Corporate Credit Risk of Indian Manufacturing Companies: Towards an Early Warning System

A thesis submitted during 2011 to the University of Hyderabad in partial fulfilment of the award of a Ph.D. degree in Economics

BY

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CERTIFICATE

This is to certify that the thesis entitled "Corporate Credit Risk of Indian Manufacturing Companies: Towards an Early Warning System" submitted by Swayam Prava Mishra bearing Reg.No. 07SEPH03 in partial fulfilment of the requirements for the award of Doctor of Philosophy in Economics is a bonafide work carried out by her under my supervision and guidance.

The thesis has not been submitted previously in part or in full to this or any other University or Institution for the award of any degree or diploma.

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DECLARATION

I Swayam Prava Mishra hereby declare that this thesis entitled “Corporate Credit Risk of Indian Manufacturing Companies: Towards an Early Warning System” submitted by me under the guidance and supervision of Dr. Debashis Acharya is a bonafide research work. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma.

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CHAPTER 1

Introduction, Motivation and Research Problem

1.1 Introduction

Risk management is not a new phenomenon whether it is business or otherwise, but the importance of risk management has grown in recent times. In February 1995, the Barings bank episode shook the markets and brought about the downfall of the oldest merchant bank in the U.K. Inadequate regulation and the poor systems and practises of the bank were responsible for the disaster. All components of risk management viz. market risk, credit risk and operational risk were thrown overboard. Shortly, thereafter, in July 1997 there was the Asian financial crisis, brought about again by the poor risk management systems in the banks / financial institutions coupled with mechanical supervision by the regulatory authorities. Such practices could have severely damaged the monetary systems of the various countries involved and led to international ramifications. Yet, the most recent global economic crisis of 2007-08 was caused due to the lax standards of credit ratings and poor risk management by financial institutions. Seeing, all these things, the international regulatory authority, the Bank for International Settlements at Basel, Switzerland, have been working on a well-structured risk management system.

Risk management by definition entails financial engineering aiming to sustain and maximise net returns on financial assets in uncertain times (Sunanda Sen, 2009). There are mainly three types of risks; market risks, credit risks and operational risks. From the current scenario it is evident that of all the risks an institution can face, Credit risk is the dominant risk. According to the Basel committee, “Credit risk is defined as the potential that a borrower or counterparty will fail to meet its obligations in accordance with agreed terms.” The RBI has defined credit risk as the possibility of losses associated with diminution in the credit quality of borrowers or counterparties. In a bank’s portfolio, losses stem from outright default due to inability or unwillingness of a customer or counterparty to meet commitments in relation to lending, trading, settlement and other financial transactions. Alternatively, losses result from reduction in portfolio value arising from actual or perceived deterioration in credit quality. Credit risk management therefore holds an important place in the theory of finance. There are various credit risk models designed to deal with optimal allocation of funds.

Credit risk evaluation originated from the analysis of financial status change of firms, since credit crisis is usually caused by financial issues, such as, cash flow reduction or decline in net worth. So through the detection of characteristic financial indicators, it is possible to identify the potential distress and build early warning systems. Such financial indicators can be used to develop credit scoring models to predict or determine the credit ratings of firms, which is the foundation for pricing credit loans and decision making for investments. Based on such motivation, researchers usually turned the measurement of credit risk into the evaluation of corporate financial health.

The prominence of Early Warning System (EWS) has grown after the global crisis. From the financial supervisor’s point of view, an early warning system (EWS) involves an ex ante approach to regulation, that is, one designed to highlight conditions that have in the past been associated with systemic risk. These are functional, data-driven approaches that draw attention to variables associated with past crisis in order to alert policy makers of potential for future crisis. They are grounded in economic theories of financial crisis and are designed to provide risk alerts on an objective, systematic basis (Gramlich et.al, 2010).

In a financial context, they may be used to extrapolate the risk of a single financial institution (micro risk) as well as that of the financial system as a whole (macro risk) (Borio, 2003). They build on two fundamental assumptions: (1) that causality (stability of relations) exists between crises and crisis-driving factors, and (2) that crisis-driving factors can be identified ex ante.

1.2 Development of Credit Risk Modelling

The importance of credit risk modelling has been felt as new markets are emerging in credit derivatives and marketability of existing loans is increasing through securitisation and loan sales market and due to the increase in the banks quantitative treatment of credit risk. According to Saunders and Allen (2002), a credit risk model is a mathematical model containing the loan applicant's characteristics either to calculate a score representing the applicant's probability of default or to sort borrowers into different risk classes. The focus of this study is on assessing the financial health of the firms by using models that can be employed by lenders and investors before making any lending and investment decisions. They can also facilitate corrective actions using appropriate strategies after the potential problems are identified. Moreover, these can be used as a part of the early warning systems to predict the financial health of the companies.

Among the most widely used models to forecast a company's default, is a class of statistical models, generally known as "credit-scoring models". These are multivariate models, which use the main economic and financial indicators of a company as inputs, attributing a weight to each of them that reflects its relative importance in forecasting default. The result is an index of creditworthiness expressed as a numerical score, which indirectly measures the borrower's probability of default.

Although the techniques underlying credit-scoring models were devised way back in 1930s, the decisive boost to the development of these models came in the 1960s, with studies of Beaver (1967), Altman (1968) and others. The Z score model of Altman was a path breaking contribution in the area of credit risk modelling. It was based on Multiple Discriminant Analysis technique and is still robust and widely accepted across the globe. Under Altman's influential work, many financial institutions in the developed countries, such as, Japan, Germany, France, England, Australia, China and Canada, have developed their own discriminant models for identifying potential distress situations.

Over the past four decades, more sophisticated methodologies have been developed to support corporate failure assessment, which included gambler's ruin, option pricing, hazard, neural networks, as well as the application of other statistical techniques, such as logit analysis, to the failure prediction problem. Despite the variety of approaches used in failure prediction, statistical methods like discriminant analysis, still dominate due to their simplicity and accuracy. In general, these models have been featured with high classification accuracy, low cost, time saving, as well as convenience in application in solving real world problems.

In the Indian context there have been very few studies on the corporate distress prediction due to the non-availability of desired data and also lack of well defined bankruptcy laws. Even then, the use of Z score is done in some studies. In this study an attempt is made to classify the manufacturing companies into healthy, moderately healthy and not-so healthy groups and to have an idea on their exposure to credit risk. Further, the use of non financial variables to assess corporate financial health and impact of macroeconomic factors on credit risk evaluation is undertaken.

1.3 Recent Developments in Indian Manufacturing Sector and the Need for Predicting Credit Risk

The manufacturing sector assumes a vital role in the Indian economy as it contributes to almost 25% of the GDP. Manufacturing exports dominate the export basket of Indian economy and account for nearly 70% of the total merchandise exports. Indian manufacturing industries have certain inherent strengths and advantages in relatively inexpensive, adequate and skilled labour force, cost-effective and competitive prices of goods produced, large manufacturing base and proximity to fast growing Asian markets. Moreover, India is one of the leading producers and exporters in a number of commodities and enjoys significant advantages in terms of lower labour costs as compared to other economies.

Thus, the manufacturing sector represents an important segment of the Indian economy. However, according to RBI, the average share of manufacturing sector in real GDP has marginally increased from about 13 per cent during 1970-75 to about 16.1 per cent in 2009-10, i.e. approximately by about 3.1 percentage points over a period of more than three decades. Thus, this increase has not matched the expectations from this sector. Also the GDP growth decelerated to 7.7 per cent in Q1 (April-June) of 2011-12 from 8.8 per cent a year ago, and 7.8 per cent in Q4 of 2010-11. From the supply side, the deceleration in growth in Q1 was mainly due to slower growth in mining, manufacturing, construction and ‘community, social and personal services’. The estimated growth rate in manufacturing is 7.2 per cent in Q1 of 2011-12 as compared to 10.6 per cent in Q1 of 2010-11. One possible reason for such a negative growth might be the poor financial health of the firms in this sector. Moreover, with the economy slowing, some of these companies are finding it difficult to service their debt. So, the investor community has also shown its apprehensions about the financial viability of these companies. Besides, poor financial health threatens the very survival and leads to business failure.

Although the manufacturing sector is of prime importance to our economy, very little work has been done for assessing its financial health. Therefore, this study uses firm-level data to examine the financial health of the manufacturing sector and evaluate its financial vulnerabilities. The study aims at signalling the corporate credit risk inherent in the manufacturing sector of the Indian economy and paving way towards an early warning system for distress prediction.

1.4 The Research Problem

This research work is an effort to analyse the credit worthiness of the manufacturing companies listed in BSE 200 Index. Specifically, an attempt is made to examine the financial health of these companies. Alongside, the study attempts to analyse whether the credit scoring models can be used for the Indian listed companies. The existing literature on credit risk evaluation reveals that such models are very useful in assessing corporate financial health. The use of non-financial variable along with other financial variables for rating a firm by credit rating agencies is also examined. The macro economic factors prevailing in any country are very crucial for the firms operating in it. Therefore, an effort is made to gauge the impact of macroeconomic factors on financial health of firms. In a nutshell, this study looks into the various traits of the manufacturing companies listed under BSE 200 and their impact upon the overall risk appetite of the sector.

1.5 Firm Intrinsic Credit Scoring Model and Early Warning System

A firm-intrinsic credit scoring model is one that uses specific information about a company, primarily its financial statements. Measures of profitability, liquidity and capital structure are usually important components of a firm-intrinsic model. These indicators are combined with some other measures to form a single measure of corporate vulnerability called a credit score. The objective of a firm-intrinsic credit model is to estimate the similarity of any individual company to hundreds of other companies that have compromised their creditors.

This model provides for stabilising the credit culture because it is rooted in accounting fundamentals and time honoured and is robust. This kind of models enables in identifying the distress. The most prominent of these models is the Altman's Z score model. Altman (1968) commented on the traditional ratio analysis and suggested that discriminant analysis can be a better tool for corporate distress predictions. The theory was that if ratios were analysed within a multivariate framework then the results would have more statistical significance than the common techniques of sequential ratio comparisons. Such kinds of model can be used for business credit evaluation, internal control procedures and investment guidelines.

Corporate Bankruptcy is certainly not desirable and an early detection of impending distress in a corporation is always enviable. Ben Gilad (2004) in his book described about competitive early warning which helps companies decipher early signs of trouble before they mushroom into a full-scale crisis and identify early signs of opportunities before everyone else sees them. An effective warning system for financial distress should take into account various indicators, as these crises are usually preceded by symptoms that arise in a number of areas (Shazly, 2002). In his study he showed that the signals approach to predicting banking and currency crises can serve as the basis for an early warning system. It basically involves monitoring the behaviour of a number of indicators as they exceed certain threshold values or critical levels.

Irrespective of the approaches and models adopted for institutionalising an early warning system, EWS should primarily capture signals on solvency and liquidity of the banks (BIS, 2000). However, Following Edison (2003), a EWS might be regarded as a diagnostic tool for monitoring the relative direction of the financial system, rather than a gauge of definitive crisis signals; in other words, a weathervane rather than a barometer. Therefore, in a dynamic world with rapidly changing markets, a EWS should take into account new data and events.

In simple terms, an early warning system (EWS) may be described as an organised procedure (often statistical) for identifying the financial weakness early in the process of deterioration, to warn or signal the management, shareholder and public at large. A well developed EWS can be very useful for an organisation. The Firm intrinsic credit score is to be used as a signal for examining the potential strength or weakness of the firm.

The study shows how the Multiple Discriminant Analysis (MDA) technique is used to assess the financial health of Indian Manufacturing firms and the credit score thus obtained from the financial variables can serve as the basis for an Early Warning System. Further, the non-financial variable which can be used for evaluating the firms is depicted through the Technical efficiency score obtained from a variable returns to scale (VRS) data envelopment analysis (DEA) model. Based on this information the policy makers can take appropriate measures to combat future distress. Taking into account the macroeconomic factors and examining their cause and effect relationship with the financial health of firms can also add to the effectiveness of an early warning system. The proposed EWS is a hybrid system, a system using the employment of several forecasting techniques. Thus, this study is a modest attempt towards designing effective Early Warning Systems for efficient dissemination of information on the real and financial sides of the economy.

1.6 Objectives of the Study

In the light of the above background, the objectives of the study are formulated as the following:

- To understand the individual credit worthiness of the Indian Manufacturing companies under BSE 200 Index through a Firm-intrinsic credit scoring model.
- To illustrate the potential use of a non-financial indicator namely technical efficiency as part of credit risk evaluation of firms.
- To examine the impact of macroeconomic factors on financial health of companies.

1.7 Hypotheses

The study seeks to verify the following hypotheses.

Hypothesis 1: Introduction of a Firm-intrinsic credit scoring model does not help to understand the credit worthiness of the Indian Manufacturing companies.

Hypothesis 2: Technical efficiency is not an important indicator of financial health of firms.

Hypothesis 3: The macro economic factors have no impact on credit risk of firms.

1.8 Justification of the study

This study assumes significance due to several factors. Firstly, the Indian manufacturing sector provides ample avenues for investment and so this study sheds light into the financial health of the companies in this sector giving the investors an opportunity to decide on their investments. Secondly, from the lender's point of view, it gives an idea to the banks and other financial institutions to take their lending business and policy decisions accordingly having seen how the companies are prone towards credit risk. Thus, this study is a path towards developing an early warning system for predicting corporate distress. Lastly, there is no comprehensive study available in the literature which has dealt with predicting corporate credit risk of the Indian manufacturing sector. In the literature, one can observe that a few studies are done on the textile, cement, paint, private manufacturing industries or a mix of all these. It indicates the necessity to have a study based on the listed manufacturing units which hold an essential place in Indian economy.

1.9 Methodology of the Study

The study is conducted within the broad framework of firm-intrinsic credit scoring model as outlined in section 1.5. This study mainly relies on econometric techniques for the analysis. The financial health of the manufacturing companies is examined through the credit scoring model based on the Multiple Discriminant Analysis (MDA), which has been extensively used in literature for predicting corporate distress or bankruptcy [Altman (1968), Altman et al (1995), Altman et al (2007), Appiah and Abor (2009)]. Using financial indicators and ratios, MDA technique measures the potential distress conditions of the companies.

A MDA is a statistical technique used to classify an observation into one of the several *a priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in the problems where the dependent variable appears in the qualitative form, e.g. male or female, bankrupt or non-bankrupt. After the groups are established and data collected on the variables, MDA then attempts to derive a linear combination of these characteristics (variables) which "best" discriminates between the groups. In this study, three groups are formed as healthy, moderately healthy and not-so healthy companies on the basis of average net worth, industry affiliation and the period of analysis. Then financial ratios reflecting profitability, liquidity, leverage, etc are composed for these groups for a period of twenty years and then MDA determines a set of discriminant coefficients which forms the basis for classification of the groups. The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms simultaneously.

The technical efficiency is taken as a non financial indicator in the Logit model to find its significance towards corporate debt ratings. The technical efficiency is obtained from Data Envelopment Analysis (DEA), a non parametric method of measuring efficiency of a decision making unit (DMU) such as a firm. DEA is based on mathematical programming to construct the best practice frontier from the observed data and to measure efficiency relative to the constructed frontier. Thus, the DEA efficiency for a DMU or firm is not defined by an absolute standard but is defined relative to other firms. The corporate debt ratings are regressed on the technical efficiency along with the financial variables in the Logit model.

To test the impact of the macroeconomic variables on corporate financial health, the Z scores obtained from the first chapter are regressed on inflation rates, growth rate of gross domestic product (GDP), growth rate of Manufacturing Component of GDP and bank rate using panel data regression analysis. The long run relationships are identified using panel unit root test, panel cointegration analysis and panel long run causality.

1.10 Nature and Source of Data

The necessary data are collected from the official website of Bombay Stock Exchange (www.bseindia.com) and CMIE-Prowess database. The Capital line plus database is also used for ‘company at a glance’, ‘credit ratings’, ‘financial overview’ and ‘balance sheet’ data . The study uses 73 companies and nine financial ratios for the Z-score model. The data set comprises of current assets, current liabilities, PBIT, net worth, interest coverage ratio, sales, retained profits, total assets, total liabilities, net cash flows from operations, borrowings, debt-equity ratio, etc. The study is based on data ranging from March1990 to March 2009.

The data on macroeconomic variables are collected from the 'Handbook of Statistics on Indian Economy' from the Reserve bank of India website (www.rbi.org.in).

1.11 Scope and Limitations of the Study

The study is based on the manufacturing companies under BSE 200. In order to meet certain methodological delineations, the manufacturing companies listed under BSE 200 Index are taken. BSE is the oldest stock exchange in India as well as Asia and has a wide variety of manufacturing firms. In other words, BSE 200 has national broad level of indices and hence covers entire manufacturing sector as a whole. However, a study of manufacturing companies under NSE might reveal some interesting results.

1.12 Organisation of the Study

The rest of the study is organised into five chapters. The second chapter contains a comprehensive review of the relevant literature with respect to the research issues under consideration. Chapters 3 to 5 detail the methodological issues and empirical results of the each research objectives.

Specifically, chapter 3 presents the Multiple Discriminant Analysis and its application to determine the credit score. The ratios to be used for developing the score are specified. Then the cut-off point is determined and classification of the companies is done. Here 73 firms are identified.

In chapter 4, the technical efficiency is obtained through Data Envelopment Analysis (DEA) and is used along with other financial variables in the Logit model to assess the impact of efficiency on ratings. The macroeconomic impact on the financial health of corporations is determined using panel data analysis in chapter 5. The summary and implications of the study are detailed in the chapter 6.

Chapter 2

Review of Relevant Literature

2.1 Introduction

The introduction of various complex financial instruments has led to the augmentation of risk elements and the major cause of concern has been to resolve the issue of credit risk. The empirical works have focussed on the risk aspects of banks and other financial institutions, industries and so on. However, there is paucity of research on examining the financial health of the listed firms in India. The issue got heightened with the collapse of one of the leading listed firms' Satyam computer services on report of falsified accounts. The scandal raised questions on the accounting standards in India as a whole with the feeling that similar facts might lie buried elsewhere too. Nonetheless, very few studies have been carried out with regard to the evaluation of the financial health of the listed firms. As a background to the present study, an attempt is made in this chapter to review the relevant literature. The review is planned in three sections covering the firm intrinsic credit scoring model, evaluation of firm performance using efficiency as a parameter and effects of macroeconomic factors on financial health of corporations. The review covers the relevant past studies in India as well as those using global data.

2.2 Firm Intrinsic Credit Scoring Model

The use of credit scoring models to predict corporate distress has been widely studied across the world. Since credit score are expected to be an important tool for analysing the probability of default, researchers are engaged to further their understanding of how credit scores can be used to engulf a broad spectrum of diverse economies across the world. In the current scenario of ongoing global meltdown, it becomes imperative for the companies to have a healthy risk culture to immune themselves from bankruptcy in the long run.

This part of the review covers the firm intrinsic credit scoring models used by various researchers. The developments of empirical models that discriminate failing firms from the surviving entities started in the mid 1960s.

Beaver (1966) emphasized upon the financial ratios as predictors of failure. His study focussed on providing an empirical verification of the usefulness of accounting data. The failed firm were characterised by a name change, merger, liquidation, lack of public interest and most importantly failure. He took paired sample and paired analysis for selection of non-failed firm based on the asset size and industry. The ratios used were – cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current ratios and no-credit interval. The findings of the study suggested that financial ratios can be useful in the prediction of failure for at least five years prior to the event.

Beaver (1968) was an extension of the former study (Beaver, 1966). However, one aspect of the data was not explored in the earlier study and that is the ratios cannot be chosen indiscriminately. The findings of the study indicate about the difference in the predictive ability of the ratios.

Altman (1968) used the Multiple Discriminant Analysis (MDA) technique along with financial ratios to predict corporate bankruptcy. He took 33 failed and 33 non-failed firms.

The failed group were the manufacturers who filed a bankruptcy petition under chapter X of the National Bankruptcy Act during 1946-1965. Group 2 consisted of a paired sample of manufacturing firms chosen on a stratified random basis. The variables used were classified into five standard ratio categories, including liquidity, profitability, leverage, solvency and activity ratios. The discriminant function yielded a score called Z score and on the basis of this a cut-off was found for classifying firms as failed, non-failed or under zone of ignorance. Based on the empirical results it was suggested that the bankruptcy prediction model is an accurate forecaster of failure up to two years prior to bankruptcy and that the accuracy diminishes substantially as the lead time increases. The Z score model has retained its reported high accuracy and is still robust despite its development over the years.

Deakin (1972) replicated Beaver (1968) study by using the same ratios. He applied the dichotomous classification test on his sample of 32 failed and an equal sample of non-failed firms during the period 1964-1970. He also used the discriminant analysis and found that it can be used to predict business failure from accounting data as far as 3 years in advance with a fairly high accuracy.

Altman (1973) used Linear Discriminant Analysis with published financial data representing discriminant variables for predicting railroad bankruptcies in America. He took bankrupt railroads on one hand and industry averages on the other. This diagnostic model was accurate in predicting two years prior to bankruptcy.

Altman and McGough (1974) attempted to develop criteria to aid the auditor in identifying situations where the status of a company as a going concern becomes doubtful, by analysing the relationship between bankrupt companies and auditor’s report prior to bankruptcy. Thirty four American companies that had entered bankruptcy since 1970 were selected for the sample and the data were collected from the annual reports for the two years prior to the date of bankruptcy. The analysis indicated the superiority of discriminant model in signalling going concern problems earlier than an auditor's opinion, up to two years prior to bankruptcy. The analysis revealed that bankruptcy model could serve as an effective aid for the auditor to form his/her judgement regarding the company's ability to continue operations.

Shashua and Goldschmidt (1974) evaluated the overall performance of a firm relative to any other firm in the same industry for Israel. The study used a measure that provided a rating having a probabilistic meaning build on a utility function. The method of analysis was such that various indicators were combined into one index yielding the relative level of success. Both profitability indicators and financial indicators were used. The data was drawn from the financial statements of 216 firms. The index was validated in that it was accepted and adopted by the various agencies working with the agricultural firms in Israel.

Sarma and Rao (1976) applied Multiple Discriminant Analysis (MDA) to financial characteristics of 60 cotton textile industry members in India. The sample of unsound firms consisted of 18 firms taken over by various textile corporations set up by the concerned governments and 12 firms whose net worth was negative for the period 1968-1972. Twenty six ratios representing liquidity, profitability, leverage, solvency and activity were considered. The analysis revealed that given favourable external factors, the firms' soundness is reflected by its earning power, dividend policy, management of current assets and net worth. The test of predictive accuracy showed that 95 percent of the firms were classified correctly. The model seemed to be accurate for periods as early as three years prior to failure.

Taffler (1976) took 23 bankrupt companies mainly manufacturers and 16 non-failed companies to predict bankruptcy in UK corporations. The application of Z score model to the failed sample for prior years showed 9 of the 23 companies appearing sound on the basis of penultimate accounts and only 8 having failure characteristics four years before failure. However, this study has been commented as being more concerned with theoretical issues for developing a Z score model.

Tisshaw (1976) analysed the unquoted privately owned manufacturing companies using Z score technique. The failed sample consisted of 31 privately owned manufacturing companies and each of these were matched by size, industry and year end with two ‘healthy’ live companies on the Jordan Dataquest database to provide the solvent group. So, it was possible to analyse the unquoted companies in UK using Z score technique.

Altman (1977) examined the financial problems in the Savings and Loan (S & L) association industry using a quadratic discriminant analysis. There were three groups of S & L’s depicting chronically ailing, temporarily unhealthy and consistently healthy characteristics. The results of the study show that a 12- variable econometric system is both accurate and practical for at least three semi-annual periods preceding the serious problem data.

Altman *et al.* (1977) constructed a second generation of model with several enhancements to the original Z score approach. It was termed as ZETA model. 53 bankrupt and 58 non-bankrupt entities were taken. The sample consisted of manufacturers and retailers and a 7 variable model was built. The ZETA model tests included quadratic as well as linear discriminant models. The model appeared to be accurate for up to five years prior to failure. The findings showed that the inclusion of retailing firms in the same model as manufacturers does not seem to affect the results negatively.

Altman *et al.* (1979) studied the business failure experience in Brazil by using the bankruptcy classification model developed by Altman (1968). A sample of 23 serious-problem firms was compared with a slightly larger control sample of healthy firms. The four variable model successfully classified 88 percent of the firms one year prior to serious problems and as much as 78 percent three years prior.

Satyanarayana (1979) examined the relevance of Altman's model (1968) in the context of Indian industry. The Z scores were calculated for three particular Indian companies and a group of 486 profit-making and 185 non-profit making companies. Companies were found to be continuing their operations even after several years of continuous losses mainly due to the financial assistance from banks and other government controlled financial institutions. The study concluded that although the Altman's model was not useful in predicting the collapse of an industry, it was certainly helpful in determining and predicting the health of a company. It would also help to know whether it was borrowing beyond its capacity. The results showed that the impact of interest was very significant on the values of Z.

Kaveri (1980) tried to predict the health of borrowers using financial ratios. The data were collected for 524 small units belonging to paper, leather, engineering, textile and chemical industrial groups covering the period from 1967 to 1973. Five ratios belonging to five different categories were selected on the basis of their statistical significance in discriminating units, possessing higher predictive ability and banker's acceptability. The model projected higher degree of prediction in the short run than in the long-run. The study suggested that there should be periodic appraisals of the model and it should be updated using additional information or by introducing new variables, if necessary.

Ohlson (1980) used conditional logit analysis to examine corporate bankruptcy. Four factors were identified to have statistically significant relationship with probability of failure viz., (a) size of the company, (b) a measure of financial structure, (c) a measure of performance, and (d) a measure of current liquidity. The sample consisted of 105 bankrupt and 2058 non-bankrupt firms and data was obtained from 10-K financial statements. Size appeared to be an important predictor in this study. The study concluded that the predictive power of any model depended upon the available financial information.

Altman and Levallee (1981) constructed a failure prediction model for Canadian firms by combining traditional financial analysis with a multivariate statistical technique. The sample comprised of 54 publicly traded Canadian firms; half bankrupt and half continuing firms. Data from the bankruptcy date showed that the Canadian Z score was accurate for 2 years prior to failure but accuracy fell dramatically as data became more remote.

