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# MULTIVARIATE MODEL FOR CORPORATE BANKRUPTCY PREDICTION IN ROMANIA

Empirical study

**Keywords**
Discriminant analysis
Risk
Failure
Financial ratios
Classification accuracy
Benchmark

**JEL Classification**
G33, M10

**Abstract**

*The current paper proposes a methodology for bankruptcy prediction applicable for Romanian companies. Low bankruptcy frequencies registered in the past have limited the importance of bankruptcy prediction in Romania. The changes in the economic environment brought by the economic crisis, as well as by the entrance in the European Union, make the availability of performing bankruptcy assessment tools more important than ever before. The proposed methodology is centred on a multivariate model, developed through discriminant analysis. Financial ratios are employed as explanatory variables within the model. The study has included 53,252 yearly financial statements from the period 2007 – 2010, with the state of the companies being monitored until the end of 2012. It thus employs the largest sample ever used in Romanian research in the field of bankruptcy prediction, not targeting high levels of accuracy over isolated samples, but reliability and ease of use over the entire population.*

## INTRODUCTION

During the last years, the corporate bankruptcy yearly frequency has increased continuously in Romania, reaching almost 3% by the end of 2013, with almost 30,000 bankruptcy cases (as shown in figure 1) to aproximatively 1,000,000 existing companies.

Before 2007, the importance of the bankruptcy phenomenon from a macroeconomic perspective was limited in Romania, as there was little culture for bankruptcy filing at microeconomic level.

The evolution of the yearly bankruptcy ratio was marked by the popularization of the bankruptcy law, the economic crisis, the entrance of Romania in the European Union, as well as by an increase in the loan default ratio, Romania topping in this regard at the end of 2012 the 4th place within the European Union and 6th place worldwide in a ranking which included 131 countries (Brîndescu-Olariu, 2014d).

With the bankruptcy not representing a concerning phenomenon in the past, limited efforts were made at national level for the development of specific bankruptcy risk assessment tools. Instead, the scientific interest for the assessment of the bankruptcy risk was purely theoretical, with most researchers settling for testing foreign models for bankruptcy prediction over small isolated samples of Romanian companies. Several national models were elaborated over time, but the development methodologies were relatively superficial, as the public interest for the subject was low. The increase of the annual bankruptcy frequency has made the public significantly more aware of the phenomenon. The state of bankruptcy affects all the stakeholders of the company, which makes the existence of instruments for bankruptcy prediction important.

Assessment of the default risk in general and of the bankruptcy risk in particular has always been in the centre of the financial ratios analysis (Brîndescu-Olariu, 2014a). Introduced in the USA in the 1860s, the financial ratios analysis only became popular in the continental Europe in the 1960s. The initial approaches of the financial ratios analysis in the prediction of bankruptcy were univariate. Some of the most important early contributions in this field include (Yadav, 1986):

- the study conducted by J.R. Ramster and L.O. Foster in 1931 over a sample of 173 companies;
- the study conducted by FitzPatrick in 1932 over a sample of 38 de companies, of which 19 were bankrupt and 19 were healthy;
- the study conducted by Raymond Smith and Winakor Arthur in 1935 over a sample of 183 companies that failed over the period 1923-1931;
- the study conducted by Charles Merwin in 1942, over a sample of 900 companies.

The scientific literature usually credits Eduard Altman as the author of the first multivariate model for the prediction of corporate bankruptcy. Nevertheless, Meir Tamari (1966) proposed a multivariate model 2 years prior to the issue of Altman's famous paper.

Inspired by the models developed by Altman (1968) through discriminant analysis and later on by Ohlson (1980), through logistic regression, multivariate studies in the field of bankruptcy prediction have been performed all over the world during the last 50 years. Some of the more recent multivariate studies are presented in table 1.

The initial multivariate studies were performed on paired samples. This approach still persists to great extent today (17 of the 40 randomly selected papers from table 1, used paired samples).

The different models and respective methodologies of analysis proposed remain strictly related to the populations on which they were developed. Thus, each model has applicability for a certain region, a certain type of company, period of time or accounting system. The lack of homogeneity of the population of companies worldwide has made the elaboration of a general accepted financial ratios analysis methodology impossible.

In Romania, many corporate stakeholders use methodologies of analysis developed in other countries, on companies with different profiles, over different periods of time and for other accounting systems. These methodologies are not adapted to the Romanian economic environment and, in many cases, present no transparent scientific background. Nevertheless, they represent important foundations in the decision-making processes of the stakeholders.

Over the last 20 years several national models for the prediction of bankruptcy were developed (Brîndescu-Olariu, 2014a). Still, the majority of these models were affected by deficiencies in terms of statistical methodology or by the use of isolated samples that did not allow for applicability over all Romanian companies:

- 1996: Mânecuță and Nicolae model (Bordeianu et. al., 2011);
- 1998: Băileșteanu model (Băileșteanu, 1998);
- 1998: Ivoniciu model (Bordeianu et. al., 2011) ;
- 2002: Lorant-Eros Stark model;
- 2002: Anghel model (Anghel, 2002);
- 2010: Cârciumaru model (Cârciumaru, 2010);
- 2010: Căprariu model (Căprariu, 2010);
- 2010: Caracota, Dumitru and Dinu model (Caracota, Dumitru, and Dinu, 2010) ;
- 2011: Bătrâncea model (Bătrâncea, 2011);
- 2012: Armeanu model (Armeanu et.al. 2012);
- 2012: Vintilă and Toroapă model (Vintilă and Toroapă, 2012);

- 2012: Mironiuc M., Robu M. and Robu I. Model (Mironiuc, Robu and Robu, 2012);
- 2013: Andreica model (Andreica, 2013).

Because of their lack of performance, the national models are generally ignored in the university environment and absent in the practice of the financial ratios analysis. Instead, older models from overseas are more valued (the Altman model from 1968, the Conan-Holder model, the Central Bank of France model).

Under these circumstances, the current study sets to create a multivariate model applicable in the Romanian practice.

Recent studies over the same population (Brîndescu-Olariu, 2014a, Brîndescu-Olariu, 2014b, Brîndescu-Olariu, 2014c) proved the potential of the financial ratios in the prediction of bankruptcy 2 years in advance. The current research attempts to increase the accuracy of the prediction by providing a multivariate model that would combine the potential of several ratios.

