IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN: 2278-487X, p-ISSN: 2319-7668. Volume 22, Issue 6. Ser. X (June. 2020), PP 13-57
www.iosrjournals.org

Predictive capability of Financial Ratios for forecasting of Corporate Bankruptcy

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Abstract:
Bankruptcy of a business firm is an event which results substantial losses to creditors and stockholders. A model which is capable of predicting an upcoming business failure will serve as a very useful tool to reduce such losses by providing warning to the interested parties. This was the main motivation for Beaver (1966) and Altman (1968) to construct bankruptcy prediction models based on the financial data (Deakin 1972). This research study also initiated with a great interest on this subject to investigate the predictive capability of financial ratios for forecasting of corporate distress and bankruptcy events. This study is expounded on similar previous studies by Altman (1968), Ohlson (1980), Beaver (1966) by examining the effectiveness of financial ratios for predicting of corporate distress. The logistics regression analysis (LRA) statistical method is used to scan the risk factors from the previous financial year data and prediction models are constructed which can reasonably classify the expected bankruptcy group and can reasonably predict the solvency status of a firm. The research has been focused on the USA companies only. A set of bankrupted and non-bankrupted company financial data are used for constructing the bankruptcy prediction model and then a second set of bankrupted and non-bankrupted company financial data has been used to test the classification accuracy of the constructed models. The result of this study is consistent with the previous bankruptcy prediction researches outcomes. This study also investigates the time factor implication of bankruptcy prediction models using 5 years financial ratios.
Like other research projects this project is not without certain limitations and weaknesses. The bankrupted company data collection and compilation was a great challenge due to most of the bankrupted companies cease to operate or cease to be existed. Thanks to the great treasure of Mergent online database which facilitated collection of bankrupted company data. In order to facilitate identifying and collecting bankrupted company data, it is presumed that the companies which show as inactive status in Mergent online database are distressed or bankrupted companies. Another practical obstacle was the functionality of SPSS software and the output interpretation of the SPSS software; I used Andy Field's "Discovering Statistics using SPSS" book to decipher the statistical jargons and to formulate the bankruptcy equations. Our constructed prediction model cannot be used universally as the study depended upon exclusively on US firm's financial data, therefore the constructed prediction model can proved to be very useful tool for the US financial analysts and turnaround specialists to identify the distressed firms. In the case we need to use this model in other geographical location, the coefficients of the predictor variables must be re-estimated using the particular country's financial data.
Key Word: *Z-Score, Altman Z-Score, Bankruptcy, Corporate Distress, Logistics Regression Analysis (LRA), Multiple Discriminant Analysis (MDA), Recovery Strategy from Bankruptcy*

Date of Submission: 09-06-2020 Date of Acceptance: 26-06-2020

I. Introduction

The current global financial climate demands even the best international companies to constantly monitor their financial situation and their related companies with which they cooperate. Globalization process has delivered a complex network of relationships in the business environment. Due to increase in complexity of related business environment, forecasting the financial health of companies nowadays became increasingly important and worthwhile to analyse (Korol 2013). Bankruptcy is a continuous process, which can be distinguished into several stages, starting 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 Bankruptcy process cycle may take up to 5–6 years which is not a sudden phenomenon and impossible to predict, however the earlier warning signals can be detected and corrective measures may avoid the ultimate bankruptcy event depending on the preparation and reactions of the management to tackle the bankruptcy (Korol 2013). Due to the recent worldwide corporate financial crisis the need to reform the existing financial architecture has been intensified. Objective of business crisis prediction is to build models that can read the risk factors from the past observations and evaluate business crisis risk of companies with a much broader scope (Lin et al. 2011). Ozkan cited in Lin et al. 2011 mentioned that financial indicators has been reviewed by number of researchers as a major basis for predicting financial distress and some common methodologies including peer group analysis, comprehensive risk assessment systems, and statistical and econometric analysis. Premachandra (2009) argued that bankruptcy prediction is important because corporate failure imposes significant direct and indirect costs on stakeholders. Warner cited in Premachandra (2009), evidence suggests that direct bankruptcy costs (such as court costs, lawyers and accountants fees) may be as low as 5%, or (Altman cited in Premachandra 2009) can shoot up to 28% when both direct and indirect costs (such as lost sales, lost profits, higher cost of credit, inability to issue new securities and lost investment opportunities) are considered. Therefore, the early detection of potential bankruptcy is very important due to corporate decision makers make their decisions in a world of dynamic technology development, imperfect knowledge and uncertainty (Premachandra 2009).

Niewrzedowski cited in Korol (2013) indicated that as per statistical analysis by Huler-Hermes, the number of potential bankruptcies has been increased in USA by 54%, in Spain by 118% and in the UK by 56%. Therefore the importance of early warning of potential bankruptcy has been increased along with the overall increase of bankruptcy risk in companies around the world. This paper is a deductive study of usefulness of financial ratios in predicting of corporate failures. In this paper bankruptcy prediction models are constructed using Logistics Regression Analysis (LRA) in SPSS software. The constructed models are analysed for their effectiveness in terms of classification accuracy, Model data fitness, predictor variable significance. Each of these model's predictor variables are analysed for their contribution towards the outcome of bankruptcy prediction equations and their individual significance towards the probability of bankruptcy status of the firms. Selected Financial Ratios are analysed and tested using IBM SPSS software and MS Excel software to answer the following research questions:-

1) How are the financial ratios relevant for predicting of upcoming bankruptcy events?
2) Are the most recent financial ratios indicating the upcoming bankruptcy more significantly than the distant financial ratios?

This study is an empirical research and analysis of secondary data which is based on previous theoretical framework and the study will contribute towards re-examining the effectiveness of financial ratios and the bankruptcy predictive models. In my paper I constructed the bankruptcy predictive models using the Binary Logistics regression analysis on 39 bankrupted firms and 50 non-bankrupted firms. Seven (7) financial ratios are being selected as predictor variables and bankruptcy and non-bankruptcy has been used as categorical variables to construct the LOGIT Model. Another set of secondary data has been collected for 27 bankrupted firms and 29 non- bankrupted firms to test the prediction classification accuracy of the bankruptcy models. In the second chapter of this paper the literature review and previous researches has been discussed and scrutinized closely to answer the research question theoretically. Bankruptcy prediction has a large number of literature and large number of statistical analysis techniques has been used by different researchers, in this study only most important and relevant researches has been discussed and analysed. The literature review chapter covers relevance of Financial Reports, predictor variables, statistical techniques i.e. Multiple Discriminant Analysis (MDA), Logistics Regression Analysis (LRA). Other research papers of Altman (1968), Beaver (1966), Zavgren (1985) are also discussed due to high relevance with corporate bankruptcy literature. The third chapter contains methodology of the research which elaborates the methods and techniques used in this paper. Methodology chapter is the basic guideline how the research has been carried out starting from selection of samples to the end how to analyse and interpret the statistical outcomes of this research. The fourth chapter contains analysis and result which depicts the detail of analysis it has been carried out in this research and the result of the research. The bankruptcy prediction models are constructed in the fourth chapter and further analysed and ranked for classification accuracy, goodness of fit test to identify the best model among all six models. The last chapter discussion and conclusion is a general discussion on research findings, theoretical implications, practical implications, limitations of the research, and future research directions.

II. Literature Review

In this chapter the prior Bankruptcy prediction research studies, bankruptcy literature, financial ratios, statistical methods are discussed in detail which underpins the theoretical framework of this study and answers the research questions theoretically. The relevance of financial statements are discussed due to the financial ratios are used to build the prediction model and we also tested the classification accuracy of these models using financial ratios. The previous researches have been discussed to compare and contrast the methods used in those researches. Lastly the statistical analysis methods are discussed to compare the strength and weaknesses of the widely used statistical methods (i.e. MDA, LRA).

2.1. Relevance of Financial Reports for Bankruptcy Literature

Financial reports are prime indicators of business performance of an enterprise. The external and internal users depend on the financial reports to take business decisions to optimize their respective interests in the business firms. Due to recent several corporate scandals the financial reports reliability and dependability has been questioned and criticized in corporate world. These incidents drawn close scrutiny, review and restructure of financial standards, corporate laws by Government authorities. During 2002 US government has introduced Sarbanes–Oxley (SOX) Act to curtail the corporate corruption and regulate the corporations. As a result of SOX, top management must now individually certify the accuracy of financial information. In addition, penalties for fraudulent financial activity are much more severe. Also, SOX increased the independence of the outside auditors who review the accuracy of corporate financial statements, and increased the oversight role of boards of directors. The bill was enacted as a reaction to a number of major corporate and accounting scandals including those affecting Enron, Tyco International, Adelphia, Peregrine Systems and WorldCom. These scandals, which cost investors billions of dollars when the share prices of affected companies collapsed, shock public confidence in the nation's securities markets (Anon 2013b).
As per Keiso et al (1992) financial reports are useful to the investors and creditors and other users in decision making process and should be comprehensive to those who have a reasonable understanding of business and economic activities. Financial reports should provide information to help investors, creditors, and others assess the amounts, timing, and uncertainty of prospective cash flows. Financial reports also should provide information about the economic resources of an enterprise, the claims to those resources and the effects of transactions that changes its resources and claims to those resources. In a nutshell the main objectives of financial reporting are to provide information that is useful in investment and credit decisions, information that is useful in assessing cash flow prospects, and information about enterprise resources, claims to those resources and changes in them (Keiso et al 1992).

Agarwal (2008) criticized the validity of the bankruptcy prediction models due to the very nature of the Financial Statements on which these models are based on. The author expressed his concern that accounting statements only reflects the past performance of a firm and may or may not be effective in predicting the future. Furthermore the conservatism and historical cost accounting do not reflect the current value of an asset and may have substantial variation from the recorded book value. Accounting records are also subject to manipulation and due to the fact that the accounting statements are prepared based on going-concern basis, they are by design has limited capability in predicting bankruptcy (Hillegeist cited in Agarwal (2008)). Altman 1993, indicated that academicians seems to be moving away from the Financial Reports as a dependable tool for the corporate decision making and theorist downgraded the dependability of Financial ratios which are widely used by the practitioners. The relevance of ratio analysis has been criticised by many scholars indicating their weakness in the case Financial ratios are used as “Nuts and Bolts” instead of being used as an integrated part of a complete corporate mechanism. This approach of using the financial ratios also handicapped the usefulness of this useful tool. Altman 1993, suggested that instead of moving away from using the financial ratios, using the financial ratios in combination with rigorous statistical analytical techniques can bring more accurate outcome instead of solely depending on the Financial ratios as standalone basis.

2.2. Previous Researches on Bankruptcy Prediction Models

Bankruptcy and insolvency have been well-researched for the last several decades by reputed researchers in developed countries (Beaver, Altman, Wilcox,Deakin, Ohlson, Taffler, Boritz, Kennedy & Sun, cited in Wang et al. 2010). A variety of models have been developed by them using techniques such as Multiple Discriminant Analysis (MDA), Logistics Regression Analysis (LRA), Probit, Recursive partitioning, Hazard models, and Neural networks (Wang et al. 2010). Although a variety of models are available the business community and researchers rely on the models developed by Altman (1968) and Ohlson (1980) (Boritz cited in Wang et al.2010). Survey shows that the majority of international failure prediction research employs MDA (Altman, Charitou, Neophytou & Charalambous cited in Wang et al. 2010). Beaver (cited in Wang et al. 2010) presented empirical evidence that certain financial ratios, more specifically cash flow/total debt, gave statistically significant signals well before actual business failure. Altman (1968) extended Beaver’s (1966) analysis by developing a discriminant function which combines ratios in a multivariate analysis. Altman initially selected twenty-two (22) ratios based on past studies. He classified those variables into five categories including liquidity, profitability, leverage, solvency and activity. Although as per Beaver 1966, the Cash flow to Debt ratio was the best single ratio Altman excluded this ratio due to lack of precise depreciation data. Altman finally selected five (5) ratios out of these ratios. Altman followed the following procedures to select his final ratios.

1) Analysis of relative contribution of the ratios
2) Correlation analysis of the ratios
3) Predictive accuracy
4) Judgement of the analysts.

(Wang et al. 2010: 76-77).
The Discriminant function of Altman (1968) is as follows: -
Z = .012X1 + .014X2 + .033X3 + .006X4 + .999X5
Where,
X1=Working capital/Total assets,
X2 = Retained Earnings/Total assets,
X3=Earnings before interest and taxes/Total assets, X4= Market value equity/Book value of total debt, X5 = Sales/Total assets,
Z = Overall Index
As per Altman (1993), the first modern analysis of corporate bankruptcy has been carried out by Beaver (1966). Beaver defined failure as the firm's inability to pay the firms current liabilities as they mature. He classified the bankrupted and non-bankrupted firms as per industry and asset size. Beaver conducted three empirical analysis as follows:-
1) Profile analysis
2) Dichotomous Classification test
3) Likelihood ratio analysis
Beaver found predictable difference in the mean values for each of the six ratios in all five years before the bankruptcy takes place. Moreover the bankrupted firms indicated a progressive indication of deterioration of ratios as the company was approaching the bankruptcy year. Contrarily the non-bankrupted companies ratios were relative constant for all the years. The dichotomous classification test involve two categorical variables i.e. bankrupted or non- bankrupted. He selected 30 ratios and arranges in ascending order, then he visually examined each pair of arrays to find the cut-off point that minimize the percentage of incorrect prediction. Beaver used the likelihood ratios to examine the overlap, skewness, and normality of the ratio distribution.

Table (I): Bankruptcy Prediction Research Summary in USA (Charitou, 2004:469-470)

Researchers (Year of Publication)	Technique Used	Period Studied	YPTF used	Estimation Sample
Beaver (1966)	Univariate	1954-64	5	79/79
Beaver (1968)	Univariate	1954-64	5	51/62
Altman (1968)	MDA	1946-65	5	33/33
Deakin (1972)	Univariate, MDA	1964-70	5	32/32
Edmister (1972)	Zero–one regression	1954-69	3	42/42
Blum (1974)	MDA	1954-68	8	115/115
Elam (1975)	Univariate, MDA	1966-72	5	48/48
Wilcox (1973, 1976	Linear gambler's-ruin score	1955-75	5	52/52
Diamond (1976)	MDA	1970-75	3	75/75
Altman et al. (1977)	MDA	1962-75	5	53/58
Deakin (1977)	MDA	1964-71	2	63/80
Dambolena and Khoury (1980)	MDA	1969-75	5	46/46
Ohlson (1980)	Logit	1970-76	3	105/2058
Zavgren (1982)	Logit	1972-78	5	45/45
Casey and Bartczak (1985)	MDA, Logit	1971-82	5	60/230
Gentry et al. (1985)	Logit	1970–81	3	33/33
Gentry et al. (1987)	Probit	1970–81	3	33/33
Platt and Platt (1990)	Logit	1972-87	1	57/57
Gilbert et al. (1990)	Logit	1974-83	1	52/208
Tennyson et al. (1990)	Logit	1978-80	2	23/23
Baldwin and Glezen (1992)	MDA	1977-83	upto six quarter	40/40
Aly et al. (1992)	MDA, Logit	1979-87	3	26/26
Ward (1994)	Logit	1988-89	3	14/37
Johnsen and Melicher (1994)	Multinomial logit	1970-83	1	112/255**/293
Platt et al. (1994)	Logit	1982-88	1	35/89
Wilson and Sharda (1994)	MDA, NNs	1975-82	1	41/ 4099
Boritz et al. (1995)	Logit, NNs	1971-84	1	80:20 %
Barniv et al. (2002)	Ordered logit	1980-92	-	49 (acquired) 119 (emerged) 69 (liquidated)

YPTF= Years examined prior to failure

One of the most common characteristics of the previous bankruptcy prediction research is that majority of the research has been done based on the financial ratios and financial data. Smith and Winakor cited in Altman 1993 argued that bankrupted firms indicate a significantly different ratio measurements than healthy firms. Beaver cited in Altman 1993: 181, "a number of indicators could discriminate between matched samples of failed and non-failed firms for as long as five years prior to failure".

According to Wu et al (2010),there are number of papers that propose various firm- characteristics that may be useful additional predictors of future bankruptcy. Rose cited in Wu et al (2010), proposed a model of diversification for the firms where diversification is used to reduce the risk of bankruptcy, particularly where the ratio of the firm-specific human capital to non-firm specific human capital is high. Denis cited in Wu et al (2010), measures firm diversification by the number of segments in the firm. Beaver cited in Wu et al (2010) argued that everything remains same the large firms have a less probability of bankruptcy than that of smaller counter parts. Wu et al (2010) insisted on firm diversification and firm size are two important characteristics that are helpful to predict future bankruptcy.

A comparative analysis by Grice (2001), of Ohlson's model and Zmijewski's model indicates that that Models developed using firms from one set of industries may not be highly accurate in predicting bankruptcies for firms in other industries. Above findings indicated that the use of Ohlson's model to predict financial distress for non-industrial companies is questionable. Consequently, applications of this model to non-industrial companies should be viewed cautiously. On the other hand, Zmijewski's (1984) model was not sensitive to industry classifications for the samples used in his research. This indicates that Zmijewski and Ohlson models are more suitable for predicting financial distress instead of predicting bankruptcy. Although these models were constructed for bankruptcy prediction, the models are capable of predicting financial distress than bankruptcy. Analysts who use these models to identify bankrupt companies use them carefully because all distressed firms will not declare bankruptcy (Grice 2001).

A large number of research works has been conducted on the bankruptcy prediction and financial distress forecasting. Although these research works have established certain generalizations regarding the performance of the models, the application of these models for assessing bankruptcy potential is still questionable. In most of the cases the methodology was univariate and individual indicators were considered as important indicators of upcoming problems. Ratio analysis presented in this way was subject to faulty outcome and was confusing. A firm with poor financial performance may be classified as potentially distressed firm (Altman 1968).

2.3. Review of Bankruptcy Predictor variables

Lin et al 2011, argued that different financial features used for predicting bankruptcy may yield different prediction results and most of the features emphasize finance ratios, such as long term capital, current ratio, inventory turnover, EPS and debt coverage stability, fixed asset turnover, profit growth rate, revenue per share, net profit growth rate before tax and after tax, etc. (Min, Lee, Shin cited in Lin et al 2011). Altman (1968) selected 5 financial ratios i.e. Working Capital/Total Assets, Retained Earnings/Total assets, Earnings before interest and taxes/Total assets, Market value equity/Book value of total debt, Sales/Total assets. Beaver (1966) selected 30 ratios which were divided into six "common element" groups. Only one ratio from each group has been selected as a focus for the analysis. Ohlson (1980) utilized nine different features including firm size.

The single financial feature used to discern the firms would show some variability, because different predicting directions and capabilities with regard to finance ratios, along with conflicting results, lead to widely different predictions. In the case an integrated combination of all significant predicted variables could be created it would reduce the quantity of variables necessary (Lin et al 2011).

In this paper seven ratios are finally selected and used for constructing the bankruptcy prediction models and further analysing the classification accuracy. These ratios are selected based on their popularity by previous bankruptcy prediction researchers as follows(Jayadev 2006): -

1) **Retained Earnings/Total Assets:**- This ratio indicates the degree of capitalization made through income generated and retained in the company. Although higher ratio indicates better financial health of the company the younger firms are expected to have relatively lower ratio.

2) **Shareholders' Equity/Total Debt: -** Debt-equity ratio is the relationship between total debt and net worth of the company and It is a standard form of expression of financial risk. High ratio indicates that the entity is managed by debt funds instead of equity funds. This ratio has great implication for the credit agency grading of its long-term loans i.e. Bonds issued to the market. The more the company is dependent on external loan the credit rating degrades accordingly.

3) **Total Liabilities/Net Worth**: - This ratio is important for determining the credit risk, whether the net worth of a firm is sufficient to meet its total debt obligations.

4) **Cash Flow from Operations/Total Assets: -** Cash flow from operations to total asset ratio is an important indicator for short term financial management efficiency of a company.

5) **Working capital/ total assets: -** The ratio measures the net liquid assets relative to total assets.
6) **Earnings before interest and taxes/ total assets: -**This is simple benchmark of profitability of a firm which evaluates the how much profit the company is making investing a certain amount of assets.
7) **Sales/ total assets: -**This ratio measures the revenue generation capacity of a company utilizing its exiting infrastructural support i.e. assets.

2.4. Review of Statistical Techniques

The researchers used different statistical methods such as Multiple Discriminant Analysis (MDA) (Altman, Beaver, Chuvakhin cited in Lin et al 2011) and Logistics Regression Analysis (LRA) (Ohlson, Zmijewski cited in Lin et al 2011). Due to technological break through the computer technology is widely used in the business prediction and applying complex algorithms in analysing huge data sets became handy and easy. Beside MDA and LRA there are new algorithms such as the Decision Tree (DT) (Tam cited in Lin et al 2011), Neural Network (Lee, Han, Ozkan-Gunay, Tam cited in Lin et al 2011) and Support Vector Machine (SVM) (Chandra, Ravi, Bose, Chen, Ding, Song, Hua, Wang, Xu, Zhang, Liang, Shin, Wu, Tzeng, Goo cited in Lin et al 2011) are used. Recently more sophisticated Case-Based Reasoning (CBR) models are developed that includes the CBR with several classifiers (Li cited in Lin et al 2011), OR- CBR (Li, Sun cited in Lin et al 2011) and ranking-order CBR (Li cited in Lin et al 2011).

2.4.1. Multiple Discriminant Analysis (MDA)

According to Altman (1993) MDA is a statistical method used to classify an observation into one of several predicting groupings depending on the characteristics of individual observation. MDA is used mainly in the case of dependent variable appears in qualitative form i.e. male or female, bankrupt or non-bankrupt. Therefore the first step in MDA is to establish categorical group classification. After grouping is done the data are collected and MDA in its most simple form derives a linear equation which best discriminate between groups. If a particular firm has financial ratios which can be quantified for all the companies in the analysis, the MDA determines a set of discriminant coefficients and these coefficients when applied to the real life financial ratios a basis for categorization into one of the mutually exclusive groupings occurs. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms and the collaboration of these properties. On the other hand a univariate study can consider only the measurements used for group assignments one at a time.

As per Altman (1968), although MDA was not a popular regression analysis, it has been used in different disciplines mainly in the biological and behavioural sciences since its first application in the 1930's. More recently MDA had been applied successfully to financial problems like consumer credit evaluation and investment classification. Walter cited in Altman (1968), utilized MDA model to classify high and low price earnings ratio firms and Smith cited in Altman (1968) used MDA model to classify standard investment categories.

Primary advantage of MDA in dealing with classification problems is its capability of analysing the whole variable profile of the object simultaneously rather than sequentially. As linear and integer programming have been developed from traditional techniques in capital budgeting, the MDA technique also has potential to reformulate the problem correctly from traditional ratio analysis. The combinations of ratios can be analysed together in order to eliminate ambiguities and misclassifications seen in traditional studies (Altman 1968).

Altman (1993) mentioned that MDA has another strength that it decreases the number of different independent variables to G-1 dimension (s), where G equals the number of original priori groups. This analysis is concerned with two groups, bankrupted and non-bankrupted. Therefore, the analysis is converted into a simple form: one dimension.

The discriminant function, Z= V1 X1 + V2 X2 + V3 X3 +------------+ Vn Xn converts the individual variable value to a single discriminant value, or Z score which is then used to classify the object.
Where, V1, V2,............., Vn = discriminant coefficients,
and X1, X2,...............Xn = independent variables
The Multiple Discriminant Analysis calculates the discriminant coefficients, V1, and the independent variables X1 are the actual values of the model and j =1,2,.........,n.

According to Ohlson (1980) although MDA was a popular technique for bankruptcy research using vectors of predictors, there are weaknesses of MDA. In MDA some statistical requirements are enforced on the distributional properties of the predictors i.e. the variance- covariance matrices of the predictors must be equal for both the groups. Furthermore, a necessity of normally distributed predictors reduces against the use of dummy independent variables. These conditions are not very important if the only purpose of the model is to develop a discriminating device. The output of a MDA model is a score which has minimal intuitive interpretation due to it is an ordinal ranking device. Further there are certain problems related to the "matching" procedures which are used in MDA. Bankrupted and healthy firms are matched according to criteria such as asset size, industry and these tend to be somewhat illogical (Ohlson 1980).

2.4.2 Logistics Regression Analysis (LRA)

Some researchers used Logistics Regression Model (Logit Model) in their research for predicting bankruptcy (Ohlson 1980, Zavgren1985, Charitou 2004). Press and Wilson cited in Aziz et al 1988, mentioned that Logistic Regression Analysis (LRA) is theoretically more appealing than the Multiple Discriminant Analysis (MDA) when dependent variables are binary or dichotomous, LRA has been recommended by Ohlson (1980) for bankruptcy prediction (Aziz et al 1988).

