# AN EXPLORATORY ANALYSIS OF FINANCIAL DISTRESS AND DEFAULT – A STUDY OF SELECT INDIAN COMPANIES

Thesis

Submitted in partial fulfilment of the requirements for the degree of

**DOCTOR OF PHILOSOPHY**

by

**SHRIDEV**

SCHOOL OF MANAGEMENT

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA,

SURATHKAL, MANGALORE -575025

DECEMBER, 2018

# DECLARATION

I hereby declare that the Research Thesis entitled "**AN EXPLORATORY ANALYSIS OF FINANCIAL DISTRESS AND DEFAULT –A STUDY OF SELECT INDIAN COMPANIES",** which is being submitted to the National Institute of Technology Karnataka, Surathkal in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy in **Management** is a bonafide report of the research work carried out by me. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

**Shridev**
HM14F04
School of Management

Place: NITK, Surathkal
Date:

# C E R T I F I C A T E

This is to certify that the Research Thesis entitled '**AN EXPLORATORY ANALYSIS OF FINANCIAL DISTRESS AND DEFAULT – A STUDY OF SELECT INDIAN COMPANIES**', submitted by **Mr. Shridev** (Register Number: 145083HM14F04) as the record of the research work carried out by him, is accepted as the Research Thesis submission in partial fulfilment of the requirements for the award of degree of Doctor of Philosophy.

Dr. Suprabha K R
Research Guide

Dr. S. Pavan Kumar
Chairman - DRPC

## ACKNOWLEDGEMENT

This thesis is the end of my journey in obtaining my Ph.D. I have not travelled in a vacuum in this journey. This thesis has been kept on track and been seen through to completion with the support and encouragement of numerous people, especially my guide, well-wishers, my friends, colleagues and family members. At the end of my thesis, I would like to thank all those people who made this thesis possible and an unforgettable experience for me.

At this moment of accomplishment, first of all I pay homage to my guide, Dr. Suprabha K R. This work would not have been possible without her guidance, support and encouragement. Under her guidance I successfully overcame many difficulties and learned a lot. Her unflinching courage and conviction will always inspire me, and I hope to continue to work with her noble thoughts. I can only say a proper thanks to her through my future work.

I thank the encouragement and support of Dr. S. Pavan Kumar, HOD, School of Management, NITK in completing this research.

I gratefully acknowledge Prof. Kiran K. B., Professor, School of Management for his continuous support, encouragement and personal attention which had provided well and smooth basis for my Ph.D. tenure.

My heartily thanks to Dr. Krishna Prasad for his valuable suggestions and continuous help during the study.

I thank my parents K.Umesh Bhat, B Ahalya Bai, my brother Shrihari Devji and my wife D. Divya and all family members for all their support they have rendered me throughout the completion of the work.

My sincere gratitude is towards Savin Kumar H. N, Natesh Pai, Ananth Shenoy, Rajesh Kalli, Madhu M and awesome guys from the banking industry. The opinion and facts provided by them were of great help in the completion of the thesis.

The Librarian and staff of Indian Institute of Management, Kozhikode gave access to books, journals and reports useful to us. I am indebted to them.

My heartfelt thanks are also due to the South Indian Bank and National Institute of Technology Karnataka, Surathkal for facilitating me in all respects to complete the thesis.

Shridev

# ABSTRACT

The issue of non-performing assets is one of the biggest issues faced by the Indian banking industry in the recent past. The default is due to the financial distress which is built over a period of time. The model to understand and the financial distress would be helpful to solve this issue. This study examines whether the financial default can be predicted using the financial and non-financial factors using the sample Indian companies. The four main categories of financial ratios are profitability, liquidity, activity and leverage ratios. The non-financial variables considered are company age, proportion of independent directors to the total, promoter shareholding, duality in leadership, board size, institutional and non-institutional variables. Multiple regression was applied to study the impact of financial ratios on financial distress. Logistic regression analysis was applied to study the impact of non-financial factors on financial distress.

The investors or potential investors can benefit from these findings on financial distress prediction because these findings would enable them to better assess the probability of the companies experiencing financial distress in the near future. One financial distress model which included financial factors and another financial distress model which included non-financial factors were constructed in the method section. Based on these two models, the present study developed a financial distress prediction model, which used not only financial factors but also non-financial factors. Further, the event study methodology was adopted to the stock market announcement on financial distress.

The investors or potential investors and lenders can benefit from these findings on financial distress prediction because these findings would enable them to better assess the probability of the companies going to experience financial distress in the near future.

***Keywords: Financial factors, Corporate governance, Altman Z Score, Logistic Regression***

# CONTENTS

# LIST OF TABLES

# LIST OF CHARTS

# ABBREVIATIONS

| | |
|---|---|
| AAR | Average Abnormal Return |
| BIFR | Board for Industrial and Financial Reconstruction |
| BLRC | Bankruptcy Law Reforms Committee |
| BS | Board Size |
| CAAR | Cumulative Average Abnormal Return |
| CEOD | Duality in Chief Executive Officer |
| CDR | Corporate Debt Restructuring |
| CUR | Current Ratio |
| CR | Cash Ratio |
| DRT | Debt Recovery Tribunals |
| EBIT | Earnings Before Interest and Tax |
| GDP | Gross Domestic Product |
| GPR | Gross Profit Ratio |
| IO | Institutional Ownership |
| MDA | Multivariate Discriminant Analysis |
| NIO | Non-Institutional Ownership |
| OLS | Ordinary Least Square |
| RBI | Reserve Bank of India |
| ROA | Return on Assets |
| ROCE | Return on Capital Employed |
| PROMSH | Promoter shareholding |
| QR | Quick Ratio |
| UK | United Kingdom |

## 1.1 INTRODUCTION

In recent years, studies on corporate failure or its prediction have been very prevalent among the academicians, financial practitioners, and watchful economic bodies. The financial crisis has already thrown many financially strong companies out of business all over the world. Corporate financial distress not only incurs a severe financial loss to its creditors but also has a high cost to the society and the country's economy. Consequently, financial distress prediction studies are significant to all those involved: owners, shareholders, lenders, suppliers, and government. With the recent global financial crisis and the failure of many organizations in the United States and the European countries, it has become all the more necessary that the stakeholders study the financial health of their organization. For companies, being able to meet their financial obligations is an integral part of maintaining operations and growing in the future. If the company is not in good financial health, it may not be able to survive in the future.

This financial distress may cause due to borrower-specific factors like reputation, leverage, volatility of earnings, collateral or may be due to market specific factors like the economic condition and level of interest rates. One of the essential aspects of financial distress and finally the bankruptcy of the companies is the lack of existence of control by the people concerned. Even the shareholders of the company may not have any say in the management of the company. When carrying out their operations, the share price decreases and the company from financial power – encounters this snag and regards as mismanagement. Being not commensurate with the financial ratio of the company-according to financial cases, it can be fulfilled by breaking the control by unsatisfied shareholders and finally lead to financial distress and bankruptcy of the company.

Prediction of corporate bankruptcy is a phenomenon of increasing interest to investors or creditors, borrowing organizations and government alike. Timely identification of organizations' impending failure is desirable. Business failure is a general term and according to the widespread definition, is the situation in which a firm cannot pay the lenders, preferred stock shareholders, suppliers, etc., or where a bill is overdrawn, or the form is legally bankrupt. Signs of potential financial distress are evident long before bankruptcy occurs.

When a company experiences financial distress, operating conditions may deteriorate, heavy financial burdens become commonplace, and an overall negative atmosphere permeates the company environment. If the company allows the situation to continue and to worsen, bankruptcy may become a reality, market shares decline, and shareholders lose everything. However, if the company takes appropriate steps to remedy the financial conditions and to improve operations, it can recover and experience a resurgence (Wang and Shiu 2014). In the late 1990s, the economic recession invaded all Asian countries including India, which illustrated the need to develop an early alert method to reduce the circumstance of corporate failure among Indian firms.

Financial distress can serve as a firm's 'early warning' system for trouble. Firms with more debt will experience financial distress earlier than firms with less debt. However, firms that experience financial distress earlier will have more time for private workouts and reorganization. Firms with low leverage will experience financial distress later and, in many instances, be forced to liquidate. Financial distress may lead a firm to default on a contract, and it may involve financial restructuring between the firm, its creditors, and its equity investors.

Ferri et al. (1998) report that the problems of corporate financial structures have been an important factor in contributing to the financial crisis and leading many corporations to bankruptcy or default. Corporate failures are a common problem of developing and developed economies (Altman et al., 1977). It is commonly described as being when an associate of the firm comes up with a resolution that the firm be wound up and assign a liquidator or the associate of the firm can satisfy a meeting of its creditors to deliberate its proposal for a voluntary winding up of the firm. Corporations are not invulnerable to failure, where commonly the firm is not able to meet its liabilities. The research findings from developed economies are not suitable to apply to Indian firms due to the differences in market structures; socioeconomic factors, provision and implementation of the law, the political environment and accounting standards in these economies, which result in differences in financial reporting (Her and Choe, 1999). The findings of Amendola, Restaino, & Sensini (2015) financial distress disrupts the business and is a costly event. There are number of studies in the Indian context on corporate financial distress.

Shilpa and Amulya (2017) examined the financial distress level of Indian automobile companies and found that there was a moderate level of financial distress in companies in the Indian automobile sector. Similarly, Ray (2011) predicted the level of financial distress in Indian glass and glassware sector. The study revealed that the level of financial distress was high among the glass and glassware sector and threatened their viability and survival. Chatterjee (2018) compared the prediction accuracy of Altman's Z score and Ohlson's model to predict the financial distress using the Indian sample companies. The study concluded that the prediction accuracy of Altman's Z score was marginally higher in comparison to Ohlson's model. Charalambakis and Garrett (2016) study the ability of choice of accounting and market information to predict the financial distress of Indian and British companies. The results suggest that the accounting choice and market information is not a good predictor of the level of financial distress. Rajashekar et.al. (2014) studied the level of financial distress of Navarathna companies of India and found 8 of the 14 companies were financially weak.

## 1.2 STATEMENT OF THE PROBLEM

Failure of a business is not an unexpected event rather it is the result of a failure path, which may consist of some phases, each characterized by specific signs of failure (Jardi and Severin, 2010). As failure is not a sudden phenomenon and if the advance warning signals are detected, the more time managers will have for preparing and reacting in subsequent phases of the crisis. Therefore, forecasting default of companies is an area which has become quite significant in recent times. The increasing default is worrying the Indian banking system to a greater extent (Bardhan and Mukherjee, 2013). Further, the previous studies in India either looked at the financial distress of firms from a specific sector or analyzed the prediction accuracy. This study is unique because of three reasons. First, to the best of our knowledge, there is no comprehensive study in the Indian context which measured the financial distress of a large number of companies across the different sector. This study examines the level of financial sectors broadly covering the important and significant industries. Second, this study analyses the financial factors and non-financial factors influencing financial distress. The study of the relationship between corporate governance variables and is the second unique feature of this study. Third, this study also analyses the market response to the default announcements. This enables us to understand how the investors reacted to the default announcements.

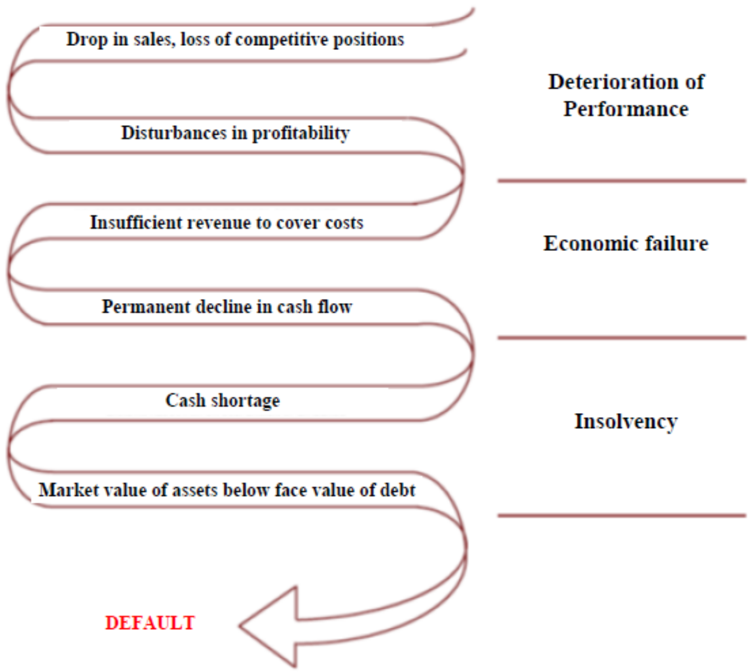
## 1.3 DEFINITION OF FINANCIAL DISTRESS

The most common terms used to describe the situations of firms facing financial difficulty are bankruptcy, insolvency, failure, distress, and default. Even though these terms are used interchangeably, sometimes, they are distinctly different in the formal usage (Altman and Hotchkiss, 2006). According to them, bankruptcy is a legal process in which insolvent enterprises or enterprises in default declare an inability to pay debts. Failure is the situation in which the realized rate of return on investment is significantly and continually lower than the prevailing rate of similar investments. The insolvent firm can be defined as a firm with negative economic net worth or the present value of the firm's cash flows is less than its total obligations. Further, the default happens when an enterprise has not met its legal obligations and legal action has been taken. Financial distress is a condition where a company cannot meet or has difficulty paying off its financial obligations, especially to its creditors. It means there is a tight cash situation and if prolonged, may lead to bankruptcy and even liquidation.

Foster (1986) notes that filing for bankruptcy has been the most commonly used criterion for corporate financial distress. He indicates that this is a legal event which is heavily influenced by the actions of bankers and or other creditors. He continues to define the term corporate financial distress to mean severe liquidity problems that cannot be resolved without a sizable rescaling of the entities either, operational or structural. According to Outecheva (2007), financial distress can be subdivided into four subintervals: deterioration of performance, failure, insolvency, and default. Whereas deterioration and failure affect the profitability of the company, insolvency and default are rooted in its liquidity. In general, financial distress is characterized by a sharp decline in the firm’s performance and value. He also notes that a company can be distressed without defaulting. However, he notes that default and bankruptcy cannot occur without the preceding period of financial distress. Financial distress is further described as a sharp failure of the firm’s performance and value (chart 1.1). If the managers identify negative effects in time, the downward spiral in the financial distress can be broken, and the firm does not turn into an insolvent one. A company is insolvent when it is unable to pay its financial obligations as they are getting due.

There are various causes of financial distress but Brownbridge (1998) attributed financial distress to insider lending, lending to high risk borrowers, macroeconomic instability, liquidity support and prudential regulation, Unlike Babalola (2009) who attributes bank distress to a chain of causation from non-panic related, observable, exogenous adverse changes in the economic conditions of banks, to intrinsic weakening of bank condition, ultimately leading to bank failure. Managerial incompetence is the most common reason for a company’s distress and possible failure according to Aasen (2011) but the ultimate cause of failure is often simply running out of cash and other liquid funds.

**Chart No. 1.1**
**Process of Default**




Source: Outecheva, N. (2007). "Corporate financial distress: An Empirical Analysis of Distress risk". Doctoral dissertation, University of St. Gallea, Bamberg, p32.

Failure does not happen suddenly, but it is a gradual process. As Outecheva (2007) points out, it is a dynamic process where a company faces financial problems, as it passes through separate phases, each of which has specific traits and subsequently, contributes differently to corporate failure. This means that financial distress is time-varying and once a company enters it, it does not stay in the same state until it is liquidated or until it recovers. Changes in financial conditions affect the transition from one state of financial distress to another. If financial conditions become aggravated, the company most probably will face bankruptcy. According to Aasen (2011) there are two types of financial distress costs. Direct bankruptcy costs include primarily legal and administrative costs while indirect bankruptcy costs reflect the difficulty of managing a company when it faces bankruptcy. According to Outecheva (2007), indirect costs are hidden and not as obvious as direct costs. He defines indirect costs as opportunities lost which the company misses due to weakening solvency position. These costs are unobservable and difficult to be estimated. Opler and Titman (1994) found out that the costs of financial distress consist of three classes of factors causing losses in sales: Customer-driven losses which reduce the willingness of the customers to pay for its products and customers ceasing to do business with the distressed firm, causing sales to collapse. Competitor-driven losses which result in competitors pursuing an aggressive marketing and price strategy to attract the customers of the vulnerable company and, therefore, squeeze the troubled competitor out of the market. An employee-driven loss decreases the incentives of the employees to work hard and stimulates them to renegotiate their compensation packages or to leave the company.

A company may be financially distressed if it is not in a position to meet its financial obligations whenever they arise (Lin, 2009). Such a definition of distress is based on the theoretical framework of 'cash flow' or 'liquid assets' model. Liquidity asset flow model by Beaver (1966) considered a company to be a reservoir of liquid assets which was supplied by inflows and drained by outflows. Basically, firms with positive cash flow would be able to raise more funds, whereas those with the negative cash flows will be unable to do so. Moreover, such firms with the negative cash flows would be unable to pay their obligations as they mature. Carmichael (1972) found that the financial difficulty that a company encounters was a situation when there was the insufficiency of liquidity, equity, liquid capital and default of debt. Foster (1986) defines distress as a serious liquidity problem which was unable to be resolved without large-scale restructuring of operations. Doumpos et al. (1998) mentioned distress regarding negative net assets value, i.e. when a company's total liabilities exceed total assets from the accounting point of view. Ross et al. (1999) summarized distress to be one of the following four conditions (a) business failure, i.e. a company cannot pay its outstanding debt after liquidation, (b) legal bankruptcy, i.e. a company or its creditors apply to the court for a declaration of bankruptcy, (c) technical bankruptcy, i.e. the company cannot fulfill the contract to repay principal and interest; and (d) accounting bankruptcy i.e. the company's book net assets are negative. Noticeably definitions of financial distress are more flexible due to their background of studies and the availability of data. A broader definition of corporate default or financial distress makes modelling easier by increasing the sample size of the distress firms, but at the same time, it brings difficulties in interpreting the results of different dependent variables (López-Gutiérrez, Sanfilippo-Azofra, and Torre-Olmo, 2015). Taking data of sick companies suffering from severe financial distress, along with the observations on the basis of finance based definition will also help in detecting early stages of distress among various companies Palinko and Svoob (2016). This thesis uses the term financial distress to describe the situations of firms that face financial difficulty and has not met its legal payment obligations which in turn led to the default of the company.

### 1.4 FINANCIAL DISTRESS: AN INDIAN PERSPECTIVE

Currently, the Indian economy is reeling under mounting bad loan pressure (Jung and Lindner (2014). Lenders in India can recover only 20% of their loans when businesses go bankrupt and an average time of 4.3 years is taken in insolvency proceedings as compared to 70% recovery rate and about 1.7 years of the average time taken for insolvency proceedings in the developed economies. (World Bank, 2016). This can be seen in table 1.1.

**Table No.: 1.1**
**Time to Resolve Insolvency (years)**

| Countries | 2013 | 2014 | 2015 | 2016 | 2017 |
|---|---|---|---|---|---|
| Australia | 1 | 1 | 1 | 1 | 1 |
| Brazil | 4 | 4 | 4 | 4 | 3.5 |
| China | 1.7 | 1.7 | 1.7 | 1.7 | 1.7 |
| India | 4.3 | 4.3 | 4.3 | 4.3 | 3.5 |
| Japan | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 |
| Russia | 2 | 2 | 2 | 2 | 2 |
| UK | | 1 | 1 | 1 | 1 |
| US | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| World | 2.4 | 2.56 | 2.56 | 2.55 | 2.32 |

*Source: World Bank Doing Business Report, 2017*

According to the World Bank estimate, 2016, corporate insolvencies in India take more than four years on average to be resolved. This is much longer than in most of the other developing and developed economies. One reason has been the lack of an overarching system for recovery of debt, forcing different classes of creditors to pursue their claims through a range of processes. The failure to achieve swift restructuring has led to extensive erosion of value in distressed companies, in some cases exacerbated by controlling shareholders transferring assets out of business. Thus, lenders and investors along with various regulators require timely information on the default risk probability of the firm within lending and investment portfolios.

Currently, India ranks 136 out of 189 countries in the World Bank's index on the ease of resolving insolvencies, compared to the 27$^{th}$ rank of Singapore and 13$^{th}$ rank for United Kingdom (UK). The distressed state of credit markets in India today is due to its weak insolvency regime and its significant inefficiencies. The absence of a well-functioning and effective corporate insolvency framework is also reflected in the state of credit markets in the country. India has a domestic credit to Gross Domestic Product (GDP) ratio of only 77% as compared to 112% in Singapore and 195% in the UK. As table 1.2 shows, bank credit constitutes as much as 93% of total credit in India compared to only 56.5% in Singapore. Banks and financial institutions in India focus to a large extent on providing credit based on the size and reputation of the debtor and also by securing collateral. Banks are the dominant source of credit to the non- financial sector in India and Singapore.

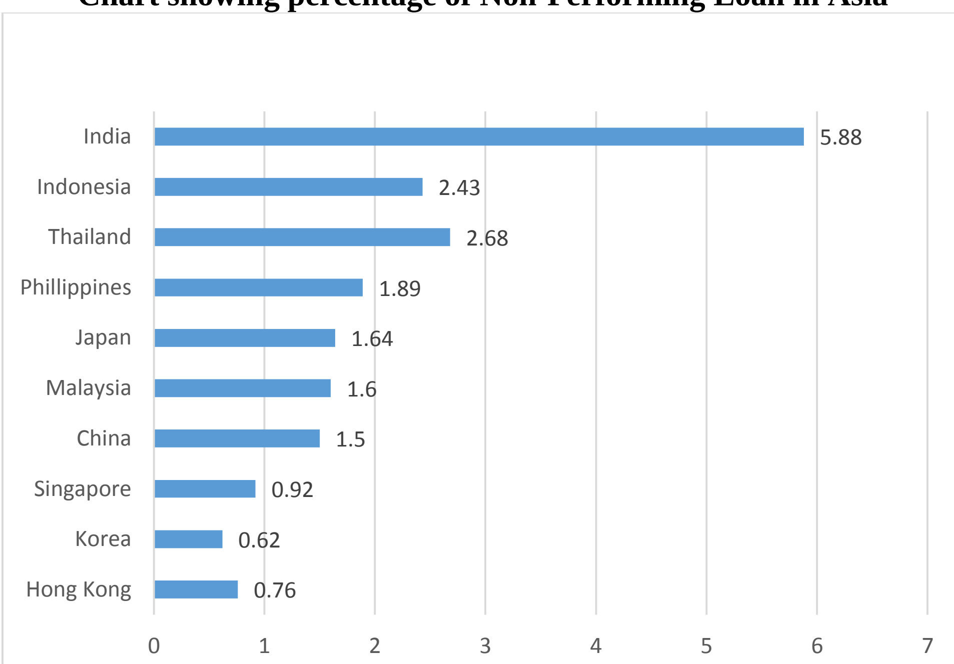
**Table No.: 1.2**
**Table showing Parameters of Insolvency Resolution and Credit Data**

| Indicator | UK | Singapore | India |
|---|---|---|---|
| Rank | 13 | 27 | 136 |
| Time (years) | 1.0 | 0.8 | 4.3 |
| Cost (% of estate) | 6.0 | 3.0 | 9.0 |
| Outcome (0-sale; 1- going concern) | 1 | 1 | 0 |
| Recovery rate (cents on dollar) | 88.6 | 89.7 | 25.7 |
| Domestic credit to GDP1 (%) | 171.5 | 126.3 | 74.8 |
| Bank credit to GDP | 85.3 | 56.5 | 93.1 |

*Source: World Bank Doing Business Report, 2017*

To add, India's non-performing loan percentage is the highest in Asia amounting to 5.88 percent, while it is 2.68 in Thailand, 2.43 in Indonesia and 1.5 in China. This is shown in chart 1.2.

**Chart No.: 1.2**
**Chart showing percentage of Non-Performing Loan in Asia**




Despite the frequency of insolvency and firm closure, the use of legal procedures associated with bankruptcy varies significantly around the world, due to differences in legal traditions, accounting standards, regulatory frameworks, and macroeconomic factors (Claessens and Klapper, 2005). For instance, bankruptcies are less common in countries with concentrated banking systems and in firms with single banking relationships and are more common in firms with more complex capital structures (Bebchuck, 1988). Furthermore, the laws in some countries only allow for the liquidation of bankrupt firms and provide limited protection for entrepreneurs and managers of bankrupt firms. Other countries have more bankruptcy options (such as reorganization and out-of-court mediation), though the effectiveness of these laws in practice varies across countries (Lee, Peng, and Barney, 2007).

Earlier there was no single comprehensive and integrated policy to deal with financially distressed firms in India. The rules related to financially distressed cases were covered by the Companies Act, 1956 and the Sick Industrial Companies Act, 1985 Bapat and Nagale (2014). "In India, an industrial company (being a company registered for not less than five years) which has at the end of any financial year accumulated losses equal to or exceeding its entire net worth would be referred to the Board for Industrial and Financial Reconstruction (BIFR) as a sick industrial company. But recently with the passage of insolvency and bankruptcy code bill, a single law to deal with distressed firms, promoters, employees, creditors, and other stakeholders is applicable In India. This law will ensure a time-bound process of winding up a distressed company" Roychoudhury (2016).

India has struggled for years to deal with the problems of bad debt in the absence of any genuine national bankruptcy law, and a legal system that was once heavily tilted towards company owners and the mission of saving businesses for the sake of their workers. The country relied on the Board for Industrial and Financial Reconstruction to deal with what it described as "sick" industrial companies, from the late 1980s. The mandate of the board, a government agency, was to oversee the revival of businesses that were still viable and to shut down the rest. But the board has been often reluctant or unable to enforce tough decisions necessary to improve the financial positions of businesses. It eventually came to be seen as a way of prolonging the existence of badly run private companies to the benefit of their controlling shareholders, and inefficient state enterprises at taxpayer expense.

## 1.5 CURRENT STATUS OF NON-PERFORMING ASSETS IN SCHEDULED COMMERCIAL BANKS OF INDIA

Non-Performing Assets (NPAs) have been hurting the Indian banking sector for a long time. In the pre-liberalization period, the origination of NPAs was mainly due to the downswings in the agricultural sector, rigid industrial licensing, sector-wise reservation, controlled interest rates and tariff protection (Khasnobis, 2008). The report submitted by the committee on Banking Sector Reforms popularly known as Narasimham Committee Report in 1991 brought in many revolutionary changes in the Indian banking sector. One of the important areas of revolution was the introduction of the concept of Non-Performing Assets (NPAs).

The realization of introducing some measures to account the bad loans was thought even earlier. In 1985-86, Reserve Bank of India (RBI) introduced a critical analysis for a comprehensive and uniform credit and monitoring by way of the health code system. This system on assessment of loan, to a great extent, was unable to reveal the real quality of the asset. This was also due to the accounting practices of the banks which allowed them to account interest on the accrual basis, thus concealing a proper demarcation between quality assets and bad assets of banks.

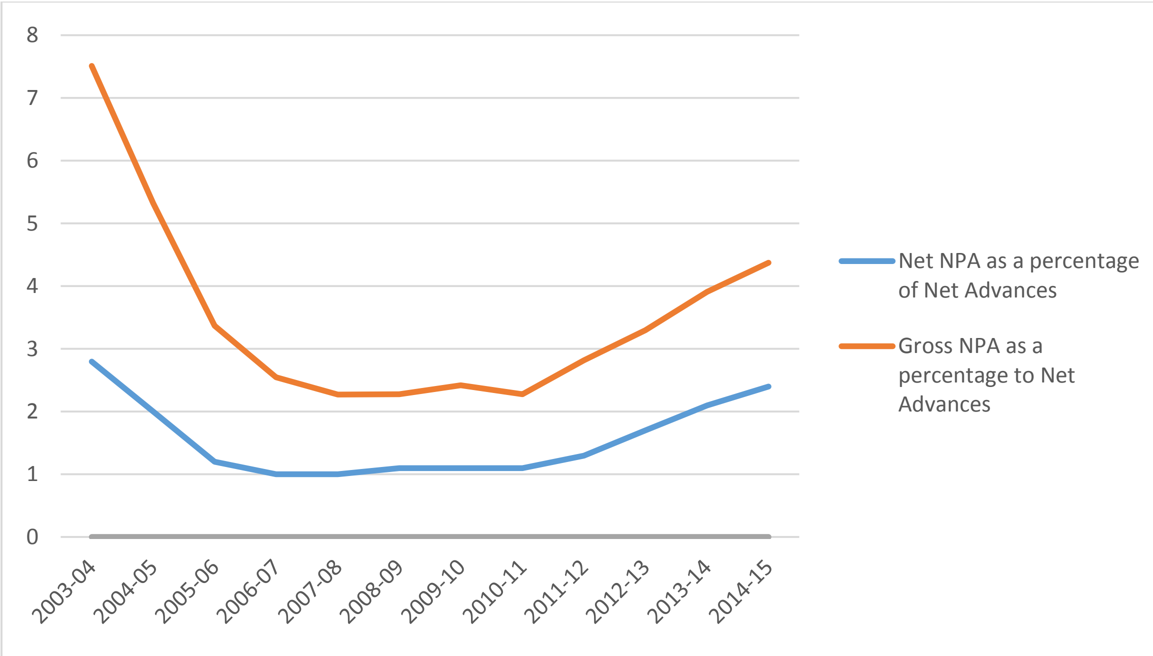
To enhance the competence of banking industry and to facilitate them to compete in the era of globalization, liberalization and opening up of the market, banking across the globe embraced prudential norms for income assessment, income classification, and provisioning (Siraj & Pillai, 2013). India could not have afforded to stay behind in the league. As a result, in 1993 the Reserve Bank of India (RBI) issued directives on Income Recognition based on Narashimam Committee Report on banking reforms. RBI compelled the banks to classify their credit portfolio into two parts, first being Standard or Performing Assets and second was Non-Performing Asset. Before 2001, the classification of NPA was done using the concept of ‘past due’. An amount is considered as past due if it remains outstanding for a period of 30 days past the due date.

If a loan is past due for more than four quarters then such asset would be considered as NPA when it introduced in 1993. However, in the year 1994 and 1995, it was reduced to 3 quarters and 2 quarters respectively. With the intention of moving towards global best practices and to ensure better transparency, ’90 days’ overdue norms for identification of NPA was introduced in the year 2004. According to the NPA classification and provisioning guidelines laid down by RBI in the Master Circular on Prudential norms on Income Recognition, Asset Classification and Provisioning (IRAC), the banks are required to separate the advances as standard assets, sub-standard assets, doubtful assets, and loss assets.

The Narasimham Committee had also recommended the formation of an Asset Creation Fund to which public sector banks would transfer their NPAs with certain safeguards. However, the recommendation was not accepted, and banks were internally dealing with their NPAs. Based on this recommendation Debt Recovery Tribunals (DRTs) were established consequent to the passing of the RDDBFI Act, 1993. The scheme of Corporate Debt Restructuring (CDR) was introduced in 2001 outside the purview of BIFR.

This legal mechanism for recovery of bad loans was cumbersome and time-consuming (Rajeev & Mahesh, 2010). Besides, many global rating agencies expressed their apprehensions about mounting NPAs in the banking industry. At some point the growth in NPA outpaced the growth in GDP this created further doubts in the minds of global rating agencies about the asset quality of Indian banks. The chart given below depicts the Gross NPA and Net NPA of Scheduled Commercials Banks in India for a decade following banking sector reforms.

**Chart No.: 1.3**
**Gross NPA and Net NPA of Scheduled Commercials Banks in India**




The chart1.3 gives a clear picture of the trends in NPAs in India from 2003-04 to 2014-15. The net NPA of Scheduled Commercial Banks in India was as high as 7.51 percent in the year 2003-04. This significantly reduced to 2.28 percent in the year 2008-09. Furthermore, in the Global NPL Report published by Ernst & Young, India stood fourth with the contribution of 2.3 percent to the total NPA of Asia in the year 2003 whereas the other developing Asian countries like Korea and Philippines contribution is just 1.2 percent and 0.7 percent respectively (Ranjan & Dhal, 2003). This called for immediate attention of the policymakers and another wave of policy reforms. As a result of this, the Government of India appointed a committee chaired by Sri TR Andhyarujina in the year 1999. The committee in its report strongly felt that that banks and financial institutions should be given the power to sell securities to recover dues; hence it recommended the policymakers to allow the banks to initiate the process of asset securitization. Based on the recommendations of the Andhyarujina Committee, The Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest (SARFAESI) Act, 2002, was enacted on December 17, 2002.

This Act provided the security factor for the banks without recourse to civil suits. The act was also passed with the intention of facilitating banks and financial institutions to realize long-term assets, manage the problem of liquidity, reduce asset-liability mismatches and improve recovery by taking possession of securities, selling them and reducing NPAs.