## 1. POPULATION

The population initially subjected to the analysis included all the companies from the Timis County (largest county in Romania) that submitted financial statements to the fiscal authorities in the period 2001 – 2011 (247,037 yearly financial statements).

Financial ratio analysis was not considered applicable for companies with no yearly income, as the continuity of the operating activity represents a fundamental hypothesis of the financial ratio analysis.

Three phenomena with national impact were also considered for their potential of changing the profile of the companies that declare bankruptcy:

- The changes brought to the laws concerning bankruptcy through the adoption of law 85/2006;
- The entrance within the European Union in 2007;
- The manifestation of the economic crisis starting with the last quarter of 2008.

Under these circumstances, it was concluded that the initial population shows important problems of homogeneity, which do not recommend a unitary treatment:

- The companies with no activity cannot be evaluated based on the same methodology as the companies with a financial history;
- The companies that became bankrupt after the issue of law 85/2006 show different characteristics compared to the companies that went bankrupt before 2007, under different laws;
- The cases of bankruptcy registered after 2009 have different causes compared to the cases appeared before the beginning of the economic crisis.

Taking all the aforementioned differences into account, the initial population was adjusted:

- only financial statements from the period 2007 – 2010 were retained;
- all the yearly financial statements that reported sales under 10000 lei (aprox. 2200 Euros) were excluded.

The research targeted the risk of bankruptcy after 2 years from the date of the financial statements taken as reference in the analysis. As the interest was focused on the phenomenon of bankruptcy during the crisis period, the first financial statements included in the study were from 2007.

The last year for which data concerning the status of the companies was available was 2012. Under these circumstances, the last financial statements included in the study were those from 2010. Financial statements from 2011 were available, but information concerning the status of the companies at the end of 2013 was not.

Holding all the above into account, the target population included all companies from Timis County that submitted yearly financial statements to the fiscal authorities during the period 2007-2010 and that registered yearly sales of at least 10000 lei (aprox. 2200 Euros).

In accordance, 53,252 financial statements from the period 2007-2010 were included in the analysis. The companies of which financial statements were included for one year were not necessarily included for the following periods. As the study did not target a dynamics analysis, the yearly financial statements can be regarded as individual subjects.

The source of the data was represented by the online publications of the Ministry of Public Finances of Romania.

## 2. METHODOLOGY

In the purpose of combining the potential of individual financial ratios, the development of a multivariate model through discriminant analysis was targeted. The discriminant analysis was chosen as it is the most popular and one of the most accurate methods (alongside logistic regression).

The data was processed by using the SPSS software. The state of the company two years from the date of the financial statements of reference was defined as a binary variable that can take the following values:

- 1, for the companies that went bankrupt 2 years after the date of the financial statements of reference;
- 0, for the companies that continued their activity under normal conditions at least until the end of 2012.

In order to simplify the explanations, the companies that went bankrupt 2 years after the date of the financial statements of reference will simply be referred to as „bankrupt”, while the companies that continued their activity under normal conditions at least until the end of 2012 will be referred to as „non-bankrupt".

When defining the target population, the companies that close their activity for other reasons than bankruptcy during the period of analysis were excluded.

As an example, the value of the variable „State" was „1" for the companies that went bankrupt in 2011 and it was associated with the financial ratios of the respective companies from 2009. These companies were not included in the analysis for the following years (for 2010 with the financial statements and for 2012 with the state variable), even if they still existed.

The purpose of the discriminant analysis performed within the SPSS environment was to elaborate a model capable of predicting the membership of a company within one of the two predefined groups (bankrupt companies or non-bankrupt companies). As the classification would be made between only 2 groups, the model would be based on only one discriminant function.

Financial ratios from 2 years prior to the date of the variable „State" were used as independent variables within the discriminant function. The result of the discriminant function for each company would not be a probability of bankruptcy, but a score. Based on the value of its score, a company could be associated with a certain probability of bankruptcy.

In the calculation of the score of a company for year N (based on witch the probability of bankruptcy for the year N+2 would be estimated), the variables $X_1$ , $X_2$ ,… $X_m$ represent financial ratios that characterise the financial state of the company in year N.

$$Score_i = a_1 X_{1i} + a_2 X_{2i} + ... + a_m X_{mi} + c$$

where:

- $Score_i$ - score of the company „i" for year N, calculated through the use of the discriminant function;
- $X_{ji}$ - financial ratio „j" from year „N" for the company „i";
- $a_j$ - coefficient of the financial ratio „j";
- c – constant.

In order to simplify the use of the model, all the independent variables were treated as being in linear relationships with the dependent variable (the score), although the linearity of the relationships between the independent variables and the probability of bankruptcy is not always evident.

The financial ratios specific to the financial statements of the companies from the target population at the end of 2010 were tested as explanatory variables within the score function used to estimate the state of the company (bankrupt or non-bankrupt) at the end of 2012. In a similar manner, the financial ratios from 2009 were correlated to the state of the company at the end of 2011, the financial ratios from 2008 were correlated to the state of the company at the end of 2010 and the financial ratios from 2007 were correlated to the state of the company at the end of 2009.

As the objective was to build a model and a methodology of analysis accessible to all the stakeholders of the company, only financial ratios that can easily be calculated based on the public data were taken into consideration. Under these circumstances, 26 financial ratios were tested as possible explanatory variables. The list of the financial ratios, together with the symbols and formulas are presented in table 2.

Only a part of the 26 financial ratios are suggested in the international literature as possible predictors of bankruptcy or were at least tested by other researchers as predictors. Thus, the ratios were not selected starting from the recommendations of the scientific literature, but from the availability to the general public of the data necessary for their calculation.

The model was configured based on the financial data specific to the target population of 2010 (15,071 financial statements). The values of the financial ratios from 2010 were associated with the state of the companies at the end of 2012. Financial data from 2011 was available, but final data concerning the state of the companies at the end of 2013 were not available at national level at the time of the research. Thus, the latest data available was used for the development of the model. Data from the previous years (financial statements from the period 2007-2009 and information concerning the state of the companies from 2009-2011) would be used for testing the model.

