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THE MODELING OF FORECASTING THE BANKRUPTCY RISK IN ROMANIA

Abstract*: Bankruptcy prediction and the understanding of the causes for economic failure have a financial utility. The purpose of this study is to compare the predictive power, on the Romanian market, of the most popular bankruptcy models considering the firms listed on the BSE during 2007-2011. Using the principal component analysis, the best bankruptcy predictors of the established financial indicators were determined for Romanian companies. Then, by using the multiple discriminant analysis and logit analysis, 12 models were developed in order to determine the best predictive function for bankruptcy.*

Keywords: *bankruptcy prediction, PCA, MDA analysis, logit analysis.*

JEL Classification: C25, C53, C83, G33

1. Introduction

In an environment characterized by interdependence, the company is not only a source of profit for shareholders, but also a vital center, around which gravitates a multitude of interests other than those of the entrepreneur. Indeed, the company creates jobs; it is a contributor to the budget, a client for banks and contractors, a potential funder or provider of social programs. An "optimal treatment" of the financial difficulties must take into account these interests, which requires the implementation of various methods and procedures for the prevention of insolvency, and in case of failure, the recovery procedures under judicial control of the court.

The prediction of corporate bankruptcy becomes necessary and is justified by several reasons.

Firstly, the business failure involves high costs and therefore corporate failure prediction research was stimulated both by private companies (who want to avoid business failure) and government (to apply measures for the recovery of business environment and eliminate the unsustainable firms from the economic circuit). The firm failure generates different types of costs, not only for the direct stakeholders (entrepreneurs, management and employees), but also for the economic environment of the company (shareholders, creditors, banks, customers and suppliers, state) and all economy. Due to the contagion effect, the failure costs of a company with a large network of interdependent companies can cause a downward spiral for the entire economy of a country with important consequences on employment and economic welfare.

Secondly, the prediction models have proved their necessity to obtain a better assessment of a company's financial situation. Although, it might be expected that the independent auditors or other decision factors should be able to make an accurate assessment on the financial health of companies, the practice has proved that private interests can distort financial reality and prepared reports do not have the accuracy of the prediction models for companies' failure.

Thirdly, the available financial funds are insufficient to fund integrally the profitable or at least good business, and therefore some valuable projects remain without financial support. In this context, the projects evaluation is one of major importance and requires the use of bankruptcy prediction models able to reduce information asymmetry and default risk.

Finally, the research on bankruptcy prediction was stimulated by the New Basel Capital Accord that stipulates that banks are allowed to use their internal rating systems in order to determine appropriate hedging equity. In this context, the New Basel Capital Accord creates an important incentive for banks to develop their own internal models for risk assessment and prediction, and, in particular the development of predictive models to determine the risk of corporate failure.

2. Literature review

The worldwide academic researchers have used various modeling techniques and procedures for evaluating and predicting the risk of bankruptcy. The most popular methods used are the multiple discriminant method (Altman, 1968) and the logit analyis (Ohlson, 1980).

Altman (1968) is a name invariably cited in studies concerning the prediction of bankruptcy; the author being the first, to use multiple discriminant analysis for bankruptcy prediction. In an article published in 1968, Altman comments traditional indicators and concludes that research analysts were unable to give importance to an indicator in detriment of another. He describes how he used statistical techniques and discriminant analysis to develop a model based on financial indicators that predict the firm bankruptcy. Based on the discriminant analysis, the method has an important place in the financial analysis. The use of financial indicators (efficiency, solvency, balance and management) to forecast the risk of company bankruptcy is justified by the fact that the systematic deterioration of these indicators reflects the difficulties in administration and management activity.

Over the years, there was a huge amount of studies based on Altman Z-score model, constantly being improved, and as generally accepted, "the standard method of bankruptcy prediction" [Altman et al. (1977), Deakin (1972), Edmister (1972), Blum (1974), Deakin (1977), van Frederikslust (1978), Bilderbeek (1979), Dambolena & Khoury (1980), Taffler (1982), Ooghe & Verbaere (1982), Micha (1984), Betts & Belhoul (1987), Gloubos & Grammatikos (1988), Declerc et al. (1991), Laitinen (1992), Lussier (1994), Altman et al. (1995)].

