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The Use of Logistic Regression with Variable Selection Algorithm to Improve the Default Probability Model for Russian Banks [3]

In the light of recent economic and geopolitical shocks in 2008–2015 in Russia, the stability of Russian banks has become an urgent issue. Since 2013, we have observed an increasing number of failed Russian banks with negative capital. Most often, these banks falsify their financial reporting to conceal that their liabilities exceed the assets available. Creditors of failed banks with negative capital always incur losses. Therefore, we aim to measure the consequences of this phenomenon for bank creditors. We suggest a model to detect these banks using statistics for the period from 2011 to the third quarter of 2014. We claim that the cases of negative capital are predictable. The model can be applied by bank creditors to avoid losses and by the Central Bank of Russia to improve supervision. To facilitate further research on the Russian banking sector, we publish a list of non-banking credit organizations, members of the main banking groups, and foreign and state banks in Russia.

JEL Classification: G21, G33, M4.

Key words: probability of default, fraudulent financial reporting, logit model, state-controlled banks, foreign-owned banks, banking groups, negative capital.

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1 Introduction

Over the past several years, there has been a growing interest in estimating the stability of the Russian banking sector. Turmoil caused by the global economic recession in 2008–2009 and geopolitical issues in 2014–2015 drew much public attention. Since 2013, more and more banks failed in Russia with negative capital. This means that The Central Bank of Russia found assets of those banks to be smaller than their liabilities. Therefore, depositors and other creditors incurred losses and paid for the mismanagement in banks. The phenomenon of failed Russian banks with negative capital was previously uncommon and little studied. The majority of papers on the financial stability of Russian banks examined the factors of bank failures in Russia and tried to make predictions (see Calabrese and Giudici, 2013; Lanine and Vennet, 2006). They defined license revocation as a default event due to various reasons, such as an inability to satisfy creditors' claims, capital inadequacy and money laundering.

We examined the consequences of bank failures according to creditor type. Only funds of individuals were guaranteed within a certain insurance limit in Russian banks, which decreased the chances of other bank creditors to recoup money. Using public information provided by the Central Bank of Russia and the Deposit Insurance Agency, we estimated that corporate depositors on average lost 74% of their funds in the failed banks, while individuals lost 25%. In addition, we considered the origin and scale of negative capital in the Russian failed banks. Given the present unstable economic circumstances in Russia, the model might be in high demand by bank creditors, including other banks, to estimate their reliability and by the Central Bank of Russia to improve supervisory practices.

Many failed banks concealed their poor performance and financial position in financial reporting. Therefore, it was initially unclear whether predicting negative capital was possible. Using statistical analysis, we concluded that cases of negative capital were predictable. A logit model with lagged predictors was designed to distinguish between healthy banks and banks with negative capital in a training sample for the period from 2011 to 2013. We successfully tested its out-of-sample forecasting power on data for January – September 2014. The model predicted more than half of the banks with negative capital that were eventually found by the Central Bank of Russia. We suggest that a high predictive accuracy in the present study was obtained due to the thorough selection of the statistics used.

Another important contribution of this work was collecting and disseminating data about the Russian banking sector. Separate lists of non-banking credit institutions, foreign banks, banks with significant participation of the government and banking group members were made and analysed for the period from 2011 to 3q2014 in Russia. We believe that high informational transparency will facilitate further research into the Russian banking sector.

The paper structure is as follows. In Section 2 we discuss the literature useful to predict the cases of negative bank capital. In Section 3 we characterize the evolution of the Russian banking sector, explaining the prerequisites of the phenomenon of negative capital in banks. Section 4 describes the methodology we applied to estimate the consequences of bank failures for various types of Russian bank creditors. The data used and the model estimation techniques are shown in Section 5. In Section 6 we present the out-of-sample forecasting power and findings. The last section concludes this paper.

2 Literature Review

Our paper unified two seemingly separate areas of economic literature. The first area of the literature addressed the issue of fraudulent financial reporting in companies. Most Russian banks with negative capital concealed their poor performance and weak financial position. The second area concerned the financial instability of Russian banks and the withdrawals of banking licenses. Most Russian banks with negative capital that were found lost their licenses, since the owners did not support them.

2.1 Literature on the Detection of Fraudulent Financial Reporting in Companies

At first glance, the ability of any model to detect companies with fraudulent financial reporting is very uncertain. However, there were successful attempts to address this issue.

Nor et al. (2010) examined misreporting by non-listed Malaysian companies in 2004. They considered firm size as an important determinant of book-cooking. On the one hand, larger firms could implement better practices of internal control. On the other hand, big companies had strong incentives to hide large profits to optimize taxes and avoid claims by employees and consumers. Using a tobit model, they supported the first hypothesis: larger companies were more transparent. Ownership type was another possible determinant of financial misstatement. Inspired by previous research, they asserted that higher control concentration facilitated misrepresentation. However, they found no evidence of this. They suggested that the size of the bank's external auditor is important. Larger auditors provided higher quality services. They also probably rejected bribery as a payment "to get things done".

Lin and Becker (2003) compared a fuzzy neural network and a logit model for the detecting of fraudulent financial statements issued by US publicly traded companies in 1980–1995. Both models exhibited good forecasting power for non-fraudulent cases while the fuzzy neural network dominated in classifying frauds. Several publicly available financial ratios were used as predictors, which confirmed that financial reporting contained indicators of misconduct. The variables employed were specific for non-banking companies so we omitted a detailed discussion here.

Using a dataset almost similar to the previous research, Kaminski et al. (2004) confirmed that financial ratios were useful for detecting the misstatements in financial records. Moreover, they emphasized that in 1997 the American Accounting Association encouraged the use of analytical tools by practitioners to improve the detection of fake financial reporting. The set of explanatory financial ratios varied from year to year, but a higher ratio of fixed to total assets significantly increased the probability of misreporting across the whole period. They faced a class imbalance problem: few cases of misreporting were available to estimate the model properly in the training set. Garcia et al. (2012) discussed the class imbalance problem and methods to overcome it.

Consistent with prior research, Kirkosa et al. (2007) demonstrated that public reporting did contain falsification indicators. Using Greek company statistics, they applied a few financial ratios to forecast falsifications in financial reporting.

2.2 Literature on the License Revocations from Russian Banks

This area is important, because most Russian banks had lost their licenses before cases of negative capital, detrimental for creditors, were discovered. That area was well studied. See Fungacova and Weill (2013); Karminsky and Kostrov (2014); Peresetsky et al. (2011) for reference. These papers motivated the selection of bank-specific financial rations in our paper.

The important evidence in the accounting literature on fraudulent financial reporting was that the explanatory variables for the probability of failure and misreporting partially coincided. Kaminski et al. (2004) noted that the ratios useful for fraud detection might transform a fraud detection model into a bankruptcy prediction one. Liou (2008) compared the models for business failure prediction and for the detection of fraudulent financial reporting. Liou proved that there was a set of common explanatory variables which were highly significant in both types of the models. Their findings confirmed the common sense: financial distress and poor performance often forced the firm's management to issue the fraudulent financial reporting.

