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ECONOMETRIC MODELING OF CREDIT RISK

Abstract: *Banking risk management systems are sets of work methods for responsible bank departments, facilitating a positive financial result under conditions of uncertainty. The object of the study is the credit risk of corporate borrowers of commercial banks in the Russian Federation. The subject of the study is credit risk management based on internal ratings of corporate borrowers. The purpose of the work is to analyze the risk management system of commercial banks and develop an internal credit risk management model for corporate borrowers. Research methods: content analysis, analytical and statistical processing of information; methods for assessing cause-and-effect relationships and expert assessments. The relevance of the presented model is due to the regulatory need for commercial banks to switch to internal ratings to assess the risk of lending. The advantages of the model include optimized costs for establishing factor indicators, as well as the valence of selected explanatory variables.*

Keywords: *econometric modeling, credit risk, rating, corporate borrowers, factor models*

1. Introduction

The marginality level of commercial banks, as a rule, is directly proportional to the credit risks assumed during planning (Dugin, 2023; Tavasiev, 2023). Risk modeling is directly related to the placement of funds in the corporate sector of the economy, hence with large amounts of reserves that affect investment attractiveness when taking into account compliance with regulatory requirements regarding capital adequacy. Reservation on loans issued acts as preventive insurance until the credit risk is disclosed, however, a large risk appetite of a credit institution jeopardizes compliance with the standard of sufficiency of own funds controlled by the mega-regulator in order to protect the rights and interests of the bank's stakeholders (Bank of Russia, 2015; Odinikova, 2020; Yanova, 2023). Building a risk model of the corporate segment of lending to commercial banks, that is, modeling the interest margin (NIM[1] — Net Interest Margin), requires planning the level of non—performing loans (NPL - Non-Performing Loans) as part of the loan portfolio of corporate borrowers. The key hypothesis is that the proposed macroparameters for constructing a model for assessing the credit risk of the corporate lending segment are econometrically and statistically significant when using the internal ratings approach by banks (IRB —

[1] The NPV indicator is calculated as the ratio of net interest income to average interest-generating assets, which include the total loan portfolio, debt securities portfolio, interbank loans.

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Internal Ratings-Based Approach).

To assess the level of non-performing loans in the loan portfolio of commercial banks, a multiple regression model is used (Burova & Popova, 2021; Khominich, 2023; Novikova, 2022; Regulation of the Bank of Russia, 2003). Its function is described by equation (1). The dependent variable Y reflects the relative value of non-performing (overdue) loans in the corporate debt loan portfolio. X is a vector of independent variables, the set of which is presented and described below. β is the vector of coefficients (parameters) of the regression equation.

$$Y = \sum \beta \times X$$

The development of an internal credit risk assessment model begins with the definition of a dependent variable or the definition of problem loans. In this capacity, the NPL indicator is used, corresponding to the methodology of the internal ratings approach, presented in percentage terms (Burova, 2022; Regulation of the Bank of Russia, 2003; Sabitova, 2022). Among the explanatory variables, taking into account the subject of the study, the following are selected:

- Debt on loans of legal entities, namely, the dynamics of absolute change for the purposes of preventive avoidance of incorrectly constructed conclusions due to the blurring of the share of overdue loans in a significant increase in the loan portfolio. The information of the initial data is presented on the website of the Central Bank of the Russian Federation in the Banking Sector section.
- The key interest rate of the Bank of Russia, calculated as a weighted average value within the periodization of observations. The use of this indicator in the model is due to the inverse dependence of the volume of loans issued to corporate borrowers. Weighted averages allow us to reflect the data most accurately, as well as smooth out the dynamic series in the conditions of economic transformation to adapt to the new challenges of unprecedented economic realities. The initial data are published in the Key Rate Database section of the Bank of Russia on the official website.
- The RTS index is included in the model as an indicator of the efficiency of equity management by companies in accordance with the dynamics of capitalization of the number of securities in free circulation (FF — free float). Since it is the segment of corporate borrowers that is being analyzed, this index is indicative of the fact that it includes public Russian companies that are distinguished by a significant scale of doing business, high dynamism of development that determines the activities of key sectors of the economy in the country. The stock index is indicated in points, published on the website of the Moscow Stock Exchange, moreover, its composition is reviewed by the index committee at the end of each quarter.
- The price of Urals crude oil, expressed in dollars per barrel, exported, is the oil benchmark in Russia. It is this marker grade of oil, and not the habitually established world grade "Brent", that is correctly used in the model, since the budget rule in Russia is that oil and gas revenues, which make up a third of the entire structure, are sent to the budget strictly calculated values based on the base price of Urals.
- The price of Urals oil, calculated in yuan per barrel, updates the model by the fact that prices for it are also formed on the stock market, but the quoted currency is expressed in Chinese yuan, that is, in a foreign currency, to which the world market switches when making settlements