Another important contributor to the study of bankruptcy prediction was J. Ohlson, in 1980. He used the logit analysis to obtain a bankruptcy prediction model using nine indicators such as business size, liquidity, profitability and performance.

This bankruptcy prediction model has also known a great emulation among researchers, the number of studies which use it is, as with the multivariate discriminant analysis, very large [Zmijewski (1984) probit model, Zavgren (1985), Keasey & Watson (1987), Peel & Peel (1987), Aziz et al. (1988), Gloubos & Grammatikos (1988), Platt & Platt (1990), Ooghe et al. (1993), Sheppard (1994), Mossman et al. (1998), Charitou et al. (2001), Lízal (2002), Becchetti & Sierra (2003)].

3. Research methodology

Our **objective** is to build different functions for predicting bankruptcy of enterprises from the most popular models in the literature, Altman and Ohlson, followed by testing these two models to determine which model is applied with better results in Romania.

For this purpose we collected financial information for a group of listed companies (in difficulty and economically viable), during 2007-2011. We want to create warning signals for companies in difficulty, using the following methods: the Principal Component Analysis and subsequently, the Multiple Discriminant Analysis and the Logit Analysis. For each company, we considered a set of 14 financial ratios, calculated and used in the study.

We used the Principal Component Analysis to reduce the dimensionality of space data and to make comparisons, seeing that the two types of companies (in difficulty and viable) are two distinct groups, suggesting that the rates used are useful to predict the occurrence of financial difficulties.

The main **assumptions** made to develop predictive functions of bankruptcy are:

- There are two discrete groups known in our case F (failed) and V (viable non-bankrupt);
- each observation of the groups considered has in view 14 financial indicators (variables X_i, $i = 1,14$);
- The two variables belong to a multivariate normal population. The covariation and variation matrix of the 14 variables is assumed to be similar for each group, but the average of the 14 variables is significantly different from one group to another.

Building bankruptcy forecasting functions for the Romanian economy is based on a sample of 100 companies, 50 viable and 50 bankrupt, which belong to 17 branches of national economy. The companies were selected on a random basis, without knowing their names, the code numbers only expressing the branch code (first two digits) and the enterprise branch code (three digits). For each firm the information in the annual accounts (including attachments) was known for the period 2007-2011.

The following six sets of data were separately analyzed:

- The first year, only when using financial ratios of 2011 to predict financial problems a year before;
- The second year, only when using financial ratios of 2010 to predict financial problems two years before;
- The third year, only when using financial ratios of 2009 to predict financial problems three years before;
- The fourth year when using only financial reports of 2008 to predict financial problems four years before;
- The fifth year when using only financial reports of 2007 to predict financial problems five years before;
- And three-year cumulative data, when using all financial reports for 2009-2011 to predict the financial problems the year before.

For this study, the public financial information for 2007-2011 was collected from the sites of the Bucharest Stock Exchange and the Ministry of Finance. The sample consisted of 100 publicly traded companies with similar characteristics that were included in about the same type of market. The choice of this sample of all companies listed on the BSE was made in order to have two equal groups of companies: “viable” and “bankrupt”, as most of the studies of bankruptcy prediction developed in literature.

A company with financial difficulties indicates that the obligations to creditors are honored with difficulty or not at all, it can even lead to bankruptcy in the future. Therefore, a company was considered "bankrupt" if the insolvency procedures were initiated against it.

Then, we compared over a period of time, based on a set of indicators likely to be significant, the two groups of firms: bankrupt and viable. The financial rates used in this approach for the determination of the financial profile of the two groups were classified into five groups, each covering a particular priority interest for user group analysis (Beaver, 1966; Altman, 1968; Ohlson, 1980; Zmijewski, 1984; Frydman, 1985; Lennox, 1999; Shumway, 2001):

- Rates of return used by shareholders and managers (the profit rate, ROA, ROE and profit per employee);
- Rates of liquidity; that highlight the ability of firms to meet due payments, which are important for short-term creditors (current ratio and quick ratio);
- Rates of debt, that interest the capital providers (debt to equity ratio and Total debt to total assets);
- Rates of activity useful for managers and third parties (Inventory, receivables and total assets turnover)
- Other economic and financial information (company size expressed as natural logarithm of total assets, the use of assets by employees expressed as logarithm of

total assets ratio to total employees and the revenues obtained by employees expressed as a natural logarithm ratio of operating income to total employees). The purpose of applying the natural logarithm was to bring all values to a similar scale.