**Table No. 1.3**

**Gross Advances and Gross NPAs of Scheduled Commercials Banks (Amount in Rupees Billion)**

| Year | Gross Advances | Gross NPA (Amount) | Gross NPAs (Percentage) |
|---|---|---|---|
| 2005-06 | 9020.26 | 648.12 | 7.2 |
| 2006-07 | 11526.82 | 593.73 | 5.2 |
| 2007-08 | 15513.78 | 510.97 | 3.3 |
| 2008-09 | 20125.1 | 504.86 | 2.5 |
| 2009-10 | 25078.85 | 563.09 | 2.3 |
| 2010-11 | 30382.54 | 683.28 | 2.3 |
| 2011-12 | 35449.65 | 846.98 | 2.4 |
| 2012-13 | 40120.79 | 979 | 2.5 |
| 2013-14 | 46488.08 | 1429.03 | 3.1 |
| 2014-15 | 59718.2 | 1940.53 | 3.2 |
| 2015-16 | 68757.48 | 2633.72 | 3.8 |
| 2016-17 | 75606.66 | 4233.45 | 4.3 |
| 2017-18 | 76302.58 | 7366.32 | 10.35 |

*Source: Report on Trend and Progress of Banking in India, RBI, Various Issues*

The table 1.3 shows the amount of Gross Advances, Gross NPA and the percentage of Gross NPA during the period of 2003-04 to 2014-15. The gross advances amount has raised from Rs. 9020.26 Billion in 2003-04 to Rs. 75606.66 billion in 2014-15. The gross NPA amount has also increased from Rs. 648.12 billion in 2003-04 to Rs. 3233.45 billion in 2014-15. Similarly, the NPA percentage is showing an increasing trend from 2.3 in 2007-08 to 4.3 in 2014-15. Furthermore, post-2008, following the emergence of the financial crisis, there was increasing defaults from borrowers and hence rise in the percentage of NPA post-2008.

**Table No. 1.4**
**Net Advances and Net NPAs of SCBs (Amount in Rupees Billion)**

| Year | Net Advances | Net NPAs (Amount) | Net NPA (Percentage) |
|---|---|---|---|
| 2003-04 | 8626.43 | 243.96 | 2.8 |
| 2004-05 | 11156.63 | 217.54 | 2 |
| 2005-06 | 15168.11 | 185.43 | 1.2 |
| 2006-07 | 19812.37 | 201.01 | 1 |
| 2007-08 | 24769.36 | 247.3 | 1 |
| 2008-09 | 29999.24 | 315.64 | 1.1 |
| 2009-10 | 34970.92 | 387.23 | 1.1 |
| 2010-11 | 42987.04 | 417 | 1.1 |
| 2011-12 | 50735.59 | 652.05 | 1.3 |
| 2012-13 | 58797.73 | 986.94 | 1.7 |
| 2013-14 | 67352.13 | 1426.56 | 2.1 |
| 2014-15 | 73881.79 | 1760.93 | 2.4 |

*Source: Report on Trend and Progress of Banking in India, RBI, Various Issues*

The above table 1.4 shows the amount of net advances, net NPA and the percentage of net NPA from the period 2003-04 to 2014-15. There was an increase in the amount of advances from Rs. 8626.43 billion in 2003-04 to 73881.79 billion in 2014-15. Further, the amount of NPA has also raised from Rs. 243.96 billion to Rs 1760.93 billion during the period (2003-04 to 2014-15). The percentage of Net NPA has first deteriorated from 2.8 in 2003-04 to 1.0 in 2007-08. Then it has raised to 2.40% in 2014-15.

## 1.6 INSOLVENCY AND BANKRUPTCY CODE

At present, there are multiple overlapping laws and adjudicating forums dealing with financial failure and insolvency of companies and individuals in India. The current legal and institutional framework does not provide aid lenders in effective and timely recovery or restructuring of defaulted assets and causes undue strain on the Indian credit system. Recognizing that reforms in the bankruptcy and insolvency regime are critical for improving the business environment and alleviating distressed credit markets, the

Government introduced the Insolvency and Bankruptcy Code Bill in November 2015, drafted by a specially constituted 'Bankruptcy Law Reforms Committee' (BLRC) under the Ministry of Finance.

After a public consultation process and recommendations from a joint committee of Parliament, the Insolvency and Bankruptcy Code, 2016 (**Code**) was passed by the Parliament. While the legislation of the Code is a historical development for economic reforms in India, its effect will be seen in due course when the institutional infrastructure and implementing rules as envisaged under the Code are formed.

The Code offers a uniform, comprehensive insolvency legislation covering all types of companies, partnership firms and individuals (other than financial firms). The Government is proposing a separate framework for bankruptcy resolution in failing banks and financial sector entities.

One of the fundamental features of the Code is that it allows creditors to assess the viability of a debtor as a business decision, and agree upon a plan for its revival or a speedy liquidation. The Code creates a new institutional framework, consisting of a regulator, insolvency professionals, information utilities and adjudicatory mechanisms, that will facilitate a formal and time-bound insolvency resolution process and liquidation.

## 1.7 RESEARCH GAP

From the review of extensive literature, it is observed that a very limited study has taken place on financial distress in a developing country like India. It is also clear that there is a clear dearth of empirical studies on financial distress in India. Even the limited number of studies dealing with this issue in the Indian context examined the financial distress prediction in general for certain industries like aluminum industry, the pharmaceutical industry, navaratna companies and so on (Pal, 2013; Rajasekar et al., 2014; Shilpa and Amulya, 2017). The studies did not consider the default status of any of the companies in these industries. The study gains importance as it contains the comparison of default companies specified by RBI with that of the healthy companies irrespective of the industry it belongs to.

Further, various factors of the financial distress remain under explored in the Indian context. Besides, the impact of different factors on default companies and non-default companies, are largely unexplored. In the previous literature, most research studies on financial distress focused their attention on the predictive ability of firm-specific financial ratios. The prior research has not considered the combined effect of financial ratios and non-financial variables in predicting financial distress of especially in developing economy like India. Further, the stock market reactions to default announcement are unexplored in the Indian context. The need for undertaking such studies on a comparative basis is, therefore, obvious. Since the data used in the study is not publicly available, the study gains importance. Therefore, a clear gap in terms of empirical findings on the prediction of financial distress is observed and the present study intends to fill this gap. This study also examines the effect of corporate governance on the level of financial distress.

## 1.8 RESEARCH QUESTIONS

The pertinent questions which the present research work addresses therefore are:

1. Are there any differences in financial and non-financial variables between default and non-default companies?
2. What is the effect of financial factors on the level of financial distress?
3. What is the impact of non-financial factors on chances of default?
4. What is the response from the stock market on default announcement?

## 1.9 RESEARCH OBJECTIVES

The thesis focuses on examining the factors influencing financial distress and default of Indian Companies. The research objectives aim the following:

1. To identify whether there are significant differences in financial and non-financial variables between default and non-default companies.
2. To study the impact of financial factors on the level of financial distress.
3. To analyze the impact of non-financial factors on the chances of default.
4. To study the stock market response to the default announcement.

## 1.10 HYPOTHESES

$H_1$There are significant differences in financial ratios between default and non-default companies.

$H_2$There are significant differences in non-financial variables between default and non-default companies.

$H_3$The extracted financial factors are significant predictors of firm's financial distress.

$H_{4a}$ Firms with a higher level of promoter shareholding have fewer chances of board ownership has fewer chances of financial distress.

$H_{4b}$ There is a significant difference between non-institutional ownership concentration and chances of financial distress

$H_{4c}$ There is a significant difference between institutional ownership concentration and chances of financial distress

$H_{4d}$ Companies with duality in CEO have greater chances of financial distress.

$H_{4e}$ Companies with the high proportion of independent directors have less likelihood of financial distress.

$H_{4f}$Companies with high board size have less likelihood of financial distress.

$H_5$ There is a negative market response to default announcement.

## 1.11 SCOPE OF THE STUDY

The present study is confined to companies from India which are defaulted in the year 2010-15, whose list is provided by Reserve Bank of India (RBI). To observe the differences, healthy companies during that period are considered. The companies whose information is publicly available are considered for studying further. In order to observe the stock market responses on default announcements, listed default companies from the sample were considered.

## 1.12 SIGNIFICANCE OF THE STUDY

The study brings out the factors determining the level of financial distress using the Indian sample companies. The findings are useful for the Indian banks which are facing the unprecedented NPA crisis today. The model developed in this study can also throw light on the factors that a lender might have to look at while lending. The model used in this study uses both financial factors as well as non-financial factors to influencing the default. Especially, the model includes the corporate governance variables. Therefore, the findings are insightful, especially for the Indian banks and regulators.

## 1.13 ORGANISATION OF THE STUDY

The study is organized into six chapters. A brief summary of each chapter is set out below.

### Chapter 1: Introduction

This chapter presents the introduction to the study, beginning with the statement of the problem. The definition of financially distressed companies is also discussed in this chapter. The research gaps, research questions, research objectives with relevant hypotheses are also stated. This chapter also presents the organization of the thesis and the contribution it makes.

### Chapter 2: Review of Literature

This chapter deals with a review of the related literature on measurement of financial distress. The predictors of financial distress are also discussed in detail in this chapter.

### Chapter 3: Data and Methodology

Chapter III is regarding the data collection and the methods used in the study. The chapter explains the source of data and discusses the sample selection method. The chapter then discusses categories of financial distress predictors and selects the financial distress predictors for the present study. Finally, the methods, which include the MWW test, factor analysis, multiple regression, logistic regression, event study methodology and distance to default are presented in this chapter.

### Chapter 4: Descriptive and Factor Analysis

In chapter 4, the first two objectives have been analyzed. The MWW test was first run to distinguish the difference between default and non-default in financial and non-financial performance. The chapter then used factor analysis to reduce a large number of ratios and variables to several factors. After the MWW test and factor analysis, the extracted financial were used as independent variables for regression analyses. Finally, relevant hypotheses are tested.

### Chapter 5: Prediction of Financial Distress

The third and fourth objectives of the study are answered in chapter 5. Logistic regression analysis is conducted to analyze the influence of non-financial factors on the chances of default. Finally, the event study methodology is used to study the response of the stock market to the default announcement.

### Chapter 6: Findings and Conclusion

The final chapter summarises the overall picture of the thesis and discusses the empirical results. The policy implications derived from the findings are also presented. The chapter ends by identifying the limitations of the study and proposing scope for further research.

## 2.1 INTRODUCTION

Practitioners and researchers have long shown interest in the prediction of financial distress and bankruptcy. Early warning of financial distress or business default has become an important research area for financial risk management. In this chapter the previous studies on financial distress models, effect of financial distress, factors affecting the level of financial distress and the fallouts of the distress or default is reviewed. The review includes studies in the global context as well as the studies in the Indian context.

According to Whitaker (1999), the process of financial distress starts with a company not being able to pay their day to day financial requirements, as and when they fall due. The main reasons behind financial distress can be attributed to inappropriate asset mix, corporate governance or financial structure (Gilbert et al, 1990). Financial distress is associated with both direct and indirect costs (O'Neill, 1986). The direct costs include legal fees, auditor expenses and other payments associated with bankruptcy proceedings. The loss of value before bankruptcy can be referred to as indirect costs which includes the decrease in the level of sales and loss of goodwill. Farooq and Jibran (2017) includes opportunity cost and risk premium as the indirect costs of financial distress. Contrarily, Ericsson and Parsons (2012) provided concluded that the tax benefits of the highly levered firm will offset the cost of financial distress. Therefore, a moderate level of financial distress due to high leverage is acceptable because the benefits may offset the cost of distress. However, it is implied that the benefit can be reaped as long as the firm experiences smooth cash flows (Khalfan and Sturluson, 2018)

According to Wruck (1990), several pointers can be used to detect financial distress in companies. A reduction in the level of dividends issued out or non-issue of dividends can be a good indicator of financial distress. Retrenchment of employees and the resignation of top management can be a good indicator of financial distress. Shahwan (2015) opines that financial distress can also be due to bad corporate governance. The lower level of corporate governance practices such as disclosure and transparency, the composition of the board of directors, shareholders' rights and investor relations and ownership and control structure could also lead to financial distress.

According to Natalia (2007), factors such as large debts, uninformed expansion, the competition which is intense, large legal costs are probable causes of financial distress. Adeyemi (2012) noted that a lack of adequate capital is one of the major factors leading to financial distress as capital can absorb losses. Lack of managers with adequate management skills can also lead to corporate failures (Ooghe & Prijcker, 2008). Most managers focus and blame external factors when their business fails rather than evaluate internal factors too (Scherrer, 2003). Financial distress prediction is a critical accounting and financial research area since the 1960s. Reviews of some of the important studies under different themes are presented in this section.

## 2.2 FINANCIAL DISTRESS PREDICTION MODELS

The research papers on corporate financial distress prediction models are reviewed in this section. There have been many models developed to predict business failures (Gep and Kumar, 2012). Academic researchers and practitioners across the globe have been evolving with a large number of corporate financial distress prediction models on the basis of different types of methodologies (Balcaen and Ooghe, 2004b). For example, Altman (1984) explained business failure prediction models developed in the various economy. Keasey and Watson (1991) indicated the usefulness of, and limitations associated with adopting financial distress prediction models. Dimitras, Zanakis and Zopounidis (1996) produced another important study, which presented a comprehensive survey of literature on business failure prediction models. Altman and Narayanan (1997) examined the studies on business failure classification models in 21 different countries. Cybinski (2001) also examined, described and explained the evolution of bankruptcy studies. These studies justify the importance of corporate financial distress prediction models.

Several researchers in the past, for example, Dambolena and Khoury (1980), Shumway, 2001, Kumar and Ganesalingam (2000) and Hensher, Jones and Greene (2007), Nilesh P. Movalia (2015), have used ratio analysis in portending corporate distress and stated that they play a dominant role in firm’s failure. Altman (1968) used multiple discriminant analysis for prediction of corporate bankruptcy. In the 1970s, multiple discriminant analysis was the primary method for prediction of corporate bankruptcy. During the 1980s, use of logistic regression analysis method was emphasized (Virag and Kristof, 2005). Ohlson (1980) applied logistic regression analysis for the first time for prediction of bankruptcy. In recent years, many researchers have begun to apply the neural network approach to the prediction of bankruptcy as they have produced promising results in the prediction of bankruptcy (Ugurlu and Aksoy, 2006). Neural networks were first used for bankruptcy prediction by Odom and Sharda (1990).

Nam and Jinn (2000) investigated the predictive model of business failure using the sample of listed companies of a variety of industries that went bankrupt during the period from 1997 to 1998 when deep recession driven by the IMF crisis started in Korea. Campbell et al. (2008) constructed a multivariate prediction model that estimates the probability of bankruptcy reorganization for closely held firms. Six variables were used in developing the hypotheses, and five were significant in distinguishing closely held firms that reorganize from those that liquidate. The five factors were firm size, asset profitability, the number of secured creditors, the presence of free assets, and the number of under-secured secured creditors. The prediction model correctly classified 78.5% of the sampled firms. This model is used as a decision aid when forming an expert opinion regarding a debtor’s likelihood of rehabilitation.

Peel et al. (1986) were among the first to apply logit analysis in the UK. In an attempt to refine the ‘classic’ financial ratio-based failure model, they added a number of non-conventional ratios and variables. Subsequently, Peel and Peel (1988) and Keasey et al. (1990) examined whether it is possible to discriminate simultaneously between healthy and failing firms for a number of reporting periods before failure, by applying multi-logit models.

In recent literature, Artificial Neural Networks (ANN) have been successfully used for modeling financial time series (Zhi Yuan Li, 2015; Padhiary, P. K., & Mishra, A. P., 2011). Another avenue of research considers macroeconomic indicators as input to the Neural Networks (NN). The prevailing economic condition (as well as the current interest rates, Gross Domestic Product (GDP), unemployment rates, price indices, inflation, investment, international trade and international finance) can have a significant effect on the probability of financial distress. However, very few studies consider these factors in conjunction with NN models.

Previous studies on neural network applications for bankruptcy prediction have been targeting a single industry or not investigated the industry difference in bankruptcy prediction. Dewaelheyns and Van Hulle (2006) suggested that models involving both bankruptcy variables defined at subsidiary level and group level provide a substantially better fit and classification performance.

Simic *et al.* 2011, examined the case of Serbia and applied multivariate statistical methods and specific artificial neural network architect assess the corporate financial health of various companies. Financial ratios drawn from corporate balance sheets become the independent variables in a Multivariate Discriminant Analysis (MDA). These financial ratios and the discriminant *Z*-score in the MDA form the input for the SOM, which creates a hybrid MDA-SOM model that is capable of predicting corporate financial insolvency. The experimental results of this research correctly estimate company financial health in 95 percent of cases. These are reliable predictions that are comparable with similar studies in other countries.

Li et.al 2012 re-examined the accuracy of the original Z-score model in predicting corporate failures in the U.S. from 2000-2010. Nicolas Emanuel Monti, Roberto Mariano Garcia, 2010predicted corporate financial distress using logistic regression as a statistical model and financial ratios as independent variables. The findings of the study indicated that the developed model is a reliable and efficient model with having better goodness of fit.

Maria H Kim (2014), investigates dynamic probability forecasts for Australian firms. Maria uses time-varying variables in forecasts from a Cox model. Not only is this one of relatively few studies to apply dynamic variables in forecasting financial distress, but to the authors' knowledge, it is the first to provide forecasts of survival probabilities using the Cox model with time-varying variables. Forecast accuracy is evaluated using receiver operating characteristics curves and the Brier Score. It was found that the dynamic model had superior predictive power, in out-of-sample forecasts, to the traditional Cox model and to the logit model.

## 2.3 CATEGORIES OF FINANCIAL DISTRESS PREDICTORS

To provide empirical evidences about the influence of variables on corporate failure and identify the potential factors of corporate financial distress. This section provides an extensive review of the predictors of financial distress in previous literature.

According to Hossari and Rahman (2005), empirical investigations of corporate failure can be classified into two categories: those studies that do not utilize financial data and those that do utilize financial data. The latter can be further classified into those that employ financial ratios and those that use non-ratio financial data in modeling corporate collapse.

### 2.3.1 Financial Data

Researchers have comprehensively explored the use of information from financial statements for corporate distress prediction. Lincoln in his study in 1984 argued that analysts should depend on financial statements in examining business failure as all the factors leading to the success of a company as reflected in its financial statements. He further elaborates that poor management will be reflected in the profit and loss statement, economic downturns will be shown in the company’s declining cash flow and tight credit or low levels of money supply growth will be reflected in the balance sheet.

The details of the existing literature regarding the use of financial data in financial distress prediction are discussed as follows.

#### 2.3.1.1 Financial Ratios

A large number of research studies have utilized financial ratios in predicting financial distress. Comparison of the values of financial ratios in bankrupt and non-bankrupt companies was demonstrated by early researchers (Ramser and Foster, 1931; Fitzpatrick, 1932; Ugurlu and Aksoy, 2006, Panovska, Boshkoska, Prisaganec, 2010, Almansour, 2015) who thereby resolved that the ratios of the bankrupt companies were poorer. The exact choice of ratios will depend on the object in view and the information available (Tamari, 1966). The findings of Ninh, Thanh and Hong (2018) show that the financial ratios are good predictors of corporate financial distress.

Beaver (1966) is considered a pioneer who came up with new and innovative methodology and used financial ratios as proxies to predict bankruptcy and corporate failure. Altman (1968) improved on Beaver's univariate method of analysis by introducing a multivariate approach that allows for the simultaneous consideration of several variables in the analysis. Altman came with the well-known Z score model with financial ratios based on MDA. The results found five financial ratios that are significant predictors in the corporate bankruptcy prediction model. These ratios are working capital to total assets, retained earnings to total assets, earnings before interest. Using financial ratios based on the logit model to predict bankruptcy, Ohlson (1980) found four basic factors that have an enormous effect on the probability of failure within one year: company size, financial structure, performance and current liquidity.

Additionally, Lensberg, Eilifsen and McKee (2004) developed a bankruptcy classification model for Norwegian companies. The authors investigated twenty-eight potential bankruptcy predictors including both financial ratios and non-financial ratio variables. The results show that accounting information is more important for larger than for smaller firms. It also suggests that for small firms, the most important information is liquidity and non-accounting information.

Due to the lack of an established theory in guiding the possible financial ratios for inclusion in corporate failure prediction models (Gilbert, Menon and Schwartz, 1990), researchers have been employed in data fitting exercises. Past studies initially considered large sets of independent variables and then used statistical techniques to obtain the selected variables in the final model. For example, Altman reduced the original twenty-two variables to five by searching through various discriminant functions to obtain the one that predicted best. Another approach is employing the variables suggested by the existing literature or those found to be significant by previous corporate failure or financial distress studies.

#### 2.3.1.1a Profitability Ratios

Profitability ratios measure the ability of the firm to generate earnings. Profit is one source of funds from operations. The more profit a firm can generate, the greater the increase in funds and liquidity position of the firm. When companies generate negative earnings, they face financial distress. Thus, profit is often used as a predictor of financial distress events (Khunthong, 1997).

On the other hand, the findings of Kimathi and Mungbai (2018) suggest that the relationship between the profitability and financial distress is insignificant. However, this finding is based on sample banks of Kenya. In this study, the relationship between profitability and financial distress of non-financial firms are examined.

Three types of profitability ratios, namely, Return on Net worth (RONW), Return on Capital Employed (ROCE), Gross Profit Ratio (GPR) and Return on Assets (ROA) are used in the present study.

ROE is a profitability measure which shows the return on capital provided by a firm’s owners. In other words, ROE measures the ability of a firm to utilize assets to generate earnings for shareholders. According to Khunthong (1997), ROE is found to be one of the significant variables in predicting failure two and three years before failure occurs for companies in Thailand. Gestel et al. (2006) also found ROE to be one of the three most important inputs for the Least Squares Support Vector Machine (LS-SVM) classifier in the analysis of the creditworthiness of a company.

In this study, ROA is defined as EBIT to total assets. As discussed in Altman (1968a), EBIT to total assets is a measure of the true productivity of the firm's assets independent of any tax and leverage factors. This ratio is particularly appropriate for studies on corporate failure since insolvency occurs when the total liabilities exceed a fair valuation of the firm's assets with the value being determined by the earning power of the assets. The earlier studies found ROA as an important factor in explaining financial failure, for example, Altman (1968a), Altman, Haldeman and Narayanan (1977), Izan (1984), McGurr and DeVaney (1998), Laitinen and Laitinen (2000), Zapranis and Ginoglou (2000),Gleason et al. (2000), Ginoglou, Agorastos and Hatzigagios (2002) and Beaver, McNichols and Rhie (2005).Altman (1968a) found that EBIT to total assets outperformed other profitability measures including cash flow. Consistent with Altman (1968a), Izan (1984) also examined the proportion of EBIT to total assets as a useful factor in discerning financially distressed companies in Australia.

Another important profitability ratio used in present research is return on capital employed. Return on capital employed (ROCE) is a financial ratio that measures a company's profitability and the efficiency with which its capital is employed. A higher ROCE reflects more efficient utilization of capital. Many studies in the past have used return on capital employed as one of the factor in predicting the distress of companies (Nirajini and Priya, 2013; Abeywardhana; 2015). Movalia (2015) analyzed the capital structure and profitability of Indian tyres industry. He employed return on capital employed, return on net worth, and return on investment of 13 tyre manufacturing companies. The study concluded that there is a significant relation between capital structure and profitability.

Based on the findings of previous studies we hypothesize that there is negative relationship between the profitability and distress. The past studies have used variety of ratios as a proxy to measure profitability. Each measure of profitability are unique and conveys different meanings. Therefore, in this study uses the exploratory factor analysis to identify a suitable measure for profitability to explain the relationship.

#### 2.3.1.1b Liquidity Ratios

The firm's ability to meet its current obligations as they occur is a measure of liquidity ratios. The short-term solvency of the company is measured through liquidity ratios. The higher level of liquidity decreases the likelihood of financial failure. Most firms meet illiquidity and then become financially insolvent and eventually become bankrupt while they still operate profitably (Khunthong, 1997). Chen and Lee (1993) confirmed that liquidity ratio is one of the significant factors affecting corporate endurance. Chiaramonte and Casu (2017) found the negative relation between the liquidity and distress level.

Studies that found that the current ratios are predominantly used in forecasting bankruptcy include Beaver (1966), Routledge and Gadenne (2000), Zapranis and Ginoglou (2000), Elloumi and Gueyle (2001), Ganesalingam and Kumar (2001), Turetsky and McEwen (2001), Parker, Peters and Turetsky (2002b), Platt and Platt (2002), Ahmad Khaliq et al. (2014), Rajkumar (2014) and Jezovita (2015). Izan (1984) utilized an industry-relative approach rather than traditional ratios in examining corporate financial distress and found that the current ratio is one variable that is univariately significant. Since the current asset measure includes cash, marketable securities, account receivable and inventory, Beaver (1968a) claimed that the inclusion of inventory impairs the current asset measure's usefulness. It has been argued that inventory is not a liquid asset because it must be sold before it can be converted into cash or account receivable. This criticism led to the development of the quick asset measure, which includes cash, marketable securities and account receivable, but not inventory.

The quick ratio was found significant as regards financial distress, financial failure or bankruptcy in Laitinen and Laitinen (2000) and Laitinen (2005). Laitinen (2005) used survival analysis to model the duration of time that precedes a firm's initial payment default. The primary covariates used in the study are financial ratios and results; quick ratio has been shown to be one of most significant financial covariates.

Studies confirmed that cash ratio is one of the liquidity ratio used in financial distress prediction. The cash ratio is the most conservative liquidity ratio among the liquidity ratios. It only measures the ability of a firm's cash along with investments that are easily converted into cash to pay its short-term obligations. Along with quick ratio, a higher cash ratio means that the company is in a better financial position (Cowen & Hoffer, 1982; Mahmood et al., 2009). Darcey McVanel and Nikita Perevalov, 2008 found that the firms holding the highest cash ratios are more likely to be financially distressed, have higher cash-flow variability, are smaller, and have higher expenditures on research and development.

Based on the review we hypothesize that the liquidity has a negative influence on the financial distress. In this study we reexamine this relationship in the Indian context. The present study uses current ratio, quick ratio and cash ratio in order to measure the liquidity of the firms.

**2.3.1.1c Leverage Ratios**

The analysis of financial leverage is related to the capital structure of the firm. These ratios reflect the proportion of funds provided from external sources with the benefit of shareholders. Leverage ratios are used to measure the long-term solvency of firms. In other words, the ratios measure the ability of firms to pay long term liabilities (Khunthong, 1997). Boubaker, Hamza and Vidal-García (2018) also confirmed the ability of leverage to capture the likelihood of corporate default.

The financial distress literature provides specific evidence for the association between financial leverage and a firm’s financial distress or failure, for example, Beaver (1966; 1968a), Dambolena and Khoury (1980), Flagg, Giroux and Wiggins (1991), Charalambous, Charitou and Kaourou (2000), Laitinen and Laitinen (2000), Zapranis and Ginoglou (2000), Charitou, Neophytou and Charalambous (2004), Beaver, McNichols and Rhie (2005) and Margrates and Psillaki (2010).

Based on univariate analysis, debt equity ratio was found to be one of the six best predictors of financial failure in Beaver (1966). Beaver (1968a) also confirmed that the debt ratio predicts financial failure better than the other ratios of leverage at one, four and five years before failure.

Incorporating financial ratio stability measurements with MDA in predicting corporate failure, Dambolena and Khoury (1980) found debt equity ratio to be one of the best predictors in discriminant function. Flagg, Giroux and Wiggins (1991) also found that debt ratio is significantly positively related with a progression towards business failure for firms that enter a potential failure process.

More recently, Beaver, McNichols and Rhie (2005) and Margrates and Psillaki (2010) have suggested that debt ratio is a significant variable for predicting bankruptcy. Additionally, after combining market-based variables with financial ratios, debt ratio remains a significant variable. The authors discussed how leverage remains significant, since the market-based variables do not distinguish between volatility induced by business risk and that induced by financial risk.

Interest coverage ratio measures a company's ability to meet its interest payments on long term debt. This ratio calculates how many times are corporate operating earnings relative to interest payments on liabilities. The higher the interest coverage ratio, the less the debt burden is on the company. The size of interest coverage ratio not only reflects corporate solvency, but also reflects its ability in paying debt capital. In fact, if a company has a high credit history in paying debt interest, i.e. it pays debt interest with the full amount all the time, it may never need to use liquid assets to pay debt capital.

Interest coverage ratio can be used to measure the severity of financial distress (James, 1996) (Mattia Iotti, Giuseppe Bonazzi, 2012), (Toni M. Whited, 1992). It shows the capability of the firm to pay interest on borrowed money and the value should be the minimum value for interest coverage ratio (Khan and Jain, 2004). Harris and Raviv (1990) suggest that leverage is inversely related to interest coverage ratio and they argue that an increase in debt will cause a higher default probability. Therefore, a high interest coverage ratio suggests a low probability of financial distress as default probability has a positive relation with the probability of financial distress.

The study by Michael Dothan (2006) states that nonlinear costs of financial distress provide a possible explanation of why firms find it optimal to have an interest coverage ratio covenant in their debt indenture, even in the absence of information asymmetries or agency costs.

Numan Khan investigated the factors that affect the derivatives usage of non-financial listed firms of Pakistan to hedge foreign exchange exposure by using data of 51 non-financial firms listed on Pakistan stock exchange. Firms such as higher financially distressed have lower interest coverage ratio as it is very difficult for them to fulfill their obligations.

The result of Petr Jakubík, Petr Teply in 2011 revealed that leverage indicators, interest coverage, gross profit margin, inventory ratio, cash ratio and return on net worth have a sufficient power to predict firm's bankruptcy.

The empirical evidence provided by the literature confirms that the leverage has a significant and positive relationship with the distress level. However, the cost of financial distress caused by high leverage is often offset by the benefits of the debt in terms of tax shields (Clemente-Almendros and Sogorb-Mira, 2018). Hence the relationship between the two is reexamined in this study by using the conservative debt puzzle. This study uses debt equity ratio and interest coverage ratio as a measure of financial leverage and a potential determinant of corporate financial distress.

#### 2.3.1.1d Activity ratios

The activity ratios present the efficiency of a firm's assets utilization and measure the ability of a firm to use assets to generate revenue or return. If a firm can use assets efficiently, it will earn more revenue and increase liquidity and net income (Khunthong, 1997).

Regarding total asset turnover, Altman (1968a) pointed out that total asset turnover is the ratio presenting the ability of a firm to generate sales of assets and it is one measure of management's capacity to dole out with competitive conditions. It should be noted that total assets turnover ranked second in its contribution to the overall discriminant ability in the Altman Z-score model.

Jili, and Sanda (2001) investigated the corporate failure in Malaysia. They have developed a logit model and investigated the factor that could be used to predict the failure. Various financial ratios have been used in the study but two main ratios were found to have a significant prediction power. These ratios include interest coverage and total assets turnover.

In the present study debtors turnover ratio measures how rapidly receivables are collected. It is determined by dividing the credit sales by receivables outstanding during the year. Shrabanti Pal (2013) analysed the impact of debtor turnover ratio and fixed assets turnover ratio in addition to profitability ratios in predicting financial distress of steel industry. The study shows that a steel company in India may become financially healthy if it implements good debtor management system as well as proper investment policy. The study indicated that a high score on debtor's turnover ratio and fixed asset turnover ratio are likely to classify a company into financially healthy group. Lesakova (2007) in her study opined that if the fixed assets turnover ratio is high, the firm may not be in a position to use its assets efficiently or a firm is undercapitalized and simply is not in a position to buy enough assets.

Ratio on Inventory turnover measures the number of times that the firm replaces its inventory in a particular period. If the inventory turnover ratio ishigh, it is assumed that the company is having good inventory management. Chakraborty's (2013) study used inventory turnover ratio, working capital turnover ratio, current asset turnover ratio, and debtor's turnover ratio to achieve good performance of the company, while in terms of current ratio and the liquidity position of the company are not good. Several studies used inventory turnover ratio in predicting financial distress namely (DeDemirhan and Anwar, 2014). Choudhary and Tripathi (2012) studied the relation of inventory turnover and financial performance on retail industry in India. The financial ratios considered in this study and their popularity in previous financial failure literature are shown in the table below.

Four activity ratios, namely, inventory turnover ratio, debtor's turnover ratio, fixed asset turnover and total assets turnover, are considered in this study.

