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The Outbreak of the Russian Banking Crisis

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Abstract Owing to a combination of domestic, regional and international factors, Russian banks have been strongly influenced by the worldwide financial crisis which started in the second half of 2008. In this paper, we estimate an early warning model for the Russian banking crisis. In a first step, we identify 47 Russian banks which failed after September 2008. Using the Bankscope dataset, we then show that balance sheet indicators were informative as early as in 2006 and 2007 about possible failures of these banks. Especially equity, net interest revenues, return on average equity, net loans, and loan loss reserves are identified as the early indicators with high predictive power.

Keywords Banking and financial crisis, early warning models, Russia, logit
JEL classification G33, G21, C25

1. Introduction

The financial market turbulence in 2008 and 2009 has led to the most severe financial crisis since the Great Depression. The crisis has not only affected the stock markets but also, to a great extent, economies around the world, causing a worldwide recession. These events provide ample evidence of how quickly trust in the financial system can vanish and how difficult it is to restore confidence in the financial markets and, more importantly, among the general public.

Russia has been affected much more strongly by the worldwide financial crisis than the majority of emerging economies and developing countries (Dreger and Fidrmuc 2011). The majority of Russian banks did not directly invest in the U.S. subprime market and, due to record-high oil prices, foreign investors considered Russia to be a relatively safe market until the middle of 2008. Eventually, the global financial crisis affected Russia in two fundamental ways. The first was the liquidity crisis, which had already affected the banking sector in the U.S.A. and in Europe. The second was a decrease in the demand for commodities due to the global economic slowdown, which in turn led to a sharp decline in oil prices. In addition the conflict in Georgia increased the political instability of Russia and further weakened the confidence of international investors. This resulted in a "flight to quality" of international investors which led to massive losses on the Russian stock market. In the months to follow, Russia did

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not only experience a severe banking crisis but also, owing to the devaluation of the Russian ruble, a currency crisis—the situation thus turned into a so-called twin crisis (Kaminsky and Reinhard 1999).

The current financial crisis provides evidence for the economic and social costs that can be associated with periods of financial, and in particular banking distress. Therefore the need for reliable early warning models to forecast potential banking crises is more present than ever (Reinhart and Rogoff 2008, 2009). The possibility to detect potential banking crises could not only reduce the associated economic costs but would also ensure a safe and sound banking system in which banks are able to perform their intermediary role. Given the importance of the subject, an extensive literature on the prediction of banking crises in general and on bank failure prediction in particular has evolved. Using a logit regression approach and balance sheet data from 2006 and 2007, we tried to identify internal factors which influenced the failure of Russian banks during the Russian financial crisis of 2008. The results indicate that liquidity plays an important role in bank failure prediction, but earnings ability and capital adequacy also turn out to be important determinants of failure.

The paper is organized as follows: the next section describes the outbreak of the financial crisis in Russia in the second half of 2008; Section 3 presents a literature review on early warning models; Section 4 describes our dataset and analyzes factors determining the probability of bank failures in logit models; the last section concludes.

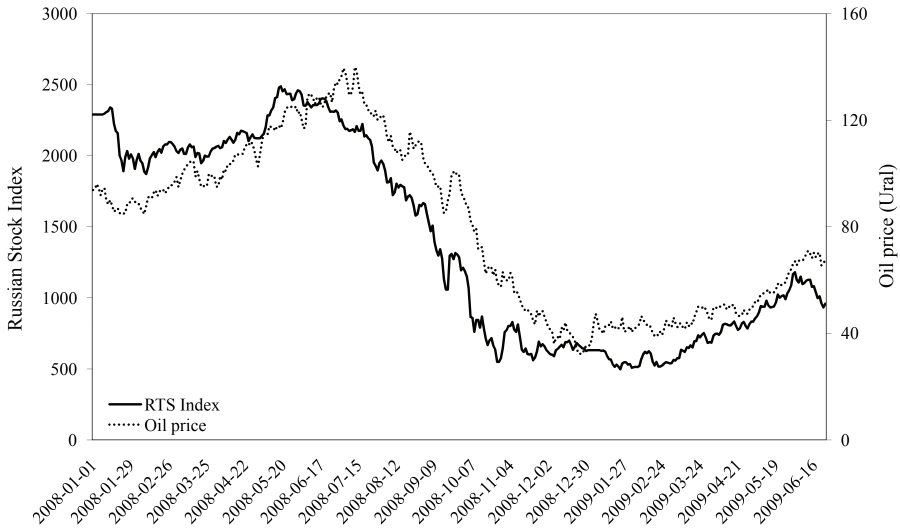
2. The Russian crisis in 2008/2009

The first signs of liquidity shortages in the Russian interbank market started to erupt in September 2008, after the bankruptcy of Lehman Brothers (Brunnermeier 2008). As a consequence, more and more investors sold their assets and the RTS Index continued to decline. Due to the increased counterparty risk and the loss of confidence between banks, the liquidity shortages in the interbank market increased. On September 17, 2008, the Russian Federal Financial Market Service decided to close the Russian stock exchange for two days to prevent the Russian stock market from collapsing. Following these events, interbank lending rates increased by 100 basis points.

