | (0.148) | (0.004) | (0.155) | (0.154) |
| *national inflation* | -0.460*** | -0.134 | -0.594*** | -0.395*** | 0.102 | -0.293 |
| | (0.031) | (0.206) | (0.208) | (0.039) | (0.378) | (0.387) |
| *national lending rate* | 0.212*** | 0.051 | 0.263 | 0.148*** | -0.157 | -0.009 |
| | (0.040) | (0.194) | (0.208) | (0.047) | (0.303) | (0.327) |
| *national GDP growth* | 0.223*** | -0.015 | 0.208 | 0.198*** | -0.074 | 0.124 |
| | (0.015) | (0.143) | (0.144) | (0.016) | (0.177) | (0.177) |
| *unemployment rate* | | | | -0.165*** | -0.467* | -0.632** |
| | | | | (0.038) | (0.247) | (0.264) |
| *urban share* | | | | 0.004 | -0.111 | -0.107 |
| | | | | (0.048) | (0.242) | (0.245) |
| *higher education share* | | | | -0.034 | -0.023 | -0.057 |
| | | | | (0.024) | (0.151) | (0.149) |
| *FDI to GRP ratio* | | | | 0.007 | -0.006 | 0.001 |
| | | | | (0.022) | (0.064) | (0.077) |
| *Constant* | 0.029*** | 0.018 | 0.047* | 0.050 | 0.140 | 0.190 |
| | (0.003) | (0.026) | (0.028) | (0.033) | (0.215) | (0.213) |
| Observations | 900 | 900 | 900 | 900 | 900 | 900 |
| Number of regions | 75 | 75 | 75 | 75 | 75 | 75 |
| Time period | ’00-’12 | ’00-’12 | ’00-’12 | ’00-’12 | ’00-’12 | ’00-’12 |
| log likelihood | 2606.6 | 641.3 | 637.6 | 2622.5 | 642.9 | 640.5 |

*Note:* The dependent variable is the change in the credit share shown at the top. The standard errors clustered on regions are in parentheses where ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

Table 3: Random slope results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| credit share | personal | corp. | total | personal | corp. | total |
| $\Delta Gini$ | 0.201*** | 2.029 | 2.259 | 0.214*** | 2.050 | 2.311 |
| | (0.069) | (1.758) | (1.746) | (0.069) | (1.760) | (1.749) |
| *real wage growth* | 0.048*** | 0.032* | 0.115*** | 0.214*** | 0.054 | 0.106*** |
| | (0.005) | (0.016) | (0.033) | (0.069) | (0.033) | (0.034) |
| *national inflation* | -0.467*** | 0.213 | -0.262 | -0.491*** | 0.352 | -0.141 |
| | (0.033) | (0.233) | (0.236) | (0.036) | (0.248) | (0.251) |
| *national lending rate* | 0.002*** | -0.003 | -0.000 | 0.002*** | -0.004 | -0.001 |
| | (0.000) | (0.003) | (0.003) | (0.000) | (0.003) | (0.003) |
| *national GDP growth* | 0.225*** | 0.000 | 0.225** | 0.230*** | 0.010 | 0.238** |
| | (0.014) | (0.097) | (0.098) | (0.014) | (0.098) | (0.100) |
| *unemployment rate* | | | | 0.044*** | -0.096 | -0.054 |
| | | | | (0.017) | (0.113) | (0.115) |
| *urban share* | | | | -0.008** | -0.008 | -0.016 |
| | | | | (0.004) | (0.027) | (0.027) |
| *higher education share* | | | | -0.003 | 0.105 | 0.108 |
| | | | | (0.011) | (0.076) | (0.077) |
| *FDI to GRP ratio* | | | | -0.033 | -0.056 | -0.082 |
| | | | | (0.021) | (0.161) | (0.163) |
| *Constant* | 0.028*** | 0.019 | 0.047** | 0.032*** | 0.002 | 0.033 |
| | (0.003) | (0.024) | (0.024) | (0.006) | (0.039) | (0.039) |
| Observations | 900 | 900 | 900 | 900 | 900 | 900 |
| Number of regions | 75 | 75 | 75 | 75 | 75 | 75 |
| Time period | ’00-’12 | ’00-’12 | ’00-’12 | ’00-’12 | ’00-’12 | ’00-’12 |
| log likelihood | 2545.5 | 755.0 | 745.4 | 2552.9 | 756.4 | 746.7 |

*Note:* The dependent variable is the change in the credit share shown at the top. The standard errors clustered on regions are in parentheses where ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