The utility of a bankruptcy prediction model is given by its accuracy in classifying the companies in one of the 2 groups defined by the state variable (bankrupt or non-bankrupt).

$$\text{general accuracy} = \frac{\text{number of companies correctly classified}}{\text{total number of companies}} \times 100\%$$

The general accuracy represents the weighted average of the sensitivity and the specificity.

$$\text{general accuracy} = w_b \times \text{sensitivity} + w_{nb} \times \text{specificity}$$

where:

$$w_b = \frac{\text{number of bankrupt companies}}{\text{total number of companies}} \times 100\% \text{ and}$$
$$w_{nb} = \frac{\text{number of non-- bankrupt companies}}{\text{total number of companies}} \times 100\%$$

The sensitivity represents the accuracy of the classification of bankrupt companies.

$$\text{sensitivity} = \frac{\text{number of bankrupt companies correctly classified}}{\text{total number of bankrupt companies}} \times 100\%$$

The specificity represents the accuracy of the classification of non-bankrupt companies.

$$\text{specificity} = \frac{\text{number of non} - \text{bankrupt companies correctly classified}}{\text{total number of non} - \text{bankrupt companies}} \times 100\%$$

In general, a model is considered useful if it can ensure an out-of-sample general accuracy of more than 25% over the "by chance" general accuracy (Chung, K., Tan, S., Holdsworth, D., 2008). As bankruptcy represents a "rare" phenomenon over the target population, the "by chance" general accuracy is very high (over 95%). No matter the intrinsic classifying performance of a model, by choosing a cut-off value that would lead to the classification of all companies as non-bankrupt, the general accuracy would equal the specificity (over 97%).

Most of the models available in the international literature cannot ensure even in-sample general accuracies at least equal to the „by chance" general accuracies. Of the 40 models presented in table 1, the highest reported in-sample (paired sample of 54 companies) accuracy was of 95.60% (Ugurlu and Aksoy, 2006).

Considering that the current research targets to develop a model that only employs data easily available to all stakeholders, an out-of-sample general accuracy close to 100% does not constitute a reasonable objective.

Instead, the purpose of the model would be to ensure the classification of the analysed companies on risk classes.

In practice, using the model, the analyst should expect every analysed company not to go bankrupt (the model would not indicate a probability of bankruptcy higher than 0.5), but it will be possible to evaluate the bankruptcy risk as higher or lower than the average.

In a first stage, the prediction capabilities of each of the 26 ratios were tested on the population of 2010 (the financial statements of 2010). The performance of each ratio was not evaluated through its general accuracy, but through its in-sample Area Under the ROC Curve (AUC), one of the most viable solutions in the valuation of the performance of a classifier (Hanely, McNeil, 1982, Faraggi and Reiser, 2002). The ROC Curve graphically reflects the relationship between the sensitivity and the specificity for all possible cut-off values (van Erkel, Pattynama, 1998).

The purpose of the tests was not to obtain practical tools of analysis, but to observe the individual potential of the ratios. Together with information concerning the inter correlations, AUC specific to each ratio in the approach was used in a second stage as reference for grouping the ratios into multivariate models.

The multivariate models were compared by their in-sample AUC. The model with the highest in-sample AUC was retained.

In a third stage, the model was tested in terms of out-of-sample performance through the AUC over the entire population for the period 2007-2009.

Many of the models presented by the international literature were elaborated based on paired – samples. The preference for the paired-samples is based on the possibility of evaluating the model by its general accuracy (as within the paired – sample the percentage of the bankrupt companies is equal to the percentage of the non-bankrupt companies and, therefore, the general accuracy cannot be manipulated through the choice of the cut-off value). The paired sample approach is usually criticised for artificially altering the structure of the sample (compared to the structure of the population), which is expected to lead to important differences between in-sample and out-of-sample performance. The current research avoided the paired sample approach for the configuration stage, in order to avoid the inherent out-of-sample performance losses. Nevertheless, once the model has been configured, it was also tested over a paired sample, which allowed for an evaluation of the performance in terms of general accuracy. The paired sample included all the companies from the target population that went bankrupt in the period 2009 – 2012 (712 companies). The financial statements taken into analysis were specific to the period 2007 – 2010. Within the sample, each company that went bankrupt was associated with a company from the same field of activity, with the same yearly turnover, that continued its activity under normal circumstances. Thus, the paired sample contained 1424 companies: 712 companies that went bankrupt within the period 2009 – 2012 and 712 companies that continued their activities under normal circumstances beyond the end of 2012. The scores specific to the proposed model were calculated for each company included in the sample. As the weight of the bankrupt companies within the paired sample is the same as that of the non-bankrupt companies, the general accuracy cannot be manipulated by choosing a cut-off value that maximises the accuracy in the classification of the predominant group. Thus, attention was not paid to the specificity and the sensitivity, but only to the general accuracy. The model would be considered of practical use if it could ensure a general accuracy 25% higher than the "by chance" accuracy. Over a paired sample, the "by chance" accuracy is of 50%, which establishes the benchmark for the acceptance of a model at 62.5%. Initially, the cut-off value that maximises the general accuracy over the 2010 paired sample (the companies that were included with their 2010 financial statements) was determined. For this, the ROC Curve for the 2010 paired sample was built. The cut-off value was determined through the inspection of the coordinating points of the ROC Curve. To also evaluate the stability of the model in time, the general accuracies over the paired samples form 2007 – 2009 were determined by using the optimal cut-off value for the 2010 paired sample.

## 3. RESULTS

Initially, the prediction capabilities of each of the 26 ratios were tested on the population of 2010 through their in-sample Area Under the ROC Curve (figure 2).

The ratios that showed the highest performances were:

- Equity working capital;
- Labour productivity in terms of profits;
- Cash to total debt ratio;
- Profitability ratio;
- Equity working capital to sales ratio.

The ratios that showed inter correlations were:

- Fixed assets ratio – Current assets ratio;
- Autonomy ratio – Debt ratio;
- Inventory conversion ratio – Tax to sales ratio;
- Autonomy ratio – Total assets turnover ratio;
- Equity working capital – Labor productivity in terms of profits;
- Profitability ratio – Equity working capital;
- Cash to total debt ratio – Solvency ratio;
- Current assets to total debt ratio – Cash to total debt ratio.

Through the use of discriminant analysis, different ratio combinations were developed into models. Combinations of ratios without important inter correlations were granted priority. Still, combinations that included ratios with medium inter correlations were tested also.