Betts and Belhoul (1982) developed a summary statistic that can be computed from published company balanced sheets and depending on the value that the statistic assumes the company can be classified as a going concern or having a failed company profile. The sample consisted of 26 failed companies and 131 going concerns sampled randomly from the EXSTAT tape. They suggested that such a statistic can be very effective in anticipating failure and thereby the government can take necessary action to prevent the company from failing.

Betts and Belhoul (1983) introduced ratio stability measures and balance sheet decomposition index of Lev (1971) and Moyer (1977) to predict company failure. The sample consisted of 50 failed and 93 non-failed companies randomly from the EXSTAT tape. The balance sheet decomposition measure indicated that a firm approaching failure undergoes great structural changes and the stability measure indicated that companies near the point of failure show a great instability in their quick assets to current assets, working capital to net capital employed and day creditor's ratios.

Betts (1983) showed how the Z score analysis using the MDA technique could be used as a screening device to identify companies at risk of failure. He took 26 failed firms and 131 going concerns as sample. He concluded that Z score helped to identify companies in a poor financial position.

Using 56 ratios, Gupta (1983) attempted to find out the best set of financial ratios which would not only identify potentially sick firms but also order them according to their financial health. The sample consisted of 21 non-sick and 20 sick companies which were not visibly sick up to 1964. The data were collected from 1962-1974 from sick textile companies. Ordered arrays of the sample companies were prepared according to the values of each ratio for each year. The cut-off point was determined which divided an array into two distinct zones of sick and non-sick companies. The point was determined so as to minimise the number of misclassifications in the array.

Betts and Belhoul (1984) extended his works further by making a new model and comparing it with the earlier ones. In this model he used semi-variance stability measures which were an improvement over his earlier studies. The sample and the financial ratios were the same that were used in the 1983 study.

Stein and Ziegler (1984) used balance sheet analysis, current account analysis and assessment of management for prognosis and surveillance of corporate credit risks. He considered 119 failed and 327 non-failed companies. Eight components were selected on basis of earning power, permanent capital, medium-term liquidity, personnel cost intensity, inventory intensity, repayment power, liquidation risk and cash liquidity. The findings showed that the analysis of the accounts data can contribute to an early warning system for risks of commercial credit borrowers.

Izan (1984) developed a five variable business failure classification model for Australia by using industry-relative approach instead of using traditional ratio analysis. This approach took into account differences across industries. The sample comprised of 53 failed and 53 non-failed firms. The model seemed to be sufficiently robust so as to be applicable across a broad cross section of firms and industries and appropriate for analysing firms of all sizes.

Takahashi *et al.* (1984) used both Principal Components Analysis (PCA) and discriminant analysis to predict corporate bankruptcy in Japan. So far as PCA was concerned it indicated that failed firms in Japan could be classified into two groups – a group having negative financial structures and a group having a declining flow of funds within a relatively short period of time. Besides, they could also be classified into two groups from the time series change i.e., those showing some improvement during two years before, and those showing improvement in the last year prior, due to some successful rescue operations undertaken by the firms before failure. The discriminant analysis indicated that by using as predictor variables both ratios and absolute amounts based on cash base financial statement data 3 years before failure, improved prediction accuracy could be obtained. There were 36 failed and an equal sample of non-failed firms in the discriminant analysis. The study showed that banks have great influence over the fate of Japanese corporations and that the auditors reports should be taken into account while studying the financial statement data. The study also confirmed the necessity and desirability of using both the financial statement data for two or more years before failure, and indices relating to short-term flow of funds to make accurate corporate bankruptcy predictions.

Lincoln (1984) examined the usefulness of accounting ratios to describe the levels of insolvency risk. The study covered four different industries: manufacturing, retail, property and finance. 90 non-failed firms and 41 failed were taken. The model in the study established two main characteristics of a firm with a high level of insolvency risk in the manufacturing and retail industries: - firstly, it is close to the limits of its borrowing capacity because of a decline in cash flow from trading operations, a build up of stocks and debtors caused due to inefficient management and a policy of placing greater reliance on debt finance than is normal for the industry. Secondly, it lacks accumulated profits because of a poor profit record or of a policy of high-dividend payouts. The findings of the study place greater reliance on financial statements as all the factors influencing the success of a company gets reflected in it. Moreover, the study suggests that the size and age variables of a firm do not have anything to do with failure.

Micha (1984) analysed the business failures in France by using the discriminant model. The sample comprised of 1,150 companies taken as normal companies and 520 failed companies identified by judicial proceedings, by merger or takeover and voluntary winding up. The use of the discriminant function in France by the Central Balance Sheet Data Office has been mainly to prevent business failures and to find out the non-bankrupt companies. Analysis of score distribution showed that although big corporations succeed in looking less vulnerable, they nevertheless tend to suffer equally in business fluctuations.

Tamari (1984) used the forecasting model to analyse the corporate behaviour in Israel. In this study, the Israeli manufacturing corporations were ranked according to a multivariate index of risk based on five financial ratios that have been shown to successfully predict financial distress 3 years prior to the actual failure. The findings of this study show that the greater use of supplier credit and recourse to more than one bank are significantly linked to a higher degree of risk as measured by the index. The firms with high ranking in the index of risk extend more credit to their customers than do those with a low index. The growth rate of sales does not seem to be significantly and unambiguously related to the risk status of the firm.

Ariyo (1986) used a consensus approach for bankruptcy prediction. The subjects for the study were 31 bank managers and officers of financial institutions in Nigeria. Based on eight previous studies, 15 financial variables were considered relevant for the experiment. The findings of the study indicate that there was a consensus on short-term liquidity ratios being consistent predictors of financial distress. The level of experience of the manager had also an important bearing on the choice of variables used in predicting bankruptcy. There were 3 ratios i.e. quick assets to current liabilities, current assets to current liabilities and cash available to current liabilities that were found to be important in predicting financial distress.

Srivastava and Yadav (1986) collected data from the financial statements of sick and non-sick companies belonging to the private manufacturing corporate sector, one to six years prior to the event. A sample of 39 companies which became sick during 1966 to 1980 was classified according to industry and size, measured by the paid-up capital and capital employed. Similarly 39 non-sick companies were also chosen. A set of 36 financial ratios representing profitability, liquidity, solvency and turnover were selected. Both univariate as well as multivariate – factor and discriminant analysis – were adopted. The discriminant analysis included 15 variables. Profitability and turnover ratios emerged to be significant discriminators. The model gave encouraging results for two years prior to failure. It was observed to predict well for short period.

Yadav (1986) also attempted to develop a comprehensive and scientific early warning system. The sample covered 39 failed and an equal number of non-failed companies, representing the manufacturing public undertakings in the private corporate sector in India during 1966-1980. Failed companies were identified from the Directory of Joint Stock Companies that have been notified to have gone into liquidation. A set of 36 financial ratios representing cash flow, income, solvency, liquidity and turnover were chosen for the preliminary analysis. The study presented the results of both the univariate and multivariate methods. The t-test and the dichotomous classification tests were also applied.

Queen and Roll (1987) examined firm mortality using market indicators. The variables were size of firm, price as given by closing price, total return, variance of return and beta given by the relative volatility of the stock as compared with a market index (beta). Total mortality was calculated as the number of companies merged, exchanged, liquidated, delisted, halted and suspended by the exchange divided by the total number of companies. The favourable mortality rate was calculated as number of companies merged, exchanged or liquidated divided by the total number of companies. The unfavourable mortality rate was calculated as number of companies delisted, halted or suspended by the exchange divided by the total number of companies. The findings of the study revealed that the size of the firm remained statistically significant for both types of mortality, price predicted favourable mortality but is insignificant for unfavourable mortality, return predicted unfavourable not favourable mortality, total variance had a strong positive association with unfavourable mortality and not favourable mortality and beta is no longer significant for either of the two mortality.

Koh and Killough (1990) examined the problems faced by the external auditor in assessing the going-concern status of his/her clients and suggested that a failure-prediction model based on MDA technique could be used by the auditor in making going-concern judgements. 22 ratios representing liquidity, profitability, leverage, activity, returns and market conditions were taken. The sample consisted of 35 failed and 35 non-failed firms. The findings of the study showed that apart from being an effective analytical tool, failure-prediction model could also be used at the beginning of the audit to help the auditor in making necessary audit procedures.

Joshi and Ramani (1991) used the multiple discriminant analysis to determine the most relevant set of financial measures to control the company level performance by taking the Paint industry in India as a case study. Seven companies in the Paint industry were selected and data on 27 financial ratios were obtained for the period 1981 to 1987 from the BSE directory. Both the canonical loadings and standardised discriminant weights produce the similar results indicating that the liquidity and sales turnover are the variables which discriminate most for the financial productivity and profitability of the Paint industry.

Altman and Fleur (1993) managed to avert a severe situation of bankruptcy in the GTI Corporation during the 1970s. Keeping a close watch on the Z score, a series of management decisions were taken which succeeded in foiling this prediction within five years. The model signalled underutilised assets to be a major contributor to the company’s deteriorating financial condition. As a follow up, the following strategies had been implemented step by step to eliminate the excess assets: (1) excess inventory were sold at the earliest; (2) corporate staff expenses were reduced through various measures; (3) all capital programs were frozen; (4) company’s creditors were asked for additional short term credit; and (5) inventories were placed under strict control. The employees were also actively involved in the process of its successful reorganisation. With continued strategies, GTI climbed higher ranges of success by 1979 and has been working as a financially sound company, pursuing new avenues to controlled growth. This study showed how Z score model could be used as a management tool with substantial success.

Panigrahy and Mishra (1993) discussed the various approaches for predicting the phenomenon of sickness in industries and presented a multivariate cash flow model to predict corporate sickness. The sample comprised of 45 sick and 45 non-sick companies. The sample of sick companies was prepared from BSE official directory for the period 1977-87 and the list of these companies were identified broadly based on the definition given by SICA, 1985. In addition, companies which had not paid dividend for several years and with low market value of shares were also included in the sample. They were matched with the non-sick companies on the basis of size, age, nature of industry and fiscal year of comparison. 16 cash flow ratios were calculated from the financial statements and MDA along with scaled vector technique and multivariate F test were used for predicting corporate sickness. The seven variable discriminant model was able to predict sickness with 78.89% accuracy for three years prior to sickness. The findings of the study indicated that cash flow ratios were good indicators of corporate health.

Altman *et al.* (1995) introduced a scoring system called EMS model for emerging markets corporate bonds, which was an enhanced version of Z score model. Unlike the original Z score model, this was meant for application to both manufacturing and non manufacturing companies as well as for privately held and publicly owned firms. This model combined fundamental credit analysis and rigorous benchmarks together with analyst-enhanced assessments to have a modified rating, which could be then compared to agency ratings and market levels. It was applied to Mexican companies and was found to be flexible in terms of future modifications depending on the operating and financial environment and sovereign risk.

Crouhy *et al.* (2000) reviewed the Credit Value-at-Risk methodologies. First, the credit migration approach, as proposed by JP Morgan with Credit Metrics based on the probability of moving from one credit quality to another, including default within a given time horizon and second, the option pricing, or structural approach, as initiated by KMV and based on the asset value model originally proposed by Merton were reviewed. Then the actuarial approach as proposed by Credit Suisse Financial Products (CSFP) with Credit Risk+ and finally, McKinsey’s Credit Portfolio View which is a discrete time multi-period model where default probabilities are conditional on the macro-variables like unemployment, the level of interest rates, the growth rate in the economy, etc were looked into. It was not clear that the proposed methodology of KMV and CreditPortfolioView performed better than a simple Bayesian model where the revision of the transition probabilities would be based on the internal expertise accumulated by the credit department of the bank, and the internal appreciation of where we are in the credit cycle given the quality of the bank's credit portfolio. These two approaches were somewhat related since the market value of the firm's assets depends on the shape of the economy.

Altman (2002) reviewed Z score and KMV's EDF models. The paper discussed the important implications of Basel 2's proposed capital requirements on credit assets and the enormous amounts and rates of defaults and bankruptcies in the US in 2001-2002. Both models were assessed with respect to default probabilities in general and in particular to the infamous Enron debacle. The study concluded that in order to be effective these and other credit risk models should be utilised by firms with sincere credit risk culture.

Mulla (2002) used the Z score analysis to evaluate the financial health of a textile mill in India. The case study was done by taking Shri Venkatesh Cooperative Textile Mills Limited, Annigeri of the Karnataka state and the required accounting information for the analysis was obtained from the annual reports of the textile mill under study covering a period of seven years. The findings of the study suggest that the textile mill under study was just on the verge of financial collapse and some type of managerial incompetence accounted for almost all failures.

Selvam *et al.* (2004) conducted a case study to predict financial health of India Cements Ltd using Z score analysis. The company was located in Tamil Nadu and it was a public limited company. The required accounting information about the company was obtained from the Prowess Corporate Database of CMIE, Chennai for a period of 5 years. The findings of the study revealed that the company faced the problem of under trading owing to excess working capital, under utilisation of available capacity led to failure of desired sales target and excess debt also led to poor financial health.

Aziz and Dar (2004) provided a critical analysis of methodologies and empirical findings of applications of various corporate bankruptcy prediction models across 10 different countries. The study's empirical exercise found that predictive accuracies of different corporate bankruptcy prediction models were, generally, comparable. Artificially Intelligent Expert System (AIES) models performed marginally better than statistical and theoretical models. Overall, the use of Multiple Discriminant Analysis (MDA) dominated the research followed by logit models. Based on the observations of this study, it seems logical to admit that almost all models of corporate bankruptcy prediction are capable of doing their job. However, the usefulness of a particular model is dependent on the particular research objective.

Altman (2005) was an extension of the earlier EMS model of Altman (1995). Here there was a description of Mexican company credits first prior to the Mexican crisis (1994) then followed by more recent data.

Bandyopadhyay (2006) used MDA technique to develop Z score models for predicting corporate bond default in India. The variables used in the model were working capital over total assets, cash profits to total assets, solvency ratio, operating profits over total assets and sales over total assets. He took a sample of 104 listed corporations from CRISIL. Logistic regression was also employed to directly estimate the probability of default using non-financial factors like age of firm, group ownership, ISO quality certification and control industry variables along with financial variables. The findings of the study showed that the Z model developed outperformed both Altman's original and Emerging Markets model. The empirical results of the logit analysis revealed that the inclusion of both financial and non-financial factors leads to more accurate default prediction.

Bandyopadhyay *et al.* (2007) attempted to empirically calibrate the default and asset correlation for large companies in India and elaborate its implications for credit risk capital estimation for a bank. The authors estimated default probabilities and default correlations of long-term bonds of 542 Indian corporates using rating transitions and pair-wise migrations over ten year cohorts of firms. Further, the implicit asset correlation from the estimated default correlations and default thresholds were derived using the asymptotic single risk factor approach. It was found that default correlations are time variant and vary across rating grades and industries. The highest correlations are observed between companies within the same rating grades (systematic risk impact) and within the same industry (industry specific impact).The findings of the study showed no significant smooth monotonic relationship between the probability of default (PD) and asset correlation as prescribed by the Basel II IRB document (2006). Moreover, it was found that the asset correlation range for Indian corporates do not match with what was prescribed for corporate exposures by BCBS.

Bandyopadhyay (2007) developed a hybrid logistic model taking inputs from BSM equity based option model. The findings of this study suggested for further enhancements in the BSM model taking into consideration the accounting information from financial statements and to develop hybrid models. The results obtained in this paper indicates that a mix of asset volatility, market value of asset and firm's leverage structure along with other financial and non financial factors could give us a more accurate prediction of corporate default than the ratio-based reduced form model.

Altman *et al.* (2007) developed a model for identifying potentially distressed firms in China. The variables used in the model were asset liability, working capital, return on total assets and retained earnings ratios. It was very similar to the EMS model of 1995. The findings of the study revealed that the model was robust with very high accuracy and was able to forecast up to three years with 80 percent accuracy for those firms categorized as Special Treatment (ST) which indicated that they were problematic firms.

Mishra *et al.* (2008) modelled the default probabilities and credit spreads for select Indian firms in the Black-Scholes-Merton framework. They showed that the objective (or 'real') probability estimates were higher than the risk-neutral estimates over the sample period. However, the probability measure was found to be robust to the 'default trigger point'. The model output also compared favourably with the default rate reported by CRISIL's Average 1-year rating transitions as well as the Altman Z-score measure. However it failed to generate spreads as high as those observed in the corporate bond market.

Miller (2009) evaluated the Distance to Default and Z-Score models for their ordinal and cardinal bankruptcy prediction abilities, rating durability over time, and rating stability. Distance to Default outperformed the Z-Score and our univariate TLTA model in both ordinal and cardinal bankruptcy prediction. Curiously, the Z-Score's ordinal ability is nearly equal to the other two models when ranking relatively safe companies, but performs worse in situations where the probability of bankruptcy is high. It was found that all three models produced actionable scores so far as rating durability was concerned. However, Distance to Default generated more durable ratings as its Ordinal Score was higher over all bankruptcy time-horizons and decayed at a slower pace than either of the other two models. However, Distance to Default had more volatile ratings than both the Z-Score and the TLTA model as it relies the most on market-based inputs, and market based inputs are usually more volatile than accounting-based inputs. Miller recommended the use of the Distance to Default model over the Z-Score model when trying to predict corporate bankruptcies subject to availability of data for each model and his results did not in any way condone the conclusion that all structural models outperformed all empirical ratio-based models.

Angur (2009) examined the aspects of corporate governance system and suggested ways to foresee a corporate fraud in the offing. Five key early warning signs in terms of high earning expectation, fraudulent accounting, dormant or non-existence of corporate governance committee, assessing the true nature of ethical and altruistic practices of the company and lookout for the Big Lie Theory were highlighted for assessment of corporate governance system. The findings of this paper suggested that corporate failures can be averted if the five key signs were closely monitored.

Appiah and Abor (2009) used MDA to develop the Z score to support the notion that Z score is an innovation to overcome the numerous difficulties associated with using single ratios to measure companies' health or risk of failure. The sample consisted of private medium-sized 31 failed and 31 non-failed manufacturing firms in the UK, during the period

1994-2004. Ten ratios were taken representing turnover, net PBIT, interest expense, current assets, quick assets, current liabilities, long-term liability, capital employed, shareholders' fund, working capital and gross profit. The initial model predicted bankruptcy with 79% accuracy whereas the modified model predicted bankruptcy with 97.3% accuracy which was done with a change in one of the variables i.e. net profit margin was included instead of gross profit margin and the sample was also changed to 17 failed and 20 non-failed firms. The findings of the study advanced the notion that net profit margin was superior to gross profit margin in discriminating between failed and non-failed UK manufacturing companies in terms of its significant contribution to Z score.

The majority of the works described above have used the Multiple Discriminant Analysis (MDA) technique to predict the corporate distress and or bankruptcy. Various other methodologies have been attempted as an improvement over MDA; however, the popularity of Discriminant analysis still dominates due to its simplicity and expediency in application.

2.3 Evaluation of Firm Performance using Efficiency as a Parameter

The financial factors in the credit risk assessment have been dealt in the first empirical chapter. Much of the earlier work has focused on the importance of traditional financial measures in prediction of distress with varying degrees of success, but the non-financial information remain largely uncharted. So, chapter 4 would look into the role of non-financial factors in the credit risk evaluation process. Here in this chapter the productive efficiency of a firm is calculated using the Data Envelopment Analysis (DEA) technique and then it is regressed upon the firm's ratings given from a public source (CARE/ICRA). Subsequently, it shows how a non-financial factor like efficiency can be an indicator of a firms' financial health.

This section of the review covers the efficiency aspect and the DEA technique used by various researchers.

DEA was introduced by Charnes *et al.* (1978); they extended Farrell's (1957) idea of estimating technical efficiency with respect to a production frontier. The resulting CCR model, named after the three authors, allowed for the calculation of the relative technical efficiency of similar Decision Making Units (DMU) in the analysis on constant returns to scale basis. This was achieved by constructing the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights for both the inputs and outputs were selected in a way that the relative efficiencies of the DMUs was maximised with the constraint that no DMU had a relative efficiency score greater than one.

There have been numerous books and articles published involving DEA since 1978 with several extensions and applications. One of the most significant developments since the CCR model was the introduction of the BCC model by Banker, Charnes, and Cooper in 1984. The BCC model relaxed the convexity constraint imposed in the CCR model which allowed for the efficiency measurement of DMUs on a variable returns to scale basis. The BCC model resulted in an aggregate measure of technical and scale efficiency, whereas CCR model was only capable of measuring technical efficiency. So, this allowed for the separation of the two efficiency measures.

Smith (1990) applied DEA to financial statements of companies in pharmaceutical industry. The model included average equity and average debt as inputs and earnings available for shareholders, interest payments and tax payments as the three outputs. The inputs and outputs were selected with the shareholders view of the firm. The study questioned the selection procedure of the variables, since there is no device to guide the analyst aside from his/her experience and some comprehensive sensitivity analysis. The author also cited the problem posed by outliers and emphasised on careful selection of the efficient DMUs. The study concluded that DEA potentially offers rich new insights into the performance of firms, and identified financial distress prediction and takeover activity as areas of possible future work.

Fernandez and Smith (1994) referred to the DEA model used in their paper as a solution intermediate between crude ratio analysis and complex regression technique. The study examined 27 datasets, each having a bankrupt firm and their healthy counterparts. The model included six financial ratios reflecting cash position (Cash/Total Assets), liquidity (Current Assets/Current Liabilities), working capital position (Working Capital/Total Assets), leverage (Net Income/Total Assets),profitability (Net Income/Total Assets) and turnover (Sales/Total Assets). All the six of these variables were taken as outputs to the DEA model and no inputs were specified. Based on the findings of the study, the authors concluded that DEA is likely to be useful for predicting bankruptcy only if it is employed in conjunction with other methods.

Thore *et al.* (1994) employed DEA to estimate the intertemporal productive efficiency of US computer manufacturers, using financial data brought from earnings statements and balance sheets. The results indicated that a few of the successful corporations were able to stay at the productivity efficiency frontier throughout the time period investigated. Other successful companies however, received inefficient ratings which seemed to indicate that sub efficiency or disequilibrium sometimes actually goes together with very rapid growth. A new Malmquist type productivity index was calculated for each corporation which measured shifts of the estimated intertemporal efficiency frontier.

Athanassopoulos and Ballantine (1995) viewed the use of DEA as complementary to ratio analysis. DEA was used in addressing a series of issues concerning the measurement of corporate performance including an assessment of sales efficiency, the effects of economies of scale, benchmarking a firm's performance and association between industry groups and performance. The sample comprised of 23 grocery firms in the UK. Various other methods like cluster analysis, ANOVA and Kruskal-Wallis test were also used. Five input variables such as capital employed, fixed assets, number of employees, number of outlets and sales area were used reflecting activity levels and resource commitments of individual grocers. Total sales figure was used as the single output variable. The findings of the study argued the use of DEA to provide useful insights into the assessment of corporate performance and also that the complementary use of both DEA and ratio analysis would greatly enhance the means of assessing corporate performance.

Majumdar (1996) examined the productivity trends in Indian industry for the period 1950-1951 to 1992-1993 using Data Envelopment Analysis. There were four inputs and one output used in the study. The inputs were rupee values of fixed and working capital, actual number of workers and actual number of administrative and support staff employed. The output variable taken was gross production expressed in crores of rupees. The data was collected from the Annual Survey of Industries (ASI) and Census of Manufacturing

Industries (CMS). The results showed that Indian industry reached its highest efficiency potential throughout the 1990s which could be attributed to the reforms of 1990s.

Retzlaff-Roberts (1997) developed one of the hybrid methods, which can be described as an efficiency approach to Discriminant Analysis (DA). Various formulation options were considered with respect to their effects o solution quality and stability. The data transformation issue was studied both for the hybrid method and also for DEA. The hybrid method was applied to an insurance data set, where some firms were solvent and others in financial distress, to further evaluate the method and its possible formulations. DA methods are applied to the same data set to provide a basis for comparison. The findings of the study showed the hybrid method to outperform the general discriminant models.

Feroz *et al.* (2003) argued that DEA can complement traditional ratio analysis if the goal is to provide information regarding the operating and technical efficiency of the firm. DEA was applied to the oil and gas industry and the inputs for the study were total assets, common equity and sales costs and the total revenue was taken as output. The empirical results showed the relationship between the deviations from the optimum DEA efficiency scores and the deviations from the optimum financial ratios i.e. the DEA deviations and the ratio deviations are somewhat correlated but not in a systematic way. Moreover, the DEA efficiency scores had incremental information contents over and above the information generated by ratios.

Saranga and Phani (2004) used the DEA on a sample of 44 pharmaceutical companies for the period 1992-2002, in order to find out the best practices in the Indian pharmaceutical industry. The inputs used for applying the DEA were cost of production and selling, cost of material and cost of manpower. The outputs were profit margin, net sales and exports. CCR and BCC models both were used to find out scale efficiency and technical efficiencies of these firms. The findings of the study revealed that size of a company does not dictate the internal efficiency ratings. The results of DEA which had been analysed along with the Compounded Annual Growth Rate (CAGR) showed that there is a direct relationship between internal efficiencies and higher growth rates in the Indian pharmaceutical industry, except for a few where companies in the mode of expansion may not have achieved full efficiencies. Regression analysis was also performed to see the correlations between various inputs/outputs and the growth rates. CCR, BCC and AR models were used to substantiate the results obtained.

Paradi *et al.* (2004) introduced the concept of worst practice DEA aimed at identifying worst performers by placing them on the frontier. A list of public companies in the manufacturing sector that filed for bankruptcy between 1996 and 1997 was taken and the sample of non-bankrupt companies were the healthy companies that did not go bankrupt before 1998. A series of variables were used for the study like total assets, working capital, EBITDA, retained earnings, shareholder’s equity, total current liabilities, interest expense, cash flow from operations, stability of earnings and total liabilities. A layering technique with risk attitudes and risk-based pricing was used instead of traditional cut-off approach. It is shown in this paper how the use of a combination of normal and worst practice DEA models enabled detection of self-identifiers. The empirical results showed 100% bankruptcy and 78% non-bankruptcy prediction accuracy in the calibration sample and also 100% and 67% out-of sample classification accuracies with the best combination of layered normal and worst practice DEA models.

Sahoo *et al.* (2007) used DEA to examine the productivity performance trends of the Indian commercial banks for the period 1997-98 to 2004-05. The increasing average annual trends in technical efficiency for all ownership groups indicated the positive effect brought by the reform process on the performance of the Indian banking sector.

