CREDIT RISK MANAGEMENT IN COMMERCIAL BANKS

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Abstract: The article proposes a model of credit risk assessment on the basis of factor analysis of retail clients / borrowers in order to ensure predictive control of the level of risk posed by potential clients in commercial banks engaged in consumer lending. The aim of the study is to determine the level of risk represented by different groups (classes) of retail clients (borrowers) in order to reduce and prevent credit risk in the future as well as to improve the management of banking risks. The main results of the study are the creation of a model of borrowers' internal credit ratings and the development of the methods of improving credit risk management in commercial banks.

Key words: credit risk management, retail clients, borrowers, consumer lending, cluster analysis, factor analysis

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Introduction

The problem of credit risk management, as well as carrying out a quantitative assessment and analysis of the credit risk and rating of borrowers, is relevant to all banks involved in lending to individuals and legal entities. In general, when commercial banks grant loans to individuals and legal entities, the credit risk involved is characterized by the following quantitative parameters: risk as the probability of the borrower's failure to repay the loan; acceptable risk; average risk; possible losses given loan default; the average value of losses; the maximum allowable losses; the number of loans given by the bank; the possible number of different loans the bank can give; the number of problem loans.

Theoretical Framework of Credit Risk Management

The management of credit risk of credit portfolios is therefore one the most important tasks for the financial liquidity and stability of banking sector in connection with increased sensitivity of banks to the credit risks and changes in the development of prices of financial instruments (Kisel'áková and Kisel'ák, 2013). The most significant impact on performance of the enterprise has just financial risk. The unsystematic risks have a higher impact on performance of the enterprise as systematic risks (Kisel'áková et al., 2015).
The determination of each individual loan, or borrower, risk assessment techniques plays a primary role in the management and minimization of the credit risk. It is only after determining the risk represented by each individual borrower and by

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each individual credit service that one can begin to manage the loan portfolio as a whole. The credit risk assessment of the borrower consists in the study and evaluation of the qualitative and quantitative indicators of the economic situation of the borrower (Korobova, 2010). The assessment of the risk factors attending the granting of a particular loan and their comprehensive and systematic analysis enable the bank to take these factors into account in credit risk management and to prevent their recurrent and adverse impact on the results of the bank's future activities (Rodina et al., 2013). The methods used to quantify credit risk are accompanied by a special transparency requirement, including a quantitative assessment of the methods' accuracy and a statistical method property known as robustness. The transparency of the credit risk methodology presents an opportunity to view a given phenomenon not only as a whole but also in detail (Dmitriadi, 2010). Transparency has become the most important characteristic of credit risk assessment methods thanks to the need for the most thorough identification of both credit risk and the credit risk model itself. Methodological transparency refers to the precision of the employed mathematical methods, the reduction of the element of subjectivity in expert assessments, the clarity of the results of risk assessment and analysis, the bank employees' thorough understanding of these results, and the accessibility of the given methods to regulatory authorities and borrowers. In order to analyze, forecast, and manage credit risk, each bank must be able to quantify relevant credit risk factors, to analyze the risk involved, and to permanently monitor credit risk factors (Andrianova and Barannikov, 2013). The bank's decisions about granting, or refusing to grant, a loan, about the interest rate, and about the level of loan default provisioning will depend on the accuracy of risk recognition and assessment. The accuracy of risk factor assessments is evaluated relative to the number of errors in the recognition of "bad" and "good" loans (i.e. borrowers) and their average number. The accuracy of risk factor assessments is determined in a similar manner when loans are classified into more than two classes. Furthermore, the stability of risk assessment methodologies is characterized by the property of statistical methods known as robustness. Different methodologies of risk assessment, or one and the same methodology used with different algorithms, yield dissimilar classifications of loans into "good" and "bad". The application of different methodologies may result in the categorization of one and the same loan as either “good” or “bad”. Such instability in loan classification may affect the assessment of 20% of total number of loans (Solojentsev, 2004). Banks need to adapt their crediting-related activities to the changing conditions of the nation's developing economy and to the changes in the standard of living. The methods used to quantify and analyze credit risk are of great importance for the smooth functioning of a bank (Seitz and Stickel, 2002). Each bank develops its own risk probability assessment model in order to quantify and analyze credit risk, taking into account the general recommendations of the Basel Committee on Banking Supervision. The high accuracy of credit risk assessment helps to minimize the bank's losses, to reduce the interest rate, and to enhance the competitiveness of the bank (BCBS, 2004). Creating an effective risk assessment model and managing credit risk successfully is possible only thanks to continuous quantitative analysis of statistical information on credit success. There are such different approaches to the determination of the credit risk posed by a particular borrower as the bank experts' subjective evaluation and automated risk assessment systems (Konovalova, 2009). Global experience shows, however, that credit risk assessment systems based on mathematical models are more efficient and reliable than any others. In order to build a credit risk assessment model, first those clients of the credit institution are selected who have already proved themselves to be either good or bad borrowers (Ralf, 2009).