Each model was evaluated by its in-sample AUC (the AUC over the 2010 population). The AUCs specific to the 10 best performing models are presented in figure 3.

The financial ratios included in the models were:

- Model 1: Total assets turnover ratio, Autonomy ratio;
- Model 2: Total assets turnover ratio, Profitability ratio;
- Model 3: Autonomy ratio, Profitability ratio;
- Model 4: Autonomy ratio, Profitability ratio, Equity working capital;
- Model 5: Profitability ratio, Equity working capital;
- Model 6: Profitability ratio, Equity working capital, Receivables collection period;
- Model 7: Profitability ratio, Equity working capital, Receivables collection period, Fixed assets ratio;
- Model 8: Equity working capital, Receivables collection period, Cash to total debt ratio;
- Model 9: Profitability ratio, Equity working capital, Receivables collection period, Labour productivity in terms of profits;
- Model 10: Profitability ratio, Equity working capital, Receivables collection period, Labour productivity in terms of profits, Equity to fixed assets ratio.

Although some inter correlations exist between the Profitability ratio and the Equity working capital, as well as between the Equity working capital and the Labour productivity in terms of profits, model 10 was selected as it showed the highest in-sample AUC (0.744).

The model has the following form:

$$\mathrm{S} = 0.085 + 0.503\mathrm{LPp} \times 10^{-5} - 0.239\mathrm{RCP} \times 10^{-3} + 0.224\mathrm{EFAr} \times 10^{-5} + 0.202\mathrm{Ewc} \times 10^{-6} - 0.398\mathrm{Pr} \times 10^{-1}$$

where:

- S – the score calculated for the analysed company;
- 0.085 – constant;
- LPp - Labour productivity in terms of profits;
- RCP - Receivables collection period;
- EFAr - Equity to fixed assets ratio;
- Ewc - Equity working capital;
- Pr - Profitability ratio.

The score calculated for a company based on its financial statements at the end of year N should provide information regarding the risk of bankruptcy for the year N+2.

The model was tested in terms of out-of-sample performance through the AUC over the entire population for the period 2007-2009.

The evaluation of models by their AUCs is usually based on the following grid (Tazhibi, Bashardoost și Ahmadi, 2011):

- 0.5 – 0.6: fail;
- 0.6 – 0.7: poor;
- 0.7 – 0.8: fair;
- 0.8 – 0.9: good;
- 0.9 – 1: excellent.

Thus, the accuracy of the proposed model can be considered as fair.

Additional performance tests were made through the general accuracy of the model over the paired sample. Initially, the ROC Curve for the 2010

paired sample was built. Through the inspection of the coordinating points of the ROC Curve, the cut-off value of the score S which maximizes the in-sample general accuracy was determined (-0.016). By classifying all the companies from the 2010 sample with scores lower than -0.016 as bankrupt and all the companies from the 2010 sample with scores higher than -0.016 as non-bankrupt, the general accuracy would be of 66.9% (over the 62.5% benchmark). The optimal cut-off value shows small variations from one year to another (figure 5).
Using the optimal cut-value of 2010 for all 4 years included in the research, the general accuracy of the classification remains over the 62.5% benchmark (figure 6), which sustains the practical use of the model.
Although the model shows potential in the estimation of the bankruptcy risk, the prediction of the state of the analysed company based on a single cut-value is not made feasible. As over the entire target population the bankruptcy represents a "rare" phenomenon, by predicting that no company will go bankrupt the analyst would obtain a general accuracy of over 97%. Most of the models presented in the international literature cannon ensure such a high level of performance (even on isolated samples). As the proposed model is only based on accounting data available to all stakeholders, it cannot realistically target a general accuracy close to 100%. The objective of the research was to create a tool specific to the Romanian companies, easily accessible to the general public. Under these circumstances, the proposed methodology does not set to ensure a perfect classification of the analysed company as bankrupt or non-bankrupt, but to associate the company to a certain risk class. For this, the bankruptcy risk was evaluated on intervals of the score.
The risk indexes reflected in table 3 were calculated for the 2010 population by comparing the bankruptcy frequency of each specific interval of the score S to the average bankruptcy frequency (over the entire population).
Based on the dynamics of the risk indexes for the 10 intervals of the score S over the 2010 population, the following risk classes are proposed:

- high bankruptcy risk, for values of the score S lower than 0;
- medium bankruptcy risk, for values of the score S within the interval [0, 0.08);
- low bankruptcy risk, for values of the score S higher than 0.08.

The definition of the 3 risk intervals remains consistent with the characteristics of the 2007 – 2009 populations (table 4).
As shown in figure 7, aprox. 15% - 30% of the companies included in the target population are associated with the high bankruptcy risk class based on the model.
As shown in figure 8, the relative risk of bankruptcy (relative to the average risk) for each of the 3 risk classes remains fairly constant over the 4 year period of analysis.

## CONCLUSIONS

The objective of the research was to create a bankruptcy prediction model easily applicable on Romanian companies. The proposed model thus only employs financial data available online to the general public. The in-sample and out-of-sample classification accuracies and AUCs of the model over paired samples recommend it as a useful tool. Still, bankruptcy represents a rare phenomenon, which makes the structure of the target population significantly different from the structure of a paired sample. As the "by chance" accuracy over the entire population was considered impossible to overpass, the model was designed not to classify a company as future bankrupt or non-bankrupt, but to assign the analysed company to a risk class.
The analyst is recommended to calculate the following score for the company being evaluated:

$$S = 0.085 + 0.503\mathrm{LPp} \times 10^{-5} - 0.239\mathrm{RCP} \times 10^{-3} + 0.224\mathrm{EFAr} \times 10^{-5} + 0.202\mathrm{Ewc} \times 10^{-6} - 0.398\mathrm{Pr} \times 10^{-1}$$

Based on the calculated score, the company should be included in one of the following 3 risk classes:

- high bankruptcy risk, for values of the score S lower than 0;
- medium bankruptcy risk, for values of the score S within the interval [0, 0.08);
- low bankruptcy risk, for values of the score S higher than 0.08.

