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Financial Risk Analysis Model in the Context of the Romanian Accounting System

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Abstract: Accounting plays an important role in the risk management process. Based on the information provided by it, potential risks can be identified and the company's exposure to specific risks can be measured. The information provided by the accounting is influenced by the accounting model adopted and the way in which it is presented varies. The Professional Management Accountants' Corps (CIMA) in London underlines the significant implications of accountants in the risk management process and internal control system of their organisations, professional knowledge adding value to processes (Collier, Berry & Burke, 2007, p. 5). The objective of this study is to create a credit risk assessment model using a number of useful financial rates in the company's creditworthiness prediction. This will be achieved through a quantitative model designed using real data from companies in operation or bankruptcy and statistical methods specific to the modelling oAf this type of risk. The aim of the research is to provide relevant scientific conclusions leading to an understanding of the relationship between the Romanian accounting model and the assessment of financial risk, how they influence each other, and the importance of knowledge link.

Keywords: financial risk; accounting model; risk management; scoring; logit model

JEL Classification: M41; G32

1. Introduction

Currently there are several approaches to *financial risk shaping*. As commercial banks generally lend to private firms and they are best suited to the scoring rating model, the study aims to create such a model. Although scoring also has some drawbacks, it is still one of the most widely used methodologies used to assess the risk profile of private firms. Three main variables affect the credit risk: the probability of bankruptcy (noted in the PD literature), default loss (LGD), bankruptcy recovery rate (RR) and bankruptcy risk exposure (EAD). The main attention was paid to the first factor assessment (Altman, Resti & Sironi, 2004, p. 183).

The first category of credit risk models were those based on the methodology developed by Merton in 1974, where the bankruptcy process was considered to be driven by the value of the company's assets. Merton's basic intuition was relatively simple: the company went bankrupt when its assets (the company's market value) were lower than its debts. The first structured models are outlined by researchers Black and Cox (1976), Geske (1977) and Vasicek (1984) (Fernandes, 2005, p. 2) and they seek an improvement in Merton's model by eliminating unrealistic assumptions. With these models new approaches and concepts are introduced, such as a more complex capital structure, interest

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expenditure, distinguishing between short- and long-term debt. Thus, all relevant elements of credit risk are recognized as functions of the structural characteristics of the company: *asset volatility* (business risk) and *leverage* (financial risk). There follow other structural models that improve existing ones. “Reduced-form” models bring certain novelty elements, which do not condition the probability of bankruptcy of the company value and its parameters do no longer require assessment in order to be implemented. These models explicitly introduce assumptions related to the dynamics of the probability of bankruptcy and the recovery rate (Altman; Resti & Sironi, 2004, p. 183-185). Value-at-risk models are expected to improve existing models.

Models using the statistical method by approaching logistics to predict the probability of bankruptcy were first brought up by Ohlson in 1980 (Ohlson, 1980, p. 111) and Platt & Platt in 1990. Since then the *logistic regression* has been intensively used for the development of classification models of the bankruptcy probability (Neophytou & Charitou, 2000, p. 6). Statistically, the logistic regression best corresponds to the characteristics of the bankruptcy prediction probability, where the dependent variable is binary (in bankruptcy/function) and the rates are discrete, unrelated and identifiable.

This study aims to create a credit risk assessment model using a number of useful financial rates in predicting the company’s creditworthiness. This will be achieved through a quantitative model that was designed using real data from bankrupt or operational companies and statistical methods specific to the modelling of this type of risk.