Credit Risk Assessment Model

In order to ensure effective credit risk management in commercial banks, it is necessary to develop the kinds of terms and conditions for those bank clients who take loans that would both attract potential borrowers and guarantee loan repayment. It would not be expedient, however, to develop a separate set of terms and conditions for every individual borrower. Instead, existing and potential bank clients should be grouped according to their similarities and differences. After that, a separate set of terms and conditions needs to be worked out for each group in accordance with the characteristic features of the group members. The classification of bank clients into distinct groups should proceed according to the method of classification that unites disparate system elements into homogeneous groups on the basis of the similarities of the elements in question. This method of classification needs to reflect the structure of the source data and to ensure the most adequate division of the data into groups. Traditionally, clustering and networking have been employed to achieve these goals. In the case of multidimensional samples, both of these methods produce similar divisions of objects into classes. In the present article, we will employ clustering as the method of credit risk assessment. In order to assess the risk of a bank's lending activities, one needs to take into account the statistics reflecting the bank customers' violations of the contract conditions and the damage caused to the bank by each such violation. The magnitude of the risk as the amount of damage (risk defined as the customer's failure to make principal payments on time) can be seen as a regressive dependence on such factors as the average loan size 1 x, the period for which the loan is issued 2 x, and a number of other factors. Specification and identification of such regressions should be performed on the basis of the information about the damage caused by each client and about the credit characteristics of each customer class. Such a model would enable the forecasting of the risk posed by each potential client.

Factor Analysis of Borrowers and Regression Dependence

We have conducted model experiments using statistical information on credit histories of clients of Latvian commercial banks engaged in consumer lending. In order to process the data, we have used the program Excel as well as the statistical program SPSS Statistics data. The peculiarities of the studied data consist in their diversity and multi-dimensionality. The study model sample includes data on 100 clients - borrowers and consists of the following indicators characterizing the borrowers: the loan term (*month*), the loan amount (*value*), the borrower's sex (0 - woman, one - man), the borrower's age (*age*), the number of the borrower's children (*children*), the borrower's average earnings (*income*). Also, each borrower is assigned a variable *problems*, characterizing the presence or absence of problems with loan repayments (0 - no problem, 1 - there is a problem), and the amount of economic damage *risk*. A fragment of the original data for analysis (20 out of 100) is presented in Table 1.

Table 1. Source Data on Clients-Borrowers *(fragment of the original data)*

Client number	Loan terms	Loan amount (EUR)	Client's age	Number of children	Sex 0 - male, 1-female	Average monthly income (EUR)	Problems with loan repayment (0 – no, 1 – yes)
1.	6	800	24	1	0	1000	0
2.	12	1000	21	0	1	1000	1
3.	12	1000	55	3	1	900	0
4.	12	1000	40	2	0	1200	0
5.	5	1500	35	1	0	800	1
6.	12	1500	43	1	0	2000	1
7.	12	2000	48	1	1	1500	0
8.	12	2200	45	0	1	1000	0
9.	6	2500	48	0	0	600	1
10.	12	2500	37	0	1	500	1
11.	24	3000	45	2	0	1200	1
12.	36	3000	30	1	0	2000	0
13.	24	3000	49	1	1	1500	0
14.	36	3500	42	1	1	1500	1
15.	36	4000	38	3	1	2000	1
16.	36	4000	23	0	0	2500	0
17.	48	4000	41	0	1	2000	0
18.	48	5000	46	1	0	1300	1
19.	54	5000	47	1	0	1000	1
20.	36	5000	30	0	1	1000	0

We will use a factor analysis module comprising the principal components of the dispersion and correlation analysis. This procedure should be carried out in stages.