Thus, the selection of main financial indicators for this study was based on previous results presented in the literature, but also limited to financial data provided by BSE and the Ministry of Finance. Therefore, there were 14 financial indicators calculated for the purpose of this study and divided into five distinct categories, reflecting the company's profitability, solvency, asset utilization and other economic and financial information.

4. Descriptive statistics

For each of the six sets of data, the descriptive analysis was performed in order to be better informed about the nature of correspondence between all 14 variables, the mean differences for each of the two types of companies, and any other features that could be useful in studying the bankruptcy prediction.

First, the mean of each of the 14 financial ratios for both types of companies, those in difficulty and the viable ones, were calculated and presented in the tables below.

Table 1. Analysis of financial ratios for viable firms (mean)

		2007	2008	2009	2010	2011	2009-2011
1	**Net profit margin**	7.494	8.373	10.824	9.971	8.904	9.903
2	**ROA**	7.821	7.862	8.259	7.618	8.159	8.012
3	**ROE**	14.922	14.136	13.218	11.161	7.758	11.025
4	**Profit per employee**	8624.228	12145.083	19218.634	23009.196	7375.533	16534.454
5	**Current rate**	2.346	2.544	2.718	3.772	4.487	3.659
6	**Quick ratio**	2.170	2.169	2.035	3.069	2.384	2.496
7	**Debt to equity ratio**	0.915	0.894	0.969	0.916	0.889	0.923
8	**Total debt to total assets**	0.657	0.611	0.869	0.893	0.739	0.833
9	**Inventory turnover**	50.377	51.606	72.724	73.405	107.844	85.477
10	**Receivables turnover**	51.343	49.509	65.254	67.125	91.951	75.507

11	**Total assets turnover**	1.107	0.961	2.159	1.147	0.964	1.475
12	**Operating income per employee**	11.494	11.660	12.067	12.284	12.361	12.237
13	**Total assets per employee**	11.688	11.902	12.068	12.326	12.624	12.329
14	**Company size**	18.031	18.047	18.358	18.584	18.496	18.473

Source: own calculations according to data provided by corporate sites, BSE and the Ministry of Finance

Following the data collection and calculation of indicators specified in the research methodology, the following preliminary observations can be drawn. First we observe that the profitability indicators: *profit rate, ROA, ROE, profit per employee* for companies in difficulty have negative values for all data sets considered and, therefore, as expected, are lower than those of viable companies.

Table 2. Analysis of financial ratios for nonviable firms (mean)

		2007	**2008**	**2009**	**2010**	**2011**	**2009-2011**
1	**Net profit margin**	-7.756	-13.984	-34.456	-43.658	-42.667	-40.266
2	**ROA**	-7.969	-10.116	-17.048	-18.749	-14.624	-16.804
3	**ROE**	-5.871	-7.469	-68.592	-48.762	-38.128	-51.825
4	**Profit per employee**	-20446.96	-6575.757	-21299.4	-35526.45	-40927.085	-32584.32
5	**Current rate**	1.052	1.045	0.797	0.706	0.737	0.745
6	**Quick ratio**	0.597	0.589	0.414	0.382	0.448	0.414
7	**Debt to equity ratio**	3.216	2.735	8.348	7.477	6.412	7.129
8	**Total debt to total assets**	1.938	1.730	2.148	2.043	1.885	2.025
9	**Inventory turnover**	103.889	105.619	137.406	260.391	184.435	192.809
10	**Receivables turnover**	91.037	92.716	137.416	404.569	186.872	243.231
11	**Total assets turnover**	2.201	2.107	2.178	1.822	2.115	1.947
12	**Operating income per**	11.118	11.143	11.211	11.356	11.493	11.353

	employee						
13	**Total assets per employee**	11.080	11.312	11.593	11.884	12.202	11.906
14	**Company size**	16.427	16.471	17.065	17.029	17.080	17.052

Source: own calculations according to data provided by corporate sites, BSE and the Ministry of Finance

Another indicator that has extremely low values for companies in difficulty is the current rate (for the first year 1.05 compared with 2.34, for the second year 1.045 compared to 2.544, for the third year 0.79 compared with 2.71, for the fourth year 0.70 compared with 3.77, in year five, 0.73 to 4.48, for the cumulated years 0.74 compared with 3.65. The quick ratio is also significantly different for viable firms compared to those in difficulty (2.17 to 0.59 for 2007; 2.16 to 0.58 for 2008; 2.03 to 0.41 for 2009; 3.06 to 0.38 for 2010; 2.38 to 0.44 for 2011; combined, 2.49 to 0.41 for 2009-2011).