**Table 2.1: Summary of Literature Review**

| Category | Financial Ratio | Code | Studies |
|---|---|---|---|
| Profitability Ratio | Gross Profit ratio | GPR | Khunthong (1997), Tirapat and Nittayagasetwat (1999), Ganesalingam, S. and Kumar, K. (2001), Parker, Peters and Turetsky (2002b),Platt and Platt 2002),Charitou, Neophytou and Charalambous (2004), Gestel et al. (2006), Hsin-Hung Chen (2008), and V Bapat & Nagale ( 2014) |
| | Return On Net worth | RONW | Dambolena and Khoury (1980), Kumar and Ganesalingam (2000), Ganesalingam and Kumar (2001), Ganesalingam, S. and Kumar, K. (2001), Lizal (2002), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004) and Gestel et al. (2006), Hsin-Hung Chen (2008), Lorenzo Garlappi and Hong Yan (2011), Yang-Cheng Lu , Chung-Hua Shen and Yu-Chen Wei (2013), Sarbapriya Ray (2014), Nilesh P. Movalia (2015), Ming-Chang Lee and Li-Er Su (2015) |
| | Return on Capital Employed | ROCE | Nirajini A and Priya K. B., (2013), Abeywardhana (2015), Gaglani Hetal, Rao Smita (2015) |
| | Return On Asset | ROA | Altman (1968a), Altman, Haldeman and Narayanan (1977), Dambolena and Khoury (1980), Frydman, Altman and Kao (1985), Molinero and Ezzamel (1991), Hill, Perry and Andes (1996), Ganesalingam and Kumar (2001), Izan (1984), Routledge and Gadenne (2000), Zapranis and Ginoglou (2000), Wruck (1990), Gleason et al. (2000) Ganesalingam and Kumar (2001), Turetsky and McEwen (2001), Ginoglou, Agorastos and Hatzigagios (2002), LeClere (2002), Lizal (2002), Platt and Platt (2002), DeYoung (2003), Beaver et al. (2005), Charitou, Neophytou and Charalambous (2004), Dursun Delen, et. al. (2013), Ming-Chang Lee and Li-Er Su (2015), |
| Liquidity | Current Ratio | CUR | Beaver (1966), Beaver (1968a), Dambolena and Khoury (1980), Ohlson (1980), McGurr and DeVaney (1998), Dimitras et al. (1999), Doumpos and Zopounidis (1999), Charalambous, Charitou and Kaourou (2000), Kumar and Ganesalingam (2000), Routledge and Gadenne (2000), Zapranis and |

| | | | |
|---|---|---|---|
| | | | Ginoglou (2000), Elloumi and Gueyle(2001), Ganesalingam and Kumar (2001), Turetsky and McEwen (2001), Ginoglou, Agorastos and Hatzigagios (2002), Parker, Peters and Turetsky (2002b), Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee (2004), Gestel et al. (2006) and Lamberto and Rath (2008). Mondal and Dilip Roy (2013), Yang-Cheng Lu , Chung-Hua Shen and Yu-Chen Wei (2013), Thai Siew Bee and Mehdi Abdo Uahi (2013), Ahmad Khaliq et al. (2014), Ming-Chang Lee and Li-Er Su (2015), |
| | Quick ratio | QR | Beaver (1966), Beaver (1968a), Dambolena and Khoury (1980), Frydman, Altman and Kao (1985), Keasey, McGuinness (1990), Luoma and Laitinen (1991), Molinero and Ezzamel (1991), Laitinen (1992), Fletcher and Goss (1993), Dimitras et al.(1999), Doumpos and Zopounidis (1999), Ganesalingam and Kumar (2001), Platt and Platt (2002), Charitou,Neophytou and Charalambous (2004), Laitinen (2005) and Gestel et al. (2006), Michael Jacobs, JR., Ahmet K.Karagozoglu and Dina Naples Lavish (2012), Yang-Cheng Lu , Chung-Hua Shen and Yu-Chen Wei (2013), Ming-Chang Lee and Li-Er Su (2015) |
| | Cash Ratio | WCA | Dursun Delen, et. al. (2013), Platt and Platt (2002), Charitou,Neophytou and Charalambous (2004), Laitinen (2005) and Gestel et al. (2006). |
| Leverage | Debt Ratio | DER | Beaver (1966), Beaver (1968a), Gordon (1971), Dambolena and Khoury (1980), Ohlson (1980), Castagna and Matolcsy (1981),Zmijewski (1984), Frydman, Altman and Kao (1985), Lau (1987), Gilbert, Menon and Schwartz (1990), Chan and Chen (1991), Charalambous, Charitou and Kaourou (2000), Kumar and Ganesalingam (2000), Elloumi and Gueyle (2001), Ganesalingam and Kumar (2001), Shumway (2001),Turetsky and McEwen (2001), LeClere (2002), Lizal (2002), Parker, Peters and Turetsky (2002b), Platt and Platt (2002), DeYoung (2003), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee (2004), Beaver, McNichols and Rhie (2005), Rommer (2005), Gestel et al. (2006) and Yu (2006), Hsin-Hung Chen (2008), Michael Jacobset al. (2016), Ashoke Mondal and Dilip Roy (2013), Thai Siew Bee and Mehdi AbdoUahi (2013), |

| | | | |
|---|---|---|---|
| | | | Nilesh P. Movalia (2015) |
| | Interest Coverage Ratio | ICR | Frydman, Altman and Kao (1985), Chan and Chen (1991), Charalambous, Charitou and Kaourou (2000), Kumar and Ganesalingam (2000), Thai Siew Bee and Mehdi AbdoUahi (2013), Nilesh P. Movalia (2015) |
| Activity | Fixed Asset turnover | CPT | Dursun Delen, et. al. (2013), Molinero and Ezzamel (1991) and Laitinen (1992), T Rajashekar,Sania Ashraf and Malabika Deo (2014), Ming-Chang Lee and Li-Er Su (2015) andDejan Jovanovic, Mirjana Todorovic, Milka Grbic, (2017) |
| | Inventory Turnover | | Gokçehan Demirhan, Waseem Anwar (2014), Dursun Delen, et. al. (2013), Dejan Jovanovic, Thai Siew Bee and Mehdi AbdoUahi (2013), Mirjana Todorovic, Milka Grbic, (2017) |
| | Total assets turnover | TAT | Ward and Foster (1997), McGurr and DeVaney (1998), Peters and Turetsky (2002b),Platt and Platt (2002), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee (2004), Hensher, Jones and Greene (2007), Lamberto and Rath (2008) and Van der Goot, Van Giersbergen and Botman (2008), Michael Jacobs, et al. (2016),Yang-Cheng Lu , Chung-Hua Shen and Yu-Chen Wei (2013), Thai Siew Bee and Mehdi AbdoUahi (2013), Sarbapriya Ray (2014). |
| | Debtor's Turnover Ratio | DTR | DeYoung (2003), Charitou, Neophytou and Charalambous (2004), Lensberg, Eilifsen and McKee (2004), Michael Jacobs, et al. (2016),Yang-Cheng Lu , Chung-Hua Shen and Yu-Chen Wei (2013), Thai Siew Bee and Mehdi AbdoUahi (2013), Sarbapriya Ray (2014). |

### 2.3.1.2 Non-Ratio Financial Data

The literature utilizing non-ratio financial data in predicting financial distress or failure can be classified into two groups, specifically, those studies that employ market-based variables and those that utilize financial statement items.

The relationship between market-based variables and corporate failure or financial distress has been examined in various studies. The significant market variables that have been confirmed by previous studies as explaining financial failure include a firm's market returns, a book to market equity (BE/ME), relative market capital size and the standard deviation of stock returns.

Previous studies support the claim that there is an association between the market returns and the likelihood of corporate financial distress. For example, Beaver (1968b) described an investigation into the extent to which changes in the market prices of stocks can be used to predict failure. The study observed the dramatic price decline in the final year before failure, and the failed firms are also riskier in terms of the variability of returns as well as default risk.

In addition, Aharony, Jones and Swary (1980) pointed out that corporate bankruptcy that incorporates accounting ratios has little or no definitive theoretical foundation regardless of the success of the models. The authors argued that market data can provide a gratifying theoretical basis for examining corporate bankruptcy. Based on market risk-return measures, the results found both the total variance and the firm-specific variance behave differently for the bankrupt and for the control groups, four years before the companies going default. Altman and Brenner (1981) assessed the market response to information about problematic firms. The selected companies were tested using a residual methodology in different variants. Although the results were rather ambiguous, it was found that

Bankrupt firms experience a consistent deterioration of capital market returns for at least one year prior to bankruptcy. Further, Campbell, Hilscher, and Szilagyi (2008) in their study in 2008 stated that the returns of stocks of distressed firms are, in fact, too low to be acquiescent within a rational framework. Specifically, they show that distressed stocks have higher market betas, standard deviations, and other measures of risk, and yet, produce very low returns. Similarly, Clark and Weinstein (1983) examined the stock returns behaviour of bankrupt corporations and suggested that there are negative market returns at least three years prior to bankruptcy.

Lindsay and Campbell (1996) used stock returns in developing a bankruptcy prediction model using nonlinear dynamics or chaos theory. The results showed that the returns of firms approaching bankruptcy exhibit significantly less chaos than at an earlier period.

Mossman et al. (1998) developed a bankruptcy prediction model based on four types of data: financial ratios, cash flow, stock returns and standard deviation. The Clark and Weinstein (1983) market return model and the Aharony, Jones and Swary (1980) market return variation model was investigated in this study. The study found that the market adjusts stock prices downward as the probability of bankruptcy increases and the returns standard deviation also shows results consistent with expectations. However, these variables do not display a strong discriminatory ability. The results confirm that the usefulness of ratio and cash flow variables is substantial in comparison with the use of market returns in isolation.

Shumway (2001) developed three market-driven variables along with an accounting variables model to identify failing firms based on a simple hazard model. The market variables include a firm’s relative market capital size, past excess returns and the idiosyncratic standard deviation of the firm’s stock returns. The accounting data employed are the variables used previously by Altman (1968) and Zmijewski (1984). The results found that half of these variables are statistically unrelated to bankruptcy probability. Shumway argued that a model that incorporates both financial ratios and market-driven variables is better than a model that uses solely financial ratios.

Three market-based variables, namely, cumulative residual returns, the standard deviation of security returns and logarithm of the ratio of the market capitalization of the firm divided by the market capitalization of the market index, are employed in Beaver, McNichols and Rhie (2005). The results showed that the market-based variables are a significant factor in predicting bankruptcy even after market-based variables have been combined with financial ratios.

Previous studies, such as Chan and Chen (1991) and Fama and French (1992), argued that a high BE/ME reflects a low stock price relative to book value, which in turn signals a negative market assessment of a firm's prospects and has a negative effect on the likelihood of a distressed firm's survival. While Fama and French (1992) consider financial distress to be the main reason behind the high expected returns of value stocks, other studies that sort stocks on distress proxies directly, such as Dichev (1998), Griffin and Lemmon (2002), and Campbell, Hilscher, and Szilagyi (2008), find that distressed stocks severely underperform healthy stock. Turetsky and McEwen (2001) also employed the absolute value of BE/ME to reflect the market perception or market risk of a firm. The results suggest that the likelihood of a dividend reduction, which precedes the subsequent stage of financial distress following the decrease in cash flow from the operations, is higher for firms that are perceived by the market to be a greater risk.

Griffin and Lemmon (2002) examined the relationship between BE/ME, distress risk and stock returns. The results found that among firms with the highest distress risk as proxied by Ohlson's (1980) O-score, the difference in returns between high and low BE/ME securities is more than twice as large as that in other firms. In contrast, Dichev (1998) used the measures of bankruptcy risk proposed by Ohlson (1980) and Altman (1968a) to identify firms with a high likelihood of financial distress. The outcomes found that corporates with a high bankruptcy risk earn significantly more depressed than average returns since 1980 and indicated that bankruptcy risk is not repaid with higher yields. These results appear to be inconsistent with the view that firms with high BE/ME earn high returns as a premium for distress risk.

In addition to market-based variables, previous studies have employed financial data, specifically, financial statements items in examining financial failure; for example, Honjo (2000) assumed that corporate failure is a resultant of the financial strength and profitability of new firms. Financial strength is then measured by the capital of new firms. The variable 'capital' is defined as the logarithm of paid up capital. It has been found that a new firm without sufficient capital has a higher risk of business failure.

To develop a bankruptcy prediction model in Norway, Lensberg, Eilifsen and McKee (2004) employed fifteen financial ratios and thirteen non-financial ratio measures of prior auditor's opinion, fraud indicators, the presence of financial stress and company start-up year using a genetic programming model. The variable analysis process reduced the number of variables from twenty-eight to six. Based on these six variables, the results confirm that the most significant variable in the final model is the prior auditor's opinion.

### 2.4.2 Non-Financial Data

Regardless of the success of financial ratio models, there is some criticism of the use of financial ratios in a financial distress prediction model, such as financial ratios being subject to window dressing (Moses, 1990; Ryan, 1994), the lack of any theoretical foundation to justify the selection of specific ratios (Aharony, Jones and Swary, 1980; Ryan, 1994; Charitou, Neophytou and Charalambous, 2004) and the fact that ratios are historical rather than prospective or *ex-post* in nature (Johnson, 1970; Moses, 1990).Accordingly, the influences of non-financial data on corporate financial distress have been investigated by few researchers. The non-financial data employed in previous literature can be divided into three categories: corporate governance attributes, company-specific variables and macroeconomic variables. The details of each category are discussed as follows.

#### 2.4.2.1 Corporate Governance Attributes

Corporate governance mechanisms have received wide care in corporate financial distress prediction researches since the occurrence of a serial publication of corporate collapses in the late 1990s (Becht, Bolton and Roell, 2002).

Studies have explored the relationship between corporate governance attributes with corporate performance in various countries, for example, in Australia (Balatbat, Taylor and Walter, 2004), China (Claessens and Djankov, 1999; Xu and Wang, 1999; Hovey, Li and Naughton, 2003; Bai et al., 2004; Li and Naughton, 2007, Lajili & Zeghal, 2010) and the UK (Weir and Laing, 2001). If corporate governance influences corporate performance, then it is expected that corporate governance attributes will affect the likelihood of corporate survival (Goktan, Kieschnick and Moussawi, 2006). The extensive literature has focused on examining corporate governance mechanisms as potential predictors of financial failure as discussed in more detail in the following sections.

Bi-Huei Tsai, 2013 adopted multinomial logit models to separately measure the extent to which financial ratios and corporate governance signal the likelihood of "slight distress events" and "reorganization and bankruptcy." The results show that corporate governance variables are closely related to the occurrence of "slight distress events." The estimated misclassification costs of the 1,000 resamples generated through bootstrapping procedures are statistically lower for a model that makes use of corporate governance (CG model) than one without corporate governance (non-CG model) at all cut-off points in 2009, and cut off points from 0.11 to 0.27 in 2008. Since corporate governance is incrementally useful in predicting financial distress, the CG model's predictive ability improves as two corporate governance factors are considered: ownership ratio of insiders and pledge-ownership ratio of insiders.

#### 2.4.2.1a. Board Size

The results regarding the influence of board size on corporate survival are indecisive. On the one hand, it is expected that a company with a larger board size will be less likely to fail as a result of the greater accountability of the directors (Lamberto and Rath, 2008) and the wider range of views and external connections (Pfeffer and Salancik, 1978). Evidence to support this argument is found in an empirical study by Chaganti, Mahajan and Sharma (1985), which found that non-failed retailing firms tend to have bigger boards than failed ones. To add, Tanna et al. studied the connection between efficiency of UK banks and board structure and concluded that there is a positive relationship between size and financial performance (Tanna et al., 2011). On the other hand, some researchers have opined that the performance of the companies can be made betterby having small number of people on the board as large number of people result in ineffective meetings and lack of proper co-ordination and difficult to come to a consensus. The problems of large board size often exist when there are too many people involved in the decision-making process (Kellen K. Kiambati et.al. 2013; Jensen, 1993; Harris & Raviv, 2008). Hence, we hypothesize that lager board size in a firm with financial distress would not be able to take quick decisions and thus leads to default.

#### 2.4.2.1b Board Independence

There is no common consensus relating to the definition of 'independence' even though the concept of board independence has been generally being acknowledged by the researchers in the past. (Brennan and McDermott, 2004; Kang, Cheng and Gray, 2007). Earlier studies use the word 'outside directors' instead of 'independent' to describe directors who are assumed to be autonomous from the management (Ajinkya, Bhojraj and Sengupta, 2005). Close to existing studies simply consider the disputes between 'executive' and 'non-executive' directors (Kang, Cheng and Gray, 2007; Lamberto and Rath, 2008). Tanna et al. (2011) showed a positive relationship between independent representatives in the board and financial efficiency, proving the fact that outsiders can bring valuable expertise and knowledge. Further, few studies contradict to the previous opinion by saying that in reality companies would prefer insider-controlled board of directors (Donaldson, 1990; Harris & Raviv, 2008; Kiel & Nicholson, 2003). They do not have enough knowledge about company that influences the poor decision-making (Schooley et al., 2010). The study hypothesizes that the presence of independent directors would improve the governance and monitoring mechanisms and thus has a negative relationship with the financial distress.

#### 2.4.2.1c. Ownership Concentration

Based on the information asymmetry theory, when stockholdings are concentrated, information asymmetries are low, so the ability of stockholders to remove a management team is high and managers are more likely to pursue strategies that are in stockholders' interests. In contrast, when stockholdings are diffused, significant information asymmetries are likely to exist and management is then more likely to pursue strategies inconsistent with stockholder's interests (Hill and Snell, 1989).

Based on agency theory, the likelihood of survival of firm is more if there is high ownership concentration. Since, shareholders are more likely to have an influence on decision making in the company, shareholders will want to expend monitoring costs as their stake in the firm is relatively high (Jensen and Meckling, 1976). Therefore, high ownership concentration is expected to increase corporate performance and, consequently, corporate survival. Investigating publicly listed Chinese companies, Bai et al. (2004) found that a high degree of concentration among other large shareholders enhanced a firm's market value.

However, using three measures of ownership structure, that is, the percentage of shares owned by the five largest shareholders, the 20 largest shareholders and the Herfindahl index, Demsetz and Lehn (1985) opined that ownership concentration has no relation with accounting profits of a company. Consistent with Demsetz and Lehn (1985), Hovey, Li and Naughton (2003) also indicated that ownership concentration does not explain performance of companies in China.

Previous studies provide mixed evidence on the influence of institutional investors on firm's performance during financial difficulties. Citron and Muradoglu in their study in 2008 finds that market reacts negatively on distress resolution for firms with government ownership and state-owned enterprise in China as compared to non-state owned enterprise while Kang, et al., 2010 finds that financial institutions in Korea, including commercial banks do not play any significant role in monitoring firms before the Asian financial crisis. However, Tykova and Borell, 2012 found that institutional investors are better able to manage distress risks than their inexperienced counterparts.

The study by Rizki (2014) focused on indicators of ownership structure on the likelihood of financial distress where liquidity as an intervening variable. The results showed that there is no significant influence between institutional ownership of the financial distress.

Further, the non-institutional ownership does not have any effect to boil down the probability of business failure in the Spanish context argued Montserrat Manzaneque et al. (2016). They further justified that dominant shareholders in the context of concentrated ownership limit the role of board's ownership to control management taking risky decisions. These results are contrary to earlier studies that shows a inverse relationship between concentration of ownership and possibility of business failure (Donker *et al*., 2009; Elloumi and Gueyie, 2001; Mangena and Chamisa, 2008). The study examines the role of ownership structure in financial distress.

#### 2.4.2.2.1.d CEO Duality

A dual leadership exist when a firm's CEO also serves as a chairman of the board of directors. If different individuals serve in these positions, then the term 'independent structure' is used. There is a mixed opinion on the effect of dual leadership and financial distress. Some studies argue that board on which the chairperson and CEO are the same is ineffective because it reduces the board's ability to fulfill its governance activities and this might create conflict of interest (Fama & Jensen, 1983; Lipton & Lorsch, 1992; Jensen, 1993). In contrast, advocates of the CEO duality structure argue that it provides a single, clear focus for objectives and operations (Rechner and Dalton, 1991). Abor and Biekpe (2007) who also found the positive but insignificant results of CEO duality with leverage.

It should be noted that Elsayed (2007) found that duality in leadership had no impact on corporate performance. However, CEO duality attracts a positive and significant coefficient only when corporate performance is low. But, Abor (2007) found that there positive but insignificant results of CEO duality with leverage. Baklouti (2016) concludes that the separation of the functions of CEO and chairman of the board makes the board more powerful, thereby giving better supervision capacity. Furthermore, Brickley, Coles and Jarrell (1997) claimed that proponents of the dual leadership structure base their arguments on a mix of anecdotal evidence and an intuitive appeal to common sense. The author suggested that there are both costs and benefits involved in using dual leadership structure. This structure may create a potential for rivalry between CEO and the chairperson, making it difficult to pinpoint the blame for poor performance.

### 2.4.2.2 Company-Specific Variables

This section reviews the company-specific variables, for example, company size, age and industry sector used in the existing literature. The firm specific variables are used as the control variables to understand the effect of financial and non-financial factors on financial distress.

**i. Company Size**

In order to study the influence of size of the company on financial distress, researchers measure company size in different ways, for example, total assets (Lamberto and Rath, 2008), the logarithm of total assets (Lizal, 2002; Parker, Peters and Turetsky, 2002b; Lensberg, Eilifsen and McKee, 2004; Rommer, 2004; Rommer, 2005; Gestel et al., 2006), the natural logarithm of total assets (Hensher, Jones and Greene, 2007), the logarithm of sales (Laitinen, 1992), the natural logarithm of sales (Chen and Lee, 1993; Hill, Perry and Andes, 1996) and the number of employees (Audretsch and Mahmood, 1995; Lennox, 1999; Audretsch and Lehmann, 2004; Kauffman and Wang, 2007).

Some of the literature supports the claims of inverse relationship between size of the firm and the likelihood of financial distress, for example, Altman, Haldeman and Narayanan (1977), Ohlson (1980), Audretsch and Mahmood (1995), Lennox (1999), Nikitin (2003), Lensberg, Eilifsen and McKee (2004) and Hensher, Jones and Greene (2007).However, Altman, et. al. (1977) found that company size is one of seven significant variables out of an initial twenty-seven variables in the MDA model. Ohlson (1980) concluded that size of the company is an important predictor of bankruptcy in all three models tested based on logit analysis and found company size had a negatively significant effect on the probability of failure within one year.

Similarly, Audretsch and Mahmood (1995) confirmed that the start-up size of the company is inversely related to new firm failure. Furthermore, Lennox (1999) examined the causes of bankruptcy for UK-listed companies and demonstrated that there is likely chances of business failure of small companies when compared to the large ones. Nikitin (2003) also found establishment size is one of the major determinants of business survival in Indonesia.

Lensberg, Eilifsen and McKee (2004) utilized firm size in a developing bankruptcy prediction model in Norway. The results suggest that the risk of financial distress is negatively related to firm size except when profits are negative, and an unfavorable audit report has a more negative bankruptcy status impact for a large firm than for a small one. After examining financial distress in the four-state failure framework, Parker, Peters and Turetsky (2002b) indicated that company size is positively associated with bankruptcy likelihood. The outcomes propose that there are likely chances for larger distressed firms to go bankrupt as they have greater difficulty in maintaining ongoing operations during periods of financial distress. This result is consistent with the study by Lamberto and Rath (2008), who suggested that the size of the firm is inversely related to survival of the company.

It should be observed that some of the previous studies have not found that company size is significantly related to the likelihood of financial distress; for example, Turetsky and McEwen (2001) examined the relationship between firm size and financial distress and the results showed that size is not significant. This is also in lines with the study by Yu (2006), who found that size in terms of total assets, did not have a significant effect on the bankruptcy hazard.

Additionally, Rommer (2005) compared the determinants of financial distress across countries, namely, Italy, France and Spain. Company size is expected to have a significantly negative effect on financial distress. The estimations show that size was an insignificant factor of corporate financial distress in the Spanish case. In the Italian case, size had positive effect while, in the French case, size had the expected sign.

**ii. Company Age**

In addition to company size, company age is another company-specific variable suggested by the literature that might significantly affect the likelihood of corporate failure. For example, Chen and Lee (1993) investigated the survival of oil and gas companies during the turmoil of the early 1980s and found that company age, which was measured by the number of years the firm had existed up to the end of 1981, was negatively related to corporate failure.

Lensberg, Eilifsen and McKee (2004), when developing their bankruptcy model for Norwegian companies, provided evidence that new companies have a considerably higher rate of bankruptcy as compared to that of established concerns. In developing a four-state failure model based on the error component logit analysis, Hensher, Jones and Greene (2007) defined company age as a dummy variable coded 1 if a firm had been established in the previous six years, and coded 0 otherwise. The finding was that the probability of failure increased for firms who were less than six years old.

Comparing the determinants of financial distress across countries, namely, Italy, France and Spain, company age has a significantly negative effect on financial distress, according to Rommer (2005). However, the study offers inconclusive results. Specifically, company age was an insignificant predictor of financial distress for Spanish company, had the expected sign in the Italian case and had an unexpected sign based on the French data.Naz Sayari and F.N. Can Simga Mugan, 2013, in their study studied whether company age and company size has any significant impact on determination of financial distress score among companies and concluded that company age are statistically significant and have a negative relation with financial distress score of companies.

**iii. Company Industry Sector**

Another company-specific variable investigated by the previous literature is industry sector. For example, Mata and Portugal (1994), in examining the survival duration time of Portuguese firms, provided evidence that corporate survival rates differ extensively across industry sectors.

Hensler, Rutherford and Springer (1997) investigated the indicators of IPO firms' survival and found that the survival of American firms varies with industry sector. Specifically, the survival time had a negative effect if the IPO firm is in the information technology, hospitality or airline industries. Further, the effect of survival time was positive for the IPO firm in optical or drug industries.

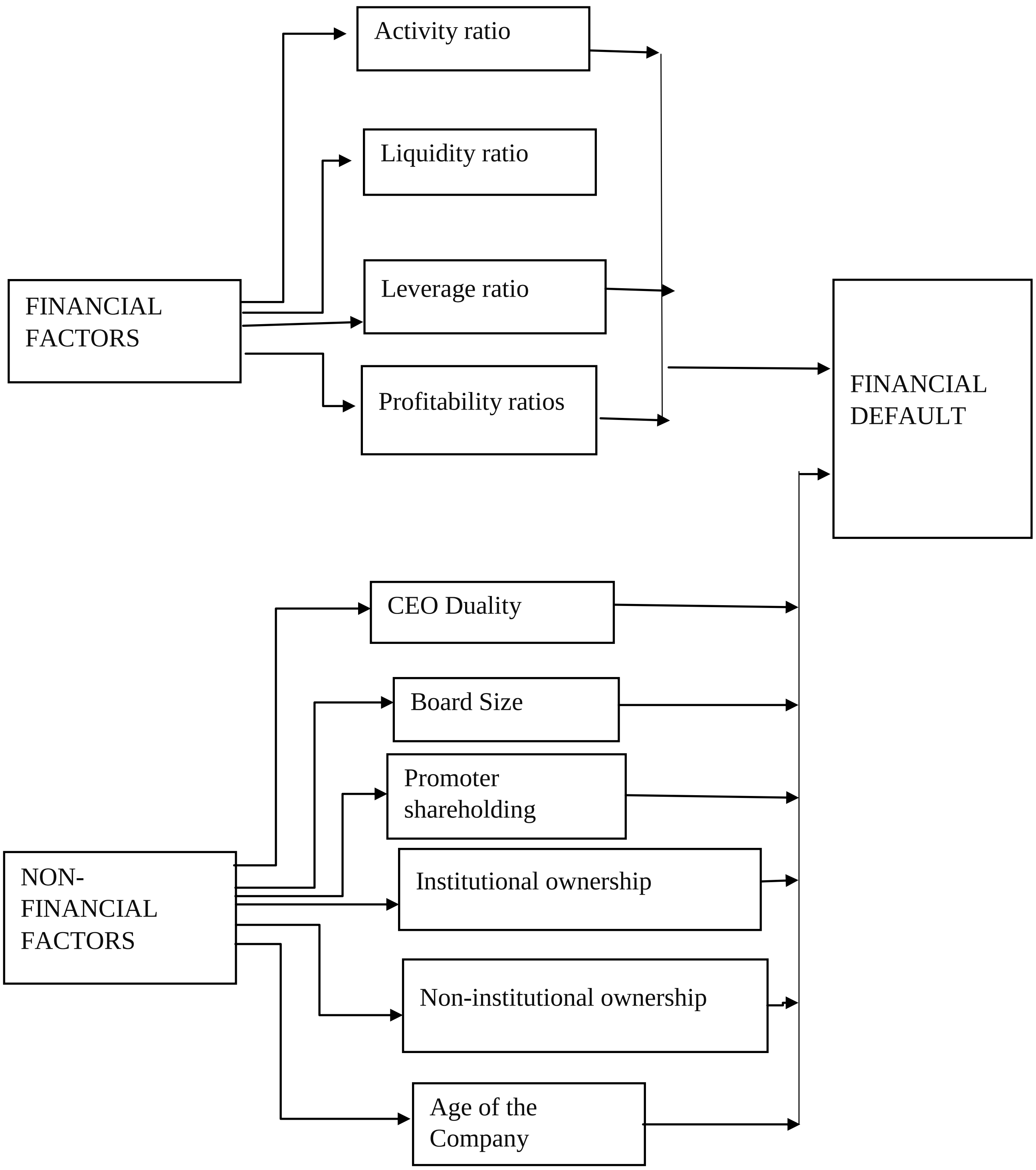
Similar results were found in Lennox (1999), which reported that company industry sector is an important predictor of bankruptcy. Specifically, companies in the construction or financial services are more likely to enter bankruptcy. Rommer (2004) also justified that the probability of financial distress varies among various business sectors. The results found that firms in the trade and hotel, transport, business, and public service activities and organizations are less likely to face financial distress compared to manufacturing firms while firms that belong to the self-constructed IT and telecommunications category have a higher financial distress likelihood than all other firms. In addition, Hensher, Jones and Greene (2007) indicated that firms in the finance sector have a higher standard deviation or variance of excess market returns and lesser standard deviation or variance of cash resources to total assets than have firms from the non-finance sector.

The review of literature reveals that there are numerous studies in the past examining the causes and effects of the financial distress. Broadly, financial factors and non-financial factors are used to predict the financial distress. However, this research examines the combined effect of the two factors on financial distress. To the best of our knowledge, there are very few studies in the Indian context examining the usefulness of non-financial factors in influencing the financial distress levels. Further, this study employs the paired sampling technique to understand the impact.

A detailed Research Framework developed based on the review of literature is shown in chart 2.1.

**Chart No.: 2.1**

**Research Framework developed based on the Review of Literature**



## 3.1 INTRODUCTION

In order to test the hypotheses stated in the earlier chapter and establish an appropriate model to identify the factors which have a high correlation with the occurrence of financial default, it is necessary to use the company's data and the proper methods to organize the financial distress predictive model. This chapter discusses and presents the process of data collection, sample selection and the methods used in the present study. The present study is based on both empirical and analytical studies using secondary data.

## 3.2 RESEARCH APPROACH

To predict the financial distress of a firm using the financial distress using financial and non-financial factors, we adopt paired sampling technique. In paired sampling technique, the firm identical to the financially distressed firm is used to understand the effect. The financially distressed firms are drawn from the list published by RBI. The data for the study is collected from CMIE Prowess and ACE Equity databases. The financial factors as well as non-financial factors used in the study are through exploratory factor analysis. Subsequently, logistic regression models are used to predict the usefulness of financial and non-financial factors in predicting the financial distress.

## 3.3 SAMPLE SELECTION IN THE PRESENT STUDY

For the purpose of study, both default and healthy Indian companies are considered. The data pertaining to defaulters list are obtained from the Reserve Bank of India. The companies who are defaulters for consecutive three years are selected. Among 1104 borrowers reported as defaulters by RBI, all the companies that had a financial default situation for the period 2010-15 were identified. The privately held firms and firms with incomplete information are excluded. As a result, 175 companies with complete corporate governance and financial data publicly available are included in the study.

Further with respect to non-default and healthy companies, matched-pairs research design was used for developing the sample. This method of constructing the sample is also developed in studies by Elloumi and Gueyie, 2001, Hosmer and Lemeshow (1989), Mangena and Chamisa (2008) and Peasnell *et al*. (2001). Based on this technique, each of these financial default observations was matched with companies which were not in financial default observations having similar size in terms of total asset, belonging to the same industry and with the same accounting period (Beasley, 1996, Mangena and Chamisa, 2008 and Peasnell *et al*., 2001).The matched pair process resulted in a final sample of 350 companies with 175 paired observations (with 175 as default and 175 non-default companies).The data pertaining to financial and non-financial variables of the selected companies are collected from CMIE Prowess and ACE Equity Database.

In terms of time period for data selection, the sample companies are examined overthe period from 2010 to 2015. Many prior research studies have demonstrated that some firm specific financial variables or non-financial variables in the last three years before financial distress are significant variables in predicting financial distress for the firms (Kuo et al., 2003; Wu, 2004; Ooghe and Balcaen, 2007). Thus, for the selected default companies, the present study uses their data in the last five years prior to the occurrence of their financial distress. Accordingly, 175 healthy companies are also studied in the respective financial year. The present study codes the year of their financial distress happening as T. According to logic, the last five years prior to the occurrence of their financial distress are coded as T-4, T-3, T-2 and T-1 respectively. The five consecutive years are coded as T-4, T-3, T-2 and T-1 respectively from the furthest year to the latest year with year T as the year of default.

## 3.4 SELECTION OF FINANCIAL DISTRESS PREDICTORS

The financial ratios of companies have been widely used as predictor variables in models that was used to forecast business distress and default (Altman 1968; Altman, Haldeman and Narayanan 1977; Barnes 1987; Kuo et al., 2003; Wu, 2004; Jones and Hensher, 2004; Smith, 2005; Chen, 2008). So a substantial number of financial ratios have thus been suggested in previous literature. For example, Smith (2005, p. 23) indicated that the influence of four key categories of financial ratios, incorporating gearing variables, liquidity ratios, profitability ratios and working capital ratios, could be combined to be a measure of financial performance and an excellent indication of financial distress. Similarly, in a mainland China's study, Wang and Li (2007) found that some categories of financial ratios (activity ratios, growth ratios, interest coverage ratios and profitability ratios) have strong classification capability in financial distress prediction of listed companies.

