



NEW INTERNAL RATING APPROACH FOR CREDIT RISK ASSESSMENT

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Abstract. The assessment and modeling of the credit risk is one of the most important topics in the field of financial risk management. In this investigation the credit risk assessment model was developed and tested for Lithuanian companies. 20 financial ratios of the companies were calculated for each year of the 3 year period of interest. The analysis of variance (ANOVA) and Kolmogorov-Smirnov test were applied and the set of variables reduced from 60 to 25. Logistic regression was used for the classification of the companies into reliable and not reliable ones. Financial ratios, having the highest correlation to the possibility of default were selected for further investigation and several credit ratings were attributed to the companies according to these variables' values. The average values of Mahalanobis Distances calculated for the most reliable companies were the lowest and these values increased with a decreased reliability of the company. The differences between Mahalanobis Distances of the companies having different credit ratings confirmed the reliability of the model results.

Keywords: credit risk assessment, analysis of variance, Kolmogorov-Smirnov test, logistic regression, Mahalanobis Distance.

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1. Introduction

Nowadays, banking sector plays a very important role in the economic and social welfare. Banks grant credit to support manufacturing, agricultural, service and other enterprises. These, in turn, provide jobs thus ameliorating purchasing power, consumption, and savings. It is, therefore, necessary to make credit granting as correctly as possible while keeping the

decision making process both efficient and effective (Bahrammirzaee *et al.* 2009). According to Twala (2010), credit risk is defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. Chen *et al.* (2010) define credit risk as the risk of loss due to a debtor's non-payment of a loan. Default occurs when a debtor has not fulfilled legal obligations according to the debt contract, or has violated a loan covenant (condition) of the debt contract, which might occur with all debt obligations including bonds, mortgages, loans, and promissory notes.

The credit risk problem is widely discussed in the financial literature (D'Amico *et al.* 2010). Risk assessment is accomplished by estimating the probability of occurrence and severity of risk impact (Zavadskas *et al.* 2010). However, the amount of enterprise performance criteria is growing continuously and evaluation methods are becoming more and more complicated (Sarka *et al.* 2008). Researchers agree that financial results of enterprises can be influenced by many factors: the situation in global economy, competition, changes of investigation methods, business technologies, politics and society (Strumickas, Valanciene 2009) as well as organizational environment – strategy, structure and culture (Susniene, Sargunas 2009). Decision making requires accounting of the impacts from cultural, social, moral, legislative, demographic, economic, environmental, governmental and technological changes, as well as changes in business world on international, national, regional and local markets (Turskis *et al.* 2009).

Since financial innovation and derivatives grow rapidly in competitive financial industry, credit risk measurement and management becomes essentially important (Chen *et al.* 2010). Due to regulatory concern of Basel II, credit risk assessment has been the major focus of financial and banking industry. Considering credit risk forecasting process, banks must differentiate good customers from bad ones in terms of their creditworthiness (Uberti and Figini 2010). The need for reliable models that predict defaults accurately is imperative so that the interested parts can take either preventive or corrective action.

Due to all these reasons, the main aim of this investigation was to evaluate statistical credit risk assesment model. The 3-year data of Lithuanian Statistical Department of Lithuanian companies were used for this purpose. To achieve the main goal, the following research methods were used: analysis of scientific publications, analysis of variance (ANOVA), Kolmogorov-Smirnov test, Logistic regression, Mahalanobis Distances calculation.

2. The methodology for credit risk assessment

Credit risk has been an important and widely studied topic in bank lending decisions and profitability for a long time. For all banks, credit remains the single largest risk, despite advances in credit measurement techniques and the diversification of portfolio. Continuing increases in the scale and complexity of financial institutions and in pace of their transactions demand that they employ sophisticated risk management techniques and monitor rapidly changing credit risk exposures. At the same time, fortunately, advances in information technology have lowered the cost of acquiring, managing and analysing data, in an effort to build more robust and sound financial systems (Angelini *et al.* 2008).

The Basel Committee, comprised of central banks and banking business representatives from various countries, formulated broad supervisory standards and guidelines for banks to implement. Due to changes in the banking business, risk management practices, supervisor approaches, and financial markets, the committee published a revised framework as the new capital adequacy framework, also known as Basel II (Khashman 2010).