Table 4: Dynamic Fixed Effects Results

| credit share | (1) personal | (2) corp. | (3) total | (4) personal | (5) corp. | (6) total |
|---|---|---|---|---|---|---|
| $\Delta Gini$ | 0.183** | 0.717** | 0.908*** | 0.156** | 0.648* | 0.811*** |
| | (0.074) | (0.336) | (0.286) | (0.076) | (0.336) | (0.299) |
| *real wage growth* | 0.049*** | 0.050 | 0.117*** | 0.048*** | 0.012 | 0.076* |
| | (0.008) | (0.044) | (0.042) | (0.008) | (0.046) | (0.045) |
| *national inflation* | -0.324*** | 0.066 | -0.247** | -0.333*** | 0.581* | 0.285 |
| | (0.032) | (0.120) | (0.109) | (0.044) | (0.342) | (0.355) |
| *national lending rate* | 0.060 | 0.074 | 0.031 | 0.066 | -0.311 | -0.361 |
| | (0.052) | (0.146) | (0.240) | (0.061) | (0.277) | (0.342) |
| *national GDP growth* | 0.158*** | 0.075 | 0.243*** | 0.145*** | 0.037 | 0.190** |
| | (0.017) | (0.057) | (0.070) | (0.017) | (0.069) | (0.080) |
| *unemployment rate* | | | | -0.077* | -0.632** | -0.746** |
| | | | | (0.042) | (0.317) | (0.338) |
| *urban share* | | | | -0.013 | 0.197 | 0.217 |
| | | | | (0.050) | (0.261) | (0.260) |
| *higher education share* | | | | -0.045** | 0.174* | 0.136 |
| | | | | (0.022) | (0.104) | (0.111) |
| *FDI to GRP ratio* | | | | 0.007 | -0.091* | -0.089 |
| | | | | (0.012) | (0.053) | (0.060) |
| Constant | 0.033*** | -0.009 | 0.032 | 0.060* | -0.141 | -0.095 |
| | (0.004) | (0.013) | (0.020) | (0.033) | (0.183) | (0.179) |
| $\Delta \ln credit_{t-1}$ | 0.497*** | 0.351 | 0.362* | 0.477*** | 0.336 | 0.338* |
| | (0.034) | (0.215) | (0.191) | (0.033) | (0.205) | (0.185) |
| $\Delta \ln credit_{t-2}$ | -0.325*** | -0.049 | -0.051 | -0.327*** | -0.050 | -0.053 |
| | (0.055) | (0.046) | (0.051) | (0.055) | (0.042) | (0.046) |
| Observations | 750 | 750 | 750 | 750 | 750 | 750 |
| Number of regions | 75 | 75 | 75 | 75 | 75 | 75 |
| Time period | '02-'12 | '02-'12 | '02-'12 | '02-'12 | '02-'12 | '02-'12 |
| log likelihood | 2263.4 | 1157.4 | 1127.9 | 2268.8 | 1171.5 | 1144.0 |

*Note:* The dependent variable is the change in the credit share shown at the top. The standard errors clustered on regions are in parentheses where ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

for corporate and total loan growth. Moreover, with the estimated impact of $\Delta Gini$ equal to 0.20 to 0.21, the economic significance of inequality is the same.

The dynamic model results in Table 4 present a slightly different picture. The effect of inequality on personal loans remains positive with a slightly smaller effect of 0.15 to 0.18. However, with the dynamic specification, we find that both corporate and total loans have a positive significant impact at the 10% and 5% level, respectively. Like before, the point estimates are considerably larger with an estimated impact of 0.70 for corporate loans and $0.80 - 0.90$ for total loans. The positive impact of inequality on total loans can be attributed to personal loans. Couple this with the insignificance of corporate loans earlier and the link between regional inequality and corporate debt is weaker than personal debt. Nevertheless, this finding suggests that inequality might affect loan growth (and thus crisis risk) through more channels than the one suggested by Rajan.

# 5 Conclusion

Russia is frequently subject to deep economic, currency, banking and financial crises. The most important outbreaks in the recent economic history include the transitional recession between 1991 and 1994, banking crisis in 1998, great recession in 2008-2009, and most recently the financial crisis of 2014-2017. These events have often damaging influence on neighboring countries and the global economy. High degree of financial vulnerability in Russia is viewed as a result of populist macroeconomic policies, weak governance, strong dependence on fuel exports, and general structural problems of the Russian economy.

This paper examines the relationship between income inequality, credits, and financial vulnerability across Russian regions which is generally known as the Rajan hypothesis (Rajan, 2010). This proposition states that rising income inequality creates political pressure for redistribution of income and subsidizing housing finance for the poor through affordable-housing mortgages. This results in expansion of credit fueling soaring housing prices which eventually leads to the banking and financial crises. There is some evidence for this channel for developed economies, but, to the best of our knowledge, there are no similar analyses for Russia or Eastern Europe so far.

The rise of income inequality constitutes one of the most important features of the current development in Russia. We show that this rise in income inequality has been accompanied by an unprecedented loan growth. Private households play an especially important role in loan expansion. We find a positive (and robust) relationship between income inequality and personal credit. Moreover, we find a statistically weaker, albeit economically larger, relationship between income inequality and corporate credit. Taken together, our results support the Rajan hypothesis where politicians respond to rising inequality in Russia by expanding housing and other private credit.

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