Economic Modelling 31 (2013) 22–30

Contents lists available at SciVerse ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Early warning models against bankruptcy risk for Central European and Latin American enterprises

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ARTICLE INFO

Article history:
Accepted 11 November 2012

JEL classification:
G33
F37

Keywords:
Bankruptcy prediction
Early warning model
Financial crisis
Artificial intelligence

ABSTRACT

This article is devoted to the issue of forecasting the bankruptcy risk of enterprises in Latin America and Central Europe. The author has used statistical and soft computing methods to program the prediction models. It compares the effectiveness of twelve different early warning models for forecasting the bankruptcy risk of companies. In the research conducted, the author used data on 185 companies listed on the Warsaw Stock Exchange and 60 companies listed on Stock Exchange markets in Mexico, Argentina, Peru, Brazil and Chile. This population of firms was divided into learning and testing setdata. Each company was analyzed using the absolute values of 14 financial ratios and the dynamics of change of these ratios.

The author's developed models are characterized by high efficiency. These studies are one of the world's first attempts at comparing differences in forecasting this phenomenon between the regions of Latin America and Central Europe. Additionally, a comparison of the effectiveness of discriminant analysis, decisional trees, and artificial neural networks models was made.

1. Introduction

This article is devoted to the issue of forecasting the bankruptcy risk of enterprises. The current global financial crisis proved that even the best international companies must constantly monitor their financial situation and those of companies with which they cooperate. The globalization process has led to the emergence of a complex network of relationships in the business environment. In a market economy, this means increased complexity and uncertainty of phenomena affecting the financial standing of entities. No company, even during a period of prosperity, can be certain of its future. The global financial crisis, which began in the second half of 2008, caused the number of companies in danger of bankruptcy to significantly increase around the world. According to statistics compiled by international company Euler-Hermes, the number of companies facing bankruptcy in the U.S. increased by 54%, in Spain by 118% and in the UK by 56% (Niewrzedowski, 2009). The overall increase of bankruptcy risk in companies around the world has increased the awareness of the need to implement methods for providing early warning to enterprises against bankruptcy risk.

Therefore, forecasting the bankruptcy of companies is an issue which nowadays is becoming increasingly important and worthwhile to analyze. In most cases, bankruptcy is a continuous process, where it is possible to distinguish several stages — from the emergence of the first signs of financial crisis, through blindness and ignorance towards the financial and nonfinancial symptoms of crisis in a firm, to inappropriate activities that lead to the final phase of the crisis, which is bankruptcy. The process of going bankrupt may even take up to 5–6 years. This is not a sudden phenomenon, impossible to predict. Therefore, the earlier warning signals are detected, the more time managers will have for preparing and reacting in subsequent phases of the crisis.

In this article, the author investigates how effective the statistical methods (discriminant analysis and decisional trees) and artificial intelligence technique (artificial neural networks) are at predicting the bankruptcy of enterprises in Latin America and Central Europe one year and two years prior to bankruptcy. Section 2 describes the methodology for forecasting corporate bankruptcy. The author of this article has conducted a review of more than 400 studies from around the world. Section 3 introduces the research assumptions. In Section 4, the author presents all twelve bankruptcy prediction models programmed by him. Also in this section a comparative analysis of achieved results is made. Section 5 is devoted to conclusions from the presented research.

2. Methodology for forecasting corporate bankruptcy

Due to the effort required to complete a full analysis of a company's financial condition, analysts have attempted to develop methods to conduct an immediate and reliable diagnosis of a company's financial

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http://dx.doi.org/10.1016/j.econmod.2012.11.017

situation, based on the smallest possible number of parameters. This has led to the development of bankruptcy prediction models. The task of an early warning system (bankruptcy prediction model) is primarily to reveal the deteriorating financial situation of a company and particularly to identify the risk of bankruptcy. Such a system does not provide any guidance on how to improve the financial condition of the company. It is, therefore, a pre-analytical tool that should be reinforced throughout the process of monitoring the financial health of the company.

In literature, these models are categorized into two main groups: statistical models and models using soft computing techniques, which are part of a separate field of science defined as *Computational Intelligence* (a term understood as solving various problems with the help of artificial intelligence). According to research conducted by Aziz and Dar on forecasting bankruptcy risk, 64% of case studies used statistical models, 25% soft computing techniques, and 11% other types of models (Aziz and Dar, 2006).

In statistical models, select financial ratios that have diagnostic value are estimated and used. The selection of each ratio is based on empirical studies of ex-post groups of companies, consisting of enterprises with good financial condition and those at risk. Furthermore, the set of indicators is reduced by excluding variables of similar information content, for example ratios that are correlated with each other. After defining a set of diagnostic variables, the model's parameters are estimated. Each variable selected receives discriminatory weight. The bankruptcy prediction model is created by a gradual "compaction" of the set of individual financial ratios, to obtain a single index called a synthetic indicator. "Compaction" is carried out using appropriate statistical and econometrical methods. Using such a model for assessing the risk of corporate bankruptcy is the substitution of the actual value of financial ratios and the calculation of the synthetic indicator of risk. This synthetic index characterizes the financial situation of the audited company.

