A Conceptual Review of Existing Models on Prediction of Corporate Financial Distress

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ABSTRACT

Corporate Financial Distress has been a hot topic in research for more than eighty years. From the univariate model of Beaver (1966), and the Multivariate Discriminant Analysis model of Altman (1968) to models based on Logit, Probit, Artificial Neural Networks (ANN), Bayesian models, Fuzzy models, Genetic Algorithms (GA), Decision trees, Support vector machines, K-nearest neighbour, Hazard and Hybrid, model building has evolved during this period with the focus of enhancing prediction accuracy. Many models have been built using quantitative parameters. These models mainly used financial data of the company whilst there has been some models which has used macro variables and market variables in model building. There has been limited studies on models built using qualitative parameters of the company. The paper discusses the existing literature in the areas of predicting Corporate Financial Distress and concludes by providing future research directions on identified gaps.

Keywords : Corporate financial distress, Prediction models, Qualitative parameters, Quantitative parameters

1 Introduction

Early stage prediction of corporate failure has been a key topic in recent times as it's a valuable piece of information for making correct business decisions. There are many stakeholders including economic agents, financial institutions, auditors, consultants, policy makers and clients that are affected by the failure of a firm. As per Beaver(1966), "Failure is defined as the inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account, or nonpayment of a preferred stock dividend." Early warning signs can be derived through the careful evaluation of the financial results. The focus of the literature in these areas tries to predict whether a corporate is under financial distress through the analysis of data using mathematical, statistical and intelligent techniques.

There are many definitions of financial distress in literature. Beaver (1966) above definition is derived using a cashflow/liquid asset framework. As per Carminchael (1972) a corporate will enter into frustration in fulfilling its obligations as a result of insufficiency of liquidity, insufficiency of equity, default of debt, and insufficiency of liquid capital. Foster(1986) in his articles defines it to be a situation of a serious liquidity problem which is unable to be resolved without large-scale restructuring of the operation or structure of economic entities. Doumpos and Zopounidis (1999), defines financial distress as a combination of inability to pay obligations and the situation of "negative equity" where enterprise's total liabilities exceed its total as-

sets. In their book of "Corporate Finance" by Ross, Westerfield, and Jaffe (1999) financial distressed can be categorise into four scenarios, namely;

1) Business failure: Company cannot pay the outstanding debt after liquidation

2) Legal bankruptcy: Company or its creditors applies to the court for a declaration of bankruptcy

3) Technical bankruptcy: Company cannot fulfill the contract on schedule to repay principal and interest

4) Accounting bankruptcy : Company's book net assets are negative a scenario of "negative equity"

1.1 Purpose of the Study

There are many studies done in the area of corporate financial distress prediction models during the last 60 years. Though many have been focusing on model development, there are considerable number of studies performed on country specific and industry specific models. The research on prediction models goes back to the early 1930's. The initial studies focused on ratio analysis technique to predict failure of firms. Univariate analysis, focus on a single factor/ratio, to predict the health of a firm. Beaver (1966), is one of the key and widely used univariate studies which acted as the foundation of many future research. The first Multivariate study was published by Altman in the early 1968 which shaped many future research. The research literature in this area varies from the initial five factor Multivariate Discriminant Analysis (MDA)

model done by Altman(1968) to 57 factor model proposed by Jo, Han and Lee (1997).

The predictive models evolved with time with reference to the methodology and also the focus area. Logit analysis, probit analysis, neural networks were some of the methodology developments which occurred over time. Industry specific models focusing on manufacturing (Altman,1968), Banking (Sinkey,1975), internet firms (Wang, 2004) etc. were introduced during this time frame. Models based on industry/firm size, Country/region etc. were developed.

Many of the above models used quantitative financial data in the predictions. Research has been very limited in the usage of qualitative data with the combination of traditional quantitative financial data in the model prediction. Thus there exists a research gap in this area.

1.2 Methodology

Literature review was employed as the main research tool whilst a deductive approach is used with the support of empirical evidence. The evolution of distress models are discussed in the paper emphasizing variations in models driven by country specific and industry specific parameters. Empirical evidence is cited on arguments to build a concept paper on the prediction of financial distress models. The paper concludes by proposing future research directions which could be further explored in the future.