Anna Ferus (2008) used DEA method to forecast credit risk of Polish companies. The sample comprised of 100 construction companies during the period 2001-2003. Six financial indicators were chosen out of 22 on basis of the weak correlation with each other. The daily return indicator and the total liabilities indicator were taken as inputs whereas net profit indicator, asset return indicator, equity capital return indicator and liquidity ratio were taken as outputs. CCR model was used to calculate the technical efficiency indicator value of the firms. The findings of the study showed the efficacy of the DEA method in forecasting financial problems better than other approaches.

Chang and Kuo (2008) proposed a novel procedure based on a bench marking model of DEA to solve the two group classification problem. A pair of nonlinear discriminant functions were constructed by the identifying the benchmarks of the two groups without pre specifying the classification functional form as in parametric discriminant approaches. This study compared the performance of the proposed approach with the Fisher's Linear Discriminant Function (FLDF) and Minimising the Sum of Individual Deviations (MSD). A layering technique was used to establish the discriminant functions. The findings of the study revealed that benchmark-DA had better classification accuracy for smaller group than other approaches.

Xu and Wang (2009) proposed a corporate financial failure prediction model using efficiency as a predictor variable. Data Envelopment Analysis was employed to evaluate the input/output efficiency of the corporations. The sample comprised of the corporations listed in the Shanghai stock exchange (SSE) and the data set contained 120 externally audited firms with 60 financially distressed and 60 non-bankrupt firms from 1999 to 2005. The CCR model was used with total assets, total liability and costs of sales as inputs and the income of sales as the output variable. To verify the efficacy of efficiency as a predictor, the accuracy of the same prediction method with and without the variable was compared. The empirical results of the multiple discriminant analysis, logistic regression and support vector machines all suggested that efficiency is a useful predictor variable.

Premachandra *et al*. (2009) proposed DEA as a quick and easy tool for assessing corporate bankruptcy. DEA is compared with logistic regression (LR) by taking a sample of large corporate failures in the US. The inputs taken were cash flow to total assets ratio, net income to total assets ratio, working capital to total assets ratio, current assets to total assets ratio, EBIT to total assets ratio, EBIT to interest expense ratio and market value of equity to book value of common equity ratio. The total debt to total assets ratio and current liabilities to total assets ratio were taken as outputs. The additive model was used. The findings of the study showed DEA outperforming LR in evaluating bankruptcy when there is no estimation sample.

Sueyoshi and Goto (2009) described a practical use of DEA-DA for bankruptcy based performance assessment. DEA-DA is used for classifying non-default and default firms based upon their financial performance. However, there are three problems when this method is used; sample imbalance problem as number of default firms is often limited, computational problem dealing with large data set and data alignment problem wherein the location of default firm may exist within that of non-default firms. This study discussed the simultaneous occurrence of these three problems from the perspective of Japanese industrial policy on construction business. To deal with the three problems, the study combined DEA-DA with principal component analysis to reduce the computational burden and then altered DEA-DA weights to address both the sample imbalance problem and location problem. A combined use of DEA-DA and Rank sum tests to examine statistically hypotheses related to bankruptcy assessment is also discussed in this paper The Japanese construction companies were taken from Nikkei Needs Corporate Financial Database of 2006. Profitability, leverage, growth, size and risk ratios were taken. The findings of the study revealed that the Japanese construction firms gradually deteriorated over the sample period (1998-2005).

Chong *et al.* (2009) analysed the survival ability of a sample of Malaysian public listed companies (PLCs) by analysing the impact of financing decision of the sample firms. DEA was used to identify the survivors among the PLCs based on their financing decisions. The PLCs were registered in the states of Selangor and Kuala Lumpur and were mainly manufacturing firms. The inputs taken were long-term debt, short-term debt and debt payables. Sales and equity were taken as outputs. BCC model in ratio form with VRS was used. The findings showed that the financing decisions help in evaluating the survival-ability of the PLCs. It was also found that the mixture of financing leverage and operating leverage that the PLCs used, determine the survival-ability of PLCs.

Ehmcke and Zloczysti (2009) analysed research efficiency at the industry level in manufacturing for 13 European member and four non-member countries during 2000 and 2004. Patent applications were used as output and human capital and R&D effort were taken as inputs. The results showed Germany, US and Denmark having highest efficiency scores on average in total manufacturing. The main industries at the technology frontier were electrical and optical equipment and machinery.

Tyagi *et al.* (2009) evaluated the performance efficiencies of 19 academic departments of IIT Roorkee, India through data envelopment analysis technique using different combinations of input and output variables. The three inputs taken for this study were Academic staff, Non-academic staff and Departmental operating cost. The outputs were Total enrolled students, Progress and Research Index. Output-oriented model was used for analysis and CRS and VRS both were used for overall performance assessment model. Four assessments namely, overall performance assessment, research performance assessment, teaching performance assessment and assessment for engineering departments was done using 10 models. Sensitivity analysis was also done in these 10 models by changing inputs and outputs. The findings of the study revealed that overall performance assessment was good for all science departments. The 4 streams comprising of Biotechnology, Chemistry, Civil Engineering and Hydrology departments were efficient in every area of research and all other departments need to pay attention for their research works.

Tripathy *et al.* (2009) examined the efficiency of pharmaceutical firms in India using firm-level data. A two stage DEA was used. In the first stage, technical efficiency analysis of 90 sample firms for the period 2001-02 to 2007-08 was undertaken using Sales of the sample firms as single output and Raw material cost, Cost of salaries and wages and Cost of advertising and marketing as the three input variables. In the second stage, the efficiency scores obtained from the first stage are regressed on external environmental factors like the age of the firms, export of goods, import of capital goods, profit rate, R&D intensity, ownership, patent regime and foreign direct investment using Tobit model. The results showed that during the study period the performance of a large number of sample firms was sub-optimal, ranging between 68% and 78%. The R&D intensive firms were more efficient than non-R&D firms. The Malmquist Productivity Index indicated that the total factor productivity of the sample firms has remained at the same level during the study period. The new patent regime, export of goods, presence of foreign direct investment, the profitability of firms and R&D intensity were found to be the important determinants of efficiency of the pharmaceutical firm’s.

Meenakumari *et al.* (2009) evaluated the relative operational efficiency of state owned electric utilities (SOEU) in India using DEA. Both CCR and BCC models were applied to study the overall efficiency and technical efficiency. 29 SOEUs in India were considered for the analysis and the relative operational efficiency scores were calculated. The results indicated that the performance of several SOEUs are sub-optimal, thereby suggesting a potential for significant improvements in the operation so as to improve the overall efficiency. Also sensitivity analysis was carried out to investigate the effect of changes in the solutions of the model.

Psillaki *et al.* (2010) investigated that technical efficiency as an important ex-ante predictor of business failure. The study outlined a flexible procedure for assessing firm performance and the likelihood for borrower default by banks. DEA is applied to estimate the directional distance function. The effect of efficiency on the likelihood of default in terms of franchise value hypothesis (which states that more efficient firms will be less likely to fail) was tested. Two French manufacturing industries for the period 2000 to 2004 were considered. DEA model used value added as output and capital stock and labour as inputs.

The DEA efficiency scores obtained along with financial performance indicators (profitability, growth, asset structure, and intangibility) and firm characteristics (size) were used as predictor variables in Probit and Logit models to determine the probability of firm's survival or failure. While estimating these models, efficiency is found to have significant explanatory power in predicting the likelihood of default over and above the effect of standard financial indicators.

Nikoomaram *et al.* (2010) used DEA and the financial variables such as Return On Investment (ROI), Residual Income (RI), Return On Sale (ROS), Earnings Per Share (EPS), Price to Earnings ratio (P/E), Return On Assets (ROA) and Operating Cash Flows to Owners' Equity (OCF) to measure the performance and efficiency of companies belonging to the metal industries and accepted in Tehran Stock Exchange Corporation. Six year data (2003-2008) on 24 companies was collected and used for the analysis. Multivariate regression was employed to study the relationship between the financial variables and DEA. The findings showed that ROS, EPS and OCF and the efficiency results of DEA are significantly related and hence can contribute towards performance and efficiency measurement of enterprises.

Data Envelopment Analysis (DEA), a mathematical programming technique has been used to evaluate the efficiency parameter of corporate performance. The power of this technique lies in its ability to handle multiple inputs and outputs and it does not require any specific functional form and also it gives a single measure of performance which takes into account the numerous dimensions of corporate activity.

2.4 Effects of Macroeconomic Factors on Financial Health of Corporations

The individual corporations and the financial institutions of a nation are very much linked to the macroeconomic conditions prevailing in that country. So, fluctuations in the macroeconomic conditions definitely have an impact over the financial health of any firm functioning inside the country. The literature contains studies focusing on explaining the relationship between business failures and fluctuations in aggregate measures of economic activities. The recent literature has emphasised on the time series analysis of business failures and macroeconomic factors and the correlations among them. Chapter 5 deals with examining the effects of macroeconomic factors on the financial health of Indian manufacturing corporations and vice - versa. Here, the long run relationships are identified using panel unit root test, panel cointegration analysis and panel long run causality. This part of the review explores the various studies done earlier in this regard and methodologies followed thereof.

Tirapat and Nittayagasetwat (1999) attempted to incorporate the macroeconomic factors in the investigation of financially distressed firms in Thailand. The sample consisted of listed firms in the Stock Exchange of Thailand (SET) that experienced financial distress in 1997. The overall sample comprised of 341 non-financially distressed firms and 55 financially distressed firms. A logit regression analysis was used to develop a macro-related micro-crisis investigation model. The significance of this model was its ability to bridge a firm's sensitivity to macroeconomic conditions and its financial characteristics in order to explore a firm's financial distress. The macroeconomic variables used were growth of industrial production, inflation, changes in interest rates and changes in money supply. The financial variables used were book value of stockholder's equity to total assets, retained earnings to total assets, operating income to net sales and net working capital to total assets. The findings of this study indicated that macroeconomic conditions are critical indicators of potential financial crisis for a firm. It also showed the higher a firm's sensitivity to inflation, the higher the firm's exposure to financial distress.

Vlieghe (2001) investigated the corporate failures in the United Kingdom using aggregate time series data using Auto Regressive Distributed Lag (ARDL) approach. The developed model suggested that corporate failure rate could be determined by profits, by the level of indebtedness and if the firms face borrowing constraints, by the level of inflation. The debt-to-GDP ratio, the real interest rate, deviations of GDP from trend and real wages were found to be long-run determinants of the liquidation rate. The birth rate of new companies, an index of property prices and nominal interest rates had significant short-term effects. It was also found that the rapidly increasing level of indebtedness in the late 1980s was the main determinant of the subsequent increase in the liquidation rate. The decrease in the liquidation rate after 1992 was primarily due to lower real interest rates, lower real wages and the cyclical recovery of GDP.

Hutchison (2002) examined whether European banking systems were vulnerable to systemic risk during 1999. Episodes of banking sector distress were linked to economic developments using cross-country panel data sets taking a sample of 90 countries over the period 1975-97. Multivariate probit models were estimated linking the likelihood of banking sector distress to a set of macroeconomic variables and institutional characteristics. The institutional characteristics included aspects of bank supervision and regulation, restrictions on bank portfolios and development of the banking system. Real GDP, inflation, exchange rate turbulence and financial liberalisation were the macroeconomic variables. Both institutional and macroeconomic variables pointed to relatively low risk of banking sector distress in EMU countries.

Liu and Wilson (2002) used quarterly data (1961.1 – 1998.2) on failure rates and potential macroeconomic determinants to test for the impact of changes to the insolvency legislation as enacted in the Insolvency Act 1986. The enactment of the 1986 Insolvency Act was incorporated into the time-series model determining failure rates along side macroeconomic variables such as the clearing bank base rate, lending to corporate sector, gross corporate profits, the retail price index, and the company birth rate. The econometric results confirmed that the Insolvency Act of 1986 had a preventive effect on business failures. It was also found that the business failure rates were responsive to the changes in the nominal interest rates, price level, costs of credit, company profits, and the population of companies over the period of 1966.1-1998.2.

Sharabany (2004) examined the effect of macroeconomic parameters on the financial stability of traded manufacturing companies. He analysed the characteristics of businesses in Israel that went into liquidation. The macroeconomic variables used were nominal and real interest rates, unexpected inflation, net debt of business sector to GDP ratio (log), the output gap, difference between the (log) change in real wage and the (log) change in labour productivity and the birth rate of new companies (log). Quarterly data (from 1990: I to 2002: I) on the compulsory company liquidation rate and potential macroeconomic determinants were used to build a time series econometric model that tested exclusively for the impact of macroeconomic variables on the number of company liquidations in Israel. The results showed that the liquidation rate rose with unexpected inflation and with positive changes in the real and nominal interest rates. The output gap negatively affected the liquidation rate. It was also found that those businesses which had fewer employees than the average, local market-oriented and were mainly in manufacturing and in particular in traditional industries were the ones that went into liquidation.

Liou and Smith (2007) took macroeconomic variables along with financial ratios to model financial distress. An investigation was made as regards to those variables which would be most useful to reduce Type II error. The macroeconomic variables used were GDP, Industrial Production Index (IPI), Base Rate (BR), Producer Price Index (PPI), Retail Price Index (RPI) and FTSE All Share Index (FTSEALL). The financial ratios used were PBT to Average current liabilities, Current assets to total liabilities, Current liabilities to total assets and No Credit Interval on days (NCI). A sample of 340 manufacturing companies were identified for the study traded on the London Stock Exchange over a twenty year period (1981- 2001). A linear discriminant analysis was adopted in this study. The result indicated that adding a macroeconomic variable as a 'second stage' to a linear discriminant model of financial distress prediction could suggest a means of reducing the element of Type II error, however, overall such models were of poor classificatory ability.

Carling *et al.* (2007) estimated a duration model to explain the survival time to default for borrowers in the business loan portfolio of a major Swedish bank over the period 1994-2000. The model took both firm-specific characteristics, such as accounting ratios and payment behaviour, loan related information and the prevailing macroeconomic conditions into account. The findings of the study showed that the output gap, the yield curve and the consumers' expectations of future economic development have significant explanatory power for the default risk of firms. The model developed here was able to account for the absolute level of risk. The other results showed firms default risk increasing monotonically over the survival of their loans and the risk of default being higher for short-term loans than for long-term credit.

Ahmad *et al.* (2008) investigated the long run dynamic linkages between the corporate failures in Malaysia and selected macroeconomic variables by employing the Autoregressive Distributed Lag (ARDL) bound test, which is a recently used robust time series technique and is applicable irrespective of the regressors being I(0) or I(1). Quarterly data from 1991:1 to 2005:4 was taken. The various macroeconomic variables used were log of Domestic credit aggregate, GDP, CPI, Average lending rate and corporate birth rate. A Dummy variable to decipher the corporate failure rates during the Asian financial crisis was also included. The findings of the study confirmed the existence of a long run relationship between macroeconomic variables and corporate failures in Malaysia. The results also revealed that corporate failure rates in Malaysia were significantly and positively associated with the average lending rate, inflation rate and the GDP in the long-run. The Asian financial crisis was also seen to be a significant contributor to the corporate failure rates in Malaysia.

Oxelheim and Wihlborg (2008) considered the impact of macro economy on corporate value and performance in evaluating corporate credit risk. They decomposed the Altman's Z scores as predictor of default into macroeconomic and intrinsic components. The decomposition proposed here relied upon market price variables on the macro-, industry- and firm levels to obtain coefficients for the sensitivity of the default indicator to changes in the different price variables. The price variables used were exchange rates, interest rates and inflation rates. The Z scores for GM and Ford were calculated and the quarterly changes during the period 1997-2005 were decomposed into macroeconomic and intrinsic components. Both GM's and Ford's Z scores fell during the period with substantial variation from quarter to quarter. The decomposition indicated that the decline in GM-score was explained by intrinsic factors while the decline in Ford's Z-score was explained mainly by macroeconomic factors. The findings suggested Ford to either consider its leverage or its approach to macroeconomic risk management.

Liu and Pang (2009) tried to investigate whether macroeconomic factors accounted for the observed fluctuations in the UK business failures during the period of 1966-2003, using vector error correction model. The variables used were business failure rates, real commercial banks' base rate, real credit, real profits, the inflation rate and the business birth rates. The major finding was that macroeconomic variables, i.e. credit, profits, inflation and company births, appeared to be the important factors influencing business failures. It was suggested that the interest rate, could be used as a feasible policy instrument to reduce the incidence of failures. It was also found that corporate failures played a significant role in macroeconomic fluctuations. An additional finding indicated that the deregulation policy adopted by the Thatcher government altered the relationships between failure rates and macroeconomic activities over the sample period.

Salman *et al.* (2009) in their paper attempted to shed some light on the influence of macroeconomic variables on the failure of small and medium sized Swedish businesses during the period 1986-2006 using quarterly data. Cointegration analysis and error correction model (ECM) was applied to study the short term and long term relationship between bankruptcies and macroeconomic variables. The findings of the study revealed that in the long run a firm's failure was negatively related to the level of industrial activity, money supply, GNP and economic openness rate and positively related to the real wage. The time series error correction model (ECM) estimates suggested that macroeconomic risk factors impinge on firm failures in the same direction in both the short run and the long run and the adjustment mechanism for stabilising the relationship was quite slow.

Santoro and Gaffeo (2009) used panel data on 20 Italian regions over the period 1985-2002 to test two competing theories of long run productivity dynamics: the opportunity-cost model, according to which productivity-enhancing activities have a comparative advantage during recessions; and the risk-aversion model, which predicts a negative relationship between transitory disturbances and productivity growth. The results suggested the existence of long-run relationship between business failures, trend output, a vertical interest spread and a measure of surprise inflation. The findings supported to the risk-aversion theory of productivity growth and showed that bankruptcy risks played a significant role in the propagation of macroeconomic shocks.

Bhattacharjee and Han (2010) studied the impact of microeconomic factors and macroeconomic conditions as well as institutional influences on financial distress of Chinese listed companies over the period 1995-2006. Hazard regression analysis was used. Business cycles, real interest rates and exchange rates were the macroeconomic variables taken in this study. The findings revealed substantial effect of firm level covariates (age, size, cash flow and gearing) on financial distress. Also macroeconomic instability and institutional factors have a significant impact on the hazard rate of financial distress. The results were robust to unobserved heterogeneity at the firm level, as well as those shared by firms in similar macroeconomic founding conditions.

Chen and Mahajan (2010) investigated the effects of macroeconomic conditions on corporate liquidity (cash holdings) in 34 countries from 1994 to 2005. The macroeconomic variables used were GDP growth, inflation, short-term interest rate, government budget deficit, credit spread, private credit and corporate tax rate. Corporate liquidity was defined as ratio of cash to net assets wherein cash referred to cash plus its equivalents plus marketable securities. Panel data model i.e. fixed effect model was conducted. The results showed that all macroeconomic variables had a direct impact on corporate cash holdings. In addition to this, it revealed that macro variables have an indirect impact on corporate cash holdings because the effects of firm-specific variables on corporate liquidity can be influenced by macroeconomic conditions.

Any institution in general faces two types of threat which determines its longevity. One is the internal threat from its own management and the other is the external threat from the economy as a whole. The above literature showed that the macro economic variables do have significance in the functioning of a firm and hence are worth consideration while exploring their financial position.

Chapter 3

Firm-Intrinsic Credit Scoring Model

3.1 Introduction

The past few decades had witnessed bank failures, foreclosures of business corporations, manufacturing units and services across the world, causing much concern to the respective managements, governments and the investor's community at large. A number of detailed investigations have been conducted both by individual researchers and organisations to trace the causes of sickness and suggest remedial measures. The attempts for devising early warning systems to aid the managements have not been scarce. The need for predicting corporate distress and to forewarn or prevent the recurrence of failures was highly felt and as a result numerous studies were done in the recent past. However, basing on the financial atmosphere of a country these systems are applicable and feasible.

The causes of declining performance of an organisation can be either internal or external or a combination of both. While the internal factors, which are under the management's purview and control affect only specific units, the external factors might affect all the units equally. A unit which might be momentarily sick can recover due to some innovations whereas a sound unit can turn sick if proper steps are not taken. So, the financial health of an organisation requires continuous monitoring.

The failure of a unit may be understood either in technical sense wherein it is unable to meet its maturing obligations or in real sense when the total value of its assets becomes smaller than liabilities. Failure may also be understood in legal sense when a unit ceases to operate.

According to the Reserve Bank of India (Ojha, 1987) an industrial unit will be termed as ‘weak’ if at the end of any accounting year it has:-

(i) Accumulated losses equal to or exceeding 50 percent of its peak net worth in the immediately preceding five accounting years

(ii) A current ratio (*current assets/current liabilities*) of less than 1:1

(iii) Suffered a cash loss in the immediately preceding accounting year

As per the Sick Industrial Companies (Special Provisions) Act (SICA), 1985, a sick industrial company can be defined as one (being registered for at least seven years) which has at the end of any financial year accumulated cash losses equal to or exceeding its entire net worth and has also suffered losses in the current as well as the immediately preceding financial year (Agarwal, 1989).

In practice the government identifies a failing unit only when it is at the verge of closure thereby leading to abrupt unemployment and so also the lending institutions identify a failing unit when there is uncertainty regarding payments of instalments. So, the need to identify sickness at an earlier stage is of paramount importance.

The earlier literature has made use of financial ratios as a potential device to predict corporate financial health. The reason cited lies with the assumption that there exists a close relationship between financial performance and overall health of an organisation. The trends in financial ratios as extracted from the financial statements reflect the ongoing process of an organisation.

The sole objective of identifying the financial indicators is to examine the financial health of a unit and to prevent it from becoming sick. Since such monitoring has to be carried out in an ongoing basis, early warning systems have come to existence for this purpose. A well developed EWS can be very useful for an organisation; however absence of accurate and timely information may act as a constraint in the functioning of the EWS as described earlier.

3.2 Failure Prediction Models

To begin with, statistical methods were used for identifying financial indicators of distress in corporations. The development of empirical models that discriminate failing firms from the surviving entities started in the mid 1960s. The univariate or single ratio approach was the most popular. The single ratio approach considers a set of ratios, one at a time and examines its significance. But after finding the limitations of this approach, multi-ratio approach came into prominence. This approach takes into account all the ratios simultaneously to obtain indices which reflect the overall status of the organisation. The most popular among the multivariate methods have been the multiple discriminant analysis (MDA). An MDA provides the Z-scores for classifying organisations and facilitates the evaluation of these organisations. The Z score is a linear combination of several independent variables and a cut off score is estimated to divide the firms into healthy and unhealthy ones.

Since then, extensive research has been carried out to evaluate the usefulness of various financial ratios for constructing the discriminant and related models. Over the years, more sophisticated methodologies have evolved to support corporate failure assessment, which included option pricing, gambler's ruin, hazard, neural networks, as well as the use of other statistical techniques, such as logit analysis, to the failure prediction problem. Such structural models were developed by Wilcox (1973), Merton (1974), and others. The commercial treatment of such an approach includes the famous KMV model (1995) which is now a part of Moody's.

A second group of models include those that look for imputing the implied probabilities of default (PD) from the term structure of yield spreads between default free and risky corporate securities. These are known as reduced-form models, e.g., Jarrow, Lando and Turnbull (1997).

A third category of models is the capital market based models, which include the mortality rate model of Altman (1988,1989) and the aging approach of Asquith, Mullins and Wolff (1989). The latest approaches include the use of neural network to support the risk classification.

Despite the variety of approaches used in failure prediction, statistical methods, like discriminant analysis, still dominate due to their simplicity and accuracy (Matthias Kerling, 1995). In general, these models have been featured with high classification accuracy, low cost, time saving, as well as convenience in application while solving the real world problems. So far, these failure prediction models have been successfully implemented in the developed nations like the United States. But in the Indian scenario, there is paucity of its applicability due to data constraints and also due to the very nature of the economy creating divergent regulatory environment, which makes the use of such models difficult.

However, the recent empirical research has made use of MDA and Z score models in India. The following section gives the theoretical support for the development of Z scores and the recent trend in its expansion and use in the Indian context with its pros and cons.

3.3 Theoretical Support

Credit risk evaluation originated from the analysis of change in financial status of firms, since credit crisis is usually caused by financial issues, such as cash flow diminution. So, it is possible to identify potential distress through the detection of characteristic financial indicators. Such financial indicators can be used to develop credit scoring or credit rating models to determine the credit ratings of firms, which is the foundation for pricing credit loans and investor's decision making. Basing on such motivation the researchers have turned the measurement of credit risk into the assessment of corporate financial health.

Altman (1968) used the multiple discriminant analysis method to study credit risk dimension of manufacturing firms in the US and developed a famous five-variable Z score model. This model was generated from the analysis of an initial 22 financial ratios, out of which five ratios were extracted and with a sample of 33 failed companies during 1946 to 1965 and an equivalent number of non-failed companies. The discriminant function yielded a score called Z score and on the basis of this, a cut-off was found for classifying firms as failed, non-failed or under zone of ignorance. This model was accurate as a forecaster of failure for up to two years prior to distress. Since then Z-Score models have been extensively applied for measuring corporate credit risk and ratings equivalent, including for firms in the emerging market. In 1977, Altman *et al.* constructed a second generation of model with several augmentations to the original Z score approach. It was termed as Zeta model. But the Z score model has retained its reported high accuracy and is still robust despite its development over the years.

Under the influential work of Altman, many financial institutions in the developed countries, such as Japan, Germany, France, China, Brazil, England, Australia and Canada have developed their own discriminant models.

In the Indian context few studies were conducted on failure prediction using the financial ratios and multiple discriminant analysis. Sarma and Rao (1976) used the MDA technique to predict the financial health of cotton textiles in India. Though their sample was small, the results showed ninety five percent of the firms to be correctly classified. The model seemed to be accurate for periods as early as three years prior to failure. Satyanarayana (1979) examined the relevance of Altman's model in the context of Indian industries. His sample consisted of a group of 486 profit-making and 185 non-profit making companies. The study concluded that though the Altman's model was not useful in predicting the collapse of an industry, it was certainly helpful in determining and predicting the financial health of a company.

Yadav (1986) attempted for a comprehensive early warning system. He took a sample of 39 failed and 39 non-failed manufacturing public undertakings under the private corporate sector in India during 1966 to 1980. The study used both univariate and multivariate methods.

