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Developing Credit Risk Assessment Methods to Make Loss Provisions for Potential Loans

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ABSTRACT

According to Bank of Russia Regulation No. 590-P dated June 28, 2017, Russian banks assess credit risk and make loss provisions for potential loans. Since 01.01.2018, credit institutions have been required to create loss provisions for expected losses in accordance with international standards (IFRS 9). This **novation** seems relevant due to the lack of a common risk assessment method and the importance of cost optimization on loan provisions. **The aim** of the study is to improve the credit risk assessment method for making loss provisions for potential loans. The author used the **methods** of system and logical analysis and synthesis, techniques of high financial calculations, the balance method, the method of financial ratios. When estimating the probability of borrowers' default, potential credit losses and loan provisions, the author applied actuarial, market, statistical and econometric methods. Based on a Russian bank's sample data for 2012–2019, the author developed a regression model that establishes the relationship between financial ratios and the default of corporate borrowers – agricultural producers, and checked the significance of the model's financial ratios. The author divided the borrowers into rating groups by score. The probability of default is the ratio of the number of defaults to the number of borrowers by group. The average default loss for each group depends on the collection / debt ratio in the bank under review. The score of a borrower brings them into a certain rating group, helps calculate the probability of a default and losses in case of default. The calculated expected losses may be of further use when determining loss provisions for potential loans. The author concludes that this method allows assessing risks and making a decision on lending to borrowers – agricultural producers. The expected credit loss approach will allow for more reasonable provisioning, which corresponds to other authors' findings. Applying this method in a particular bank requires considering the specifics of the composition and structure of the loan portfolio. It is necessary to analyze the impact of the expected credit loss method on the profitability of banks.

Keywords: financial condition; credit risk; actual losses; financial ratios; expected credit losses; loss provisions for potential loans

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INTRODUCTION

Lending to corporate borrowers is associated with credit risk factors that may lead to potential loan losses. To reduce the risk, banks create loss provisions for potential loans, loan and similar debt (the principal debt),¹ as well as provisions for potential losses (interest, commissions, penalties, state duty) in accordance with the Bank of Russia regulations.² Provisions are made in accordance with Russian requirements by the method of actually incurred losses. To determine provisions, the loan category with collateral is also considered, since this factor minimizes the created provisions.

Banks can assess risks and create provisions based on incurred losses in two ways: individually (for each specific loan) or on a portfolio of homogeneous loans. With an individual approach, provisions are created based on the loan quality. Loans are classified by quality according to the financial condition of the borrower and the quality of debt service. In case of portfolio provisioning, portfolios of homogeneous loans with similar characteristics of credit risk are created, which meet certain requirements and are isolated to make provisions.

According to IFRS 9, since 01.01.2018, simultaneously with creating provisions by Russian standards, commercial banks have been calculating provisions based on expected losses.³ Table 1 presents the main differences in ap-

proaches to creating provisions by the method of incurred losses and expected credit losses.

Under IFRS 9, provisions are created in three stages depending on changes in credit risk. *Stage 1* — Expected credit losses are calculated within 12 months after the reporting date. *Stage 2* — A significant increase in the credit risk of a financial asset, for example, a decrease in collateral value, more than 30 days of delay, unfavorable changes in business, etc. *Stage 3* — A financial asset becomes objectively impaired; there is a real credit loss due to events that negatively affect the receipt of future cash flows (overdue more than 90 days, probable bankruptcy, or default). For *Stages 2* and *3*, expected credit losses are recognized over the life of the financial instrument.

Expected credit losses at the reporting date are determined as follows:

1) for financial assets at *Stages 1* and *2* — as the present value of all expected not received funds or the difference between the cash flows owed to the bank under the agreement and the cash flows that the bank expects to receive, formulas (1), (2);

2) for financial assets at *Stage 3* — as the difference between the gross carrying amount of assets and the present value of estimated future cash flows, formula (3):

$$\text{Provision}_{\text{stage1}} = PD * LGD * EAD, \quad (1)$$

$$\text{Provision}_{\text{stage2}} = LGD * \sum PD_k * CF_k / (1 + i)^k, \quad (2)$$

$$\text{Provision}_{\text{stage3}} = LGD_{\text{in default}} * EAD, \quad (3)$$

where PD is the probability of default (determined based on statistical models or available market data);

LGD is the loss given default (share of losses in the default amount): the indicator can be estimated by modeling expected cash flows, regression on historical data or based on market prices of non-problematic loans;

EAD is the exposure at default, debt at the reporting date subject to the risk of impairment (the default amount); calculated separately for each financial asset;

i is the effective interest rate;

¹ Bank of Russia Regulation No. 590-P, dated 28 June 2017, "On the Procedure for Credit Institutions to Make Loss Provisions for Loans, Loan and Similar Debts": [together with the "Procedure for Assessing Credit Risk of Portfolio (Portfolios) of Homogeneous Loans"]: (registered in the Ministry of Justice of Russia on 12 July 2017 No. 47384). URL: http://www.consultant.ru/document/cons_doc_LAW_220089/ (accessed on 10.10.2020).

