CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

Business failure leading to bankruptcy or insolvency is associated with managerial inefficiencies. Economic consequence of business failure is enormous. It entails huge losses to shareholders, lenders, creditors, employees and customers. The Government also suffers loss of tax revenue from such businesses. Large scale business failure depresses the economy. The social costs of such events are also very high. Failures do not happen overnight. Every business passes through a series of events before it becomes insolvent. Hence it is very important to identify the distress signals as early as possible so that the business can turn around. The earliest researchers have described the various stage of financial distress – incubation, shortage of cash, financial distress and finally bankruptcy. There are many factors which can lead to distress and finally bankruptcy. These factors can be classified into external factors and internal factors:

a) External factors affecting the business operations and profitability: Inflation, interest rates, exchange rates, GDP etc.

b) Internal factors affecting business operations and profitability: Operating costs, cash inflows, levels of debt, efficiency in asset management etc.

A distress prediction model incorporating the influence of internal and external factors can be of immense value to all stakeholders to identify signals of distress as early as possible. Such a comprehensive model can help the shareholders, managers, creditors, lenders in taking appropriate steps to improve the performance, minimize losses and avoid failure. The objective of this research is to develop a robust distress prediction model which can serve as an early warning system to manufacturing companies in India.
As a first step in that direction, it is important to review and assess existing literature in this area so that significant inferences can be drawn and the current study can become more effective and impactful. An in depth and meaningful review of existing school of work in the area of financial distress in India and other countries can add immense value to this study. To achieve this objective, literature from 1968 till date was reviewed. Literature on corporate distress and bankruptcy was gathered accessing research journals from libraries and Online Databases like EBSCO and Proquest. These were reviewed to identify the gap in literature. Extensive review was also done to understand and identify variables, statistical techniques and tools adopted in studies on corporate distress and bankruptcy.

This chapter is organized in four sections as under:

1. Review of Studies on Corporate Distress and Bankruptcy.


3. Review of Statistical Tools, Techniques and Models used in studies on Corporate Distress and Bankruptcy.

4. Review of Financial and Non-Financial variables used in studies on Corporate Distress and Bankruptcy.

2.2 Review of Studies on Corporate Distress and Bankruptcy

Extensive study has been done by researchers in the field of corporate distress and failure in the quest to develop a distress prediction model. The important research studies in the area are presented in chronological order and discussed under the following heads:

a) Pre – 1990’s,  b) 1991-2000  and  c) Post 2000  d) Research in India
2.2.1 Pre – 1990’s era

The most important studies in the pre-1990 era were:

1. Beaver (1966)
2. Altman (1968)
3. Altman, Haldeman and Narayanan (1977)
7. Odom and Sharda (1990)

The important findings of these studies are discussed below:

**Beaver (1966)**

This is one of the earliest study done in the area of financial distress. Beaver used financial ratios to predict failure in business. Failed firms were identified by their inability to repay obligations namely debt default and default in payment of preference dividend. 79 failed publicly traded firms in US during the period from 1954 to 1964 were selected for the study. The financial data for 5 years before the failure was reviewed. These firms were also characterized by industry and size of Total Assets. Each such failed company was matched with a healthy company of the same industry and similar size. He selected 30 ratios and classified them into six groups like net income ratios, debt to total asset, current assets to total assets, current assets to current liabilities, turnover ratios and cash flow ratios. Doing dichotomous classification test, he analysed likelihood ratios, based on which firm’s failure was predicted. Six ratios were found significant in predicting failure viz current ratios, cash flow to total debt, total debt to total assets, net income to total assets, no-credit interval and working capital to total assets. Not all ratios predicted failed and non-failed with equal degree of success. Since Beaver used univariate analysis to distinguish between failed and non-failed companies, only one ratio could be examined at a time.
This study investigated the predictive ability of financial ratios. Financial ratios were found useful in predicting failure at least 5 years before the event. This was one of the pioneering work in the field of corporate distress.

**Altman (1968)**

Altman in his study tried to alleviate the shortcomings of univariate model developed by Beaver by incorporating more ratios and using Multivariate Discriminant Analysis (MDA) as the statistical tool to develop model for prediction of bankruptcy. This method is used to classify an observation into predetermined groups based on the characteristics of the observations. Hence an attempt was made to link the traditional ratio analysis with statistical techniques to predict failure. Manufacturing companies which had filed for bankruptcy during the period 1945-1965 formed the sample. The sample comprised of 33 failed manufacturing companies from different industries. Each of these company was matched with a non-failed company for the same period. 22 ratios classified as leverage, activity, profitability, solvency and efficiency ratios were studied to develop a bankruptcy prediction model. Five ratios were found to be important in predicting failure which were used to develop the ‘z’ score model:

\[
Z = 0.12 \times X_1 + 0.14 \times X_2 + 0.033 \times X_3 + 0.006 \times X_4 + 0.999 \times X_5
\]

Where:
- \(X_1\) is working capital / total assets ratio
- \(X_2\) is retained earnings / total assets ratio
- \(X_3\) is earnings before interest and taxes / total assets ratio
- \(X_4\) is market value of equity / book value of total debt ratio
- \(X_5\) is sales / total assets ratio
- \(Z\) is overall index

A ‘z’ score of less than 1.81 signified that the firm may become bankrupt in the next two years and a ‘z’ score of more than 2.99 indicated non-bankruptcy. A score between 1.81 – 2.99 was indicated as grey zone. This study was very important because it established MDA as a very useful and popular technique in corporate distress studies. There were two refinements to this model
I. To incorporate private firms, in variable X4, market value of equity was substituted by book value of equity. The revised model was:

\[ Z' = 0.717 \times X1 + 0.847 \times X2 + 3.107 \times X3 + 0.420 \times X4 + 0.998 \times X5 \]

II. To incorporate non-manufacturing firms the model was further revised by excluding the X5 as:

\[ Z'' = 6.56 \times X1 + 3.26 \times X2 + 6.72 \times X3 + 1.05 \times X4 \]

Altman, Haldeman and Narayanan (1977)

In 1977, Altman, Haldeman and Narayanan constructed a new model ZETA® Credit Risk Model incorporating latest developments in the area of business failures. This model was developed using manufacturing and retail firms in US as sample. 53 bankrupt and 58 non bankrupt firms were selected for the study. The study added several new ratios. These were capitalization ratios, liquidity ratios, profitability ratios, leverage ratios etc. A seven variable model was developed with variables:

1. Return on Assets - EBIT/Total Assets
2. Stability of Earnings – Normalised measure of standard error of estimate
3. Debt service – EBIT/ Interest payment
4. Cumulative Profitability – Retained Earnings/ Total Assets
5. Liquidity – Current Assets/ Current Liabilities
6. Capitalisation – Common Equity / Total capital
7. Size – Total Assets

Cumulative Profitability, Stability of Earnings and Capitalisation were observed to be most important factors. ZETA model showed over 90% accuracy in bankruptcy prediction one year before failure and over 70% five years before failure.
Ohlson (1980)

Another important milestone in corporate distress studies was the development of Ohlson’s ‘o’ score for predicting business failures. Ohlson (1980) used the logistic model to determine the probability of business failure. He analysed financial ratios of 105 bankrupt and 2058 non bankrupt companies in US. The period of study was 1970–76.

\[ Y(\text{log odd score}) = -1.3 - 0.4Y_1 + 6.0Y_2 - 1.4Y_3 + 0.1Y_4 - 2.5Y_5 + 1.8Y_6 + 0.3Y_7 - 1.7Y_8 - 0.5Y_9 \]

Where
- \( Y_1 = \log \left( \text{Total Assets/GNP price level index} \right) \)
- \( Y_2 = \text{Total Liabilities/Total Assets} \)
- \( Y_3 = \text{Working capital/Total Assets} \)
- \( Y_4 = \text{Current Liabilities/Current Assets} \)
- \( Y_5 = 1 \) if Total liabilities > Total Assets else \( Y_5 = 0 \)
- \( Y_6 = \text{Net Income/Total Assets} \)
- \( Y_7 = \text{Funds from operations/Total Liabilities} \)
- \( Y_8 = 1 \) if Net Income is negative else \( Y_8 = 0 \)
- \( Y_9 = \text{measure of change in Net Income} \)

The model could predict firms’ bankruptcies with an accuracy rate of 96% one year prior to bankruptcy. Size of the firm, capital structure, liquidity were found to be significant in identifying bankruptcy.

Mensah (1984)

This study investigated the issues in previous corporate distress studies and compile the factors to be considered in bankruptcy studies. Logistic model and Factor analysis was done to review the selected bankrupt companies. The study was conducted for four
different periods to check the consistency of results. 38 financial ratios were used. Some important conclusions were drawn from the study. It was observed that model structure and accuracy varied in different economic conditions. It was also suggested that reduction in multicollinearity can improve general application of the model across industries.

**Zmijewski (1984)**

Sampling bias and oversampling of distressed firms were the criticisms raised by Zmijewski about distress prediction models. To overcome this, maximum likelihood method was suggested. Zmijewski used probit analysis to develop his model from a sample of 40 bankrupt and 800 non bankrupt firms in US. He selected three financial ratios in his final model.

\[
X = -4.3 - 4.5X1 + 5.7X2 - 0.004X3
\]

Where  
\(X1 = \text{Net Income/ Total Assets}\)  
\(X2 = \text{Total Debt/ Total Assets}\)  
\(X3 = \text{Current Assets/Current Liabilities}\)  
\(X = \text{Overall index}\)

It was observed that adding more predictors increases the forecasting ability of the model.

**Odom and Sharda (1990)**

Odom and Sharda were the pioneers in using Artificial Neural Networks (ANN) as a technique for bankruptcy prediction. The predictive ability of ANN and MDA was compared in the study. These sample firms consisted of 129 firms. 65 of these firms went bankrupt between 1975 and 1982 and the remaining 64 non-bankrupt firms were
matched to the bankrupt group by year and industry. A subsample of 74 firms, which contained 38 bankrupt firms and 36 non-bankrupt firms, was used to develop the model using ANN and MDA. The second sample, which consisted of 27 bankrupt firms and 28 non-bankrupt firms, was used as to test the model. Odom and Sharda used financial ratios which were selected by Altman (1968) in his model for bankruptcy prediction. The ratios were analysed using ANN and MDA. It was observed that MDA classified 86.8% of bankrupt firms correctly and ANN classified all the bankrupt firms correctly. It was stated that neural networks are more reliable than discriminant analysis.

Summary

Since the earliest study on financial distress and bankruptcy in 1966 by Beaver (1966), lot of research interest has been displayed in the area of corporate distress. All the above studies discussed developed distress prediction model using various techniques and was reasonably successful in identification of bankrupt companies. Financial ratios were accepted as important predictors of corporate distress. However, most of these studies were based in US. The validity of the models in other nations were not yet tested.

2.2.2 1991-2000 era

This period was marked by lot of interest and curiosity shown by academicians and practitioners in the area of corporate distress. Different techniques, inclusion of more variables, testing the validity and applicability of earlier models were the prime focus of the research during this period. Some prominent work during this period are discussed in the following paragraphs.