Stage One: setting initial parameters of the problem. We will determine the number of factors equal to the number of input variables that is six, as the *risk* and *problems* variables are not taken into consideration when performing factor analysis. In the course of the sequential factor selection, the factors comprise less and less variability. Therefore, the next stage is limited to three factors.
Stage Two: calculating the eigenvalues of the factors involved. The eigenvalues reflect the dispersion of the newly selected factor. Table 2 shows that the first factor explains 34% of the total dispersion, the second factor explains 21.5 % of the total dispersion, and the third, 17%. On the basis of the information received about the dispersion explained by each factor, we can proceed to the question about the number of factors that should be kept. For this purpose, we will use factor loadings, which can be interpreted as the correlations between the selected factors and the baseline variables.

Table 2. The eigenvalues and the explained variation of selected factors

Factors	Eigenvalue	Percentage of total dispersion (explained variation)	Cumulative eigenvalue	Cumulative explained variation
1.	1.978521	34.02199	1.978521	34.02199
2.	1.375280	21.53989	3.353801	55.56188
3.	1.158236	17.23621	4.512037	72.49809

Stage Three: a study of factor loadings. First, we estimate the factor loadings without rotation for all six original variables (Table 3).

Table 3. The values of the factor loadings for the operation "without rotation"

Variable	Factor 1	Factor 2	Factor 3
month	0.525012	0.127251	0.627152
value	0.831036	-0.357891	-0.167013
age	-0.485724	-0.281432	0.680030
children	-0.219991	-0.738915	-0.325576
sex	0.293715	0.716111	-0.381722
income	0.871327	-0.395768	0.122874

The selection of the relevant factors is done so that subsequent factors include less and less dispersion. Factor 1, as can be seen from Table 2, has the highest loadings values for the variables pertaining to the clients' economic characteristics. Factor 2 reflects the maximum loadings for the variables related to the social status of the client.
Stage Four: specification of the number of relevant factors. We will use the method *Varimax row*, which is the most common rotation method. The use of this method allows factors to remain independent of each other, so that the values of the variables of one factor are not correlated with the values of other factors (Table 4).

The specification of the descriptive characteristics of the selected factors shows that the first factor is related to the financial and economic parameters of the borrower (the average income, the amount of the loan); the second factor is related to the client's social parameters (the number of children); the third factor reflects his/her personal characteristics (age, belonging to a particular sex). Besides, the three selected factors most fully describe 75% of the variations of the initial data. Therefore, it is advisable to continue factor analysis on the basis of the three selected factors.

Table 4. The values of the factor loadings for the operation *Varimax row*

Variable	Factor 1	Factor 2	Factor 3
month	0.405878	0.602158	0.277682
value	0.891231	-0.123397	-0.169583
age	-0.235723	0.171479	0.750813
children	0.177915	-0.812786	0.221899
sex	-0.020836	0.317501	-0.771215
income	0.921728	0.197343	0.027119

<u>Stage Five</u>: assessing the adequacy of the achieved solutions. In order to verify the validity of the selection of the relevant factors, it is necessary to build a correlation matrix. If the coefficients of this reproduced correlation matrix turn out to be close to those of the original matrix, then this will validate the selection of the relevant factors. In order to determine the extent of the possible deviations of the elements of this matrix from those of the original one, we need to build a matrix of residual correlations, the elements of which are equal to the differences between the elements of the original and reproduced matrices. The initial and residual correlation matrices are shown in Tables 5 and 6.

Table 5. The original correlation matrix

Variable	month	value	age	children	sex	income
month	1.00	0.28	0.03	-0.36	0.07	0.32
value	0.28	1.00	-0.25	0.18	0.20	0.72
age	0.03	-0.25	1.00	0.07	-0.33	-0.20
children	-0.36	0.18	0.07	1.00	-0.35	-0.05
sex	0.07	0.20	-0.33	-0.35	1.00	-0.01
income	0.32	0.72	-0.20	-0.05	-0.01	1.00

Table 6. The matrix of residual correlations

Variable	month	value	age	children	sex	income
month	**0.25**	-0.09	-0.14	0.17	0.02	-0.12
value	-0.09	**0.19**	0.20	-0.05	0.09	-0.07
age	-0.14	0.20	**0.35**	0.01	0.25	0.03
children	0.17	-0.05	0.01	**0.27**	0.18	-0.06
sex	0.02	0.09	0.25	0.18	**0.30**	-0.02
income	-0.12	-0.07	0.03	-0.06	-0.02	**0.18**

Inputs in the matrix of residual correlations can be interpreted as the total correlations that the selected factors cannot account for. The diagonal elements of the matrix contain standard deviations that these factors cannot account for. A thorough analysis of the residual matrix shows that there are virtually no residual correlations larger than the modulus of 0.25. Consequently, the selected factors adequately reflect the original information.