In order to achieve the objective, there was followed the methodology described below:

- A data set achivement and the database establishment;
- Prediction variables selection;
- Statistic model in use;
- Results display;
- Model validation;

2. Literature Review

The accounting models were an intense concern of the researchers, their influence factors, and the differences between them being identified in a wide range of works, both in foreign literature (as reference names Choi, Frost & Meek with the paper “International Accounting”, Nobes & Parker authors of the book “Comparative international accounting”, etc.), as well as in the literature Romanian (Feleaga “Compared Accounting Systems”, Ristea, L. Olimid & D. Calu “Accounting Systems compared”, Ionaşcu “Dynamics of contemporary accounting doctrines” and so on). The peculiarity of our research lies in emphasizing the characteristics of the Romanian accounting model as well as in spotting their connections with financial risks. The possible implications have been highlighted neither by accounting researchers nor by risk researchers so far, although the literature on the risk issue is rich s and extensive. In this respect, there have been studied books and articles related to the development of the concept of financial risk and risk, their evaluation methods, as well as various financial analysis books due to the close link with the concept of risk (work reference A. Malz “Financial risk management – models, history and institutions”, T. Aven “Quantitative risk assessment”, K. Horcher “Essentials of financial risk management”, M. Niculescu “Strategic Global Diagnosis”, E. Druic “Risk Economy. Theory and Applications”, I. Vasile “Financial management of the enterprise”, etc.).

3. Research Methodology

The information and ideas that came out of the theoretical documentation led to empirical research, using qualitative and quantitative methods (qualitative data analysis and case study). The use of qualitative methods was chosen because for the research topic it was imperative to understand the processes, events and relationships in the economic and social context.

The research aimed to identify the ways of reporting financial risks within the Romanian accounting model, with a view to highlighting the types of financial risk, as well as the information related to them presented in the Annual financial statements.

A combination of methods was used to finally get the accurate perception of reality. Using deduction as a general method of knowledge, after the theoretical documentation an assessment of the financial risk (credit risk) was carried out, in the context of the Romanian accounting system, in order to identify the current relationship and the mutual implications. The conclusions of the theoretical documentation and the empirical research results enabled the emphasis of the contribution to identify the impact of the Romanian accounting model on the financial risk assessment.

4. Characteristics of the Companies in the Used Database

In order to create the database necessary for the model projection, a company dealing with the provision of financial data, was asked to provide certain balance sheet indicators as well as the profit and loss account for 200 companies, out of which 50 would be bankrupt. For these companies information was requested according to the table below:

Tabel 1. Information About the Companies in the Database

Identification data	Company name, tax code, CAEN code for the field of activity and company status (bankruptcy or function).
Financial data	Fixed assets, current assets, stocks, house and bank accounts, short-term liabilities, long-term liabilities, advances, prepayments, share capital, equity, turnover, personnel expenses, operating income, interest expenses, financial expenses, gross result, net profit.

Source: own processing

Using these data, specific to the Romanian accounting system, the indicators presented in table no. 2 were calculated for each company separately. The final database that will be used in the design of the model contains:

- Indicator codings: RF has the values 0 or 1, depending on the state of the company, bankruptcy or function, and R1, . . . , R15 the indicators used;
- Indicator values for each company separately.
- The distribution of companies from the database according to the turnover is shown in figure no. 1:

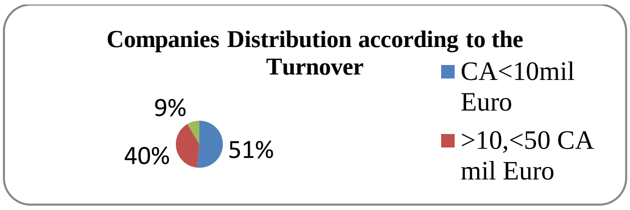

Figure 1. Distribution of the Companies in the Database Set

Source: Own Processing

There can be noticed that about 90% of the companies in the database are small and medium-sized companies. By analyzing the number of employees, the proportions highlighted in the previous graph are kept.

Although the rate of bankruptcies in our country is about 6-7%, in the data used to create the model, for an accurate estimation, we chose 25% of insolvent companie.

5. Selection of Prediction Variables

Of a whole list of possible economic indicators, the most independent indicators had to be chosen, with the help of literature. There is a large number of possible rates that can be used and they have proved to be useful in predicting the bankruptcy risk (Altman & Sabato, 2005, p. 13). Fernandes J. E. (2005) showed that the selected, combined indicators should have the following characteristics (Fernandes, 2005, p. 14):

- High discriminating power with little to estimate parameters;
- Statistical significance: all individual variables but also the model as a whole must be significant, with weak correlations between variables;
- Intuitive – the sign of the estimated parameters must be economically logical, and the selected variables must represent relevant risk factors.