² Bank of Russia Regulation No. 611-P, dated 23.10.2017, "On the Procedure for Creating Loss Provisions by Credit Institutions": (registered in the Ministry of Justice of Russia on 15 March 2018 No. 50381). URL: <http://docs.cntd.ru/document/542611725> (accessed on 10.10.2020).

³ International Financial Reporting Standard (IFRS) 9 Financial Instruments principles (came into effect in the Russian Federation in accordance the Ministry of Finance Order No. 98n, dated 27 June, 2016). URL: http://www.consultant.ru/document/cons_doc_LAW_202060/ (accessed on 10.10.2020).

CF_k is the cash flow generated by the financial instrument.

To calculate expected credit losses for each loan agreement, it is necessary to know the probability of default, the loss given default and the exposure at default.

Based on IFRS 9, the Bank of Russia, has developed recommendations for commercial banks for calculation of credit risk by internal ratings,⁴ as well as on accounting for provisions.⁵ Under the Basel Agreements and the Bank of Russia recommendations, commercial banks create their own methods for assessing credit risk and provisions [1].

M. M. Selezneva, D. V. Novoselov, V. A. Pozdyshev, O. V. Oboznaya and others note the positive result of the transition of Russian banks to a new model of creating provisions, which consists in a more accurate and advanced risk assessment [2–5]. V. Bitvutskii, G. Penikas, E. Mikheeva and G. Holt predict the need to increase provisions for most banks [6–8]. O. Yu. Yakovlev and Yu. M. Porozova emphasize that the new approach does not allow banks to underestimate the amount of provisions to improve their financial condition in the reporting by overstating the financial position of borrowers [9, 10].

Famous Russian and foreign rating agencies Fitch Ratings, AKRA and others indicate that the approach based on expected credit losses causes an adjustment in the profitability of Russian banks, namely, its decrease.⁶

⁴ Bank of Russia Ordinance No. 483-P, Dated 6 August 2015, 'On the Procedure for the IRB Calculation of Credit Risk'. Bank of Russia Bulletin. 2015 No. 81 as amended on 01.12.2015.

⁵ Bank of Russia Regulation No. 605-P, Dated 2 October 2017, "On the Procedure for Credit Institutions to Account Transactions to Place Funds under Loan Agreements, Transactions to Purchase Receivables from Third Parties Related to the Performance of Cash Liabilities, Transactions Related to Liabilities under Bank Guarantees Issued and Funds Provision" (as amended by the instructions of the Central Bank of the Russian Federation dated June 21, 2018 No. 4827-U, dated December 18, 2018 No. 5017-U).

⁶ Fitch Ratings: Stage 3 loans under IFRS 9 better reflect the risks of Russian banks. Fitch Ratings. URL: <https://www.fitchratings.com/site/pr/10041086> (accessed on 01.03.2020); IFRS 9 — Accounting for risks in the financial statements of banks. Financial Accounting. URL: <http://fin-accounting.ru/articles/2018/ifrs-9-accounting-and-credit-risk-in-finan>

M. Vlasenko, A. Tkachev and other authors believe that creating the expected credit loss model should be based on the large amounts of information available to commercial banks [11, 12]. The main criterion for the model adequacy can be the compliance of its assessments with the bank requirements for borrowers.

The above emphasizes the importance of the cost optimization on provisions by the expected credit loss method, especially with no generally accepted method for calculating the probability of default and the loss given default. In this regard, it is relevant to study the method for calculating credit risks in accordance with the approach based on expected losses. The aim of the study is to improve the credit risk assessment method for making loss provisions for potential loans.