with the devaluation of the dollar and euro. A combined approach to the cost of resources is used to account for changes in market conditions.

- The export of energy goods by the Russian Federation is an indicator of the activity of corporations in the key sector of the country's economy. Moreover, the export is based not on the exchange, but on the contract value of Russian raw materials, that is, taking into account the discount. The dynamic series is indicated in accordance with the macroeconomic statistics presented in the Statistics section of the Central Bank of Russia.

The relevance of the presented model is due to the need for commercial banks to switch to internal ratings for assessing the risk of lending to the corporate sector of the economy. The advantages of the model include optimized costs for establishing factor indicators, as well as the valence of selected explanatory variables (Karminsky, 2015; Kovalev, 2019; Penikas, 2020).

2. Materials and Methods

A multiple regression model is used to assess the level of non-performing loans in the loan portfolio of commercial banks.

The approach of internal ratings is a new approach, since it is not bankruptcy that is subject to research, but the forecasting of overdue debts (Pomazanov, 2022; Tikhonov, 2021; Vishnyakova, 2019).

The methods used for the internal ratings approach are interpretable and reproducible, adjusted to the specifics of lending and the strategic orientation of banks, in contrast to the assessments of external rating agencies.

3. Results

To identify the relationship of the selected factors with the dependent variable and the independent factors among themselves, a correlation matrix is constructed (Figure 1) reflecting the relationship of the variables in the data set. The conducted multiple regression analysis showed that only statistically significant factors remained in the corporate borrowers' credit risk assessment model (Table 1), which is confirmed by a high level of correlation (multiple R = 99.46%). The value of the coefficient of determination (R2) indicates a high accuracy of the approximation of the model, in which variable factors by 98.92% have an analytical dependence of the formation of the level of credit risk for the placement of funds by commercial banks in the corporate business segment on the evaluation parameters embedded in the model.

The specification of the intrabank model for assessing the credit risk of corporate borrowers with fixed effects of the simulated data confirming the first hypothesis has the form of equation. The estimates are carried out on homogeneous quarterly data based on multiple regression for dependent variables.

$$NPL = 0.004\times X\_1 - 0.152\times X\_2 + 0.024\times X\_3 + 0.180\times X\_4 - 17E(-8)\times X\_5,$$

where X1 – RTS index;

X2 – the price of brand oil Urals, USD/BBL;

X3 – the price of brand oil Urals, CNY/BBL;

X4 – weighted average value of the key rate of the Bank of Russia, %;

X5 – change in debt on loans of legal entities, million rubles.

Quantitative assessment of credit risk in the NPL model of the corporate lending segment is an urgent topic in banking risk management. The quality of internal valuation models is subject to control during lending and related margin planning of banks. A preliminary assessment allows you to measure risks in advance and adapt risk appetite without additional time and financial costs.