The research on Indian companies to predict financial health is meagre due to some precise limitations. The first among this is the lack of proper bankruptcy laws which stops from identifying the distressed firms and hence demarcation of the groups into healthy and distressed becomes difficult. The second limitation is with regard to data availability. Most often it is seen that the variables used in prior research are not available for Indian corporations.

Keeping in mind these limitations, the present study however, has taken enough precision in conducting this work. To deal with the first limitation, a criterion has been devised for dividing the sample into three groups as healthy, moderately healthy and not-so-healthy groups. These groups were matched by industry affiliation and the period of analysis. The criterion for division was based on the average net worth of the companies during the year 1990 to 2009. A company having the average net worth value greater than 1,250 rupees crore is classified as a healthy company; a company with average net worth value greater than 450 rupees crore but less than 1,250 rupees crore is taken as moderately healthy and a company with average net worth value less than 450 rupees crore is taken as not-so-healthy. The number of observations for the healthy, moderately healthy and not-so-healthy categories is 26, 22 and 25. These are the manufacturing firms listed under BSE 200. So far as the financial ratios to be used are concerned, nine financial ratios have been chosen based on their relevance in literature and availability of data over the twenty year period i.e. from 1990 to 2009. The next section presents in detail the model and its development.

3.4 Concept of Firm-Intrinsic Credit Scoring Model

A firm-intrinsic credit scoring model is one that uses specific information about a company, primarily its financial statements. Measures of profitability, liquidity and capital structure are usually important components of a firm-intrinsic model.[1] Capital market prices and evaluations can be used in tandem with financial statements to further enhance the effectiveness of such models. These indicators are combined with some other measures to form a single measure of corporate vulnerability called a credit score. The objective of a firm-intrinsic credit model is to estimate the similarity of any individual company to hundreds of other companies that have compromised their creditors.

These models provide with the best anchor for stabilising the credit culture because they are embedded with accounting fundamentals and are time honoured and robust. This kind of models enables in estimating the probability of default. The most prominent of these models is the Altman's Z score model. Altman (1968) commented on the traditional ratio analysis and suggested that discriminant analysis can be a better tool for corporate distress predictions. The theory was that if ratios were analysed within a multivariate framework then the results would have more statistical significance than the common techniques of sequential ratio comparisons. Such a model can be used for business credit evaluation, internal control procedures and investment guidelines.

The process starts by developing financial and capital markets data of individual firms comprising clearly identifiable, unambiguous groupings (e.g., bankrupt vs. non-bankrupt, default vs. non-default, etc.). The variables used to establish the credit model are primarily

[1]Altman, Edward I. and Haldeman, R. (1995) 'Corporate Credit Scoring Models: Approaches and Tests for Successful Implementation', *Journal of Commercial Lending*, May, pp. 10-22.

financial ratios derived from financial statements at various points prior to the credit-event. These ratios can be supplemented by capital market data such as stock and bond prices and their resultant equity and debt values. The firm specific variables are then rigorously analysed by statistical methodologies such as parametric discriminant, logit or probit classification techniques, non-parametric methods such as recursive partitioning analysis or expert systems such as neural networks. These techniques, with the exception of the last one, have the important quality that they are essentially transparent to the analyst, can be understood, rigorously analysed, tested, and compared with existing techniques.

Till date such models find their existence in the sphere of credit analysis. A very recent work to mention here is the study by Appiah and Abor (2009) for predicting the financial health of UK's manufacturing companies by developing a firm-intrinsic credit scoring Z model using the MDA.

In India also as already mentioned, few studies have followed the firm-intrinsic credit scoring approach like Z score models for determining the financial soundness of the Indian companies. The variables used in these studies were chosen based on the availability across the firms taken as the sample.

3.5 Multiple Discriminant Analysis

Multiple discriminant analysis (MDA) is a statistical technique used to classify an observation into one of the several *a priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, e.g., male or female, bankrupt or non-bankrupt. The first step is to set up explicit group classifications. The number of original groups can be two or more. After the groups gets established, data are collected for the objects in the groups; MDA then attempts to derive a linear combination of these characteristics which “best” discriminates between the groups. If a particular object, for instance a corporation, has characteristics (financial ratios) which can be quantified for all the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratio, a basis for classification into one of the mutually exclusive groupings exists.

There are some assumptions involved in this technique, which are as follows:-

(a) Independence of observations, (b) multivariate normality i.e. the observations based on the discriminator variables are normally distributed and (c) homogeneity of covariance matrices i.e. the population covariance matrices based on the discriminator variables are equal. Current evidence suggests that discriminant analysis is robust with respect to violation of assumptions of multivariate normality and of homogeneity of covariance matrices (Stevens, 1996).

The MDA technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties whereas a univariate study only considers the measurements used for group assignments one at a time. Another advantage of MDA is the reduction of the analyst’s space dimensionality, i.e., from the number of different independent variables to G-1 dimension(s), where G equals the number of original *a priori* groups. The discriminant function is of the form:

$$Z = V_1 X_1 + V_2 X_2 + \ldots\ldots\ldots\ldots V_n X_n \qquad (3.1)$$

This transforms individual variable values to a single discriminant score or Z value which is then used to classify the object. Where V_1, V_2 … V_n = Discriminant coefficients and X_1, X_2 … X_n = Independent variables.

The MDA computes the discriminant coefficients, V_j, while the independent variables X_j are the actual values, where j= 1, 2…n.

However, the primary advantage of MDA in dealing with classification problems is the potential of analysing the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. Hence the MDA approach has improved upon the traditional ratio analysis and has the potential to reformulate the problem correctly. Precisely, combinations of ratios can be analysed together in order to remove possible ambiguities and misclassifications observed in earlier traditional studies.

3.6 Development of the Model

In this section, the various stages in the development of the credit model are dealt with. It begins with the data and sample selection, followed by the estimation procedure and the subsequent section presents the empirical and classification results and the determination of the cut-off score.

3.6.1 Data and Sample Selection

All the data were extracted from the CMIE prowess database and 'Company at a glance' data from the Capitaline plus database. The list of the manufacturing companies was obtained from the official website of Bombay Stock Exchange. The sample of manufacturing companies was based on the NIC two digit 2004 classification. There were 23 divisions under manufacturing which includes manufacture of food products and beverages; tobacco products, textiles, wearing apparel, tanning and dressing of leather; wood and products of wood and cork; paper and paper products; publishing, printing and reproduction of recorded media; coke, refined petroleum products and nuclear fuel; chemicals and chemicals products; rubber and plastics products; other non-metallic mineral products; basic metals, fabricated metal products, machinery and equipment; office, accounting and computer machinery; electrical machinery and apparatus; radio, TV and communication equipment and apparatus; medical, precision and optical instruments, watches and clocks; motor vehicles, trailers and semi-trailers; other transport equipment; furniture and Recycling. The total number of manufacturing units identified for the study was 73 firms listed under BSE 200. Moreover, the study was based on data ranging from March 1990 to March 2009.

The literature on foreign studies conducted especially in case of the developed economies had an advantage over India in terms of selection of the failed sample. This was because the legal structure in those nations comprised of well defined Bankruptcy Acts and Laws due to which the sample of bankrupt or distress firms could be easily located. But in case of India, there is lack of uniformity in the recognition of distress firms. The SICA and the RBI had their own stance on identification of sick units as mentioned earlier in section 3.1. The second most important limiting factor is the lack of information on the default companies. So far as the Board for Industrial and Financial Reconstruction (BIFR) which was set up by SICA is concerned, it has names of mainly unlisted companies, which are not relevant for this present study. Similarly, the Credit Information Bureau (India) Limited (CIBIL) which was established with a view to collect credit related information regarding commercial and consumer borrowers and to maintain the credit default data contains only the names of the default companies and not the financial data.

In case of India bankruptcy data is not available for listed companies. Though, for the unlisted companies' data can obtained from BIFR as mentioned earlier, it becomes all the more imperative to look into the listed firms and devise some credit risk measure for predicting financial health of these corporations. So, the present study becomes exploratory in nature wherein it was tried to develop a model that is in line with Altman's Z model to predict the financial health of BSE 200 manufacturing firms.

In this study open-end classes were taken to divide the data into 3 groups based on average net worth value. The reason is when we use Multiple Discriminant Analysis (MDA) technique the number of groups in the study should have more or less same sample size. So as the technique demands it, the study took open end classes.

As mentioned earlier, the average net worth criterion for the period 1990 to 2009 was designed, where a firm is taken as healthy if its average net worth is greater than 1,250 rupees crore; a company with average net worth value greater than 450 rupees crore but less than 1,250 rupees crore is taken as moderately healthy and a company with average net worth value less than 450 rupees crore is taken as not-so-healthy. Out of the total sample of 73 firms, the development sample consists of 63 firms of which the number of observations for the healthy, moderately healthy and not-so-healthy categories is 23, 18 and 22. For the hold-out sample 10 firms are randomly selected from the 73 firms.

3.6.2 Estimation Procedure

Further, nine financial ratios were selected to cover the aspects of profitability, liquidity, solvency, capital structure, efficiency, financial leverage, sales generating capacity and activity. As for the selection of variables, based on the comprehension manifestation of a company's financial status, the present study considered those ratios that were widely used in India as well as which had been used in previous studies including some variables used in Altman's Z score model and earlier Indian studies. The financial ratios taken were as follows:-

Working capital to total assets (X_1), Retained profits to total assets (X_2), Profit before interest and taxes to total assets (X_3), Net cash flow from operating activities to total borrowings or debt (X_4), Debt-equity ratio(X_5), Total liabilities to total assets (X_6), Interest coverage ratio (X_7), Sales to total assets (X_8) and Profit after tax to net worth (X_9).

The details of these ratios and their expected influence on the discriminant function are given below:-

Working capital to total assets or X_1 : - Working capital is the difference between current assets and current liabilities. It is frequently used in corporate studies, is a measure of the net liquid assets relative to total assets. A unit experiencing consistent operating losses or cash losses will have marginal current assets in relation to total assets. This ratio is expected to have positive influence on the discriminant function.

Retained profits to total assets or X_2 : - Retained profits are taken in lieu of Retained earnings and this ratio indicates the degree of capitalisation made through retained profits or internal funds. Higher ratio indicates the better financial health of the company. The age of the firm is implicitly considered here and younger firms are expected to have relatively lower ratio because it has not had time to build up its cumulative profits.

Profit before interest and taxes to total assets or X_3: - Profit before interest and taxes (PBIT) is a substitute to Earnings before interest and taxes (EBIT). This ratio measures the profitability generated on a firm's assets independent of leverage and taxes. The survival of a firm depends on the earning power of its assets and a high ratio of this is expected with the discriminant function.

Net cash flow from operating activities to total borrowings or debt or X_4: - This ratio tells us about how the company's are comfortable in repaying their debts? In a way, it reveals the debt paying capacity of a firm so, is a measure of activity. It should be positively associated with the discriminant function.

Debt-equity ratio or X_5 : - It is a measure of a company's financial leverage. Total debt is defined as the sum of secured loans, unsecured loans, and current liabilities. A high debt-equity ratio generally means a company has been aggressive in financing its growth with debt. A high ratio (more than 2) indicates that the entity is managed by debt funds and any decline in operating cash flows due to business risks factors may force the firm in delaying the payment of debt obligations. Persistence of this situation for a longer time leads to default. Almost all the credit rating models of the Indian banks assess the financial risk of borrowers by using this ratio.

Total liabilities to total assets or X_6: - It a measure of long term solvency. If the total liabilities of a firm exceed the total assets then the firm can go insolvent. A lower ratio shows that the proportion of self-owned asset is high and the proportion of liabilities is low, which provides a high safety in covering liabilities. So, creditors prefer this ratio to be as low as possible, as at a lower ratio the company is more secured to cover liabilities.

Interest coverage ratio or X_7 : - It is the relationship between operating cash flows and interest. Operating cash flows are also defined as earnings before interest, depreciation and tax. It depicts how easily a company can pay interest on outstanding debt? The lower the ratio, the more the company gets burdened by debt expense. A fall in ratio below one leads a firm to default on interest payments.

Sales to total assets or X_8 : - It is asset turnover ratio indicating sales generating capacity of the firm's assets. It also measures the management's ability to deal with competitive conditions. This ratio varies among industries. A higher ratio means there is efficient investment and as profits would increase.

Profit after tax to net worth or X_9 : - It can be seen as an efficiency parameter. Profit after tax or PAT is the net profit earned by the company after deducting all expenses like interest, depreciation and tax. A high ratio represents a healthy scenario. So, this ratio is expected to be positively related to the discriminant function.

As mentioned earlier, the statistical theory assumes that discriminating variables have a multivariate normal distribution and an equal variance-covariance matrix within each group. Two methods of selecting discriminating variables are there. One is the direct method and other is the stepwise method. The present study has used the direct or descriptive discriminant analysis method wherein all the variables are entered into the analysis together. Researchers often use stepwise discriminant analysis method in an effort to discover the "best" subset of discriminator variables to use in discriminating groups. But stepwise discriminant analysis is far less likely to yield replicable results than descriptive discriminant analysis because of its "outrageous" capitalisation on chance and the nuances of the particular sample (Thompson, 1995). So, it was not used in this study. For comparing the relative strength of variables to discrimination, we can use the standardised discriminant function coefficients and the structure matrix coefficients.

After considering a number of combinations of the nine characteristic variables, the final model for capturing corporate distress of Indian manufacturing firms included four variables. This model resembled the EMS model for emerging markets developed by Altman et al in 1995 except for the fact that the EMS model used inverse of Debt-equity ratio, and three variables of this model were similar to the Altman's original Z score model (1968). The four variables included are X_1 , X_2 , X_3 and X_5. It is of the form:

$$Z_I = 0.945X_1 - 0.976X_2 + 1.026X_3 + 0.180X_5 \qquad (3.2)$$

Where X_1 = working capital to total assets;

X_2 = retained profits to total assets;

X_3 = profit before interest and taxes to total assets;

X_5 = debt-equity ratio;

Z_I = the Z score for Indian manufacturing firms.

The above coefficients are the standardised canonical discriminant coefficients obtained from the MDA.

3.7 Empirical Results

The Eigen value indicates the ratio of between-groups variability to within-groups variability for a function. It represents discriminating power of the function. When there are more than one discriminant function, the function with the largest Eigen value is considered as the most powerful discriminator. The per cent of variance as given in table 3.1 represents the practical value of a function. It indicates the relative contribution of one function to the others. The canonical correlation coefficient is a measure of association which summarizes the degree of relatedness between the groups and the discriminant function. A value of zero implies no relationship whereas large numbers indicate increasing degree of association. Table 3.1 represents the Eigen values of the first two canonical discriminant functions (as there are 3 groups hence, we got two discriminant functions), % of variance and canonical correlation.

It can be seen from the table that function 1 has a higher Eigen value than function 2. Similarly it has a higher relative percentage (84.6%) and a higher canonical correlation coefficient. So, function 1 is considered for further analysis as it is the most powerful discriminator among the two.

Moreover the Box's M test results in table 3.2 are found to be significant thereby violating the assumption of homogeneity of covariance matrices. However the discriminant analysis is robust to violation of this assumption when the number of observations is large, as it was here.

From the analysis it is seen that, all the variables passed the tolerance criteria (the minimum tolerance level being .001) except X_6(the total liabilities to total assets ratio) as it was a constant in the sample.

The Wilks' Lambda values are used to measure residual discrimination. Residual discrimination means the ability of the variable to discriminate among the groups beyond the information that has been extracted by the previously computed functions. So, they are the inverse measure of discriminating power of the functions. A near zero Wilks' Lambda denotes high discrimination. To test the significance, each Wilks' Lambda is converted into a variable with chi-square distribution. The chi-square value indicates whether the variability that is systematically related to group differences is statistically significant. Table 3.3 shows the Wilks' Lambda.

Both the functions are significant at the 5% level of significance (as χ^2 = 26.2962 with *df* =16 and χ^2 = 14.0671 with *df* =7 at 0.05 level of significance). Function 1 has less value of Wilks' Lambda than function 2, showing comparatively better discrimination in the case of function 1.

The standardised canonical discriminant function coefficients represent the relative contribution of the associated variables to that function. The larger the magnitude, the greater is the variables contribution (ignoring the sign). The Z scores are obtained by multiplying the standardised coefficients by data values. Table 3.4 depicts the standardised coefficients.

In case of function one, the variables X_1, X_2, X_3 and X_5 are the variables contributing more to the discriminant function. As we are not dealing with function 2 we are ignoring it.

The structure matrix values indicate the importance of that particular variable in the discriminant function or a structure coefficient tells us how closely a variable and a function are related. When the absolute magnitude of the coefficient is very large (near +1.0 or – 1.0), the function is carrying nearly the same information as the variable. When the coefficient is near zero, they have very little in common. These values may be useful for assigning the weights to various ratios while architecting the internal rating models. The structure matrix is given in table 3.5.

Here, one can see a little diversion. Though in case of function 1, the variables having larger coefficients are the same as far as X_1, X_2 and X_3 are concerned but X_5 is not having any significance in terms of the coefficient value. This is because the structure coefficients tell us something else than standardised coefficients. The standardised coefficients take into consideration the simultaneous contribution of all the other variables whereas the structure coefficients are simple bivariate correlations, so they are not affected by relationships with the other variables.

The group centroids represent the mean discriminant score of the members of a group on a given discriminant function. They reveal how much and in what ways the groups are differentiated on each function. The absolute magnitude indicates the degree to which a group is differentiated on a function and the sign indicates the direction of the differentiation. Table 3.6 shows the functions at group centroids.

Function 1, discriminates healthy firms from moderately healthy and not so healthy. Healthy firms scored at the negative end of the function and the rest two on the positive end. Function 2 discriminates moderately healthy from healthy and not so healthy firms, with moderately healthy firms at the positive end of the function and healthy and not so healthy at the negative end of the function.

For classification and prediction purposes, the discriminant score of each group case (i.e. each entity) is compared to each group centroid and the probability of group membership is calculated. The closer a score is to a group centroid; the greater the probability the case belongs to that group.

3.7.1 Classification Results

The classification presented in table 3.7 shows the practical results of using the discriminant model. Out of the cases used to create the model, 263 of the 420 firms are correctly classified as healthy; similarly 95 of 323 and 201 of 407 are classified correctly as moderately healthy and not so healthy respectively. Overall 48.6% of the original grouped cases are correctly classified in case of the development sample. Table 3.7 shows these details.

The percentage of cases on the diagonal is the percentage of correct classifications, and this percentage is called the hit ratio. The hit ratio must be compared not to zero but to the percent that would have been correctly classified by chance alone. If group sizes are known a priori, the best strategy by chance is to pick the largest group for all cases, so the expected percent or the expected hit ratio is then the largest group size divided by N. Here for the development sample it is 36.52 %(420/1150 = 0.3652). When the hit ratio is compared to the expected hit ratio it can be seen that it is superior in case of healthy and not so healthy i.e. it is 62.6%, and 49.4% respectively.

3.7.2 Determination of the Cut-off Point

In order to verify the discrimination effect of the model and to determine a cut-off point, a hold-out sample of 10 randomly selected manufacturing firms with the composition of 3 healthy, 4 moderately healthy and 3 not so healthy has been taken. The classification in table 3.8 shows that 33 of the 57 firms are correctly classified as healthy; similarly 39 of 66 and 40 of 53 are classified correctly as moderately healthy and not so healthy respectively. Overall 63.6% of the original grouped cases are correctly classified in case of the hold out sample. This suggests that overall; the model is in fact correct almost about two out of three times.

Moreover, the hit ratio is greater than the expected hit ratio. The expected hit ratio is (66/176 = 0.375) or 37.5%, whereas the in case of healthy, moderately healthy and not so healthy it is 57.9%, 59.1% and 75.5% respectively.

The discriminant function (3.2) is used to calculate Z-scores for these 10 firms. After looking at the results of the development sample and the hold out sample, the empirical discriminant criterion is as follows:-

- If a firm has Z score which is closer to 0.519, it is classified as healthy.
- If a firm has Z score which is closer to 0.172, it is classified as moderately healthy and hence close watch is required.
- If a firm has Z score which is closer to 0.399, it is classified as not so healthy or technically distressed firm.

The values of 0.519, 0.172 and 0.399 are the values of the group centroids of discriminant function 1 given in table 3.6. The Z scores of each of the firms are compared with these values and we derive the cut-off.

Table 3.9 shows that out of the sample of 73 firms, 35 firms have Z score close to 0.519; only 6 have Z score close to 0.172 and 32 firms have Z score close to 0.399. Therefore, out of a sample of 73 manufacturing firms, 47.94% are healthy, 8.22% moderately healthy and 43.84% are not so healthy. Table 3.10 and table 3.11 shows the companies in the development and hold out sample and their respective Z scores.

3.8 Conclusion

The prediction of corporate distress is a common issue in developed economies but has only recently emerged in less developed economies such as India. Since the initial work of Altman (1968), numerous studies have attempted to improve upon and replicate the model in different markets worldwide. However, this topic has been less well-researched in emerging markets due to several major impediments. Moreover, this study is important to investors and from lender's point of view because the financial health of the firms got revealed here. A model for predicting the financial health for Indian manufacturing was developed using MDA technique. The model was tested for its predictive accuracy using a hold-out sample validation test. The model shows good performance with 48.6% prediction accuracy being observed in the development sample and 63.6% in case of the hold-out sample. The variables contributing more to the discriminant functions are working capital to total assets ratio, retained profits to total assets ratio, PBIT to total assets ratio and debt-equity ratio. With these variables the Z score was developed for the Indian manufacturing firms and the cut-off for division into healthy, moderately healthy and not so healthy was done accordingly.

This model is in line with the EMS model of Altman, which was not a predictor of emerging markets company bankruptcy due to the very fact that there were no defaults on Mexican Eurobonds and the economic and political environment in Mexico were different from U.S. which made bankruptcy prediction more difficult. Similarly this model not only resembles EMS model in terms of variables but also helps to assess the relative credit risk of Indian manufacturing firms which comes under emerging markets, however, this model is also not a bankruptcy prediction model, rather a corporate financial health assessment model.

The implications of this study can be viewed in terms of developing early warning systems by using the significant variables by the policy makers for detecting failures at an early stage and mitigating the risks thereafter. The investors and banks can assess the investment and loan prospects respectively as well.

However, the limitations of this study include the fact that it only concentrates on manufacturing firms. So, future research can be undertaken for firms from other sectors.

Another limitation is with regard to the criterion taken for dividing the firms. As it is difficult to take two or three criteria together, the robustness check can be done by substituting net worth by sales or turn over etc. Moreover, other methodologies should be used in predicting corporate financial distress such as neural networks and other advanced methods.

Table 3.1

Eigen Values

Function	Eigen value	% of variance	Cumulative %	Canonical correlation
1	.164	84.6	84.6	.375
2	.030	15.4	100.0	.170

Table 3.2

Box's M Test of Equality of Covariance Matrices Results

	Box's M	5254.650
F	Approx.	72.257
	df1	72
	df2	3309622.656
	Sig.	.000

Variables Failing Tolerance Test[a]

	Within-Groups Variance	Tolerance	Minimum Tolerance
$X_6 = TL/TA$	.000	.000	.000

All variables passing the tolerance criteria are entered simultaneously.

a. Minimum tolerance level is .001

Table 3.3

Wilks' Lambda

Test of function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.835	206.728	16	.000
2	.971	33.436	7	.000

Table 3.4

Standardised Canonical Discriminant Function Coefficients

Variables	Function 1	Function 2
X_1	.945	.209
X_2	-.976	.859
X_3	1.026	-.155
X_4	-.084	-.283
X_5	.180	-.162
X_7	.167	.492
X_8	-.103	-.489
X_9	.159	-.338

Table 3.5

Structure Matrix

Variables	Function 1	Function2
X_1	.628*	.375
X_3	.160*	.082
X_4	-.133*	-.037
X_2	-.190	.516*
X_8	.038	-.466*
X_7	.143	.395*
X_5	.097	-.239*
X_9	.050	-.058*

Note. The variables are ordered by absolute size of correlation within function and '*' denotes the largest absolute correlation between each variable and any discriminant function.

Table 3.6

Group Centroids

Category	Function 1	Function 2
Healthy	-.519	-.051
Moderately healthy	.172	.265
Not so healthy	.399	-.158

Table 3.7

Classification Results [a] (Development Sample)

			Predicted group membership			
		Category	Healthy(H)	Moderately healthy(MH)	Not-so healthy(NSH)	Total
Original	Count	H	263	91	66	420
		MH	112	95	116	323
		NSH	124	82	201	407
	%	H	62.6	21.7	15.7	100.0
		MH	34.7	29.4	35.9	100.0
		NSH	30.5	20.1	49.4	100.0

a. 48.6% of original grouped cases correctly classified.

Table 3.8

Classification Results [a] (Hold-out Sample)

			Predicted group membership			
		Category	Healthy(H)	Moderately healthy(MH)	Not-so healthy(NSH)	Total
Original	Count	H MH NSH	33 20 13	7 39 0	17 7 40	57 66 53
	%	H MH NSH	57.9 30.3 24.5	12.3 59.1 .0	29.8 10.6 75.5	100.0 100.0 100.0

a. 63.6% of original grouped cases correctly classified.