3 Development of the Russian Banking Sector

Commercial banking in contemporary Russia started in the late 1980s when the USSR was on the verge of collapse. We identify four stages of the development of the Russian banking sector: Formation (1989–1999), Rapid growth (2000–2008), Sustainable growth (2009–2013) and Self-reliant restructuring (2014–today). A notable point is that crises bound each stage: the default of Russian sovereign debt in 1998, the recent world economic crisis in 2008–2009 and the partial isolation of Russia in 2014. We did not claim to provide a comprehensive description for each period, which was beyond the scope of our paper. We tried to outline the process and stress the most important points that could lead to the observed phenomenon of negative capital in banks and the overall vulnerability of the Russian banking sector.

3.1 Formation (1989–1999)

In early post-Soviet times, there was economic and political turmoil in Russia that was intensified by weak legislation. The banking system was definitely affected. The number of banks was rising extremely quickly (see Figure 1) due to many reasons:

1. Many players decided to enter a large market with promising opportunities for growth.

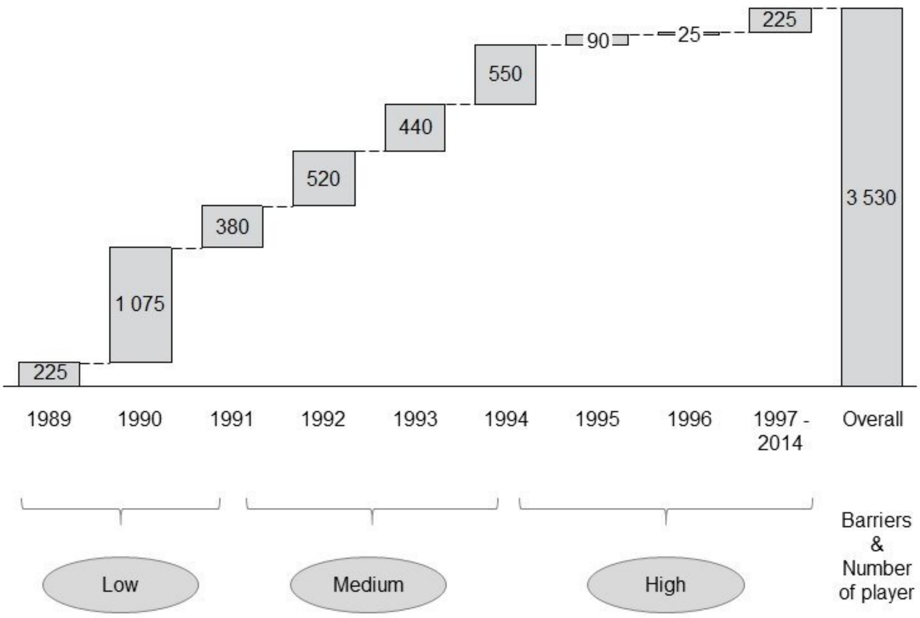


Figure 1: Number of credit organizations launched in the Russian banking sector, 1989–2014

2. Entrance barriers were very low. Before 1991, the minimum bank capital required was about[1] USD 15 000. The next year the threshold got higher. In 1992–1993 the required bank capital rose to USD 100 000 – 200 000. In 1994, the cutoff was set at the level of USD 1.2 million.

3. A lack of trust and security in the young transition economy forced companies to create their own captive banks. Businesses tried to guarantee the safety of funds and financial operations.

4. Criminals launched banks to launder money and finance illegal activities as a result of weak authorities, institutions and legislation.

At the end of 2014 there was still a truly abnormal number of banks in Russia given the size and scale of the national economy: slightly less than 800 banks[2] were operating. Russia has the third-largest number of banks after Germany and the USA. The abnormal number of banks in those countries was also explained by the formation of their banking sectors. The US McFadden Act of 1927, which prohibited interstate branching, and the US Bank Holding Company Act of 1956, which prohibited interstate acquisitions, were implemented to support competition but caused micro-banking as well. The laws were repealed in 1994, but the consequences are still evident. This was also the case for Germany: after World War II, regions of the country were isolated from one another for a long time.

[1] The absence of a free exchange market at those times made the estimates in US dollars imprecise.

[2] Hereafter we distinguish between banks and non-banking credit institutions in Russia. The later are primary focused on cash and settlement services and payment processing.