From July 3 to September 12, 2008, the RTS Index declined by 38 % (see Figure 1). During this time, a high correlation of the RTS Index and the oil price could be observed (Sutela 2008). Figure 1 reveals that as a reaction to the conflict in Georgia, which started in August 2008, the RTS Index fell by 6.5 %. This fact provides ample evidence of how nervous international markets reacted during these turbulent times. Following these events, the devaluation pressure on the Russian ruble increased. Up to this point Russian banks had not yet experienced liquidity shortages.

Due to the growing uncertainties on the international financial markets and the associated flight to quality, Russia began to experience a sudden stop and a reversal of capital flows. In the fourth quarter of 2008, net capital outflows came to USD 130.5 billion, with USD 56.2 billion from the banking sector and USD 74.3 billion from the non-banking sector.

This trend corresponds to the high short-term repayment obligations of Russian



Source: Datastream.

Figure 1. Financial developments in Russia

banks and companies. By mid 2008, Russia's external debt had risen to USD 527 billion. Banking sector debt accounted for 37 % and corporate debt for 56 % of overall debt (Bogetic 2008). Especially small and medium-sized banks had relied on short-term foreign borrowing as a funding source due to their weak deposit base given the dominance of state-controlled banks. This fact made these banks especially vulnerable to sudden changes in capital flows as the refinancing conditions for their foreign loans worsened.

To mitigate the effects of the financial crisis, the Russian government and the Central Bank of Russia (CBR) implemented a number of measures to support the Russian banking sector with liquidity and the corporate sector with loans. Russian companies, which to a great extent had used international financial markets as a source of funding, also faced difficulties. The reason for this is that Russian companies in many cases used shares as collateral for their loans. After the stock market had experienced a massive decline, the value of companies' collateral decreased accordingly, which worsened their refinancing capabilities. Given the fact that many companies and banks had taken up foreign currency loans, the continuing devaluation of the Russian ruble made loan repayments even more expensive. To increase the level of liquidity and confidence in the interbank market the CBR decided to apply two measures. In a first step the reserve requirements for all bank liabilities were lowered by 4 basis points. This measure increased the liquidity level on the interbank market by approximately RUB 300 billion. In a second step the CBR announced that it would compensate those banks with a rating of above BB-/Ba3 for any losses incurred on the interbank market. The aim of this measure clearly was to increase confidence between banks on the interbank market.

Larger banks no longer had to worry about counterparty risk. Previously larger banks were hesitant to lend money to small and medium-sized banks because they feared possible bankruptcies of these institutions. The CBR expected that the liquidity in the interbank market would therefore spread more evenly.

An additional measure to support the banking system and companies was approved by the Russian parliament. On September 29, 2008, the Russian parliament adopted the law “On additional measures to support the financial system of the Russian Federation”. The aim of this law was to provide Russian banks and companies with liquidity to repay their foreign loans. For this purpose the Bank for Development and Foreign Economic Affairs (VEB) received USD 50 billion from the CBR. These funds were available for the repayment of all foreign loans shown on the balance sheets of selected companies and banks before September 25, 2008.

However, only those companies which were regarded as being of strategic importance to the Russian economy were eligible to apply for these rescue loans. Most of the companies whose rescue loans were approved belonged to the aluminium, oil, banking and construction sectors. Under the same law, the Russian National Wealth Fund and the Stabilization Fund of the Russian Federation were enabled to deposit up to RUB 450 billion with VEB. VEB used these funds to provide unsecured subordinated loans to commercial banks. VEB distributed these loans to the following banks: the majority state-owned VTB Bank and the state-owned Russian Agricultural Bank received RUB 200 billion and RUB 25 billion, respectively. The remaining funds were granted to those banks which either had an international rating of B-/B3 and above or a national investment grade rating.

The CBR also provided Sberbank with unsecured loans to the amount of RUB 500 billion. The initial idea was that these banks would distribute the additional liquidity within the banking system. Unfortunately the loans granted to the state-owned banks did not reach the interbank lending market and therefore did not ease the liquidity shortage because the high concentration of the Russian banking system prevented the government’s liquidity injections from spreading evenly in the interbank market (Barisitz 2008).

Especially small and medium-sized banks were still short of liquidity. To solve this situation the State Duma passed a new law on October 28, 2008: “On additional measures to stabilize the banking system during the period up to 31 December 2011”. This law enabled the Russian Deposit Insurance Agency (DIA) to prevent Russian banks from going bankrupt. Under this law, the DIA was able to choose between different bail-out options. It could either find investors for those banks which were on the verge of going bankrupt, and assist the investors with the restructuring of the respective bank or, if no investor could be found, the DIA itself could acquire 75 % of the bank in question. For this purpose the DIA received RUB 200 billion from the government.