Zavgren (1985), in her research paper identified that conditional probability models estimate the probability of occurrence of a choice or outcome; they depend on the attribute vector of predictor variable to estimate the probability of the occurrence. LRA model was initially developed by a biologist (Finney cited in Zavgren 1985) which can assess the probability of commercial distress also. Conditional probability models estimate the probability of a dichotomous dependent variable by using coefficients on the predictor variables. These coefficients can be interpreted as the effect of a unit change in a predictor variable on the probability of the dependent variable. A cumulative probability distribution is required to constrain the result of the analysis within the acceptable limit (0 or 1) values of probability distributions. Therefore in the case the logistic function is used this constitutes the Logit model (Zavgren 1985).

As per Field (2009) in logistics regression the probability of outcome of Y event occurrence is predicted instead of predicting the value of this variable. The logistic regression equation has many similarities to the linear regression equations. When there is only one predictor variable X1, the logistic regression equation from which the probability of Y is predicted is given by in which P(Y) is the probability of Y occurring and (exp) is the base of natural logarithms, and the other coefficients form a linear combination the same way as in simple regression. The bracketed portion of the equation is similar to the linear regression equation where the constant is (β0), predictor variables (X1, X2,...... Xs) and coefficients attached to those predictors are (β1 ,β2,...... βs).

As per Dielman (cited in Charitou 2004) the Logit model uses the coefficients of the predictor variables to predict the probability of occurrence of a dichotomous dependent variable. For predicting bankruptcy this technique weighs the financial ratios and yields a score for each firm to classify as either failed or non-failed.

The logit model can be written as follows:-

$$P_{jt}(Y=1) = \frac{1}{(1+e^{-z})} = \frac{1}{1 + exp - \left(\beta_0 + \beta_1\, X_{1,jt} + \beta_2\, X_{2,jt} + \;---\; + \beta_n\, X_{n,jt}\right)}$$

Where,

$P_{jt}(Y=1)$ = Probability of failure for entity j at the end of year t;

exp = exponential function;

$\beta_1\,,\beta_2\;---\;\beta_n$ = Slope coefficients;

$X_1,\; X_2 ---\; X_n$ = Predictor variables

The critical value used for classifying firms between the two groups was set to the default value of 0.50, which presumes an equal probability of group membership (Charitou 2004).

Zavgren (1985) states that deciding between discriminant analysis or a conditional probability model depends mainly on the intended use. Dichotomous classification requires only discriminant analysis and this dichotomous partition of the outcome space is less useful for an investor in capital stock, purchaser of bonds, or a banker making a commercial loan decision than a core evaluation of financial risk. Martin cited in Zavgren 1985, indicated that for many decisions the user may need to be capable of varying the levels of response to risk of failure. For example, when discussing the commercial loan noncompliance Chesser (cited in Zavgren 1985) observes that noncompliance not necessarily means that a borrower will completely default on his loan but rather that some special agreement have to be arranged which will result in settlement of the loan under conditions less favorable than those specified in the original agreement. The likelihood assessment of such an event makes possible some adjustments as risk-premiums in addition to the prevailing interest rates. Martin (cited in Zavgren 1985) used an alternative of discriminant analysis which uses a maximum likelihood estimation technique to assess probabilities. Using a logit model he tested the results of this estimation against the null hypothesis that the probability of failure is equal to the prior probability in the population. Martin found that both linear and quadratic discriminant functions had likelihood functions significantly lower than the null hypothesis. This means that the null hypothesis will provide a better probability estimate than either discriminant function. On the other hand the Logit model had a likelihood function significantly higher than the null hypothesis, which indicates the Logit model provided significantly better probability estimates from the same data (Martin cited in Zavgren 1985). Martin (cited in Zavgren 1985) indicated that although classification accuracy is high, the probabilities obtained from the discriminant function may be far from accuracy. When a population contains irregular proportions of groups the classification accuracy can be improved by increasing the size of the smaller group. It is not unusual that the use of a non-representative group will influence the results of discriminant analysis since most research studies used equal- sized matched samples (Martin cited in Zavgren 1985).

As demonstrated in the above literature review it is clear that the financial ratios are a useful tool for the corporate bankruptcy predication. The majority of the literature suggests that Financial statement and ratios are a crucial information for predicting of corporate distress. Most of the researchers started with a wide number of ratios and then they narrowed down the list to minimum number of ratios which they find indicating the corporate distress more clearly than others. The studies of Altman (1993) suggest that the financial ratios should be used along with statistical methods in order to achieve optimal result. Different researchers used different statistical methods for constructing the prediction models the MDA and LRA are the most commonly used statistical methods which are used in the construction of the models. As we can see from table-(I) that much of the bankruptcy research has been conducted analysed data from the 60s and 70s, our research study will contribute towards the effectiveness of financial ratios as it is based on the contemporary data and will reflect more recent effectiveness of the financial ratios contrary to the previous studies which has been conducted based on the old data.

III. Methodology

In this chapter we discussed the methodology adopted in this research study. In this study financial data ratios of bankrupted and non-bankrupted companies are used for 5 years period. Logistics regression analysis (LRA) is used as statistical analytical tool for constructing bankruptcy prediction models and further analysis of the model classification accuracy, fitness and effectiveness for predicting of bankruptcy status.

3.1.Selection of Predictor variables

The first step of our methodology is selecting predictive variables which is done based on previous research papers and literature review. In this study I used all the variables which were used by Altman (1968), in his research study except for the Market value of equity/ Total debt. This ratio has been replaced with Owner's Equity/ Total debt due to non-availability of the market value of the bankrupted firms in the Megent online database. The Owner's equity/ Total debt ratio and Total liabilities/ Net Worth ratio were selected which were used by Charitou (2004) in their research paper. Another important ratio the Cash-flow from operations/ Total assets ratio is selected which was used by Deakin (1972), and Ohlson (1980).

Table (II): Financial Ratios used as Predictor Variables

Sl. No.	Category	Variable Name	Variable Definition	Variable Symbol	Mentioned By
1	Financial Leverage	REAT	Retained Earnings/Total Assets	X_1	Altman (1968)
2	Financial Leverage	SEQDT	Shareholders' Equity/Total Debt	X_7	Charitou (2004)
3	Financial Leverage	TLNW	Total Liabilities/Net Worth	X_2	Charitou (2004)
4	Operating Cash flow	CFFOAT	Cash Flow from Operations/Total Assets	X_3	Deakin (1972), Ohlson (1980)
5	Liquidity	WCAT	Working Capital/Total Assets	X_4	Beaver (1966), Altman (1968)
6	Profitability	EBITAT	Earnings Before Interest & Taxes/Total Assets	X_5	Altman (1968)
7	Activity	SALEAT	Sales/Total Assets	X_6	Altman (1968)

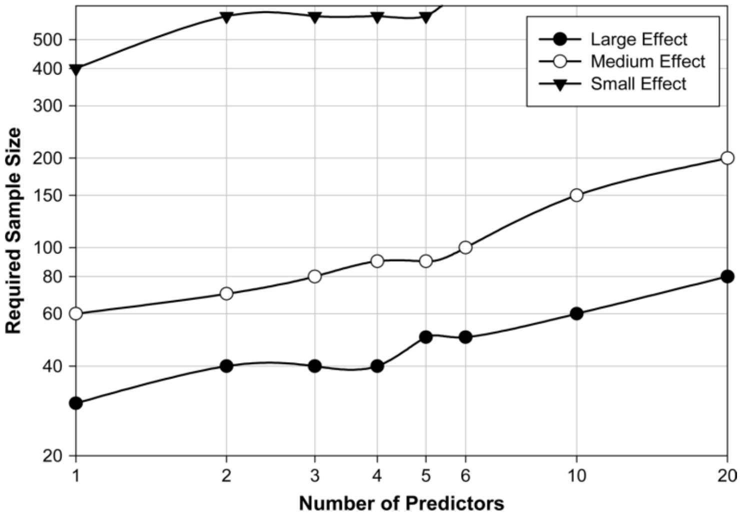


Figure 1: Graph to show the sample size required in regression depending on the number of predicator and size of expected effect (Miles and Shevlin cited in Field 2009: 223)

3.2. Study Population

Green (cited in Field 2009) suggested two rules of thumb for the minimum acceptable sample size, the first based on whether we want to test the overall fit of our regression model and the second based on whether we want to test the individual predictors. If we want to test the model overall, then it was recommended a minimum sample size of 50 + 8k, where k is the number of predictors. So, with five predictors, we would need a sample size of 50 + 40 = 90. If we want to test the individual predictors then it was suggested a minimum sample size of 104 + k, so again taking the example of 5 predictors you'd need a sample size of 104 + 5 = 109. Based on the above rules initially 50 bankrupted firms and 60 non-bankrupted firms have been selected. The selected number of bankrupted firms dropped to 39 firms and the number of non-bankrupted dropped to 50 due to non-availability of required financial data.

3.3. Selection of Bankrupted and Non-bankrupted firms

The most difficult task of data collection was finding a complete list of Bankrupted companies due to most of the bankrupted companies cease to operate and does not publish any more financial statements. The Mergent online database has been used in this research for collecting Bankrupted and Non-bankrupted company financial data. The firms which are showing as inactive in Mergent online database are presumed as bankrupted firms. In order to avoid lengthy and costly way to collect Bankrupted data from an authenticated authority like Dun & Bradstreet the bankrupted firms are selected which are showing as inactive and has available Financial data for at least 5 years period counting back word from year 2011 and the firms which are being inactivated on or before 2011. I also assumed that the latest financial available data is one year prior data from the actual bankruptcy date of the respective firms. Therefore it is assumed that the inactivated companies have issued their last Financial report one year prior to the actual bankruptcy date. The selected bankrupted firm's financial reports falls between year 1997 to 2011, therefore the selected companies bankruptcy dates will fall tentatively between year 1998 to 2012.

Initially fifty (50) bankrupted firms and sixty (60) non bankrupted firms were selected to use in this study. Due to non-availability of complete Financial reports eleven (11) firms were excluded from the bankrupted selected pool. Although the non-bankrupted firm Financial information is easy to collect ten (10) initially selected firms were excluded due to lack of financial information which is required to calculate the selected ratios. The Mergent online database was also mainly used for collecting the non-bankrupted company Financial data. Financial Institutions and Insurance companies have been excluded from the research data pool due to non-availability of essential elements for calculating the Financial ratios in these companies financial statements. The research geographical parameter has been limited within USA due to two main reasons, the companies operates under one corporate Law will give more uniform Financial information than companies operate under different taxation laws and corporate laws. Secondly the bankrupted company data is very difficult to obtain for other countries other than USA.

As suggested in the research paper of Peel (1988) in this study the financial year end, firm size, industry of the selected firms were not attempted to be matched.

3.4. Construction of Prediction Models

Takahashi et al 1984 in their research paper identified that the prediction models can be constructed and several different types of prediction models can be developed depending upon what financial statement data and indices are used as follows: -

a) Non-adjusted data or data adjusted to reflect the exceptions, reservations and/or qualifications appearing in the audit reports;

b) Accrual or cash base financial data indices;

c) Index values for three years before failure or only for the first year before failure

d) Ratios alone, or a combination of ratios and absolute amounts.

Theoretically, combination of (a), (b), (c), and (d) above could produce 16 different model types. The prediction models developed by Altman (1968) and Altman et al. (1977) are different in that the former uses financial statement data ratios for the first year before failure alone, while the later uses both financial statement data ratios and absolute amounts for more than one year before bankruptcy.

In this study I used Logistics Regression analysis in IBM SPSS software to construct the prediction models. The bankrupted firms financial ratios has been used in the analysis based on the last available report of the respective firms. Individual Logit model has been created using each of the years financial ratios and going back word 4 years from the last reporting year. The non-bankrupted Financial statements has been used for period 2008 to 2012 for a span of 5 years against the bankrupted companies financial data using the following matching principal: -

Table (III): Pairing of Financial Year data for Bankrupted and Non-bankrupted Firms

	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
	Year-t	Year t-1	Year t-2	Year t-3	Year t-4	5 Years pooled data
Bankrupted Financial Data	Last Reporting Year	One (1) year earlier than Last Reporting Year	Two (2) years earlier than Last Reporting Year	Three (3) years earlier than Last Reporting Year	Four (4) years earlier than Last Reporting Year	5 Years pooled data
Non-Bankrupted Financial Data	2012	2011	2010	2009	2008	5 Years pooled data

The 2012 financial data for non-bankrupted companies has been paired with the last reporting year data of bankrupted firms as exhibited in Exhibit-1. This way I find five (5) different sets of financial data for both bankrupted and non-bankrupted firms which have been plotted in the SPSS to construct prediction models. Further another set of financial data has been built using 5 years pooled ratios together assuming that all these financial data belongs to one single year. Each of the bankrupted and non-bankrupted company five years financial ratios (predictor variables) are then analysed in the SPSS software using the Binary Logistics Regression Analysis. From the SPSS output we find the coefficients (B Value) of the predictor variables to construct the bankruptcy prediction models. The SPSS outputs a set of coefficients for each year's financial ratios. The models are constructed using the B value of each year's SPSS output. The B value is the unstandardized beta, the S.E stands for standard error, Wald stands for each of the variables significance and the Exp (B) is the odd ratio which indicates the relationship of the predictor and the occurrence of the event. The coefficient (B Value) for each of these outputs has been formulated in the following equations to build the final models: -

Model-1 (Year-t)

SPSS output for Model-1 (Year-t) Logistics Regression Analysis

Classification Table[a]

Observed			Predicted: Bankruptcy Status: Non-bankrupted	Predicted: Bankruptcy Status: Bankrupted	Percentage Correct
Step 1	Bankruptcy Status	Non-bankrupted	46	4	92.0
		Bankrupted	7	32	82.1
	Overall Percentage				87.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	VAR00001	-2.558	1.122	5.196	1	.023	.077	.009	.699
	VAR00002	-.002	.008	.086	1	.770	.998	.982	1.013
	VAR00003	.741	1.273	.339	1	.561	2.097	.173	25.424
	VAR00004	-.398	1.736	.053	1	.819	.671	.022	20.166
	VAR00005	-11.620	4.348	7.142	1	.008	.000	.000	.045
	VAR00006	.070	.223	.098	1	.754	1.072	.693	1.659
	VAR00007	-.527	.914	.332	1	.564	.590	.099	3.539
	Constant	.309	.609	.258	1	.611	1.363		

a. Variable(s) entered on step 1: VAR00001, VAR00002, VAR00003, VAR00004, VAR00005, VAR00006, VAR00007.

$$P\,(Y) = \frac{1}{1 + exp - (.309 - 2.558\,X_1 - .002\,X_2 + .741\,X_3 - .398\,X_4 - 11.62\,X_5 + .070\,X_6 - .527\,X_7)}$$

Model-2 (Year t-1)

SPSS output for Model-2 (Year t-1) Logistics Regression Analysis

Classification Table[a]

Observed			Predicted: Bankruptcy Status: Non-bankrupted	Predicted: Bankruptcy Status: Bankrupted	Percentage Correct
Step 1	Bankruptcy Status	Non-bankrupted	43	7	86.0
		Bankrupted	11	28	71.8
	Overall Percentage				79.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	VAR00008	-3.111	1.068	8.479	1	.004	.045	.005	.362
	VAR00009	-.043	.043	.992	1	.319	.958	.881	1.042
	VAR00010	-1.984	2.085	.905	1	.341	.137	.002	8.188
	VAR00011	1.672	1.522	1.206	1	.272	5.323	.269	105.211
	VAR00012	-4.708	1.601	8.651	1	.003	.009	.000	.208
	VAR00013	-.011	.214	.002	1	.960	.989	.650	1.506
	VAR00014	-1.540	1.066	2.089	1	.148	.214	.027	1.730
	Constant	1.080	.715	2.283	1	.131	2.944		

a. Variable(s) entered on step 1: VAR00008, VAR00009, VAR00010, VAR00011, VAR00012, VAR00013, VAR00014.

$$P\,(Y) = \frac{1}{1 + exp - (1.080 - 3.111\,X_1 - .043\,X_2 - 1.984\,X_3 + 1.672\,X_4 - 4.708\,X_5 - .011\,X_6 - 1.54\,X_7)}$$

Model-3 (Year t-2)

SPSS output for Model-3 (Year t-2) Logistics Regression Analysis

Classification Table[a]

Observed			Predicted: Bankruptcy Status: Non-bankrupted	Bankrupted	Percentage Correct
Step 1	Bankruptcy Status	Non-bankrupted	45	5	90.0
		Bankrupted	8	31	79.5
	Overall Percentage				85.4

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	VAR00015	-.940	1.086	.750	1	.386	.390	.047	3.278
	VAR00016	-.060	.061	.951	1	.330	.942	.835	1.062
	VAR00017	-.353	1.021	.119	1	.730	.703	.095	5.199
	VAR00018	2.190	1.903	1.324	1	.250	8.935	.214	372.478
	VAR00019	-17.399	6.322	7.574	1	.006	.000	.000	.007
	VAR00020	.015	.256	.003	1	.955	1.015	.615	1.674
	VAR00021	-1.480	.976	2.300	1	.129	.228	.034	1.541
	Constant	1.371	.689	3.956	1	.047	3.938		

a. Variable(s) entered on step 1: VAR00015, VAR00016, VAR00017, VAR00018, VAR00019, VAR00020, VAR00021.

$$P\ (Y) = \frac{1}{1 + exp - (1.371 - .94\ X_1 - .060\ X_2 - .353\ X_3 + 2.19\ X_4 - 17.399\ X_5 + .015\ X_6 - 1.48\ X_7)}$$

Model-4 (Year t-3)

SPSS output for Model-4 (Year t-3) Logistics Regression Analysis

Classification Table[a]

Observed			Predicted: Bankruptcy Status: Non-bankrupted	Bankrupted	Percentage Correct
Step 1	Bankruptcy Status	Non-bankrupted	44	6	88.0
		Bankrupted	14	25	64.1
	Overall Percentage				77.5

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	VAR00022	-1.597	.899	3.152	1	.076	.202	.035	1.180
	VAR00023	-.063	.068	.852	1	.356	.939	.821	1.073
	VAR00024	-8.754	5.133	2.909	1	.088	.000	.000	3.692
	VAR00025	2.801	1.681	2.775	1	.096	16.454	.610	443.921
	VAR00026	-4.009	3.931	1.040	1	.308	.018	.000	40.284
	VAR00027	-.009	.248	.001	1	.970	.991	.609	1.612
	VAR00028	-.103	.273	.142	1	.707	.902	.528	1.542
	Constant	.564	.610	.853	1	.356	1.757		

a. Variable(s) entered on step 1: VAR00022, VAR00023, VAR00024, VAR00025, VAR00026, VAR00027, VAR00028.

$$P(Y) = \frac{1}{1 + exp - (.564 - 1.597\ X_1 - .063\ X_2 - 8.754\ X_3 + 2.801\ X_4 - 4.009\ X_5 - .009\ X_6 - .103\ X_7)}$$

Model-5 (Year t-4)

SPSS output for Model-5 (Year t-4) Logistics Regression Analysis

Classification Table[a]

Observed			Predicted		
			Bankruptcy Status		Percentage Correct
			Non-bankrupted	Bankrupted	
Step 1	Bankruptcy Status	Non-bankrupted	44	6	88.0
		Bankrupted	9	30	76.9
	Overall Percentage				83.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	VAR00029	-2.064	.909	5.163	1	.023	.127	.021	.753
	VAR00030	-.045	.056	.648	1	.421	.956	.857	1.066
	VAR00031	-4.119	3.016	1.866	1	.172	.016	.000	6.000
	VAR00032	3.039	1.429	4.519	1	.034	20.879	1.268	343.883
	VAR00033	-.574	2.222	.067	1	.796	.563	.007	43.852
	VAR00034	.004	.157	.001	1	.980	1.004	.738	1.367
	VAR00035	-.217	.309	.494	1	.482	.805	.440	1.474
	Constant	.150	.432	.121	1	.728	1.162		

a. Variable(s) entered on step 1: VAR00029, VAR00030, VAR00031, VAR00032, VAR00033, VAR00034, VAR00035.

$$P(Y) = \frac{1}{1 + exp - (.150 - 2.064\,X_1 - .045\,X_2 - 4.119\,X_3 + 3.039\,X_4 - .574\,X_5 + .004\,X_6 - .217\,X_7)}$$

Model-6 (5 year's pooled data)

SPSS output for Model-6 (5 year's pooled data) Logistics Regression Analysis

Classification Table[a]

Observed			Predicted		
			Bankruptcy Status		Percentage Correct
			Non-bankrupted	Bankrupted	
Step 1	Bankruptcy Status	Non-bankrupted	218	32	87.2
		Bankrupted	61	134	68.7
	Overall Percentage				79.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	VAR00001	-2.634	.377	48.917	1	.000	.072	.034	.150
	VAR00002	-.019	.013	2.279	1	.131	.981	.957	1.006
	VAR00003	-.661	.481	1.887	1	.170	.516	.201	1.326
	VAR00004	2.247	.663	11.475	1	.001	9.457	2.577	34.697
	VAR00005	-3.902	.737	28.021	1	.000	.020	.005	.086
	VAR00006	.003	.088	.001	1	.970	1.003	.844	1.193
	VAR00007	-.407	.197	4.272	1	.039	.666	.453	.979
	Constant	.236	.207	1.305	1	.253	1.266		

a. Variable(s) entered on step 1: VAR00001, VAR00002, VAR00003, VAR00004, VAR00005, VAR00006, VAR00007.

$$P(Y) = \frac{1}{1 + exp - (.236 - 2.634\,X_1 - .019\,X_2 - .661\,X_3 + 2.247\,X_4 - 3.902\,X_5 + .003\,X_6 - .407\,X_7)}$$

Solving these equations using respective actual ratios of a firm indicates whether the firm belongs to Bankrupted or Non-bankrupted group. The result of these equations either yields Zero (0) for the Non-bankrupted firms or one (1) for the Bankrupted firms which is the indication whether they belongs to bankrupted group or non-bankrupted group. Using the same methodology, the analysts can use these models effectively to classify the failed and non-failed firms with reasonable accuracy.

IV. Empirical Analysis and Results

In this chapter the results of this study is analysed using the methodologies described in the earlier chapter. In this study 39 bankrupted firms and 50 non-bankrupted firms has been finally selected for building up of the prediction models and further the statistical outputs has been analysed to answer the research question.

The logistics regression analysis output indicates three major benchmark of the models and the predictor variables as follows:-

1) Classification Accuracy of models
2) TheModel'sfitness
3) The predictor variable's significance

4.1. Classification Accuracy of the Constructed models

The classification accuracy is the most easy-to-understand bench mark of the models effectiveness. Table (IV) as below shows the classification accuracy of different models which indicates different classification accuracy capability of the models. As we can see the null model before adding any predictor variable shows an uniform outcome of 56.18% which indicates that the models can predict the bankruptcy status of a firm with 56.18% accuracy.

Table IV: Logistics Regression Models Classification Accuracy Assessment (SPSS output)

Logit Models	Classification Accuracy (Null Model)	Classification Accuracy (Predictor Variable Model)	Classification Accuracy Improvement Due to Addition of Predictor Variables	% Improvement from Baseline
Model-1	56.18	87.64	31.46	56%
Model-2	56.18	79.78	23.60	42%
Model-3	56.18	85.39	29.21	52%
Model-4	56.18	77.53	21.35	38%
Model-5	56.18	83.15	26.97	48%
Model-6	56.18	79.10	22.92	41%

After the predictor variables are introduced in the models the classification accuracy has been improved dramatically with a maximum accuracy improvement of 31.46% occurred for the model-1 and the lowest improvement of 21.34% in classification accuracy occurred for the model-4. Apparently, the Table (VI) indicates that there is a substantial improvement of the predicative capacity of the models ranging from 56% to 38% depending on the year of data used to construct the models.

4.2. Classification Accuracy Test using secondary data:-

The constructed models are now being tested on secondary data using 5 years' same ratios. In this stage another 35 bankrupted and 30 non-bankrupted firms secondary financial data for 5 years are collected from the Mergent online database. Finally out of those 65 bankrupted and non-bankrupted firms, I was able to find usable data for 27 bankrupted companies and 29 non- bankrupted companies. In this second time data collection the same matching principal has been used demonstrated in table (III). The same seven ratios are calculated from these financial data in order to test the prediction models.