A company included in the high bankruptcy risk class should not necessarily be expected to go bankrupt. For the 2010 target population, of the 15,071 companies, 4,257 were included in the high bankruptcy risk class. Of the 4,257 companies, 276 went bankrupt within a 2 – year horizon (until the end of 2012). Thus, the bankruptcy frequency for the high bankruptcy risk class was of 6.48%. This suggests that a company included in the high bankruptcy risk class will probably not go bankrupt, but the probability of it going bankrupt in a 2 – year time horizon is higher than the average.
The information offered to the analyst by the proposed methodology is that:

- out of 1,000 companies included in the low bankruptcy risk class, approximately 10 would go bankrupt in a 2 – year time horizon;
- out of 1,000 companies included in the medium risk class, approximately 20 would go bankrupt in a 2 – year time horizon;

- out of 1,000 companies included in the high bankruptcy risk class, approximately 65 would go bankrupt in a 2 – year time horizon;
- without taking into account the value of the score, out of 1,000 companies being analysed, approximately 29 would go bankrupt in a 2 – year time horizon.

Thus, by employing the proposed methodology, the stakeholders should adopt different strategies for companies from different risk classes. A capital supplier could choose to finance more easily companies from the low risk class, while demanding more guaranties and increasing the financing costs for companies from the medium risk class and even avoid companies from the high risk class.

Further studies that are considered useful over the same population should target:

- the correlation between the dynamics of the financial ratios and the probability of bankruptcy;
- the possibility of valuating the bankruptcy risk through scores assigned for each ratio, in accordance with its value;
- the correlation between the probability of bankruptcy and the absolute and relative deviations of the ratios compared the sector means;
- the possibilities of predicting the bankruptcy risks based on non-financial indicators that are publicly available.

The proposed methodology should be updated on a yearly basis, so it can remain adapted to the changing characteristics of the target population.

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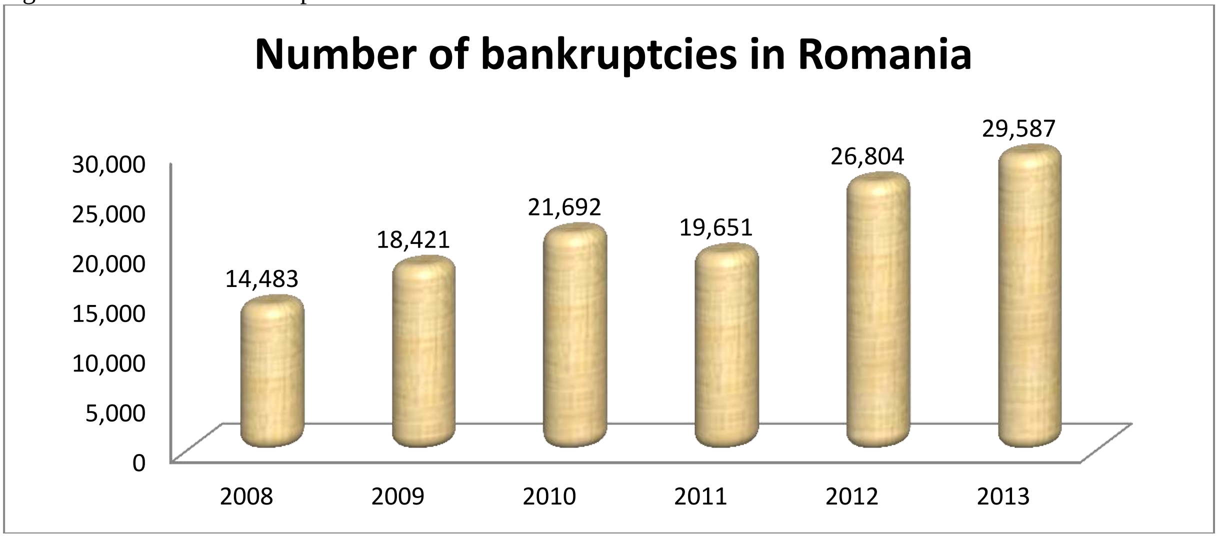
Figures and tables