Initially the government had decided to only support larger banks in case they faced liquidity problems. However, after small and medium-sized banks had been effectively cut off the interbank market and as the largest banks were hoarding liquidity, the government changed its approach. In an atmosphere prone to rumors, the difficulties which small and medium-sized banks faced might have easily caused problems in the entire banking sector and might even have led to bank runs. For this reason the government had been reluctant to allow even the smallest banks to go bankrupt (Fungáčová and Solanko 2008a, 2008b).

However, the results of these policy measures were limited. From September 29 to November 13, 2008, the RTS Index fell by 48 % and the oil price by 43 %. After the massive decline of the RTS Index, the Russian government decided to support the financial markets. For this reason VEB received resources amounting to RUB 175 billion from the National Wealth Fund. VEB therefore acted as an investment agent on the stock market to prevent a further decline of stock prices.

By October 2008, the confidence of the Russian population in the banking system seemed to have decreased markedly. In October 2008 the banking system experienced an average deposit outflow of around 5–6 %. Small and medium-sized banks recorded far greater deposit outflows of around 10–12 %. Even Sberbank saw deposit outflows of 3.2 %. The reasons why the Russian population withdrew deposits from the banks were twofold. Firstly, speculations about possible bank defaults increased. Secondly, as fears of a further devaluation of the ruble increased, the population converted its ruble deposits into foreign currency deposits. Within just one month the share of foreign currency deposits increased from 21.2 % to 26.5 %. This reaction is even more astonishing when one keeps in mind that the government had increased its guarantee on deposits from RUB 400,000 to RUB 700,000 on October 10, 2008.

The continuing sharp decline of the oil price contributed to increasing capital outflows which in turn led to a further decline of the RTS Index. In addition the decline of the oil price fuelled expectations that Russia's current account surplus might turn into a deficit, which increased the pressure on the ruble. To fight the devaluation of the ruble, the CBR had used its foreign reserves. Russia's foreign reserves thus decreased from around USD 600 billion in August to USD 475 billion in November 2008. In mid November the CBR therefore launched a controlled devaluation policy (Sutela 2008). On November 11, 2008, the CBR widened the basket band in which the currency could trade from 30.40 to 30.70 of RUB per 1 USD. Having set this new basket band, the CBR spent almost USD 7 billion on the first day to defend the ruble basket exchange rate at the newly set level. It has to be noted that the devaluation pressure on the ruble was also elevated through speculative attacks. Along the market participants that speculated against the ruble were not only foreign investors but, interestingly, some of the largest state-controlled banks. In addition, the state-controlled banks used the funds they had received from the government to stabilize the interbank market for these speculative attacks.

During the period of November 11 to January 22, 2009, the CBR gradually devaluated the ruble through a regular widening of the ruble basket band. This policy resulted in the ruble's nominal depreciation of almost 40 % against the U.S. dollar and almost 29 % against the euro. The CBR justified its chosen strategy of gradual ruble devaluation by the need for domestic companies and households to adjust to the new exchange rate regime. The gradual ruble devaluation strategy appeared to be very costly for the government: Russia's international reserves decreased from USD 475 billion in November 2008 to USD 386 billion in January 2009. To mitigate further outflows of international investors' capital, the CBR increased its interest rate at a time when other central banks cut their rates (Lehmann 2008).

3. Literature survey

Failure prediction models have a long history in corporate finance literature. The basic model was developed by Altman (1968). In his study Altman used multivariate discriminant analysis to analyze the probability of failure among manufacturing firms. The model uses five financial ratios to predict bankruptcy one and two years before the firm in question actually fails or survives. Altman's results showed that firms with certain financial structures (characterized by their financial ratios) have a higher probability of failure than firms with different characteristics. Altman's groundbreaking results led to an increased research interest in this field. His model was extended and eventually applied to predict bank failures.

The study of bank failures is important for two reasons. Firstly, understanding the factors related to a bank's failure enables regulatory authorities to manage and supervise banks more efficiently. Secondly, the ability to differentiate between sound and troubled banks will reduce the expected costs of a bank failure. If a problem bank can be detected early enough, actions can be taken to either prevent the bank from failing or to minimize the costs to the public. Therefore, to prevent bank failures, regulators are interested in developing early warning systems (EWS) in order to identify problem banks and to avoid bankruptcies. The current crisis, which started as a banking crisis and later evolved into a global financial crisis, exemplifies the importance of bank failure prediction models. Not only did the current crisis show how costly the bailout of banks can be, it also made clear how important it is to maintain a safe and sound banking system for each and every economy. In the following, we will discuss whether bank failure prediction models might have been able to predict the current Russian banking crisis.

Martin (1977) applied Altman's results to predict bank failures. He employed a logit model to predict bank failures, using a two year horizon between the statement year of the financial ratio data and the observation year during which a bank could either have failed or survived. Using all Federal Reserve member banks, he identified 58 banks which failed during a seven year period in the 1970s. The results of Martin's study showed that different indicators on capital adequacy, liquidity, asset quality and earnings were not only significant, but actually able to predict bank failure. Martin's model can therefore be described as an early warning system (EWS) for bank failures. Another author, Sinkey (1975, 1978) also found evidence for the assumption that poor asset quality and low capital ratios could best identify potential problem banks.