Moreover, the companies in difficulty are relying more on indebtedness, the debt rates were suggestively different from viable companies. The *debt to equity* indicator reported for viable firms presents subunitary values (0.91, 0.89, 0.96, 0.91, 0.88 and 0.92) compared to its significant values for bankrupt firms (3.21, 2.73, 8.34, 7.47, 6.41, 7.41). The indicator *total debt to total assets* has higher values of 1.7 for bankrupt companies, compared with the subunit values for viable companies.

Other indicators that have considerable differences among the values of financial ratios for viable companies and those in difficulty are *inventory turnover* (50.37 compared with 103.88 for the first year, 49.5 compared with 92.71 for the second year, 137.4 compared with 72.72 the third year; 73.4 compared with 260 in the fourth year, 107.84 compared with 184.43 in the fifth year and 84.47 compared to 194.8 for the three years cumulatively), *receivables turnover* (51.34 compared with 91.03 in the first year, 49.50 compared with 92.71 in second year, 65.25 compared with 137.41 in the third year, 67.12 compared with 404.56 in the fourth year, 91.95 to 186.87 in the fifth year, 74.77 versus 242.95 for the three years cumulatively), *total assets turnover* (1.10 compared with 2.20 for 2007, 0.96 compared with 2.10 for 2008, 2.15 compared with 2.17 for 2009, 1.14 compared with 1.82 for 2010, 0.90 to 2.11 for 2011, 1.40 compared with 2.03 for the three years cumulatively).

The means of the indicator *firm size* are quite close between the viable and the distressed companies, for all tables (values around 18 compared with 17 for bankrupt companies) showing that the viable companies and those in difficulty of the original sample were well chosen, based on similarity. The *operating income per employee* also knows small variations between the viable and the bankrupt firms (around 12 for viable companies, and 11 for the non-viable ones), which can be explained by the fact that the calculation is performed by applying the natural logarithm on the initial reports.

5. The selection of financial indicators using Principal Component Analysis

The method of Principal Components Analysis (PCA) is one of the most used methods of multidimensional factor analysis. Starting from a set of data, which shows the distribution of statistical units after the variation of numerical variables, X1, X2, ..Xp, PCA reveals a factorial axes system which concentrates the information contained in the original table for a better view (Andrei, 2008).

The process of solving the principal components analysis is: the original data matrix M (n*p), the variance and covariance matrix calculation Vpp or correlation matrix R, extracting the factorial axes (eigenvectors of V or R), the choice of the k main axes, the calculus of the principal axes coordinate units, the calculus of correlations between the principal axes and the original variables.

Thus, supposing that n units are characterized by p variables, the data are presented as a matrix of the dimension n*p,

$$X = (x_{ij}) \text{ i=1,n} \quad \text{j=1,p}$$

The information within a unit i participating to the cloud point, can be expressed by the distance from the point representing it, to the center of gravity of the cloud point, by the mean coordinates of the variable p, namely:

$$I_i = \sum_{j=1}^{p} (x_{ij} - \bar{x}_j)^2$$

The PCA problem is to reduce the first p variables into a number of q variables called "principal components" or factors, q <p. This involves passing from a data matrix of size {n (units) * p (variables)} of the form:

$$X = \begin{bmatrix} x_{11}x_{12}......x_{1p} \\ .... \\ x_{i1}x_{i2}......x_{ip} \\ .... \\ x_{n1}x_{n2}......x_{np} \end{bmatrix} \text{ to a reduced matrix, (n*q) } F = \begin{bmatrix} f_{11}\,f_{12}......f_{1q} \\ .... \\ f_{i1}\,f_{i2}......f_{iq} \\ .... \\ f_{n1}\,f_{n2}......f_{nq} \end{bmatrix}$$