Table 3.9

Frequency Distribution of Firms as per the Empirical Discriminant Criterion

Discriminant score	Original sample			Hold out sample			Total
	H	MH	NSH	H	MH	NSH	
Z closer to 0.519	5	11	15	1	2	1	35(47.94%)
Z closer to 0.172	4	1	0	0	0	1	6(8.22%)
Z closer to 0.399	14	6	7	2	2	1	32(43.84%)
Total	63			10			73

Table 3.10

The Companies in the Development sample and their Z scores

Company Names	**Z scores**
Category 1 (healthy)	
A C C Ltd.	0.362905
Aditya Birla Nuvo Ltd.	0.404064
Ambuja Cements Ltd.	0.37978
Bharat Heavy Electricals Ltd.	0.378263
Bharat Petroleum Corpn. Ltd.	0.225195
Dr. Reddy'S Laboratories Ltd.	0.513591
Hindalco Industries Ltd.	0.336782
Hindustan Petroleum Corpn. Ltd.	0.264577
Hindustan Unilever Ltd.	0.318644
Hindustan Zinc Ltd.	0.331273
Indian Oil Corpn. Ltd.	0.347974
Ispat Industries Ltd.	0.936592
I T C Ltd.	0.427657
Larsen & Toubro Ltd.	0.344648
Mahindra & Mahindra Ltd.	0.436759
Maruti Suzuki India Ltd.	0.247879
National Aluminium Co. Ltd.	0.327563
N M D C Ltd.	0.41671

Ranbaxy Laboratories Ltd.	0.551926
Reliance Industries Ltd.	0.276764
Steel Authority of India Ltd.	0.542585
Sterlite Industries (India) Ltd.	0.498852
Tata Chemicals Ltd.	0.415933
Category 2 (moderately healthy)	
A B B Ltd.	0.400751
Ashok Leyland Ltd.	0.564811
B E M L Ltd.	0.658821
Bharat Electronics Ltd.	0.348095
Bharat Forge Ltd.	0.51411
Bhushan Steel Ltd.	0.602859
Bosch Ltd.	0.296556
Century Textiles & Inds. Ltd.	0.521647
Chambal Fertilisers & Chemicals Ltd.	0.535973
Cipla Ltd.	0.518113
Cummins India Ltd.	0.491847
GlaxoSmithKline Pharmaceuticals Ltd.	0.378397
G T L Ltd.	0.660566
Gujarat Mineral Devp. Corpn. Ltd.	0.296177
Hero Honda Motors Ltd.	0.172733
India Cements Ltd.	0.684976
Jindal Saw Ltd.	0.541591
Sesa Goa Ltd.	0.369912

Category 3 (not-so-healthy)	
Amtek Auto Ltd.	0.605785
Areva T & D India Ltd.	0.324948
Asian Paints Ltd.	0.413544
Bajaj Hindusthan Ltd.	0.789504
Balrampur Chini Mills Ltd.	0.579201
Bombay Dyeing & Mfg. Co. Ltd.	0.510638
Castrol India ltd.	0.572645
Colgate-Palmolive (India) Ltd.	0.317294
Crompton Greaves Ltd.	0.57212
Dabur India Ltd.	0.500605
Exide Industries Ltd.	0.558646
Godrej Industries Ltd.	0.463453
Jai Corp Ltd.	0.425576
Jain Irrigation Systems Ltd.	0.751404
Jubilant Organosys Ltd.	0.665787
Lupin Ltd.	4.733294
Madras Cements Ltd.	0.535742
Nestle India Ltd.	0.37645
Pantaloon Retail (India) Ltd.	0.592977
Piramal Healthcare Ltd.	0.442304
Praj Industries Ltd.	0.309429
Sintex Industries Ltd.	0.529349

Table 3.11

The Companies in the Hold out sample and their Z scores

Company Names	**Z scores**
Category 1 (healthy)	
Tata Motors Ltd.	0.311908
Tata Steel Ltd.	0.309079
Videocon Industries Ltd.	0.589196
Category 2 (moderately healthy)	
Siemens Ltd.	0.294383
Sun Pharmaceutical Inds. Ltd.	0.48092
Tata Tea Ltd.	0.324601
United Phosphorus Ltd.	0.804359
Category 3 (not-so-healthy)	
Thermax Ltd.	0.232716
Titan Industries Ltd.	0.75805
Voltas Ltd.	0.36218

Chapter 4

Evaluation of Firm Performance using Efficiency as a Parameter

4.1 Introduction

In this chapter an attempt is being made to include non-financial factors for credit risk evaluation. The earlier empirical research has emphasised the importance of financial measures in predicting the financial health of corporations. Though it has gained success in various degrees, the role of non-financial indicators remains largely uncharted. With a view that a combination of both financial as well as non-financial factors would enhance the predictive accuracy of financial distress, the non-financial measure in terms of technical efficiency is explored in this chapter.

Moreover, India has a natural competitive advantage in terms of a strong and large resource base and abundant cheap labour. However, such an advantage is not enough owing to increased international trade and competition. Therefore, enhanced efficiency and productivity are essential to meet the emerging challenge of global trade. In light of this changing scenario the efficiency of the Indian manufacturing firms need to be examined.

Technical efficiency refers to the ability of the production unit to produce as much output as possible for a given set of inputs, or conversely to use as little input as possible for a given output requirement. However, it is difficult to evaluate the technical efficiency of a firm from the information obtained in its financial statements. Therefore, Data Envelopment

Analysis (DEA) is used for efficiency evaluation. It has the advantage of giving a measure of performance by simultaneously handling multiple inputs and outputs without making any judgement on their relative importance in advance. The other advantage of DEA includes the non-requirement of any *a priori* specification of a functional form for the input-output correspondences.

So, this chapter uses the DEA to obtain the efficiency scores for the sample of manufacturing firms and use these as one of the predictor variables to derive further empirical results.

4.2 Data Envelopment Analysis and Efficiency

Data Envelopment Analysis (DEA) is a relatively new "data oriented" approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs), which convert multiple inputs into multiple outputs. The definition of DEA is generic and flexible. In the recent years there has been a wide variety of applications of DEA for performance evaluation of many different kinds of entities engaged in different activities in many different contexts. These DEA applications have used DMUs of various forms to evaluate the performance of entities, such as hospitals, cities, courts, business firms, universities, and others, including the performance of countries, regions, etc.

Since its first introduction in 1978, researchers have been able to use DEA for modelling operational processes for performance evaluations. In their originating study, Charnes, Cooper, and Rhodes (1978) described DEA as a 'mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations – such as the production functions and/or efficient production possibility surfaces – that are cornerstones of modern economics'. The resulting CCR model, named after the three authors, allowed for the calculation of the relative technical efficiency of similar Decision Making Units (DMU) in the analysis on constant returns to scale basis. This is achieved by constructing the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights for both the inputs and outputs are selected so that the relative efficiencies of the DMUs are maximised with the constraint that no DMU can have a relative efficiency score greater than one.

One of the most significant developments since the CCR model was the introduction of the BCC model by Banker, Charnes, and Cooper in 1984. The BCC model relaxes the convexity constraint imposed in the CCR model which allows for the efficiency measurement of DMUs on a variable returns to scale basis. The BCC model results in an aggregate measure of technical and scale efficiency, whereas CCR model is only capable of measuring technical efficiency. So, this allows for the separation of the two efficiency measures. The scale efficiency measurement indicates whether a DMU is operating at the most efficient scale, whereas technical efficiency is a measure of how well the DMU is allocating its resources to maximise its output generation. There were further advancements in the DEA technique in terms of development of the Additive model and Multiplicative models.

Advantages of DEA

The application of DEA for performance measurement is widespread. Data Envelopment Analysis has numerous advantages associated with its use.

- First DEA is a non-parametric approach. It does not require any specific functional form.
- Secondly, DEA is distribution-free because it does not need to specify the distribution of variables. The computational process of DEA classifies all observations as efficient or inefficient. All efficient observations consist of an efficiency frontier and all the inefficient observations exist below the efficiency frontier. The DEA-based efficiency evaluation does not assume any distribution in relation to the degree to which each observation locates from the efficiency frontier. In this way, DEA is also distribution-free.
- DEA gives a single measure of performance which can take into account all dimensions of corporate activity. It has the ability to simultaneously handle multiple inputs and outputs without making judgements on their relative importance.
- DEA is also helpful to managers. It gives a set of targets for performance improvements that managers can utilise to improve the firm's performance. Moreover, it allows them to determine and focus on the most important factors in the firms' operations.

The application of DEA in the past has been in the industries of finance, airline, healthcare, transportation, computer, mining, pharmaceuticals, banking, monetary aggregates, the U.S. army, etc.

Efficiency

In a production process, a set of appropriate inputs are transformed into desirable outputs by some production unit. Farell (1957) proposed that efficiency of a firm consists of two components, namely, technical efficiency, which reflects ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects ability of a firm to use inputs in optimal proportions, given their respective prices. In this chapter technical efficiency is being estimated and used in the credit risk model.

The production function that governs the relationship between the consumption of resources and the production of outputs defines the outputs in terms of all the inputs and identifies the production frontier for the production possibility sets. The efficiency of a production unit can be measured against the theoretical production frontier, but in practice this frontier rarely exists and in reality only observational data is available. The observed data points comprise of the empirical production frontier or envelopment surface. Relative efficiency is measured by the distance from the empirical frontier and indicates performance with respect to best observed performance exhibited by other similar units.

There are two methods of studying comparative efficiency namely parametric and non-parametric. Stochastic Frontier Analysis (SFA) is a parametric method which determines comparative efficiency levels by hypothesising a functional form. Data Envelopment Analysis (DEA) is a non-parametric method which employs mathematical programming (linear programming model) (Coelli *et. al.* 1998).

The mathematical programming approach due to DEA is used to measure technical efficiency in this chapter. This nonparametric approach calculates efficiency in two stages. First, the empirical production frontier is found based on the observed inputs and outputs of the decision making units of interest. This frontier is known as the envelopment surface and acts as the benchmark for all the DMUs in the analysis. The DMUs are the manufacturing units in this case. The second stage involves the computation of the efficiency score for each

DMU as indicated by its distance from the frontier. The efficiency score indicates the proportion by which the unit can increase its outputs without consuming any more inputs, or conversely the proportion by which it can decrease its inputs and maintain the same level of output.

There are mainly four types of DEA models[2]. They are the CCR ratio model (Charnes et. al, 1978), BCC returns to scale model (Banker et. al, 1984), additive model and multiplicative model. Here, the BCC model is used for estimating the technical efficiency scores of the firms. A brief account of the CCR model proposed by Charnes, Cooper and Rhodes in 1978 is given below. The following notations are used in the description of the CCR model below.

Let us assume n DMUs with m inputs and s outputs. Let

$x_{i,j} \rightarrow$ ith input of DMU j where $i = 1,\ldots,m$ and $j = 1,\ldots,n$.

$y_{i,j} \rightarrow$ ith output of DMU j where $i = 1,\ldots,s$ and $j = 1,\ldots,n$.

$u_i \rightarrow$ ith weight corresponding to output $y_{i,o}$ where $i = 1,\ldots,s$ and $o = 1...n$ is the DMU that is being evaluated.

$v_i \rightarrow$ ith weight corresponding to input $x_{i,o}$ where $i = 1,\ldots,m$ and $o = 1...n$ is the DMU that is being evaluated.

[2] Charnes , A., Cooper, W., Lewin, A. Y. and Seiford, L. M. (1994) 'Data envelopment analysis : Theory, methodology and application', Dordrecht; Boston and London, Kluwer Academic.

The CCR model of DEA can be expressed in the form of the following linear programming model.[3]

$$\text{Max} \qquad \theta = u_1 y_{1o} + \ldots + u_s y_{so} \tag{4.1}$$

$$\text{Subject to} \qquad v_1 x_{1o} + \ldots + v_m x_{mo} = 1 \tag{4.2}$$

$$u_1 y_{1j} + \ldots + u_s y_{sj} \leq v_1 x_{1j} + \ldots + v_m x_{mj} \qquad j = 1, \ldots, n \tag{4.3}$$

$$v_1, v_2, \ldots v_m \geq 0 \tag{4.4}$$

$$u_{1,} u_2, \ldots u_s \geq 0 \tag{4.5}$$

θ gives the efficiency of the DMU *O*. Since there are n companies, there will be *n* optimisations to measure the efficiency of each DMU. DMU *O* is CCR - efficient if $\theta^* = 1$ and there exists at least one optimal solution ((v^*, u^*) with $v^* > 0$ and $u^* > 0$, where (θ^*, v^*, u^*) is the optimal solution to the LP (4.1) – (4.5). Otherwise, DMU *O* is CCR – inefficient. In case of inefficient DMU, DEA also gives the degree of inefficiency and benchmarks a corresponding reference set of efficient DMUs, also called the peer group. The peer DMUs are the efficient units closest to it and are observed to produce the same or higher levels of outputs with the same or less inputs in relation to the inefficient DMU being compared. This enables the inefficient DMUs to know if there is excessive wastage of inputs and/or if there is any scope for improvements in outputs.

The above mentioned Constant Returns to Scale (CRS) DEA model implies that the size of a DMU should not matter for the efficiency. To facilitate ease of calculations, the dual of the LP- model (4.1) – (4.5) was developed, where a virtual DMU, which is the

[3] Cooper, W.W., Seiford, L.M. and Tone, K. (2000) 'Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software', Kluwer Academic Publishers, Boston.

linear combination of all the DMUs of the sample, is compared with each DMU under consideration, to calculate the efficiencies as follows:

Min θ (4.6)

Subject to the constraints,

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \; i = 1,2,\ldots,m \tag{4.7}$$

$$\sum_{j=1}^{m} \lambda_j y_{rj} \geq y_{ro}, \; r = 1,2, \ldots, s \tag{4.8}$$

$$\lambda_j \geq 0, \; j = 1,2,\ldots,n \tag{4.9}$$

Where, λ_j are the multipliers corresponding to each of the DMUs in the linear combination of the virtual DMU, and therefore the weights of inputs and outputs of the virtual DMU. Each DMU is compared with the virtual DMU to see if it can produce equal or more output than the virtual DMU with the same or lesser input. If it can, then that particular DMU is efficient and forms a part of efficient frontier with $\theta = 1$, $\lambda_o = 1$ and $\lambda_j = 0$, $\forall_j \neq 0$. If not, it is inefficient and the degree of inefficiency depends on the efficient companies on the frontier. The optimal value θ of the CCR model is the overall technical efficiency of the DMU *O*, which signifies the extent to which the inputs need to be reduced to bring DMU *O* onto the best practice frontier without worsening outputs under constant returns to scale.

Banker, Charnes and Cooper[4] (BCC) developed a DEA-model that calculates "pure" technical efficiency, which is consistent with a maintained hypothesis of Varying Returns to Scale (VRS). The BCC model is given by the dual of CCR model (4.6) – (4.9), with an extra constraint on λ_j, given by equation (4.10), which restricts the feasible region to a convex hull and at the same time ensuring the varying returns to scale.

$$\lambda_1 + \lambda_2 + ... + \lambda_n = 1 \qquad (4.10)$$

The BCC VRS Model is as follows:-

Max φ

Subject to the constraints,

$$\sum_{i=1}^{m} \lambda_i y_{ri} \geq \varphi\, y_{ro}, \; r = 1, 2, \ldots, s$$

$$\sum_{i=1}^{m} \lambda_i x_{ij} \leq x_{jo}, \; j = 1, 2, \ldots, n$$

$$\lambda_i \geq 0, \quad i = 1,2,\ldots,m$$

$$\sum \lambda_i = 1, \quad i = 1,2,\ldots,m$$

The optimal value of ϕ of the BCC model is the pure technical efficiency of DMU *O* which signifies the extent to which the outputs need to be maximised to bring DMU *O* onto the best practice frontier without worsening inputs under variable returns to scale.

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[4] Banker, R. D. , Charnes, A. and Cooper, W.W. (1984) 'Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis', *Management Science*,Vol. 30, No. 9, pp. 1078-1092.

4.3 Some Past Studies

Various analytical tools have been used for the assessment of credit risk. These include statistical methods such as linear, multivariate and quadratic discriminant analysis, logistic and probit regression analysis; neural networks; and operational research methods such as linear and quadratic programming and data envelopment analysis (DEA). In spite of their wide applicability, each technique has its own advantages as well as disadvantages.

In this chapter an attempt is made to establish the link between a non-financial measure i.e. technical efficiency and credit risk. Recent work on production frontiers and performance measurement was taken as the core behind such an attempt. It's an exploratory attempt to examine the significance of a non-financial indicator in measuring the corporate financial health.

After the introduction of the DEA in 1978, researchers have used it in various fields. Smith (1990) applied DEA to financial statements of companies in pharmaceutical industry. The model included average equity and average debt as inputs and earnings available for shareholders, interest payments and tax payments as the three outputs. The study concluded that DEA potentially offers rich new insights into the performance of firms, and identified financial distress prediction and takeover activity as areas of possible future work.

Feroz *et al.* (2003) argued that DEA can complement traditional ratio analysis if the goal is to provide information regarding the operating and technical efficiency of the firm. DEA was applied to the oil and gas industry and the inputs for the study were total assets, common equity and sales costs and the total revenue was taken as output. The findings of the study revealed that the DEA efficiency scores had incremental information contents over and above the information generated by ratios.

Some of the recent studies include Paradi *et al.* (2004) introducing the concept of worst practice DEA aimed at identifying worst performers by placing them on the frontier, Anna Ferus (2008) using the DEA method to forecast credit risk of polish companies, Premachandra *et al*. (2009) proposing DEA as a quick and easy tool for assessing corporate bankruptcy, Sueyoshi and Goto (2009) describing a practical use of DEA-DA for bankruptcy based performance assessment, etc.

Psillaki *et al.* (2010) investigated technical efficiency as an important ex-ante predictor of business failure wherein DEA was used to estimate the directional distance function.

In case of India, Saranga and Phani (2004) used the DEA on a sample of 44 pharmaceutical companies for the period 1992-2002, in order to find out the best practices in the Indian pharmaceutical industry. The inputs used for applying the DEA were cost of production and selling, cost of material and cost of manpower. The outputs were profit margin, net sales and exports. Both CCR and BCC models were used to find out scale efficiency and technical efficiencies of these firms. The findings of the study revealed that size of a company does not dictate the internal efficiency ratings. The results of DEA, which had been analysed along with the Compounded Annual Growth Rate (CAGR) showed that there is a direct relationship between internal efficiencies and higher growth rates in the Indian pharmaceutical industry, except for a few where companies in the mode of expansion may not have achieved full efficiencies.

Some other Indian studies using DEA were those of Majumdar (1996) examining the productivity trends in Indian industry for the period 1950-1951 to 1992-1993 using Data Envelopment Analysis, Sahoo *et al.* (2007) using DEA to examine the productivity performance trends of the Indian commercial banks for the period 1997-98 to 2004-05, Tyagi *et. al.* (2009) evaluating the performance efficiencies of 19 academic departments of IIT Roorkee, India through data envelopment analysis technique, Tripathy *et al.* (2009) examining the efficiency of pharmaceutical firms in India using a two stage DEA, etc. Meenakumari *et al.* (2009) evaluated the relative operational efficiency of state owned electric utilities (SOEU) in India using DEA.

In light of the above applications in the recent past, the Data envelopment analysis technique is used in this chapter to obtain technical efficiency scores of the manufacturing firms. Taking two inputs (capital employed and labour) and one single output in terms of net sales, the technical efficiency scores for 85 firms for the period 2005-2009 is calculated. Then, logistic regression analysis is employed with the financial ratios and technical efficiency scores being the independent variables and the corporate debt ratings for the firms as the dependent dummy variable.

4.4 Methodology

A two step methodology is followed to evaluate the financial health here. First, a set of observed inputs and output is used to derive efficiency scores for the sample of manufacturing firms. In the second stage, the DEA efficiency scores thus obtained, along with the financial variables, are used as predictor variables in the logit model to determine the probability of firms to have good or bad ratings and hence to assess the importance of efficiency in evaluation of corporate financial health or credit risk over and above of that explained by financial factors.

4.4.1 *DEA Framework*

For employing DEA, three components are therefore essential namely the set of DMUs, their inputs and their outputs. The manufacturing firms are the DMUs in this chapter. Two inputs, namely, capital employed and labour in terms of salaries, wages and bonus and one single output in terms of net sales are employed for computing technical efficiency scores. Due to data constraints the sample size in this chapter is limited to 85 manufacturing firms. The period of analysis is from 2005-2009 on annual basis.

Here, the output oriented BCC model of Variable returns to scale is estimated to obtain the technical efficiency scores of the firms. The VRS implies that an increase in inputs may result in either more or less than proportionate increase in the output. The VRS model incorporates the dual of CRS model with an extra convexity constraint on λ as mentioned earlier.

All the data relating to the inputs and output for the years 2005 to 2009 was culled out from the Capitaline plus database. The selection of inputs and outputs is very crucial while making use of DEA. For any given firm in an industry, the performance or efficiency is a relative concept and therefore the efficiency scores could be very sensitive to changes in the data and depend deeply on the number and type of input and output factors considered. In this study, consistent with recent literature [Psillaki et. al (2010)] the two inputs are taken namely capital employed and labour in terms of salaries, wages and bonus. The choice of inputs is also governed by the fact that capital and labour are the basic inputs for any firm or organisation for its operation. The net sales are taken as the output for DEA due to the fact that the output variable should depict the performance of the firm.

The DEA efficiency score lies in the interval 0 and 1, with a value 1 indicating the most efficient DMU and 0 showing the least efficient DMU. The input and output data have been used for computing the VRS technical efficiency scores of the firms using DEA software, version 2.1 (DEAP 2.1) downloaded at www.uq.edu.au/economics/cepa/deap.htm.

4.4.2 *Logit Analysis*

For the logit analysis, the credit ratings of the firms for the year 2009 are taken as the dependent dummy variable. These ratings were obtained from Capitaline plus database. Capitaline plus uses CARE and ICRA ratings.

Credit Analysis & Research Ltd. (***CARE Ratings***) is a full service rating company that offers a wide range of rating and grading services across sectors. CARE is recognised by Securities and Exchange Board of India (SEBI), Government of India (GoI) and Reserve Bank of India (RBI) etc. CARE was promoted by major Banks/FIs (financial institutions) in India. The three largest shareholders of CARE are IDBI Bank, Canara Bank and State Bank of India. CARE‘s Credit Rating is an opinion on the relative ability and willingness of an issuer to make timely payments on specific debt or related obligations over the life of the instrument.

ICRA Limited (formerly Investment Information and Credit Rating Agency of India Limited) was set up in 1991 by leading financial/investment institutions, commercial banks and financial services companies as an independent and professional Investment Information and Credit Rating Agency. ICRA is a Public Limited Company, with its shares listed on the BSE and the NSE. It is an associate of the international credit rating agency Moody's Investors Service.

Just as CARE ratings, an ICRA Rating is also a symbolic indicator of ICRA's current opinion on the relative capability of the corporate entity concerned to timely service debts and obligations, with reference to the instrument Rated. The Rating is based on an objective analysis of the information and clarifications obtained from the entity, as also other sources considered reliable by ICRA.

Both ICRA and CARE offer its credit rating services to a wide range of issuers including manufacturing companies, commercial banks, non-banking finance companies, financial institutions, public sector undertakings and municipalities, among others. Apart from ratings they also provide various specialised grading/rating services like corporate governance rating, Issuer ratings, IPO grading, MFI grading, etc.

As credit rating gives an opinion about the financial health of firms, it is taken as dependent variable and an attempt is made to trace the significance of a non financial variable like efficiency score towards rating. Then, a dummy variable (D) was defined which takes the value 1 if the firm had good rating in 2009 and if the firm had a bad rating in 2009, the D value equals 0.

While assigning a good or a bad rating to a firm, the focus was mainly on considering the corporate debt rating i.e. rating of short term and long term debts. This is because the debt ratings allow investors to factor credit risk in their investment decision.

Short-term ratings are assigned to instruments such as commercial paper, certificates of deposit, short-term debentures, and other money market related instruments maturing within one year from the date of issuance and bank loans with contractual maturity of up to one year. CARE assigns PR1 to PR5 to short term instruments, wherein PR1 implies lowest credit risk and PR5 implies default or likely to default on maturity.

The symbols for short term ratings vary from A1 to A5 in case of ICRA. While the short-term rating of A1 indicates that the rated debt issuance has the highest credit quality, A5 indicates that the rated debt is either in default or is expected to default on its repayment obligations.

Similarly the long term ratings include all bonds, NCDs, and other debt instruments (excluding Public Deposits) with original maturity exceeding one year. It varies from CARE AAA to CARE D and LAAA to LD for ICRA. A suffix of "+" (plus) or "-" (minus) may be appended to the rating symbols to indicate their relative position within the rating categories concerned.

The financial variables are the same four financial ratios that were used in Z score model in the previous chapter. They are Working capital to total assets, Retained profits to total assets, Profit before interest and taxes to total assets and Debt-Equity ratio. These financial variables along with the VRS technical efficiency scores representing the non financial variable are taken together as the independent variables for the logit model.

To predict the probability that a given firm will have a good rating, the study estimates the logit model by fitting the data into the logistic function given below:

$$f(Y) = \frac{1}{1+e^{-Y}} \tag{4.11}$$

Where Y is the ratings dummy variable for the firms under consideration.

Y = 1, if the firm had a good rating in 2009.

= 0, if the firm had a bad rating in 2009.

It is assumed that Y is linearly related to the variables shown below:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon_t \tag{4.12}$$

Where Y_i = 1 if the firm had a good rating in 2009, 0 otherwise;

X_1 = Working capital to total assets;

X_2 = Retained profits to total assets;

X_3 = Profit before interest and taxes to total assets;

X_4 =Debt-equity ratio;

X_5 = DEA VRS technical efficiency score;

β's are the coefficients which determine the relationship between the independent variables and the dependent variable.

ε_t is the error term.

4.5 Empirical Results

4.5.1 Results of DEA

Table 4.1 gives the descriptive statistics for the input and output variables used in the study for 2005 to 2009. A great deal of heterogeneity can be seen in case of Net sales/output variable ranging from a maximum of Rs. 306548.9 crores to a minimum of Rs.187.81 crores. A similar pattern can be seen in case of the input variables.

Average Efficiencies

Table 4.2 gives the summarised form of the average efficiency figures of all firms.

The average VRS TE for the firms was 0.41, 0.64, 0.30, 0.58 and 0.53 respectively for the period from 2005 to 2009. If the firms would have been efficient, they could have increased their output by 59%, 36%, 70%, 42% and 47% respectively, for the given set of inputs.

From 2005 to 2006 the Average TE was increasing and suddenly came down to 0.30 in 2007 and then again started increasing in 2008. The fact that 2007 was a crisis year could be easily seen from this whereby the average efficiency of all firms declined.

The companies along with the average VRS TE scores are given in table 4.3. Looking at the table, it can be seen that Tata Motors Ltd. has the highest average VRS TE score of 0.801 and the lowest score is 0.2366 which is of Ranbaxy Laboratories Ltd.

Frequency Distribution

Table 4.4 reveals the yearly pattern of the VRS TE.

The firms in the range of less than 0.2 ($x < .2$) was 25 in 2005 which came down to 1 in 2006 and even 0 in 2008, however, 57 (67.06%) firms were in this range in 2007, clearly indicating that most of the firms were inefficiently operating in 2007.