To determine the credit risk for each class (cluster), we have calculated the following parameters: 1) expected result of a credit transaction; 2) spread of possible outcomes of the operation with respect to the expected value (result); 3) dispersion and the average linear deviation; 4) credit risk on the basis of the average linear deviation and of the most expected result of the operation.

The calculation results are shown in Table 7.

Table 7. The findings about the identified classes of borrowers and the credit risk level in each class (cluster)

Indicators	**Value of the indicator in the class (cluster)**			
Cluster	**1.**	**2.**	**3.**	**4.**
Number of borrowers in a class	23	13	21	43
Number of a client/borrower	69, 71 – 75, 84 – 100	48, 59 –61, 70, 76 – 83	39 – 44, 46, 50 – 58, 64 – 68	1 – 38, 45, 47, 49, 62 – 63
Total loan amount	395000	161000	57000	64500
Share of the total loan amount,%	58.3	23.8	8.4	9.5
Minimum loan amount	12500	8000	6000	800
Maximum loan amount	20000	15000	10000	5000
The average loan period, months	37.1	18.0	49.5	23.7
Credit risk level	0.26	0.34	0.23	0.38

The members of the most numerous class, the fourth (43 borrowers), have taken the lowest loan amounts (from 800 EUR to 5,000 EUR). The level of credit risk in this class of borrowers is the highest: 38%. However, the share of loans in this class is insignificant: 9.5%. The third cluster is quite stable: the coefficient of variation is 23%; the loan amounts are small: from 6 to 10 thousand EUR and they constitute 8.4% of the total loan amount. However, the loan terms of the customers in this class are the longest: an average of 49.5 months. The second class is not numerous (only 13 customers); its members have taken a relatively large average loan amount; and it can be characterized by the average level of stability.

The highest income class is the first (almost ¼ of all clients), and its members have taken large loans for the average term of 3 years. In general, this class is stable.
This analysis would further facilitate credit risk management. We have established the regression dependence of the level of risk on the following factors: the loan amount (*value*), the average earnings (*income*), and the loan term (*month*) for the fourth class of customers:

Risk = – 3112 + 37.96 x *month – 0.12* x *value* + 0.29 x *income*, $R^2 = 0.98; dw = 2.9$
Statistical error 653 41 0.01 0.02

The identified model is statistically significant. Standard errors of the model parameters do not exceed 1/4 of the value of the corresponding parameter; the coefficient of determination equal to 0.98 explains the variation in the values of damage by the change of the factors included in the model by 98%; the residual dispersion is only 2%. The developed econometric model is the basis for the assessment and prediction of the level of risk caused by potential customers belonging to the fourth cluster.

Credit Risk Management on the Basis of the Obtained Results

In managing credit risk, one needs to create a system of interconnected and interdependent methods of deliberate action aimed at minimizing risk and uncertainty in crediting-related activities. Using the proposed model of credit risk assessment makes it possible to take a differentiated approach to credit risk management. Credit risk management can be represented as a process consisting of the following stages: 1) risk factor identification; 2) assessment of the potential consequences of an identified risk factor; 3) choice of managerial strategies aimed at counteracting the consequences of a given risk factor; 4) supervision (monitoring) of the implementation of the chosen strategies aimed at minimizing and neutralizing the effects of a given risk factor. At the stage of credit risk identification, the potential risk is assessed in terms of its quantitative and qualitative parameters within the framework of the risk factor analysis adopted by the bank in order to determine the degree of the severity posed by the risk in question. At the stage of the identification of a potential credit risk, one can also predict the results of the management of the identified risk in consequence of the various sets of management methods employed; thus, one is enabled to compare and contrast various sets of risk management methods in order to be able to select the best set of methods to be used in future according to the criteria identified above. It is also necessary to assess the consequences of a potential credit risk from the standpoint of the magnitude of their impact and probability of occurrence. The credit risks identified at the first stage of credit risk management need to be assessed according to the following temporal parameters: past data, present data, and predicted future data. As a result of the identification and assessment of a potential credit risk, it is necessary to decide upon the set of credit risk management strategies, which is the third stage of credit risk management. As credit risk factors tend to change in the course of time, it is imperative that these changes be monitored in order for the bank management to provide a timely response to the increase in the degree of the credit risk by comparison with the predicted credit risk value. Credit risk control is the essence and the purpose of the final stage of credit risk management. What needs to be emphasized is the functional and organizational unity of all the stages of credit risk management. Indeed, all the stages of credit risk management are inextricably interconnected, and their unity is the main principle of credit risk management.