	NPL, %	Change Debt on loans of legal entities, million rubles.	Key bid Central Bank of the Russian Federation, weighted average %	RTS Index	Urals crude oil price, USD/BBL	Urals crude oil price, CNY/BBL	Russia's exports of energy goods, billion $
NPL, %	1.0						
Change in debt on loans of legal entities, million rubles.	-0.4	1.0					
Key rate of the Central Bank of the Russian Federation, weighted average %	0.08	-0.1	1.0				
RTS index	0.11	0.1	-0.3	1.0			
Urals crude oil price, USD/BBL	-0.10	0.2	0.6	0.1	1.0		
Urals crude oil price, CNY/BBL	-0.09	0.2	0.6	0.0	0.98	1.0	
Russia's exports of energy goods, billion $	0.06	0.2	0.5	0.2	0.86	0.87	1.0

Figure 1. Correlation matrix of regression variables. Source Compiled by the authors based on materials (Bank for International Settlements, 2015; Bank of Russia, 2022a, b, d; 10. Investing.com, 2022; Moex.com, 2022)

Table 1. Results of regression statistics of the final data set

OUTPUT OF RESULTS						
Regression statistics						
Multiple R	0.994611439					
R-square	0.989251916					
Normalized R-square	0.919719093					
Standard error	0.803610212					
Observations	20					
Analysis of variance						
	df	SS	MS	F	Significance of F	
Regression	5	891.5752019	178.3150404	276.1195028	1.80532E-13	
Remains	15	9.686840583	0.645789372			
Total	20	901.2620425				
t-Student 0.063840253						
	Coefficients	Standard error	t-statistics	P-Value	Lower 95%	Upper 95%
Change in debt on loans of legal entities, million rubles.	-1.73576E-07	1.6216E-07	-1.070398725	0.301361957	-5.19211E-07	1.7206E-07
Key rate of the Central Bank of the Russian Federation, weighted average %	0.179753609	0.099995943	1.797609017	0.092395338	-0.033382699	0.392889917
RTS index, p	0.003979411	0.000599065	6.642702121	7.83873E-06	0.002702534	0.005256288
. Urals crude oil price, USD/BBL	-0.152444216	0.06787037	-2.246108513	0.040187226	-0.297106486	-0.007781947
Urals crude oil price, CNY/BBL	0.023569611	0.010524606	2.239476891	0.040701969	0.001136945	0.046002277

The uniqueness of the model is confirmed by the fact that overdue debt is considered as a dependent variable of the multiple regression model, and this determines the novelty of the proposed approach.

Table 1 shows the output of the validation results of the constructed model. The assessment of whether the hypothesis of linear regression between the result (the level of non-performing loans in the loan portfolio of corporate borrowers) and independent factors (RTS index, discount rate, oil price, debt change) is correct was carried out according to Fischer's F-criterion. The model is recognized as significant, and the linearity hypothesis has been confirmed.

The compiled regression model of credit risk assessment based on internal ratings corresponds to the initial data, namely, the external indicators of the financial market used by 98.92% influence the formation of the level of credit risk represented by the dynamics of the level of overdue debt of corporate borrowers.

Summarizing the model, it becomes obvious that the null hypothesis about the invalidity of the model is rejected.

Let's pay attention to the resulting output of the residuals (Table 2), which represent the deviation of the actual values of the dependent variable NPL from the predicted ones. On average, the balances amount to a two percent deviation of the predictive values from the actual ones, which indicates a qualitative basis for predicting credit risk assessment.

The Darbin Watson test performed with respect to the autocorrelation of the residuals of the regression model with a sample size of 20 observations and the number of explanatory variables in the regression equation equal to 5 revealed a positive correlation; the residuals retain the "+" sign for a long time.