Studies conducted by J. Olhson and then confirmed by other researchers have concluded that there are four statistically significant factors affecting the probability of bankruptcy: the size of the company, the size of the financil structure, measure of performance, measure of liquidity (Ohlson, 1980, p. 111).

Thus, most of the outlines were based on factors in the categories of profitability, liquidity, indebtedness and the company’s activity.

Table No. 2 contains the initial indicators taken into account when making the model and the coefficient of correlation with the company’s status: operation or bankruptcy.

Table 2. List of the Indicators Used for the Model

Category	Notation	Name and method of calculation
Profitability	R1	Commercial profitability $\frac{Gross\ profit}{Turnover}$
	R2	Commercial profitability $\frac{Gross\ profit}{Total\ assets}$
	R3	Financial profitability $\frac{Net\ profit}{Equity}$
Liquidity	R4	$\frac{House\ and\ bank\ accounts}{Debts < 1year}$
	R5	General Liquidity $\frac{Current\ assets}{Debts<1year}$
	R6	Immediate Liquidity $\frac{Current\ assets - stocks}{Debts<1year}$
	R7	$\frac{House\ and\ bank\ accunts}{Total\ Assets}$
Indebtness	R8	Overall duty rate $\frac{Total\ debts}{Equity}$
	R9	Global financial autonomy rate $\frac{Equity}{Total\ liability}$
	R10	Global indebtness ratio $\frac{Total\ debts}{Total\ liability}$
	R11	Financial leverage $\frac{Total\ assets}{Equity}$
Company activity	R12	Level of interest expenses $\frac{Interest\ expenses}{Turnover}$
	R13	Leve lof financial expenses $\frac{Financial\ expenses}{Turnover}$
	R14	Return on assets $\frac{Turnover}{Total\ assets}$
	R15	Level of staff expenditure $\frac{Staff\ expenditure}{Turnover}$

Source: own processing

All these indicators have an influence on the bankruptcy risk. In order to apply the statistical model in this list, there were chosen some indicators in poor correlatio with each other. To do this, with the help of the program, a correlation matrix has been developed and it provides information related to the correlation coefficients between these indicators, namely the existence and intensity of their stochastic link (Gheorghe, 1999, p. 43). The closer this value is to 0, the weaker the correlation, and if this coefficient is equal to 0, the variables are independent. The resulting correlation matrix is presented as follows:

Correlation matrix between indicators under analysis

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
R1	1	0.604	-0.084	0.140	0.165	0.147	0.150	0.022	0.567	-0.567	0.022	-0.550	-0.577	0.061	-0.583
R2	0.604	1	-0.032	0.094	0.159	0.147	0.029	0.010	0.894	-0.894	0.010	-0.173	-0.324	0.040	-0.289
R3	-0.084	-0.032	1	-0.200	-0.017	-0.012	-0.026	-0.038	-0.003	0.003	-0.038	-0.001	-0.025	-0.004	0.205
R4	0.140	0.094	-0.200	1	0.488	0.398	0.540	-0.28	0.100	-0.100	-0.280	-0.112	-0.099	0.102	-0.057
R5	0.165	0.159	-0.017	0.488	1	0.980	0.085	-0.022	0.148	-0.149	-0.022	-0.123	-0.110	0.041	-0.197
R6	0.147	0.147	-0.012	0.398	0.980	1	0.078	-0.009	0.129	-0.129	-0.009	-0.124	-0.108	0.069	-0.188
R7	0.150	0.029	-0.026	0.540	0.085	0.078	1	-0.042	-0.019	0.019	-0.042	-0.157	-0.103	0.137	-0.020
R8	0.022	0.010	-0.038	-0.28	-0.022	-0.009	-0.042	1	0.002	-0.002	0.999	-0.027	-0.025	-0.008	-0.067
R9	0.567	0.894	-0.003	0.100	0.148	0.129	-0.019	0.002	1	-0.999	0.002	-0.161	-0.382	0.002	-0.280
R10	-0.567	-0.894	0.003	-0.100	-0.149	-0.129	0.019	-0.002	-0.999	1	-0.002	0.161	0.382	-0.002	0.280
R11	0.022	0.010	-0.038	-0.280	-0.022	-0.009	-0.042	0.999	0.002	-0.002	1	-0.027	-0.025	-0.008	-0.067
R12	-0.550	-0.173	-0.001	-0.112	-0.123	-0.124	-0.157	-0.027	-0.161	0.161	-0.027	1	0.763	-0.081	0.124
R13	-0.577	-0.324	-0.025	-0.099	-0.110	-0.108	-0.103	-0.025	-0.382	0.382	-0.025	0.763	1	-0.089	0.167
R14	0.061	0.040	-0.004	0.102	0.041	0.069	0.137	-0.008	0.002	-0.002	-0.008	-0.081	-0.089	1	-0.122
R15	-0.583	-0.289	0.205	-0.057	-0.197	-0.188	-0.020	-0.067	-0.280	0.280	-0.067	0.124	0.167	-0.122	1

Source: own processing using the R System software

Of a particular importance it is also the identification of the link of each indicator with the company's status, bankruptcy or operation. This correlation was also carried out with the help of the software, and the results are presented in table no. 3:

Tabel 3. Indicators Correlation to Company Status

Correlation indicators	Value of the corelation indicators	Explain of the correlation
RF~R1	-0.598	Corelaţie puternică negativă
RF~R2	-0.401	Corelaţie puternică negativă
RF~R3	0.129	Corelaţie moderată pozitivă
RF~R4	-0.132	Corelaţie moderată negativă
RF~R5	-0.102	Corelaţie moderată negativă
RF~R6	-0.089	Corelaţie slabă negativă
RF~R7	-0.120	Corelaţie moderată negativă
RF~R8	-0.050	Corelaţie slabă negativă
RF~R9	-0.291	Corelaţie moderată negativă
RF~R10	0.298	Corelaţie moderată pozitivă
RF~R11	-0.050	Poorly negative correlation
RF~R12	0.342	Corelaţie moderată pozitivă
RF~R13	0.245	Corelaţie moderată pozitivă
RF~R14	0.083	Corelaţie slabă pozitivă
RF~R15	0.521	Corelaţie puternică pozitivă

Source: own processing

Further to the analysis, the decision was to use the indicators commercial and financial profitability, general liquidity, overall indebtedness rate and return on assets in the realization of the model, using the following correlations:

Tabel4. Correlation Matrix between Selected Indicators

	R1	R3	R5	R10	R14
R1	1	-0. 0838	0. 1654	-0. 5674	0. 0611
R3	-0. 0838	1	-0. 0167	0. 0029	-0. 0045
R5	0. 1654	-0. 0167	1	-0. 1485	0. 0412
R10	-0. 5674	0. 0029	-0. 1485	1	-0. 0021
R14	0. 0611	-0. 0045	0. 0412	-0. 0084	1

Source: own processing

It is noted that indicators R1 and R10 cannot be called poorly correlated, but were chosen due to the impact on the bankruptcy risk. This correlation will lead to some higher standard errors, but the accuracy of the model will be increased.

Statistical software helps us find out the influence of these indicators on the bankruptcy risk. Using the specific function in the program the results are the graphs in Figure No. 2, illustrating the values in Table No. 3.

