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Predicting Corporate Bankruptcy: Lessons from the Past

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Abstract

The need for corporate bankruptcy prediction models arises in 1960 after the increase in incidence of some major bankruptcies. Over the years, the episodes of financial turmoil increase in number and so does these bankruptcy prediction models. Existing reviews of bankruptcy models are either narrowly focused or outdated. Current study aims to provide an overview of the existing models for predicting bankruptcy and review the significance of these models. Furthermore, it highlights the problems and issues in the existing models which hinders the accuracy in predicting bankruptcy.

Keywords: financial crisis, corporate failure, bankruptcy prediction

Introduction

Over the last fifteen years, numerous episodes of global financial turmoil have created periods of extreme economic contraction and waves of financial distress. In the wake of these episodes, the incidence of corporate bankruptcies around the world has been on the rise. The bankruptcy rate is highest in the US, followed by UK, and Taiwan holds the third rank. Bankruptcies in the United States during third quarter of 2016 were 24457 companies, followed by Hong Kong bankruptcies of 6460 companies. Bankruptcies in Italy rose to 3800 companies in second quarter of year 2016 from 3640 companies in first quarter of the same year. Bankruptcies in the United Kingdom grew to 3633 companies in Q3 2016 from 3617 companies in Q2 2016. Taiwan bankruptcies went up to 2132 companies in Nov 2016 from 1981 companies in Oct 20161.

Corporate bankruptcy has considerable impact on clients, employees, financial institutions, owners, suppliers, and government. This is best explained by the study of Graham *et al.* (2014) which showed a 30 percent decrease in annual wages of employees just after a year of bankruptcy. According to Eckbo *et al.* (2012), two-third executives face a median present value income loss equal to five times their pre-departure income in the state of bankruptcy. The harsh consequences of corporate bankruptcy for stakeholders necessitates the need to investigate the reasons for bankruptcy and identify the more accurate predictors.

This study provides an overview of the existing models for predicting bankruptcy of the firm. Furthermore, it highlights the problems and issues in the existing models which hinders the accuracy in predicting bankruptcy.

Literature review

The success and health of the firm is of basic concern to customers, industry participants, managers, investors, creditors and policy makers. If a company come to be financially distressed or bankrupt, there are huge negative consequences for its managers, investors, employees, suppliers, customers, the wider society and economy. High social, economic and individual costs associated with bankruptcies have encouraged researchers to search for better prediction measure (Nanni & Lumini, 2009). The prediction of distress or bankruptcy is highly significant for investors and creditors in decision making. According to Zhang and Wu (2011) and Min and Jeong (2009) accurate prediction of the probability and number of failing firms can be used as the development and robustness index of an economy.

According to Altman *et al.* (1979), corporate bankruptcy is a very common phenomenon of developed and developing countries or economies. Over the years, corporate financial failure is defined in many ways. For example, financial failure is "administration, receivership, or creditors' voluntary liquidation" (Taffler, 1983).

Bankruptcy prediction is necessary to separate companies which can fulfill their future financial obligations from those that are unable to fulfil these obligations. As we can say, it helps to distinguish good companies from bad companies. Obviously, none of these models can have hundred percent predictive accuracy or are successful in separating Bad from Goods. Still, researchers continue to try different statistical methods for finding ways to improve accuracy of their models. The most

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frequently used models that are clearly divided into Artificial Intelligence Expert Systems and Statistical Models are discussed below.

Artificial Intelligence Expert Systems (AIES) Methods

After 1970s, the advancement in computer science leads to the development of programmes that are capable of learning new skills and mimic human attributes of dealing with new information (McKee & Lensberg, 2002). These programs are known as machine learning algorithms. Their learning capabilities have reulted in efficient processing in several streams. In this study, their applications of successful bankruptcy predictions are reviewed.