Figure 1. Number of bankruptcies in Romania




Source of data: National Registry of Commerce

Figure 2. Area Under the Curve (AUC) for individual ratios

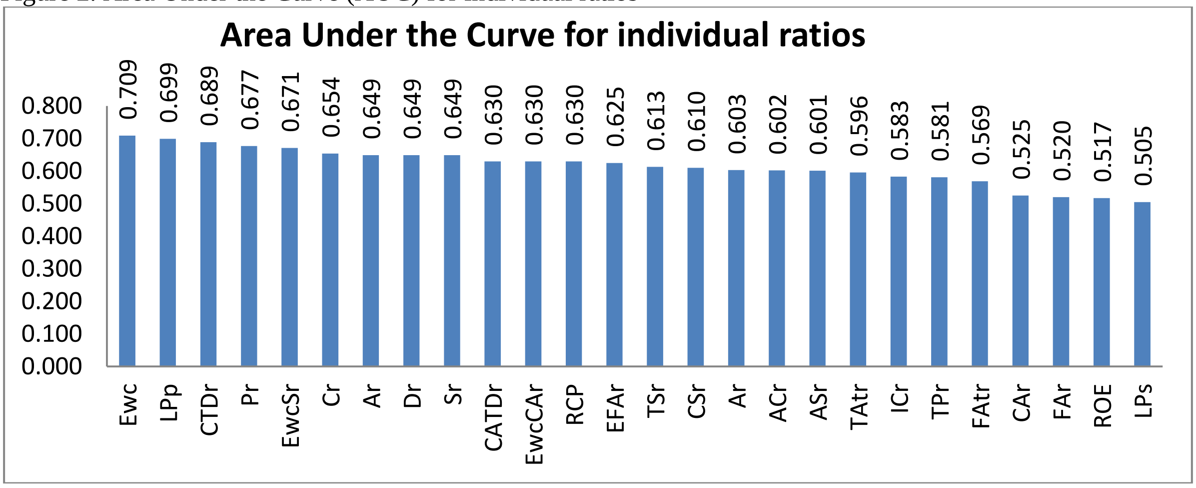



Figure 3. In-sample AUCs of the 10 best performing models

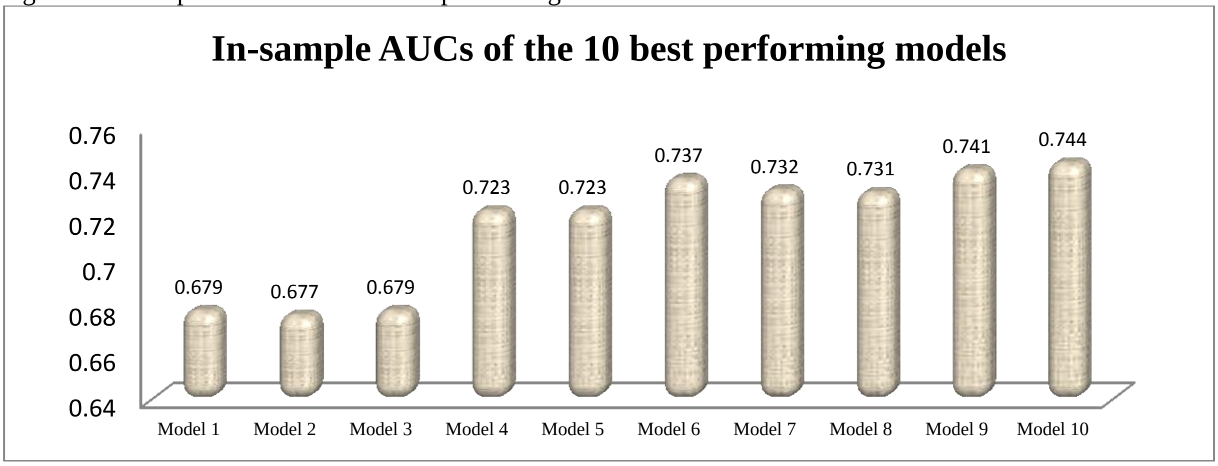


Figure 4. AUC over the target population

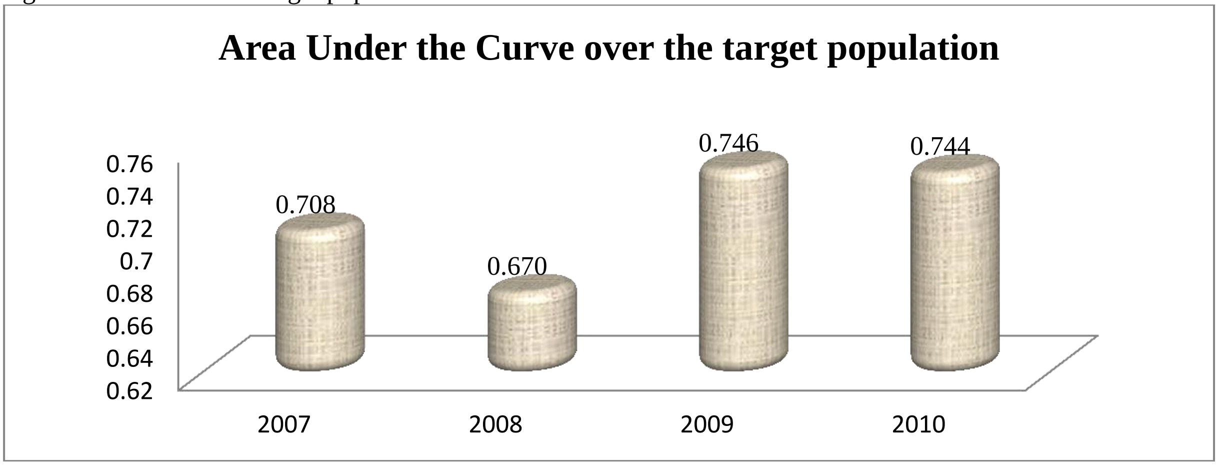



Figure 5. Optimal cut-off value over the paired – sample

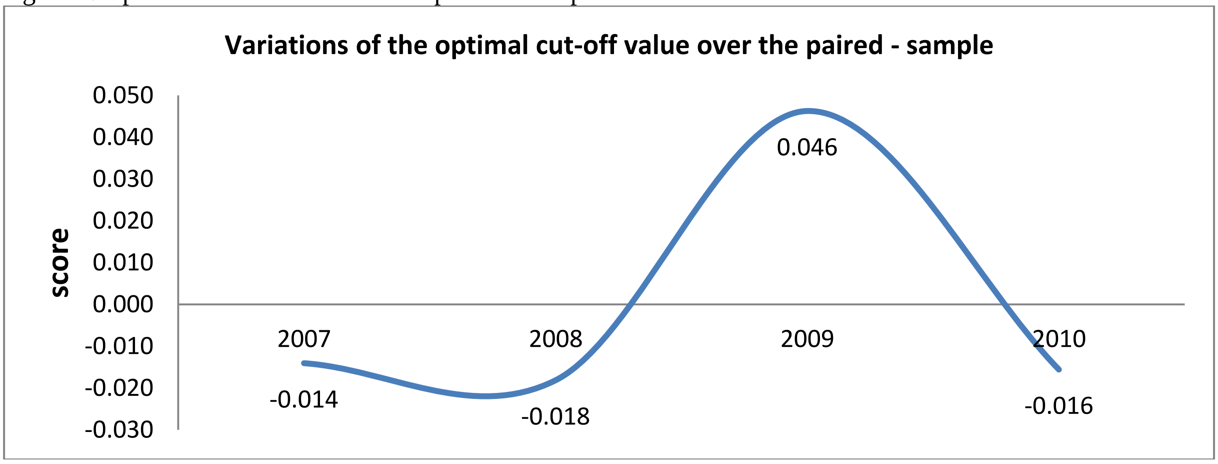



Figure 6. General accuracy over the paired – sample

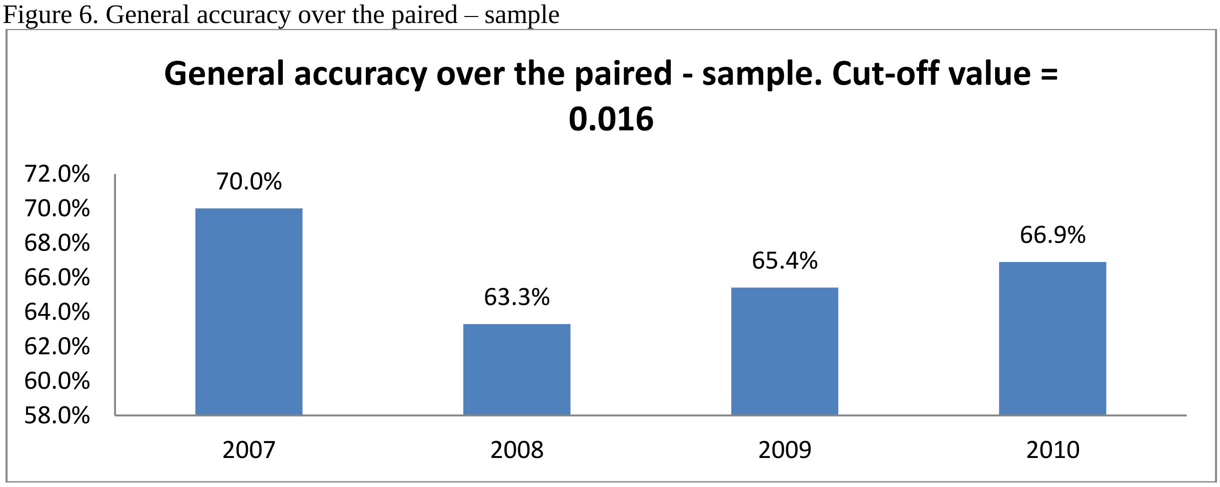


Figure 7. Distribution of the companies on risk classes

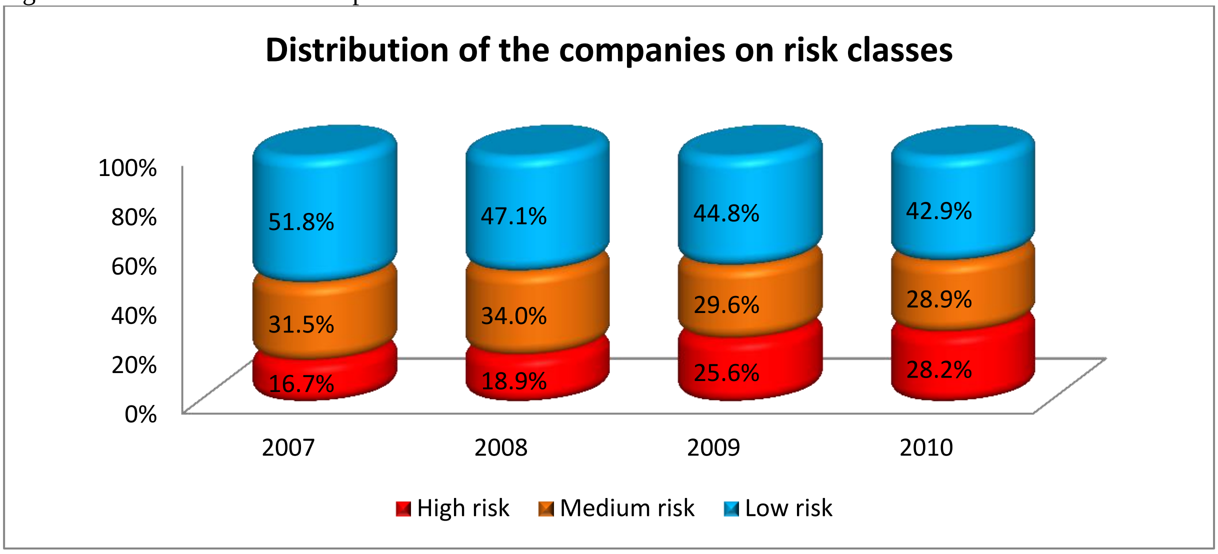



Figure 8. Dynamics of the risk indexes on intervals of the score S

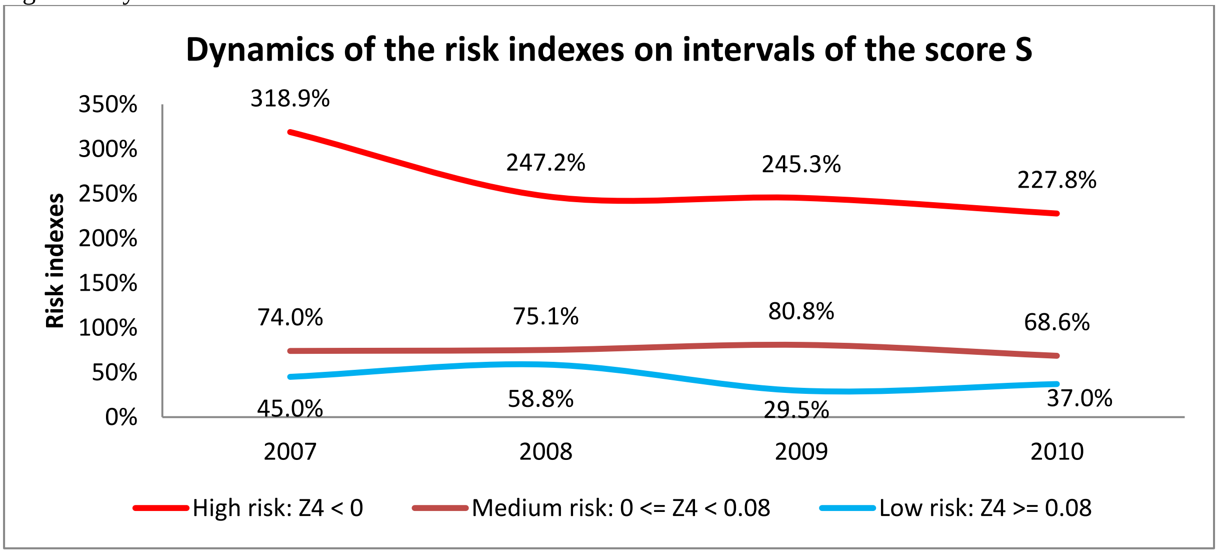


Table 1. Bankruptcy prediction studies

| No. | Country | Sample | Main author | Year |
|---|---|---|---|---|
| 1 | USA | 1,249 | Hatem Ben-Ameur | 2008 |
| 2 | China | unspecified | Wang Ying | 2010 |
| 3 | USA | 468 | EMEL KAHYA | 1999 |
| 4 | Turkey | 54 | Mine Ugurlu | 2006 |
| 5 | Italy | 40,574 | Giovanni Butera | 2006 |
| 6 | Pakistan | 52 | Abbas Qaiser | 2011 |
| 7 | Canada | 633 | S. Ben Amor | 2009 |
| 8 | USA | 2,128 | Gregory Kane | 1998 |
| 9 | India | 70 | A.V.N. Murty | 2004 |
| 10 | Taiwan | 54 | Tsung-Kang Chen | 2011 |
| 11 | Singapore | 34 | Zulkarnain Muhamad Sori | 2009 |
| 12 | USA | 14,303 | Stephen A. Hillegeist | 2003 |
| 13 | Norway | 98,421 | Daniel Berg | 2005 |
| 14 | Tunisia | 60 | Mondher Kouki | 2011 |
| 15 | Japan | 3,586 | Ming Xu | 2009 |
| 16 | Great Britain | 7,833 | Dionysia Dionysiou | 2008 |
| 17 | USA | 16,816 | Sudheer Chava | 2004 |
| 18 | Croatia | 156 | Ivica Pervan | 2011 |
| 19 | France | 190 | Conan - Holder | 1979 |
| 20 | Tunisia | 120 | Hamadi MATOUSSI | 1999 |