The maximum number of firms are in the range of greater than 0.2 and less than 0.5($.2 < x < .5$) and greater than 0.5 and less than 0.8 ($.5< x < .8$), with an exception in 2005 and 2007.

The number of firms with VRS TE in the range of greater than 0.8 and less than 1($.8 < x < 1$), shows fluctuations from 2005 to 2009, with 15 as the largest number of firms in this range in 2008.

The most efficient VRS TE of 1($x = 1$) range has 14 firms in 2006, followed by 11 in 2009.

4.5.2 Results of Logit Analysis

After obtaining the DEA TE scores, the next step is to regress through the Logit model, the ratings dummy dependent variable on the financial variables and the VRS TE scores being considered as the non financial indicator.

Table 4.5 gives the descriptive statistics of the variables used in the logit model. The mean of the Debt –Equity ratio (X_4) is highest followed by VRS TE (X_5).

The results of the Logit estimation are presented in table 4.6.

Table 4.6 shows all variables to be significantly related to ratings at 1% and 10% level of significance. X_1, X_3 and X_4 are negatively and significantly related to the ratings whereas X_2 and X_5 are positively and significantly related to ratings.

X_1 (working capital to total assets ratio) is a liquidity measure . X_1 is expected to be negatively and significantly related to debt i.e. the more liquid the firm is, the less it resorts to borrowings. In fact with higher liquidity the firms would pay off short term obligations and may also use their liquidity to finance part of their long term investments. A good rated firm will prefer liquidity to debt. So, more of X_1 implies less of short term and long term debts and hence is the negative relationship between X_1 and corporate debt ratings.

X_2 (Retained profits to total assets) tells about the age of a firm and small firms present a hurdle in getting high ratings commensurate with company financials. Large firms on the other hand have higher sustenance power even during troubled times. A good rated firm is expected to have good capitalisation made through retained profits or internal funds and so is likely to be positively and significantly related to X_2. The regression result conveys the same thing.

X_3 (PBIT to total assets) is a profitability measure independent of leverage and taxes. A good rated firm definitely will have higher profits and at the same time they prefer investing in short term debt instruments as they can refinance them at the opportune time. Now when PBIT/TA is expected to fall or decreases then the firms tend to get short term debt at lower cost thereby increasing the financial risk of firms. In other words, Short term debt increases with decrease in X_3, so there is a negative relation between these two. As a good rated firm prefers more of short term debt over long term debt and so it is also negatively related to X_3 and is significant due to the presence of the element of risk. Therefore, X_3 is negatively associated to ratings as shown in table 4.6.

X_4 (Debt-Equity ratio) is a measure of a company's financial leverage. A high debt-equity ratio generally means a company has been aggressive in financing its growth with debt. Persistence of this situation for a longer time leads to default. Therefore, a good rated company will have a low X_4 and hence ratings are negatively and significantly related to X_4.

As the objective is to show that efficiency is a significant predictor of ratings and thereby the corporate financial health, X_5 (DEA VRS TE) is expected to be positively and significantly related to ratings. The coefficient of X_5 in the logistic regression analysis shows it to be positive and significant at 10% level of significance. Even if it is not significant at 1% or 5% level but in the business world it is of important consideration. Therefore, the hypothesis that technical efficiency of a firm is not an important indicator of corporate financial health is rejected.

Moreover, the odds ratio[5] column shows the odds that an efficient firm has good ratings increases 82.4% over that of an inefficient firm with each unit increase in TE score.

The LR statistic which is used to test the overall significance of the model is significant at 1% level of significance. The McFadden R-squared is 0.124362.

4.6 Conclusion

First, with the help of Data Envelopment Analysis (DEA) this study encompasses the technical efficiency of the sample of 85 manufacturing firms using capital employed and labour (in terms of salaries, wages and bonus) as two inputs and Net sales as the single output during 2005-2009. The range of average VRS TE score varies from 0.2 to 0.8 and in order to become efficient, these firms need to increase their output with a given set of inputs. Further, as manufacturing sector is very central to the Indian economy, it is imperative that efforts be taken to increase the efficiency of the less efficient firms.

The second stage of the empirical analysis involving a Logit estimation identifies the significance of a non-financial performance parameter like efficiency to be a useful determinant of rating and thereby the corporate financial health.

The findings of the present study hold important policy implications. The prospective use of a non-financial indicator in the credit risk evaluation process is illustrated in the study. So, it can be useful for the banks in the overall credit risk assessment. The Credit Rating

[5] The odds ratio for a predictor is defined as the relative amount by which the odds of the outcome increase (odds ratio >1) or decrease (odds ratio <1) when the value of the predictor variable is increased by 1 unit.

Agencies (CRAs) can also make use of technical efficiency in their rating methodologies and check for robustness of the ratings.

Further, more firms being in the lowest VRS TE range during 2007 crisis period shows that the efficiency of the firms is dependent on the global economy. Therefore, the task ahead of policy makers and government is to create a healthy environment with stable internal efficiencies.

A limitation of this study is that it has used 2 inputs and 1 output for developing TE scores and used only manufacturing firms. So, an interesting avenue of exploration for future research could be to test for various other combinations of input and output and on other sectors.

TABLE 4.1

Descriptive Statistics of the Output and Input Variables

Output variable	**Observations**	**Mean**	**Std. Dev.**	**Maximum**	**Minimum**
Net Sales	425	10724.73	29996.71	306548.9	187.81
Input variables					
Capital employed	425	6619.07706	15041.8078	188494.12	42.19
Labour(Salaries, Wages& Bonus)	425	348.4859	679.8001	6665.63	6.77

TABLE 4.2

Average VRS TE Score of the Manufacturing Firms

Description of all firms(85)	**2005**	**2006**	**2007**	**2008**	**2009**
Mean	0.41	0.64	0.30	0.58	0.53
Standard Deviation	0.29	0.24	0.32	0.27	0.30
Maximum	1	1	1	1	1
Minimum	0.039	0.162	0.017	0.25	0.099

TABLE 4.3

Companies with Average VRS TE Scores

SL. No.	Average VRS TE Score	Company Names
1	0.525	A B B Ltd.
2	0.529	A C C Ltd.
3	0.4394	Aditya Birla Nuvo Ltd.
4	0.4422	Alstom Projects India Ltd.
5	0.3974	Ambuja Cements Ltd.
6	0.7222	Amtek Auto Ltd.
7	0.5596	Areva T & D India Ltd.
8	0.6008	Ashok Leyland Ltd.
9	0.6144	Asian Paints Ltd.
10	0.6206	Bajaj Hindusthan Ltd.
11	0.6008	Balrampur Chini Mills Ltd.
12	0.4064	B E M L Ltd.
13	0.4028	Bharat Electronics Ltd.
14	0.3996	Bharat Forge Ltd.
15	0.4048	Bharat Heavy Electricals Ltd.
16	0.3718	Bharat Petroleum Corpn. Ltd.
17	0.438	Bhushan Steel Ltd.

18	0.5162	Bombay Dyeing & Mfg. Co. Ltd.
19	0.471	Bosch Ltd.
20	0.4852	Castrol India ltd.
21	0.598	Century Textiles & Inds. Ltd.
22	0.6274	Chambal Fertilisers & Chemicals Ltd.
23	0.6022	Cipla Ltd.
24	0.5588	Colgate-Palmolive (India) Ltd.
25	0.6272	Crompton Greaves Ltd.
26	0.5386	Cummins India Ltd.
27	0.5192	Dabur India Ltd.
28	0.52	Dr. Reddy'S Laboratories Ltd.
29	0.585	Exide Industries Ltd.
30	0.6044	GlaxoSmithKline Pharmaceuticals Ltd.
31	0.5558	Glenmark Pharmaceuticals Ltd.
32	0.4834	Godrej Industries Ltd.
33	0.4626	Grasim Industries Ltd.
34	0.4114	G T L Ltd.
35	0.4298	Gujarat Mineral Devp. Corpn. Ltd.
36	0.5946	Gujarat N R E Coke Ltd.
37	0.641	Hero Honda Motors Ltd.
38	0.6906	Hindalco Industries Ltd.
39	0.7148	Hindustan Petroleum Corpn. Ltd.
40	0.6532	Hindustan Unilever Ltd.
41	0.5706	Hindustan Zinc Ltd.

42	0.5906	India Cements Ltd.
43	0.6252	Indian Oil Corpn. Ltd.
44	0.5954	Ispat Industries Ltd.
45	0.6948	I T C Ltd.
46	0.518	Jai Corp Ltd.
47	0.296	Jain Irrigation Systems Ltd.
48	0.312	Jindal Saw Ltd.
49	0.3414	Jindal Steel & Power Ltd.
50	0.3284	J S W Steel Ltd.
51	0.5634	Jubilant Organosys Ltd.
52	0.365	Lakshmi Machine Works Ltd.
53	0.383	Larsen & Toubro Ltd.
54	0.4048	Lupin Ltd.
55	0.391	Madras Cements Ltd.
56	0.7616	Mahindra & Mahindra Ltd.
57	0.5248	Maruti Suzuki India Ltd.
58	0.538	National Aluminium Co. Ltd.
59	0.4858	Nestle India Ltd.
60	0.4946	N M D C Ltd.
61	0.3262	Pantaloon Retail (India) Ltd.
62	0.2732	Piramal Healthcare Ltd.
63	0.2552	Praj Industries Ltd.
64	**0.2366**	Ranbaxy Laboratories Ltd.
65	0.2502	Reliance Industries Ltd.

66	0.3968	Sesa Goa Ltd.
67	0.347	Shree Renuka Sugars Ltd.
68	0.3828	Siemens Ltd.
69	0.4408	Sintex Industries Ltd.
70	0.3646	Steel Authority of India Ltd.
71	0.4964	Sterling Biotech Ltd.
72	0.4312	Sterlite Industries (India) Ltd.
73	0.3804	Sun Pharmaceutical Inds. Ltd.
74	0.3522	Suzlon Energy Ltd.
75	0.332	Tata Chemicals Ltd.
76	**0.801**	Tata Motors Ltd.
77	0.6764	Tata Steel Ltd.
78	0.6666	Tata Tea Ltd.
79	0.7058	Thermax Ltd.
80	0.6974	Titan Industries Ltd.
81	0.4616	United Phosphorus Ltd.
82	0.3878	United Spirits Ltd.
83	0.3972	Videocon Industries Ltd.
84	0.4328	Voltas Ltd.
85	0.414	Welspun-Gujarat Stahl Rohren Ltd.

TABLE 4.4

Frequency Distribution of VRS TE

VRS TE	**2005**	**2006**	**2007**	**2008**	**2009**
$x < .2$	25	1	57	0	9
$.2 < x < .5$	29	24	11	43	39
$.5 < x < .8$	19	36	3	17	13
$.8 < x < 1$	4	10	6	15	13
$x = 1$	8	14	8	10	11
Total	85	85	85	85	85

TABLE 4.5

Descriptive Statistics of the Variables used in Logit analysis

Variables	**No. of Obs.**	**Mean**	**Std.Dev.**	**Maximum**	**Minimum**
X_1	389	0.152356	0.163045	0.691035	-0.33921
X_2	389	0.070369	0.059535	0.479188	-0.08697
X_3	389	0.163818	0.108864	0.742312	-0.1223
X_4	389	0.697095	0.799538	5.83	0
X_5	389	0.48629	0.31164	1	0.017

TABLE 4.6

Results of Logit Regression Analysis

Dependent Variable: Ratings dummy

Binary Logit analysis results

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**	**Odds ratio**
C	2.335952	0.429909	5.433601	0.0000	10.33929826
X_1	-3.84677	0.878488	-4.37885	0.0000	0.021348688
X_2	18.55966	3.783445	4.905491	0.0000	114910026.3
X_3	-10.1504	1.986477	-5.10974	0.0000	3.90616E-05
X_4	-0.68201	0.176626	-3.86133	0.0001	0.505599209
X_5	0.601014	0.407365	1.475369	0.1401	1.823967366

McFadden R-squared	0.124362
LR statistic	55.40892
Prob(LR statistic)	0.0000
Obs with Dep=0	101
Obs with Dep=1	288
Total obs	389

Chapter 5

Effects of Macroeconomic Factors on Corporate Distress

5.1 Introduction

To reiterate, a firm's financial health could be affected by the economic circumstances within which the firm operates. The manufacturing sectors being one of the traditional sectors are most likely to be affected by changes in the macroeconomic conditions. Some of the past studies have confirmed the relationship between macro economy and corporate distress.

A firm usually fails because of a combination of factors. The failure rates of corporations are determined by three factors i.e. firm risk which is dependent on the effectiveness of the management and adequacy of its capital; industry risk i.e. a shock to a specific industry such as its exposure to import reform, tariff reform etc.; and macroeconomic risk i.e. risk deriving from the macroeconomic or monetary factors (Sharabany,2004).

It is seen that the number of failures rise during a crisis or a recessionary phase. But the company failures also affect the bank capital. If the realised losses on the company loan book are unanticipated, the bank capital gets eroded and hence weakens the banking system. In this way both corporate distress and macro economy are linked.

The basic objective of this chapter is to study the link between the macroeconomic factors and the corporate financial health indicator in the form of Z scores. Here the macroeconomic variables are the bank rate, growth rate of GDP, inflation rates and the growth rate of manufacturing component of GDP. The long run relationships are identified using panel unit root test, panel cointegration analysis and panel long run causality.

5.2 Macro Economy and Corporate Financial Health

The literature in this area contains studies that focused on explaining the relationship between business failures and fluctuations in aggregate measures of economic activities. The cyclical variations in business failures and macroeconomic aggregates are actually correlated in two ways. When companies are in distress, they are likely to cut investment and production, weakening economic growth. In addition, the expected economic downturn heightens corporate sector vulnerability. It is also observed that corporate failures occur frequently in recessionary periods that show the importance of factors external to the company.

First, the macroeconomic conditions affect the financial health of firms. Altman (1983) used augmented distributed lags (ADLs) to demonstrate that GNP, gross corporate profits and money supply have impacts on a marginal firm's ability to survive. Following a different, though related, line of research, Liu and Wilson (2002) constructed measures of the effects of the macro economy using error-correction information, showing that interest rate and insolvency legislation are the important variables in determining business failures in the long run.

Secondly, the corporations' health also influences the macro economy through the following links. When firms experience financial difficulties they dispose assets at 'fire-sale' prices so that net worth reduces and asset value falls (Pulvino, 1998); firms bear the risk of being excluded from access to credit, with an accompanying collapse in investment demand (Bernanke and Gertler, 1995). Corporate balance sheets weaken when distressed firms incur high direct costs to stay afloat financially, which offset the value of tax relief of an increasing debt level, hence exerting a negative effect on firm value. These two mechanisms lead firms to curtail investment plans and cut down productions, thus causing economic downturns and significantly impairing economic growth (Vlieghe, 2001).

The current global economy, which is characterised by economic slowdown, deflation, reduced interest rate, worsening government budget deficit, elevated credit risk, tighter credit and other economic difficulties etc. makes the firms to think of necessary adjustments for their businesses to survive in view of the changing macroeconomic conditions. It is worth exploring the relationship between firms' financial health and the major macroeconomic factors or how the firm responds to the changes in the macroeconomic conditions.

Against this backdrop the current chapter explores the relationship between the corporate financial health indicators of the manufacturing firms in terms of the Z scores and the macroeconomic variables like inflation, bank rate, index of industrial production and GDP for the Indian scenario.

5.3 Brief Review of Past Studies

Corporate distress prediction models were being initiated by Beaver (1966) and Altman (1968) using univariate test and multivariate discriminant analysis. Since then the prediction of corporate failure became a topic of much interest and the recent works have extended this line of research in three areas: statistical techniques, definitions of bankruptcy and a wider variety of explanatory variables. The third area involves some adjustments of explanatory variables either by including variables other than financial ratios or industry-adjusted ratios. Some studies include macroeconomic variables to control for changes in the business environment. Most of the empirical research, including the episode of recent global meltdown shows that the incidence of default rises during economic recession. Several studies have used macroeconomic variables for corporate distress prediction.

Wadhwani (1986) examined the determinants of corporate liquidations to test the hypothesis that inflation played a significant role. In theory, firms financed by variable-rate debt should not be affected by inflation in a perfectly indexed economy, because the increase in interest payments due to higher nominal rates can be financed by an increase in debt, to match the increase in the nominal value of assets. However, in the absence of perfect capital markets, firms may not be able to increase their borrowing and therefore, might face a cash flow shortage as the increase in interest payments is proportionally larger than the increase in revenues.

To test this hypothesis, Wadhwani regressed the liquidation rate of firms (as measured by the ratio of compulsory and creditors' voluntary liquidations divided by the number of active companies on the register) on a number of macroeconomic and financial variables. He found that real wages, real input prices, capital gearing (using market values), the real interest rate, the nominal interest rate and measures of aggregate demand are significant. The rate of new company registrations is not reported in the final specification and a measure of the standard deviation of prices was not significant. The fact that both real and nominal interest rates are significant is taken as evidence that inflation directly affects the liquidation rate.

Cuthbertson and Hudson (1996) in their ADL (Autoregressive Distributed Lag) model demonstrated that birth rate, profits and interest-gearing variables are the key variables influencing compulsory liquidations, though interest-gearing had only short-run effect. Vlieghe (2001) examined UK aggregated corporate liquidations within the ADL framework and found that real interest rate and debt-to-GDP ratio are the long-run determinants of liquidation rate, while property prices, nominal interest rate and business birth rate had significant short-term effects. Following a different, though related, line of research, Liu and Wilson (2002) constructed measures of the effects of the macro economy using error-correction information, showing that interest rate and insolvency legislation to be the important variables in determining business failures in the long run.

Liu and Pang (2009) tried to investigate whether macroeconomic factors accounted for the observed fluctuations in the UK business failures during the period of 1966-2003, using vector error correction model. The major finding was that macroeconomic variables, i.e. credit, profits, inflation and company births, appeared to be the important factors influencing business failures. It was suggested that the interest rate, could be used as a feasible policy instrument to reduce the incidence of failures. It was also found that corporate failures played a significant role in macroeconomic fluctuations.

Bhattacharjee and Han (2010) studied the impact of microeconomic factors and macroeconomic conditions as well as institutional influences on financial distress of Chinese listed companies over the period 1995-2006. The findings revealed substantial effect of firm level covariates (age, size, cash flow and gearing) on financial distress. Also macroeconomic instability and institutional factors have a significant impact on the hazard rate of financial distress.

Chen and Mahajan (2010) showed that all macroeconomic variables had a direct impact on corporate cash holdings.

The financial health of manufacturing firms has not received much attention from macroeconomic theory. However, logic suggests that macroeconomic developments or changes may have an important role in explaining corporate distress. It is for this reason that an attempt is being made here to study the relationship between macroeconomic conditions and corporate financial health of manufacturing units in India.

5.4 Methodology

The analysis is based on the recently developed panel integration (unit roots), cointegration and causality tests. These tests are used to determine the long-run dynamic linkages between the variables under consideration in a panel set up. For gaining statistical power over time series tests and to avoid the low power of classical panel tests which have an assumption of series being stationary, the above tests are applied to a panel data set in this chapter. Moreover, these panel data techniques allow for heterogeneity among cross-sections and individual intercept for each cross-section to capture the firm specific effect. This allows one to test directly for the existence of long run equilibrium.

Given the time series element present in the panel data, in the first step one determines the order of integration of each of the data series. The concept of cointegration is associated with the long-run equilibrium relationship between two or more variables, so in the second step test for the existence of long run relationship is carried out between the variables using cointegration test developed by Pedroni (1999). If the series are cointegrated, the long run coefficients are estimated by employing the Fully Modified Ordinary Least Square Method (FMOLS) developed by Pedroni (2000). This is followed by investigating long run dynamic linkages between the variables, using panel long run causality test developed by Canning & Pedroni (2008) based on Engle & Granger (1987) specification.

The independent macro variables are annual growth rates of GDP at Factor cost at Current Prices, Bank rate, WPI and Manufacturing component of GDP at Factor cost at Current Prices from 1990 to 2009. The data on macroeconomic variables are collected from the ‘Handbook of Statistics on Indian Economy’ from the Reserve bank of India website (www.rbi.org.in). The dependent variables are the Z scores of the 73 firms obtained in chapter 3. As the growth rates of variables are not linear, the log of each of variables is taken. The independent variables and their expected relationship with Z score are explained below.

Gross domestic product (GDP) refers to the market value of all final goods and services produced within a country in a given period. It is often considered an indicator of a country's standard of living. It aims to represent the total economic activity of a specific country by totalling the value of its production, the income earned from this production or series of more complex assessments. Moreover, in the recent literature (e.g. Liou & Smith (2007), Chen & Mahajan (2010), etc.) it has been taken. So, here the GDP growth rate which is the percentage change in GDP is taken. GDP growth rate is expected to be positively associated with the Z score because growth in GDP creates better investment opportunities for firms and also increases corporate liquidity leading to improved corporate financial health.

Bank rate, also referred to as the discount rate, is the rate of interest which a central bank charges on the loans and advances that it extends to the commercial banks and other financial intermediaries. Changes in the bank rate are often used by central banks to control the money supply, and hence is a crucial variable. When the central bank reduces the bank rate, the commercial banks borrow more, thus increasing the money supply. So, commercial banks start extending their loan base without much stringent rules which increases the risk of default. Whereas, when the central bank increases the bank rate, commercial banks borrow less and the lending rates of commercial banks rise. The commercial banks become cautious about the credit worthiness of the firms while giving loans and moreover as the commercial banks charge higher rates, consequently only financially healthy firms can afford to borrow. Therefore, bank rate is expected to be positively related to Z score.

The Wholesale Price Index or WPI is the price of a representative basket of wholesale goods. It is used as a measure of Inflation. The Wholesale Price Index focuses on the price of goods traded between corporations, rather than goods bought by consumers, which is measured by the Consumer Price Index. The purpose of the WPI is to monitor price movements that reflect supply and demand in industry, manufacturing and construction. Inflation correlates with the increasing prices and the direct costs of material, labour, operations, R&D, etc. So, it would favour larger and healthier companies with well established economies of scale relative to smaller and newer firms. Thus, WPI is expected to be positively associated with Z score in the short run but the higher a firm's sensitivity to inflation, the more likely the firm's exposure to financial distress. Therefore, in the long run WPI is expected to be negatively related to Z score.

The Manufacturing component of GDP at Factor cost at current prices indicates the share of manufacturing in GDP. The good manufacturing firms are likely to have a higher manufacturing component in GDP. So, this too is expected to be positively related to Z score. This variable is chosen since the sample in this study comprises of manufacturing firms and hence the study intended to check how the corporate financial health indicator via Z score for the manufacturing firms is affected by this variable. An obvious question could be why Index of Industrial Production (IIP) is not used. The answer lies in the fact that IIP is a measure of status of production in the industrial sector as a whole for a given period of time as compared to a reference point of time, and not of manufacturing sector alone.

To investigate the relationship between Z score and the macro economic variables the following model is used:

$$LZ_{it} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LBR_{it} + \beta_3 LWPI_{it} + \beta_4 LMNFC_{it} + e_{it} \qquad (5.1)$$

where LZ_{it} is the logarithm of the Z score obtained in chapter 3 for firm i in the year t, $LGDP_{it}$ is the logarithm of the annual growth rate of Gross Domestic Product at Factor cost at Current Prices for firm i in the year t, LBR_{it} is the logarithm of the Bank rate for firm i in the year t, $LWPI_{it}$ is the logarithm of the annual growth rate of Wholesale Price Index for firm i in the year t and $LMNFC_{it}$ is the logarithm of annual growth rate of manufacturing component of GDP at Factor cost at Current Prices for firm i in the year t, and e_{it} is the error term.

Equation 5.1 can be considered as the long run equilibrium relation.

5.4.1 Panel Unit Root Test

While estimating the panel data models, the time-series properties of the cross-sections exert an important influence on the specification of the econometric model and the choice of estimators. Therefore, testing for stationarity is very crucial for analysing panel data models. A stochastic process is said to be stationary if it oscillates around the constant mean over the period with some confidence interval. Most of the financial and macroeconomic time-series data are non-stationary and testing for non-stationarity means testing for presence of a unit root.

When dealing with panel data, because the procedure is more complex, the conventional ADF and DF tests can result in inconsistent estimators. So, several statistical methods (Levin, Lin and Chu, 2002; Im, Pesaran and Shin, 2003; Choi, 2001; Breitung, 2000; and Hadri, 2000) are constructed to test for unit roots in panel data.

In this study, panel unit root test proposed by Hadri (2000) is used. It is similar to the KPSS unit root test and has a null hypothesis of stationarity or no unit root in any of the series in the panel. Just as the null of the KPSS test differs from that of Dickey–Fuller style tests in assuming stationarity rather than nonstationarity, Hadri’s test generalizes this notion to the panel context. The test statistic is distributed as standard Normal under the null hypothesis. As in the univariate KPSS test, the series may be stationary around a deterministic level (specific to the unit–i.e. a fixed effect) or around a unit–specific deterministic trend. The error process may be assumed to be homoskedastic across the panel or heteroskedastic across units. Serial dependence in the disturbances may also be taken into account using a Newey–West estimator of the long–run variance. The residual–based test is based on the squared partial sum process of residuals from a demeaning (detrending) model of level (trend) stationarity.

Like the KPSS test, the Hadri test is based on the residuals from the individual OLS regressions of y_{it} on a constant, or on a constant and a trend. For example, if we include both the constant and a trend, we derive estimates from:

$$y_{it} = \delta_i + \eta_i t + \varepsilon_{it} \qquad (5.2)$$

Given the residuals $\hat{\varepsilon}$ from the individual regressions, we form the LM statistic:

$$LM_1 = \frac{1}{N}\left(\sum_{i=1}^{N}\left(\sum_t S_i(t)^2 / T^2\right) / \bar{f}_0\right) \qquad (5.3)$$

Where $S_i(t)$ are the cumulative sums of the residuals,

$$S_i(t) = \sum_{s=1}^{t} \hat{\varepsilon}_{it} \qquad (5.4)$$

And $\bar{f}_0$ is the average of the individual estimators of the residual spectrum at frequency zero:

$$\bar{f}_0 = \sum_{i=1}^{N} f_{i0} / N \qquad (5.5)$$

Hadri shows that under mild assumptions,

$$Z = \frac{\sqrt{N}(LM - \xi)}{\zeta} \rightarrow N(0, 1) \qquad (5.6)$$

where $\xi = 1/6$ and $\zeta = 1/45$, if the model only includes constants (η_i is set to 0 for all *i*), and $\xi = 1/15$ and $\zeta = 11/6300$, otherwise. The Hadri panel unit root tests require only the specification of the form of the OLS regressions: whether to include only individual specific constant terms, or whether to include both constant and trend terms.

