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Does a financial crisis change a bank's exposure to risk? A difference-in-differences approach

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Abstract

Can a major financial crisis trigger changes in a bank's risk-taking behavior? Using the 2008 Global Financial Crisis as a quasi-natural experiment and a difference-in-differences approach, I examine whether the worst crisis-hit Russian banks – the banks that have strong incentives to behavior-altering changes – can decrease their post-crisis exposure to risk. A shift in risk-taking behavior by these banks indicates the learning hypothesis. The findings are mixed. The evidence concerning credit risk is inconsistent with the learning hypothesis. On the other hand, the evidence concerning solvency risk is consistent with the learning hypothesis and corroborates evidence from the Nordic countries (Berglund and Mäkinen, 2019). As such, bank learning from a financial crisis may not depend on the institutional context and the level of development of national financial market. Several robustness checks with alternative regression specifications are provided.

Keywords: financial crisis; bank learning; bank risk; Russian banks.

JEL Classification Numbers: G01; G21; G32.

Mikko Mäkinen, orcid.org/0000-0001-5898-5277. Bank of Finland Institute for Emerging Economies (BOFIT), Snellmaninaukio, PO Box 160, FI-00101 Helsinki, Finland. Email: mikko.makinen@bof.fi.

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1 Introduction

The 2008 Global Financial Crisis (GFC) was the worst economic disaster since the Great Depression of the 1930s. Contracting GDP, declining house prices, increasing unemployment and plunging stock prices were the norm in many countries. Financial intermediaries, too, suffered large losses. In the midst of the crisis, the IMF (2009) predicted that the potential writedowns of banks for 2007-2010 could total USD 2.8 trillion in assets originated in the US, Europe, and Japan.

Financial crises, however, are not uccommon events as they have been occured at least as far back as the Middle Ages (e.g. Reinhart and Rogoff, 2009). They also often share common features. For example, crises have often preceded by excessive bank credit growth and leverage (e.g. Minsky, 1977; Schularick and Taylor, 2012; Jorda et al., 2013). Likewise, the systematic errors in beliefs of market participants prior to the 2008 GFC share key characteristics with other crises (Gennaioli and Shleifer, 2018).

Studies in economics and finance suggest that individuals and organizations can learn from their bad experiences. The early-life experience of an economic crisis, for example, can significantly affect the behavior and performance of investors and managers in later life (e.g. Malmendier and Nagel, 2011; Malmendier, Tate and Yan, 2011). Individuals may also learn from personal experiences with high inflation (Malmendier and Nagel, 2015). Organizations may change their behavior after a bad experience (e.g. Gerstner, 2002; Gennaioli et al., 2012).

Based on the above stylized facts, this paper asks whether banks could learn from their experience of financial crisis. Previously, only few empirical studies have examined this issue. Fahlenbrach, Prilmeir and Stulz (2012) (hereafter FPS) use data on listed US banks to analyze whether a bank's poor stock return performance in the 1998 crisis predicted its performance in the 2008 GFC. They find that the bank's performance in the prior crisis was a strong predictor of its poor performance and likelihood of failure in the subsequent crisis. This is inconsistent with the learning hypothesis, suggesting a persistence in bank business model over time.

Berglund and Mäkinen (2019) (hereafter BM) provide evidence for the learning hypothesis in a European context. In the early 1990s, three Nordic countries – Finland, Norway and Sweden – experienced an economic and systemic banking crisis that other European countries largely avoided. The economic and social costs of the 1990's crisis to Finland, Norway, and Sweden were so large that Reinhart and Rogoff (2008) include the Nordic crisis among the five worst post-World War II banking crises in industrialized countries. Consistent with the learning hypothesis, BM (2019) find that retail banks in the three Nordic countries were more profitable and less exposed to financial instability than other European retail banks during the 2008 GFC, implying that Nordic banks retained their bitter lessons from the 1990's crisis.

While FPS (2012) and BM (2019) consider bank performance in two subsequent crises, Bouwman and Malmendier (2015) take a different view by looking at whether a bank's history of financial crises is related to its capitalization and risk-taking. Using data for commercial US banks from 1984 to 2010, they find that bank experiences of difficult times predict more careful lending behavior and higher capitalization over the long run. Berger and Udell (2004) test their institutional memory hypothesis by analyzing whether loan officer skills deteriorate among US banks over time following a loan bust. They show that the trauma of the loan bust initially dominates the judgment of loan officers, but credit standards ease as times go by, suggesting that the learning effects from a financial crisis attenuate over time.

This paper relates to the above studies in three ways. First, the paper studies bank learning from financial crisis in an emerging market context. Second, the paper focuses on the hardest-hit banks. Third, the paper examines bank learning from the 2008 GFC.