The commercial banks have a choice between two broad methodologies for calculating their capital requirements for credit risk. One alternative, the standardised approach, is to measure credit risk in a standardised manner, supported by external credit assessments. National supervisors are responsible for determining whether an external credit assessment institution (ECAI) meets the necessary criteria (Basel Committee on Banking Supervision 2006). Three credit rating agencies are recognized worldwide: Standard & Poor's, Moody's Investor Service and Fitch Ratings. In practice, credit ratings are assigned to companies on the basis of certain financial ratios, which are used to determine the fiscal health and profitability of the given company.

According to Basel Committee on Banking Supervision, an ECAI must satisfy each of six criteria:

Objectivity: The methodology for assigning credit assessments must be rigorous, systematic, and subject to some form of validation based on historical experience.

Independence: An ECAI should be independent and should not be subject to political or economic pressures that may influence the rating.

Transparency: The individual assessments should be available to both domestic and foreign institutions with legitimate interests and at equivalent terms. The general methodology used by the ECAI should be publicly available.

Disclosure: An ECAI should disclose the following information: its assessment methodologies, including the definition of default, the time horizon, and the meaning of each rating; the actual default rates experienced in each assessment category; and the transitions of the assessments.

Resources: An ECAI should have sufficient resources to carry out high quality credit assessments.

Credibility: To some extent, credibility is derived from the criteria above. The credibility of an ECAI is also underpinned by the existence of internal procedures to prevent the misuse of confidential information (Basel Committee on Banking Supervision 2006).

The other alternative, the internal ratings-based approach, which is subject to the explicit approval of the bank's supervisor, would allow banks to use their internal rating systems for the credit risk (Basel Committee on Banking Supervision 2006). Internal models offer an opportunity for a bank to measure and price counter-party risk and systemize risks inherent in lending. Prediction of default probability (PD) for each borrower or a group of borrowers is the key input for the estimation of regulatory capital as well as economic capital for banks. It is also equally important for the banking industry and financial institutions to differentiate the good (non-defaulting) borrowers from the bad (defaulting) ones. This will not only help them to take lending decisions but also to practice better pricing strategies to cover against the counter party risk (Bandyopadhyay 2006).

3. Statistical methods for the analysis of credit applicants data

The risk of default is commonly defined as the risk that an obligor is unable to meet a specific financial obligation. Mathematically this may be quantified as a probability that a certain event occurs. Let i be an obligor and D_i the default indicator at time t of the obligor i , defined by:

$D_i(t) = 1$ if the obligor goes default at time t ,

$D_i(t) = 0$ else.

The risk of default at the time t of obligor i is the probability $P(D_i(t) = 1)$. The New Basel Capital Accord edited by the Basel Committee on Banking Supervision allows banks to evaluate credit risk and adequate capital requirements by using internal models (Beran and Djaidja 2007).

The internal credit risk estimation models are widely used in banking industry nowadays, especially after Basel Accord II was implemented in 2007. Scores earned by applicants for new loans or existing borrowers seeking new loans are used to evaluate their credit status. Credit scores are awarded on the basis of different techniques designed by individual lenders. However, irrespective of the varying nature of techniques used, credit scoring is invariably used to answer one key question – what is the probability of default within a fixed period, usually 12 months (Dong *et al.* 2010). Classification or regression methods are then applied to create predictive models for new credit applications in the future (Finlay 2010). Over the last decade a number of the world's largest banks have developed sophisticated systems in an attempt to model the credit risk arising from important aspects of their business lines (Twala 2010). There is a wide range of quantitative methods to assess the creditworthiness of loan applicants and to estimate probabilities of default (PD). As well-developed statistical models often outperform a subjective credit risk assessment, quantitative methods are common in banks' credit risk assessment (Trustorff *et al.* 2010).

The traditional method for studying default probability is to collect the default information from the historical data. The major study about default determinate factors is based on classification method. Classification model considers the default measurement as the pattern recognition where borrowers are divided to normal and default borrowers based on their financial and non-financial position, then to summary classification rule from financial-index data, and construct evaluation model that is used to discriminate new sample. This kind of study includes binary differentiation that focuses on defaulted firms and normal firm and multi-differentiation which are used to attribute credit ratings (Zhou *et al.* 2008).