Table 2. Output of the remnants of the predictive model

WITHDRAWAL OF THE REMAINDER				
The Darbin Watson Test = 1,141				
Observation	Predicted NPL, %	Remains	e_t^2	$(e_t - e_{t-1})^2$
Q1 2018	6.01	0.89	0.800	X
Q2 2018	5.72	0.98	0.975	0.007
Q3 2018	6.21	0.39	0.156	0.341
Q4 2018	6.41	-0.11	0.011	0.251
Q1 2019	6.73	1.17	1.371	1.631
Q2 2019	7.04	0.16	0.026	1.019
Q3 2019	7.37	0.02	0.000	0.021
Q4 2019	7.67	-0.42	0.173	0.187
Q1 2020	6.65	0.40	0.162	0.669
Q2 2020	6.13	0.66	0.430	0.064
Q3 2020	5.79	0.85	0.721	0.037
Q4 2020	5.77	0.59	0.345	0.069
Q1 2021	6.48	-0.24	0.056	0.679
Q2 2021	6.86	-0.88	0.768	0.409
Q3 2021	7.61	-0.80	0.640	0.006
Q4 2021	7.75	-1.01	1.020	0.044
Q1 2022	6.16	0.44	0.197	2.116
Q2 2022	7.80	-1.21	1.456	2.726
Q3 2022	6.44	-0.35	0.119	0.742
Q4 2022	6.30	-0.53	0.277	0.033
			9.687	11.050

Thus, the predicted values of NPL in the larger case (55%) are slightly lower than the real ones, in other cases they numerically exceed the input data. When interpreting these discrepancies, it is important to focus on the absolute change in the debt of the studied sector. Figure 2 clearly shows the reason for significant positive and negative regression residuals.

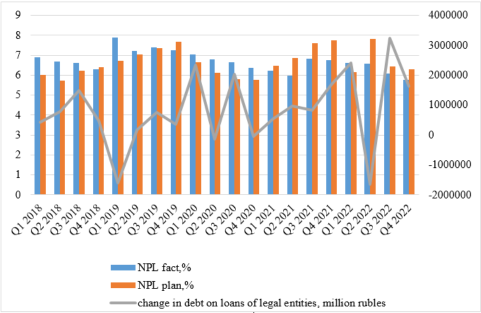

Figure 2. Causal relationship of model residuals

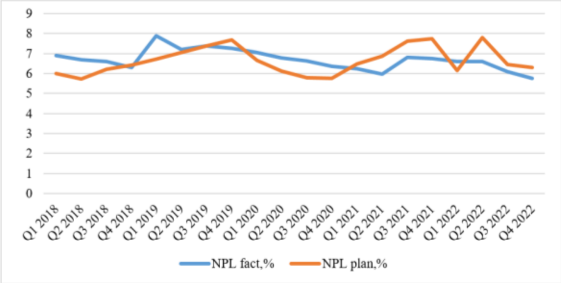

Figure 3. Graphical representation of forecast statistics

The degree of similarity between the simulated and subsequent observations in a given time series of consecutive intervals represents the relationship of this series with its lag values. Simply put, past (actual) data affects future (forecast) data. The autocorrelation, equal to 1.141, does not fall within the interval of the lower and upper bounds of DW in accordance with the parameters of the model, and therefore the null hypothesis about the absence of autocorrelation of residues is refuted

Figure 3 clearly shows the predictive significance of the simulated dynamics of the level of credit risk. Lower forecast values in comparison with the actual ones indicate that the management has put credit risks in the cost of products through the customer rate, and exceeding the forecast indicates a more optimistic financial model, i.e. in these observations, the quality of borrowers is arranged in the best way.

4. Discussion

The effectiveness of this factor model in saving labor costs due to the proposed version of internal ratings is noted. Factor analysis, as a result of econometric tests to improve the regression model, was reduced by one variable within the framework of the initial indicators, which reduces time and labor costs in the modeling process. Moreover, the optimized process eliminates time costs in terms of collecting the necessary information from customers when assessing risk.

Reasonable metrics of the model quality within the framework of its optimization and the details of the data obtained give a result that is used for predictive statistics used to manage credit risk to increase the marginality of the business.

Estimates were carried out on quarterly data based on multiple regression for the following dependent variables: change in debt on loans of legal entities (million rubles), the key rate of the Central Bank of the Russian Federation (weighted average percentage), the RTS index (p.), the price of Urals crude oil (USD/BBL and CNY/BBL). On the basis of multiple regression coefficients and using actual data for each period of the study, an assessment of the fundamentally sound values of credit risk in lending to corporate borrowers based on internal models of banks was obtained.