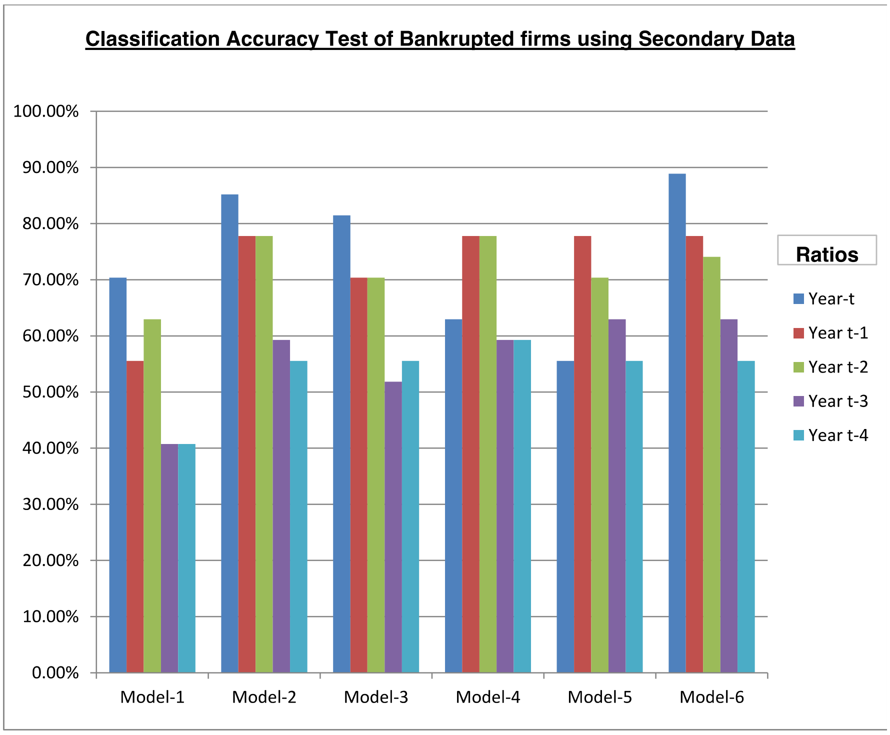
4.2.1. Bankrupted firms Classification Accuracy

The classification accuracy for the bankrupted firms are demonstrated in table(V), where Model- 1 shows maximum classification accuracy of 70.37% for the year before the bankruptcy (Year t). The classification accuracy has been declined to 40.74% for this model progressively and consistently for the earlier years till the 5th year prior to the bankruptcy (year t-4). The model-2, year t classification accuracy is more than model-1 which is 85.19% and also progressively declined to 55.56% for the year t-4. The model-3 classification accuracy for the year t is less than model 2 but more than model-1 which is 81.48%. The classification accuracy for model-3 also shows a consistent decline as we go back word till year t-4. The model-4 classification accuracy sustains only 62.96% which increases in year t-1 and t-2 and again declined for year t-3 and t-4 till 59.26%. Interestingly the model-5 year t and year t-4 shows same classification accuracy of 55.56%, for model 5 the middle year's classification accuracy shows increase in the year t-1 and further decline till year t-4. Model-6 which was constructed using the 5 year's pooled data shows the highest accuracy of all the models with accuracy of 88.89% for the year t. For model-6 the other year's accuracy also declines consistently till 55.56%. The analysis clearly indicates that the models are able to predict the bankruptcy more accurately for year t (1 year prior to the bankruptcy) than for year t-4 (5th year prior to the bankruptcy). This indicates that the most recent data prior to the bankruptcy plays an important role in business crisis prediction and the importance diminishes progressively as the earlier year's data is applied going back word till year t-4. The above analysis also indicates that the pooled data constructed model, model-6 is able to predict the bankruptcy with maximum accuracy on the year before the bankruptcy event takes place.

Table V: Classification Accuracy Test for Bankrupted firms using secondary data

Ratios used / Models used		Year-t	Year t-1	Year t-2	Year t-3	Year t-4
Model-1	Bankrupted Firms classified as Bankrupted	19	15	17	11	11
	Bankrupted Firms classified as Non-bankrupted	8	12	10	16	16
	Classification Accuracy	**70.37%**	**55.56%**	**62.96%**	**40.74%**	**40.74%**
Model-2	Bankrupted Firms classified as Bankrupted	23	21	21	16	15
	Bankrupted Firms classified as Non-bankrupted	4	6	6	11	12
	Classification Accuracy	**85.19%**	**77.78%**	**77.78%**	**59.26%**	**55.56%**
Model-3	Bankrupted Firms classified as Bankrupted	22	19	19	14	15
	Bankrupted Firms classified as Non-bankrupted	5	8	8	13	12
	Classification Accuracy	**81.48%**	**70.37%**	**70.37%**	**51.85%**	**55.56%**
Model-4	Bankrupted Firms classified as Bankrupted	17	21	21	16	16
	Bankrupted Firms classified as Non-bankrupted	10	6	6	11	11
	Classification Accuracy	**62.96%**	**77.78%**	**77.78%**	**59.26%**	**59.26%**
Model-5	Bankrupted Firms classified as Bankrupted	15	21	19	17	15
	Bankrupted Firms classified as Non-bankrupted	12	6	8	10	12
	Classification Accuracy	**55.56%**	**77.78%**	**70.37%**	**62.96%**	**55.56%**
Model-6	Bankrupted Firms classified as Bankrupted	24	21	20	17	15
	Bankrupted Firms classified as Non-bankrupted	3	6	7	10	12
	Classification Accuracy	**88.89%**	**77.78%**	**74.07%**	**62.96%**	**55.56%**

Figure-2: Classification Accuracy Test of Bankrupted firms using Secondary Data



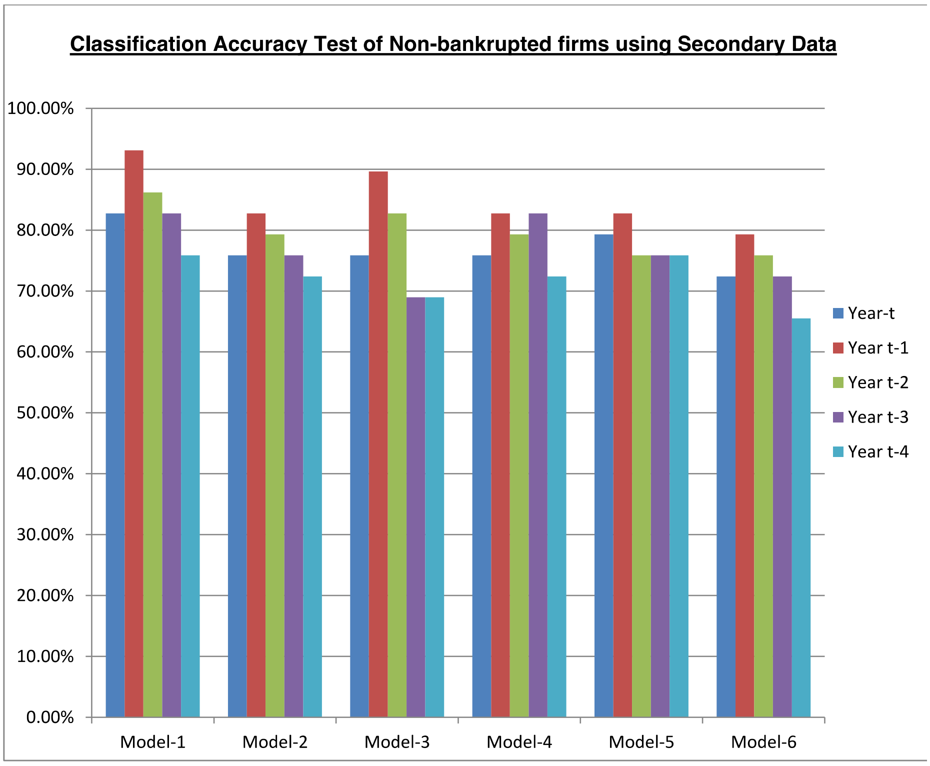
4.2.2. Non-bankrupted firms classification accuracy

The classification accuracy for non-bankrupted firm's is demonstrated in table-(VI), where it shows model-1 classification accuracy for year t is 82.76% which increases to 93.10% for year t-1 and then progressively declines till 75.86% for year t-4. The model-2 classification accuracy for year t shows 75.86% which increases to 82.76% for the year t-1 and later declined till 72.41% for year t-4. Model-3 and 4 also has same classification accuracy for year t and with similar trend the year t-1 classification accuracy increases for both the models and declined to 68.97% and to 72.41% respectively for year t-4. For the model-5 the year t classification accuracy is also ranked second highest likewise of other models. Model-5 subsequent 3rd, 4th and 5th year classification accuracy shows same percentage of 75.86%. Model-6 year t shows a classification accuracy of 72.41% which increases to 79.31% for year t-1 and further declines to 65.52% for year t-4. The analysis of non-bankrupted firms data indicates that all of our models are able to classify the non-bankrupted firms with a reasonable accuracy.

Table (VI) : Classification Accuracy Test for Non-bankrupted firms using secondary data

Ratios used / Models used		Year-t	Year t-1	Year t-2	Year t-3	Year t-4
Model-1	Non-bankrupted Firms classified as Non-bankrupted	24	27	25	24	22
	Non-bankrupted Firms classified as Bankrupted	5	2	4	5	7
	Classification Accuracy	**82.76%**	**93.10%**	**86.21%**	**82.76%**	**75.86%**
Model-2	Non-bankrupted Firms classified as Non-bankrupted	22	24	23	22	21
	Non-bankrupted Firms classified as Bankrupted	7	5	6	7	8
	Classification Accuracy	**75.86%**	**82.76%**	**79.31%**	**75.86%**	**72.41%**
Model-3	Non-bankrupted Firms classified as Non-bankrupted	22	26	24	20	20
	Non-bankrupted Firms classified as Bankrupted	7	3	5	9	9
	Classification Accuracy	**75.86%**	**89.66%**	**82.76%**	**68.97%**	**68.97%**
Model-4	Non-bankrupted Firms classified as Non-bankrupted	22	24	23	24	21
	Non-bankrupted Firms classified as Bankrupted	7	5	6	5	8
	Classification Accuracy	**75.86%**	**82.76%**	**79.31%**	**82.76%**	**72.41%**
Model-5	Non-bankrupted Firms classified as Non-bankrupted	23	24	22	22	22
	Non-bankrupted Firms classified as Bankrupted	6	5	7	7	7
	Classification Accuracy	**79.31%**	**82.76%**	**75.86%**	**75.86%**	**75.86%**
Model-6	Non-bankrupted Firms classified as Non-bankrupted	21	23	22	21	19
	Non-bankrupted Firms classified as Bankrupted	8	6	7	8	10
	Classification Accuracy	**72.41%**	**79.31%**	**75.86%**	**72.41%**	**65.52%**

Figure-3: Classification Accuracy Test of Non-bankrupted firms using Secondary Data



4.3. Ranking and Selection of best Constructed Model based on Classification Accuracy

The classification accuracy test on the secondary data as demonstrated in Table-(V) & (VI) shows that the most recent year's financial data plays a major role in financial prediction. The above analysis also shows that the ratio distributions of non-bankrupted firms are quite stable throughout the five years before failure. As per Table (V) the model-6 performs best to classify the bankrupted firms almost 89% for the year t which declines to 55.56% for year t-4. Further the Model-6 is able to classify the non-bankrupted firms with reasonable accuracy with a maximum accuracy of almost 80% for year t-1 which declines to 65.52% for year t-4.

As per table (V) and (VI) the Model-1 is the nearest competitor of Model-6 which is able to predict the bankruptcy with good accuracy for the Non-failed firms with a maximum accuracy of 93.10% for year t-1 which declines to 75.86% for year t-4. The Model-1 classification accuracy for bankrupted firm is poor which is maximum of 70.37% which declines till 40.74% for the year t-4 which placed the model-6 rank well below the rank of model-1.

Based on the above analysis the Model-6 shows best classification accuracy among all six prediction models for both bankrupted and non-bankrupted firms.

Therefore the following prediction model represents the best model out of all of the constructed models:-

$$P(Y) = \frac{1}{1 + exp - (.236 - 2.634\, X_1 - .019\, X_2 - .661\, X_3 + 2.247\, X_4 - 3.902\, X_5 + .003\, X_6 - .407\, X_7)}$$

Therefore the following prediction model represents the best model out of all of the constructed models:-

Where,

X_1 = Retained Earnings/ Total Sales

X_2 = Shareholders' Equity/Total Debt

X_3 = Total Liabilities/Total Net worth

X_4 = Cashflow from operations/Total Assets

X_5 = Working Capital/Total Assets

X_6 = Earnings before interest and taxes/Total Assets

X_7 = Sales/ Total Assets

4.4. Assessing the Model's fitness [Log-likelihood (-2LL statistics), R & R^2 s]

As mentioned by Field 2009, log-likelihood is an indicator of how much unexplained information remained after the model has been fitted, in other words log-likelihood value indicates the overall fit of the new model. Therefore larger values of the log-likelihood statistics indicate poorly fitted statistical models, because the larger the value of the log-likelihood, the more unexplained observations are left over. In the case a model is better fitted, the predictor variable inclusion in the model reduces the value of the -2LL comparing to the null model -2LL value.

Table (VII): Logistics Regression Models Fitness Assessment

Logit Models	-2 LL (Null Model) A	Chi-square B	-2 LL (Predictor Variable Model) (A-B)=C	-2LL reduction % (A-C)/A	Cox & Snell R^2	Nagelkerke R^2
Model-1	122.011	62.271	59.740	51%	0.503	0.674
Model-2	122.017	53.193	68.824	44%	0.450	0.603
Model-3	122.017	56.256	65.761	46%	0.469	0.628
Model-4	122.017	37.020	84.997	30%	0.340	0.456
Model-5	122.017	29.658	92.359	24%	0.283	0.380
Model-6	610.086	194.504	415.582	32%	0.354	0.475

Table (VII) shows a substantial drop in -2LL value from the null model -2LL value which indicates that the models predictive capacity improves due to the introduction of the predictor variables. The chi-square statistics measures the difference between the -2LL values before and after introduction of the predictor variables in the model. The table (VII) shows the maximum reduction percentage (51%) of the -2LL value for the model-1 which indicates that model-1 is the best fitted model and minimum reduction percentage (24%) of the -2LL value for the model-5 indicates that it is the poorest fitted model out of all of the six constructed models.

Before going to the analysis of the R^2, it would be worth to look at the relations between the different R^2. As per Field 2009, the multiple correlation coefficients R and the corresponding R^2-value are useful measures of how well the model fits the data. R-statistics is the partial correlation between the outcome variable and each of the predictor variables and it may vary from -1 to 1. Positive value of R-statistics indicates that as the predictor variable increases, the likelihood of the event occurring is also increases. The negative value indicates that as the predictor variable increased, the likelihood of the event occurring reduces. Further when a variable is having a smaller value of R then the variable contributes only a smaller amount to the model. The equation for Rs are as follows (Field 2009):-

$$R = \pm\sqrt{\left(\frac{\text{Wald} - (2 \text{ X df})}{-2\text{LL (Original)}}\right)}$$

Hosmer and Lemeshow's R_L^2 equation :-

$$R_L^2 = \frac{-2\text{LL (Model)}}{-2\text{LL (Original)}}$$

Cox and Snell's R_{CS}^2 equation:-

$$R_{CS}^2 = 1 - e^{\left[-\frac{2}{n}(\text{LL(new)}) - (\text{LL(Baseline)})\right]}$$

Nagelkerke's R_N^2 Equation:-

$$R_N^2 = \frac{R_{CS}^2}{1 - e^{\left[\frac{(2\text{LL(Baseline)})}{n}\right]}}$$

The Hosmer and Lemeshow'sR^2_L can vary from 0 (indicating that the predictor is useless at predicting the outcome of the variable) and 1 (indicating that the model predicts the outcome variable perfectly). However Hosmer and Lemeshow's $R^2_L$is not the measure can vary from 0 (indicating the predictor is useless used by SPSS rather SPSS uses Cox and Snell's R^2_{CS}which is based on the log- likelihood of the model (LL(New)) and the log-likelihood of the of the original model (LL(baseline)), and the sample size, n. Due to Cox and Snell's R^2_{CS}statistics never reaches its theoretical maximum of 1, Nagelkerke suggested that the Cox and Snell's R^2_{CS}should be amended as depicted in the above equation for Nagelkerke'sR^2_N .

As presented in Table (VII) the model-1 shows most significant and values of 0.674 and 0.503 which indicates that model-1 predicts the outcome variable most perfectly. On the other hand model-5 shows the lowest of all and values of 0.380 and 0.283 which indicates that model-5 predicts the outcome variable least perfectly. The model-2 and model-3 shows slightly less and values of 0.603 and 0.450 for Model-2 and 0.628 and 0.469 for model-3. This scores of R2 for model-2 and 3 indicates that the variables for these models are capable of predicting the variable outcome whether the firm is going to fail or not but comparatively with less accuracy than that of model-1. Further as we can see from table (VII) that model-4 and 6 R square scores show more value than that of model-5 outcome, therefore we can conclude that model-4 and model-6 is more capable of predicting the variable outcome more accurately than that of other models.

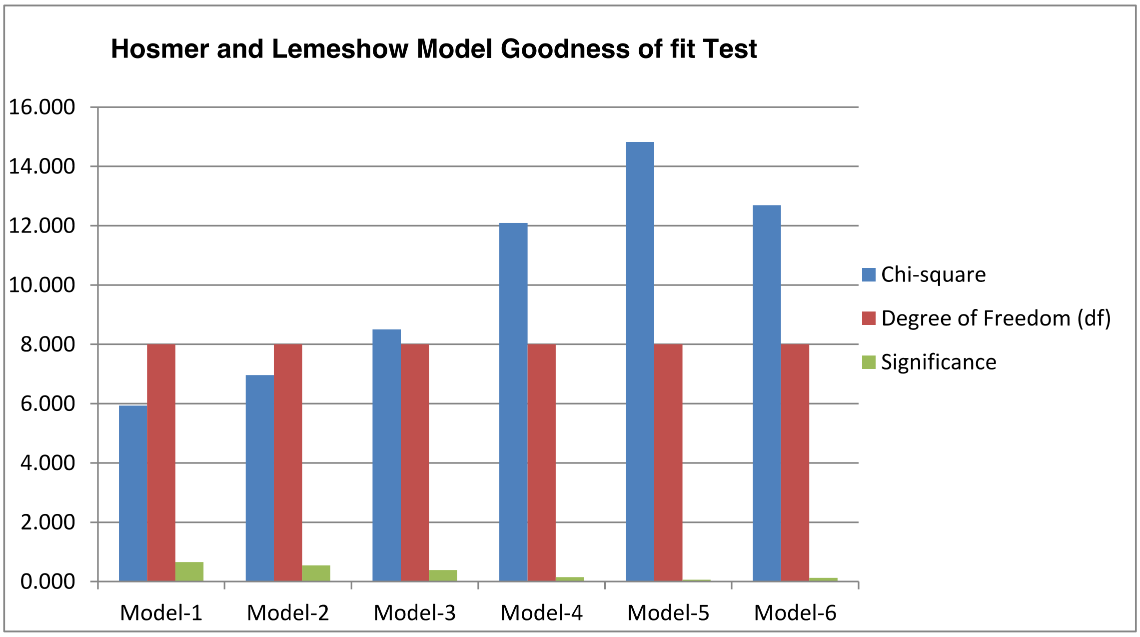
4.5. Hosmer and Lemeshow Goodness-of-Fit (GOF) Test

As per Hosmer (1991) the Logistic Regression model is being used more frequently in recent years than before. During 1989 over 30% of the articles published in the American Journal of Public Health used some form of Logistic regression modeling. Although Logistics Regression is used massively the assessment of the models are not done adequately which has a substantial risk of ending up with a faulty model. We therefore will apply the Hosmer and Lemeshow test in order to assess the goodness of fit for our model.

Figure 4: Chart of Hosmer and Lemeshow Model Goodness of fit Test

Table (VIII): Hosmer and Lemeshow Model Goodness of fit Test

MODEL	Chi-square	Degree of Freedom (df)	Significance
Model-1	5.934	8	.655
Model-2	6.960	8	.541
Model-3	8.499	8	.386
Model-4	12.092	8	.147
Model-5	14.817	8	.063
Model-6	12.695	8	.123



As illustrated in Table (VIII), the model 1 shows a significant (> .05) H-L significance is .655 which is good indication of goodness of fit of the model for predicting the observed data. The H- L significance for model-2 is lower than model-1 which is .541 indicates lower capability of fitness of the model for the observed data. Model-3 H-L significance is .386 which is rather more lower than both model-1 and 2 significance. The H-L significance of model-4 and 5 are less than the earlier models which is .147 and .063 respectively. Although the model-5 H-L significance is relatively very lower than the earlier models, it is above the threshold of .05 therefore this model is also capable of predicting the observed data with reasonable accuracy. The model-6 which was constructed based on pooled data is model with H-L significance of .123 which is above the threshold of .05. Therefore as per the Hosmer and Lemeshow Goodness-of-Fit Test all of our models are capable of predicting a significant number of data. Further analysing the Chi-square result for the six models indicates progressive increase in the chi-square score of the models starting from year t to year t-4. Both chi-square and the H-L significance indicates that the model-1 is the best model which is capable of predicting maximum number of observed data against the expected outcome.

4.6. Analysing the predictor variable significance [Unstandardised Beta Coefficient (B), Wald Statistics, Exponential Beta/ Odd Ratio (Exp(B)]:-

Unstandardised Beta Coefficient Analysis:-

The unstandardised beta coefficient analysis is very important outcome of Logistics Regression analysis because it indicates the estimates for the coefficients for the predictors included in the models. This output inform us the coefficients and statistics for the variables that have been included in the model (namely

Intervention and the constant). This b-value is the same as the b- value in linear regression: they are the values that we need to replace in equation to establish the probability that a case falls into a certain category. In linear regression the value of b represents the change in the outcome resulting from a unit change in the predictor variable. The interpretation of this coefficient in logistic regression is very similar in that it represents the change in the logit of the outcome variable associated with a one-unit change in the predictor variable. The logit of the outcome is the natural logarithm of the odds of Y occurring (Field 2009).
Table-(IX) shows the unstandardized beta coefficient for the respective predictor variables which determines the outcome of the equation whether the firm is belongs to bankrupted group (1) or belongs to non-bankrupted group (0).

Table (IX): Unstandardized Beta Coefficients of Predictor Variables

			Unstandardized Beta Coefficient (β)					
Variable Name	**Variable Definition**	**Variable Symbol**	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6
REAT	Retained Earnings/Total Assets	X_1	-2.558	-3.111	-0.940	-1.597	-2.064	-2.634
TLNW	Total Liabilities/Net Worth	X_2	-0.002	-0.043	-0.060	-0.063	-0.045	-0.019
CFFOAT	Cash Flow from Operations/Total Assets	X_3	0.741	-1.984	-0.353	-8.754	-4.119	-0.661
WCAT	Working Capital/Total Assets	X_4	-0.398	1.672	2.190	2.801	3.039	2.247
EBITAT	Earnings Before Interest & Taxes/Total Assets	X_5	-11.620	-4.708	-17.399	-4.009	-0.574	-3.902
SALEAT	Sales/Total Assets	X_6	0.070	-0.011	0.015	-0.009	0.004	0.003
SEQDT	Shareholders' Equity/Total Debt	X_7	-0.527	-1.540	-1.480	-0.103	-0.217	-0.407
	Constant		0.309	1.080	1.371	0.564	0.150	0.236

4.7. Wald Statistics Analysis:-

As per Field (2009) the Wald statistic tells us whether the b coefficient for that predictor is significantly different from zero. If the coefficient is significantly different from zero then we can assume that the predictor is making a significant contribution to the prediction of the outcome (Y). The Wald statistic is used to determine whether a predictor variable is a significant predictor of the event occurance; however, it is more accurate to examine the likelihood ratio statistics.

Menard cited in Field (2009), the Wald statistic should be used cautiously due to when the regression coefficient (b) is large, the standard error become inflated, which results underestimation of the Wald statistic. The increase of the standard error increases the probability of exclusion of a predictor variable as being significant when in reality it is making a significant contribution to the model.

Table (X): Wald Statistics Significance Analysis of Predictor Variables

		Wald Statistics					
Variable Name	**Variable Symbol**	**Model-1**	**Model-2**	**Model-3**	**Model-4**	**Model-5**	**Model-6**
REAT	X_1	5.196	8.479	0.750	3.152	5.163	48.917
TLNW	X_2	0.086	0.992	0.951	0.852	0.648	2.279
CFFOAT	X_3	0.339	0.905	0.119	2.909	1.866	1.887
WCAT	X_4	0.053	1.206	1.324	2.775	4.519	11.475
EBITAT	X_5	7.142	8.651	7.574	1.040	0.067	28.021
SALEAT	X_6	0.098	0.002	0.003	0.001	0.001	0.001
SEQDT	X_7	0.332	2.089	2.300	0.142	0.494	4.272

		Rankings					
REAT	X_1	2	2	5	1	1	1
TLNW	X_2	6	5	4	5	4	5
CFFOAT	X_3	3	6	6	2	3	6
WCAT	X_4	7	4	3	3	2	3
EBITAT	X_5	1	1	1	4	6	2
SALEAT	X_6	5	7	7	7	7	7
SEQDT	X_7	4	3	2	6	5	4

As per Table-(X), our predictor variables are showing different level of significance for different models. The Table-(X) ranking shows clearly that the variable X_5 (Earnings Before Interest & Taxes/Total Assets) shows the best significance for the model 1, 2 and 3; however the variable X_1 (Retained Earnings/Total Assets) shows the best significance for the model 4, 5 and 6. This indicates that for the model 1, 2 and 3 the Earning ratio is most important which can influence the prediction outcome of these respective models substantially. On the other hand for model 4, 5 and 6 the predictor variable X_1 is most significant which indicates that Retained earnings ratio has a substantial influence on the prediction outcome of these models. From table-(X) it is also visible that the variable X_6 (Sales ratio) is least significant for almost all the model therefore this variable has lowest importance for the predication outcome of these models.