RESEARCH METHODS

We plan to assess the expected credit loss risk by the following algorithm:

1) segmentation of corporate borrowers by industry, business size and other parameters. An example of segmentation is dividing borrowers into two groups based on the industry and seasonality of activity: agribusiness enterprises and non-agribusiness enterprises. Moreover, each group should include potential bankrupts and non-bankrupts;

2) sampling enterprises from a specific segment within the framework of a regional or national market;

3) preparing initial data (financial ratios) for each enterprise from the sample (preferably for five annual dates preceding the date of the analysis);

4) calculating financial ratios, which are independent variables, in the following areas of

cial-statements (accessed on 01.03.2020); Report on results from the EBA impact assessment of IFRS 9. European Banking Authority. November 2016. URL: <http://www.eba.europa.eu/documents/10180/1360107/EBA+Report+on+impact+assessment+of+IFRS+9> (accessed on 01.03.2020); The new era of expected credit loss provisioning. BCBS. 6 March, 2017. URL: https://www.bis.org/publ/qtrpdf/r_qt1703f.htm (accessed on 01.03.2020).

Table 1

Approaches to creating loss provisions

Approach	Actual Loss Model	Expected Credit Loss Model
Calculation of provisions	Difference between the carrying loan value and the fair value	Lost funds considering the probability of the borrower's default within one year
Probability of default (PD)	Determined indirectly by the loan category	Within one year or throughout the entire term of the financial instrument, depending on the risk
Default detection	Signs of impairment	The bank's internal policy on credit risk management, including the rebuttable assumption of a delay of 90 days
Loss given default (LGD)	Determined indirectly by the loan category	Basel estimates, subject to the exclusion of certain components
Exposure at default (EAD)	Determined indirectly by the loan category with collateral	Analysis for the entire life of a financial instrument
Expected Losses (EL)	Determined indirectly by the loan category with collateral	Losses within one year or throughout the entire life of a financial instrument in case of an increase in credit risk

Source: compiled by the author.

analysis: profitability, liquidity, solvency, and turnover. Assigning a specific weight to each coefficient by expert means, based on the influence on the financial condition and the probability of default;

5) determining non-financial indicators related to industry prospects, competition, seasonality, market position (usually about 20 indicators); assigning a specific weight to each indicator depending on the influence on the probability of default (we did not use non-financial indicators to assess the probability of default due to the lack of relevant informa-

tion and the complexity of an objective assessment);

6) determining the maximum score for each financial coefficient based on the weight, formation of intervals of values, assigning points for each interval;

7) establishing a statistical relationship between the values of financial ratios and a borrower's default;

8) calculating points for each borrower, classifying borrowers into rating groups based on their financial condition and ability to repay their obligations to creditors on time;

9) establishing the correspondence between the score for each borrower from the sample and the fact of default for the past year;

10) calculating the probability of default for each rating group as the proportion of the group's borrowers who defaulted during the year;

11) calculating the level of losses on default of the obligations of the borrower (4):

$$LGD = 1 - \frac{\text{Amount of debt repayment under the agreement}}{\text{Credit agreement amount}} \times 100\%. \quad (4)$$

The ratio of the amount of debt repayment to the credit agreement amount can be calculated according to the banking statistics of transactions of assignment (sale) of rights (claims) under credit agreements [indicator "recovery rate" ("collection/debt")]. In this case, the agreement price for the assignment of rights of claims is made up based on the value of the collateral and non-tax property, as well as the income and property of the guarantors. The indicator of the amount of debt assigned under the credit agreement is taken from the financial statements. It is necessary to calculate the *LGD* indicator for each rating group separately;

12) calculating the expected losses of the lender as the product of the probability of default, the level of losses in case of default and the amount of the credit exposed at default. Creating provisions for loss provisions for potential loans, loan and similar debt based on the indicator of expected losses.

RESEARCH RESULTS

We chose the agribusiness enterprises business segment for the study. The sample included 57 agricultural enterprises of the Samara region that are borrowers of the bank (for 24 of them, a default was recorded as of 01.01.2020). The main debt of the enter-

prises in the sample amounts to 5,798 million roubles, or 42% of the bank's corporate portfolio.

The following financial ratios were selected as independent variables: financial independence ratio K1, equity ratio K2, current liquidity ratio K3, quick liquidity ratio K4, net profit margin K5, current assets turnover K6, and debt/EBITDA K7. The dependent variable is the probability of default, which equals to 1 if the borrower does not fulfill its obligations to the bank, and it equals to 0 if there are no overdue obligations. We calculated the above indicators for each enterprise as of 01.01.2020.

We calculated the weight of the financial ratios using the expert judgment method; the maximum possible score is 100; we accepted scoring intervals (*Table 2*).

We corrected the initial data to obtain an objective result. We took the financial independence ratio with a negative value of equity capital equal to zero. *Table 3* presents the results.