Since the predictive model is comparable with the actual data on the level of credit risk of legal entities (Figure 3), this is the basis for constructing its planned trajectory. Having the output data for making a forecast, equation (3) is used when predicting problem assets in the structure of the loan portfolio of the corporate lending segment. The planning horizon is defined for the current year with a quarterly observation interval. In table 3, the output data of the internal estimates model are supplemented with predictive estimates of explanatory variables included in the calculation of forecasted credit risk values.

Similar economic growth rates are used as forecasting changes in the loan portfolio of legal entities (the data are indicated in the

Forecast of socio-economic Development of the Russian Federation for 2023 and for the planning period of 2024 and 2025).

The gross product of the country in the forecast period is relatively stable, which is determined by the policy in the field of income growth and the implementation of measures to ensure the sustainable and efficient functioning of the labor market and tax policy. The key rate according to the base forecast of the Bank of Russia for an average of 2023 will be in the range of 6.5-8.5% per annum, which is set out in the forecast of the main macroeconomic indicators of the document of the Main Directions of the unified state monetary policy for 2023 and the period 2024 and 2025 of the Central Bank of Russia.

The trajectory of the Urals oil price per barrel is predicted by the Ministry of Economic Development, based on a higher oil price in 2022 on the forecast horizon, expects a gradual correction in 2023 at an average of $70 (Bank of Russia, 2022c). The forecast for the RTS index and the cross-rate of the dollar to the yuan is indicated in accordance with the assessment of the domestic investment company BCS, which increases the target level of the RTS, taking into account the expected exchange rate from 1250 to 1300 points; the growth potential is 35 % (Ministry of Economic Development of the Russian Federation, 2022).

Table 3. Predictive regression output model (Calculated and built by the authors)

Period	NPL, %	Change Debt on loans of legal entities, million rubles	Key rate of the Central Bank of the Russian Federation, weighted average %	PTC Index	Urals crude oil price, USD/BBL	Urals crude oil price, CNY/BBL
Q1 2018	6,90	434 000	7,60	1 251,07	66,06	416,05
Q2 2018	6,70	771 000	7,25	1 149,80	75,12	484,89
Q3 2018	6.60	1 493 000	7.29	1 126.12	77.24	528.14
Q4 2018	6.30	481 000	7.54	1 121.34	60.61	420.50
Q1 2019	7.90	-1 592 115	7.75	1 180.57	65.44	438.60
Q2 2019	7.20	165 002	7.71	1 276.43	69.01	471.75
Q3 2019	7.38	762 372	7.27	1 336.41	62.31	440.08
Q4 2019	7.25	349 484	6.60	1 438.05	63.86	447.74
Q1 2020	7.05	2 340 629	6.11	1 367.64	40.78	285.61
Q2 2020	6.78	-142 311	5.54	1 162.51	32.80	232.50
Q3 2020	6.64	2 033 057	4.32	1 244.87	43.05	295.84
Q4 2020	6.36	- 45 666	4.25	1 220.42	45.00	297.00
Q1 2021	6.24	538 449	4.28	1 451.58	60.79	394.21
Q2 2021	5.98	976 334	4.95	1 556.67	69.45	446.79
Q3 2021	6.81	830 534	6.28	1 670.90	73.57	474.99
Q4 2021	6.74	1 667 951	7.43	1 728.34	79.41	506.29
Q1 2022	6.60	2 414 751	12.74	1 146.16	89.74	568.68
Q2 2022	6.59	-1 637 752	13.98	1 177.30	69.48	462.71
Q3 2022	6.10	3 234 820	8.33	1 178.80	77.12	533.34
Q4 2022	5.77	1 628 729	7.50	1 060.83	66.12	470.56
Forecast						
Q1 2023	7.30	257 268	7.00	1 312.72	71.50	499.04
Q2 2023	6.90	282 995	6.50	1 286.35	70.40	483.46
Q3 2023	6.97	385 902	6.00	1 344.57	69.60	475.80
Q4 2023	6.80	360 175	5.50	1 377. 04	68.90	462.29

Commercial banks assess the likelihood of deterioration of economic conditions in the country and their consequences for the bank and its financial result. By modeling credit risk, it is possible to determine the direction of the forecast dynamics of the bank's profitability based on its forecast values. This procedure allows you to quickly take into account the information in the marginality model for preventive minimization of negative consequences and restructuring of lending taking into account new factors.