To shed more light on these issues, I use a rich body of bank-level financial statements data from Russia covering the period 2005-2013. As I discuss in more detail later, the Russian economy was severely hit by the 2008 GFC; in 2009, real GDP plunged by 7.8% and unemployment rate climbed to 8.3%. The crisis was, however, a short-term blow to the economy as real GDP grew by 4.5% in 2010, followed by growth of 3.1% in 2011, 4.0% in 2012, and 1.8% in 2013. Thus, the swift economic recovery after the crisis gave banks a favorable environment in which to change their post-crisis exposure to risk, if anything. More importantly, the 2008 GFC was an exogenous shock to the economy since the crisis emerged outside Russia. Hence, my identification strategy uses the 2008 GFC as a quasi-natural experiment (i.e. a source of independent variation across the banks).[1]

This paper contributes to the literature on bank learning from financial crisis in four ways. First, the paper considers evidence from an emerging market economy. Previous studies have focused on advanced economies such as the US (e.g. Berger and Udell, 2004; FPS, 2012; Bouwman and Malmendier, 2015) and the European banking sector (BM 2019). The institutional characteristics of Russia's financial markets, however, can be expected to bear on the ability and willingness of banks to respond to financial shocks – particularly how they alter their post-crisis exposure to risk compared with banks in advanced economies. Besides a less developed financial sector, Russia's banking sector during the period of this study was characterized by insufficient supervision and a lack of transparency. The banking sector was also dominated by a few state-owned banks, while most banks were small and undercapitalized. Taken together, these differences with banks of advanced economies suggest fairly muted incentives for the Russian banks to change their post-crisis exposure to risk.

Second, unlike previously published studies on the topic, the paper utilizes a difference-in-differences approach that shows the *causal effect* of financial crisis on bank post-crisis exposure to risk. This importantly extends previous studies by FPS (2012) who examine how a bank's performance in a prior crisis predicts its performance in a subsequent crisis, BM (2019) who compare bank performance and financial stability during the subsequent crisis, as well as Bouwman and Malmendier (2015) who analyze whether a bank's history of financial crisis is correlated with its capitalization and risk appetite in the long-run.

[1] Identification strategies that use an exogenous crisis as a source of an independent variation across observations include, among others, Beltratti and Stultz (2012) and Chodorow-Reich (2014).

Third, the paper takes advantage of rich panel data for the various types of banks in a single country. This is contrast to FPS (2012), who only use data on listed US banks, and BM (2019), who focus on Europe's retail-oriented banking sector.

Fourth, I study bank learning from the 2008 GFC, the worst economic crisis since the Great Depression of the 1930s, while acknowledging, of course, that the ultimate impacts of the COVID-19 pandemic have yet to be known. In FPS (2012) the prior crisis is the 1998 Russian sovereign debt crisis, while BM (2019) look to the Nordic crisis of the early 1990s.

The findings indicate that the worst crisis-hit Russian banks were more exposed to post-crisis credit risk compared with other banks. This is inconsistent with the learning hypothesis. For solvency risk, however, the evidence is consistent with the learning hypothesis. This finding comports with BM (2019), who look at bank learning from a financial crisis in the Nordic economies. As such, bank learning from a financial crisis may not depend on the institutional context or the level of financial market development.

The paper is organized as follows. Section 2 provides a brief overview of the 2008 GFC in Russia. Section 3 describes the data and empirical approach. Section 4 presents the key findings as well as several robustness checks. The final section concludes and discusses implications for policy.

2 The 2008 GFC and the Russian economy

While the effects of the 2008 GFC on the Russian economy are well-documented (see, e.g., Aslund et al., 2010; Gaddy and Ickes, 2010; Suvankulov and Ogucu, 2012; Fungacova et al., 2013; Mäkinen and Solanko, 2018; Ananyev and Guriev, 2018), it is worthwhile to summarize some of the main Russia-specific features of the crisis.

The 2008 GFC was fundamentally an exogenous shock to the Russian economy. First, the crisis emerged outside of Russia, after the meltdown of US housing market. Second, Russian banks had virtually no direct exposure to US subrime mortages. Third, when the crisis sent global commodity prices into a tailspin, it affected to the Russian economy due to its high dependence on exports of oil and other commodities. As crude oil prices are based on supply and demand in global commodity markets, no single country can unilaterally dictate the market price. Relying on these stylized facts, my identification strategy uses the 2008 GFC as a quasi-natural experiment.

Russian real GDP growth plunged by 7.8% in 2009. Based on quarterly GDP growth rates at constant prices, the on-year economic growth was -9.2% in 2009Q1, -11.2% in 2009Q2, -8.6% in 2009Q3, and -2.6% in 2009Q4. Thus, the economic stress was most severe in the first three quarters of 2009. The crisis was short-lived, however, as real GDP growth of 4.5% roared back in 2010, followed by 3.1% growth in 2011, 4.0% in 2012 and 1.8% in 2013.