The PCA technique used to pass variables from p to q, q <p, consists in designing the cloud point on a subspace of size q, R^q, with minimum distortion possible and loss of information. Thus, we consider a direction in space F; which can be expressed by the vector u,

$$\text{u} = (u_1, u_2, ...u_p)$$

The PCA goal is to determine the directions that maximize the total information retained, respectively (relative to maximizing u):

$$\max I_u = \max \sum_{i=1}^{n} (x_{i1}u_1 + x_{i2}u_2 + ... + x_{ip}u_p)^2$$

with the restriction:

$$u_1^2 + u_2^2 + ... + u_p^2 = 1$$

Therefore, we have to identify the main directions (main factors) that ensure the projection of cloud point and provide the maximum information. The main factors (principal components) must verify the following conditions: the initial descriptive variables $(X_1, X_2, ...X_p)$ are grouped into synthetic factors F_k through a linear combination of the form:

$$F_k = \sum_{j=1}^{p} a_{kj} x_j \qquad k = \overline{1, p}$$

the factors, the principal components, are independent:

$$cor(F_k, F_m) = 0 \qquad k \neq m$$

The purpose of this analysis was to reduce the initial information space to four or five dimensional spaces without losing more information and then to see which indicator describes best the main components from financial reports. The SPSS 17.0 software was used for this type of analysis. The data set consisted of financial ratios for the total sample of 100 listed companies, of which 50 are "viable" and 50 "bankrupt" for each of the six data sets.

The PCA will decide which of the 14 variables can provide important information for both companies: viable and bankrupt, calculating the correlation coefficients among each of the 14 variables (listed below).

The first principal component is strongly correlated with profitability (the profit rate for 2007, 2009, 2010 and cumulative 2009-2011; ROA for 2008, 2009, 2010, 2011 and cumulative 2009-2011, ROE for 2009, 2011 and cumulative 2009 – 2011), providing information about company's financial performance.

The second component is strongly correlated with firm liquidity (current rate for 5 of the 6 periods analyzed, 2007, 2008, 2009, 2010 and cumulative 2009 to 2011, quick ratio for 2010, 2011 and cumulative 2009-2011), providing information to creditors, and especially for the short term periods.

Table 3. The eigenvalues of the correlation matrix and variable coordinates of the factorial axes for 2007-2011

Component Matrix[a]						
Component						
	2007	**2008**	**2009**	**2010**	**2011**	**2009-2011**
Components extracted	4	5	8	7	7	10
Net profit margin	.689		.770	.715		.752
ROA		.829	.866	.837	.616	.806
ROE			.582		.521	.680
Profit per employee						
Current rate	.572	.837	.626	.823		.597
Quick ratio				.633	.746	.608
Debt to equity ratio		.605			.636	.536
Total debt to total assets	.727		.527	.676	.593	.651
Inventory turnover		.510	.618		.626	.659
Receivables turnover	.673	.679	.849	.540		.802
Total assets turnover					.903	
Operating income per employee						
Total assets per employee						
Company size			.692	.537		.713
Extraction Method: Principal Component Analysis.						

Source: our own calculations using SPSS 17.0

The third component is highly correlated with the degree of indebtedness (the indicator debt to equity manifesting in the years 2008, 2011 and cumulative for 2009-2011, while the indicator debt to total asset for 5 of the 6 periods in the years 2007, 2009, 2010, 2011 and 2009-2011 combined), presenting interest for capital providers.

The fourth component is strongly correlated with the business activity (inventory turnover for the years 2008, 2009, 2011 and cumulative 2009 to 2011, receivables turnover strongly correlated for five of six periods in 2007, 2008, 2009, 2010, and cumulative 2009-2011; total assets turnover in 2011).

The last component is correlated with other financial indicators (actually only the indicator company size occuring in 2009, 2010 and cumulative 2009-2011, the other two indicators not occuring in any year).

6. The bankruptcy prediction using the Discriminant Multiple Analysis

In this section, we develop using the technique of discriminant analysis a set of functions based on linear combinations of previously established significant ratios Z (Xi). This part of the analysis involves the determination of equations for the risk of bankruptcy based on the discriminant analysis.

The discriminant analysis is a method that belongs to the group of explanatory data analysis methods. It uses a variable to explain (Y) and several explanatory, quantitative or binary variables $\left(X_1, X_2, ..., X_p\right)$.