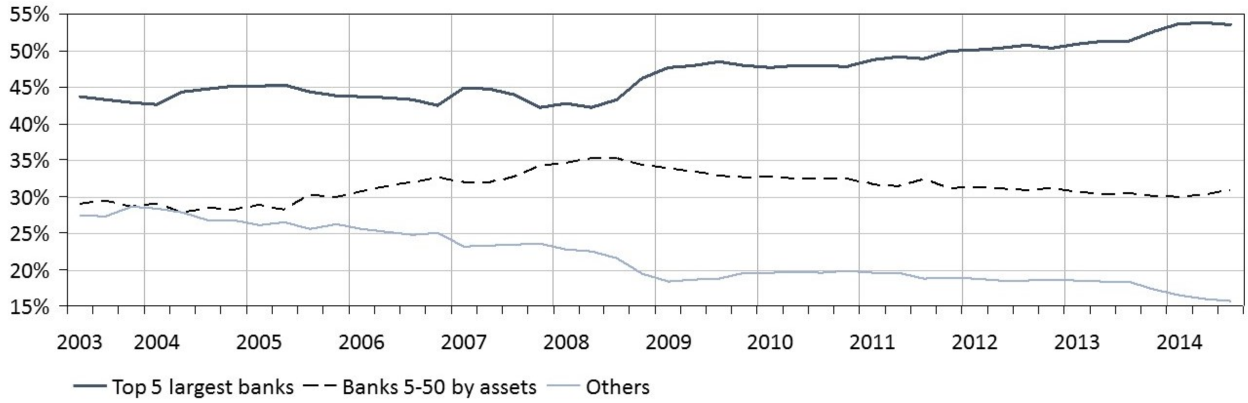


Figure 2: Concentration in the Russian Banking Sector, 2q2003–3q2014, quarterly

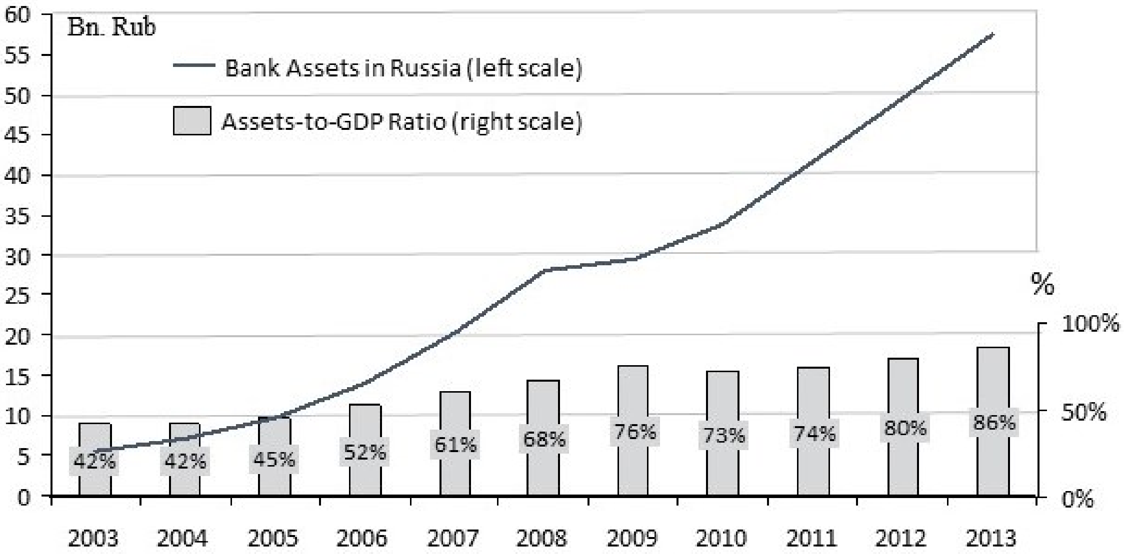


Figure 3: Development of the Russian banking sector

3.2 Rapid Development (2000–2008)

During this period, GDP growth rate in Russia fluctuated between 5% and 10%. The banking sector environment improved significantly. Deposit insurance and Basel I compliance requirements were adopted in Russia and the quality of supervision by the banking regulator was enhanced. The market share by assets of the top-5 banks was within the range of 40-45%. However, overall concentration was slightly increasing (see Figure 2). Generally, exponential growth was very typical for the Russian economy in 2000–2008 and the upward trend in the development of the banking sector was very strong. The ratio of bank assets to GDP ratio constituted 68% in 2008 after a modest 42% in 2003 (see Figure 3). Loan portfolios to corporate clients and individuals were growing at impressive rates of 40-50% and over 80%, respectively, as Figure 4 demonstrates.

What partially explains these large quantitative growth rates is a low base effect. The share of impaired loans stayed persistently low (see Figures 5(a) and 5(b)). There were two reasons for this. Firstly, an intensive growth in the size of the loan portfolio kept the share of bad loans persistently

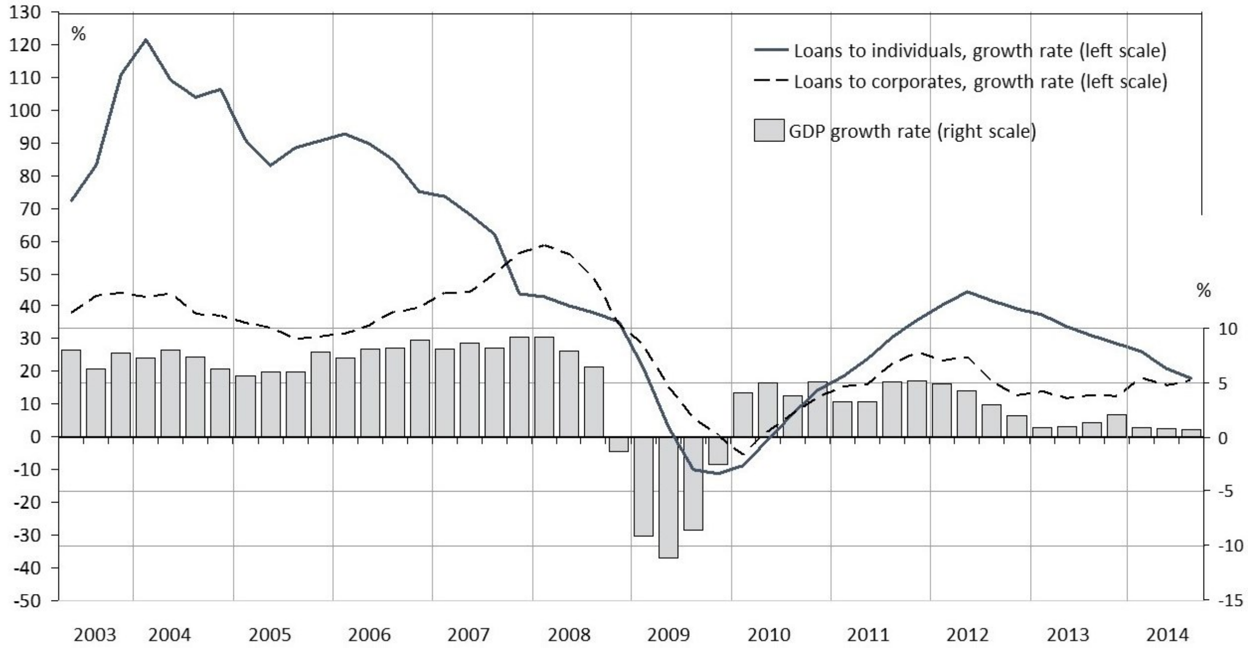


Figure 4: GDP growth rate, growth rate of loans to corporates and individuals, 2q2003 - 3q2014. In comparison with a respective quarter of the previous year, %

low for both types of borrowers. Secondly, economic euphoria led to an underestimation of risks. In 2007–2008, scientists and authorities warned about an overheating in the Russian economy. Meanwhile, the crisis was coming.

3.3 Crisis 2008–2009

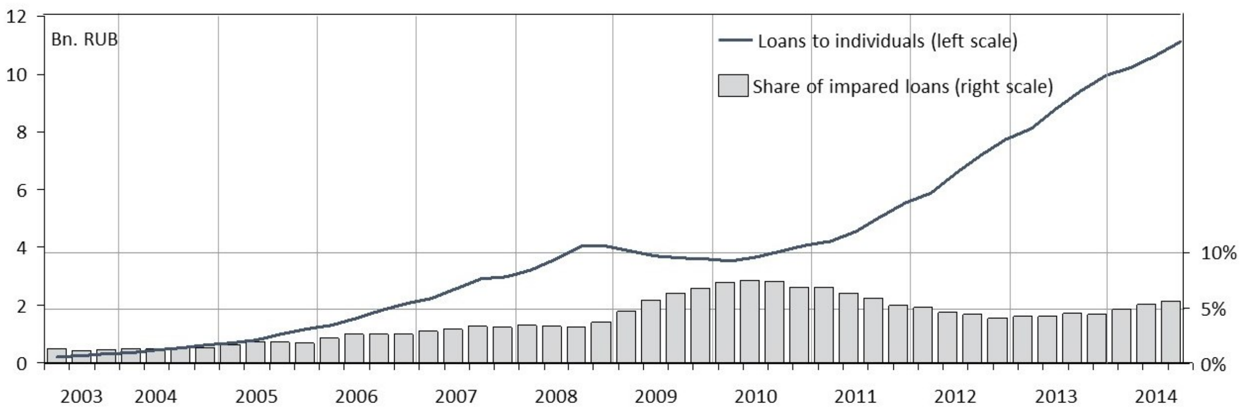
Financial Crisis 2008–2009 affected the Russian economy much more severely than in other BRICS and CIS countries. Understanding the sources of that crash is crucially important to estimate the stability of the Russian banking sector today. We also considered measures taken by the government to remedy the economy with a focus on the long-term efficiency of those measures. Aleksashenko et al. (2011) suggested the internal and external reasons for the deep downturn of the Russian economy in 2008–2009.