The banking sector grew rapidly in the 2000s. During the decade, growth averaged over 35% a year and the banking sector credit and assests to GDP ratios more than doubled, reaching 75% and 40%, respectively, by the end of 2010 (Fungacova et al., 2013). State-controlled banks (at least half of equity) played a dominant role in the sector. Although the number of state-controlled banks was about 40 in 2007, all of the five biggest banks in the sector were state-controlled. Moreover, state-controlled banks held 50-55% of the sector's total assets in 2007-2011 (Vernikov, 2012). During the decade, the number of foreign banks increased from 174 banks in 2000 to 220 banks in 2010, and foreign banks' share of the sector's total assests was about 20 % in the 2000s (Fungacova et al., 2013). Domestic private banks made up the rest of the sector. With about 700 banks, this was the largest group of banks, but most were small and their combined share of the sector's total assests was only about 5% (Fungacova et al., 2013).

The number of operating banks licensed to take private deposits decreased from about 1,100 banks in 2008 to about 920 banks in 2013. Based on Mäkinen and Solanko (2018), the sudden fall in global oil prices and subsequent drop in the ruble and stock prices increased the amount of non-performing loans and diminished bank profits during the crisis. The foreign credit supply for banks, mostly short-term funding, was cut down during the crisis, leading to financial difficulties. Further, heightened counterparty risk and loss of confidence raised liquidity shortages in the interbank markets. Bank lending, which had seen about 45% annual average growth between 2002 and 2007, dropped to -2.5% in 2009 (Fungacova et al., 2013).

However, central bank funding and government support loans, the dominant role of state-owned banks, and relatively low leverage ratios helped the banking sector through the crisis relatively unscathed. Despite the financial woes of the worst crisis-hit banks (the mean ROA for this group of banks dropped from 1.6% in 2007 to -1.1% in 2009), the crisis never threatened the financial stability of the sector.

The aftermath of the crisis induced large changes in bank regulation and supervision and changed the sector thoroughly from 2013 onwards. Between 2013 and 2016, over 300 credit institutions lost their licenses, forcing them either to liquidate or restructure their operations. However, since it is empirically unfeasible to distinguish the effects of bank learning from financial crisis from the effects of (i) the major consolidation of the banking sector between 2013 and 2016, (ii) the first Western sanctions on Russia that were imposed in spring 2014, and (iii) the 2015 depression (Russian real GDP growth contracted by 2% in 2015) on banks' post-crisis risk-taking, I limit my focus here to the period 2005 to 2013.

3 Data and empirical approach

3.1 Data

The data of individual banks have been extracted from the website of the Central Bank of Russia (CBR). For the purpose of this study, I focus on annual balanced panel data on the period before and after the 2008 GFC. These rich balance-sheet data have previously used in a number of empirical banking studies (e.g. Fungacova et al., 2013; Mäkinen and Solanko, 2018 among many others).

Several issues affect the definitions of pre-treatment, treatment and post-treatment periods in the paper. First, the *pre-treatment period* is 2005-2007. To mitigate potential anticipation concerns of the 2008 GFC among banks, I exclude 2008 from the sample. Second, the three-year *treatment period* is 2009-2011. Russian real GDP growth declined by 7.8% in 2009, but as banks may need time to change their behavior after the crisis, I include 2010 and 2011 in the treatment period. Moreover, it is difficult to distinguish empirically the effects between bank learning from the crisis and immediate behavioral responses of banks to the crisis. Third, the two-year *post-treatment period* is 2012-2013. As part of the robustness checks, however, I consider a longer time period in Section 4.2.

In defining the groups of treated and non-treated banks, I utilize the percentiles of return-on-assets (ROA) distribution in the banking sector in 2009. In the baseline specification, the treated banks is the bottom 20% of the banks in the distribution, while the control group is the top 80%. However, I include a robustness check with other percentiles of ROA distribution in the banking sector in 2009 as cut-offs in Section 4.2.

I construct the estimable sample of banks as follows. First, I use a balanced panel data set of banks to be able to apply the difference-in-differences approach (i.e. the banks that have lost their banking license during 2005-2013 are excluded).[2] Second, following Berger and Bouwman (2013), I require that banks included in the sample have more than 1% outstanding customer loans and customer deposits. Third, following BM (2019), I exclude banks if the ratio of total loans to total deposits (LDR) exceeds 500%. Fourth, banks with missing observations are dropped from the sample. Fifth, to mitigate the effects of extreme values in estimations, I winsorize dependent and independent variables at the 1% and 99% levels. The estimable balanced panel data include 434 banks that operated over the full sample period of 2005-2013, or 2,170 bank-year observations. Table 1 shows summary statistics over the sample period for all banks, treated banks and non-treated banks.