The problem to be solved can be formulated as follows: given a variable to explain (Y) with *k* states and *p* explanatory variables $\left(X_1, X_2, ..., X_p\right)$, one or more linear combinations of explanatory variables have to be found of the form,

$$Z = \sum_{i=1}^{p} a_i X_i$$

best differentiating the k groups formed by reporting to the states of the variable to explain (Y). The solving process is based on the fact that the total matrix of variance covariance T, can be decomposed into two parts: the variance-covariance matrix between groups (B) and variance-covariance matrix within groups (W), determined as a sum of k matrices, each matrix being the variance-covariance of the group (T = B + W).

First, we have to study the discrimination power of each variable using the analysis of variance. Having the decomposition equation of the total variance for a variable X_i respectively:

$$\sum_{h=1}^{k}\sum_{j=1}^{N_h}\left(X_{ijh} - \overline{X_i}\right)^2 = \sum_{h=1}^{n} N_h\left(\overline{X_{ih}} - \overline{X_i}\right)^2 + \sum_{h=1}^{k}\sum_{j=1}^{N_h}\left(X_{ijh} - \overline{X_{ih}}\right)^2$$

Total variance = variance between groups + variance within groups

In order to measure the discrimination power of the variable, the ratio of determination is used:

$$r^2(X_i, Y) = \frac{Variancebetweengroups}{Variancetotal}$$

When the ratio tends to 1, the discrimination power of the variable is greater. The Fisher variable F, where:

$$F = \frac{Variancebetweengroups / k - 1}{Varianceingroups / N - k}$$

for a significance level $P = prob\left(F\left(k-1; N-k\right) \geq F\right)$ allows to specify which are the variables significantly discriminating.

Using the SPSS 17.0 program, for data previously obtained by means of Principal Component Analysis, we obtain the following results, detailed below in table 4.

Table 4. The function coefficients of bankruptcy prediction using MDA

Standardized Canonical Discriminant Function Coefficients						
	2007	**2008**	**2009**	**2010**	**2011**	**2009-2011**
Net profit margin (pm)	.614		.088	.253		.353
ROA		-.424	.767	.797	.443	.515
ROE			.267		.609	.372
Profit per employee (pe)						
Current ratio (cr)	.511	-.454	.310	.242		.181
Quick ratio (qr)				.107	.339	.169
Debt to equity ratio (de)		.422			-.074	.143
Total debt to total assets (dta)	-.295		.253	.042	-.018	-.151
Inventory turnover (it)		.313	-.092		-.112	-.227
Receivables turnover (rt)	-.379	.343	-.115	.009		.042
Total assets turnover (tat)					-.366	
Operating income per employee (oie)						
Total assets per employee (tae)						
Company size (cs)			.356	.350		.389

Source: our own calculations using SPSS 17.0

The bankruptcy prediction equations according to the discriminant analysis are:

Z (2007) = 0.614 pm + 0.511 cr - 0.295 dta - 0.379rt
Z (2008) = -0.424ROA - 0.454cr + 0.422de + 0.313it + 0.343rt
Z (2009) = 0.088pm + 0.767ROA + 0.267ROE + 0.310cr + 0.253dta + 0.356cs-0.092it - 0.115rt
Z (2010) = 0.253pm + 0.797ROA + 0.242cr + 0.107qr + 0.042dta + 0.350cs + 0.009rt
Z (2011) = 0.443ROA + 0.609ROE + 0.339qr - 0.074de - 0.018dta - 0.112it - 0.366tat
Z (2009-2011) = 0.353pm + 0.515ROA + 0.372ROE + 0.181cr + 0.169qr + 0.143de -0.151dta +0.389cs - 0.227it + 0.042rt

For each year, the threshold values are calculated distinguishing the viable from non-viable firms, while the results for the periods under analysis are presented in table 5.