External reasons:

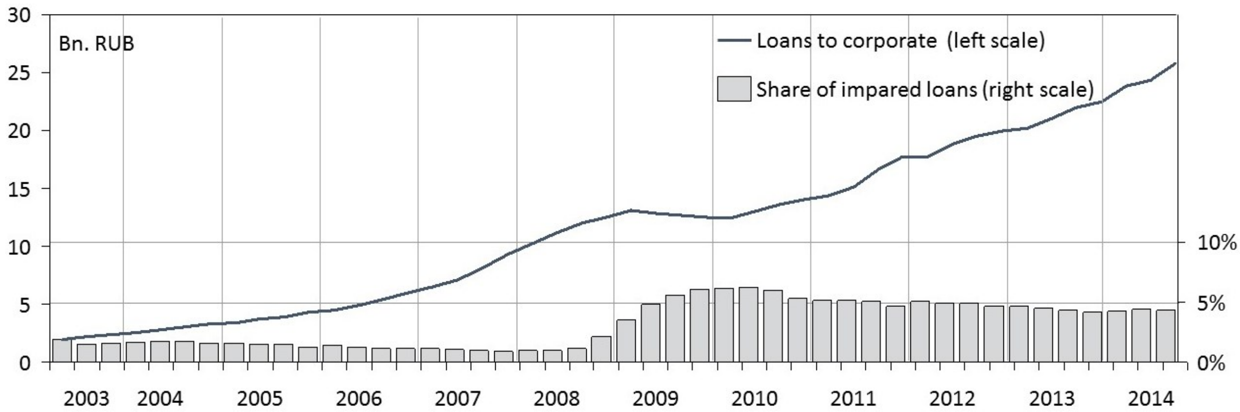
- *Slump in demand for natural resources exported from Russia.* Export of oil, natural gas and some raw materials decreased almost by half. The sharp drop in physical quantities of exported goods was amplified by price falls.

- *Large corporate debt to foreign sector.* Stress in the international loanable funds market precluded Russian banks and businesses from borrowing abroad. At the same time, short-term external funding was the dominant source for many Russian banks. Their internal sources could hardly cover the lack of liquidity. Moreover, exchange rate risks were not properly hedged.

Internal reasons:



(a) Loans to individuals



(b) Loans to corporates

Figure 5: Loan portfolios and their quality, 2q2003–3q2014

- *Overheating of the Russian economy*. In 2008, the IMF identified signs that the economy was overheated.

- *Regulatory mistakes*. The Central Bank of Russia did not save the banking sector from large open foreign currency positions and a shortage of liquid assets. As Figure 4 shows, growth rates of loan portfolios followed the GDP growth rate with a lag of two quarters. Loans to individual and corporate clients stopped rising and even shrank during the recession. In addition, prior underestimation of risks materialized in the deterioration of the loan portfolio quality: the share of impaired loans to individuals and corporates rose sixfold and twofold, respectively.

Authorities supported and stabilized the banking sector of Russia with the following actions:

- *Provide liquidity to the Russian banking sector*. The Central Bank of Russia poured liquidity into the financial sector through cheap Repo operations, lending with soft debt guarantees, deposit facilities and lower prudential requirements.

- *Prevent a bank run*. Authorities almost doubled the insurance coverage for deposit in October 2008. As Figure 6 shows, they succeeded in stopping an emerging outflow of funds of individuals from the banking system. In addition, banks enhanced the effect by increasing

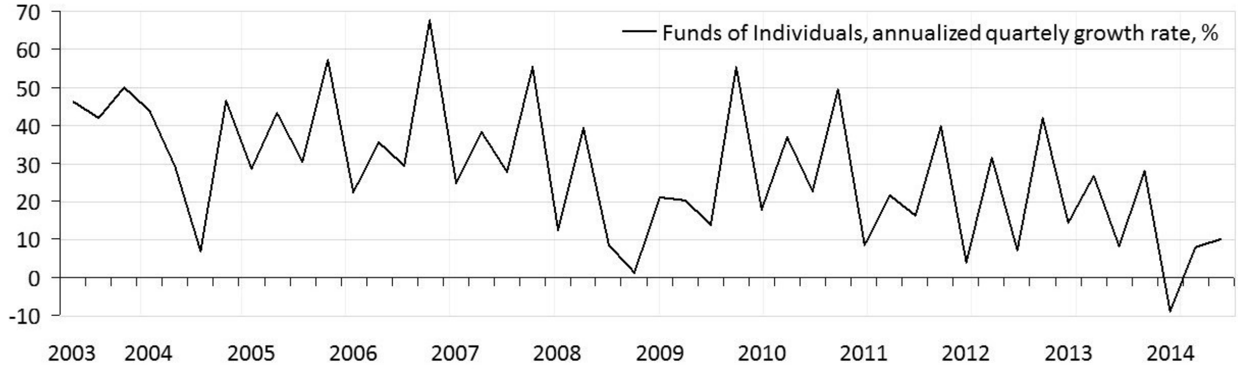


Figure 6: Funds of individuals, 3q2003–3q2014 annualized growth rates

the interest rate on deposits. However, some particular banks experienced a considerable leakage of funding.

- *Support some vulnerable banks*. In 2008–2009, authorities rescued several banks that were believed to be systematically important and potential triggers of collapse. Aleksashenko et al. (2011) claimed that total expenses on bank sanitations were as large as 1% of Russian GDP. Unlike in developed economies, the ability of the Russian authorities to recoup that money was very low.

As one can see in Figure 2 the events of 2008–2009 stimulated higher concentration in the Russian banking sector. The events of the crisis period had a direct bearing on the present environment in the banking sector.

3.4 Sustainable Growth (2010–2013)

After the crisis, the topic of sustainable development gained prominence on the world agenda. Adoption of Basel III as a set of best practices in banking supervision was a revealing example. Very similar processes were occurring in the Russian banking sector. The Central Bank of Russia applied stricter regulations for the open foreign currency position and announced an implementation plan for the adapted version of Basel III in Russia.

After the post-crisis rebound in 2010–2012, the Russian economy slowed down. As Figure 4 shows, the Russian GDP growth rate was approximately 1-2%. Lending was also slowing down. The share of impaired loans levelled off at 5% for both types of borrowers (much higher in comparison with pre-crisis values). Concentration in the banking sector continued to grow. The Central Bank of Russia adopted a policy to remove tiny, opaque and poorly performing banks from the banking system. That policy became a core one after the new chief executive Elvira Nabiullina became the head of the Central Bank of Russia in the second half of 2013. The period of her continuing governance is often called ”cleaning up” the Russian banking sector. An important feature of that period was the increase in the number of closed banks with negative bank capital. Moreover, in most cases banks concealed weak financial positions in their financial reporting. In Section 4, we describe our methodology and show that bank failures since 2010 had led to larger and more frequent losses for bank creditors. This observation served as an important motivation to write the present research paper.

3.5 Self-reliant Restructuring (2014–today)

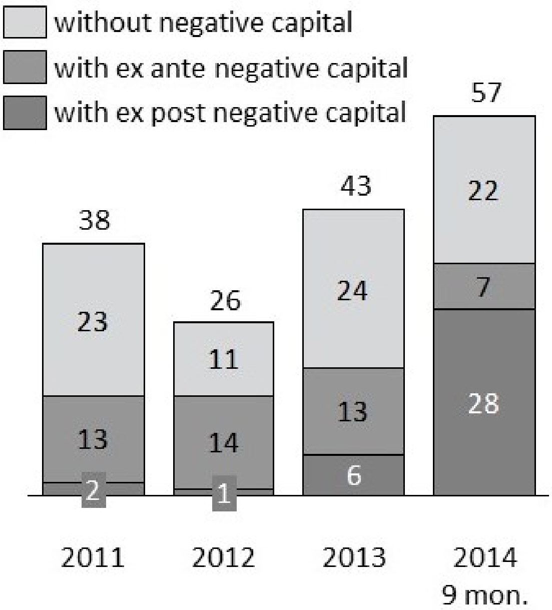
In 2014, the Russian GDP almost stopped growing. There were several reasons for this.