The best example of an expert decision making behaviour imitation process is Expert Systems (ES). The decision that an expert make about whether to provide credit to an applicant or not actually depend on his knowledge which is built upon several rules. This make ES similar to Recursive Partitioning Alogrithm (RPA), except that ES holds the ability to update their knowledge from the results (Dietterich, 2002). In expert systems, by using a set of characteristics (financial ratios), firms are classified into two classess (non-bankrupt / bankrupt) based on their cut-off scores (Dimitras *et al.*, 1996). Once the ideal calssification is formed, one can extract a decision tree from the system. Based on data-driven method, Messier Jr and Hansen (1988) predicted business failure using ES. The initial rules were set with the help of experts opinion. After adding human judgment, Kattan *et al.* (1993) used machine learning process to compare neural network, Quilan's ID3 and recursive partitioning. They identified that human judgment have increased the strategies accuracy, however, no significant changes were observed in the large or small decision trees. Similarly, Gepp *et al.* (2010) made a comparison of decision trees and identified that complexity and size of trees does not matter. They found that smaller tress with less complex strucutre were better predictor than more complex ones. Recently decision trees were also developed by Bou-Hamad *et al.* (2011) and Bou-hamad *et al.* (2009) and are known as survival trees and forests.

Artificial Neural Networks (NN) were developed to model the communication and information processing mechanism in the human brain. Artificial NN strucuture use a number of variables (inputs) and multiply them with their weights (dendrites) and then transform the sum of these weighted scores into neurons. These neurons then become an input for other neurons (Dietterich, 2002). Based on the tapologies employed, Artificial NN may be categorized into Auto Associative NN (AANN), Bach Propogation NN (BPNN), Cascade Correlation NN (CCNN), Probabilistic NN (PNN) and Self-organising feature map (SOFM). Several studies found in the literature have also used NN in corporate credit risk prediction. One of the earliest studies conducted to predict bank failure in Texas have used BPNN Tam (1991). Findings suggest that BPNN shows more predictive accuracy than K-Nearest Neighbour and DA. Similarly, CCNN was used by Lacher *et al.* (1995) to assess future health of a firm and SOFM for bankruptcy prediction was used by Kaski *et al.* (2001). Fisher information matrix was used to measure local displacement in primary data space. Additionally, bankruptcy problems were identified by Yang *et al.* (1999) using pattern normalization in PNN. Other examples using NN includes Tsai and Wu (2008), Salchenberger *et al.* (1992), Leshno and Spector (1996) and Wilson and Sharda (1994). Furthermore, Atiya (2001) have provided a detialed review of ANN in predicting bankruptcies.

The Genetic Algorithm (GA) is "a procedure for systematically searching through a population of potential solutions to a problem so that candidate solutions that come closer to solving the problem have a greater chance of being retained in the candidate solution than others" (Thomas et al, 2002, p. 29). Using natural genetics and seclection mechanics and global search, Back *et al.* (1996) predict failure of 37 firms in Finland based on 31 financial ratios. They identified that GA achieve better results than Logit and Discriminant analysis. Later on, Shin and Lee (2002) used both ANN and GA for bankruptcy prediciton. They commented that GA are much easier to understand as ANN provide classification rules that increase complexity in results identification.

Rough Set Theory, another articial intelligence method proposed by Pawlak (1982) replace original sets, where objects and information are indiscernible, by using upper and lower approximations. These sets were integrated with decision trees which can be easily used in failure prediction of business by discovering the group of attributes connected to financial distress (Dimitras *et al.*, 1999). By using data for 80 firms from Greece, Dimitras *et al.* (1999) used rough sets and suggested that they are much better in failure prediction than Logit and DA. Furhtermore, they stated that these models can reflect the experience of a given sample. When applied to a different set, the decision rule identification procedure need to be repeated. Moreover, Tay and Shen (2002) guided about the issues in rough set theory. They disucessed that validatiom, dicretisation and selection of indicator may be well managed in the cases of financial and economic predictions.

Case-based reasoning (CBR) is based on the idea of problem solving where people look back on similar cases from their past and use their experience to identify the most suitable answer for the current problem. Thus, in the event of firm failure, CBR help us by providing the cases of firms that failed in the past due to similar characteristics and provide a justification for this prediction (Kumar & Ravi, 2007). CBR model was designed for banruptcy prediction by Bryant (1997) using data of 2000 non-bankrupt and 85 bankrupt firms. However, findings suggest that his LR outperformed CBR. Since most of CBR algorithms work on matching similar cases, they usually use k-NN methodology. Therefor, in bankruptcy prediction using CBR, Park and Han (2002) have used weighted k-NN algorithm that use analytic Hierarchy process. The resultant model can easily handle both financial ratios (quantitative) and non-financial variables (qualitative) at the same time.