[2] The number of operating banks licensed to attract personal deposits declined by 28% between 2005 and 2013. Importantly, there were no significant changes in banking supervision during the period. The CBR's current governor, Elvira Nabiullina, took the helm in the mid-2013, and the major clean-up of the banking sector began in 2014. Between 2013 and 2016, the number of operating banks dropped by over 30%. See e.g. Mäkinen and Solanko (2018) for more on bank license withdrawals in Russia.

Table 1. Summary statistics

	(1) All banks		(2) Non-treated banks (top 80%)		(3) Treated banks (bottom 20%)	
	Mean	SD	Mean	SD	Mean	SD
CAR	15.51	8.01	15.97	8.29	13.29	6.03
Bad Loans/TL	3.83	4.64	3.56	4.33	5.10	5.72
Liquid Assets/TA	28.86	14.12	28.68	14.11	29.72	14.18
Loans/TA	64.33	14.57	64.64	14.54	62.81	14.61
Deposits/TA	46.75	16.18	46.18	16.27	49.51	15.45
Bank Size	15.17	1.91	15.07	1.86	15.68	2.09
N	2170		1795		375	

3.2 Dependent and control variables

For the dependent variable, I use two common risk-exposure measures employed in literature, solvency and credit risk. A bank's solvency risk is measured by its capital adequacy ratio, *CAR*, a proxy for its financial strength. *CAR* is calculated as the ratio of bank capital to total assets (%), where capital denotes a bank's own equity, calculated as the sum of statutory capital, surplus capital, current and past retained earnings, and other capital. Following Poghosyan and Cihak (2011), I use the unweighted capital ratio as the data do not include information on bank risk-weighted assets. The higher the ratio, the more stable and efficient the bank is and, therefore, the less likely it is to become insolvent. A bank's credit risk is proxied by *Bad Loans*, calculated as the sum of credit losses and overdue loans. Overdue loans are included in *Bad Loans* since e.g. lax accounting standards may allow financially troubled banks to delay reporting of loan losses from overdue loans. *Bad Loans* is measured by the ratio of bad loans to total loans (%). To be financially successful, a bank needs to keep the level of its bad loans at a minimum.

Considering bank-level control variables, I follow much of empirical banking studies using a standard set of covariates. First, *Bank Size* may bear upon exposure to risk. For example, large banks may be able to tolerate more risk than smaller banks, or use their scale to gain a competitive edge. I use the logarithm of total assets as a proxy for *Bank Size*. To control for potential non-linearities with respect to *Bank Size*, I add its square as control variable. Second, to control for observable differences across banks, I include *Liquid Assets/Total Assets*, *Total Loans/Total Assets*, and *Total Deposits/Total Assets* as control variables.

3.3 Empirical approach

Contrast to the previous studies, I use the difference-in-differences (DID) approach. This is a feasible method when the observations in two groups are otherwise similar, but one group is exposed to some form of treatment, broadly understood, that the other group is not. The key benefit of the DID approach here is that it explicitly shows whether the 2008 GFC *effects* on bank post-crisis risk exposure, i.e. whether the worst-hit banks show evidence of learning from the crisis, the key question of this paper.

I classify banks into treated and non-treated[3] groups based on the percentiles of ROA distribution in the banking sector in 2009, when real GDP growth contracted by 7.8%. In the baseline specification the group of treated banks (T_i) is the bottom 20% of ROA distribution. The top 80% of banks, a group of banks that is less affected by the 2008 GFC, is the control group (C_i).[4] Since I have a balanced panel data set of individual banks, I apply the fixed effects panel data difference-in-differences estimator, which allows controlling for unobserved heterogeneity across banks.

The outcome of interest $Y_{i,t}$ is modeled as follows in the baseline specification:

$$Y_{i,t} = \beta_0 + \beta_1 T_i + \beta_2 POST + \beta_3 T_i * POST + \beta_4 X_{i,t} + \beta_5 YEAR_t + FE_i + \epsilon_{i,t}. \tag{1}$$

In Eq. (1) $Y_{i,t}$ is a measure for risk exposure (CAR or *Bad Loans*) and $X_{i,t}$ is the vector of control variables (*Bank Size*, *Bank Size*^{2}, *Liquid Assets/Total Assets*, *Total Loans/Total Assets*, *Total Deposits/Total Assets* and an outcome variable not explained in the model).

[3] Alternatively, the group of non-treated banks can be seen as the group of banks receiving standard treatment.

[4] As alternative classifications for the treated banks in the robustness checks, I use the bottom 10% and the median of the banks in the ROA distribution in 2009.

$POST$ equals one for the post-treatment period 2012-2013, and zero otherwise. To control for pre-crisis differences across banks, I include bank-level observations for 2005-2007. As said earlier, due to potential anticipation and the early stage effects of the crisis, I drop 2008 from the sample. I also exclude observations for 2010 and 2011 since it may be challenging for banks to alter their behavior immediately after the crisis.[5] Further, to isolate potential effects of the first Western sanctions imposed on Russia in spring 2014 as well as to anticipate the increasing trend of bank license withdrawals after 2013, the last year in the sample is 2013. In other words, in Eq. (1) time t=2005, 2006, 2007, 2012, 2013.[6] The binary variable T_i equals one for treated banks, and zero otherwise. I also include bank fixed effects (FE_i) to control for the unobserved heterogeneity across banks.