- *Oil price shock.* As in 2008–2009, the Russian economy was still very dependent on export of natural resources. The price of crude oil dropped approximately by half in 2014.
- *Geopolitical pressure on Russia and its partial isolation.* Russian business lost access to borrowing from abroad as a result of anti-Russian sanctions. The open currency position of banks was much lower than 5 years ago in 2008–2009, but borrowing abroad was still an important source of funding for companies. In addition, trade turnover between Russia and the rest of the world was impacted. Some industrial producers could no longer purchase components and equipment from abroad and attempts to substitute them were not always successful.

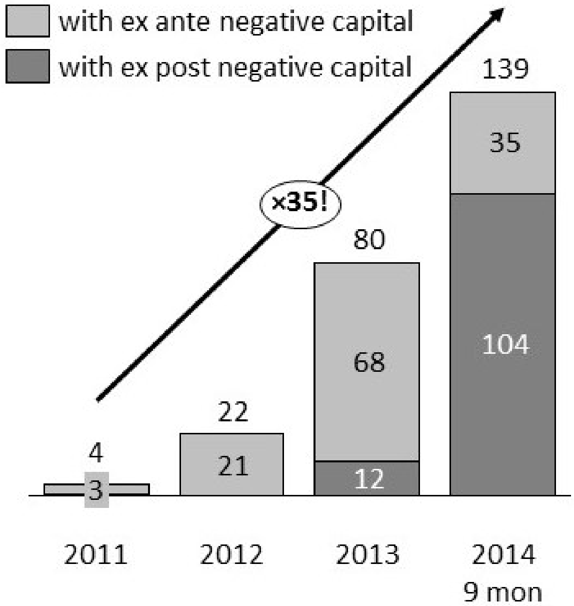
The Russian Ruble depreciated significantly and subsequently there was high volatility of the exchange rate at the turn of the year 2014/15. To cool the exchange market down the Central Bank of Russia raised the key interest rate in the Russian economy, which created additional stress for the national banking system. At the beginning of 2015, the Center for Macroeconomic Analysis and Short-term Forecasting (CMASF), an independent Russian forecasting agency, warned about a forthcoming economic recession, illiquidity and reaccumulation of risks in the Russian banking sector (Mamonov and Solntsev, 2015). They emphasized that over 250 Russian banks would probably face trouble with capital adequacy in 2015. Those banks would require additional capitalization and state support. In March 2015, the deputy chairperson at the Central Bank of Russia announced that 183 banks were submitting their financial reporting to the banking regulator on a daily basis, which was applicable for unstable banks only. CMASF underlined that ”negative capital” would probably appear in many banks. We consider that point in detail in the next section.

4 The Disaster of Negative Capital and Losses to Bank Clients

As we have already outlined, there are many banks in Russia in spite of attempts to ”clean up” the banking sector. As Figures 7(a) and 7(b) show, there was a large surge in the number of failed banks with negative capital in the Russian banking system. Bank capital becomes negative when its liabilities exceed assets due to asset devaluation. When asset value declines, a bank capital absorbs losses (see Figure 8), since the bank owners are responsible for the financial result. However, their responsibility is limited by the size of bank capital. When losses are so large that bank capital is completely exhausted, bank creditors incur losses.



(a) Number of the failed banks



(b) Total size of negative capital in the failed banks

Figure 7: Russian banks fail more and more often generating larger losses to clients, 2011–3q2014. Losses are measured in billion RUB.

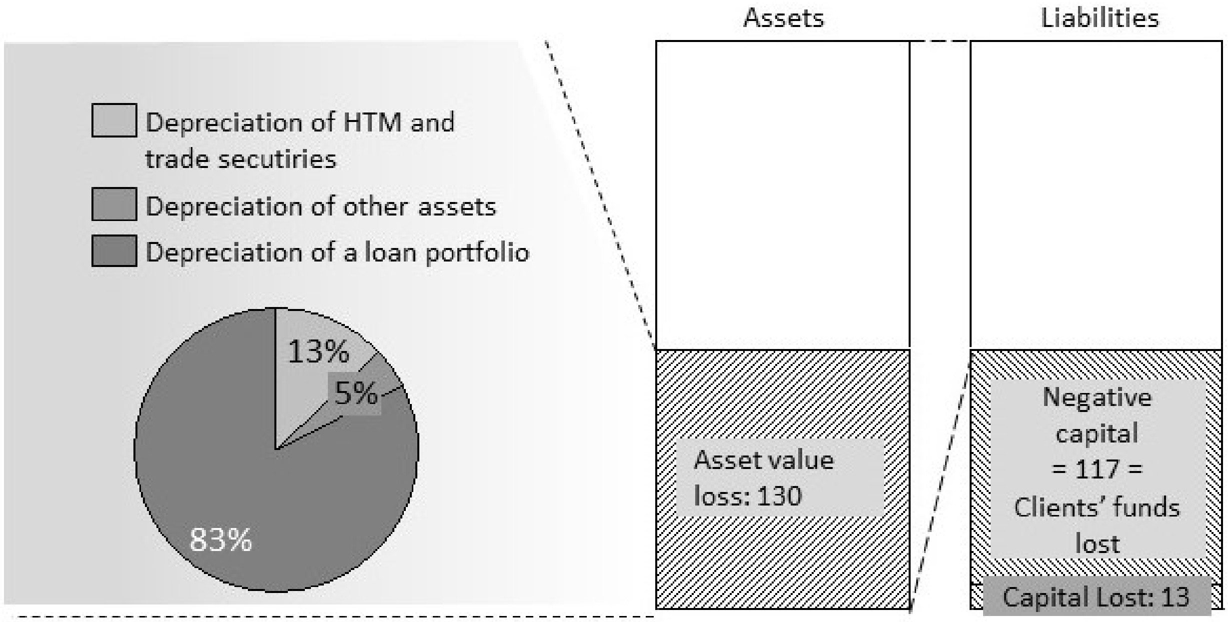


Figure 8: The structure and consequences of asset value losses by banks with negative capital

4.1 The Scale of Disaster

The first important issue was why assets depreciated, leading to negative capital. Often banks concealed their capital insufficiency in financial reporting. Nevertheless, specialists from the Central Bank of Russia, who participated in field inspections, were able to spot banks' misbehaviour. Sometimes the regulator spent much time finding out that a portion of bank assets no longer existed leading to negative capital. We call such affairs "ex post negative capital" as opposed to "ex ante negative capital" for ordinary cases. For banks with "ex post negative capital", the Central Bank of Russia published reports, which reflect the sources of asset value loss. Reports were available for the period since the end of 2010. We analysed 37 cases of banks with negative capital for the period from January 2011 to September 2014. Inspections take time, so reports for the most recent bank failures were unavailable. As Figure 8 shows, banks with ex post negative capital lost RUB 130 billion in assets, which completely wiped out their capital and caused a loss of RUB 117 billion for bank clients.