The use of statistical models requires that the variables used in the model meet the following assumptions:

√ indicators should have normal distributions,
√ indicators must be independent,
√ indicators must have a high discriminative ability of separating solvent companies from insolvent ones,
√ observations for each individual object (solvent and insolvent companies) must be complete — that is should have values for all indicators of all enterprises,
√ enterprise classifications must be clearly defined — belonging to one company group excludes its belonging to a second group.

In contrast to the statistical models, methods of soft computing techniques effectively cope with imprecisely defined problems, incomplete data, imprecision, and uncertainty. The issue of business bankruptcy prediction has all of the above characteristics. In addition, soft computing models are suitable for use in dynamic systems designed to fit certain internal parameters to changing environmental conditions (so-called learning systems).

The difference between statistical models and soft computing models is based on aspects such as the precision, reliability, and accuracy of variables used. These elements are the basis of statistical models, while the starting point for artificial intelligence models, is the thesis that precision and certainty carry a cost, and calculating, reasoning, and decision making should exploit tolerance for imprecision and uncertainty wherever possible. Soft computing techniques, in contrast to statistical models, thus tolerate inaccurate data, uncertainty, and approximation. The essence of models based

Table 1
Systematization of statistical models used for predicting business bankruptcy.

Model type	Author	Model Form [F(1) — function of the model for 1 year before; F(2) — function of the model for 2 years before; in other cases there is no differentiation or lack of data]	Effectiveness in percent (1 year/2 years)	Number of firms used, country & year
Logit model	Altman and Sabato (2007)	F = 4.28 + 0.18 × EBIT/AT − 0.01 × SL/EQ + 0.08 × NP/AT + 0.02 × cash/AT + 0.19 × EBIT × INT	75.43/NA	432; USA; 2003–2004
Logit model	Pang-Tien et al. (2008)	F(1) = −4.44 + 0.08 × TL/AT − 0.042 × EBIT/INT − 0.021 × OP/INT F(2) = −7.03 + 0.067 × TL/AT + 0.044 × OC/TR − 0.00000042 × NP/TR + 0.027 × GP/NP	92.9/94.9	116; Taiwan; 2002–2007
Logit model	Lin and Piesse (2004)	F(1) = 0.2 − 0.33 × NP/AT − 0.17 × cash/TL − 0.95 × (AC-SL)/AT F(2) = 1.73 − 1.78 × NP/AT − 0.7 × (AC-SL)/OC	8052/87	77; Great Britain; 1985–1995
Logit model	Joo-Ha and Taehong (2000)	F = 0.1062 × INT/TR − 0.00682 × EBIT/TL − 0.1139 × TR/REC	80.4/76.1	46; South Korea; 1997–1998
Logit model	Chen and Zhang (2006)	Financial ratios used in the model (there is no information about their weights): EBIT/AT; market value of 1 share/booking value of 1 share	87.37/NA	1029; China; 1999–2003
Discriminant analysis	Bandyopadhyay (2006)	F = −3.337 + 0.736 × (AC-SL)/AT + 6.95 × cash/AT + 0.864 × AT/TL + 7.554 × OP/AT + 1.544 × TR/AT	88/68	50; India; 2004
Probit model	Gray et al. (2006)	F = 0.132 − 0.15 × EBIT/INT + 1.016 × OP/TL − 0.759 × OP/TR + 2.866 × LL/AT + 0.418 × value of sector beta index	71.43/57.13	392; Australia; 1995–2002
Discriminant analysis	Yim and Mitchell (2004)	F = 1.057 − 0.014 × NP/AT − 0.039 × EQ/AT + 0.32 × LL/EQ	81	70; Japan; 1998–2001
Discriminant analysis	Galvao et al. (2004)	F = 0.2171 × (AC-SL)/AT + 0.3788 × NP/AT + 0.4666 × EQ/TL + 0.1244 × TR/AT	74	70; Great Britain; 1997–2000
Discriminant analysis	Altman et al. (1979)	F = −1.84 − 0.51 × (AC-SL)/AT + 6.23 × EBIT/AT + 0.71 × market_EQ/TL + 0.56 × TR/AT	87/84.2	200; Brasil
Probit model	Ginoglou and Agorastos (2002)	F = −0.138 + 16.555 × NP/AT + 3.54 × GP/AT + 0.002 × TL/EQ + 0.789 × (AC-SL)/AT	NA	40; Greece; 1981–1985
Discriminant analysis	Emel et al. (2003)	F = −0.8 + 0.3 × (1 − AF/EQ) + 3.1 × bankcredits/SL + 1.7 × SL/TR − 1.2 × (AC-INV)/SL − 1.6 × EQ/AT	91.5	82; Turkey;
Decisional trees	Lin and McClean (2001)	NP/AT; TR/AT; TL/AT; (AC-SL)/AT (the structure of the tree was not given)	88.7	1133; Great Britain; 1980–1999
Discriminant analysis	Kuruppu et al. (2003)	F = 3.298 × TR/AF − 3.92 × (AC-INV)/AT + 0.163 × AC/SL − 2.671 × TR/AT + 5.03 × NP/AT + 3.654 × TL/AT − 0.119 × NP/EQ + 0.023 × (AC-SL)/TR + 0.005 × TR/REC − 0.002 × TR/(AC-SL) − 0.425 × NP/TL + 1.727 × EQ/AT − 2.786	71,1	135; New Zealand; 1987–1993

The source: based on own studies.