Currently, many models are available for credit risk measurement and credit rating. The various statistical methods are commonly used for credit risk prediction. It includes logistic regression, k -nearest neighbour, multiple discriminant analysis (Chen *et al.* 2010), linear regression, probit analysis, mathematical programming, non-parametric smoothing methods, Markov chain models, expert systems, artificial neural networks, genetic algorithms (Abdou *et al.* 2008), multivariate adaptive regression splines, classification and regression trees, case based reasoning (Chuang and Lin 2009) and other methods. The general effort in credit rating prediction using statistical methods was that a simple model with a small list of financial variables was succinct and was easy to explain. However, the problem is that the multivariate normality assumptions for independent variables are frequently violated in financial data

sets, which makes these methods theoretically invalid for finite samples. Recently, Artificial Intelligence (AI) techniques, particularly neural networks, have been used to support credit rating and bankruptcy predictions. An increasing field of research in artificial neural networks is the one mainly concerned with interactions between economics and computer science, studying their potential applications to economics (Boguslauskas, Mileris 2009). However, models obtained in this machine learning method are usually very complicated and hard to explain, and they heavily rely on the samples and experimental data (Chen *et al.* 2010).

In order to develop the statistical model it is necessary to find objective criteria for the default prediction such as financial information, income statements, predictive revenue, location and business potential, etc. (Yoon and Kwon 2010). Chen *et al.* (2009) affirm that in case of commercial and industrial lending, applicants are required to submit written profile of business ownership, management team, company literature, historical (generally past 3 years), current as well as future projection of financial statements – balance sheet, income statement, and statements of cash flows.

Banks' internal credit ratings summarize the risk properties of the bank loan portfolio and are used by banks to manage their risk. These ratings reflect the probability of default (Jacobson *et al.* 2006). Ratings-based techniques attribute a rating to each default able investment in a portfolio. Then banks estimate the probability of upward or downward moves in ratings using historical data on ratings transitions. The probabilities are collectively termed the ratings transition matrix. By simulating rating scenarios that are consistent with the transition probabilities one can derive the empirical distribution of the value of the portfolio and calculate the portfolio's value-at-risk (Nickell *et al.* 2007). By using internal rating models the borrowers are grouped into rating grades which are abbreviated with letters. For example, banks and rating agencies usually use grades from AAA (the highest rating: the obligor's capacity to meet its financial commitment on the obligation is extremely strong) over AA, A, BBB, and so on, to D (bankruptcy of a company). Default probabilities are assigned to a grade by calculating the observed default rate of all borrowers within this grade in each year and averaging these figures over a historical horizon (Rosch 2005).

4. Credit risk assessment model

The credit risk estimation model was developed to measure the credit risk of Lithuanian companies. The data sample consisted of 198 Lithuanian companies: 50 bankrupted and 148 – not bankrupted. The financial reports of 3 years were used to calculate initial variables. 20 financial ratios were calculated for every year's data.

So, the initial set of variables consisted of 60 independent variables X_1, X_2, \dots, X_{60} . The dependent variable was the information about a company: 0 – the company was not bankrupted and 1 – the company was bankrupted.

Data reduction for the development of credit risk estimation model was accomplished by analysis of variance (ANOVA) and Kolmogorov-Smirnov test. The ANOVA test was used to determine the significant differences between means of independent variables in groups of bankrupted and not bankrupted companies. If the means did not differ significantly, the variable X_i was not included into further analysis. The Kolmogorov-Smirnov test was used

to verify if the variable X_i had the normal distribution. Also, variables which did not satisfy this condition were rejected. So, the initial set of 60 variables was reduced to 25 variables. The actual variables for the estimation of credit risk are marked “+” in Table 1. The columns of the table include the periods of financial reports for the calculation of financial ratios:

1 year – the last year financial data (eg. 2009).

2 year – the financial report that was prepared 2 years ago (eg. 2008).

3 year – the financial report that was prepared 3 years ago (eg. 2007).

