Economic Efficiency of the Mechanism for Credit Risk Management

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Abstract. The article discusses the results of credit risks management mechanism application in the credit organization. It is pointed out that the statistical information about borrowers can be divided into four classes, each of which is characterized by a certain level of credit risk. An optimal structure of the borrowers was built, management decisions for changing the existing structure in order to bring it closer to the optimal one were made. Solutions have been developed for managing credit risks in certain classes of customers. It is shown that the application of the credit risk management mechanism ensures the growth of the working capital up to 4.6% and depends on the propensity of decision-makers to take risks.

Keywords: computer modeling, risk management, credit risks, statistical analysis of financial information, optimization model, decision making

1 Introduction

Most significant risks in banking are: credit risk, interest rate risk and liquidity risk. Credit risks are one of the basic bank risks and are associated with non-payment of liabilities in borrowing activities performance. This risk appears in the full or partial non-return of borrowed resources or interests. Credit risk can be defined as the probability and loss incurred by the credit institution due to the borrower's inability or unwillingness to repay the loan debt and interests. Interest rate risk arises from adverse fluctuations in the interest rate, which leads to costs of paying interest increasing or to income decreasing from investments and proceeds from loans. The liquidity risk appears in the lack of funds to satisfy an unexpected cash needs.

Traditionally, in order to monitor the customers solvency credit institutions use scoring models and analyze previous clients credit histories to compile a rating of borrowers and determine the probability of loan repayment by a potential borrower [9, 14, 18]. The main problems solved in scientific research and related to scoring models in decision making can be integrated into two groups.

The first group of problems is related to the selection of an adequate complexity toolkit to the solved problems, to the identification and justification of factors included in the model. Known models for assessing of credit risk use a statistical approach and are based on the processing of empirical information about past credit histories, but these models differ by the methods and algorithms for approximating dependences designing – neural network, fuzzy and hybrid algorithms [10, 11]; econometric methods [2, 6–8, 12, 13, 17, 20, 21]. The methods of gathering the necessary information, the number of qualitative characteristics for accurate description of the borrower portrait to be included into the model as well as methods for models identification, analysis of their quality and prognostic properties are discussed [1, 4, 5].

The second group of problems is connected with the automated systems development for collecting, processing and storing information about borrowers, with the design of decision support systems for making investment decisions in banking [3], with the development of customer databases. In the conditions of a large number of heterogeneous customers, the main requirement in such systems development is the rate of decision making.

The analysis of existing methodological approaches and analytical tools showed that existing models for credit risk assessment do not allow to reveal trends in customers with a similar economic profile behavior [9, 14]. The organization of such clients groups will allow, on the one hand, to identify common patterns of economic agent behavior, on the other hand, to form a set of differentiated requirements on the part of the credit organization, presented to certain groups of borrowers, taking into account their specificity; thirdly, to take into account the propensity to take risks of the decision- maker about loan characteristics – volumes, terms and interests.

Under highly competitive economic conditions, significant factors that determine the competitive advantages of the credit services market are: decreased decision-making time, reduction of requirements to the documents submitted to the financial organization, reduction of the securing credit requirements. In this connection banks rely on the rate and coverage of their services. It should be noted that banks are interested not only in large amounts of loans issued, but in large amounts of loans that will be timely returned. Solving these problems requires the use of modern and effective tools that ensure minimal losses due to credit risks [15, 16, 19].

The authored mechanism for credit risks management ensuring credit risks minimization of the financial organization consists of the next stages:

- Stage 1. Classification of customer-borrowers;
- Stage 2. Risk assessment by borrowers groups;
- Stage 3. Development of the optimal structure of borrowers;
- Stage 4. Management of the borrower's structure.
- Stage 5. Working out of management decisions.

In the article we apply this mechanism in one the financial organization in Bashkortostan republic and assess the mechanism economic efficiency.

2 Classification of borrowers

Model experiments are conducted using statistical information about borrowers' credit histories in the financial organization and statistical processing program

Statistica 7.0. The data features are their heterogeneity and multidimensionality. The model sample includes data about 38 clients and consists of the following indicators characterizing borrowers: credit period (*month*), credit value (*value*), gender (0 – male, 1 – female), age (*age*), children (*children*), average monthly income (*income*). For each borrower we also introduce a variable characterizing the presence or absence of *problems* with the credit repayment (0 – there is no problem, 1 – the problem exists), and the economic losses *risk* for the organization. The fragment with initial data for analysis is presented below, Table 1.