Motivated by these research results, the US Federal Deposit Insurance Corporation introduced a bank monitoring system in 1977 to help structure their bank monitoring process. This system consisted of 12 financial ratios which can be categorized into the following groups: Capital adequacy (C), Asset quality (A), Management competence (M), Earnings ability (E) and Liquidity (L).[1] Hence, the term CAMEL rating was created. This rating method allows regulators to identify potential problem banks by comparing each observed financial ratio with a benchmark. If a particular bank does not meet the minimum ratio requirements, it is reviewed by the regulators.

Most of the failure prediction models use variables which can be categorized under four of the five CAMEL factors. The variable which is usually missing is the one that assesses management quality. In a way this is surprising, because many bank failure prediction studies have concluded that poor quality and efficiency of bank management are the leading causes of bank failure (see e.g. Barr and Siems 1997; Wheelock and Wilson 2000; and Derviz and Podpiera 2008). Currently, a large number of failure prediction models are used, based on various types of modeling such as logit models, survival analysis, decision trees, trait recognition and neural networks.

The health of the banking sector is a prerequisite to increase private savings and allocate loans to their most productive use (Hanousek et al. 2007). This is especially important in transition economies such as Russia (Fungáčová and Poghosyan 2011; Fungáčová and Weill 2009). We will therefore now briefly outline the results of bank failure prediction models in Russia. Kuznetsov (2003) applied a logit model to analyze which factors influenced the failures of banks during the Russian banking crisis of 1998. He concludes that medium-sized banks with large investments in government bonds were more likely to survive the crisis. The profitability and liquidity of banks turned out to have no influence on the probability of failure. Golovan et al. (2003) are the first to divide all Russian banks into clusters and then employ a logit regression to each cluster. Their results show that the probability to fail is negatively related to capital adequacy, liquidity and the share of government bonds. Lanine and Vander Vennet (2005), using a logit and trait recognition model, also studied the banking crisis of 1998 and came to the same conclusion. The study by Konstandina (2006) also applied a logit regression to identify potential factors which influence bank failure. According to her results, bank efficiency clearly matters. Less efficient banks have a higher chance of failure. Higher levels of non-performing loans also bring a higher risk of failure, as does the holding of government securities. Liquidity also appears to be a significant factor that influences bank failure.

4. Early warning model for the Russian banking crisis

4.1 Data description

The data used in this paper were drawn from the Bankscope database. The initial sample consisted of 1,120 Russian banks. Due to a large number of missing values, this sample was reduced to 875 banks. Most models which try to predict bank failures use balance sheet data to construct financial ratios. These financial ratios are designed to reflect the soundness of a bank in several aspects. Given the importance of the subject, extensive research has been devoted to the design and identification of such financial ratios. As a result, earlier research used over a hundred financial ratios on the

[1] Newer versions of CAMEL models also comprise the additional category of sensitivity to market risk. These models are referred to as CAMELS (Flannery 1998, BIS 2002).

basis of raw balance sheet data. For the identification of problem banks, these financial ratios are believed to be more effective explanatory variables than raw balance sheet data.

The explanatory variables usually include the financial ratios belonging to the CAMEL categories (Zhao et al. 2009). A bank's capital base is a crucial explanatory variable since it shows the financial strength of the institution (Estrella and Park 2000). Capital adequacy is a measure of the level and quality of a bank's capital base. Asset quality measures the level of risk of a bank's assets. This is related to the quality and diversity of borrowers and their ability to repay loans. Management quality is a measure of the quality of a bank's officers and the efficiency of its management structure. Earnings ability is a measure of the performance of a bank and the stability of its earnings stream. Liquidity measures a bank's ability to meet unforeseen deposit outflows within a short time (Karas et al. 2010). Each of these general characteristics could in theory have an impact on a bank's failure.

Table 1. Descriptive statistics of banking indicators, 2007

	No Failure		Failures		Equality test	
	Mean	S.D.	Mean	S.D.	F-test	p-value
Loan loss reserve / Gross loans	5.709	6.772	4.060	4.778	0.633	0.427
Impaired loans / Gross loans	1.885	5.469	3.681	1.961	0.006	0.936
Impaired loans / Equity	7.871	32.909	22.568	9.143	0.050	0.823
Equity / Total assets	20.212	13.977	7.282	14.284	6.044	0.014
Equity / Net Loans	50.035	67.970	49.742	31.856	2.380	0.123
Equity / Liabilities	32.891	49.465	11.921	17.673	3.207	0.074
Net interest margin	6.908	3.644	1.777	5.730	3.520	0.061
Net interest rev / Avg assets	5.959	2.690	1.641	4.764	6.611	0.010
Oth operational income / Avg assets	6.457	6.383	5.347	6.620	0.022	0.883
Non interest expend. / Avg assets	9.395	7.522	5.075	9.022	0.082	0.775
Return on average assets (ROAA)	2.003	3.944	1.014	1.564	0.419	0.518
Return on average equity (ROAE)	12.872	12.056	9.717	13.009	0.004	0.948
Cost to income ratio	65.837	17.914	23.431	75.482	9.226	0.002
Recurring earning power	4.134	3.088	2.468	2.776	6.409	0.012
Net loans / Total assets	54.668	19.333	15.970	59.448	2.022	0.155
Net loans / Total dept & borrowing	80.074	49.315	20.877	76.072	0.222	0.638
Liquid assets / Total dept & borrowing	49.696	44.103	18.775	32.002	5.428	0.020

Source: Bankscope, own calculations.