Papoulias and Theodossiou (1992)

The economic crisis in Greece during the 1980’s led to this analysis of business failures. This study involves review of bankrupt companies in Greece to determine probabilities of failure. 33 companies that failed during the period 1982-85 and 68 healthy companies were selected as sample firms. Companies that had filed for bankruptcy and with negative net worth were defined as failed companies. Seven financial variables are used
as potential predictors of business failures viz current assets / current liabilities, working capital/ total assets , quick assets / current liabilities, gross profit / total assets, long term debt / total assets, total debt / total assets. Along with logit and probit, a Bayesian approach to discriminant analysis were used to construct models. It was observed that all models were accurate in identifying majority of bankrupt firms in Greece.

**Chen et al (1993)**

A relatively new technique called Survival Analysis was used to assess financial risk in oil and gas sector in Canada. This study was done to longevity of the endurance of firms in the wake of an adversity (in this case, oil price decline). This was a new direction in the field of distress research. 175 firms during the period 1981-88 were selected for study. 67 firms were classified as failed on account of filing for protection, debt default and non-payment of preference dividend. The financial parameters at the onset of adversity is observed and analysed. Liquidity ratio, leverage ratio, operating cash flows, age and size were analysed. The focus was not only on predicting business failure but also on how long a firm can endure a crisis before failure. Financial structure was observed to be an important factor in survival time. It was observed that survival analysis has predictive capability and it can also give the probability of endurance of a firm in times of adversity.

**Poston et al (1994)**

This study was done to test the ability of ratio based models in classifying a distressed firm into firms which can turn around and firms which eventually fail. The sample for research comprised of companies that were in the initial stage of financial distress. 204 companies in US during the period 1970-76 of which 46 were business failures were selected for study. Altman’s z-score model and four different probit models were constructed using 7 financial ratios. It was observed that z-score model classified distressed firms as failures. Probit models classified distressed firms as turnarounds. The results suggested that financial ratios had limited value to identify a distressed company that can remedy their weak condition and companies which cannot. It was
concluded that most of the distress prediction models needs to be re-evaluated. This observation gave a very important perspective to subsequent distress prediction studies.

**Kahya and Theodossiou (1999)**

The objective of this study was to use statistical methodology of time series cumulative sums (CUSUM) to distinguish changes in financial variables due to serial correlation or due to change in structure due to financial distress. 189 firms listed in NYSE and AMEX were selected for the period 1974-91. Financial ratios were used as variables. Change in the logarithm of deflated total assets, change in the ratio of inventory to sales, change in the ratio of fixed assets to total assets and operating income to sales were explanatory variables identified by the model. It was observed that none of the ratios used in past distress prediction models could be identified as explanatory variable. CUSUM model outperforms the discriminant logit models as memory features is sensitive to negative changes in financial performance which will serve as an alert to financial analysts.

**Whitaker (1999)**

This study examines the role of economic distress and poor management as reasons for a firm entering financial distress. 267 companies in US for the period 1980-92 were selected for study. The authors have classified selected companies into two groups: firms distressed due to economic conditions and firms distressed due to ineffective management actions. Jensen’s Hypothesis was tested for the sample firms. It was observed that poor management represents more significant reason for a financially distressed firm. Jensen’s Hypothesis that financial distress triggers management action to improve firms performance is proved in this study. Logit regression was used to identify factors that distinguish firms that recover from firms that do not recover.

**Summary**

During the period from 1991-2000, there were many studies done in the area of financial distress. The ability of financial ratios in identifying distress predictors were examined across various economies and different sectors. Along with Multivariate
Discriminant Analysis, logit, probit and neural networks were increasingly used as statistical techniques in these studies. Research during this period pointed out the need to include non-financial variables like management efficiency along with financial variables to improve the accuracy and applicability of bankruptcy prediction models. The studies were concentrated on US companies.

2.2.3 Post 2000

Research in the area of financial distress increased its boundaries to European and Asian countries during this period. This period saw many interesting studies testing the applicability of earlier established models, use of new methods and techniques for developing models, use of cash flow ratios and inclusion of macroeconomic indicators along with financial ratios to construct distress prediction models.

Some of the important developments in the study of corporate distress and bankruptcy are discussed in the following paragraphs:

**Turetsky and McEwen (2001)**

The heterogeneous nature of financial distress have been highlighted by this study. According to this study, different stages of distress can lead to changes in accounting variables. A positive association of default with business failure has been observed. Negative cash flows from operations is used as the initial distress signal. Companies with volatile decrease in cash flows from operations were selected for study. 2671 firms in US were studied during the period 1988 onwards. Survival analysis is used to determine the predictive ability of accounting variables in distinguishing a failed firm and a successful firm. It was observed that after successive decrease in cash flow, accounting variables gives signals at various state of distress. Large firms are more likely to default and restructure their debt. ROA is an important measure to identify the success of a firm. The event of default has a significant positive relationship with business failure.
Murugan et al (2001)

Artificial Neural Network (ANN) was used to develop a bankruptcy prediction model. As compared to other studies where distressed firms are normally matched with non-distressed firms, only financially distressed companies were selected. 522 distressed firms in US from 1989 to 1996 formed the sample. Negative cash flows from operations, reduction or non-payment of dividend, debt default, troubled debt restructuring were used as potential signals of distress. This paper uses Generic Algorithm ANN and Back propagation ANN model to predict financial distress. Zmijewski’s distress score is used as the predictor variable. This score is derived from profitability, solvency and liquidity ratios. The results using ANN was compared with Discriminant Analysis model. It was observed that ANN classification accuracy were in the range of 90.4% - 100%. The cost of misclassification in ANN model was found to be lower than other models.

Grice and Dugan (2001)

The limitations and problems associated with bankruptcy prediction models were highlighted in this study. Inappropriate use of bankruptcy prediction models can give misleading results Zmijewski (1984) and Ohlson (1980) model were studied for sensitivity to time period and industry. 183 distressed and 841 non distressed companies were studied for two sets of time period 1988-1991 and 1992-1999. The selected companies were from the period and industries which were different from those used in the original model. Companies filing for bankruptcy, companies with poor bond rating, and companies with low stock ratings were identified as financially distressed companies. The assumption about stability of the models across different economic conditions were proved wrong. It was observed that application of the model for any time period may not give accurate results. Also models developed with one set of industries may not be applicable to other sectors. However Zmijewski (1984) model was not sensitive to industries. It was also observed that these models were more useful for financial distress prediction rather than predicting bankruptcy.
Tan and Dihardjo (2001)

The authors have compared ANN and Probit models as bankruptcy predictors. Credit unions which were placed under direction / notice of direction in Australia were identified as distressed firms. The sample consisted of 2144 companies. 13 financial ratios were used to test the models. The usefulness of ANN to develop early warning system for financial distress was examined. It was observed that ANN models performed better than Probit models. Also the accuracy rate of models improved with inclusion of early warning signals.

Ganesalingam and Kumar (2001)

42 successful and 29 failed companies listed in from Australian Stock Exchange were selected to develop a model for prediction of bankruptcy using financial ratios as independent variables. The ratios measured profitability, capital structure, liquidity, asset utilisation and debt management. Liquidity, debt management and profitability were observed to discriminate distressed and non-distressed firms. The ability of Principal Component Analysis, Factor Analysis, Discriminant Analysis and Cluster Analysis as techniques to classify companies according to distress levels were examined. Multi variate statistical tools were observed to be very effective in classification of companies into distressed and non-distressed.

Li-Jen Ko et al (2001)

The paper studies financial ratios of 53 companies listed in Taiwan Stock Exchange during the period 1981-85 to develop a distress prediction model. Initially 14 ratios were used for study. Using step wise regression, five financial ratios viz Total Assets/Total Liabilities, Quick Assets/Current Liabilities, Sales/Fixed Assets, Margin/Sales and Cash dividend/ share were used to construct distress prediction models. A new method Composite Rule Induction System (CRIS) was used to develop the model. The classification accuracy of CRIS was compared to logit and ANN. It was observed that all models had significant predictive abilities however CRIS and ANN out performs logit model in indicating financial distress in companies. However the rules derived under CRIS are easier to learn and apply.
Abid and Zouari (2002)

In this study the author has constructed nine different neural network models (NNM) considering various time horizons and information structure to predict financial distress. 70 healthy firms and 17 distressed firms for the period 1993-96 were selected for study. The distressed firms were identified using Value at Risk approach. The probability that a firm will be distressed next year was determined using Black & Scholes (1974) model. Nine neural network models were constructed using cascade correlation architecture. 15 financial ratios were used as inputs. It was observed that NNM is a discriminative tool for predicting healthy and financially distressed firms. Indebtedness, capital structure, sales growth and liquidity were the important contributors for distress prediction.

Hall (2002)

In his paper, the author has re-examined Altman’s ‘z’ score model. The study stresses that distress prediction models will work only if financial statements reflect the correct financial position of the company. The author has urged the analysts to review the financial statements closely and also look at other indicators to predict financial distress.


The authors have tried to develop an early warning system to predict financial distress in automobile supplier industry in US. 25 stressed companies with indicators like years of losses, non-payment of dividend, major restructuring and who have approached consulting firms for turnaround were selected for study. Logit regression was used to establish the parameters of the model. It was concluded that variables indicating profit margin, leverage, liquidity and growth were strong indicators of financial distress. The model developed could correctly classify 98% of the sample. One major limitation pointed out in earlier research about bias due to matched sample design was also tested through simulation. The results of simulation showed that with the increase in the proportion of distressed firms to non-distressed firms in a sample, bias sets in. It was recommended that models should be used cautiously and the proportion of distressed
to healthy firms in the sample should match the proportion of distressed firms to healthy firms in the population.

Gruszczynski (2004)

The author has examined financial status of 200 unlisted companies in Poland to identify main determinants of financial distress. 17 financial ratios representing profitability, liquidity, asset management and debt ratios were studied. Binomial and trinomial logit regression was used to construct distress prediction models. It was concluded that logit models gives satisfactory results. The prediction accuracy 1 year lag was more than prediction accuracy 2 years lag. The difference in forecast precision is higher in binomial models than trinomial models.

Fitzpatrick (2004)

The author has done a comprehensive analysis of distress among US publicly traded non-financial companies. 4777 companies were selected for study for the period 1988-1998 She has developed and tested a model that measures a firm’s ‘Financial Condition Score’ (FCS). FCS is based on 3 variables viz: the firms’ size, its leverage and standard deviation of the firm’s assets calculated using stock returns and Black Scholes (1973) Option pricing Model. It was observed that FCS is effective in sorting firms according to their failure rates. A vast majority of the failed firms were sorted into the two highest FCS quintiles. Distressed firms that issue debt was observed to have a higher probability of failure as compared to distressed firms that issue equity.