In addition to firm-specific financial ratios, different firm-specific non-financial variables, such as management measures, corporate governance variables can also be used to forecast a firm's distress. For instance, Keasey and Watson (1987) employed several firm-specific non-financial variables of management structure, accounting information system.

Table 3.1 shows the firm-specific financial ratios along with their formulae and nonfinancial variables which are used in the present study. The market related information is discussed separately in this chapter.

**Table No.: 3.1**
**Financial Distress Predictors used in the Present Study**
**(Panel A Firm-specific financial ratios used in this study)**

| Category | Financial Ratios | Abbreviations | Definition |
|---|---|---|---|
| Profitability Ratios | Return on Assets | ROA | Net Profit or Loss / Total Assets *100 |
| | Return on Net Worth | RONW | Net after-tax profits÷ (Shareholder capital + Retained earnings) |
| | Return on Capital Employed | ROCE | Earnings before interest and taxes÷ ( Total assets - Current liabilities) |
| | Gross Profit Ratio | GPR | (Gross Profit ÷ Net Sales) * 100 |
| Liquidity Ratios | Current Ratio | CUR | Current Assets ÷ Current Liabilities |
| | Quick Ratio | QR | (Current Asset – Stock)÷ Current Liability |
| | Cash Ratio | CR | (Cash + Short-term marketable securities) ÷ current liabilities |
| Activity Ratios | Inventory Turnover Ratio | ITR | Cost of Goods Sold ÷ Average Inventory |
| | Assets Turnover Ratio | ATR | Net revenues ÷ Average total assets |
| | Fixed Asset Turnover Ratio | FATR | Net Revenue ÷ Total Fixed Assets |
| | Debtor's Turnover Ratio | DTR | Cost of Goods Sold ÷ Average Debtors |
| Leverage Ratio | Debt Equity Ratio | DER | (Total Debts ÷ Equity) *100 |
| | Interest Coverage Ratio | ICR | Earnings before interest and taxes ÷ Interest payments |

**(Panel B Firm-specific non-financial variables used in this study)**

| Non-Financial Variables | Abbreviation | Explanation |
|---|---|---|
| Promoter shareholding | PROMSH | The percentage of shares held by promoter and promoter group. |
| CEO Duality | CEOD | Duality in Leadership |
| Institutional ownership concentration | IO | Percentage of shares owned by institutional large shareholders (large shareholders are those that owns three percent or more of shares) |
| Non-institutional ownership concentration | NIO | Percentage of shares owned by non-institutional large shareholders (large shareholders are those that owns three percent or more of shares) |
| Independent Director | PID | Proportion of independent outside directors on the board of directors |
| Board Size | BS | Total number of Board of Directors |
| Age | AGE | Age of the Company |

## 3.5 METHODOLOGY

### 3.5.1 Mann Whitney Wilcoxon Test

The present study uses the Mann Whitney Wilcoxon Test to examine the difference in financial and non-financial factors between default and non-default companies. The MWW Test is a nonparametric test developed jointly by Mann, Whitney and Wilcoxon. It is also called the Mann-Whitney U test or the Wilcoxon rank sum test. In other words, both the Mann-Whitney U test and Wilcoxon rank sum test are equivalent (Anderson, Sweeney and Williams, 2008). Therefore, the present study refers these two tests as the Mann-Whitney-Wilcoxon (MWW) test. The MWW test can be used to determine whether there is a difference between two populations.

Unlike the t-test, MWW test does not require the assumption of normal distributions nor requires interval data. There are only two requirements of the MWW test. The first requirement is that the measurement scale for the data is at least ordinal. The second requirement is that the two samples from two populations should be independent. Hence, the MWW test examines whether two populations are identical instead of testing for the difference between the two populations' means (Anderson, Sweeney and Williams, 2008).

### 3.5.2 Factor Analysis

Factor analysis is used in the present study to minimize thirteen financial ratios to several financial factors. The main purpose of using factor analysis is to extract common factors and to modify multicollinearity among variables. The extracted variables are then used further to develop multiple regression model in studying the impact of financial factors in the influence of financial distress.

Factor analysis is a data reduction technique used for reducing a large number of variables to a lesser number of presumed underlying hypothetical entities called factor (Fruchter, 1967). The 'factor' in factor analysis refers to the group or clump of related variables. Therefore, this technique is designed to take a number of variables and let the data be summarized using a smaller set of components or factors. In addition, factor analysis can reduce a large set of related variables to a smaller and more manageable number prior to using the data in other analyses (Pallant, 2007). In the present study, 'Principal Components Varimax Rotated Method' of factor analysis has been used in order to identify the causes of financial distress.

According to Pallant (2007), there are certain assumptions underlying the application of factor analysis. The first assumption is the size of the sample. Even though, there is no common agreement in the literature pertaining to how large the sample should be, the overall sample size of 100 or more than 100 is acceptable and a minimum of five cases for each of the variables is required for factor analysis (Coak, 2005, p.154; Pallant, 2007, p.185). For the Year T, data of 350 companies are selected. These data incorporate the values of thirteen financial variables. Therefore, the sample size for the Year T is suitable for factor analysis.

Another assumption is that the correlation matrix should have at least some correlations with *r* being no less than 0.3. Moreover, the Kaiser-Meyer-Olkin value ranges from 0 to 1 and should be no less than 0.5 (Child, 2006, p.55). The Bartlett's test of Sphericity should have a *p* value less than 0.05 (Pallant, 2007, p.185).

Further, catell's scree test is another commonly used technique. This technique plots and graphically displays the eigenvalues for each of the factors. It then inspects the plot to find the point at which the shape of the curve makes an elbow and becomes less steep. Finally, all the factors, which are after the factor starting the elbow, should be dropped and the remaining factors should be retained. These remaining factors explain most of the variance in the data set (Pallant, 2007).

### 3.5.3 Altman's Z Score

The financial distress level of the companies is measured by Altman Z Score model. The Z score is considered as the dependent variable to study the impact of financial factors on the company's financial distress. The independent variables are the extracted factors from factor analysis.

Altman used five ratios to calculate the Z-Score. These different ratios were combined into a single measure Z-Score Analysis with the help of MDA. The formula used to evaluate the Z-Score analysis as established by Altman is as follows:

*Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5*

*Where,*

*"Z" is the overall index and*

*X1 = ratio of working capital to total assets*

*X2 = ratio of retained earnings to total assets*

*X3 = ratio of earnings before interest and taxes to total assets*

*X4 = ratio of market value of equity to book value of debt*

*X5 = ratio of sales to total assets*

This model predicts that the lower the Z-score, the greater a firmsdistresspotential. The optimal or cutoff scores are 1.81 and 2.67 and the scores between1.81 and 2.67 represent the grey area, called the zone of ignorance.

For Private Firms:

$Z = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$

$X_1$ = (current assets − current liabilities) / total assets

$X_2$ = retained earnings / total assets

$X_3$ = earnings before interest and taxes / total assets

$X_4$ = book value of equity / total liabilities

$X_5$ = sales / total assets

Further, if $Z > 2.9$ – "Safe" Zone

$1.23 < Z' < 2.9$ – "Grey" Zone; $Z < 1.23$ – "Distress" Zone

For Non- manufacturers:

$Z = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$

$X_1$ = (current assets − current liabilities) / total assets

$X_2$ = retained earnings / total assets

$X_3$ = earnings before interest and taxes / total assets

$X_4$ = book value of equity / total liabilities

Further, if $Z > 2.6$ – “Safe” Zone

$1.1 < Z < 2.6$ – “Grey” Zone

$Z < 1.1$ – “Distress” Zone

Each company’s Z score model was calculated based on the nature of the company and used as dependent variable for analyzing the financial distress for achieving the second objective in the present study.

The Z score, developed by Professor Edward I. Altman, is perhaps the most widely recognized and applied model for predicting financial distress (Bemmann, 2005). Altman developed this intuitively appealing scoring method at a time when traditional ratio analysis was losing favor with academics (Altman, 1968).

### 3.5.4 Multiple Regression

The present study applied multiple regression analysis to study the impact of financial factors on the level of financial distress. The extracted financial factors are used as independent variables for developing multiple regression analyses. The dependent variable is the Altman Z-Score of the respective companies. The equation for multiple regression analysis is presented below:

$$FD_{it} = f\,(PROF_{it} + SOLV_{it} + LIQ_{it} + ACT_{it}) + u_{it}$$

where, $FD_{it}$ = Altman Z Score for company *i* at time *t*; $PROF_{it}$ are the extracted profitability ratios (namely return on networth at time T, T-1, T-2, T-3, gross profit ratio at T-4) for company *i* at time *t*; $SOLV_{it}$ are extracted solvency ratios (namely debt equity ratio at time T, T-1, T-2, T-3, T-4 and interest coverage ratio for company *i* at time T, T-1, T-2, T-3, T-4); $LIQ_{it}$ are extracted liquidity ratios (namely current ratio at time T, T-1, T-2, T-3, T-4; $ACT_{it}$ are extracted activity ratios (namely inventory turnover ratio at time T, T-1, T-2, T-3 T-4, debtor’s turnover ratio at time T-1, T-2, fixed asset turnover ratio T, T-3, T-4) for company *i*..

### 3.5.5 Logistic Regression

To analyze the impact of non-financial factors on chances of default, logistic regression is applied. Here, the dependent variable is whether the companies experienced default or not (default = 1, non-default =0). The study tried to analyze the two models. Model 1 considering only financial ratios. The non-financial factors along with the financial ratios are considered in model 2 taking financial factors as controlled variables in predicting financial distress.

Model based on Financial Data (Pindado et al., 2008):

$$FD = \beta_0 + \beta_1 RONW_{it} + \beta_2 CUR_{it} + \beta_3 ICR_{it} + \beta_4 ITR_{it} + d_t + n_{it} + u_{it} \qquad \text{....(1)}$$

Model based on Financial Data and Corporate Governance Variables:

$$FD = \beta_0 + \beta_1 RONW_{it} + \beta_2 CUR_{it} + \beta_3 ICR_{it} + \beta_4 ITR_{it} + \beta_5 NIO_{it} + \beta_6 IO_{it} + \beta_7 PROMSH_{it} + \beta_8 CEOD_{it} + \beta_9 PID_{it} + \beta_{10} BS_{it} + \beta_{11} AGE_{it} + d_t + n_{it} + u_{it} \qquad \text{....... (2)}$$

Where;

*FD* = Financial distress (measured as a dummy variable coded one for default and zero for non-default companies); *RONW* = Return on Net worth; *CR*= Current ratio; *ICR* = Interest Coverage Ratio; *ITR*= Inventory Turnover Ratio; NIO = Non-institutional Ownership; *IO* = Institutional ownership concentration; *PROMSH* = Promoter Shareholding; *CEOD* = duality in CEO (measured as a binary variable which takes value 1 when Chair and Chief Executive Officer are the same person and 0, when they are not); *PID*= Proportion of independent outside directors to the number of members in the board; *BS* = number of board members; *AGE* = age of the company; $d_t$ = Time effect; $n_{it}$ = Individual effect; $u_{it}$ = Random disturbance

### 3.5.6 Market Response to Financial Distress

In order to ascertain the stock market response to announcement of default (objective 4), the event study methodology was adopted. Hypothesis 5 was associated with this objective. All listed companies who are defaulters for consecutive three years are considered for the purpose. Among the 175 default companies selected, 79 companies were listed in the stock exchange.

Event study methodology was applied to observe the trend of returns of the select listed companies during pre-and post-windows. An event study is a statistical method which is normally used to measure the impact of an event on the value of a firm. In this study, the trends of returns before and after distress announcements were observed.

The parameters of the market model like alpha, and beta based on returns on stocks and market index in the estimation period are estimated, and then expected returns on each stock are calculated based on the market model in order to measure the abnormal gains/losses to target company shareholders. The estimated abnormal returns (ARs) of each stock are added and then average ARs are computed for each day during the event window to calculate AARs. The following market model proposed by Sharpe in 1963 is used in the study to compute the abnormal return:

$$AR_{it}=R_{it}-(\alpha_i+\beta_i R_{mt})$$

The cumulative AARs of different days during the event window are designated as the CAARs. Each security return is divided into two parts. These are those returns which can be attributed to market movement and those which cannot be attributed to market movement but to takeover announcement. The stock price responses to the takeover announcement or the event are measured by eliminating the market's influence on stock's observed rate of return. The methodology employed for the purpose is called 'Residual Analysis Methodology' since it involves calculation of residuals defined as that part of stock's returns which is not explained by movement of the market. These residuals are explained by the event-related news of a particular company for which these are calculated. In the present analysis, the market model measures the returns of stocks related to market movement. The market model is based on the fact that the most important factor affecting a stock's returns is market factor and it is captured in the market model in the form of beta (β). It is a simple model to analyze the risk component of stocks in terms of systematic and unsystematic risks. Thus, the market model relates the return on any stock or portfolio of securities to the return on the market in a linear fashion. The actual tests are performed on the returns in these types of studies. Mathematically, the market model can be expressed as:

$$E(R_{it}) = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad \text{for } i = 1, \ldots, n$$

Thus, the market model divides security returns into two components — systematic component ($\beta_i R_{mt}$) and an unsystematic component ($\varepsilon_{it}$). The systematic component measures the impact of general market movement, and unsystematic component, also called error term, measures the influence of micro event on the rate of return of individual security. Thus, the error term is a firm-specific component.

Further, logarithmic form of the model is also used in this study which is stated below:

$$\text{Log}R_{it} = \alpha_i + \beta_i log_e L_t + u_{it}$$

Where,

$R_{it}$z= Price relative of í'th security in time 't'; $\alpha_i$ = Alpha coefficient of ith security; $+\beta_i$= Beta coefficient of ith security; $u_{it}$= an error term with zero mean and a constant variable during time period 't'.

After computing the AARs and CAARs, statistical significance of these computed values are tested at a required confidence level. The statistical significance of AARs and CAARs are tested by using cross sectional standard deviation of ARs. These values are generated from the estimation period.

Statistical Significance of AARs: The hypothesis is that the cross-sectional AARs are zero. The statistical significance of AAR for each day't' surrounding the event day is assessed by dividing $AAR_t$by its standard deviation which is denoted by $\sigma AAR_t$.

$$\text{Test Statistic} = \frac{AAR_t}{\sigma AAR_t}$$

Where,

$$AAR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N}$$

$AAR_t$= Average abnormal return on day 't'in the event window

$AR_{it}$= Abnormal returns on security í'on day 't'

N = Total number of securities

t = the days surrounding the event day.

$\sigma AAR_t$= Standard deviation of $AAR_t$

$$\sigma_{AARt} = \sqrt{\frac{\sum_{t=1}^{T}(AAR_t - \overline{AAR})^2}{(N-1)}}$$

Where,

$$\overline{AAR} = \frac{\sum_{t=1}^{T} AAR_t}{N}$$

$AAR_t$ = Average abnormal return on day ‘t’in the estimation period

$\overline{AAR}$ = Mean of AARs in the estimation period

N= total number of days in the estimation period

The above model was employed by Dodd (1980), Gong and Firth (2006) and Mann and Kohli (2008).

The test statistic to assess the statistical significance of CAARs is:

$$Z = \frac{CAAR}{\sigma AAR_t * \sqrt{T}}$$

where, CAAR = $\sum_{t=1}^{T} AAR_t$

The market response to the financial distress announcement compliments the study to understand price reaction and the market efficiency. In an efficient market, it is expected that the price incorporates the future information about the firm. This also indicates that the market expectations for the firm which are in the verge of default. For instance, if the firm is getting into the financial distress the prices would incorporate this expectation in the price. So we assume that the stock price is also one of the good predictor of default.

### 3.6 CONCLUSION

In summary, this chapter began with describing the sample of default and non-default companies. The variables used in the study are clearly defined and the methodology to be adopted for achieving each objective is clearly stated in this chapter.

This main purpose of this chapter is to analyze the data and test the hypothesis. The first two objectives would be analyzed in detail and the corresponding hypothesis would be tested. As discussed in the earlier chapter, the present study codes the year of their financial default happening as T. According to logic, the last five years prior to the occurrence of their financial distress and default are coded as T-4, T-3, T-2 and

T-1 respectively. The level of financial distress of the companies is measured by Altman Z Score model.

This chapter is divided into five sections for the Year T, T-1, Year T-2, Year T-3 and Year T-4. In each section, the present study uses three methods to analyze the data for the corresponding year and test the hypotheses along with narrating the description of the sample for analyzing the first two objectives.

The Mann Whitney Wilcoxon test was firstly run to distinguish the difference between default and non-default companies in financial and non-financial performance. This method is used to test Hypothesis 1 and Hypothesis 2.

## 4.1 INTRODUCTION

The present study then used factor analysis to reduce thirteen financial ratios to several financial factors. This resulted in a manageable number of factors which could be used in multiple regression.

After the MWW test and factor analysis, the extracted financial factors were used as independent variables for regression analyses. The dependent variable is the distress level of firms derived from Altman Z Score. This chapter then used multiple regression analyses to test Hypothesis 3.

## 4.2 DATA ANALYSIS FOR THE DATA OF YEAR T

### 4.2.1 Descriptive Statistics

Table 4.1 narrates the financial ratios of both default and non-default companies in the year by default. It could be observed here that the profitability ratios of default companies, namely, return on assets, return on capital employed, gross profit ratio and return on net worth were negative. While the non-default firms had a higher profitability ratio. Further the interest coverage ratio and the debt equity ratio are also negative for default firms. The asset turnover ratio was higher for non-default firms when compared with the default companies.

**Table No.: 4.1**
**Test Statistic for Financial Ratios of Select Companies at Year T**

| Ratios | Default Companies | | | | Non-Default Companies | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | $25^{th}$ | $75^{th}$ | Mean | SD | $25^{th}$ | $75^{th}$ |
| ATO | 0.66 | 0.83 | 0.08 | 0.08 | 1.07 | 1.27 | 0.24 | 1.36 |
| CR | 273.83 | 790.14 | 28.20 | 181.98 | 178.06 | 579.95 | 28.73 | 114.81 |
| CUR | 2.18 | 6.29 | 0.40 | 1.83 | 25.80 | 157.07 | 0.96 | 1.99 |
| DER | -1.87 | 63.11 | -1.30 | 3.19 | 3.14 | 21.09 | 0.02 | 1.73 |
| DTR | 9.70 | 17.67 | 1.51 | 9.66 | 879.77 | 9871.15 | 3.08 | 12.45 |
| FATR | 6.21 | 27.48 | 0.16 | 1.90 | 18.60 | 145.17 | 0.92 | 5.24 |
| GPR | -77.04 | 408.86 | -27.21 | 0.00 | -13.25 | 170.71 | 0.00 | 14.75 |
| ICR | -80.19 | 678.69 | -1.71 | 1.13 | 83.96 | 538.89 | 1.08 | 8.75 |
| ITR | 9.12 | 22.41 | 1.46 | 8.18 | 1862.34 | 20787.31 | 3.41 | 11.62 |
| QR | 1.60 | 5.94 | 0.22 | 1.38 | 33.96 | 262.06 | 0.73 | 2.28 |
| ROA | -10.85 | 28.23 | -15.84 | 0.26 | 2.61 | 7.16 | -0.22 | 5.69 |
| ROCE | -1.60 | 35.46 | -10.32 | 8.22 | 8.35 | 22.99 | 0.04 | 16.00 |
| RONW | -78.65 | 419.22 | -23.51 | 0.00 | -5.45 | 95.38 | 0.00 | 13.78 |

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.2.2 Mann-Whitney-Wilcoxon Test for Year T

According to statistical theory as stated earlier, the MWW test is used to determine whether there is a difference between two populations. The present study used the MWW test to test Hypothesis 1 and Hypothesis 2.

In order to test these two hypotheses, the present study firstly inputted the values of all thirteen corporate financial ratios, and six non-financial variables into the SPSS. MWW test was then used to observe the difference in financial ratios and non-financial variables between default and non-default companies.

Hypothesis 1and Hypothesis 2 is tested by using the MWW test as follows.

Hypothesis 1:

Null Hypothesis 1: There are no significant differences in financial ratios between default and non-default companies.

Alternative Hypothesis 1: There are significant differences in financial ratios between default and non-default companies.

The MWW test statistics for financial ratios at year T is presented in Table 4.2. In this table, the Z means the Z-score and the Asymp. Sig. (2-tailed) refers to the two-tailed *p* value which has been corrected for ties. The output of the test indicates that all the financial ratios except for debt equity ratio have two-tailed *p* values less than 0.05.

In other words, the MWW test results of thirteen financial ratios, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Only the debt equity ratio's result of MWW test is not significant at five per cent level of significance.

The results of MWW test show that there is a significant difference in the Year T's twelve financial variables between the default and non-default companies.

Therefore, for all the tested financial variables except for debt equity ratio, the Null Hypothesis 1 cannot be accepted. For only one financial variable (debt equity ratio), however, the Null Hypothesis 1 cannot be rejected.

**Table No. 4.2**
**MWW Test for Financial Ratios at Year T**

| **Particulars** | **ATR** | **CR** | **CUR** | **DER** | **DTR** |
|---|---|---|---|---|---|
| Mann-Whitney U | 9434 | 9409.5 | 9202 | 11858.5 | 8407.5 |
| Wilcoxon W | 22637 | 20584.5 | 20983 | 23793.5 | 19285.5 |
| Z | -4.378 | -1.819 | -3.95 | -0.758 | -3.033 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.009 | 0.000 | 0.448 | 0.002 |
| **Particulars** | **FATR** | **GPR** | **ICR** | **ITR** | **ROA** |
| Mann-Whitney U | 7954.5 | 7547.5 | 4882 | 6795.5 | 5630.5 |
| Wilcoxon W | 21157.5 | 20750.5 | 16510 | 16948.5 | 18833.5 |
| Z | -5.644 | -6.684 | -8.475 | -3.845 | -8.886 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **Particulars** | **ROCE** | **RONW** | **QR** | | |
| Mann-Whitney U | 7491 | 6946 | 7486.5 | | |
| Wilcoxon W | 19426 | 18881 | 20366.5 | | |
| Z | -6.14 | -6.901 | -6.553 | | |
| Asymp. Sig. (2-tailed) | 0.000 | 0.000 | 0.000 | | |

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

Hypothesis 2:

Null Hypothesis 2: There are no significant differences in non-financial variables between default and non-default companies.

Alternative Hypothesis 2: There are significant differences in non-financial variables between default and non-default companies.

Table 4.3 exhibits MWW test statistics for the non-financial variables for year T. The output of the test indicates that all the non-financial variables except duality in CEO have two-tailed *p* values less than 0.05. Accordingly, all the six non-financial variables' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Thus, the results of MWW test reveals that there are significant differences in the Year T's five non-financial variables between the default and non-default firms.

**Table No.: 4.3**

**MWW for Non-Financial Factor at Year T**

| **Particulars** | **AGE** | **BS** | **CEOD** | **IO** | **NIO** | **PID** | **PROMSH** |
|---|---|---|---|---|---|---|---|
| Mann-Whitney U | 12953.5 | 11939.5 | 12231 | 625 | 1968 | 809.5 | 1120.5 |
| Wilcoxon W | 26156.5 | 23874.5 | 25434 | 13828 | 15171 | 12744.5 | 14152.5 |
| Z | -0.200 | -0.663 | -1.798 | -9.647 | -5.86 | -14.9 | -4.907 |
| Asymp. Sig. (2-tailed) | 0.002 | 0.007 | 0.072 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

### 4.2.3 Factor Analysis and Multiple Regression for Year T

As discussed earlier, the present study used factor analysis to reduce thirteen financial ratios to several factors. Further, using factor analysis to extract the common factors made possible the modification of multicollinearity among all the ratios and variables considered in the present study (Kuo et al., 2003). The basic purpose of conducting factor analysis in the present study was to extract the factors or variables required to further conduct multiple regression in order to test hypothesis 3.

The extracted financial factors could then serve as inputted independent variables for multiple regression. The dependent variable is the distress level of the companies which is derived by Altman Z Score. The present study then used regression analyses to test Hypothesis 3.

### 4.2.3a Factor Analysis for Financial Ratios

The Kaiser-Meyer-Olkin measure of sampling adequacy and the results of the Bartlett's test of Sphericity for the year T are illustrated in Table 4.4. The Kaiser-Meyer-Olkin Measure is 0.525 which is greater than 0.5. It means that the financial ratios are adequate for factor analysis. Moreover, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. This in turn suggests that there are significant correlations between the financial ratios.

On the whole, according to, Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's Test of Sphericity, it can be concluded that the data of the present study is suitable for factor analysis.

**Table No. 4.4**
**KMO and Bartlett's Test for Year T**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .525 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 861.913 |
| | Sig. | .000 |

The present study used factor extraction to determine the smallest number of financial factors that could best represent the interrelations among a group of financial ratios. All the available financial ratios for the Year T were inputted into the SPSS. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

As was discussed in Chapter 3, factors with eigen value greater than 1 could be retained for further investigation. In table 4.5, there are six factors (Factor 1, 2, 3, 4, 5 and 6) with their eigen values greater than 1. Overall, these six factors explain about 72 per cent of the original variance.

Secondly, in Figure 4.1, the scree plot line begins to flatten out from seventh factor. As a result, according to theory of Catell's scree test discussed in earlier chapter, the scree plot also shows that it is appropriate to retain six factors for running regression analysis.

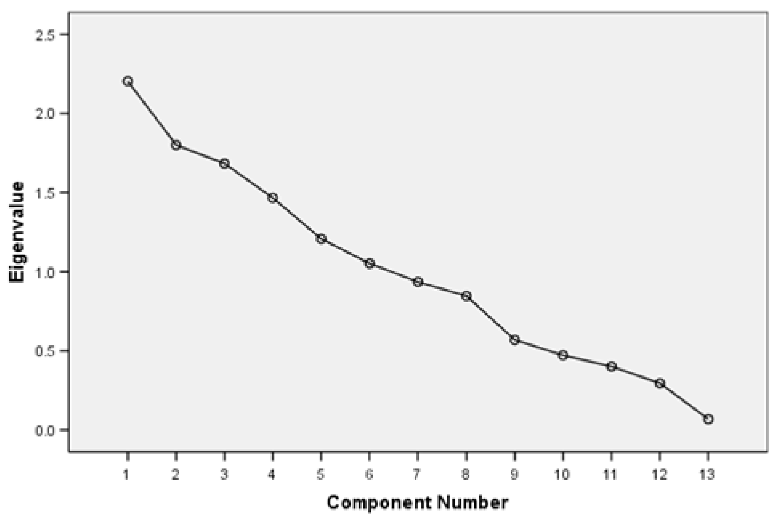
**Table No. 4.5**
**Total Variance Explained for Financial Factors for Year T**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 2.203 | 16.949 | 16.949 | 2.203 | 16.949 | 16.949 | 1.934 | 14.879 | 14.879 |
| 2 | 1.801 | 13.852 | 30.801 | 1.801 | 13.852 | 30.801 | 1.818 | 13.983 | 28.862 |
| 3 | 1.684 | 12.953 | 43.754 | 1.684 | 12.953 | 43.754 | 1.698 | 13.065 | 41.927 |
| 4 | 1.466 | 11.278 | 55.032 | 1.466 | 11.278 | 55.032 | 1.503 | 11.563 | 53.490 |
| 5 | 1.207 | 9.285 | 64.317 | 1.207 | 9.285 | 64.317 | 1.319 | 10.146 | 63.636 |
| 6 | 1.051 | 8.086 | 72.403 | 1.051 | 8.086 | 72.403 | 1.140 | 8.767 | 72.403 |
| 7 | .935 | 7.196 | 79.599 | | | | | | |
| 8 | .847 | 6.515 | 86.115 | | | | | | |
| 9 | .569 | 4.376 | 90.491 | | | | | | |
| 10 | .472 | 3.629 | 94.120 | | | | | | |
| 11 | .401 | 3.085 | 97.205 | | | | | | |
| 12 | .295 | 2.270 | 99.475 | | | | | | |
| 13 | .068 | .525 | 100.000 | | | | | | |

Extraction Method: Principal Component Analysis.

**Chart No. 4.1**

**Scree plot for Year T**




After the rotation, the number of complex variables among factors decrease and the factors become easier to be interpreted. The rotated factors are shown in the rotated factor matrix. The extracted factors from the component matrix of the factor analysis is used as independent variable to run the OLS regression to determine the influence of financial factors on the distress level.

The component matrix in table 4.6 groups the variables into different factors. From each of the group, one variable having higher eigen value was selected for running multiple regression. From the above table, return on net worth, interest coverage ratio, inventory turnover ratio, current ratio, debt equity ratio and fixed asset turnover ratio have been extracted as independent variable. As discussed earlier Altman Z Score was taken as dependent variable.

**Table No.: 4.6**
**Component Matrix for Year T**

| | Factor | | | | | |
|---|---|---|---|---|---|---|
| **Variabkes** | **1** | **2** | **3** | **4** | **5** | **6** |
| ROCE | 0.604 | | | | | |
| RONW | 0.714 | | | | | |
| GPR | 0.705 | | | | | |
| ROA | 0.595 | | | | | |
| ATR | 0.451 | | | | | |
| ICR | | 0.742 | | | | |
| CR | | 0.445 | | | | |
| ITR | | | . 637 | | | |
| CUR | | | | 0.663 | | |
| QR | | | | 0.638 | | |
| FATR | | | | | 0.530 | |
| DTR | | | | | 0.374 | |
| DER | | | | | | 0.814 |

Extraction Method: Principal Component Analysis.
a 6 components extracted.

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.2.3b Correlation Matrix

In order to check the multicollinearity of all these six ratios, the present study checked the intercorrelation among these ratios. Multicollinearity occurs when these factors are highly correlated with the value of *r* being more than 0.4 (Tabachnick and Fidell, 2007). The values of correlation are presented in Table 4.6 show that the values of *r* are all less than 0.4. Therefore, there are no multicollinearities among these six ratios and all these factors can be retained.

**Table No.: 4.7**
**Correlation Matrix of Financial Ratios for the Year T**

| **Variables** | RONW | ITR | CUR | ICR | DER | FATR |
|---|---|---|---|---|---|---|
| RONW | 1 | .010 | .017 | .011 | .012 | .016 |
| ITR | .010 | 1 | -.001 | .005(**) | -.001 | -.015 |
| CUR | .017 | -.001 | 1 | .019 | -.004 | .009(**) |
| ICR | .011 | .005(**) | .019 | 1 | -.002 | .029 |
| DER | .012 | -.001 | -.004 | -.002 | 1 | -.004 |
| FATR | .016 | -.015 | .009(**) | .029 | -.004 | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio and RONW is return on net-worth.*

### 4.2.3c Regression Analysis

The extracted financial factors are used for running multiple regression analysis.

Table 4.8 narrates the influence of financial ratios on the distress level.

**Table No.: 4.8**
**Estimates of Regression Analysis for the Year T**

| | **Unstandardized Coefficients** | | **Standardized Coefficients** | | |
|---|---|---|---|---|---|
| **Variables** | **B** | **Std. Error** | **Beta** | **T** | **Sig.** |
| (Constant) | -4.781 | 1.412 | | -3.385 | .001 |
| RONW | .000 | .004 | -.001 | -1.037 | .007 |
| ITR | .003 | .000 | .902 | 33.132 | .000 |
| CUR | 2.886 | .280 | .240 | 10.302 | .000 |
| ICR | -.002 | .005 | -.012 | -.426 | .670 |
| DER | .011 | .025 | .010 | .430 | .667 |
| FATR | -.126 | .058 | -.054 | -2.171 | .031 |

*$R^2 = 0.875$*

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio and RONW is return on net-worth.*

Based on the above table, it is observed that return on networth, inventory turnover ratio, current ratio and fixed asset turnover ratio were significant at 5% level of significance as the *p* value was less than 0.05. It is observed that these ratios had a significant affect on financial distress prediction. Interest coverage ratio, though was not significant had a negative effect on the level of distress i.e. increase in interest coverage ratio would lead to decrease in the level of distress of the company. Debt equity ratio and interest coverage ratio did not have significant power in explaining the level of financial distress.

## 4.3 DATA ANALYSIS FOR THE DATA OF YEAR T -1

### 4.3.1 Descriptive Statistics

Table 4.9 provides the summary descriptive statistics for the entire sample companies selected. It could be observed here that return on assets (mean = 2.6) and return on capital employed (mean 8.35) was higher in healthy companies compared to the default companies with -10.8 and -7.7 respectively.