Table 1. The actual variables for the estimation of credit risk

Financial ratios	No.	Ratio	1 year	2 year	3 year
Liquidity	1.	Current ratio (BPK)	+	-	-
	2.	Quick ratio (SPK)	+	-	-
	3.	Cash to current liabilities (PGP)	-	-	-
	4.	Working capital to total assets (GST)	+	+	+
Profitability	5.	Gross profitability (BP)	-	-	+
	6.	Net profit margin (GP)	+	+	+
	7.	Net profit to total assets (TP)	+	+	+
	8.	Net profit to equity (NKP)	-	-	-
Financial structure	9.	Total liabilities to total assets (IK)	+	+	+
	10.	Total debt to equity (SNK)	-	-	-
	11.	Long term debt to equity (ISK)	-	-	-
	12.	Equity to total assets (NKT)	-	-	-
Activity	13.	Sales to total assets (TA)	-	-	-
	14.	Sales to long term assets (ITA)	-	-	-
	15.	Cash to total assets (GP/T)	-	-	+
Other	16.	Current assets to total assets (TT/T)	-	-	-
	17.	Unappropriate balance to total assets (NP/T)	+	+	+
	18.	Working capital to sales (GAK/P)	-	-	-
	19.	EBIT to total assets (TVP/T)	+	+	+
	20.	EBIT to sales (TVP/P)	+	+	+

The logistic regression method was applied for the classification of companies. The Companies were classified into 2 groups: reliable and not reliable. The individual possibility of default (p) for every company was calculated as:

$$p = \frac{e^{\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n}}{1 + e^{\alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n}}, \quad (1)$$

where α is the intercept and $\beta_1, \beta_2, \dots, \beta_n$ are the regression coefficients of variables x_1, x_2, \dots, x_n respectively.

If we denote that:

$$Z = \alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n. \quad (2)$$

Then the developed logistic regression model is:

$$Z = 4,369 - 0,925 \times \text{BPK1} - 2,6156 \times \text{GST1} + 16,8242 \times \text{TP1} + 4,5762 \times \text{IK1} + 2,6439 \times \text{GP1} + 0,9115 \times \text{SPK1} - 20,0507 \times \text{TVP/T1} + 5,3164 \times \text{NP/T1} + 39,0135 \times \text{TVP/P1} +$$

$$5,9507 \times \text{GST2} + 7,2504 \times \text{TP2} - 16,7569 \times \text{IK2} + 18,8240 \times \text{GP2} + 7,8331 \times \text{TVP/T2} - 12,2667 \times \text{NP/T2} - 41,6082 \times \text{TVP/P2} + 1,1088 \times \text{GST3} - 26,2628 \times \text{TP3} + 8,6205 \times \text{IK3} + 54,9958 \times \text{GP3} + 18,0501 \times \text{TVP/T3} + 9,7489 \times \text{NP/T3} - 4,1720 \times \text{BP3} - 7,0197 \times \text{TVP/P3} - 5,8053 \times \text{GP/T3}.$$

All possibility of default (p) values is in the range [0; 1]. The purpose of classification by logistic regression was to classify companies into 2 groups, so the classification threshold was set to $p = 0.5$. If p of a company was in the range [0; 0.5), this company was assigned to the group of reliable clients. If p of a company was in the range [0.5; 1], this company was assigned to the group of not reliable clients. The rating D1 was attributed for these not reliable companies.

The classification matrix was used to estimate the classification results of the logistic regression model (Table 2). Values 0 and 1 are the dependent variables in this matrix.

Table 2. Classification matrix

		Model	
		0	1
Actual	0	TN (144)	FP (4)
	1	FN (9)	TP (41)

The calculated rates of classification accuracy are presented in Table 3. Here, N is the number of analyzed companies.

The total accuracy indicates the proportion of correctly classified companies by logistic regression model. The sensitivity (Se) of model is the proportion of correctly classified not reliable companies, specificity (Sp) – correctly classified reliable companies. 93.43% of all companies were classified correctly by logistic regression model. Also, this model correctly classified 82% of not reliable (bankrupted) and 97.3% reliable (not bankrupted) companies.

Table 3. Rates of classification accuracy

Rate	Calculation	%
Total accuracy	$TA = (TP+TN)/N$	93.43
Sensitivity	$Se = TP/(TP+FN)$	82.00
Specificity	$Sp = TN/(TN+FP)$	97.30

The Basel II Accord requires classifying reliable companies into not less than 7 groups. So, credit ratings AAA, AA, A, BBB, BB, B and C were attributed for reliable companies according to 7 financial ratios and the individual possibility of default, calculated by logistic regression model. Also rating D2 was attributed to the companies that were classified as reliable ones by the logistic regression model, but their financial ratios were low and the individual possibility of default was high. The process of rating attribution for companies is illustrated in Fig. 1.