Murty and Misra (2004)

The usefulness of cash flow ratios as indicators of financial distress was investigated in departure to the normally used financial ratios. In this study cash flow ratios were used as variables to identify sickness in Indian companies. 35 companies reporting sickness during the period 1977-87 ranging across 13 sectors formed the sample. These companies were matched with healthy companies. 9 cash flow ratios were studied of which 5 ratios were found to be significant viz cash flow / total assets, cash flow / total liabilities, cash flow / current assets, cash flow / current liabilities, cash flow / capital employed. Principal Component Analysis was used as for factor analysis. Multi variate
discriminant analysis was applied to construct distress prediction model. The model had a predictive accuracy of 80%. It was observed that cash flow ratios are good indicators of corporate health.

**Jones and Hensher (2004)**

In this paper mixed logit model is tested for effectiveness in prediction of financial distress as compared to multinomial logit model. The sample comprised of distressed and non-distressed firms from Australian Stock Exchange. The estimation sample and validation sample were selected from different time periods. The model classified firms as: a) Non-failed b) Insolvent firms c) Firms filing for bankruptcy. From the mix of cash flow and financial ratios used, cash flow to assets, working capital to total assets, net operating cash flows to assets was observed to have strong predictive powers. The mixed logit model was found to be superior to standard logit model.

**Stephan et al (2004)**

In this paper the effectiveness of Altman’s z-score and Ohlson (1980) model in analysing the probability of bankruptcy is studied. The above scores are compared with market measure of bankruptcy using Black Scholes Merton model –BSM Probability. It is observed that BSM Probability provides more information than other accounting measures.

**Leano Hector (2004)**

Bankruptcy prediction models using Principal Component Analysis, Discriminant Analysis and Linear regression were developed using bankrupt US companies as samples. Models were also developed for determining distressed firms that filed for bankruptcy and distressed firms that did not file for bankruptcy (had a successful turnaround). It was observed that a combination of these models can classify companies as solvent, distressed and bankrupt. These models were also applied to firms involved in M&A. Macroeconomic factors like Consumer price index, Industrial Production index, prime interest rate etc. were included as distress factors along with financial
ratios. The inclusion of these factors increased the model’s classification and predictive accuracy.


An innovative statistical procedure Sliced Average Variance estimation (SAVE) to identify financial ratios to predict bankruptcy. The effectiveness of the model was compared with the distress prediction models developed using Discriminant Analysis, Generalised Smoothing Spline model and Recursive Partition Tree model. It is observed that SAVE is more effective in identifying financial ratios to construct distress prediction model. Ratios indicating profitability, cash position and receivable turnover are selected as the best indicators of distress. It was also observed that Discriminant Analysis based on linear discriminant function cannot extract all the information from financial information.

**Becerra et al (2005)**

The authors have used linear discriminant models, neural networks and wavelet networks for corporate financial distress prediction. 60 failed and non-failed UK firms were selected for the study for the period 1997-2000. Financial ratios were used as variables. It was observed that non-linear models are an alternative to linear models in developing distress prediction models. Wavelets networks were found to be more advantageous over neural networks.

**Laitinen (2005)**

Survival Analysis as a technique was used to construct a model which indicates predictors that precedes a firm’s default. Cox Proportional Hazard model is used. The target variable is Payment default and financial ratios are used as descriptive variables. Ratios to indicate low profitability-high growth, low cash flow, increased debt, increased current debt, decrease in financial assets and payment default indicates the process of financial distress before default. It was observed that the advantages of Survival Analysis in comparison to statistical models used by credit companies. Equity
ratio, cash flow ratio and quick ratio are significant. Survival Analysis provides more information than simple cross sectional methods.

**Hossari and Rahman (2005)**

Popular financial ratios used in constructing financial distress prediction models were listed and ranked according to popularity and usefulness. 53 studies on financial distress conducted during 1966-2002 formed the sample. A formal ranking of 48 ratios on the basis of utility was done. It was observed that only 12% of studies used a particular financial ratio. Five ratios – net income / total assets, current Assets/current liabilities, total liabilities/total assets, working capital/total assets and earnings before interest / total assets was observed to be useful in more than 25% of the studies and hence has been given top rankings.

**Brockett et al (2006)**

The effect of statistical models and variables to identify financially troubled life insurers in US was attempted in this study. Four set of variables were examined – 22 variable set comprising of ratios like gains/premiums, liabilities /surplus, net operating income after tax and dividend, IRIS variables, FAST variables and Texas EWIS variables. The first 3 are financial ratio based and the last set consists of binary indicator variables constructed by Texas Early Warning Information System. It was observed that 22 variable set and Texas EWIS variables were more predictive in identifying financial distress among selected companies.

**Mine et al (2006)**

Study was done to identify predictors of financial distress in emerging market over a period of economic turbulence. Financial ratios were used as variables. 27 failed and non-failed manufacturing firms listed in ISE were selected for the period 1996-2003. 80 financial ratios were initially selected for study. Using factor analysis, 22 variables were identified to be significant in prediction of financial distress. EBITDA/total assets was identified as the most important predictor of financial distress. Other significant variables were operating profit margin and the proportion of trade credit to total claims.
Kane et al (2006)

In this paper the authors have examined the usefulness of financial reporting data to predict the probability of a firm recovering from financial distress. The authors have used stock based and flow based financial data for analysis. It was observed that cash flow has the most predictive ability. For a firm to emerge from a state of financial distress, efforts to increase operational profitability is the key factor. 423 firms during the period 1989-98 with a ‘z’ score less than 1.81 were selected for study. Altman’s model and logit regression were used as statistical tools for the study.

Marc Le Clere (2006)

The relationship between different sets of financial variables used in financial distress studies were examined. The selected distress studies were those of Altman (1968), Deakin (1972), Dambolena and Khouri (1980) and Ohlson (1980). These studies were selected due to their choice of statistical techniques viz Discriminant Analysis or Logit Regression. Canonical correlation and multi variate analysis was used for the purpose. It was observed that variables used in financial distress studies do not represent similar relationship. Common information between the variable sets are very small. It indicated adhoc selection of financial variables.


Identifying the unique features of failed companies and the syndromes leading to such failures were observed from a sample of 41 failed companies and 40 healthy companies. These companies were classified into 3 models based on common syndromes a) Black hole – negative funds flow from operations b) Failed growth – rapid size increase c) Setback – low interest and debt coverage. Equity/Total Assets, Total Financing/Funds from Operations, EBIT / Interest, Return on Assets, Asset Growth and Operating Revenue growth were used as variables. Nominal regression (multivariate analysis) has been used for statistical analysis. This study attempted to provide a theoretical framework to corporate failure.
Wang and Li (2007)

A rough set model was used to construct a distress prediction model of Chinese companies. 212 healthy companies and 212 failed companies were selected for study for the period 1998-2005. 34 financial variables and 5 non-financial variables like ownership concentration, affiliated debt and pledge were used to construct the model. Growth ratio per equity share, net return on assets, EPS, interest coverage, net profit margin were found be most significant variables in identifying distress. Ownership concentration was observed to be very powerful variable. Models combining financial and non-financial variables has better predictive power as compared to models using only financial ratios.

Hou and Chuang (2007)

This study aims to provide evidence as to the important determinants of financial distress. Along with financial ratios, the author has included Earnings management index and corporate governance variables to form Cox proportional hazard regression model for prediction of financial distress. 625 companies over a period of 1996-2006 listed in Taiwanese Stock Exchange were selected for study. Distressed companies were identified on the basis of legal insolvency faced due to debt default. It was observed that three indicators viz financial ratios covering profitability, liquidity, leverage and activity, earnings management index, corporate governance ratios covering size of Board of Directors, their shareholdings, pledge ratios of directors and number of independent directors were useful in identifying financial distress. Companies with higher earnings management index and pledge ratio of directors have greater chances of becoming financially distressed.

Beneda Nancy (2007)

This paper studies after market returns and probability of bankruptcies among new companies. Around 500 companies with IPO were studied for a period from 1995-2002. Olson’s (1980) o ratio was used to predict the incidence of bankruptcies. Market to book ratio and underwriter’s share was also studied as variables. The study concludes
that the above 3 ratios were good indicators for creating a good portfolio of IPOs. Along with Ohlson (1980) model, regression analysis was also done on the selected variables.

**Smith and Liou (2007)**

The applicability of one model across all sectors and whether ratios indicating financial distress differ sector wise was investigated. Financial ratios of 1000 companies from 5 different sectors were studied. Ratios selected indicated productivity, liquidity, turnover, profit margin and rate of return. Pearson’s correlation coefficient was used to analyse the correlation between ratios of failed firms and the sectors. Taffler (1983) discriminant model was applied. It was observed that industry wide models can be universally applied however some sectors may have to be modelled separately to achieve greater accuracy. It was also observed that such models have great longevity w.r.t variables used as well as weightages.

**Sharpe and Stadnik (2007)**

The objective of this study was to identify Australian general insurers experiencing financial distress. 69 general insurers were selected for the study for the period 1998-2001. Financial ratios like profitability ratios, underwriting expense ratio, cession ratio, scale, growth, asset composition and insurance lines were used as variables. It was observed that holding of property, reinsurance assets, and mix of insurance lines influences financial distress.

**Gepp and Kumar (2008)**

Survival Analysis (SA) has been used for prediction of financial distress. In SA, past data is used to calculate the value of the function. SA analysis explains the relationship between the survival function - the descriptive variable and the set of explanatory variables. Cox SA uses regression to predict financial distress. The results were also compared using Discriminant and Logit models. Hybrid models combining SA with DA and LA were also constructed and studied. It was observed that Cox model predicts
business failure as well as DA or Logit models. However hybrid models were not found be appropriate.

**Hui and Jing-Jing (2008)**

The authors have tried to establish a relationship between indirect financial distress cost borne by a companies under distress and corporate governance. 193 distressed Chinese companies were studied during the period 2000-06. Financial distress costs is measured by the reduction in EBITDA/Market value of equity. Ownership structure, Board composition, overhead costs were the variables for corporate governance. It was noted that ownership balancing reduces the cost of financial distress and overhead costs increased the cost of financial distress. Company’s financial health can improve with good corporate governance.

**Coyne et al (2008)**

Financial ratios of 13 bankrupt health care systems and 7 solvent health care systems were studies for a 7 year period prior to bankruptcy. Ratios like Operating cash flow percentage change, operating cash flows / Net revenues, days of cash on hand, Cash flow / Total Liabilities, Debt / Equity, Debt Service Coverage Ratio; Days of receivables were selected for the study. It was observed that Operating cash flow changes, operating cash flows /Net revenues and Cash flow / Total Liabilities emerged as distinct indicators of financial distress. It shows the sensitivity of health care systems to cash management.