The largest portion of asset devaluation was due to negative revaluation of the loan portfolio value. This means that the banks issued loans to unreliable or even non-existing borrowers and those funds would never be repaid. The value of securities is written off when they do not belong to a bank or were initially overpriced. Other assets included fixed bank assets. It was obvious that the remaining assets of banks with negative capital were inherently insufficient to satisfy creditors' claims. Moreover, bank creditors incurred losses unequally.

4.2 Methodology to estimate the consequences of bank failures for bank creditors

In this section, we develop a methodology to estimate the consequences of bank failures for various types of bank creditors. The Federal Law defined the order of precedence for claimants on remaining banks assets.

- *First priority*. The Deposit Insurance Agency redeemed money to individuals with funds on accounts in a bank within an insurance limit of RUB 700 000[3]. After that, the Agency moved on to the highest place in the queue.
- *Second priority*. Compensation and benefits payable to bank employees take the second line. Banks almost never had wage arrears, but particular values were non-public.
- *Third priority*. Finally, they distributed the remaining assets among other creditors (such as corporates, individuals with more than RUB 700 000 on accounts in failed banks, other banks etc., see Figure 9)

If asset value was insufficient to satisfy creditors' claims of a particular order, available funds were distributed among claimants in proportion to the claim values. In that case, creditors of lower

[3] At the beginning of 2015, the deposit insurance limit for individuals was increased to RUB 1.4 million in Russia.

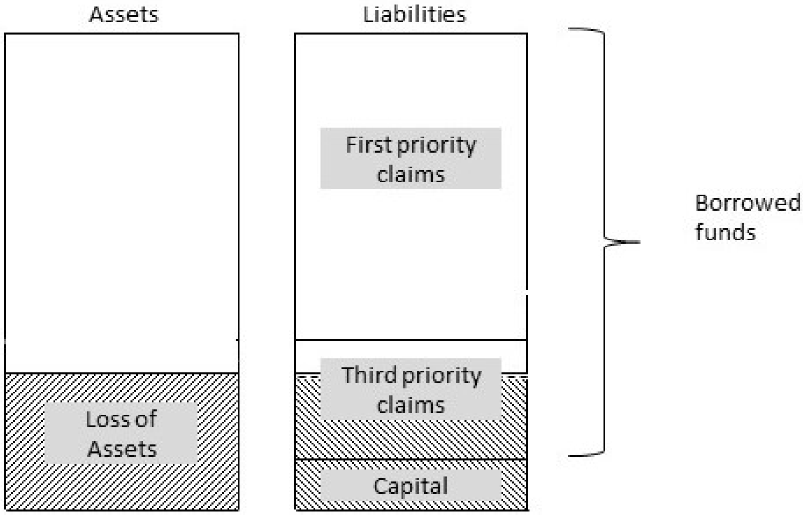


Figure 9: A distribution of losses due to negative bank capital among its creditors. Third priority claimants lost almost all their funds

priority got nothing. We distinguish 3 types of bank creditors: individuals with less than RUB 700 000 on accounts in the bank, individuals with more that RUB 700 000 and other fund providers including corporate clients, other banks, etc.

We employed balance sheet information for closed banks with negative capital published by the Central Bank of Russia. From the balance sheet we used the value of the remaining bank assets and funds borrowed by the bank from various creditors. The amount of funds reimbursed to individual clients of each failed bank was also available on the site of the Deposit Insurance Agency. We used it as a proxy for claims of the first priority. This is why the second priority claims were relatively small and could be neglected without a loss of accuracy. Under those assumptions, claims of the third priority were the difference between total borrowed funds and first priority claims.

In 2011–3q2014, corporate depositors of banks with negative capital lost RUB 91 billion or 74% of funds on their accounts. Even the Deposit Insurance Agency, which guaranteed the funds of individuals up to RUB 700 000 , incurred losses. In spite of the highest priority among claimants on bank assets, in 2011–3q2014 the Deposit Insurance Agency failed to recoup RUB 70 billion or 25% of its insurance payments to individual depositors. The explanation was that in some cases, e.g. failures of Fininvest and Intrastbank in 2014, available bank assets were tiny in comparison with insured liabilities. Therefore, the Deposit Insurance Agency bore the loss. We could expect that individuals did not exceed the insurance limit per bank when they opened accounts and deposits. It was possible to split a large deposit into smaller ones and keep them in a few banks to stay completely insured by the Deposit Insurance Agency. However, they did not: individuals lost RUB 60 billion in banks with negative capital in 2011–3q2014. They probably pursued higher interest rates on deposits and tried to avoid transaction costs related to splitting deposits.

A banking license withdrawal does not necessarily imply the weak financial position of the bank. Sometimes banks stop operating voluntarily, e.g. due to mergers, acquisitions or exiting the market. The official reasons for the license revocations were provided in orders of Central Bank of Russia to revoke licenses. For 31 banks out of 84 banks with negative capital, at the moment of

Table 1: Banks with negative capital eventually found by the Central Bank of Russia: official reasons for the revocations of banking licenses, 2011 - 3q2014

Reasons for the license withdrawal	*Number of cases*
Capital inadequacy or inability to satisfy creditors' claims mentioned	53
The only reason is money laundering and breaking Federal law	21
Other reasons	10
Total	84

license revocation there was no information about capital inadequacy or inability to satisfy creditors' claims (see Table 1). It proves that very often book-cooking in banks was not evident even for inspectors from the Central Bank of Russia. Moreover, in 21 cases, they explained the license withdrawal as a consequence of money laundering and breaking Federal law, the most common and indistinct reason. In light of the negative economic trends in Russia, "cleaning up" the national banking sector and the increasing losses from failed banks with negative capital, the financial society needed a model to forecast bank failures in advance. That model could be also useful for bank counterparties and the Central Bank of Russia to spot vulnerable and poorly performing banks.

5 Data and Model

5.1 Financial Bank-specific Statistics

We used bank-specific financial statistics from the Banks and Finance database for the Russian banking sector, from 2011 to 3q2014, on a monthly basis. The list of failed banks and banks with negative capital was available on the website of the Central Bank of Russia.

5.2 Non-financial Bank-specific Information

We believe that our significant contribution is in collecting and disseminating unique databases on the ownership structure of Russian banks, a list of participants in Russian banking groups and non-banking credit organizations in the banking sector.

The topic of ownership types in Russian banking was thoroughly discussed by Prof. Andrei Vernikov (e.g. see Vernikov, 2011). In line with the definition by Mamonov and Vernikov (2015), the 50-plus-one-share package of a state-controlled bank was controlled by the state directly or through state-controlled companies. We also identified banks with significant (25-plus-one-share package) participation of the government. The Central Bank of Russia provided a list of banks which were with 100% foreign-controlled. That list is simultaneously misleading and incomplete (see Mamonov and Vernikov, 2015). Firstly, Russians own and run some banks in that list from abroad. Second, many captive banks of foreign industrial companies operated in Russia without any specific competences in banking. Third, some subsidiary banks of the international banking corporations were partially owned by foreigners (e.g. Societe Generale Group holds approximately 99% in Rosbank currently). According to our definition of a foreign bank, a foreign banking corporation holds an over 50% share in its capital. Participation in a Russian banking group or holding was also important for the correct evaluation of a bank's financial stability. On the one hand, within a group, resources of one bank could be reallocated to support another bank. On the other hand, the financial problems of any group participant implicitly affect all group members. There were cases in Russia when all members of the banking group failed approximately at the same time (e.g. Moy Bank and Smolenskiy banking groups).