**Table No.: 4.9**
**Test Statistic for Financial Ratios of Select Companies at Year T-1**

| Ratios | Default Companies | | | | Non-Default Companies | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | 25th | 75th | Mean | SD | 25th | 75th |
| ATO | 0.67 | 0.76 | 0.15 | 0.95 | 1.07 | 1.27 | 0.24 | 1.36 |
| CR | 190.20 | 451.39 | 30.76 | 174.22 | 178.06 | 579.95 | 28.73 | 114.81 |
| CUR | 2.60 | 4.03 | 0.62 | 3.30 | 25.80 | 157.07 | 0.96 | 1.99 |
| DER | -2.93 | 62.81 | -1.53 | 3.54 | 3.14 | 21.09 | 0.02 | 1.73 |
| DTR | 9.06 | 16.67 | 1.66 | 8.40 | 879.77 | 9871.15 | 3.08 | 12.45 |
| FATR | 6.66 | 27.58 | 0.28 | 2.42 | 18.60 | 145.17 | 0.92 | 5.24 |
| GPR | -42.22 | 158.87 | -28.16 | 0.00 | -13.25 | 170.71 | 5.89 | 14.75 |
| ICR | -81.65 | 597.55 | -1.29 | 1.11 | 83.96 | 538.89 | 1.08 | 8.75 |
| ITR | 9.19 | 21.88 | 1.56 | 7.65 | 1862.34 | 20787.31 | 3.41 | 11.62 |
| QR | 1.88 | 3.47 | 0.36 | 1.97 | 33.96 | 262.06 | 0.73 | 2.28 |
| ROA | -10.81 | 31.65 | -13.30 | 0.18 | 2.61 | 7.16 | -0.22 | 5.69 |
| ROCE | -7.73 | 81.79 | -10.03 | 7.89 | 8.35 | 22.99 | 0.04 | 16.00 |
| RONW | -37.67 | 151.84 | -26.53 | 0.01 | -5.45 | 95.38 | 0.00 | 13.78 |

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

Though the gross profit ratio and return on net worth of both default and non-default companies were negative, it was least for the defaulted companies -42.22 and -37.7 as compared to the non-default firms with an average of -13.24 and -5.45 respectively. Further the average liquidity ratios namely current and quick ratio was more for the non- default companies. The activity ratios were also high for the non-default firms compared to the defaulted companies. The asset turnover ratio of non-default company was 1.07 while it was 0.67 for the distressed firm. Further, the mean of fixed asset turnover ratio was 18.59 for the non-default company while it was 6.66 for the distressed firm.

### 4.3.2 Mann Whitney Wilcoxon Test for Year T-1

Table 4.10 presents the MWW test statistics for financial ratios. The output of the test indicates that all the financial ratios except for debt equity ratio and current ratio, have two-tailed *p* values less than 0.05. Eleven financial ratios' results of MWW test namely return on capital employed, return on assets, gross profit ratio, return on net worth, inventory turnover ratio, debtors' turnover ratio, fixed asset turnover ratio, asset turnover ratio, quick ratio, cash ratio and interest coverage ratio, with correction for Z-score conversion and ties, are significant at five per cent level of significance. Therefore, for eleven financial ratios, the Null Hypothesis 1 can be rejected. However, for debt equity ratio and current ratio, the Null Hypothesis 1 cannot be rejected.

**Table No.: 4.10**

**MWW Test for Financial Ratios at Year T-1**

| **Particulars** | **ATR** | **CR** | **CUR** | **DER** | **DTR** |
|---|---|---|---|---|---|
| Mann-Whitney U | 9803.5 | 9221.5 | 11486.5 | 12454.0 | 8460.0 |
| Wilcoxon W | 23006.5 | 20396.5 | 23267.5 | 24389.0 | 19635.0 |
| Z | -3.939 | -2.26 | -1.122 | -0.025 | -3.128 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.024 | 0.262 | 0.980 | 0.002 |
| **Particulars** | **FATR** | **GPR** | **ICR** | **ITR** | **ROA** |
| Mann-Whitney U | 8624.5 | 7354.5 | 4716.5 | 6974.5 | 5629.5 |
| Wilcoxon W | 21827.5 | 20557.5 | 16192.5 | 17414.5 | 18832.5 |
| Z | -4.821 | -6.891 | -8.639 | -3.731 | -8.887 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **Particulars** | **ROCE** | **RONW** | **QR** | | |
| Mann-Whitney U | 7332.5 | 6852.0 | 9874.5 | | |
| Wilcoxon W | 19267.5 | 18787.0 | 22754.5 | | |
| Z | -6.334 | -6.991 | -3.694 | | |
| Asymp. Sig. (2-tailed) | 0.000 | 0.000 | 0.000 | | |

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

Table 4.11 displays MWW test statistics for non-financial variables. The output of the test indicates that six out of seven non-financial variables have two-tailed *p* values less than 0.05. Accordingly, these six non-financial variables' results of MWW test namely non-institutional investors, institutional investors, promoter shareholding, board size, proportion of independent directors and age of the company, with correction for Z score conversion and ties, are significant at five per cent level of significance. Therefore, for these non-financial variables, the Null Hypothesis 2 can be rejected Only one nonfinancial variable (duality in CEO) has two-tailed *p* value more than 0.05. Thus, the results of MWW test reveals that there are significant differences in the Year T-1's six non-financial variables between the default and non-default firm. On the other hand, there are no significant differences between default and non- default companies with regards to the duality in CEO which was similar to year T. However, for duality in CEO, the Null Hypothesis 2 cannot be rejected.

**Table No.: 4.11**
**MWW for Non-Financial Factor at T-1**

| **Particulars** | **AGE** | **BS** | **CEOD** | **IO** | **NIO** | **PID** | **PROMSH** |
|---|---|---|---|---|---|---|---|
| Mann-Whitney U | 13082.50 | 11686.00 | 12474.00 | 673.00 | 1983.00 | 730.00 | 992.0 |
| Wilcoxon W | 26285.50 | 23621.00 | 25677.00 | 13876.00 | 15186.00 | 13133.00 | 24012.5 |
| Z | -0.05 | -0.98 | -1.35 | -9.49 | -5.81 | -15.14 | -4.47 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.028 | 0.177 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

### 4.3.3 Factor Analysis and Multiple Regression for Year T-1

The present study used factor extraction to determine the smallest number of financial factors that could best represent the interrelations among a group of financial ratios for the year T-1. All financial ratios related to year T-1 was taken for the purpose. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

#### 4.3.3a Factor Analysis for Financial Ratios

Initially, Kaiser's criterion was used to assist in the decision concerning retaining the factors. This could be seen in table 4. 12. The Kaiser-Meyer-Olkin Measure of

Sampling Adequacy for the year T-1 was .542 which is greater than .5. This suggests that the financial variables are adequate for running factor analysis. In addition, the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It indicates that there are significant correlations between the variables.

**Table No.: 4.12**
**KMO and Bartlett's Test for Year T-1**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .542 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 268.577 |
| | Sig. | .000 |

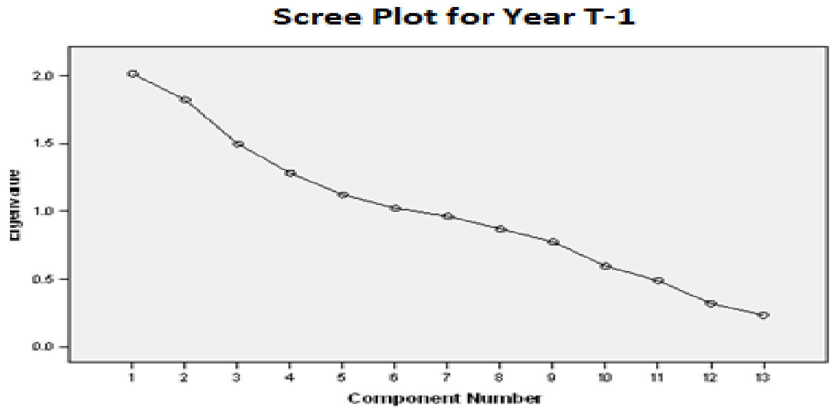
As discussed in Chapter 3, factors with eigenvalue greater than 1 could be retained for further investigation. In Table 4.13, there are six factors (Factor 1, 2, 3, 4, 5 and 6) with their eigenvalues greater than 1. Overall, these three factors explain about 67 per cent of the original variance.

**Table No.: 4.13**
**Total Variance Explained for Financial Factors for Year T-1**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 2.014 | 15.496 | 15.496 | 2.014 | 15.496 | 15.496 |
| 2 | 1.821 | 14.011 | 29.506 | 1.821 | 14.011 | 29.506 |
| 3 | 1.497 | 11.513 | 41.019 | 1.497 | 11.513 | 41.019 |
| 4 | 1.281 | 9.855 | 50.874 | 1.281 | 9.855 | 50.874 |
| 5 | 1.122 | 8.631 | 59.505 | 1.122 | 8.631 | 59.505 |
| 6 | 1.022 | 7.859 | 67.364 | 1.022 | 7.859 | 67.364 |
| 7 | .963 | 7.405 | 74.769 | | | |
| 8 | .869 | 6.688 | 81.457 | | | |
| 9 | .774 | 5.954 | 87.411 | | | |
| 10 | .595 | 4.576 | 91.987 | | | |
| 11 | .487 | 3.749 | 95.736 | | | |
| 12 | .320 | 2.461 | 98.197 | | | |
| 13 | .234 | 1.803 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

**Chart No.: 4.2**




The component matrix grouped different financial ratios into six factors. Among the six factors grouped, return on net worth, inventory turnover ratio, current ratio, interest coverage ratio, debtor's turnover ratio and debt equity ratio were considered for running multiple regression.

**Table No.: 4.14**
**Component Matrix for Year T-1**

| | Factors | | | | | |
|---|---|---|---|---|---|---|
| **Ratios** | **1** | **2** | **3** | **4** | **5** | **6** |
| ROCE | 0.327 | | | | | |
| RONW | 0.730 | | | | | |
| GPR | 0.711 | | | | | |
| ROA | 0.421 | | | | | |
| ATR | 0.573 | | | | | |
| ITR | | 0.722 | | | | |
| CR | | 0.412 | | | | |
| CUR | | | 0.688 | | | |
| FATR | | | 0.432 | | | |
| QR | | | 0.609 | | | |
| ICR | | | | 0.871 | | |
| DTR | | | | | 0.513 | |
| DER | | | | | | 0.630 |

Extraction Method: Principal Component Analysis.

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.3.3b Correlation matrix

Table 4.15 shows that the correlation matrix of all extracted financial variables for the Year T-1 to check for collinearity. The table shows six ratios with *r* being lesser than 0.4. Therefore, the matrix is suitable for regression analysis.

**Table No.: 4.15**
**Correlation Matrix of Financial Ratios for the Year T-1**

| **Ratios** | RONW | ITR | CUR | ICR | DER | DTR |
|---|---|---|---|---|---|---|
| RONW | 1 | .014 | .020 | .002 | .102 | .029 |
| ITR | .014 | 1 | -.001 | .005(**) | .000 | -.004 |
| CUR | .020 | -.001 | 1 | .020 | -.004 | -.005 |
| ICR | .002 | .005(**) | .020 | 1 | .000 | -.003 |
| DER | .102 | .000 | -.004 | .000 | 1 | .005 |
| DTR | .029 | -.004 | -.005 | -.003 | .005 | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

The component matrix grouped different financial ratios into six factors. Among the six factors grouped, return on net worth, inventory turnover ratio, current ratio, interest coverage ratio, debtor's turnover ratio and debt equity ratio were considered for running multiple regression. These ratios were considered as independent variables in predicting financial distress. The Altman Z Score is taken as dependent variable. Table 4.16 shows regression coefficients of all the financial variables extracted for the Year T-1.

### 4.3.3c Regression Analysis

The OLS regression analysis was conducted for Year T-1 based on the factors extracted. The details of the same are given below. Based on the above table, it is observed that return on net worth, inventory turnover ratio, current ratio and debtor's turnover ratio are significant at 5% in the year T-1. It is observed that these ratios have a significant effect on financial distress prediction. Interest coverage ratio again had a negative effect on the level of distress i.e. increase in interest coverage ratio would lead to decrease in the level of distress of the company. Similar to the year of default, debt equity ratio and interest coverage ratio did not have significant power in explaining the level of financial distress and hence hypothesis 3 is not accepted for these two ratios.

**Table No.: 4.16**
**Estimates of Regression Analysis for the Year T-1**

| Variables | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | -3.527 | 1.036 | | -3.405 | .001 |
| RONW | .005 | .007 | .910 | 12.630 | .000 |
| ITR | .003 | .000 | .936 | 45.381 | .000 |
| CUR | 2.579 | .190 | .227 | 13.569 | .000 |
| ICR | -.002 | .004 | -.010 | -.487 | .626 |
| DER | .022 | .018 | .021 | 1.224 | .222 |
| DTR | -.085 | .038 | -.038 | -2.254 | .025 |

$R^2 = .934$

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth*

## 4.4 DATA ANALYSIS FOR THE DATA OF YEAR T -2

### 4.4.1 Descriptive Statistics

Table 4.17 describes the financial ratios of the selected sample for the year T-2. It could be observed here that the average of asset turnover ratio is more for the non-default companies (1.07) as compared to the default companies with an average of 0.77. The fixed asset turnover ratio was also greater for non-default companies. The liquidity ratios also showed a similar trend. The debtor's turnover ratio was 879.77 in the case of non-default companies when compared to 8.03 in case of defaulted firms.

Even though, the gross profit ratio and return on net worth showed a negative value for both default and non- default firms, it was least for distressed firms when compared to the non-default companies. The return on capital employed and return on assets were also more for the non-default firms.

**Table No.: 4.17**
**Test Statistic for Financial Ratios of Select Companies at Year T-2**

| Ratios | Default Companies | | | | Non-Default Companies | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | $25^{th}$ | $75^{th}$ | Mean | SD | $25^{th}$ | $75^{th}$ |
| ATO | 0.77 | 0.88 | 0.22 | 1.05 | 1.07 | 1.27 | 0.24 | 1.36 |
| CR | 137.05 | 227.67 | 31.92 | 133.90 | 178.06 | 579.95 | 28.73 | 114.81 |
| CUR | 4.07 | 10.52 | 0.83 | 3.54 | 38.14 | 349.36 | 1.02 | 2.05 |
| DER | 2.16 | 9.65 | -1.11 | 3.66 | 32.80 | 349.34 | 0.01 | 1.89 |
| DTR | 8.03 | 10.49 | 2.20 | 9.13 | 879.77 | 9871.15 | 3.08 | 12.45 |
| FATR | 13.74 | 78.73 | 0.27 | 3.68 | 18.60 | 145.17 | 0.92 | 5.24 |
| GPR | -25.67 | 129.35 | -22.46 | 4.66 | -13.25 | 170.71 | 0.00 | 14.75 |
| ICR | 14.29 | 399.00 | -1.06 | 1.39 | 83.96 | 538.89 | 1.08 | 8.75 |
| ITR | 11.43 | 31.57 | 2.01 | 7.92 | 1862.34 | 20787.31 | 3.41 | 11.62 |
| QR | 3.28 | 10.25 | 0.39 | 2.20 | 33.96 | 262.06 | 0.73 | 2.28 |
| ROA | -5.76 | 20.30 | -11.87 | 1.41 | 2.61 | 7.16 | -0.22 | 5.69 |
| ROCE | 1.49 | 26.87 | -7.20 | 10.28 | 8.11 | 36.10 | 0.00 | 16.22 |
| RONW | -26.26 | 132.16 | -22.98 | 4.94 | -6.28 | 93.21 | 0.00 | 13.54 |

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.4.2 Mann-Whitney-Wilcoxon Test for Year T-2

The MWW test for financial ratios for the year T-2 is presented in table 4.18. With respect to year T-2, the output of the test indicates that the debt equity ratio, current ratio and quick ratio have *p* value more than 0.05, while the other financial ratios namely, return on capital employed, return on assets, gross profit ratio, inventory turnover ratio, debtor's turnover ratio, asset turnover ratio, fixed asset turnover ratio, cash ratio, return on net worth and interest coverage ratio had a p-value less than 0.05. Therefore, for current ratio, debt equity ratio and quick ratio, the null hypothesis 1 cannot be rejected. However, for the rest of the financial ratios, the null hypothesis 1 can be rejected.

**Table No.: 4.18**
**MWW Test for Financial Ratios at T-2**

| **Particulars** | **ATR** | **CR** | **CUR** | **DER** | **DTR** |
|---|---|---|---|---|---|
| Mann-Whitney U | 10646.00 | 10050.5 | 11607.50 | 11187.50 | 9200.50 |
| Wilcoxon W | 23849.00 | 21225.5 | 24327.50 | 24390.50 | 20525.50 |
| Z | -2.939 | -1.318 | -0.794 | -1.677 | -2.195 |
| Asymp. Sig. (2-tailed) | 0.003 | 0.007 | 0.427 | 0.094 | 0.028 |
| **Particulars** | **FATR** | **GPR** | **ICR** | **ITR** | **ROA** |
| Mann-Whitney U | 9501.00 | 8912 | 5302.5 | 7326.0 | 7034.5 |
| Wilcoxon W | 22542.00 | 22115 | 16627.5 | 17766.0 | 20237.5 |
| Z | -3.667 | -5.02 | -7.795 | -3.197 | -7.221 |
| Asymp. Sig. (2-tailed) | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 |
| **Particulars** | **ROCE** | **RONW** | **QR** | | |
| Mann-Whitney U | 8921 | 9063 | 11379.00 | | |
| Wilcoxon W | 21011 | 21153 | 24259.00 | | |
| Z | -4.456 | -4.306 | -1.893 | | |
| Asymp. Sig. (2-tailed) | 0.000 | 0.000 | 0.058 | | |

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

**Table No.: 4.19**
**MWW for Non-Financial Factor at Year T- 2**

| **Particulars** | **AGE** | **BS** | **CEOD** | **IO** | **NIO** | **PID** | **PROMSH** |
|---|---|---|---|---|---|---|---|
| Mann-Whitney U | 13083 | 7172 | 13041 | 279.5 | 1129.5 | 1228 | 1241.5 |
| Wilcoxon W | 26286 | 12528 | 26244 | 13482.5 | 14332.5 | 6584 | 13965 |
| Z | -0.046 | -1.941 | -0.179 | -9.537 | -6.961 | -11.82 | -6.94 |
| Asymp. Sig. (2-tailed) | 0.963 | 0.002 | 0.858 | 0.000 | 0.000 | 0.000 | 0 |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

Table 4.19 indicates MWW test statistics for non-financial variables at year T-2. The output of the test indicates that two out of six non-financial variables namely duality in CEO and age of the company have two-tailed *p* values more than 0.05. Accordingly, the rest of the nonfinancial variables' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance as they are less than 0.05.

### 4.4.3 Factor Analysis and Multiple Regression for Year T-2

Factor extraction was used to determine the smallest number of financial factors that could best represent the interrelations among a group of financial ratios. All the financial ratios for the Year T-2 were considered for analysis. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

#### 4.4.3a Factor Analysis for Financial Ratios

The Kaiser-Meyer-Olkin measure of sampling adequacy and the results of the Bartlett's test of Sphericity are illustrated in table 4.20. The Kaiser-Meyer-Olkin value is 0.549 which is greater than 0.5. It means that the financial ratios are adequate for factor analysis. Moreover, the Bartlett's test of Sphericity is significant with the value less than 0.05. It suggests that there are significant correlations between the financial ratios.

**Table No.: 4.20**
**KMO and Bartlett's Test for Year T-2**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .549 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 436.777 |
| | Sig. | .000 |

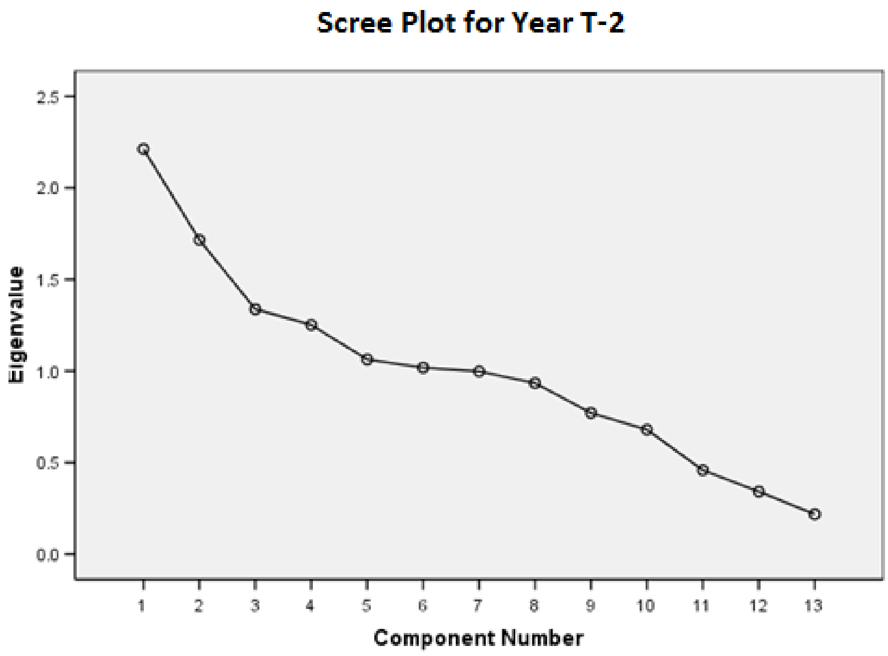
Factors with eigenvalue greater than 1 is retained for further investigation. In table 4.21, there are six factors (Factor 1, 2, 3, 4, 5 and 6) with their eigenvalues greater than 1. Overall, these three factors explain about 66 per cent of the original variance.

**Table No.: 4.21**
**Total Variance Explained for Financial Factors for Year T-2**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 2.212 | 17.017 | 17.017 | 2.212 | 17.017 | 17.017 |
| 2 | 1.716 | 13.199 | 30.216 | 1.716 | 13.199 | 30.216 |
| 3 | 1.337 | 10.288 | 40.504 | 1.337 | 10.288 | 40.504 |
| 4 | 1.251 | 9.625 | 50.129 | 1.251 | 9.625 | 50.129 |
| 5 | 1.063 | 8.179 | 58.308 | 1.063 | 8.179 | 58.308 |
| 6 | 1.019 | 7.835 | 66.144 | 1.019 | 7.835 | 66.144 |
| 7 | .998 | 7.678 | 73.821 | | | |
| 8 | .934 | 7.185 | 81.006 | | | |
| 9 | .771 | 5.933 | 86.939 | | | |
| 10 | .680 | 5.228 | 92.168 | | | |
| 11 | .459 | 3.528 | 95.696 | | | |
| 12 | .342 | 2.628 | 98.324 | | | |
| 13 | .218 | 1.676 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

**Chart No.: 4.3**




Secondly, in Figure 4.3, the scree plot line begins to flatten out after the sixth factor. As a result, the scree plot also suggests that it is appropriate to retain six factors.

Based on the component matrix stated in table 4.22, the independent financial variables considered for regression analysis are return on net worth, current ratio, debt equity ratio, interest coverage ratio, inventory turnover ratio and fixed assets turnover ratio and Altman Z Score was considered as independent variable. The results of the correlation analysis are displayed in table 4.22.

**Table No.: 4.22**
**Component Matrix for Year T-2**

| | Factor | | | | | |
|---|---|---|---|---|---|---|
| **Variables** | **1** | **2** | **3** | **4** | **5** | **6** |
| ICR | 0.817 | | | | | |
| ROA | 0.746 | | | | | |
| ROCE | 0.695 | | | | | |
| RONW | | 0.705 | | | | |
| GPR | | 0.633 | | | | |
| ATR | | 0.397 | | | | |
| FATR | | | 0.506 | | | |
| CR | | | 0.341 | | | |
| CUR | | | | 0.720 | | |
| QR | | | | 0.587 | | |
| ITR | | | | | 0.574 | |
| DTR | | | | | 0.509 | |
| DER | | | | | | 0.896 |

Extraction Method: Principal Component Analysis.

*Note: ATO is asset turnover ratio, CR is cash ratio, CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ICR is interest coverage ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.4.3b Correlation Matrix

The correlation matrix for the extracted ratios for the year T-2 is stated in table4.23. The results suggest that all the variables have r less than 0.4. Hence, the extracted ratios are suitable for running multiple regression.

**Table No.: 4.23**
**Correlation Matrix of Financial Ratios for the Year T-2**

| **Variables** | RONW | CUR | DER | ICR | ITR | FATR |
|---|---|---|---|---|---|---|
| RONW | 1 | .012 | -.036 | .051 | .013 | .017 |
| CUR | .012 | 1 | .000 | .025 | .000 | -.008 |
| DER | -.036 | .000 | 1 | -.021 | -.006 | -.003 |
| ICR | .051 | .025 | -.021 | 1 | .339 | .022 |
| ITR | .013 | .000 | -.006 | .339 | 1 | -.009 |
| FATR | .017 | -.008 | -.003 | .022 | -.009 | 1 |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.4.3c Regression Analysis for Year T-2

The results of the regression analysis is stated in Table 4.24.

**Table No.: 4.24**
**Estimates of Regression Analysis for the Year T-2**

| **Variables** | **Unstandardized Coefficients** | | **Standardize d Coefficients** | **T** | **Sig.** |
|---|---|---|---|---|---|
| | **B** | **Std. Error** | **Beta** | | |
| (Constant) | -3.863 | 1.586 | | -2.436 | .016 |
| RONW | .001 | .012 | .423 | 6.120 | .005 |
| CUR | 2.964 | .362 | .188 | 8.190 | .000 |
| DER | -.024 | .023 | -.024 | -1.047 | .296 |
| ICR | .050 | .008 | .447 | 6.367 | .000 |
| ITR<br>FA TO | .003 | .000 | .896 | 35.023 | .000 |
| R2 | | 20.856 | 0.869 | | |

*$R^2$ = 0.869*

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

It is observed in table 4.24 that return on net worth, inventory turnover ratio, current ratio, interest coverage ratio and fixed asset turnover ratio had a *p* value less than 0.05 in the year T-2. It is observed that these ratios have a significant effect on prediction of financial distress. Irrespective of the proportion of debt to equity, this ratio did not influence the level of financial distress.

## 4.5 DATA ANALYSIS FOR THE DATA OF YEAR T -3

### 4.5.1 Descriptive Statistics

It could be observed from table 4.25 that the ratios of non-default companies are at the higher end compared to the default companies. There is a considerable gap in liquidity ratios of default and non-default companies. The average of current ratio was 269.43 for non-default and 24.80 for default companies. Similarly, the average of quick ratio was 262.06 for non-default and 22.60 for default companies.

Eventhough, the gross profit ratio and return on networth showed a negative value for both default and non- default firms, it was least for default firms when compared to the non-default companies. The return on capital employed and return on assets were also more for the non-default firms.

**Table No.: 4.25**
**Test Statistic for Financial Ratios of Select Companies at Year T-3**

| | Default Companies | | | | Non-Default Companies | | | |
|---|---|---|---|---|---|---|---|---|
| **Ratios** | **Mean** | **SD** | **25th** | **75th** | **Mean** | **SD** | **25th** | **75th** |
| ATO | 0.85 | 0.94 | 0.24 | 1.06 | 1.07 | 1.27 | 0.24 | 1.36 |
| CR | 189.81 | 703.42 | 28.93 | 130.40 | 178.06 | 579.95 | 28.73 | 114.81 |
| CUR | 24.80 | 250.05 | 0.94 | 3.67 | 35.59 | 269.43 | 1.20 | 2.62 |
| DER | 4.86 | 29.80 | 0.00 | 3.11 | 8.97 | 77.69 | 0.00 | 1.90 |
| DTR | 9.14 | 10.87 | 2.51 | 11.76 | 879.77 | 9871.15 | 3.08 | 12.45 |
| FATR | 22.28 | 162.90 | 0.32 | 4.61 | 18.60 | 145.17 | 0.92 | 5.24 |
| GPR | -14.46 | 136.61 | 0.00 | 12.67 | -13.25 | 170.71 | 0.00 | 14.75 |
| ICR | 30.05 | 429.56 | -0.53 | 2.00 | 83.96 | 538.89 | 1.08 | 8.75 |
| ITR | 11.65 | 30.80 | 2.42 | 8.01 | 1862.34 | 20787.31 | 3.41 | 11.62 |
| QR | 22.60 | 244.62 | 0.48 | 2.38 | 33.96 | 262.06 | 0.73 | 2.28 |
| ROA | 6.14 | 98.68 | -7.36 | 3.92 | 2.61 | 7.16 | -0.22 | 5.69 |
| ROCE | 21.83 | 182.05 | -0.64 | 14.28 | 12.43 | 23.05 | 0.16 | 17.33 |
| RONW | -12.40 | 137.21 | 0.00 | 12.80 | 8.62 | 53.80 | 7.36 | 18.44 |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.5.2 Mann-Whitney-Wilcoxon Test for Year T-3

The MWW test for financial ratios at T-3 are demonstrated in the table 4.26. It can be seen here that debtor's turnover ratio, cash ratio, current ratio and quick ratio had *p* value more than 0.05. The null hypothesis 1 for these ratios cannot be rejected. The rest of the ratios had *p* value less than 0.05. Hence there is significant difference in all the financial ratios except for the liquidity ratio namely current ratio, cash ratio and quick ratio and debtor's turnover ratio in the year T-3.

Table 4.27 shows MWW test statistics for non-financial variables for the year T-3. The output of the test indicates that five out of seven non-financial variables similar to year T-2 namely board size, institutional and non-institutional ownership, proportion of independent directors and promoter shareholding have two-tailed *p* values less than 0.05. Accordingly, these five nonfinancial variables' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. While the age of the company and duality in CEO have *p* value more than 0.05 which leads to not rejecting null hypothesis 2.

**Table No.: 4.26**
**MWW Test for Financial Ratios for Year T-3**

| **Particulars** | **ATR** | **CR** | **CUR** | **DER** | **DTR** |
|---|---|---|---|---|---|
| Mann-Whitney U | 11167.50 | 10678.00 | 12390.00 | 10544.50 | 10216.50 |
| Wilcoxon W | 24370.50 | 21853.00 | 24480.00 | 23747.500 | 21391.50 |
| Z | -2.319 | -0.371 | -0.202 | -2.466 | -0.705 |
| Asymp. Sig. (2-tailed) | 0.020 | 0.710 | 0.840 | 0.014 | 0.481 |
| **Particulars** | **FATR** | **GPR** | **ICR** | **ITR** | **ROA** |
| Mann-Whitney U | 9928.00 | 11392.00 | 6948.00 | 7828.00 | 9852.50 |
| Wilcoxon W | 22969.00 | 24595.00 | 18123.00 | 17839.00 | 23055.50 |
| Z | -3.141 | -2.061 | -5.511 | -2.171 | -3.878 |
| Asymp. Sig. (2-tailed) | 0.002 | 0.039 | 0.000 | 0.03 | 0.000 |
| **Particulars** | **ROCE** | **RONW** | **QR** | | |
| Mann-Whitney U | 10241.00 | 9793.50 | 12199.5 | | |
| Wilcoxon W | 22331.00 | 21883.50 | 25402.5 | | |
| Z | -2.837 | -3.404 | -1.094 | | |
| Asymp. Sig. (2-tailed) | 0.005 | 0.001 | 0.274 | | |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

**Table No.: 4.27**
**MWW for Non-Financial Factor for Year T-3**

| Particulars | AGE | BS | CEOD | IO | NIO | PID | PROMSH |
|---|---|---|---|---|---|---|---|
| Mann-Whitney U | 13058 | 6611.5 | 12806.5 | 260 | 1218 | 907.5 | 1301 |
| Wilcoxon W | 26261 | 10097.5 | 26009.5 | 13463 | 14421 | 4393.5 | 14156 |
| Z | -0.076 | -0.213 | -0.671 | -9.412 | -6.376 | -11.159 | -6.525 |
| Asymp. Sig. (2-tailed) | 0.939 | 0.001 | 0.502 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

### 4.5.3 Factor Analysis and Multiple Regression for Year T-3

#### 4.5.3a Factor Analysis for Financial Ratios

TheKaiser-Meyer-Olkin Measure of Sampling Adequacy for year T-3 is 0.526. Hence, the data on financial variables are adequate for factor analysis. Further the Bartlett's test of Sphericity is significant with the *p* value less than 0.05. It indicates that there are significant correlations between the variables.

**Table No.: 4.28**
**KMO and Bartlett's Test for Year T-3**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .526 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 1755.997 |
| | Sig. | .000 |

Factors with eigenvalue greater than 1 could be retained for further investigation. In Table 4.26, there are six factors (Factor 1, 2, 3, 4, 5 and 6) with their eigenvalues greater than 1. Overall, these six factors explain about 75 per cent of the original variance.

**Table No.: 4.29**

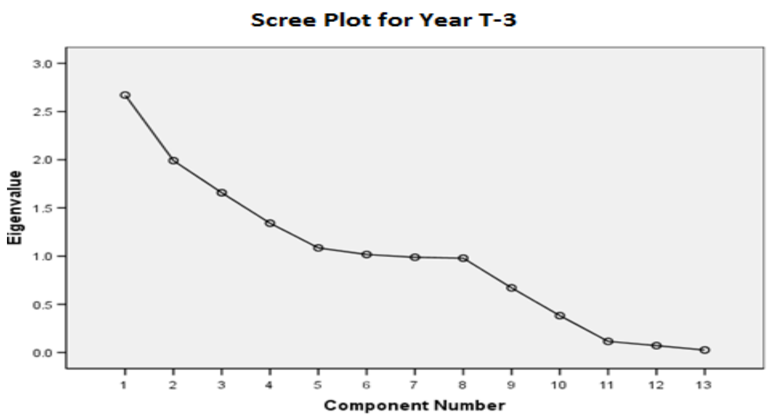
**Total Variance Explained for Financial Factors for Year T-3**

| **Component** | **Initial Eigenvalues** | | | **Extraction Sums of Squared Loadings** | | |
|---|---|---|---|---|---|---|
| | **Total** | **% of Variance** | **Cumulative %** | **Total** | **% of Variance** | **Cumulative %** |
| 1 | 2.671 | 20.545 | 20.545 | 2.671 | 20.545 | 20.545 |
| 2 | 1.991 | 15.313 | 35.858 | 1.991 | 15.313 | 35.858 |
| 3 | 1.658 | 12.754 | 48.612 | 1.658 | 12.754 | 48.612 |
| 4 | 1.342 | 10.319 | 58.932 | 1.342 | 10.319 | 58.932 |
| 5 | 1.086 | 8.352 | 67.283 | 1.086 | 8.352 | 67.283 |
| 6 | 1.017 | 7.825 | 75.108 | 1.017 | 7.825 | 75.108 |
| 7 | .988 | 7.602 | 82.710 | | | |
| 8 | .979 | 7.531 | 90.242 | | | |
| 9 | .671 | 5.159 | 95.401 | | | |
| 10 | .383 | 2.946 | 98.347 | | | |
| 11 | .116 | .893 | 99.240 | | | |
| 12 | .072 | .556 | 99.796 | | | |
| 13 | .027 | .204 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

Further, the scree plot line begins to flatten out between the sixth and the seventh factor. As a result, it suggests that it is appropriate to retain six factors for the year T-3.

