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ESTIMATING BANKRUPTCY PROBABILITY OF CREDIT ORGANIZATIONS

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ABSTRACT

The paper discusses the issue of bankruptcy of credit institutions in the Russian Federation. In addition, this work reveals the causes for the formation of effective systems for preventing defaults, and presents the analysis of the causes for the deterioration of financial stability of credit institutions. Also, this work reviews the main approaches and authoring techniques used in world practice to assess the probability of bankruptcies; as well as a system of factors that affect the financial stability of a credit institution up to its possible default is formed. Moreover, a system for forecasting the risk of bankruptcy in a Russian bank with a forecast horizon of 5 months and a classification accuracy of 88.33% was proposed. The proposed diagnostic system was based on a logistic regression model of binary choice, what makes it possible to distinguish between financially stable and problem banks. The sample included all banks that suffered a default in the period under study. The comparatively high classification ability of the model presented allows it to be used in practice by both credit institutions in formulating a development strategy, developing measures to prevent bankruptcy and improving financial stability, and the Central Bank of the Russian Federation when monitoring the Russian banking sector and identifying banks that are at risk.

1. INTRODUCTION

In the modern world, one of the main institutions of a market economy is the banking system; its development and competitiveness directly affects the efficiency of economy in any country. The banking sector manages the system of payments and settlements, redistributes funds, and implements monetary policy. However, any credit institution is a complex mechanism which is subject to a number of "diseases", what in turn can lead to its dissolution. Therefore, on the one hand, a bankruptcy of credit institutions as economic entities is a natural process of clearing the market of

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noncompetitive structures, and on the other hand, given the importance of this institution in the national economy, it makes irreparable damage not only to the bank itself, its customers and counterparties, but indirectly to economics, social, investment and political climate in the country, as evidenced by the financial crises that affected the world economy during the last decade.

These circumstances necessitate the formation of appropriate effective forecasting systems that allow identifying problem banks before their licenses are revoked, which is particularly important against the backdrop of the following facts: in 2014, licenses were withdrawn from 86 credit institutions, in 2015 - in 93, in 2016 - in 103 , in 2017 - 47 (Zakirova D.F., Zakirova, 2017; List of banks deprived of licenses in 2017). These forecasting systems will allow the management of the credit institution, as well as the supervisory authority, to take timely measures to improve the banks, thus preventing their closure and the development of new financial crises.

2. METHODS

In the present study a logistic regression model was chosen as a basic model for the formation of a system for forecasting the probability of bankruptcy of Russian credit institutions; the model makes it possible to distinguish between financially stable and problem banks.

To build the model, a sample of banks was formed, in which the license was withdrawn from January 1, 2017 to December 31, 2017 (bankrupt banks), as well as credit institutions soundly operating in this period (non-bankrupt banks). In total, 41 Russian banks were deprived of the license for the analyzed period (List of banks deprived of licenses in 2017), 21 of them were registered in the city of Moscow what is associated with a high concentration of the banking sector (65.7%) in the Russian capital (as of 01.01.2017, 376 out of 572), 5 - in the city of Kazan, 2 - in the city of St. Petersburg (Kahn, 2013). There was no more than 1 failed bank per city in other Russian cities where a bankruptcy took place.

The banks were excluded from the initial sample, which licenses were withdrawn for reasons not related to their financial stability.

When forming a sample of non-bankrupt banks, the method of selection by similarity was used, the criterion of which was the amount of the balance currency for the date closest to the revocation of the license, which allows a significant difference to level between the two groups caused by the difference in size. The source of the information was the ratings of the site www.banki.ru compiled on the basis of the value of the balance currency. Each bankrupt bank was put in accordance to 5 banks soundly operating during the period under study. In addition, bankrupt banks in which external management was already conducted were excluded from the sample.

As a result, 19 bankrupt banks and 95 non-bankrupt banks were included into the initial (training) sample. A similar approach was used to create a testing sample, which included 10 bankrupt banks which licenses were withdrawn between January 1, 2016 and December 31, 2016, and 50 credit institutions operating in the period.