2 Theoretical Review on Financial Distress

Most financial distress data in the literature is based on the most serious form of financial distress. Bose(2006) and Ravisankar, Ravi, and Bose (2010) in their papers defined it to be the situation where the stock prices were less than 10 cents. The definition of financial distress varied on country specific studies. Lin (2009) in his study on Taiwan companies defined it to be the scenario of the firms inability to pay it's liabilities as and when they mature which included bankruptcy, bond default, an overdraft of bank account, events signifying an inability to pay debts as they come due, entrance into a bankruptcy proceeding, an explicit agreement with creditors to reduce debts, or being classified as "full delivery stock" by Taiwan Stock Exchange or Gre Tai Securities Market. In China the distress is defined as the scenario that a firms profits continue to be negative for two consecutive years or their per-share net assets are lower than per-share stock face value as mentioned in literature by Ding, Song, and Zen (2008), Sun et.al(2006) and Sun et.al(2011). In their study on Iranian companies by Rafiei, Manzari and Bostanian (2011) distress was defined as the scenario where retained losses exceeded fifty percent of the capital of the company. Furthermore the concept of relative financial distress was introduced by Sun et.al(2006) where the author compares the changes in the financial health against the life cycle of the company.

3 Empirical Review on Corporate Financial Distress Predictions

Corporate Financial Distress Predictions have evolved with time from the initial ratios based predictions to complex models based on learning. Definition of bankruptcy varies from paper to paper thus making comparison difficult (Constand & Yazdipour, 2011). There are two main types of bankruptcy as defined by Bellovary, Giacomino, and Akers (2007), namely;

1) A stage seen as a legal procedure and the companies have already taken a legal action. This is a situation where the company is in the final steps of liquidation.

2) A stage seen as financial distress where the company cannot meet their payment obligations. This situation can be seen as a short term phenomena where there is a chance of being reorganized and to continue companies activities.

Bankruptcy prediction models can be mainly divided into two main types, namely; parametric models and non parametric models. Multivariate Discriminant Analysis (MDA) and Logistic Analysis (LA) are the two main parametric models. The parametric models can be of univariate or multivariate in nature. Artificial Neural Networks (ANN), Bayesian models, Fuzzy models, Genetic Algorithms (GA), decision trees, support vector machines, k-nearest neighbour, Hazard models and hybrid models, or models in which several of the former models are combined constitutes the non parametric type of models. These are univariate in nature. Companies are classified into two groups in the MDA based models. Financial ratios are used for the classification of the two groups which are assigned coefficients/weights accordingly. The output score allows the classification of bankrupt or non-bankrupt status. The first logistical analysis was introduced by Ohlson (1980) which used logistic distribution and takes into account the probability of failure of a company. Learning and training the relevant variables are a feature of ANN models thus capturing non linear relationships. Whilst this encompasses the advantage of non-linear models, inability to explain causal relationship is the one of its disadvantages limiting it's use in decision making process of management as shown by Lee & Choi (2013).

Research during the early years focused on univariate studies which evaluated individual ratio analysis extracted from the financial statements of the company. The ratios were compared against failed firms and successful firms.

Bureau of Business Research carried out a study in 1930 concentrating on 29 firms focusing on 24 ratios of failing firms to derive common characteristics. There were eight ratios identified which were able to predict weaknesses in financials of the firm. The study done by FitzPatrick (1932) evaluated 13 ratios of 19 firms each of failed and successful category. The Net worth to Debt and Net Profit to Net Worth were identified as the two major ratios among the 13 which indicated weaknesses in the financials. For firms with long-term liabilities, examining the Current Ratio and Quick Ratio had less value.A follow up study on the Bureau of Business Research carried out in 1930 was performed by Smith and Winakor (1935). The research examined 183 failed firms and they concluded that

Working Capital to Total Assets had superior prediction power on the finances of the firm than both Cash to Total Assets and the Current Ratio. As the firm approached closer to bankruptcy the Current Assets to Total Assets ratio dropped drastically. The first study focusing on small manufacturing firms was performed by Merwin(1942). Net Working Capital to Total Assets, Current Ratio, and Net Worth to Total Debt were three ratios that came out as significant during Merwin's study. Furthermore, he concluded that weaknesses could be detected four or five years prior to the failure through the analysis of the above ratios. The first study focusing on Financial structures was performed by Chudson(1945). Though he concluded that there is no general financial structure on an economy-wide level, clustering is possible on an industry basis considering industry, size and profitability. Thus models developed for general application could not be used for industry specific analysis.

Beaver (1966), in his scholarly article on univariate study, examined the mean values of 30 ratios and also considered the predictive power of these ratios for bankruptcy prediction. Beaver evaluated 79 failed firms and 79 successful firms which spanned over 38 industries. In his study, Net Income to Total Debt had the highest predictive ability of 92% accuracy one year prior to failure. Net Income to Sales had a 91% accuracy while Net Income to Net Worth, Cash Flow to Total Debt and Cash Flow to Total Assets all had an accuracy of 90% in predicting failure one year prior to the occurrence.