**Mahdi and Bizhan (2009)**

30 failed and 30 non failed companies in Tehran SE was examined for financial distress. Multi variate discriminant analysis was used to construct distress prediction model. Of the 22 ratios for a 3 year period selected for study, 5 ratios were found to be significant i.e. working capital / total assets, current assets /current liabilities, profit before interest and tax/total assets, sales/total assets total earnings /total assets. It was concluded that the model can predict distress 3 years prior to failure.
Oberholzer (2010)

The interrelationship between four performance parameters i.e. a) Technical efficiency b) Altman’s revised z-score, Return on Equity (ROE) as internal measure and Price to Book Value (P/B) as external measure were studied. 55 manufacturing companies listed in Johannesburg Stock Exchange were studied during the period 2003-08. The study concludes that return on equity was closely related to technical efficiency and hence return on equity can be substituted for technical efficiency which is difficult to measure. There was no significant relationship between other variables.

Ying and Campbell (2010)

This paper has applied Altman’s z-score model to predict financial distress in publicly listed Chinese companies. 42 delisted companies and 42 listed companies were used as a sample to check the predictive accuracy of Altman’s z-score model. The model’s coefficient was re-estimated and tested with the selected sample. A sixth variable X6 was developed as Total Assets 1 yr prior to delisting/Total Assets 2 yr prior to delisting. A revised z-score model with original model’s X4 & X5 and new variable X6. Z-score model was found to be effective in predicting failure. Re-estimated model has better predictive abilities and revised model with 3 variables has higher levels of predictability as compared to both the models.

Yazdipour and Constand (2010)

This study focuses on using behavioural finance in constructing failure prediction models especially for Small and Medium Enterprises. It states that there is a relationship between probability of failures and the ‘intensity of cognitive biases’ of an entrepreneur. This study observes that managerial decision making (cause) cannot be ignored while analysing financial distress through financial variables (effect). The authors have suggested that heuristics can be utilised in strengthening distress prediction models.
**Julien le Maux and Morin (2011)**

The objective of this paper is to analyse whether Lehman’ Bros. Downfall could have been predicted. It was observed that signs of financial distress were existing in 2005-07 financial statements. Chronic inability to generate cash flows from operating activities, heavy investments in working capital, use of long term debt to offset shortfall in operations, decreasing cash flows over years. Cash flow statements were found to be very informative and can disclose signals of financial distress as compared to Income statement and Balance Sheet.

**Hodgkin and Marchesini (2011)**

The authors have studied companies which has defaulted on loan payments. Two multivariate financial distress models developed by Zmijewski and Marchesini were tested for predictive accuracy. 91 leveraged companies listed by Credit Suisse as defaulters were selected for study for the period of recession 2000-01. MBP logit model and ZMI probit model was applied to the datasets. It was observed that for both models prediction accuracy rates were similar for default period and two immediate period prior to default. However some disparity was observed in ‘likely to default category’. Logit and probit models applied to carefully selected datasets may yield usefully accurate prediction.

**Xie et al (2011)**

The authors have used Support vector machine and MDA to develop models to predict financial distress. 260 Chinese listed companies were used as samples. 130 companies having consecutive negative losses were matched with 130 good companies. Along with financial ratios, internal governance, external market variables as well as macroeconomic variables were used as indicators of financial distress. It was observed that SVM model was more accurate in predicting financial distress 3 years prior to the occurrence of the event. However sensitive factors could be discriminated through MDA model. GP ratio, Cash flow from operations, total asset turnover and growth rate of income are critical variables indicating financial distress.
Ehab Zaki (2011)

Distress prediction models for commercial and Islamic banks in UAE during the period 2000-08 were developed. 16 financial institutions were studied for the period 2000-08. The objective was to establish fundamental and external factors leading to financial distress. Panel discrete choice models was used to analyse the variables. It was observed that Cost to Income ratio, Equity to total assets, total asset growth were significant indicators of financial distress. Macroeconomic factors did not impact the probability of financial distress.

Ong et al (2011)

The authors have reviewed 105 Malaysian companies to develop a distress prediction model. Logistic regression is used as the statistical tool. Financial and cash flow ratios were used as variables. Current Asset turnover, Asset turnover, Days sales in receivables, cash flow to total debt and total liabilities to total assets were observed to be significant indicators of corporate distress.

Lin et al (2012)

In this paper, the authors have developed different models for predicting corporate bankruptcy using different definitions of ‘failing businesses. Small business (SME’s) were selected for analysis and grouped into four categories – Insolvency, Stock based distress, Flow based distress and Healthy. Financial ratios were used as variables. It was observed that continuous growth in profitability, annual sales and operating revenue are important for small business to be successful. Also ‘default definition’ has effect on model composition. Binary logit regression was used for analysis.429 small firms whose liabilities > Assets and interest coverage < 1 were selected for study.

Polemis and Gounopoulos (2012)

In this study the authors have tried to identify financial characteristics of companies in financial distress. 76 firms were selected as samples. Liquidation, voluntary liquidation,
appointment of administrator and delisting from London Stock Exchange were used as criteria to select financially distressed companies. A discriminant model was constructed using binary logit regression. A univariate analysis was done to identify potential targets for M&A. It was observed that efficient firms are more liquid in terms of meeting short term liabilities. Such firms have large assets and hence have less chances of becoming bankrupt.

Dave (2012)

Through this paper the author has tried to establish relationship between financial management and profitability. 64 listed companies from Indian pharmaceutical sector were selected as samples. Using multiple regression analysis, it was observed that Total Assets to sales and creditors velocity has great influence on profitability of an organisation.

Sheikhi et al (2012)

In this study the author has used financial ratios like liquidity ratios, profitability ratios, activity ratios, leverage ratios to observe financial distress in selected companies. A new variable -distress score reflecting poor management of a company is also used along with other variables. 304 corporations from Tehran Stock Exchange were been selected for the study for a period between 2001-2008. 79 of these were distressed and 225 none distressed. It was observed that the accuracy of distress prediction model can be improved by including distress score obtained through Data Envelopment Analysis.

Lakshan and Wijekoon (2013)

The authors have used financial ratios to predict corporate failure. 70 failed and 70 non failed companies listed in Colombo stock exchange were studied during the period 2002-08. Logit regression was used to construct corporate failure prediction model. It was observed that cash flows, leverage, liquidity were important indicators of corporate failure.
Mahdi et al (2013)

120 companies were selected from companies listed in Teheran Stock Exchange. 24 financial ratios covering profitability, activity ability, debt ability and growth ability are selected as initial variables. The authors have applied support vector data description (SVDD) to suggest the new model. To evaluate the predictability of SVDD, its performance is compared with fuzzy c-means (FCM). Grid search technique using 3-fold cross validation is used to select the optimal values of the upper bound C and kernel parameter g. The results of the above study shows that SVDD out performs other methods.

Grunberg and Lukason (2014)

Bankruptcy prediction models using Logistic Regression and Neural Networks were developed for Estonian manufacturing firms. 14 financial ratios including size of firm, size of revenues, size of total assets and age of the firm were included in the study. Models using logistic regression were observed to have better classification abilities as compared to Neural Networks model.

Altman et al (2014)

A very comprehensive study was done to examine the applicability of Altman (1968) ‘z’ score model for prediction of corporate distress across different countries. Post 2000, 34 scientific papers have been published on application of the ‘z’ score model in different countries. The question was ‘Can one model fit internationally to all data?’ After applying the model to 32 European and 3 non-Europeans countries data, it was observed that the model fits reasonably well in most of the countries with a classification accuracy rate of 75%. However the accuracy levels can be increased tremendously by incorporating country specific estimates. Additional information through more predictor variables can also improve the classification accuracy.
Boda & Uradnicek (2016)

A study of Slovakian companies for the period 2009-2013 was done to test the applicability of Altman (1968) bankruptcy model. It was observed that though the model is portable. However the coefficients of the ‘z’ score model needs to be re-estimated if distressed companies are to classified with high degree of accuracy.

Summary

Research on corporate distress post 2000 saw increased interest in incorporating new definitions of corporate distress. Along with debt default as a proxy for failure, loss of capital, poor credit rating, delisting on stock exchanges, continuous losses, negative or decreasing cash flows negative net worth were used to identify distressed companies. Though financial ratios continued to act as important predictors of financial distress, other indicators like size, leverage, corporate governance, cash flow ratios, market risks, and macroeconomic factors like money supply were being increasingly used as distress predictors. Different techniques were also adopted to construct bankruptcy models most interesting being Survival Analysis, Rough Set model, Wavelet Network Support Vector, Cumulative sums multivariate time series The need to incorporate behavioural finance in corporate distress studies also gave a new direction to distress studies. Studies were also done to test the validity of most popular and established models. Many studies investigated and compared the effectiveness of various statistical methods used for developing distress prediction models. Though extensive research was done, there was no consensus about the ideal financial ratios for predicting failure or the most ideal method of constructing distress prediction models. Most of the corporate distress and bankruptcy prediction studies were concentrated in developed nations like US, UK and Australia. There were very few studies done for emerging and developing nations. Also the need for country specific distress prediction model was impressed
2.2.4 Research in India

In relation to the quantum of studies on corporate distress conducted in US, European and Asian countries, review of corporate distress and bankruptcy in Indian companies is limited. Some of the major studies are discussed in the following paragraphs.

Bhunia and Sarkar (2011)

64 companies in pharmaceutical sector were analysed for distress using 16 financial ratios. A discriminant function was modelled with 7 ratios. It was observed that MDA is still a reliable statistical tool for financial distress prediction. 32 failed and 32 non failed companies were selected for study. It was observed that financial ratios have a predictive ability to identify a failed company and a non-failed company. Ratios measuring liquidity and profitability are most important in identifying a failed company and a successful company.

Bhunia et al (2011)

17 failed companies from different sectors were reviewed for financial distress. Companies incurring losses for 3 years or more continuously and companies having negative cash flows for 3 years or more were defined as failed companies. Each of these 17 failed companies were matched with a non-failed company. The study used 64 financial ratios. Using Discriminant analysis, a discriminant model was developed. Two ratios cash flow to assets and days sales in receivables were found to be significant to discriminate between failed and non –living companies. The model showed an accuracy rate of 80%.

Arun and Kasilingam (2011)

In this paper, Altman’s z-score model has been applied to 17 companies from Indian IT sector for the period 2003-2009. The correlation between financial variables has been observed using Pearson’s correlation coefficient. Regression analysis was done to
measure the average relationship between the variables. EBIT/TA emerged as the significant variable in computation of z-score

**Sarbapriya Ray (2011)**

The financial health of Indian automobile industry was examined using Altman’s ‘z’ score. Companies in automobile sector during the period 2004-2010 were selected for study. All the companies were observed to be in ‘grey zone’ as defined by Altman (1968). This study was limited by its scope. Also the applicability of the 1968 model to current economic and industrial conditions were not conclusively proven.

**Reddy and Reddy (2010)**

The sugar sector in India was investigated for financial distress in this study. Three major sugar mills were selected for the study. Financial ratios indicating solvency, working capital investment efficiency, liquidity were analysed. Altman (1968) ‘z’ score model was applied to predict bankruptcy. The selected companies were observed for the period 2004-2010. It was observed that financial ratios reflects the financial health of the companies.