Lastly, Support Vector Machine (SVM), the most famous artificil intelligence model, developed by Vapnik and Vapnik (1998) is discussed in this study. Using a linear model, SVM is developed to create a hyperplane in a multi-dimensional space by taking input vectors nonlinearly and predicting their class. When the sapce margin between two classes is maximum, hyperplane is formed. Samples that have the smallest distance or are nearest to the hyperplane are known as vector support. In order to identify the optimal parameteres, SVM with kernel function was used developed by Min and Lee (2005) to classify a paired sample of around 2000 Korean firms. Results of their study suggest that BPNN, Logit and MDA were outperformed by SVM in predictive accuracy. Another study by Shin *et al.* (2005) for predicting corporate bankruptcy also found that BPNN were outperformed by SVM.

Automatic clustering and feature selection (Wu, 2010), Multinorm analysis (de Andrés *et al.*, 2012) and Bayesian Networks (Sarkar & Sriram, 2001; Sun & Shenoy, 2007) are some other intelligence methods used in bankruptcy predicitons. Some other examples of intelligence models with application of statistical methods include Zhou *et al.* (2012) and Tseng and Hu (2010). AIES due to different modifications have many derivatives as discussed previously. One of the major addition to the literature of AIES is done by Aziz and Dar (2006) and Kumar and Ravi (2007). These AIES methodologies were not as standard as statistical models as it becomes very difficult to compare and interpret the results.

A careful analysis of various bankruptcy prediction models shows that there is very little difference between them. Since 1980s, after the advancement in technology the statistical models were replaced by technology-drivenn models. For instance, multivariate and univariate statistical techniques were exploited by AIES methods and are thought-off automated offspring for the statistical models. Henceforth, all the current models are actually dependent on statistical techniques in eitherways. Therefore, advancement in AIES models may only be achieved by development in statistical methods.

Statistical Methods

Since initial works of Beaver (1966) and well recognized model of Altman (1968), the estimation models of bankruptcy prediction have evolved over five decades. The dichotomous classification test used by Beaver (1966) was a simplified univariate discriminant analysis (UDA) by which a cut-off to accounting ratios was directly applied. Later, Altman (1968) employed a Multiple Discriminant Analysis (MDA or DA for short) model commonly known as Z-score. In this model, the discriminant function is denoted by letter “Z” which is the dependant variable. Five ratios were used in the model including; working capital to asset, sales to assets, retained earnings to asset, maket to book value and EBIT to total asset. The Z-score model was a great success which leads to the development of hundreds of bankruptcy prediction models. Few of the most recognized and widely accepted models followed him (Abidali & Harris, 1995; Deakin, 1972; Grice & Ingram, 2001), even himself Altman extended his work to a quadratic discriminant analysis (Altman & Loris, 1976), and later on to Zeta by considering seven different accounting ratios (Altman *et al.*, 1977). It is important to point out that even now, Altman Z-score model is considered as a base model for bankruptcy prediction even after recent development in the given field and in the presence of several alternative models (Altman *et al.*, 1994).

However, in practice, MDA has some big weaknesses. These include the violation of the assumption of a multivariate normal distribution of the variables, unequal dispersion matrices in linear equations and difficulties in interpreting the role of independent variables (Eisenbeis, 1977). Moreover, MDA does not provide the relative weight of the variables during individual estimation (Dimitras *et al.*, 1996). Interpretation of standardized coefficients that MDA yields cannot be done like slopes of regression. Review of literature showed that after 1980s, use of MDA in bankruptcy models was reduced. On the contrary, bankruptcy prediction models developed using conditional probability models gain importance over time.