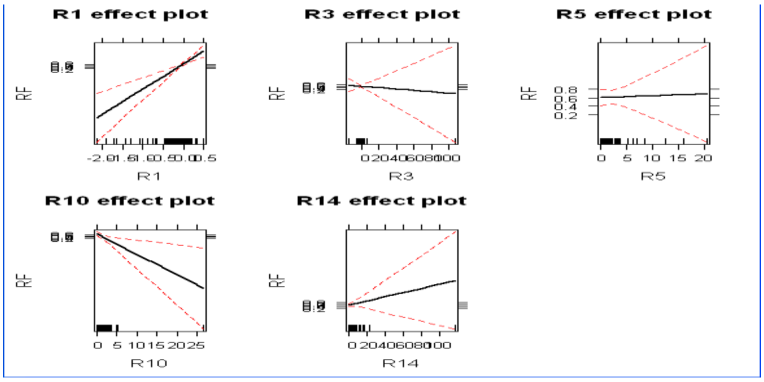

Figure 2. Relationship between Indicators and the Risk of Bankruptcy Related to the Data Set

Source: own processing using the R System Software

5. The Statistical Model and Its Results

As we have seen, the scoring functions summarize the information contained in factors that influence the probability of bankruptcy. This type of standard models approach it in the simplest way, linearly combining these factors. The econometric methods for calculating this type of risk mainly use logit and probit.

They are used if the dependent variable in a regression model is dichotomic, the regression function obtained will result in a probability that aim as being based on the independent variables as well as on the value of which the alternative will be chosen 0 or 1 of the dependent variable, in our case the probability of going bankrupt or not. Since these results are, by definition, estimated for the dependent variable in the range [0. 1] the interpretation of the results is eased. Like the scoring method, we need accessible and qualitative information.

Logit regression analysis is a single or multivariate technique that allows to estimate the probability that an event will happen or not, by predicting a dependent variable using a set of independent variables. To determine the probability of default, there is used a model, generally represented as follows below:

$$Y = f\left(\beta_0 + \sum_{i=1}^{n} \beta_i X_i\right)$$

Where:

β_0 - a constant value;

β_i - estimated weights of X_i, representing transformation of initial data.

The logit model requires an independency of indicators X_i, so the rates that will be used for the construction of the model must be poorly correlated, but influential on the probability of bankruptcy. Similar to discriminating analysis, this technique weights independent variables and assigns Y the score in the form of a probability of bankruptcy to each company in the sample.

From a statistical point of view, the logit model explains the values of Y mirrored by X values, by noting the *i* company result with y_i as correlated with explanatory values $x_{1i,\ldots}, x_{ki}$. . . . They were notted with Y=1 if the company is bankrupt and with Y=0 its survival. Thus, using logistic regression, the probability of going bankrupt for a company is explained by:

$$P(Y = 1|x_1, \dots, x_k) = f(x_1, \dots, x_k)$$

Function *f* represents the distribution function, thus obtaining as follows:

$$P(Y = 1|x_1, \dots, x_k) = \frac{exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}{1 + exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}$$

The logistic distribution transforms regression in the range (0. 1). Further, defining logit(x) as follows:

$$logit(x) = log\left(\frac{x}{1 - x}\right)$$

the model can be rewritten as

$$logit\big(P(Y = 1|x_1, \dots, x_k)\big) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$$

having the actual constants β_0,β_1,. . . ,β_n. The logit model can be estimated by using numerical methods and calculating the maximum probability. The advantage of this approach is that it does not involve multivariate normality and matrices of equal covariance[12].

After estimating the model, there will be obtained values for the β parameters to be interpreted in correlation with economic laws as first warning on the correctness of the parameters obtained. Thus, depending on the effect on the risk of bankruptcy, the resulted parameters must meet the following criteria:

- β_i>0, if X_i has a positive effect on the probability of bankruptcy;
- β_i>0, if X_i has a negative effect on the probability of bankruptcy (Harari-Kermadec, 2009, p. 3).

As mentioned above, all these calculations were performed using the R System program, a program that contains a number of methods for manipulating data and performing calculations and that includes tools for statistical and graphical modeling. However, some of the commands were made using R Commander, a graphical interface with R usage menus, which made it easier to analyze data (Gutermuth, 2010, p. 3).