The key parameter of interest is β_3, showing whether treated banks, on average, change their exposure to risk, due to the crisis, more than other banks. In other words, β_3 shows the mean difference between treated (T) and non-treated banks (C) from pre- to post-period: $\hat{\beta}_3 = [\overline{Y}_{T,after}$ - $\overline{Y}_{C,after}]$ - $[\overline{Y}_{T,before}$ - $\overline{Y}_{C,before}]$.

[5] It is evident that both treated and non-treated banks faced financial challenges from the 2008 GFC. As the Russian economy recovered swiftly after the crisis, improved macroeconomic environment helped banks to change their exposure to solvency and credit risk as well as make other performance-enhancing choices. Thus, the baseline DID model tests for whether there was a significant difference in risk exposure between the worst crisis-hit banks and other banks during 2012-2013, compared to the pre-crisis level. If there is no significant difference between these two groups of banks in 2012-2013, this is taken as the evidence of bank learning from financial crisis, and vice versa.

[6] As shown on page 14, the reported key findings are robust to different time definitions.

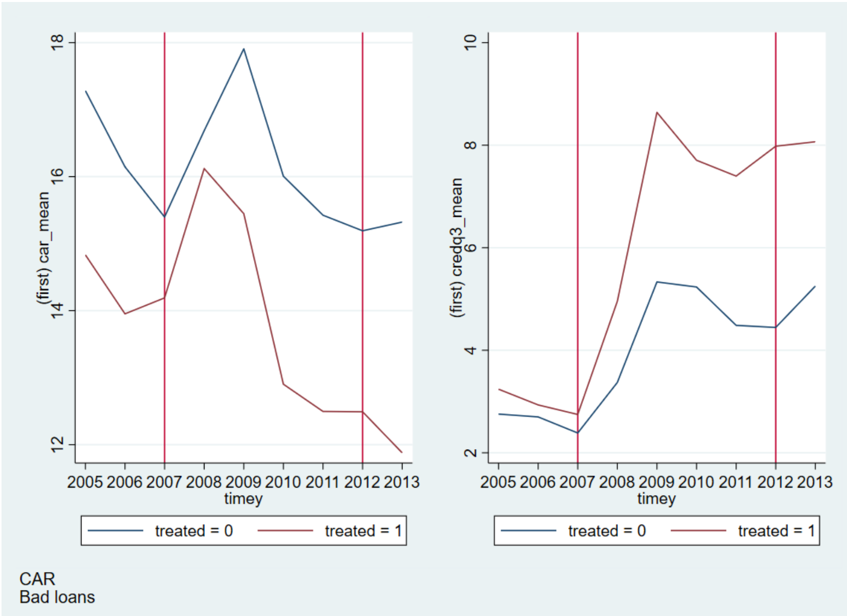
Eq. (1) yields the key hypotheses of the paper:

- H1 (*Bad Loans*). If $\beta_3 < 0$, the expected mean change in *Bad Loans* has been lower for treated banks from pre- to post-crisis period (i.e. exposure to credit risk has declined). This would be consistent with the learning hypothesis. If $\beta_3 > 0$, this would be inconsistent with the learning hypothesis.

- H2 (*CAR*). If $\beta_3 > 0$, the expected mean change in *CAR* has been greater for treated banks from pre- to post-crisis period (i.e. exposure to solvency risk has delined). This would be consistent with the learning hypothesis. If $\beta_3 < 0$, this would be inconsistent with the learning hypothesis.

The key assumption in applying the difference-in-differenced approach is the parallel pre-treatment trends between treated and non-treated groups. To explore whether this assumption holds in the baseline model, I perform two exercises. First, Figure 1 shows a visual inspection of the parallel trends assumption using the mean values of *CAR* and *Bad Loans* over time, separately for treated and the non-treated banks. The common trends assumption appears to apply visibly for *Bad Loans*, and it seems to hold for *CAR* at least approximately.

Figure 1. Common trends assumption



Second, to test statistically the validity of the common trends assumption, I re-estimate Eq. (1) using the interactions of the year dummies $YEAR_t$, where t=2005, 2006, 2007, 2012, 2013, and the treatment indicator T_i as follows:

$$Y_{i,t} = \beta_0 + \beta_1\, T_i + \beta_2\, YEAR_t + \beta_3\, T_i * YEAR_t + \beta_4\, X_{i,t} + FE_i + \epsilon_{i,t}. \tag{2}$$

If the null hypothesis of the common trends in the pre-crisis period is not rejected, the interactions of $T_i * YEAR_{t=2006}$ and $T_i * YEAR_{t=2007}$ in Eq. (2) should be statistically insignificant. As Table 2 shows, both for CAR and $Bad\ Loans$, the estimated coefficients for the differing pre-crisis trends are insignificant at 10% level. Hence, the key DID assumption does not appear to be violated here.

