Proposal for a Decision Support System to Predict Financial Distress

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Abstract

In the context of economic instability a decision support system that could provide early warning signals of financial distress to a company a few years before actually turning to insolvency could play an important role in the decision making processes inside a company.

Thus, the aim of this paper consists in developing a decision support system for financial distress for the case of the Romanian companies listed on the Bucharest Stock Exchange. A practical solution for predicting financial distress with one or even two years in advance is presented and the results of the models' prediction accuracy are encouraging us to believe that these models can actually improve the strategic management and planning departments in a company.

Keywords: *SMEs, decision support system, financial distress, prediction.*

JEL classification: G32, C61

Introduction

In the context of economic instability and uncertainty, when more and more companies struggle with financial difficulties to keep in business, it becomes more obvious of the necessity of a sound strategic planning and an efficient management system. Thai is why I believe that a decision support system that could provide early warning signals of financial distress to a company a few years before actually turning to insolvency or bankruptcy becomes a true necessity.

Having these arguments into perspective, this paper will try to offer a practical solution for predicting financial distress one or even two years in advance.

The fact that more and more western companies use strategic management represents a guarantee for the Romanian companies, that by using strategic management they can overcome the challenges of the Romanian economic environment. These benefits contribute not only to improving the quality of management, but also to increase the competitiveness of the companies and their profitable adaptation to new demands and challenges.

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1. International approach to financial distress prediction

According to Andreica et al. (2014), in the context of a globalized economy, SMEs must be prepared to face a wide range of economic challenges that could force the managers to adapt their strategies and actions accordingly. The first step in the evolution of the quantitative firm failure prediction model was taken by Beaver (1966), who developed a dichotomous classification test based on a simple *t*-test in a univariate framework.

He was followed by Altman (1968), who suggested a Multivariate Discriminant Analysis (MDA) that was able to provide a high predictive accuracy of 95% one year prior to failure. However, Eisenbeis (1977) found some inadequacies in the MDA with respect to the assumptions of normality and group dispersion.

Further on Ohlson (1980) proposed the use of the logit model in the financial distress prediction problem, while the hazard model, which is actually a multi-period logit model, was introduced by Shumway (2001). Later on Nam et al. (2008) extended the work and developed a duration model with a baseline hazard function incorporating macroeconomic variables, such as exchange rate volatility or interest rate.

In recent years many heuristic algorithms such as neural networks and decision trees have also been applied with success to the bankruptcy prediction problem. For instance, Zheng and Yanhui (2007) used decision tree methodologies for corporate financial distress prediction and presented the advantages of using CHAID decision trees in comparison to a neural network model, which is complicated to build up and to interpret or to a statistic model such as logistic regression, where the patterns need to be linearly separable. Another similar study based on CHAID decision tree models for distress prediction problem was made by Koyuncugil et al. (2007) who identified profitability ratios to be the best predictors of financial distress.

As noticing from the international experience, distress prediction remains an opened challenge, especially in times of economic instability and therefore early warning signals could play a significant role in preventing bankruptcy.

2. The architecture of the decision support system

In this paper a decision support system for financial distress is proposed, based on the particularities of a sample of Romanian companies. The architecture of the proposed decision support system is further on described, based on the following main components:

- the database and the management of the database;
- the knowledge management system;
- the user system interface.

Regarding **the database and the management of the database component**, in order to build the prediction models for financial distress, financial data from the Bucharest Stock Exchange website were collected for 102 Romanian firms. Out of the total sample, 50 firms were facing financial difficulties, while the rest of 52 firms were considered healthy companies, as they had not registered any losses or debts during the last three financial years starting with 2011.

Since there is no standard definition for a "distressed" company, I followed the same main classification criteria used in other similar studies (Psillaki et al. (2008), Zheng and Yanhui (2007)) who considered a company as "distressed" if it had losses and outstanding payments for at least 2 consecutive years.

The selection of the main set of financial ratios for each company was conditioned by those variables that appeared in most empirical work, but also restricted to the availability of the financial data. 14 financial ratios were calculated for this study reflecting the company's profitability, solvency, asset utilization, growth ability and size. They are presented in table 1.