There is a close relationship between financial ratios and the probability of default as of 01.01.2020. This is evidenced by the value of the multiple correlation coefficient Multiple R, equal to 0.93. The value of the determination coefficient Multiple R² is 0.87, i.e. the probability of default of an enterprise is 87% determined by the selected financial ratios; other changes depend on random factors. The other indicators (Adjusted R², Fisher criterion) meet the requirements. All financial ratios are significant, except the equity ratio due to the negative/or close to zero value of the indicator for many borrowers. The inverse relationship between the quick ratio and the probability of default is explained by the fact that extreme values of the indicator (large or small) are equally impractical, since they reflect low business efficiency and lost profit.

We built a linear multivariate regression model, where the dependent variable de-

Table 2

Financial position score

Ratio	Ratio values					
Financial independence ratio K1	$K \geq 0.4$	$0.3 \leq K < 0.4$	$0.2 \leq K < 0.3$	$0.1 \leq K < 0.2$	$0.05 \leq K < 0.1$	$0.05 > K$
Points	20	15	12	8	5	0
Equity ratio K2	$K \geq 0.2$	$0.1 \leq K < 0.2$	$0.05 \leq K < 0.1$	$0.01 \leq K < 0.05$	$0 < K < 0.01$	$K \leq 0$
Points	15	12	10	5	3	0
Current liquidity ratio K3	$K \geq 1.5$	$1.3 \leq K < 1.5$	$1.2 \leq K < 1.3$	$1.1 \leq K < 1.2$	$1 \leq K < 1.1$	$K < 1$
Points	20	15	12	8	5	0
Quick liquidity ratio K4	$K \geq 0.5$	$0.3 \leq K < 0.5$	$0.1 \leq K < 0.3$	$0.05 \leq K < 0.1$	$0.01 \leq K < 0.05$	$K < 0.01$
Points	10	8	6	3	2	0
Net profit margin K5	$K \geq 0.01$	$0 \leq K < 0.01$	$K < 0$			
Points	15	8	0			
Current assets turnover K6	$K > 3$	$2 \leq K < 3$	$1 \leq K < 2$	$0.5 \leq K < 1$	$K < 0.5$	
Points	20	15	10	5	0	
Total points	100	73	50	29	15	0
Financial position	good		average	bad		

Source: compiled by the author.

Table 3

Regression summary for dependent variable

N = 57	Regression summary for dependent variable: Var8 (Spreadsheet4) $R = 0.93065278$ $R^2 = 0.86611460$ Adjusted $R^2 = 0.84698811$ $F(7,49) = 45.284$ $p < 0.0000$ Std. Error of estimate: 0.19656					
	b^*	Std. Err.	b	Std. Err.	t (49)	p-value
Intercept			0.97335	0.064505	15.08964	0.000000
Var1	-0.38867	0.140749	-0.65277	0.236384	-2.76147	0.008076
Var2	0.18735	0.107068	0.38223	0.218431	1.74987	0.086401
Var3	-1.57190	0.462818	-0.19195	0.056517	-3.39637	0.001363
Var4	1.73174	0.445216	0.21145	0.054362	3.88967	0.000303
Var5	-0.34743	0.098730	-1.14411	0.325121	-3.51903	0.000946
Var6	-0.35390	0.068559	-0.22464	0.043518	-5.16203	0.000004
Var7	0.15889	0.062817	0.00215	0.000850	2.52942	0.014693

Source: compiled by the author.

Table 4

Financial condition according to the score

Financial condition	Score	Financial condition description
1	2	3
Good	91–100	Stability of production, positive value of net assets, profitability and solvency, compliance with the mandatory financial relative indicators, absence of negative phenomena that can affect the financial stability of the borrower in the future: net loss, decrease by more than 25% in production / sales (revenue) / profitability, growth of accounts payable / receivable compared to the previous reporting period or the same period last year by more than 25%)
	83–90	
	66–82	
	62–65	
	58–61	
	53–57	
Average	41–52	No direct threats to the current financial position in the presence of negative phenomena that can affect the financial stability of the borrower in the future: decrease in net assets, decrease in production / sales (revenue) / profitability, increase in accounts payable / receivable compared to the previous reporting period or the same period last year with the share of overdue debt 25–40%)
	31–40	
	26–30	
Bad	16–25	Threatening negative phenomena (net loss in the reporting period, decrease in production (revenue) by more than 50%, increase in overdue payables / receivables with a share of more than 40% in total payables / receivables, decrease in net assets by 50% or more) whose likely result may be bankruptcy or persistent insolvency of the borrower
	0–15	

Source: compiled by the author.

scribes the probability of default, and the independent variables characterize the values of financial ratios as of 01.01.2020:

$$B = 0.973 - 0.653K1 - 0.192K3 + 0.211K4 - 1.144K5 - 0.225K6 + 0.002K7, (5)$$

where K1 is the financial independence ratio;
K3 is the current liquidity ratio;
K4 is the quick liquidity ratio;

K5 is the net profit margin;
K6 is the current assets turnover;
K7 is the debt/EBITDA.