Keeping this is in mind, we decided to look initially at 36 financial ratios available in the Bankscope database, dividing them into the different CAMEL categories. We did not include indicators of management quality because a large number of values on this item was missing from the dataset. After controlling for these missing values, 17 financial ratios remained (see Table 1).

A positive (negative) sign indicates that the probability of failure will increase (decline) if the financial ratio increases. The ratio of loan loss reserves to gross loans indicates the portfolio quality. The higher the ratio, the poorer the quality of the loan portfolio will be. Hence, we expect this variable to have a positive sign. The same is true for the other two ratios belonging to the asset quality category.

Better capitalized banks have higher chances of surviving since their cushion for losses is larger. We expect to see a negative sign for the ratio of equity to total assets. The same is true for the ratio of equity to net loans, which increases the cushion available to absorb losses and hence decreases the probability of failure.

All ratios under the category earnings ability decrease the probability of failure if they rise themselves, because an increase in any of these ratios is equivalent to higher profitability, and thus the probability of failure should decrease. The only exception is the cost to income ratio. If this ratio increases, the general earning power of the respective bank decreases. Therefore, we expect that if this ratio increases, the probability of failure will increase as well. The higher the ratio of net loans to total assets, the less liquid a bank will be, which in turn should raise the probability of failure.

The descriptive statistics in Table 1 reveal that especially the following variables show major differences between the two groups: equity to total assets, equity to net loans, equity to liabilities, net loans to total assets, and the cost to income ratio.

5. Definition of bank failure

Enterprises are normally defined as bankrupt when their net worth becomes negative. Most bank problems are, however, resolved in some way before a bank's net worth actually becomes negative. The current crisis once again showed that it is also reasonable to regard a bank as failed if it has received either funds from the government. Such a government intervention usually happens if the effects of a bank failure on the real economy and the banking system in general are unforeseeable. Another option to save a bank from actually failing is its compulsory merger with a state-controlled bank.

The Russian government used each of the described options to stabilize the national banking system. The related interventions were mainly carried out by the Deposit Insurance Agency or by government-owned or -controlled banks such as Sberbank, Vnesheconombank and the National Reserve Bank. Not only did the government act as a stabilizing factor in these turbulent times, privately and publicly owned banks also used the opportunity to acquire troubled banks.

For the purpose of this paper, a bank is therefore considered as failed if it meets one of the following conditions: the bank's license was revoked; a direct state bailout was performed; the bank received funds from a government entity (other than an earlier ownership participation as in the case of the state banks mentioned above); or a compulsory merger or takeover took place. Table 2 lists all identified bank failures with a short description of their cases.

