Bankruptcy Prediction Model Using Neural Networks

Xavier Brédart[1]

[1] Warocqué School of Business and Economics, University of Mons, Mons, Belgium

Correspondence: Xavier Brédart, Warocqué School of Business and Economics, University of Mons, Place Warocqué, 17, 7000, Mons, Belgique. Tel: 32-0-6537-3213. E-mail: xavier.bredart@umons.ac.be

Abstract

Belgium has faced an important number of corporate bankruptcies during the last decade. The aim of this paper is to develop a model that predicts bankruptcy using three financial ratios that are simple and easily available, even for small businesses. We used a sample of 3,728 Belgian Small and Medium Enterprises (SME's) including 1,864 businesses having been declared bankrupt between 2002 and 2012 and conducted a neural network analysis. Our results indicate that the neural network methodology based on three financial ratios that are simple and easily available as explanatory variables shows a good classification rate of more or less 80 percent. Results of this study may be of interest for financial institutions and for academics.

Keywords: Bankruptcy, Neural network, Prediction model

1. Introduction

In recent years, Belgium faces many cases of corporate bankruptcies. Financial distress is a topic that interests many actors (Daubie & Meskens, 2001) such as investors and shareholders, lawmakers, central banks, auditors and managers.

In this context, the theme of business failure has attracted the attention of researchers for many years. Studies regarding bankruptcy prediction generally aim to determine one or several variable(s) that make it possible to discriminate between bankrupt and healthy businesses (Refait, 2004). The pioneers are called Beaver (1966) and Altman (1968) using univariate and linear discriminant analyses, respectively. More recently, studies using different statistical techniques have been led such as Logit (Ohlson, 1980) and Probit models (Zmijewski, 1984). However, statistical methods depend on restrictive hypotheses. In the nineties, thanks to the evolution of computer sciences, some authors have had the idea to resort to artificial intelligence algorithms such as neural networks (Odom & Sharda, 1990; Altman et al., 1994; Hu et al., 1999; Platt et al., 1999; Lee, 2001; Alam et al., 2005; Hu & Tseng, 2010; Kim & Kang, 2010). Murtaza & Shah (2000) use a neural network to predict bankruptcy of US firms between 1992 and 1994 using 9 ratios; they report a good classification rate of 73 percent. Also using neural networks, the study of Abou-Seada et al. (2005), led on British corporations between 1997 and 2000, reports a good classification rate of 83 percent using 5 ratios.

Few models dedicated to bankruptcy prediction applied to the Belgian case (Ooghe & Verbaere, 1982; Declerc et al., 1992; Ooghe et al., 2005). None of these use artificial intelligence. In this context, this article will help to fill this gap on the Belgian literature relative to bankruptcy via the setting up of a neural network.

The aim of this paper is to build a "user friendly" bankruptcy prediction model using three simple and easily accessible ratios. To this end, we conduct a neural network analysis upon a sample of 3,728 Belgian SME's among which 1,854 were declared bankrupt between 2002 and 2012. A neural network is then built to determine the probability that bankruptcy occurs for a business. An important part of the setting of the neural network is related to the selection of discriminant financial ratios. Solvency, liquidity and profitability ratios show very high discriminating power (Refait, 2004) regarding bankruptcy prediction. More precisely, we will use the following ratios that are used in many studies aiming to predict bankruptcy (Akers, et al., 2007) to train our neurons: total equity/total assets for solvency, current ratio for liquidity and EBIT/total assets for profitability ratio. We hypothesize that these ratios are variables that allow discriminating between bankrupt and healthy businesses. Variables that are introduced into the model are recorded the year before the potential bankruptcy filing.

The results of our study show that these three ratios are good predictors of bankruptcy. The good classification rate of this tool is higher than 80% for the bankrupt businesses. Moreover, the ratios that are used to train the neural network are simple and easily available, even for small businesses. This study may be of interest for financial institutions who are interested by the potential bankruptcy of their clients. Academics may also be interested by the results of this study because the methodology that is used is uncommon in the Belgian literature regarding bankruptcy prediction.

The paper proceeds as follows. In section 2, we detail our sample and the methodology used to predict bankruptcy. Section 3 concerns descriptive statistics and results of the neural network. Section 4 will discuss the results and highlights the main conclusions of this research.

2. Methodology

2.1 Sample and data

For this study, we used a sample of 3,728 Belgian Small and Medium Enterprises (SME's) including 1,864 businesses having been declared bankrupt between 2002 and 2012 and conducted a neural network analysis. The Belfirst database (Bureau Van Dijk) has been utilized to collect all the information regarding this sample of businesses. We first selected bankrupt businesses for which we had enough information for our analysis. In a second step, we randomly selected "healthy" businesses among the entire list of businesses of the Belfirst database (Bureau Van Dijk). We finally collected accounting information on Belfirst database (Bureau Van Dijk).