Table 2. DID panel data FE regressions: common trends assumption

	(1) Bad Loans	(2) CAR
treated=1 × 2006=1	-0.483	0.318
	(-0.89)	(0.39)
treated=1 × 2007=1	-0.498	1.065
	(-0.91)	(1.32)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Banks	434	434
Observations	2170	2170
Adjusted R-squared	0.336	0.357

t statistics in parentheses

Notes: Treated banks=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2012-13.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4 Estimation results

4.1 Main findings

Table 3 shows the baseline estimation results for Eq. (1), where the bottom 20% of banks in the 2009 ROA distribution is defined as treated banks and top 80% as non-treated banks. In column (1) of Table 3, where the dependent variable is *Bad Loans*, a proxy for bank credit risk, the estimated coefficient of $POST$=1 is 4.7 and significant at the 1% level. This can be interpreted as mean change of time in *Bad Loans* from 2005-2007 to 2012-2013. The estimated parameter of the interaction term shows that mean change in *Bad Loans* from 2005-2007 to 2012-2013 differs between treated and non-treated banks. The interaction term is positively (2.9) significant at the 1% level, indicating that the mean increase in *Bad Loans*, from the pre- to post-crisis period, was greater for treated banks than other banks. This finding is inconsistent with the learning hypothesis (H2: $\beta_3 > 0$). In column (2) of Table 3, the outcome variable is CAR, a proxy for bank solvency risk. The estimated mean effect of time, i.e. the coefficient of $POST$=1, is positive (5.5) and significant at the 1%

level. This implies that banks, on average, were able to enhance their capitalization from 2005-2007 to 2012-2013. Importanly, the parameter estimate of the interaction term is -0.7 but insignificant. This implies that there is no statistically significant difference in CAR between treated and other banks in 2012-2013, which is consistent the learning hypothesis.

Table 3. DID panel data FE regressions: treated banks bottom 20%

	(1) Bad Loans	(2) CAR
post=1	4.665***	5.482***
	(12.40)	(9.70)
treated=1 × post=1	2.935***	-0.702
	(8.22)	(-1.31)
ROA	-0.0564	0.871***
	(-0.85)	(9.09)
Liquid Assets/TA	-0.0372*	-0.295***
	(-1.83)	(-10.07)
Loans/TA	-0.121***	-0.203***
	(-6.18)	(-7.04)
Deposits/TA	-0.00576	-0.194***
	(-0.70)	(-17.20)
Bank Size	-7.078***	-2.403**
	(-10.19)	(-2.28)
Bank Size^2	0.191***	-0.0286
	(8.29)	(-0.82)
CAR	0.00300	
	(0.18)	
Bad Loans/TL		0.00656
		(0.18)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Banks	434	434
Observations	2170	2170
Adjusted R-squared	0.335	0.357

t statistics in parentheses

Notes: Treated banks=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2012-13.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tables 4 and 5 show the estimation results using alternative definitions for treated and non-treated banks.[7] In Table 4, treated banks are defined as the bottom 10% of banks' ROA distribution in 2009. In other words, the group of treated banks is now *more severely* affected by the 2008 GFC than in Table 3. Column (1) of Table 4 shows that the coefficient of $POST$ (4.9) is positively significant at the 1% level. As earlier, this indicates an increase in *Bad Loans*, a proxy for bank credit risk, from 2005-2007 to 2012-2013. The estimated parameter of the interaction term is 3.3 and significant at the 1% level. This shows that mean increase in *Bad Loans*, from pre- to post-crisis period, was greater for treated banks. This is again inconsistent with the learning hypothesis. When the depended variable is CAR, a proxy for bank solvency risk, column (2) of Table 4 shows that the estimated coefficient of $POST$=1 is 5.6 and significant at the 1% level. Thus, on average, banks have been able to enhance their capitalization from 2005-2007 to 2012-2013. Contrast to Table 3, however, the interaction term is now negatively significant (-2.4) at the 1% level. This is inconsistent with the learning hypothesis, implying treated banks' exposure to solvency risk is greater in the post-crisis period.

[7] The null hypothesis of common trends is not rejected in Tables 4 and 5 as the estimated coefficients for the differing pre-crisis trends are insignificant. These are not reported here but available upon request.