Table 2. Descriptive statistics of banking indicators, 2007

Bank name	Acquired by	Involvement	Date	Bankscope
Svyat bank	VEB	Direct state bailout	23.9.2008	Yes
KIT Finance	Alrosa	State-controlled	10.10.2008	No
Soyuz	Gazenergoprombank	State-controlled	11.10.2008	Yes
Globex	VEB	Direct state bailout	17.10.2008	Yes
VEFK*	DIA	Direct state bailout	21.10.2008	Yes
Sobinbank*	Gazenergoprombank	State-controlled	15.10.2008	Yes
Severnaya Kazna*	Alfa Bank	DIA	9.12.2008	Yes
Russky Bank Razvitiya	Otkritie	DIA	13.12.2008	No
Russian Capital Bank	Nat. Reserve Bank	CBR support	14.1.2009	No
Elektronika*	Nat. Reserve Bank	DIA	1.12.2008	Yes
Gubernsky Bank*	Sinara Group	DIA	11.11.2008	Yes
Nizhegorodpromstroybank*	Sarovbusinessbank	DIA	17.11.2008	Yes
Bank 24.ru*	Probusinessbank	DIA	7.12.2008	Yes
Yarsotsbank*	Promsvyazbank	CBR support	21.10.2008	No
Potenzial*	Solidarnost Bank	DIA	10.11.2008	Yes
Gasenergobank*	Probusinessbank	DIA	14.11.2008	Yes
Bashinvest*	Binbank	DIA	24.11.2008	Yes
Moscow Zalogovy Bank	Bank of Moscow	DIA	29.12.2008	No
Moskovsky Kapital	Nomos Bank	DIA	19.12.2008	No
Nizhniy Novgorod*	Promsvyazbank	DIA	28.11.2008	Yes
Russian Develop. Bank	DIA	DIA	6.11.2008	Yes
Investment Bank Trust*	National Bank Trust	Merger	20.11.2008	Yes
APR Bank*	Onexim Group	Merger	24.11.2008	Yes
MDM Namk*	URSA Bank	Merger	3.12.2008	Yes
Tharkhany Bank	Morskoy	DIA	22.12.2008	Yes
Kauri Bank	License revoked	License revoked	10.2.2009	Yes
Econats Bank	License revoked	License revoked	22.12.2008	Yes
Peace Bank	License revoked	License revoked	22.12.2008	No
Bank Eurasia Center	License revoked	License revoked	22.12.2008	Yes
Sakhalin Vest*	License revoked	License revoked	22.12.2008	Yes
West Bank Premier	License revoked	License revoked	22.12.2008	No
Lefco Bank	License revoked	License revoked	12.11.2008	Yes
Sibcontact	License revoked	License revoked	6.2.2009	Yes
ZelAK Bank	License revoked	License revoked	18.1.2009	Yes
Bank Sochi	License revoked	License revoked	17.11.2008	Yes
Setevoi Neftyanoy Bank*	License revoked	License revoked	16.12.2008	Yes
Agrokhimbank*	License revoked	License revoked	30.12.2008	Yes
Baltcreditbank	License revoked	License revoked	19.12.2008	Yes
Net Oil Bank	License revoked	License revoked	19.12.2008	Yes
Inkasbank*	License revoked	License revoked	19.2.2009	No
Sudcombank*	License revoked	License revoked	19.2.2009	Yes
Prikamye Bank	License revoked	License revoked	19.1.2009	Yes
Uraykombank	License revoked	License revoked	10.2.2009	Yes
Integro*	License revoked	License revoked	27.11.2008	Yes
Kurganprombank*	License revoked	License revoked	27.11.2008	Yes
Gazinvestbank	License revoked	License revoked	17.12.2008	Yes

Source: Deposit Insurance Agency (DIA), Reuters, Interfax, Bloomberg, Renaissance Capital.
*Banks whose equity is below EUR 5 million.

Because the Russian financial crisis started in August 2008, we will focus on those banks which met one of the above criteria between August 2008 and February 2009. Various researchers mentioned in their papers that it is a challenging task to find reliable information about the Russian banking system in general and about Russian banks in particular. We experienced similar problems when we tried to find information about those banks which failed during that time. Therefore, we do not claim that the list of failed banks in Table 2 is complete. If some of the failed banks might be missing, it is more than likely that these banks resemble so-called pocket or highly specialized banks whose equity is very small. We will therefore estimate a model in which we exclude those banks whose equity is below EUR 5 million, although we are aware that these banks may be regionally specialized. All in all, we were able to find 47 banks which failed during the analyzed period. Out of this number, nine banks were not covered by the Bankscope database. We use different versions of bank failures in the sensitivity analysis as described below.

6. An early warning model for Russian banks

We estimate the probabilities of defaults when the dependent variable q equals 1, given the available information set on the Russian bank i in time $t-p$,

$$P\left(q_{it}=1|\Omega_{t-p}\right)=\mathbf{F}_{t-p}\beta+\varepsilon_{it}, \tag{1}$$

where matrix $\mathbf{F}$ includes several financial ratios from the bank's balance sheet as discussed above and ε is the error term. These variables are lagged either by one (explanatory variables are for 2007) or two (data for 2006) years. The results of the logit regression model are displayed in Table 3. The signs of the coefficients indicate the direction an independent variable has on the dependent variable. All variables (except the ratio of loan loss reserves to gross loans) that were included in the model prove to be statistically significant in the basic specification for 2007. The remaining variables each represent one of the CAMEL categories. As expected, equity to total assets is negative and significant at the 5 % level and has the expected effect on bank failure. This result is in line with other studies. Konstandina (2006) and Männasoo and Mayes (2009) come to the same result. Therefore the result shows that better capitalized banks have a lower probability of failure because their cushion against asset malfunction is greater.

The ratio of net interest revenue (income) to average assets is also negative and highly significant and also has the expected effect on bank failure. This result is in line with Peresetsky and Karminsky (2008). It indicates that the higher the profitability of a bank, the lower is the probability that it will fail.

The ratio of net loans to total assets is positive and significant at the 5% level and has the expected effect on bank failure. This result is plausible because the higher this ratio is, the higher is the risk of potential loan losses and the less liquid a bank will be. Again this result is in line with Konstandina (2006). Less liquid banks therefore have a higher probability of failure.