Table 5. The threshold values for discriminant function years 2007-2011

Functions at Group Centroids						
	2007	2008	2009	2010	2011	2009-2011
Viable	4.677	3.889	1.299	1.369	.846	1.559
Bankrupt	-4.677	-3.889	-1.299	-1.369	-.846	-1.559
Unstandardized canonical discriminant functions evaluated at group means						

Source: our own calculations using SPSS 17.0

7. The bankruptcy prediction using the Logit Analysis

Ohlson estimated the probability of bankruptcy by means of the PROB variable. The probability of a firm going bankrupt is calculated by estimating the following logistic regression model:

$$PROB = [1 + EXP(-Y)]^{-1}$$

The logit regression model was developed to avoid the disadvantages of conventional regression and it can be applied in cases where the dependent variable is a qualitative variable. Compared to the discriminant analysis, the logit regression exceeds the assumption that independent variables are consistent with the hypothesis of normal distribution and it can estimate the probability of failure companies. The estimation equation is calculated as follows (Bourbonnais, 2008):

$$y_i = a_0 + \sum_{j=1}^{k} a_j x_{ij} + b_i$$

where:
a is the estimated parameter, X is the independent variable, bi is the random error, yi the variable which can not be observed (business credit score, which is usually called "latent variable"). We can use a dummy observable variable yi as a substitute variable yi *.

If the company goes bankrupt yi = 1, otherwise it is 0, as shown below:

Yi=1 if yi>0;

Yi=0 otherwise.

The logit analysis combines several features of the firm into a probability score for each company, which indicates "the likelihood of failure". The logit function implies that the logit score (meaning the probability of failure) P1 has a value within the interval [0, 1], and if it approaches the value 1 then there is a high probability of bankruptcy, and in case of the value 0, there is a high probability of non-bankruptcy.

Based on the above equation, we define the probability Pi when yi=1:

$$P_i = \Pr ob(y_i = 1) = \Pr ob[(b_i > -(b_0 + \sum_{j=1}^{k} a_j x_{i,j})]$$
$$= 1 - F[-(a_0 + \sum_{j=1}^{k} a_j x_{i,j})] = F[a_0 + \sum_{j=1}^{k} a_j x_{i,j}]$$

where F is the function sum of the probability distribution. Moreover, we can express the probability function; as follows:

$$\mathrm{L} = \prod_{y_i=1} \mathrm{P_i} \prod_{y_i=0} (1 - \mathrm{P_i})$$

The logit regression model assumes that the function F follows a logistic distribution. Under these circumstances we can use the maximum likelihood method to estimate the parameter Bi.

$$\mathrm{F(Z_i)} = \frac{\exp(\mathrm{Z_i})}{1 + \exp(\mathrm{Z_i})}, \quad \mathrm{Z_i} = \beta_0 + \sum_{j=1}^{k} \beta_j \mathrm{X_{i,j}}$$

The following financial ratios, obtained by means of the PCA method, were selected for the logit analysis for the periods analyzed; the results are shown in table 6.

Tabel 6. The function coefficients of bankruptcy prediction using Logit

Method: ML - Binary Probit (Quadratic hill climbing)						
	2007	**2008**	**2009**	**2010**	**2011**	**2009-2011**
Net profit margin (pm)	0.067		-0.004	0.024		0.001
ROA		0.152	0.029	0.028	0.044	0.026
ROE			0.002		0.006	0.005
Profit per employee (pe)						
Current ratio (cr)	0.402	0.228	0.004	0.032		-0.035
Quick ratio (qr)				0.034	-0.004	0.051
Debt to equity ratio (de)		-0.771			0.029	0.041
Total debt to total assets (dta)	-0.007		-0.059		0.036	-0.015
Inventory turnover (it)		-0.002	0.001		-0.001	0.005
Receivables turnover (rt)	-0.374	-0.007	-0.004	-0.006		-0.031
Total assets turnover (tat)					0.011	
Operating income per employee (oie)						
Total assets per employee (tae)						
Company size (cs)			0.015	0.006		0.019

Source: our own calculations using SPSS 17.0

The bankruptcy prediction equations according to the logit version are as follows:

P (2007) = $\dfrac{1}{1+e^{0.067pm+0.40cr-0.007dta-0.374rt}}$

P (2008) = $\dfrac{1}{1+e^{0.152roa+0.228cr-0.771de-0.002it-0.007rt}}$

P (2009) = $\dfrac{1}{1+e^{-0.004pm+0.029roa+0.002roe+0.004cr-0.059dta+0.001it-0.004rt+0.015cs}}$

P (2010) = $\dfrac{1}{1+e^{0.024pm+0.028roa+0.032cr+0.034qr-0.006rt+0.006cs}}$

P (2011) = $\dfrac{1}{1+e^{0.044roa+0.006roe-0.04qr+0.029de+0.036dta-0.001it+0.011tat}}$

P(2009-2011) =

$$\frac{1}{1+e^{0.001pm+0.026roa+0.005roe-0.035cr+0.051qr+0.041de-0.015dta+0.005it-0.031rt+0.019cs}}$$

8. The analysis of power prediction of bankruptcy functions

The **apriori analysis** of the success rate function is performed by comparing the predictive classification with the known condition of the companies, from the sample.