5.3 Data Cleaning

An application of almost any binary choice model for making predictions implies estimation the model on a training set and further testing its forecasting power on another subset. The out-of-sample performance of the model was heavily dependent on the quality of the training set. If the classes were weakly separable in the training set, the model would probably be poorly estimated and its forecasting power would be below the expected level. Consequently, we tried to remove the observations that created noise in the training set.

First, we removed the banks with significant state participation in its capital. Those banks were stable no matter what happened to their financial results and assets. If the adverse shocks took place, these banks received immediate financial support from the owner or the sanitizer. They operated in a specific environment where losses to creditors were almost impossible. Second, we removed observations for banks under sanitation. Most of them had negative capital and corresponding financial ratios. However, they brought no losses to creditors and were rescued by the Deposit Insurance Agency or another bank. It is hardly possible to predict if any particular bank is supported or closed if it experiences financial problems. The answer depends on many factors, such as the opinion of the Central Bank of Russia regarding its systematic importance, the scale of financial distress and the presence of investors to support it. This issue is beyond the scope of our paper and needs further consideration. Third, we removed the observations for foreign banks as defined above. They had access to the best practices and the support from the mother foreign bank to avoid negative capital. The Central Bank of Russia successfully precluded the reverse possible impact on the bank in Russia from abroad. Finally, we dropped one year of observation before and after bank sanitation or banking license revocation with subsequent negative capital discovered. Observations for the non-banking credit organizations were also removed.

5.4 Estimating the Model

We used a subsample from 2011 to 2013 to estimate the model. Using public financial information about a bank at the beginning of a month, the model was designed to predict bank failures with negative capital during that month. A pooled logit regression with a lag of one month for factors was applied. Selecting the predictors, we tried to cover indicators warning that bank capital was probably negative and the Central Bank of Russia should apply extreme measures.

- *Capital adequacy*. Capital adequacy was estimated by a ratio of capital to assets. Low capital adequacy was among the most frequent reason for license withdrawals. Negative capital in the case of fair reporting means a negative capital adequacy ratio accordingly.
- *Liquidity*. A ratio of liquid to total assets characterized the bank's liquidity position. Bank illiquidity might result in license revocation. As we showed above, most cases of negative capital originate from the depreciation of illiquid assets.
- *Violating the mandatory requirements of the Central Bank of Russia*. This dummy variable indicated if a capital adequacy or liquidity were so low that the mandatory banking requirements were violated.
- *Share of loss reserves in assets*. A high share of loan loss reserves in assets indicated that assets performed poorly. Moreover, if the risks were underestimated, making additional reserves might result in capital deterioration.
- *Share of non-government securities in assets*. A high share of non-government securities in banks' assets characterised risk-taking by a bank.
- *Outflow of the individuals' funds from a bank*. Cases of negative capitals were unexpected. This was why we did not expect that the bank run preceded license withdrawals with negative capital. Conversely, these banks might absorb the additional funds of individuals who were sensitive to the interest rate. They could probably aim to hide more funds before the oncoming failure. An outflow of funds of individuals from a bank was measured as the change in funds of individuals during the previous 6 months over total assets.
- *Bank size*. The Central Bank of Russia was probably reluctant to withdraw licenses from large banks so as not to stress the economy severely. They would prefer to sanitize a bank in this situation. Bank size was measured by the logarithm of assets.

A logit model (1) was applied for predicting and provided $\widetilde{P}^i_{t+1}$, the raw probability of bank failure with negative capital for the bank i.

$$\widetilde{P}^i_{t+1}\,(\text{Failure}) = \frac{e^{z^i_t}}{e^{z^i_t}+1}, \tag{1}$$

where $\widetilde{P}^i_{t+1} \in [0,1]$ and

$$z^i_t = \beta_0 + \beta_1 \times \log(TA)^i_t + \beta_2 \times \left(\frac{CAP}{TA}\right)^i_t + \beta_3 \times \left(\frac{LA}{TA}\right)^i_t + \beta_4 \times OFI^i_t + \\ \beta_5 \times Viol^i_{\text{dummy},\,t} + \beta_6 \times \left(\frac{LR}{TA}\right)^i_t + \beta_7 \times \left(\frac{NGS}{TA}\right)^i_t .$$

Table 2: In-sample estimation of the model

Description	*Variable*	*Coefficient*
$\log(TA)$	Logarithm of total assets	-0.44***
CAP_TA	Ratio of capital to total assets	-7.70***
LA_TA	Ratio of liquid to total assets	-5.64***
OFI	Outflow in funds of individuals during the previous 6 months	-5.64***
$Viol_{dummy}$	Indicates if any mandatory requirement was broken	-3.29***
LR_TA	Ratio of loss reserves to total assets	4.58***
NGS_TA	Ratio of non-government securities to total assets	4.83**
$\chi^2 - stat.\ vs\ constant\ model$: $p - value = 0.00$; $R^2_{adj} = 0.13$		

***, ** and * - an estimate is significant at the 1%, 5% and 10% levels, respectively

Table 3: Number of banks with probability of the failure with negative capital above the threshold, January – September 2014, monthly

Threshold	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
0.5%	19	21	29	38	47	62	64	60	60
1%	7	4	7	11	9	12	18	17	18
10%	3	-	2	3	1	2	1	3	2
50%	1	-	2	2	1	1	1	-	-
Total number	755	745	748	742	740	748	748	738	738

Then the raw probability of bank failure with negative capital $\widetilde{P}^i_{t+1}$ was adjusted to the participation of banks in Russian banking groups. Suppose there is a banking group with a mother bank Z and X, a set of dependent participants. Then the raw probability of bank i failure with negative capital is transformed as in (2).

$$P^i_{t+1} = \begin{cases} 0.5 \times \widetilde{P}^i_{t+1} + 0.5 \times \sum_{m \in X} \left(\widetilde{P}^m_{t+1} \times w^m \right), \text{ for } Z \\ 0.5 \times \widetilde{P}^i_{t+1} + 0.5 \widetilde{P}^z_{t+1}, \text{ if } i \in X \end{cases}, \tag{2}$$

where $w^m = \frac{\text{Assets}^m}{\sum_{m \in X} \text{Assets}^m}$. If a group member failed, we used $\widetilde{P}_{t+1} = 1$ during 6 months after the failure event in our calculations. Then, the number of banks in the group was decreased.

The training sample contained 29 511 observations, including 49 observations for failed banks with negative capital. Fortunately, a class imbalance problem did not lead to any negative consequences in our research and was neglected. Table 2 provides the model estimation results in-sample, which were in line with prior expectations. The next section concerns the out-of-sample predicting procedure and the model performance.