With the purpose of constructing hypotheses about the factors influencing the probability of bankruptcy, an analysis was made of the reasons connected with the deterioration of financial stability of credit institutions, according to which the Bank of Russia withdrew the license. As a result, it was revealed that such are loss of liquidity and a decrease in the value of own funds. The primary cause for the decrease in the value of own funds was the conduct of a high-risk credit policy without creating an adequate level of reserves for possible bad debts, loan and equivalent debts. This circumstance necessitates the quality of explanatory factors in the construction of the model to take into account the indicators reflecting the adequacy of own funds and the amount of reserves formed on the loan portfolio. In addition, we consider it permissible not to take into account macroeconomic indicators in the model, since all sample banks operated within the same country, which is characterized by the same economic conditions, the change of which can be neglected due to the short period of time being considered for analysis.

3. RESULTS

The review of theoretical and empirical works (Kahn, 2013; Lanine and Vennet, 2006; Zhao et al, 2009; Oreshko and Savina, 2016; Emelyanov and Bruzhova, 2013; Golovan et al, 2014; Karminsky et al, 2012), in the field of assessing the probability of bank failures, as well as an analysis of the main reasons for revocation of licenses allowed to form the following system of factors affecting the financial stability of a credit institution up to its possible default: return on assets (Kahn, 2013); share of liquid assets in currency (current liquidity); share of investments in government securities in the balance currency (Golovan et al, 2014); share of equity in the balance sheet currency; the specific weight of the loan portfolio in the balance sheet currency (Zhao et al, 2009); the proportion of overdue loans in the loan portfolio; the share of formed reserves in the loan portfolio (Karminsky et al, 2012); balance currency; the share of deposits of individuals in the balance sheet currency; share of loans to the real sector in the balance currency; share of long-term debts in the loan portfolio.

Table 1: Selection of financial stability indicators through one-dimensional variance analysis (ANOVA) *

	p-value	F	F-critical	Average value		Dispersion	
				B	NB	B	NB
Return on Assets	0	36.02	3.93	-0.053	0.005	0,0078	0.0002
Share of liquid assets in the balance sheet currency	0	8.95	3.93	0.101	0.225	0,0123	0.0302
Share of state treasury bills investments in balance sheet currency	0.417	0.66	3.93	0.004	0.002	0.0002	0
Share of equity in the balance sheet currency	0,711	0.14	3.93	0.135	0.148	0.0186	0.0196
Share of loan portfolio in balance sheet currency	0.009	7.15	3.93	0.395	0.268	0.0489	0.033
Share of overdue loans in the loan portfolio	0,321	0.993	3.93	0.067	0.105	0.003	0.026
Share of reserves formed in the loan portfolio	0.968	0,001	3.93	0.205	0.203	0.019	0.053
Log of the balance currency	0.17	1.91	3.93	16	16.705	3.773	4,148
Share of deposits of individuals in the balance sheet currency	0.076	3,214	3.93	0.23	0.166	0.024	0.02
Share of loans to the real sector in the balance sheet currency	0	18,973	3.93	0.263	0.135	0.031	0.01
Share of long-term debts in the loan portfolio	0	73.36	3.93	0.35	0.09	0.059	0.006

* where B: bankrupt banks from the sample; NB: financially sound credit institutions

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The next step in selecting indicators that explain financial sustainability is to assess their discriminatory capacity. To achieve this goal, a one-dimensional variance analysis (ANOVA) was used.

The source of analytical information for calculating the indicators presented in Table 1 was the published reporting posted on the website www.cbr.ru . All calculations were made using the Excel software.

Conducting this test showed that the most descriptive ability (F-statistics <F critical) refers to the return on assets, the share of liquid assets in the balance currency, the specific weight of the loan portfolio in the balance currency, the share of loans to the real sector in the balance currency, the share of long-term debts in the loan portfolio.

For the purpose of eliminating the multicollinearity of factors, an analysis of pair correlations of the selected indicators was performed (Table 2).

Table 2: Checking the factors for multicollinearity

Correlation	Return On Assets	Share of liquid assets in the balance sheet currency	Share of loan portfolio in balance sheet currency	Share of loans to the real sector in the balance sheet currency	Share of long-term debts in the loan portfolio
Return On Assets	1.00				
Share of liquid assets in the balance sheet currency	0.15	1.00			
Share of loan portfolio in balance sheet currency	0.04	0.22	1.00		
Share of loans to the real sector in the balance sheet currency	- 0.09	0.08	0.55	1.00	
Share of long-term debts in the loan portfolio	- 0.21	- 0.01	0.49	0.21	1.00

As can be seen from Table 2, there is a lack of a strong linear relationship between the indicators under study, therefore, all the presented indicators must be taken into account when constructing the model. The variable "Probability of bankruptcy" assumes two meanings: bankrupt and non-bankrupt, which makes it possible to apply a model of binary choice to it, namely, a logistic regression model.