After setting functions for each of the five years, and separately for the cumulative years, we will determine their ability predictability. Thus, for this approach we will consider, the previously proposed sample consisting of 100 companies from BSE, of which 50 are bankrupt and 50 are viable, followed by the calculation for each of these firms of the score function value.

For each of the predictive functions, we calculate the success rate in the predictability of bankruptcy. Thus the following results are obtained:

Table 7. The success rate of apriori bankruptcy predictability

	Correct values	**Incorrect values**	**Successful Percentage**
Discriminant Multiple Analysis			
2007	69	31	69%
2008	75	25	75%

2009	84	16	84%
2010	91	9	91%
2011	92	8	92%
cumulated years	96	4	96%
Logit analysis			
2007	57	43	57%
2008	68	32	68%
2009	73	27	73%
2010	78	22	78%
2011	81	19	81%
cumulated years	84	16	84%

Source: our own calculations using SPSS 17.0

As we can notice, the function that has the best success rate is the cumulative function for the three years.

The **aposteriori analysis** of the success rate by means of the analysis of the relevance degree is performed on another sample of firms. The constructed function has an a priori success rate of 96% and is likely to be effective for a subsequent period, for a much larger population of Romanian enterprises. The certification of this hypothesis will be a test on another sample, randomly chosen.

Considering a different sample of firms also separated into two groups viable and, bankrupt, we will analyze the achieved prediction accuracy by previously developed function. The sample used to validate the proposed model includes 40 companies, 20 belonging to the bankrupt group and the other 20 to the viable group. The test sample firms are similar in size and industry sectors with the original sample.

For each of the predictive functions, we calculate the success rate in the predictability of bankruptcy for the new sample, consisting of 40 companies. Thus, we obtain the following results:

Table 8. The success rate of aposteriori bankruptcy predictability

	Correct values	**Incorrect values**	**Successful Percentage**
Discriminant Multiple Analysis			
2007	27	13	68%
2008	29	11	74%
2009	32	8	82%
2010	36	4	90%
2011	36	4	91%
cumulated years	38	2	95%
Logit analysis			
2007	21	19	53%

2008	25	15	65%
2009	28	12	71%
2010	30	10	76%
201	32	8	80%
cumulated years	33	7	82%

Source: our own calculations using SPSS 17.0

Under these conditions, we observe that the prediction success rate is similar to the apriori analysis; the success rate being 95% in the total sample tests. This highlights that the cumulative function is effective for the three years and can be applied to companies in the Romanian economy (taking into account the limits considered to build the model).

9. Conclusions

Given the current context, it is a challenge trying to build a bankruptcy prediction function for the Romanian companies, primarily because the bankruptcy process has completely different coordinates in Romania compared to most of the countries for which bankruptcy prediction methodologies are developed. One of the major difficulties was that Romania has a high number of bankruptcies de facto, but a relatively small number of bankruptcies de jure. In fact, the demarcation success failure could be a limit to the previously developed models: the sample and the separation of the two groups were based only on the legal declaration of bankruptcy.

The purpose of this study was to build a quick warning model for the Romanian companies in difficulty, using the following methodologies: the Principal Components Analysis, the Multivariate Discriminant Analysis and the Logit analysis. Subsequently, based on statistical analyses, we determined which the best predictors of bankruptcy are for the Romanian companies within the initial financial indicators. Starting from 6 different data sets, we also built six separate functions for bankruptcy prediction.

The use of financial reports for the analysed periods shows that the best predictor for the Romanian market is the Multiple Discriminant Analysis method, the logit method registering slightly weaker results. Thus, the predictive power of ADM is located between 68-95%, while the logit one lies between 53-82%.

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