Table 4. DID panel data FE regressions: treated banks bottom 10%

	(1) Bad Loans	(2) CAR
post=1	4.920***	5.577***
	(13.08)	(9.93)
treated3=1 × post=1	3.330***	-2.358***
	(6.22)	(-2.98)
ROA	-0.0683	0.859***
	(-1.02)	(8.98)
Liquid Assets/TA	-0.0283	-0.303***
	(-1.37)	(-10.30)
Loans/TA	-0.112***	-0.210***
	(-5.63)	(-7.30)
Deposits/TA	-0.00472	-0.193***
	(-0.57)	(-17.09)
Bank Size	-7.525***	-2.247**
	(-10.78)	(-2.13)
Bank Size^2	0.206***	-0.0357
	(8.88)	(-1.03)
CAR	0.00611	
	(0.37)	
Bad Loans/TL		0.0131
		(0.37)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Banks	434	434
Observations	2170	2170
Adjusted R-squared	0.324	0.359

t statistics in parentheses

Notes: Treated banks=the bottom 10 percent of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2012-13.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 5 the cut-off for treated banks is the median (50%) of the banks' ROA distribution in 2009. Thus, the group of treated banks is now *less exposed* to the 2008 GFC crisis compared with Table 3. In column (1) of Table 5, when the dependent variable is *Bad Loans*, by and large the findings are consistent with those of reported for the baseline model in column (1) of Table 3. Likewise, when the depended variable is CAR, in column (2) of Table 5 the findings are in line with the results reported in column (2) of Table 3.

Table 5. DID panel data FE regressions: treated banks below median

	(1) Bad Loans	(2) CAR
post=1	4.621***	5.640***
	(11.63)	(9.60)
treated2=1 × post=1	1.413***	-0.591
	(5.22)	(-1.48)
ROA	-0.0756	0.872***
	(-1.13)	(9.10)
Liquid Assets/TA	-0.0429**	-0.294***
	(-2.08)	(-10.03)
Loans/TA	-0.125***	-0.202***
	(-6.35)	(-7.02)
Deposits/TA	-0.00373	-0.195***
	(-0.45)	(-17.25)
Bank Size	-7.287***	-2.417**
	(-10.38)	(-2.29)
Bank Size^2	0.194***	-0.0275
	(8.32)	(-0.79)
CAR	0.00189	
	(0.11)	
Bad Loans/TL		0.00404
		(0.11)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Banks	434	434
Observations	2170	2170
Adjusted R-squared	0.320	0.357

t statistics in parentheses

Notes: Treated banks=the median or less of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2012-13.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Robustness checks

I start with three exercises to assess whether alternative definitions for the pre- and post-treatment periods have any bearing on the key findings. First, I estimate Eq. (1) using simple means of dependent and independent variables in the pre-treatment period 2005-2006 and the post-treatment period 2012-2013 (i.e. the two-year average values). Second, I estimate Eq. (1) using just two-years of data: 2005 (pre) and 2013 (post). Third, I define the pre-treatment years as 2005-2007, the treatment years as 2008-2009 and use individual dummy variables for the post-treatment years 2010, 2011, 2012 and 2013. The reported findings in Tables 6-8 are qualitatively similar to those discussed earlier. For the sake of brevity, I do not report the estimated coefficients for control variables in Tables 6-8.

Table 6. DID panel data FE regressions: two-year averages

	(1) Bad Loans	(2) CAR
post=1	4.279***	5.701***
	(6.25)	(5.90)
(first) treated=1 × post=1	2.462***	-0.0989
	(3.32)	(-0.11)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Control variables	Yes	Yes
Banks	428	428
Observations	856	856
Adjusted R-squared	0.334	0.409

t statistics in parentheses

Notes: Treated=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=averege(2005-06), Post=average(2016-17).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. DID panel data FE regressions: 2005 vs. 2013

	(1) Bad Loans	(2) CAR
post=1	6.039***	8.446***
	(5.07)	(7.96)
treated=1 × post=1	4.929**	-0.957
	(2.50)	(-0.52)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Control variables	Yes	Yes
Banks	376	376
Observations	752	752
Adjusted R-squared	0.435	0.451

t statistics in parentheses

Notes: Treated=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=2005, Post=2015.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. DID panel data FE regressions: individual post-treatment years

	(1) Bad Loans	(2) CAR
treated=1 × 2010=1	1.700***	-0.423
	(3.61)	(-0.67)
treated=1 × 2011=1	2.581***	-0.636
	(5.51)	(-1.01)
treated=1 × 2012=1	3.115***	-0.643
	(6.65)	(-1.02)
treated=1 × 2013=1	2.509***	-1.041*
	(5.34)	(-1.65)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Control variables	Yes	Yes
Banks	427	427
Observations	2989	2989
Adjusted R-squared	0.313	0.364

t statistics in parentheses

Notes: Treated=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2010-13.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the second check, following Mäkinen and Solanko (2018), I exclude from the estimable sample the six largest state-controlled banks[8] as well as the largest foreign-owned banks[9]. While these banks may have learned from the bad experience of financial crisis, they differ in many respects from other banks in Russia. As reported in Table 9, the key findings remain qualitatively unaltered.