| 21 | Greece | 58 | THEOHARRY GRAMMATIKOS | 1984 |
| 22 | Belgium | 306 | N. DEWAELHEYNS | 2004 |
| 23 | SUA | 1.203 | Mary Hilston Keener | 2013 |
| 24 | Russia | 120 | Elena Makeeva | 2013 |
| 25 | Poland | 13,288 | Kamil Fijorek | 2012 |
| 26 | Belarus | unspecified | Chernovalov, A. | 2004 |
| 27 | Albania | unspecified | Shkurti Rezarta | 2010 |
| 28 | Brazil | 12 | Matias Alberto Borges | 2011 |
| 29 | Serbia | 232 | Nemanja Stanišić | 2013 |
| 30 | Hungary | 154 | Ottó Hajdu | 2001 |
| 31 | Czech Republic | 757 | Petr Jakubík | 2008 |
| 32 | Slovenia | 19,627 | Dusan Mramor | 2003 |
| 33 | Slovenia | 29,698 | Arjana Brezigar-Masten | 2012 |
| 34 | Sweden | 3,982 | Darush Yazdanfar | 2008 |
| 35 | Sweden | 4,496 | Darush Yazdanfar | 2011 |
| 36 | Europe | 25,722 | Kevin Keasey | 2013 |
| 37 | Finland | 2,243 | Laura Kainulainen | 2011 |
| 38 | Portugal | 2,288 | M. F. Santos | 2006 |
| 39 | Lithuania | 230 | O. Purvinis | 2008 |
| 40 | Estonia | 16,443 | Martin Grünberg | 2014 |

Table 2. Financial ratios tested as explanatory variables

| No. | Financial ratios | Symbol | Formula |
|---|---|---|---|
| 1 | Equity working capital | Ewc | Equity+Provisions-Fixed assets |
| 2 | Labor productivity in terms of profits | LPp | Gross profits/No. of employees |
| 3 | Profitability ratio | Pr | Net profits/Sales |
| 4 | Tax to profits ratio | TPr | Income tax/Gross profits |
| 5 | Autonomy ratio | Ar | (Equity+Provisions)/Total assets |
| 6 | Debt ratio | Dr | Total debt/Total assets |
| 7 | Solvency ratio | Sr | Total assets/Total debt |
| 8 | Equity working capital to sales ratio | EwcSr | Equity working capital / Sales |
| 9 | Arrears to sales ratio | ASr | Arrears/sales |
| 10 | Equity to fixed assets ratio | EFAr | Equity/Fixed assets |
| 11 | Arrears to cash ratio | ACr | Arrears/Cash |
| 12 | Cash to total debt ratio | CTDr | Cash/Total debt |