**Chart No.: 4.4**




The component matrix grouped different financial ratios into six factors. Based on the component matrix, return on assets, return on net worth, current ratio, inventory turnover ratio, interest coverage ratio and asset turnover ratio was considered as independent variable to fit the regression model. And as stated earlier, Altman Z Score was considered as dependent variable in running multiple regression analysis.

**Table No.: 4.30**
**Component Matrix for Year T-3**

| Variables | Factors 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ROA | 0.940 | | | | | |
| ROCE | 0.929 | | | | | |
| CUR | | 0.981 | | | | |
| QR | | 0.979 | | | | |
| CR | | 0.153 | | | | |
| RONW | | | 0.816 | | | |
| GPR | | | 0.762 | | | |
| ATR | | | | 0.625 | | |
| ITR | | | | | 0.727 | |
| DTR | | | | | 0.314 | |
| FATR | | | | | 0.521 | |
| ICR | | | | | | 0.887 |
| DER | | | | | | 0.859 |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.5.3b Correlation Matrix

In order to check the multicollinearity of all these six factors, correlation was conducted for the year T-3. The values of Pearson correlation in Table 4.31 show that the values of *r* are all less than 0.4. Therefore, there are no multicollinearities among these six factors and all these factors can beretained.

**Table No.: 4.31**
**Correlation Matrix of Financial Ratios for the Year T-3**

| Variables | RONW | ITR | ICR | ROA | ATR | CUR |
|---|---|---|---|---|---|---|
| RONW | 1 | .006 | .039 | .027 | .064 | .003 |
| ITR | .006 | 1 | .020(**) | .017 | -.052 | -.003 |
| ICR | .039 | .020(**) | 1 | .192(**) | -.043 | .020 |
| ROA | .027 | .017 | .192(**) | 1 | .066 | -.005 |
| ATR | .064 | -.052 | -.043 | .066 | 1 | -.089 |
| CUR | .003 | -.003 | .020 | -.005 | -.089 | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.5.3c Regression Analysis for Year T-3

The table 4.32 shows the results from multiple regression analysis. It could be observed here that interest coverage ratio, return on assets and asset turnover ratio had no influence on the prediction of financial distress. However, the current ratio, inventory turnover ratio and the return on net worth influenced the distress prediction as the *p* value of these ratios were lesser than 0.05. It could also be observed that these three ratios were significant even in the year T, T-1 and T-2 respectively.

**Table No.: 4.32**
**Estimates of Regression Analysis for the Year T-3**

| Variables | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | -1.252 | 2.493 | | -.502 | .616 |
| RONW | 3.712 | 1.870 | .048 | 1.985 | .048 |
| ITR | .004 | .000 | .942 | 33.584 | .000 |
| ICR | -.004 | .006 | -.024 | -.595 | .552 |
| ROA | .086 | .085 | .039 | 1.019 | .309 |
| ATR | .978 | 1.597 | .015 | .613 | .541 |
| CUR | .136 | .097 | .032 | 1.405 | .006 |

$R^2$= 0.873

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

## 4.6 DATA ANALYSIS FOR THE DATA OF YEAR T -4

### 4.6.1 Descriptive Statistics

Table 4.33 displays the average and the standard deviation of the financial factors in the year T-4. It could be observed here that the average of asset turnover ratio is slightly more for the non-default companies (1.10) as compared to the default companies with an average of 0.92. The current ratio was also greater for non-default companies. The liquidity ratios also showed a similar trend. The debtor’s turnover ratio was 873.78 in the case of non-default companies when compared to 9.24 in case of defaulted firms.

**Table No.: 4.33**
**Test Statistic for Financial Ratios of Select Companies at Year T-4**

| Ratios | Default Companies | | | | Non-Default Companies | | | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **$25^{th}$** | **$75^{th}$** | **Mean** | **SD** | **$25^{th}$** | **$75^{th}$** |
| ATO | 0.92 | 1.01 | 0.27 | 1.13 | 1.10 | 1.29 | 0.26 | 1.37 |
| CR | 88.63 | 138.93 | 27.60 | 115.27 | 177.08 | 578.12 | 28.89 | 114.26 |
| CUR | 4.96 | 10.53 | 1.09 | 4.67 | 22.41 | 200.00 | 1.34 | 3.73 |
| DER | 3.08 | 14.58 | 0.07 | 2.76 | 6.54 | 70.18 | 0.00 | 1.72 |
| DTR | 9.24 | 11.18 | 2.92 | 11.28 | 873.78 | 9837.08 | 3.12 | 12.37 |
| FATR | 24.66 | 164.46 | 0.39 | 5.29 | 18.64 | 145.17 | 0.92 | 5.42 |
| GPR | 2.42 | 38.18 | 0.00 | 16.41 | 13.21 | 170.72 | 0.00 | 14.75 |
| ICR | 6.58 | 665.25 | -0.30 | 2.54 | 84.60 | 540.68 | 1.09 | 8.83 |
| ITR | 16.16 | 70.17 | 3.12 | 8.25 | 1848.36 | 20708.44 | 3.44 | 12.19 |
| QR | 9.97 | 81.53 | 0.68 | 3.06 | 14.03 | 68.04 | 0.73 | 2.28 |
| ROA | 0.15 | 22.05 | -4.72 | 5.40 | 2.62 | 7.16 | -0.22 | 5.69 |
| ROCE | 14.34 | 77.02 | 0.00 | 16.56 | 11.45 | 19.37 | 0.05 | 17.90 |
| RONW | 4.76 | 33.85 | 0.00 | 16.83 | 18.24 | 236.29 | 0.00 | 17.16 |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.6.2 Mann Whitney Wilcoxon Test for Year T-4

Table 4.33displays the MWW Test for financial ratios at year T-4. Debt equity ratio, return on capital employed, return on assets, fixed asset turnover ratio, quick ratio and interest coverage ratio had *p* values less than 0.05. There is significant difference in these financial ratios between default and non-default companies. Further, the *p* value is more than 0.05 for current ratio, debtor's turnover ratio, inventory turnover ratio, gross profit ratio, cash ratio, asset turnover ratio and return on net worth. Hence null hypothesis 1 cannot be rejected for these ratios stated.

**Table No.: 4.34**
**MWW Test for Financial Ratios at T-4**

| **Particulars** | **ATR** | **CR** | **CUR** | **DER** | **DTR** |
|---|---|---|---|---|---|
| Mann-Whitney U | 11493.00 | 10949.00 | 12280.00 | 10467.50 | 10179.00 |
| Wilcoxon W | 24696.00 | 22274.00 | 24061.00 | 23670.50 | 20910.00 |
| Z | -1.933 | -0.001 | -0.14 | -2.384 | -0.566 |
| Asymp. Sig. (2-tailed) | 0.053 | 0.999 | 0.889 | 0.017 | 0.572 |
| **Particulars** | **FATR** | **GPR** | **ICR** | **ITR** | **ROA** |
| Mann-Whitney U | 10272.00 | 12854.50 | 8133.00 | 8517.50 | 11215.00 |
| Wilcoxon W | 23313.00 | 26057.50 | 19308.00 | 18957.50 | 24418.00 |
| Z | -2.718 | -0.319 | -3.828 | -1.489 | -2.262 |
| Asymp. Sig. (2-tailed) | 0.007 | 0.75 | 0.000 | 0.136 | 0.024 |
| **Particulars** | **ROCE** | **RONW** | **QR** | | |
| Mann-Whitney U | 11459.00 | 11676.50 | 12408.50 | | |
| Wilcoxon W | 23240.00 | 23457.50 | 25611.50 | | |
| Z | -1.156 | -0.892 | -0.846 | | |
| Asymp. Sig. (2-tailed) | 0.008 | 0.373 | 0.007 | | |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

**Table No.: 4.35**
**MWW for Non-Financial Factor at T 4**

| **Particulars** | **AGE** | **BS** | **CEOD** | **IO** | **NIO** | **PID** | **PROM SH** |
|---|---|---|---|---|---|---|---|
| Mann-Whitney U | 13116 | 6383 | 12798 | 286.5 | 1322.5 | 445.5 | 1525.4 |
| Wilcoxon W | 26319 | 10211 | 26001 | 13489.5 | 14525.5 | 4273.5 | 14825.5 |
| Z | -0.007 | -1.233 | -0.922 | -9.529 | -6.351 | -12.52 | -9.669 |
| Asymp. Sig. (2-tailed) | 0.994 | 0.008 | 0.357 | 0.000 | 0.000 | 0.000 | 0.000 |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

Table 4.35 shows MWW test statistics for non-financial variables for the year T-4. The output of the test indicates that five out of seven non-financial variables similar to year T-2 and T-3 namely proportion of independent directors, promoter shareholding, institutional and non-institutional ownership and size of the board have two-tailed *p* values less than 0.05. Accordingly, these five nonfinancial variables' results of MWW test, with correction for Z-score conversion and ties, are significant at five per cent level of significance. While the age of the company and duality in CEO have *p* value more than 0.05. Hence null hypothesis 2 cannot be rejected for these two variables.

### 4.6.3 Factor Analysis and Multiple Regression for Year T-4

Factor extraction was used to determine the smallest number of financial factors that could represent the interrelations among a group of financial ratios. All the financial ratios for the Year T-4 were considered for analysis. The most commonly used extraction technique (principal components) was then used to extract the underlying financial factors.

### 4.6.3a Factor Analysis for Financial Ratios

The Kaiser-Meyer-Olkin measure of sampling adequacy and the results of the Bartlett's test of Sphericity are illustrated in table 4.36. The Kaiser-Meyer-Olkin value is 0.596 which is greater than 0.5. It means that the financial ratios are adequate for factor analysis. Even, the Bartlett's test of Sphericity has a value less than 0.05 which is significant which in turn suggests that there are significant correlations between the financial ratios.

**Table No.: 4.36**
**KMO and Bartlett's Test for Year T-4**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .596 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 1046.674 |
| | Sig. | .000 |

Factors with eigenvalue greater than 1 is retained for further investigation. In Table 4.37, there are six factors (Factor 1, 2, 3, 4, 5 and 6) with their eigenvalues greater than 1. Overall, these three factors explain about 69 per cent of the original variance. The scree plot for T-4 is shown in chart 4.5. The scree plot line begins to flatten out between the sixth and the seventh factor. As a result, according to theory of Catell's scree test discussed in Chapter 4, the scree plot also suggests that it is appropriate to retain six factors.

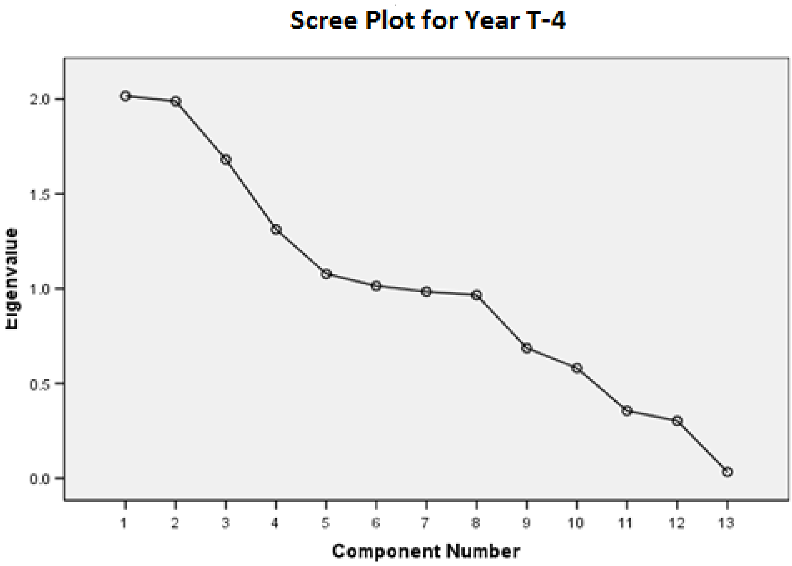
**Table No.: 4.37**

**Total Variance Explained for Financial Factors for Year T-4**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 2.016 | 15.506 | 15.506 | 2.016 | 15.506 | 15.506 |
| 2 | 1.989 | 15.297 | 30.804 | 1.989 | 15.297 | 30.804 |
| 3 | 1.681 | 12.932 | 43.735 | 1.681 | 12.932 | 43.735 |
| 4 | 1.312 | 10.094 | 53.830 | 1.312 | 10.094 | 53.830 |
| 5 | 1.078 | 8.295 | 62.125 | 1.078 | 8.295 | 62.125 |
| 6 | 1.014 | 7.804 | 69.928 | 1.014 | 7.804 | 69.928 |
| 7 | .984 | 7.569 | 77.497 | | | |
| 8 | .966 | 7.434 | 84.932 | | | |
| 9 | .686 | 5.279 | 90.211 | | | |
| 10 | .581 | 4.469 | 94.679 | | | |
| 11 | .355 | 2.734 | 97.414 | | | |
| 12 | .303 | 2.329 | 99.743 | | | |
| 13 | .033 | .257 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

**Chart No.: 4.5**




The component matrix grouped different financial ratios into six factors.Among these six factors, current ratio, interest coverage ratio, gross profit ratio, inventory turnover ratio, debt equity ratio and fixed asset turnover ratio were taken as independent variable. Altman Z score was taken as dependent variable and regression was run. Table 4.40 gives the results of multiple regression analysis.

**Table No.: 4.38**
**Component Matrix for Year T-4**

| Variables | Factors 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| ICR | 0.716 | | | | | |
| ROCE | 0.586 | | | | | |
| ROA | 0.478 | | | | | |
| CUR | | 0.883 | | | | |
| QR | | 0.877 | | | | |
| GPR | | | 0.689 | | | |
| RONW | | | 0.638 | | | |
| FATR | | | | 0.619 | | |
| ATR | | | | 0.578 | | |
| ITR | | | | | 0.653 | |
| DTR | | | | | 0.331 | |
| CR | | | | | 0.142 | |
| DER | | | | | | 0.926 |

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.6.3b Correlation Matrix

In order to check the multicollinearity of all these six factors, the present study checked the intercorrelation among these factors for year T-5. The values of Pearson correlation in Table 4.39 show that the values of *r* are all less than 0.4. Therefore, there are no multicollinearities among these six factors and all these factors can be retained.

**Table No.: 4.39**
**Correlation Matrix of Financial Ratios for the Year T-4**

| Variables | CUR | ITR | ICR | GPR | FATR | DER |
|---|---|---|---|---|---|---|
| CUR | 1 | -.002 | .147(**) | .002 | -.010 | -.005 |
| ITR | -.002 | 1 | .309(**) | .007 | -.008 | -.006 |
| ICR | .147(**) | .309(**) | 1 | .013 | .011 | -.014 |
| GPR | .002 | .007 | .013 | 1 | .030 | -.007 |
| FATR | -.010 | -.008 | .011 | .030 | 1 | .014 |
| DER | -.005 | -.006 | -.014 | -.007 | .014 | 1 |

** Correlation is significant at the 0.01 level (2-tailed).

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

### 4.6.3c Regression Analysis for Year T-4

The extracted financial factors are used further to run regression analysis. Table 4.40 depicts the regression results for the year T-4

**Table No.: 4.40**
**Estimates of Regression Analysis for the Year T-4**

| Variables | Unstandardized Coefficients | | Standardized Coefficients | T | Sig. |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | | |
| (Constant) | 4.141 | 1.754 | | 2.361 | .019 |
| CUR | .010 | .122 | .002 | .085 | .932 |
| ITR | .004 | .000 | .922 | 35.513 | .000 |
| ICR | -7.74E-006 | .003 | .000 | -.003 | .998 |
| GPR | .004 | .012 | .009 | .347 | .729 |
| FATR | .002 | .012 | .003 | .132 | .895 |
| DER | -.031 | .029 | -.026 | -1.050 | .295 |
| $R^2$ | | 25.98 | .851 | | |

$R^2 = 0.851$

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth.*

Table 4.40 explains the regression analysis for the year T-4 i.e. four years prior to announcement of financial default. Based on factor analysis, current ratio, inventory turnover ratio, interest coverage ratio, gross profit ratio, fixed asset turnover ratio and debt equity ratio were selected as independent variables. The distress level computed as Altman Z Score was considered as dependent variable.

It can be observed here that only inventory turnover ratio had a *p* value less than 0.05 for the year T-4. While all the other ratios showed that they did not influence the company's financial distress. In other words, there was no significant difference between all other financial ratios except inventory turnover ratio in the year T-4 between default and non- default companies.

## 4.7 SUMMARY OF FINDINGS

The Table 4.41 presents the summary of the findings of this study. The findings of study were consistent for all the four years. The financial and non-financial factors are useful in predicting the financial distress of the firms. This implies that the continuous monitoring of financial factors are non-financial factors used in this study would help the managers, investors, creditors and regulators to identify the financial distress and take corrective actions to avoid default.

**Table No.: 4.41**
**Summary of findings**

| Factors | Variables | t-4 | t-3 | t-2 | t-1 |
|---|---|---|---|---|---|
| Financial Factors | **ATR** | Significant | Significant | Significant | Significant |
| | **CR** | Not significant | Not significant | Significant | Significant |
| | **CUR** | Not significant | Not significant | Not significant | Not significant |
| | **DER** | Significant | Significant | Significant | Not significant |
| | **DTR** | Not significant | Not significant | Significant | Significant |
| | **FATR** | Significant | Significant | Significant | Significant |
| | **GPR** | Significant | Significant | Significant | Significant |
| | **ICR** | Significant | Significant | Significant | Significant |
| | **ITR** | Not significant | Significant | Significant | Significant |
| | **ROA** | Significant | Significant | Significant | Significant |
| | **ROCE** | Significant | Significant | Significant | Significant |
| | **RONW** | Not significant | Significant | Significant | Significant |
| | **QR** | Significant | Not significant | Significant | Significant |
| Non-Financial Factors | **AGE** | Not significant | Not significant | Not significant | Significant |
| | **BS** | Significant | Significant | Significant | Significant |
| | **CEOD** | Significant | Significant | Significant | Not significant |
| | **IO** | Not significant | Not significant | Not significant | Significant |
| | **NIO** | Significant | Significant | Significant | Significant |
| | **PID** | Significant | Significant | Significant | Significant |
| | **PROM SH** | Significant | Significant | Significant | Significant |

## 5.1 INTRODUCTION

The basic aim of this chapter is to analyses the third and the fourth objective of the study. In order to achieve the third objective, logistic regression was used. The non-financial factors namely company size, age of the company, institutional ownership, non-institutional ownership, promoter shareholding, duality in leadership and proportion of independent directors to the total directors were taken for the purpose of the study.

The fourth objective aims to study the stock market response on financial default announcement. Event study methodology was implemented to achieve the above objective. The listed default companies among the sample was considered for the said purpose.

## 5.2 IMPACT OF NON-FINANCIAL FACTORS ON CHANCES OF DEFAULT

The study aims to investigate the effects of non-financial factors on the chances of corporate financial default in this section. Table 5.1 presents the summary descriptive statistics variables for the entire sample of 350 companies in order to analyze its characteristics. The results in table 5.1 specifies that institutional and non-institutional investors have a similar mean participation in both shareholding i.e. 8.95 and 8.25 respectively. In case of variable on board composition, the results indicate that the average proportion of independent directors is around 31% of total board members and the mean size of the board is around 6 members. The duality in CEO is hardly 11.4% of the analyzed companies. The average board ownership indicated 24% which highlights the inclination of interests between board of directors and ownership.

**Table No.: 5.1**
**Sample Statistics Summary**

| Variables | Mean | 25th | 75th | Std. dev. |
|---|---|---|---|---|
| PID | .3181 | .00 | .6 | .33286 |
| BS | 5.3762 | 3 | 7 | 3.40186 |
| PROMSH | 0.242 | 0.008 | 0.483 | 0.240 |
| NIO | 8.95 | .00 | 37.57 | 60.01 |
| IO | 8.25 | .00 | 5.25 | 17.17 |
| AGE | 46.58 | 13 | 27 | 220.41 |
| CEOD | Coded 1 | 11.4% | | |
| | Coded 0 | 88.6% | | |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

Table 2 reports descriptive statistics for default and non-default companies studied. In case of corporate governance variables related to ownership, the participation of non-institutional investors (NIO) was greater for default companies compared to non-default companies. The mean of non-default companies was higher in case of institutional ownership (IO). Further, the non-default companies tend to have more independent board (58.7% of member of the board). 86.8% of the companies did not have duality in CEO in default companies, which was slightly larger from the non-default companies. The composition of the board of directors' ownership is greater for non-default companies with a mean (median) of 27% than the defaulted firms with a mean of 23%.

Further, Spearman's rho Correlations between all variables included in the model are presented in table 5.3. The possible existence of multicollinearity between the variables in the studied model, and its consequences on the regression analysis is ruled out, because although there are some significant correlations, almost all are below 0.4 (Tabachnick and Fidell, 1996).

**Table No.: 5.2**
**Mean Comparison Test for Default and Non-Default companies.**

| Variables | Default Companies | | | | Non-Default Companies | | | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **25th** | **75th** | **SD** | **Mean** | **25th** | **75th** | **SD** |
| PROMSH | 0.226 | 0.009 | 0.495 | 0.237 | 0.269 | 0.009 | 0.551 | 0.352 |
| NIO | 21.1178 | .00 | 42.57 | 25.32753 | 16.8294 | 0 | 17.97 | 80.6248 |
| IO | 4.4640 | .00 | 4.7225 | .36746 | 11.9638 | 0 | 24.96 | 21.64341 |
| BS | 6.2102 | 4 | 7.25 | 2.86293 | 4.5582 | 2 | 7 | 3.68074 |
| PID | .5876 | .4520 | .7500 | .24619 | .0538 | 0 | 0 | .1374 |
| AGE | 20.64 | 13 | 26 | 11.245 | 71.37 | 10.75 | 29 | 309.52 |
| **Categorical Variable** | | | | | | | | |
| CEOD Coded 1 | 13.2% | | | | 9.6% | | | |
| Coded 0 | 86.84% | | | | 90.4% | | | |

*Note: AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

**Table No.: 5.3**
**Correlation Matrix**

| Variables | RONW | CR | ICR | ITR | CEOD | BS | PID | NIO | IO | PROMSH | AGE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FD | 1 | | | | | | | | | | |
| RONW | 1 | | | | | | | | | | |
| CR | .009 | 1 | | | | | | | | | |
| ICR | -.052* | -.003 | 1 | | | | | | | | |
| ITR | .009 | -.001 | -.004 | 1 | | | | | | | |
| CEOD | -.032 | .004 | -.018 | -.021 | 1 | | | | | | |
| BS | -.004 | -.046 | .094** | -.060* | .184** | 1 | | | | | |
| PID | -.033 | -.042 | -.051 | -.060* | .038 | .092 | 1 | | | | |
| NIO | -.003 | -.017 | .009 | -.054 | .065* | .173 | -.286 | 1 | | | |
| IO | -.008** | .053 | .093** | .177** | .246** | .262 | -.442 | .258 | 1 | | |
| PROMSH | -.05 | -.02 | 0.09 | -.11** | 0.07 | -0.06 | -0.11** | -0.12** | -0.08** | 1 | |
| AGE | .020 | -.014 | -.005 | .015 | -.034 | -.047 | -.089 | .030 | .198 | .022 | 1 |

** significant at the 0.01 level, * significant at the 0.05 level

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth. AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

### 5.1.1 Logistic Regression Analysis

Further, an attempt is made to estimate the financial distress likelihood using logistic regression analysis. Following the study of Mangena and Chamisa (2008), this methodology is applied for two main purposes: (a) the logistic regression overcomes the limitations of ordinary least squares (OLS) to estimate the parameters when the dependent variable is dichotomous, as is the case studied by Hosmer and Lemeshow

(1989); Tabachnick and Fidell (1996); and (b) this methodology preserves the marched character of the sample (Hosmer and Lemeshow, 1989).

The dependent variable in the present study is whether the companies experienced default status or not where default is coded as 1 and non-default is coded as 0. The present study then uses binary logistic regression analyses to establish two types of financial distress models. The first type of model considered firm-specific financial factors only, whereas the second type of model considered firm-specific non-financial factors and financial factors in predicting the chances of default.

In this section, the results of conditional logistic regression are presented. The results of the logistic regression are shown in table 5.4. Two models were built depending on the variables included. Only financial variables are used in Model 1 and the non-financial corporate governance variables are added in Model 2, taking financial factors here as controlled variables.

Model 1 consisted of financial ratios namely return on net worth, current ratio, interest coverage ratio and inventory turnover ratio. Return on net worth was taken as a proxy to profitability ratios. Current ratio was taken as a proxy to liquidity ratio, interest coverage ratio was taken as a proxy to leverage ratios and inventory turnover ratio was taken as a proxy to activity ratios. Further, these financial ratios were common factors extracted across the years with the help of factor analysis in the earlier chapter.

From the table 5.4, it could be observed that the coefficient of the variables (PROMSH) promoter shareholding and (CEOD) duality in leadership are not significant as the *p* value is not less than 0.05 and thus the hypotheses $H_{4a}$ and $H_{4d}$ are not supported. With respect to concentration of ownership (PROMSH), there is a positive coefficient suggesting that the financial distress likelihood increases with ownership concentration. This indicates that large shareholders are submissive and as a result they do not have enough incentives to hold back the financial distress. So, this result is consistent with earlier empirical evidences explained by Elloumi and Gueyie, 2001; Lee and Yeh, 2004; Mangena and Chamisa, 2008; Parker et al., 2002. In terms of duality in CEO (CEOD) there is positive value of coefficient although results are not significant as in the study by Mangena and Chamisa (2008). This result is consistent with the studies by Daily and Dalton (1994a) and Hiu and Jing-Jing (2008).

**Table No.: 5.4**
**Logistic Regression Analysis**

| Variable | Model 1 | | | | | Model 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Beta** | **SE** | **Wald** | **Sig** | **Odds ratio** | **Beta** | **SE** | **Wald** | **Sig** | **Odds ratio** |
| Constant | .240 | .067 | 12.782 | .000 | 1.271 | 6.660 | 1.290 | 26.651 | .000 | 780.33 |
| RONW | -.002 | .001 | 1.854 | .173 | .998 | -.002 | .001 | 6.264 | .012 | 0.998 |
| CUR | -.005 | .004 | 1.644 | .200 | .995 | -.051 | .054 | .896 | .344 | .950 |
| ICR | -.001 | .000 | 13.481 | .000 | .999 | -.001 | .001 | 1.994 | .158 | .999 |
| ITR | -.012 | .003 | 18.306 | .000 | .988 | -.038 | .012 | 9.738 | .002 | .963 |
| PROMSH | | | | | | 0.462 | .025 | 20.11 | 0.135 | 1.677 |
| NIO | | | | | | -.064 | .013 | 26.229 | .000 | .938 |
| IO | | | | | | -.174 | .020 | 75.461 | .000 | .840 |
| CEOD | | | | | | -.475 | .607 | .612 | .434 | 1.608 |
| PID | | | | | | 9.729 | 1.499 | 42.136 | .000 | 16804.2 |
| BS | | | | | | -.277 | .078 | 12.597 | .000 | .758 |
| Age | | | | | | -.009 | .017 | .249 | .618 | .991 |
| -2 Log Likelihood | 1618.26 | | | | | 130.016 | | | | |
| De Nagalkerke | .094 | | | | | 0.912 | | | | |
| Cox and Snell | .071 | | | | | .602 | | | | |
| McFadden | .016 | | | | | .121 | | | | |
| Chi2 | 90.449** | | | | | 754.838** | | | | |
| Prediction Accuracy | 65.32% | | | | | 94.7% | | | | |

** significant at the 0.01 level, * significant at the 0.05 level

*Note: CUR is current ratio, DER is debt equity ratio, DTR is debtors turnover ratio, FATR fixed asset turnover ratio, GPR is gross profit ratio, ITR is inventory turnover ratio, QR is quick ratio, ROA is return on assets, ROCE return on capital employed and RONW is return on net-worth. AGE is age of the company, BS is board size, CEOD CEO duality, IO is institutional ownership, NIO is non-institutional shareholding, PID proportion of independent directors and PROMSH is promoter shareholding.*

The coefficient indicates that institutional ownership has an inverse influence on financial distress likelihood. This is also specified in the outcome derived by Deng and Wang (2006) for the Chinese market and Karamanou and Vafeas (2005). There was altogether a refuting outcome given by Mangena and Chamisa (2008). These results could be contradictory to the fact that institutional investors do not have power or incentives to make the firms perform better (Edelen, 2001; Fich and Slezak, 2008). Hence, $H_{4c}$ is significant.

In case of proportion of independent directors (PID), the relationship obtained is positive and is significant with a *p* value less than 0.05. This makes $H_{4e}$ significant. Hence, it is acceptable that companies with high proportion of independent directors have less likelihood of financial distress. Companies with more proportion of independent directors have more likelihood to suffer a financial distress situation. This result is consistent with Wang and Deng (2006), Hiu and Jing-Jing (2008) and Mangena and Chamisa (2008), highlighting the importance of independent boards to monitoring and control management decisions, especially those affecting the company survival.

The effect of Board size (BS) on financial distress likelihood is negative. It also has a p value less than 0.05. Hence, $H_{4f}$ is also significant. However, this result is contrary to that obtained by Lajili and Zeghal (2010) or Mangena and Chamisa (2008), those who do not find a relationship between board size and distressed companies. This is consistent with the argument of the Resources Dependency Theory (Pearce and Zahra, 1992; Pfeffer, 1972), according to which companies with more size board have the ability to control management and to access the resources and information. The board of directors may also contribute varied point of view with broad range of interests and knowledge, reducing the financial distress likelihood.

The results of non-institutional shareholders showed an inverse relationship with negative beta co-efficient. The *p* value is also less than 0.05. Hence, there is significant difference between non-institutional shareholder's ownership (NIO) and chances of company facing financial distress situation.  This is similar to the previous empirical evidence (Lee and Yeh, 2004; Mangena and Chamisa, 2008). Thus, the hypotheses $H_{4b}$ is supported by the results.

However, on the one hand, although the square of R in McFadden Nalgerkerke indicate an acceptable overall fit, it is slightly higher for the model that includes the variables of corporate governance than for the model which has only economic and financial variables.

The results in table 5.4 also provide some information about the usefulness of the model. The values of Cox and Snell R Square and the value of Nagelkerke R Square are 0.071 and 0.094 respectively for model 1. In other words, between 7.1 percent and 9.4 per cent of the variability in the dependent variable is explained by the independent variables for model 1.

For model 2, the result of Cox and Snell R Square and Nagelkerke R Square are .602 and .911 respectively. It means around 60 to 91 percent of the variability in the dependent variable is explained by the independent variable.

Further, comparing the two models, improvements are observed. Indeed, the model Chi-Square value is improving between Model 1 and Model 2 with Chi2 of 90.449, p <.001 and Chi2 of 754.57, p <.001 respectively. The prediction accuracy is also better in Model 2 with 94.7% than in Model 1 with 65.32%. In other words, adding non-financial variables, corporate governance variables in particular, improves the model.

To sum up, this section provides the evidence that non-financial factors with financial factors contain incremental information beyond financial ratios in predicting financial distress. Therefore, another reason why Model 2 is better than Model 1 in financial distress prediction could be that some firm-specific non-financial factors are more relevant to financial distress than firm-specific financial factors alone for distressed and non-default companies in India.

## 5.3 STOCK MARKET RESPONSES TO DEFAULT ANNOUNCEMENTS

Studying the reaction of equity market to announcement of corporate failure offers a unique context to the ongoing deliberation on financial distress and default. There is a continuous debate explaining the degree to which market prices reflect sufficient information to predict a firm's default, or does the event of default come as a surprise to investors. If as a surprise, the announcement of distress will release significant amounts of inside information about the firm. While markets for corporate bonds and equities may reflect a partial release of information about the financial health of a company, firm managers may still retain information impacting their decision to default on their debt. In this sense, even their decision to not default communicates useful information about a defaulted firm.