Table 1. Financial Ratios

CATEGORY	CODE	FINANCIAL RATIOS	DEFINITION
Profitability	**I1**	Profit Margin	Net Profit or Loss / Turnover *100
	I2	Return on Assets	Net Profit or Loss / Total Assets *100
	I3	Return on Equity	Net Profit or Loss / Equity *100
	I4	Profit per employee	Net Profit or Loss / number of employees
	I5	Operating Revenue per employee	Ln(Operating revenue / number of employees)
Solvency	**I6**	Current ratio	Current assets / Current liabilities
	I7	Debts on Equity	Total Debts / Equity *100
	I8	Debts on Total Assets	Total Debts / Total Assets *100
Asset utilization	**I9**	Working capital per employee	Working capital / number of employees
	I10	Total Assets per employee	Ln(Total Assets / number employees)
Growth ability	**I11**	Growth rate on net profit	(Net P/L_1 - Net P/L_0) / Net P/L_0
	I12	Growth rate on total assets	Total $Assets_1$ – Total $Assets_0$) / Total $Assets_0$
	I13	Turnover growth	($Turnover_1$- $Turnover_0$) / $Turnover_0$
Size	**I14**	Company size	ln (Total Assets)

Regarding **the modelbase and the management of the modelbase component**, CHAID decision tree models were implemented in order to predict financial distress. According to Andreica (2008; 2009; 2013) a decision tree is a predictive model build in the process of learning from instances, which can be viewed as a tree. Each branch of the tree is a classification question and the leaves of the tree are partitions of the dataset with their classification.

There are a lot of useful decision tree algorithms, out of which the Chi-square Automatic Interaction Detector called CHAID was selected, as it has the advantage of generating non-binary trees. CHAID model finds the pair of values that is least significantly different with respect to the target attribute. The significant difference is measured by the p-value obtained from a Pearson chi-square test. For each selected pair, CHAID checks if p-value obtained is greater than a certain merge threshold. If the answer is positive, it merges the values and searches for an additional potential. The two alpha levels: α_{merge} and α_{split} values were set at a 5% level.

The initial sample of 102 companies was divided into a 70% training sample and a 30% test sample. In order to measure the decision tree model's efficiency, the out-of-sample performances were calculated and then compared between each other.

Testing decision tree for 1 year ahead prediction **Testing decision tree for 2 years ahead prediction**

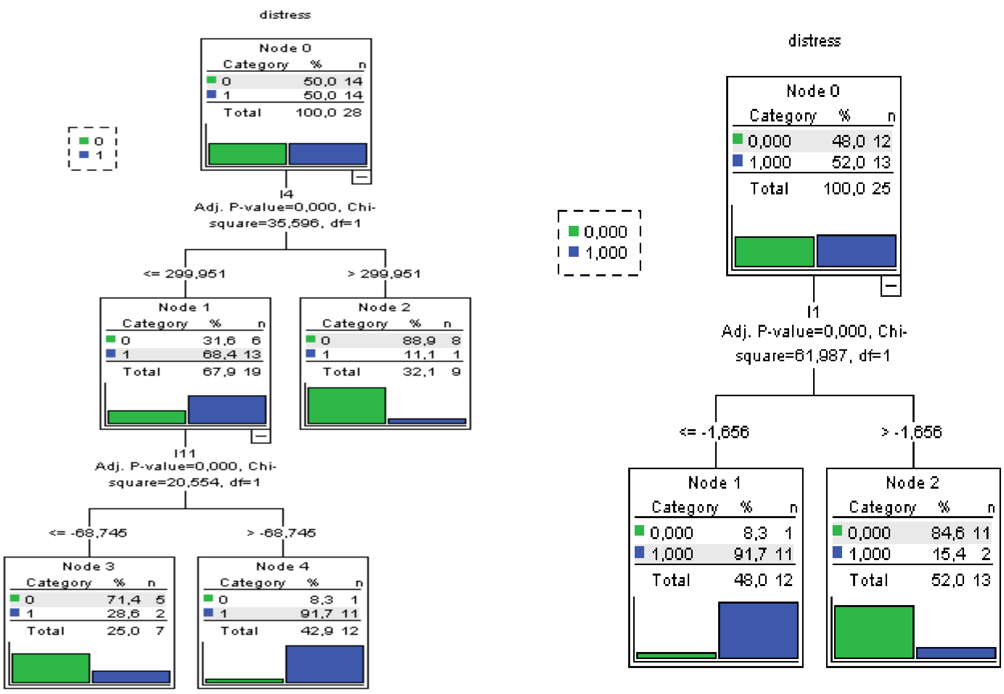

Figure 1. The testing decision trees for financial distress prediction
Source*:* own calculation using SPSS

Firstly, when considering the first CHIAD model for a one year ahead prediction of financial distress, there are three layers and two splits, indicating that the two variables that are relevant to classify the initial sample into "healthy" and "unhealthy" companies are **Profit per employee (I4)** and **Growth rate on net**

profit (I11). As noticing, the results indicated a profitability financial ratio and also growth ability ratio to be the best predictors on this set of data.