Table 9. DID panel data FE regressions: major foreign and state-owned banks excluded

	(1) Bad Loans	(2) CAR
post=1	4.710***	5.647***
	(12.49)	(9.83)
treated=1 × post=1	2.667***	-0.663
	(7.42)	(-1.21)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Control variables	Yes	Yes
Banks	423	423
Observations	2115	2115
Adjusted R-squared	0.328	0.360

t statistics in parentheses

Notes: Major foreign and state-owned banks excluded. Treated=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2012-13.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the third check, I note that bank learning from financial crisis might take longer to materialize after the crisis than in the baseline model. A convincing counter-argument to this is that worst-hit banks face strong incentives to change their post-crisis exposures to risk as soon as possible after the crisis to be able to survive in the banking business. As pointed out earlier, it is empirically challenging in the case of Russia to distinguish the effect of the 2008 GFC on bank learning over the longer time period due to other factors, including (i) the first Western sanctions, (ii) the major consolidation of the banking sector, and (iii) the 2015 economic depression. Nevertheless, with these caveats, I proceed with the robustness

[8] These are Sberbank, VTB, VTB24, Gazprombank, Rosselkhozbank, and Bank Moskvi.

[9] The largest foreign-owned banks in Russia are Unicredit, Raiffeisen, Citibank, Rosbank (Societe General) and Nordea.

check estimating Eq. (1) using 2005-2007 as the pre-treatment period and 2012-2017 as the post-treatment period. Table 10 shows that the findings are consistent, if not even stronger, with the baseline findings reported in Table 2.

Table 10. DID panel data FE regressions: 2005-07 vs. 2012-17

	(1) Bad Loans	(2) CAR
post=1	11.98***	9.203***
	(13.25)	(14.35)
treated=1 × post=1	7.464***	1.136*
	(8.56)	(1.80)
Bank fixed effects	Yes	Yes
Year dummies	Yes	Yes
Control variables	Yes	Yes
Banks	273	273
Observations	2457	2457
Adjusted R-squared	0.365	0.367

t statistics in parentheses

Notes: Treated=the bottom 20 percent of ROA distribution in the banking sector in 2009. Pre=2005-07, Post=2012-17.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

This paper analyzed whether a financial crisis can trigger changes in the risk-taking behavior of banks focusing on an emerging market economy, where institutions are weaker and financial markets less-developed compared with advanced economies, and the worst crisis-hit banks due to their strong incentives to change risk-taking behavior after the crisis. If the learning hypothesis applies, banks worst-hit by the 2008 Global Financial Crisis (GFC) are expected to have made larger adjustments to their post-crisis exposure to credit and solvency risk than other banks. Conversely, a failure to adapt bolsters the non-learning hypothesis.

Using a difference-in-differences approach and rich panel data of Russia banks from 2005 to 2013, I find that bank exposure to solvency risk does not differ between the treated and other banks in the post-crisis period. This finding indicates that worst crisis-affected banks learned from their experience of the 2008 GFC. It corroborates a previous study from the Nordic countries (Berglund and Mäkinen, 2019), which suggests that bank learning from a financial crisis may not depend on the institutional context and the level of development of national financial market. With respect to bank exposure to credit risk, the worst crisis-hit banks are more exposed to post-crisis credit risk than other banks. This implies that they have been unable to change their risk-taking behavior after the crisis, which is inconsistent with the learning hypothesis.

The policy implications are quite straightforward. While the worst-hit banks were able to enhance their post-crisis solvency risk compared with other banks, the opposite applies to credit risk, which remained elevated long after the 2008 GFC. The implication here is that the worst-hit banks managed to postpone the final write-off of their bad loans from their books. While this may not be a financial instability concern for regulators, the reluctance of banks to deal with their bad loans constitutes a potential drag on economic growth through a decline in (i) the risk-taking capacity of banks due to eroded profitability as well as (ii) overall confidence in the financial system. As a remedy, financial market regulators could consider (i) set deadlines for banks by which their bad loans need to cleared from their balance sheets, and (ii) provide frameworks that support clean-up of bank balance sheets (e.g. the establishment of a bad bank).

I recognize potential limitations of this study. First, differences in bank exposure to credit and solvency risk may reflect to some extent changes in bank supervision and regulation over time. Due to the lack of appropriate data, this is a difficult topic to be taken into account in empirical analysis. I have attempted to control this issue by including time fixed effects. In addition, major changes in bank regulation in Russia were implemented after 2013, not during the time period of the study. Second, the worst crisis-hit banks may have changed the composition of top management following a bank's poor performance during the 2008 GFC. Unfortunately, I do not have access to data on changes in top management before and after the 2008 GFC crisis. Without doubt, the role of changes in the composition of bank top management team on bank learning offers a potential research direction in future studies.

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