Summary

When lending to individuals (retail clients) the most significant factors affecting the value of the credit risk of a bank are the average income of the borrower, the loan amount, and the loan term.

In determining the values of factor loadings, it has been revealed that the primary factor that has the highest values of loadings for the variables is related to the customers' economic characteristics, such as the loan amount (*value*) and earnings.

The main source of information in determining the level of credit risk for the creditor banks is the credit history of the client.

Based on these findings, we have developed the following suggestions for the improvement of credit risk management in commercial banks, lending to retail customers.

To form a predictive assessment of credit risk in commercial banks, it is necessary to use the methodology of factor analysis utilized in the current article. This methodology is based on the study of borrowers' credit histories and it takes into account the amounts and terms of loans.

The proposed methodology should be based on the use of clustering methods, the method of dispersion analysis and the analysis of principal factors.

Credit risk management on the basis of the proposed methodology should aim at achieving the following objectives:

– to identify common patterns of bank customers' economic behavior,
– to formulate a set of differentiated requirements for borrowers in particular groups in accordance with their specificity,
– to determine the risk appetite of the person making decisions about the amount and the term of a loan to be granted and about the interest on this particular loan.

The differentiation of the methods used in credit risk management in different groups of borrowers is due to the international standards and requirements of the Basel Committee and it will contribute to banks' transition to the use of an internal ratings approach in assessing and managing credit risk.

It should be noted that the current study is limited in its scope as it has researched only those loans that are given to retail clients. This limitation determines the future direction of the research, which will involve the study of credit risk management in those cases when loans are given to other categories of borrowers, such as small and medium enterprises (SME) and large industrial businesses.

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ZARZĄDZANIE RYZYKIEM KREDYTOWYM W BANKACH KOMERCYJNYCH

Streszczenie: W artykule zaproponowano model oceny ryzyka kredytowego na podstawie analizy czynnikowej klientów detalicznych/kredytobiorców w celu zapewnienia prognostycznej kontroli poziomu ryzyka stwarzanego przez potencjalnych klientów w bankach komercyjnych zaangażowanych w udzielanie kredytów konsumpcyjnych. Celem badania jest określenie poziomu ryzyka reprezentowanego przez różne grupy (klasy) klientów detalicznych (kredytobiorców) w celu zmniejszenia i zapobiegania ryzyka kredytowego w przyszłości, jak również do poprawy zarządzania ryzykiem bankowym. Głównym wynikiem badania jest stworzenie modelu wewnętrznych ratingów kredytowych kredytobiorców oraz rozwój metod poprawy zarządzania ryzykiem kredytowym w bankach komercyjnych.
Słowa kluczowe: zarządzanie ryzykiem kredytowym, klienci detaliczni, kredytobiorcy, kredyty konsumpcyjne, analiza skupień, analiza czynników

信貸風險管理商業銀行

摘要：文章提出，以確保潛在客戶在從事消費貸款的商業銀行帶來的風險級別的代碼預測控制信貸風險評估的零售客戶/借款人的因素分析的基礎上的模型。這項研究的目的是確定由零售客戶（借款人）的不同組（類），以減少和防止在未來的信用風險以及提高銀行風險管理代表的風險水平。這項研究的主要結果是借款人的內部信用評級模型的創建及其在商業銀行提高信用風險管理方法的發展。
關鍵詞：信用風險管理，零售客戶，借款人，消費貸款，聚類分析，因子分析