Here both individual effects and individual linear trends were used.

5.4.2 Panel Cointegration Analysis

To test the cointegration relationship we use Pedroni's method (1999, 2004) which extends the idea of residual based cointegration, proposed by Engle and Granger (1987). Pedroni's formulation allows for the heterogeneity across the cross-sections by permitting individual specific fixed effect, slopes and deterministic time trend for each cross-section. To test the cointegration, we estimate the following bi-variate regression equation:

$$Y_{i,t} = \alpha_i + \delta_i t + b_t + \beta_i X_{i,t} + e_{i,t} \qquad (5.7)$$

where *i* is the index for the *N* cross-sections, *t* is the index for time over the sample period of length *T*. The same equation can be extended for the multi-variate specification. Each firm has its own relationship between variables $Y_{i,t}$ and $X_{i,t}$. The slope coefficient β in cointegrated relationship is permitted to vary across individual member of the panel. The parameter α_i is the member specific fixed effect or intercept and the parameters $\delta_i t$ represent individual specific deterministic time trend. The time specific dummies b_t capture the common time specific effect that would tend to cause the individual firm variables to move together over time. The variable $e_{i,t}$ represents the individual panel specific error term. If the long run cointegration relationship exists between $Y_{i,t}$ and $X_{i,t}$, then the error term $e_{i,t}$ should be stationary. Under the null hypothesis of no cointegration in heterogeneous panels i.e. $e_{i,t}$ is non-stationary, Pedroni (1999, 2004) develops seven different test statistics based on the estimated error term $e_{i,t}$ in equation. These test statistics are divided in two groups. The first group, "within dimensions" contains four test statistics termed as panel - ν, panel - ρ, panel - t non-parametric (PP), and panel - t parametric (ADF). The panel - ν and panel - ρ statistics are similar to the Phillips and Perron, (1988) test. Likewise panel - t non-parametric (PP), and panel - t parametric (ADF) are similar to the single equation Augmented Dickey-fuller (ADF) test. The second group "between dimensions" contains three test statistics termed as group - ρ, group - t non-parametric (PP), and group - t parametric (ADF). These test statistics are comparable to the group mean panel tests of Im *et al.*, (2003). Both panel and group statistics are based on the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) method. These heterogeneous panel and heterogeneous group mean panel test statistics to test panel cointegration are as follows *(Pedroni, (1999, Pages: 660-661, Table: 1)* :

1. Panel ν-Statistic:

$$T^2 N^{3/2} Z_{\hat{\nu},N,T} = T^2 N^{3/2} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1}$$

2. Panel ρ-Statistic:

$$T\sqrt{N} Z_{\hat{\rho}N,T-1} = T\sqrt{N} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right)$$

3. Panel t-Statistic (non-parametric):

$$Z_{tN,T} = \left(\tilde{\sigma}_{N,T}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right)$$

4. Panel t-Statistic (parametric):

$$Z_{tN,T}^{*} = \left(\tilde{s}_{N,T}^{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*}$$

5. Group ρ-Statistic:

$$TN^{-1/2} \tilde{Z}_{\hat{\rho}N,T^{-1}} = TN^{-1/2} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{e}_{i,t-1}^{2} \right)^{-1} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_{i} \right)$$

6. Group t-Statistic (non-parametric):

$$N^{-1/2} \tilde{Z}_{tN,T^{-1}} = N^{-1/2} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{e}_{i,t-1}^{2} \right)^{-1/2} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_{i} \right)$$

7. Group t-Statistic (parametric):

$$N^{-1/2} \tilde{Z}_{tN,T}^{*} = N^{-1/2} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{s}_{i}^{*2} \hat{e}_{i,t-1}^{*2} \right)^{-1/2} \sum_{t=1}^{T} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*}$$

Where

$$\hat{\lambda}_{i} = \frac{1}{T} \sum_{s=1}^{k_i} \left(1 - \frac{s}{k_i + 1} \right) \sum_{t=s+1}^{T} \hat{\mu}_{i,t} \hat{\mu}_{i,t-s} \qquad \hat{s}_{i}^{2} = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{i,t}^{2} \qquad \hat{\sigma}_{i}^{2} = \hat{s}_{i}^{2} + 2\hat{\lambda}_{i}$$

$$\tilde{\sigma}_{NT}^{2} = \frac{1}{T} \sum_{t=1}^{T} \hat{L}_{11i}^{2} \hat{\sigma}_{i}^{2} \qquad \hat{s}_{i}^{*2} = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{i,t}^{*2} \qquad \tilde{s}_{N,T}^{*2} = \frac{1}{N} \sum_{i=1}^{N} \hat{s}_{i}^{*2}$$

$$\hat{L}_{11i}^{2} = \frac{1}{T} \sum_{t=1}^{k_i} \hat{\eta}_{i,t}^{2} + \frac{2}{T} \sum_{t=1}^{T} \left(1 - \frac{s}{k_i + 1} \right) \sum_{i=s+1}^{T} \hat{\eta}_{i,t} \hat{\eta}_{i,t-s}$$

Where the residuals $\hat{\mu}_{i,t}$, $\hat{\mu}_{i,t}^{*}$ and $\hat{\eta}_{i,t}$ are obtained from the following regressions:

$$\hat{e}_{i,t} = \hat{\gamma}_{i} \hat{e}_{i,t-1} + \hat{\mu}_{i,t}$$

$$\hat{e}_{i,t} = \hat{\gamma}_{i} \hat{e}_{i,t-1} + \sum_{k=1}^{K_i} \hat{\gamma}_{i,k} \Delta \hat{e}_{i,t-k} + \hat{\mu}_{i,t}^{*}$$

$$\Delta Y_{i,t} = \sum_{m=1}^{M} \hat{b}_{mi,t} \Delta X_{mi,t} + \hat{\eta}_{i,t}$$

The “within dimension” test statistics are constructed by summing both numerator and denominator terms over the individual separately, whereas in “between dimension” numerator is divided by denominator prior to the summation. Moreover, the autoregressive parameter in “within dimension” statistics is restricted to be the same across all cross-sections. The rejection of null of no cointegration indicates that the variables under consideration are said to be cointegrated for all panel members. However, the autoregressive parameter in “between dimension” statistics is allowed to vary across cross-sections. The estimated statistic will be the average of individual statistics. The rejection of null of no cointegration indicates that the cointegration holds at least for one individual. Therefore, “between dimension” statistics offers an additional source of heterogeneity among the panel members. Pedroni standardized all these statistics to the standard normal distribution, based on the moments of the vector of Brownian motion function. Using simulated moments, Pedroni constructed approximations for the asymptotic distributions, and consequently computed approximate critical values for different values of number of regressors. The asymptotic distributions for each of the seven panels and group mean statistics can be expressed as follows:

$$\kappa = \frac{\kappa_{N,T} - \mu\sqrt{N}}{\sqrt{\nu}} \Rightarrow N(0,1)$$

Pedroni (1999) reports the critical values for μ and ν for different values of number of regressors in cointegration relationship. The reported values are with and without intercepts and deterministic trends. The small sample size and power properties of all seven tests are discussed in Pedroni (1997). He finds that the change in test statistics due to size are minor, the power of the tests are high for all statistics when the time period is long. Panels with shorter size and time period shows more varied evidence. However, in the presence of a conflict in the evidence provided by each of the statistics, Pedroni shows that the Group-ADF statistic and Panel-ADF statistic generally perform best.

While performing the Pedroni's cointegration analysis, the study assumes an intercept and deterministic trend for the variables in the tests.

5.4.3 Panel Fully Modified Ordinary Least Square (FMOLS)

To estimate the long run relationship between the heterogeneous cointegrated panels, Fully Modified Ordinary Least Square (FMOLS) method is used. FMOLS regression was originally introduced by Phillips and Hansen (1990) to provide optimal estimates of cointegrating regressions. The cointegrating links between the non-stationary series can lead to endogeneities in the regressors that cannot be avoided by using vector auto-regressions (VAR'S) as if they were simply reduced forms. In FMOLS setting, non-parametric techniques are exploited to transform the residuals from the cointegration regression and can get rid of these nuisance parameters. Pedroni (1996, 2000, and 2001) extended the idea of FMOLS to panel data and accounted for the serial correlation effects and the endogeneity in the regressors that resulted from the existence of a cointegrating relationship in panel data. It also allowed for the heterogeneity in short run dynamics and the fixed effects. This methodology allows consistent and efficient estimation of cointegrating vector and also addresses the problem of simultaneous bias. The cointegrated regression for estimation is:

$$Y_{i,t} = \alpha_i + \beta X_{i,t} + e_{i,t} \quad (5.8)$$

$$X_{i,t} = X_{i,t-1} + \varepsilon_{i,t} \quad (5.9)$$

Where i is the index for the N cross-sections, t is the index for time over the sample period of length T. The vector error process $\xi_{i,t} = \left(e_{i,t}, \varepsilon_{i,t}\right)'$ is stationary with asymptotic covariance matrix Ω_i. The asymptotic covariance matrix Ω_i is given by $\lim_{T\to 0} E\left[T^{-1}\left(\sum_{t=1}^{T}\xi_{i,t}\right)\left(\sum_{t=1}^{T}\xi_{i,t}\right)\right]$. The estimator β will be consistent when the error process $\xi_{i,t} = \left(e_{i,t}, \varepsilon_{i,t}\right)'$ satisfies the assumption of cointegration of order one between $Y_{i,t}$ and $X_{i,t}$. A semi-parametric correction can be made to the OLS estimator that eliminates the second order bias caused by the fact that the regressors are endogenous.

Pedroni (1999, 2000) estimate the test statistic for both "within dimension" and for "between dimension" estimators. Test statistics constructed from the within-dimension estimators are designed to test the null hypothesis H_0: $\beta_i = \beta_0$ for all i versus the alternate hypothesis H_a: $\beta_i = \beta_a \neq \beta_0$ for all i against where the value β_a is the same for all i. Test statistics constructed from the between-dimension estimators are designed to test the null hypothesis H_0: $\beta_i = \beta_0$ for all i versus the alternate hypothesis H_a: $\beta_i \neq \beta_0$ for all i, where values for β_i are not same under the alternative hypothesis. Clearly, this is an important advantage of "between-dimension" that it does not restrict the value of β to a common value. Another advantage of the "between-dimension" is that the estimator is a point estimate and has a more useful interpretation by providing additional source of heterogeneity in cointegrating vectors. The group mean fully modified t-statistic (between dimension) can be calculated as:

$$\bar{t}_{\beta^*_{NT}} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \hat{L}_{11i}^{-1} \left(\sum_{t=1}^{T} \left(X_{it} - \overline{X}_i \right)^2 \right)^{-1/2} \left(\sum_{t=1}^{T} \left(X_{i,t} - \overline{X}_i \right) Y_{i,t}^* - T\hat{\gamma}_i \right) \Rightarrow N(0,1)$$

Where $Y_{i,t}^* = \left(Y_{i,t} - \overline{Y}_i \right) - \dfrac{\hat{L}_{21i}}{\hat{L}_{22i}} \Delta X_{i,t}$

The test statistic is distributed standard normal and can be interpreted as the mean value for the cointegrating vectors. The "between-dimension" estimate is better in case of small panels as compare to "within-dimension" estimators (Pedroni, 2001).

5.4.4 Panel Long Run Causality

To identify the direction and sign of long run causality in Cointegrated panels we use methodology developed by Canning and Pedroni (2008) based on Granger representation theorem (Engle and Granger, 1987). According to Granger representation theorem, the series that are individually non-stationary but together cointegrated can be represented in the form of a dynamic error correction model. To construct this dynamic error correction model first we calculate the disequilibrium term $\hat{e}_{i,t}$ by using the long run Cointegrated relationship estimated in previous section. This can be calculated using the following equation:

$$\hat{e}_{i,t} = Y_{i,t} - \hat{\alpha}_i - \hat{b}_t - \hat{\beta}_i X_{i,t} \qquad (5.10)$$

This disequilibrium term is further used to construct the dynamic error correction model. This can be represented as follows:

$$\Delta Y_{i,t} = c_{1,i} + \lambda_{1,i} \hat{e}_{i,t-1} + \sum_{j=1}^{k} \varphi_{11,i,t} \Delta X_{i,t-j} + \sum_{j=1}^{k} \varphi_{12,i,t} \Delta Y_{i,t-j} + \varepsilon_{1,i,t} \qquad (5.11)$$

$$\Delta X_{i,t} = c_{2,i} + \lambda_{2,i}\,\hat{e}_{i,t-1} + \sum_{j=1}^{k}\varphi_{21,i,t}\Delta X_{i,t-j} + \sum_{j=1}^{k}\varphi_{22,i,t}\Delta Y_{i,t-j} + \varepsilon_{2,i,t} \qquad (5.12)$$

where *i* is the index for the *N* cross-sections, *t* is the index for time over the sample period of length *T* and *k* is the number of lags selected for the VAR representation. $\lambda_{1,i}$ and $\lambda_{2,i}$ are adjustment coefficients or correction to the disequilibrium term, so that it causes the variable to adjust towards equilibrium and keep the long run relationship intact. At least one of them must be non-zero if a long run relationship between the variables is to hold. Based on the Granger representation theorem for time series models, Canning and Pedroni (2008) developed the similar methodology for panel data and showed that:

1. The coefficient λ_1, on the lagged equilibrium cointegrating relationship in the dynamic error correction equation for ΔY_i is zero if, and only if, innovations to X_i have no long run causal effect on Y_i. Similarly, the statement is true for λ_2.

2. The ratio of the coefficients -λ_2 / λ_1, on the lagged equilibrium cointegrating relationship in the dynamic error correction equation for ΔY_i and ΔX_i, has the same sign as the long run causal effect.

The test of significance (on either tail) for coefficient $\lambda_{1,i}$, for the null hypothesis H_0= $\lambda_{1,i}$ = 0 can be interpreted as $X_{i,t}$ has a long run causal effect on $Y_{i,t}$. Similarly, a test of significance (on either tail) for coefficient $\lambda_{2,i}$, for the null hypothesis H_0= $\lambda_{2,i}$ =0 can be interpreted as $Y_{i,t}$ has a long run causal effect on $X_{i,t}$. The coefficients λ_1 and there tests of significance are associated with individual firm in the panel. However, in practice the reliability of these various point estimates and associated test for any one firm are likely to be poor given the relatively short time sample over which data is observed (Canning and Pedroni, 2008). To test whether on average there exists a long run causal relationship in either direction between Y_t and X_t for the panel as a whole; the group mean panel estimate is computed as the sample average of the individual firm's λ coefficient i.e. $\bar{\lambda} = \frac{1}{N}\sum_{i=1}^{N}\hat{\lambda}_i$.

Similarly, the group means panel test statistic for panel as a whole is computed as the average of individual country test statistic i.e. $\bar{t}_\lambda = \frac{1}{N}\sum_{i=1}^{N} t_{\lambda_i}$. The test statistic $\bar{t}_\lambda$ has a standard normal distribution under the null hypothesis of no long run causal effect. The null hypothesis can be rejected on either tail of the distribution.

Canning and Pedroni (2008) also defined the Lambda-Pearson panel test to compute the accumulated marginal significance associated with these test statistics. The p-values associated with each of the individual firm test statistic are used to compute the Lambda-Pearson panel test statistic. The Lambda-Pearson panel test statistic can be computed as P_λ = - $2\sum_{i=1}^{N}\ln p_{\lambda_i}$, where $\ln p_{\lambda_i}$ is the natural log of p-values associated with individual panel member test statistic. The value P_λ has a chi-square distribution with *2N* degrees of freedom, under the null hypothesis of no long run causal effect. The null hypothesis can be rejected only on the right tail of the distribution. They also suggested that there could be the possibility that in some cases $\bar{t}_\lambda$ fails to reject the null whereas P_λ rejects the null. In those cases also we can still say that there exists a long run causal relationship. In those cases we do not reject that average value for λ_i is zero but we reject that it is pervasively zero in the panel.

Furthermore, they also defined sign ratio - λ_2/λ_1, which can be interpreted as the sign of long run causal effect between the two variables and constructed a panel based test to test the significance of this ratio. Since the ratio follows a Cauchy distribution, this test is based on group median estimator and associated standard errors for the panel. The distribution of each individual ratio is formed from the ratio of dependent non-identical normal distributions. Moreover, the variance of each panel member, for each variable is simulated in order to get the corresponding group median estimate.

5.5 Empirical Results

5.5.1 Descriptive Statistics of Variables

Table 5.1 shows the descriptive statistics of the variables used in the panel analysis in the study from 1990 to 2009. The standard deviation shows small statistical dispersion in data used for panel regression analysis. This also means that the data points are not highly variable.

5.5.2 Results of Unit Root Tests

Table 5.2 gives the results of the Hadri panel unit root test. In this the null hypothesis of stationarity is rejected at 1% level of significance for all the variables in the log levels. But in first difference all variables except the LBR happens to be a stationary process, which is stationary after second differencing. Therefore, it can be concluded that the panel variables follow I (1) process.

5.5.3 Panel Cointegration Results

Table 5.3 depicts the Pedroni residual panel cointegration results. Under the null hypothesis of no cointegration and deterministic intercept and trend assumption, seven test statistics are computed namely the Panel ν - statistic, panel ρ - statistic, panel PP statistic, panel ADF statistic, the group ρ statistic, group PP statistic and group ADF statistic. The first four tests are known as the 'within dimension' panel tests while the last three are known 'between dimension' group tests.

It can be seen from table 5.3 that the null of no cointegration is rejected for first four tests for all panels at various conventional levels. The Group tests show some variations. In case of the two panels' log of Z –score on log of BR and the log of Z –score on log of WPI; all seven tests reject the null of no cointegration at conventional levels.

For the panel log of Z-score on log of GDP, six out of seven tests succeed to reject the null and for the panel log of Z-score on log of manufacturing component of GDP five out of seven tests reject the null.

Moreover, the Panel ADF statistic and Group ADF statistic for all panels reject the null of no cointegration except for log of Z-score on log of manufacturing component of GDP where panel ADF rejects the null but Group ADF does not.

Taken together, there is reasonable evidence from Pedroni's residual cointegration test that Z score and GDP, Z score and bank rate, Z score and WPI are panel cointegrated and have long term relationships. However, panel cointegration between Z score and

Manufacturing component of GDP is not very clear. Even though Panel ADF statistic represents cointegration but Group ADF statistic rejects cointegration. So, the study suggests the presence of long term relationship between Z score and manufacturing component of GDP is not strong enough.

5.5.4 Panel FMOLS Results

Table 5.4 gives the panel FMOLS results. All the coefficients of Log of GDP, log of bank rate, log of WPI and log of manufacturing component of GDP are positive, which shows that as expected these variables are positively related with Z score. However, the t-statistic shows that all variables except the log of manufacturing component of GDP are significant. That means the manufacturing component of GDP has no significant impact on the financial health of corporations or Z score.

5.5.5 Panel Long-run Causality Results

The long-run Granger causality results are reported in table 5.5. Results are reported for each of the four panels and their associated Group Mean and Lambda Pearson test statistics.

First, the panel long-run causality running from Z score to GDP, Z score to Bank rate, Z score to WPI and Z score to Manufacturing component of GDP is considered. Based on the Group mean test statistic, one can not reject the null of “no long run causal effect” for all the panels. In other words for all the panels the Group mean test statistic, accept the null of no Granger causality.

The Lambda Pearson test statistic rejects the null of “no long run causal effect” for the panels except for the panel running from Z score to Manufacturing component of GDP. The null is rejected at 1% level for the panel Z score to Bank rate and at 5% level for Z score to GDP and Z score to WPI.

Next the panel long-run causality running from GDP to Z score, Bank rate to Z score, WPI to Z score and Manufacturing component of GDP to Z score is considered. Based on the Group mean test statistic, one can reject the null of no long run causal effect for all the panels. That is to say for all the panels the Group mean test statistic showed presence of long-run Granger causality running from GDP to Z score, Bank rate to Z score, WPI to Z score and Manufacturing component of GDP to Z score. The null is rejected at 1% level for the panel Bank rate to Z score and at 5% level for GDP to Z score, WPI to Z score and Manufacturing component of GDP to Z score.

The Lambda Pearson test statistic rejects the null of no long run causal effect for all the panels. The null is rejected at 1% level for the panels GDP to Z score, Bank rate to Z score, WPI to Z score and Manufacturing component of GDP to Z score. So, there is presence of long-run Granger causality running from GDP to Z score, Bank rate to Z score, WPI to Z score and Manufacturing component of GDP to Z score.

In choosing between the two tests, the nature of panel is of importance. As noted by Canning and Pedroni (2008) if the panel consists of a heterogeneous set of countries then the Group Mean test statistic, by its construction can be dictated by those countries having high (in absolute values) *t* - statistics. In this case, as the Lambda Pearson test is based on *p* – values, it is a more reliable test.

Thus, taking evidence from the Lambda Pearson test, one can find significant evidence of long-run panel Granger causality running from Z score to GDP, Z score to Bank rate, and Z score to WPI. Similarly, one can find the long-run panel Granger causality running from GDP to Z score, Bank rate to Z score, WPI to Z score and Manufacturing component of GDP to Z score.

So, there is two way long run Granger causality between Z score and GDP, Z score and Bank rate and Z score and WPI whereas there is existence of one way Granger causality between manufacturing component of GDP to Z score.

Therefore, as expected the macroeconomic variables have significant impact on the financial health of corporations via Z score and vice-versa. But the manufacturing component of GDP has impact on the financial health of manufacturing corporations whereas their financial health indicator is not dependent on composition of manufacturers in GDP.

The sign effect based on the ratio of λ coefficients, which proffer the sign of the long-run causality, reveals a positive sign for all the panels except the panel running from Z score to WPI. For this panel, evidence suggests that improved corporate financial health is accompanied by fall in Inflation rates or inflation hinders the financial health of the corporations.

5.6 Conclusion

In this chapter an attempt is made to examine the influence of macroeconomic variables on the corporate financial health in terms of Z score in panel framework for a sample of 73 firms during 1990 to 2009. The macroeconomic variables taken were the growth rate of GDP, the bank rate, inflation rates and the growth rate of manufacturing component of GDP. The long-run relationships are identified using panel unit root test, cointegration analysis, Panel FMOLS and panel long-run causality tests.

The findings of the study reveal the existence of a two-way causal relationship between the corporate financial health and GDP, corporate financial health and Bank rate and corporate financial health and WPI. There is a however, a one-way relationship between Manufacturing component of GDP to Z score. The sign effect reveals a positive sign for all the panels except the panel running from Z score to WPI. For this panel, evidence suggests that improved financial health of corporations is accompanied by decline in Inflation rates or in other words, inflation hinders the financial health of the corporations.

The implications of the study are in terms of growth of the Indian economy in terms of GDP and increased bank rate, that could lead to successful manufacturing units and better firms in return would lead to increased output and add to the growth of the economy. So, it is a vicious circle and hence policy makers should be cautious of the link between macroeconomic variables and corporate financial health while targeting such variables mainly inflation rates. Another implication is that financial fragility of the corporate sector in the worsening macroeconomic environment can play a role in triggering the financial and monetary instability and prolonging recessions. Therefore, the role of financial distress in the macroeconomic fluctuations and the transmission of recessions deserve further attention.

The limitations of the study are in terms of number of macro variables taken as more of such variables can be taken. An interesting area for future research could be to employ more macro economic variables and to interlink both macro and micro variables and check their impact on corporate financial health.

TABLE 5.1

Descriptive Statistics of the Panel Variables

Variables	**Observations**	**Mean**	**Std. Dev.**	**Maximum**	**Minimum**
LZ-score	1460	0.362905	0.123751	0.578942	0.133348
LGDP	1460	2.587684	0.241412	2.838030	2.047947
LBR	1460	2.110111	0.296095	2.484907	1.791759
LWPI	1460	1.844102	0.413289	2.617396	1.193922
LMNFC	1460	2.504805	0.483630	3.220224	1.386933

TABLE 5.2

Hadri Panel Unit Root Test

Null Hypothesis: Stationarity (Absence of Unit root)

Exogenous variables: Individual effects, individual linear trends

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 1460

For Levels				
Panel	**Period**	**Number of firms**	**Hadri Z-stat**	**Prob.**
LZ-score	1990-2009	73	8.79761	0.0000*
LGDP	1990-2009	73	11.7225	0.0000*
LBR	1990-2009	73	8.17191	0.0000*
LWPI	1990-2009	73	17.9550	0.0000*
LMNFC	1990-2009	73	8.33736	0.0000*
For First Differences				
Panel	**Period**	**Number of firms**	**Hadri Z-stat**	**Prob.**
LZ-score	1990-2009	73	-2.09774	0.2593
LGDP	1990-2009	73	-2.96840	0.9985
LBR LBR (2nd diff.)	1990-2009	73	2.82923 (-3.20236)	0.0008* (0.9993)
LWPI	1990-2009	73	-0.82133	0.7943
LMNFC	1990-2009	73	-3.39290	0.9993

Note: Probabilities are computed assuming asymptotic normality.

* Significance at 1% level.