4.8. Exponential beta/ Odd Ratio [EXP(B)] Analysis:-

The odds of an event occurring are defined as the probability of an event occurring divided by the probability of that event not occurring and should not be confused with the more colloquial usage of the word to refer to probability. This proportionate change in odds is the odds ratio, and we can interpret it in terms of the change in odds: if the value is greater than 1 then it indicates that as the predictor increases, the odds of the outcome occurring increase. Conversely, a value less than 1 indicates that as the predictor increases, the odds of the outcome occurring decrease (Field 2009).

Table (XI): Exponential Beta/ Odd Ratio[Exp (B)] Significance Analysis of Predictor Variables (Individual Significance of Variables when other variables are controlled)

		Odd Ratios					
Variable Name	**Variable Symbol**	**Model-1**	**Model-2**	**Model-3**	**Model-4**	**Model-5**	**Model-6**
REAT	X_1	0.077	0.045	0.390	0.202	0.127	0.072
TLNW	X_2	0.998	0.958	0.942	0.939	0.956	0.981
CFFOAT	X_3	2.097	0.137	0.703	0.000	0.016	0.516
WCAT	X_4	0.671	5.323	8.935	16.454	20.879	9.457
EBITAT	X_5	0.000	0.009	0.000	0.018	0.563	0.020
SALEAT	X_6	1.072	0.989	1.015	0.991	1.004	1.003
SEQDT	X_7	0.590	0.214	0.228	0.902	0.805	0.666

		Rankings					
REAT	X_1	6	6	5	5	6	6
TLNW	X_2	3	3	3	3	3	3
CFFOAT	X_3	1	5	4	7	7	5
WCAT	X_4	4	1	1	1	1	1
EBITAT	X_5	7	7	7	6	5	7
SALEAT	X_6	2	2	2	2	2	2
SEQDT	X_7	5	4	6	4	4	4

Table-(XI) demonstrates the odd ratios of the predictor variables which shows relationship of the predictor variable to the occurrence of the bankruptcy. Apparently the predictor variable X4 (Working Capital/Total Assets) shows the largest odd ratios which indicates that when this predictor variable increases the chance of the bankruptcy occurrence increases dramatically. On the other hand odd ratio of the predictor variable X5 (Earnings Before Interest & Taxes/Total Assets) is less than 1, which means that when this variable increases the chance of bankruptcy reduces.

4.9. Research Results

The classification accuracy test on the secondary data shows that our model is capable of predicting the bankruptcy with a reasonable accuracy. Furthermore our study also shows that the most recent year's financial data plays a major role in financial prediction which is in line with the research finding of Beaver (1966) and Altman (1968). The above analysis also endorses the finding of Beaver (1966) that the ratio distributions of non-bankrupted firms are quite stable throughout the five years before failure. The ratio distributions of the bankrupted firms exhibit a marked deterioration as failure approaches (Beaver 1966).

Based on the above we therefore can conclude that financial ratio is useful in the prediction of corporate bankruptcy. Our research also demonstrates that the most recent year's financial ratios are able to predict the bankruptcy more accurately than that of earlier years' ratios.

V. Discussion

5.1. Summary of Findings

This study examines the relevance of financial ratios in forecasting of corporate distress. The research outcome is in accordance with previous research outcomes of Altman (1968), Beaver (1966), Ohlson (1980) and many others who also find that financial ratio can effectively discriminate between failed and non-failed firms in the case the ratios are used in combination with statistical analysis. In this study seven selected financial ratios are used and 89 failed and non-failed firm's financial data has been analysed to construct the bankruptcy prediction model. The bankruptcy models shows significant accuracy in predicting of bankruptcy status of firms and able to classify the firms with reasonable rate of accuracy which ranges from 70% to 88%. Further the study scrutinized and identified most useful financial ratios which significantly influence the result of bankruptcy status outcome of a given firm.

The second question examines the time relevance of financial ratios for predicting corporate distress which also in line with previous research outcome of Altman (1968) and Beaver (1966). Altman 1968 mentioned that the early warning and trend implication "the observed ratios show a deteriorating trend as bankruptcy approaches and that the most serious change in majority of these ratios occurred between the third and second year prior to bankruptcy".

This study constructed six (6) predictive models which has different degree of predictive capacity. The model-1 which is created based on most recent financial ratios from the hypothetical bankruptcy dates show most consistent outcome. Model-1 also yields best classification accuracy when analysed on individual year's financial ratios. The model-6 which was constructed based on pooled data also show good level of classification accuracy. A comparative analysis shows that the model-6 is a better model in terms of capability of classification accuracy than that of model-1. Beside classification accuracy analysis the model fitness test, predictor variable assessment tests also given significant positive outcome.

5.2. Theoretical & Empirical Implications

Theoretical contribution

This study contributes to the ratio analysis theory by indicating that the ratios are not as effective as financial models for diagnosis of corporate distress and bankruptcy. The research paper also indicated that some certain financial ratios more worth to be monitored than others due to their significance in the bankruptcy event occurrence.

Empirical contribution

This study empirically proved that financial ratio is an effective tool for predicting of corporate distress. The result of this research can be used for future reference in the study of bankruptcy models. Further the bankruptcy prediction model constructed in this study can be used for watching the financial health of distressed firms and can be used effectively in a turn-around strategic business plan. As our prediction model is built based on the contemporary US company data, this model is a useful tool for the US analysts and the turnaround specialists. As Altman (1993) mentioned in his book "Corporate Financial Distress and Prediction" about a successful turn-around case study of GTI Corporation (Page-267), similarly our model can be used for improving financial condition of a distressed firm. Due to the fact that the model is built based on US data therefore this model is useful for predicting bankruptcy situation of the US firms and using this model for other geographical location may lead to erroneous results, however this model can be reconstructed using same methodology and financial data from other geographically located corporations which shall yield similar classification accuracy and results.

5.3. Limitations

During ratio calculation I realized that some of the figures are not readily available i.e. total liability is the most common balance sheet item which was absent in several company balance sheets. In this cases the total liability is calculated deducting the total equity from total asset (as per accountancy golden rule Total Assets= Total Liabilities+ Total Equity). Some of samples companies income statement does not show the EBIT (Earnings Before Interest and Taxes) which I calculated by adding the net income with the interest and tax expenses.

Some of the bankrupted company's certain data is not available in the Financial statement which resulted a null result for the calculated ratio. I used zero (0) for these ratios. I excluded the bankrupted company sample in the case the Financial data is not sufficient to calculate more than one ratio.

I excluded some companies from my selected pool due to non-uniformity of balance sheet structure, nature of business and size of the company. I had to exclude most mega-companies like Bank of America, Citigroup and insurance companies for the same reason.

5.4. Directions for Future Research

Bankruptcy prediction has drawn substantial interests from researchers and a large number of researches have been done on this subject for the last several decades. Most of the research has been done based on developing corporate and economic environment (i.e. USA, CANADA and other developed countries),however this type of research can bring important insights for other country's practitioners of corporate world for constructing bankruptcy analytical tools and techniques.

Most of the researches on bankruptcy prediction model are concentrated in whether a firm is going to bankrupt or not, majority of the research does not answer a question "when the bankruptcy will take place?" In this regard Storey et al cited in Peel (1988): 310 mentioned that, "A final general criticism of existing studies is that they exhibit a lack of concern with the process of failure. Indeed we are not aware of any studies that have attempted to determine when a business will fail as opposed to whether it will fail. In our view a concern with the former question would lead to a greater emphasis upon the process of failure which we believe to be a most fruitful area for analysis." Therefore, there is an important field of unexplored research area for determining the tentative future date of a bankruptcy event. As we discussed earlier that our bankruptcy prediction model is constructed based on recent USA company data therefore the model is effective for predicting corporate distress for US firms. The similar research can be carried out using other geographical firm's financial data to reconstruct the prediction model which may prove to be a useful tool for the analysts of this geographic location.

5.5. Reflections

Bankruptcy is generally an event that is the combined result of an ineffective organization and its management and the decision of the creditors who try to recover their investments within the scope of the bankruptcy code; as such the bankruptcy is generally a “behavioral” event. During early 1980s the International Harvester Corporation (I-H) and Chrysler Corp. were in deep distress with Z-score far below 1.8. The Z-Score model was clearly classifying both companies as prime candidate for bankruptcy. Both I-H and Chrysler did not bankrupt due to the supports from the creditors and suppliers. Chrysler was supported by U.S. government played an important role on the other hand I-H’s financial officers convinced its bankers to extend loans in exchange of preferred stock. As a result their creditors became shareholders and the banker- creditors agency conflicts were reduced. I-H began to rebound subsequent to the firm’s low point during 1982 by selling assets and finally sold their huge farm equipment division. The turnaround was further observed as the restructured and renamed (Navistar) company first issued low-grade “junk” bonds to repay their bank loans and then common stock to repay most of the public bonds. Both the financial and operating performance improved (Altman 1993). During 1980 Chrysler Corporation recovered from its risky situation through the government loan guarantee of $ 3 billion and a successful introduction of new car models. Without the government loan support, Chrysler would have has little choice but to file for bankruptcy protection. The loan guarantee reduced certain direct and indirect costs of distress and the bailout was a success. The Chrysler turnaround was dramatic but there was doubt whether the turnaround was permanent. Chrysler and other U.S. automakers experienced challenging times and substantial losses in the late 1980s and early 1990s. The Chrysler’s Z-scores droppedinto the distressed zone again in 1990. The most recent Z-scores of I-H and Chrysler include the activities of their captive finance company subsidiaries, which will invariably lower the score even further (Altman 1993). The I-H and Chrysler case study indicates that although the bankruptcy model score shows a negative result, the bankruptcy event can be averted through effective strategic planning and actions which can bring about benefit not only to the shareholders but also countless stakeholders of the corporations.

This study responds the research questions clearly through empirical analysis. More importantly the research has clarified the usefulness of financial ratios when used in combination with Logistics Regression Analysis for predicting of corporate distress with significant classification accuracy. The constructed models shows acceptable level of fitness for predicting bankrupted firms.

The research process took substantial amount of time in collecting financial data for the bankrupted and non-bankrupted companies from Mergent online database. Compiling the financial ratios of 89 companies for 5 years also took a substantial amount of time due to a large number of observations has been calculated [3115 (89 firms X 5 year X 7 ratios)] using financial statement data. Secondly understanding SPSS statistical analytical tools for analysing and formulating the bankruptcy models took a substantial amount of time and effort. The research process was a great journey of exploring unexplored knowledge areas which delivered countless challenges to overcome. Every time these obstacles have been overcome a new area of knowledge has been exposed in front of me. This knowledge exploration venture would not be such effective without enduring this strenuous process of study and research.

VI. Conclusion

In this study we constructed Logistics Regression models to classify the bankrupted and non-bankrupted firms. We also tested the pattern of significance of the financial attributes of the constructed models. Our models found to be highly significant in distinguishing between bankrupted and non-bankrupted firms over the five-years period. The models are being ranked according to their effectiveness and one of the models found to be best out of all prediction models. The models have been assessed for effectiveness using Hosmer and Lemeshow Goodness-of-fit, Log-likelihood tests which indicates that these models reasonably predicting the observed data.

As per Zavgren (1985) many intangible factors influence the vulnerability of an individual firm which includes the unmeasured qualities of assets, the creativity of management, random events, government regulation and courts of law. Any econometric model containing only financial statement information will not predict with certainty the failure or non-failure of a firm. As Martin recognized, when discussing bank failure (p. 257): "These excluded variables (most of which cannot be directly observed) determine how vulnerable, in terms of the included variables, a bank would have to be in order to fail." These factors determine the "tolerance for vulnerability", beyond which the firm will fail. McFadden also discusses this issue in terms of "representative" characteristics of the population; thus the prediction of an outcome for an individual will be correct only if the representative element of his outcome function dominates the distinctive element (McFadden, p. 108).

As suggested by Beaver (1966) although ratio analysis may provide useful information, ratios must be used carefully as all ratios do not predict equally well. The cash-flow to total-debt ratio has excellent discriminatory power throughout the five-year period. However, the predictive capacity of the liquid asset ratios is much less. The ratios also do not predict failed and non failed firms with the same degree of accuracy. Non-failed firms can be correctly classified to a greater extent than failed firms. The investor can not completely eliminate the possibility of investing in a firm that will bankrupt in near future.

Although our research shows that the financial ratios are effective tool for assessing the financial health of a corporation the financial ratios should not be used as a stand-alone tool. In the case a financial decision is taken based on the current financial ratio of the company there is a high risk remains for the decision to be wrong due to not considering the risk factors the company sustained historically. On the other hand if a company is assessed using the financial model the decision not only considers the current financial indicator but also integrates many other factors to assess the viability of the corporation. Therefore financial ratios used in combination with statistical methods can help the decision makers to take organizational decisions more accurately.

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APPENDICES

Appendix A : Sample Selection of Bankrupted companies (USA)

Sl. No.	Company Name	SIC	Bankruptcy Year (t+1)	Last Reporting Year (t)	Year (t-1)	Year (t-2)	Year (t-3)	Year (t-4)
1	Dayton Superior Corporation (NBB: DSUP Q)	3318	2009	2008	2007	2006	2005	2004
2	Eagle Food Centers Inc (NBB: EGLE)	5412	2004	2003	2002	2001	2000	1999
3	Foamex International Inc. (NBB: FMXL Q)	3087	2008	2007	2006	2005	2004	2003
4	Footstar Inc. (OTC: FTAR)	6720	2012	2011	2010	2009	2008	2007
5	Harvard Industries, Inc. (NBB: HAVA)	3070	2001	2000	1999	1998	1997	1996
6	Huntsman Polymers Corp. (:)	2822	2002	2001	2000	1999	1998	1997
7	Lenox Group Inc (NBB: LENX Q)	3270	2008	2007	2006	2005	2004	2003
8	Carbide/Graphite Group, Inc. (NMS: CGGI)	3625	2001	2000	1999	1998	1997	1996
9	Fleetwood Enterprises Inc (NBB: FLTW Q)	3717	2009	2008	2007	2006	2005	2004
10	Daisytek International Corp. (NBB: DZTK Q)	5113	2003	2002	2001	2000	1999	1998
11	Geotek Communications, Inc. (OTC: GOTK Q)	3664	1998	1997	1996	1995	1994	1993
12	Global Telesystems Inc (: GTS)	4814	2001	2000	1999	1998	1997	1996
13	GST Telecommunications, Inc. (OTC: GSTX Q)	4814	2000	1999	1998	1997	1996	1995
14	Hayes Lemmerz International Inc (NBB: HAYZ Q)	3715	2010	2009	2008	2007	2006	2005
15	JumboSports, Inc. (FL) (:)	5942	2000	1999	1998	1997	1996	1995
16	Kasper A.S.L. Ltd. (NBB: KASP Q)	2338	2003	2002	2001	2000	1999	1998
17	Kellstrom Industries Inc. (NBB: KELL Q)	3725	2001	2000	1999	1998	1997	1996
18	KENETECH Corp. (OTC: KWND)	3630	2000	1999	1998	1997	1996	1995
19	Laclede Steel Co. (NBB: LCDS Q)	3313	2001	2000	1999	1998	1997	1996
20	Ladish Co., Inc. (NMS: LDSH)	3470	2011	2010	2009	2008	2007	2006
21	Maxicare Health Plans, Inc. (NBB: MAXI)	6325	2006	2005	2004	2003	2002	2001
22	Midway Airlines Corp. (NBB: MDWY Q)	4513	2001	2000	1999	1998	1997	1996
23	Pacific Gateway Exchange Inc. (NBB: PGEX Q)	4814	2000	1999	1998	1997	1996	1995
24	Paracelsus Healthcare Corp. (OTC: PLHC Q)	8063	2000	1999	1998	1997	1996	1995
25	Sun Television & Appliances, Inc. (OTC: SNTV Q)	5732	1999	1998	1997	1996	1995	1994
26	Tower Automotive, Inc. (NBB: TWRA Q)	3470	2007	2006	2005	2004	2003	2002
27	Trans World Airlines, Inc. (NL:)	4513	2000	1999	1998	1997	1996	1995
28	WCI Steel, Inc. (NYS: WRN)	3313	2002	2001	2000	1999	1998	1997
29	Weirton Steel Corp. (NBB: WRTL Q)	3313	2004	2003	2002	2001	2000	1999
30	WorldCom Inc (GA) (OTC: WCPO Q)	4814	2005	2004	2003	2002	2001	2000
31	Zenith Electronics Corp. (OTC: ZNCT)	3652	2001	2000	1999	1998	1997	1996
32	Northwest Airlines Corp. (NYS: NWA)	4513	2009	2008	2007	2006	2005	2004
33	Oakwood Homes Corp. (NBB: OKWH Q)	2452	2004	2003	2002	2001	2000	1999
34	Oneida Ltd. (NBB: ONEI)	3915	2007	2006	2005	2004	2003	2002
35	Peregrine Systems Inc. (NBB: PRGN)	7373	2006	2005	2004	2003	2002	2001
36	Pierre Foods Inc (OTC: FOOD)	2054	2009	2008	2007	2006	2005	2004
37	Polaroid Corp. (OTC: PRDC Q)	3862	2001	2000	1999	1998	1997	1996
38	Polymer Group Inc. (OTC: POLG A)	2222	2012	2011	2010	2009	2008	2007
39	Smith International, Inc. (NYS: SII)	3534	2010	2009	2008	2007	2006	2005

Appendix B : Sample Selection of Non-bankrupted companies (USA)

Sl. No.	Company Name	Primary SIC	Year (t)	Year (t-1)	Year (t-2)	Year (t-3)	Year (t-4)
1	Exxon Mobil Corp. (NYS: XOM)	2912	2012	2011	2010	2009	2008
2	Wal-Mart Stores, Inc. (NYS: WMT)	5332	2012	2011	2010	2009	2008
3	Chevron Corporation (NYS: CVX)	2912	2012	2011	2010	2009	2008
4	General Motors Co. (NYS: GM)	3712	2012	2011	2010	2009	2008
5	Valero Energy Corp. (NYS: VLO)	2912	2012	2011	2010	2009	2008
6	McKesson Corp. (NYS: MCK)	5123	2012	2011	2010	2009	2008
7	Apple Inc (NMS: AAPL)	3572	2012	2011	2010	2009	2008
8	International Business Machines Corp. (NYS: IBM)	7380	2012	2011	2010	2009	2008
9	Costco Wholesale Corp (NMS: COST)	5332	2012	2011	2010	2009	2008
10	Archer Daniels Midland Co. (NYS: ADM)	2042	2012	2011	2010	2009	2008
11	Walgreen Co. (NYS: WAG)	5913	2012	2011	2010	2009	2008
12	Boeing Co. (The) (NYS: BA)	3722	2012	2011	2010	2009	2008
13	PepsiCo Inc. (NYS: PEP)	2087	2012	2011	2010	2009	2008
14	Johnson & Johnson (NYS: JNJ)	2835	2012	2011	2010	2009	2008
15	Dow Chemical Co. (NYS: DOW)	2822	2012	2011	2010	2009	2008
16	United Parcel Service Inc (NYS: UPS)	4216	2012	2011	2010	2009	2008
17	Lockheed Martin Corp. (NYS: LMT)	3762	2012	2011	2010	2009	2008
18	Coca-Cola Co (The) (NYS: KO)	2087	2012	2011	2010	2009	2008
19	Cisco Systems, Inc. (NMS: CSCO)	3662	2012	2011	2010	2009	2008
20	Disney (Walt) Co. (The) (NYS: DIS)	7813	2012	2011	2010	2009	2008
21	Johnson Controls Inc (NYS: JCI)	2532	2012	2011	2010	2009	2008
22	Google Inc (NMS: GOOG)	7376	2012	2011	2010	2009	2008
23	Honeywell International, Inc. (NYS: HON)	3715	2012	2011	2010	2009	2008
24	World Fuel Services Corp. (NYS: INT)	5173	2012	2011	2010	2009	2008
25	Xerox Corp (NYS: XRX)	3578	2012	2011	2010	2009	2008
26	Bristol-Myers Squibb Co. (NYS: BMY)	2835	2012	2011	2010	2009	2008
27	Freeport-McMoRan Copper & Gold Inc. (NYS: FCX)	1022	2012	2011	2010	2009	2008
28	Whirlpool Corp (NYS: WHR)	3640	2012	2011	2010	2009	2008
29	CenturyLink, Inc. (NYS: CTL)	4814	2012	2011	2010	2009	2008
30	NextEra Energy Inc (NYS: NEE)	4912	2012	2011	2010	2009	2008
31	Kellogg Co (NYS: K)	2044	2012	2011	2010	2009	2008
32	Reynolds American Inc (NYS: RAI)	2112	2012	2011	2010	2009	2008
33	Dover Corp (NYS: DOV)	3560	2012	2011	2010	2009	2008
34	CenterPoint Energy, Inc (NYS: CNP)	4912	2012	2011	2010	2009	2008
35	Gilead Sciences, Inc. (NMS: GILD)	2837	2012	2011	2010	2009	2008
36	Republic Services, Inc. (NYS: RSG)	4954	2012	2011	2010	2009	2008
37	Grainger (W.W.) Inc. (NYS: GWW)	5100	2012	2011	2010	2009	2008
38	AutoZone, Inc. (NYS: AZO)	5532	2012	2011	2010	2009	2008
39	Becton, Dickinson and Co. (NYS: BDX)	3842	2012	2011	2010	2009	2008
40	Dana Holding Corp (NYS: DAN)	3715	2012	2011	2010	2009	2008
41	Calpine Corp (NYS: CPN)	4912	2012	2011	2010	2009	2008
42	Cliffs Natural Resources, Inc. (NYS: CLF)	1100	2012	2011	2010	2009	2008
43	Weyerhaeuser Co. (NYS: WY)	6799	2012	2011	2010	2009	2008
44	Cognizant Technology Solutions Corp. (NMS: CTSH)	7372	2012	2011	2010	2009	2008
45	Newell Rubbermaid, Inc. (NYS: NWL)	3090	2012	2011	2010	2009	2008
46	Avis Budget Group Inc (NMS: CAR)	7515	2012	2011	2010	2009	2008
47	Live Nation Entertainment, Inc. (NYS: LYV)	7997	2012	2011	2010	2009	2008
48	Graybar Electric Co., Inc. (: GRBE)	5064	2012	2011	2010	2009	2008
49	Harley-Davidson Inc (NYS: HOG)	3752	2012	2011	2010	2009	2008
50	Yahoo! Inc. (NMS: YHOO)	7374	2012	2011	2010	2009	2008

Appendix C : Five Years Financial Ratios of Bankrupted Companies used for Constructing of Bankruptcy Prediction Models

Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Dayton Superior Corporation (NBB: DSUP Q)	Year-1	-1.02	-3.82	0.01	-0.86	0.15	1.59	-0.26
2	Eagle Food Centers Inc (NBB: EGLE)	Year-1	-0.31	-29.99	0.02	-0.03	-0.04	3.42	-0.03
3	Foamex International Inc. (NBB: FMXL Q)	Year-1	-1.11	-2.44	-0.04	0.25	0.07	2.72	-0.41
4	Footstar Inc. (OTC: FTAR)	Year-1	0.00	0.41	2.83	0.77	0.00	0.00	0.00
5	Harvard Industries, Inc. (NBB: HAVA)	Year-1	-0.46	5.59	-0.05	-0.05	-0.13	1.19	0.18
6	Huntsman Polymers Corp. (:)	Year-1	-1.38	-4.63	0.00	-1.00	-1.23	0.97	-0.28
7	Lenox Group Inc (NBB: LENX Q)	Year-1	0.71	1.59	0.00	-0.14	-0.02	1.28	0.63
8	Carbide/Graphite Group, Inc. (NMS: CGGI)	Year-1	0.18	2.50	0.02	-0.17	-0.02	0.83	0.40
9	Fleetwood Enterprises Inc (NBB: FLTW Q)	Year-1	-0.76	6.25	0.00	0.17	0.03	2.65	0.16
10	Daisytek International Corp. (NBB: DZTK Q)	Year-1	0.25	1.11	-0.02	0.49	0.06	2.86	0.90
11	Geotek Communications, Inc. (OTC: GOTK Q)	Year-1	-1.67	-5.21	-0.35	-0.06	-0.67	0.20	-0.19
12	Global Telesystems Inc (: GTS)	Year-1	-0.98	-5.22	-0.10	-0.15	-0.51	0.36	-0.37
13	GST Telecommunications, Inc. (OTC: GSTX Q)	Year-1	-0.51	-4.93	0.00	0.07	-0.09	0.29	-0.20
14	Hayes Lemmerz International Inc (NBB: HAYZ Q)	Year-1	-1.19	-4.74	-0.06	-0.42	-0.23	1.74	-0.21
15	JumboSports, Inc. (FL) (:)	Year-1	-0.63	-7.83	0.09	0.45	-0.30	1.18	-0.13
16	Kasper A.S.L. Ltd. (NBB: KASP Q)	Year-1	-0.40	8.50	0.36	0.16	0.25	1.51	0.12
17	Kellstrom Industries Inc. (NBB: KELL Q)	Year-1	0.04	3.05	0.04	0.17	-0.04	0.58	0.33
18	KENETECH Corp. (OTC: KWND)	Year-1	-3.81	0.52	-0.07	0.84	-0.01	0.11	1.92
19	Laclede Steel Co. (NBB: LCDS Q)	Year-1	-0.73	0.00	0.06	0.08	-0.07	1.18	-0.48
20	Ladish Co., Inc. (NMS: LDSH)	Year-1	0.35	0.92	0.05	0.31	0.10	0.83	1.08
21	Maxicare Health Plans, Inc. (NBB: MAXI)	Year-1	-135.20	-1.40	-0.57	0.00	-0.32	0.03	-0.72
22	Midway Airlines Corp. (NBB: MDWY Q)	Year-1	0.04	2.43	0.02	-0.01	-0.07	0.81	0.41
23	Pacific Gateway Exchange Inc. (NBB: PGEX Q)	Year-1	0.13	2.26	0.08	-0.15	0.03	1.61	0.44
24	Paracelsus Healthcare Corp. (OTC: PLHC Q)	Year-1	-0.51	83.10	-0.10	-0.71	0.06	1.18	0.01
25	Sun Television & Appliances, Inc. (OTC: SNTV Q)	Year-1	-0.06	1.96	-0.16	0.29	-0.12	2.28	0.51
26	Tower Automotive, Inc. (NBB: TWRA Q)	Year-1	-0.62	-4.18	0.03	-0.28	-0.02	1.21	-0.24
27	Trans World Airlines, Inc. (NL:)	Year-1	-0.42	-13.50	0.00	-0.22	-0.16	1.55	-0.07
28	WCI Steel, Inc. (NYS: WRN)	Year-1	-0.45	-3.24	-0.11	0.11	-0.15	1.02	-0.31
29	Weirton Steel Corp. (NBB: WRTL Q)	Year-1	-2.90	-1.47	-0.07	0.44	-1.17	1.77	-0.69
30	WorldCom Inc (GA) (OTC: WCPO Q)	Year-1	-0.23	3.03	0.05	0.17	-0.19	1.21	0.33
31	Zenith Electronics Corp. (OTC: ZNCT)	Year-1	-6.71	-1.67	-0.08	-0.05	-0.31	3.77	-0.60
32	Northwest Airlines Corp. (NYS: NWA)	Year-1	-0.03	13.15	-0.03	-0.04	-0.03	0.10	0.08
33	Oakwood Homes Corp. (NBB: OKWH Q)	Year-1	-0.84	-2.85	-0.13	0.18	-0.60	0.70	-0.35
34	Oneida Ltd. (NBB: ONEI)	Year-1	-0.35	-10.01	0.05	-0.43	-0.07	1.16	-0.10
35	Peregrine Systems Inc. (NBB: PRGN)	Year-1	-0.10	0.89	0.00	-0.05	-0.05	0.45	1.13

36	Pierre Foods Inc (OTC: FOOD)	Year-1	-0.26	-4.81	0.01	-0.79	-0.71	1.84	-0.21
37	Polaroid Corp. (OTC: PRDC Q)	Year-1	0.60	4.45	0.00	0.16	0.05	0.91	0.22
38	Polymer Group Inc. (OTC: POLG A)	Year-1	-0.10	6.34	0.07	0.14	0.04	1.13	0.16
39	Smith International, Inc. (NYS: SII)	Year-1	0.27	0.97	0.12	0.32	0.06	0.77	1.03
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Dayton Superior Corporation (NBB: DSUP Q)	Year-2	-0.93	-4.54	0.00	0.20	0.13	1.52	-0.22
2	Eagle Food Centers Inc (NBB: EGLE)	Year-2	-0.23	31.39	-0.01	0.09	0.04	3.62	0.03
3	Foamex International Inc. (NBB: FMXL Q)	Year-2	-0.77	-2.42	0.19	0.04	0.21	2.40	-0.41
4	Footstar Inc. (OTC: FTAR)	Year-2	0.00	0.68	0.69	0.75	0.00	0.00	0.00
5	Harvard Industries, Inc. (NBB: HAVA)	Year-2	-0.27	2.96	0.01	-0.03	-0.24	1.20	0.34
6	Huntsman Polymers Corp. (:)	Year-2	-0.09	1.69	0.81	0.04	-0.02	0.59	0.37
7	Lenox Group Inc (NBB: LENX Q)	Year-2	0.71	1.64	-0.04	-0.14	-0.09	1.34	0.61
8	Carbide/Graphite Group, Inc. (NMS: CGGI)	Year-2	0.20	2.37	0.06	-0.20	0.03	0.88	0.42
9	Fleetwood Enterprises Inc (NBB: FLTW Q)	Year-2	-0.68	7.36	0.00	0.20	-0.10	2.86	0.14
10	Daisytek International Corp. (NBB: DZTK Q)	Year-2	0.42	1.39	0.02	0.47	0.06	3.12	0.72
11	Geotek Communications, Inc. (OTC: GOTK Q)	Year-2	-0.78	3.53	-0.21	0.24	-0.32	0.22	0.28
12	Global Telesystems Inc (: GTS)	Year-2	-0.29	4.37	-0.08	0.25	-0.11	0.21	0.04
13	GST Telecommunications, Inc. (OTC: GSTX Q)	Year-2	-0.33	-9.62	0.00	0.08	-0.12	0.14	-0.10
14	Hayes Lemmerz International Inc (NBB: HAYZ Q)	Year-2	-0.51	7.93	0.06	0.09	-0.02	1.18	0.13
15	JumboSports, Inc. (FL) (:)	Year-2	-0.22	8.62	-0.07	0.42	-0.24	1.13	0.12
16	Kasper A.S.L. Ltd. (NBB: KASP Q)	Year-2	-0.39	13.34	0.07	-0.59	-0.16	1.42	0.07
17	Kellstrom Industries Inc. (NBB: KELL Q)	Year-2	0.10	2.16	-0.09	0.60	0.10	0.53	0.46
18	KENETECH Corp. (OTC: KWND)	Year-2	-2.69	-26.00	-0.66	0.37	2.47	2.98	-0.04
19	Laclede Steel Co. (NBB: LCDS Q)	Year-2	-0.63	0.00	0.10	0.11	-0.11	1.27	-0.45
20	Ladish Co., Inc. (NMS: LDSH)	Year-2	0.31	1.08	0.12	0.29	0.02	0.75	0.93
21	Maxicare Health Plans, Inc. (NBB: MAXI)	Year-2	-85.61	-1.72	-0.60	0.00	-0.37	0.01	-0.58
22	Midway Airlines Corp. (NBB: MDWY Q)	Year-2	0.11	2.09	0.09	0.02	0.07	0.85	0.48
23	Pacific Gateway Exchange Inc. (NBB: PGEX Q)	Year-2	0.17	1.34	0.12	-0.04	0.12	1.98	0.75
24	Paracelsus Healthcare Corp. (OTC: PLHC Q)	Year-2	-0.26	19.85	-0.01	0.03	0.00	0.93	0.05
25	Sun Television & Appliances, Inc. (OTC: SNTV Q)	Year-2	0.08	0.00	-0.04	0.25	-0.18	2.65	0.00
26	Tower Automotive, Inc. (NBB: TWRA Q)	Year-2	-0.48	-5.70	-0.03	0.02	-0.04	1.43	-0.18
27	Trans World Airlines, Inc. (NL:)	Year-2	-0.21	12.78	-0.03	-0.16	-0.03	1.28	0.08
28	WCI Steel, Inc. (NYS: WRN)	Year-2	-0.17	-6.93	0.08	0.29	0.07	1.17	-0.14
29	Weirton Steel Corp. (NBB: WRTL Q)	Year-2	-1.49	-2.05	-0.04	0.38	-0.15	1.49	-0.54
30	WorldCom Inc (GA) (OTC: WCPO Q)	Year-2	-2.95	-2.19	0.05	0.08	-0.16	1.21	-0.46
31	Zenith Electronics Corp. (OTC: ZNCT)	Year-2	-3.34	-2.76	-0.23	-0.19	-0.09	2.99	-0.36
32	Northwest Airlines Corp. (NYS: NWA)	Year-2	0.01	2.32	0.01	0.04	-0.23	0.47	0.43
33	Oakwood Homes Corp. (NBB: OKWH Q)	Year-2	-0.22	17.41	-0.02	-0.14	-0.36	1.22	0.06
34	Oneida Ltd. (NBB: ONEI)	Year-2	-0.26	-91.83	-0.10	0.27	-0.15	1.26	-0.01
35	Peregrine Systems Inc. (NBB: PRGN)	Year-2	-0.04	0.89	0.01	0.01	-0.01	0.27	1.12
36	Pierre Foods Inc (OTC: FOOD)	Year-2	0.25	3.00	0.02	0.15	0.05	0.81	0.33
37	Polaroid Corp. (OTC: PRDC Q)	Year-2	0.59	4.51	0.06	0.18	0.05	0.97	0.22
38	Polymer Group Inc. (OTC: POLG A)	Year-2	-0.07	4.66	0.02	0.14	-0.01	1.04	0.21
39	Smith International, Inc. (NYS: SII)	Year-2	0.27	1.38	0.06	0.20	0.15	1.00	0.73
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Dayton Superior Corporation (NBB: DSUP Q)	Year-3	-0.93	-4.17	0.00	0.25	0.10	1.49	-0.24
2	Eagle Food Centers Inc (NBB: EGLE)	Year-3	-0.22	19.16	0.03	0.02	-0.03	3.94	0.05
3	Foamex International Inc. (NBB: FMXL Q)	Year-3	-0.74	-2.45	-0.04	-0.03	0.00	2.18	-0.41

4	Footstar Inc. (OTC: FTAR)	Year-3	0.00	1.13	2.84	0.74	0.00	0.00	0.00
5	Harvard Industries, Inc. (NBB: HAVA)	Year-3	-2.51	-1.52	-0.07	-0.36	0.01	0.35	-0.83
6	Huntsman Polymers Corp. (:)	Year-3	-0.05	1.51	-0.99	0.03	-0.01	0.42	0.40
7	Lenox Group Inc (NBB: LENX Q)	Year-3	0.67	1.91	0.13	-0.29	0.07	0.70	0.52
8	Carbide/Graphite Group, Inc. (NMS: CGGI)	Year-3	0.19	2.41	0.06	-0.23	-0.01	1.02	0.42
9	Fleetwood Enterprises Inc (NBB: FLTW Q)	Year-3	-0.45	4.04	0.00	0.26	0.03	2.82	0.25
10	Daisytek International Corp. (NBB: DZTK Q)	Year-3	0.57	0.77	0.01	0.41	0.03	2.84	1.30
11	Geotek Communications, Inc. (OTC: GOTK Q)	Year-3	-0.67	2.84	-0.14	0.24	-0.29	0.27	0.35
12	Global Telesystems Inc (: GTS)	Year-3	-0.21	5.48	-0.05	0.34	-0.06	0.14	0.16
13	GST Telecommunications, Inc. (OTC: GSTX Q)	Year-3	-0.26	-119.88	0.00	0.25	-0.02	0.04	-0.01
14	Hayes Lemmerz International Inc (NBB: HAYZ Q)	Year-3	-0.43	15.61	0.05	0.08	0.00	1.22	0.06
15	JumboSports, Inc. (FL) (:)	Year-3	0.02	2.29	0.03	0.30	-0.09	1.19	0.44
16	Kasper A.S.L. Ltd. (NBB: KASP Q)	Year-3	-0.08	2.60	-0.03	-0.27	0.01	1.19	0.38
17	Kellstrom Industries Inc. (NBB: KELL Q)	Year-3	0.07	1.90	-0.21	0.53	0.09	0.34	0.53
18	KENETECH Corp. (OTC: KWND)	Year-3	-3.96	-1.69	-0.12	-1.64	-0.22	0.45	-0.59
19	Laclede Steel Co. (NBB: LCDS Q)	Year-3	-0.46	0.00	0.02	-0.36	-0.24	1.07	0.00
20	Ladish Co., Inc. (NMS: LDSH)	Year-3	0.27	1.27	0.06	0.27	0.08	0.92	0.00
21	Maxicare Health Plans, Inc. (NBB: MAXI)	Year-3	-53.29	-2.56	-0.13	-0.28	0.51	0.65	-0.39
22	Midway Airlines Corp. (NBB: MDWY Q)	Year-3	0.10	1.89	0.10	0.16	0.13	1.04	0.53
23	Pacific Gateway Exchange Inc. (NBB: PGEX Q)	Year-3	0.12	1.24	0.20	0.08	0.10	1.74	0.81
24	Paracelsus Healthcare Corp. (OTC: PLHC Q)	Year-3	-0.25	16.49	0.01	0.05	0.00	0.90	0.06
25	Sun Television & Appliances, Inc. (OTC: SNTV Q)	Year-3	0.23	0.00	0.04	0.34	0.05	2.83	0.00
26	Tower Automotive, Inc. (NBB: TWRA Q)	Year-3	-0.28	-22.18	0.03	-0.11	-0.10	1.24	-0.05
27	Trans World Airlines, Inc. (NL:)	Year-3	-0.15	9.34	0.00	-0.11	-0.01	1.20	0.11
28	WCI Steel, Inc. (NYS: WRN)	Year-3	-0.17	-6.87	0.06	0.24	0.05	1.11	-0.15
29	Weirton Steel Corp. (NBB: WRTL Q)	Year-3	-1.27	-2.60	-0.15	0.33	-0.45	1.33	-0.40
30	WorldCom Inc (GA) (OTC: WCPO Q)	Year-3	0.04	0.79	0.08	0.00	0.03	0.34	1.26
31	Zenith Electronics Corp. (OTC: ZNCT)	Year-3	-2.68	-1.96	-0.43	-1.06	-0.70	2.81	-0.51
32	Northwest Airlines Corp. (NYS: NWA)	Year-3	-0.56	-2.65	0.02	0.03	0.04	0.58	-0.38
33	Oakwood Homes Corp. (NBB: OKWH Q)	Year-3	0.03	2.86	0.05	-0.05	-0.17	1.09	0.35
34	Oneida Ltd. (NBB: ONEI)	Year-3	-0.07	18.54	0.03	-0.20	-0.17	1.03	0.05
35	Peregrine Systems Inc. (NBB: PRGN)	Year-3	-11.81	-2.32	-0.15	0.46	0.00	0.14	-0.43
36	Pierre Foods Inc (OTC: FOOD)	Year-3	0.31	2.19	0.06	0.13	0.05	0.91	0.46
37	Polaroid Corp. (OTC: PRDC Q)	Year-3	0.56	4.64	0.04	0.16	-0.02	0.84	0.22
38	Polymer Group Inc. (OTC: POLG A)	Year-3	0.00	0.00	-0.03	0.00	-0.02	0.10	0.00
39	Smith International, Inc. (NYS: SII)	Year-3	0.37	1.34	0.11	0.42	0.23	1.45	0.75
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Dayton Superior Corporation (NBB: DSUP Q)	Year-4	-1.00	-2.64	0.01	0.23	-0.24	1.49	-0.38
2	Eagle Food Centers Inc (NBB: EGLE)	Year-4	-0.11	0.00	0.01	-0.27	0.03	3.58	0.00
3	Foamex International Inc. (NBB: FMXL Q)	Year-4	-0.60	-2.80	0.00	-0.09	0.08	1.96	-0.36
4	Footstar Inc. (OTC: FTAR)	Year-4	0.65	0.23	0.00	0.81	-0.03	0.02	4.28
5	Harvard Industries, Inc. (NBB: HAVA)	Year-4	-1.87	-1.73	0.08	0.01	-0.11	2.24	-0.75
6	Huntsman Polymers Corp. (:)	Year-4	-0.02	1.78	0.28	0.02	-0.01	0.33	0.36
7	Lenox Group Inc (NBB: LENX Q)	Year-4	1.80	0.16	0.11	0.44	0.19	0.98	6.08
8	Carbide/Graphite Group, Inc. (NMS: CGGI)	Year-4	0.28	1.45	0.14	-0.15	0.16	1.23	0.69
9	Fleetwood Enterprises Inc (NBB: FLTW Q)	Year-4	-0.35	7.05	-0.06	0.17	-0.04	2.35	0.14
10	Daisytek International Corp. (NBB: DZTK Q)	Year-4	0.50	1.01	0.04	0.44	0.11	2.88	0.99
11	Geotek Communications, Inc. (OTC: GOTK Q)	Year-4	-0.61	1.32	-0.14	0.26	-0.23	0.41	0.75
12	Global Telesystems Inc (: GTS)	Year-4	-0.31	12.40	-0.06	0.37	-0.11	0.06	0.04

13	GST Telecommunications, Inc. (OTC: GSTX Q)	Year-4	-0.26	-19.31	0.00	0.10	-0.12	0.15	-0.05
14	Hayes Lemmerz International Inc (NBB: HAYZ Q)	Year-4	-0.31	8.82	-0.01	0.11	-0.22	1.27	0.11
15	JumboSports, Inc. (FL) (:)	Year-4	0.08	1.59	-0.02	0.39	0.02	1.08	0.63
16	Kasper A.S.L. Ltd. (NBB: KASP Q)	Year-4	0.00	1.77	0.10	0.29	0.04	0.94	0.57
17	Kellstrom Industries Inc. (NBB: KELL Q)	Year-4	0.09	1.69	-0.17	0.26	0.13	0.53	0.59
18	KENETECH Corp. (OTC: KWND)	Year-4	-2.71	-2.26	-0.20	-1.15	-0.26	0.75	-0.44
19	Laclede Steel Co. (NBB: LCDS Q)	Year-4	-0.05	0.00	-0.03	0.18	-0.02	1.04	0.00
20	Ladish Co., Inc. (NMS: LDSH)	Year-4	0.28	0.89	0.10	0.34	0.14	1.11	0.00
21	Maxicare Health Plans, Inc. (NBB: MAXI)	Year-4	-109.63	-1.28	-0.22	-2.84	-0.48	0.32	-0.78
22	Midway Airlines Corp. (NBB: MDWY Q)	Year-4	0.03	1.85	0.06	0.16	0.11	1.31	0.54
23	Pacific Gateway Exchange Inc. (NBB: PGEX Q)	Year-4	0.07	0.66	0.13	0.34	0.09	1.56	1.51
24	Paracelsus Healthcare Corp. (OTC: PLHC Q)	Year-4	-0.23	14.94	-0.03	0.04	-0.30	0.64	0.07
25	Sun Television & Appliances, Inc. (OTC: SNTV Q)	Year-4	0.21	0.00	-0.01	0.35	0.11	2.69	0.00
26	Tower Automotive, Inc. (NBB: TWRA Q)	Year-4	-0.06	5.88	0.06	-0.13	-0.02	0.99	0.17
27	Trans World Airlines, Inc. (NL:)	Year-4	-0.12	10.26	-0.01	-0.15	-0.07	1.33	0.10
28	WCI Steel, Inc. (NYS: WRN)	Year-4	-0.18	-6.42	0.16	0.23	0.14	1.45	-0.16
29	Weirton Steel Corp. (NBB: WRTL Q)	Year-4	-0.39	10.80	-0.09	0.36	-0.04	1.13	0.07
30	WorldCom Inc (GA) (OTC: WCPO Q)	Year-4	0.03	0.78	0.08	-0.08	0.08	0.40	1.27
31	Zenith Electronics Corp. (OTC: ZNCT)	Year-4	-1.25	-6.93	-0.05	-0.29	-0.51	2.22	-0.14
32	Northwest Airlines Corp. (NYS: NWA)	Year-4	-0.35	-3.32	0.08	0.02	0.13	0.38	-0.30
33	Oakwood Homes Corp. (NBB: OKWH Q)	Year-4	0.18	1.83	0.13	0.06	-0.09	1.04	0.55
34	Oneida Ltd. (NBB: ONEI)	Year-4	0.13	3.06	0.05	0.35	0.05	0.91	0.33
35	Peregrine Systems Inc. (NBB: PRGN)	Year-4	-7.79	-2.48	-0.22	-0.25	-0.34	0.43	-0.40
36	Pierre Foods Inc (OTC: FOOD)	Year-4	0.29	2.40	0.03	0.13	0.03	0.59	0.42
37	Polaroid Corp. (OTC: PRDC Q)	Year-4	0.61	3.40	0.06	0.26	-0.07	1.01	0.29
38	Polymer Group Inc. (OTC: POLG A)	Year-4	-0.17	4.11	0.09	0.24	0.07	1.51	0.23
39	Smith International, Inc. (NYS: SII)	Year-4	0.31	1.69	0.05	0.35	0.20	1.37	0.59

Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Dayton Superior Corporation (NBB: DSUP Q)	Year-5	-0.42	-7.99	-0.07	0.24	0.04	1.06	-0.13
2	Eagle Food Centers Inc (NBB: EGLE)	Year-5	-0.08	0.00	0.07	0.06	0.03	3.33	0.00
3	Foamex International Inc. (NBB: FMXL Q)	Year-5	-0.30	-4.89	0.02	0.04	0.08	1.65	-0.20
4	Footstar Inc. (OTC: FTAR)	Year-5	0.28	1.30	0.00	0.44	0.30	3.49	0.77
5	Harvard Industries, Inc. (NBB: HAVA)	Year-5	-0.30	-20.78	0.02	-0.01	-0.60	1.31	-0.22
6	Huntsman Polymers Corp. (:)	Year-5	0.00	4.59	0.00	0.11	0.00	0.15	0.18
7	Lenox Group Inc (NBB: LENX Q)	Year-5	1.95	0.25	0.25	0.29	0.19	1.35	4.08
8	Carbide/Graphite Group, Inc. (NMS: CGGI)	Year-5	0.23	1.85	0.08	-0.15	0.14	1.22	0.54
9	Fleetwood Enterprises Inc (NBB: FLTW Q)	Year-5	-0.18	3.37	0.00	0.26	0.04	2.42	0.30
10	Daisytek International Corp. (NBB: DZTK Q)	Year-5	0.57	0.77	-0.08	0.50	0.12	3.07	1.30
11	Geotek Communications, Inc. (OTC: GOTK Q)	Year-5	-0.49	0.96	0.00	0.43	-0.38	0.35	1.04
12	Global Telesystems Inc (: GTS)	Year-5	-0.53	0.98	-0.16	0.20	-0.24	0.10	0.97
13	GST Telecommunications, Inc. (OTC: GSTX Q)	Year-5	-0.25	12.86	0.00	0.18	-0.14	0.14	0.08
14	Hayes Lemmerz International Inc (NBB: HAYZ Q)	Year-5	-0.05	2.28	0.07	0.08	0.01	0.98	0.44
15	JumboSports, Inc. (FL) (:)	Year-5	0.09	1.16	-0.12	0.43	0.07	0.98	0.86
16	Kasper A.S.L. Ltd. (NBB: KASP Q)	Year-5	0.02	1.17	-0.06	0.43	0.08	1.16	0.85
17	Kellstrom Industries Inc. (NBB: KELL Q)	Year-5	0.10	0.63	-0.09	0.46	0.16	0.00	1.58
18	KENETECH Corp. (OTC: KWND)	Year-5	-0.62	-73.18	-0.07	-0.01	-0.62	0.82	-0.01
19	Laclede Steel Co. (NBB: LCDS Q)	Year-5	-0.04	0.00	0.04	0.19	-0.05	1.01	0.00
20	Ladish Co., Inc. (NMS: LDSH)	Year-5	0.23	1.15	0.00	0.38	0.15	1.12	0.00
21	Maxicare Health Plans, Inc. (NBB: MAXI)	Year-5	-56.17	-1.66	-6.08	-1.00	-0.63	0.59	-0.60

22	Midway Airlines Corp. (NBB: MDWY Q)	Year-5	-1.73	-2.04	0.14	-1.00	-0.56	4.42	-0.49
23	Pacific Gateway Exchange Inc. (NBB: PGEX Q)	Year-5	0.07	9.29	0.25	-0.22	0.12	2.57	0.11
24	Paracelsus Healthcare Corp. (OTC: PLHC Q)	Year-5	0.29	2.28	0.04	0.18	0.06	1.48	0.44
25	Sun Television & Appliances, Inc. (OTC: SNTV Q)	Year-5	0.19	0.00	0.00	0.41	0.13	2.63	0.00
26	Tower Automotive, Inc. (NBB: TWRA Q)	Year-5	-0.02	4.00	0.05	-0.12	0.04	1.08	0.25
27	Trans World Airlines, Inc. (NL:)	Year-5	-0.01	8.41	0.01	-0.04	0.00	0.39	0.12
28	WCI Steel, Inc. (NYS: WRN)	Year-5	-0.19	-6.18	0.08	0.18	0.15	1.42	-0.16
29	Weirton Steel Corp. (NBB: WRTL Q)	Year-5	-0.25	5.71	0.07	0.45	-0.08	0.92	0.15
30	WorldCom Inc (GA) (OTC: WCPO Q)	Year-5	-0.01	0.78	0.12	-0.08	0.09	0.41	1.29
31	Zenith Electronics Corp. (OTC: ZNCT)	Year-5	-0.47	3.72	-0.03	0.03	-0.22	1.68	0.27
32	Northwest Airlines Corp. (NYS: NWA)	Year-5	-0.14	-5.55	0.09	-0.07	-0.20	0.90	-0.18
33	Oakwood Homes Corp. (NBB: OKWH Q)	Year-5	0.23	1.73	-0.04	0.10	-0.03	1.04	0.58
34	Oneida Ltd. (NBB: ONEI)	Year-5	0.12	3.29	0.08	0.36	0.07	0.91	0.30
35	Peregrine Systems Inc. (NBB: PRGN)	Year-5	-0.46	0.44	-0.05	0.10	-0.37	0.14	2.26
36	Pierre Foods Inc (OTC: FOOD)	Year-5	0.16	0.00	0.06	0.22	0.08	1.43	0.00
37	Polaroid Corp. (OTC: PRDC Q)	Year-5	0.66	2.34	0.14	0.28	0.02	1.03	0.43
38	Polymer Group Inc. (OTC: POLG A)	Year-5	-0.16	3.71	0.14	0.23	0.07	1.26	0.26
39	Smith International, Inc. (NYS: SII)	Year-5	0.30	1.57	0.05	0.37	0.17	1.37	0.64

