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 innovation 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), as well as provisions for potential losses (interest, commissions, penalties, state duty) in accordance with the Bank of Russia regulations. 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. Table 1 presents the main differences in approaches 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):

Provision_{stage 1} = PD * LGD * EAD,

Provision_{stage 2} = \sum PD_k * CF_k/(1 + i)^k,

Provision_{stage 3} = LGD_{in default} * EAD,

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;

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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. Selizneva, 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. Bityutskii, 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 overestimating 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); 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).
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 information 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;

| 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.
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):

\[
\text{LGD} = 1 - \frac{\text{Amount of debt repayment under the agreement}}{\text{Credit agreement amount}} \times 100%. \tag{4}
\]

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 enterprise 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 $R^2$ 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 $R^2$, 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 ≥ 0.4  
0.3 ≤ K < 0.4  
0.2 ≤ K < 0.3  
0.1 ≤ K < 0.2  
0.05 ≤ K < 0.1  
0.05 > K | Points |
| Points:                           | 20  
15  
12  
8  
5  
0 |  |
| Equity ratio K2                    | K ≥ 0.2  
0.1 ≤ K < 0.2  
0.05 ≤ K < 0.1  
0.01 ≤ K < 0.05  
0 ≤ K < 0.01  
K ≤ 0 | Points |
| Points:                           | 15  
12  
10  
8  
5  
0 |  |
| Current liquidity ratio K3         | K ≥ 1.5  
1.3 ≤ K < 1.5  
1.2 ≤ K < 1.3  
1.1 ≤ K < 1.2  
1 ≤ K < 1.1  
K ≤ 1 | Points |
| Points:                           | 20  
15  
12  
8  
5  
0 |  |
| Quick liquidity ratio K4           | K ≥ 0.5  
0.3 ≤ K < 0.5  
0.1 ≤ K < 0.3  
0.05 ≤ K < 0.1  
0.01 ≤ K < 0.05  
K < 0.01 | Points |
| Points:                           | 10  
8  
6  
3  
2  
0 |  |
| Net profit margin K5               | K ≥ 0.01  
0 ≤ K < 0.01  
K ≤ 0 | Points |
| Points:                           | 15  
8  
0 |  |
| Current assets turnover K6         | K > 3  
2 ≤ K < 3  
1 ≤ K < 2  
0.5 ≤ K < 1  
K < 0.5 | Points |
| Points:                           | 20  
15  
12  
8  
5  
0 |  |
| Total points                       | 100  
73  
50  
29  
15  
0 |  |

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

\[
B = 0.973 - 0.653K_1 - 0.192K_3 + 0.211K_4 - 1.144K_5 - 0.225K_6 + 0.002K_7, \quad (5)
\]

where \(K_1\) is the financial independence ratio; \(K_3\) is the current liquidity ratio; \(K_4\) is the quick liquidity ratio; \(K_5\) is the net profit margin; \(K_6\) is the current assets turnover; \(K_7\) 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 4

| Financial condition | Score | Financial condition description |
|---------------------|-------|-------------------------------|
| 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.
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).

### Table 5

| 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                     |                     |
| 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                    |                     |
| 31–40 | 76                                       | 126                             | 202                       | 70               | 34.65                    |                     |
| 26–30 | 59                                       | 89                              | 148                       | 56               | 37.84                    |                     |
| 16–25 | 22                                       | 32                              | 54                        | 21               | 38.89                    |                     |
| 0–15  | 10                                       | 0                               | 10                        | 10               | 100.00                   |                     |
| Total | 253                                      | 458                             | 711                       | 189              | 26.58                    |                     |

*Source: compiled by the author.*
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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