Table 1. Initial data about borrowers (fragment)

Client's number	Months	Value, rub.	Age	Children	Gender (0-male, 1-female)	Income, rub.	Problems
1	5	10000	25	1	0	15000	1
2	12	10000	36	2	0	10000	1
3	12	13000	56	3	0	8000	0
4	12	15000	45	4	0	12000	0
5	6	15000	39	2	0	11256	0
6	12	17000	42	0	0	18000	1
7	12	25000	44	0	1	23000	1
8	12	25000	48	0	0	25035	1
9	6	25000	20	0	1	30000	0
10	12	25000	21	0	1	15065	0

2.1 Factor analysis of borrowers

We solve the problem of reducing the dimensionality of data and predicting the risk of credit non-repayment using factor analysis. To reduce the dimension of the initial data and to identify the most significant factors that affect credit risk, we will use the factor analysis module which includes the methods of the main components, dispersion and correlation analysis. The procedure is carried out step by step.

Step 1. Set the initial parameters. Define the number of factors equal to the number of initial variables (variables *risk* and *problems* are not taken into account in factor analysis).

Step 2. Calculation of factors eigenvalues which reflects the variance of the newly identified factor, Table 2. In the third column the total variance percentage for each factor is given.

It can be seen from the table above that the first factor accounts for 33.3% of the total variance, factor 2 – 23.2%, and the third factor – 18.9%. Based on the information received about the variance explained by each factor, we can go on

Table 2. Factors eigenvalues

Factor	Eigenvalue	Explained variation	Accumulated explained variation
1	1.997931	33.29886	33.29886
2	1.394679	23.24464	56.54350
3	1.134050	18.90083	75.44433

to the question about the number of factors that should be left. For this "factor loads" are used and can be interpreted as correlations between allocated factors and the original variables.

Step 3. Investigation of factor loads. First, we estimate the factor loads without rotation for all six initial variables. The results of the analysis of factor loads without rotation are given in Table 3.

Table 3. Values of factor loads for operation "without rotation"

Variable	Factor 1	Factor 2	Factor 3
month	0.540868	0.104905	0.655439
value	**0.818261**	-0.333261	-0.195093
age	-0.405546	-0.251135	0.639473
children	-0.205777	**-0.778772**	-0.377427
gender	0.330074	**0.703828**	-0.324087
income	**0.848576**	-0.328151	0.111284

The identification of factors is such that subsequent factors include an ever smaller and smaller variance. Factor 1, as can be seen from Table 2, has the highest load values for variables related to the economic characteristics of customers. Factor 2 has maximum loads for variables related to the client social status.

Step 4. Clarification of number of factors. To compare and finalize the decision about the number of factors, the factors are rotated. We use the method *varimax rotation* – the most common method of rotation, in which factors remain independent with respect to each other, so that the values of variables of one factor do not correlate with other factors. Results of rotation factors are given in Table 4.

Clarification of the descriptive characteristics of the identified factors shows that the first factor is related to the financial and economic parameters of the borrower (average income, credit value, month), the third reflects his personality (age, gender), the second is related to social parameters (number of children). In addition, three factors describe 76% of the variation in initial data. Therefore, it is advisable to continue the analysis on the basis of three identified factors.

Table 4. Values of factor loads for the operation "varimax rotation"

Variable	Factor 1	Factor 2	Factor 3
month	**0.461165**	0.674559	0.255813
value	**0.875882**	-0.108511	-0.199325
age	-0.238427	0.136053	**0.749069**
children	0.140263	**-0.840554**	0.250341
gender	-0.016102	0.359075	**-0.761683**
income	**0.909886**	0.109644	0.015300

Step 5. Evaluation of the solution adequacy. To verify the correctness of the number of selected factors, it is necessary to construct a reproduced correlation matrix, which by its coefficients should be close to the original correlation matrix if the factors are correctly distinguished. To determine the degree of possible deviation of the elements of this matrix from the original one, a matrix of residual correlations is formed whose elements are equal to the difference between the elements of the original and reproduced matrices. The initial and residual correlation matrices are shown in Tables 5 and 6.