| 13 | Current assets to total debt ratio | CATDr | Current assets/Total debt |
| 14 | Cash ratio | Cr | Cash/Total assets |
| 15 | Equity working capital to current assets ratio | EwcCAr | Ewc/Current assets |
| 16 | Receivables collection period | RCP | (Receivables/Sales)x360 |
| 17 | Total assets turnover ratio | TAtr | Sales/Total assets |
| 18 | Arrears ratio | Ar | Arrears / Total debt |
| 19 | Cash to sales ratio | CSr | Cash/Sales |
| 20 | Fixed assets turnover ratio | FAtr | Sales/Fixed assets |
| 21 | Inventory conversion ratio | ICr | (Inventory/Sales)x360 |
| 22 | Tax to sales ratio | TSr | Income tax/Sales |
| 23 | Fixed assets ratio | FAr | Fixed assets/Total assets |
| 24 | Labor productivity in terms of sales | LPs | Sales/No. of employees |
| 25 | Current assets ratio | CAr | Current assets/Total assets |
| 26 | Return on equity | ROE | Net profits/(Equity+Provisions) |

Table 3 Risk indexes on intervals of the score S for the 2010 population

| No. | Z4 | 2010 |
|---|---|---|
| 1 | S < -0.1 | 324% |
| 2 | -0.1 <= S < 0 | 118% |
| 3 | 0 <= S < 0.05 | 81% |
| 4 | 0.05 <= S < 0.08 | 55% |
| 5 | 0.08 <= S < 0.1 | 46% |
| 6 | 0.1<= S < 0.13 | 38% |
| 7 | 0.13 <= S < 0.18 | 24% |
| 8 | 0.18 <= S < 0.25 | 27% |
| 9 | 0.25 <= S < 0.4 | 43% |
| 10 | S >= 0.4 | 38% |

Table 4 Risk indexes on intervals of the score S for the 2007 - 2009 populations

| No. | Z4 | 2007 | 2008 | 2009 |
|---|---|---|---|---|
| 1 | S < -0.1 | 421% | 274% | 306% |
| 2 | -0.1 <= S < 0 | 227% | 221% | 179% |
| 3 | 0 <= S < 0.05 | 96% | 73% | 100% |
| 4 | 0.05 <= S < 0.08 | 57% | 77% | 61% |
| 5 | 0.08 <= S < 0.1 | 0% | 72% | 29% |
| 6 | 0.1<= S < 0.13 | 64% | 45% | 35% |
| 7 | 0.13 <= S < 0.18 | 0% | 52% | 40% |
| 8 | 0.18 <= S < 0.25 | 55% | 37% | 23% |
| 9 | 0.25 <= S < 0.4 | 172% | 102% | 25% |
| 10 | S >= 0.4 | 50% | 48% | 19% |