Table 3. Early crisis prediction model for Russian banks

	2007		2006		License revoked		Equity over EUR 5 mil.	
Constant	−5.792***		−2.422*		−8.528***		−4.416**	
Asset quality:								
Loan loss reserves / Gross loans	0.044		0.014		0.074*		0.019	
	(0.033)		(0.045)		(0.038)		(0.046)	
Capital adequacy:								
Equity / Total assets	−0.053**		−0.066**		−0.054		−0.053*	
	(0.025)		(0.028)		(0.034)		(0.03)	
Earnings ability:								
Cost to income ratio	0.037***				0.049***		0.031**	
	(0.011)				(0.014)		(0.012)	
Net interest revenue / Average assets	−0.265**		−0.204**		−0.185			
	(0.104)		(0.101)		(0.138)			
Net interest margin							−0.075	
							(0.112)	
Return on average equity			−0.049**					
			(0.024)					
Liquidity:								
Net loans / Total assets	0.036**		0.031**		0.045**		0.006	
	(0.012)		(0.013)		(0.017)		(0.015)	
Number of observations	875		802		875		543	
Number of failed banks	34		29		18		20	
Omnibus test of model coefficients	0.000***		0.001***		0.001***		0.025**	
−2 log likelihood	255.958		229.011		145.552		171.375	
Cox & Snell R^2	0.035		0.025		0.023		0.023	
Nagelkerke R^2	0.126		0.094		0.129		0.081	
Predictive power (cut level):	0.05	0.04	0.04	0.05	0.04	0.05	0.04	0.05
Specificity in %	76.0	66.2	66.2	76.2	98.2	92.2	60.3	71.8
Sensitivity in %	52.9	58.6	58.6	55.2	52.9	29.4	59.1	40.9
Overall accuracy (correct rate) in %	75.1	66.0	66.0	75.4	88.5	91.7	60.2	70.5

Note: Standard errors are reported in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

The cost to income ratio is highly significant and has the expected positive effect on bank failure. If this ratio increases, the efficiency of the respective bank decreases and therefore its probability of failure increases. Finally, the ratio of loan loss reserves to gross loans is not significant but it keeps the correct sign.

We have performed several sensitivity tests. First, we estimate the same logit regression using balance sheet data for 2006. These results are also displayed in the second column of Table 3. The results confirm that all variables, except the ratio of loan loss reserves to gross loans, are significant at the 5% level. Again all variables have the expected signs.

Next, we change the definition of bank failure. In this model, those banks are labeled as failed whose licenses were revoked during the period from August 2008 to February 2009. Under the current legislation, the CBR is obligated to revoke the license of a bank if the bank's capital adequacy ratio falls below 2 %. Using this definition of bank failure, the number of failed banks dropped from 34 to 18. The results of the logit regression for 2007 are presented in the corresponding column in Table 3. In this model, only three independent variables are significant: the cost to income ratio, the ratio of net loans to total assets, and the ratio of loan loss reserves to gross loans. The other explanatory variables have the expected effect on bank failure but are not significant.

Finally, we follow Karas and Schoors (2007) and exclude those banks from the initial sample of 2007 whose equity is below EUR 5 million. The reason for excluding these banks is that we want to make sure that we observe "real" banks and not pocket or highly specialized small banks. To be able to compare the results of this model with the results from the initial model of 2007 we decided to use the same variables as in the initial model for 2007. Therefore, we will only present the results of the regression model. Due to the new EUR 5 million equity threshold, the remaining dataset consists of 543 banks of which 20 actually failed. In this sensitivity analysis, only two variables are significant: the ratio of equity to total assets and the cost to income ratio. Nevertheless, the remaining variables have the expected signs and therefore the expected effect on bank failure, which confirms the overall robustness of our early warning model for Russia.

7. Bank failure predictions

After having identified ratios which affect the probability of failure, the final step tries to observe how many of the actual failures and non-failures can be predicted by the estimated models. Actually, none of the discussed specifications were able to identify any of the actually failed banks if we used a cut-value of 0.5. Therefore, we look for the optimal cut-value as follows. When classifying a bank into one of the two possible categories, failure or non-failure, the following two misclassification problems can appear (Hwang et al. 1997): first, a Type I error, $P(N|F)$, occurs when a failure is classified as non-failure, this leads to misclassification costs of $C(N|F)$; second, a Type II error, $P(F|N)$, occurs when a non-failure is classified as failure, resulting in misclassification costs of $C(F|N)$. Choosing the prior probabilities or cut-value depends on the balancing costs of Type I and Type II errors.

Most published studies (e.g. Barr and Siems 1997) assert that the cost of misclassifying a bank that fails (Type I error) is greater than the cost of misclassifying a bank that continues to survive (Type II error). They argue that the cost of performing an on-site examination which results in significant operating improvements is less than the cost of a bailout of the same bank if it had not been examined and failed. Especially in the current situation, where major financial institutions around the world have had to be supported with government funds, this argument seems to be reasonable.

In the base model of 2007, we started with the assumption that the prior probabilities and misclassification costs of failure were equally assigned. Therefore, we chose a cut-value of 0.5 (Martin 1977; Sinkey 1975). Applying this cut-level, the model did not forecast any of the failed banks. Lowering the cut-level allows more banks to be picked up, thereby the Type I error is reduced, which on the other hand raises the frequency of the Type II error.