Table 5. Initial correlation matrix

Variable	Month	Value	Age	Children	Gender	Income
Month	1.00	0.20	0.01	-0.25	0.05	0.37
Value	0.20	1.00	-0.20	0.13	0.18	0.70
Age	0.01	-0.20	1.00	0.06	-0.25	-0.17
Children	-0.25	0.13	0.06	1.00	-0.34	-0.04
Gender	0.05	0.18	-0.25	-0.34	1.00	-0.02
Income	0.37	0.70	-0.17	-0.04	-0.02	1.00

Table 6. Residual correlations matrix

Variable	Month	Value	Age	Children	Gender	Income
Month	0.27	-0.08	**-0.17**	**0.18**	0.01	**-0.13**
Value	-0.08	0.18	**0.17**	-0.04	0.08	-0.08
Age	**-0.17**	**0.17**	0.36	0.02	**0.26**	0.02
Children	**0.18**	-0.04	0.02	0.21	**0.16**	0.08
Gender	0.01	0.08	**0.26**	**0.16**	0.29	-0.03
Income	**-0.13**	-0.08	0.02	-0.08	-0.03	0.16

The inputs in the residual correlations matrix can be interpreted as total correlations, for which the factors obtained can not be responsible. The diagonal elements of the matrix contain standard deviations, for which these factors can not be responsible, and are equal to the square root of unity minus the corresponding generalities for the two factors. The generality of a variable is variance which is explained by the selected factors. A careful analysis of the residual matrix shows that there are in fact no residual correlations larger in modulus 0.26. Consequently the identified factors adequately reflect the initial information.

2.2 Cluster analysis of borrowers

First, homogeneous groups of customers are formed according to two indicators determined by the first factor, selecting the variable "month" and "value". Clustering is carried out in two stages – qualitative analysis using hierarchical methods and analysis using the k-means method. Exploration analysis to determine the possible number of groups is carried out using a hierarchical classification using different measures of similarity and differences in objects in groups – Euclidean distance, Manhattan distance, Chebyshev distance – to assess the degree of proximity of objects within groups and measures of distances between clusters – single, complete communication. By varying the distance measures, one can qualitatively evaluate the possible composition of clusters and the number of clusters. The analysis of the different partitions of the original sample by the method of hierarchical classification showed that it is possible to form three to six clusters. For a more reasonable object grouping it is necessary to use clustering methods that use quantitative criteria to assess the partition quality. These methods include the k-means method. Below the results of partitioning in which four groups ($k = 4$) and showing a significant difference between the classes formed among themselves are presented. The results of a single-factor analysis of variance to determine the similarity/difference groups are presented in Table 7.

Table 7. Results of single-factor analysis of variance

Variable	The intergroup sum of squares of deviations for the number of degrees of freedom equal to 3	The intragroup sum of the squares of deviations for the number of degrees of freedom equal to 34	F-test
Month	781505.7	6325.706	14.0017
Value	489827.5	4565.484	121.5945

The data was supplemented with information about the cluster to which the particular client belongs. Further we calculate the basic descriptive statistics, build regression models and generate forecasts for each cluster. The statistical characteristics (the mean, the standard deviation and the number of objects in each class) are shown in Table 8.

Table 8. Descriptive statistics for selected clusters

Cluster	Number of borrowers	Borrowers numbers	Descriptive statistics for the variable month		Descriptive statistics for the variable value	
			Mean	Standard deviation	Mean	Standard deviation
1	7	1–16, 24, 30	33.4	15.44	327142.9	76313.9
2	6	17–21, 37	16	15.95	125000	41833.0
3	7	25, 31–36	51.4	13.35	52142.9	11495.3
4	18	22, 23, 26–29, 38	14.6	12.26	22222.2	8292.8

At the next stage the following information has been received: the number of borrowers clusters, cluster size, the share of working capital of each class in their total value, information about unit working capital. The most numerous cluster (18 borrowers) is the fourth characterized by the lowest credit values, from 10 to 35 thousand rubles, and the average credit fluctuation is quite high (37%). This cluster is rather unstable and determines about 10% of the total credit value, as shown in Table 9.