The creation of a logit model in the R System program was done with the help of the glm function. The first step was to create the database containing the information useful for creating the logistics model. Therefore, there were calculated the rates selected to be used in shaping the risk of bankruptcy with the help of financial information for the 200 companies. Initially, the file contained 16 columns, each of which represented:

RF – No or Yes, depending on the company's condition – operation or bankruptcy;

R1,. . . ,R15 – initial indicators.

The next step was to load the database using R Commander to make it easier the model creation. The application of the logit model was done by introducing the dependent and independent variable and by choosing the useful distribution type (in our case the binomial distribution). The command window looks like this:

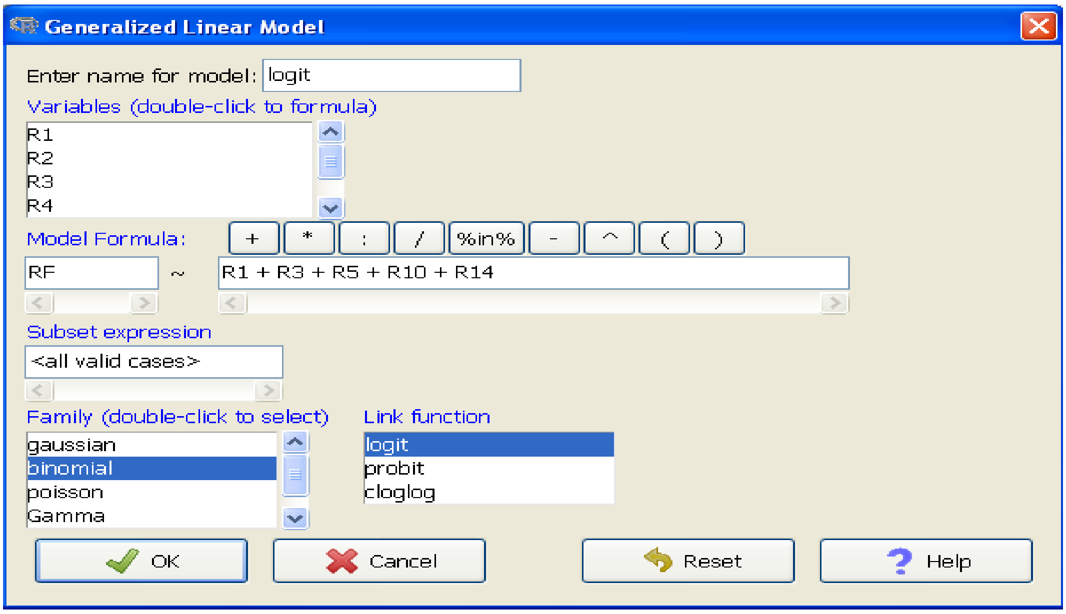

Figure 3. Mainboard Window for Model Creation Orders

Source: R System Informatic Program

The application of this generalized linear model has led to the following coefficients:

Table 5. Logit Model Coeficients

Indicator	Coeficient	Standard error	z value
$\boldsymbol{\beta_0}$	-3. 33212	0. 75019	-4. 442
R1	-16. 21909	3. 75772	-4. 316
R3	0. 04173	0. 13757	0. 303
R5	-0. 02090	0. 14076	-0. 149
R10	1. 80502	0. 71617	2. 520
R14	-0. 11235	0. 11477	-0. 979

Source: own processing

By analyzing the obtained values it is noted that the factor R1 – commercial profitability mostly influences the probability of bankruptcy (according to the z value). The next factor is R10 – the overall debt ratio. The increase in commercial profitability negatively influences the likelihood of bankruptcy, i. e. it decreases, while the increase in global indebtedness is getting higher.

Due to accepted standard errors, the function values were removed from 0 and 1, its application and the achieved results can be interpreted as follows:

• For a function value of less than 0, the company is in a safe area;

• For a value of the positive function the company is bankrupt.