Meyer and Pifer (1970) introduced Linear Probability Models (LPM) for bankruptcy prediction. The technique was based on linear regression model using Ordinary Least Squares (OLS). However, the method was criticized as the predicted probabilities of the LPM does not lie between 0 and 1. Martin (1977) introduced logistic regression to give early warnings about profit declines and bank failures. Later in 1980, logistic regression was used by Ohlson for prdicting bankruptcy. The O-score model (developed by Ohlson, 1980) soon became dominant over the other credit models, including MDA, due to its predictive accuracy and less stringent requirements. Furthermore, the predicted probabilities of O-score model lie between 0 to 1. The model was widely accepted and were used by several others such as Gilbert *et al.* (1990), Tennyson *et al.* (1990) and Zavgren (1985). Later on, Lin and McClean (2001), Mossman *et al.* (1998) and BarNiv and Hershbarger (1990) have compared it with other algorithms. In 2008, Ting used it as a benchmark alongside the Z-score for prediction of firm failures (Ting et al, 2008). Another model commonly known as Probit model was introduced by Zmijewski (1984). The model was similar to LR but was apparently less used in literature (Gentry *et al.*, 1985; Grunert *et al.*, 2005; Lennox, 1999).

Probit, Logit and MDA are the most widely used statitcial algorithms but they are also highly criticized. For instance, these models have problems in defining optimization, variable identification, sample selection sensitivity, data instability, non-stationarity and dichotomous criteria (Balcaen & Ooghe, 2006), although the same is true for all the other models. Furthermore, these statistical models ignore the time and also have problem of data pooling for different years (see, for example, Altman, 1968; Zmijewski, 1984). Resultantly there exist a sample selection bias (Shumway, 2001). Additionally, results are misleading as there is an increased possibility of multicollinearity among variables which keep them uninterpretable. Although in real business one cannot ignore the misclassification cost (see, for example, Zavgren, 1985), but still Koh (1992) was convinced that optimal cutt-off have equal allocation for misclassification costs and the problem is not so big. The only study which considered different types of misclassification cost was Taffler (1982).

The issue of dependendant variable dichotomy in bankruptcy prediction was resolved by Multinominal Logit model, firstly used by Lau (1987). Later on Johnsen and Melicher (1994) added that, multinominal outcomes help by providing additional informartion in bankruptcy modelling. Moreover, they also argued that the definitiion used by Lau (1987) violate the assumptions of identical and independent distribution of dependent variable. Therefore, Johnsen and Melicher (1994) considered varying financial distress as they use ordered LR in bankruptcy prediction model. The model was tested for different assumptions of bankruptcy, insolvent and healthy companies and provided better results and hence proved its superiority over Multinominal and Binary techniques. Later, Nested logit, another advanced logit model was used by Jones and Hensher (2007) for predicting bankruptcy. In this study, they have provided some more weaknessess and strengths of the LR models.

Survival analysis a prominent model in medical science used to determine the death time of organisms. The prediction accuracy was obtained by adding time deimension inot the regression model. By using this model probabilities, covariates and prediction parameters are all calculated dynamically. A similar predictive model, commonly known as continuous hazard model was used by Cox and Oakes (1984), Cox (1972) and Lane *et al.* (1986) to predict failure of banks. Later, Shumway (2001) proposed discrete time hazard model and used macroeconomic and financial variables to predict failure. The model is more suitable with these covariates and produce better results, as endorsed by Chava and Jarrow (2004) alongwith several others (see for example Agarwal & Taffler, 2008; Beaver *et al.*, 2005; Charalambakis & Garrett, 2015; Cheng *et al.*, 2010; Nam *et al.*, 2008; Tinoco & Wilson, 2013).

Methodology

This paper tries to understand different models used for bankruptcy prediction. The objective is attained by targeting the papers that used different models for corporate bankruptcy prediction. Bankruptcy prediction has multiple meanings; therefore, studies relevant to bankruptcy and firm failure aspects are critically reviewed. The sample consisted of peer-reviewed articles published, and collected using various search engines (science directory, google scholar and journals websites). The search was restricted but not limited to keywords bankruptcy prediction, firm failure and financially distressed firms.

Conclusion

Bankruptcy prediction is a critical issue that has been widely explored in the finance and accounting literature. The extensive studies on failure prediction in the past literature emphasized the need to understand the techniques and methodologies adopted for the study. In the last four decades, several artificial intelligence and statistical models were used by researchers to reconcile and understand the probabilities of default, to compare failed and non-failed firms, and predict bankruptcy. The use of different techniques is associated with developing a better model, which can provide most reliable and accurate prediction of the firms, over different time periods. Although improvements have been noted in the construction of bankruptcy prediction models over the past decades, a long way has still to be done regarding the accuracy of those models.

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