These results justify the correspondence between the statistics and expert assessments.

The enterprises that were the bank's borrowers in 2012–2019 are divided into 9 rating groups according to the score. When making the rating groups, it was necessary to detail the characteristics of the financial

Table 5

Correspondence between the type of financial condition, probability of default and losses in case of default

Score	Number of troubled borrowers (in default)	Number of non-troubled borrowers	Total number of borrowers	Number of defaults	Probability of default, %	Default loss rate, %
1	2	3	$4 = 2 + 3$	5	$6 = 5/4 * 100\%$	8
91–100	2	12	14	0	0.00	Less than 30
83–90	6	56	62	1	1.61	
66–82	9	29	38	1	2.63	
62–65	4	24	28	1	3.57	
58–61	10	21	31	2	6.45	
53–57	20	25	45	6	13.33	
41–52	35	44	79	21	26.58	31–70
31–40	76	126	202	70	34.65	
26–30	59	89	148	56	37.84	
16–25	22	32	54	21	38.89	More than 70
0–15	10	0	10	10	100.00	
Total	253	458	711	189	26.58	

Source: compiled by the author.

condition to consider the factors influencing the probability of default (*Table 4*).

The probability of default was calculated as the ratio of the number of default cases of borrowers in a given group to the total number of borrowers in the group. The movement of borrowers from the problematic to non-problematic category due to the improvement of the financial condition and elimination of the circumstances based on which the debt was recognized as problematic was not considered. The level of default losses was determined as follows. The main methods of debt repayment by borrowers in good financial condition are repayments by the agreement schedule or the

settlement agreement schedule. Losses are associated with a shortfall in funds during the sale of property in the procedure of enforcement proceedings. Debt repayment by borrowers with average and poor financial condition is the sale of property in bankruptcy and enforcement proceedings, as well as the assignment (sale) of rights (claims). The level of losses given default was established based on the average “recovery rate” (“collection/debt”) for the bank for the given period by formula (4). We compiled a table of correspondence between the type of financial condition, the probability of the borrower’s default and the level of losses in case of default (*Table 5*).

There is a close relationship between the type of financial condition, the probability of default and the level of losses in case of default.

We can assess the model's forecasting potential by substituting the initial data of borrowers in formula (5). Based on *Table 5* and the score of the financial condition, we can determine the probability of the borrower's default and the level of losses in this case. Expected credit losses are calculated by multiplying the probability of default by the borrower, the level of losses given default and the amount of debt on the reporting date that is at risk of default. Loan provision is created in the amount of expected credit losses. A certain conventionality of the model is worth noting, since we use a limited list of indicators. The research effectiveness is confirmed by the positive results.

CONCLUSIONS

We considered the method for calculating credit losses under IFRS 9. Based on sample data for 57 borrowers who are agricultural enterprises, we calculated the financial ratios and defined the score for the financial condition, scoring intervals and the status of the borrower (in default or not). We built a regression model where the independent variables are financial ratios, and the dependent variable is the probability of default. When the result of the calculation according to a model

close to 1, the probability of default is high, with a value close to zero, the probability of default is low.

We studied the financial condition of 711 borrowers of the bank for the period 2012–2019: the score was calculated, the borrowers were divided into rating groups. The probability of default is calculated as the ratio of the number of default cases of borrowers in a given group to the total number of borrowers in the group. The level of losses given default was formed based on the average “recovery rate” (“collection/debt”) for the bank for the period under review. If we know the probability of default, the level of losses and loan debt, we can determine the expected credit losses and the amount of provisions.

The model makes it possible to roughly estimate the probability of borrowers' default. The calculation of the score according to the selected financial ratios helps assign borrowers to a certain rating group, determine credit risks and the possibility of providing loans. Our contribution to theoretical science consists in a combination of expert and statistical approaches to assessing financial ratios that determine the probability of borrowers' default. The practical significance of the study is in applying the approaches to a large array of initial data over a long observation period. Improving the model requires considering non-financial indicators when the probability of default is assessed.

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