Table 9. Summary information about the received classes of clients

Indicator	The value of the indicator in the cluster			
	1	2	3	4
Number of class, people.	7	6	7	18
Total credit, rub.	2 290 000	750 000	365 000	400 000
Share of total credit, %	60.2	19.7	9.6	10.5
Minimum credit, rub.	290 000	100 000	40 000	10 000
Maximum credit, rub.	500 000	200 000	70 000	35 000
Average credit, rub.	327 143	125 000	52 143	22 222
Average credit period, months.	33.4	16	51.4	14.6
Standard deviation for credit, rub.	76 314	41 833	11 495	8 293
Variation for credit	0.23	0.33	0.22	0.37

The third cluster is quite stable – the variation is about 22%, the credit value is low – from 40 to 70 thousand rubles and about of 9.6% of total credit sum, but the credit period for this cluster is the largest – an average of 51.4 months. The second cluster includes few clients, has a high value of the average credit, can be characterized as a medium stable. The cluster which gives the highest income is the first one, it is about 20% of all customers who take significant credits for not very long tome – on average 33 months, the cluster is stable.

For a deeper analysis of each customer cluster and for decision-making on credit policy, it is necessary to investigate statistics on the credit repayment. It is possible to design the regression model (for each cluster) of the credit repayment (in accordance with contractual obligations) from the variables of credit value, credit period and other significant factors.

3 Development of the optimal structure of borrowers

Before working out the optimal structure of borrowers on the criterion of risk minimization, it should be clarified what input data is available. The whole set of customers is classified, each cluster is characterized by a set of characteristics: number, total income in the client's cluster, the specific volume of working capital per customer, the variation in the deviation of the cash flow in case of violation of the contract terms. The function to be minimized has the form

$$f(n) = \frac{\sum_{i=1}^{k} r_v V_i Dy_i n_i}{\sum_{i=1}^{k} Dy_i n_i} \to \min,$$

where k – number of classes of clients; n_i – number of i-th class; V_i – coefficient of variation in the i-th class; r_v is a coefficient reflecting the propensity of the decision maker to take risks; Dy_i – the specific volume of working capital for each client in the i-th class; $Dy_i n_i$ – working capital in the i-th class. Coefficient of variation and the value of assets per member of the cluster are known. The function $f(n)$ in fact reflects the risk/profitability ratio.

To solve this problem it is required to determine the values of the decreasing coefficients r_v, reflecting the propensity of the decision maker to take risk for each customers' cluster. For the pessimistic option the value of r_v is equal to 1. In this case, it is implied that all possible risk situations are realized and the risk situation in the organization will definitely occur. For a realistic case, one should choose a value r_v, in which the amount $\sum_{i=1}^{k} r_v V_i Dy_i n_i$ will be correlated with the actual risk in organization in the period under study. The value of r_v for the realistic case is equal to 0.4, for the optimistic case $r_v = 0.2$.

The next step is to formulate constraints. To obtain a limit on the number, it is necessary to determine the growth rate of the customers number. Based on the data of previous years, we can conclude that the growth rate of the customers number is about 43% per year. Thus, the limitation on the consumers number will be $\sum n_i \geq 754 \cdot 1.43$. The total number of borrowers in the planned period should be at least 1,078 people.

Then it is necessary to determine the minimum share of working capital of each class in the total volume of working capital in the organization. For this we engage experts from the organization – director, deputy director, directors of credit branches. Experts were acquainted with the results of the classification and with the characteristics of the borrower clusters obtained. Each expert gives an estimate of the minimum share of working capital attributable to each borrowers cluster. Experts, based on their experience working with borrowers in a particular organization, have established the lower working capital attributable to each received borrowers luster. Then all experts' assessments have been averaged.

All the obtained data necessary to calculate the optimal borrowers structure in terms of risk minimizing are summarized in the Table 10.

Table 10. Values of indicators required to calculate the optimal structure of clients

Cluster	Working capital per borrower	Variation, %	Minimum share of working capital of borrower cluster in the total working capital (Dmin) ,%	Number of cluster
1	103 961.41	9.11	20	n_1
2	83 178.54	12.00	25	n_2
3	47 092.33	11.12	10	n_3
4	3 080 000.00	0.00	15	n_4

The problem of development of the optimal borrowers structure is carried out in the Excel package. The target cell is given a ratio that should be minimized: $\frac{\sum_{i=1}^{k} \mathrm{r_v} V_i D y_i n_i}{\sum_{i=1}^{k} D y_i n_i}$. Following restrictions are introduced:

- restriction on the minimum number of borrowers: $\sum n_i \geq 1078$;
- restriction on the minimum amount of working capital in the cluster: $D y_i n_i \geq D \min_i$.

Results of optimization which were obtained for the three cases of variable r_v are presented in table 11.