Building on Beaver's 1966 study and his recommendation that combining multiple ratios may have higher prediction ability, Altman(1968) developed the first multivariate study which used five factors in predicting bankruptcy in the manufacturing sector. The multivariate discriminant analysis (MDA) introduced the "Z-score" which was used to predict the prediction ability if it fell within a certain range had a 95% accuracy in the predictive power one year before failure. Similar to other models, the predictive ability decreased to 72% in year two, 48% and 29% respectively in year three and four prior to the actual event of bankruptcy. The accuracy of prediction was at 79% for a hold out sample.

Daniel (1968) ten factor MDA, Meyer and Pifer(1970) thirty two factor MDA, Deakin (1972) fourteen factor MDA, Marais(1980) four factor MDA, Keasey and Watson(1986) five factor MDA were some examples of the many models which were developed using the MDA enhancing the predictive power compared to the original Altman "Z-score" model.

The first work using neural networks was done by Wilson and Sharda (1994) with the use of five accounting ratios using resampling and neural networks. His study involved 65 bankrupt firms and 64 non-bankrupt firms which resulted in good prediction accuracy when compared to MDA. Serrano–Cinca (1996) used nine financial ratios to prove that his neural network model had superior prediction power when compared against LDA. Charalambous et al (2000) compared five neural network methods, namely; Learning Vector Quantization, Radial Basis Func-

tion, Feed-forward networks that use the conjugate gradient optimization algorithm, the back-propagation algorithm and the logistic regression in his study. He used 139 matched pairs of bankrupt and non-bankrupt firms in his analysis.

There were close to 35 models developed using Neural Networks and 16 models developed using Logit analysis during the decade prior to 2000 (Bellovary et al., 2007). The focus during the period after 2000 was to improve the model accuracy compared to previous research. Neural networks have dominated the accuracy followed by MDA and logistic regression models. Esteban et al (2008) compared AdaBoost with Neural Network based prediction model and showed that the model was capable of predicting the firm health with a 91% accuracy and further more proved that the Ada-Boost ensemble of trees outperforms Neural Networks namely with reference to the cross-validation and test set estimation of the classification error. In his article "Comparing Models of Corporate Bankruptcy Prediction: Distance to Default vs. Z-Score" by Miller(2009) , he compares two models Altman Z-Score model and the structural Distance to Default model which currently underlies Morningstar's Financial Health Grade for public companies (Morningstar 2008). The results from the study indicated that Distance to Default had superior ordinal and cardinal bankruptcy prediction power on the data set.

There have been development on country specific models in literature. Bellovary et al. (2007) in his study referred to 18 different work carried out in literature regarding country-specific models. Seven mod-

els were tested by Ooghe and Balcaen (2007) on Belgian failure data to test whether country-specific models can be applied in other areas. Through the re-estimation of some of the variables, the authors proved that the models were able can be used in the Belgium context. Laitinen (2002) used data from US and 17 European countries to develop a uniform model. He used Binary Logistic regression analysis to and proved that the uniform model had better prediction power compared to the individual country specific models. Laitinen and Suvas(2013) developed a uniform model to predict financial distress across European countries. The data was collected from 30 European countries which included ten thousand financial distressed firms and one million non-financial distress firms and used Binary Logistic Regression Analysis as the predictive model. The model had a minimum 70% accuracy across all the countries.

During early periods, models were developed using developed economies due to the ease of obtaining information, more stringent company and bankruptcy laws. There has been a late tendency of model development targeting economies of developing countries. Oduro and Aseidu (2017) developed three logit model, namely; model with financial ratios, model with non financial ratios and a mix model which had financial and non financial ratios, targeting companies listed in Ghana stock exchange. The non financial variables included Corporate Governance related ratios. Paired sampling technique was used and 40 companies were selected. The mix model yielded the highest accuracy of prediction of 89% which states the fact that bankruptcy models should be developed with conjunction

of non-financial variables similar to Nisansala and Abdul (2015) conclusion. Similarly Singh and Mishra(2016), used 208 Indian manufacturing companies on a re-estimation of Altman(1968) Z-Score, Ohlson(1980) Y-Score and Zmijewski (1984) X-Score models where it uses the MDA, Logit and Probit techniques for the analysis. The results conclude that the re-estimation increases the accuracy in the Indian context. Nouri and Soltani (2016) developed a bankruptcy prediction model using accounting, market and macroeconomic varibales. They examined 53 companies in the Cyprus stock exchange for the period from 2007 to 2012 using a logistic regression model. The model had an accuracy of 91.2% and 82.1% when used accounting and market data respectively. Furthermore he concluded that there is no significant influence between macro variables and the probability of bankruptcy.