The present study contributes to the literature by examining whether the capital market reacts differently according to the outcomes of financial distress for default companies at the time firms announce their distress condition, which is a matter of concern to both academics and business professionals. It is expected that capital market participants will make prior assessments of the outcomes of financial distress from the sufficient publicly available information. In other words, the severity of the financial distress condition might have been detectable even before the announcement of financial default. Consequently, it is argued that if a market is efficient, it will be able to distinguish between failing companies which are capable of restructuring and resuming business (good news) and those that have failed. These different outcomes carry different values for the shareholders, and the market may have a certain insight or foresight into companies' future prospects, which may cause different stock price reactions. In this regard, it would be of considerable interest to assess whether the Indian market is efficient enough to distinguish between the companies that have successfully restructured and those that have failed. Therefore, this section tries to observe stock market reactions to financial default announcements for default companies.

As discussed earlier, the data pertaining to defaulters is obtained from Reserve Bank of India. All listed companies who are defaulters for consecutive three years are considered for the purpose. Further, event study methodology was also adopted to observe the trend of returns during pre and post windows. It has been used in a variety of researches for gauging the effect of new information on the market value of a security.

The parameters of the market model like alpha, and beta based on returns on stocks and market index in the estimation period are estimated, and then expected returns on each stock are calculated based on the market model in order to measure the abnormal gains/losses to target company shareholders. In order to calculate AARs, the estimated abnormal returns (ARs) of each stock are added and then average ARs are computed for each day during the event window.

The event study is based on the following assumptions. • Under the market efficiency hypothesis, the impact of an event (default announcement) will be instantly reflected in stock prices. Therefore, the market reaction to the event can be measured by stock returns over the study time period. • The event is unforeseen. Abnormal (excess) stock returns indicate the market reaction to the unanticipated event. • During the event window, there are no confounding effects, meaning that the effect of other events is isolated.

### 5.3.1 Event Study Methodology to assess Stock Market Responses to Default Announcements

The result of the empirical study on the stock price response of the default firm on the announcement of list of default firms by RBI is presented in this section. Log returns are used for the computation of abnormal returns. Results are based on log returns for event window of 15 months (-11 to +3). Table 5.5 reports the abnormal returns to the shareholders of default firms on announcement of default by RBI and multi-period event windows. It contains average abnormal return (AAR), cumulative average abnormal return (CAAR), and Z value. Additionally, it presents proportion of positive and negative average abnormal return.

It is clear from the table that shareholders of defaulted firm earn negative average abnormal returns of 0.57 percent on the announcement day for default. The proportion of stocks having positive return on the announcement day is more than 57 percent.

Relevant data contained in table 5.5 also shows that the shareholders of default firms experience CAAR of -3.32 percent on the day of announcement and this is significant at 1 percent level (z = 5.013). Two CAARs of 15-month event window was not statistically significant.

The finding for the post-default announcement period is also in lines with Pandey (2001) and Chakraborty (2010). However, this study finds small but statistically significant CAARs in the post-announcement period. Pandey finds negative and statistically insignificant returns for the period after announcement and Chakraborty finds positive but statistically not significant gains for the study period.

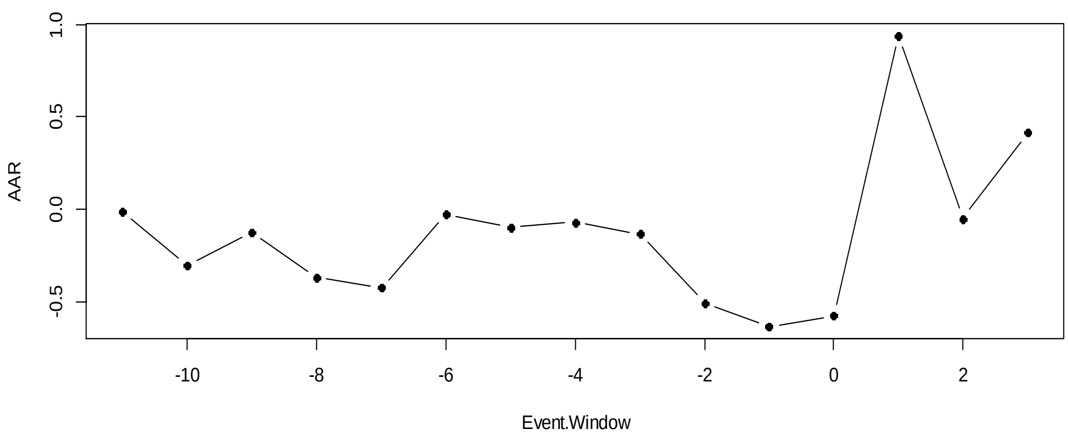
Figure 5.1 displays the trend of AAR during pre-and post-windows (-11, +3). The graph shows that abnormal returns start declining two months before the announcement. It was least during one month before the announcement. It went up during the immediate month post-default announcement.

**Table No.: 5.5**
**AARs and CAARs of Target Company Shareholders with Z values**

| Event Window | AAR | CAAR | Positive: Negative | Z Value |
|---|---|---|---|---|
| -11 | -0.0162 | -0.0450 | 45:14 | -2.4226* |
| -10 | -0.3017 | -0.3467 | 36:23 | -1.0011 |
| -9 | -0.1250 | -0.4717 | 47:12 | -3.2877*** |
| -8 | -0.3683 | -0.8400 | 39:20 | -1.9868 |
| -7 | -0.4265 | -1.2665 | 33:26 | -2.5867** |
| -6 | -0.0299 | -1.2964 | 50:09 | -37.8252*** |
| -5 | -0.1008 | -1.3972 | 44: 15 | -12.0735*** |
| -4 | -0.0709 | -1.4681 | 40:19 | -18.0298*** |
| -3 | -0.1328 | -1.6009 | 43: 16 | -10.5001*** |
| -2 | -0.5104 | -2.1113 | 33: 26 | -3.6034*** |
| -1 | -0.6358 | -2.7471 | 26:33 | -3.7639*** |
| 0 | -0.5777 | -3.3249 | 25:34 | -5.0132*** |
| 1 | 0.9413 | -2.3836 | 43: 16 | -2.2060 |
| 2 | -0.0520 | -2.4356 | 34: 25 | -40.8294*** |
| 3 | 0.4141 | -2.0215 | 42: 17 | -4.2529*** |

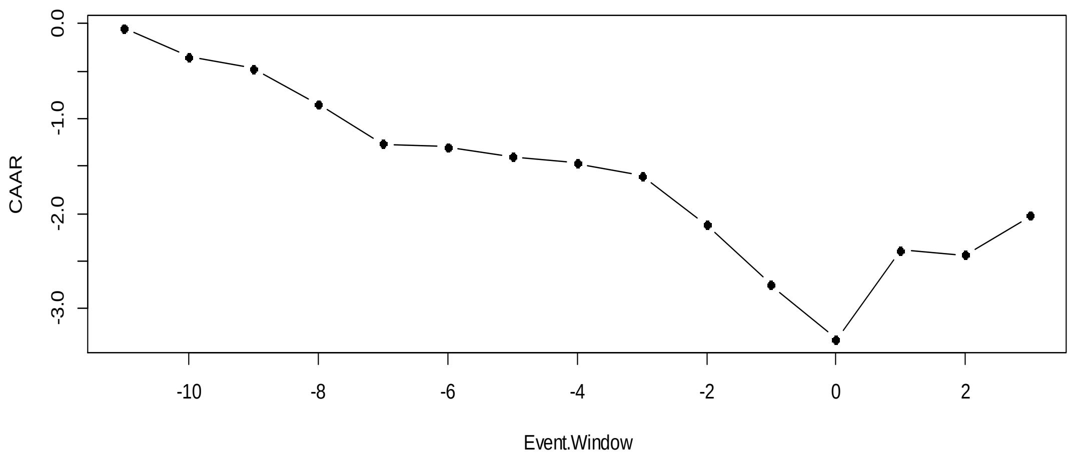
*** significant at the 0.01 level, ** significant at the 0.05 level, significant at the 0.10 level

**Chart No.:5.1**
**Event Window of AAR of Target Companies**




CAAR trend shows clearly the declinging trend. We could infer that shareholders were expecting this announcement. Efficient market hypothesis states that all stock price discounts all the information. This means using the financial models of prediction, shareholders already had predicted the default which resulted in declining CAAR.

**Chart No.: 5.2**
**Event Window of CAARs of Target Companies**




The main implication from this study is that a major portion of CAARs is negative at or before the announcement date suggesting that either there was a leakage of information to the market before the event day or the market expected the happening of default. Overall, the results suggest that announcements of financial default are associated with negative abnormal returns. Furthermore, the results indicate that the market differentiates the outcomes of the firms around the financial default announcement. Interestingly, a small part of CAARs is realized by the target shareholders in the post default announcement stating that the market took some time to absorb fully the information content of the event. Based on the event windows, it can be observed that the abnormal returns declined and was least from one month before and on the month of default announcement. The conclusion of this study provides indication and caution to the investors in general, and shareholders of the target company. Similarly, the announcements offer an opportunity to shareholders of target companies and general investors to make profits both in the period before and after the announcement by going short on the target company stocks.

This chapter presents the summary and conclusion of the thesis. The chapter begins with the summary of the study, which will provide an overall picture of the thesis.

The discussion of the empirical results and major findings with limitations and directions for future research will be presented in this chapter.

As stated earlier, financial distress is a situation where a company cannot meet nor has intricacy paying off its financial obligations to its creditors. The chance of financial distress increases when a firm has high fixed costs, illiquid assets, or revenues that are perceptive to economic downturns. Financial distress is a term in corporate finance used to point out a circumstance when promises to creditors of a company are broken or honored with difficulty. If financial distress cannot be relieved, it can lead to bankruptcy.

In the existing literature, financial ratios or factors are the most frequently used prognosticators in the models that forecast corporate financial distress. Some important research studies suggested they were the most important predictors for forecasting the financial distress (Altman, 1968; Altman, Haldeman and Narayanan, 1977; Ohlson, 1980). In contrast, the present study's findings are different. The logistic regression model incorporating firm-specific non-financial factors was better in predicting financial distress than the model which only included firm-specific financial factors. Several researchers found that some enterprises were prone to window-dressing or even falsifying their accounting data prior to releasing their financial statements (He and Liu, 2008; Xin, 2008). Therefore, one reason for Model 2 being better than Model 1 in financial distress prediction is that some enterprises might publish window-dressed financial data.

Firstly, although the financial ratios and non-financial variables have been demonstrated to have correlation with corporate financial distress, the past research has not considered the collective effect of financial ratios and non-financial variables in the company's distress prediction especially for Indian firms. In most of the existing studies on financial distress, researchers focused their attention on the predictive ability of firm-specific financial ratios. Furthermore, many other financial distress predictive research studies have examined the non-financial variables, but no studies covered both until recently. The present study is the combination of financial ratios, non-financial variables and response from stock market on company's default.

## 6.1 FINDINGS OF THE STUDY

### 6.1.1 Objective 1: To identify whether there are significant differences in financial and non-financial variables between default and non-default companies

In order to achieve the above objective, Mann Whitney Wilcoxon Test was conducted for all the five years ranging from the year T to T-4. The year-wise findings are presented below. Hypothesis 1 and Hypothesis 2 were associated with the above objective. Hypothesis 1 states that there are significant differences in financial ratios between default and non-default companies. Hypothesis 2 states that there are significant differences in non-financial ratios between default and non-default companies.

#### 6.1.1a Summary of data analysis and results (Year T)

In the year T or in the year of default, all the financial ratios except for debt equity ratio have two-tailed *p* values less than 0.05. The twelve financial ratios' results namely current ratio, quick ratio, inventory turnover ratio, debtor's turnover ratio, interest coverage ratio, return on net worth, total asset turnover ratio, cash ratio, return on capital employed, return on assets and gross profit ratio, had significant differences between default and non-default companies for the year T. Only the debt equity ratio's result of MWW test is not significant at five per cent level of significance. Therefore, for all the tested financial variables except for debt equity ratio, the Null Hypothesis 1 has to be rejected. For only one financial variable (debt equity ratio), however, the Null Hypothesis 1 cannot be rejected. Further, in the case of non-financial variables, the output of the test indicates that only duality in CEO has two-tailed *p* values more than 0.05, while it is less than 0.05 for the rest of the non-financial variables selected. In other words, the Null Hypothesis 2 can be rejected for nonfinancial variables, namely board size, proportion of independent directors, non-institutional investors, institutional investors, promoter shareholding and age of the company. Hence, there are significant differences among all non-financial variables except for duality in CEO or dual leadership between default and non-default companies for the year T.

#### 6.1.1b Summary of data analysis and results (Year T-1)

In case of Hypothesis 1, eleven financial ratios' results of MWW test, namely return on capital employed, return on assets, gross profit ratio, return on net worth, inventory turnover ratio, debtors' turnover ratio, asset turnover ratio, fixed asset turnover ratio, quick ratio and interest coverage ratio, had significant p value. Hence, there are significant differences in financial ratios between default and non-default companies for all these above mentioned ratios except for the debt equity ratio and current ratio. The Null Hypothesis 1 cannot be rejected for debt equity and current ratio between default and non-default companies for the year T-1.

With regards to the non-financial variables, the output of the test indicates that six out of seven non-financial variables have two-tailed *p* values less than 0.05. Accordingly, these six non-financial variables' results of MWW test, namely board size, proportion of independent directors, institutional ownership, non-institutional ownership, promoter shareholding and age of the company, with correction for Z score conversion and ties, are significant at five per cent level of significance. Only one nonfinancial variable (duality in CEO) has two-tailed *p* value more than 0.05. Thus, the results of MWW test reveal that there are significant differences in the Year T-1's six non-financial variables between the default and non-default firm.

#### 6.1.1c Summary of data analysis and results (Year T-2)

Hypothesis 1 states that there are significant differences in financial ratios between default and non-default companies. With respect to year T-2, the output of the MWW test indicates that the debt equity ratio, current ratio and quick ratio have p value more than 0.05. Therefore, for current ratio, debt equity ratio and quick ratio, the null hypothesis 1 cannot be rejected. However, for the rest of the financial ratios, the null hypothesis can be rejected. In other words, there are significant differences in financial ratios between default and non-default companies for all other financial variables except for current ratio, quick ratio and debt equity ratio in the year T-2.

Hypothesis 2 states that there are significant differences in non-financial ratios between default and non-default companies. The output of the MWW test indicates that two out of seven non-financial variables, namely duality in the CEO and the age of the company have two-tailed *p* values more than 0.05. Hence there are significant differences in non-financial variables, between default and non-default companies for the year T-2.

### 6.1.1d Summary of data analysis and results (Year T-3)

The MWW test for financial ratios states that debtor's turnover ratio, current ratio and quick ratio are not significant and hence the null hypothesis 1 for these ratios cannot be rejected in the year T-3. The rest of the ratios had a *p value* less than.05. Hence there is a significant difference in all the financial ratios except for the liquidity ratio, namely current and quick ratio and debtor's turnover ratio.

The output of the MWW test for non-financial variables indicates that five out of seven non-financial variables, similar to year T-2 have two-tailed *p* values less than 0.05. While the age of the company and duality in CEO have *p* value more than 0.05 which leads to not rejecting null hypothesis 2. Hence there is significant difference between default and healthy companies.

### 6.1.1e Summary of data analysis and results (Year T-4)

In the year T-4, debt equity ratio, return on capital employed, return on assets, fixed asset turnover ratio, quick ratio and interest coverage ratio had p values less than 0.05. There is a significant difference in these financial ratios between default and non-default companies and hence H1 cannot be rejected. Further, the p value is more than 0.05 for current ratio, total asset turnover ratio, debtor's turnover ratio, inventory turnover ratio, gross profit ratio and return on net worth. Hence null hypothesis 1 cannot be rejected for these ratios stated.

The results of MWW test statistics for non-financial variables for the year T-4states that five out of seven non-financial variables, similar to year T-2 and T-3 namely board size, promoter shareholding, institutional ownership, non-institutional ownership and proportion of independent directors to the total directors have two-tailed *p* values less than 0.05. Accordingly, there are significant differences between the stated non-financial variables between default and non- default companies for the year T-4. The age of the company and duality in CEO have p value more than 0.05. Hence null hypothesis 2 cannot be rejected for these two variables. Overall using MWW test, it is evident that as the years are near to default, the default companies have a significant difference in the performance as compared to non-default healthy companies.

### 6.1.2 Objective 2: To study the impact of financial factors on the level of financial distress

Hypothesis 3 was associated with this objective. Hypothesis 3 states that the extracted financial factors are significant predictors of firm's financial distress. The above objective was achieved by running a multiple regression analysis. The independent variables for fitting the regression model was extracted with the help of factor analysis conducted every year from T to T-4. The basic purpose of using factor analysis was to reduce the multicollinearity between the financial ratios and also to reduce the large number of financial ratios to several financial factors. The extracted key financial factors were then served as inputted independent variables for running multiple regression each year.

#### 6.1.2a Summary of data analysis and results (Year T)

In the year T, return on net worth, inventory turnover ratio, current ratio, interest coverage ratio, debt equity ratio and fixed asset turnover ratio were considered as independent variable and Altman Z Score was considered as the dependent variable.

In the year T, it is observed that return on net worth, inventory turnover ratio, current ratio and fixed asset turnover ratio were significant at 5% level of significance as the p value was less than 0.05. Hence, these ratios turned to be a significant prognosticator of firm's financial distress in the year T.

#### 6.1.2b Summary of data analysis and results (Year T-1)

In order to achieve Hypothesis 3, factor analysis and multiple regression was run. In factor analysis, among the six factors grouped, return on net worth, inventory turnover ratio, current ratio, interest coverage ratio, debtor's turnover ratio and debt equity ratio were extracted as independent variables for running multiple regression.

Based on multiple regression analysis, it was observed that return on net worth, inventory turnover ratio, current ratio and debtor's turnover ratio are significant at 5% in the year T-1. Other factors such as debt equity ratio and interest coverage ratio did not have significant power in explaining the level of financial distress.

#### 6.1.2c Summary of data analysis and results (Year T-2)

Similar to year T and T-1, six factors were extracted with the help of factor analysis. In the year T-2, return on net worth, inventory turnover ratio, current ratio, interest coverage ratio and the fixed asset turnover ratio had a p value less than 0.05. Hence, these ratios have a significant effect on prediction of financial distress. Debt equity ratio did not influence the level of financial distress in the year T-2.

#### 6.1.2d Summary of data analysis and results (Year T-3)

Initially, factor analysis was conducted and six factors were extracted for the year T-3as a first step in achieving hypothesis 3. Hypothesis 3 states that the extracted financial factors are significant predictors of firm's financial distress.Return on assets, return on net worth, current ratio, inventory turnover ratio, interest coverage ratio and total asset turnover ratio was considered as independent variable based on factor analysis to fit the regression model and Altman Z score was considered as the dependent variable. The results from multiple regression analysis state that interest coverage ratio, return on assets and asset turnover ratio had no influence on the prediction of financial distress. However, the current ratio, inventory turnover ratio and the return on net worth influenced the distress prediction as the *p* value of these ratios were lesser than 0.05.

#### 6.1.2e Summary of data analysis and results (Year T-4)

Current ratio, inventory turnover ratio, interest coverage ratio, gross profit ratio, fixed asset turnover ratio and debt equity ratio were extracted as independent variables using factor analysis in the year T-4. The distress level computed with Altman Z Score was considered as the dependent variable.

Based on the regression analysis, only inventory turnover ratio had a p value less than 0.05 for the year T-4. While all the other ratios showed that they did not influence the company's financial distress. In other words, the extracted financial variables did not influence the distress level except for inventory turnover ratio for the year T-4.

### 6.1.3 Objective 3: To analyze the impact of non-financial factors on the level of financial distress.

Hypothesis 4a, 4b, 4c, 4d, 4e and 4f is related to objective 3 trying to analyze the impact of non-financial factors on the chances of default. Logistic regression was used to test these hypotheses.

Hypothesis 4a states that firms with higher level of promoter shareholding have less chances of financial distress. Based on logistic regression analysis, it was observed that promoter shareholding had no influence on the companies going to default status. This also indicates that the promoters are submissive, having less control on reviving financial distress situation.

Hypothesis 4b states that there is a significant difference between non-institutional ownership concentration and chances of financial distress. This is not rejected in the present study as the logistic regression result gives a p value less than 0.05.

The results of non-institutional shareholders showed an inverse relationship with negative beta co-efficient. The *p* value is also less than 0.05. Hence, there is a significant difference between non-institutional shareholder's ownership and chances of company facing financial distress situation. This is similar to the previous empirical evidence provided by Lee and Yeh (2004) and Mangena and Chamisa (2008). Thus, the hypotheses H4b is supported by the results.

Hypothesis 4c states that there is a significant difference between institutional ownership concentration and chances of financial distress. This is also accepted in the present study as the logistic regression result gives a p value less than 0.05.

Hypothesis $4_d$ states that companies with duality in CEO have greater chances of financial distress. This is not accepted in the present study as the *p* value is more than 0.05. This depicts that dual leadership has no impact on corporate performance.

Hypothesis 4*e* states that companies with high proportion of independent directors have less likelihood of financial distress. The hypothesis is accepted in the study as the *p* value is less than 0.05.

Hypothesis $4_f$ states that companies with high board size have less likelihood of financial distress. The results of logistic regression depict that the *p* value in terms of board size is significant at 5 percent. Due to greater accountability of directors, possessing a wide range of ideas and external relations, there is less possibility of companies becoming default. Hence H*4f* cannot be rejected.

### 6.1.4 Objective 4: To ascertain the stock market response to the default announcement.

Hypothesis 5 is related to the present objective. The hypothesis 5 states that there is a negative market response to default announcement. The main findings from the present study are that a major portion of CAARs is negative at or before the announcement date. This depicts that either there was a leakage of information to the market before the event day or the market expected the happening of default. Overall, the results suggest that announcements of financial distress are associated with negative abnormal returns.

## 6.2 LIMITATIONS OF THE STUDY

The interpretation of empirical results in the study should be made with the acknowledgement of the number of limitations. The following are the limitations of the study:

### 6.2.1 Limited Time Period

The study is restricted to five years. The study could provide vary if longer time is taken for the study. Due to lack of availability of data for uniform number of years across the companies, information for five years before the default was considered. Further, the data pertaining to post- default is not available. Hence, event window is constructed only up to the point of time the information is available.

### 6.2.2 Small sample size of financially defaulted companies

In the present study, the small number of companies is another limitation. Due to lack of availability of data pertaining to default companies in the public domain, the study focuses on the companies for which complete financial and non-financial data is available. Hence the sample size is limited. Further, in order to achieve the fourth objective, only listed companies were considered. Among the 175 default companies, only 79 were listed.

## 6.3 DIRECTIONS FOR FURTHER RESEARCH

### 6.3.1 Include more variables

The corporate governance variables used in the present study could be further researched in other facets since corporate governance mechanisms relate to various aspects of corporate. For instance, the board's remuneration, frequency of meetings, structure of audit committee, structure of remuneration committee and so on. The frequency of the enterprise delaying the payment of bank loans, the magnitude of the enterprise's short-term debt and the number of the enterprise's correspondent banks could also be included which cannot be obtained from publicly available information. Macroeconomic variables like GNP, interest rates, etc. could be employed to study the financial distress model.

### 6.3.2 Sector-wise Comparison

Incidence of corporate financial distress might vary between different industrial sectors and the models for predicting financial distress can be exclusively designed for particular industrial sectors.

### 6.3.3 Study on Willful Defaulters

Willful defaulters could be studied as a separate sample in addition to default and non-default companies.

## 6.4 CONTRIBUTION OF THE THESIS

### 6.4.1 Theoretical contribution

In the present study, a financial distress prediction model, which uses financial ratios, non-financial variables and stock market, was established. In addition, stock market response to the default announcement was also observed. The predictive ability of this model is greater than the model which only considers financial ratios and this model is particularly useful for predicting the financial distress of Indian companies.

### 6.4.2 Practical contribution

In the earlier studies, companies in general, irrespective of the distress level, sector-wise were considered in predicting financial distress particularly in the Indian context.

The present study compares the default companies declared by Reserve Bank of India with the non-default companies in predicting the factors influencing financial distress situation.

Market based data is valuable information for detecting the possibility of financial distress. The investors and the management can use market data in addition to financial data in examining corporate financial distress to enable them to make better decisions in relation to predicting corporate failure, which consequently might reduce losses.

### 6.4.3 Methodological Contributions

The study uses the three unique methodological technique to predict the default. First, the study uses factor analysis to identify the financial and non-financial factors which can be used to predict the financial distress. This increases the power of the explanatory variables selected for the prediction. Second, the study uses paired sampling technique to identify the factors which are not same in the financially distressed and financially sound companies. Finally, logistic regression is used to test the effectiveness of a indicator in predicting the financial default.

## 6.5 CONCLUSION

This thesis focuses on examining financial distress situations of default and healthy companies considering financial and non-financial factors. Overall, the results suggest that financial ratios do help in predicting the distress level. Further, institutional and non-institutional ownership do affect the financial distress situation. There are high chances of suffering with financial difficulty for firms having large proportion of independent directors. Overall, the study evidences that board configuration do influence and contribute to the incidences of financial default of the companies. In terms of stock market responses to default situation, the market differentiates the outcome of the firms around the announcements of default.

## References

Aasen, M. R. (2011), Applying Altman's Z-score to the financial Crisis. An empirical study of financial Distress on Oslo Stock Exchange, (Unpublished Master's Thesis), Norwegian School of Economics, Norway.

Abdullah, N. A. H., & Ahmad, A. H. (2008). Predicting corporate failure of Malaysians listed companies: Comparing multiple discriminant analysis, logistic regression and the hazard model*International Research Journal of Finance and Economics*(15), 201-217.

Abeywardhana D.K.Y, (2015), Capital Structure and Profitability: An Empirical Analysis of SMEs in the UK,*Journal of Emerging Issues in Economics, Finance and Banking,* 4 (2)

Abor, J. (2007). Corporate Governance and Financing Decisions of Ghanaian Listed Firms, *International Journal of Business in Society*, 7.
Adeyemi, B. (2012), Bank Failure in Nigeria: A Consequence of Capital Inadequacy, Lack of Transparency and Non-Performing Loans,*Banks and Bank System,* 6(1), 99- 109

Aharony J., Jones C.P., & Swary, I. (1980), An Analysis of risk and return characteristics of corporate bankruptcy using capital market data, *Journal of Finance,*

35, pp 1001-1016.

Ahmad Khaliq, Basheer Hussein Motawe Altarturi, Hassanudin Mohd Thas Thaker, Md Yousuf Harun, Nurun Nahar (2014), Identifying Financial Distress Firms: A Case Study of Malaysia's Government Linked Companies (GLC), *International Journal of Economics, Finance and Management*, 3(3).

Ajinkya, B., Bhojraj, S. and Sengupta, P. (2005), The association between outside directors, institutional investors and the properties of management earnings forecasts, *Journal of Accounting Research,* 43(3), 343-376.

Altman, E.I. (1968a), Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance*, 23(4), 589-609.

Altman, E.I. and Brenner, M. (1981), Information effects and stock market response to signs of firm deterioration', *Journal of Financial and Quantitative Analysis,* 16(1), 35-51.

Altman E.I., Narayanan P., (1997), An international survey of business failure classification models,*Financial Markets, Institutions and Instruments,* Vol. 6(2), p. 1-57.

Altman, E. I., Haldeman, R. G. and Narayanan, P. (1977), ZETA analysis: A new model to identify bankruptcy risk of corporations, *Journal of Banking and Finance*, 1(1)

Altman, E. I., & Hotchkiss, E. (2006),*Corporate Financial Distress and Bankruptcy* (3rd ed.). John Wiley & Sons, Inc., Hoboken, New Jersey.

Amendola, A., Restaino, M., & Sensini, L. (2015). An analysis of the determinants of financial distress in Italy: A competing risks approach. *International Review of Economics & Finance, 54*(1), 396–404. https://doi.org/http://dx.doi.org/10.1016/j.iref.2014.10.012

Audretsch, D.B. and Lehmann, E.E. (2004),*The effects of experience, ownership and knowledge on IPO survival: Empirical evidence from Germany*, Discussion Paper, The Group Entrepreneurship, Growth and Public Policy, Jena, Germany.

Audretsch, D. B and Mahmood, T. (1995), New firm survival: New results using a hazard function, *The Review of Economics and Statistics,* 77(1), 97-103.

Babalola, S. S. (2009). Perception of Financial Distress and Customers Attitude towards Banking, *International Journal of Business and Management*, 4(10), 81-88.

Bai, C.E., Liu Q., J. Lu and F. M. Song, J. Zhang, (2004), Corporate governance and market valuation in China, *Journal of Comparative Economics*, 32, 599-611.

Bai, C.E., Liu, Q., Lu, J., Song, F.M. and Zhang, J.(2004), Corporate governance, insider ownership and operating performance of Australian initial public offerings, *Accounting and Finance*, 44(3), 299-328.

Balatbat, M.C.A., Taylor, S.L. and Walter T.S. (2004), Çorporate governance, insider ownership and operating performance of Australian initial public offerings, *Accounting and Finance*, 44(3), 299-328.

Balcaen, S., and Ooghe, H. (2006). 35 years of studies on business failure: an overview of the classic statistical methodologies and their related problems, *The British Accounting Review*, 38(1), 63-93.

Bapat, V., and Nagale, A. (2014), Comparison of Bankruptcy Prediction Models: Evidence from India,*Accounting and Finance Research*, 3(4), p91.

Beaver, W.H.( 1966), 'Financial ratios as predictors of failure', *Empirical Research in Accounting: Selected Studies,* Supplement to Vol.4, 71-111.

Beaver, W.H. (1968a), Alternative accounting measures as predictors of failure, *The Accounting Review*, 43(1), 113-122.

Beaver, W. H., McNichols, M.F. and Rhie, J.-W. (2005), Have financial statements become less informative? Evidence from the availability of financial ratios to predict bankruptcy, *Review of Accounting Studies*, 10(1), 93-122.

Beaver, W.H., McNichols, M.F. and Rhie, J.-W. (2005), Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy, *Review of Accounting Studies,* 10(1), 93-122.

Bebchuk, L., (1988), A New Approach to Corporate Reorganizations. Harvard Law Rev. 101:

Becht, M., Bolton, P. and Roell, A.A. (2002), *Corporate governance and control,* Finance Working Paper No. 02/2002, European Corporate Govrnance Institute.

Bi-Huei Tsai, (2013), An Early Warning System of Financial Distress using Multinomial Logit Models and a Bootstrapping Approach, *Emerging Markets Finance and Trade*, Vol.49, (S2) 43-69.

Boubaker, S., Hamza, T., & Vidal-García, J. (2018). Financial distress and equity returns: A leverage-augmented three-factor model. *Research in International Business and Finance*, *46*, 1–15. https://doi.org/https://doi.org/10.1016/j.ribaf.2016.09.003.

Brickley, J.A., Coles, J.L. and Jarell, G. (1997), Leadership structure: Separating the CEO and chairman of the board, *Journal of Corporate Finance,* 3(3), 189-220.

Brennan, N. and Mc Dermott, M, (2004), Alternative perspectives on independence of directors, *Corporate Governance: An International Review,* 12(3), 325-336.

Brownbridge, M. (1998), Financial Distress in Local Banks in Kenya. Nigeria,Ug anda and Zambia: Causes and Implications for Regulatory Policy, (Working Paper No 132) Retrieved from uncad.org/en/docs/dp_132.en.pdf

Campbell John Y., Jens Hilscher, and Jan Szilagyi, (2008), In search of distress risk, *Journal of Finance*, 63, 2899-2939.

Carmichael, D.R. (1972), The Auditor's Reporting Obligation, Auditing Research Monograph No. 1 (New York: AICPA).

Chaganti, R. S., Mahajan, V. and Sharma, S. (1985), Çorporate board size, composition and corporate failures in retailing industry, *Journal of Management Studies,* 22(4), 400-417.

Chan, K.C. and Chen, N.F. (1991), Structural and return characteristics of small and large firms, *Journal of Finance,* 46(4), 1467-1484.

Charalambakis, E. C., & Garrett, I. (2016). On the prediction of financial distress in developed and emerging markets: Does the choice of accounting and market information matter? A comparison of UK and Indian Firms. *Review of Quantitative Finance and Accounting*, *47*(1), 1–28. https://doi.org/10.1007/s11156-014-0492-y

Chatterjee, A. (2018). Predicting Corporate Financial Distress for Widely Held Large - Cap Companies in India : Altman Model vs. Ohlson Model. *Indian Journal Of Finance*, *12*(8), 36-49.

Charitou, A., Neophytou, E. and Charalambous, C. (2004), Predicting corporate failure: Empirical evidence for the UK, *European Accounting Review,* 13(3), 465-497.

Chiaramonte, L., & Casu, B. (2017). Capital and liquidity ratios and financial distress. Evidence from the European banking industry. *The British Accounting Review*, *49*(2), 138–161. https://doi.org/https://doi.org/10.1016/j.bar.2016.04.001

Chen, K.C.W., & Lee, C.W.J. (1993), Financial Ratios and Corporate Endurance: A case of the Oil and Gas Industry, *Contemporary Accounting Research*, 9(2), 667-694.

Choudhary H. and Tripathi G. (2012), An Analysis of Inventory Turnover and its Impact on Financial Performance in Indian Organized Retail Industry, *Journal of Services Research*, 12(1), pp. 43-63.