Appendix D : Five Years Financial Ratios of Non-bankrupted Companies used for Constructing of Bankruptcy Prediction Models

Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Exxon Mobil Corp. (NYS: XOM)	Year-1	1.10	-1.66	0.17	0.00	0.24	1.36	1.06
2	Wal-Mart Stores, Inc. (NYS: WMT)	Year-1	0.36	1.48	0.13	-0.06	0.14	2.29	0.67
3	Chevron Corporation (NYS: CVX)	Year-1	0.69	0.69	0.17	0.09	0.20	0.99	1.43
4	General Motors Co. (NYS: GM)	Year-1	0.07	3.04	0.07	0.11	-0.20	1.02	0.33
5	Valero Energy Corp. (NYS: VLO)	Year-1	0.38	1.47	0.12	0.10	0.09	3.13	0.68
6	McKesson Corp. (NYS: MCK)	Year-1	0.30	0.16	0.07	0.05	0.07	3.52	1.45
7	Apple Inc (NMS: AAPL)	Year-1	0.58	0.49	0.29	0.11	0.31	0.89	2.04
8	International Business Machines Corp. (NYS: IBM)	Year-1	0.99	5.28	0.16	0.05	0.19	0.88	0.19
9	Costco Wholesale Corp (NMS: COST)	Year-1	0.29	1.17	0.11	0.05	0.10	3.65	0.85
10	Archer Daniels Midland Co. (NYS: ADM)	Year-1	0.29	1.36	0.05	0.28	0.03	1.04	0.74
11	Walgreen Co. (NYS: WAG)	Year-1	0.60	0.83	0.13	0.06	0.10	2.14	1.20
12	Boeing Co. (The) (NYS: BA)	Year-1	0.34	0.13	0.08	0.14	0.07	0.80	0.56
13	PepsiCo Inc. (NYS: PEP)	Year-1	0.58	2.33	0.11	0.02	0.12	0.88	0.43
14	Johnson & Johnson (NYS: JNJ)	Year-1	0.71	0.58	0.13	0.18	0.12	0.55	1.15
15	Dow Chemical Co. (NYS: DOW)	Year-1	0.27	2.33	0.06	0.18	0.04	0.82	0.43
16	United Parcel Service Inc (NYS: UPS)	Year-1	0.21	0.50	0.19	0.19	0.04	1.39	0.36
17	Lockheed Martin Corp. (NYS: LMT)	Year-1	0.34	990.21	0.04	0.04	0.12	1.22	0.00
18	Coca-Cola Co (The) (NYS: KO)	Year-1	0.67	1.63	0.12	0.03	0.14	0.56	0.61
19	Cisco Systems, Inc. (NMS: CSCO)	Year-1	0.12	0.79	0.13	0.48	0.12	0.50	1.27
20	Disney (Walt) Co. (The) (NYS: DIS)	Year-1	0.57	0.88	0.11	0.01	0.13	0.56	1.13
21	Johnson Controls Inc (NYS: JCI)	Year-1	0.28	1.67	0.05	0.06	0.05	1.36	0.60
22	Google Inc (NMS: GOOG)	Year-1	0.52	0.31	0.18	0.49	0.14	0.53	3.25
23	Honeywell International, Inc. (NYS: HON)	Year-1	0.43	2.23	0.08	0.11	0.10	0.90	0.45
24	World Fuel Services Corp. (NYS: INT)	Year-1	0.25	1.66	0.04	0.28	0.06	9.48	0.59
25	Xerox Corp (NYS: XRX)	Year-1	0.27	1.50	0.09	0.08	0.05	0.73	0.64
26	Bristol-Myers Squibb Co. (NYS: BMY)	Year-1	0.91	1.63	0.19	0.03	0.07	0.49	0.61
27	Freeport-McMoRan Copper & Gold Inc. (NYS: FCX)	Year-1	0.07	0.66	0.11	0.20	0.16	0.51	1.24
28	Whirlpool Corp (NYS: WHR)	Year-1	0.33	2.61	0.05	0.02	0.05	1.18	0.38
29	CenturyLink, Inc. (NYS: CTL)	Year-1	0.02	1.80	0.11	-0.02	0.05	0.34	0.56
30	NextEra Energy Inc (NYS: NEE)	Year-1	0.17	0.75	0.06	-0.06	0.06	0.22	0.33
31	Kellogg Co (NYS: K)	Year-1	0.37	5.28	0.12	-0.08	0.10	0.93	0.19
32	Reynolds American Inc (NYS: RAI)	Year-1	-0.10	2.15	0.09	0.06	0.13	0.48	0.47
33	Dover Corp (NYS: DOV)	Year-1	0.69	1.12	0.12	0.10	0.12	0.78	0.89
34	CenterPoint Energy, Inc (NYS: CNP)	Year-1	0.01	4.32	0.08	-0.03	0.05	0.33	0.23
35	Gilead Sciences, Inc. (NMS: GILD)	Year-1	0.17	1.28	0.15	0.09	0.19	0.46	0.78
36	Republic Services, Inc. (NYS: RSG)	Year-1	0.12	1.55	0.08	-0.02	0.06	0.41	0.65
37	Grainger (W.W.) Inc. (NYS: GWW)	Year-1	1.05	0.66	0.16	0.36	0.23	1.78	1.52
38	AutoZone, Inc. (NYS: AZO)	Year-1	-0.16	-5.05	0.20	-0.11	0.26	1.37	-0.20
39	Becton, Dickinson and Co. (NYS: BDX)	Year-1	0.92	1.75	0.15	0.29	0.14	0.68	0.57
40	Dana Holding Corp (NYS: DAN)	Year-1	-0.15	1.79	0.07	0.32	0.09	1.40	0.56
41	Calpine Corp (NYS: CPN)	Year-1	-0.45	3.08	0.04	0.09	0.06	0.33	0.32
42	Cliffs Natural Resources, Inc. (NYS: CLF)	Year-1	0.24	1.36	0.04	0.02	-0.02	0.43	0.59
43	Weyerhaeuser Co. (NYS: WY)	Year-1	0.02	2.06	0.05	0.17	0.06	0.56	0.48
44	Cognizant Technology Solutions Corp. (NMS: CTSH)	Year-1	0.71	0.34	0.18	0.53	0.21	1.13	2.91
45	Newell Rubbermaid, Inc. (NYS: NWL)	Year-1	0.37	2.12	0.10	0.11	0.10	0.95	0.47
46	Avis Budget Group Inc (NMS: CAR)	Year-1	-0.16	19.10	0.12	0.02	0.04	0.48	0.05
47	Live Nation Entertainment, Inc. (NYS: LYV)	Year-1	-0.17	2.90	0.07	0.01	0.00	1.10	0.34
48	Graybar Electric Co., Inc. (: GRBE)	Year-1	0.27	1.81	0.04	0.25	0.09	3.21	0.55
49	Harley-Davidson Inc (NYS: HOG)	Year-1	0.80	2.59	0.09	0.28	0.11	0.54	0.39
50	Yahoo! Inc. (NMS: YHOO)	Year-1	0.34	0.17	-0.02	0.26	0.03	0.29	5.83
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Exxon Mobil Corp. (NYS: XOM)	Year-2	1.00	-1.75	0.17	-0.01	0.22	1.41	0.94
2	Wal-Mart Stores, Inc. (NYS: WMT)	Year-2	0.36	1.55	0.13	-0.04	0.14	2.29	0.64

3	Chevron Corporation (NYS: CVX)	Year-2	0.67	0.71	0.20	0.09	0.23	1.17	1.39
4	General Motors Co. (NYS: GM)	Year-2	0.05	2.71	0.06	0.08	0.04	1.04	0.37
5	Valero Energy Corp. (NYS: VLO)	Year-2	0.36	1.61	0.09	0.08	0.09	2.94	0.62
6	McKesson Corp. (NYS: MCK)	Year-2	0.29	0.12	0.09	0.06	0.06	3.71	1.91
7	Apple Inc (NMS: AAPL)	Year-2	0.54	0.52	0.32	0.15	0.29	0.93	1.93
8	International Business Machines Corp. (NYS: IBM)	Year-2	0.90	4.75	0.17	0.08	0.18	0.92	0.21
9	Costco Wholesale Corp (NMS: COST)	Year-2	0.27	1.13	0.12	0.06	0.09	3.32	0.85
10	Archer Daniels Midland Co. (NYS: ADM)	Year-2	0.31	1.29	0.07	0.30	0.05	2.14	0.78
11	Walgreen Co. (NYS: WAG)	Year-2	0.69	0.85	0.13	0.15	0.16	2.63	1.18
12	Boeing Co. (The) (NYS: BA)	Year-2	0.34	0.18	0.05	0.11	0.07	0.72	0.28
13	PepsiCo Inc. (NYS: PEP)	Year-2	0.55	2.49	0.12	-0.01	0.13	0.91	0.40
14	Johnson & Johnson (NYS: JNJ)	Year-2	0.71	0.62	0.13	0.28	0.11	0.57	1.01
15	Dow Chemical Co. (NYS: DOW)	Year-2	0.28	2.11	0.06	0.14	0.07	0.87	0.47
16	United Parcel Service Inc (NYS: UPS)	Year-2	0.29	0.47	0.20	0.17	0.18	1.53	0.63
17	Lockheed Martin Corp. (NYS: LMT)	Year-2	0.31	36.87	0.11	0.05	0.10	1.23	0.03
18	Coca-Cola Co (The) (NYS: KO)	Year-2	0.67	1.53	0.12	0.02	0.15	0.58	0.65
19	Cisco Systems, Inc. (NMS: CSCO)	Year-2	0.08	0.84	0.12	0.46	0.10	0.50	1.19
20	Disney (Walt) Co. (The) (NYS: DIS)	Year-2	0.53	0.93	0.10	0.02	0.12	0.57	1.08
21	Johnson Controls Inc (NYS: JCI)	Year-2	0.30	1.69	0.04	0.04	0.07	1.38	0.59
22	Google Inc (NMS: GOOG)	Year-2	0.52	0.25	0.20	0.60	0.17	0.52	4.03
23	Honeywell International, Inc. (NYS: HON)	Year-2	0.40	2.68	0.07	0.10	0.07	0.92	0.37
24	World Fuel Services Corp. (NYS: INT)	Year-2	0.23	1.75	-0.04	0.30	0.07	9.36	0.57
25	Xerox Corp (NYS: XRX)	Year-2	0.23	1.43	0.07	0.05	0.06	0.73	0.67
26	Bristol-Myers Squibb Co. (NYS: BMY)	Year-2	1.00	1.08	0.15	0.23	0.22	0.64	0.93
27	Freeport-McMoRan Copper & Gold Inc. (NYS: FCX)	Year-2	0.02	0.73	0.21	0.22	0.28	0.65	1.16
28	Whirlpool Corp (NYS: WHR)	Year-2	0.32	2.63	0.03	0.01	0.01	1.23	0.38
29	CenturyLink, Inc. (NYS: CTL)	Year-2	0.04	1.70	0.07	-0.01	0.04	0.27	0.59
30	NextEra Energy Inc (NYS: NEE)	Year-2	0.17	0.74	0.07	-0.03	0.06	0.27	0.35
31	Kellogg Co (NYS: K)	Year-2	0.56	5.76	0.13	-0.02	0.17	1.11	0.17
32	Reynolds American Inc (NYS: RAI)	Year-2	-0.10	1.60	0.09	0.00	0.15	0.50	0.62
33	Dover Corp (NYS: DOV)	Year-2	0.70	0.93	0.11	0.23	0.13	0.84	1.08
34	CenterPoint Energy, Inc (NYS: CNP)	Year-2	0.01	4.14	0.09	-0.01	0.08	0.39	0.24
35	Gilead Sciences, Inc. (NMS: GILD)	Year-2	0.10	1.57	0.21	0.66	0.22	0.48	0.64
36	Republic Services, Inc. (NYS: RSG)	Year-2	0.11	1.55	0.09	-0.03	0.07	0.42	0.65
37	Grainger (W.W.) Inc. (NYS: GWW)	Year-2	1.02	0.79	0.16	0.28	0.22	1.71	1.26
38	AutoZone, Inc. (NYS: AZO)	Year-2	-0.11	-5.68	0.22	-0.11	0.26	1.38	-0.18
39	Becton, Dickinson and Co. (NYS: BDX)	Year-2	0.92	1.16	0.16	0.27	0.17	0.75	0.86
40	Dana Holding Corp (NYS: DAN)	Year-2	-0.19	2.05	0.07	0.29	0.07	1.43	0.49
41	Calpine Corp (NYS: CPN)	Year-2	-0.44	2.98	0.04	0.08	0.03	0.39	0.33
42	Cliffs Natural Resources, Inc. (NYS: CLF)	Year-2	0.30	1.07	0.16	0.02	0.17	0.47	0.77
43	Weyerhaeuser Co. (NYS: WY)	Year-2	0.01	1.95	0.02	0.16	0.05	0.49	0.51
44	Cognizant Technology Solutions Corp. (NMS: CTSH)	Year-2	0.65	0.39	0.16	0.52	0.21	1.11	2.54
45	Newell Rubbermaid, Inc. (NYS: NWL)	Year-2	0.34	2.33	0.09	0.08	0.04	0.95	0.43
46	Avis Budget Group Inc (NMS: CAR)	Year-2	-0.21	30.40	0.12	0.01	0.02	0.46	0.03
47	Live Nation Entertainment, Inc. (NYS: LYV)	Year-2	-0.15	2.48	0.03	0.02	0.00	1.06	0.40
48	Graybar Electric Co., Inc. (: GRBE)	Year-2	0.27	1.98	0.06	0.23	0.08	3.15	0.50
49	Harley-Davidson Inc (NYS: HOG)	Year-2	0.71	3.00	0.09	0.19	0.09	0.48	0.33
50	Yahoo! Inc. (NMS: YHOO)	Year-2	0.16	0.17	0.09	0.15	0.05	0.34	5.70
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT

1	Exxon Mobil Corp. (NYS: XOM)	Year-3	0.99	-1.65	0.16	-0.01	0.18	1.22	1.02
2	Wal-Mart Stores, Inc. (NYS: WMT)	Year-3	0.35	1.54	0.13	-0.04	0.14	2.32	0.65
3	Chevron Corporation (NYS: CVX)	Year-3	0.65	0.75	0.17	0.11	0.17	1.07	1.33
4	General Motors Co. (NYS: GM)	Year-3	0.00	2.74	0.05	0.04	0.04	0.98	0.37
5	Valero Energy Corp. (NYS: VLO)	Year-3	0.36	1.50	0.08	0.13	0.05	2.19	0.66
6	McKesson Corp. (NYS: MCK)	Year-3	0.27	0.15	0.08	0.12	0.06	3.63	1.80
7	Apple Inc (NMS: AAPL)	Year-3	0.49	0.57	0.25	0.28	0.24	0.87	1.74
8	International Business Machines Corp. (NYS: IBM)	Year-3	0.82	3.90	0.17	0.07	0.18	0.88	0.26
9	Costco Wholesale Corp (NMS: COST)	Year-3	0.28	1.18	0.12	0.07	0.09	3.27	0.84
10	Archer Daniels Midland Co. (NYS: ADM)	Year-3	0.28	1.24	-0.06	0.34	0.08	1.91	0.81
11	Walgreen Co. (NYS: WAG)	Year-3	0.64	0.82	0.14	0.17	0.13	2.57	1.21
12	Boeing Co. (The) (NYS: BA)	Year-3	0.36	0.22	0.04	0.08	0.07	0.77	0.22
13	PepsiCo Inc. (NYS: PEP)	Year-3	0.54	2.17	0.12	0.02	0.13	0.85	0.46
14	Johnson & Johnson (NYS: JNJ)	Year-3	0.76	0.58	0.16	0.24	0.17	0.60	1.22
15	Dow Chemical Co. (NYS: DOW)	Year-3	0.25	2.19	0.06	0.14	0.06	0.77	0.46
16	United Parcel Service Inc (NYS: UPS)	Year-3	0.42	0.48	0.11	0.17	0.17	1.47	0.74
17	Lockheed Martin Corp. (NYS: LMT)	Year-3	0.35	8.46	0.10	0.05	0.13	1.31	0.12
18	Coca-Cola Co (The) (NYS: KO)	Year-3	0.68	1.35	0.13	0.04	0.21	0.48	0.74
19	Cisco Systems, Inc. (NMS: CSCO)	Year-3	0.07	0.83	0.13	0.40	0.12	0.49	1.20
20	Disney (Walt) Co. (The) (NYS: DIS)	Year-3	0.50	0.84	0.10	0.02	0.10	0.55	1.18
21	Johnson Controls Inc (NYS: JCI)	Year-3	0.30	1.56	0.06	0.03	0.07	1.33	0.64
22	Google Inc (NMS: GOOG)	Year-3	0.48	0.25	0.19	0.55	0.19	0.51	3.98
23	Honeywell International, Inc. (NYS: HON)	Year-3	0.40	2.55	0.11	0.09	0.09	0.88	0.39
24	World Fuel Services Corp. (NYS: INT)	Year-3	0.25	1.28	-0.01	0.28	0.07	7.45	0.78
25	Xerox Corp (NYS: XRX)	Year-3	0.20	1.45	0.09	0.07	0.04	0.69	0.66
26	Bristol-Myers Squibb Co. (NYS: BMY)	Year-3	1.02	0.99	0.14	0.21	0.20	0.63	1.02
27	Freeport-McMoRan Copper & Gold Inc. (NYS: FCX)	Year-3	-0.09	1.02	0.21	0.21	0.31	0.65	0.84
28	Whirlpool Corp (NYS: WHR)	Year-3	0.30	2.69	0.07	0.07	0.05	1.18	0.37
29	CenturyLink, Inc. (NYS: CTL)	Year-3	0.15	1.28	0.09	0.01	0.09	0.32	0.78
30	NextEra Energy Inc (NYS: NEE)	Year-3	0.17	0.73	0.07	-0.03	0.07	0.29	0.38
31	Kellogg Co (NYS: K)	Year-3	0.52	4.49	0.09	-0.02	0.17	1.05	0.22
32	Reynolds American Inc (NYS: RAI)	Year-3	-0.03	1.62	0.07	0.03	0.14	0.48	0.62
33	Dover Corp (NYS: DOV)	Year-3	0.70	0.89	0.11	0.24	0.12	0.83	1.12
34	CenterPoint Energy, Inc (NYS: CNP)	Year-3	-0.04	5.29	0.07	0.00	0.06	0.44	0.19
35	Gilead Sciences, Inc. (NMS: GILD)	Year-3	0.10	0.98	0.24	0.28	0.35	0.69	1.02
36	Republic Services, Inc. (NYS: RSG)	Year-3	0.10	1.48	0.07	-0.07	0.07	0.42	0.68
37	Grainger (W.W.) Inc. (NYS: GWW)	Year-3	1.11	0.77	0.15	0.35	0.22	1.84	1.30
38	AutoZone, Inc. (NYS: AZO)	Year-3	-0.04	-8.54	0.21	-0.08	0.24	1.32	-0.12
39	Becton, Dickinson and Co. (NYS: BDX)	Year-3	0.90	0.78	0.17	0.29	0.18	0.76	1.29
40	Dana Holding Corp (NYS: DAN)	Year-3	-0.23	2.03	0.06	0.30	0.02	1.20	0.49
41	Calpine Corp (NYS: CPN)	Year-3	-0.44	2.70	0.05	0.10	0.03	0.38	0.37
42	Cliffs Natural Resources, Inc. (NYS: CLF)	Year-3	0.38	1.03	0.17	0.20	0.18	0.60	0.98
43	Weyerhaeuser Co. (NYS: WY)	Year-3	0.01	1.91	0.06	0.11	0.04	0.49	0.52
44	Cognizant Technology Solutions Corp. (NMS: CTSH)	Year-3	0.59	0.28	0.17	0.56	0.19	1.00	3.59
45	Newell Rubbermaid, Inc. (NYS: NWL)	Year-3	0.32	2.37	0.09	0.07	0.07	0.90	0.42
46	Avis Budget Group Inc (NMS: CAR)	Year-3	-0.26	24.19	0.16	0.07	0.02	0.50	0.04
47	Live Nation Entertainment, Inc. (NYS: LYV)	Year-3	-0.13	2.81	0.03	0.02	-0.01	0.97	0.36
48	Graybar Electric Co., Inc. (: GRBE)	Year-3	0.28	1.72	-0.01	0.27	0.05	3.04	0.58
49	Harley-Davidson Inc (NYS: HOG)	Year-3	0.67	3.27	0.12	0.22	0.05	0.44	0.31