6 Out-of-sample Forecasting Procedure and the Key Findings

We tested the out-of-sample forecasting power of the model on observations for January – September 2014. We made one-month-ahead predictions iteratively, expanding the training subsample. Thirty-five cases of license revocations from banks with negative capital occurred in January – September 2014. There was no the predefined level to set as a threshold separating the predictions of two classes. As a consequence, we examined a set of values (see Table 3). Banks with a probability of failure above the threshold were expected to fail:

$$\text{Failure}_{t+1}^{i,f} = \begin{cases} 1, \text{ if } P_{t+1}^{i} \geq \bar{P} \\ 0, \text{ if } P_{t+1}^{i} < \bar{P} \end{cases}, \tag{3}$$

where $\bar{P}$ is a threshold defined and for $\text{Failure}_{t+1}^{i,f} = 1$ we forecast that a bank i will finish the month between t and $t+1$ with negative capital.

As Table 3 shows, in January – September 2014 the distribution of banks by the probability of failure was shifting towards a more risky state. The traditional approach to threshold selection based on assumptions about the cost of type I and type II errors was hardly applicable here, since the scale of losses varied dramatically among banks. Thus, averaging was irrelevant in our case.

The final decision on the selection of $\bar{P}$ is up to the final user of the model. We analysed the forecasting power for two different kinds of thresholds.

6.1 Forecasting with a Threshold of Top 5 Banks

In the first case, as equation (4) shows, the 5 banks with the highest probability to fail were predicted to bring losses to creditors.

$$\text{Failure}_{t+1}^{i,f} = \begin{cases} 1, \text{ if } P_{t+1}^{i} \in W_t \\ 0, \text{ if } P_{t+1}^{i} \notin W_t \end{cases}, \tag{4}$$

where W_t is a set $\{P_1^{t+1}; P_2^{t+1}; P_3^{t+1}; P_4^{t+1}; P_5^{t+1}\}$, the five highest probabilities of failure with negative capital for banks predicted at time t.

Table 4 provides the forecasting results on monthly basis. We reorganized the data to conclude about the forecasting power of the model under the "top 5 banks" threshold criterion (see Table 5).

Table 4: Forecasting results: top 5 banks by probability to fail were predicted to bring losses to clients, January – September 2014, monthly and overall

Type of prediction	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Overall*
Prediction: negative capital, Actually: negative capital	2	1	2	2	1	-	-	4	2	14
Prediction: negative capital, Actually: no negative capital	3	4	3	3	4	5	5	1	3	31
Prediction: no negative capital, Actually: negative capital	1	1	2	2	4	4	3	1	3	21
Prediction: no negative capital, Actually: no negative capital	749	739	741	735	731	739	740	732	730	6 636
Total	755	745	748	742	740	748	748	738	738	6 702

Table 5: Two-by-two matrix classifying the prediction outcomes. Threshold: top 5 banks with the highest probability to fail with negative capital

Predicted outcome	*Actual outcome*		
	Negative capital	No negative capital	Overall
Negative capital	14	31	45
No negative capital	21	6 636	6 657
Overall	35	6 667	6 702

$$\begin{aligned} \text{Number of correct predictions for failed banks} &= \textstyle\sum_1^N 1_{\text{ Failure}^{i,f}=1|\text{ Failure}^{i,\text{ act}}=1}, \\ \text{Number Type I errors} &= \textstyle\sum_1^N 1_{\text{ Failure}^{i,f}=0|\text{ Failure}^{i,\text{ act}}=1}, \\ \text{Number Type II errors} &= \textstyle\sum_1^N 1_{\text{ Failure}^{i,f}=1|\text{ Failure}^{i,\text{ act}}=0}, \\ \text{Number of correct predictions overall} &= \textstyle\sum_1^N 1_{\text{ Failure}^{i,f}=\text{ Failure}^{i,\text{ act}}}, \end{aligned} \tag{5}$$

where $\text{Failure}^{i,f}$ and $\text{Failure}^{i,\text{ act}}$ are the forecast and the actual outcome regarding bank i failure and N is number of observations considered within a prediction period.

The H_0 hypothesis was that a bank would have negative capital. Using a very simple prediction criterion we managed to forecast 14 out of 35 cases of negative bank capital. We made 21 Type I errors and 31 Type II errors defined in (5). The probability of type I and type II errors were 60% and 0,5%, respectively, and 99.2% of banks were correctly classified within a forecast period.

Table 6: Forecasting results: banks with probability to fail with negative capital over 1% were predicted to bring losses to clients, January – September 2014, monthly and overall

Type of prediction	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Overall*
Prediction: negative capital, Actually: negative capital	2	1	2	2	1	-	1	4	3	16
Prediction: negative capital, Actually: no negative capital	5	3	5	9	8	12	17	13	15	87
Prediction: no negative capital, Actually: negative capital	1	1	2	2	4	4	2	1	2	19
Prediction: no negative capital, Actually: no negative capital	747	740	739	729	727	732	728	720	718	6 580
Total	755	745	748	742	740	748	748	738	738	6 702

$$\begin{aligned} P\left(\text{Correct prediction}\right) &= \frac{\text{Number of correct predictions overall}}{\text{Number of obs.}} \\ P\left(\text{Type I errors}\right) &= \frac{\text{Number of type I errors}}{\text{Number of actual bank failures}} \\ P\left(\text{Type II errors}\right) &= \frac{\text{Number of type II errors}}{\text{Number of obs. for banks with no failures actually}} \end{aligned}, \tag{6}$$

6.2 Forecasting with the Threshold of 1% Banks with the Highest Probability to Fail with Negative Capital

With a threshold of 1%, as equation (7) presents, banks with probability of failure above this level were predicted to stop operating with negative capital.

$$\text{Failure}_{t+1}^{i,f} = \begin{cases} 1, \text{ if } P_{t+1}^{i} \geq 1\% \\ 0, \text{ if } P_{t+1}^{i} < 1\% \end{cases}. \tag{7}$$

Under the same H_0 hypothesis, we constructed a two-by-two matrix (see Tables 6 and 7). We correctly forecast 16 out of 30 cases of negative bank capital. We managed to decrease the number of a type I errors at the expense of more type II ones made. The probability of type I error constituted 54% while the probability of a type II error increased to 1.3%. Overall 98,4% of banks were correctly classified.

We could also remark that the risk group defined with a threshold of 1% was rather stable: on average, month-to-month turnover in January – September 2015 was less than 50%. Table 8 demonstrates that we were able to predict failures with negative capital for banks of various size.

Table 7: Two-by-two matrix classifying the prediction outcomes. Threshold: the probability of negative capital of 1%

Predicted outcome	*Actual outcome*		
	Negative capital	No negative capital	Overall
Negative capital	16	87	103
No negative capital	19	6 580	6 599
Overall	35	6 667	6 702

Table 8: Clustering the forecasting results by the size of bank assets

Cluster by assets	*Number of forecasts to fail*		*Actual number of failures*
	Total	*Correct*	
Top 100	1	0	0
101-200	8	4	7
201-400	26	6	13
401+	68	6	15
Overall	103	16	35

7 Conclusion

This study explores the phenomenon of bank failures with negative capital, which bring losses to their creditors. In 2011–3q2014, corporate creditors of such banks lost 74% of their funds. We considered the formation of negative capital in banks and suggested a parsimonious model to forecast those events. We claim that such events are predictable. The model correctly forecast over 50% of bank failures out-of-sample for January-September 2014. The model can be applied by bank counterparties in risk-management and by the Central Bank of Russia for supervisory purposes. The research does not aspire to provide an in-depth analysis in the forecasting section, which is a topic for future research.

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