Secondly, the resulted CHAID model for 2 years ahead prediction has two layers and has split just one time, indicating that the only variable that is relevant to classify the initial sample of 50 companies into "healthy" and "unhealthy" companies is **Profit Margin (I1).** The results indicated once again that profitability financial ratio tend to be the best predictors of financial distress.

When computing the prediction ability of the two models based on the in-sample and out-of-sample models one can notice that the 2 years ahead prediction model is more efficient in terms of predictability as compared to the one year ahead prediction model. The out-of-sample testing phase indicated a 85,7% accuracy in prediction for the first CHAID model and a 88% probability of correct out-of-sample prediction for the case of a two years ahead prediction model. The statistics are summarized in table 2.

Table 2. Prediction accuracy of the CHAID models

	In sample			**Out-of-sample**		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	47	27	74	16	12	28
First model						
% corect	63,5%	36,5%	**87%**	57,1%	42,9%	**85,7%**
Second model						
% corect	50,6%	49,4%	**94,8%**	52%	48%	**88%**

Source: own calculation using SPSS

Regarding **the knowledge management system component**, the decision trees play an important role not only by defining the variables that can be used in the measurement of financial distress, but also by determining consistent classification rules, mainly because of their tree structure and their ability to easily generate rules for segmentation of the original database. Since a decision tree generates a rule for each of its leaves, in the case of a one year ahead prediction model there are three classification rules, based on the values of the I4 and I11. More precisely, the decision tree classifies a company as being healthy if I4 is higher than 299.95. In the other case, the company is considered distressed only if the I11 is higher than -68.7%.

For the second CHAID model with two years ahead predictability, there are only 2 classification rules, based on the values of I1. More precisely, the decision tree classifies a company as being distress if I1 is less than -1.66%. In the other case, the company is considered non-distressed. As a conclusion, however, it is obvious that these rules are very sensitive to the initial data set.

Regarding **the user system interface**, the SPSS statistical software was used in order to compute the financial ratios and to build the decision trees, since it has a friendly user interface and can offer support to solving various decision problems. A capture of the SPSS window when building the CHAID decision tree models is presented in fig. 2.

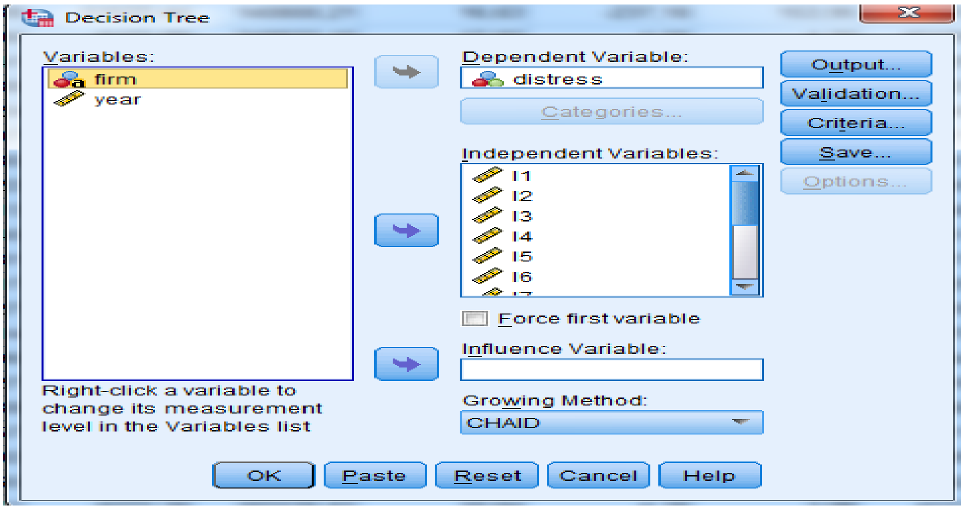

Figure 2. Capture of SPSS window when building CHAID decision trees

Conclusions

In the context of economic instability and uncertainty, when more and more companies struggle with financial difficulties, it is more obvious than ever the necessity of a sound strategic planning and an efficient management system. That is why, a decision support system that could provide early warning signals of financial distress to a company a few years before actually turning to insolvency or bankruptcy could play an important role in the decision making processes inside a company, where both financial aspects and strategic planning management should be taken into consideration.

Thus, the aim of this paper consists in developing a decision support system for financial distress for the case of the Romanian companies listed on the Bucharest Stock Exchange. A practical solution for predicting financial distress with one or even two years in advance is presented and the results of the models' prediction ability are encouraging us to believe that these models can actually improve the strategic management and planning departments in a company.

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