Financial ratios that have the highest correlation coefficients (r) with the individual possibility of default were selected. These ratios were: net profit margin (GP1), earnings before interest and taxes to total assets (TVP/T1), net profit to total assets (TP1), earnings before

interest and taxes to sales (TVP/P1), current ratio (BPK1), quick ratio (SPK1) and debt ratio (IK1). These ratios were calculated according to the last financial reports of companies.

The highest (Max), the least (Min) values and the median (Me) of financial ratios and the individual possibility of default (p) were found. The intervals of values were divided into two parts: from Min to Me and from Me to Max (Fig. 2). Every of these two parts were divided into 4 equal intervals. The scores (0–7) were attributed to these 8 intervals. The higher scores indicate the stronger financial condition of companies. So the highest scores were attributed to companies which were characterized by low debt ratio (IK1) and low individual possibility of default (p). All other financial ratios and scores are relevant: the higher financial ratio – the higher score. The credit rating of a company depends on the sum of scores (Table 4).

The rating model is valid for use in practice if the probability of default is relative to credit ratings. The probabilities of default (PD) in each rating are illustrated in Fig. 4.

These PD values indicate the proportion of bankrupted companies in every credit rating is:

$$PD = \frac{I_k}{N_k} \cdot 100\%, \tag{3}$$

where I_k is the number of bankrupted companies in rating k and N_k is the total number of companies in rating k .

Fig. 3 illustrates the distribution of credit ratings in analyzed data sample.

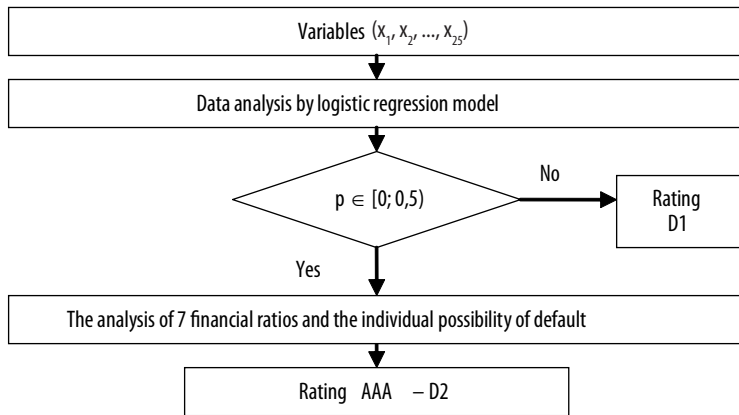


Fig. 1. The process of rating attribution for companies

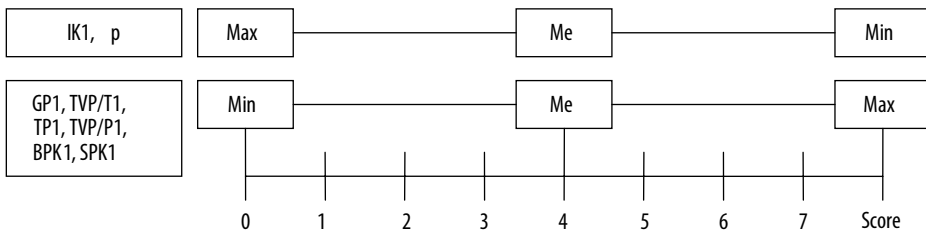


Fig. 2. The attribution of scores for the intervals of financial ratios and the individual possibility of default

Table 4. The attribution of credit ratings AAA – D2 for companies

Rating	Sum of scores
AAA	49 – 56
AA	46 – 48
A	39 – 45
BBB	32 – 38
BB	24 – 31
B	13 – 23
C	9 – 12
D2	0 – 8