**Bardia (2012)**

Long term solvency position of two large steel companies in India were examined in this study. Common size analysis of assets and liabilities, ratio analysis and Altman (1980) ‘z’ score model was used to assess the solvency of the selected companies. The period of the study was 1998-2009. It was observed that common size analysis and ratio analysis could be used to investigate the financial health of the company.

**Kumar and Kumar (2012)**

This study was done to test the applicability and accuracy of established models when applied to Indian companies. Altman (1968) ‘z’ score model, Ohlson (1980) ‘o’ score model and Zmijewski (1984) model were applied to Indian company. The period of study was 2005-2009. It was observed that the accuracy of new models developed through new data is substantially higher than the existing models. Of the three Ohlson
(1980) model was found to be most accurate owing to the use of binary logistic regression.

**Mondal and Roy (2013)**

The authors have developed models for predicting business sickness in Indian Steel sector using financial ratios as variables. Financial ratios of 40 companies from the steel sector were examined. Financial ratios indicating liquidity, profitability, activity, solvency and growth were selected as variables. Initial classification of companies into sick and non-sick was done on the basis of net worth. Using Hierarchical Cluster Analysis, the companies were again classified. Step wise regression analysis was used to identify the most powerful independent variables. Debt Equity ratio, Fixed Assets Turnover ratio, Debtors Turnover ratio and Rate of growth in Profit after Tax were found to be significant in classifying a company into sick and non-sick. Earning power represented by Rate of growth in Profit after Tax and capital structure represented by Debt Equity were identified as the most important predictors of financial distress. The developed model could correctly classify 92.5% of the selected companies into sick and non-sick.

**Panda and Behera (2015)**

Financial distress in pharmaceutical companies were examined using Altman (1968) ‘z’ score model for the period 2001-2012. 5 large pharmaceutical companies in India were selected for the study. A paired sample ‘t’ test analysis among financially distressed and non-distressed companies revealed significant difference in means of ratios of distressed and non-distressed companies.

**Summary**

Research in the field of corporate distress in India has not been very encouraging. Very few studies as seen above have been conducted for analysing and predicting financial distress. Most of the studies conducted focused on application of existing model to Indian companies. There is lack of efforts seen in developing a distress prediction model for Indian companies. Research has established the need for country specific
model incorporating the aspects unique to the business and economic environment of the country.

2.3 Review of studies on Macroeconomic Factors and its influence on Corporate Distress and Bankruptcy

Several attempts have been made to establish the impact of macroeconomic environment on the performance of companies. Many studies have suggested a relationship between macroeconomic factors and corporate failure. Some important studies are discussed in the following paragraphs.

Kane et al (1996)

This is one of the earliest studies connecting macroeconomic environment and financial distress. The authors have examined whether recession is an informative factor to increase the predictive and explanatory power of failure prediction models based on accounting variables. Companies listed in NYSE/AMEX/NASDAQ which have filed for bankruptcy during the period 1968-90 and 2000 non-failed companies were reviewed. It was observed that addition of recession indicators adds incremental, explanatory and predictive power of distress models.

Tirapat and Aekkachai (1999)

This study bridges a firm’s sensitivity to macroeconomic conditions and financials leading to distress. 459 distressed listed firms from Stock Exchange of Thailand were observed. Along with financial variables, macroeconomic variables like monthly growth of Production Index, monthly inflation, monthly changes in interest rates, monthly change in money supply are important indicators of financial crisis. Inflation emerged as the most critical factor.
Agarwal (2001)

The impact of interest rates and exchange rates on increase in spread of financial inclusion in an economy was observed for four Asian economies like South Korea, Malaysia, Thailand and Indonesia. Real interest rates and real exchange rates affect investment ratios in an economy. Interest rate liberalisation in a controlled manner minimizes the potential for financial distress. This study clearly shows a strong relationship between macro-economic factors and financial distress.

Pompe and Bilderbeek (2005)

The influence of the year prior to failure and effects of economic decline were observed for 3600 Belgian small and medium sized industrial firms. The study was done for the period 1988-1991. Economic decline witnessed a rapid increase in the number of bankruptcies.

Bhattacharjee et al (2009)

The impact of macroeconomic environment on business and consequent exists were reviewed in this study. Listed UK companies for period 1965 to 2002 spanning business cycles were reviewed. Per capital output, real interest rates, real effective exchange rate were used to represent macroeconomic environment along with financial variables like firm size, cash flow to total assets, current ratio, interest to EBIT, debt to sum of debt plus equity. Hazard Regression models were applied for inference. Industry type, size of the firm affects business exits. Instability in prices and long term interest rates affects newly established firms more than old firms.

Smith and Liou (2007)

Relationship between corporate failure and macroeconomic factors was reviewed for UK manufacturing sector to identify the most significant variable depicting distress. 340 companies with negative ‘z’ score as per Taffler’s model were studied. GDP, Industrial Production Index, Interest rates, Inflation, Retail Price index, FTSE All share index were used as variables. GDP, Retail Price Index and Industrial Production Index
emerged as influencing variables which improved the classificatory ability of failure prediction models.

Gertler et al (2007)

The relationship between exchange rates and distress was studied for Korean economy. Reduction in output, employment and production can be well explained by changes in macroeconomic factors. Credit market also affects investment demand thereby influencing output, employment and labour productivity. International trade also greatly affects economic crisis.

Gulzar and Hi Xiao (2008)

The study evaluates the relationship between exchange rates and micro economic conditions. It was observed that stabilisation of exchange rate helps achieve economic growth, control inflation and achieve independent monetary and fiscal policy. It also increases the confidence of foreign investors leading to all round well-being of the economy which is conducive for growth of firms.

Nandy (2008)

Macro- economic factors and their influence on capital structure decisions were studied for BSE 30 companies in India. The impact of inflation rates, stock market performance, interest rates and GDP on a firms Debt/Equity were observed. Inflation, GDP, Stock market returns has a negative impact on Debt Equity ratio of a firm whereas rate of interest has a positive relation with the capital structure of the firm.

Jia Liu (2009)

The interaction between business failures and macroeconomic factors on UK firms were observed. Interest rate, credit policy, inflation have differential impact on business failures both in short run and long run. Business failures are the reaction to monetary
policy changes. Vector Autoregression (VAR) model is used to analyse the dynamics of business failures. High inflation leads to rise in failure rates.

**Tsai and Cheng (2010)**

A two stage distress model incorporating financial variables with macroeconomic variables was developed for Taiwanese companies using Discrete Time hazard Model. 172 distressed firms were observed for a period 1986-2004. Along with financial variables, market variables significantly predict financial distress. Abnormal negative returns indicate potentially distress. Also in emerging markets, failure is more related to local economic environment as compared to developed markets. Once the first stage model estimating firm specific probability of financial distress is identified, macroeconomic data can be incorporated to identify potential financial distress.

**Oxelhein and Wihlborg (2012)**

The differential impact of macro-economic factors on credit risk of the firms was studied in the context of General Motors and Ford during the period 1996-2008. Interest rate, exchange rate, price levels and gasoline price changes are used as macroeconomic factors. The indication of distress probability is divided into values that is explained by firm specific factors and values explained by macro-economic factors. Altman’s ‘z’ score was used as an indicator of default probability. For both the companies in the same industry and same ‘z’ values, firm specific macro-economic influences affects the probability of distress.

**Mishra (2013)**

The relation between macro-economic variables and corporate health indicator was studied using 73 firms for the period 1990-2003. Corporate health was denoted by Altman’s ‘z’ score and Bank Rate, GDP, Inflation and Trade Openness were the macro-
economic variables examined. Using Panel Unit Root test, Panel Cointegration Analysis and Panel Long run Causality, it was established that there is a two way relation between ‘z’ score with Bank Rate and GDP. Financial distress can trigger monetary instability in worsening macro-economic environment.

**Ben Sami (2014)**

The link between failure of companies and macro-economic factors were examined in the context of bankrupt French companies during 1999-2008. Consumer Price Index, Producers Price Index, Industrial Product Price Index and M2 money supply are the macro economic factors used in the study. Using PLS regression, it was observed that Industrial Price index and Product Price index are important factors influencing distress. However these factors are to be used with caution as failure is the result of firm specific factors and macro-economic factors are not decisive in the phenomenon of failure.

**Zhang and Nielson (2015)**

Variations in Business and Market Environment influences insolvency. A study on US Insurance companies for the period 1996-2008 revealed that inflation, unemployment rate, stock market returns increased the probability of insolvency. Focusing on local markets and concentrating on specialised business lines lead to better financial performance. It was also observed sufficient cash flow, with high return on equity, with lower liability to asset ratio and being members of larger groups, are less likely to become insolvent.

**Oz and Yelkenci (2015)**

The most cited Distress Prediction model developed by Ohlson (1980), Taffler (2001), Zmijewski (1984) and Shumway (2001) were tested on publicly listed industrial firms in Turkey. The objective of this study was to check whether the applicability of these models can be generalised across countries and time periods. The impact of 2008 financial crisis was also assessed to check the model accuracy. The sample companies
were checked using original coefficients and re-estimated coefficients. All models gave highly accurate classification results based on original coefficients. Only Ohlson (1980) model improved the prediction accuracy with re-estimated coefficients.

**Ojha and Vrat (2016)**

Critical factors impacting the growth of manufacturing in India were studied. A scenario analysis using Interpretive Structural Modelling and System Dynamics was done by forecasting an increase in manufacturing company’s share in GDP from 15% to 25% by 2025. Goods governance, simplifying business regulations, curbing red tapeism, effectiveness in natural resource management were the important factors identified to improve manufacturing companies contribution to GDP.

**Summary**

Studies have suggested that macroeconomic factors can impact business failures. Recession, inflation, credit policy, trade openness, gross domestic product, exchange rates, oil price changes are some of the factors investigated for their impact on business failures. However it is notable that these factors rarely appear as variables in predictive models that identify distress and failure. Importance of financial distress in economic fluctuation and its role in increasing financial instability deserves proper attention. Hence an attempt have been made to incorporate macro-economic factors along with financial variables in this study.

**2.4 Review of Statistical Methods, Techniques and Models used in studies on Corporate Distress and Bankruptcy**

Bankruptcy prediction has interested and intrigued accountants and researchers alike since early 1930’s. One of the earliest study in this field was by Fitzpatrick where he analysed the ratios of 20 failed firms. These firms were matched with equal number of healthy firms and the trend in ratios were interpreted. No statistical method was used. Since then, there has been numerous studies done in the area of corporate distress and
bankruptcy. The empirical and theoretical research conducted till date seek to find answers to the following questions:

1. What are the most appropriate predictors of financial distress: financial factors, market based factors, macroeconomic factors?
2. Which is the best statistical method to develop distress / bankruptcy prediction models?
3. What is the validity of the models developed across different industries, sectors and countries?

A critical review of various models developed for bankruptcy prediction and the statistical methods adopted are discussed below.