Chou, H.-I., Li, H., & Yin, X. (2010). The effects of financial distress and capital structure on the work effort of outside directors. *Journal of Empirical Finance*, *17*(3), 300–312. https://doi.org/https://doi.org/10.1016/j.jempfin.2009.12.005

Claessens, S. and Djankov, S. (1999), Ownership concentration and corporate performance in the Czech Republic, *Journal of Comparative Economics, 27(3), 498-513.*

Claessens, S., Klapper, L.,(2005), Bankruptcy around the World: Explanations of its Relative Use, *American Law and Economic Review*, 7: 253-83.

Clemente-Almendros, J. A., & Sogorb-Mira, F. (2018). Costs of debt, tax benefits and a new measure of non-debt tax shields: examining debt conservatism in Spanish listed firms. *Revista de Contabilidad*, *21*(2), 162–175. https://doi.org/https://doi.org/10.1016/j.rcsar.2018.05.001

Cowen, S.S. & Hoffer, J.A. (1982),Usefulness of financial ratios in a single industry, *Journal of Business Research*, March, 10(3), 80–89.

Clark, T.A. and Weinstein, M.I. (1983), The behavior of the common stock of bankrupt firms, *Journal of Finance,* 38(2), 489-504.

Cowen, S.S. & Hoffer, J.A. (1982). Usefulness of financial ratios in a single industry,*Journal of Business Research*, 10(3), 80–89.

Cybinski P (2001),Discription, Explanation, Prediction the Evolution of Bankruptcy Studies, Faculty on International Business and Politics. Giftin University. Brisbane 27(4): 29-44.

Dambolena, I. G. and Dalton, D. R. (1994), Corporate governance and the bankrupt firm: An empirical assessment, *Strategic Management Journal*, 15(8), 643-654.

Dambolena, I. G. and Khoury, S. J. (1980), Ratio stability and corporate failure, *Journal of Finance*, 35(4), 1017-1026.

Darcey McVanel and Nikita Perevalov (2016), Financial Constraints and the Cash-HoldingBehaviour of Canadian Firms, Bank of Canada, Discussion Paper/Document d’analyse www.bank-banque-canada.ca

Dejan Jovanovic, Mirjana Todorovic, Milka Grbic, (2017), Financial Indicators As Predictors Of Illiquidity, *Romanian Journal of Economic Forecasting* –XX (1) 2017

Demsetz, H. and Lehn, K. (1985), The structure of corporate ownership: Causes and consequences, *The Journal of Political Economy,* 93(6), 1155-1177.

Dewaelheyns, N., and C. Van Hulle (2004). The Impact of Business Groups on Bankruptcy Prediction Modeling, Review of Business and Economics 4(1), 623-645. (2006).

DeYoung, R. (2003), The failure of new entrnats in commercial banking markets: A split-popultaion duration analysis, *Review of Financial Economics,* 12(1), 7-33.

Dichev, I.D. (1998), Is the Risk of Bankruptcy a Systematic Risk?*Journal of Finance,* 53(3), 1131-1147.

Dimitras ,A I,Zanakis S.H, and Zopounidis C (1996) A survey of business failures with an emphasis on prediction methods and industrial applications, *European Journal of operation research,90,487-503.*

Donaldson, L. (1990). The Ethereal Hand: Organizational Economics and Management Theory, *Academy of Management Review*, 1990, 15 (3), 369-381.

Donker, H., Santen, B., and Zahir, S. (2009). Ownership structure and the likelihood of financial distress in the Netherlands,*Applied Financial Economics*, 19, 1687–1696.

Doumpos, M. and C. Zopounidis (1998), A Multinational Discrimination Method for the Prediction of Financial Distress: The Case of Greece, *Multinational Finance Journal*, 3: 71–101.

Dragan Simić, Svetlana Simić, (2011), *A review: approach of fuzzy models applications in logistics, Computer Recognition System*s, Springer Berlin Heidelberg, 2011

Du Jardin, P., & Séverin, E. (2010), Dynamic analysis of the business failure process: a study of bankruptcy trajectories. Portuguese Finance Network

Dursun Delen, Cemil Kuzey, Ali Uyar, (2013), Measuring firm performance using financial ratios: A decision tree approach, Expert Systems with Applications

Elloumi, F., & Gueyie, J. (2001), Financial distress and corporate governance: An empirical analysis,*Corporate Governance*: *The International Journal of Business in Societ*y, 1, 15–23

Elsayed, K. (2007), Does CEO duality really affect corporate performance? *Corporate Governance: An International Review,* 15(6), 1203-1214.

Elkamhi, R., Ericsson, J., & Parsons, C. A. (2012). The cost and timing of financial distress. *Journal of Financial Economics*, *105*(1), 62–81. https://doi.org/https://doi.org/10.1016/j.jfineco.2012.02.005

Erkki K. Laitinen, (2005) Survival Analysis and Financial Distress Prediction: Finnish Evidence,*Review of Accounting and Finance*,4(4), pp.76-90

Fama, E.F. and French, K.R. 1992, The cross-section of expected stock returns, *Journal of Finance*, 47(2), 427-465.

Fama, E.F. and Jensen, M.C. 1983, Separation of Ownership and Control, *Journal of Law and Economics, 26, 301-325.*

Farooq, U., & Jibran, A. Q. (2017). Scope, measurement, impact size and determinants of indirect cost of financial distress: A systematic literature review. *Qualitative Research in Financial Markets*, *10*(1), 111–129. https://doi.org/10.1108/QRFM-08-2017-0080

Ferri, G., Hahm, H. and Bongini, P. (1998). Corporate Bankruptcy in Korea: Only the Strong Survive. World Bank Report.

Fitzatrick, P. (1932),A comparison of ratios of successful industrial enterprises with those of failed firms, *Certified Public Accountant*, 2, 598-605.

Flagg, J. C., Giroux, G. A. and Wiggins, C. E. (1991), Predicting corporate bankruptcy using failing firms, *Review of Financial Economics,* 1(1), 67-68.

Foster, G. (1986). Financial Statement Analysis.Retrieved from http://www.slieshare.net/ mpalash2/financial-statement-analysis-by-george-foster

Frydman, H., Altman E.I. and Kao, D. L. (1985), Introducing Recursive partitioning for financial classification: The case of financial distress, *Journal of Finance,* 40(1), 269-291.

Gaglani Hetal and Rao Smita, (2015), A Study on the liquidity, profitability abd financial health of Sun Pharmaceutical Ltd., *ZENITH International Journal of Business, Economics and Management Research*, 5(6)

Ganesalingam, S. and Kumar, K. (2001), Detection of financial distress via multivariate statistical analysis, *Managerial Finance,* 27(4), 45-46.

Gepp, Adrian & Kumar, Kuldeep (2012), Business failure prediction using statistical techniques: A review, business papers, faculty of Business, Bond University

Gestel, T. V., Baesens, B., Suykens, J.A.K., Van Den Poel, D., Baestaens, D. E. and Willekens, M. (2006), Bayesian kernel based classification for financial distress detection, *European Journal of Operation Research*, 172(3), 979-1003.

Gilbert, L. R., Menon, K. and Schwartz, K. B. (1990), Predicting Bankruptcy for Firms in Financial Distress, *Journal of Business Finance*, pp. 161-171.

Ginoglou, D., Agorastos, K. & Hatzigagios, T. (2002), Predicting Corporate Failure of Problematic Firms in Greece with LPM Logit Probit and Discriminant Analysis Models, *Journal of Financial Management & Analysis*, 15, 1, 1

Gleason K.C., Mathur I. and M. Singh (2000), Wealth effects for acquirers and divestors related to foreign divested assets, *International Review of Financial Analysis*, 9:1, 5-20.

Gokçehan Demirhan H and Waseem Anwar, (2014), Factors Affecting The Financial Performance Of The Firms During The Financial Crisis: Evidence From Turkey, *Ege Strategic Research Journal,* 10(1)

Goktan, M.S., Kieschnick, R. and Moussawi, R. (2006), *Corporate Governance and corporate survival,* Working Paper, University of Texas at Dallas.

Griffin, J.M and Lemmon, M.L. 2002, 'Book-to-market equity, distress risk, and stock returns', *TheJournal of Finance,* 57(5), 2317-2336.

Harris, M. & Raviv, A. (2008). A Theory of Board Control and Size. The Review of

Financial Studies, 21(4), 1797-1832.

Hensher, D.A., Jones, S. and Greene, W.H. (2007), Án error component logit analysis of corporate bankruptcy and insolvency risk in Australia, *Economic Record, 83 (260), 86-103.*

Hensler, D.A., Rutherford, R.C. and Springer, T.M. (1997), The survival of initial public offereings in the aftermarket, *Journal of Financial Research,* 20(1), 93-110.

Her, Y-W. and Choe C. (1999). A Comparative Study of Australian and Korean Accounting Data in Business Failure Prediction Models. La Trobe University Working Paper 99.07.

Hill, C.W.L. and Snell, S.A. (1989), Effect of ownership structure and control on corporate productivity, *Academy of Management Journal*, 32(1), 25-46.

Hill, N.T., Perry, S.E. and Andes, S. (1996), Evaluating firms in financial distress: An event history analysis, *Journal of Applied Business Research,* (12) 3, 60-71.

Honjo, Y. (2000), Business failure of new firms: An empirical analysis using a multiplicative hazards model, *International Journal of Industrial Organisation,* 18(4), 557-574.

Hossari, G. and Rahman, S. (2005), A comprehensive formal ranking of the popularity of financial ratios in multivariate modeling of corporate collapse, *Journal of American Academy of Business,* Cambridge, 6(1),321-327.

Hovey, M., Li, L. and Naughton, T. (2003), The relationship between valuation and ownership of listed firms in China, *Corporate Governance: An International Review*, 11(2), 112-122.

Hsin-Hung Chen, (2008), The Timescale Effects of Corporate Governance Measure on Prediciting Financial Distress, *Rev. Pac. Basin Finan. Mark. Pol.*, **11**, 35.
Iotti, M. and G. Bonazzi, 2012. EBITDA/EBIT and cash flow based ICRs: A comparative approach in the agro-food system in Italy. Financial Asset Invest., 2: 19-31. DOI: 10.5817/FAI2012-2-2
Izan, H. (1984). Corporate Distress in Australia,*Journal of Banking & Finance*, 8(2), 303-320.

James, C. (1996), Bank debt restructuring and the composition of exchange offers in financial distress. *Journal of Finance*, Vol. 51, pp. 711-27.

Jensen, M. C. (1993), 'The modern industrial revolution, exit, and the failure of internal control systems', *The Journal of Finance,* 48(3), 831-880.

Jensen, M.C. and Meckling, W.H. (1976), 'Theorem of the firm: Managerial behavior, agency costs and ownership structure', *Journal of Financial Economics,* 3(4), 305-360.

June Li,(2012), Prediction of Corporate Bankruptcy from 2008 Through 2011, *Journal of Accounting and Financ,* 12(1).

Jung, S. E., & Lindner, P. (2014), Corporate Vulnerabilities in India and Banks' Loan Performance.

Joo-Ha Nam, Taehong Jinn, (2000), Bankruptcy Prediction: Evidence from Korean Listed Companies during the IMF Crisis, *Journal of International Financial Management and Accounting,* 11:3 2000

Kam A, D Citron and G Muradoglu (2008), Distress and Restructuring in China: Does Ownership Matter?**,** *China Economic Review*, 19(4), p.567-579;

Kam A., Citron, D. and Muradoglu, G. (2010), Financial distress resolution in China two case studies**,** *Qualitative Research in Financial Markets*, 2(2), p.46-79;

Kang, H., Cheng, M. and Gray, S. J. (2007), Corporate governance and board composition: Diversity and independence of Australian boards, *Corporate Governance: An International Review*, 15(2), 194-207.

Kang J. K., I. Lee, and H. S. Na (2010), Economic shock, owner-manager incentives, and corporate restructuring: Evidence from the financial crisis in Korea, *Journal of Corporate Finance*,16, pp. 333–351.

Kauffiman, R.J. and Wang, B. (2007), *Duration of internet firms: A semiparametric Cox and baysian survival analysis,* Working Paper, Carlson School of Management, University of Minnesota.

Keasey, K. and McGuinness, P. (1990) The failure of UK industrial firms 1976–1984, logistic analysis and entropy measures, Journal of Business Finance and Accounting, 17(1), pp. 119– 135

Keasey, K., & Watson, R. (1987). Non-Financial Symptoms and the Prediction of Small Company Failure : a Test of Arcenti ' S Hypotheses. *Journal of Business Finance & Accounting*, *14*(3), 335–354. doi:Article

Keating, E., Fischer, M., Gordon, T., & Greenlee, J. (2005). Assessing financial vulnerability in the nonprofit sector (Harvard University Faculty Research Working Paper Series No. 27). Cambridge, MA: Hauser Center for Nonprofit Organizations.

Kellen K. Kiambati, Patrick Ngugi, Paul Katuse, and Anthony Waititu, (2013), Role of board size on financial performance of commercial banks,*Prime Journal of Social Science*, 2(3), pp. 259-262.

Khalfan, T., & Sturluson, J. Þ. (2018). Corporate finance approaches of Icelandic private firms after the financial crisis. *Managerial Finance*, *44*(11), 1274–1291. https://doi.org/10.1108/MF-05-2017-0167

Khan, M. Y. and Jain, P. K. (2004). *Financial Management, Text Problems and Cases*, 4th ed. Tata McGraw-Hill Publishing Company Ltd, New Delhi,

Khasnobis, S. (2008), NPAs Emerging Challenges in India,*RBI Bulletin*. Mumbai.

Khunthong, J. (1997), 'Red flags of financial failure: The case of Thai corporations', Ph.D. thesis, The National Institute of Development Administration, Thailand

Kiel, G.. C., & Nicholson, G. J. 2003 Board Composition and Corporate Performance: How the Australian Experience Informs Contrasting Theories of Corporate Governance. Corporate Governance, 48, 189-205.

Kim, M. H. & Partington, G. (2014). Dynamic forecasts of financial distress of Australian firms, *Australian Journal of Management*, 40 (1).

Kimathi, C. M., & Mungai, J. (2018). Financial Distress and Profitability of Tier Three Commercial Banks in Kenya. *American Journal of Finance*, *3*(1), 46–66.

Kuo, H.-C., Wang, L.-H., Sheu, H.-J., & Li, F.-K. (2003). Credit Evaluation for Small and Medium-sized Enterprises by the Examination of Firm-specific Financial Ratios and Non-financial Variables: Evidence from Taiwan. *Review of Pacific Basin Financial Markets and Policies*, *06*(01), 5–20. https://doi.org/10.1142/S0219091503000980

Laitinen, E.K., & Laitinen, T. (2000), Bankruptcy prediction: Application of the Taylor's expansion in logistic regression,*International Review of Financial Analysis*, 9(4), 327-349.

Li, L. and Naughton, T. (2007), Going public with good governance: Evidence from China, *Corporate Governance: An International Review*, 15(6), 1190-1202.

Lindsay, D.H. and Campbell, A. (1996), A chaos approach to bankruptcy prediction, *Journal of Applied Business Research*, 12(4),1-9.

López-Gutiérrez, C., Sanfilippo-Azofra, S., & Torre-Olmo, B. (2015). Investment decisions of companies in financial distress. *BRQ Business Research Quarterly*, *18*(3), 174–187. https://doi.org/https://doi.org/10.1016/j.brq.2014.09.001

J. (2000), The occurrence and timing of events: Survival analysis applied to the study of financial distress, *Journal of Accounting Literature*, 19, 158-159.

Lamberto, A.P. and Rath, S. (2008), *The survival of initial public offerings in Australia*, Working Paper, Curtin University of Technology.

Lee, S., Peng,M.W., Barney, J.B., (2007), Bankruptcy law and Entrepreneurship Development: a real options perspective. Academy of Management Review, 32(1): 257–272.

Lennox, C. (1999), 'Identifying failing companies: A re-evaluation of the logit, probit and DA approaches', *Journal of Economics and Business*, 51(4), 347-364.

Lin, T.H. (2009), A Cross Model Study of Corporate Financial Distress Prediction in Taiwan: Multiple Discriminant Analysis, Logit, Probit and Neural Networks Models, Neurocomputing 72: 3507–3516.

Lipton, M. and Lorsch, J.W.1992, A modest proposal for improved corporate governance', *Business Lawyer*, 48(1), 59-77.

Lizal, L. (2002), *Determinants of financial distress: What drives bankruptcy in a transition economy? The Czech Republic case*, Working Paper No. 451, William Davidson.

López-Gutiérrez, C., Sanfilippo-Azofra, S., & Torre-Olmo, B. (2015). Investment decisions of companies in financial distress. *BRQ Business Research Quarterly*, *18*(3), 174–187. https://doi.org/https://doi.org/10.1016/j.brq.2014.09.001

Lubica, Lesakaova (2007), Uses and Limitations of Profitability Ratio Analysis in Managerial Practice, 5th International Conference on Management, Enterprise and Benchmarking, Hungary.

Lu, Ralph and Shen, Chung-Hua and Wei, Yu-Chen, Revisiting Early Warning Signals of Corporate Credit Default Using Linguistic Analysis (February 8, 2013). Available at SSRN:https://ssrn.com/abstract=2214840 or http://dx.doi.org/10.2139/ssrn.2214840

Luoma, M. and Laitinen, E. (1991), Survival analysis as a tool for company failure prediction, *Omega*, 19(6), 673-678.

Mahmood, J.A. & Talal, A. (2009). Research presented to the Seventh International Scientific Conference of Zarqa Private University.
Ma-Ju Wang (Taiwan), Heng-Ruei Shiu (Taiwan),(2014), Research on the common characteristics of firms in financial distress into bankruptcy or recovery, *Investment Management and Financial Innovations*, 11(4)

Mangena, M., & Chamisa, E. (2008),Corporate governance and incidences of listing suspension by the JSE Securities Exchange of South Africa: An empirical analysis,*The International Journal of Accounting*, 43, 28–44.

Margaritis,D. and Psillaki,M., (2010),Capital Structure, Equity Ownership and Firm

Performance, *Journal of Banking and Finance,* 34:621-632.

Mata, J. and Portugal, P. (1994), Life duration of new firms, *The Journal of Industrial Economics*, 42(3), 227-245.

McGurr, P.T., & DeVaney, S.A. (1998). Predicting business failure of retail firms: An analysis using mixed industry models,*Journal of Business Research*, 43(3), 169-176.

Michael Dothan, (2006),Costs of Financial Distress and Interest Coverage Ratios, *The Journal of Financial Research*, Volume 29, Issue 2. Michael Jacobs Jr, Ahmet K. Karagozoglu, Dina Naples Layish, (2016) Credit risk signals in CDS market vs agency ratings, *The Journal of Risk Finance*,17(2), pp.194-217

Ming-Chang Lee and Li-Er Su, (2015), Comparison Of Wavelet Network And Logistic Regression In Predicting Enterprise Financial Distress, *International Journal of Computer Science & Information Technology*, 7(3)

Molinero, C.M. and Ezzamel, M. (1991), Multidimensional Scaling applied to corporate failure, *Omega,19(4), 259-274.*

Mossman, C.E., Bell, G.G., Swartz, L.M. and Turtle, H. (1998), An empirical comparison of namkruptcy models, *Financial Review*, 33(2)

Natalia, O. (2007), Corporate Financial Distress: An Empirical Analysis of Distress Risk, (Doctorial Dissertation No. 3430, University of St. Gallen, St. Gallen, Switzerland).

Naz Sayari, Can Simga Mugan F.N., (2013), Cash Flow Statement as an Evidence for Financial Distress, *Universal Journal of Accounting and Finance*, 1(3): 95-103,

Nicolas Emanuel Monti, Roberto Mariano Garcia, (2010), A Statistical Analysis to Predict Financial Distress,*Journal of Service Science & Management*, Vol. 3

Nikitin, G. (2003), *Plant failure and survival in the Indonesian financial crisis,* Working Paper, Boston Univesity.

Nilesh P. Movalia, (2015), A Study on Capital Structure Analysis and Profitability of Indian Tyres Industry*, Pacific Business Review International,* 8(3).

Nirajini,A , Priya,K B, (2013), Impact of Capital Structure on Financial Performance of the Listed Trading Companies in Sri Lanka, *International Journal of Scientific and Research Publications*, 3(5)

Nizar Baklouti, Frederic Gautier, Habib Affes (2016), Corporate Governance and Financial Distress of European Commercial Banks, *Journal of Business Studies Quarterly*, Vol. 7, No. 3

Odom, M. D. and Sharda, R. (1990), A neural network model for bankruptcy prediction, Proceedings of Neural Networks, 1990, 163-168.

Ohlson, J.A.(1980), 'Financial ratios and the probabilistic prediction of bankruptcy',*Journal of Accounting Research,* 18(1), 109-131.

O'Neill, H. (1986), An Analysis of the Turnaround Strategy in Commercial Banking *Journal of Management Studies*, 165-188.

Ooghe H, De Prijcker S (2008). Failure Process and Causes of Company Bankruptcy: a Typology, *Manage. Decis*., 46(2): 223-242.

Opler, T. C & Titiman, S. (1994). Finance Distress and Corporate Performance,*TheJournal of Finance*, 49(3), 1015-1040.

Outecheva, N. (2007), Corporate Financial Distress: An Empirical Analysis of Distress Risk, (Unpublished doctoral dissertation),University of St Gullen,Switzerland.

Padhiary, P. K., & Mishra, A. P. (2011). Development of improved artificial neural network model for stock market prediction,*International Journal of Engineering Science and Technology*, 3(2), 1576-1581

Parker, S., Gary, F., & Howard, F. (2002). Corporate governance and corporate failure: A survival analysis,*Corporate Governance*: *The International Journal of Business in Society*, 2, 4–12.

Pálinkó, É., & Svoób, Á. (2016). Main Causes and Process of Financial Distress. *Public Finance Quarterly*, *61*(4), 516–532.

Parker, S., Peters, G. & Turetsky, H. (2002a), *Corporate governance factors and auditor going concern assessments*, Working Paper, Santa Clara University.

Peel, M. J. and Peel, D. A. (1988), A multilogit approach to predicting corporate failure – some evidence for the UK corporate sector, *Omega International Journal of Management Science*, 16(4), pp. 309– 318.

Perinpanathan, Rajkumar, (2014),Impact of Financial Leverage on Financial Performance: Special Reference to John Keells Holdings plc in Sri Lanka, *Scientific Research Journal*, 2 (2), 6

Petr Jakubík, Petr Teplý, (2011), The JT Index as an Indicator of Financial Stability of Corporate Sector, *Prague Economic Papers*, 2, 2011.

Pfeffer, J. and Salancik, G. R. (1978), *The external control of organisations: A resource dependence prespective* New York: Harper and Row.

Pham Vo Ninh, B., Do Thanh, T., & Vo Hong, D. (2018). Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam. *Economic Systems*, *42*(4), 616–624. https://doi.org/https://doi.org/10.1016/j.ecosys.2018.05.002

Piesse, J. and Wood, D& Foster, L. (1931). A Demonstration of Ratio Analysis, Bulletin 40, Bureau of Business Research, University of Illinois, Urbana.IL.

Platt, H.D. and Platt, M.B. (2002), Predicting corporate financial distress: Reflections on choice-based sample bias,*Journal of Economics and Finance,* 26(2), 184-199.

Rajasekar T, Sania Ashraf and Malabika Deo (2014), An Empirical Enquiry on the Financial Distress of Navratna Companies in India, *Journal of Accounting and Finance*, 14(3)

Rajeev, M., & Mahesh, H. P. (2010). Banking Sector Reforms and NPA: A study of Indian Commercial Banks. Working Paper Series 252, The Institute for Social and Economic Change, Bangalore.

Ranjan, R., & Dhal, S. C. (2003). Non-Performing Loans and Terms of Credit of Public Sector Banks in India: An Empirical Assessment,*Reserve Bank of India Occasional Papers*, *24*(3), 81–121.

Ray, S. (2011). Prediction of corporate financial distress in glass and glassware sector of India. *International Journal of Business Excellence*, *4*(6), 678–695. https://doi.org/10.1504/IJBEX.2011.042905

Rechner, P.L. and Dalton, D.R. (1991), CEO duality and organisational performance: A longitudinal analysis, *Strategic Management Journal*, 12(2), 155-160.

Reserve Bank of India, *Report on Trend and Progress of Banking in India, RBI, Various Issues*

Rizky, (2014). Pengaruh Struktur Kepemilikan terhadap Financial Distress dengan likuiditas sebagai variabel intervening. Unpublished Thesis. Jakarta: Universitas Mercu Buana.

Rommer, A. D. (2004), *Firms in financial distress: An exploratory analysis,* Working Paper No. 17, Danmarks National bank and Center for Applied Econometrics (CAM), Institute of Economics University of Copenhagen, Copenhagen, Denmark.

Rommer, A.D. (2005), *A Comparative analysis of the determinants of financial distress in French,Italian and Spanish firms*, Working paper, Danmarks National Bank, Copenhagen, Denmark.

Ross, S.A., R.W. Westerfield, and J.F. Jaffe (1999), *Corporate Finance*, Second ed., Homewood IL, Irwin/Mcgraw-Hill.

Routledge, J. and Gadenne, D. (2000), Financial distress, reorganization and corporate performance, *Accounting and Finance*, 40(3), 233-259.

Roychoudhury, A. (2016), Rajya Sabha passes Bankruptcy Code. Business Standard,p.7.

Samaresh Bardhan, Vivekananda Mukherjee, (2013), Willful Default In Developing Country Banking System: A Theoretical Exercise,*Journal Of Economic Development*38(4)

Sarbapriya Ray, (2011), Assessing Corporate Financial Distress in Automobile Industry of India: An Application of Altman's Model, *Research Journal of Finance and Accounting*, 2(3)

Scherrer, P. S. (2003) Management Turnarounds: Diagnosing Business Ailments, *Corporate Governance Journal*, Vol. 3, No. 4, pg 52-62

Schooley, D., Renner, S., Allen, M. (2010). Shareholder Proposals, Board Composition and Leadership Structure, *Journal of Managerial Issues*, 22(2), 152-165.

Shahwan, T. M. (2015). The effects of corporate governance on financial performance and financial distress: evidence from Egypt. *Corporate Governance: The International Journal of Business in Society*, *15*(5), 641–662. https://doi.org/10.1108/CG-11-2014-0140

Shilpa N. C, Amulya. M, (2017), Corporate Financial Distress: Analysis of Indian Automobile Industry, SDMIMD Journal of Management, Vol. 8 (1).

Shrabanti Pal, (2013), A Study On Financial Distress In Indian Steel Industry Under Globalization, *IOSR Journal of Business and Management.* 14(2).

Siraj, K. K., & Pillai, P. S. (2013). Efficiency of NPA Management in Indian SCBs, *Journal of Applied Finance & Banking*, *3*(2), 123–137.

Shumway, T. (2001), Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business,* 74(1), 101-124.

Smith, N., Smith, V. and Verner, M. (2005), *Do women in top management affect firm performance. A panel study of 2500 Danish firms,* Discussion papersNo. 1708, The Institute for the Study of Labor, Bonn.

Sulairnan, M., Jili, A., & Sanda, A. U. (2001), Predicting corporate failure in Malaysia: An application of the Logit Model to financial ratio analysis, *Asian Academyof Management Journal*, 6(1), 99-118.

Tamari, M. (1966),Financial Ratios as a Means of Forecasting Bankruptcy, *Management International Review* , 15-21

Tanna, S., F. Pasiouras, and M. Nnadi.(2011),The effect of board size and composition on the efficiency of UK banks. *International Journal of the Economics of Business* 18:3: 441-462.

Terje Lensberg, Aasmund Eilifsen, Thomas E. McKee., (2004), Bankruptcy theory development and classification via genetic programming, *European Journal of Operational Research* 169 (2006) 677–697

Thai Siew Bee, Abdollahi Mehdi, (2013), Corporate Failure Prediction: Malaysia's Emerging Market, *International Journal of Finance*, 25(4), 7985-8011

Tirapat, S. and Nittayagasetwat, A. (1999), An investigation of Thai listed forms'financial distress using macro and micro variables, *Multinational Finance Journal,* 3(), 103-125.

Turetsky, H.F. and McEwen, R.A. (2001), An empirical investigation of firm longevity: A model of the ex ante predictors of financial distress, *Review of Quantitative Finance and Accounting,* 16(4), 323-343.

Tykvova. T, and Borell. M. (2012), Do private equity owners increase risk of financial distress and bankruptcy? Journal of Corporate Finance, vol. 18, pp. 138–150.

Ugurlu, M. & Aksoy, H. (2006). Prediction of corporate financial distress in an emerging market: the case of Turkey, *Cross Cultural Management: An International Journal,* 13(4), 277-295.

Van der Goot, T., Van Giersbergen, N. and Botman, M. 2008, 'What determines the survival of internet IPOs,*Applied Economics*, 99999(1), 1-15.

Virag, M. & Kristof, T. (2005). Neural Networks in Bankruptcy Prediction-A Comparative Study on the Basis of the First Hungarian Bankruptcy Model, *Acta Oeconomica*, 55(4), 403-426.

Ward, T.J.. and Foster, B.P. (1997), A note on selecting a response measure for financial distress, *Journal of Business Finance and Accounting,* 24(6), 869-879.

Weir, C. and Laing, D. (2001), Governance strucutres,director independence and corporate performance in the UK, *European Business Review,* 13(2), 86-94.

Whitaker, R (1999), The Early Stages of Financial Distress,*Journal of Economics and Finance,* 23(2), 123-133.

World Bank (Doing business in 2005 -India Regional Profile)

Wruck, K (1990). Financial Distress, Reorganization, and Organizational Efficiency, *Journal of Financial Economics*, 27, 419-444.

Xu, X. and Wang, Y. (1999), Ownership structure and corporate governance in Chinese stock companies, *China Economic Review,* 10(1), 75-98.

Yu, X. (2006), *Competing risk analysis of Japan's small financial institutions,* Discussion Paper No. 2006-E-7, Institute for Monetary and Economic Studies.

Zapranis, A., & Ginoglou, D. (2000). Forecasting corporate failure with neural network approach: The Greek case, *Journal of Financial Management and Analysis*, 13(2), 11-20.

Zmijewski, M.E.,(1984), Methodological issues related to the estimation of financial distress prediction models, *Journal of Accounting Research,* Supplement to Vol.22, 59-82.

Zhi-Yuan Li1, (2015), Enterprise Financial Distress Prediction Based On Backward Propagation Neural Network: An Empirical Study On The Chinese Listed Equipment Manufacturing Enterprises, *U.P.B. Sci. Bull.*, Series C, Vol. 77, Iss. 1, 2015.

## ANNEXURE

### Sector-wise break-up of sample default companies

| Sector | Number |
|---|---|
| Auto Ancillary | 3 |
| Ceramics/Marble/Granite/Sanitaryware | 6 |
| Chemicals | 5 |
| Construction - Real Estate | 10 |
| Consumer Food | 6 |
| Diamond & Jewellery | 5 |
| Electronics - Components | 7 |
| Engineering | 7 |
| Film Production, Distribution & Entertainment | 4 |
| Finance - Investment | 14 |
| Hotel, Resort & Restaurants | 7 |
| IT - Software | 14 |
| Logistics | 8 |
| Mining & Minerals | 9 |
| Paper & Paper Products | 4 |
| Pesticides & Agrochemicals | 6 |
| Petrochemicals | 7 |
| Pharmaceuticals & Drugs | 6 |
| Plastic Products | 5 |
| Power Generation/Distribution | 10 |
| Steel & Iron Products | 7 |
| Telecommunication - Service Provider | 7 |
| Textile | 6 |
| Trading | 5 |
| Wood & Wood Products | 7 |
| Total | 175 |

# BIO DATA

**SHRIDEV**
Shivakripa,
Bankodi House,
Ananthashayana, Karkala,
Udupi District,
Karnataka, India

**Date of Birth**: 7th December, 1987

**Qualification:**

- Master of Business Administration - Mangalore University – First Class with distinction (2008-2010)
- Master of Commerce - Mangalore University– First Class
- Certified Analyst - Indian Institute of Banking and Finance – First Class (2012)
- Bachelor of Business Management – Mangalore university – First Class (2005l;-2008)

**Details of Publications:**

Prasad, K., Suprabha, K. R., & Shridev. (2018). Influence of financial distress on exchange rate exposure: evidence from India. Afro-Asian Journal of Finance and Accounting, 8(4), 389–403. https://doi.org/10.1504/AAJFA.2018.095239

Shridev, Suprabha K. R, Krishna Prasad, (2016), "Corporate Governance and Financial Distress: Evidence from Indian Companies", *International Journal of Economic Research,*13(7) (Published)

Shridev, Suprabha K.R, (2016), "Corporate Financial Distress and Stock Return:Evidence from Indian Stock Market", *Nitte Management Review*, 10(1). (Published)

Shridev, Suprabha K. R, Determinants of Financial Distress: Evidence from Indian Firms, *The International Journal of Accounting* (Under Review)

**Paper presented in Conference:**

1. Presented a paper titled "Performance and Efficiency of Indian Banks: A DEA Approach", in the International Conference on Business Paradigms in Emerging Markets at NIT Rourkela on 12th and 13th December, 2014.