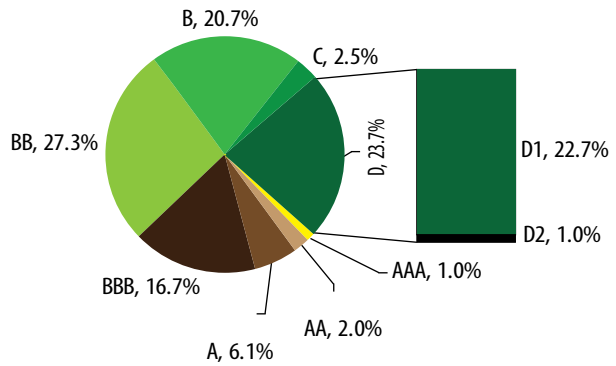


Fig. 3. The distribution of credit ratings

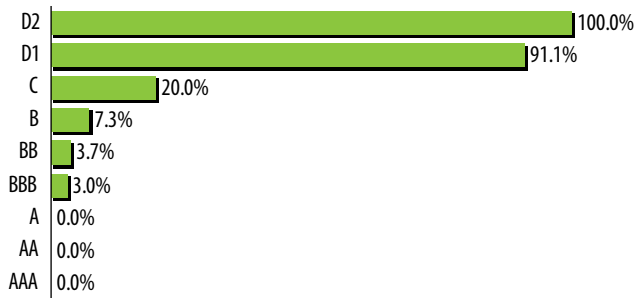


Fig. 4. Probabilities of default in each credit rating

5. Mahalanobis Distances’ calculation

Considerable researchers use Mahalanobis Distance to determine similarities of values from known and unknown samples. It can also be used for prediction and diagnosis, which illustrates the methodology’s accuracy and effectiveness (Cudney *et al.* 2007). In this investigation Mahalanobis Distances (MDs) of the companies having different ratings were calculated in order to test the reliability of the credit risk assessment model results.

The first step for calculation of MDs is to construct a measurement scale (Boguslauskas and Adlyte 2010a). For this purpose a data set of so-called “normal” observations must be collected. The collected normal observations are then standardized using the following formula:

$$Z_{i,j} = (x_{i,j} - \bar{x}_i) / s_i, i = 1, k, j = 1, n, \tag{4}$$

where k – a total number of selected variables;

n – a total number of observations;

x_{ij} – the value of the i -th characteristic in the j -th observation;

\bar{x}_i – mean of the i -th variable of normal group;

s_i – a standard deviation of the i -th variable of normal group.

The distance measure is based on the correlation between variable and different patterns that could be identified and analyzed with the respect to a base or reference point. Calculation of MDs is performed by using the following formula (Cudney *et al.* 2007):

$$MD_j = \frac{1}{k} \cdot Z_{i,j}^T \cdot R^{-1} \cdot Z_{i,j}, \quad i = \overline{1, k}, \quad j = \overline{1, n}, \quad (5)$$

where R^{-1} is the inverse matrix of the correlation matrix of the normal group.

The average value of MDs is 1 for observations of the normal group:

$$E(MD) = E\left(\frac{1}{k} \cdot Z_{i,j}^T \cdot R^{-1} \cdot Z_{i,j}\right) \approx 1, \quad i = \overline{1, k}, \quad j = \overline{1, n}. \quad (6)$$

Mahalanobis distances calculated for “abnormal” objects must be significant larger than 1 (Boguslauskas and Adlyte 2010b).

In this investigation the companies that were assigned to the most reliable ones in credit risk assessment model (rating groups AAA and AA) were selected as the set of normal observations for the construction of a measurement scale. Statistical characteristics of normal observations for each variable (GP1, TVP/T1, TP1, TVP/P1, BPK1, SPK1, IK1) selected in credit rating model were calculated and the data was standardised. After this procedure the following correlation matrix was obtained:

$$R := \begin{pmatrix} 1.00 & 0.31 & 0.33 & 1.00 & -0.81 & -0.77 & 0.56 \\ 0.31 & 1.00 & 1.00 & 0.30 & -0.71 & -0.81 & 0.79 \\ 0.33 & 1.00 & 1.00 & 0.31 & -0.73 & -0.81 & 0.80 \\ 1.00 & 0.30 & 0.31 & 1.00 & -0.79 & -0.76 & 0.54 \\ -0.81 & -0.71 & -0.73 & -0.79 & 1.00 & 0.95 & -0.81 \\ -0.77 & -0.81 & -0.81 & -0.76 & 0.95 & 1.00 & -0.84 \\ 0.56 & 0.79 & 0.80 & 0.54 & -0.81 & -0.84 & 1.00 \end{pmatrix}$$

The following equation (5), Mahalanobis Distances for each rating group were calculated.