2.4.1 Univariate Analysis

Univariate Analysis is a technique which uses one variable as the explanatory variable for an event. It explores each variable in the dataset and describes the pattern of response to the variable. Each variable in the dataset is used to classify the sample. The cutoff point for such classification is based on the percentage of misclassification. Beaver (1966) used univariate analysis using 30 ratios to develop bankruptcy prediction model. 79 failed and 79 non-failed firms were selected across 38 industries. Under this method, one financial ratio of the sample firm is compared with standard ratio to classify the firm into failed or non-failed category. This method assumes that one ratio can predict distress in firms. Beaver observed that Net Income / Total Debt has the highest predictive accuracy (92%). Pinches et al, 1975 and Chen and Shimerda, 1981 were some of the other researchers to have used this technique, (Bellovary, 2007).

Critical Evaluation

Though this technique is very simple, inconsistencies may arise if an individual financial ratio is used as a predictor of failure. Also different ratios can give different results for the same firm, (Chancharat, 2008). A major limitation of univariate analysis apart from relying on one ratio at a time is the assumption of proportional relationship between factors, Suntraruk (2010). Beaver (1966) himself noted that multiple ratios
may have higher predictive ability than single ratios. A single financial ratio cannot include all information. Financial health of a firm cannot be explained by a single ratio. There are various factors which simultaneously affect a firm.

2.4.2 Multi variate Discriminant Analysis (MDA)

One of the most popular and extensively used methods in studies of corporate bankruptcy is Multi variate Discriminant Analysis. This technique overcomes the limitations of univariate analysis. Altman used this technique in his study on corporate distress. In MDA method, an observation is classified into one of the a priori groups based on unique characteristics of the observation, (Avenhuis, 2013). Several variables are combined into a single weighted index. Such a combination of variables which maximizes the between group variance in relation to within group variance is determined. The ratio of between group variance and within group variance is shown as a relation. The resulting relationship is expressed in the form of a linear equation:

\[ z = c + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \]

Where \( z \) = Discriminant score  
\( c \) = intercept  
\( \beta_1 - \beta_n \) = coefficients or weights  
\( X_1 - X_n \) = independent variables

A cut off score is calculated according to priori probabilities of group membership and the cost of misclassification. Based on the cut off score and the Z score, a firm is classified into failed and non-failed. A firm is classified as failed if its z score is less than cut off score and non-failed if it is equal or more than the cut off score.

Altman (1968) used a sample of 33 bankrupt manufacturing firms in US and matched each bankrupt firm with a non-bankrupt firm from the same industry and size. He excluded very small and very large firms from the sample. The period of study was
1946 – 1965. The firms which had filed for bankruptcy during the period of study were identified as bankrupt firms. Altman (1968) initially reviewed 22 ratios which were considered relevant for the study. The final discriminant function with five explanatory ratios is:

\[ Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.9X5 \]

where:

- \( Z \) = Discriminant Score
- \( X1 \) = Working Capital/ Total Assets. This variable is a measure of liquidity.
- \( X2 \) = Retained Earnings/ Total Assets. This variable incorporates the impact of age of the firm since an older firm will have larger retained earnings
- \( X3 \) = EBIT/ Total Assets. Earnings before interest and taxes (EBIT) represents the earnings from operating activities
- \( X4 \) = Market Value of equity/Book Value of debt. This variable measures leverage of the firm.
- \( X5 \) = Sales/Total Assets. This variable measures the efficiency in use of assets for sales.

As seen above, there is no intercept in the model and the coefficients are standardized to determine the impact of independent variable on dependent variables if the unit of measurement of the variables are different (Avenhuis, 2013).

Thus Altman (1968) used measures of liquidity, profitability and leverage for developing his model. The value of ‘\( z \)’ is a cut off value which would classify a firm into failed and non-failed. Initially the cut off was given at 2.67. The cutoff is based on the number of Type I and Type II errors in classification. All firms having a ‘\( z \)’ score of less than 2.67 were classified as failed. This score was later revised to 1.81. The scores between 1.81-2.67 was defined as ignorance zone which implied that there is a high probability of failure, (Muller et al, 2009).

The model’s predictive ability was very high 1 year and 2 year before failure for the sample (95% and 72% respectively. The accuracy level for the holdout sample was 84%. However the accuracy rates declined drastically for 3 yrs., 4 yrs. and 5 yrs. before failure.
To extend the model to private firms, in variable X4, market value of equity was substituted by book value of equity. The revised model was:

$$Z' = 0.717(X1) + 0.847(X2) + 3.107(X3) + 0.420(X4) + 0.998(X5)$$

To incorporate non-manufacturing firms the model was further revised by excluding the X5 as:

$$Z = 6.56 (X1) + 3.26 (X2) + 6.72 (X3) + 1.05 (X4)$$

Altman, Haldeman and Narayanan (1977) constructed a new model ZETA® Credit Risk Model incorporating latest developments in the area of business failures. This model was developed using manufacturing and retail firms in US as sample.

Altman’s model was criticized in subsequent research on following grounds:

1. Normality of data and proportional variance-covariance of factors is a major assumption of Discriminant Analysis. If this assumption is not fulfilled the results may not be accurate, (Suntraruk, 2010).
2. Limited interpretational value of Z-score.
3. Use of only manufacturing firms in sample limits the wide applicability of the model.
4. Small sample size of only 33 failed companies matched with equal number of non-failed companies.
5. Theoretical issues like research method used, definition of failure, issue of ratio instability were also questioned (Balcen and Ooghe, 2006 in Agarwal and Taffler, 2007)

**Agarwal and Taffler (1983)**

Agarwal and Taffler also used MDA to develop a new ‘z’ score model for firms in UK. Taffler selected 80 ratios of listed industrial firms in UK which failed during the period 1968-76. These firms were matched with 46 randomly selected non-failed firms. (Agarwal and Taffler, 2007). The model is given by:
$Z = 3.20 + 12.18X1 + 2.50X2 - 10.68X3 + 0.029X4$

Where

$X1 = \text{Profit before tax/ Current liability measuring profitability (53\%)}$

$X2 = \text{Current Assets / Total Liabilities measuring working capital management (13\%)}$

$X3 = \text{Current Liabilities/ Total Assets measuring financial risks (18\%)}$

$X4 = \text{no credit interval measuring liquidity (16\%)}$

The percentages given in brackets indicate the Mosteller-Wallace contribution of the respective independent variable to the discriminant function. The cutoff point was zero. A firm having a $z$ score of less than zero was identified as financially unhealthy firms with a risk of failure.

The technique uses a combination of several variables and converts it into a single weighted index, hence it alleviates the limitation on of univariate analysis. Models developed using MDA have immense predictive value. Such models can provide a scientific base for banks to review debts. However the technique is criticized for the assumption of normal distribution of independent variables. Also the group dispersion matrices are assumed to be equal across failed and nonfailed firms. It has been observed that assumption of normality often gets violated resulting in significant bias. The validity of models has to be investigated with major changes in economic and business environment, (Agarwal and Taffler, 2007).

### 2.4.3 Logit / Probit Analysis

Due to the limitations in MDA as a technique for developing prediction model, researchers started using logit and probit analysis. For any binary dependent variable where the outcome is dichotomous, logit/probit analysis was found to be appropriate. These method employs cumulative probability distribution due to which the value of the outcome lies between 1 and 0.
The normal logit/probit function is given as:

\[
P(y=1) = \frac{e^{(b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n)}}{1 + e^{(b_0 + b_1x_1 + b_2x_2 + \ldots + b_nx_n)}}
\]

Where \(Pr(y=1, x_1, \ldots, x_n)\) is the probability that \(y=1\)

\(X_1, \ldots, X_n\) are independent variables

\(\beta_1, \ldots, \beta_n\) are the coefficients.

Logit/Probit models test the relationship between the likelihood of a particular outcome and the independent variables. Maximum Likelihood Estimation is used to calculate the values of the coefficients. This method helps select the best independent variables to predict the value of dependent variable. To classify whether a firm is distressed or not, the probability function of each firm is calculated using equation as above. The value \(Pr(Y)\) is used to classify the firms as distressed and non-distressed based on a cutoff score. The cut-off score is generally taken at 0.50 as the value of the dependent variable lies between 0 and 1, (Suntraruk, 2010). Logit/Probit Analysis was advocated as a better method for developing distress prediction models due to its obvious advantages:

1. No assumption about distribution of data related to independent variables.
2. Maximum Likelihood Estimation helps a researcher to identify the best independent variable to predict the value of dependent variable.
3. Logistic regression is appropriate when the dependent variable can be expressed in qualitative terms. In distress prediction studies the outcome can be defined in the form binary outcome i.e. a bankrupt or non-bankrupt firm.
4. The probability of financial distress can easily be prediction using this method.
5. The results of Logistic Regression Analysis can be easily interpreted.

Two very popular models used Logit/Probit analysis to develop distress prediction models:
1. Ohlson (1980)

**Ohlson (1980)**

James Ohlson developed a bankruptcy prediction model using logit analysis in 1980. Ohlson’s ‘o’ score is determined using nine ratios. The period of study was 1970-76. 105 bankrupt firms and 2058 non-bankrupt firms were selected as samples. Bankrupt firms were those firms which had filed for bankruptcy. All the firms belonged to industrial sector in US. The Ohlson’s logit model is given as:

\[
Pr(Y) = -1.3 - 0.41X1 + 6.0X2 - 1.4X3 + 0.1X4 + 2.5X5 - 1.8X6 + 0.3X7 - 1.7X8 - 0.5X9
\]

Where

- \(X1 \) = log (Total Assets/GNP price level index)
- \(X2 \) = Total Liabilities/Total Assets
- \(X3 \) = Working capital / Total Assets
- \(X4 \) = Current Liabilities / Current Assets
- \(X5 \) = 1 if Total liabilities > Total Assets else \(X5 \) = 0
- \(X6 \) = Net Income/Total Assets
- \(X7 \) = Funds from operations/ Total Liabilities
- \(X8 \) = 1 if Net Income is negative else \(X8 \) = 0
- \(X9 \) = measure of change in Net Income

The independent variables in the above model represents profitability, liquidity and leverage. The overall accuracy rate of the model was 96% for the estimation sample and 85% for holdout sample, (Avenhuis, 2013).

Ohlson’s model was criticized on the grounds of rigidity of parameters and lack of definition of errors. A mixed logit model recognizes “the substantial amount of heterogeneity that can exist across and within all firms in terms of the role that attributes play in influencing an outcome domain”, (Jones and Hensher, 2004). The accuracy rates of Ohlson (1980) and Zmijewski (1984) model was compared using samples from
different industries and time periods. The accuracy rates of the models improved when the coefficients were re-estimated, (Grice and Dugan, 2001).