The next stage in the construction of the model is to study its ability to distinguish between financially sustainable and problem banks. One of the mechanisms for resolving this issue is sample balancing.

Three variants of forming subsamples were considered depending on the number of non-bankrupt banks supplemented by default banks: 1:5 (basic variant), 1:3, 1:2. The coefficients of the logistic regression model were determined for each sub-sample structure, using the maximum probability method and the Gretl 1.9.92 application software package. The results of the data analysis are presented in Table 3.

Table 3: Estimation of the logistic regression model coefficients for samples with different structure *

Factor	Ratio of the number of bankrupt banks and non-bankrupt banks		
	1: 5 (basic version)	1: 3	1: 2
Return on assets of a credit institution	-100,949 (10.35)	-593,223 (5.52)	-132.089 (4.16)
Share of liquid assets in the balance of the credit organization	-22,466 (0.83)	-306.410 (0.86)	-22,381 (0.84)
Share of the loan portfolio in the balance of the credit organization	-4,873 (0.68)	-20,025 (0.66)	-0.007 (0.64)
Share of loans to the real sector in the balance sheet of the credit institution	10,6768 (0.81)	105,976 (0.84)	0,0011 (0.84)
Share of long-term debts in the loan portfolio of a credit institution	17.407 (1.15)	176,869 (1.14)	12.678 (1.12)
Constant	-3.015	-13,121	-1.179

* - the variation coefficient value is shown in parentheses.

Table 3 shows that with a decrease in the number of observations in the sample, the estimates of the variation coefficients become more stable. Another criterion for selecting a subsample structure is the classification accuracy that the model demonstrates, and the weighted efficiency index which is calculated using the following formula (Kolari et al, 2000):

$$WE = \frac{FCC}{PF} * \frac{FCC}{AF} * CC \qquad (1)$$

Where WE is the weighted indicator of model efficiency;

FCC - the number of correctly classified bankrupts,

PF - the number of banks classified as a bankrupt,

AF - the number of actual bankrupt,

CC is the percentage of correctly classified banks.

An assessment of the banks classification accuracy was carried out on the basis of the testing sample; the results are presented in Table 4.

Table 4: Classification table

Ratio of the numbers of bankrupt banks to non-bankrupt banks	1: 5 (basic version)		1: 3		1: 2	
	Actual		Actual		Actual	
Model	Non-bankruptcy	Bankrupt	Non-bankruptcy	Bankrupt	Non-bankruptcy	Bankrupt
Non-bankruptcy	47	1	49	1	48	2
Bankrupt	3	9	1	9	2	8
% True	94.00	90.0	98.0	90.0	96.0	80.0
% Total True	93.33		96.67		93.33	
Weighted efficiency indicator	0.63		0.78		0.60	

The results in Table 4 show that the most acceptable is the 1: 3 sub-sample, where a comparatively high overall accuracy (96.67%) is achieved and the weighted efficiency index has increased by 1.24 times.

A period of 5 months was determined in the capacity of an optimal forecasting horizon. As a result of the calculations, the following model for diagnosing the risk of bankruptcy of a credit institution was built:

$$P_i = \frac{1}{1+e^{-Z}} \tag{2},$$

$$Z = -10{,}377 - 302{,}573x_1 - 161{,}537x_2 - 121{,}11x_3 + 77{,}623x_4 + 93{,}376x_5$$

Where P_i – probability of bankruptcy of the credit organization (in fractions of a unit);

e - the base of the natural logarithm (Euler number, e = 2.71828),

Z_i - the linear combination of independent variables;

x_1 – the return on assets of a credit organization;

x_2 – the share of liquid assets in the balance sheet of the credit institution;

x_3 – the specific weight of the loan portfolio in the balance sheet of the credit organization;

x_4 – the share of loans to the real sector in the balance sheet of the credit institution;

x_5 – the share of long-term debts in the credit portfolio of the credit institution.

If the binary variable $p_i \in (0.5; 1]$, the risk of bankruptcy is high; if $p_i \in [0; 0.5]$, then the risk of bankruptcy is low. Negative coefficients in front of variables suggest that an increase in the profitability of assets, an increase in the balance sheet of liquid assets and a loan portfolio lead to a decrease in the probability of bankruptcy and increased financial stability. The growth in the share of loans to the real sector and long-term debts lead to a deterioration in the financial condition of a bank and increase the risk of bankruptcy. In addition, the largest absolute value of the coefficient in front of this variable indicates the greatest influence of this factor on the change in the probability of bankruptcy.