TABLE 5.3

Pedroni Residual Cointegration Test Results

Null Hypothesis: No cointegration

Trend assumption: Deterministic intercept and trend

Period: 1990 – 2009

Number of Firms: 73

Newey-West automatic bandwidth selection and Bartlett kernel

Panel	**Panel ν-stat**	**Panel ρ-stat**	**Panel PP-stat**	**Panel ADF- stat**	**Group ρ-stat**	**Group PP-stat**	**Group ADF-stat**
LZ-score on LGDP	5.892741 (0.0000) *	-1.859281 (0.0315)**	-15.34349 (0.0000) *	-7.867346 (0.0000) *	-0.330528 (0.3705)	-15.69506 (0.0000) *	-7.578810 (0.0000) *
LZ-score on LBR	8.563088 (0.0000) *	-3.753476 (0.0001) *	-8.297447 (0.0000) *	-9.289390 (0.0000) *	-1.171721 (0.1207)***	-7.436708 (0.0000) *	-8.513582 (0.0000) *
LZ-score on LWPI	6.279760 (0.0000) *	-5.583058 (0.0000) *	-9.437983 (0.0000) *	-4.006397 (0.0000) *	-2.612608 (0.0045) *	-8.549010 (0.0000) *	-2.652370 (0.0040) *
LZ-score on LMNFC	5.056591 (0.0000) *	-3.234103 (0.0006) *	-6.168748 (0.0000) *	-2.331741 (0.0099) *	-0.714121 (0.2376)	-5.125749 (0.0000) *	-0.960216 (0.1685)

Note: Pedroni Panel ν, panel ρ, panel PP and panel ADF statistics alternative hypothesis: common AR coeffs. (within- dimension) and Pedroni Group ρ, group PP and group ADF statistics alternative hypothesis: individual AR coeffs. (between-dimension). **‘*’** Significance at 1% level, ‘**’ Significance at 5% level and ‘***’ Significance at 10% level.

TABLE 5.4

Panel Group FMOLS Results

Number of Cross sections (Firms): 73

Time periods: 20

Number of Regressors: 1 (LZ-score)

Variables	**Coefficients**	**t-statistic**
LGDP	0.34	5.65*
LBR	0.45	23.48*
LWPI	0.32	11.05*
LMNFC	0.08	-0.73

Note: * Significant

TABLE 5.5

Long-Run Panel Causality Test Results

LZ-score on LGDP							
$\lambda_2 : LZ_{it} \rightarrow LGDP_{it}$			$\lambda_1 : LGDP_{it} \rightarrow LZ_{it}$			$-\lambda_2/\lambda_1$	
	Estimate	Test	p-value	Estimate	Test	p-value	Median
Group mean	0.49	0.47	(0.68)	-0.70	-1.65	(0.05)**	0.37
Lambda Pearson		175.13	(0.05)**		551.60	(0.00)*	(0.23)
LZ-score on LBR							
	$\lambda_2 : LZ_{it} \rightarrow LBR_{it}$			$\lambda_1 : LBR_{it} \rightarrow LZ_{it}$			$-\lambda_2/\lambda_1$
	Estimate	Test	p-value	Estimate	Test	p-value	Median
Group mean	0.46	1.07	(0.86)	-1.42	-2.45	(0.01) *	0.42
Lambda Pearson		325.15	(0.00) *		770.37	(0.00) *	(0.08)
LZ-score on LWPI							
$\lambda_2 : LZ_{it} \rightarrow LWPI_{it}$			$\lambda_1 : LWPI_{it} \rightarrow LZ_{it}$				$-\lambda_2/\lambda_1$
	Estimate	Test	p-value	Estimate	Test	p-value	Median
Group mean	-0.40	-0.33	(0.37)	-0.87	-1.74	(0.04)**	-0.46

Lambda Pearson		178.64	(0.03)**		466.29	(0.00) *	(0.36)
LZ-score on LMNFC							
$-\lambda_2/\lambda_1$	$\lambda_2 : LZ_{it} \rightarrow LMNFC_{it}$			$\lambda_1 : LMNFC_{it} \rightarrow LZ_{it}$			
	Estimate	Test	p-value	Estimate	Test	p-value	Median
Group mean	-0.31	-0.30	(0.38)	-0.69	-1.69	(0.05)**	0.08
Lambda Pearson		147.83	(0.44)		572.18	(0.00) *	(0.47)

Note: * Significance at 1% level.

** Significance at 5% level.

Chapter 6

Summary and Implications

6.1 Introduction

Analysis and management of credit risk has assumed increased importance in recent years. New regulations such as BASEL II and III force banks and other financial institutions to make credible efforts to chart and manage the risks associated with their client portfolio. In addition, harder competition in the financial markets has also increased the need to monitor the risk/reward relationship for various customers.

Corporate defaults are one of the main sources of loss for a bank or any financial institution. The definition of corporate default risk is the counterpart failure to comply with their obligations to service debt. This risk is critical since the default of a small number of important customers can generate large losses, potentially leading to insolvency. There are various default events: delay or omission in payment obligations, restructuring of debt obligations due to a major deterioration of the credit standing of the borrower and, finally, formal bankruptcy and liquidation. The last state implies that non-payment will be permanent and will trigger a significant loss in most cases. For a bank or financial institution trying to control these risks, bankruptcy assessment models are important due to the various reasons. For example – these models give the expected probability of default for the sample under consideration and give input to the risk side of various types of business. Moreover, the BASEL II and III directive give banks an incentive (through capital requirement reduction) to develop proper bankruptcy and credit risk models. As a consequence, one can expect more banks (also smaller ones) and financial institutions to put more effort in developing and enhancing bankruptcy prediction/ assessment models.

Indeed, cases of corporate bankruptcy in India are extremely rare partly owing to the cumbersome legal framework. Bankruptcy procedures under the Sick Industrial Companies Act (1985), which governs financial reorganisation of distressed companies, continue to be time consuming and burdensome, owing to indefinite stays on creditors' claim. Liquidation under the Companies Act (1956) is even more complicated and long court delays are common. Since the early 2000s, out-of-court corporate restructuring mechanisms such as the Corporate Debt Restructuring forum and the Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest (SARFAESI) Act, 2002 have facilitated the restructuring of distressed assets. Unfortunately, data on corporate debt restructuring undertaken by banks are not publicly available.

Hence, the lack of data on actual corporate bankruptcies and debt restructuring in India prevents one from relating corporate vulnerability indicators to actual firm distress. That is why this study is meant to look into the corporate financial health of the manufacturing companies under BSE 200 and create a path for an early warning system. Corporate financial health assessment intends to know a priori about the well being of any firm. It analyses how a firm would react to a crisis or how far is it expected to be affected by such a crisis. The earlier literature has shown Z score models to be a prolific device in the credit risk appraisal of corporate. So, in light of this model, this study tried to figure out the credit risk associated with the Indian manufacturing firms.

To be specific, this study analyses the individual credit worthiness of the BSE 200 Manufacturing companies through a Firm-intrinsic credit scoring model. This study mainly relies on econometric techniques for the analysis. The financial health of manufacturing firms is examined by using 'Multiple Discriminant Analysis (MDA) technique' which is widely used in the literature for corporate credit risk assessment [Altman (1968), Altman *et. al.* (1995), Bandyopadhyay (2006) and Altman *et al.* (2007)]. Multiple discriminant analysis (MDA) is a statistical technique used to classify an observation into one of the several *a priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, e.g., male or female, bankrupt or non-bankrupt. The first step is to set up explicit group classifications. The number of original groups can be two or more. After the groups gets established, data are collected for the objects in the groups; MDA then attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. If a particular object, for instance a corporation, has characteristics (financial ratios) which can be quantified for all the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratio, a basis for classification into one of the mutually exclusive groupings exists.

The literature on studies conducted especially in case of the developed economies had an advantage over India in terms of selection of the failed sample for applying the MDA technique. In case of India, there is lack of uniformity in the recognition of distress firms. The second most important limiting factor is the lack of information on the default companies. Moreover, bankruptcy data is not available for listed companies in India, though for unlisted companies data can be obtained from BIFR and so it becomes all the more imperative to look into the listed firms and device some credit risk measure for predicting the financial health of these corporations. So, the present study becomes exploratory in nature wherein an attempt is made to develop a model which is in line with Altman's Z model to predict the corporate financial health of Indian manufacturing firms.

The criterion designed is the average net worth for the period 1990 to 2009, wherein a firm is taken as healthy if its average net worth is greater than 1,250 rupees crore; a company with average net worth value greater than 450 rupees crore but less than 1,250 rupees crore is taken as moderately healthy and a company with average net worth value less than 450 rupees crore is taken as not-so-healthy. Out of the total sample of 73 firms, the development sample consists of 63 firms of which the number of observations for the healthy, moderately healthy and not-so-healthy categories is 23, 18 and 22. For the hold-out sample 10 firms are randomly selected from the 73 firms. Further, four financial ratios were selected that covered the aspects of profitability, liquidity, capitalisation and financial leverage and Z scores were obtained accordingly.

As mentioned, the manufacturing sector plays a pivotal role in India and hence its efficiency needs to be improved so that it can add to the growing requirements of the economy for years to come. Therefore, the next objective is to analyse the efficiency of these firms and also to check the contribution of 'efficiency' as a parameter in the corporate financial health assessment. The Data Envelopment Analysis (DEA) and Logistic regression analysis are employed to analyse this. Data Envelopment Analysis (DEA) is a relatively new "data oriented" mathematical programming approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. It is extensively used in literature [Charnes *et. al.* (1978), Saranga and Phani (2004) and Psillaki *et al.* (2010)]. Here a two step methodology is followed to evaluate corporate financial health. First, a set of observed inputs and output is used to derive efficiency scores for the sample of manufacturing firms. The BCC model is used for calculating the VRS technical efficiency of the sample of firms. In the second stage, the DEA efficiency scores obtained along with the financial variables are used as predictor variables in the logit model to determine the probability of firms to have good or bad ratings and hence to assess the importance of efficiency in evaluation of corporate financial health or credit risk over and above of that explained by financial factors.

The interlinked Indian economy facilitates risk mitigation through transference of risk between economic agents of various risk appetites. The manufacturing sector is not debarred from this as it has every chance of being affected and affecting the macro economic factors. Therefore, it is necessary to gauge the long run relationship between the corporate financial health parameter via Z score and the macro economic factors in the Indian economy. So the last objective is to analyse the link between the macroeconomic factors and the corporate financial health indicator in the form of Z scores. Here the macroeconomic variables are the bank rate, growth rate of GDP, inflation rates and the growth rate of manufacturing component of GDP. The long run relationships are identified using panel unit root test, panel cointegration analysis and panel long run causality.

Given the time series element present in the panel data, in the first step the study determines the order of integration of each of the data series. The concept of cointegration is associated with the long-run equilibrium relationship between two or more variables, so in the second step the study test for the existence of long run relationship between the variables using cointegration test developed by Pedroni (1999). If the series are cointegrated, the long run relationship between the variables is estimated by employing the Fully Modified

Ordinary Least Square Method (FMOLS) developed by Pedroni (2000). This is followed by investigating long run dynamic linkages between the variables, using panel long run causality test developed by Canning & Pedroni (2008) based on Engle & Granger (1987) specification.

The study is based on the Indian manufacturing companies under BSE 200 based on the NIC two digit 2004 classification. All the data is extracted from the CMIE prowess database and the Capitaline plus database. The list of the manufacturing companies is obtained from the official website of Bombay Stock Exchange. The data on macroeconomic variables are collected from 'Handbook of Statistics on Indian Economy' from Reserve bank of India (www.rbi.org.in).

The total number of manufacturing units identified for the study is 73 firms listed under BSE 200 for the first and third objectives and using data ranging from March 1990 to March 2009. For the second objective the number of firms were 85 and from 2005-2009.

6.2 Main Findings

The main findings of the study are as follows:

(i) A model for predicting corporate financial health for Indian manufacturing was developed using MDA technique. The model was tested for its predictive accuracy using a hold-out sample validation test. The model shows good performance with 48.6% prediction accuracy being observed in the development sample and 63.6% in case of the hold-out sample. The variables contributing more to the discriminant functions are working capital to total assets ratio, retained profits to total assets ratio, PBIT to total assets ratio and debt-equity ratio. With these variables the Z score was developed for the Indian manufacturing firms and the cut-off for division into healthy, moderately healthy and not so healthy was done accordingly.

(ii) This model is in line with the EMS model of Altman, which was not a predictor of emerging markets company bankruptcy due to the very fact that there were no defaults on Mexican Eurobonds and the economic and political environment in Mexico were different from U.S. which made bankruptcy prediction more difficult. Similarly this model not only resembles EMS model in terms of variables but also helps to assess the relative credit risk of Indian manufacturing firms which comes under emerging markets, however, this model is also not a bankruptcy prediction model rather a corporate financial health assessment model.

(iii) Next with the help of Data Envelopment Analysis (DEA) this study encompasses the technical efficiency of the sample of 85 manufacturing firms using capital employed and labour (in terms of salaries, wages and bonus) as two inputs and Net sales as the single output during 2005-2009. The range of average VRS TE score varies from 0.2 to 0.8 and in order to become efficient, these firms need to increase their output with a given set of inputs. Further, as manufacturing sector is very central to the Indian economy, it is imperative that efforts be taken to increase the efficiency of the less efficient firms.

(iv) The second stage of the empirical analysis involving a Logit estimation identifies the significance of a non-financial performance parameter like efficiency to be a useful determinant of rating and thereby the corporate financial health.

(v) The long-run panel causality analysis reveals the existence of a two-way causal relationship between the corporate financial health and GDP, corporate financial health and Bank rate and corporate financial health and WPI. There is a however, a one-way relationship between Manufacturing component of GDP to Z score. The sign effect reveals a positive sign for all the panels except the panel running from Z score to WPI. For this panel, evidence suggests that improved financial health of corporations is accompanied by decline in Inflation rates or in other words, inflation hinders the financial health of the corporations.

It may be recalled that this study is based on three major hypotheses namely; the introduction of a Firm-intrinsic credit scoring model does not help to understand the credit worthiness of the Indian manufacturing companies; the technical efficiency is not an important indicator of financial health of firms and the macro economic factors have no impact on credit risk of firms. The Z score model developed would come under the first hypothesis, the VRS technical efficiency under the second and long-run panel causality would come under the third objective. The overall results of this study thoroughly reject the hypotheses by establishing empirically the Z score model for the Indian manufacturing units, by corroborating the technical efficiency as a significant indicator for distress studies and by generating the link between macro economic variables and Z score.

6.3 Implications of the Study

The following are the implications of this study:

(i) The implications of this study can be viewed in terms of developing early warning systems by using the significant variables by the policy makers for detecting failures at an early stage and mitigating the risks thereafter. The investors and banks/financial institutions can assess the investment and loan prospects respectively as well. So, this study is important from lender's point of view.

(ii) The prospective use of a non-financial indicator in the credit risk evaluation process is illustrated in the second objective. So, it can be useful for the banks in the overall credit risk assessment. The Credit Rating Agencies (CRAs) can also make use of technical efficiency in their rating methodologies and check for robustness of the ratings.

(iii) Further, more firms being in the lowest VRS TE range during 2007 crisis period shows that the efficiency of the firms is dependent on the global economy. Therefore, the task ahead of policy makers and government is to create a healthy environment with stable internal efficiencies.

(iv) The implications of the study are in terms of growth of the Indian economy in terms of GDP and increased bank rate that could lead to successful manufacturing units and better firms again would lead to increased output and growth of the economy. So, it is a vicious circle and hence policy makers should be cautious of the link between macroeconomic variables and corporate financial health while targeting such variables mainly inflation rates.

(v) Another implication is that financial fragility of the corporate sector in the worsening macroeconomic environment can play a role in triggering the financial and monetary instability and prolonging recessions. Therefore the role of financial distress in the macroeconomic fluctuations and the transmission of recessions deserve further attention.

6.4 Suggestions for Future Research

This study primarily focuses on manufacturing sector. Therefore, it is could be interesting to concentrate on various other sectors and check for their credit risk appraisal. Another area is regarding the criterion taken for dividing the firms. As it is difficult to take two or three criteria together, the robustness check can be done by substituting net worth by sales or turn over etc. Moreover, other methodologies should be used in predicting corporate financial distress such as neural networks and other advanced methods. So, also an interesting avenue of exploration for future research could be to test for various other combinations of input and output used in Data Envelopment Analysis and altering the macro variables used in panel long-run causality. Similarly, future researchers by using NSE data may shed some more interesting results.

Appendix

Discriminant Analysis. Discriminant analysis (also known as discriminant function analysis) is a powerful descriptive and classificatory technique developed by R. A. Fisher in 1936. It is a statistical technique which allows the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously.

The data requirements for Discriminant analysis are as follows:

(a) The data set should consist of two or more groups having at least ordinal scores on two or more discriminator variables.

(b) The discriminator variables should measure dimensions that the investigator views as important to understanding the differences that exist among groups. Importance can be determined on the basis of theory, past research, another compelling rationale.

(c) The discriminator variables should not be interconnected with each other.

(d) The number of variables should not exceed the number of groups.

Multiple Discriminant Analysis. Multiple discriminant analysis (MDA) is a statistical technique used to classify an observation into one of the several *a priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, e.g., male or female, bankrupt or non-bankrupt. The first step is to set up explicit group classifications. The number of original groups can be two or more. After the groups gets established, data are collected for the objects in the groups; MDA then attempts to derive a linear combination of these characteristics which "best" discriminates between the groups. If a particular object, for instance a corporation, has characteristics (financial ratios) which can be quantified for all the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratio, a basis for classification into one of the mutually exclusive groupings exists.

There are some assumptions involved in this technique, which are as follows:-

(a) Independence of observations, (b) multivariate normality i.e. the observations based on the discriminator variables are normally distributed and (c) homogeneity of covariance matrices i.e. the population covariance matrices based on the discriminator variables are equal.

Altman's Z score. E.I. Altman in 1968 used the Multiple Discriminant Analysis (MDA) technique along with financial ratios to predict corporate bankruptcy. He took 33 failed and 33 non-failed firms. The failed group were the manufacturers who filed a bankruptcy petition under chapter X of the National Bankruptcy Act during 1946-1965. Group 2 consisted of a paired sample of manufacturing firms chosen on a stratified random basis. The variables used were classified into five standard ratio categories, including liquidity, profitability, leverage, solvency and activity ratios. The discriminant function yielded a score called Z score and on the basis of this a cut-off was found for classifying firms as failed, non-failed or under zone of ignorance. Based on the empirical results it was suggested that the bankruptcy prediction model is an accurate forecaster of failure up to two years prior to bankruptcy and that the accuracy diminishes substantially as the lead time increases. The Z score model has retained its reported high accuracy and is still robust despite its development over the years.

Early Warning Systems. In simple terms, an early warning system (EWS) may be described as an organised procedure (often statistical) for identifying the financial weakness early in the process of deterioration, to warn or signal the management, shareholder and public at large. A well developed EWS can be very useful for an organisation. However, in a dynamic world with rapidly changing markets, a EWS should take into account new data and events.

Eigen Values. Eigen values indicate the ratio of between-groups variability to within-groups variability for a function. The larger the eigen value, the better at accounting for the group differences are the discriminator variables loading on the function.

Relative Percent. The relative percent statistic is of the practical rather than the statistical significance of the functions for group discrimination. The relative percent statistic, also known as the percent of variance accounted for and the percent of variance explained, is obtained by dividing each eigen value by the sum of the eigen values and is a direct index of the relative importance of each function in accounting for between-group differences. The relative percent shows the proportion of the total amount of between-group variance that is attributable to a particular function.

Canonical Correlation. The canonical correlation coefficient is a measure of association which summarizes the degree of relatedness between the groups and the discriminant function. A value of zero denotes no relationship at all, while large numbers represent increasing degrees of association with 1 being the maximum.

Box's M. Box's M is a test for the equality of the group covariance matrices. For sufficiently large samples, a non significant p value means there is insufficient evidence that the matrices differ. The test is sensitive to departures from multivariate normality.

Wilks' Lambda. Wilks' lambda is a test statistic used in multivariate analysis of variance (MANOVA) to test whether there are differences between the means of identified groups of subjects on a combination of dependent variables. It is the ratio of within-group variability to total variability on the discriminator variables. Values close to 1 indicate that almost all of the variability in the discriminator variables is due to within-group differences (differences between cases in each group); values close to 0 indicate that almost all of the variability in the discriminator variables is due to group differences. In other words, values of lambda which are near 0 denote high discrimination and values near 1 denote less discrimination. When lambda equals 1, the group centroids are identical (no group differences). A chi-square test based on lambda indicates whether the variability that is systematically related to group differences is statistically significant.

Standardised Canonical Discriminant Function Coefficients. These are used to determine the comparative relations of discriminator variables to the functions. The larger the magnitude of these coefficients, the greater is that variable's contribution (ignoring the sign).

Structure Matrix. A structure coefficient tells how closely a variable and a function are related. The structure coefficients tell us something quite different from what is communicated by the standardised coefficients. The standardised coefficients take into consideration the simultaneous contribution of all the other variables whereas the structure coefficients are simple bivariate correlations, so they are not affected by relationships with the other variables.

Group Centroids. The group centroids represent the mean discriminant score of the members of a group on a given discriminant function. They reveal how much and in what ways the groups are differentiated on each function. The absolute magnitude indicates the degree to which a group is differentiated on a function and the sign indicates the direction of the differentiation.

Hit Ratio and Expected Hit Ratio. The percentage of cases on the diagonal is the percentage of correct classifications, and this percentage is called the hit ratio. The hit ratio must be compared not to zero but to the percent that would have been correctly classified by chance alone. If group sizes are known a priori, the best strategy by chance is to pick the largest group for all cases, so the expected percent or the expected hit ratio is then the largest group size divided by N.

Data Envelopment Analysis and CCR Model. Data Envelopment Analysis (DEA) is a mathematical programming technique which is used to evaluate the efficiency parameter of corporate performance. It was first introduced by A. Charnes, W.W.Cooper and E.Rhodes in 1978. They described DEA as a ‘mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations – such as the production functions and/or efficient production possibility surfaces – that are cornerstones of modern economics’. The resulting CCR model, named after the three authors, allowed for the calculation of the relative technical efficiency of similar Decision Making Units (DMU) in the analysis on constant returns to scale basis. This is achieved by constructing the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights for both the inputs and outputs are selected so that the relative efficiencies of the DMUs are maximised with the constraint that no DMU can have a relative efficiency score greater than one.

BCC Model. One of the most significant developments since the CCR model was the introduction of the BCC model by R.D.Banker, A. Charnes, and W.W.Cooper in 1984. The BCC model relaxes the convexity constraint imposed in the CCR model which allows for the efficiency measurement of DMUs on a variable returns to scale basis.

Technical Efficiency. Technical efficiency refers to the ability of the production unit to produce as much output as possible for a given set of inputs, or conversely to use as little input as possible for a given output requirement.

Odds Ratio. The odds ratio for a predictor is defined as the relative amount by which the odds of the outcome increase (odds ratio >1) or decrease (odds ratio <1) when the value of the predictor variable is increased by 1 unit.

LR Statistic and Probability (LR Stat). The LR Statistic tests the joint null hypothesis that all slope coefficients except the constant are zero is used to test the overall significance of the model. The Probability (LR Stat) is the *p*-value of the LR test statistic. Under the null hypothesis, the LR test statistic is asymptotically distributed as a chi-square variable, with degrees of freedom equal to the number of restrictions under test.

McFadden R-squared. The McFadden R-squared is the likelihood ratio index. This is an analog to the R^2 reported in linear regression models. It has the property that it always lies between zero and one.

List of Sample Companies taken in the Study

Sl. No.	Company Name
1	A B B Ltd.
2	A C C Ltd.
3	Aditya Birla Nuvo Ltd.
4	Alstom Projects India Ltd.
5	Ambuja Cements Ltd.
6	Amtek Auto Ltd.
7	Areva T & D India Ltd.
8	Ashok Leyland Ltd.
9	Asian Paints Ltd.
10	Bajaj Hindusthan Ltd.
11	Balrampur Chini Mills Ltd.
12	B E M L Ltd.
13	Bharat Electronics Ltd.
14	Bharat Forge Ltd.
15	Bharat Heavy Electricals Ltd.
16	Bharat Petroleum Corpn. Ltd.
17	Bhushan Steel Ltd.
18	Bombay Dyeing & Mfg. Co. Ltd.
19	Bosch Ltd.
20	Castrol India ltd.
21	Century Textiles & Inds. Ltd.
22	Chambal Fertilisers & Chemicals Ltd.

23	Cipla Ltd.
24	Colgate-Palmolive (India) Ltd.
25	Crompton Greaves Ltd.
26	Cummins India Ltd.
27	Dabur India Ltd.
28	Dr. Reddy'S Laboratories Ltd.
29	Exide Industries Ltd.
30	GlaxoSmithKline Pharmaceuticals Ltd.
31	Glenmark Pharmaceuticals Ltd.
32	Godrej Industries Ltd.
33	Grasim Industries Ltd.
34	G T L Ltd.
35	Gujarat Mineral Devp. Corpn. Ltd.
36	Gujarat N R E Coke Ltd.
37	Hero Honda Motors Ltd.
38	Hindalco Industries Ltd.
39	Hindustan Petroleum Corpn. Ltd.
40	Hindustan Unilever Ltd.
41	Hindustan Zinc Ltd.
42	India Cements Ltd.
43	Indian Oil Corpn. Ltd.
44	Ispat Industries Ltd.
45	I T C Ltd.
46	Jai Corp Ltd.

47	Jain Irrigation Systems Ltd.
48	Jindal Saw Ltd.
49	Jindal Steel & Power Ltd.
50	J S W Steel Ltd.
51	Jubilant Organosys Ltd.
52	Lakshmi Machine Works Ltd.
53	Larsen & Toubro Ltd.
54	Lupin Ltd.
55	Madras Cements Ltd.
56	Mahindra & Mahindra Ltd.
57	Maruti Suzuki India Ltd.
58	National Aluminium Co. Ltd.
59	Nestle India Ltd.
60	N M D C Ltd.
61	Pantaloon Retail (India) Ltd.
62	Piramal Healthcare Ltd.
63	Praj Industries Ltd.
64	Ranbaxy Laboratories Ltd.
65	Reliance Industries Ltd.
66	Sesa Goa Ltd.
67	Shree Renuka Sugars Ltd.
68	Siemens Ltd.
69	Sintex Industries Ltd.
70	Steel Authority of India Ltd.

71	Sterling Biotech Ltd.
72	Sterlite Industries (India) Ltd.
73	Sun Pharmaceutical Inds. Ltd.
74	Suzlon Energy Ltd.
75	Tata Chemicals Ltd.
76	Tata Motors Ltd.
77	Tata Steel Ltd.
78	Tata Tea Ltd.
79	Thermax Ltd.
80	Titan Industries Ltd.
81	United Phosphorus Ltd.
82	United Spirits Ltd.
83	Videocon Industries Ltd.
84	Voltas Ltd.
85	Welspun-Gujarat Stahl Rohren Ltd.

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