Next, following Demirgüç-Kunt and Detragiache (1998, 2005), we set the cut-level to 0.05, 0.04 and 0.02 to identify which of these cut-levels leads to the best predictive power of the model and, therefore, minimizes the costs of misclassifying banks. As discussed previously, one has to keep in mind that the costs associated with a Type I error are much greater than the costs associated with a Type II error. Hence we analyze four different scenarios where the ratios of costs of a Type I error to those of a Type II error are: 2:1, 5:1, 10:1 and 20:1. The 5:1 ratio for example assumes that the cost of misclassifying a bank that in fact fails is 5 times the cost of misclassifying a bank that survives. This analysis reveals that a cut-level of 0.05 or 0.04 should be selected.

This decision should, however, not be made without keeping the overall predictive power of the model in mind. The results for the selected cut-values can be found in Table 3. When we use a cut-level of 0.05, the overall predictive power of the 2007 model reaches 75.1 %. In this case, 52.9 % of those banks which actually failed were predicted to fail. This is referred to as the sensitivity of the prediction. Of the non-failed banks, 76 % were correctly classified by the model. This is known as the specificity of the prediction. When we use a cut-level of 0.04, the overall predictive power of the model decreases to 66.9 %. The percentage of correctly predicted failed banks, however, increases to 64.7 %. Therefore, we select the cut-level of 0.05 because this level seems to offer a good trade-off between the Type I and Type II errors. Hence the model is able to actually predict over 50 % of the actually failed banks.

For the model using balance sheet data from 2006, the model with a cut-value of 0.5 is again not able to identify any of the actual failures. Table 3 shows the results for the two most powerful cut-levels, 0.05 and 0.04. As in the model of 2007, we can see that the cut-value of 0.05 is sufficient due to the fact that this value seems to be able to balance the trade-off between Type I and Type II errors. Furthermore, the overall predictive power even increases slightly when compared to the model for 2007. The model for 2006 is able to predict 55.2 % of the actual failures and 76.2 % of the non-failures. The corresponding predictive powers of the 2007 model are 52.9 % and 76.0 %, respectively. This result is in line with the results from other studies. Amongst others, Westgaards and van der Wijst (2001) find that the predictive power of the model increases when moving from a one year ahead to a two year ahead model.

Changing the definition of bank failure to "withdrawal of the banking license", the overall predictive power of the model even reaches 91.7 % when using a cut-level of 0.05. However, in this case the model is only able to predict 29.4 % of the failed banks. However, when a cut-level of 0.04 is applied, the predictive power is substantially improved and the model is able predict 52.9 % of the observed failures. The major difference to the 2007 model is that the model with the alternative definition of failure is able to predict 98.2 % of non-failed banks. The overall predictive power of the model reaches 88.5 %. Compared to the previous models, therefore, this model has by far the best overall predictive power.

Finally, the predictive power of the model which applies the EUR 5 million equity restriction turns out to be satisfactory. Similarly to the alternative definition of bank failure, the cut-level of 0.04 seems to be the appropriate cut-level in this model: using a cut-level of 0.04, the overall predictive power of the model reaches 60.2 %. The model is able to predict 59.1% of the failed banks and 60.3 % of the non-failed banks. However, the overall predictive power of the model increases when using a cut-level of 0.05 to 70.5 %.

8. Conclusions

In the second half of 2008, the global economy entered into the first recession since the Great Recession. The impact of the global financial crisis turned out to be much deeper than expected. The impact of the crisis on Russia did not only disclose the structural weaknesses of the Russian economy, such as its high dependence on the oil price. The crisis also put the Russian banking system in severe distress. Large government interventions were needed to mitigate the effects of the financial crisis on the banking system, the currency and the general economy. These government measures provide evidence for the fact that the financial crisis in Russia was at least partially home-made.

The Russian financial sector faced four shocks during the global crisis. Firstly, the global credit crisis caused a sudden stop and then a reversal in capital flows as investors fled to quality. Secondly, the crisis affected Russia's banking system, which led to a liquidity crisis. Thirdly, a sharp drop in the oil price and devaluation pressure on the ruble decreased Russia's foreign reserves. Finally, Russia's stock market experienced a massive decline losing two thirds of its value in less than five month. In general Russia's policy response was proactive and larger than that of many other G-20 member countries and by far greater than the internationally recommended 2 % of GDP. However, the current financial crisis revealed the structural weaknesses inherent in the Russian banking system.

Especially small and medium-sized banks were affected by the financial crisis and were basically cut off the interbank market. This was due to their weak deposit base, given the dominance of either state-owned or -controlled banks. In addition these banks had to rely on international borrowing, which exposed them to a reversal in capital flows. The financial crisis revealed the need for restructuring. The results of the bank failure prediction model revealed that especially better capitalized banks have a lower probability of failure. Finally, our results indicate that less liquid banks have a higher probability of failure and that the higher the profitability of a bank the lower is the probability that it will fail.

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