The quality of the constructed model was evaluated by the accuracy of the classification of banks included in the testing sample. The results of the evaluation are presented in Table 5.

Table 5: Classification table

Model	Actual	
	Non-bankruptcy	Bankrupt
Non-bankruptcy	45	2
Bankrupt	5	8
% true	90.00	80.00
% Total True	88.33	
WE	59.62	

The classification ability of the model is 88.33%; the category of 53 banks out of 60 was defined correctly. However, 7 errors were made: 2 errors of the first kind and 5 errors of the second kind, i.e. the model classified 20% of bankrupt banks as the financially-stable and recognized almost 10% of operating banks as bankrupts. The weighted efficiency indicator for the analyzed model was 59.62%. Thus, the constructed model is more suitable for the detection of financially stable banks than for identifying potential bankruptcies.

4. DISCUSSION

With the purpose of early warning on the probability of default, the supervisory authorities of different countries apply different models, and some even several models.

So, for example, the CAMEL system is used in the USA; it is based on 6 aspects of the credit organization's activity: capital adequacy, asset management quality, profitability, liquidity, sensitivity to risk. Germany uses the method of coefficient analysis BAKIS, which is based on a system of 47 indicators affecting the assessment of credit risk, market risk, liquidity, profitability. In the UK, a RATE system is used; it based on risk assessment, oversight tools and evaluation of the effectiveness of these instruments. In Russia, all credit institutions are grouped into 5 classification groups based on the characteristics of the level of their financial stability with regard to their capital, assets, profitability, liquidity, interest rate risk, and concentration risk, quality of management and transparency of ownership structure. Among the shortcomings of the reviewed systems for assessing the financial stability of credit institutions the following should be noted: subjectivity of opinions (USA, Russia), labor intensity (Germany), and duration of the study (UK).

Another direction of early diagnosis of default is creation of ratings (Expert RA, RBC, AK & M, Interfax, Moody's, IMF, etc.).

In the economic literature, authoring methods are also found, which are based on calculating and analyzing the stability coefficients (A.K. Muravieva, E.A. Tarkhanova), on econometric models (A.A. Peresetsky, O.P. Ovchinnikova, A. Yu Bets) (Lukin, 2017), etc., which are mainly focused on assessing the current financial state of a bank, rather than predicting a default. From the point of view of forecasting, multiple discriminant analysis (the Altman model) is used for companies, and a logistic regression model for foreign banks (Kolari et al, 2000). Thus, at present there is no effective methodology based on economic and mathematical methods for forecasting bankruptcy of credit institutions for Russian banks.

5. SUMMARY

In order to ensure greater stability of the banking system of the Russian Federation, the urgency of forming a system for forecasting bankruptcy of credit institutions is undoubtedly urgent, taking into account that bankruptcies become of a large scale due the worsening of the general economic situation and the impact of economic sanctions. In the course of the study, a system of factors including 5 indicators was formed using a one-dimensional variance analysis and testing factors for multicollinearity: the profitability of assets, the share of liquid assets in the balance currency, the specific weight of the loan portfolio in the balance currency, the share of loans to the real sector in the balance currency, and the share of long-term debts in the loan portfolio. It was also found that an increase in the values of the first three factors of this system leads to a decrease in the probability of bankruptcy and increased financial stability, and an increase in the share of loans to the real sector and long-term debts leads to a deterioration in the financial condition of the bank and increases the risk of bankruptcy. Thus, monitoring these indicators is an important step in the process of preventing bankruptcy. Based on these factors, a logistic regression model was constructed that allowed us to demarcate financially stable and problem banks with a forecast horizon of 5 months and with a classification accuracy of 88.33%.

6. CONCLUSION

The results of the study can be used:

- By credit organizations in the formation of their development strategy, identifying measures to prevent bankruptcy and improve financial sustainability. In this regard, it is important to know the system of factors that affect the change in the probability of bankruptcy, as well as the nature of this influence;
- The Central Bank of the Russian Federation in monitoring the financial stability of the banking sector of the Russian Federation and identifying banks those are at risk;
- Scientists-economists and financiers to expand and deepen the subject areas of scientific research.

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