50	Yahoo! Inc. (NMS: YHOO)	Year-3	0.13	0.19	0.08	0.18	0.05	0.42	5.39
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Exxon Mobil Corp. (NYS: XOM)	Year-4	1.19	-1.88	0.12	0.01	0.15	1.29	0.98
2	Wal-Mart Stores, Inc. (NYS: WMT)	Year-4	0.39	1.34	0.15	-0.04	0.14	2.37	0.75
3	Chevron Corporation (NYS: CVX)	Year-4	0.65	0.78	0.12	0.07	0.11	1.02	1.28
4	General Motors Co. (NYS: GM)	Year-4	-0.03	3.71	0.01	0.05	-0.04	0.42	0.20
5	Valero Energy Corp. (NYS: VLO)	Year-4	0.37	1.42	0.05	0.09	0.00	1.91	0.70
6	McKesson Corp. (NYS: MCK)	Year-4	0.26	0.09	0.08	0.16	0.07	3.86	3.28
7	Apple Inc (NMS: AAPL)	Year-4	0.36	0.93	0.19	0.32	0.14	0.68	1.07
8	International Business Machines Corp. (NYS: IBM)	Year-4	0.74	3.79	0.19	0.12	0.17	0.88	0.26
9	Costco Wholesale Corp (NMS: COST)	Year-4	0.28	1.18	0.10	0.05	0.08	3.25	0.84
10	Archer Daniels Midland Co. (NYS: ADM)	Year-4	0.33	1.16	0.09	0.30	0.10	1.96	0.86
11	Walgreen Co. (NYS: WAG)	Year-4	0.61	0.75	0.16	0.21	0.13	2.52	1.34
12	Boeing Co. (The) (NYS: BA)	Year-4	0.37	0.26	0.09	0.04	0.03	0.92	0.16
13	PepsiCo Inc. (NYS: PEP)	Year-4	0.85	1.28	0.17	0.10	0.21	1.08	0.75
14	Johnson & Johnson (NYS: JNJ)	Year-4	0.74	0.60	0.18	0.19	0.17	0.65	1.15
15	Dow Chemical Co. (NYS: DOW)	Year-4	0.25	2.21	0.03	0.10	0.03	0.68	0.45
16	United Parcel Service Inc (NYS: UPS)	Year-4	0.40	0.43	0.17	0.10	0.12	1.42	0.80
17	Lockheed Martin Corp. (NYS: LMT)	Year-4	0.35	7.50	0.09	0.05	0.13	1.29	0.13
18	Coca-Cola Co (The) (NYS: KO)	Year-4	0.85	0.96	0.17	0.08	0.19	0.64	1.04
19	Cisco Systems, Inc. (NMS: CSCO)	Year-4	0.06	0.76	0.15	0.45	0.11	0.53	1.31
20	Disney (Walt) Co. (The) (NYS: DIS)	Year-4	0.49	0.87	0.08	0.05	0.10	0.57	1.15
21	Johnson Controls Inc (NYS: JCI)	Year-4	0.28	1.64	0.04	0.05	-0.01	1.18	0.61
22	Google Inc (NMS: GOOG)	Year-4	0.50	0.12	0.23	0.65	0.21	0.58	8.01
23	Honeywell International, Inc. (NYS: HON)	Year-4	0.49	3.07	0.11	0.08	0.10	0.86	0.33
24	World Fuel Services Corp. (NYS: INT)	Year-4	0.30	1.37	0.04	0.30	0.09	6.49	0.73
25	Xerox Corp (NYS: XRX)	Year-4	0.24	2.34	0.09	0.22	0.04	0.60	0.42
26	Bristol-Myers Squibb Co. (NYS: BMY)	Year-4	0.99	1.10	0.13	0.25	0.19	0.61	0.91
27	Freeport-McMoRan Copper & Gold Inc. (NYS: FCX)	Year-4	-0.22	1.42	0.17	0.17	0.25	0.58	0.60
28	Whirlpool Corp (NYS: WHR)	Year-4	0.28	3.12	0.10	0.07	0.03	1.13	0.32
29	CenturyLink, Inc. (NYS: CTL)	Year-4	0.14	1.38	0.07	-0.03	0.05	0.22	0.72
30	NextEra Energy Inc (NYS: NEE)	Year-4	0.00	0.73	0.09	-0.04	0.06	0.32	0.37
31	Kellogg Co (NYS: K)	Year-4	0.49	3.93	0.15	0.02	0.18	1.12	0.25
32	Reynolds American Inc (NYS: RAI)	Year-4	-0.03	1.77	0.08	0.31	0.10	0.45	0.56
33	Dover Corp (NYS: DOV)	Year-4	0.69	0.93	0.10	0.20	0.08	0.73	1.07
34	CenterPoint Energy, Inc (NYS: CNP)	Year-4	-0.05	6.49	0.09	-0.01	0.05	0.42	0.15
35	Gilead Sciences, Inc. (NMS: GILD)	Year-4	0.21	0.52	0.32	0.30	0.37	0.72	1.91
36	Republic Services, Inc. (NYS: RSG)	Year-4	0.09	1.58	0.07	-0.07	0.07	0.42	0.63
37	Grainger (W.W.) Inc. (NYS: GWW)	Year-4	1.06	0.72	0.20	0.36	0.19	1.67	1.38
38	AutoZone, Inc. (NYS: AZO)	Year-4	0.03	-13.28	0.17	-0.03	0.22	1.28	-0.08
39	Becton, Dickinson and Co. (NYS: BDX)	Year-4	0.83	0.81	0.18	0.31	0.18	0.77	1.24
40	Dana Holding Corp (NYS: DAN)	Year-4	-0.23	2.02	0.04	0.28	-0.06	1.03	0.50
41	Calpine Corp (NYS: CPN)	Year-4	-0.45	2.74	0.05	0.08	0.06	0.39	0.36
42	Cliffs Natural Resources, Inc. (NYS: CLF)	Year-4	0.43	0.83	0.04	0.13	0.07	0.50	1.21
43	Weyerhaeuser Co. (NYS: WY)	Year-4	0.17	2.76	-0.01	0.18	-0.06	0.36	0.36
44	Cognizant Technology Solutions Corp. (NMS: CTSH)	Year-4	0.59	0.26	0.20	0.50	0.19	0.98	3.87
45	Newell Rubbermaid, Inc. (NYS: NWL)	Year-4	0.28	2.61	0.09	0.07	0.09	0.87	0.38
46	Avis Budget Group Inc (NMS: CAR)	Year-4	-0.27	44.46	0.15	0.04	0.01	0.51	0.02
47	Live Nation Entertainment, Inc. (NYS: LYV)	Year-4	-0.19	2.59	0.02	-0.01	-0.02	1.79	0.39

48	Graybar Electric Co., Inc. (: GRBE)	Year-4	0.30	1.66	0.08	0.30	0.05	3.06	0.60
49	Harley-Davidson Inc (NYS: HOG)	Year-4	0.69	3.34	0.07	0.23	0.02	0.47	0.30
50	Yahoo! Inc. (NMS: YHOO)	Year-4	0.11	0.19	0.09	0.19	0.03	0.43	5.17
Sl. No.	Company Name	Year	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT
1	Exxon Mobil Corp. (NYS: XOM)	Year-5	1.16	-2.69	0.26	0.10	0.36	2.02	0.00
2	Wal-Mart Stores, Inc. (NYS: WMT)	Year-5	0.39	0.00	0.14	-0.04	0.14	2.46	0.00
3	Chevron Corporation (NYS: CVX)	Year-5	0.63	0.86	0.18	0.03	0.27	1.64	1.16
4	General Motors Co. (NYS: GM)	Year-5	-0.78	-2.07	-0.20	-0.34	-0.18	0.52	-0.48
5	Valero Energy Corp. (NYS: VLO)	Year-5	0.45	1.20	0.09	0.09	0.02	3.46	0.83
6	McKesson Corp. (NYS: MCK)	Year-5	0.24	0.11	0.05	0.12	0.05	4.22	2.47
7	Apple Inc (NMS: AAPL)	Year-5	0.35	0.88	0.24	0.52	0.16	0.82	1.13
8	International Business Machines Corp. (NYS: IBM)	Year-5	0.64	7.13	0.17	0.06	0.16	0.95	0.14
9	Costco Wholesale Corp (NMS: COST)	Year-5	0.26	1.23	0.11	0.03	0.10	3.50	0.81
10	Archer Daniels Midland Co. (NYS: ADM)	Year-5	0.28	1.34	0.17	0.33	0.09	2.19	0.75
11	Walgreen Co. (NYS: WAG)	Year-5	0.62	0.74	0.14	0.17	0.15	2.63	1.35
12	Boeing Co. (The) (NYS: BA)	Year-5	0.42	0.16	-0.01	-0.09	0.08	0.93	-0.17
13	PepsiCo Inc. (NYS: PEP)	Year-5	0.85	1.97	0.19	0.06	0.20	1.20	0.00
14	Johnson & Johnson (NYS: JNJ)	Year-5	0.75	0.66	0.18	0.16	0.20	0.75	1.00
15	Dow Chemical Co. (NYS: DOW)	Year-5	0.37	2.37	0.10	0.06	0.04	1.26	0.42
16	United Parcel Service Inc (NYS: UPS)	Year-5	0.39	0.45	0.26	0.03	0.17	1.62	0.69
17	Lockheed Martin Corp. (NYS: LMT)	Year-5	0.35	10.67	0.13	0.00	0.15	1.28	0.09
18	Coca-Cola Co (The) (NYS: KO)	Year-5	0.95	0.98	0.19	-0.02	0.19	0.79	1.02
19	Cisco Systems, Inc. (NMS: CSCO)	Year-5	0.00	0.71	0.21	0.37	0.17	0.67	1.41
20	Disney (Walt) Co. (The) (NYS: DIS)	Year-5	0.45	0.93	0.09	0.00	0.13	0.61	1.07
21	Johnson Controls Inc (NYS: JCI)	Year-5	0.29	1.65	0.08	0.03	0.05	1.52	0.61
22	Google Inc (NMS: GOOG)	Year-5	0.43	0.12	0.25	0.56	0.18	0.69	8.00
23	Honeywell International, Inc. (NYS: HON)	Year-5	0.46	3.94	0.11	0.03	0.12	1.03	0.25
24	World Fuel Services Corp. (NYS: INT)	Year-5	0.29	1.31	0.28	0.30	0.11	13.18	0.76
25	Xerox Corp (NYS: XRX)	Year-5	0.24	2.60	0.04	0.12	0.01	0.75	0.38
26	Bristol-Myers Squibb Co. (NYS: BMY)	Year-5	0.76	1.41	0.13	0.27	0.20	0.70	0.71
27	Freeport-McMoRan Copper & Gold Inc. (NYS: FCX)	Year-5	-0.35	2.29	0.14	0.09	-0.54	0.76	0.36
28	Whirlpool Corp (NYS: WHR)	Year-5	0.30	3.50	0.02	0.04	0.03	1.40	0.29
29	CenturyLink, Inc. (NYS: CTL)	Year-5	0.38	1.61	0.10	0.01	0.09	0.31	0.62
30	NextEra Energy Inc (NYS: NEE)	Year-5	0.15	0.74	0.08	-0.05	0.06	0.37	0.35
31	Kellogg Co (NYS: K)	Year-5	0.44	6.56	0.12	-0.09	0.18	1.17	0.15
32	Reynolds American Inc (NYS: RAI)	Year-5	-0.03	1.91	0.07	0.06	0.13	0.46	0.52
33	Dover Corp (NYS: DOV)	Year-5	0.67	1.07	0.13	0.17	0.13	0.96	0.93
34	CenterPoint Energy, Inc (NYS: CNP)	Year-5	-0.05	8.66	0.04	0.01	0.06	0.58	0.12
35	Gilead Sciences, Inc. (NMS: GILD)	Year-5	0.05	0.69	0.31	0.44	0.39	0.76	1.45
36	Republic Services, Inc. (NYS: RSG)	Year-5	0.07	1.74	0.03	-0.06	0.01	0.18	0.58
37	Grainger (W.W.) Inc. (NYS: GWW)	Year-5	1.04	0.73	0.15	0.39	0.22	1.95	1.37
38	AutoZone, Inc. (NYS: AZO)	Year-5	0.04	21.89	0.18	0.01	0.21	1.24	0.05
39	Becton, Dickinson and Co. (NYS: BDX)	Year-5	0.86	0.60	0.21	0.28	0.20	0.90	1.66
40	Dana Holding Corp (NYS: DAN)	Year-5	-0.13	1.78	-0.16	0.23	-0.08	1.31	0.56
41	Calpine Corp (NYS: CPN)	Year-5	-0.37	0.00	0.02	0.09	0.05	0.48	0.00
42	Cliffs Natural Resources, Inc. (NYS: CLF)	Year-5	0.44	1.34	0.21	0.00	0.18	0.88	0.74
43	Weyerhaeuser Co. (NYS: WY)	Year-5	0.20	2.48	-0.08	0.14	-0.16	0.48	0.40
44	Cognizant Technology Solutions Corp. (NMS: CTSH)	Year-5	0.60	0.21	0.18	0.46	0.22	1.19	4.81
45	Newell Rubbermaid, Inc. (NYS: NWL)	Year-5	0.24	3.21	0.07	0.03	0.00	0.95	0.31

46	Avis Budget Group Inc (NMS: CAR)	Year-5	-0.23	120.70	0.15	0.01	-0.11	0.53	0.01
47	Live Nation Entertainment, Inc. (NYS: LYV)	Year-5	-0.15	2.98	-0.02	-0.05	-0.11	1.68	0.34
48	Graybar Electric Co., Inc. (: GRBE)	Year-5	0.27	2.09	0.10	0.28	0.10	3.47	0.48
49	Harley-Davidson Inc (NYS: HOG)	Year-5	0.83	2.70	-0.09	0.35	0.13	0.71	0.37
50	Yahoo! Inc. (NMS: YHOO)	Year-5	0.35	0.00	0.14	0.22	0.00	0.53	0.00

Appendix E : Classification Accuracy Test of Model-6 using Secondary data of Bankrupted Companies

	Year	1	1	1	1	1	1	1	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	Applied Extrusion Technologies, Inc. (NBB: APXT A)	-0.30	-71.35	-0.04	-0.73	-0.02	0.65	-0.01	1
2	Aurora Foods Inc (OTC: AURF Q)	-0.51	29.96	0.00	-0.01	-0.06	0.62	0.03	1
3	Drypers Corp. (OTC: DYPR)	-0.10	7.46	-0.02	0.08	0.02	1.07	0.13	1
4	Greyhound Lines, Inc. (NL:)	-0.45	-11.94	0.07	-0.08	0.00	1.79	-0.08	1
5	Hines Horticulture, Inc (NBB: HORT Q)	-0.35	35.83	-0.04	0.20	-0.04	0.68	0.03	1
6	House of Fabrics Inc. (NAS: HFAB Z)	0.01	2.41	-0.03	0.28	0.03	1.04	0.41	1
7	International FiberCom Inc. (NBB: IFCI Q)	0.08	1.17	-0.02	0.40	0.09	1.16	0.86	1
8	ITC DeltaCom Inc (OTC: ITCD)	-0.09	1.95	0.08	0.02	-0.04	0.74	0.51	1
9	Jacobson Stores Inc. (NBB: JCBS Q)	0.01	14.64	0.07	0.09	-0.27	1.78	0.07	1
10	Solutia, Inc. (NYS: SOA)	-0.13	2.84	0.06	0.10	0.11	0.59	0.35	1
11	Source Interlink Companies Inc (NBB: SORC Q)	-0.03	4.53	0.03	-0.01	0.01	0.93	0.21	1
12	Special Metals Corp. (OTC: SMCX Q)	-0.14	-8.98	0.08	0.00	0.03	1.04	-0.11	1
13	Thorn Apple Valley, Inc. (OTC: TAVI)	0.06	8.37	0.03	0.16	0.02	2.05	0.12	1
14	Winn-Dixie Stores, Inc. (NMS: WINN)	0.02	1.08	0.08	0.12	-0.01	3.82	0.92	1
15	Birmingham Steel Corp (NL:)	-1.34	-2.87	0.05	0.20	-0.12	1.20	-0.35	1
16	Global Crossing Ltd. (NMS: GLBC)	-0.84	-5.84	0.08	-0.10	0.01	1.13	-0.17	1
17	Dyersburg Corp. (NBB: DBGC)	0.09	3.18	0.06	0.02	-0.01	1.06	0.31	0
18	Covanta Energy Corp. (NBB: CVGY Q)	0.02	10.34	0.06	0.10	0.04	0.30	0.05	1
19	FiberMark Inc. (OTC: FMKI Q)	-0.43	-4.98	0.03	0.19	-0.01	1.08	-0.20	1
20	Medical Resources, Inc. (NMS: MRII)	-0.46	2.47	0.04	-0.34	-0.19	0.72	0.38	1
21	Milacron, Inc. (NBB: MZIA Q)	-0.79	-13.20	0.02	0.24	0.01	1.34	-0.08	1
22	Mirant Corp (NYS: GEN WSA)	-0.18	1.22	0.08	0.21	0.07	0.24	0.82	1
23	Movie Gallery Inc. (NBB: MVGR Q)	-1.61	-1.77	-0.07	-1.16	-0.70	3.70	-0.56	1
24	National Convenience Stores, Inc. (NL:)	0.06	2.55	0.07	0.03	0.06	3.19	0.39	0
25	National Gypsum Co. (NMS: NGCO W)	0.17	0.65	0.20	0.20	0.22	1.06	1.54	0
26	National Steel Corp. (NBB: NSTL Q)	-0.25	-3.44	0.10	0.17	-0.08	1.18	-0.29	1
27	Superior Telecom, Inc. (OTC: SESX V)	-1.57	-1.76	-0.02	-2.12	-0.90	2.52	-0.67	1

Bankrupted Firms classified as Bankrupted	24
Bankrupted Firms classified as Non-bankrupted	3
Classification Accuracy	88.89%

	Year	2	2	2	2	2	2	2	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	Applied Extrusion Technologies, Inc. (NBB: APXT A)	-0.18	10.87	-0.05	0.07	0.03	0.61	0.09	1
2	Aurora Foods Inc (OTC: AURF Q)	-0.09	2.38	0.05	-0.01	0.05	0.60	0.42	1
3	Drypers Corp. (OTC: DYPR)	-0.08	4.94	-0.06	0.09	0.05	1.11	0.20	1
4	Greyhound Lines, Inc. (NL:)	-0.41	-8.50	0.07	-0.11	-0.01	1.81	-0.12	1
5	Hines Horticulture, Inc (NBB: HORT Q)	-0.18	5.65	0.02	0.24	0.05	0.84	0.18	1
6	House of Fabrics Inc. (NAS: HFAB Z)	-0.28	-16.03	0.14	0.43	-0.02	0.48	-0.06	1

7	International FiberCom Inc. (NBB: IFCI Q)	0.09	1.12	-0.10	0.23	0.10	1.06	0.89	0
8	ITC DeltaCom Inc (OTC: ITCD)	-0.04	2.25	0.06	0.03	-0.03	0.72	0.44	1
9	Jacobson Stores Inc. (NBB: JCBS Q)	0.22	2.73	-0.08	0.35	-0.02	1.72	0.37	1
10	Solutia, Inc. (NYS: SOA)	-0.20	3.83	0.08	0.11	0.07	0.55	0.26	1
11	Source Interlink Companies Inc (NBB: SORC Q)	-0.04	1.30	-0.02	0.03	-0.02	1.84	0.77	1
12	Special Metals Corp. (OTC: SMCX Q)	-0.04	26.06	-0.04	0.36	-0.02	0.85	0.04	1
13	Thorn Apple Valley, Inc. (OTC: TAVI)	0.22	2.93	0.10	0.19	0.02	3.16	0.34	0
14	Winn-Dixie Stores, Inc. (NMS: WINN)	0.06	0.99	0.09	0.13	0.02	3.94	1.01	0
15	Birmingham Steel Corp (NL:)	-0.54	-100.55	0.01	-0.30	-0.06	1.08	-0.01	1
16	Global Crossing Ltd. (NMS: GLBC)	-0.71	-7.91	0.10	-0.05	0.01	1.02	-0.13	1
17	Dyersburg Corp. (NBB: DBGC)	0.15	2.59	0.06	0.23	-0.01	0.96	0.39	1
18	Covanta Energy Corp. (NBB: CVGY Q)	-0.13	-45.57	0.01	0.12	0.00	0.30	-0.05	1
19	FiberMark Inc. (OTC: FMKI Q)	-0.37	-6.81	-0.02	0.15	-0.19	0.99	-0.15	1
20	Medical Resources, Inc. (NMS: MRII)	-0.17	1.44	0.05	0.11	-0.04	0.63	0.67	1
21	Milacron, Inc. (NBB: MZIA Q)	-0.59	-31.54	-0.03	0.24	-0.01	1.26	-0.03	1
22	Mirant Corp (NYS: GEN WSA)	-0.21	1.84	0.06	0.18	0.13	0.30	0.54	1
23	Movie Gallery Inc. (NBB: MVGR Q)	-0.38	-5.88	-0.01	-0.02	0.08	2.20	-0.17	1
24	National Convenience Stores, Inc. (NL:)	0.04	3.01	0.08	0.03	0.07	2.94	0.33	0
25	National Gypsum Co. (NMS: NGCO W)	0.03	1.27	0.02	0.17	0.05	0.45	0.79	0
26	National Steel Corp. (NBB: NSTL Q)	-0.18	-8.43	-0.10	-0.03	-0.20	1.08	-0.12	1
27	Superior Telecom, Inc. (OTC: SESX V)	0.03	7.82	0.03	-0.21	0.05	0.93	0.05	0
		Bankrupted Firms classified as Bankrupted							21
		Bankrupted Firms classified as Non-bankrupted							6
		Classification Accuracy							77.78%

	Year	3	3	3	3	3	3	3	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	Applied Extrusion Technologies, Inc. (NBB: APXT A)	-0.14	9.45	-0.01	0.10	-0.01	0.62	0.11	1
2	Aurora Foods Inc (OTC: AURF Q)	-0.08	2.29	-0.01	0.02	0.01	0.56	0.44	1
3	Drypers Corp. (OTC: DYPR)	-0.08	2.69	-0.03	0.24	0.10	1.40	0.37	1
4	Greyhound Lines, Inc. (NL:)	-0.34	-5.95	0.17	-0.13	0.01	1.77	-0.17	1
5	Hines Horticulture, Inc (NBB: HORT Q)	-0.17	5.52	0.05	0.19	0.10	0.84	0.18	1
6	House of Fabrics Inc. (NAS: HFAB Z)	0.02	4.95	-0.01	0.55	-0.04	1.02	0.20	1
7	International FiberCom Inc. (NBB: IFCI Q)	0.07	0.52	0.00	0.31	0.20	1.24	1.91	0
8	ITC DeltaCom Inc (OTC: ITCD)	-0.02	2.39	-0.01	0.03	-0.02	0.04	0.42	1
9	Jacobson Stores Inc. (NBB: JCBS Q)	0.26	2.14	0.07	0.29	0.02	1.92	0.47	0
10	Solutia, Inc. (NYS: SOA)	-0.24	4.51	0.08	0.14	0.07	0.51	0.22	1
11	Source Interlink Companies Inc (NBB: SORC Q)	-0.01	0.92	0.07	0.06	0.04	1.73	1.08	0
12	Special Metals Corp. (OTC: SMCX Q)	0.01	9.64	0.01	0.35	-0.02	0.74	0.10	1
13	Thorn Apple Valley, Inc. (OTC: TAVI)	0.21	3.26	-0.08	0.18	-0.08	3.01	0.31	1
14	Winn-Dixie Stores, Inc. (NMS: WINN)	0.04	1.06	0.11	0.16	0.05	4.06	0.94	0
15	Birmingham Steel Corp (NL:)	-0.16	4.11	-0.05	0.15	-0.28	0.97	0.24	1
16	Global Crossing Ltd. (NMS: GLBC)	-0.68	-9.80	0.09	-0.07	-0.03	1.10	-0.10	1
17	Dyersburg Corp. (NBB: DBGC)	0.18	2.35	0.07	0.23	0.10	1.15	0.43	0
18	Covanta Energy Corp. (NBB: CVGY Q)	-0.14	-17.48	0.04	0.04	-0.04	0.32	-0.06	1
19	FiberMark Inc. (OTC: FMKI Q)	-0.06	12.63	0.03	0.19	-0.01	0.80	0.08	1
20	Medical Resources, Inc. (NMS: MRII)	-0.09	1.58	-0.02	-0.17	-0.07	0.60	0.61	1
21	Milacron, Inc. (NBB: MZIA Q)	-0.50	-132.69	0.01	0.28	0.02	1.20	-0.01	1
22	Mirant Corp (NYS: GEN WSA)	-0.37	0.78	0.08	0.57	0.07	0.21	1.28	1
23	Movie Gallery Inc. (NBB: MVGR Q)	-0.30	-7.51	0.10	-0.11	-0.35	1.43	-0.13	1
24	National Convenience Stores, Inc. (NL:)	0.01	3.44	0.09	0.04	0.03	1.00	0.29	0

26	National Steel Corp. (NBB: NSTL Q)	0.10	2.57	0.04	0.07	-0.04	1.16	0.39	1
27	Superior Telecom, Inc. (OTC: SESX V)	0.05	7.13	0.05	-0.24	0.07	1.03	0.06	0

Bankrupted Firms classified as Bankrupted	20
Bankrupted Firms classified as Non-bankrupted	7
Classification Accuracy	74.07%

	Year	4	4	4	4	4	4	4	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	Applied Extrusion Technologies, Inc. (NBB: APXT A)	-0.04	4.37	0.01	0.17	0.04	0.66	0.23	1
2	Aurora Foods Inc (OTC: AURF Q)	-0.04	2.21	0.01	-0.55	0.03	0.54	0.45	0
3	Drypers Corp. (OTC: DYPR)	-0.11	1.81	-0.03	0.06	0.07	1.38	0.55	1
4	Greyhound Lines, Inc. (NL:)	-0.11	2.66	0.07	-0.02	0.04	1.49	0.38	1
5	Hines Horticulture, Inc (NBB: HORT Q)	-0.19	6.63	0.06	0.15	0.09	0.84	0.15	1
6	House of Fabrics Inc. (NAS: HFAB Z)	0.26	1.61	0.14	0.14	-0.20	1.06	0.62	1
7	International FiberCom Inc. (NBB: IFCI Q)	-0.13	0.41	0.01	0.19	0.05	0.84	2.44	0
8	ITC DeltaCom Inc (OTC: ITCD)	-2.03	-23.03	0.13	0.11	-0.05	1.13	-0.04	1
9	Jacobson Stores Inc. (NBB: JCBS Q)	0.25	2.34	0.05	0.32	0.01	1.88	0.43	1
10	Solutia, Inc. (NYS: SOA)	-0.18	6.17	0.01	0.16	0.04	0.48	0.16	1
11	Source Interlink Companies Inc (NBB: SORC Q)	-0.12	0.55	-0.06	0.21	0.09	1.80	1.82	0
12	Special Metals Corp. (OTC: SMCX Q)	0.04	6.54	0.03	0.39	0.02	0.30	0.15	1
13	Thorn Apple Valley, Inc. (OTC: TAVI)	0.45	1.07	0.11	0.16	0.05	3.64	0.93	0
14	Winn-Dixie Stores, Inc. (NMS: WINN)	0.02	1.15	0.12	0.18	0.02	4.10	0.87	1
15	Birmingham Steel Corp (NL:)	-0.11	2.80	0.14	0.13	0.05	0.81	0.36	1
16	Global Crossing Ltd. (NMS: GLBC)	-0.50	-43.33	-0.01	-0.04	-0.03	0.85	-0.02	1
17	Dyersburg Corp. (NBB: DBGC)	0.16	2.63	0.05	0.22	0.08	0.68	0.38	0
18	Covanta Energy Corp. (NBB: CVGY Q)	-0.06	509.06	0.03	-0.08	-0.07	0.34	0.00	0
19	FiberMark Inc. (OTC: FMKI Q)	0.05	5.42	0.09	0.13	0.00	0.76	0.18	1
20	Medical Resources, Inc. (NMS: MRII)	0.02	0.55	0.01	0.26	0.06	0.57	1.83	0
21	Milacron, Inc. (NBB: MZIA Q)	-0.42	13.68	-0.06	0.26	-0.02	1.05	0.07	1
22	Mirant Corp (NYS: GEN WSA)	-0.49	1.60	0.01	0.41	0.11	0.27	0.63	1
23	Movie Gallery Inc. (NBB: MVGR Q)	0.28	0.49	0.21	-0.06	0.17	1.61	2.06	0
24	National Convenience Stores, Inc. (NL:)	-0.73	-3.32	0.11	0.09	-0.69	3.57	-0.30	1
25	National Gypsum Co. (NMS: NGCO W)	-0.76	-2.53	0.08	0.18	-0.16	1.28	-0.40	1
26	National Steel Corp. (NBB: NSTL Q)	0.13	2.24	0.00	0.13	0.00	1.06	0.45	0
27	Superior Telecom, Inc. (OTC: SESX V)	0.05	7.10	0.06	-0.21	0.10	1.01	0.06	0