**Zavgren (1985)**

In 1985, Christine Zavgren (1985), developed a bankruptcy prediction model based on logit regression. The model is given as:

\[ y = 0.23883 - 0.108x1 - 1.583x2 - 10.78x3 + 3.074x4 + 0.486x5 - 4.35x6 - 0.11x7 \]

\( x1: \) Sales / Average Inventory,
\( x2: \) Average inventory / Average accounts receivable,
\( x3: \) Total assets / Cash balance + Short-term investments,
\( x4: \) Current liabilities / Immediate assets,
\( x5: \) Total assets - Current liabilities / Operating profit,
\( x6: \) Total assets - Current debt / Long-term liabilities,
\( x7: \) Fixed assets + Net working capital / Sales,

\[ \frac{1}{(1 + e^y)}: \] the probability of bankruptcy.

**Zmijewski (1984)**

Zmijewski (1984) in his study emphasized on two estimation biases which may exist if samples are taken on nonrandom basis. (Avenhuis, 2013). The two biases as stated by Zmijewski are:

1. **Choice based bias**: In a matched firm sample where each failed firm is matched with a non-failed firm, there is a probability of overestimation of financial distress if the proportion of failed firms to non-failed firms in the sample is different from that of the population.

2. **Sample selection bias**: If complete data on distressed firms is not available then the predictive accuracy of the model is compromised.
To overcome these limitations, Zmijewski (1984) selected all firms listed in American and New York Stock Exchange during the period 1972-78. His sample comprised of 40 bankrupt and 800 non-bankrupt firms as estimation sample and 41 bankrupt and 800 non-bankrupt firms as validation sample. Bankrupt firms were defined as those firms which had filed for bankruptcy during the period of study. He employed Probit Analysis as the statistical tool to develop bankruptcy prediction model. As logit, probit also gives the value of probability between 0 and 1. The cut off was set at 0.50. All firms having a score of less than 0.5 was identified as non-failed and all firms having a score of more than 0.5 were classified as failed.

Zmijewski (1984) probit model is given as:

\[ X = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \]

where

- \( X_1 = \) Net Income/Total Assets
- \( X_2 = \) Total Debt/Total Assets
- \( X_3 = \) Current Assets/Current Liabilities
- \( X = \) Overall index

The model had an accuracy rate of 99% for estimation sample. The predictive power of this model was criticized for the ratio selection method used by Zmijewski. It was pointed out that ratios were selected on the basis of their use in earlier studies and not on conceptual grounds, (Grice and Dugan, 2001). It was also criticized on the grounds that the variable Net Income/Total Assets is influenced by Capital Structure of the firm and the variable Total Debt/Total Assets also indicated capital structure. Hence there is strong correlation between these two variables, (Shumway, 2001). However, Zmijewski model was considered to be better than MDA model for its interpretational value.

In logit and probit models, no assumptions are made with regards to distribution of independent variables. However standard logit model is limited by the restrictive assumption related to independence and identically distributed condition. Such a limitation may lead to information loss and affect the predictive performance of the model. Advanced models like nested logit model, multinomial logit model are developed to increase the statistical and predictive power of standard logit model,
(Jones and Hensher, 2004). In a study of corporate distress in Estonian manufacturing companies it was observed that logistic regression models have better classification abilities than other methods, (Grünberg and Lukason, 2014).

2.4.4 Artificial Neural Networks (ANN)

Of all the modern techniques of forecasting, Artificial Neural networks (ANN) is gaining lot of prominence amongst researchers across the world. ANN are parts of systems where information beyond the data are processed and transferred to a network structure. Artificial neural networks establishes relationship between networks by analysing the data. The output is used to estimate values for a new set of data, (Mahdi et al, 2013). ANN are models that recreates the interaction between the brain cells. ANN recognizes a pattern in sample data. It predicts values for new data by identifying similar patterns. (Sharma, 2012) The neural networks relates inputs to outputs using layers to create a ‘learned algorithm’, (Muller et al, 2009). Each layer is connected through neurons. The value of each neuron is transferred to other neurons through layers in the network. Thus each neuron receives input which is multiplied by its weights. If the sum of these weighted inputs exceeds a cut-off point, the output is activated. Thus an output is activated if:

\[ f (X_1.W_1 + X_2.W_2 + \ldots + X_n.W_n) > C \]

where \( X_1.W_1 \ldots X_n.W_n \) are weighted inputs

\[ C = \text{cut off value} \]

Odom and Sharda (1980) were one of the earliest researchers to use ANN as a technique to predict bankruptcy. (Mahdi et al, 2013) Neural networks were observed to have a very high accuracy and predictive power as compared to statistical techniques. Some prominent studies on corporate distress using neural networks include Studies have observed that ANN models outperform logit and MDA models, (Abid and Zouari, 2002) The advantage of ANN over other method stems from the fact that it can identify complex relationship between dependent and independent variables. It can also detect all possible relationships between variables, (Brockett et al, 2006). However this
technique is criticized for its computational difficulties and empirical nature. ANN as a technique for bankruptcy prediction needs to be further investigated to optimize the classification results, (Tan and Dihardjo, 2001). Logit models works as well as ANN models. Since ANN is a new technique, the empirical validity of ANN models in bankruptcy prediction is yet to be established, (Grünberg and Lukason, 2014).

The advantage of using ANN is its ability to analyze complicated data patterns and represent non-linear distribution function with high accuracy, (Chancharat, 2008). It does not have restrictive assumptions leading to unbiased analysis. It can also deal with missing data. ANN is not free from limitations. It does not reveal the significance of individual variable. Also, the rationale behind the classification into failed and nonfailed is not revealed. This restricts the use of this technique, (Balcaen and Ooghe, 2006). Also the interpretation of neural network model requires expertise.

2.4.5 Other Emerging Techniques

Some other techniques which are being used in corporate distress studies are Recursive Partitioning Algorithm, Survival Analysis and Support Vector Data Analysis.

A non-parametric procedure Recursive Partitioning Algorithm (RPA) for financial analysis is an emerging technique. It is a form of binary classification based on pattern recognition which outperforms traditional Discriminant Analysis, (Frydman et al, 1985). A dynamic logit model (DLM) with auto correlation structure for predicting recurrent financial distresses was also used to construct distress prediction model, (Hwang et al, 2013). A dynamic distress prediction model for Chinese listed companies was developed using Kayman’s Filtering Technique with panel data to estimate model parameters. The study emphasized on time series data to incorporate the cumulative impact of financial ratios, (Bao et al, 2015). In a study of 191 pairs of distressed and non-distressed firms in China, Support Vector Machine (SVM) a non-parametric test was combined with Choquet Integral as a combination classifier. It was observed that SVM classifier combination is more suitable for predicting financial distress as it improves the stability of predictive performance, (Li et al, 2015). However it should be used with caution as ensemble method’s reliability lies on base classifier’s diversity. One of the most important issues in Financial Distress Prediction is an effective
algorithm leading to high predictive accuracy. One such method used was Sequential Floating Forward Selection (SFFS) in combination with SVM. It was compared with other combined feature selection methods like Artificial Bee Colony (ABC), Genetic Algorithm (GA), and Principal Component Analysis (PCA). Combined model of SVM can yield greater accuracy, (Fallahpour et al, 2017). Use of alternative data mining techniques was emphasized by many researchers. Semi parametric Cox Survival Analysis and Non parametric CART Decision Tree was used to construct distress prediction model. This was compared with MDA and Logistic Regression methods. Contemporary techniques were observed to have good prediction accuracy, (Gepp and Kumar, 2008). The relation between data mining techniques and professional understanding of the characteristics of the variables was also explored. No significant difference was observed with variable selection guided by data mining techniques and that done by domain knowledge. A combination of two can outperform existing models, (Zhou et al, 2015). Time varying variables in a Cox model was also used to develop a dynamic forecast model for prediction of financial distress, (Kim and Partington, 2015).

2.4.6 Summary

As seen from the review above, researchers have used different parametric and non-parametric techniques to develop distress prediction models. The need to acclimatize the models with the current economic conditions was observed, (Grice and Dugan, 2001) Models developed by Altman (1968), Ohlson (1980), Zmijewski, (1984), Hillegeist et al, (2004) were tested for their applicability in US firms for the period 1980-2006. The study revealed that Ohlson (1980) model has the highest discriminating ability, (Avenhuis, 2013). The effectiveness of Altman (1968) model was also reviewed in international context. The model was applied to 32 European and 3 non-European countries. The period of study was 2007-1010. The study concluded that inclusion of country specific information increases the classification accuracy of the model, (Altman et al, 2014). It is also recommended that available models should be used widely to reaffirm the validity. This will ensure the effectiveness of the existing bankruptcy prediction models developed during the last few decades, (Bellovary et al, 2007).

Another insight made available is that model coefficients should be re-estimated with a bigger sample to improve its predictive power, (Avenhuis, 2013).
Past studies have used different statistical techniques to construct distress/bankruptcy prediction models. Logistic Regression and Multivariate Discriminant analysis have emerged as most popular though techniques like Artificial Neural Networks is also gaining prominence.

2.5 Review of Accounting and Non-Accounting Variables used in studies on Corporate Financial Distress and Bankruptcy

2.5.1 Accounting Variables

Literature on bankruptcy studies is enormous. The most important challenge in such studies is to select potentially informative ratios amongst more than hundred ratios. The common thread observed in most of the corporate distress studies is ratios indicating profitability, efficiency and liquidity have emerged as the most popular categories of ratios though individual ratios for these parameters are different. Hence there is no consensus on which ratio is the most important predictor of corporate financial distress. And also it is proved in most of these studies that a single parameter may not be a sufficient indicator of distress. Multiple aspects of the business viz. profitability, liquidity, solvency, efficiency and cash flows have emerged important.