Analyzing the achieved results on the sample of companies, it was not recommended that other additional methods of the risk assessment of bankruptcy should be applied for function values between -1 and 0, this area being the one where there is the possibility of errors on model.

6. Model Validation

The performance of the model can be achieved by using the ROC (Receiver Operating Characteristic) curve. This is a technique of visualization, organization and selection based on the qualities and performance of the model. The ROC curve is plotted bydrawing the relationship between the correct forecasts and the positive false alarms, where the sensitivity (the rate of correct forecasts) is located on one axis and the rate of false positive alarms on the other axis. The ROC curve is analysed taking into account two important aspects: the space under the curve and its shape. If this curve increases covering as much as the upper left corner, the higher the value of the area below the curve increases as well and the performance test is good. The value of the area below the curve is between 0 and 1. If the curve decreases from the top left corner to the right corner, the performance test demonstrates a high degree of false positive alarms (Sing, Sander, Beerenwinkel & Lengauer, 2005, p. 3940).

The performance of the model will be carried out by using the ROCR package available in the R System, which allows evaluation and visualization of performance. The functions available in this package also calculate the area below the curve, called AUROC (Area under the Receiver Operating Characteristic). It provides information about the performance of a prediction model, and equals the likelihood that the model will randomly choose a positive example, and in the case of a good prediction model, it is much higher than when choosing a negative example.

In the case of the achieved model, the program returns the value 0. 9473333 for AUROC. The graph of the ROC curve is, as follows:

ROC Curve

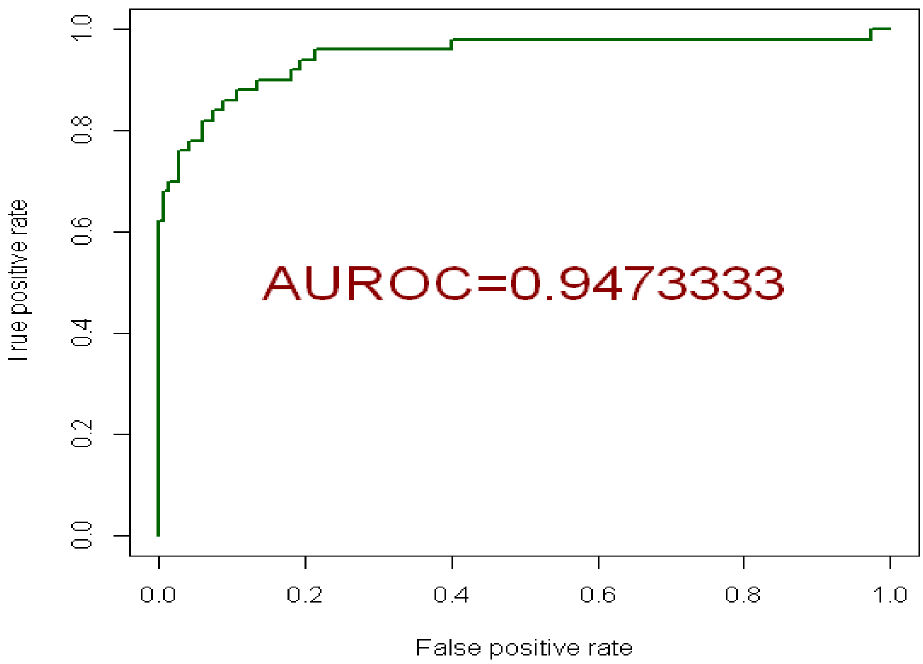

Figure 4. The ROC Curve and the AUROC Value for the Created Model

Source: Own Processing Using the R System Software

In conclusion, the ROC curve and the value of the AUROC indicator validate the proposed model. A scoring system with good predictive power could be achieved only with financial, quantitative information. This has led to an assessment of the risk of bankruptcy for each company.

Certainly, the inclusion of quantitative information in a risk assessment system leads to predictability improvement, but this information is not always available. The proposed model is folded on the Romanian accounting system due to the particularity of using the rates in the financial analysis of the companies. They have multiple uses due to the information they provide.

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