Though bankruptcy prediction models were previously developed solely using accounting data, a new tendency emerged where studies were carried out using market and macroeconomic variables. A Logit model was developed by Dastgir et al. (2009) using quick ratio, total liabilities to equity, equity to total assets, operational earning to equity, operational earning to sales, inventory turnover ratio, accounts receivable turnover ratio and cost of goods sold to sales. He concluded that all the above accounting variables had predictive power in predicting bankruptcy of a firm. Christidis & Gregory (2010) developed a model targeting UK firms. They used working capital to total assets, total liabilities to total assets, cash flow to total assets, change in net income, return on capital employed,

quick assets to current assets, and funds from operation over total liabilities as accounting variables while total liabilities to market value of equity, stock return, cash flow to market value of total assets, standard deviation of firm stock returns over a 6-month period, stock price, net income to market value of total assets, total liabilities to adjusted total assets and log of firm's market equity to the total valuation of Financial Times and the London Stock Exchange (FTSE) as Market variables. Inflation rate and interest rate were the Macroeconomic variables that were used in the study. During their study they proved that incorporating macro variables enhanced the predictive power of the model. Furthermore it was shown that industry controls in the model gave modest improvement in the predictive power on a combined model of accounting, market and macro variables compared to a higher enhancement on a pure accounting model. Fadaienezhad & Eskandari (2011) focused on designing a model using data of Tehran stock exchange. Earnings Before Interest Tax (EBIT) to sales, return of equity, return of assets, interest coverage ratio, quick ratio, current ratio, working capital to total assets, total liabilities to total assets, total liabilities to equity, equity turnover ratio, asset turnover ratio were used as accounting variables while risk, stock return, relative market price of stock, market to book ratio, type of industry, history of firm, firm size, stock free float, stock base volume were used as market variables. He concluded in his study that the market information is more effective than using financial ratios. Furthermore the market information is more effective than the use of market data and financial ratios. Also he proved that a trained model using optimization algorithm of particle aggre-

gation on market data had a predictive power of 92.6%. Karami & Hosseini (2012) used profitability, liquidity and leverage as accounting ratios and real return, market value of the firm, risk, risk premium, expected return, systematic risk and Sharp ratio as Market variables. He concluded that the predictive power of accounting variables are much more superior to market variables. Tinoco & Wilson (2013) in his model used total funds from operations to total liabilities, total liabilities to total assets, no credit interval and interest coverage as accounting variables, inflation rate (retail price index), interest rate (the UK short term (3-month) treasury bill rate) and economic growth rate as Macroeconomic variables and equity price, lagged cumulative security residual return, the size of the company and ratio of market capitalization to total debt as Market variables in his module. In his study he compared neural network, a Multilayer Perceptron (MLP) model and Altman's model against his combined model and concluded that the predictive power increases in the combined model.

There has been limited work on using qualitative parameters in the development of prediction models. Kim and Han (2003) used genetic algorithm based data mining approach from expert qualitative decisions to develop rules for bankruptcy prediction. Seven qualitative risk factors which included industry, management, financial flexibility, credibility, competitiveness and operating risk were considered in the model. The model showed agreement between the model output and the expert based decision. Martin, Lakshmi and Venkatesm (2014) used sixty eight external risk factors and fourteen internal risk factors, which in-

cluded risk of industry, management, financial flexibility, credibility, competitiveness, operating risk, performance analysis parameters, firm default analysis parameters, reorganization parameters, pricing, differential parameters, marketing parameters delivery parameters and productivity in his qualitative model using Ant-Miner algorithm.

4 Conclusion and Further Research Directions

There are many stakeholders interested in a firm and specially its' financial health. Thus this is an important area of research thus they are aware of financial risk, methods of preventing corporate financial distress and how to avoid bankruptcy liquidation. Though this field of research has seen publications dating back from 1930's, there still exist some areas of value for future research as follows;

1) There has been limited research in developing models incorporating both quantitative and qualitative data. Quantitative data could include financial, market or economic. Thus mix model research provides a valuable window for model enhancement into the future.

2) There are very limited dynamic models developed in the field of bankruptcy prediction which are capable of adapting to changes in the business environment. Thus there possess a window for future research in this area.

3) Simple model development is needed so that it can be used by all stakeholders where they are capable to understand, explain and interpret the model scenarios.

4) Though there has been many models developed in literature on bankruptcy prediction the area lacks a frame work of early warning system. Therefore there is a need to develop an early warning system framework for bankruptcy prediction.

5) There are has been limited work done in the Sri Lankan context. The main model used has been Altman model. Therefore there is a need for extensive research targeting Sri Lankan companies.

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