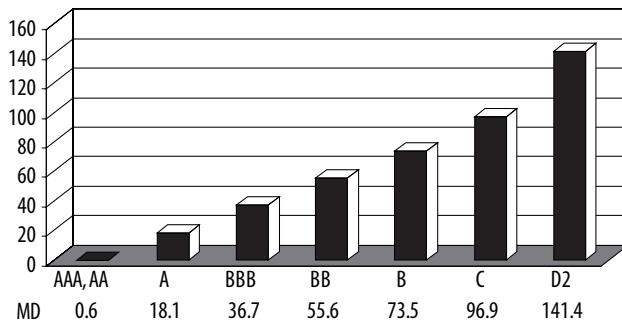


Fig. 5. The average Mahalanobis Distances for each group of credit ratings

The average values of Mahalanobis Distances calculated for the most reliable companies were the lowest and these values increased in the decrease of the reliability of the company. Correlation ratio between average values of possibility of default and Mahalanobis Distances calculated for the companies of each rating was equal to 0.91. The differences between Mahalanobis distances of the companies with different credit ratings confirmed the reliability of the model results.

6. New company's credit risk assessment

Credit risk assessment of companies seeking to get a bank loan can be performed according to the proposed model. Firstly, company's financial data from the last three-year period are investigated and probability of company's default is estimated. Financial data are further used for the assignment of the individual credit rating for the company. Proposed model reflects a new internal rating approach for credit risk assessment of the company and is a part of the company's overall judgement in the banking system.

7. Conclusions

Credit risk is determined as the risk of loss due to a debtor's non-payment of a loan. Due to this reason a reliable credit risk assessment model must be developed. Commercial banks can measure credit risk in two different ways: 1) measuring the credit risk in a standardised manner, supported by external credit assessments; 2) using internal ratings-based approach. Various statistical methods can be used for the credit risk measurement and credit rating.

The proposed statistical credit risk assessment model was evaluated using 3-year financial data of 198 Lithuanian enterprises. Application of logistic regression method allowed classifying correctly 93.43% of all investigated companies into to groups: reliable (97.3%) and not reliable (82%).

Credit rating system was created using 7 financial ratios: net profit margin, earnings before interest and taxes to total assets, net profit to total assets, earnings before interest and taxes to sales, current ratio, quick ratio and debt ratio. Different credit ratings were assigned to the companies according to their financial ratios and the possibility of default.

Mahalanobis Distances were calculated for the companies having different credit ratings. The average values of Mahalanobis Distances calculated for the most reliable companies were nearly equal to 1. These values increased with the decreasing reliability of the company.

Performed validation indicated the reliability of the proposed model for the credit risk assessment in the banking system.

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NAUJAS VIDAUS REITINGŲ MODELIS KREDITO RIZIKOS VERTINIMUI

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Santrauka. Kredito rizikos vertinimas ir modeliavimas – viena iš aktualiausių temų, kalbant apie finansinės rizikos valdymą. Atlikto tyrimo metu buvo sukurtas kredito rizikos modelis. Šis modelis išbandytas 198 įmonių aibėje, skaičiuojant po 20 finansinių rodiklių 3 analizuojamų metų laikotarpiu. Panaudojus ANOVA metodą ir Kolmogorovo – Smirnovio statistiką, kintamųjų kiekis buvo sumažintas nuo 60 iki 25 rodiklių. Įmonių klasifikavimui į 2 grupes: patikimus ir nepatikimus banko klientus, atsižvelgiant į jų įsipareigojimų nevykdymo tikimybę, buvo naudojama logistinė regresija. 97 proc. patikimų (nebankrutavusių) ir 82 proc. nepatikimų (bankrutavusių) įmonių suklasifikuotos teisingai. Tolimesniam tyrimui atrinkti 7 finansiniai rodikliai, kurių koreliacinis ryšys su įsipareigojimų nevykdymo tikimybė buvo didžiausias. Atsižvelgiant į šių kintamųjų reikšmes, įmonėms buvo priskirti 9 kredito reitingai. Vidutinės Mahalanobio atstumų reikšmės, apskaičiuotos patikimiausioms kompanijoms buvo mažiausios; šios reikšmės didėjo, mažėjant įmonių patikimumui. Skirtingų reitingų įmonėms apskaičiuoti Mahalanobio atstumų skirtumai, pagrindė modelio rezultatų patikimumą.

Reikšminiai žodžiai: kredito rizikos vertinimas, dispersinė analizė, Kolmogorovo –Smirnovio testas, logistinė regresija, Mahalanobio atstumas.

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