2.2 Measures

Because we aim to explain the bankruptcy probability of businesses, we utilize, as dependent variable, a binary variable as it is the case in many studies about bankruptcy prediction such as the ones of Olhson (1980) or Bhabra et al. (2009). The name of our dependent variable is *Bankruptcy*. This variable takes the value 1 if the business has been declared bankrupt between 2002 and 2012 and 0 otherwise.

The neural network accounts for three explanatory variables. These are the solvency, the liquidity and the profitability of the businesses. *Solvency* is defined as the ratio total equity/total assets on the latest accounting fiscal year before bankruptcy. *Liquidity* is reflected by the current ratio on the latest accounting fiscal year before bankruptcy. Finally, *profitability* refers to the ratio net income/total assets on the latest accounting fiscal year before bankruptcy.

2.3 Methodology

An artificial neural network is layered; each of these layers has several neurons that are connected to other neurons belonging to the preceding and following layer. Figure 1 show neurons arranged in three layers, an input layer, a hidden layer and output layer. The numbers of neurons of the input and output layers are respectively equal to the number of variables presented simultaneously to the network and to the number of variables that the neural network must estimate. In the case of bankruptcy prediction on the basis of solvency, liquidity and profitability ratios, the number of variables presented to the network is equal to 3 and the single variable to be estimated is the bankruptcy of the company. The output neuron takes the value 0 if the company is healthy and 1 if it is bankrupt. Neurons are connected together via synaptic weights W which are incrementally estimated during the learning phase.
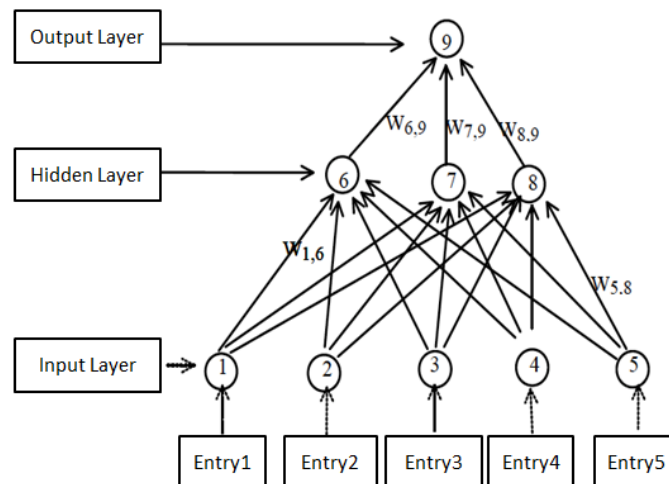

Figure 1. Architecture of a layered neural network

Each neuron collects the outputs provided by the neurons of the preceding layer to determine its activation potential. The latter is then converted by an activation function in an output potential sent to the next layer of neurons. Each function increasing and odd can be selected but the most commonly used is the sigmoid function. The neural network training is based on the back propagation algorithm that adopts an iterative gradient descend method to minimize a cost function represented by the sum of errors to the square produced by the network with respect to the expected outputs (Hinton et al., 1986). The cost function mentioned above is used to determine the changes to be made to the synaptic weights at the next training epoch. The use of multiple hidden layers may lead to a too advanced fitting that decreases the generalization capabilities of the neural network although it increases the training performances (Paquet, 1997). After determining the network architecture, its implementation requires three data samples. The first set of data is used for the training, the second for the validation and the third is used to evaluate the generalization capabilities of the network. Beyond a certain number of iterations, the error committed on the validation sample no longer decreases and the network specializes in the training data. The weights corresponding to the lowest error on the validation sample are used to assess the capacity of the network to correctly classify the test sample that has never been presented to the neural network before.

The neural network is been realized using Matlab software.

3. Results

3.1 Correlations and descriptive statistics

Table 1 presents the correlations between the variables that have been introduced into the neural network. We may remark that all the correlations are under 0.5 and that independent variables have Variance Inflating Factors (VIF) under the value of 10. With these tests, we do conclude that we have no important issue regarding the correlation between explanatory variables.

Table 1. Correlation matrix for explanatory variables

		VIF	1	2	3
1	**Solvency**	1.25	1		
2	**Liquidity**	1.13	0.34	1	
3	**Profitability**	1.12	0.33	0.12	1

Descriptive statistics are reported in table 2. Descriptive statistics regarding solvency, liquidity and profitability ratios are mentioned for the entire sample, for the group of bankrupt businesses and, finally, for the group of healthy businesses.