Table 4. Data from the regression model of margin management of a commercial bank when lending to corporate clients

Period	NPL, %	NIM for corporate clients, %
Q1 2018	6.01	0.07
Q2 2018	5.72	0.06
Q3 2018	6.21	0.07
Q4 2018	6.41	0.05
Q1 2019	6.73	0.06
Q2 2019	7.04	0.05
Q3 2019	7.37	0.06
Q4 2019	7.67	0.06
Q1 2020	6.65	0.07
Q2 2020	6.13	0.04
Q3 2020	5.79	0.05
Q4 2020	5.77	0.05
Q1 2021	6.48	0.06
Q2 2021	6.86	0.05
Q3 2021	7.61	0.06
Q4 2021	7.75	0.07
Q1 2022	6.16	0.06
Q2 2022	7.80	0.06
Q3 2022	6.44	0.07
Q4 2022	6.30	0.08
Forecast		
Q1 2023	7.30	0.07
Q2 2023	6.90	0.06
Q3 2023	6.97	0.06
Q4 2023	6.80	0.06

Source: Calculated and built by the authors.

Table 4 shows a regression model of marginality of commercial banks by corporate clients (Net interest margin, NIM). This factor is the ratio of the percentage result to the net assets of the bank. NIM is nothing more than an indicator of the effectiveness of banks' implementation of their own credit ratings.

According to the interpretation of such econometric indicators for assessing the quality of the derived marginality model of commercial banks with calculated values of NPL (Table 5) as the coefficient of determination, Student's t-distribution, Fisher's criterion, multiple R and P-statistics, the statistical significance of regression and the practical operability of the constructed model in the corporate lending segment is established.

Table 5. Output of regression statistics

OUTPUT OF RESULTS						
Regression statistics						
Multiple R (correlation coefficient)	0.983768697					
R-squared (coefficient of determination)	0.967800849 High level of approximation					
Normalized R-square	0.91516927					
Standard error	0.011231977					
Observations	20					
Analysis of variance				F-Fisher 0,458239947		
	df	SS	MS	F	Significance of F	
Regression	1	0.0702045628	0.072045628	571.0776745	4.36748E-15	
Remains	19	0.2396989	0.000126157			
Total	20	0.074442617				
t-Student 0,063586882				p-Value $4,367*10^{-15}$		
	Coefficients	Standard error	t-statistics	P-Value	Lower 95%	Upper 95%
NPL, %	0.008989278	0.000376164	23.89723152	1.22404E-15	0.008201958	0.009776599
Withdrawal of the remainder						
Observation	Predicted NIM by corporate clients, %	Remains				
Q1 2018	0.05	0.0160				
Q2 2018	0.05	0.0090				
Q3 2018	0.06	0.0135				
Q4 2018	0.06	-0.0084				
Q1 2019	0.06	0.0012				
Q2 2019	0.06	-0.0158				
Q3 2019	0.07	-0.0087				
Q4 2019	0.07	-0.0114				
Q1 2020	0.06	0.0106				
Q2 2020	0.06	-0.0184				
Q3 2020	0.05	0.0018				
Q4 2020	0.05	0.0027				
Q1 2021	0.06	-0.0030				
Q2 2021	0.06	-0.0067				
Q3 2021	0.07	-0.0066				
Q4 2021	0.07	-0.0039				
Q1 2022	0.06	0.0092				
Q2 2022	0.07	-0.0057				
Q3 2022	0.06	0.0149				
Q4 2022	0.06	0.0209				
Q1 2023	0.07	-				
Q2 2023	0.06	-				
Q3 2023	0.06	-				
Q4 2023	0.06	-				

Source: Calculated and built by the authors

Figure 5 shows a graph comparing the actual values of the interest margin on the corporate business of banks with the predicted regression data. There is a unidirectional movement of the simulated values, which suggests that the explanatory factor of non-performing loans of legal entities has financial consequences for assessing the performance of banks.