Bankrupted Firms classified as Bankrupted	17
Bankrupted Firms classified as Non-bankrupted	10
Classification Accuracy	62.96%

	Year	5	5	5	5	5	5	5	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	Applied Extrusion Technologies, Inc. (NBB: APXT A)	0.01	2.90	-0.02	0.11	0.05	0.69	0.35	1
2	Aurora Foods Inc (OTC: AURF Q)	-0.03	1.37	0.04	-0.02	-0.02	0.55	0.73	0
3	Drypers Corp. (OTC: DYPR)	-0.13	2.29	0.05	-0.03	-0.08	1.19	0.44	1
4	Greyhound Lines, Inc. (NL:)	-0.12	1.85	0.05	-0.06	0.06	1.50	0.53	0
5	Hines Horticulture, Inc (NBB: HORT Q)	-0.21	8.71	0.07	0.03	0.10	0.83	0.11	1
6	House of Fabrics Inc. (NAS: HFAB Z)	0.34	1.13	-0.08	0.24	-0.10	1.43	0.88	0
7	International FiberCom Inc. (NBB: IFCI Q)	-1.16	2.08	-0.17	-0.10	-0.60	1.79	0.48	1
8	ITC DeltaCom Inc (OTC: ITCD)	-1.92	-31.86	0.18	0.09	0.04	1.23	-0.03	1
9	Jacobson Stores Inc. (NBB: JCBS Q)	0.24	2.37	0.11	0.34	0.01	1.92	0.42	1
10	Solutia, Inc. (NYS: SOA)	-0.47	-2.66	-0.16	-0.15	0.56	0.13	-0.38	0
11	Source Interlink Companies Inc (NBB: SORC Q)	-0.22	1.45	0.07	0.12	0.11	2.03	0.69	1
12	Special Metals Corp. (OTC: SMCX Q)	0.20	0.36	0.16	0.49	0.26	1.31	2.75	0

13	Thorn Apple Valley, Inc. (OTC: TAVI)	0.49	0.93	0.12	0.28	0.13	4.16	1.08	0
14	Winn-Dixie Stores, Inc. (NMS: WINN)	0.02	1.10	0.06	0.29	0.03	2.71	0.91	1
15	Birmingham Steel Corp (NL:)	0.11	1.70	0.04	0.19	0.03	0.91	0.59	0
16	Global Crossing Ltd. (NMS: GLBC)	-0.50	-11.48	-0.03	-0.05	-0.07	0.92	-0.09	1
17	Dyersburg Corp. (NBB: DBGC)	0.24	1.20	0.07	0.27	0.10	1.00	0.84	0
18	Covanta Energy Corp. (NBB: CVGY Q)	0.01	13.23	-0.02	0.05	-0.02	0.31	0.08	1
19	FiberMark Inc. (OTC: FMKI Q)	0.11	2.75	0.06	0.20	0.10	0.92	0.36	0
20	Medical Resources, Inc. (NMS: MRII)	-0.10	1.60	0.05	0.24	0.14	1.18	0.62	1
21	Milacron, Inc. (NBB: MZIA Q)	-0.35	-21.99	0.01	0.02	-0.12	1.04	-0.05	1
22	Mirant Corp (NYS: GEN WSA)	-0.58	2.35	0.00	0.08	0.03	0.32	0.43	1
23	Movie Gallery Inc. (NBB: MVGR Q)	0.20	0.45	0.50	-0.04	0.18	1.49	2.22	0
24	National Convenience Stores, Inc. (NL:)	-0.03	4.20	0.04	0.00	0.01	2.95	0.24	1
25	National Gypsum Co. (NMS: NGCO W)	-0.60	-2.99	0.03	0.17	-0.49	1.38	-0.33	1
26	National Steel Corp. (NBB: NSTL Q)	0.17	1.92	0.01	0.13	0.05	1.15	0.52	0
27	Superior Telecom, Inc. (OTC: SESX V)	0.04	19.65	0.01	-0.19	0.03	0.26	0.05	0
		Bankrupted Firms classified as Bankrupted							15
		Bankrupted Firms classified as Non-bankrupted							12
		Classification Accuracy							55.56%

Appendix F : Classification Accuracy Test of Model-6 using Secondary data of Non- bankrupted Companies

	Year	1	1	1	1	1	1	1	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	AK Steel Holding Corp. (NYS: AKS)	-0.20	3.84	0.02	0.27	0.01	1.63	0.26	1
2	Amazon.com Inc. (NMS: AMZN)	-0.09	2.11	0.20	0.17	0.12	2.31	0.47	1
3	American Electric Power Company, Inc. (NYS: AEP)	0.09	3.20	0.06	-0.06	0.07	0.32	0.31	0
4	Arrow Electronics, Inc. (NYS: ARW)	0.22	1.66	0.09	0.33	-0.07	2.35	0.60	1
5	Boston Scientific Corp. (NYS: BSX)	-0.10	1.06	0.04	0.08	-0.06	0.30	0.94	1
6	Caterpillar Inc. (NYS: CAT)	-0.08	9.25	0.07	0.08	0.07	0.76	0.10	1
7	Chesapeake Energy Corp. (NYS: CHK)	0.12	1.36	0.14	0.02	0.04	0.30	0.74	0
8	CMS Energy Corp (NYS: CMS)	-0.13	5.05	0.04	0.06	0.06	0.46	0.20	1
9	Colgate-Palmolive Co. (NYS: CL)	1.18	4.19	0.22	0.08	0.30	1.54	0.24	0
10	Emerson Electric Co. (NYS: EMR)	0.67	1.31	0.16	0.13	0.18	1.18	0.76	0
11	Marriott International, Inc. (NYS: MAR)	0.40	5.45	0.07	0.09	0.10	1.45	0.18	0
12	Masco Corp. (NYS: MAS)	0.23	2.33	0.08	0.18	0.00	1.01	0.43	0
13	McDonald's Corp (NYS: MCD)	1.02	1.13	0.21	0.03	0.24	0.83	0.89	0
14	Medtronic, Inc. (NYS: MDT)	0.55	0.84	0.16	0.18	0.12	0.62	1.19	0
15	Motorola Solutions Inc. (NYS: MSI)	0.14	1.93	0.01	0.24	-0.09	1.08	0.52	1
16	NIKE, Inc (NYS: NKE)	0.41	0.52	0.13	0.49	0.15	1.45	1.91	0
17	Pfizer Inc (NYS: PFE)	0.44	0.92	0.16	0.14	0.09	0.43	1.08	0
18	Spectra Energy Corp (NYS: SE)	0.04	2.96	0.08	0.03	0.10	0.23	0.34	0
19	Symantec Corp. (NMS: SYMC)	-0.49	1.70	0.16	-0.02	-0.60	0.58	0.59	1
20	Campbell Soup Co. (NYS: CPB)	1.47	6.27	0.17	-0.05	0.19	1.18	0.16	0
21	Darden Restaurants, Inc. (NYS: DRI)	0.14	2.37	0.14	-0.09	0.09	1.23	0.42	0
22	General Dynamics Corp. (NYS: GD)	0.52	2.01	0.08	0.12	0.02	0.92	0.50	0
23	Halliburton Company (NYS: HAL)	0.63	0.74	0.13	0.30	0.14	1.04	1.36	0
24	Mattel Inc (NMS: MAT)	0.54	1.13	0.20	0.28	0.16	0.98	0.89	0
25	SanDisk Corp. (NMS: SNDK)	0.20	0.42	0.05	0.26	0.06	0.49	2.36	0
26	Wesco International, Inc. (NYS: WCC)	0.24	1.98	0.06	0.24	0.07	1.42	0.51	0
27	Sherwin-Williams Co. (NYS: SHW)	0.20	2.48	0.14	0.20	0.15	1.53	0.40	0
28	Mohawk Industries, Inc. (NYS: MHK)	0.41	0.69	0.09	0.27	0.06	0.92	1.44	0
29	Alliant Techsystems Inc. (NYS: ATK)	0.57	1.90	0.06	0.30	0.10	1.00	0.52	0

Non-bankrupted Firms classified as Non-bankrupted	21
Non-bankrupted Firms classified as Bankrupted	8
Classification Accuracy	72.41%

	Year	2	2	2	2	2	2	2	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	AK Steel Holding Corp. (NYS: AKS)	-0.31	10.80	-0.04	0.03	-0.05	1.45	0.10	1
2	Amazon.com Inc. (NMS: AMZN)	0.08	2.26	0.15	0.10	0.04	1.90	0.44	0
3	American Electric Power Company, Inc. (NYS: AEP)	0.11	2.56	0.07	-0.05	0.06	0.29	0.39	0
4	Arrow Electronics, Inc. (NYS: ARW)	0.28	1.68	0.01	0.31	0.09	2.18	0.60	0

5	Boston Scientific Corp. (NYS: BSX)	-0.21	0.88	0.05	0.06	0.04	0.36	1.14	1
6	Caterpillar Inc. (NYS: CAT)	-0.08	5.08	0.09	0.12	0.09	0.74	0.19	1
7	Chesapeake Energy Corp. (NYS: CHK)	0.04	1.52	0.14	-0.09	0.07	0.28	0.66	0
8	CMS Energy Corp (NYS: CMS)	-0.09	4.43	0.07	0.01	0.06	0.40	0.23	1
9	Colgate-Palmolive Co. (NYS: CL)	1.23	4.01	0.23	0.05	0.30	1.32	0.23	0
10	Emerson Electric Co. (NYS: EMR)	0.73	1.29	0.14	0.12	0.16	1.02	0.77	0
11	Marriott International, Inc. (NYS: MAR)	0.54	-8.57	0.18	-0.21	0.09	2.08	-0.12	0
12	Masco Corp. (NYS: MAS)	0.01	8.83	0.03	0.15	-0.03	1.02	0.08	1
13	McDonald's Corp (NYS: MCD)	1.11	1.29	0.22	0.03	0.26	0.82	0.77	0
14	Medtronic, Inc. (NYS: MDT)	0.53	0.93	0.14	0.11	0.14	0.49	1.07	0
15	Motorola Solutions Inc. (NYS: MSI)	0.07	1.67	0.06	0.36	0.06	0.59	0.60	1
16	NIKE, Inc (NYS: NKE)	0.36	0.49	0.12	0.50	0.19	1.56	2.04	0
17	Pfizer Inc (NYS: PFE)	0.25	1.28	0.11	0.16	0.08	0.36	0.78	0
18	Spectra Energy Corp (NYS: SE)	0.07	2.16	0.08	0.04	0.08	0.19	0.46	0
19	Symantec Corp. (NMS: SYMC)	-0.22	1.52	0.15	0.01	0.12	0.52	0.65	0
20	Campbell Soup Co. (NYS: CPB)	1.34	5.26	0.17	0.00	0.19	1.12	0.19	0
21	Darden Restaurants, Inc. (NYS: DRI)	0.53	2.23	0.13	-0.17	0.12	1.35	0.45	0
22	General Dynamics Corp. (NYS: GD)	0.54	1.64	0.09	0.12	0.11	0.94	0.61	0
23	Halliburton Company (NYS: HAL)	0.63	0.79	0.16	0.31	0.19	1.05	1.26	0
24	Mattel Inc (NMS: MAT)	0.56	1.17	0.12	0.42	0.18	1.10	0.85	0
25	SanDisk Corp. (NMS: SNDK)	0.18	0.44	0.10	0.32	0.15	0.56	2.27	0
26	Wesco International, Inc. (NYS: WCC)	0.29	1.29	0.05	0.29	0.11	1.99	0.78	0
27	Sherwin-Williams Co. (NYS: SHW)	0.14	2.45	0.14	0.02	0.15	1.68	0.41	0
28	Mohawk Industries, Inc. (NYS: MHK)	0.38	0.80	0.05	0.21	0.05	0.91	1.24	0
29	Alliant Techsystems Inc. (NYS: ATK)	0.49	2.67	0.08	0.24	0.11	1.02	0.37	0

Non-bankrupted Firms classified as Non-bankrupted	23
Non-bankrupted Firms classified as Bankrupted	6
Classification Accuracy	79.31%

	Year	3	3	3	3	3	3	3	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	AK Steel Holding Corp. (NYS: AKS)	-0.28	5.53	-0.03	0.13	-0.03	1.42	0.18	1
2	Amazon.com Inc. (NMS: AMZN)	0.07	1.74	0.19	0.18	0.08	1.82	0.58	0
3	American Electric Power Company, Inc. (NYS: AEP)	0.10	2.69	0.05	-0.03	0.06	0.29	0.37	0
4	Arrow Electronics, Inc. (NYS: ARW)	0.23	1.95	0.02	0.29	0.08	1.95	0.51	0
5	Boston Scientific Corp. (NYS: BSX)	-0.22	0.96	0.01	0.05	-0.03	0.35	1.04	1
6	Caterpillar Inc. (NYS: CAT)	-0.06	4.65	0.08	0.15	0.06	0.67	0.21	1
7	Chesapeake Energy Corp. (NYS: CHK)	0.01	1.44	0.14	-0.03	0.08	0.25	0.70	0
8	CMS Energy Corp (NYS: CMS)	-0.11	4.59	0.06	0.05	0.07	0.41	0.22	1
9	Colgate-Palmolive Co. (NYS: CL)	1.28	2.97	0.29	0.00	0.31	1.39	0.32	0
10	Emerson Electric Co. (NYS: EMR)	0.69	1.33	0.14	0.11	0.14	0.92	0.75	0
11	Marriott International, Inc. (NYS: MAR)	0.37	4.67	0.13	0.10	0.08	1.30	0.21	0
12	Masco Corp. (NYS: MAS)	0.09	4.15	0.06	0.24	-0.06	0.93	0.21	1
13	McDonald's Corp (NYS: MCD)	1.06	1.18	0.20	0.05	0.23	0.75	0.84	0
14	Medtronic, Inc. (NYS: MDT)	0.53	0.91	0.12	0.14	0.14	0.52	1.10	0
15	Motorola Solutions Inc. (NYS: MSI)	0.17	1.35	0.06	0.33	0.04	0.75	0.74	1
16	NIKE, Inc (NYS: NKE)	0.39	0.52	0.12	0.49	0.19	1.39	1.91	0
17	Pfizer Inc (NYS: PFE)	0.22	1.21	0.06	0.16	0.06	0.35	0.82	0
18	Spectra Energy Corp (NYS: SE)	0.06	2.14	0.05	0.03	0.08	0.19	0.47	0
19	Symantec Corp. (NMS: SYMC)	-0.32	1.76	0.14	-0.03	0.07	0.49	0.56	1
20	Campbell Soup Co. (NYS: CPB)	1.40	5.76	0.17	-0.06	0.22	1.22	0.17	0
21	Darden Restaurants, Inc. (NYS: DRI)	0.53	1.82	0.16	-0.11	0.14	1.37	0.55	0

22	General Dynamics Corp. (NYS: GD)	0.52	1.44	0.09	0.09	0.12	1.00	0.69	0
23	Halliburton Company (NYS: HAL)	0.68	0.76	0.12	0.33	0.15	0.98	1.31	0
24	Mattel Inc (NMS: MAT)	0.50	1.06	0.10	0.35	0.17	1.08	0.94	0
25	SanDisk Corp. (NMS: SNDK)	0.09	0.52	0.17	0.35	0.17	0.55	1.93	0
26	Wesco International, Inc. (NYS: WCC)	0.25	1.46	0.05	0.28	0.08	1.79	0.68	0
27	Sherwin-Williams Co. (NYS: SHW)	0.93	2.21	0.14	0.03	0.14	1.50	0.45	0
28	Mohawk Industries, Inc. (NYS: MHK)	0.36	0.84	0.05	0.20	0.05	0.87	1.17	0
29	Alliant Techsystems Inc. (NYS: ATK)	0.45	2.81	0.09	0.22	0.12	1.09	0.35	0
		Non-bankrupted Firms classified as Non-bankrupted							22
		Non-bankrupted Firms classified as Bankrupted							7
		Classification Accuracy							75.86%

	Year	4	4	4	4	4	4	4	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	AK Steel Holding Corp. (NYS: AKS)	-0.24	3.86	0.01	0.21	-0.01	0.95	0.26	1
2	Amazon.com Inc. (NMS: AMZN)	0.01	1.63	0.24	0.18	0.09	1.77	0.61	0
3	American Electric Power Company, Inc. (NYS: AEP)	0.09	2.66	0.05	-0.01	0.06	0.28	0.37	0
4	Arrow Electronics, Inc. (NYS: ARW)	0.22	1.66	0.11	0.32	0.04	1.89	0.60	0
5	Boston Scientific Corp. (NYS: BSX)	-0.15	1.05	0.03	0.04	-0.04	0.33	0.96	1
6	Caterpillar Inc. (NYS: CAT)	-0.06	5.46	0.11	0.12	0.02	0.54	0.17	1
7	Chesapeake Energy Corp. (NYS: CHK)	-0.04	1.61	0.15	-0.01	-0.31	0.26	0.62	1
8	CMS Energy Corp (NYS: CMS)	-0.13	4.86	0.06	0.05	0.05	0.41	0.21	1
9	Colgate-Palmolive Co. (NYS: CL)	1.18	2.42	0.29	0.02	0.33	1.38	0.40	0
10	Emerson Electric Co. (NYS: EMR)	0.74	1.31	0.16	0.14	0.13	1.06	0.76	0
11	Marriott International, Inc. (NYS: MAR)	0.39	5.95	0.11	0.07	-0.04	1.38	0.17	0
12	Masco Corp. (NYS: MAS)	0.20	2.26	0.08	0.18	0.01	0.85	0.41	0
13	McDonald's Corp (NYS: MCD)	1.03	1.15	0.19	0.01	0.23	0.75	0.87	0
14	Medtronic, Inc. (NYS: MDT)	0.53	0.92	0.15	0.17	0.16	0.56	1.09	0
15	Motorola Solutions Inc. (NYS: MSI)	0.15	1.62	0.02	0.30	0.00	0.86	0.62	1
16	NIKE, Inc (NYS: NKE)	0.42	0.48	0.22	0.53	0.17	1.32	2.09	0
17	Pfizer Inc (NYS: PFE)	0.19	1.35	0.08	0.11	0.06	0.23	0.73	0
18	Spectra Energy Corp (NYS: SE)	0.05	2.14	0.07	0.02	0.08	0.19	0.47	0
19	Symantec Corp. (NMS: SYMC)	-0.41	1.47	0.15	0.05	0.09	0.53	0.68	1
20	Campbell Soup Co. (NYS: CPB)	1.37	7.32	0.19	-0.01	0.20	1.25	0.14	0
21	Darden Restaurants, Inc. (NYS: DRI)	0.50	1.77	0.17	-0.11	0.12	1.36	0.56	0
22	General Dynamics Corp. (NYS: GD)	0.49	1.50	0.09	0.09	0.12	1.03	0.67	0
23	Halliburton Company (NYS: HAL)	0.66	0.89	0.15	0.35	0.10	0.89	1.12	0
24	Mattel Inc (NMS: MAT)	0.49	0.89	0.20	0.31	0.15	1.14	1.13	0
25	SanDisk Corp. (NMS: SNDK)	-0.08	0.54	0.08	0.34	0.08	0.59	1.87	1
26	Wesco International, Inc. (NYS: WCC)	0.23	1.50	0.12	0.26	0.08	1.85	0.67	0
27	Sherwin-Williams Co. (NYS: SHW)	1.04	1.90	0.20	0.09	0.15	1.64	0.53	0
28	Mohawk Industries, Inc. (NYS: MHK)	0.31	0.98	0.11	0.23	0.01	0.84	1.01	0
29	Alliant Techsystems Inc. (NYS: ATK)	0.44	3.79	0.05	0.24	0.13	1.24	0.26	0
		Non-bankrupted Firms classified as Non-bankrupted							21
		Non-bankrupted Firms classified as Bankrupted							8
		Classification Accuracy							72.41%

	Year	5	5	5	5	5	5	5	
Sl. No.	Company Name	REAT	TLNW	CFFOAT	WCAT	EBITAT	SALEAT	SEQDT	Classification
1	AK Steel Holding Corp. (NYS: AKS)	-0.20	3.84	0.02	0.27	0.01	1.63	0.26	1
2	Amazon.com Inc. (NMS: AMZN)	-0.09	2.11	0.20	0.17	0.12	2.31	0.47	1
3	American Electric Power Company, Inc. (NYS: AEP)	0.09	3.20	0.06	-0.06	0.07	0.32	0.31	0
4	Arrow Electronics, Inc. (NYS: ARW)	0.22	1.66	0.09	0.33	-0.07	2.35	0.60	1

5	Boston Scientific Corp. (NYS: BSX)	-0.10	1.06	0.04	0.08	-0.06	0.30	0.94	1
6	Caterpillar Inc. (NYS: CAT)	-0.08	9.25	0.07	0.08	0.07	0.76	0.10	1
7	Chesapeake Energy Corp. (NYS: CHK)	0.12	1.36	0.14	0.02	0.04	0.30	0.74	0
8	CMS Energy Corp (NYS: CMS)	-0.13	5.05	0.04	0.06	0.06	0.46	0.20	1
9	Colgate-Palmolive Co. (NYS: CL)	1.18	4.19	0.22	0.08	0.30	1.54	0.24	0
10	Emerson Electric Co. (NYS: EMR)	0.67	1.31	0.16	0.13	0.18	1.18	0.76	0
11	Marriott International, Inc. (NYS: MAR)	0.40	5.45	0.07	0.09	0.10	1.45	0.18	0
12	Masco Corp. (NYS: MAS)	0.23	2.33	0.08	0.18	0.00	1.01	0.43	0
13	McDonald's Corp (NYS: MCD)	1.02	1.13	0.21	0.03	0.24	0.83	0.89	0
14	Medtronic, Inc. (NYS: MDT)	0.55	0.84	0.16	0.18	0.12	0.62	1.19	0
15	Motorola Solutions Inc. (NYS: MSI)	0.14	1.93	0.01	0.24	-0.09	1.08	0.52	1
16	NIKE, Inc (NYS: NKE)	0.41	0.52	0.13	0.49	0.15	1.45	1.91	0
17	Pfizer Inc (NYS: PFE)	0.44	0.92	0.16	0.14	0.09	0.43	1.08	0
18	Spectra Energy Corp (NYS: SE)	0.04	2.96	0.08	0.03	0.10	0.23	0.34	0
19	Symantec Corp. (NMS: SYMC)	-0.49	1.70	0.16	-0.02	-0.60	0.58	0.59	1
20	Campbell Soup Co. (NYS: CPB)	1.22	3.91	0.12	-0.11	0.17	1.24	0.26	0
21	Darden Restaurants, Inc. (NYS: DRI)	0.47	2.13	0.16	-0.11	0.12	1.44	0.47	0
22	General Dynamics Corp. (NYS: GD)	0.47	1.82	0.11	0.06	0.13	1.03	0.55	0
23	Halliburton Company (NYS: HAL)	0.65	0.86	0.19	0.32	0.22	1.27	1.16	0
24	Mattel Inc (NMS: MAT)	0.45	1.21	0.09	0.24	0.12	1.27	0.83	0
25	SanDisk Corp. (NMS: SNDK)	-0.16	0.87	0.01	0.24	-0.32	0.57	1.15	1
26	Wesco International, Inc. (NYS: WCC)	0.18	2.72	0.10	0.20	0.13	2.25	0.37	0
27	Sherwin-Williams Co. (NYS: SHW)	0.96	1.75	0.20	-0.01	0.18	1.81	0.57	0
28	Mohawk Industries, Inc. (NYS: MHK)	0.31	1.04	0.09	0.21	-0.18	1.06	0.96	1
29	Alliant Techsystems Inc. (NYS: ATK)	0.41	4.84	0.12	0.16	0.11	1.28	0.21	0

Non-bankrupted Firms classified as Non-bankrupted	19
Non-bankrupted Firms classified as Bankrupted	10
Classification Accuracy	65.52%

Md Saiful Islam. "Predictive capability of Financial Ratios for forecasting of Corporate Bankruptcy." *IOSR Journal of Business and Management (IOSR-JBM)*, 22(6), 2020, pp. 13-57.