Table 2. Descriptive Statistics

	Total sample		Bankrupted	Healthy
	Mean	Std. Dev.	Mean	Mean
Solvency	13.63	37.18	-5.61	32.87
Liquidity	1.85	4.96	0.90	2.81
Profitability	13.32	50.48	-2.06	28.70

The analysis of the descriptive statistics (table 2) makes it possible to highlight some differences between the two groups of firms to discriminate (the group of bankrupt businesses and the group of healthy businesses). First, let us notice that the solvency ratio is quite different for the two subsamples. The mean value of the solvency ratio is negative for the group of bankrupt businesses (mean = -5.61); this means that these businesses have negative equity. For the group of healthy businesses, the mean value of the solvency ratio is positive (mean = 32.87). The mean value of the liquidity ratio is much smaller for the group of bankrupt businesses (mean = -0.90) than for the group of healthy businesses (mean = 2.81). Let us also notice that the value of this ratio is inferior to the value of 1 for the group of bankrupt businesses; this means that the businesses of this group cannot face their short term obligations. Regarding the profitability ratio, the mean value of the ratio EBIT/total assets is negative for the group of bankrupt businesses (mean = -2.06); this means that bankrupt businesses make, on average, no profits. For the group of healthy businesses, the mean value of the profitability ratio is positive (mean = 28.70).

3.2 Neural network

The results of the neural network aiming to discriminate between bankrupt and healthy firms are briefly presented in this section. The next session will discuss the findings in detail. The results of the neural network are shown in Table 3.

Table 3. Neural network (dependent variable: bankruptcy)

	Observations	Status	Percentage of good predictions	Percentage of incorrect predictions
Training	2,609	Healthy	74.50%	25.50%
		Bankrupt	83.60%	16.40%
Validation	373	Healthy	82.70%	17.30%
		Bankrupt	77.60%	22.40%
Test	746	Healthy	69.90%	30.01%
		Bankrupt	81.50%	18.50%

The total sample of businesses has been split into three parts: 70 percent of the observations make part of the training group, 10 percent of the data form the validation group and 20 percent of the observations are used for the test. The neural network has first been trained with 2,609 observations. On this training subsample, the percentage of good predictions reached 83.60 percent for the bankrupt businesses; this means that, using this neural network, 83.60 percent of the bankrupted firms are correctly classified. The misclassification rate for bankrupt firms is therefore 16.4 percent. The trained neural network is, in a second step, tested on a second subsample of 746 businesses. On the test subsample, the percentage of good predictions reached 81.50 percent for the bankrupt businesses; this means that, using this neural network, 81.50 percent of the bankrupted firms are correctly classified. The misclassification rate for bankrupt firms is therefore 16.4 percent for the test subsample.

4. Discussion and conclusion

Bankruptcy prediction is a very important topic for different groups of people, especially for managers, lenders, investors who want to avoid bankruptcy because it would cause major problems for their companies. Aiming to predict the bankruptcy probability of Belgian Small and Medium Enterprises (SME's) over the period 2002-2012, we developed a neural network. We utilized a database from Bureau Van Dijk comprising 3,728 Belgian SME's among which 1,854 were declared bankrupt between 2002 and 2012. Because our objective is to create a ''user friendly'' way to discriminate between bankrupt and healthy businesses, we choose, as explanatory factors, three simple, uncorrelated and easily accessible ratios. These ratios are "equity/total assets" for the solvency, the current ratio for the liquidity and, finally "net income/total assets" for profitability. Then, we analyzed the data via the descriptive statistics and the results of the neural network. As per the descriptive statistics, it appears that solvency, liquidity and profitability ratios are very different between the two groups (healthy and bankrupt) of businesses. As expected, the group of healthy businesses shows much better mean values for these variables. Regarding the results of the neural network performed with Matlab sotfware, it appears that the good classification rate for the bankrupt businesses of this tool is higher than 80%, even when testing the neural network on a separate sample. This result is higher than the one reported by Murtaza & Shah (2000) and a bit lower than the one reported by Abou-Seada et al. (2005). Nevertheless, we used fewer ratios to discriminate between bankrupt and healthy businesses. Moreover, solvency, liquidity and profitability are simple and easily available financial ratios, even for small businesses. Finally, these ratios appear to be good predictors of bankruptcy. This result is in line with our hypothesis stating that these ratios are variables that allow discriminating between bankrupt and healthy businesses.

This study has some limitations. First, our analysis has been led on a particular country; a similar model could therefore be tested on different countries to strengthen our conclusions. Second, as this model takes into account financial ratios only, it does not take the specificities inherent to each firm into consideration. This study may be of interest for financial institutions who are interested by the bankruptcy of their clients. Academics may also be interested by the results of this study because the methodology that is used is uncommon in the Belgian literature regarding bankruptcy prediction.

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