Table 11. Results of optimization in depending on r_v

Cluster	Working capital per borrower	Number of borrower	Sum of working capital	Share of working capital in total, %	Risk level under the propensity to take risks of the decision maker		
					Case 1 r_v=1	Case 2 r_v=0.4	Case 3 r_v=0.2
1	103 961.41	295	30 702 666.46	27	9.11	3.71	1.85
2	83 178.54	410	34 114 073.85	30	12.00	4.87	2.44
3	47 092.33	362	17 057 036.92	15	11.12	4.56	2.28
4	3 080 000.00	10	31 839 802.26	28	0.00	0.00	0.00

The ratio of risk/profitability is 7.73% (for case 1), 3.09% (for case 2) and 1.55% (for case 3).

Next, we need to compare the existing borrowers structure with the obtained optimal structure. To ensure comparability, it is necessary to increase the number of each cluster in the existing structure in proportion to the received growth factor. This coefficient is equal to 1.43.

Table 12. Comparison of the existing and optimal structures of borrowers

Cluster	Number of cluster with the current structure, people	Comparable class size under the existing structure, people	Number of cluster s with the optimal structure, people	Difference between the current and optimal class size	Ratio of current and optimal class numbers,%
1	238	340	295	-45	86.76
2	351	499	410	-89	82.16
3	163	232	362	130	156.03
4	5	7	10	3	142.86
Total	754	1 078	1 078	-	-

The numbers of the first and second cluster need to be reduced. The first cluster of borrowers is characterized by credit value ranging from 15 to 290 thousand rubles. The credit period in the first cluster is from 30 to 60 months. The second cluster is also characterized by a long credit period – from 20 to 24 months. The third cluster is comparable to the first two by the credit value, but the credit period is from 1 to 12 months. The number of the third cluster needs to be increased. It is proposed to do this by moving the customers of the first two classes. The total number of customers which is to be reduced in the first two classes is comparable to the appropriate one in the third cluster which is to be increased.

Thus, it is required to increase the attractiveness of credit services which are characterized by a credit value from 20 to 350 thousand rubles and credit period from 1 to 12 months. For the customers wishing to take credit for longer that one year it is recommended to make the obligation requirement more strict.

The fourth cluster is significantly different from the first one. The credit value in this cluster is in the range of 2 to 4 million rubles. This segment includes borrowers who take credits to invest into projects. The fourth cluster is weakly filled. Accordingly, it is possible to study in detail each customer and evaluate the investment attractiveness of the project for which the credit is taken. This explains the minimum risk level in this cluster.

In order to achieve the optimal ratio of risk/profitability it is necessary to increase the size of the fourth cluster to 10 people. To increase the attractiveness of this cluster it is necessary to develop an individual approach for each customer, for example, providing variable credit conditions. This cluster is the safest from the point of view of contract terms that is it is possible to reduce credit conditions in order to increase the number of this cluster.

4 Economic efficiency of decisions

Having the risk values in each cluster, we can compare the risk/profitability ratios, reduced to comparable cluster numbers for the proposed optimal structure and the current structure.

Table 13. Current and optimal cluster structure on the risk/profitability ratio

Risk appetite	Existing structure		Optimal structure		Change in working capital with risk, mln.r
	Working capital, mln.r	Risk/ profitability ratio, %	Working capital, mln.r	Risk/ profitability ratio, %	
Pessimistic option		8.61		7.73	4 998.99
Realistic option	109 338	3.44	113 713	3.09	4 622.50
Optimistic option		1.72		1.55	4 493.06

Changing in working capital applying the proposed decision to minimize risks is calculated as follows. The expected value of working capital is reduced by the risk value that the organization may incur as a result of risk situations. This risk is calculated from the risk/profitability ratio and depends on the propensity to take risk of the decision-maker. Thus, the expected values of the organization's circulating assets taking into account the risk are obtained. The difference between the funds that are expected under the existing organization policy and the funds that can be received if the proposed management decisions are taken is calculated.

As a result of the developed mechanism, the growth of working capital in the organization is about from 4.1% to 4.6% depending on the propensity of the decision maker to take risks.

5 Results and conclusions

The results of the developed mechanism application in the credit organization have proved the reliability of the developed mechanism, and its economic effectiveness has been confirmed. The results obtained will contribute to the effective use of the developed risk management mechanism for the sustainable organization development, to the well-founded planning of working capital and to the investment efficiency growth of the credit organization as a whole.

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