One of the most popular study on corporate financial distress is by Altman (1968). Of the 22 potentially helpful ratios, 5 ratios were selected using the following parameters (i) statistical significance and relative contribution of each variable (ii) inter correlation between variables (iii) predictive accuracy of the variables and (iv) analyst’s judgment. EBIT/TA was the profitability ratio used in the Z-Score discriminant function, (Altman et al, 2014). A formal analysis of the most popular ratios adopted in studies on corporate distress was done to identify the most popular ratios. Profitability, Capital Turnover, Financial Leverage, Short term liquidity, Cash Position and Inventory Turnover were the seven factors identified. Since each ratio provided common well as unique information, an attempt has to be made to understand the unique information provided by each ratio so as to enable better selection of ratios, (Chen and Shimerda, 1981). In another study, Operating Profit/ Total Assets, Operating Profit/ Fixed assets
and Retained earnings/ Total Assets representing profitability, Current Assets/ Total Assets and Quick Assets/ Current Liabilities representing liquidity, Long term Liabilities/Total Assets for leverage, Market Value of Equity/ Total Liabilities to reflect market structure was used to create the model, (Gepp and Kumar, 2008). Operating cash flow / Total Assets, Cash resources/ Total Assets, Operating cash flow/ Interest payments as measures of profitability and liquidity and Sales/Total Assets Working Capital/Total Assets as measures of efficiency were used in creating a distress prediction model using mixed logit, (Jones and Hensher, 2004). Return on Equity is also observed as a good estimate of technical efficiency and degree of financial distress, (Oberholzer, 2010). Ratios like Cash/Total Assets, Cash/Total Sales, Market Value of Equity/Total capital Employed, Standard deviation of EBIT/ Total Assets were used to construct a default rating mode, (Wang Zheng, 2004). In an interesting study, a formal ranking of the ratios based on popularity and utility in 53 studies on corporate collapse was done. 48 ratios were ranked of which 5 ratios were found to be useful in more than 25% of the studies done. Net Income/Total Assets, Current Assets/Current Liabilities, Total liabilities/ Total Assets, Working Capital/ Total Assets and EBIT / Total Assets were observed to be most useful ratios, (Hossari and Rahman, 2005). Cash flow ratios were found to be good indicators of corporate health. Cash flow/ Total Assets, Cash flow/ Total Liabilities, Cash flow/ Current Assets, Cash flow/Current Liabilities, Cash flow/ Capital Employed were significant in prediction of distress, (Murty and Misra, 2004). Along with other ratios, growth rate in earnings, revenues, total assets, cash flow per share also had an important bearing on financial distress, (Wang and Li, 2007). Ratios like log of enterprise value, total debt to enterprise value were also used to identify bankrupt companies, (Polemis and Gounopoulos, 2012). Ratio of salary of shareholders to total assets was used as one of the discriminating factors in research on corporate bankruptcy, (Mahdi and Bizhan, 2009). Other important ratios were Log of deflated sales, total assets and number of employees, (Kahya and Theodossiou, 1999). Cash flow to sales and day’s sales in receivables, (Bhunia et al, 2011). Research has also emphasized on long term solvency ratios like proprietary ratio, debt equity ratio, capital gearing ratio as variables to detect financial distress, (Bardia, 2012). In a study of small and medium enterprises in Belgium three ratios which could distinguish a bankrupt company from a non-bankrupt company were identified. Equity / Total Assets representing solvency, Current Assets / Current Liabilities for liquidity and Net Income/ Total Assets for profitability were used to develop bankruptcy Prediction Model,
(Brédart, 2014). In a study done by Reserve Bank of India to identify important variables to model corporate distress in India, long term Liabilities / Total Assets and Operating Profits/ Total Liabilities and Current Assets / Current Liabilities were identified as important ratios, (Senapati. and Ghosal, 2016).

2.5.2 Non Accounting Variables

Most of the models discussed above used accounting information to develop models for prediction. There has growing interest among the researchers to examine the influence of non-accounting, market data and macroeconomic variables on corporate distress. Poor management is an important factor of financial distress, (Whitaker, 1999). A study on economic crisis of firms in Thailand established that macroeconomic conditions are critical indicators of financial crisis, (Tirapat and Aekkachai, 1999). Qualitative factors like omission/reduction of dividend payments, debt restructuring are important indicators of corporate distress, (Murugan et al, 2001). Other non-accounting ratios like market to book ratio and underwriter quality are good indicators of distress in newly formed public companies, (Beneda, 2007). Factors like ownership concentration, affiliated debt, existence of pledge in corporate distress influence corporate distress. Ownership structure and governance have great influence on a firm’s financial situation, (Wang and Li, 2007). Other non-financial variables like growth per equity share, ownership concentration were also used to develop distress prediction models. It was observed that inclusion of non-financial factors improves the predictive accuracy of the model. In a study of Taiwanese firms, earnings management index and corporate governance were used as variables along with accounting variables, (Hou et al, 2007). Market risks also was identified as an important indicator of financial distress, (Turetsky and McEwen, 2001). Firms’ market size, stock returns along with accounting variables in Altman (1968) model and Zmijewski (1984) model and compared the results with original variables. It was observed that accuracy of the models improved with the inclusion of market variables, (Shumway, 2001). Studies have shown that market based variables are more relevant than accounting variables since market price reflect rich information about the market. Such information is available on a daily basis as compared to accounting information. Market variables can also provide better metrics of volatility, (Avenhuis, 2013). Study have shown that market based models outperform accounting based models, (Stephan et al, 2004).
Macroeconomic variables are closely related to failure and are good predictors of distress, (Smith and Liou, 2007). Bankruptcy depend on macro-economic environment, (Bhattacharjee et al, 2009). In a study on UK firms to compare the performance of market based variables and accounting variables, it was observed that accounting model’s advantage lies in the fact that accounting data can capture the process of financial distress, (Agarwal and Taffler, 2007). The information about debt default is available in accounting data. However accounting data is recorded on historical value basis and hence may not reflect current asset values. Moreover the accounting data is subject to distortion. It was observed that accounting based approach has benefits over market based approach. A two stage approach to forecast financial distress in emerging market using Discrete time hazard model of Shumway (2001) revealed that firm specific factors and macro-economic factors could effectively identify financial distress in a firm in emerging markets, (Tsai and Chang, 2010). Variables like shares concentration, board size, liquidity of stock, auditor’s opinion were also used to develop distress prediction model, (Xie et al, 2011). The importance of understanding the behavioral pattern of managers and their cognitive biases that may lead to wrong decision making leading to distress, (Yazdipour and Constand, 2010). Corporate governance indicated by ownership concentration, chairman’s duality, and proportion of independent directors are very important factors affecting corporate distress, (Hui and Jing-Jing, 2008). Earnings management index and pledge ratio of directors along with financial ratios were used to examine financially distressed companies in Taiwan, (Hou et al, 2007).

Market variables and credit cycle are good indicators of financial distress. Negative book equity is also an important indicator of distress, (Tsai and Chang, 2010). In a study of Spanish companies, technology, rivalry amongst existing competitors and bargaining power of buyers were identified as non-financial factors influencing financial distress, (Madrid-Guizarro et al, 2011). Firms with negative book equity have reported poor returns and are exposed to distress and failure risks, (Ang, 2015). In a study of bankrupt Spanish companies during the period 2007-13, it was observed that a negative relationship exists between board size and likelihood of financial distress whereas ownership concentration did not have any significant impact, (Manzaneque et al, 2016).
2.5.3 Summary

Review of accounting and non-accounting variables used in past distress studies indicates that different studies have used different financial ratios as independent accounting variables to identify significant variables predicting corporate distress. However most of the ratios used in earlier studies depict the following aspects of a business:

1. Profitability: Net Profit margin, Return on Capital employed, Return on equity, Operating Profit to total assets, operating cash flow to interest payments, Retained earnings to total assets.

2. Efficiency: Sales to Total Assets, Working capital to Total Assets, Total Liabilities to Total Assets, Working capital to Total Assets, Cash flow to Capital Employed

3. Long term solvency: Proprietary ratio, Debt Equity, Capital gearing

4. Liquidity : Current Assets to Total Assets, Quick Assets to Current Liabilities, Total Liabilities to Total Assets, Cash flow to sales, Days sales in receivables .

Other ratios used are Market value of equity to Total Capital employed, growth rate in revenues, and number of employees.

Non-accounting variables used in corporate distress studies can be grouped under three heads:

1. Management and governance: Corporate governance, dividend payments, debt restructuring, ownership structure, shareholders concentration, proportion of independent directors are some of the variables representing management and governance.

2. Macro-economic factors: Business cycles, bank lending, recession, consumer price index, producer price index, interest rate, gross domestic product, money
supply, inflation, credit cycle are the variables used to study the impact of macroeconomic factors on corporate health.

3. Market measures: Market risks, market size, market value to book value, growth per equity share are the factors found significant in studies on financial distress.

There is no consensus as to the most relevant and significant accounting and non-accounting variables especially in the Indian context. The applicability of variables in predicting corporate distress for US and Indian companies was investigated observed that market information fails to predict bankruptcy in India whereas accounting ratios best estimates the probability of corporate distress in India, (Charalambakis and Garrett, 2016). Variables indicating profitability, efficiency, long term solvency, liquidity, management, governance, stock market and macro-economic conditions are frequently used in studies on corporate financial distress.
A. Studies on Corporate Distress and Bankruptcy

**Pre-1990 era**
- Preliminary studies in the area of corporate distress.
- Examination of ability of financial ratios in identifying distress predictors.
- Validity of models not done.
- Focus on US companies.

**1990-2000**
- Increased interest in the area of corporate financial distress.
- Ability of financial ratios in identifying distress predictors tested and validated.
- The need to include non-financial variables like management efficiency along with financial variables to improve the accuracy and applicability of bankruptcy prediction models was emphasized.
- Focus of US companies.
Post 2000

- New definitions of business failure.
- Studies in corporate distress extended to European and Asian countries.
- Applicability of earlier established models tested.
- Use of cash flow ratios and inclusion of macroeconomic indicators along with financial ratios to construct distress prediction models.

Research in India

- Few studies on corporate distress.
- Research focused on application of existing models on Indian companies
- Research focused on certain sectors like Steel, Pharma etc.
B. Review of Statistical Models and Tools used in studies on corporate financial distress

**Statistical Techniques**

- Univariate analysis
- Multivariate Discriminant Analysis
- Logit/Probit Analysis
- Artificial Neural Networks
- Emerging Techniques - Recursive Partitioning Algorithm, Survival Analysis, and Support Vector Data Analysis.

**Models for Bankruptcy Prediction**

- Beavers Univariate Model (1966)
- Altman’s ‘z’ score Model (1968)
- Altman, Haldeman and Narayanan ZETA score model (1977)
- Ohlson’s ‘o’ score model (1980)
- Agarwal and Taffler’s ‘z’ score model for UK companies (1983)
- Zmijewski’s Probit model (1984)
C. Review of Accounting and Non-Accounting Variables used in studies on corporate financial distress

**Accounting Variables**

- Most commonly used ratios (category wise)

**Profitability** – Gross Profit margin, Return on Equity, Operating Profit to Total Assets, Net Income to Total Assets.

**Liquidity** – Current ratio, Quick ratio, Current Assets to Total Assets

**Efficiency** – Sales to Total Assets, Working Capital to Total Assets, Turnover ratios

**Leverage** – Debt to equity, Capital gearing, Proprietary ratio

**Cash Flow** – Operating Cash flow to Total Assets, Operating Cash flow to Interest, Cash to Total sales, Cash flow to Current Assets

**Others** – Growth in earnings, cash flow per share, Log of Enterprise Value

No consensus on the most significant ratios
2.6 Gap Analysis

Review of literature on corporate distress and bankruptcy clearly highlights the gap in research. The need for a distress prediction model for Indian companies is long overdue. The current study aims to cover this gap by:

(i) Identifying the financial factors which can help identify distress in Indian companies.
(ii) Developing a distress prediction model for Indian manufacturing companies
(iii) Examining the influence of macro-economic factors on financial distress in companies.

Non Accounting Variables

- Used along with accounting variables

Management and Governance – Dividend payments, number of independent directors, debt restructuring, corporate governance

Macro-economic factors – Business cycles, Bank lending rate, inflation, consumer price index, producer’s price index, inflation

Market measures – Market risks, market size, Market value of equity to book value, growth per equity share

- No consensus on the most significant ratios