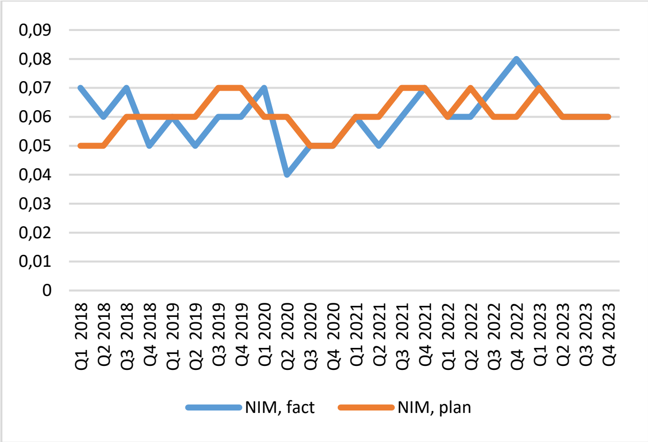

Figure 5. Graphical statistics of the simulated parameters. *Source* Built by the authors

5. Conclusion

The main conclusion is that the use of such macroparameters as the absolute change in debt on loans of legal entities, the dynamics of weighted average values of the key interest rate of the Bank of Russia, the values of the RTS index, as well as the cost of Urals crude oil, expressed in dollars and yuan per barrel, allow us to most accurately assess the dynamics of NPL, based on forecast the values of which are used to predict NIM in the field of corporate lending. Comparison of the retrospective marginality data with the predicted values makes it possible to assess the implementation of the credit risk of corporate borrowers within the risk model. The deviation of the actual margin values from the calculated ones allows us to draw conclusions about the conservativeness of the reservation and, along with the simulated forecast, to assess the credit risk of borrowers for the formation of an internal risk appetite strategy of a commercial bank.

The method proposed in this paper for assessing the credit risk embedded in the marginality of banks is based on the forecast of the level of non-performing loans at a given interval. The ranking ability forecast is based on econometric approaches capable of solving several business problems. Among these tasks are market coverage, expansion of the customer base, risk appetite of the loan portfolio, forecasting changes in risk-weighted assets that require the formation of reserves that fluctuate the amount of the bank's capital (Risk-weighted assets, RWA), pricing, risk cost management while maximizing the profit of the corporate portfolio. A key area of application of the internal valuation model is a preliminary assessment of the risk level to ensure the target level of profitability of the bank. Thus, modeling serves as a lever for managing the loan portfolio in the risk management system within the framework of achieving the set goals in terms of marginality.

The retrospectivity of the explanatory variables of the internal assessment model makes it possible to measure credit risk, and the use of predictive parameter values in the econometric model makes it possible to manage risk appetite and funding of active operations in the bank at the lowest cost through optimization and validation procedures.

The conducted modeling on the management of the loan portfolio of corporate borrowers allows us to draw the following conclusions:

- the effectiveness of planning is based on extrapolation of data, the achievability of goals depends on the correlation of the forecast with the simulated dynamics of interrelated indicators based on expert assessments;
- the forecasted values of credit risk based on the results of modeling non-performing loans allows us to determine the financial consequences for assessing the bank's performance;
- comparing the predictive dynamics of marginality with actual data allows us to draw conclusions about the preventive coverage of risks in pricing;
- the use of the proposed model of internal ratings allows you to make decisions on the management of the loan portfolio in order to mitigate potential losses.

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